FAST

Financial Allocation Study for Texas **2014**

Connecting the Dots:
School Spending and
Student Progress

Technical Appendix: FAST Methodology

Get the in-depth methodology behind the district and campus FAST results.

TABLE OF CONTENTS

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.

Texas Education Code Section 39.0821, 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 State Test math score
- prior-year State Test 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 4-5)
- grade by test interactions

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.

The Composite Academic Progress Percentile (CPP) is calculated as the average of math and reading progress. This represents a summary academic rating with equal weights given to math and reading.

Scores have the same interpretation as any percentile number. A campus CPP 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 Execu-tive Summary for a list of the technical team members). The model included all students with two consecutive years of State Test scores. For students who were retested, the highest score was used. Due to STAAR implementation, some students took STAAR in the current year, and TAKS in the previous year. These students were included in the study, since they have consecutive scores on the State Test. 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/STAAR 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/STAAR-Modified; or
- took TAKS/STAAR Linguistically Accommodated Testing.

Students who took TAKS/STAAR-Alternative tests were not included, unless their score was coded for inclusion in accountability 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/STAAR scores were excluded, as were any campuses or districts with fewer than 10 students.

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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 hierarchical linear modeling, to accommodate students, campuses and districts.[3] This approach measures academic growth by modeling current-year student achievement on TAKS/STAAR reading or mathematics by how the student performed in the prior year, 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 and campuses to academic growth. This technique is known as a multi-level, random intercepts mixed model, with students and campuses 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 current year score regressed on his or her prior-test score, and any characteristics important to maintaining fairness. 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/STAAR 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,…,57 for reading student-level variables
p = 1,…,64 for math 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 prior-year test score
a_2 = Math prior-year test score squared
a_3 = Reading prior-year test score
a_4 = Reading prior-year 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 current-year test, grades 4-5 (=1 if Spanish test)
a_{22} = Spanish-language prior-year reading, grades 4-5 (=1 if Spanish test)
a_{23} = Spanish-language test prior-year math, grades 4-5 (=1 if Spanish test)
a_{24} = Spanish-language test prior-year reading, grades 4-5 x Reading prior-year test score
a_{25} = Spanish-language test prior-year math, grades 4-5 x Math prior-year test score
a_{26} = Gifted class (=1 if Gifted)
a_{27} = Special education class (=1 if Special Education)
a_{28}-a_{57} = Grade x reading test interactions (e.g. =1 if English I and grade 8)
a_{28}-a_{64} = Grade x math test interactions (e.g. =1 if Geometry and grade 8)

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 $r_{0jk} \sim N(0; \tau_2^2)$

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 $\mu_{00k} \sim N(0; \tau_2^2)$

DISTRICT MODEL

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

The district level is:

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

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

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

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. 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.[4]

These calculated effects were best linear unbiased predictions, often called 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 existing 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 legislative requirements, the FAST project must identify efficient school expenditure practices that advance student achievement. The existing data are informative, but lack nuance needed for this analysis. For this report, the research team created new cost measures from existing indicators.

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 the American Community Survey to generate a Comparable Wage Index (ACS-CWI), which measures regional variations in the prevailing wage for college graduates. The ACS-CWI accounts for higher wages in areas with higher costs of living or without 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 ACS-CWI predicts that Dallas teachers and principals also should be paid 15 percent more than the Texas average for teachers and principals.

The study also adapted the ACS-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. 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:

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

All four cases require additional resources per student, including smaller required class sizes and specialized teachers and supplies. **Exhibit 1** describes the cost factors used in this analysis.[5]

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 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.[6] 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. The propensity score technique matches 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 requires 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.[7] 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).

EXHIBIT 1

DISTRICT COST FACTORS, THREE-YEAR AVERAGE 2011-2013

	MEAN	MINIMUM	MAXIMUM
INPUT PRICES			
COMPARABLE WAGE INDEX	0.91	0.76	1.09
HIGH SCHOOL COMPARABLE WAGE INDEX	0.93	0.81	1.08
SCHOOL DISTRICT SIZE			
ENROLLMENT	4,070	13	203,294
SQUARE MILES	265	5	4,866
STUDENT NEED			
PERCENT LIMITED ENGLISH PROFICIENT	9.03	0	93.7
PERCENT ECONOMICALLY DISADVANTAGED	59.83	0	100
PERCENT HIGH NEEDS SPECIAL EDUCATION	5.52	0	59.9
PERCENT OTHER SPECIAL EDUCATION	4.15	0	15.33

Sources: Texas Education Agency, U.S. Census Bureau and Texas Comptroller of Public Accounts..

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 campus-level data with a similar methodology. 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.

To facilitate comparisons over time, school district fiscal peers for 2014 are generally the same as the fiscal peers for 2013 and are there-fore based on data from the 2010, 2011 and 2012 school years. However, there are a few exceptions to this rule. Seven school districts (four of them charters) closed or were annexed to another district and therefore no longer exist in 2013. These districts have been re-placed by the next nearest neighbor whenever they were considered the fiscal peer of another district. Eight newly established charter school districts were assigned fiscal peers using the propensity score matches they would have been assigned had they been operational in 2012. In addition, one charter school district, Jaime's House Charter School, changed status and was reclassified as an Alternative Education Accountability (AEA) district for 2013.

School-level characteristics are more volatile, with many schools changing not only their size and student demographics but also their grade level classifications from one year to the next. Furthermore, nearly 200 new schools entered the analysis in 2013 and 75 schools that were operational in 2012 closed their doors or dropped below the average enrollment threshold for analysis (25 students), greatly changing the set of potential fiscal peers. Therefore, the fiscal peers for each school have been re-calculated, and the campus-level fiscal peers for 2014 have been identified based on data from 2011, 2012 and 2013.

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, seven Texas districts had a three-year average share of special education students exceeding 38.9 percent. No other district had a share exceeding 30.3 percent. Arguably, then, these seven districts should be matched only with one another. Similarly, while

CALCULATING CORE OPERATING EXPENDITURES

Core operating expenditures are current operating expenditures as defined by TEA, but excluding student transportation (function 34), food service (function 35), the incremental costs associated with the chapter 41 purchase or sale of WADA (function 92) and payments to juvenile justice alternative education programs (function 95). These categories of spending are not considered core operating expenditures because they represent additional functions of local school districts not directly related to student achievement. To reduce the influence of one-time events, the study employed a three-year average from the 2011, 2012 and 2013 school years.

FISCAL AGENTS

Core operating expenditures used in the FAST analysis have been adjusted for the fact that some school districts act as a fiscal agent for another district or group of districts. Fiscal agents collect funds from the member districts in a shared service agreement, and make purchases or pay salaries with those shared funds on behalf of the other member districts. As a result, the spending of fiscal agents is artificially inflated while the spending by member districts is artificially suppressed.

To correct for this pattern, we rely on TEA data from the F-33 files. The F-33 files are generated annually by fiscal agents, and indicate the amount they spent on behalf of the member districts each year. We use these data to allocate the spending by fiscal agents to the member districts on a proportional basis. For example, in 2009-10, Coleman ISD spent $243,547 from shared service funds on instruction, $56,596 on curriculum and staff development, and $18,503 on miscellaneous other functions. Coleman's F-33 report indicates that it spent 48.3 percent of those funds ($153,916) on behalf of Santa Anna ISD, 32.4 percent ($103,287) on behalf of Panther Creek CISD and 19.3 percent ($61,443) on behalf of Novice ISD. Therefore, we allocate 48.3 percent of Coleman ISD's shared service spending for instruction, 48.3 percent of its shared service spending for curriculum development and 48.3 percent of its shared service spending for other functions to Santa Anna ISD. We similarly allocate 32.4 percent of Coleman ISD's shared service spending in each category to Panther Creek CISD and 19.3 percent of Coleman ISD's shared service spending to Novice ISD.

Unfortunately, the F-33 reports from roughly two-thirds of the fiscal agents are either missing or do not balance with their actual financial reports in PEIMS (see **Exhibit 2**). For example, Stamford ISD reported on the PEIMS actual financial report for 2009-10 that it spent a total of $593,487 from shared service fund 313 on behalf of its member districts. However, Stamford ISD's F-33 report for the same year indicates that it spent a total of $975,984 from shared service fund 313 on behalf of 10 member districts (including $116,923 on its own behalf). Either the actual financial report or the F-33 report is incorrect. Because the actual financial report is audited and the F-33 report is generally not, we treat the actual financial report as the more reliable source of information. Whenever the F-33 data are off by more than 2 percent and by more than $2,000, we conclude that it was not possible to reliably determine how those funds should be distributed and do not allocate the shared service spending. This means that total spending will be overstated for fiscal agents that file inconsistent F-33 reports (or fail to file any F-33 report at all), and will be somewhat understated for their corresponding member districts.

EXHIBIT 2

DISTRICTS WITH INCONSISTENT FINANCIAL DATA

	2008-09	2009-10	2010-11	2011-12	2012-13
NUMBER OF DISTRICTS SERVING AS FISCAL AGENTS	308	298	275	262	253
NUMBER OF FISCAL AGENTS FAILING TO FILE F-33	93	66	28	27	30
NUMBER OF DISTRICTS FILING AN INCONSISTENT F-33	121	155	150	150	135
NUMBER OF DISTRICTS FILING A CONSISTENT F-33	94	77	97	85	88

Note: An inconsistent F-33 report diverges from the PEIMS actual financial report by more than 2% and by more than $2,000.
Source: Texas Education Agency and Texas Comptroller of Public Accounts.

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 3**). 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 40 districts, then all districts in the stratum were designated as fiscal peers, and propensity score matching was not used.

The six 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 stu-dents; 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 125 students. Twenty-six K-12 districts had an average of fewer than 125 students in fall enrollment, so each of the smallest K-12 districts had 25 fiscal peers.

The 18 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 25 fiscal peers.

The second smallest stratum contained seven charter school districts specializing in special education (i.e. those with at least a 38.9 per-cent share of special education students). All seven districts also were AEA districts. No other districts had a special education share within 8 percentage points of these districts, so they represent an independent stratum, giving each six fiscal peers.

AEA districts serve students at high risk of dropping out and are subject to different accountability standards. Eighteen K-12 districts with less than a 38.9 percent share of special education students served both elementary and secondary grades and were classified as AEA districts by TEA. These eighteen charter school districts represent an independent stratum in which each school district has 17 fiscal peers.

Similarly, 39 school districts have no elementary grade levels. All of them are charter school districts except for South Texas ISD, the state's only all-magnet school district. Most of them are AEA districts. All of the districts in this stratum were designated as fiscal peers, so each had exactly 38 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

EXHIBIT 3

TEXAS SCHOOL DISTRICTS BY STRATUM, 2012-13

	NUMBER OF TRADITIONAL SCHOOL DISTRICTS	NUMBER OF CHARTER SCHOOL DISTRICTS	TOTAL NUMBER OF DISTRICTS	PROPENSITY SCORE MATCHED?
SPECIAL EDUCATION DISTRICTS	0	7	7	no
VERY SMALL K-12	6	0	6	no
VERY LARGE K-12	18	0	18	no
AEA DISTRICTS	0	18	18	no
NO ELEMENTARY GRADES	1	38	39	no
NO HIGH SCHOOL GRADES	53	78	131	yes
ALL OTHER DISTRICTS	947	59	1,006	yes
TOTALS	1,025	200	1,225	

Note: "Special Education" school districts have at least 38.9 percent special education students. "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 have fewer than 38.9 percent special education students and serve both elementary and secondary grade levels.
Source: Texas Comptroller of Public Accounts.

metropolitan and nonmetropolitan districts and then subdivided into quintiles based on core operating expenditures per pupil.[8] 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.

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.[9] 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.[10]

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 full set of K-12 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.

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. All but two of the 1,006 propensity-scored K-12 districts have 40 fiscal peers. Fort Hancock ISD, which has an unusual mix of low population density and a high share of LEP students, has only one identified fiscal peer, and Fannindel ISD has only 35 fiscal peers.

The final remaining stratum contains the school districts with no high school.11 Because the stratum is not small, we used propensity score matching to find fiscal peers for each of these districts. The stratum is not large enough, however, to be divided into 10 sub-groups, as was done with the All Other Districts stratum. Furthermore, more than a third of these districts 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 1,006 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.

Again, the 40 school districts with the nearest propensity scores to those of each designated treatment district were identified, and po-tential matches outside of a two-standard-deviation band were discarded. All 131 districts had at least 27 viable propensity score matches, and most (128) had 40 viable 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.

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.[12]

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.[13] 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 4 illustrates the Spearman correlations among the scoring variables (propensity scores with cost function predictions and with 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 case in which cost function predictions were not significantly correlated with the propensity scores was the K-6 school districts model. The lack of correlation between the propensity scores and cost projections for the K-6 model could cast doubt on the propensity score matches. On the other hand, the instructional technology used in K-6 districts may be so different from that used in other districts that that the cost function model (which was estimated using data on K-12 districts) cannot fully reflect important cost differences for this subset of schools. If so, then the lack of correlation could arise because the cost function matches are inferior.

In the end, the goal of the each of the matching strategies is to identify up to 40 peer districts that are highly similar to each individual district. Match quality is evaluated 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.[14] It represents the average deviation from baseline for the districts in the peer group. **Exhibits 5** and **6** illustrate the distribution of mean squared errors for each of the eight cost factors across each of the three alternative grouping strategies. Lower MSEs indicate better matches; higher MSEs indicate poorer matches.

Exhibit 5 presents mean squared errors for the All Other Districts stratum. As expected, the average MSE for propensity score matching was significantly 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 cases and significantly lower in all but one case (percent low income). The evidence, then, suggests that the propensity score matching strategy yields fiscal peer groups which are more internally similar than those that would be generated by cost function matching.

Exhibit 6 presents mean squared errors for school districts with no high school grades. Here, the evidence was more mixed. For the size-related cost factors (enrollment and square miles) and the share of high-needs special education students, the propensity score-based groups were more internally similar, but for the share of low-income students the cost function-based groups were more internally similar. There were no statistically significant 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 better and no worse than those arising from cost function analysis.

The propensity score matching strategy used to identify fiscal peers for the All Other Districts stratum in 2011, 2012 and 2013 differs slightly from the matching strategy used for that stratum in the first year of the FAST study (2010). In the original analysis, we divided the school districts into ten subgroups of roughly comparable size by first dividing the districts into two groups—metropolitan and nonmetropolitan districts—and then subdivided each group of school districts into quintiles

EXHIBIT 4

SPEARMAN CORRELATIONS AMONG SCORING VARIABLES

	COST FUNCTION SCORES	RANDOM SCORES
SMALL METROPOLITAN DISTRICTS MODELS		
PROPENSITY SCORE MODEL 1	-0.062	0.016
PROPENSITY SCORE MODEL 2	0.436	-0.012
SMALL NONMETROPOLITAN DISTRICTS MODELS		
PROPENSITY SCORE MODEL 1	0.345	-0.004
PROPENSITY SCORE MODEL 2	0.616	-0.003
PROPENSITY SCORE MODEL 3	0.790	-0.019
PROPENSITY SCORE MODEL 4	0.858	0.002
MIDSIZED DISTRICT MODELS		
PROPENSITY SCORE MODEL 1	-0.634	-0.013
PROPENSITY SCORE MODEL 2	-0.531	-0.022
LARGE DISTRICTS MODELS		
PROPENSITY SCORE MODEL 1	-0.831	-0.016
PROPENSITY SCORE MODEL 2	-0.779	-0.014
K-8 MODELS		
PROPENSITY SCORE MODEL 1	-0.637	-0.067
PROPENSITY SCORE MODEL 2	0.620	0.090
K-6 MODEL		
PROPENSITY SCORE MODEL 1	-0.263	-0.022

Source: Texas Comptroller of Public Accounts.

EXHIBIT 5

MEAN SQUARED ERRORS FOR ALTERNATIVE GROUPING STRATEGIES – ALL OTHER DISTRICTS STRATUM

	OBSERVATIONS	MEAN	MINIMUM	MAXIMUM
ENROLLMENT				
PROPENSITY SCORE	1,006	8.490	0.525	52.539
COST FUNCTION	1,006	25.892*	2.658	306.501
RANDOM ASSIGNMENT	1,006	61.200*	18.557	274.312
LEP				
PROPENSITY SCORE	1,006	15.028	1.101	224.947
COST FUNCTION	1,006	21.168*	1.382	240.977
RANDOM ASSIGNMENT	1,006	22.068*	2.000	231.298
LOW INCOME				
PROPENSITY SCORE	1,006	9.775	1.331	89.741
COST FUNCTION	1,006	9.972	2.367	67.863
RANDOM ASSIGNMENT	1,006	12.483*	4.222	68.073
HIGH NEEDS SPECIAL ED.				
PROPENSITY SCORE	1,006	0.920	0.063	40.687
COST FUNCTION	1,006	1.040	0.071	41.100
RANDOM ASSIGNMENT	1,006	3.327*	0.253	50.517
OTHER SPECIAL ED.				
PROPENSITY SCORE	1,006	0.772	0.120	9.152
COST FUNCTION	1,006	0.982*	0.107	9.651
RANDOM ASSIGNMENT	1,006	1.175*	0.270	11.555
SQUARE MILES				
PROPENSITY SCORE	1,006	42.952	0.085	258.935
COST FUNCTION	1,006	67.865*	18.263	330.247
RANDOM ASSIGNMENT	1,006	75.659*	19.275	367.653
HS-CWI				
PROPENSITY SCORE	1,006	0.839	0.021	5.104
COST FUNCTION	1,006	1.142*	0.094	4.669
RANDOM ASSIGNMENT	1,006	1.661*	0.598	4.209
CWI				
PROPENSITY SCORE	1,006	1.239	0.059	7.008
COST FUNCTION	1,006	1.551*	0.296	9.338
RANDOM ASSIGNMENT	1,006	2.375*	0.901	5.925

* indicates that the difference in means from propensity score matching is statistically significant at the 5 percent level. Cost factors based on a three-year average of data from 2010, 2011 and 2012. This analysis covers only the 1,006 K-12 districts that were operational in 2012.
Source: Texas Comptroller of Public Accounts.

based on the core operating expenditures per pupil. Now, we divided the school districts into ten subgroups by first dividing the districts into four groups—small metropolitan, small non-metropolitan, midsized and large school districts—and then subdivided each group of school districts based on their core operating expenditures per pupil. The change in grouping strategy was designed to reduce the variation within the fiscal peer groups with respect to school district size, and only applies to the elementary and secondary school districts where propensity score matching is used to identify fiscal peers. The new grouping strategy generates fiscal peer groups that are much more internally similar with respect to enrollment than the fiscal peer groups generated by the original grouping strategy, with only modest impact on the MSE for the other cost factors.

EXHIBIT 6

MEAN SQUARED ERRORS FOR ALTERNATIVE GROUPING STRATEGIES – NO HIGH SCHOOL GRADES STRATUM

	OBSERVATIONS	MEAN	MINIMUM	MAXIMUM
ENROLLMENT				
PROPENSITY SCORE	127	16.434	4.324	85.241
COST FUNCTION	127	29.986*	2.407	162.261
RANDOM ASSIGNMENT	127	75.325*	19.483	309.503
LEP				
PROPENSITY SCORE	127	53.086	5.596	201.535
COST FUNCTION	127	43.186	1.708	244.277
RANDOM ASSIGNMENT	127	47.084	2.598	226.420
LOW INCOME				
PROPENSITY SCORE	127	25.929	8.664	98.842
COST FUNCTION	127	18.451*	3.237	78.518
RANDOM ASSIGNMENT	127	20.495*	4.782	73.053
HIGH NEEDS				
PROPENSITY SCORE	127	1.271	0.294	16.946
COST FUNCTION	127	2.012*	0.154	16.131
RANDOM ASSIGNMENT	127	4.548*	0.330	24.560
OTHER SPECIAL				
PROPENSITY SCORE	127	2.343	0.487	32.923
COST FUNCTION	127	2.615	0.198	28.543
RANDOM ASSIGNMENT	127	2.433	0.307	32.842
SQUARE MILES				
PROPENSITY SCORE	127	48.064	7.467	562.542
COST FUNCTION	127	116.417*	31.298	238.034
RANDOM ASSIGNMENT	127	123.142*	30.473	275.376
HS-CWI				
PROPENSITY SCORE	127	1.696	0.544	4.365
COST FUNCTION	127	1.887	0.098	4.816
RANDOM ASSIGNMENT	127	2.084*	0.698	4.032
CWI				
PROPENSITY SCORE	127	2.184	0.831	5.657
COST FUNCTION	127	2.549	0.273	7.947
RANDOM ASSIGNMENT	127	2.846*	0.924	5.665

* indicates that the difference in means from propensity score matching is statistically significant at the 5-percent level. Cost factors based on a three-year average of data from 2010, 2011 and 2012. The analysis covers only the 127 K-8 districts that were operational in 2012.
Source: Texas Comptroller of Public Accounts.

The data used to identify fiscal peers in 2013 also differs slightly from that used in previous years. Starting with the 2013 analysis, the input price measures have been constructed using data from the American Community Survey (see "Input Prices"). Previously, the input prices were based on updates to the NCES Comparable Wage index. Unlike the updates to the NCES CWI, the ACS-CWI does not rely on the assumption that there has been no appreciable change in worker demographics since 1999.

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 ACS -CWI measure.[19]

COMPARABLE WAGE INDEX

The ACS-CWI and HS-CWI are based on analyses of public use micro-data from the 2009, 2010 and 2011 American Community Surveys (ACS).[15] The ACS, which is conducted annually by the U.S. Census Bureau, has replaced the decennial census as the primary source of demographic information about the U.S. population. It provides information about the earnings, age, occupation, industry, and other demographic characteristics for millions of U.S. workers. The ACS-CWI measures earnings differences for college graduates; the HS-CWI measures earnings differences for high school graduates who do not have a bachelor's degree. In both cases, the analysis is modeled after the baseline analysis used to construct the NCES CWI.[16]

Like the NCES CWI, the ACS-CWI is derived from a regression analysis of individual earnings data. Workers with incomplete data and workers without a high school diploma were excluded from the ACS regression analysis, as was anyone who had a teaching or educational administration occupation or who was employed in the elementary and secondary education industry. Self-employed workers were excluded because their reported earnings may not represent the market value of their time. Individuals who reported working less than half time or for more than 90 hours a week were also excluded, as were workers under the age of 18 and over the age of 80. Finally, individuals employed outside the United States were excluded because their earnings may represent compensation for foreign travel or other working conditions not faced by domestic workers.

The ACS-CWI is estimated from nationwide data because the national sample is much larger and yields much more precise estimates of wag-es by industry and occupation than could be generated using only the ACS data for the state of Texas. For similar reasons, the analysis com-bines data from the three most recent ACS reports. Data from 2012 could not be incorporated at this time because the Census Bureau changed the way it defines geographic areas, making the publicaly available data for 2012 a poor match for the publicaly available data from earlier years.

Exhibit 7 presents the results from the two regression analysis (one for the ACS-CWI, one for the HS-CWI). The dependent variable in each case is the log of annual wage and salary earnings. Key independent variables include the age, gender, race, educational attainment, language ability and amount of time worked for each individual in the national sample. The model includes the interaction between gender and age, to allow for the possibility that men and women have different career paths, and therefore different age-earnings profiles. In addition, the estimation includes indicator variables for occupation and industry for each year.[17] This specification allows wages to rise (or fall) more slowly in some occupations or industries than it does in others. Such flexibility is particularly important because the analysis spans the "Great Recession" and some industries and occupations fell more sharply and/or are recovering more slowly than others. Finally, each regression includes indicator variables for each labor market area.

The labor markets are based on "place-of-work areas" as defined by the Census Bureau. Census place-of-work areas are geographic regions designed to contain at least 100,000 persons. The place-of-work areas do not cross state boundaries and generally follow the boundaries of county groups, single counties, or census-defined places (Ruggles et al. 2012). Counties in sparsely-populated parts of a state are clustered together into a single Census place-of-work area. All local communities in the United States are part of a place-of-work area. Individuals can live in one labor market, and work in another. Their wage and salary earnings are attributed to their place of work, not their place of residence. Following the NCES CWI, the labor markets used in these analyses are either single places of work, or a cluster of the places-of-work that comprise a metropolitan area.

As **Exhibit 7** illustrates, the estimated model is consistent with reasonable expectations about labor markets. Wage and salary earnings increase with the amount of time worked per week and the number of weeks worked per year. Earnings also rise as workers get older, but the increase is more rapid for men than for women (perhaps because age is not as good an indicator of experience for women as it is for men). Workers with advanced degrees earn systematically more than workers with a bachelor's degree (in the ACS-CWI model) while workers with an associate's degree earn significantly more than workers with a GED (in the HS-CWI model).Whites earn systematically more than apparently comparable individuals from other racial groups. Workers who do not speak English well earn substantially less than other workers, all other things being equal.

The predicted wage level in each labor market area captures systematic variations in labor earnings while controlling for demographics, industrial and occupational mix, and amount of time worked.[18] Dividing each local wage prediction by the corresponding national average yields the ACS-CWI, and the HS-CWI, respectively.

EXHIBIT 7

ESTIMATING THE ACS-CWI AND HS-CWI

EXPLANATORY VARIABLES	HS-CWI MODEL		ACS CWI MODEL	
	ESTIMATE	STANDARD ERROR	ESTIMATE	STANDARD ERROR
USUAL HOURS WORKED PER WEEK	0.9790	0.0019	0.9281	0.0029
WORKED 27-39 WEEKS	-0.4460	0.0020	-0.5318	0.0037
WORKED 40-47 WEEKS	-0.2038	0.0019	-0.2555	0.0032
WORKED 48-49 WEEKS	-0.0862	0.0028	-0.1136	0.0044
FEMALE	0.3124	0.0073	0.3047	0.0144
AGE	0.0614	0.0003	0.0861	0.0005
AGE, SQUARED	-0.0006	0.0000	-0.0008	0.0000
FEMALE*AGE	-0.0209	0.0004	-0.0164	0.0007
FEMALE*AGE, SQUARED	0.0002	0.0000	0.0001	0.0000
NOT AN ENGLISH SPEAKER	-0.3037	0.0070	-0.4067	0.0248
REGULAR HIGH SCHOOL DIPLOMA	-0.0397	0.0012		
GED	-0.0963	0.0019		
LESS THAN 1 YEAR OF COLLEGE	0.0000			
SOME COLLEGE, NO DEGREE	0.0212	0.0012		
ASSOCIATE'S DEGREE	0.0501	0.0014		
BACHELOR'S DEGREE			-0.1989	0.0034
MASTER'S DEGREE			-0.0798	0.0035
PROFESSIONAL DEGREE			0.0000	
DOCTORAL DEGREE			0.0726	0.0041
HISPANIC	-0.0826	0.0015	-0.0953	0.0028
AMERICAN INDIAN	-0.0604	0.0041	-0.0607	0.0099
BLACK	-0.0990	0.0014	-0.1218	0.0025
CHINESE	-0.1703	0.0052	-0.1087	0.0037
JAPANESE	-0.0159	0.0084	-0.0670	0.0079
OTHER ASIAN/PACIFIC ISLANDER	-0.1251	0.0026	-0.1117	0.0025
OTHER RACE, N.E.C.	-0.0395	0.0025	-0.0736	0.0059
MIXED RACE	-0.0469	0.0028	-0.0679	0.0046
WHITE	0.0000		0.0000	
INDUSTRY*YEAR INDICATORS?	Yes		Yes	
OCCUPATION * YEAR INDICATORS?	Yes		Yes	
LABOR MARKET INDICATORS?	Yes		Yes	
NUMBER OF OBSERVATIONS	1,361,022		767,877	

Source: Ruggles et al. (2012) and author's calculations.

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 8** compares spending measures broken down by spending index rating.

CAMPUS-LEVEL MATCHES

The Texas public school system includes more than 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 2011 through 2013.

It seemed most appropriate to match schools that serve similar grade levels. Therefore, the campuses were stratified according to the grade levels served in 2013 (early elementary, elementary, middle, secondary and multi-level).20 The secondary campuses also were di-vided into very large high schools and other high schools. (The very large high schools have at least 2,000 students, 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 campuses, AEA nonresidential campuses, juvenile justice campuses and special education campuses (those serving more than 75 percent special education students). **Exhibit 9** displays the number of campuses in each stratum.

Propensity score matching then was applied within each stratum containing more than 40 members. 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.[21] 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 operating expenditures.

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 early elementary schools, large secondary schools and AEA strata, so these strata are not

EXHIBIT 8

DISTRICT EXPENDITURES BY SPENDING INDEX

SPENDING INDEX	DISTRICTS	CORE SPENDING*	ADJUSTED CORE SPENDING**
VERY LOW	202	$7,513	$7,549
LOW	255	8,462	8,950
AVERAGE	309	8,898	9,764
HIGH	253	9,744	10,954
VERY HIGH	183	11,803	13,530
N/A***	26	–	–

* Core operating expenditures per pupil.
** Cost-adjusted core operating expenditures per pupil.
*** Insufficient data to receive a Spending Index.

EXHIBIT 9

TEXAS PUBLIC SCHOOL CAMPUSES BY STRATUM, 2012-2013

TYPE OF CAMPUS	NUMBER OF CAMPUSES	PROPENSITY SCORE MATCHED?
EARLY ELEMENTARY SCHOOLS*	343	Yes
ELEMENTARY SCHOOLS	4,218	Yes
MIDDLE SCHOOLS	1,629	Yes
VERY LARGE SECONDARY SCHOOLS*	243	Yes
OTHER SECONDARY SCHOOLS	1,008	Yes
MULTI-LEVEL SCHOOLS	293	Yes
AEA RESIDENTIAL SCHOOLS		
SECONDARY SCHOOLS	25	No
OTHER SCHOOLS	34	No
AEA NON-RESIDENTIAL SCHOOLS		
MIDDLE SCHOOLS	11	No
SECONDARY SCHOOLS	202	Yes
MULTI-LEVEL SCHOOLS	38	No
JUVENILE JUSTICE SCHOOLS	81	Yes
SPECIAL EDUCATION ELEMENTARY SCHOOLS	4	No
SPECIAL EDUCATION NON-ELEMENTARY SCHOOLS	22	No
TOTAL	8,151	

Note: "Early elementary" schools serve students up through the second grade. "Very large" secondary schools have more than 2,000 students. Juvenile Justice schools are either Juvenile Justice Alternative Education Program (JJAEP) or Disciplinary Alternative Education Program (DAEP) schools. Special education schools serve at least 75 percent special education students.
Source: Texas Comptroller of Public Accounts.

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 10** displays the descriptive statistics on the six variables used in the campus-level matching analysis.

Exhibit 11 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 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. Match quality was assessed using the same techniques employed in the district analysis, arriving at the same conclusions.

CAMPUS SPENDING INDEX

As with the district analysis, each campus fiscal peer group was sorted into quintiles by the ACS-CWI spending measure. The spending measure consisted of campus-related activities per pupil, adjusted for geographic wage variations using the ACS-CWI measure. 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.

Exhibits 12 and **13** show results from the district-level propensity score models. The top number in each row is the estimated coefficient, and the bottom number in parenthesis is the estimated standard error.

EXHIBIT 10

CAMPUS COST FACTORS, THREE-YEAR AVERAGE 2011-2013

	MEAN	MINIMUM	MAXIMUM
LABOR COSTS			
ACS COMPARABLE WAGE INDEX	0.97	0.76	1.09
HIGH SCHOOL COMPARABLE WAGE INDEX	0.98	0.81	1.08
SCHOOL SIZE			
CAMPUS ENROLLMENT	584	1	5,319
STUDENT NEED			
PERCENT LIMITED ENGLISH PROFICIENCY	15.95	0	100
PERCENT ECONOMICALLY DISADVANTAGED	62.37	0	100
PERCENT SPECIAL EDUCATION	10.23	0	100

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

EXHIBIT 11

MEAN SQUARED ERRORS FOR PROPENSITY SCORE MATCHES BY CAMPUS TYPE

	OBSERVATIONS	MEAN	MINIMUM	MAXIMUM
EARLY ELEMENTARY SCHOOLS				
ENROLLMENT	343	10.31	0.87	219.70
LEP	343	53.15	2.58	326.80
LOW INCOME	343	10.18	0.09	118.43
SPECIAL ED.	343	4.35	0.33	163.46
HS-CWI	343	1.51	0.07	4.17
CWI	343	2.11	0.32	6.97
ELEMENTARY SCHOOLS				
ENROLLMENT	4,217	4.24	0.09	99.59
LEP	4,217	49.54	1.05	449.33
LOW INCOME	4,217	20.14	0.18	122.90
SPECIAL ED.	4,217	1.28	0.12	33.22
HS-CWI	4,217	0.90	0.01	4.91
CWI	4,217	1.17	0.08	8.20
MIDDLE SCHOOLS				
ENROLLMENT	1,639	10.74	0.32	139.31
LEP	1,639	9.79	0.12	190.89
LOW INCOME	1,639	10.74	0.16	94.77
SPECIAL ED.	1,639	1.55	0.13	15.25
HS-CWI	1,639	0.82	0.01	4.41
CWI	1,639	1.11	0.06	5.93
VERY LARGE SECONDARY SCHOOLS				
ENROLLMENT	248	0.82	0.14	7.22
LEP	248	1.84	0.12	15.06
LOW INCOME	248	10.47	1.96	51.94
SPECIAL ED.	248	0.78	0.15	6.30
HS-CWI	248	0.87	0.00	4.34
CWI	248	1.18	0.04	5.79
SECONDARY SCHOOLS				
ENROLLMENT	1,228	13.82	0.03	150.19
LEP	1,228	7.04	0.08	489.81
LOW INCOME	1,228	11.50	0.00	63.39
SPECIAL ED.	1,228	4.25	0.02	164.09
HS-CWI	1,228	0.81	0.01	4.52
CWI	1,228	1.11	0.00	6.46
MULTI-LEVEL SCHOOLS				
ENROLLMENT	341	7.44	0.64	62.11
LEP	341	11.04	0.95	386.97
LOW INCOME	341	12.23	1.52	92.67
SPECIAL ED.	341	4.69	0.59	247.57
HS-CWI	341	1.16	0.04	4.95
CWI	341	1.63	0.22	8.25

Source: Texas Comptroller of Public Accounts.

EXHIBIT 12

COEFFICIENT ESTIMATES FROM PROBIT, K-12 DISTRICTS

	SMALL METROPOLITAN		SMALL NONMETROPOLITAN				MIDSIZED		LARGER	
	HALF 1	HALF 2	QUARTILE 1	QUARTILE 2	QUARTILE 3	QUARTILE 4	HALF 1	HALF 2	HALF 1	HALF 2
ENROLLMENT (LOG)	17.644	8.553	11.617	12.310	10.471	11.517	79.001	69.041	24.029	25.525
	(2.609)**	(1.490)**	(2.749)**	(2.451)**	(2.292)**	(3.213)**	(10.174)**	(8.782)**	(3.522)**	(4.076)**
HIGH NEEDS SP. ED.	-2.109	8.933	1.288	11.735	-4.415	-4.254	29.894	-63.774	86.868	86.697
	(13.198)	(11.980)	(33.645)	(17.736)	(20.022)	(18.302)	(45.990)	(39.867)	(101.046)	(73.363)
LEP	-1.912	-5.457	2.276	-0.928	-1.406	7.033	3.618	-4.845	3.479	0.321
	(2.552)	(2.267)*	(2.863)	(2.760)	(2.244)	(2.964)*	(3.688)	(3.014)	(5.382)	(4.369)
LOW INCOME	3.127	-2.956	1.410	3.901	4.345	-7.727	8.981	-4.848	6.529	-7.174
	(1.848)	(1.750)	(2.610)	(2.861)	(3.298)	(21.249)	(2.861)**	(8.594)	(2.785)*	(2.659)**
OTHER SP. ED	5.298	33.316	77.870	-5.005	32.244	0.697	12.053	17.912	44.681	-99.462
	(25.622)	(21.381)	(39.915)	(29.310)	(24.690)	(17.421)	(61.988)	(50.697)	(81.280)	(81.913)
SQUARE MILES (LOG)	0.705	0.468	2.193	1.903	0.734	0.857	0.323	-0.170	0.014	0.112
	(0.496)	(0.345)	(0.646)**	(0.705)**	(0.593)	(0.757)	(0.554)	(0.484)	(0.800)	(0.704)
HS-CWI	66.123	200.026	224.071	128.897	437.925	265.712	-19.740	1.041	-76.373	56.377
	(52.449)	(49.124)**	(124.313)	(119.881)	(205.608)*	(262.699)	(58.425)	(60.618)	(77.294)	(86.298)
CWI	18.757	-6.973	70.424	-35.153	19.590	142.912	38.370	8.865	28.794	-31.272
	(34.903)	(30.946)	(51.064)	(47.748)	(53.078)	(85.551)	(36.573)	(41.822)	(44.818)	(50.256)
ENROLLMENT (LOG), SQUARED	-1.133	-0.598	-0.726	-0.697	-0.581	-0.457	-4.936	-4.269	-1.247	-1.316
	(0.184)**	(0.117)**	(0.142)**	(0.129)**	(0.125)**	(0.151)**	(0.640)**	(0.553)**	(0.186)**	(0.213)**
HIGH NEEDS SP. ED., SQUARED	-28.702	4.939	-266.361	-37.296	-8.581	45.067	-378.972	595.640	-1,059.662	-566.293
	(85.130)	(78.427)	(309.335)	(134.703)	(159.816)	(143.781)	(402.322)	(334.297)	(907.037)	(661.767)
LEP, SQUARED	7.087	12.476	-8.915	0.056	7.334	-19.119	-9.472	8.060	-15.347	1.943
	(6.335)	(5.657)*	(10.457)	(10.653)	(6.529)	(10.192)	(9.411)	(6.302)	(13.763)	(8.518)
LOW INCOME, SQUARED	-3.780	3.577	-2.035	-3.668	-2.246	0.574	-10.828	7.734	-7.610	8.631
	(1.750)*	(1.567)*	(2.323)	(2.460)	(2.704)	(2.938)	(2.706)**	(2.653)**	(2.651)**	(2.496)**
OTHER SP. ED, SQUARED	-273.396	-320.068	-711.377	-9.788	-252.230	20.712	-336.277	-86.073	-295.646	1,042.219
	(313.629)	(229.831)	(415.409)	(285.729)	(231.899)	(155.158)	(736.610)	(582.096)	(1,023.364)	(1,024.719)
SQUARE MILES (LOG), SQUARED	-0.147	-0.040	-0.246	-0.179	-0.044	-0.025	-0.063	0.043	0.003	-0.018
	(0.060)*	(0.037)	(0.066)**	(0.066)**	(0.053)	(0.066)	(0.059)	(0.052)	(0.084)	(0.073)
HS-CWI, SQUARED	-29.025	-101.123	-134.732	-82.515	-259.510	-143.578	12.747	-1.286	41.860	-31.051
	(28.625)	(27.026)**	(71.372)	(69.128)	(119.452)*	(152.012)	(32.067)	(31.382)	(40.653)	(45.344)
ACS-CWI, SQUARED	-2.617	10.355	-27.824	38.187	5.147	-74.246	-23.228	3.219	-16.855	17.452
	(19.628)	(17.972)	(29.839)	(28.452)	(32.047)	(49.549)	(20.849)	(20.509)	(24.083)	(26.899)
ENROLLMENT * ACS-CWI	-2.789	-1.637	-2.309	-4.290	-4.578	-9.003		-1.463		
	(1.410)*	(1.151)	(2.647)	(2.193)	(2.173)*	(3.343)**		(2.041)		
LOW INCOME * ACS-CWI						40.215		-1.774		
						(16.348)*		(16.723)		
LOW INCOME * HS-CWI						-29.167		0.041		
						(26.423)		(20.332)		
OBSERVATIONS	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034

Standard errors in parentheses: * p<0.05 ** p<0.01
Source: Texas Comptroller of Public Accounts.

EXHIBIT 13

COEFFICIENT ESTIMATES FROM PROBIT, K-8 DISTRICTS

	LOW-SPENDING K-8	HIGH-SPENDING K-8	K-6
ENROLLMENT (LOG)	8.366** (3.275)	-1.285 (1.930)	-0.603 (1.680)
HIGH NEEDS SP. ED.	46.05 (31.46)	40.78 (28.31)	-31.06 (24.89)
LEP	-3.382 (3.445)	0.163 (3.756)	0.622 (3.077)
LOW INCOME	2.343 (6.539)	-10.58 (7.068)	5.740 (5.511)
OTHER SP. ED	-15.24 (16.90)	18.32 (15.49)	4.765 (17.80)
SQUARE MILES (LOG)	0.552 (2.136)	3.151*** (1.027)	-1.817*** (0.699)
HS-CWI	-125.9 (90.08)	0.834 (91.41)	64.83 (85.09)
CWI	106.0* (63.23)	-51.26 (61.59)	-21.68 (50.69)
ENROLLMENT (LOG), SQUARED	-0.635** (0.277)	0.106 (0.177)	-0.00610 (0.147)
HIGH NEEDS SP. ED., SQUARED	-447.2 (338.2)	-98.30 (253.2)	53.64 (264.5)
LEP, SQUARED	3.491 (7.132)	-2.777 (7.881)	2.442 (6.360)
LOW INCOME, SQUARED	-1.998 (2.438)	1.717 (2.506)	0.725 (2.012)
OTHER SP. ED, SQUARED	37.69 (179.5)	-80.23 (151.5)	-52.65 (245.5)
SQUARE MILES (LOG), SQUARED	-0.102 (0.309)	-0.355*** (0.129)	0.199** (0.0810)
HS-CWI, SQUARED	61.88 (48.20)	3.018 (50.13)	-34.20 (45.60)
CWI, SQUARED	-53.82 (33.79)	21.67 (34.35)	14.53 (28.07)
LOW INCOME * CWI	0.490 (6.946)	9.293 (7.397)	-6.796 (5.594)
OBSERVATIONS	127	127	127

Standard errors in parentheses: * $p<0.05$ ** $p<0.01$
Source: Texas Comptroller of Public Accounts.

ENDNOTES

1 William J. Webster and George T. Olson, *An Empirical Approach to Identifying Effective Schools*, presented at the Annual Meeting of the American Educational Research Association, (New Orleans, Louisiana, April 23-27, 1984), pp. 1-35, http://www.dallasisd.org/eval/research/articles/Webster-An-Empirical-Approach-to-Identifying-Effective-Schools-1984.pdf ; William J. Webster, Robert L. Mendro, and Ted O. Almaguer, *Effectiveness Indices: The Major Component of an Equitable Accountability System*, presented at the Annual Meeting of the American Educational Research Association, (Atlanta, Georgia, April 12-16, 1993), pp. 1-40, http://www.eric.ed.gov/PDFS/ED358130.pdf ; William J. Webster, Robert L. Mendro, Karen L. Bembry and Timothy H. Orsak, *Alternative Methodologies for Identifying Effective Schools*, presented at the Annual Meeting of the American Educational Research Association, (San Francisco, California, April 17-21, 1995), pp. 1-78, http://www.dallasisd.org/eval/research/articles/Webster- Alternative-Methodologies-For-Identifying-Effective Schools-95. pdf ; Robert L. Mendro, William J. Webster, Karen L. Bembry and Timothy H. Orsak, *An Application of Hierarchical Linear Modeling in Determining School Effectiveness*, presented at the Annual Meeting of the American Educational Research Association, (San Francisco, California, April 17-21, 1995), pp. 1-44, http://www.dallasisd.org/ eval/research/articles/Mendro-Application-of-HLM-in-Determining- School-Effectiveness-1995.pdf; William J. Webster, Robert L. Mendro, Timothy H. Orsak and Dash Weerasinghe, *An Application of Hierarchical Linear Modeling to the Estimation of School and Teacher Effect*, presented at the Annual Meeting of the American Educational Research Association, (San Diego, California, April 13-17, 1998), pp.1-27, http://www.dallasisd.org/eval/research/articles/Webster- An-Application-of-Hierarchical-Linear-Modeling-1998.pdf; Dash Weerasinghe and Timothy Orsak, *Can Hierarchical Linear Modeling Be Used to Rank Schools: A Simulation Study with Conditions under which Hierarchical Linear Modeling is Applicable*, presented at the Annual Meeting of the American Educational Research Association, (San Diego, California, April 13-17, 1998), pp. 1-12, http://www. dallasisd.org/eval/research/articles/Weerasinghe-Can-Hierarchical- Linear-Modeling-Be-Used-to-Rank-Schools.pdf; Dash Weerasinghe, Mark Anderson, and Karen Bembry, *Precision of Measures of Central Tendency: Computing an Effectiveness Index for Teachers*, presented at the Annual Meeting of the Southwestern Educational Research Association, (New Orleans, Louisiana, February 2001), pp. 1-12, http://www.dallasisd.org/eval/research/articles/Weerasinghe- Precision-of-Measures-Computing-an-Effectiveness-Index-for- Teachers-2001.pdf (last visited November 28, 2010); and William J. Webster and Robert L. Mendro, "The Dallas Value-Added Accountability System," in *Grading Teachers, Grading Schools: Is Student Achievement a Valid Evaluation Measure?* by Jason Millman, ed., (Thousand Oaks, California: Corwin Press, 1997).

2 W.L. Sanders, A. Saxton, and S.P. Horn, "The Tennessee Value- Added Accountability System: A Quantitative, Outcomes-Based Approach to Educational Assessment," in *Grading Teachers, Grading Schools: Is Student Achievement a Valid Evaluation Measure?* by Jason Millman, ed., (Thousand Oaks, California: Corwin Press, 1997); Dale Ballou, William Sanders and Paul Wright, "Controlling for Student Background in Value-Added Assessment of Teachers," *Journal of Educational and Behavioral Statistics* (Spring 2004), pp. 37-65, http://web.missouri.edu/~podgurskym/Econ_4345/syl_articles/ ballou_sanders_value_added_ JEBS.pdf; Carnegie Corporation of New York, *Evaluating Value-Added Models for Teacher Accountability*, by Daniel F. McCaffrey, J.R. Lockwood, Daniel M. Koretz and Laura S. Hamilton, Rand Corporation (New York, New York, 2003), http://www.rand.org/pubs/monographs/2004/R AND_MG158.pdf; Steven Ponisciak and Anthony Bryk, "Value-Added Analysis of the Chicago Public Schools: An Application of Hierarchical Models," in *Value Added Models in Education: Theory and Applications*, by Robert Lissitz, ed., (Maple Grove, Minnesota: JAM Press, 2005); Robert Lissitz, Harold Doran, William Schafer and Joseph Willhoft, "Growth Modeling, Value Added Modeling, and Linking: An Introduction," in *Longitudinal and Value-Added Models of Student Performance*, by Robert Lissitz, ed., (Maple Grove, Minnesota: JAM Press, 2005) ; and Stephen W. Raudenbush, "Adaptive Centering with Random Effects: An Alternative to the Fixed Effects Models for Studying Time-Varying Treatments in School Settings," *Education Finance and Policy* (Fall 2009), pp. 468-491.

3 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.)

4 Tom. A.B. Snijders and Roel J. Bosker, *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*; Stephen W. Raudenbush and Anthony S. Bryk, *Hierarchical Linear Models: Applications and Data Analysis Methods*, 2nd ed.; and Anders Skrondal and Sophia Rabe-Hesketh, *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models*.

5 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.

6 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.)

7 Core operating expenditures consists of 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.

8 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.

9 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 ACS-CWI; and the interaction between district enrollment and the ACS-CWI.

10 The district-level regression models were not updated for 2013. Therefore, all 10 models were based on data from the 1,034 K-12 school districts that were operational during 2012. 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.

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

12 Timothy J. Gronberg, Dennis W. Jensen and Lori L. Taylor, "The Adequacy of Educational Cost Functions: Lessons from Texas," *The Peabody Journal of Education*, (January 2011), pp. 3-27.

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

$$\begin{aligned} 1n(E) = a_0 &+ \sum_{i=1}^{2} a_i q_i + \sum_{i=1}^{2} b_i w_i + \sum_{i=1}^{6} c_i x_i + 0.5 \sum_{i=1}^{2}\sum_{j=i}^{2} d_{ij} q_i q_j + \sum_{i=1}^{2}\sum_{j=i}^{2} e_{ij} q_i w_j \\ &+ 0.5 \sum_{i=1}^{2}\sum_{j=i}^{2} f_{ij} w_i w_j + \sum_{i=1}^{6}\sum_{j=i}^{2} g_{ij} x_i w_j + \sum_{i=1}^{2}\sum_{j=i}^{6} h_{ij} q_i x_j + 0.5 \sum_{i=1}^{6}\sum_{i=1}^{6} k_{ij} x_i x_j \\ &+ a_4 x_1^3 + v + u \end{aligned}$$

14 We calculate the mean squared error for school district j as

$$MSE_j = \frac{100 \bullet \Sigma_j (x_i - x_j)^2}{n\bar{x}}$$

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, x-bar 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.

15 The data for this analysis come from Ruggles et al. 2012. The analysis is based on annual files for each survey administration, and not on the combined three-year file.

16 Taylor and Fowler (2006).

17 The model also includes random effects for states. Treating state effects as random rather than fixed ensures that the predicted wage is the same in Kansas City, Kansas as it is in Kansas City, Missouri, while allowing for a correlation in the errors among labor markets within any given state.

18 Formally, the predicted wage level in each market is the least-squares mean for the market fixed effect. The least-squares mean (or population marginal mean) is defined as the expected value of the mean for each effect (in this context, each market) that you would expect from a balanced design holding all covariates at their mean values and all classification variables (such as occupation or gender) at their population frequencies.

19 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.

20 Early elementary campuses serve students up through the second grade. For matching purposes, Northwest Preparatory Campus (Wylevale Campus), an alternative education campus serving grades 3-8, was categorized as a middle school, and Nacogdoches Boys Ranch was classified as an alternative education residential campus.

21 Campus-related activities are all operating expenditures in functions 11-33, and objects 6100-6499.

This is the Technical Appendix of the Texas (FAST) report.

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