Anticipating the Consequences of School District Consolidation in Major Metropolitan Areas

A Simulation Based on Cost Function Analysis

August 2014

Prepared for

The University of Texas at Dallas Education Research Center and
The Texas Education Agency

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The authors thank the University of Texas at Dallas Education Research Center for research support on this project. All views expressed are those of the authors alone. The conclusions of this research do not necessarily reflect the opinion or official position of the Texas Education Agency or the State of Texas.

Executive Summary

Senate Bill (SB) 2 (83rd Texas Legislature, Regular Session) added Section 12.1013 to the Texas Education Code (TEC). Among other provisions, this new section requires the Texas Education Agency (TEA) to provide "an analysis of whether the performance of matched traditional campuses would likely improve if there were consolidation of school districts within the county in which the campuses are located." The new section further clarifies that the analysis requirement "applies only to a county that includes at least seven school districts and at least 10 open-enrollment charter schools." This report represents the required analysis of the potential gains from school district consolidation in the five counties that match that description—Bexar, Dallas, Harris, Tarrant and Travis.

Consolidating all of the school districts in each of these five counties would create new districts that are very large by Texas and national standards. With an enrollment of just over 803,000 students, the consolidated Harris County Independent School District (ISD) would be the second largest school district in the country (behind only New York City Schools). The consolidated Dallas County ISD (enrollment 437,642) would be the fourth largest school district in the country, ahead of the Chicago Public School system, but smaller than Los Angeles Unified School district (which would be the third largest district). The consolidated Tarrant County ISD (enrollment 341,855) and Bexar County ISD (enrollment 321,072) would be the nation's seventh and eighth largest districts, respectively. Even the consolidated Travis County ISD (enrollment 145,846) would be among the 20 largest districts nationwide.

Texas has no historical experience with consolidation on such a grand scale. There have been only 20 school district consolidations in Texas since 1994–95. In all but two of the 20 cases (Wilmer-Hutchins ISD and North Forest ISD) the consolidation folded a single-campus district into another, larger district. None of the consolidations involved more than two districts.

Given the lack of historical precedents, anticipating the likely effects of consolidation requires a simulation based on a formal analysis of the relationship between school student achievement and school district size. The simulation presented here uses cost function analysis to answer two key questions:

1. To what extent do the mergers lower the expected per-pupil cost of education?
2. To what extent do the mergers lower the expected efficiency of the affected districts?

Consolidation is expected to reduce the cost of education because research has demonstrated that the per-pupil cost of operating a very small school district is much higher than the per-pupil cost of operating a larger district. Consolidation is expected to increase inefficiency because research has also demonstrated that school districts tend to be more efficient (in the sense that they are able to produce higher student performance from the same level of resources) when there is more choice, and consolidation clearly reduces school choice.

The analysis supports three key findings.

- Cost savings can be expected for consolidations involving small districts, but as the size of the consolidated district increases past 3,200 students, costs are expected to rise, not fall.
- Competitive pressure leads to greater school district efficiency in Texas, so any consolidation is expected to lead to a loss of school district efficiency.
- There are no expected cost savings from any of the targeted consolidations under analysis. Consolidation in the designated counties increases the predicted expenditure per pupil by 6.5% in Bexar County, 4.9% in Dallas County, 4.1% in Harris County, 6.1% in Tarrant County, and 2.8% in Travis County. Expenditures are also expected to rise in the rest of their metropolitan areas (due to the loss of competition in those education markets).

Importantly, this simulation has been constructed assuming that the consolidated, countywide school districts did not close any campuses in the wake of consolidation. That is a reasonable assumption given the political difficulties associated with closing a viable, neighborhood school, and the near impossibility of accurately predicting the nature of any school-level consolidations. After all, most of the districts in the potentially consolidating counties already have the option of campus consolidation, and have chosen not to use it. However, it is likely that at least some campuses in the new, countywide school districts will be eliminated, allowing the average campus size to grow. The cost function analysis indicates that there can be substantial cost savings from campus consolidation. (If nothing else changes, combining two 200-student campuses into one 400-student campus, for example, is expected to reduce operating costs by 14%, on average.) Therefore, the simulation likely overstates somewhat the increase in expenditures post consolidation for Bexar, Dallas, Harris, Tarrant and Travis counties.

Given the lack of cost savings under the simulation, it is highly unlikely that performance would improve if there were consolidation in the designated counties. While there are many counties in Texas where all of the districts are sufficiently small to gain from consolidation, the existing districts in the specific counties under analysis already enjoy substantial economies of scale and would lose important incentives to behave efficiently were they to be consolidated. There is no reason to believe that this proposal would lead to improvements in student performance, and good reason to believe student performance would fall. The bottom line is that bigger is not always better in Texas.

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Glossary of Terms

Core-Based Statistical Area (CBSA): A term used by the U.S. Office of Management and Budget and U.S. Census Bureau to refer collectively to all metropolitan and micropolitan areas. A metropolitan area is a county or cluster of counties with a central, urbanized area of at least 50,000 people. A micropolitan area is a county or cluster of counties with a central city of at least 10,000 people. Two counties are considered part of the same CBSA whenever commuting patterns indicate that the counties are part of the same integrated labor market area. In Texas, College Station-Bryan is a metropolitan area, and Nacogdoches is a micropolitan area.

Cost Function: A mathematical description of the relationship between the inputs, outputs and expenditures of a firm. In the educational context, a cost function describes the relationship between school spending and student performance, given the price of educational inputs (such as teachers or school supplies), student characteristics, and other determinants of the educational environment such as school district size.

Cost Function Analysis: The estimation of a cost function using statistics or some other data-driven technique.

Economies of scale: Economies of scale exist when it is possible to reduce per-pupil costs by increasing the size of the school or district.

Efficient: A school or district is efficient (i.e., behaving efficiently) when it is not possible to increase educational outputs without increasing expenditures on purchased inputs.

Herfindahl Index: A measure of the amount of competition in a market. In the education context, it is defined as the sum of the squared local education agency (LEA) enrollment shares, where an LEA's enrollment share is its own enrollment divided by the total enrollment in the CBSA. The Herfindahl index increases as the level of enrollment concentration increases (i.e., as the level of competition decreases). A Herfindahl index of 1.00 indicates a metropolitan area with a single LEA; a Herfindahl index of 0.10 indicates a metropolitan area with 10 LEAs of equal size.

Inefficient: A school or district is inefficient when it is possible to increase educational outputs without increasing educational expenditures.

Inputs: The equipment, personnel or raw materials used to produce outputs/outcomes.

Outputs/Outcomes: The goods or services produced. In the education context, the primary outcome is total student performance, which can be measured by average student performance times the number of students served.

Stochastic Frontier Analysis (SFA): SFA is a statistical technique used to describe the best—as opposed to average—practice in the data. In this project, the cost function is estimated using SFA. Other statistical approaches to cost function estimation assume that, on average, school spending equals the cost of education. SFA explicitly allows for the possibility that spending could be systematically higher than cost. If school districts are behaving efficiently, SFA yields the same cost function estimates as other techniques.

Introduction

Senate Bill (SB) 2 (83rd Texas Legislature, Regular Session) added Section 12.1013 to the Texas Education Code (TEC). Among other provisions, this new section requires the Texas Education Agency (TEA) to provide "an analysis of whether the performance of matched traditional campuses would likely improve if there were consolidation of school districts within the county in which the campuses are located." The new section further clarifies that the analysis requirement "applies only to a county that includes at least seven school districts and at least 10 open-enrollment charter schools." This report represents the required analysis of the gains from targeted school district consolidations.

Lawmakers might reasonably expect gains from school district consolidation whenever there are economies of scale (i.e., whenever the per-pupil cost of operating a larger school district is lower than the per-pupil cost of operating a smaller one). Each district, regardless of size, must have a superintendent and the usual complement of central administrators. By combining into a single provider, districts can avoid bureaucratic duplication and therefore lower costs. Further cost savings may be achieved by consolidating campuses or classrooms. If the cost savings are wisely reinvested by the newly consolidated district, then student performance should improve.

On the other hand, consolidation also leads to a reduction in school choice, and the economics literature strongly suggests that school districts are more efficient (in the sense that they are able to produce higher educational outcomes from the same level of resources) when there is more choice.[1] If the consolidation of school districts reduces the competitiveness of the local school market, then at least some of the cost savings from the melding of districts may be squandered instead of wisely reinvested, and student performance may not improve.

The net benefits from school district consolidation hinge, therefore, upon the answers to two key questions:

3. To what extent do the mergers lower the expected per-pupil cost of education?
4. To what extent do the mergers lower the relative efficiency of the affected districts?

Cost function analysis is a common strategy for quantifying both economies of scale and relative efficiency, and is therefore the best available strategy for answering these questions. In the educational context, researchers use cost function analysis to summarize the available data about how schools or districts combine purchased educational resources (such as teachers, administrators, software and pencils) with an array of environmental factors that are not purchased (such as student abilities or parental involvement) to produce educational outcomes (such as test scores or graduation rates).

This report proceeds as follows. The first section presents a review of the academic literature on the expected effects of school district consolidation. The next two sections describe the consolidation proposed in TEC Section 12.1013, and the history of school district consolidation in Texas. The fourth section describes the cost function analysis underlying the

[1] For example, see Belfield & Levin (2002); Dee (1998); Gronberg, Jansen, Karakaplan & Taylor (2013); Gronberg, Jansen, Taylor & Karakaplan (2010); Grosskopf, Hayes, Taylor & Weber (2001); Kang & Greene (2002); or Millimet & Collier (2008).

consolidation simulation, and the fifth section describes that simulation. The final section concludes and provides policy recommendations.

Note that this simulation anticipates the short-term effects of school district consolidation, not campus consolidation. Over time, the consolidated districts may redraw attendance zones and change the demographic make-up of individual schools. With the data currently available, one cannot anticipate the school-level changes that might occur in the wake of consolidation. Therefore, in order to evaluate whether or not the performance of traditional campuses would likely improve, the policy simulation must assume that campus size, location and student demographics will remain unchanged.

Note also that most of the potential gains from consolidation will accrue to the districts, not the state. Under TEC Sections 13.281 and 13.282, consolidating districts are entitled to receive incentive aid. That incentive aid is structured so that for 10 years the state must pay at least as much under the Foundation School Program (the Texas school funding formula) after consolidation as it would have paid prior to consolidation. Thus, there are no expected financial gains to the state from consolidation, although the state would clearly benefit from any improvements in student performance.

The Literature

Cost reduction is the fundamental argument in favor of school district consolidation. Potential sources of cost savings from sizing up include reduced duplication of centralized inputs (e.g. administrative staff or counselors) and better utilization of decentralized inputs (e.g. science teachers and science labs). Increasing size can, however, lead to undesirable changes in behavior. Teachers and students may be less motivated in larger school settings, and parents and voters may be less engaged. Disengagement could increase cost directly by reducing parental contributions to the educational process,[2] and indirectly by reducing local oversight of school district decision making. Given the potential tradeoffs associated with increasing size, the question of whether bigger is better is an empirical issue.

Consolidation and Economies of Scale in Education

A small number of researchers have examined economies of scale in education by examining the effects of actual school district consolidations. Most found evidence of substantial cost savings or student performance gains in the wake of consolidation. For example, Duncombe and Yinger (2007) used data from rural school districts in New York to estimate the impact of the twelve consolidations that occurred from 1987 to 1995. They found that doubling enrollment cut operating costs per pupil by 62% for a 300–pupil district and by 50% for a 1,500–pupil district (all other things being equal). Berry and West (2010) examined the relationship across U.S. states between long-term student outcomes (earnings as an adult and years of schooling completed) and consolidations at the campus or district levels. They found small

[2] For example, Dee, Ha & Jacob (2006) find smaller high schools increase the probability that parents take part in PTA activities and volunteer at the school. As discussed in Overstreet, Devine, Bevans & Efreom (2005) other researchers have linked these types of parental engagement to improvements in student performance.

gains from district consolidation, but losses from campus consolidation, suggesting there may be long-term benefits from both larger districts and smaller schools. De Haan, Leuven, and Ooasterbeek (2014) analyzed a 15% reduction in the number of primary schools that occurred in the Netherlands during the 1990s. They found that the reform led to improved student achievement on a nationwide exit exam and that cost savings from economies of scale were the source of those achievement gains. On the other hand, Gordon and Knight (2008) examined administrative consolidations of school districts in Iowa and found no evidence of improvements in either cost or student performance.

Other researchers have used cost function analyses to simulate potential consolidations. For example, Dodson and Garrett (2004) simulated the savings from consolidating four small rural Arkansas districts into a single county district. Based upon their estimated cost function, they found per-pupil cost savings of between 19% and 54%. Duncombe, Miner and Ruggiero (1995) simulated the consolidation of New York school districts with fewer than 500 students and found large potential cost savings. Zimmer, DeBoer and Hirth (2009) also found large potential gains from their simulated consolidation of smaller (i.e., fewer than 1,000 pupils) districts in Indiana. Gronberg et al. (2010, 2013) simulated consolidation to the county level throughout Texas and found that consolidation would reduce per-pupil costs in many rural Texas counties, but raise per-pupil costs in most metropolitan counties.

Additional evidence on the likely impact of school district consolidation comes from studies that did not simulate consolidation but did estimate the relationship between school district size and the cost of education. Andrews, Duncombe and Yinger (2002) surveyed this literature and concluded that the relationship between school district size and the per-pupil cost of education was shaped like a Nike swoosh; per-pupil cost was very high for school districts with fewer than 500 students, lowest for school districts in the 2,000 to 5,000 student range, and somewhat higher for school districts with more than 5,000 students. They concluded that per-pupil costs tended to increase with district size for districts with more than 5,000 students, suggesting that consolidation would not reduce costs for districts with more than 5,000 students.

More recent cost-function analyses using Texas data reached similar conclusions about the high cost of operating small districts, but generally implied that there may also be cost savings from consolidating larger school districts. For example, Imazeki and Reschovsky (2006) found that most of the savings from economies of scale were realized by the time the district reaches 10,000 students, but that costs continued to decline with size until enrollments reached approximately 85,000 students. Gronberg, Jansen, and Taylor (2011a) found that most of the savings from economies of scale were realized at district enrollments near 11,000, but that costs continued to decline with size for even the largest districts. On the other hand, Gronberg, Jansen, and Taylor (2012) found that when charter schools were included in the analysis and campus size was not allowed to change, the economies of scale were fully exhausted when district enrollment reached 1,200 students.

Thus, there is a consensus in the literature that small school districts are much more expensive to operate than midsized or larger school districts, and therefore that consolidating small districts should lower the cost of education. There is much less agreement in the literature about whether or not consolidating midsized or larger school districts would be expected to lead to cost savings.

Consolidation and the Loss of Competition in Education

Although school district consolidation may lower the cost of education by allowing the consolidated school district to exploit economies of scale, it also reduces school choice. Researchers have generally found that a lack of choice among educational providers reduces the efficiency of the public school system.[3] For example, Grosskopf, Hayes, Taylor, and Weber (1999), Grosskopf et al. (2001) and Gronberg et al. (2013) found that Texas school districts were less efficient (i.e., got less educational bang for the buck) when they were located in metropolitan areas with less choice. Misra, Grimes, and Rogers (2012) found that elementary and secondary schools in Mississippi were more efficient in urban areas where competition from private schools was higher. Kang and Greene analyzed school districts in New York and concluded that efficiency was lower in counties with less competition. Husted and Kenny (1996) and Millimet and Collier (2008) reached similar conclusions about the relationship between competition and school district efficiency.

The Consolidation Proposal

TEC Section 12.1013 calls for an analysis of the likely impact of a consolidation of school districts within any county that includes at least seven school districts and at least 10 open-enrollment charter schools. There are five Texas counties that fit that description—Bexar, Dallas, Harris, Tarrant and Travis. Thus, the consolidation proposal only affects the core counties of major metropolitan areas.

Table 1 indicates the 72 school districts that are eligible for consolidation under this proposal. Because TEC Section 12.1013 distinguishes between school districts and open-enrollment charter schools, and specifically references the consolidation of school districts, it seems clear that open-enrollment charter schools in the designated counties would not have their charters revoked and would continue to operate independently under this proposal. Therefore, open-enrollment charter schools are not included in Table 1 or in the simulated school district consolidation.

[3] For surveys of the literature, see Belfield & Levin (2002) or Taylor (2000).

Table 1: School District Enrollments in the Counties Referenced by TEC Section 12.1013

	Enrollment Fall 2012
Bexar County	
Alamo Heights ISD	4,805
East Central ISD	9,562
Edgewood ISD	11,931
Ft Sam Houston ISD	1,605
Harlandale ISD	15,154
Judson ISD	22,576
Lackland ISD	1,054
North East ISD	67,701
Northside ISD	99,426
Randolph Field ISD	1,192
San Antonio ISD	54,236
Somerset ISD	3,888
South San Antonio ISD	9,828
Southside ISD	5,123
Southwest ISD	12,991
County Total	321,072
Dallas County	
Carrollton-Farmers Branch	26,325
Cedar Hill ISD	8,243
Coppell ISD	10,960
Dallas ISD	158,680
Desoto ISD	8,884
Duncanville ISD	13,238
Garland ISD	57,914
Grand Prairie ISD	26,803
Highland Park ISD	6,828
Irving ISD	34,961
Lancaster ISD	6,536
Mesquite ISD	39,028
Richardson ISD	37,954
Sunnyvale ISD	1,288
County Total	437,642
Travis County	
Austin ISD	86,233
Del Valle ISD	11,317
Eanes ISD	7,837
Lago Vista ISD	1,339
Lake Travis ISD	7,779
Manor ISD	8,039
Pflugerville ISD	23,302
County Total	145,846

	Enrollment Fall 2012
Harris County	
Aldine ISD	65,415
Alief ISD	45,748
Channelview ISD	8,750
Crosby ISD	5,145
Cypress-Fairbanks ISD	109,733
Deer Park ISD	12,790
Galena Park ISD	22,012
Goose Creek CISD	21,743
Houston ISD	202,586
Huffman ISD	3,272
Humble ISD	36,867
Katy ISD	64,408
Klein ISD	46,778
North Forest ISD	6,690
La Porte ISD	7,723
Pasadena ISD	53,449
Sheldon ISD	7,549
Spring Branch ISD	34,778
Spring ISD	36,028
Tomball ISD	11,723
County Total	803,187
Tarrant County	
Arlington ISD	64,913
Azle ISD	5,912
Birdville ISD	24,119
Carroll ISD	7,697
Castleberry ISD	3,808
Crowley ISD	15,000
Eagle Mt-Saginaw ISD	17,674
Everman ISD	5,385
Fort Worth ISD	83,255
Grapevine-Colleyville ISD	13,328
Hurst-Euless-Bedford ISD	21,775
Keller ISD	33,254
Kennedale ISD	3,147
Lake Worth ISD	3,243
Mansfield ISD	32,831
White Settlement ISD	6,514
County Total	341,855

Note: ISD is the abbreviation for Independent School District. Because few students have perfect attendance, average daily attendance (ADA), the indicator used to adjust for size in the Foundation School Program, is systematically lower than fall enrollment (the size indicator shown here).
Source: Texas Academic Performance Reports (TAPR) 2012–13.

As the table illustrates, only a handful of the school districts in these five counties are small by the standards of Texas' school funding formula (see the box). Three of the five districts that are small enough to be eligible for the small schools funding adjustment—Lackland Independent School District (ISD), Randolph Field ISD and Ft. Sam Houston ISD—are located on military bases in Bexar County. The other small districts are Sunnyvale ISD in Dallas County and Lago Vista ISD in Travis County.

There are fewer than 10 districts in the five counties that are small enough to be eligible for the mid-sized district adjustment. Three are in Bexar County (Alamo Heights, Somerset and Southside ISDs); two are in Harris County (Crosby and Huffman ISDs) and the rest are in Tarrant County (Everman, Lake Worth, Kennedale and Castleberry ISDs).

If the incentive aid provisions (TEC Sections 13.281 and 13.282) were repealed, then the state would benefit directly from consolidation because it would no longer be obliged to pay the small and midsized funding supplements to the districts that were consolidated. However, the potential financial gains to the state from the proposed consolidations would be modest even if the incentive aid provisions were eliminated because so few districts in the five counties are deemed small or midsized. Less than 2.2% of the more than 2 million students directly affected by the proposed consolidations attend small or midsized school districts.

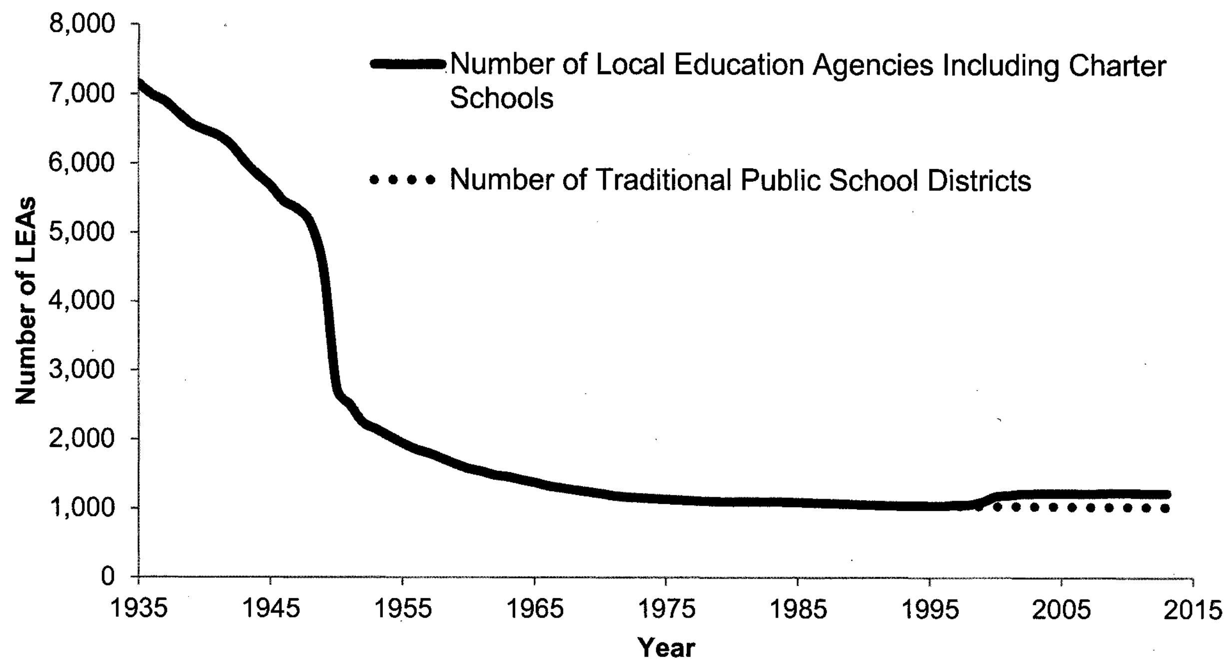
Furthermore, most of the districts in the five counties are already large enough to take full advantage of the typical economies of scale in education. As discussed in the previous section, researchers typically find that the cost savings from getting larger are nearly exhausted once district enrollment reaches 5,000 students. Only 11 of the 72 districts under consideration have enrollments below 5,000. On the other hand, 31 of the 72 districts have enrollments below 11,000, a threshold suggested by some of the recent cost function analyses of Texas.

The Foundation School Program, Texas' school funding formula, provides additional per-student funding to smaller districts. The small district adjustment provides supplemental funding, per pupil, to school districts with fewer than 1,600 students in average daily attendance (ADA). Small districts that encompass more than 300 square miles receive an additional adjustment. Districts with more than 1,600 but less than 5,000 students in ADA (regardless of geographic size) qualify for the less-generous, mid-sized district adjustment. The small and mid-sized adjustments shrink as districts get larger, so the smallest districts receive the largest benefits of the adjustments—which can be substantial. Eighty-four percent of Texas school districts were eligible for a size adjustment to the funding formula during the 2012–13 school year. Open-enrollment charter schools are not eligible for the size adjustments.

The History of School District Consolidations in Texas

Texas has experienced substantial school district consolidation in the past. In the 30 years between the 1934–35 and the1964–65 school years, the number of school districts in Texas declined by more than 80% (see Figure 1). In the next 30 years (from 1964–65 to 1994–95) the number of districts declined by another 76%. Since 1994–95, however, the number of traditional public school districts has declined by less than 2%, and the total number of local education agencies (which includes charter school operators) has increased.

Figure 1: The Number of Local Education Agencies in Texas, 1934–35 through 2013–14



Source: Karakaplan (2012), Academic Excellence Indicator System (AEIS) and Texas Academic Performance Reports (TAPR).

Twenty school district consolidations occurred during the period from 1994–95 through 2013–14 (Table 2). Only three of the 20 consolidations since 1994–95 involved school districts in major metropolitan areas—Wilmer-Hutchins ISD was annexed to Dallas ISD in 2006; Kendleton ISD was annexed to Lamar Consolidated ISD in 2010; and North Forest ISD consolidated with Houston ISD in 2013. In all but two of the 20 cases (Wilmer-Hutchins ISD and North Forest ISD) the consolidation folded a single-campus district into another, larger district.

Table 2: Texas School District Consolidations Since 1994–95

	Average Campus Enrollment	Number of Campuses	Total Enrollment After Consolidation
Allamoore ISD and Culberson County ISD	197	4	
➥ Culberson County-Allamoore ISD	265	3	795
Allison ISD and Fort Elliott CISD	74	2	
➥ Fort Elliott CISD	155	1	155
Asherton ISD and Carrizo Springs CISD	374	7	
➥ Carrizo Springs CISD	362	7	2,534
Bledsoe ISD and Whiteface CISD	136	4	
➥ Whiteface CISD	134	4	536
Byers ISD and Petrolia ISD	170	3	
➥ Petrolia ISD	238	2	476
Goree ISD and Munday ISD	163	3	
➥ Munday CISD	156	3	468
Kendleton ISD and Lamar CISD	681	35	
➥ Lamar CISD	682	36	24,552
Lakeview ISD and Memphis ISD	117	5	
➥ Memphis ISD	142	4	568
Marietta ISD and Pewitt CISD	252	4	
➥ Pewitt CISD	322	3	966
Mcfaddin ISD and Refugio ISD	217	4	
➥ Refugio ISD	274	3	822
Megargel ISD and Olney ISD	213	4	
➥ Olney ISD	276	3	828
Mirando City ISD and Webb CISD	95	4	
➥ Webb CISD	134	3	402
North Forest ISD and Houston ISD	740	283	
➥ Houston ISD	742	285	211,552
Novice ISD and Coleman ISD	237	4	
➥ Coleman ISD	291	3	873
Rochester County Line ISD and Haskell CISD	216	3	
➥ Haskell CISD	214	3	642
Samnorwood ISD and Wellington ISD	145	4	
➥ Wellington ISD	195	3	585
Spade ISD and Olton ISD	156	5	
➥ Olton ISD	235	3	705
Three Way ISD and Sudan ISD	101	4	
➥ Sudan ISD	125	3	375
Union ISD and Wellman ISD	163	2	
➥ Wellman-Union CISD	238	1	238
Wilmer-Hutchins ISD and Dallas ISD	698	230	
➥ Dallas ISD	734	219	160,746

Sources: School District Consolidations and Annexations (TEA 2013), Texas Education Directory (2014), Academic Excellence Indicator System (AEIS) and Texas Academic Performance Reports (TAPR).

In many cases, the consolidation had no discernible effect on average campus size or the number of campuses in the district. Table 2 compares the average campus size in the affected districts before and after consolidation. For example, Rochester County Line and Haskell ISDs consolidated in 2005. The average campus enrollment for the two districts in the school year immediately prior to consolidation was 216 students whereas the average campus enrollment for the consolidated district in the school year immediately after consolidation was 214 students. The number of campuses did not change after this consolidation.

In other cases, consolidation led school districts to reduce the number of campuses. For example, when Allamoore and Culberson County ISDs combined, the very tiny Allamoore Elementary school (which had an enrollment of three students in 1994-95) ceased operations.

The bottom line is that Texas' previous experience with school district consolidation provides little guidance as to the potential impact of consolidating all of the districts in the core county of a major metropolitan area. There are examples of consolidated school districts that redrew attendance zones and closed at least one existing campus, but there are also examples of consolidated school districts that left the campuses largely intact while consolidating central administration. Meanwhile, there are no examples of what happened when many large school districts consolidated simultaneously. Therefore, responding to TEC Section 12.1013 requires a simulation based on a formal analysis of the relationship between school district expenditures, student achievement and economies of scale.

The Cost Function Analysis

Cost function analysis provides a formal, analytic framework in which to simulate the impact of school district consolidation. Cost function analysis has been widely used in all sorts of contexts for more than 60 years, and in education contexts for at least 30 years. As discussed in Gronberg et al. (2011a), when properly specified and estimated using stochastic frontier analysis (SFA), the educational cost function is a theoretically and statistically reliable method for estimating the relationship between school district size and the cost of education.

The key components of the cost function analysis are summarized in Table 3, and described in the sections below. For a technical description of the cost function analysis, see Appendix A.

Units of analysis

TEC Section12.1013 specifically requires a report on likely outcomes for individual campuses. Therefore, this simulation is based on a campus-level analysis of the cost function. The analysis covers the five most recent school years with complete data (2008–09 through 2012–13).

Table 3: Key Components of the Educational Cost Function

Component	Measured by
Units of Analysis	All Standard Campuses in Traditional Public School Districts All CBSAs (i.e., All Metropolitan or Micropolitan Areas) Five Most Recent School Years (2008–09 through 2012–13)
Expenditures	Operating Expenditures Excluding Food and Transportation
Outcomes	Conditional NCE Scores in Mathematics and Reading on the State Assessments Campus Number of Students Enrolled
Input Prices	Teacher Salary Index Distance to the Center of the Nearest Metropolitan Area
Environmental Factors	Campus % Economically Disadvantaged Campus % Ever Limited English Proficient (Ever-LEP) Campus % Special Education Campus Type School District Size
Controls for Inefficiency	Stochastic Frontier Analysis Degree of School Choice

Source: Appendix A.

To develop the best possible estimates of the size-cost relationship, the cost-function analysis includes all standard accountability campuses in traditional public districts located in a metropolitan or micropolitan core-based statistical area (CBSA).[4][5] Standard accountability campuses are subject to all the rules and regulations pertaining to the Texas Accountability Rating System and therefore share a similar set of goals, objectives and educational processes (TEA, 2014). Alternative Education Accountability (AEA) campuses (e.g., juvenile justice campuses, disciplinary education campuses, residential campuses and all other alternative education campuses) have been excluded because they are subject to different accountability requirements and may have different cost structures than other campuses. Schools in rural areas (i.e., counties without a central city of at least 10,000 people) were not included because TEC Section 12.1013 specifically focuses on estimating the effects of consolidation in major metropolitan areas and limiting the analysis in this way provides additional validity (by making the cost and competitive environments for the campuses more similar). Because they operate under a different set of rules and regulations than traditional public school districts and

[4] Although many Texas school districts cross county lines, TEA officially associates each school district with a single county. Those official designations have been used to identify CBSA locations for campuses in traditional public school districts, using the CBSA definitions developed by the U.S. Office of Management and Budget and published by the U.S. Census Bureau. A metropolitan area is a county or cluster of counties with a central, urbanized area of at least 50,000 people. A micropolitan area is a county or cluster of counties with a central city of at least 10,000 people. Two counties are considered part of the same CBSA whenever commuting patterns indicate that the counties are part of the same integrated labor market area. In Texas, College Station-Bryan is a metropolitan area, and Nacogdoches is a micropolitan area.

[5] Virtual campuses and campuses that lack reliable data on student performance (such as elementary education campuses that serve no students in tested grades, or very small campuses) have also been excluded.

consolidation does not imply deregulation, open-enrollment charter schools have also been excluded from the data set.

Expenditures

The educational cost function seeks to explain variations in educational expenditures using data on educational outcomes, input prices and environmental factors. Here, educational expenditures are measured as operating expenditures per pupil, excluding food and student transportation expenditures. It is customary to exclude food and transportation expenditures from the measure of expenditures used in cost function analyses because those categories of expenditures are unlikely to be explained by the same factors that explain student performance, and therefore add unnecessary noise to the analysis.[6] (As discussed in Appendix A, including these categories has no qualitative effect on the key parameters of the cost function, but does reduce both the precision of the estimates and the estimate of cost efficiency.)

The actual expenditures data come from the Public Education Information Management System (PEIMS) and have been adjusted to account for school districts that serve as a fiscal agent for another school district or group of districts. [7] All expenditures have also been adjusted to account for the fact that districts differ in the percentage of their total spending they attribute to specific campuses. Some districts provide maintenance services centrally, for example, whereas other districts assign maintenance personnel to specific buildings. To ensure that all of the educational resources in a district are accounted for, school district expenditures that were not associated with a specific campus have been allocated to the district's campuses on a per pupil basis.[8] Thus, for example, if Little Elementary serves 20% of the students in its district, it is presumed to be responsible for 20% of the unallocated spending.

Figure 2 illustrates the distribution of operating expenditures per pupil for all the standard accountability campuses used in this analysis.[9] As the figure illustrates, operating expenditures in 2012-13 ranged from $4,500 to more than $16,500, per pupil. Expenditures per pupil were significantly higher for multi-grade campuses (those that could not be classified as elementary, middle or high schools) than for any other type of campus, largely because this category includes a number of small, single campus districts such as Slidell ISD in Wise County (part of the Fort Worth metropolitan area).[10] On average, spending was significantly higher in high schools (where the mean in 2012-13 was $8,899) than in elementary schools (where the mean was $7,310) or middle schools (where the mean was $7,632). The difference in average spending between elementary and middle schools was not statistically significant.

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[6] For examples, see Gronberg, Jansen & Taylor (2011a, 2011b), Gronberg, Jansen, Taylor & Booker (2004, 2005); or Imazeki & Reschovsky (2006).

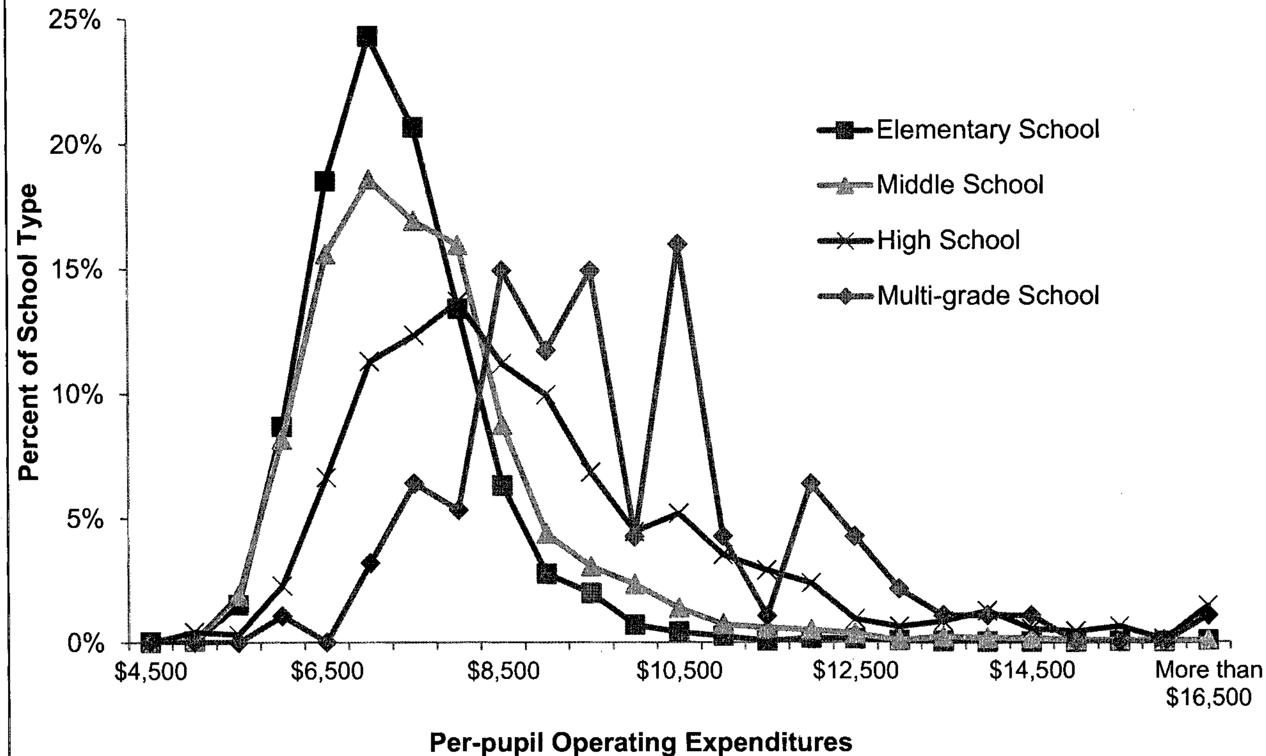
[7] Fiscal agents collect funds from member districts in a shared service agreement, and make purchases or pay salaries with those shared funds on behalf of the member districts. As a result, spending of fiscal agents is artificially inflated while the spending by member districts is artificially suppressed. See Appendix A.

[8] Gronberg et al. (2012) and Grosskopf, Hayes, Taylor & Weber (2013) also followed this approach.

[9] Per-pupil operating expenditures less than $3,500 or more than $33,000 were deemed implausible and treated as missing in this analysis.

[10] Throughout this report, the term "significantly" indicates something that is statistically significant at the 5% level, meaning that there is less than a 5% chance that the difference is due to chance alone.

Figure 2: Operating Expenditures per Pupil for Standard Accountability Campuses in Core Based Statistical Areas, by School Type, 2012–13

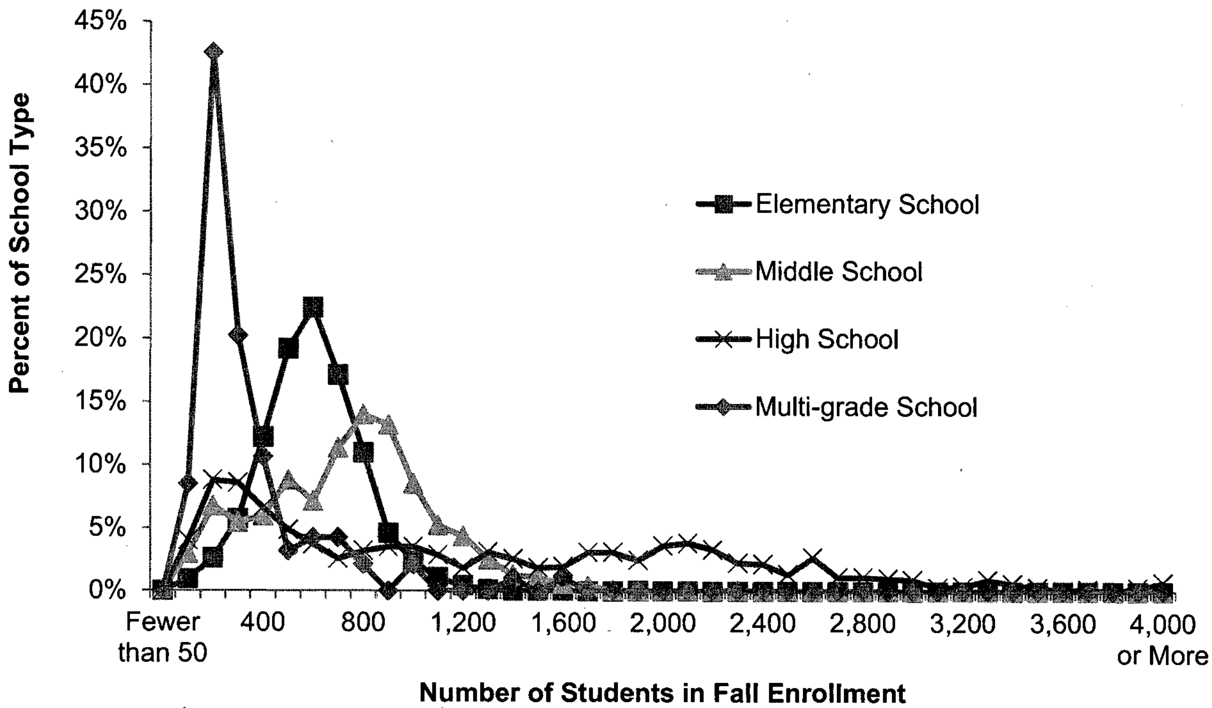


Sources: Public Education Information Management System (PEIMS) and Texas Academic Performance Reports(TAPR).

Outcomes

If schools are behaving efficiently, then increases in educational outcomes will lead to increases in educational expenditures. Total educational outcomes have both a quantity and a quality dimension. Quantity is measured using the number of students in fall enrollment at the campus. In 2012–13, campus enrollment ranged from 43 to 4,618 students; the average campus had 732 students (Figure 3). As a general rule, elementary schools were significantly smaller than middle schools which in turn were significantly smaller than high schools. Typically, multi-grade schools were the smallest type of all, but there were a few exceptions to this rule. For example, Sharpstown International School in Houston ISD (which serves grades 6-12) was a multi-grade campus with an enrollment above 1,000 in 2012–13.

Figure 3: Campus Enrollment for Standard Accountability Campuses in Core Based Statistical Areas, by School Type, 2012–13



Source: Texas Academic Performance Reports (TAPR).

The two quality measures used in this analysis capture differences in average student performance in reading and mathematics, respectively. These measures are based on student performance on the Texas Assessment of Knowledge and Skills (TAKS) and the State of Texas Assessments of Academic Readiness (STAAR®) Grades 3-8 and end-of-course (EOC) exams. Although schools clearly produce outcomes that may not be reflected in mathematics and reading test scores, these are performance measures for which districts are held accountable by the state, and the most common measures of school district outcome in the literature.[11] Therefore, they are reasonable outcome measures for cost analysis.

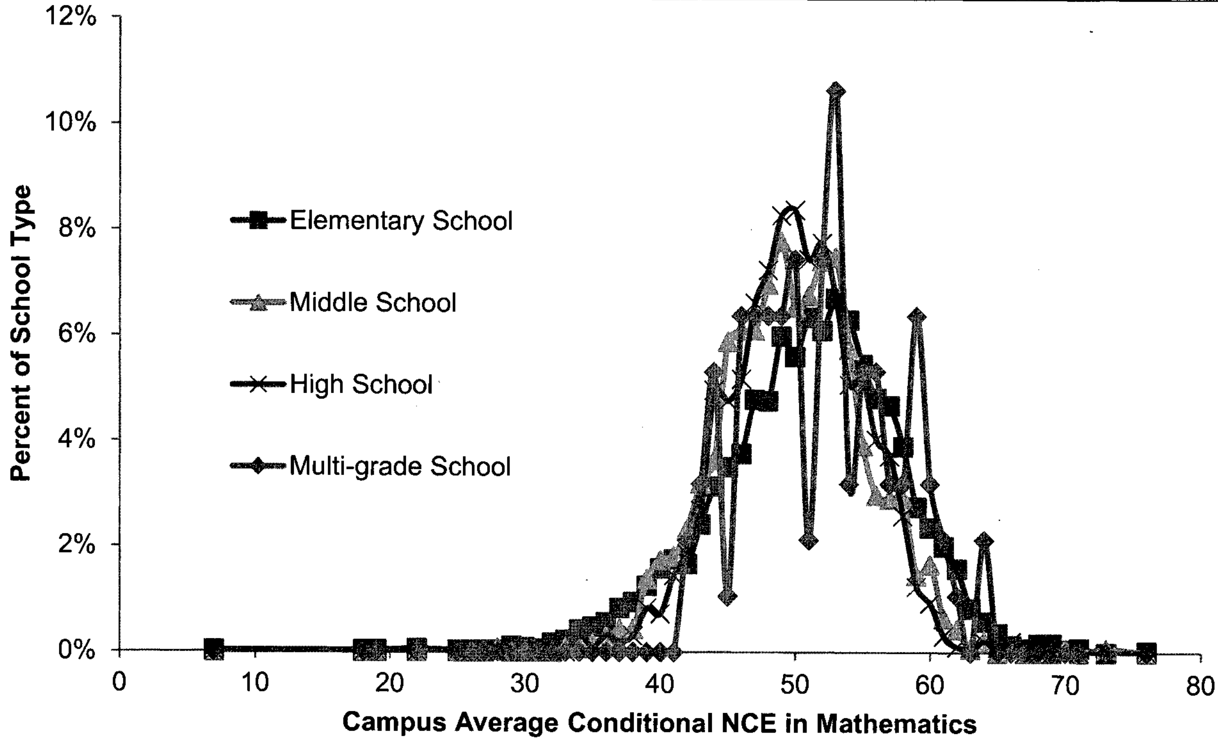
TAKS, STAAR Grades 3-8 and EOC scores can be difficult to compare across grades, years or testing regimes. Therefore, the various test scores have been transformed into conditional normal curve equivalent (NCE) scores.[12] A conditional NCE score describes a student's performance relative to what would have been expected given his or her prior test score (i.e., conditional on the prior test score). A conditional NCE score of 50 indicates that the student performed at the 50th percentile (i.e., exactly as expected given his or her prior test performance) and a conditional NCE score of 90 indicates that the student performed as well or

[11] For example, see Gronberg et al. (2011a, 2011b); Grosskopf et al. (2013); Grosskopf, Hayes & Taylor (2014); or Imazeki & Reschovsky (2006).
[12] For more on the construction of conditional NCE scores, see Appendix A.

better than 90% of his or her academic peers. The average conditional NCE scores for each campus in mathematics and reading form the two quality measures used in this analysis.

Figure 4 illustrates the distribution of average conditional NCE scores in mathematics in 2012–13. (The pattern for reading is very similar.) As the figure illustrates, the distribution of average conditional NCE scores is bell-shaped, with most standard accountability campuses in CBSAs having average conditional NCE scores between 40 and 60.[13]

Figure 4: Campus Average Conditional NCE Scores in Mathematics for Standard Accountability Campuses in Core Based Statistical Areas, by School Type, 2012–13



Source: Authors' calculations from Public Education Information Management System (PEIMS) data.

Input Prices

One key to estimating an educational cost function is identifying a measure of the price schools must pay for their most important input—teachers. Unfortunately, the average salary in a campus or district is not a good measure of price because it reflects the mix of teacher characteristics. For example, the average salary in a district that employed only inexperienced teachers would be lower than the average salary in a district that employed only highly experienced teachers, even if the price each district paid for each type of teacher (i.e., the steps on the salary schedule) were identical.

[13] In the interests of statistical reliability, campuses with fewer than 25 students for whom a conditional NCE could be calculated were excluded from the analysis.

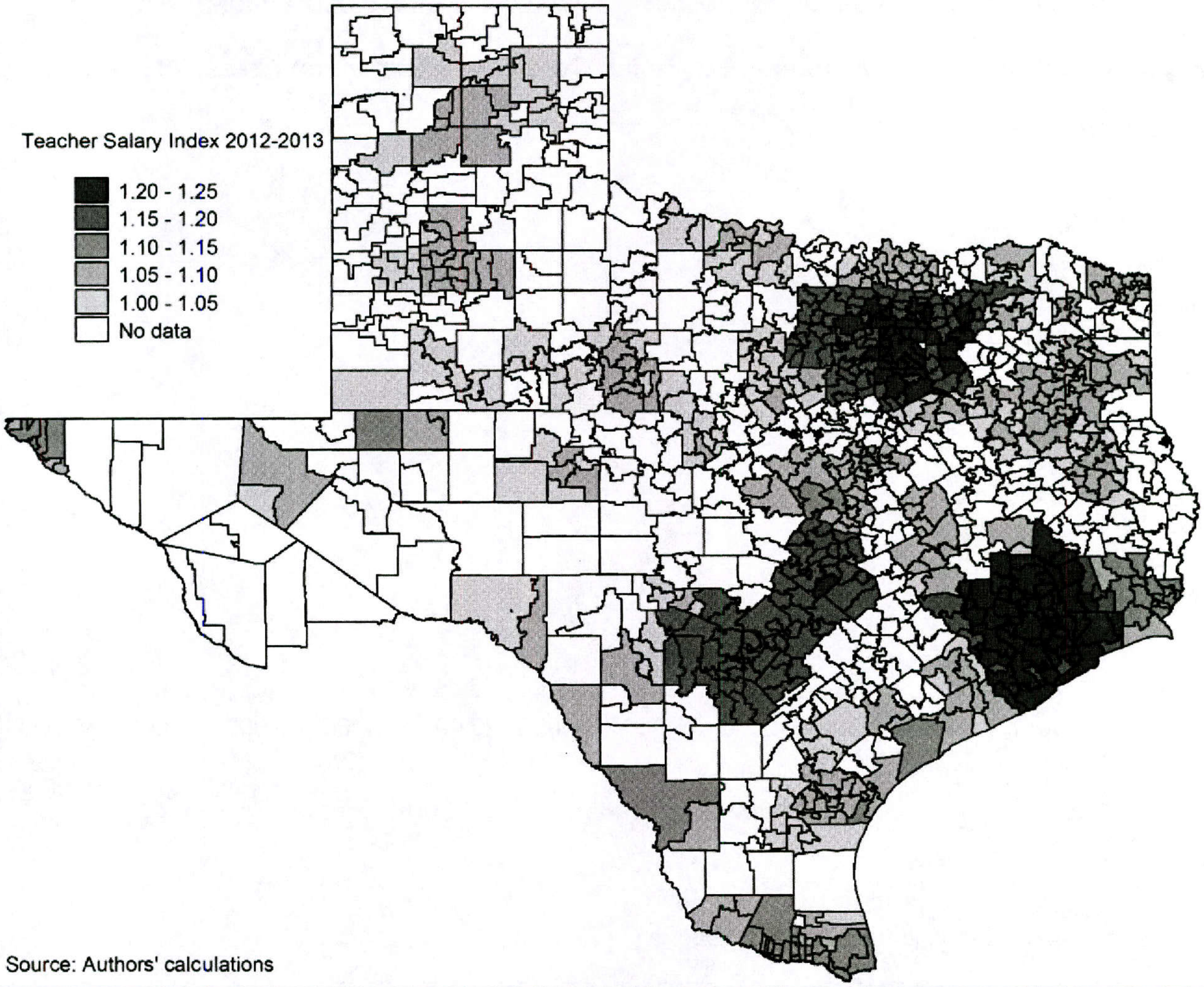
A common strategy for generating a price measure that does not reflect personnel choices is to estimate a hedonic wage model. (See Appendix B.) A hedonic wage model can be used to isolate the part of teacher salaries that is outside of school district control. Hedonic wage models have a long history in labor economics, and have been used in education finance contexts for more than 30 years. The Texas Cost of Education Index (which is a component of the Foundation School Program) is based on a hedonic wage model (Taylor, Alexander, Gronberg, Jansen & Keller, 2002).

The hedonic wage model used in this analysis describes the observed pattern of teacher salaries in Texas' CBSAs as a function of labor market characteristics, job characteristics, and individual teacher characteristics. Using the model, one can predict how much each campus must pay, each year, in order to hire a teacher with standard characteristics (i.e., a master's degree and 10 years of experience, or a bachelor's degree with zero years of experience). The Teacher Salary Index (TSI) for each campus (each year) is the predicted salary at that campus for a teacher with a standard set of characteristics, divided by the minimum predicted salary in a CBSA (for that year).[14] Each year during the five-year analysis period, the TSI ranged from 1.00 to 1.25 indicating that the cost of hiring teachers was up to 25% higher in some of the campuses under analysis than in others.

Figure 5 maps the average TSI values, by school district, for the 2012–13 school year. As the figure illustrates, on average the TSI is highest in the Houston and Dallas metropolitan areas and lowest in the Snyder, and Sweetwater micropolitan areas

[14] The TSI would be identical if it were constructed based on the predicted wage for a teacher with 10 years of experience and a master's degree or zero years of experience and a bachelor's degree. All that matters in the construction of the index is that the wage projections be based on a common set of teacher characteristics.

Figure 5: The Teacher Salary Index in Core Based Statistical Areas 2012–13



Source: Authors' calculations

Ideally, the analysis would also include direct measures of local prices for instructional equipment and classroom materials. Unfortunately, such data are not available. However, prices for pencils, paper, computers, and other instructional materials are largely set in a competitive market (and therefore unlikely to vary across schools), and prices for nonprofessional labor or building rents are largely a function of school location (and therefore likely to be highest in the central cities and lowest in the suburbs or the micropolitan areas). Therefore, as in in Gronberg et al. (2011a) the cost analysis includes the distance to the center of the nearest metropolitan area as a proxy for differences in the cost of non-labor inputs.[15]

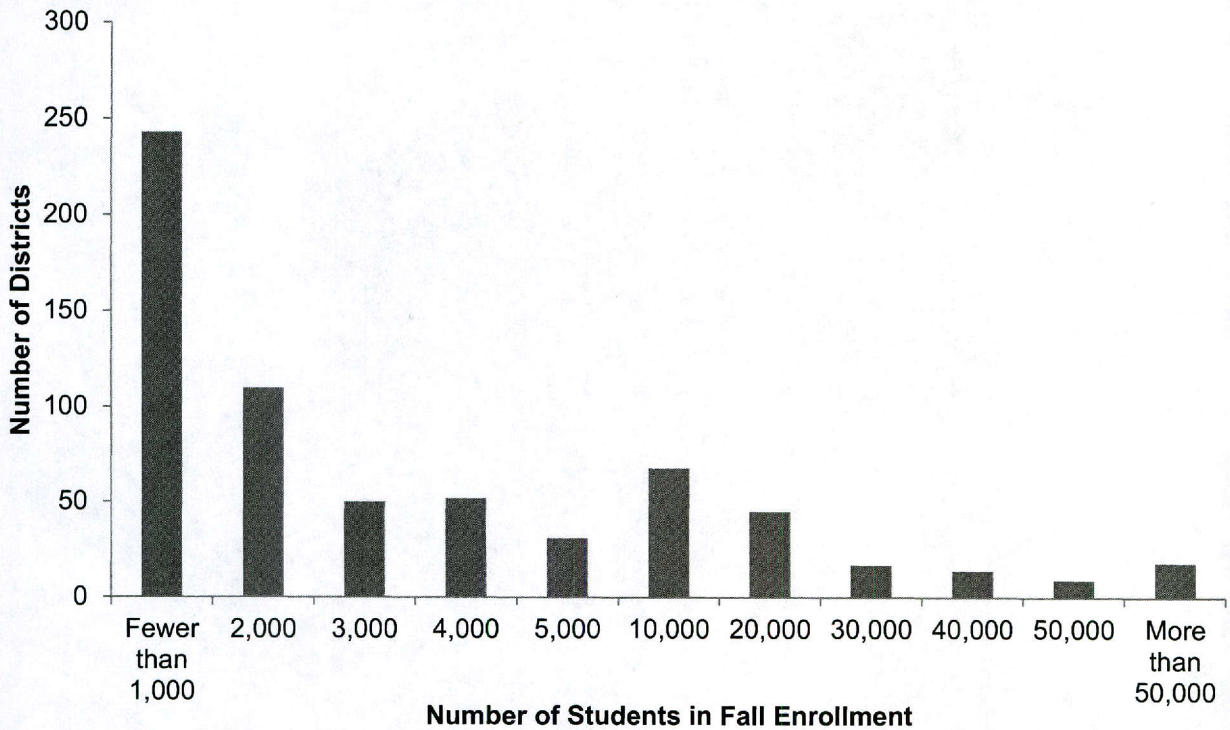
Environmental Factors

There are several environmental factors that influence the cost of education but are not purchased inputs. One such factor is the size of the school district. As Figure 6 illustrates,

[15] Miles to the center of the nearest metropolitan area was calculated as-the-crow-flies for each campus using latitude and longitude information.

district enrollment for the campuses used in this analysis ranges from fewer than 1,000 students to more than 200,000 students. The median school district in a Texas CBSA has fewer than 1,700 students and three quarters of the districts have fewer than 5,000 students.

Figure 6: School District Enrollment in Texas Core Based Statistical Areas, 2012–13



Source: Texas Academic Performance Reports (TAPR).

The other factors identified as influencing the educational environment are student need and school type. To capture variations in cost that derive from variations in student need, the analysis includes three measures of student demographics for each campus—the percentages of students who were identified as economically disadvantaged, special education or limited English proficient (LEP).[16] To capture differences in the cost of education that arise from differences in mandatory class sizes, or the scope of instruction, the analysis also includes indicators for elementary, middle and multi-grade schools.

[16] For statistical reasons, the measure of LEP status used in this analysis includes not only students who are currently LEP, but also any students who have ever been identified as LEP by the Texas school system. The percentage of students who had ever been identified as LEP greatly exceeds the percentage of students currently identified as LEP in some campuses.

Controlling for inefficiency

One of the keys to cost function analysis is the choice of estimation strategy. This analysis relies on SFA because, unlike other statistical techniques, SFA explicitly allows for the possibility that spending could be systematically higher than cost. If schools are behaving efficiently, then SFA generates the same cost function estimates as other estimation techniques. Therefore, SFA can be thought of as a more general approach.

When the educational cost function is estimated using SFA, school spending is presumed to depend not only on the direct determinants of educational cost (outcomes, input prices and environmental factors) but also on a set of factors that could lead one school district to behave more efficiently than another. Because previous researchers have found that competition affects cost efficiency[17], this analysis includes a measure of educational competition as one of the factors that might influence school district efficiency.

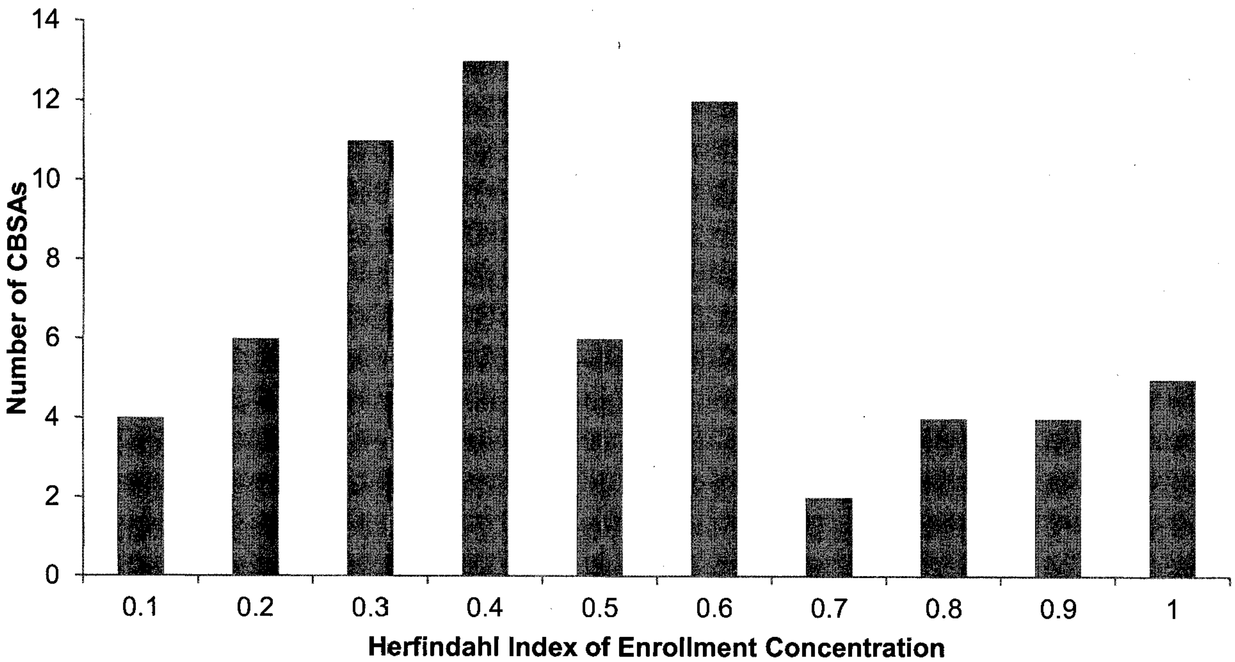
As is common in the literature, the degree of educational competition is measured using a Herfindahl index of enrollment concentration in the local labor market[18]. A Herfindahl index of 1.00 indicates a metropolitan area with a single local education agency (LEA); a Herfindahl index of 0.10 indicates a metropolitan area with 10 LEAs of equal size. Thus, the Herfindahl index increases as the level of enrollment concentration increases (or equivalently, as the level of educational competition decreases).

Figure 7 illustrates the distribution of educational competition among Texas' CBSAs. As the figure indicates, some Texas education markets—such as the Dallas and Houston metropolitan areas—are highly competitive (i.e., have a Herfindahl index below 0.10) while others—such as the Andrews, Del Rio or Eagle Pass micropolitan areas—are highly concentrated (i.e., have a Herfindahl index above 0.90).

[17] For example, see Belfield & Levin (2002); Millimet & Collier (2008); or Taylor (2000).

[18] A Herfindahl index is defined as the sum of the squared local education agency (LEA) enrollment shares, where an LEA's enrollment share is its own enrollment divided by the total enrollment in the CBSA. Both traditional public school districts and open enrollment charter schools are included in the calculation of enrollment concentration because both are included in the public school choices available to parents

Figure 7: Herfindahl Index of Educational Competition by Core Based Statistical Area, 2012–13



Source: Authors' calculations from Texas Academic Performance Reports (TAPR).

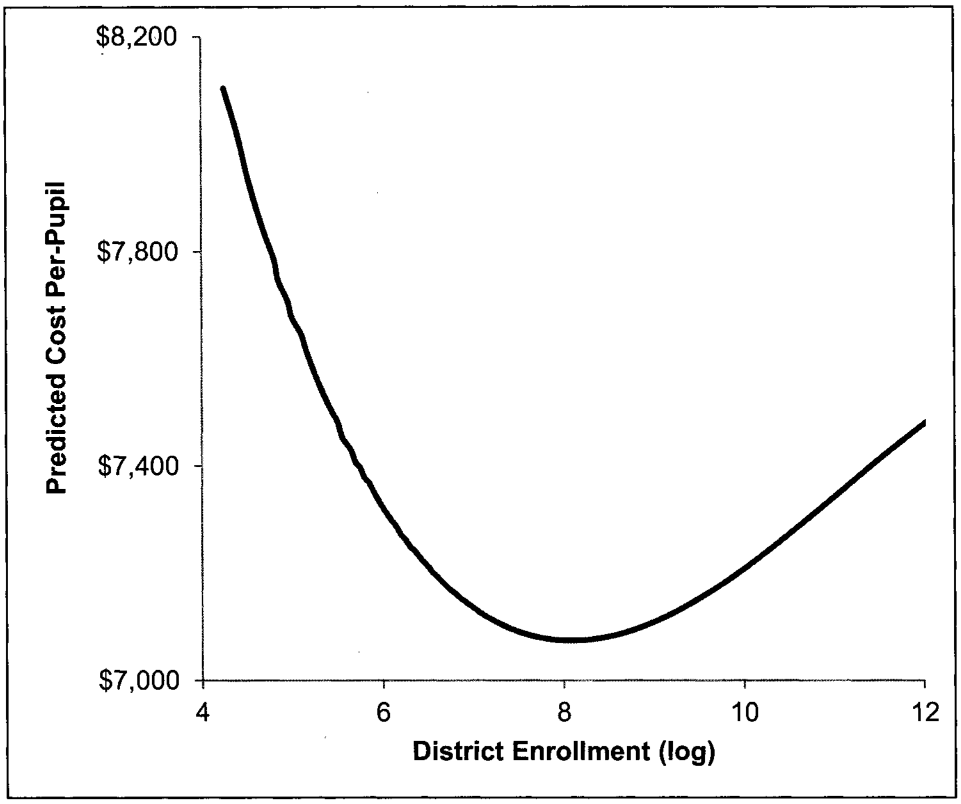
Cost Function Results

As discussed in Appendix A, the cost function analysis yields a reasonable picture of the educational process in Texas. According to the cost function estimates, increases in average student performance require increases in educational expenditures. This is true for both mathematics and reading. Campuses with a higher TSI have a higher cost of education. Students with greater needs are more costly to educate, and high schools are more costly to operate than elementary or middle schools.

The analysis reveals significant economies of scale for both campuses and districts. As a general rule and holding everything else constant, increases in campus size lead to decreases in the cost of education. For example, the cost function indicates that all other things being equal, a campus with 200 students costs 14% more to operate than a campus with 400 students.

There is a roughly U-shaped relationship between the cost of education and school district size. Figure 8 graphs the impact of changes in log district enrollment on predicted cost (holding everything else constant at the mean). As the figure illustrates, costs are highest for very small districts, but holding campus size constant, the differences are not large. A district with one campus and 600 students, for example, is predicted to cost 2.2% more to operate than a district with five campuses and 3,000 students. As district size increases, costs tend to fall until the log of district enrollment reaches a value of 8.07 (or 3,200 students). As district enrollment increases beyond that point, costs per student also increase. Thus, there are clear economies of scale in Texas education, but, consistent with the literature discussed above, the cost savings from increases in district size are largely exhausted at relatively low levels of enrollment.

Figure 8: The Estimated Relationship between Per-Pupil Cost and School District Enrollment



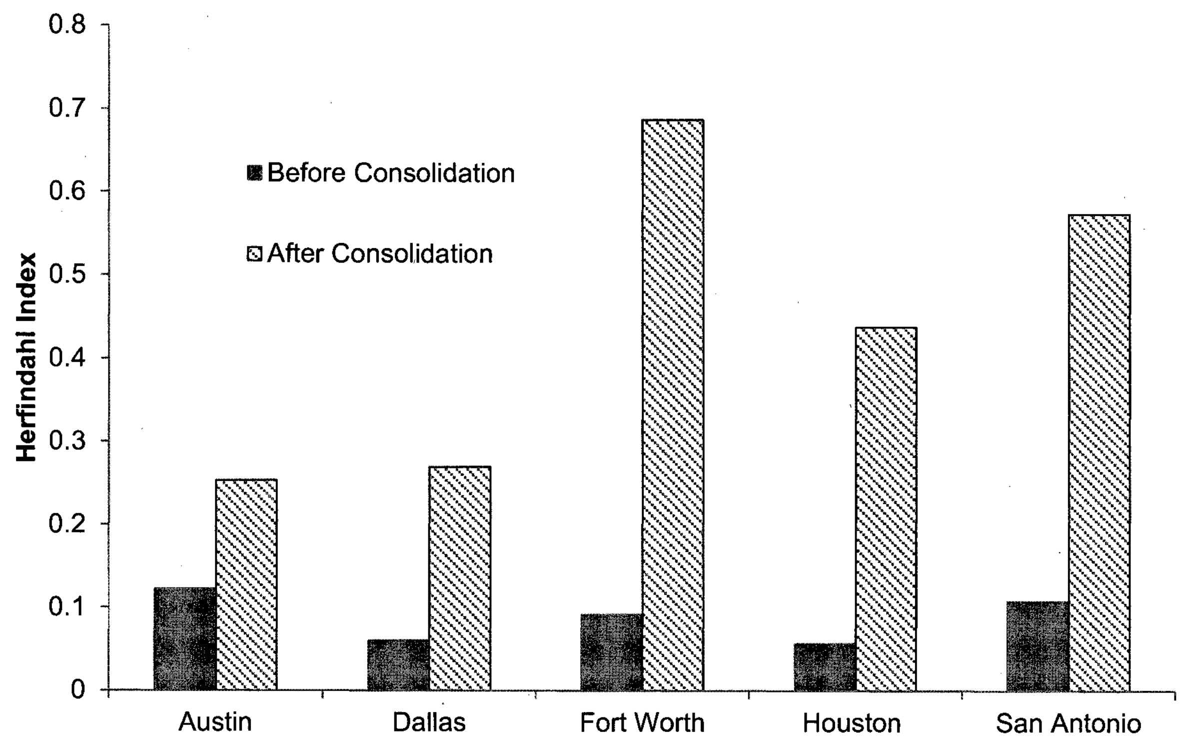
The analysis also finds clear evidence that expenditures exceed what would be expected if campuses were operating efficiently, and that the degree of inefficiency (i.e., the extent of the unexplained expenditures) is an increasing function of enrollment concentration. In other words, the analysis supports the hypothesis that more choice leads to more efficiency in education.

Simulating Consolidation

The results of the cost function analysis were used to simulate the consolidation to the county level of all traditional public school districts in the five counties (Bexar, Dallas, Harris, Tarrant and Travis) that are referenced by TEC Section12.1013. This simulation, which is described in greater detail in Appendix A, compares the predicted spending at each campus in the five counties under two scenarios—before consolidation and after consolidation.

The consolidation would clearly change the level of enrollment concentration in the affected metropolitan areas. Figure 9 compares the Herfindahl index for the five affected metropolitan areas before and after all traditional public school districts in the core county have been consolidated. As the figure illustrates, consolidating the traditional public school districts in these five counties would have a large impact on the level of enrollment concentration in their metropolitan areas. Currently, the metropolitan areas affected by the proposed consolidations are five of the seven most competitive education markets in Texas. (The other two are Longview and McAllen.) After consolidation, only Austin would even be in the top 20. The Herfindahl index would more than double for the Austin metropolitan area, and would more than quadruple for the other metropolitan areas. Consolidation would have a particularly large effect on enrollment concentration in Fort Worth, where the Herfindahl index would increase sevenfold (from 0.09 to 0.67).

Figure 9: The Effect of Consolidation on Enrollment Concentration in Referenced CBSAs



Source: Authors' calculations from Texas Academic Performance Reports (TAPR).

Consolidation would also create new districts that are very large by Texas and national standards. With an enrollment of just over 803,000 students, the consolidated Harris County ISD would be the second largest school district in the country (behind only New York City Schools).[19] The consolidated Dallas County ISD (enrollment 437,642) would be the fourth largest school district in the country, ahead of the Chicago Public School system, but smaller

[19] Data on school district enrollment outside of Texas come from the Digest of Education Statistics 2012 (Snyder & Dillow, 2013).

than Los Angeles Unified School district (which would be the third largest district). The consolidated Tarrant and Bexar County ISDs would be the nation's seventh and eighth largest districts, respectively, while the consolidated Travis County ISD would be among the 20 largest districts nationwide.

The simulation exercise compared the predicted expenditure per pupil in a campus before consolidation with the predicted expenditure per pupil in that campus after consolidation. In addition, in order to see the overall impacts of the consolidation, the pre-consolidation predicted total expenditures in a county were compared with the post-consolidation predicted total expenditures in that county. (The assumptions that underlie the simulation are described in Appendix A.)

The simulation predicts the change in expenditures per pupil for all of the campuses impacted by the consolidation. There are two types of impacted campuses: those that are part of the consolidation and those that are located in a metropolitan area where consolidation occurs. For campuses that are part of the consolidation, there are two impacts.

1. District size increases, which is expected to reduce the per-pupil cost of education for campuses in small districts, but increase the per-pupil cost of education for campuses in midsized or larger districts.
2. Enrollment concentration increases, which has no effect on cost, but is expected to increase inefficiency.

Campuses that are located in an affected metropolitan area but not an affected county would experience the second impact but not the first. Therefore, inefficiency in those campuses would unambiguously be expected to rise, leading to an increase in spending (assuming they maintain their current levels of student performance).

To illustrate the extent of the potential gains, consider Alamo Heights High School in Bexar County which had 1,471 students in 2012–13. Predicted per pupil expenditure before consolidation is $7,813, and predicted per pupil expenditure after consolidation is $7,102. Hence the simulation is predicted to generate savings of $711 per pupil (9%).

On the other hand, Serene Hills Elementary School is in Travis County with enrollment of 635 students in 2012–13. The school's predicted expenditure per pupil is $6,440 before consolidation, and $6,632 afterwards, or an increase in per pupil expenditures of $192 (3%).

Finally, consider Alvarado Junior High in Johnson County, which had an enrollment of 504 students in 2012–13. The school's predicted expenditure per pupil is $7,136 before consolidation, and $7,296 after consolidation, or a predicted increase in per pupil expenditures of $160 (2%). This increase is completely attributable to the predicted increase in inefficiency due to a loss of competition in the Fort Worth metropolitan area.

The first column in Table 4 presents the number of campuses in which consolidation decreases the predicted expenditures per pupil. For example the table indicates that consolidation is cost saving for 27 campuses in Bexar County, and 227 campuses in the five counties combined. That is, consolidation would reduce predicted expenditures in roughly 10% of the campuses in these five counties.

Table 4: Simulation Results for Campuses in Consolidating Counties, 2012–13

	Number of campuses in which predicted expenditure decreases after consolidation	Number of campuses in which predicted expenditure increases after consolidation
Bexar	27	338
Dallas	55	500
Harris	90	720
Tarrant	43	394
Travis	12	166
Total	227	2,118

Source: Authors' calculations.

Expected increases in expenditures are much more common than expected decreases. The second column in Table 4 shows the number of campuses in which consolidation increases the predicted expenditures. On average, consolidation simulation increases predicted expenditures in 338 campuses in Bexar County and a total of 2,118 campuses in the five counties. That corresponds to 90% of the standard accountability campuses in these counties.

As a general rule, high school campuses are much more likely to benefit from county consolidation than are elementary or middle school campuses. All but 5 of the 227 campuses where expenditure is predicted to decrease are secondary schools. Campuses with a large percentage of students enrolled in special education programs and campuses with a small percentage of economically disadvantaged students are also more likely than other campuses to be among the 227 campuses that are expected to benefit from consolidation.

The predicted expenditures for the campuses are then aggregated to generate predicted impacts on county level expenditures in the simulated consolidation to county districts. Table 5 demonstrates the change in predicted expenditures per pupil for each of the five counties. Consolidation is expected to increase the predicted expenditure per pupil by 6.5% in Bexar County, 4.9% in Dallas County, 4.1% in Harris County, 6.1% in Tarrant County, and 2.8% in Travis County. After consolidation, the expected increase in total county expenditure ranges from $39 million in Travis County to $325 million in Harris County.

Table 5: Consolidation Simulation Results for Counties and Core Based Statistical Area

County	Total Enrollment	Average Predicted Expenditure per Pupil Before Consolidation	Average Predicted Expenditure per Pupil After Consolidation	Total Increase in Predicted Expenditures (in millions)
Bexar County	321,072	$7,354	$7,885	$170.4
Rest of San Antonio	88,273	$7,293	$7,429	$12.0
Dallas County	437,642	$7,615	$8,076	$201.7
Rest of Dallas	385,496	$7,248	$7,356	$41.5
Harris County	803,187	$7,313	$7,718	$325.4
Rest of Houston	375,788	$7,138	$7,289	$56.8
Tarrant County	341,855	$7,260	$7,771	$174.6
Rest of Fort Worth	56,750	$7,542	$7,713	$9.7
Travis County	145,846	$7,627	$7,894	$38.9
Rest of Austin	157,956	$7,142	$7,196	$8.6

Note: The rest of the CBSA refers to the school districts in the designated metropolitan area, but outside of the core county.
Source: Authors' calculations

Importantly, this simulation has been constructed assuming that the consolidated, countywide school districts did not close any campuses in the wake of consolidation. That is a reasonable assumption given the political difficulties associated with closing a viable, neighborhood school, and the near impossibility of accurately predicting the nature of any school-level consolidations. After all, most of the districts in the potentially consolidating counties already have the option of campus consolidation, and have chosen not to use it. However, it is likely that at least some campuses in the new countywide school districts will be eliminated, allowing the average campus size to grow. As the cost function analysis indicates, there can be substantial cost savings from campus consolidation—if nothing else changes, combining two 200 student campuses into one 400 student campus is expected to reduce operating costs by 14%, for example. Therefore, the estimates in Table 5 likely overstate somewhat the increase in expenditures post consolidation for Bexar, Dallas, Harris, Tarrant and Travis counties.

That said, the best available evidence suggests that consolidating all of the school districts in the core counties of major metropolitan areas would not generate any expenditure savings that could be turned into achievement gains. Instead, expenditures are expected to rise in each of the consolidating counties—and to a lesser extent in all of the school districts that share a metropolitan area with a consolidating county—without any improvement in student performance. If expenditures were unable to rise as predicted after consolidation, then the simulation suggest that student performance would fall in all five metropolitan areas.

Conclusions

This report presents findings from a formal analysis of the potential gains from a targeted policy of school district (but not campus) consolidation. The analysis supports three key findings.

- Cost savings can be expected for consolidations involving small districts, but as the size of the consolidated district increases past 3,200 students, costs are expected to rise, not fall.
- Competitive pressure leads to greater school district efficiency in Texas, so any consolidation is expected to lead to a loss of school district efficiency.
- There are no expected cost savings from the targeted consolidations under analysis. Instead, expenditures are expected to increase by up to 6.5%, depending on the county. Expenditures are expected to rise not only in Bexar, Dallas, Harris, Tarrant and Travis counties, but also in all of the other districts in the corresponding metropolitan areas (due to the loss of competition in those education markets).

Given the lack of cost savings under the simulation, it is highly unlikely that performance would improve if there were consolidation in the designated counties. While there are many counties in Texas where all of the districts are small enough to unambiguously gain from consolidation, the existing districts in the specific counties under analysis already enjoy substantial economies of scale and would lose important incentives to behave efficiently were they to be consolidated. Therefore, there is no reason to believe that this proposal would lead to improvements in student performance, and good reason to believe student performance would fall. The bottom line is that bigger is not always better in Texas.

References

Andrews, M., Duncombe, W., & Yinger, J. (2002). Revisiting economies of size in American education: Are we any closer to a consensus? *Economics of Education Review, 21*, 245-262. doi: 10.1016/S0272-7757(01)00006-1

Belfield, C. R., & Levin, H. M. (2002). The effects of competition between schools on educational outcomes: A review for the United States. *Review of Educational Research, 72*, 279-341. doi: 10.3102/0034654307200227

Berry, C. R., & West, M. R. (2010). Growing pains: The school consolidation movement and student outcomes. *Journal of Law, Economics, and Organization, 26*, 1-29. doi: 10.1093/jleo/ewn0

Dee, T. S. (1998). Competition and the quality of public schools. *Economics of Education Review, 17*, 419-427. doi: 10.1016/S0272-7757(97)00040-X

Dee, T. S., Ha, W., & Jacob, B. A. (2006). The effects of school size on parental involvement and social capital: Evidence from the ELS: 2002. *Brookings Papers on Education Policy*, 2006, 77-97.

de Haan, M., Leuven, E., & Oosterbeek, H. (2014). *School supply and student achievement: Evidence from a school consolidation reform*. Retrieved August 1, 2014 from http://www.economists.nl/files/20140306-DeHaanLeuvenOosterbeekFeb2014_submission.pdf

Dodson, M. E., & Garrett, T. A. (2004). Inefficient education spending in public school districts: A case for consolidation? *Contemporary Economic Policy, 22*, 270-280. doi: 10.1093/cep/byh019

Duncombe, W., Miner, J., & Ruggiero, J. (1995). Potential cost savings from school district consolidation: A case study of New York. *Economics of Education Review, 14*, 265-284. doi: 10.1016/0272-7757(94)00011-T

Duncombe, W., & Yinger, J. (2007). Does school district consolidation cut costs? *Education Finance and Policy, 2*, 341-375. doi: 10.1162/edfp.2007.2.4.341

Gordon, N., & Knight, B. (2008). The effects of school district consolidation on educational cost and quality. *Public Finance Review, 36*, 408-430. doi: 10.1177/1091142107305219

Gronberg, T. J., Jansen, D. W., Karakaplan, M. U., & Taylor, L. L. (2013). *School District Consolidation: Market Concentration and the Scale-Efficiency Tradeoff*. Retrieved August 1, 2014 from http://econweb.tamu.edu/karakaplan/Karakaplan%20-%20Scaling.pdf.

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2011a). The adequacy of educational cost functions: Lessons from Texas. *Peabody Journal of Education, 86*, 3-27. doi: 10.1080/0161956X.2011.539953

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2011b). The impact of facilities on the cost of education. *National Tax Journal, 64*, 193-218.

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2012). The relative efficiency of charter schools: A cost frontier approach. *Economics of Education Review, 31*, 302-317. doi: 10.1016/j.econedurev.2011.07.001

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Booker, K. (2004). *School outcomes and school costs: The cost function approach*. Austin, TX: Texas Joint Select Committee on Public School Finance.

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Booker, K. (2005). *School outcomes and school costs: A technical supplement*. Austin, TX: Texas Joint Select Committee on Public School Finance.

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Karakaplan, M. U. (2010). *Costs, competition, and consolidation*. College Station, TX: State of Texas Education Research Center at Texas A&M University.

Grosskopf, S., Hayes, K. J., & Taylor, L. L. (2014). Efficiency in education: Research and implications. *Applied Economic Perspectives and Policy, 36*, 175-210. doi: 10.1093/aepp/ppu007

Grosskopf, S., Hayes, K. J., Taylor, L. L., & Weber, W. L. (1999). Anticipating the consequences of school reform: A new use of DEA. *Management Science, 45*, 608-620. doi: 10.1287/mnsc.45.4.608

Grosskopf, S., Hayes, K. J., Taylor, L. L., & Weber, W. L. (2001). On the determinants of school district efficiency: Competition and monitoring. *Journal of Urban Economics, 49*, 453-478. doi: 10.1006/juec.2000.2201

Grosskopf, S., Hayes, K., Taylor, L. L., & Weber, W. L. (2013). Centralized or decentralized control of school resources? A network model. *Journal of Productivity Analysis*, 1-12. doi: 10.1007/s11123-013-0379-2

Husted, T. A., & Kenny, L. W. (1996). Efficiency in education: Evidence from the states. In *Proceedings of the 89th Annual Conference on Taxation*. Washington, DC: National Tax Association, 282-290.

Imazeki, J., & Reschovsky, A. (2006). Does No Child Left Behind place a fiscal burden on states? Evidence from Texas. *Education Finance and Policy, 1*, 217-246. doi: 10.1162/edfp.2006.1.2.217

Kang, B. G., & Greene, K. V. (2002). The effects of monitoring and competition on public education outputs: A stochastic frontier approach. *Public Finance Review, 30*, 3-26. doi: 10.1177/109114210203000101

Karakaplan, M. U. (2012). *The Effects of multi-dimensional competition on education market outcomes* (Unpublished doctoral dissertation). Texas A&M University, College Station. Available electronically from http://hdl.handle.net/1969.1/ETD-TAMU-2012-08-11835

Millimet, D. L., & Collier, T. (2008). Efficiency in public schools: Does competition matter? *Journal of Econometrics, 145*, 134-157. doi: 10.1016/j.jeconom.2008.05.001

Misra, K., Grimes, P., & Rogers, K. (2012). Does competition improve public school efficiency? A spatial analysis. *Economics of Education Review, 31*, 1177-1190. doi: 10.1016/j.econedurev.2012.08.001

Overstreet, S., Devine, J., Bevans, K., & Efreom, Y. (2005). Predicting parental involvement in children's schooling within an economically disadvantaged African American sample. *Psychology in the Schools, 42*, 101-111. doi: 10.1002/pits.20028

Snyder, T.D., & Dillow, S.A. (2013). *Digest of education statistics 2012* (NCES 2014-015). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Taylor, L. L. (2000). The evidence on government competition. *Federal Reserve Bank of Dallas Economic and Financial Review, 2*, 1-9.

Taylor, L. L., Alexander, C. D., Gronberg, T. J., Jansen, D. W., & Keller, H. (2002). Updating the Texas cost of education index. *Journal of Education Finance, 28*, 261-284.

Texas Education Agency (2013). *School district consolidations and annexations for Texas public school districts from 1983-1984 to 2013-13.* Retrieved July 25, 2014 from http://www.tea.state.tx.us/index2.aspx?id=2147487003&menu_id=645&menu_id2=789

Texas Education Agency (2014). 2013 *Accountability manual.* Retrieved August 1, 2014 from http://ritter.tea.state.tx.us/perfreport/account/2013/manual/index.html

Texas Comptroller of Public Account. 2013. *Technical appendix: FAST methodology.* Retrieved August 1, 2014 from http://www.fastexas.org/pdf/2013/fast-2013-methodology.pdf

Zimmer, T., DeBoer, L., & Hirth, M. (2009). Examining economies of scale in school consolidation: Assessment of Indiana school districts. *Journal of Education Finance, 35*, 103-127. doi: 10.1353/jef.0.0012

Technical Appendix A: The Cost Function Model

As discussed in Gronberg, Jansen and Taylor (2011a), when properly specified and estimated using stochastic frontier analysis (SFA), the educational cost function is a theoretically and statistically reliable method for estimating the relationship between school district size and the cost of education. In the absence of profit-maximizing incentives, the possibility of cost inefficiency looms larger in the public sector and must be addressed in any analysis of educational cost. The stochastic cost frontier approach allows the data to reveal the degree of cost inefficiency while identifying properties of the true cost function.

This analysis uses SFA to estimate an educational cost function for Texas. The standard stochastic frontier model starts with a cost function. A cost function – a cost frontier – specifies the minimum cost necessary to achieve certain outcomes with specified inputs and specified environmental factors. The cost function can be written as:

$$C = C(Z \mid \beta) \cdot \exp(\varepsilon) \qquad (1)$$

where C is cost, $C(Z \mid \beta)$ is the cost function or cost frontier, $Z = \{w_1, \ldots, w_k;\ z_1, \ldots, z_m; y\}$ is a vector of variables affecting the frontier level of cost, where, w_l are input prices, z_j are quasi-fixed inputs including environmental factors, y is a vector of outcomes, β is the cost parameter vector to be estimated, and ε is a random noise component representing exogenous random shocks (e.g., a rainy testing day). This cost frontier is the true deterministic neo-classical cost function, the object of discovery. The error term, ε, indicates random deviations from the cost frontier due to measurement error and unforeseen random changes in cost due to factors not modeled in the cost function $C(Z \mid \beta)$,

Equation (1) presents a standard empirical cost function, including the modeled cost frontier and the allowance for random deviations from the cost frontier.

In the stochastic frontier approach, the cost function in (1) is regarded as a frontier, a minimum cost of attaining given outputs with given inputs including environmental factors. Spending may then deviate from this cost frontier, exceeding the minimum cost specified in the cost frontier. Thus the stochastic frontier approach starts with (1) and adds the assumption that spending exceeds the cost frontier due to random errors but also due to inefficiency. The stochastic frontier approach basically takes equation (1) and assumes that the random error, ε, consists of two parts, a standard two-sided random error that can be positive or negative and on average is zero, and a one-sided error that is always positive (or at least not negative). This one-sided error captures the idea that individual decision making units – districts or campuses – can at best be on the cost frontier, plus or minus the value specified in the two-sided random error. The one-sided error captures the idea that decision making units can at best be on the cost frontier, if they are fully efficient, and if they are inefficient this is captured or modelled by the one-sided error. The larger the one-sided error, the further a decision making unit is from the frontier, and hence the more inefficient is the decision making unit.

To model this, equation (1) is altered to specify the error term, ε, as consisting of two components, *v* plus *u*. The two sided error is *v*, and the one-sided error is *u*. Because inefficiency increases cost above the frontier (i.e., above the minimum possible cost), $u_i \geq 0$, where i indicates the specific decision making unit.

The stochastic frontier cost function is given as:

$$= C(Z \mid \beta) \cdot \exp(v + u), \tag{2}$$

where E is actual or observed spending and $C(Z \mid \beta)$ is the cost frontier as described above. Here v is a random noise component representing an exogenous random shock (e.g.a rainy testing day) and u is a one-sided error term that captures cost inefficiency. Then cost efficiency is defined as $CE_i = \exp(-u_i) \leq 1$.

Cost frontier estimates indicate the cost of achieving certain educational outcomes after controlling for cost and other environmental factors. The educational outcomes include a quantity dimension – the number of students enrolled – and a quality dimension. The quality dimension considered here is a measure of the gains in student performance relative to an expected level of performance based on past scores.

It is common to estimate our stochastic frontier cost function in per-pupil terms – see Andrews, Duncombe and Yinger (2002) or Gronberg, Jansen, Karakaplan and Taylor (2013). The unit of observation is the campus, so here N denotes *campus* enrollment and S denote student achievement. The per pupil stochastic frontier model is:

$$^* \equiv \frac{}{N} = \frac{C(w_1, \dots, w_k;\, z_1, \dots, z_m;\, S, N \mid \beta) \cdot \exp(v + u)}{N} \tag{3}$$

Taking natural logarithms of equation (3) gives

$$\ln E^* = \ln C(\cdot) - \ln N + v + \tag{4}$$

The economic concept of "economies of scale" is, in principle, measured with respect to campus enrollment, N, or with respect to quality, S. However, the most common measure -- and the one relevant to consolidation issues -- is enrollment. In fact, Andrews, Duncombe and Yinger (2002) refer to this as economies of size (usually defined with respect to district enrollment). This paper considers both economies of size with respect to campus enrollment and with respect to district enrollment. Economies of size is defined here as the enrollment elasticity of per pupil expenditures ($\eta = \partial \ln E^* / \partial \ln N$), holding constant student achievement (S), input prices (w), quasi-fixed inputs (z) and cost inefficiency. Using equation (4) this yields

$$\eta = \theta - 1, \tag{5}$$

where $\theta = \partial \ln C / \partial \ln N$ is the enrollment elasticity of total cost. Economies of size exist if $\eta < 0$, or correspondingly if $\theta < 1$.

An important feature of the decision-making environment facing school officials is the competitiveness of the district's relevant education market. Indeed, the literature finds that competition is one factor that can influence a school district's cost inefficiency.[20] The argument

[20] For example, see Belfield & Levin (2002); Dee (1998); Gronberg et al. (2013); Gronberg, Jansen, Taylor & Karakaplan (2010); Grosskopf, Hayes, Taylor & Weber (2001); Kang & Greene (2002); or Millimet & Collier (2008).

is that competition serves to discipline the tendency of districts to engage in excessive spending. This implies a negative relationship between the competitiveness of a district's education market and the magnitude of that district's cost inefficiency.

The stochastic cost frontier framework can accommodate models of how factors impact the one-sided error term (u). In particular, suppose that

$$= u(x, \delta), with\, u \geq 0 \tag{6}$$

where x includes factors impacting inefficiency, such as a measure of competition, andδ is a parameter vector. Substituting (6) into the per pupil expenditure equation (4). yields

$$\ln E^* = \ln C(\cdot) - \ln N + v + u(x, \delta) \tag{7}$$

Equation (7) can be used to examine the effects of a school district consolidation on per pupil expenditures. Consolidation involves a direct change in N but also a potential change in school district market competitiveness and with it a change in efficiency.

Letting x_1 denote a measure of competition measure and differentiating equation (7) with respect to ln$N$ yields

$$\eta = (\theta - 1) + \left(\frac{\partial u}{\partial x_1}\right) \cdot \left(\frac{\partial x_1}{\partial N}\right) \cdot N \tag{8}$$

As discussed in Gronberg et al.(2013), the spending response to consolidation can be decomposed into two effects, a cost economy effect $(\theta - 1)$ and a competitive efficiency effect $(\partial u/\partial x_1) \cdot (\partial x_1/\partial N) \cdot N$. The competitive efficiency hypothesis implies both $(\partial u/\partial x_1) < 0$ and $(\partial x_1/\partial N) < 0$, so when $(\theta - 1) < 0$ the potential per pupil cost savings from consolidation will be dampened by the spending increase from increased inefficiency.

Specification of the Econometric Model

This analysis estimates a (slightly modified) translog frontier cost function. As indicated above, the dependent variable is operating expenditures per pupil (E^*). The explanatory variables – the right-hand-side variables -- include n_1 output variables (enrollment, $N = q_1$, and the quality measures q_i) , n_2 input prices denoted by w_l , and n_3 environmental factors denoted by z_j. All variables except those already expressed as percentages or percentage points are in natural logarithms.

The model for campus expenditures per pupil is:

$$\ln E^* = \alpha_0 + \sum_{i=1}^{n_1} \alpha_{1i} q_i + \sum_{i=1}^{n_2} \alpha_{2i} w_i + \sum_{i=1}^{n_3} \alpha_{3i} z_i + 0.5 \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} \alpha_{4ij} q_i q_j + 0.5 \sum_{i=1}^{n_2} \sum_{j=1}^{n_2} \alpha_{5ij} w_i w_j$$

$$+ 0.5 \sum_{i=1}^{n_3} \sum_{j=1}^{n_3} \alpha_{6ij} z_i z_j + \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \alpha_{7ij} q_i w_j + \sum_{i=1}^{n_1} \sum_{j=1}^{n_3} \alpha_{8ij} q_i z_j + \sum_{i=1}^{n_2} \sum_{j=1}^{n_3} \alpha_{9ij} w_i z_j \quad (9)$$

$$+ \alpha_{10} \cdot z_1^3 + v +$$

where usual symmetry restrictions ($\alpha_{ij} = \alpha_{ji}$) apply. Equation (9) includes both district and campus enrollment. Campus enrollment interacts with all other variables as well as entering as a quadratic. District enrollment is modeled similarly, except that, as school district size in Texas varies so greatly, a cubic term for enrollment is added.[21]

Following Gronberg et al. (2013) the one-sided error (*u*) is modeled as a function of a Herfindahl index of school district competition. This Herfindahl index is based on the enrollment shares of districts within a given county. The Herfindahl index for a perfectly competitive market with an infinity of small firms is zero; the Herfindahl index for a monopoly market with only a single firm is one. Larger values of the Herfindahl index indicate lower levels of competition.

Equation (9) nests the popular Cobb-Douglas as a special case, as well as the modified Cobb-Douglas specification including a limited set of quadratic terms that has been used by Imazeki and Reschovsky (2006), among others. It also nests the classical (non-frontier) linear regression specification of the translog (if the one-side error term is restricted to be identically zero). Thus, the general specification used in this analysis allows researchers to test empirically for alternative specifications common in the literature.

It bears emphasis, however, that many previous cost function estimates have been at the district level. Equation (9) is estimated for campus-level observations, and hence the direct economies-of-scale issue is with respect to campus enrollment. That said, district enrollment is an important environmental variable impacting campus costs, and district size is at the heart of consolidation issues.

Because school quality is frequently thought of as a choice variable for school district administrators, the possible endogeneity of school quality indicators is a common concern for researchers estimating educational cost functions. (For example, see the discussion in Duncombe & Yinger (2005, 2011); Imazeki & Reschovsky (2004); or Gronberg et al. (2011a.)) Unfortunately, the literature provides little guidance as to the appropriate instruments for campus-level outputs or the proper way to address endogeneity concerns in a stochastic frontier setting; all of the previous work in this area has used two-stage least squares and district-level data. Furthermore, the translog specification means that not only does one need instruments for the two quality indicators, one also needs instruments for all of the quality interaction terms. The large number of potentially endogenous variables compounds the usual problems associated

[21] Gronberg et al. (2011a) also use this cubic specification for enrollment. Other researchers have dealt with this issue by excluding the largest Texas districts from analysis (e.g., Imazeki & Reschovsky (2004)) but that option is not viable for this analysis because Dallas and Houston ISDs are among the districts to be included in the consolidation simulation.

with weak instruments.[22] Because weak instruments are often worse than no instruments at all, all of the independent variables are treated as exogenous in this estimation.[23]

Data

The data for this analysis come from administrative files and public records of the Texas Education Agency (TEA), the Education Research Center at the University of Texas at Dallas, the National Center for Education Statistics (NCES), the U.S. Bureau of Labor Statistics (BLS), the U.S. Department of Housing and Urban Development (HUD) and the U.S Census Bureau. The analysis covers the five year period from 2008–09 through 2012–13.

The unit of analysis is the standard accountability campus in all traditional public districts located in a core based statistical area (CBSA).[24] The sample is restricted to the 26 metropolitan and 41 micropolitan areas in Texas because TEC Section 12.1013 specifically focuses on estimating the effects of consolidation in major metropolitan areas and limiting the analysis in this way provides additional validity (by making the cost and competitive environments for the districts more similar). Alternative Education Accountability (AEA) campuses (e.g. juvenile justice campuses, disciplinary education campuses, residential campuses and all other alternative education campuses) have been excluded because they are subject to different accountability requirements and may have different cost structures than other campuses (TEA 2014). Because they may have a different education technology that will not be available to traditional school districts (either before or after consolidation), open-enrollment charter schools have also been excluded from the cost function analysis (although they are included in the measure of educational competition). Virtual campuses and campuses that lack reliable data on student performance (such as elementary education campuses that serve no students in tested grades, or very small campuses) have also been excluded.

Table A1 provides means and standard deviations for the variables use in this analysis. Enrollment (both campus and district), the teacher salary index, and miles to the metro center enter the stochastic frontier regression in logs, while variables already in percentages (including the NCE scores) and the indicator variables are not logged before entering the stochastic frontier regression.

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[22] The references on weak instruments include classic early papers such as Nelson & Startz (1990) and more recent papers on constructing confidence intervals with weak instruments such as Staiger & Stock (1997) and Zivot, Startz & Nelson (1998). Murray (2006) has a fairly recent survey paper on instruments.
[23] We note that this approach was also taken in Gronberg, Jansen & Taylor (2011b).
[24] TEA officially associates each school district with a single county. Those official designations have been used to identify CBSA locations for campuses in traditional public school districts, using the CBSA definitions developed by the U.S. Office of Management and Budget and published by the U.S. Census Bureau.

Table A1: Descriptive Statistics for Campuses in Texas Core Base Statistical Areas, 2008-09 to 2012-13

	Mean	Std. Dev.	Minimum	Maximum
Per-pupil operating expenditure	$7,922.54	$1,598.08	$4,306.91	$28,306.80
Campus enrollment	721.38	501.28	32	4,697
Conditional NCE, math	0.50	0.06	0.07	0.77
Conditional NCE, reading	0.50	0.04	0.13	0.72
Teacher salary index	1.15	0.06	1.00	1.25
Miles to the metro center	19.24	15.61	0.25	143.51
District enrollment	39,423.20	48,943.40	66	203,294
% Economically disadvantaged	0.60	0.27	0.00	1.00
% Ever limited English proficient	0.28	0.23	0.00	0.98
% Special education	0.09	0.03	0.00	0.32
Elementary campus	0.60	0.49	0.00	1.00
Middle school campus	0.23	0.42	0.00	1.00
Mixed grade campus	0.01	0.12	0.00	1.00
Major Urban Area	0.62	0.49	0.00	1.00
Micropolitan Area	0.09	0.29	0.00	1.00
Herfindahl Index	0.18	0.18	0.06	1.00
K–8 district	0.01	0.07	0	1
Share of spending imputed	0.19	0.06	0	0.74
Number with NCE scores	368.31	382.24	25	2951
Number of observations		29,746		

Note: Open-enrollment charter, virtual school, alternative education, juvenile justice and disciplinary justice campuses have been excluded, as have all campuses with fewer than 25 students with conditional normal curve equivalent (NCE) scores.
Sources: Academic Excellence Indicator System (AEIS), Texas Academic Performance Reports (TAPR), Public Education Information Management System (PEIMS), National Center for Education Statistics (NCES), Appendix B.

The Dependent Variable

The dependent variable used in the analysis is the log of actual current, per-pupil operating expenditures, excluding food and student transportation expenditures. As in Imazeki and Reschovsky (2006) and Gronberg, Jansen, Taylor and Booker (2004, 2005) and Gronberg et al. (2011b), food service expenditures have been excluded on the grounds that they are unlikely to be explained by the same factors that explain student performance, and therefore that they add unnecessary noise to the analysis. Transportation expenditures have been excluded on similar grounds.

All expenditures data have been adjusted to account for school districts that serve as a fiscal agent for another school district or group of districts.[25] Fiscal agents collect funds from member districts in a shared service agreement, and make purchases or pay salaries with those shared funds on behalf of the member districts. As a result, the spending of fiscal agents is artificially inflated while the spending by member districts is artificially suppressed. However,

[25] For more on the allocation procedure, see Texas Comptroller of Public Account (2013)

fiscal agents report annually to TEA about the amounts they spent on behalf of their member districts. These F-33 data have been used to allocate spending by fiscal agents to their member districts on a proportional basis. [26]

Because not all school district expenditures are allocated to the campus level, and the share of allocated expenditures varies from district to district, researchers have distributed unallocated school district expenditures to the campuses on a per pupil basis.[27] Thus, for example, if Little Elementary serves 20% of the students in its district, it is presumed to be responsible for 20% of the unallocated spending.

Outputs

As noted above, the independent variables measuring education output include both a quantity dimension of output — enrollment — and a quality dimension. Quantity is measured as the number of students in fall enrollment at the campus. The campus enrollment variable ranges from 32 to 4,697 with a mean of 721.

The quality measure captures differences in student performance. The measure is a normalized gain score indicator of student performance on the Texas Assessment of Knowledge and Skills (TAKS) and the State of Texas Assessments of Academic Readiness (STAAR®) Grades 3-8 and end-of-course (EOC) exams. Although schools clearly produce unmeasured outcomes that may be uncorrelated with math and reading test scores, and standardized tests may not measure the acquisition of all important higher-order skills, these are performance measures for which districts are held accountable by the state, and the most common measures of school district output in the literature (e.g. Gronberg, Jansen & Taylor, 2011a, 2011b or Imazeki & Reschovsky, 2006). Therefore, they are reasonable output measures for cost analysis.

TAKS, STAAR Grades 3-8 and EOC scores can be difficult to compare across grades, years or testing regimes. Therefore, this analysis relies on normalized (or equivalently, standardized) test scores. The normalization follows Reback (2008) and yields gain score measures of student performance that are not biased by typical patterns of reversion to the mean.

The calculation of normalized gain scores proceeds in three steps. First, transform the scores of individual students into conditional z-scores. Denote the test scores for student (i), grade (g), and time or year (t), as S_{igt}, and measure each student's performance relative to others with same prior score in the subject as:

$$Y_{igt} = \frac{S_{igt} - E(S_{igt}|S_{i,g-1,t-1})}{[E(S_{igt}^2|S_{i,g-1,t-1}) - E((S_{igt}|S_{i,g-1,t-1})^2]^{.5}} \qquad (10)$$

For example, consider all Grade 6 students who had a raw score of 30 on the prior year's Grade 5 TAKS-Mathematics. For this subgroup of students with a Grade 5 score of 30, calculate the mean and standard deviations of the Grade 6 scores for TAKS-Mathematics. The

[26] Due to data limitations, spending by fiscal agents could not be allocated back to specific campuses within member districts.
[27] Gronberg, Jansen & Taylor (2012) and Grosskopf, Hayes, Taylor & Weber (2013) also followed this approach.

mean is the expected score in Grade 6 ($E(S_{igt}|S_{i,g-1,t-1})$) for someone with a Grade 9 score of 30; the standard deviation is the denominator in equation (10). Thus, the variable Y_{ijgt} measures individual deviations from the expected score, adjusted for the variance in those expected scores. This is a type of z-score. Transforming individual TAKS/STAAR scores into z-scores in this way allows researchers to aggregate across different grade levels and different test regimes despite the differences in the content or scaling of the various tests. It also provides a common frame of reference for incorporating the scores of students who, for example, took the STAAR-Mathematics in Grade 7, but the Algebra 1 EOC in Grade 8.[28]

Second, calculate the average conditional z-score (i.e., the average Y_{igt}) for all of the students attending each school.[29] An average conditional z-score of 1 indicates that, on average, the students at Little Elementary scored one standard deviation above the expected score for students with their prior test performance. An average conditional z-score of -1 indicates that, on average, the students scored one standard deviation below expectations.

Finally, for ease of interpretation, transform the z-scores into conditional normal curve equivalent (NCE) scores. NCE scores (defined as 50+21.06*z) are a monotonic transformation of z-scores that are commonly used in the education literature and can be interpreted as percentile ranks.[30] A conditional NCE score of 50 indicates that (on average) the students performed exactly as expected given their prior test performance; and a conditional NCE score of 90 indicates that (on average) they performed as well or better than 90% of their peers.

For estimation purposes, the conditional NCE scores are expressed as percentages. As Table A1 documents, the campus-level average conditional NCE math scores had a mean of 0.50 (i.e., 50%) with a minimum of 0.07 and a maximum of 0.77. The NCE reading scores had a mean of 0.50 with a minimum of 0.13 and a maximum of 0.72.

Input Prices

The most important education inputs are teachers, and the cost function model includes the required teacher wage variable. Public schools take differing approaches to hiring teachers. If there were a teacher type hired by all traditional public schools—for example, a teacher with a bachelor's degree from a selective university and two years of experience—then arguably the model should use the wages paid to those teachers as the labor price measures. However, it is not possible to identify a teacher type that is hired by all the school districts under analysis, and any observed average wage—such as the average salary for beginning teachers—reflects school and district choices about the mix of teachers to hire and the salary structure offered to teachers in the hiring process.

This issue can be dealt with using a wage index that is independent of school and district choices. Such an index is constructed here by estimating a hedonic wage model for teacher salaries and using that model to predict the wages each school would have to pay to hire a teacher with constant characteristics (see Appendix B). The resulting teacher price index ranges

[28] Y_{igt} for this population is calculated by taking the mean and standard deviations of the Algebra 1 EOC scores among all of the students who took the Algebra 1 EOC and shared a common score on the prior year's STAAR-Mathematics.
[29] Only students in the accountability subset (i.e., students who attended the same campus in the fall of the academic year as they did in the spring) are included in the campus average.
[30] Technically, this interpretation only holds if the scores are normally distributed. Given the large number of students tested each year in Texas, normality is a reasonable assumption.

from 1.00 to 1.25 and indicates that the cost of hiring teachers is 25% higher in some of the campuses under analysis than it is in others.[31]

In an ideal situation, the estimated cost function would include direct measures of local prices for instructional equipment and classroom materials. Such data are, unfortunately, not available to researchers. However, prices for pencils, paper, computers, and other instructional materials are largely set in a competitive market (and therefore unlikely to vary across schools), and prices for nonprofessional labor or building rents are largely a function of school location. Therefore, the cost analysis includes a measure of the distance to the center of the nearest metropolitan area.[32] This variable had an average value of 19.24 miles, a minimum of 0.25, and a maximum of 143.51, indicating the rather large distances sometimes involved in Texas.

Other Environmental Factors

The model includes indicators for a variety of environmental factors that influence district cost but which are not purchased inputs. A major environmental factor in this study is district enrollment. This study includes both campus enrollment and district enrollment, and at the campus level campus enrollment is considered the output variable and district enrollment the environmental variable. District enrollment averages 39,423 students, with a minimum of 66 and a maximum of 203,294. This large variation in district enrollment numbers is an important attribute of Texas data. To capture variations in costs that derive from variations in student needs, the cost function includes the percentages of students in each district who were identified as ever having been limited English proficient (Ever-LEP), special education, and economically disadvantaged.[33] To allow for the possibility that the education technology differs according to the grade level of the school, the cost model includes indicators for school type (elementary, middle and mixed grade). Fixed effects for year control for inflation and other time trends in Texas education. Indicators for whether or not the campus is located in a major metropolitan area (Austin, Dallas, Fort Worth, Houston and San Antonio) or a micropolitan area have been included to control for other, unobserved differences in the educational environment.

Efficiency Factors

The error terms for all frontier specifications depend on a number of factors that theory suggests may explain differences in school efficiency. Prior research has demonstrated that competition can reduce inefficiency in public education (e.g., Belfield & Levin, 2002; Millimet &

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[31] In Texas, teachers participate in a single statewide teacher retirement system. Thus, teachers can move from one school district to another without affecting their pension eligibility or their credited years of service. Contributions to the teacher retirement system are a function of the salaries paid to individual teachers, so the price index for teacher salaries should be highly correlated with a price index for teacher salaries and benefits.

[32] Miles to the center of the metropolitan area for each campus was calculated as-the-crow-flies using latitude and longitude information. The latitude and longitude of metro centers come from the U.S. Census Bureau. Where available, latitude and longitude information for campuses are taken from the NCES' Common Core Database. The remaining campuses are assigned latitudes and longitudes according to the zip codes at their street address.

[33] Students who perform well on the English/Language Arts tests are no longer considered LEP, making the percentage LEP endogenous and introducing potential estimation problems. Therefore, each student's complete academic history was used to identify those students who have been categorized as LEP, at some point during their experience in Texas (Ever LEP). While only 8% of students statewide are identified as LEP in any given year, more than 14% of the students could be identified as Ever LEP.

Collier, 2008; Taylor, 2000). Therefore, the one-sided variance function is modeled as a linear combination of two variables—the degree of educational competition, measured as the natural logarithm of the Herfindahl index, and an indicator for campuses in a district that only serves grades K – 8.[34]

As is common in the literature, the degree of educational competition is measured as the Herfindahl index of enrollment concentration in the metropolitan area. A Herfindahl index (which is defined as the sum of the squared enrollment shares) increases as the level of enrollment concentration increases. A Herfindahl index of 1.00 indicates a metropolitan area with a single local education agency (LEA); a Herfindahl index of 0.10 indicates a metropolitan area with 10 LEAs of equal size. Both traditional public school districts and open enrollment charter schools are included in the calculation of enrollment concentration. Table A1 reports the mean value for the Herfindahl index in the sample is 0.18, with a minimum value of 0.06 and a maximum of 1.00.

The K–8 indicator takes on the value of one if the school district does not operate any high school grades, and zero otherwise. It has been included because the restricted grade range of a K–8 school district may allow it to allocate its personnel more efficiently than a district of similar size attempting to serve the full range of grades.

Heteroskedasticity in the two-sided error may also arise. To capture such a possibility, the two-sided variance is modeled as a function of the share of campus expenditures that was specifically allocated to the campus. This variable has been included because measurement error in the dependent variable (a common source of heteroskedasticity) is likely to be a function of the extent to which the dependent variable was imputed. Also included is the number of students who had a conditional NCE score. The second factor has been included because the larger the number of tested students, the smaller is the potential for measurement error in this key independent variable.

Results

It is customary in the literature to demonstrate that an empirical model is robust by presenting coefficient estimates and marginal effects from alternative specifications. This analysis presents four alternative specifications:

1. The baseline, which is the preferred specification.
2. An alternative model that excludes school districts with more than 140,000 students. This alternative has been included to demonstrate that the results are not being driven by the cost and efficiency patterns in the state's largest school districts—Dallas ISD and Houston ISD.
3. An alternative model that excludes spending on athletics and extracurricular activities from the dependent variable, but otherwise mirrors the baseline specification. This alternative has been included to illustrate the extent to which measured inefficiency

[34] By assumption, the one-sided error term has a half-normal distribution. Jenson (2005) finds that specifying a half-normal distribution for the inefficiency term generates more reliable estimates of technical efficiency than other assumptions about the distribution of inefficiency

arises from spending on activities that may be only indirectly linked to student performance.

4. An alternative that adds food expenses and transportation expenses to the expenditure measure in the baseline model. This alternative has been included to demonstrate that the findings of the baseline model are not sensitive to the inclusion or exclusion of these expenditure types that (much like athletics) may not be explained by the same factors that explain student performance.

Table A2 reports a subset of the coefficient estimates from each of the four specifications—the coefficient estimates of the variables impacting the one-sided and two-sided error variances.[35] These indicate that an increase in concentration (an increase in the (logged) Herfindahl index) leads to an increased variance of the one-sided error, and hence an increase in inefficiency. The impact of the Herfindahl index on the one sided error variance is strongly statistically significant. The indicator variable for a K–8 district is also strongly statistically significant, and indicates that the campuses in these districts have a higher one-sided error variance, and hence a higher inefficiency, than campuses not in K–8 districts.

Table A2: Coefficient Estimates on Error Variances from Cost Function Models

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
One-sided error				
Herfindalh Index (log)	0.3413***	0.4130***	0.3222***	0.3768***
	(0.0587)	(0.0671)	(0.0572)	(0.0593)
K8 district indicator	0.9754***	0.8776***	0.9607***	1.4119***
	(0.2346)	(0.2630)	(0.2313)	(0.2236)
Constant	-4.5637***	-4.5445***	-4.5702***	-4.5464***
	(0.1253)	(0.1302)	(0.1223)	(0.1298)
Two-sided error				
% expenditures imputed	3.9287***	3.8417***	4.1872***	3.4610***
	(1.0609)	(1.0753)	(1.0736)	(1.1498)
Number of students with NCE scores (log)	-0.0899***	-0.0714**	-0.0968***	-0.1306***
	(0.0307)	(0.0344)	(0.0315)	(0.0312)
Constant	-5.2421***	-5.2815***	-5.2964***	-5.0299***
	(0.3237)	(0.3434)	(0.3304)	(0.3371)
Observations	29,746	27,427	29,746	29,746

Note: Robust standard errors clustered by district-year in parentheses. The asterisks indicate a coefficient estimate that is statistically significant at the 1% (***) 5%(**) or 10%(*) levels.
Source: Authors' calculations.

Table A2 also contains results for the two-sided error. As expected, campuses with a higher percentage of expenditures that have been imputed have a higher two-sided error variance, as do campuses with lower numbers of students with NCE scores.

While the translog specification has the benefit of flexibility and generality compared to, say, the Cobb Douglas or other simple forms, the coefficient estimates from the translog

[35] The remaining coefficient estimates and robust standard errors are presented in Appendix C.

specification are not readily interpretable. Most researchers present the change in cost arising from a small change in each explanatory variable, the so-called marginal effects. These implied marginal effects depend on the values of all the explanatory variables. For comparability it is common to report the marginal effects calculated at the mean of the values of the explanatory variables.

As an example, the marginal effect of a change in the variable q_1 in equation (9), here labeled $me(q_1)$, is:

$$me(q_i) = a_{1,1} + \sum_{j=1}^{n_1} a_{4,1,j} q_j + \sum_{j=1}^{n_2} a_{7,1,j} q w_j + \sum_{j=1}^{n_3} a_{8,1,j} z_j \qquad (11)$$

Table A3 indicates the marginal effects of a change in the various outputs, prices, and environmental variables on expenditures per pupil. For each explanatory variable three entries are provided in each column. First is the marginal effect at the mean—the marginal effect on per-pupil cost of a change in the explanatory variable in question, holding all other variables at their respective sample mean values. Second is the mean of the marginal effects—the mean of the marginal effect of the variable in question, calculated for each data point in the sample. Third is the probability value for the null hypothesis for the variables in question that all the coefficients on the direct effect and all interaction effects are jointly zero.

There are four columns of results reported in Table A3. The first column results are for the baseline model. The second column reports results when the two largest districts are excluded from the estimation. The third column reports results when spending on athletics and extracurricular activities are not included in the campus spending measure. The fourth column reports results when spending on food and transportation is added to the campus spending measure from the baseline model. These last three models serve as robustness checks on the baseline model.

The first variable listed in Table A3 is the log of District Enrollment. The marginal effect of a change in district enrollment calculated at the mean of all variables in the sample is 0.0151, indicating that a one unit change in the log of district enrollment is calculated to increase the log of cost per student at the sample mean of all variables by 0.151. Alternatively put, a 1% increase in district enrollment, at the mean of all variables in the sample, causes a 0.0151% increase in cost per student at the campus level. To convey the magnitude of this effect, a 1% increase in district enrollment at the sample mean is an increase of about 394 students. This causes a 0.0151% increase in costs per pupil, or an increase of about $1.19 per student.

Table A3: Marginal Effects from Alternative Specifications

	Baseline	Excluding Very Large Districts	Excluding Athletics and Extras	Including Food and Transportation
District Enrollment (log)				
Marginal effect at the mean	0.0151	0.0176	0.0209	0.0101
Mean of the marginal effects	0.0089	0.0045	0.0136	0.0060
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average Mathematics NCE (log)				
Marginal effect at the mean	0.0236	0.0079	0.0259	0.0295
Mean of the marginal effects	0.0237	0.0079	0.0260	0.0296
Joint p-value	(0.0038)	(0.0023)	(0.0040)	(0.0006)
Average Reading NCE (log)				
Marginal effect at the mean	0.0674	0.0528	0.0721	0.0498
Mean of the marginal effects	0.0676	0.0523	0.0724	0.0500
Joint p-value	(0.0000)	(0.0002)	(0.0000)	(0.0000)
Teacher Salary Index				
Marginal effect at the mean	1.0525	0.9567	1.0523	1.0233
Mean of the marginal effects	1.0521	0.9563	1.0518	1.0228
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Miles to Metro Center (log)				
Marginal effect at the mean	-0.0002	0.0034	0.0009	0.0033
Mean of the marginal effects	-0.0003	0.0034	0.0009	0.0033
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
% Students Econ. Disadv.				
Marginal effect at the mean	0.1219	0.1187	0.1316	0.1498
Mean of the marginal effects	0.1218	0.1187	0.1315	0.1497
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
% Ever LEP				
Marginal effect at the mean	0.0892	0.1001	0.0930	0.0730
Mean of the marginal effects	0.0891	0.1000	0.0930	0.0730
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
% Special Education				
Marginal effect at the mean	0.9257	1.0206	0.9012	0.8095
Mean of the marginal effects	0.9290	1.0242	0.9044	0.8129
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Campus Enrollment (log)				
Marginal effect at the mean	-0.1784	-0.1824	-0.1805	-0.1648
Mean of the marginal effects	-0.1783	-0.1825	-0.1805	-0.1648
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Elementary campus				
Marginal effect at the mean	-0.2215	-0.2215	-0.1727	-0.2004
Mean of the marginal effects	-0.2874	-0.2990	-0.1875	-0.2706
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Middle school campus				
Marginal effect at the mean	-0.1527	-0.1470	-0.1202	-0.1353
Mean of the marginal effects	-0.2585	-0.2669	-0.1841	-0.2437
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Multigrade campus				
Marginal effect at the mean	-0.0348	-0.0350	-0.0125	-0.0195
Mean of the marginal effects	-0.0059	-0.0343	0.0464	0.0123
Joint p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)

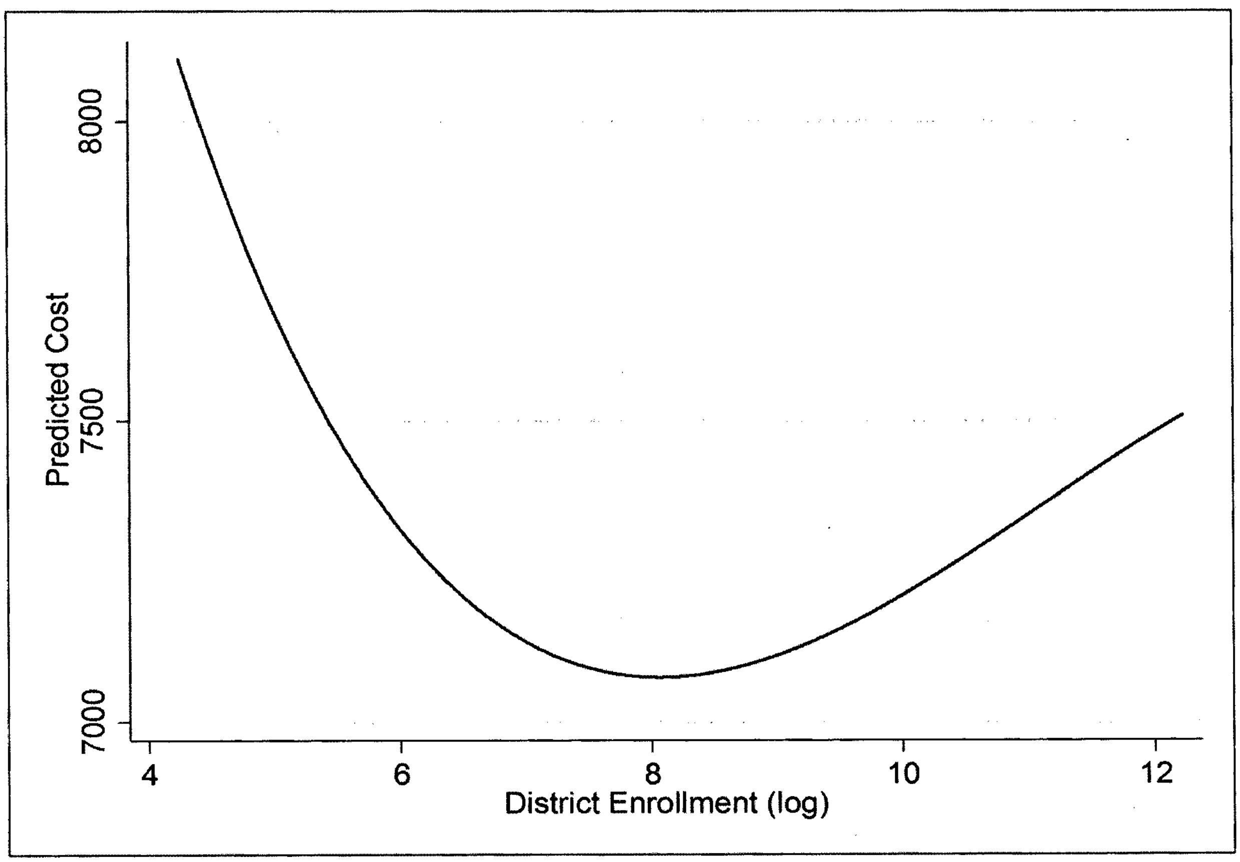
Source: Authors' calculations from coefficient estimates in Appendix C.

The mean of the marginal effects calculates the marginal effect of an increase in district enrollment for every sample data point and then averages those estimates to yield the mean of the marginal effects. Here a 1% increase in district enrollment has a mean marginal effect of 0.0089, or a 1% increase in district enrollment generates a mean response of 0.0089% in cost per student.

Finally, the joint p-value for the coefficients on district enrollment and its interactions is zero to four decimal places, indicating that the coefficients on district enrollment in the cost function are jointly strongly statistically significant.

Figure A1 graphs the impact of changes in log district enrollment on predicted cost. The slope of the graph is the marginal effect, and the shape of the graph in Figure A1 indicates that there are initial economies of scale as district size increases, up to about a log value of 8 (or about 3,200 students). As district enrollment increases beyond that point, costs per student increase. A log enrollment value of 10 corresponds to about 22,000 students enrolled, and a log enrollment value of 12 corresponds to about 163,000 students enrolled. The mean district enrollment in the sample, 39,423 students, has a log enrollment value of 10.6.

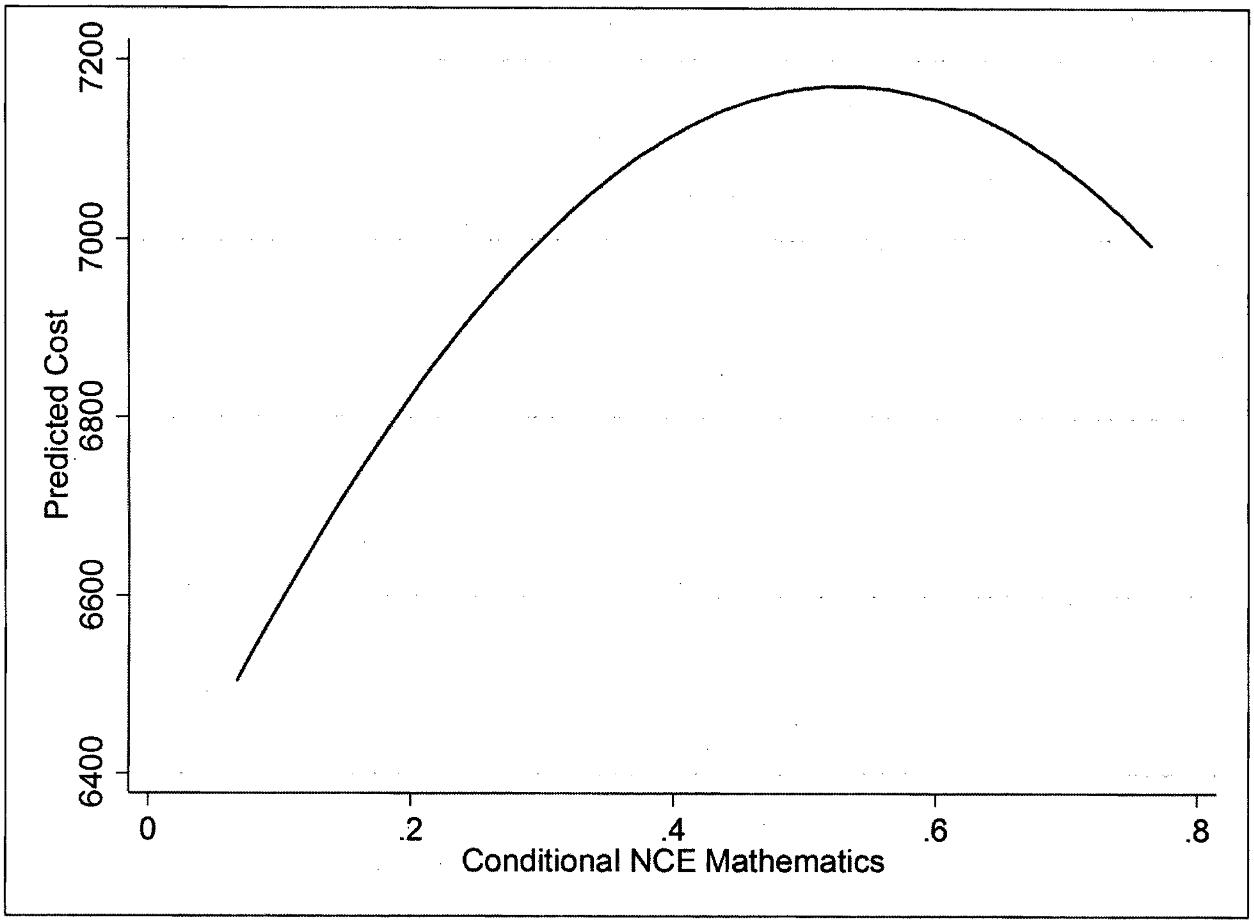
Figure A1: The Estimated Relationship between Per-Pupil Cost and School District Enrollment



For the average conditional NCE scores in mathematics, the marginal effect at the mean and the mean marginal effect are both about 0.024, and the p-value is 0.0038, indicating strong statistical significance. To place this marginal effect in perspective, the model predicts that a one standard deviation increase in average conditional NCE scores in mathematics (0.06 in Table A1) would require a 0.0014% increase in per-pupil cost, or equivalently an increase of $11 per student.

Figure A2 presents a graph of how changes in campus average conditional NCE scores in mathematics impact cost. Recall that these conditional NCE scores range from 0.07 to 0.77, with a mean of 0.50. For conditional NCE scores in mathematics ranging from 0.07 to a bit over 0.50, increasing the campus average requires higher cost, but beyond that the estimated cost per student of an increase in the campus average actually declines somewhat.

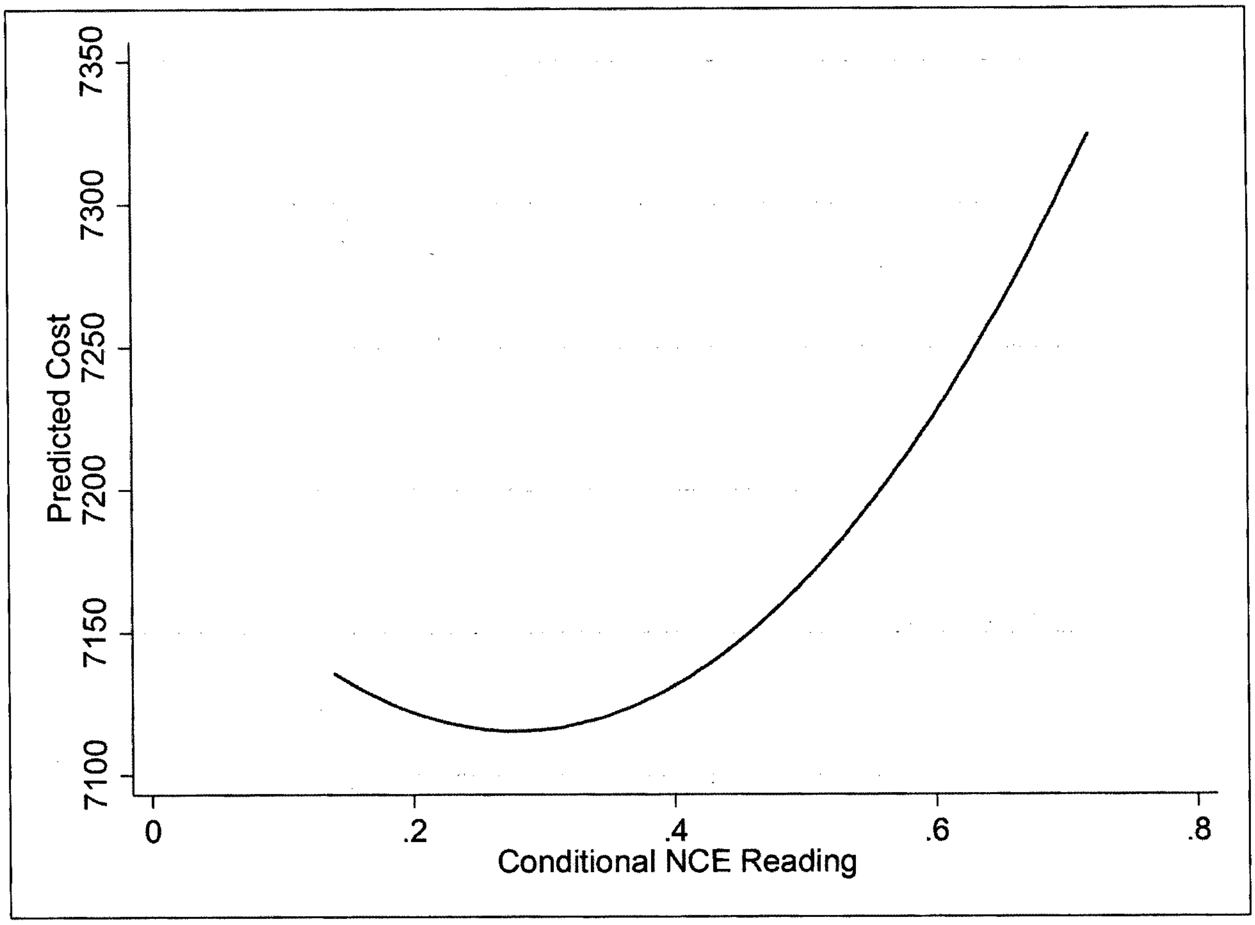
Figure A2: The Estimated Relationship between Per-Pupil Cost and the Conditional NCE in Mathematics



For the average conditional NCE scores in reading, the marginal effect at the mean and the mean marginal effect are both about 0.068. The coefficients are strongly statistically significant, with a marginal probability value of zero to four decimal places. To place the marginal effect estimate in perspective, a one standard deviation increase in average conditional NCE scores in reading (0.04 in Table A1) would require a 0.0026% increase in per student cost, or an increase of $22 per student.

Figure A3 present a graph of how changes in campus average conditional NCE scores in reading impact cost. The scores in sample range from 0.13 to 0.72, and over nearly this entire range an increase in scores requires an increase in cost per student.

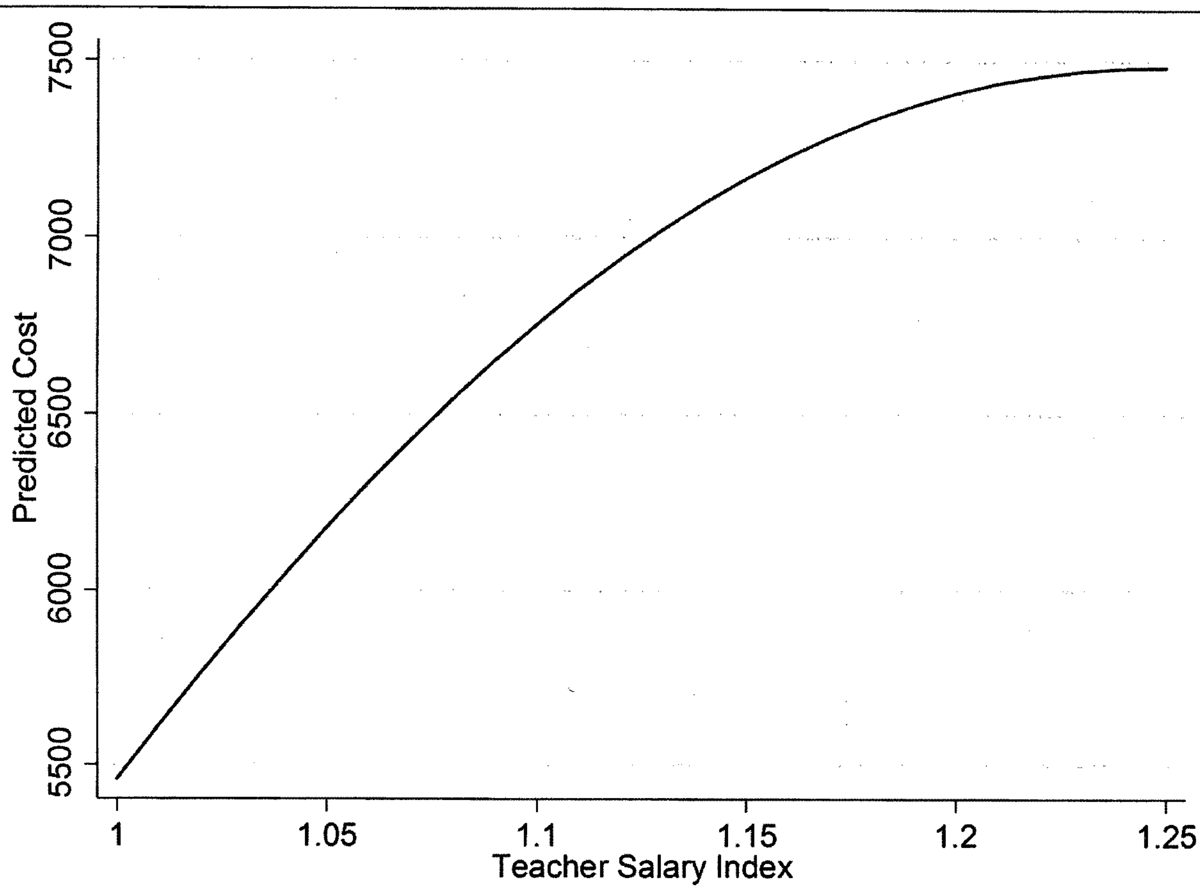
Figure A3: The Estimated Relationship between Per-Pupil Cost and the Conditional NCE in Reading



The teacher salary index (TSI) has a marginal effect at the mean and a mean marginal effect both about 1.05, and the coefficients on the teacher salary index are strongly statistically significant. An increase in teacher salaries of 1% results in a 1.05% increase in per pupil costs, evaluated at the sample means. This large impact is to be expected with teacher salaries such a large component of school spending.

Figure A4 graphs the impact of the TSI on cost per student as the teacher salary index ranges from 1.00 to 1.25 in our sample. Increases in teacher salaries have a fairly linear positive impact on cost per student.

Figure A4: The Estimated Relationship between Per-Pupil Cost and the Teacher Salary Index



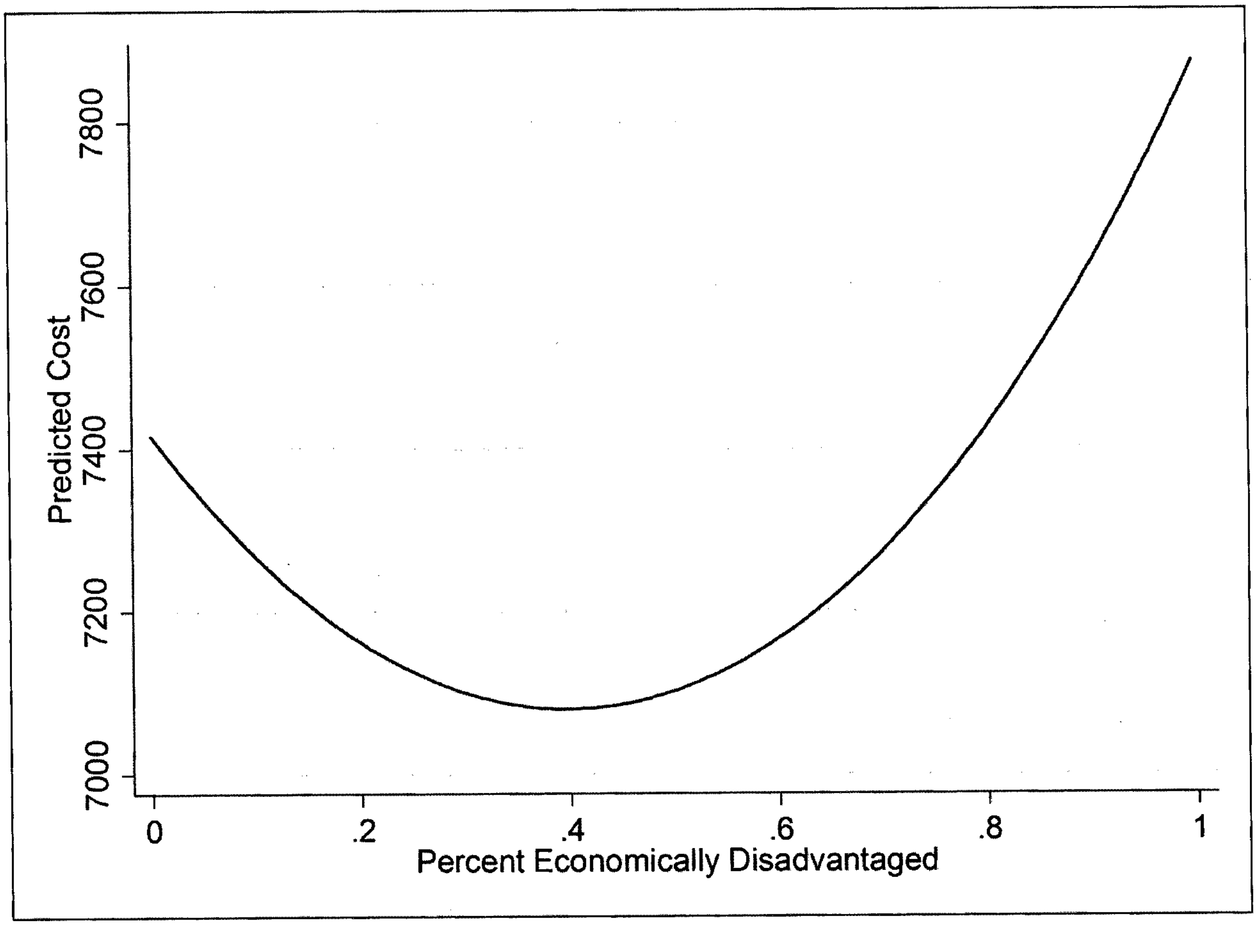
The Miles to Metro Center variable, in logs, has a marginal effect at the mean, and a mean marginal effect, of -0.0002. A 1% increase in distance from the metro center leads to a per-pupil cost reduction of 0.0002%, and this effect, while small in magnitude, is strongly statistically significant. To provide some perspective on the magnitudes here, the model predicts that a campus situated 10 miles from the metro center costs $4 more per pupil to operate than a campus located 30 miles from the metro center.

There are several other environmental variables, including the percentage of students classified as Economically Disadvantaged, the percentage of students who have ever been classified as LEP, and the percentage of students receiving Special Education treatment. Increases in these three environmental variables all serve to increase per student cost, and for each of them the marginal effect at the mean, and the mean marginal effect, are essentially the same.

An increase in the percentage of economically disadvantaged students at a campus is associated with a percentage increase in campus per pupil costs of 0.122 times the increase in the percentage of economic disadvantage students. Thus, the analysis indicates that for a campus with average characteristics (i.e., a campus at the sample mean values for all of the explanatory variables) the cost of educating an economically disadvantaged student is 12%

higher than is the cost of educating a student who is not economically disadvantaged.[36] However, the estimated effect is not linear. As Figure A.5 illustrates, the marginal cost of serving an increased percentage of economically disadvantaged student is sharply higher (i.e., the slope is steeper) for campuses that already have a high percentage of economically disadvantaged students.

Figure A5: The Estimated Relationship between Per-Pupil Cost and the Percentage Economically Disadvantaged Students



An increase in the percentage of students ever classified as LEP is associated with a percentage increase in campus per pupil costs of 0.0892 times the increase in the percentage of Ever-LEP students. Therefore, for a campus with average characteristics, the estimated cost

36 This estimated marginal effect at the mean is smaller than the Foundation School Program weight for economically disadvantaged students (20%). This should not be interpreted as evidence that the Foundation School Program weight is too high because the cost function models marginal cost as nonlinear (meaning that the implied funding formula weights are different for different campus configurations) and the estimation does not include the one-third of Texas school districts located in rural areas.

of educating a student who has ever been designated LEP is 9% higher than the estimated cost of educating a student who has never been designated LEP.[37]

Finally, an increase in the percentage of special education students is associated with a percentage increase in per student costs of 0.9257 times the increase in the percentage of special education students. In other words, for a campus with average characteristics, the estimated cost of educating a special education student is nearly double (93% higher than) the cost of educating a student who is not in the special education program.

Figure A6: The Estimated Relationship between Per-Pupil Cost and Campus Enrollment

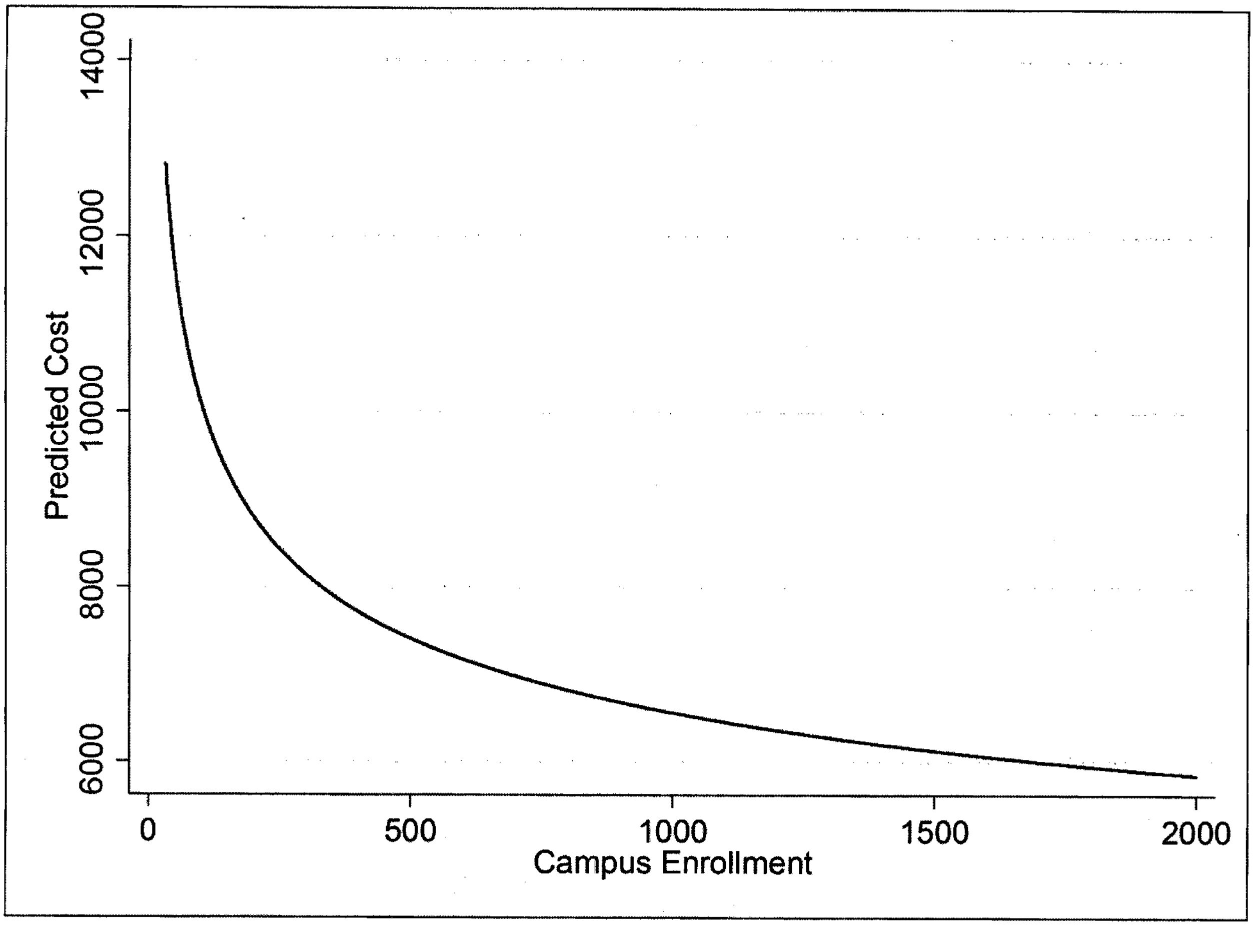


Figure A6 graphs the relationship between campus size and cost per student, holding all other variables at their sample mean values. As the figure illustrates, campus enrollment has a strong negative impact on per student costs at the campus level. In other words, larger campus enrollments reduce cost per student. A 1% increase in campus enrollment leads to a 0.18% decrease in per pupil costs. This effect is strongly statistically significant. Thus, the cost function indicates that all other things being equal, a campus with 200 students costs 14% more to

[37] Again, this marginal effect is not strictly comparable to the Foundation School Program weight for students in bilingual education/English as a second language. The cost function models marginal cost as nonlinear (meaning that the implied funding formula weights are different for different campus configurations) and the estimation does not include the one-third of Texas school districts located in rural areas.

operate than a campus with 400 students, which in turn costs 8% more to operate than a campus with 600 students.

The model also includes an indicator for elementary campus, middle school campus, and multi-grade campus. The omitted category is high school campus. Elementary schools have 22% lower costs than high schools, and middle schools have 15% lower costs than high schools. Multi-grade campuses have 3% lower costs than high schools. These effects are all strongly statistically significant.

The second, third, and fourth columns of results in Table A3 are robustness checks, to examine the sensitivity of the results to certain changes in the data. Comparing the results across columns indicates that while the estimated marginal effects do vary somewhat across the columns, there are strong regularities in the estimated marginal effects. The largest differences are for district enrollment, and this is expected given the large disparity in district size and the impact of excluding large districts. Figure A7 presents the estimated relationship between school district size and the cost of education for each of the four models. As the figure illustrates, holding all other campus characteristics constant at the mean, all four specifications indicate that cost is minimized for a district with log enrollment less than 8.34 (4,200 students).

Figure A7: The Estimated Relationship between Per-Pupil Cost and District Enrollment For Alternative Specifications

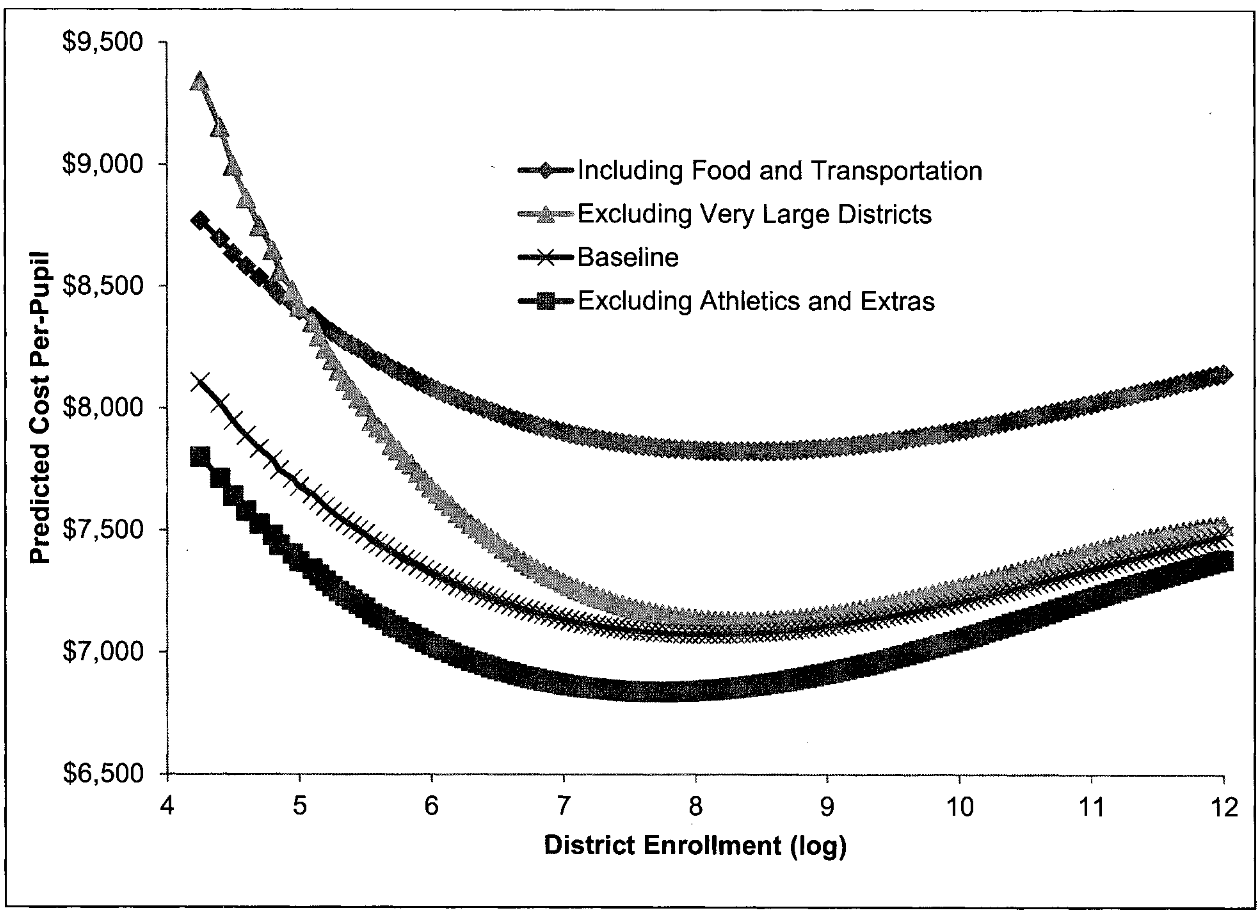


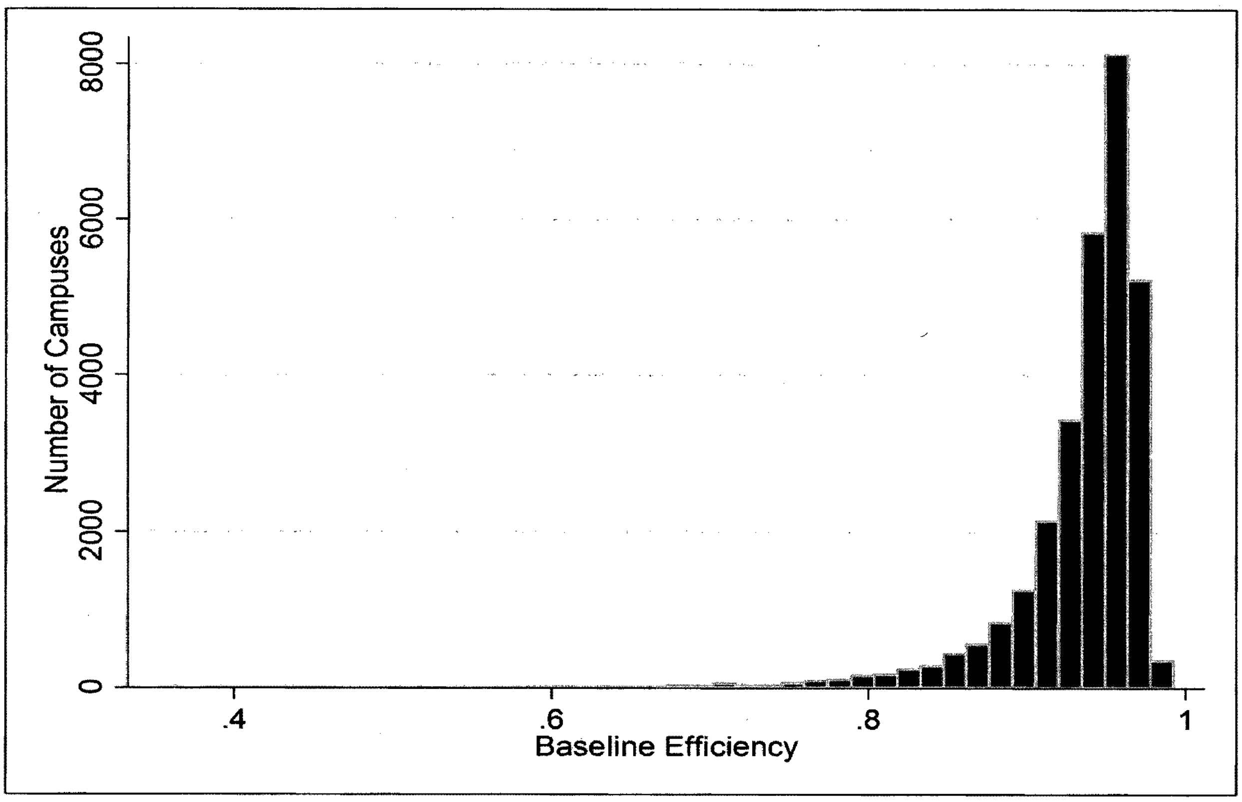
Table A4: Cost Efficiency Measures

	Mean	Std. Dev.	Minimum	Maximum	Correlation with Baseline Efficiency
Baseline	0.933	0.050	0.353	0.993	1.000
Excluding Very Large Districts	0.936	0.046	0.409	0.992	0.994
Excluding Athletics and Extras	0.932	0.051	0.356	0.992	0.990
Including Food and Transportation	0.934	0.050	0.267	0.994	0.979

Source: Authors' calculations

An important part of this study is the estimation of cost efficiency, or inefficiency. Table A4 summarizes the cost efficiency estimates for all four models in Table A3, and Figure A8 graphs the distribution of cost efficiency for the baseline model.[38] In the baseline model, the average cost efficiency score is 0.93, indicating that campuses are producing 93% of their potential output, on average. Given that inefficiency in this context means unexplained expenditures, not necessarily waste, and that many campuses may be producing outcomes that are not reflected in test scores, the average efficiency level is quite high. However, the minimum efficiency scores are well below 50%, suggesting that some campuses spend much more than can be explained by measured outcomes, input prices or student need.

Figure A8: Histogram of Cost Efficiency Measures for Baseline Model



[38] Cost efficiency was estimated following Battese and Coelli (1995).

For comparison, Figures A9, A10, and A11 graph the cost efficiency measures for the model estimated without the large ISDs, the model estimated without athletics or extracurricular spending in the cost measure, and the model estimated with the cost measure including food and transportation spending. These figures look similar to Figure A8, and indeed the summary measures reported in Table A4 are similar.

The various efficiency measures assigned to each campus are very highly correlated across the four estimates. Table A4 presents the correlations of the baseline measure with the other three estimates, and these correlations range from 97.7% to 99.4%, indicating a strong degree of agreement across the four models on the efficiency score assigned to each campus.

Figure A9: Histogram of Cost Efficiency Measures for Model Excluding Very Large Districts

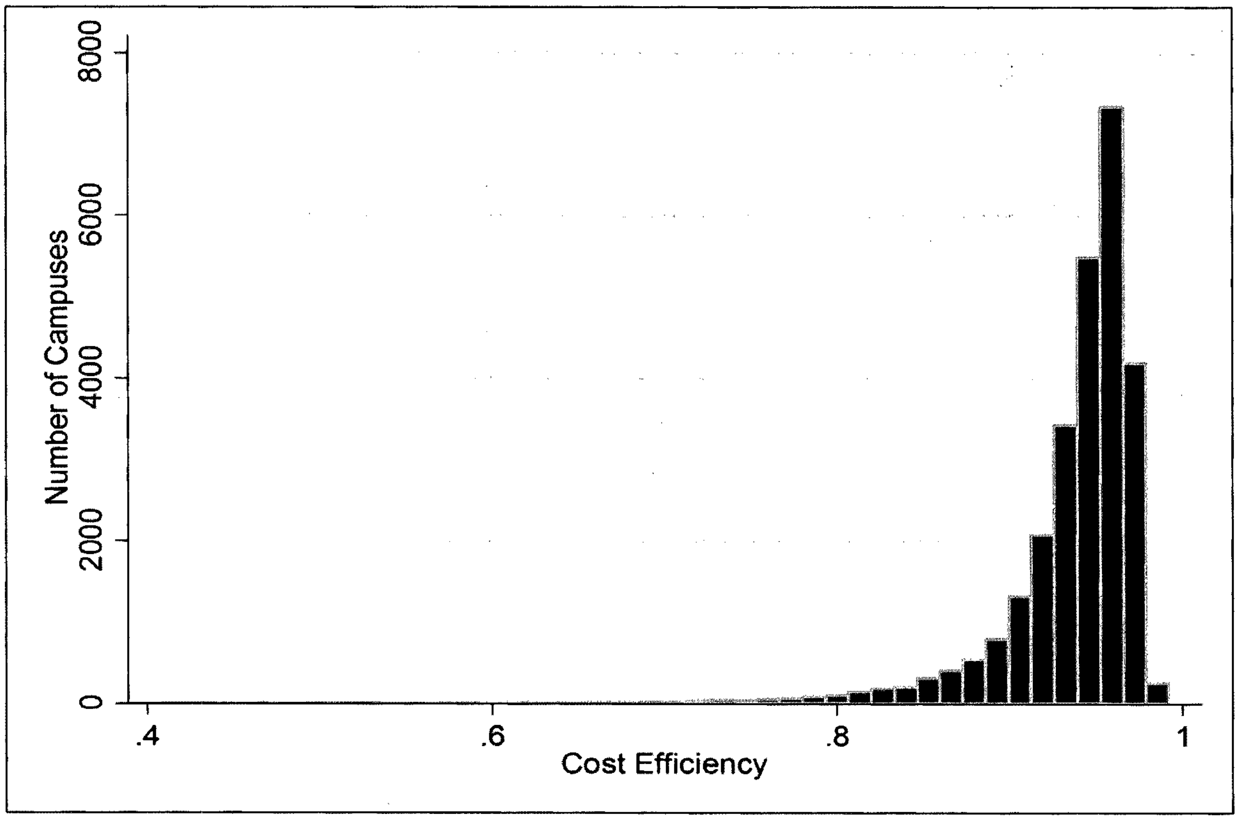


Figure A10: Histogram of Cost Efficiency Measures for Model Excluding Athletics and Extras

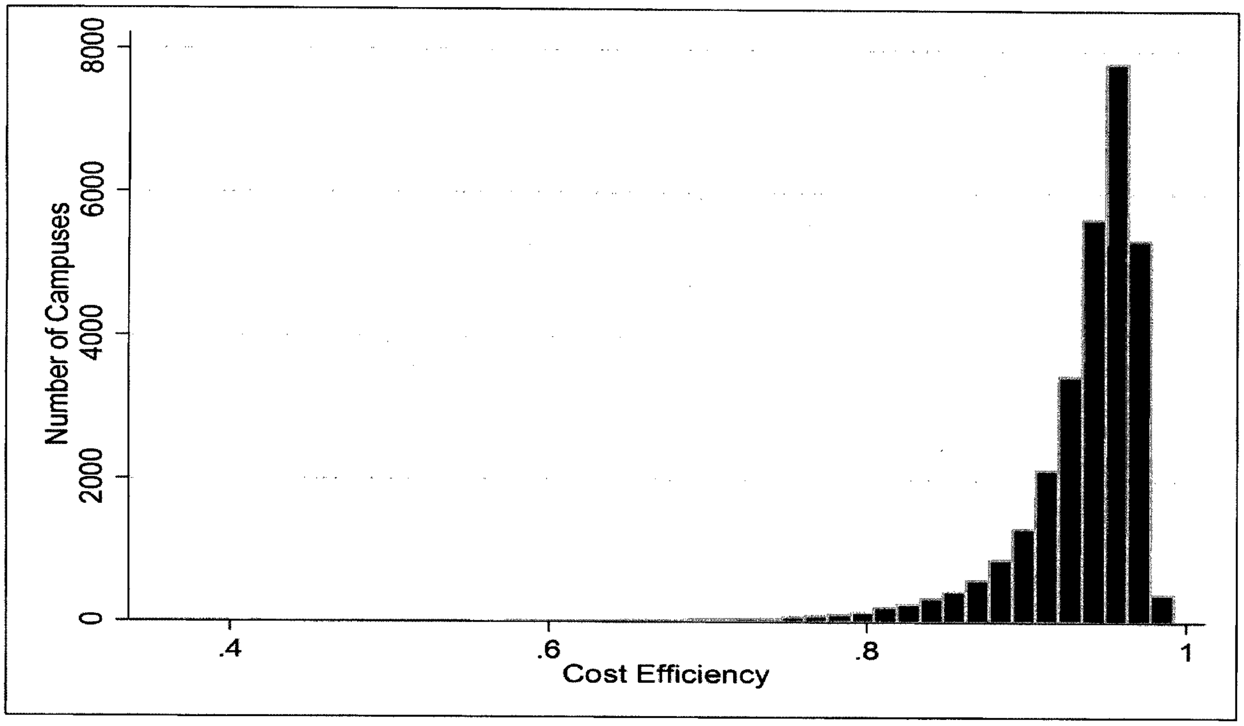
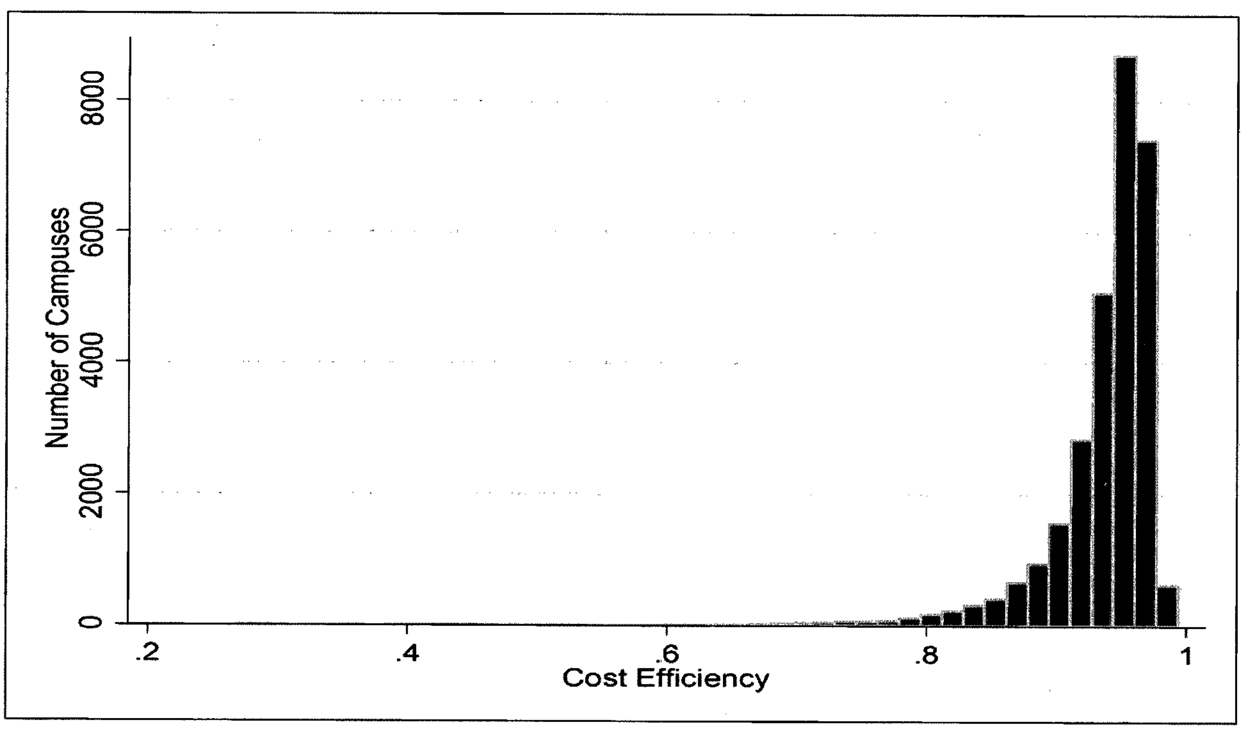


Figure A11: Histogram of Cost Efficiency Measures for Model Including Food and Transportation



Simulating Consolidation

The results of the cost function analysis presented in this report can be used to simulate different consolidation scenarios. This section illustrates the magnitude of the changes in per pupil expenditure by simulating the policy action that consolidates the districts to county level in five counties (Bexar, Dallas, Harris, Tarrant and Travis). The simulation here is designed to analyze the effects of changes in the education market structure on per pupil expenditures in these counties, and examine if such a scenario would generate per pupil and overall savings.

The simulation compares, campus by campus, the predicted expenditure per pupil pre-consolidation with the predicted expenditure per pupil post-consolidation. A county-by-county impact of consolidation is also calculated.

Several assumptions are needed in order to conduct this consolidation simulation. The consolidation of the districts in Bexar, Dallas, Harris, Tarrant and Travis counties to the county level assumes that total campus and county enrollments and the local demographic structure would not change as a result of the consolidation. In the long run it is certainly possible that parents might move in response to the consolidation, but the maintained assumption here is that such movement does not occur in the short run post-consolidation. It is also assumed that charter school enrollments do not change after the consolidation. Pre-consolidation values of campus-level variables are assumed not to change after the consolidation. Finally, in all but one case (Travis County) the consolidated school district would be substantially larger than any other district currently operating in Texas. In order to conduct the simulation, one must assume that the estimated relationship between district size and the cost of education is sufficiently robust to support extrapolation to a district nearly four times larger than any observed in the data.

The simulation proceeds as follows: First, the campus pre-consolidation expenditure per pupil is predicted using the regression results from the estimated baseline model including the estimate of cost inefficiency. The pre-consolidation predicted per pupil cost uses campus-level values of the variables in the baseline model. Any missing values of these variables are assumed to be at the state average, so that most of the campus observations can be included in the analysis. Next, the campus post-consolidation expenditure per pupil is predicted using the regression results and campus characteristics, but assuming that district size increases to the consolidated level (for consolidating campuses) and the level of enrollment concentration increases to its post-consolidation level (for both consolidated campuses and other campuses in affected metropolitan areas. Finally, the two predictions are compared campus by campus and in the aggregate.

Table A5: Consolidation Simulation Results for Counties

County	Total County Enrollment	Predicted Expenditure per Pupil Before Consolidation	Predicted Expenditure per Pupil After Consolidation	Total Increase in Predicted County Expenditures
Bexar	321,072	$7,354	$7,885	$170,352,055
Dallas	437,642	$7,615	$8,076	$201,743,559
Harris	803,187	$7,313	$7,718	$325,430,351
Tarrant	341,855	$7,260	$7,771	$174,568,890
Travis	145,846	$7,627	$7,894	$38,935,968

Source: Authors' calculations.

Table A5 summarizes pre- and post-consolidation predicted expenditures per pupil at the county level and the increase (or decrease) in predicted expenditures of the five counties.[39] On average, consolidation increases the predicted expenditure per pupil by 6.5% in Bexar County, 4.9% in Dallas County, 4.1% in Harris County, 6.1% in Tarrant County, and 2.8% in Travis County. After consolidation, predicted expenditures increase by $170 million in Bexar County, $202 million in Dallas County, $325 million in Harris County, $174 million in Tarrant County, and $39 million in Travis County.

Table A6 provides some insight into the consolidation results. First, the Herfindahl values of the five counties increased tremendously post-consolidation, from an average of 0.08 to 0.45. The maximum Herfindahl value among the five counties was 0.12 pre-consolidation, while the minimum Herfindahl value was 0.25 post-consolidation. This leads directly to an increase in inefficiency (i.e., a reduction in efficiency) from an average inefficiency of 0.05 pre-consolidation to an average of 0.07 post-consolidation. Thus, post-consolidation, if nothing else changes spending will rise 2% just because of increased inefficiency.

Second, predicted cost per pupil on the cost frontier (i.e., with absolute zero inefficiency) increased from an average of $7,028 before consolidation to $7,318 after consolidation. This increase is due to the scale diseconomies of increasing district size for these large counties, as the resulting consolidated district is well beyond the minimum cost district size. Thus, predicted expenditures (including predicted inefficiency) increases from an average of $7,405 pre-consolidation to an average of $7,852 post-consolidation.

[39] Only campuses included in the cost function analysis are included in the simulation.

Table A6: Summary of Pre- and Post-Consolidation Concentration, Inefficiency, Cost, and Expenditure Values in Bexar, Dallas, Harris, Tarrant and Travis Counties, 2012–13

	Mean	Std. Dev.	Minimum	Maximum
Pre-Consolidation Values				
Herfindahl	0.077	0.024	0.057	0.122
Inefficiency	0.054	0.003	0.051	0.059
Predicted Cost Per Pupil	$7,028	712	$5,279	$13,614
Predicted Expenditure per Pupil	$7,405	750	$5,549	$14,311
Post-Consolidation Values				
Herfindahl	0.452	0.154	0.253	0.688
Inefficiency	0.073	0.005	0.066	0.080
Predicted Cost Per Pupil	$7,318	850	$5,082	$15,067
Predicted Expenditure per Pupil	$7,852	908	$5,455	$16,172

Source: Authors' calculations

Conclusion

The stochastic frontier cost function results presented here indicate that the cost function estimates provide intuitively plausible and robust characterization of the cost frontier for public school campuses in the sample of Texas schools examined in this study, as well as plausible and robust characterization of the efficiency – or inefficiency – of these campuses. These cost function estimates, especially the impact of district size and the impact of competition summarized in the Herfindahl index, provide the basic inputs that lead to the simulation results and the conclusion regarding the impact of proposed consolidation on cost per pupil at these Texas campuses. In particular, the diseconomies of scale in the range of the proposed consolidation, and the increased concentration resulting from the proposed consolidation, both act to increase spending post consolidation.

Not surprisingly, given the patterns indicated by the cost function analysis, the simulation exercise indicates that consolidation increases educational expenditures in all five metropolitan areas referenced in TEC Section 12.1013. Thus, consolidating school districts in the core counties of major metropolitan areas is likely to have unintended, adverse effects in terms of per pupil and total expenditures. The overall increase in expenditures can be as high as 6.5% of the total expenditures. These increases in expenditures are due to diseconomies of scale among large school districts, sharp declines in the competitiveness in education markets and large increases in cost inefficiency.

References

Andrews, M., Duncombe, W., & Yinger, J. (2002). Revisiting economies of size in American education: Are we any closer to a consensus?. *Economics of Education Review, 21*, 245-262. doi: 10.1016/S0272-7757(01)00006-1

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325-332. doi: 10.1007/BF01205442

Belfield, C. R., & Levin, H. M. (2002). The effects of competition between schools on educational outcomes: A review for the United States. *Review of Educational Research, 72*, 279-341. doi: 10.3102/00346543072002279

Dee, T. S. (1998). Competition and the quality of public schools. *Economics of Education Review, 17*, 419-427. doi: 10.1016/S0272-7757(97)00040-X

Duncombe, W.A., & Yinger, J. (2005). How much more does a disadvantaged student cost? *Economics of Education Review*, *24*, 513–532. doi: 10.1016/j.econedurev.2004.07.015

Duncombe, W.A., & Yinger, J. (2011). Are education cost functions ready for prime time? An examination of their validity and reliability. *Peabody Journal of Education, 86*, 28-57. doi: 10.1080/0161956X.2011.539954

Gronberg, T. J., Jansen, D. W., Karakaplan, M. U., & Taylor, L. L. (2013). *School district consolidation: Market concentration and the scale-efficiency tradeoff.* Retrieved August 1, 2014 from http://econweb.tamu.edu/karakaplan/Karakaplan%20-%20Scaling.pdf

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2011a). The adequacy of educational cost functions: Lessons from Texas. *Peabody Journal of Education*, *86*, 3-27. doi: 10.1080/0161956X.2011.539953

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2011b). The impact of facilities on the cost of education. *National Tax Journal, 64*, 193-218.

Gronberg, T. J., Jansen, D. W., & Taylor, L. L. (2012). The relative efficiency of charter schools: A cost frontier approach. *Economics of Education Review, 31*, 302-317. doi: 10.1016/j.econedurev.2011.07.001

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Booker, K. (2004). *School outcomes and school costs: The cost function approach.* Austin, TX: Texas Joint Select Committee on Public School Finance.

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Booker, K. (2005). *School outcomes and school costs: A technical supplement.* Austin, TX: Texas Joint Select Committee on Public School Finance.

Gronberg, T. J., Jansen, D. W., Taylor, L. L., & Karakaplan, M. U. (2010). *Costs, competition, and consolidation.* College Station, TX: State of Texas Education Research Center at Texas A&M University.

Grosskopf, S., Hayes, K. J., Taylor, L. L., & Weber, W. L. (2001). On the determinants of school district efficiency: Competition and monitoring. *Journal of Urban Economics, 49*, 453-478. doi: 10.1006/juec.2000.2201

Grosskopf, S., Hayes, K., Taylor, L. L., & Weber, W. (2013). Centralized or decentralized control of school resources? A network model. *Journal of Productivity Analysis*, 1-12. doi: 10.1007/s11123-013-0379-2

Imazeki, J., & Reschovsky, A. (2004). Is No Child Left Behind an un (or under) funded federal mandate? Evidence from Texas. *National Tax Journal, 57*, 571-588.

Imazeki, J., & Reschovsky, A. (2006). Does No Child Left Behind place a fiscal burden on states? Evidence from Texas. *Education Finance and Policy, 1*, 217-246. doi: 10.1162/edfp.2006.1.2.217

Jensen, U. (2005). Misspecification preferred: The sensitivity of inefficiency rankings. *Journal of Productivity Analysis, 23*, 223-244. doi: 10.1007/s11123-005-1330-y

Kang, B. G., & Greene, K. V. (2002). The effects of monitoring and competition on public education outputs: A stochastic frontier approach. *Public Finance Review, 30*, 3-26. doi: 10.1177/109114210203000101

Millimet, D. L., & Collier, T. (2008). Efficiency in public schools: Does competition matter? *Journal of Econometrics, 145*, 134-157. doi: 10.1016/j.jeconom.2008.05.001

Murray, M. (2006). Avoiding invalid instruments and coping with weak instruments. *Journal of Economic Perspectives, 20*, 111-132. doi: 10.1257/jep.20.4.111

Nelson, C. R., & Startz, R. (1990). Some further results on the exact small sample properties of the instrumental variable estimator. *Econometrica, 58*, 967-976. doi: 10.2307/2938359

Reback, R. (2008). Teaching to the rating: School accountability and the distribution of student achievement. *Journal of Public Economics, 92*, 1394-1415. doi: 10.1016/j.jpubeco.2007.05.003

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65*, 557-586. doi: 10.2307/2171753

Taylor, L. L. (2000). The evidence on government competition. *Federal Reserve Bank of Dallas Economic and Financial Review, 2*, 1-9.

Zivot, E., Startz, R., & Nelson, C. R. (1998). Valid confidence intervals and inference in the presence of weak instruments. *International Economic Review, 39*, 1119-1144. doi: 10.2307/2527355

Technical Appendix B: Estimating the Teacher Salary Index

There are three basic reasons why average teacher salaries differ from one campus to the next. First, differences in individual teacher characteristics will drive differences in wages. All other things being equal, teachers with more experience earn higher wages than other teachers. Second, differences in job characteristics drive differences in salaries. Schools with particularly difficult working conditions must pay higher salaries than other schools to attract the same caliber of teacher. Finally, locational characteristics drive differences in wages. Teachers in areas with a low cost of living or an abundance of local amenities will accept a lower nominal wage than otherwise equal teachers in a less attractive locale.

Hedonic wage models use regression analysis to divide the observed variation in teacher salaries into that which is attributable to teacher characteristics, that which is attributable to job characteristics and that which is attributable to locational characteristics. Hedonic wage models have a long history in labor economics, and have been used in education finance contexts for more than 30 years.[40] The Texas Cost of Education Index (CEI) is based on a hedonic wage model that was estimated using teacher salary data from 1990 (Taylor, Alexander, Gronberg, Jansen & Keller, 2002).

The hedonic wage model used in this analysis describes wages as a function of labor market characteristics, job characteristics, observable teacher characteristics, and unobservable teacher characteristics. Formally, the specification can be expressed as:

$$\ln(W_{idjt}) = D_{dt}\beta + T_{it}\delta + M_{jt} + \alpha_i + \varepsilon_{idjt} \qquad (1)$$

where the subscripts i,d,j and t stand for individuals, districts, labor markets and time, respectively, W_{idjt} is the teacher's full-time-equivalent monthly salary, D_{dt} is a vector of job characteristics that could give rise to compensating differentials, T_{it} is a vector of individual teacher characteristics that vary over time, M_{jt} is a vector of labor market characteristics, and the α_i are individual teacher fixed effects. Any time-invariant differences in teacher quality—such as the teacher's verbal ability or the selectivity of the college the teacher attended—will be captured by the teacher fixed effects.

The data on teacher salaries and individual teacher characteristics come from the Public Education Information Management System (PEIMS). The hedonic wage analysis covers the same five-year period as the cost function analysis (2008–09 through 2012–13). As in the cost function analysis, data from open enrollment charter campuses, virtual campuses and all alternative education campuses have been excluded. All teachers with complete data who worked at least half time for a traditional public district in a metropolitan or micropolitan area have been included in the analysis.[41]

The measure of teacher salaries that is used in this analysis is the total, full-time-equivalent (FTE) monthly salary, which is calculated as the observed total monthly salary divided by the percent FTE.

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[40] For more on the use of hedonic wage models in education, see Chambers (1998); Chambers & Fowler (1995); Goldhaber (1999); Stoddard (2005); or Taylor (2008a, 2008b, 2010, 2011).

[41] For purposes of this analysis, a teacher is someone with a PEIMS role code of 25, 29 or 87, who spends at least 95% of his or her time teaching.

The hedonic model includes controls for teacher experience (the log of years of experience, the square of log experience and an indicator for first-year teachers) and indicators for the teacher's educational attainment (no degree, master's degree or doctorate) and whether or not the individual is new to the district,

Job characteristics in the analysis include indicators for teaching assignment (general elementary, language arts, mathematics, science, social studies, health and physical education, foreign languages, fine arts, computers, vocational/technical subjects, special education and standardized-tested subjects or grades) and student populations served (non-graded students, elementary students, secondary students, pre-kindergarten students or kindergarten students). Any given teacher could have multiple teaching assignments (such as an individual teaching both math and science) or serve multiple student populations (such as kindergarten and pre-kindergarten).

Other job characteristics in the analysis include an indicator for whether or not the individual was assigned to multiple campuses and indicators for whether or not the teacher had additional duties as a department head, administrator or professional staff member.

The campus characteristics used in the hedonic wage analysis allow for compensating differentials based on factors that are largely outside of school district control—student demographics, school size and school type. The student demographics used in this analysis are the percentage of students in the campus who are identified as economically disadvantaged, limited English proficient or special education students. School size is measured as the log of campus enrollment. There are three indicators for school type (elementary

Table B1: Hedonic Wage Model

	Coefficients
Years of experience (log)	-0.0066***
	(0.0011)
Years of experience (log), sq.	0.0133***
	(0.0006)
First year teacher	-0.0082***
	(0.0007)
No degree	-0.0028*
	(0.0016)
Master's degree	0.0243***
	(0.0003)
PhD	0.0352***
	(0.0031)
New hire	-0.0048***
	(0.0002)
Assigned multiple campuses	0.0055***
	(0.0005)
General elementary teacher	-0.0002
	(0.0002)
Language arts teacher	-0.0005***
	(0.0002)
Mathematics teacher	-0.0002
	(0.0002)
Science teacher	-0.0006**
	(0.0002)
Social studies teacher	-0.0006***
	(0.0002)
Health & P.E. teacher	0.0081***
	(0.0003)
Foreign language teacher	-0.0067***
	(0.0004)
Fine arts teacher	-0.0012***
	(0.0002)
Computer teacher	-0.0022***
	(0.0003)
Vocational/technical teacher	0.0004
	(0.0005)
Special education teacher	0.0002
	(0.0003)
Tested grade or subject teacher	-0.0007***
	(0.0002)
Assigned non graded students	-0.0010***
	(0.0002)
Assigned elementary students	-0.0024***
	(0.0003)

	Coefficients
Assigned secondary students	0.0023***
	(0.0003)
Assigned pre-k students	-0.0003
	(0.0004)
Assigned kindergarten students	-0.0020***
	(0.0002)
Department head	0.0177***
	(0.0035)
Administrator	0.1100***
	(0.0190)
Support staff	0.0041
	(0.0051)
Campus% econ. disadvantaged	0.0098***
	(0.0008)
Campus% limited English	0.0179***
	(0.0012)
Campus% special education	0.0085***
	(0.0028)
Campus enrollment (log)	0.0149***
	(0.0004)
Elementary campus	0.0022
	(0.0014)
Middle school campus	0.0085***
	(0.0014)
High school campus	0.0114***
	(0.0014)
Comparable wage index	0.0892***
	(0.0041)
Fair market rent (log)	0.0260***
	(0.0014)
Unemployment rate	0.0036***
	(0.0001)
Major urban area indicator	0.0723***
	(0.0017)
Micropolitan area indicator	-0.0124***
	(0.0022)
Observations	1,398,111
Number of teacher fixed effects	378,792
Adjusted R-squared	0.494

Note: The model also includes year indicators. Robust standard errors are in parentheses. Asterisks indicate a coefficient that is statistically significant at the 1%*** 5%** or 10%* levels.
Source: Authors' calculations.

schools, middle schools, and high schools).

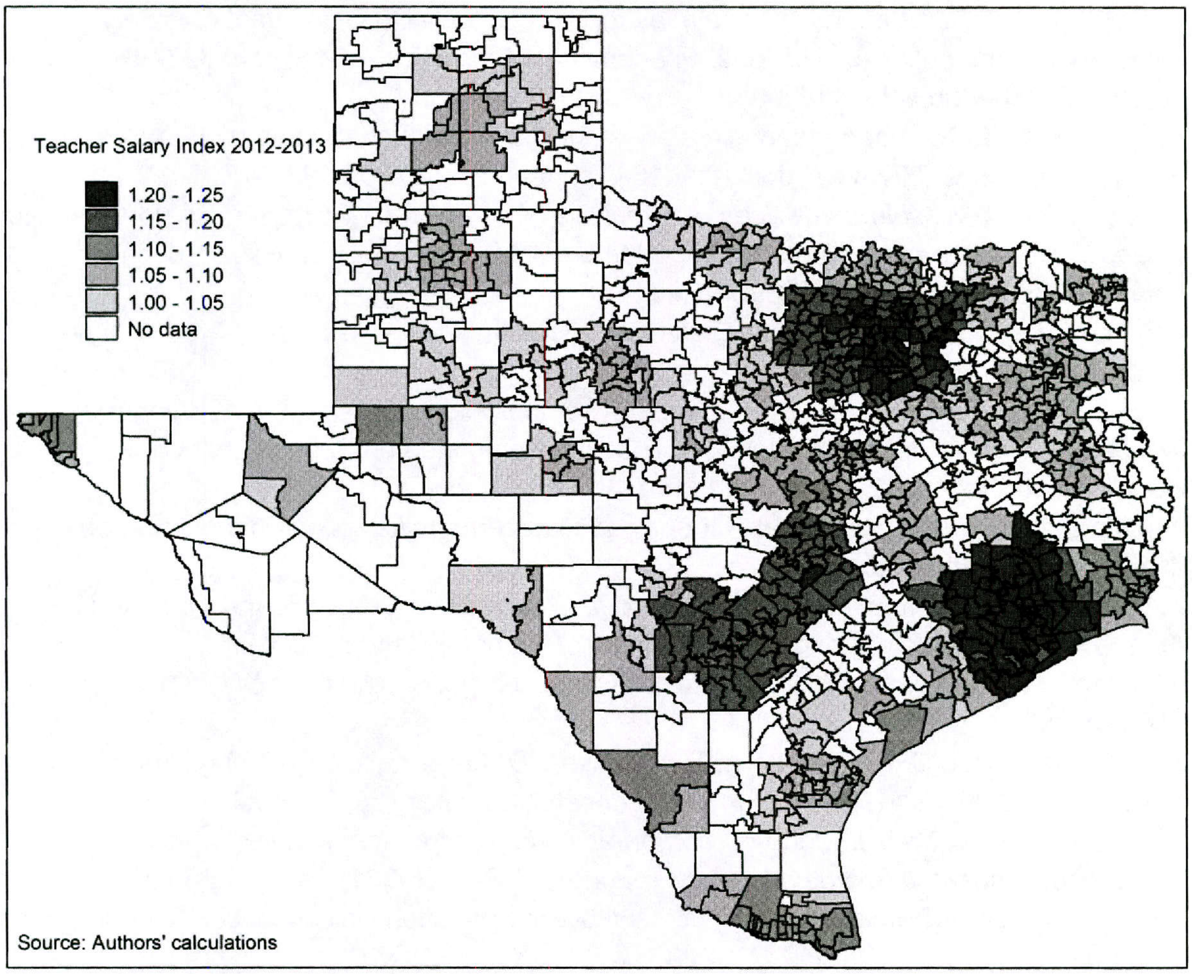
The hedonic wage model also includes four indicators for local labor market conditions. Researchers updated the National Center for Education Statistics' Comparable Wage Index to measure the prevailing wage for college graduates in each school district (Taylor and Fowler, 2006). The U.S. Department of Housing and Urban Development's estimate of Fair Market Rents for a two-bedroom apartment (in logs) captures deviations in the cost of living, and the U.S. Bureau of Labor Statistic's measure of the metropolitan area unemployment rate captures job prospects outside of teaching. Finally, the model includes indicators for whether or not the school district is located in a major metropolitan area (Austin, Dallas, Fort Worth, Houston and San Antonio) and for whether or not the school district is located in a micropolitan area.

Table B.1 presents the coefficient estimates and robust standard errors for the hedonic wage model. As the table illustrates, the hedonic wage model is consistent with reasonable expectations. Wages rise with experience, particularly for teachers who are relatively inexperienced. Teachers with a Master's degree earn 2.5% more than teachers with a bachelor's degree, all other things being equal, whereas teachers with a PhD earn 3.7% more. Teachers with additional administrative duties earn significantly higher salaries than those without such responsibilities. The cost of hiring teachers is higher when campuses have a larger percentage of students identified as economically disadvantaged or LEP. Salaries increase as campus enrollment increases, and are significantly higher in high schools than in elementary schools. Salaries are also systematically higher in major metropolitan areas, all other things being equal.

The Teacher Salary Index (TSI) for each campus is based on the predicted wage for a teacher with zero years of experience and a bachelor's degree, holding all other teacher characteristics and job characteristics constant at the statewide mean, but leaving the campus and labor market characteristics unchanged. Dividing the predicted wage by the minimum predicted wage (each year) yields the TSI. It ranges from 1.00 to 1.25 indicating that the cost of hiring teachers is up to 25% higher in some core based statistical areas than in others.

Figure B.1 maps the average TSI values, by school district, for the 2012–13 school year. As the figure illustrates, on average the TSI is highest in the Houston and Dallas metropolitan areas and lowest in the Sweetwater and Snyder micropolitan areas.

Figure B1: The Teacher Salary Index 2012–13



References

Chambers, J. G. (1998). *Geographic variations in public schools' costs* (NCES 98-04). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Chambers, J. G., & Fowler Jr., W. J. (1995). *Public school teacher cost differences across the United States*. Analysis/methodology report (NCES-95-758). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Goldhaber, D. D. (1999). An alternative measure of inflation in teacher salaries. In W.J. Fowler, Jr. (Ed.), *Selected papers in school finance, 1997–99* (NCES 99-334) (pp. 29– 54). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Stoddard, C. (2005). Adjusting teacher salaries for the cost of living: The effect on salary comparisons and policy conclusions. *Economics of Education Review, 24*, 323-339. doi: 10.1016/j.econedurev.2004.06.004

Taylor, L. L. (2008a). Comparing teacher salaries: Insights from the US census. *Economics of Education Review, 27*, 48-57. doi: 10.1016/j.econedurev.2006.06.002

Taylor, L. L. (2008b). *Washington wages: An analysis of educator and comparable non-educator wages in the state of Washington*. A report to the Joint Task Force on Basic Education Finance. Retrieved July 7, 2014 from http://www.leg.wa.gov/JointCommittees/BEF/Documents/Mtg11-10_11-08/WAWagesDraftRpt.pdf.

Taylor, L. L. (2010). *Putting teachers in context: A comparable wage analysis of Wyoming teacher salaries*. A report prepared for the Select Committee on School Finance Recalibration. Retrieved July 7, 2014 from http://legisweb.state.wy.us/lsoweb/schoolfinance/documents/taylorwyomingcomparablewagesreportfinaldecember2010.pdf

Taylor, L. L. (2011). *Updating the Wyoming hedonic wage index*. A report to the Wyoming Joint Appropriations and Joint Education Committees. Retrieved July 7, 2014 from http://legisweb.state.wy.us/2011/Interim%20Studies/Taylor_UpdatingTheWyomingHedonicWageIndexFinal.pdf

Taylor, L. L., Alexander, C. D., Gronberg, T. J., Jansen, D. W., & Keller, H. (2002). Updating the Texas cost of education index. *Journal of Education Finance, 28*, 261-284.

Taylor, L. L., & Fowler Jr, W. J. (2006). *A comparable wage approach to geographic cost adjustment. Research and development report* (NCES-2006-321). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Technical Appendix C: Supplemental Table

Table C1: Coefficient Estimates from Cost Function Models

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
District Enrollment	-0.2268**	-0.3180***	-0.2370***	-0.1562*
	(0.0892)	(0.1065)	(0.0889)	(0.0834)
District Enrollment, squared	0.0244**	0.0492***	0.0285***	0.0172*
	(0.0101)	(0.0127)	(0.0103)	(0.0097)
District Enrollment, cubed	-0.0007**	-0.0016***	-0.0009**	-0.0005
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
District Enrollment * NCE Math	0.0076	-0.0220	0.0035	0.0052
	(0.0218)	(0.0226)	(0.0220)	(0.0205)
District Enrollment * NCE Reading	-0.0189	-0.0889**	-0.0169	-0.0166
	(0.0298)	(0.0357)	(0.0300)	(0.0285)
District Enrollment * Teacher Salary Index	0.0759**	0.0956**	0.0665*	0.1053***
	(0.0383)	(0.0379)	(0.0385)	(0.0386)
District Enrollment * Distance to MCSA Center	-0.0060**	0.0002	-0.0055**	-0.0080***
	(0.0027)	(0.0026)	(0.0027)	(0.0025)
District Enrollment *% Econ. Disadvantaged	0.0046	0.0081	0.0027	-0.0038
	(0.0070)	(0.0087)	(0.0071)	(0.0067)
District Enrollment *% Ever-LEP	0.0001	-0.0061	-0.0016	0.0032
	(0.0068)	(0.0098)	(0.0069)	(0.0066)
District Enrollment *% Special Education	0.3680***	0.3829***	0.3400***	0.3906***
	(0.0319)	(0.0437)	(0.0315)	(0.0300)
District Enrollment * Campus Enrollment	-0.0118**	-0.0301***	-0.0124**	-0.0123***
	(0.0050)	(0.0037)	(0.0053)	(0.0047)
District Enrollment * Elementary school campus	0.0345***	0.0266***	0.0188***	0.0364***
	(0.0046)	(0.0058)	(0.0046)	(0.0044)
District Enrollment * Middle school campus	0.0339***	0.0337***	0.0206***	0.0339***
	(0.0039)	(0.0047)	(0.0038)	(0.0036)
District Enrollment * Multigrade campus	0.0255***	0.0265***	0.0136*	0.0278***
	(0.0082)	(0.0100)	(0.0081)	(0.0077)
NCE Math	0.8988**	0.6936	0.7235*	0.8459**
	(0.4037)	(0.4271)	(0.4027)	(0.3960)
NCE Math, squared	-0.4556*	-0.5806**	-0.4570**	-0.4768**
	(0.2328)	(0.2378)	(0.2305)	(0.2264)
NCE Math * NCE Reading	-0.3282	-0.0212	-0.2454	-0.3443
	(0.5375)	(0.6025)	(0.5305)	(0.5244)
NCE Math * Teacher Salary Index	-0.7495*	-0.7960*	-0.6571	-0.6871*
	(0.4088)	(0.4146)	(0.4072)	(0.3946)
NCE Math * Distance to MCSA Center	-0.0304	-0.0365	-0.0281	-0.0311
	(0.0253)	(0.0273)	(0.0254)	(0.0242)

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
NCE Math *% Econ. Disadvantaged	-0.1062	-0.1429	-0.0488	-0.0783
	(0.0955)	(0.1081)	(0.0945)	(0.0932)
NCE Math *% Ever-LEP	0.0431	0.0395	-0.0002	0.0411
	(0.0995)	(0.1195)	(0.0988)	(0.0965)
NCE Math *% Special Education	-0.4658	-1.0126	-0.4087	-0.4959
	(0.6224)	(0.6879)	(0.6135)	(0.6035)
NCE Math * Campus Enrollment	-0.0057	0.0707	0.0161	0.0089
	(0.0588)	(0.0576)	(0.0591)	(0.0567)
NCE Math * Elementary school campus	-0.0634	0.0091	-0.0749	-0.0646
	(0.0812)	(0.0913)	(0.0794)	(0.0767)
NCE Math * Middle school campus	0.1256	0.1637*	0.1123	0.1201
	(0.0821)	(0.0904)	(0.0796)	(0.0777)
NCE Math * Multigrade campus	0.1162	0.1106	0.0849	0.0782
	(0.2038)	(0.2068)	(0.1894)	(0.1912)
NCE Reading	0.7382	-0.2688	0.9266	0.4420
	(0.7110)	(0.6729)	(0.7030)	(0.6866)
NCE Reading, squared	0.1495	0.3649	0.1756	0.3637
	(0.5315)	(0.5716)	(0.5252)	(0.5023)
NCE Reading * Teacher Salary Index	0.7728	0.5194	0.6921	0.3534
	(0.6181)	(0.6220)	(0.6114)	(0.5977)
NCE Reading * Distance to MCSA Center	-0.0374	-0.0733*	-0.0383	-0.0298
	(0.0389)	(0.0432)	(0.0391)	(0.0367)
NCE Reading *% Econ. Disadvantaged	-0.2924*	-0.1945	-0.3122*	-0.1583
	(0.1762)	(0.1758)	(0.1758)	(0.1762)
NCE Reading *% Ever-LEP	-0.0597	0.0287	-0.0569	-0.1533
	(0.1481)	(0.1711)	(0.1470)	(0.1477)
NCE Reading *% Special Education	-1.6416*	0.1115	-1.6824*	-1.6726*
	(0.9523)	(1.0888)	(0.9256)	(0.9282)
NCE Reading * Campus Enrollment	-0.0653	0.1010	-0.0982	-0.0530
	(0.0656)	(0.0783)	(0.0657)	(0.0644)
NCE Reading * Elementary school campus	0.3343***	0.4938***	0.2958***	0.2833***
	(0.1085)	(0.1252)	(0.1058)	(0.1053)
NCE Reading * Middle school campus	0.2543**	0.3857***	0.2111*	0.2038*
	(0.1201)	(0.1335)	(0.1168)	(0.1140)
NCE Reading * Multigrade campus	1.1805***	1.0902***	1.2372***	1.0733***
	(0.2902)	(0.3057)	(0.2754)	(0.2718)
Teacher Salary Index	2.1081***	2.1865***	1.9729***	1.9218***
	(0.6219)	(0.6186)	(0.6229)	(0.6018)
Teacher Salary Index, squared	-6.4226***	-7.1623***	-6.2251***	-8.3176***
	(1.9470)	(1.8819)	(1.9637)	(1.8196)
Teacher Salary Index * Distance to MCSA Center	-0.1379**	-0.1112*	-0.1336**	-0.1078*
	(0.0617)	(0.0637)	(0.0624)	(0.0593)

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
Teacher Salary Index *% Econ. Disadvantaged	-0.6687***	-0.6127***	-0.5870***	-0.3778*
	(0.2079)	(0.2103)	(0.2061)	(0.2034)
Teacher Salary Index *% Ever-LEP	0.3121	0.3413	0.3584*	0.0695
	(0.2099)	(0.2131)	(0.2099)	(0.2094)
Teacher Salary Index *% Special Education	-0.9000	-0.3109	-0.7934	-1.6069*
	(0.8849)	(0.9062)	(0.8680)	(0.8328)
Teacher Salary Index * Campus Enrollment	0.0664	0.0432	0.0925	0.1505*
	(0.0838)	(0.0803)	(0.0833)	(0.0799)
Teacher Salary Index * Elementary school campus	0.5143***	0.4812***	0.4083***	0.3869***
	(0.0896)	(0.0889)	(0.0873)	(0.0862)
Teacher Salary Index * Middle school campus	0.1365**	0.1229*	0.0449	0.1145*
	(0.0667)	(0.0661)	(0.0645)	(0.0645)
Teacher Salary Index * Multigrade campus	-0.0566	-0.0742	-0.1343	-0.0885
	(0.1873)	(0.1917)	(0.1819)	(0.1760)
Distance to MCSA Center	0.0202	0.0709**	0.0317	0.0330
	(0.0377)	(0.0361)	(0.0381)	(0.0364)
Distance, squared	-0.0008	0.0002	-0.0006	-0.0007
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Distance *% Economically Disadvantaged	0.0428***	0.0492***	0.0467***	0.0366***
	(0.0118)	(0.0132)	(0.0121)	(0.0117)
Distance *% Ever-LEP	0.0083	-0.0130	0.0003	0.0086
	(0.0117)	(0.0130)	(0.0120)	(0.0112)
Distance *% Special Education	0.0504	-0.0235	0.0298	0.0870
	(0.0579)	(0.0598)	(0.0572)	(0.0548)
Distance * Campus Enrollment	0.0083*	-0.0039	0.0065	0.0085**
	(0.0047)	(0.0041)	(0.0046)	(0.0043)
Distance * Elementary school campus	0.0133*	0.0019	0.0078	0.0142**
	(0.0072)	(0.0063)	(0.0069)	(0.0067)
Distance * Middle school campus	0.0075	0.0003	0.0034	0.0081*
	(0.0049)	(0.0042)	(0.0047)	(0.0046)
Distance * Multigrade campus	-0.0163	-0.0198*	-0.0146	-0.0194*
	(0.0115)	(0.0115)	(0.0109)	(0.0108)
% Econ. Disadvantaged	-0.2978*	-0.3327*	-0.2934*	-0.2652
	(0.1638)	(0.1702)	(0.1640)	(0.1668)
% Econ. Disadvantaged, squared	0.2947***	0.3182***	0.3068***	0.2932***
	(0.0319)	(0.0339)	(0.0320)	(0.0337)
% Econ. Disadvantaged *% Ever-LEP	-0.3318***	-0.3588***	-0.3672***	-0.3214***
	(0.0462)	(0.0565)	(0.0463)	(0.0528)
% Econ. Disadvantaged *% Special Education	-0.8110***	-0.7390***	-0.8770***	-0.7876***
	(0.1944)	(0.2319)	(0.1926)	(0.1920)
% Econ. Disadvantaged * Campus Enrollment	0.0603***	0.0454**	0.0616***	0.0557***
	(0.0170)	(0.0179)	(0.0173)	(0.0164)

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
% Econ. Disadvantaged * Elementary school campus	-0.0424*	-0.0319	-0.0759***	-0.0456**
	(0.0245)	(0.0279)	(0.0234)	(0.0232)
% Econ. Disadvantaged * Middle school campus	0.0213	0.0322	-0.0025	0.0149
	(0.0211)	(0.0239)	(0.0202)	(0.0197)
% Econ. Disadvantaged * Multigrade	-0.1120	-0.0639	-0.1090	-0.1545**
	(0.0768)	(0.0787)	(0.0719)	(0.0700)
% Ever-LEP	0.2036	0.2466	0.3138*	0.1895
	(0.1664)	(0.1846)	(0.1693)	(0.1644)
% Ever-LEP, squared	0.0722**	0.0909**	0.0736**	0.0799**
	(0.0323)	(0.0385)	(0.0327)	(0.0330)
% Ever-LEP *% Special Education	0.7021***	0.7542***	0.7423***	0.5725**
	(0.2243)	(0.2754)	(0.2222)	(0.2230)
% Ever-LEP * Campus Enrollment	-0.0183	-0.0106	-0.0246	-0.0115
	(0.0167)	(0.0213)	(0.0170)	(0.0161)
% Ever-LEP * Elementary school campus	0.0484**	0.0344	0.0526**	0.0577**
	(0.0242)	(0.0282)	(0.0230)	(0.0230)
% Ever-LEP * Middle school campus	0.0513**	0.0419*	0.0515**	0.0529***
	(0.0219)	(0.0240)	(0.0208)	(0.0203)
% Ever-LEP * Multigrade campus	0.1280	0.0908	0.1100	0.1497*
	(0.0878)	(0.0964)	(0.0873)	(0.0775)
% Special Education	4.8480***	4.4425***	5.0042***	4.6372***
	(0.7410)	(0.8304)	(0.7392)	(0.7349)
% Special Education, squared	-2.0050***	-2.7045***	-1.7948***	-1.9775***
	(0.6684)	(0.6849)	(0.6672)	(0.6383)
% Special Education * Campus Enrollment	-0.8286***	-0.8191***	-0.8204***	-0.8336***
	(0.0675)	(0.0799)	(0.0675)	(0.0657)
% Special Education * Elementary school campus	-0.5833***	-0.6999***	-0.5070***	-0.6580***
	(0.1231)	(0.1204)	(0.1229)	(0.1177)
% Special Education * Middle school campus	-0.5294***	-0.7684***	-0.4639***	-0.5173***
	(0.1186)	(0.1048)	(0.1200)	(0.1156)
% Special Education * Multigrade campus	0.3235	0.0099	0.2604	0.2982
	(0.2496)	(0.2452)	(0.2594)	(0.2366)
Campus Enrollment	-0.0335	-0.2125***	-0.0715	-0.0364
	(0.0748)	(0.0729)	(0.0768)	(0.0742)
Campus Enrollment, squared	0.0068	0.0267***	0.0096	0.0061
	(0.0066)	(0.0044)	(0.0068)	(0.0063)
Campus Enrollment * Elementary school campus	-0.1037***	-0.0756***	-0.0889***	-0.0981***
	(0.0110)	(0.0107)	(0.0116)	(0.0108)
Campus Enrollment * Middle school campus	-0.0379***	-0.0381***	-0.0242***	-0.0319***
	(0.0085)	(0.0088)	(0.0086)	(0.0080)
Campus Enrollment * Multigrade campus	-0.0667***	-0.0686***	-0.0502**	-0.0757***
	(0.0217)	(0.0231)	(0.0208)	(0.0201)

	Baseline Model	Excluding Very Large Districts	Excluding Athletics and Extra	Including Food and Transportation
Elementary school campus	-0.0701	-0.2479**	0.1022	-0.0557
	(0.0940)	(0.0998)	(0.0936)	(0.0916)
Middle school campus	-0.4476***	-0.4854***	-0.3135***	-0.4364***
	(0.0786)	(0.0855)	(0.0769)	(0.0740)
Multigrade campus	-0.4512**	-0.3797*	-0.4177**	-0.2925
	(0.2156)	(0.2304)	(0.2060)	(0.1964)
School year 2009–10	0.0292***	0.0313***	0.0288***	0.0276***
	(0.0064)	(0.0063)	(0.0065)	(0.0061)
School year 2010–11	0.0125*	0.0144**	0.0113*	0.0137**
	(0.0067)	(0.0061)	(0.0068)	(0.0063)
School year 2011–12	-0.0407***	-0.0370***	-0.0427***	-0.0358***
	(0.0065)	(0.0063)	(0.0066)	(0.0061)
School year 2012–13	-0.0374***	-0.0301***	-0.0402***	-0.0303***
	(0.0069)	(0.0064)	(0.0069)	(0.0065)
Major metropolitan area	-0.0914***	-0.0812***	-0.0889***	-0.0901***
	(0.0203)	(0.0193)	(0.0208)	(0.0192)
Micropolitan area	-0.0089	-0.0057	-0.0062	-0.0014
	(0.0107)	(0.0109)	(0.0106)	(0.0104)
Constant	9.5420***	10.4943***	9.4772***	9.4604***
	(0.4331)	(0.4540)	(0.4342)	(0.4273)
Observations	29,746	27,427	29,746	29,746

Note: Robust standard errors clustered by district-year in parentheses. The asterisks indicate a coefficient estimate that is statistically significant at the 1% (***) 5%(**) or 10%(*) levels.
Source: Authors' calculations.