Are Charters the Best Alternative? A Cost Frontier Analysis of Alternative Education Campuses in Texas

by

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Abstract

Previous research suggests that charter schools are able to produce educational outcomes at lower cost than traditional public schools. However, that analysis focused exclusively on schools which serve a general student population. In Texas, as in many other states, some charter schools have been designed specifically to serve students who are at risk of dropping out of school. Such schools, which are designated as "alternative education campuses," may have very different cost and efficiency profiles than schools designed to serve students in regular education programs. In this paper, we estimate a translog stochastic cost frontier model using panel data for alternative public high school campuses in Texas over the five-year period 2007-2011, and find that alternative education high school campuses operated by charter schools are systematically more efficient than alternative education high school campuses operated by traditional public school districts. Policies that encourage the formation of alternative education charter campuses may thus be a sensible component of strategies to combat the pervasive and pernicious problem of high school dropouts.

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Introduction

Programs designed to prevent or discourage students from dropping out of school before they receive a high school diploma can generate significant benefits to both individuals and to society. In the current environment of increasing returns to skill, the importance of completing high school on future wages is magnified. In addition to the direct effect on the individual students, the potential reduction in the incidence of various correlates of dropping out, such as incarceration, represents a social return to retention-type programs.

One institutional approach to addressing the dropout problem is the creation of designated campuses that specialize in the education of students identified as being "at risk of dropping out of school". These alternative education campuses offer nontraditional programs and accelerated instructional services to targeted "at risk" students. Students are identified as "at risk" based on statutory criteria including poor academic performance and difficult personal circumstances (such as pregnancy). As a result of the selected student population and of the differentiated program objectives, the alternative education campuses may have very different cost and efficiency profiles than schools designed to serve students in regular education programs.

In this paper, we examine the cost structure and relative cost efficiency of alternative education high schools in Texas, where charter schools have emerged as a major player in the provision of alternative education. We estimate a translog stochastic cost frontier model using panel data for public school campuses in Texas over the five-year period 2007-2011. We find that charter alternative education campuses (C-AECs) operate closer to optimal size and closer to the cost frontier than alternative education campuses operated by traditional public school districts (T-AECs), suggesting that charter schools may be the most cost-effective provider of educational services to this key demographic.

Nontraditional Education in Texas

Texas has been part of the charter school movement since 1995, when the 74th Texas Legislature authorized the State Board of Education (SBOE) to establish open enrollment (OE) charter schools in the state.[1] OE charter schools are completely independent local education agencies. Although legally designated as public schools, they function as school districts, and will therefore be referred to hereafter as OE charter districts.

Like traditional public school (TPS) districts, OE charter districts are monitored and accredited under the statewide testing and accountability system. They may operate multiple campuses, and they are not allowed to charge tuition. Unlike traditional school districts, OE charters are less heavily regulated, may operate in more than one metropolitan area, may serve only a subset of grades, and may place limits on the number of children allowed to enroll.[2]

According to the Texas Education Agency (TEA), in 2010-11 there were 199 OE charter districts operating 482 campuses in Texas.[3] Those 482 campuses served 133,697 students—or nearly 3% of the public school students in Texas.

Figure 1 provides information about the composition of OE charter school campuses in Texas. As the figure illustrates, a disproportionate number of OE charter campuses are classified

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[1] Under Texas law, there can also be district charter schools (which are wholly-owned subsidiaries of traditional public school districts), home rule charter schools and college or university charter schools. The only functional difference between a college or university charter school and the other OE charter schools is that the state has no limit on the number of college and university charters whereas there is a limit on the number of OE charters that can be issued. We treat the three college or university charter schools as OE charters for the purposes of this analysis. There are no home rule charters.

[2] Only OE charter districts with the appropriate provisions in their charter may operate in multiple metropolitan areas. There are 23 charter school districts with campuses in more than one metropolitan area.

[3] Nineteen charter holding companies operated two or more OE charter districts during the 2010-11 school year (Taylor and Perez 2012). KIPP-affiliated charter holders operated 5 OE charter districts in Texas during 2010-11. Uplift Education and America Can! each operated another 5 OE charter districts in Texas during 2010-11, while Cosmos Foundation, Inc., operated 11 OE charter districts (including the Harmony Science Academy Laredo and the Harmony Science Academy Waco). If the Cosmos Foundation charter-holding company were considered a single OE charter district, it would have been the largest in the state, with 33 campuses and a total enrollment of 16,721.

as AECs. While OE charter districts run 308 standard campuses and 127 AECs of Choice, traditional public school districts run 7,576 standard campuses but only 216 AECs of Choice.

AECs are campuses that (1) are dedicated to serving students at risk of dropping out of school; (2) are eligible to receive an alternative education accountability (AEA) rating; and (3) register annually for evaluation under AEA procedures (TEA 2011). AECs can be classified as AECs of Choice, which are day schools, and Residential AECs. More than half of the residential AECs in Texas are OE charter school campuses, and nearly 10 percent of the OE charter campuses are residential.[4]

There are obvious differences between residential and nonresidential campuses. As the name implies, residential campuses provide round-the clock services to students and most residential campuses provide services to students in a juvenile justice or treatment center context. This analysis excludes residential campuses because their cost structures and objectives are clearly different from those of day schools.

AECs of Choice are mostly a high school phenomenon. For OE Charter Districts, 72 of 127 AECs are high schools. For Traditional Public School Disricts, 188 of 216 AECs are high schools.

There are also major differences between AECs of Choice and what Texas labels standard accountability campuses. AECs of Choice are not disciplinary alternative or juvenile justice alternative education campuses (TEA 2011). They also are not stand-alone General Educational Development (GED programs). Rather, AECs of Choice are campuses that offer nontraditional programs and accelerated instructional services to students designated at risk of dropping out of school, where students are identified as “At Risk” based on statutory criteria

[4] Texas is at the vanguard of emergence of charter school suppliers of AEC services. Nearly half of the charter alternative schools in the U.S. in 2011-12 were located in Texas (National Center for Education Statistics 2014).

including poor performance on standardized tests, a history of being held back in school, limited English proficiency, pregnancy, homelessness, placement in an alternative education program, or residence in a residential placement facility (AEIS Glossary). Each AEC of Choice—henceforth to be referred to simply as AEC—must have a minimum percentage of at-risk students enrolled on the AEC in order to remain registered and be evaluated under AEA procedures. "The at-risk criterion began at 65% in 2006 and increased by five percentage points annually until it reached 75% in 2008, where it remains" (TEA 2011). However, if an AEC met the at risk criterion in the previous year (or was not operating in the previous year) then it can still be considered an AEC during the current year even if the at risk percentage falls below the eligibility threshold.

AECs in Texas are subject to less stringent accountability standards than standard accountability campuses, regardless of whether they are operated by TPS or OE charter districts. During the period of our analysis, all standard campuses were rated Exemplary, Recognized, Academically Acceptable, or Academically Unacceptable based on Texas Assessment of Knowledge and Skills (TAKS) passing rates, English language learner (ELL) progress rates, completion rates, and annual dropout rates. AECs were rated either Academically Acceptable or Academically Unacceptable based on a TAKS progress measure, a modified completion rate, and the annual dropout rate for grades 7-12.[5]

The highest rating possible for an AEC was Academically Acceptable. To have been assigned this rating in 2010-11, either 55% of the TAKS tests taken by all students and by each evaluated subgroup (African American, Hispanic, non-Hispanic white, and economically disadvantaged students) must have met the passing standard (regardless of the subject matter of

[5] Campuses with no students enrolled in grades higher than kindergarten, Juvenile Justice Alternative Education Program (JJAEP) campuses, and Disciplinary Alternative Education Program (DAEP) campuses, as well as campuses with very small numbers of usable test scores and campuses where TEA had concerns about data quality, were not rated.

the test) or else the campus must have been making required improvement (i.e., their passing rate was rising fast enough to meet the standard in 2 years).[6] The campus must have also satisfied rating criteria with respect to the ELL progress measure, modified completion rates, and annual dropout rates.

For a standard accountability campus to have received a rating of Academically Acceptable in 2010-11, 70% of the students as a whole and in each evaluated subgroup must have passed the TAKS in reading/ELA, writing, and social studies, 65% must have passed in mathematics, and 60% must have passed in science. Campuses that were below the TAKS performance threshold, but were making required improvement (defined as above) were also rated as Academically Acceptable. There were no necessary performance levels with respect to the ELL progress measure, but the campus must have satisfied rating criteria with respect to completion rates and annual dropout rates.

Not only were the passing rate standards lower for AECs, the graduation standard was also less rigorous. AECs were evaluated using a modified completion rate that considers GED recipients as completers whereas the standard accountability completion rate did not. Furthermore, the threshold completion rate was lower for AECs (60%) than for standard accountability campuses (75%). Finally, the dropout rate standard was much less rigorous for AECs. To be considered academically acceptable, a standard accountability campus must have an annual dropout rate for grades 7 and 8 below 1.6 percent; an AEC must have an annual dropout rate for grades 7 through 12 below 20 percent.

In addition to pursuing different objectives, AECs in Texas were also serving a systematically different student population. As figure 2 illustrates, nonresidential, non-

[6] Any subgroup with at least 50 students is evaluated separately, as is any subgroup with at least 30 students that also represents at least 10% of campus enrollment.

elementary AECs attracted a student population that was disproportionately nonwhite, low income and limited English proficient. Students attending AECs were less likely to participate in gifted education programs or career and technology programs, and more likely to participate in bilingual education programs than were students attending standard accountability TPS campuses. AECs were also disproportionately located in metropolitan areas. Only 73 of the 341 AECs were located outside of a metropolitan area, and only 9 of the 112 AECs operated by an OE charter district were nonmetropolitan.

As a general rule, the demographic differences between C-AECs and T-AECs were insignificant. However, during the analysis period (2007-2011) C-AECs served a significantly higher percentage of economically disadvantaged students and a significantly lower percentage of at-risk students than did T-AECs.

The Cost Function Model

Following Gronberg et al. (2012), we model educational cost as a function of the quantity and quality of educational outcomes, the prices of variable inputs and the quantities of the environmental factors that directly influence the education production process.

Our baseline model uses a (modified) translog stochastic frontier specification.[7] The stochastic frontier methodology is particularly well-suited to the analysis of organizations that are inefficient, and has been used successfully in previous work on public education.. The advantages and the challenges of applying the stochastic frontier methods to school cost function estimation are discussed in a recent paper by Gronberg, Jansen, and Taylor (2011a).

[7] This model 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 (2004), 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).

We model school expenditures per pupil as a function of output indicators (q), input prices (w) and environmental factors (x). Formally, our model is:

$$\ln(E_i) = a_0 + \sum_{i=1}^{n_1} a_i q_i + \sum_{i=1}^{n_2} b_i w_i + \sum_{i=1}^{n_3} c_i x_i + .5\sum_{i=1}^{n_1}\sum_{j=1}^{n_1} d_{ij} q_i q_j + .5\sum_{i=1}^{n_1}\sum_{j=1+}^{n_2} e_{ij} q_i w_j$$
$$+ .5\sum_{i=1}^{n_2}\sum_{j=1}^{n_2} f_{ij} w_i w_j + .5\sum_{i=1}^{x_3}\sum_{j=1}^{x_2} g_{ij} x_i w_j + .5\sum_{i=1}^{n_1}\sum_{j=1}^{n_2} h_{ij} q_i x_j + .5\sum_{i=1}^{n_3}\sum_{j=1}^{n_3} k_{ij} x_i x_j + l q_1^3 + v_i + u_i \quad (1)$$

where v_i is a random noise component (representing an exogenous random shock, such as a rainy testing day), and u_i is a one-sided error term that captures inefficiency. [8] The dependent variable $E_{i,t}$ is a measure of per-pupil operating expenditures, described in more detail below. We impose the usual symmetry restrictions ($d_{ij} = d_{ji}$, $f_{ij} = f_{ji}$, and $k_{ij} = k_j$) and assume that the one-sided error u_i has a half-normal distribution. Inefficiency increases cost above minimum cost, so $u_i \geq 0$, and cost efficiency is defined as $\exp(-u_i) \leq 1$. In addition, our estimated models all include year fixed effects.

The stochastic cost frontier framework can accommodate impacts of exogenous environmental factors on efficiency via modeling of the one-sided error term. In particular, we specify that

$$u = u(x_{i,t}, \delta) \quad (2)$$

where $u(.,.)>0$, $x_{i,t}$ is a vector of environmental efficiency factors and δ is a parameter vector.

The Data and Model Specification

The data for our analysis come from administrative files and public records of the TEA and cover high schools operating during the five-year period from 2006-07 through 2010-11. Given

[8]To accommodate the extraordinary range of this variable and to enhance the flexibility the model, we also include the cube of the first environmental factor—school district enrollment. We also include year and metropolitan area fixed effects which are not indicated in equation (1).

our focus on AECs, and the demonstrated differences between standard accountability campuses and AECs, we adopt as our unit of analysis the high school AEC, both C-AECs and T-AECs. Because so few charter schools are located outside of metropolitan areas, we further restrict our attention to high school AECs that are located in metropolitan areas.[9] Figure 3 provides descriptive statistics on the schools included in this analysis for our panel of data.

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. [10] The data come from the state's Public Education Information Management System (PEIMS) which traces all local education agency expenditures to the fund, function, object, and campus level. As in Imazeki and Reschovsky (2004) and Gronberg et al (2004, 2005 and 2011b), we exclude food and transportation expenditures on the grounds that they are unlikely to be explained by the same factors that explain student performance, and therefore that they add unnecessary noise to the analysis.

On average, 88 percent of school district expenditures are allocated to the campus level in PEIMS. We distribute unallocated school district expenditures to the campuses on a per pupil basis.[11] Per-pupil operating expenditures below $3,000 or above $30,000 were deemed implausible and treated as missing.

[9] Juvenile justice or disciplinary education campuses and residential AECs have been excluded.
[10] The expenditures data have been adjusted to account for school districts that serve as a fiscal agent for another school district or group of districts. 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. We use TEA data from F-33 files generated annually by fiscal agents indicating the amount they spent on behalf of member districts. We use these data to allocate spending by fiscal agents to member districts on a proportional basis. Due to data limitations, we are unable to allocate spending by fiscal agents to specific campuses within member districts.
[11] We note that Gronberg et al. (2012) also followed this approach.

By construction, the dependent variable includes all operating expenditures in the designated categories, regardless of the funding source. Expenditures funded by charitable donations, federal grants, local tax revenues and state funding formula aid are all included as are all types of operating expenditures. The dependent variable includes direct salary expenditures, contributions to the statewide teacher pension system, payments for group health and life insurance, and other outlays for employee benefits. It includes payments for contracted workers as well as employees. It also includes payments for rents, utilities and supplies. It does not include capital outlays or debt service, nor does it include imputed rent for buildings owned by the district or charter school.

Outputs

Our independent variables include both a quantity dimension of output — the number of students served — and two quality dimensions. We measure quantity as the number of students in fall enrollment at the campus. The enrollment variable ranges from 25 to 942, with a mean of 178 and a median of 156. As reported in Figure 3, the average enrollment at (high school) C-AECs was 229, while at T-AECs it was 140. This contrasts with the enrollments at standard accountability campuses, where TPS campuses have much higher enrollment, on average, than OE charter campuses.

One dimension of quality is defined as a transformed version of the annual dropout measure used in the state's accountability system for AEA campuses. This variable is 1 minus the annual dropout rate for students in grades 7 through 12, where the annual dropout rate is the number of students in grades 7 through 12 who dropped out during the school year, divided by the number of students who enrolled.[12] It ranges from a low of 49.5 percent to a high of 100 percent.

We measure a second dimension of quality using a normalized gain score indicator of student performance on the Texas Assessment of Knowledge and Skills (TAKS).[13] Every year, Texas administers tests of student achievement in mathematics and reading/language arts in grades 3-11.[14] We have data on the TAKS scores of individual students in reading and math from 2005 through 2011 and use those data to generate our measure of school quality. Although we recognize that schools produce unmeasured outcomes that may be uncorrelated with math and reading test scores, and that standardized tests may not measure the acquisition of important higher-order skills such as problem solving, these are the 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 and Taylor 2011a, and 2011b or Imazeki and Reschovsky 2004).

We normalize the annual gain scores in each subject as in Reback (2008), in order to control for mean reversion in student test scores. For this normalization, we use test scores for student (i), grade (g), and time or year (t), denoted as S_{igt}. All students statewide, not just those

[12] According to the TEA, a dropout is a student who is enrolled in public school in Grades 7-12, does not return to public school the following fall, is not expelled, and does not: graduate, receive a GED, continue school outside the public school system, begin college, or die. A student who completes the school year but does not return in the fall is: (a) considered a dropout from the grade, district, and campus in which he or she was enrolled at the end of the school year just completed; and (b) included in the dropout count for the school year just completed (TEA 2011). Because of the delays associated with data collection, the state's accountability ratings are based on a one-year lag of this indicator; our analysis uses contemporaneous values.

[13] Our use of standardized test scores as an indicator for the quality of district output – the quality of the educational experience districts offer to students – is mandated by data availability. While standardized tests provide a measure of student achievement, they typically measure minimal expected learning, and emphatically do not measure deeper learning or student performance at the highest end of the achievement scale.

[14] Tests in other subjects such as science and history are also administered, but not in every grade level.

attending AECs are included in this calculation. We measure each student's performance relative to others with same past score in the subject as:

$$Y_{igt} = \frac{S_{igt} - E(S_{igt} \mid S_{i,g-1,t-1})}{[E(S_{igt}^2 \mid S_{i,g-1,t-1}) - E(S_{igt} \mid S_{i,g-1,t-1})^2]^{0.5}} \tag{3}$$

In calculating Y_{igt} for math, we calculate the average test score in math at time t, grade g, for students scoring $S_{i,g-1,t-1}$ in math at time t-1, grade g-1. Thus, for example, we consider all tenth-grade students with a given ninth-grade score in math, and calculate the expected score on the tenth-grade test as the average math score at time t for all tenth-grade students with that common lagged score.[15] Our variable Y_{ijgt} measures individual deviations from the expected score, adjusted for the variance. This is a type of z-score. Transforming individual TAKS scores into z-scores allows us to aggregate across different grade levels despite the differences in the content of the various tests. For ease of interpretation, we further transform the z-scores into normal curve equivalent (NCE) scores. NCE scores are a monotonic transformation of z-scores that are commonly used in the education literature. Thus, the second quality measure in our analysis is the average NCE gain score in reading and mathematics for each campus. It ranges from 11.1 to 59.4, with a mean of 40.5.

Input Prices

Teachers are obviously the most important educational input, and one of the ways in which charter schools differ from traditional public schools is in their teacher hiring and compensation practices. As discussed in Taylor et al (2012) charter schools pay much lower full-time-equivalent salaries, on average, than do traditional public schools in Texas. The lower salaries

[15] We utilize data of students with a missing prior test score by using (5) where the conditioning score is 'missing.' For these students we are comparing their current performance relative to others with missing prior scores. (We could have assigned such students a prior score of the state-wide mean and obtained the same result.)

are at least partially explained by the fact that the average teacher in a charter school is less experienced, less highly educated and less likely to hold a teaching certificate than the average teacher in a traditional school district.[16]

If there were a teacher type that was hired by all OE charter schools and traditional public schools—say, for example, a teacher with a bachelor's degree from a selective university and two years of experience—then arguably we would be best served by using the wages paid to those teachers as our input price measure. However, it is impossible to identify a teacher type that is hired by all the OE charter and TPS districts under analysis, and any observed average wage—such as the average salary for beginning teachers—would reflect school and district choices about the mix of teachers to hire

We deal with this source of potential endogeneity by using a wage index that does not depend on school and district choices. To construct such an index, we followed Gronberg et al. (2012) and used a hedonic wage model to predict the wages each school would have to pay to hire a teacher with constant characteristics.[17] (See Appendix.) The teacher salary index for each AEC is based on the predicted wage for a teacher with zero years of experience and a bachelor's degree, holding all other observable teacher characteristics constant at the statewide mean, and suppressing any charter school differentials. Thus, the predicted wage for a C-AEC is the same as the predicted wage for an otherwise equivalent T-AEC. The predicted wage is then divided by

[16] Texas has a minimum salary scale for teachers in TPS districts. However, the salary scale does not apply to charter schools and is generally not binding for TPS districts in metropolitan areas. Less than 0.3 percent of metropolitan area teachers in Texas received the state's minimum salary during the analysis period.

[17] We note that teachers in charter schools participate in the same statewide teacher retirement system as teachers in TPS districts, and that years of service in the system are counted without regard as to whether the employer was a charter school or a TPS district. Thus, teachers can move from one TPS district to another, or from a charter school to a TPS district 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.

the minimum predicted wage to yield the salary index. The index indicates that labor cost is more than 20 percent higher in some AECs than in others each year.

Ideally, we 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. Therefore, we include the distance to the center of the metropolitan area to capture variation in non-labor input prices. [18]

Other Environmental Factors

The model includes indicators for several environmental factors that influence district cost but which are not purchased inputs. Because previous researchers have found significant economies of scale in district-level cost functions (Andrews, Duncombe and Yinger 2002), we include the log of school district enrollment.[19] To capture variations in costs that derive from variations in student needs, we include the percentages of students in each district who were LEP, special education or economically disadvantaged students. We include fixed effects for year to control for inflation and other time trends in Texas education.

Finally, in some specifications we also include an indicator that takes on the value of one if the campus is part of an OE charter district, and zero otherwise. This indicator allows for the

[18] 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 county centers come from the U.S. Census Bureau. Where available, latitude and longitude information for campuses are taken from the National Center for Education Statistics' Common Core Database. The remaining campuses are assigned latitudes and longitudes according to the zip codes at their street address.

[19] District enrollment is top-coded at 120,000 students. Only one district in the sample, Houston ISD which operated only two high school AECs during the analysis period, had more than 120,000 students.

possibility that the less heavily regulated C-AEC technology is different from the more heavily regulated T-AEC technology.

Efficiency Factors

We model the one-sided variance function as depending on the indicator variable for an OE charter district.[20] This specification allows for the possibility that charter school efficiency may differ systematically from the efficiency of traditional public schools.

Heteroskedasticity in the two-sided error may also arise. To capture such a possibility, we model the two-sided variance as a function of the share of campus expenditures that was specifically allocated to the campus and the log of the number of students with TAKS scores. We include the first because measurement error in the dependent variable is likely to be a function of the extent to which the dependent variable was imputed. We include the second because the larger the number of tested students, the smaller is the potential for measurement error in this key independent variable.

Estimation Results

Marginal effects evaluated at the sample mean for a number of alternative models are reported in Figure 4. Robust standard errors (clustered by district-year) are in parentheses. Given the flexibility of the translog specification, the marginal effects can be very close to zero at the sample mean, but significantly different from zero elsewhere in the distributions. The p-values indicate the probability that a variable and all of its interaction terms are jointly zero.

The first model (baseline model) assumes that OE charters and traditional public schools share a common cost frontier (i.e. a common cost function). In this specification the only

[20] We specify the one-sided error term as having 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

difference between C-AECs and T-AECs is in the efficiency estimate, as we explicitly allow C-AECs to have a different one-sided error term than T-AECs. This allows us to judge the relative efficiency of OE charters and other public schools in operating an AEC, assuming these schools share a common technology.

As the first column of results in Figure 4 illustrates, estimated marginal effects for the model with a common cost frontier generally correspond to expectations. Increases in the salary index have a positive and statistically significant impact on cost while increases in distance to the center of the metropolitan area have a significantly negative effect. The student body characteristics we include – percent economically disadvantaged, percent LEP and percent special education – are all associated with a higher average cost per student, although the marginal effect is very small and not statistically significant for the percent LEP.

The model indicates that school and district size have an important and complicated relationship with cost for AECs. Holding all other characteristics (including school quality) constant at the mean, the model indicates that cost falls with campus size. The predicted cost of operating an average quality campus is $9,142 per pupil when there are 140 students (the T-AEC average), but falls by 13 percent to $7,950 per pupil when there are 229 students (the C-AEC average). Meanwhile, holding campus size constant at the mean, the predicted cost of an average quality education has a U-shaped relationship with school district size, with cost minimized at a district enrollment of 570 students. OE charter districts are systematically closer than TPS districts to the cost-minimizing district size. Thus, in both size dimensions, the analysis suggests that C-AECs enjoy a considerable cost advantage over T-AECs.

The model suggests a significant, positive relationship between cost and increases in the student retention rate (i.e. the transformed dropout rate). To the best of our knowledge, ours is the first peer-reviewed paper to find a significant, positive relationship between retention and cost. Evaluated at the mean, we find that a five percentage point increase in the annual student retention rate is associated with a 2.6 percent increase in the per-pupil cost of education, all other things being equal. Furthermore, the estimate of cost is highly sensitive to campus size. A five percentage point increase in the student retention rate is associated with a 3 percent increase in cost for a campus with 140 students (the T-AEC average), but only a 1 percent increase in cost for a campus with 229 students (the C-AEC average).

The insignificant marginal effect for the TAKS output measure is somewhat surprising, and arises from important nonlinearities in the relationship between TAKS output and cost. Figure 5 illustrates the relationship between TAKS score gains and cost, holding all other variables constant at the mean. As the figure illustrates, costs rise with TAKS scores for most of the relevant range but have no apparent relationship at the TAKS score mean. The hypothesis that the TAKS score and all of its interaction terms are jointly zero can be rejected at the 10-percent level, but the marginal effect at the mean is not significantly different from zero.

This finding that costs are a function of retention rates but not a function of academic gains (once gains are above a certain threshold) is consistent with the overarching, dropout-prevention mission of AECs. Most students attending AECs have been identified as at risk of dropping out of school, and retaining those students is the primary concern for T-AECs and C-AECs (if for no other reason than because the state funding formula ties school district revenues to average daily attendance). We also note that Texas holds AECs accountable for their dropout rates (which are a monotonic transformation of the retention rates used here) but not for test score gains so it is natural for school administrators to focus their resources on boosting their retention rates.

The bottom panel in Figure 4 presents the estimated relationship between the one-sided errors and the model determinant of inefficiency (charter school status and a constant). These are not coefficient estimates in the traditional sense. Rather, they represent the marginal effect of each variable on the standard deviation of the one-sided error. Nevertheless, a positive coefficient can be interpreted as indicating a factor that increases inefficiency, while a negative coefficient indicates a factor that decreases inefficiency. As the first column of Figure 4 illustrates, we find evidence that C-AECs are systematically more efficient (i.e. have a smaller standard deviation of the one-sided error) than T-AECs.

Because school quality is frequently thought of as a choice variable for school district administrators, the possible endogeneity of the school quality indicators is a common concern for researchers estimating educational cost functions.[21] 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. By analogy, control function corrections (as in Heckman and Navarro-Lozano, 2004 or Gronberg et al., 2015) should generalize to the stochastic frontier setting. We adopt a control function approach to explore the potential endogeneity of the outcomes variables.

The key to implementing the control function corrections is the identification of viable instruments for school quality. Human capital theory suggests that local labor market conditions can influence the demand for educational quality and the opportunity cost of staying in school.[22] This seems particularly plausible for alternative education populations. Furthermore, Arkes

[21] For example, see the discussion in Duncombe and Yinger 2011, 2005, Imazeki and Reschovsky 2004 or Gronberg, Jansen and Taylor 2011a.
[22] For example, see Black, McKinnish, and Sanders. (2005); or Clark (2011).

(2010) demonstrates that unemployment rates can be used successfully as instruments for educational attainment—a close correlate with our completion measure of school quality. Therefore we use labor market indicators in the vicinity of the school site as instruments for our outcomes measures. The first labor market indicator—the unemployment rate in the zip code area—comes from Census Bureau tabulations using five years of the American Community Survey (2007-2011). Because the samples are small, the Census Bureau pools all five years, making this indicator time-invariant. The second labor market indicator—the share of potential employers that is either a restaurant or a retailer—reflects the availability of the types of jobs most commonly held by teenagers, comes from the ZIP Business Patterns produced by the Census Bureau, and does vary annually.

These labor market indicators meet the necessary conditions for instrumental variables, being conceptually exogenous and well correlated with the two indicators of school quality.[23] They are conceptually exogenous because, given the highly redistributive nature of the Texas school finance formula, even if labor market conditions at the zip-code level affect the taxable property wealth of a school district as a whole (which is questionable) property wealth has no direct impact on expenditures per pupil in our sample.[24] They are well correlated with quality based on the usual, first-stage F-statistics for the joint significance of the excluded instruments.[25]

[23] The standard errors are clustered by district-year and the reported F-statistics are robust to both arbitrary heteroskedasticity and arbitrary intra-group correlation.

[24] The Texas school finance formula guarantees each OE charter and TPS district a minimum level of revenue per pupil and provides additional revenues to OE charter and TPS districts according to formula weights that depend on the number of students who participate in particular programs, including special education, career and technology education, bilingual/ESL education, state compensatory education, and/or gifted and talented education. The revenue that an OE charter district receives (per weighted student) is the same in all locations (Taylor et al. 2012). The revenue that a TPS district receives (per weighted student) can vary with property wealth. However, we found no significant correlation between our dependent variable (the log of operating expenditures per pupil, excluding food and transportation) and school district property wealth (per pupil) for the TPS districts in our sample. Estimates are available upon request.

[25] The first-stage F-statistics are 9.93 with 2 and 516 degrees of freedom for the conditional NCE TAKS score and 13.14 with 2 and 516 degrees of freedom for the dropout indicator.

The second column of Figure 4 presents marginal effects from a control-function corrected version of the baseline model. The residuals from each of the two first-stage regressions have been included as regressors in the stochastic frontier model. Those control-function regressors are individually and jointly insignificant at the 5-percent level, indicating that endogeneity is unlikely to be a source of bias in our specification. Notably, this model also indicates that C-AECs are systematically more efficient than T-AECs.

The relative efficiency of C-AECs could arguably arise from differences in scope between the two types of high schools. As Figure 3 illustrates, T-AECs spend twice as much as C-AECs on athletics and extracurricular activities, on average. T-AECs schools that appear comparatively inefficient in this analysis may simply be producing outputs that are costly to produce and uncorrelated with the basic academic outcomes measured here. The efficiency advantage of C-AECs may disappear if we exclude athletics and extracurricular activities from the analysis.

The third column of Figure 4 explores that possibility. Here, the dependent variable has been modified to exclude all expenditures on athletics and other extracurricular activities. As the column illustrates, differences in spending on extracurriculars or athletics cannot explain the observed differences in efficiency. The charter school efficiency advantage is essentially unchanged from that observed in the baseline specification.

Some previous cost analyses of Texas (such as Imazeki and Reschovsky 2004) excluded the Dallas and Houston Independent School Districts (ISDs) on the grounds that these districts are so much larger than the rest that they must operate under a very different cost structure.[26] The model presented in the fourth column of Figure 4 excludes these two districts and their 7

[26] Dallas ISD has no AECs in the sample, so this exclusion only applies to Houston ISD. Houston ISD is twice as large as the next-largest district in our sample. .

campus-by-year observations from the full model analysis. As the column indicates, excluding the largest districts in the state has no discernable effect on the relative efficiency of charter schools, although it does have an impact on some of the estimated marginal effects (particularly the marginal effect of school district size).

The fifth column in Figure 4 presents a version of the Common Cost Frontier but adds an indicator for OE charter district to the explanatory variables in our modified translog cost function. This indicator is interacted with the constant and the first order terms in the translog. This allows OE charter schools to have a different slope as well as a different cost intercept, while not estimating two distinct frontiers or cost functions. (Unfortunately, sample size limitations prevent us from reliably estimating separate frontiers for each type of campus.) We explore this specification because charter schools represent a deregulated version of traditional public schools, and those regulations might constrain T-AECs to adopt less efficient technologies.

As the fifth column indicates, at the mean, C-AECs have a lower estimated cost per student than T-AECs. However, we cannot reject the hypothesis that the charter school indicator and all of its interaction terms are jointly zero. In other words, the charter school indicator does not belong in the main effects specification of the cost function. There is no evidence that OE charter schools have access to a lower cost technology unavailable to TSP campuses. This finding is robust to the inclusion or exclusion of athletics expenditures and is not driven by the unusual influence of very large school districts, or by endogeneity with respect to the output variables in this specification.

However, the finding is not robust to the inclusion or exclusion of the district size indicator. District size is a significant determinant of cost in all of the above specifications, and excluding it from any model is rejected at all common levels of significance. Nevertheless, because OE charter districts are systematically smaller than TPS districts, we explored a specification that excludes district size as an indicator. As the sixth column of Figure 4 illustrates, when district size is not included in the model, C-AECs appear to have a different cost technology than T-AECs—and a considerable cost advantage.

Figure 6 presents efficiency estimates for the six models reported in Figure 4. As the figure illustrates, when we restrict traditional and nontraditional public schools to have a common cost function, we estimate that C-AECs are 6 percentage points more efficient than T-AECs, on average. Taken at face value, the average C-AEC could reduce cost by 9 percent without reducing output; the average T-AEC could reduce it by 15 percent. This general pattern holds for all of the alternative specifications. When we allow OE charter and TPS AECs to have a different cost function than other public schools, the general pattern observed under a common cost frontier is unchanged, although the gap narrows slightly. T-AECs are less efficient, on average than are C-AECs. In all six cases, the difference in means is statistically significant at the 5-percent level.

What explains the relative cost inefficiency of T-AECs? Although an empirical analysis of this question is beyond the scope of this paper, we offer three hypotheses. The first two are related to teacher input choices. First, charter schools may be employing a less expensive mix of personnel. Charters do not face the same teacher certification requirements as do traditional public school operators, and C-AECs employ, on average, a higher proportion of uncertified teachers. If certification is not highly correlated with productivity, then T-AECs would be less efficient operations. C-AECs are also, on average, choosing to deliver educational services with a higher proportion of less experienced teachers than do TPS operators. If, as many researchers believe, experience is not an indicator of teacher effectiveness, then the significantly higher level of average teacher experience in T-AECs would also push T-AECs above the best practice cost frontier.

Second, the hedonic wage analysis suggests that teachers in TPS districts receive systematically higher wages than one would expect given their qualifications, when compared with teachers in OE Charter schools. Perhaps teachers assigned to T-AECs are receiving rents, on average. We speculate that many TPS districts may feel constrained by the salary schedule that they use for their standard accountability campuses (which would lead to teacher rents if teachers sort themselves according to working conditions and AECs are perceived as less attractive). C-AECs, particularly those that do not operate any standard accountability campuses, may feel no such constraint.

Finally, we note that the C-AECs in our analysis are generally much newer than the T-AECs. Two thirds of the T-AECs were providing education services in Texas before the first charter school opened its doors in 1997. If the age of the school is a good indicator for the age of the facility, then part of their efficiency advantage may be attributable to the relatively new vintage of the charter school's capital stock. Gronberg et al. (2011b) find that differences in capital stock can be reflected in the efficiency parameters of stochastic frontier cost functions.

As expected, there are a few important caveats to our analysis. First, although families of students make a conscious decision to attend either type of AEC, charter schools can attract students across school district lines and may make a deliberate effort to attract students with specific demographic characteristics. As a result, students attending C-AECs may be systematically different from students attending T-AECs. We address this concern as best we can by including a school quality measure that is based on changes over time in the performance of individual students and by instrumenting for school quality in some models. However, our approach may not be sufficient to account for unobserved differences between OE charter and TPS students. Some of the differences in measured efficiency between C-AECS and T-AECS may arise from differences in student and family inputs rather than from differences in the school districts. Second we note that our measures of school quality may not be capturing all of the important dimensions of school district output. Schools that appear relatively less efficient in this analysis may simply be producing outputs that are costly to produce and uncorrelated with the basic academic outcomes measured here.

Our results suggest that OE charters are on average more efficient than are traditional public schools at providing alternative education, at least at the high school level. In contrast, Gronberg, Jansen and Taylor (2012) and Carpenter and Noller (2010) found that charter schools are *less* efficient than traditional public schools in operating "standard accountability campuses," at least at the elementary level. We can only speculate on the reasons behind this finding. Certainly high school AECs at traditional public schools already act more like charter schools, having fewer extra-curricular activities and smaller enrollments. It is possible they also share a more common technology. Both C-AECs and T-AECs are serving a student population that was failing, or in danger of failing, in the traditional school model. In TPS districts, alternative accountability campuses draw students from across the district, somewhat like OE charter district draw students from across (and between) districts. TPS standard accountability campuses drawn students from designated attendance zones. Thus T-AECs are more similar to C-AECs in this dimension than they are to TPS standard accountability campuses. Along these lines, it is possible that C-AECs face more competition from T-AECs, on average, than standard accountability charter schools face from traditional public schools.

One bit of supporting evidence is our finding that we cannot reject the hypothesis that for high school AECs, the technology for OE charter operators and TPS operators are the same. In contrast, Gronberg, Jansen and Taylor (2012) found that the technology of charter operators and TPS operators was different at standard accountability campuses, at least for elementary schools.

We tested, and rejected, the idea that OE charter districts that specialize in AECs—that exclusively provide alternative education services—were different in efficiency from OE charters that did not so specialize. We found no difference in efficiency in this comparison.[27] Of course, TPS districts do not specialize in alternative education services. They all operate standard accountability campuses.

There are some additional subtleties here. At the elementary level if we impose that charters and TPS standard accountability districts have the same frontier, we find charters more efficient. But when we relaxed this constraint and allowed different frontiers, we found that charters had a lower cost frontier but charters and TPS campuses were essentially equally efficient. Of course, for this comparison there were thousands of TPS campuses, while charters were a small part of the sample.

Here we look at high schools, and in particular at AEC high schools. Here we do not reject the common frontier restriction, and we find that charter AECs are more efficient. With separate frontiers we found that C-AECs had lower costs and were still more efficient that T-AECs. Again, as pointed out above, C-AECs and T-AECs were more nearly equal in number in our sample, and are more nearly of the same average enrollment, suggesting again that the common cost frontier is more appropriate for AECs.

[27] Estimates available upon request.

Finally, as we mentioned above, TPS districts are bound by their salary schedule, and teachers at T-AECs are paid on the same scale as teachers at TPS standard accountability campuses. Charters have no salary schedule, and do not have to match salaries at C-AECs with salaries at other schools in the charter district. This feature is further facilitated by the fact that charter districts often operate in geographically separate areas. TPS districts are tied to the geographic footprint of their district boundaries. In the end, our analysis suggests that charters may be a better source for alternative education in Texas. Among AECs, OE charters have the same cost frontier as traditional public providers, but are more efficient relative to that frontier. In other words, the evidence suggests that alternative education charter schools are able to produce educational outcomes at lower cost than traditional public alternative education schools.

Conclusion

Alternative education campuses are an increasingly common strategy for addressing the high school dropout problem in the United States. During the 2000-01 school year, 39 percent of public school districts administered at least one alternative school or program for at-risk students (Kleiner, Porch and Farris 2002); by 2007-08, that percentage had risen to 64 percent (Carver and Lewis 2010). By 2011-12, alternative schools were operating in all but three U.S. states—Maine, New Hampshire and North Dakota (Keaton 2013).

Despite the growing role of alternative schools in the U.S. educational system, they are seldom studied. This paper provides the first careful, empirical study of the costs of alternative education. In addition to including a standard test score performance measure of the quality of educational output in our cost function analysis, we include a retention performance measure as well. We find a generally insignificant relationship between test score performance and cost, and a positive and significant relationship between increases in retention and cost. These results accord well with the heavy emphasis on dropout prevention in alternative schools.

The policy lens is focused upon the relative efficiency of charter schools and traditional public schools in delivering alternative education services over the period 2007-2011 in Texas. We find that the cost frontier for C-AECs is no different from the frontier for T-AECs, but that C-AECs tend to operate in a lower-cost region of that frontier. In particular, we find that holding outputs constant, the cost of alternative education falls with campus size but rises with district size; charters are closer to optimal size in both dimensions.

We also find that charter schools are typically closer to the frontier than are traditional public schools. Thus, the evidence suggests that charters are more efficient than are traditional public schools, and that their efficiency advantage is not driven by their access to a superior educational technology. One key area of differences in operating environment is in teacher hiring requirements and conventions. The results in this paper suggest that cost inefficiencies from these environmental differences could be large.

Our Texas evidence thus suggests that the increased flexibility with respect to enrollment and increased degrees of freedom in operating strategies that are available to charter alternative schools are associated with increased cost-effectiveness. Policies that encourage the formation of alternative education charter campuses are thus a sensible component of strategies to combat the pervasive and pernicious problem of high school dropouts.

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Figure 1: The Number of Campuses by Grade-level and AEC Type, 2010-11

	Standard Campuses	AEC of Choice	Residential AEC
OE charter districts			
Elementary schools	118	11	2
Middle schools	38	2	2
High schools	29	72	15
Multi-level schools	123	42	28
Total	308	127	47
Traditional public school districts			
Elementary schools	4,447	2	1
Middle schools	1,421	12	0
High schools	1,320	188	23
Multi-level schools	388	14	18
Total	7,576	216	42

Notes: Non-charter campuses with less than 5 students have been excluded. Elementary schools serve grades PK-6, exclusively. Multi-level schools serve a mix of elementary, middle and high school grades

Sources: Academic Excellence Indicator System (AEIS) and the Texas Education Directory.

Figure 2: Student Demographics by Charter and Accountability Status for Non-residential, Non-elementary campuses (2010-11)

	OE Charter Districts		Traditional Public School Districts
Standard Campuses			
Percent of students who were:			
Non-Hispanic white	18.58%	*	34.03%
African American	19.96%	*	12.90%
Hispanic	53.49%		47.43%
Economically disadvantaged	63.40%	*	53.23%
At risk	37.65%	*	43.22%
Limited English proficient	11.67%	*	7.57%
Special education program	5.53%	*	9.87%
Gifted education program	2.61%	*	10.35%
Bilingual education program	10.98%	*	7.13%
Career & technology program	4.38%	*	44.76%
Number of campuses	190		3,343
Number of campuses in metropolitan areas	185		2,247
Number of students	69,696		2,266,111
AECs of Choice			
Percent of students who were:			
Non-Hispanic white	19.30%	#	20.99%
African American	19.51%		19.09%
Hispanic	58.81%	#	56.46%
Economically disadvantaged	77.79%	*#†	64.81%
At risk	86.74%	*#†	92.87%
Limited English proficient	13.82%	#	14.58%
Special education program	11.07%	†	9.42%
Gifted education program	0.18%	*#†	0.65%
Bilingual education program	13.25%	#	13.87%
Career & technology program	28.91%	#†	34.26%
Number of campuses	116		214
Number of campuses in metropolitan areas	107		162
Number of students	23,382		21,079

Notes: Pupil-weighted averages from campus-level data. Residential campuses and traditional public school campuses with fewer than 5 students have been excluded, as have campuses that exclusively serve grades PK-6. The asterisk indicates a difference between OE charter school districts and traditional public school districts that is statistically significant at the 5% level, adjusting for clustering of the data by district. The # indicates a difference between TPS standard accountability campuses and TPS AECs of Choice that is statistically significant at the 5% level, adjusting for clustering of the data by district. The † indicates a difference between OE charter standard accountability campuses and OE charter AECs of Choice that is statistically significant at the 5% level, adjusting for clustering of the data by district.

Sources: Academic Excellence Indicator System (AEIS) and authors' calculations.

Figure 3: Descriptive Statistics for High School AECs of Choice in Metropolitan Texas, 2006-07 to 2010-11

	OE Charter School Districts		**Traditional Public School Districts**	
	Mean	Std. Dev.	Mean	Std. Dev.
Per-pupil expenditure	$8,822	2620.371	$13,177	5,007.240
District enrollment	851	943	28,415	32,521
Conditional NCE TAKS	40.884	5.949	40.215	7.096
1-dropout rate	0.878	0.095	0.870	0.094
Teacher salary index	0.281	0.056	0.254	0.065
Miles to the MCSA center	11.587	8.024	15.784	10.276
Campus enrollment	228.716	122.308	139.805	102.991
Percent economically disadvantaged	0.688	0.209	0.565	0.216
Percent Limited English proficient	0.093	0.172	0.066	0.105
Percent special education	0.126	0.066	0.083	0.058
Athletics and extracurricular activities expenditure per pupil	$34.14	59.097	$70.74	64.885
Number of observations		278		370

Note: Juvenile Justice and Disciplinary Justice campuses have been excluded, as have all campuses with fewer than 25 students.

Figure 4: Marginal Effects at the Sample Mean

	Baseline	Including Control Function	Excluding Athletics and Extras	Excluding Large ISDs	Allowing for Charter Cost Differences	Excluding District Size
District Enrollment (log)	0.374	0.272	0.349	0.691	-0.080	
	(0.442)	(0.523)	(0.443)	(0.466)	(0.465)	
p-value	0.000	0.000	0.000	0.000	0.000	
Conditional NCE TAKS	-0.079	-0.560	-0.079	-0.063	-0.081	-0.079
	(0.088)	(0.268)	(0.087)	(0.086)	(0.089)	(0.090)
p-value	0.097	0.061	0.089	0.100	0.099	0.027
100- Dropout Rate	0.486	1.130	0.486	0.425	0.564	0.560
	(0.151)	(0.642)	(0.152)	(0.149)	(0.161)	(0.166)
p-value	0.030	0.031	0.030	0.021	0.015	0.010
Teacher Salary Index	0.665	0.658	0.671	0.671	0.826	0.815
	(0.289)	(0.294)	(0.287)	(0.289)	(0.328)	(0.301)
p-value	0.028	0.011	0.020	0.007	0.019	0.005
Miles to MCSA Center	-0.042	-0.060	-0.040	-0.046	-0.046	-0.075
	(0.020)	(0.025)	(0.020)	(0.020)	(0.020)	(0.020)
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Percent Econ. Disadvantaged	0.194	0.201	0.193	0.188	0.168	0.144
	(0.062)	(0.071)	(0.062)	(0.062)	(0.065)	(0.060)
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Percent LEP	0.001	-0.055	0.021	0.028	0.059	0.156
	(0.185)	(0.196)	(0.184)	(0.187)	(0.210)	(0.180)
p-value	0.019	0.008	0.022	0.007	0.033	0.020
Percent Special Education	0.862	0.562	0.878	1.008	0.950	0.784
	(0.224)	(0.271)	(0.224)	(0.216)	(0.238)	(0.233)
p-value	0.000	0.188	0.000	0.000	0.000	0.000
Campus Enrollment	-0.275	-0.259	-0.275	-0.278	-0.243	-0.202
	(0.024)	(0.025)	(0.024)	(0.024)	(0.030)	(0.024)
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Charter School					-0.227	-0.347
					(0.030)	(0.024)
p-value					0.194	0.000
First stage residual TAKS		0.497				
		(0.275)				
p-value		0.071				
First-stage residual Dropout		-0.659				
		(0.641)				
p-value		0.304				
One Sided Error:						
Charter School	-1.078	-1.025	-1.085	-1.118	-0.733	-1.010
p-value	0.018	0.031	0.015	0.016	0.129	0.052
Constant	-3.461	-3.509	-3.433	-3.434	-3.568	-3.682
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Number of Observations	648	648	648	641	648	648

Note: All models also include fixed effects for year. Marginal effects estimated at the sample mean. Robust standard errors for the marginal effect at the mean (clustered by district-year) are in parentheses. The p-value indicates the probability that the variable and all its interaction terms are jointly zero.

Figure 5: The Estimated Relationship Between TAKS NCE Scores and Cost, Holding All Other Variables Constant at the Mean

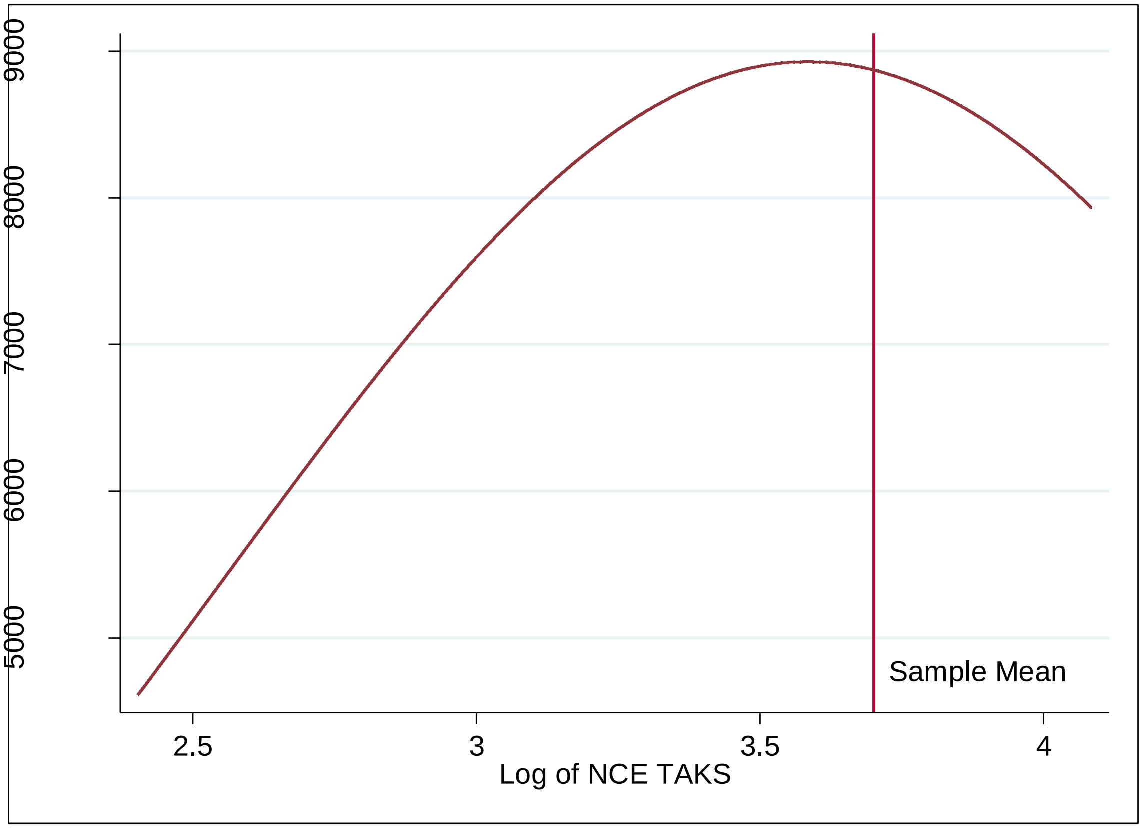

Figure 6: Cost Efficiency Estimates for High School AECs of Choice

	Mean	Std. Dev.	Minimum	Maximum
Baseline				
Open Enrollment Charter	0.907	0.060	0.475	0.977
Traditional Public School District	0.849	0.088	0.490	0.948
Including Control Function				
Open Enrollment Charter	0.906	0.060	0.483	0.977
Traditional Public School District	0.852	0.085	0.502	0.948
Excluding Athletics and Extras				
Open Enrollment Charter	0.906	0.061	0.467	0.977
Traditional Public School District	0.846	0.089	0.490	0.948
Excluding Large Districts				
Open Enrollment Charter	0.907	0.060	0.474	0.977
Traditional Public School District	0.847	0.089	0.477	0.946
Allowing for Charter Cost Differences				
Open Enrollment Charter	0.896	0.068	0.415	0.977
Traditional Public School District	0.856	0.086	0.484	0.951
Allowing for Charter Cost Differences and Excluding District Size				
Open Enrollment Charter	0.913	0.0511	0.524	0.975
Traditional Public School District	0.863	0.075	0.522	0.957

Note: In all cases, the mean cost efficiency for open enrollment charters is significantly higher than the mean cost efficiency for traditional public school districts at the 5% level..

Appendix A: The Hedonic Wage Index

Our hedonic wage index is based on a simple model wherein wages are a function of labor market characteristics, job characteristics, observable teacher characteristics, and unobservable teacher characteristics. Following Gronberg et al. (2012) we allow charters to differ in the premium they pay for teacher characteristics, and focus exclusively on metropolitan areas.

The labor market characteristics used in this analysis include metropolitan area fixed effects and three indicators for local labor market conditions outside of education—the cost of living (as measured by the U.S. Department of Housing and Urban Development's Fair Market Rents), the metropolitan area unemployment rate and the prevailing wage for college graduates (as measured by an updated version of the National Center for Education Statistics' Comparable Wage Index).. For additional flexibility, we also include the interactions among the three labor market indicators.

The job characteristics used in this analysis allow for a compensating differential based on student demographics, school size (measured by the log of campus enrollment), and school type. Indicators for charter school status and AEC status are also included.

The data on teacher salaries and individual teacher characteristics come from the TEA and Texas' State Board for Educator Certification (SBEC). The measure of teacher salaries is the total, full-time equivalent monthly salary, excluding supplements for athletics coaching. 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), teaching assignment (math, science, special education, health and physical education or language arts) and certification status (certified in any subject, and specifically certified in mathematics, science, special education or bilingual education). Only teachers with complete data who worked at least half time for an urban OE charter or TPS district during the analysis period are included in the analysis. Notably, the hedonic wage analysis includes not only teachers in alternative education high schools but also teachers in standard accountability high schools and all elementary, middle and mixed-grade schools. These additional urban public schools were included in the hedonic wage analysis to ensure that the resulting wage index was estimated as precisely as possible in areas where there are only a small number of alternative education high schools. The hedonic wage analysis covers the same five-year period as the cost function analysis (2006-07 through 2010–11). As in the cost function analysis, data from residential campuses, juvenile justice campuses, and disciplinary alternative campuses have been excluded. Figure A1 provides descriptive statistics for the data used in this analysis.

Figure A2 presents the coefficient estimates and robust standard errors for the hedonic wage model. As the table illustrates, there are systematic differences between OE charter schools and traditional public schools in the premiums paid for teacher characteristics. On average, OE charter schools pay lower salaries even after controlling for teacher demographics. Compared with other public schools, OE charter schools pay a larger premium for a teaching certificate (especially in bilingual/ESL or mathematics). On the other hand, OE charter schools pay a much smaller premium for teacher experience than do traditional public school districts. Intriguingly, whereas traditional public school districts pay a very small premium to teachers in AECs, OE charter schools pay a significant discount. All other things being equal, predicted salaries are at least 13.6 percent higher in T-AECs than in C-AECs.

Figure A1: The Characteristics of Teachers in Texas Metropolitan Areas, 2007-2011

	OE Charter Districts		**TPS Districts**	
	Mean	Std. Dev.	Mean	Std. Dev.
Standard Campuses				
FTE Monthly Salary	$3,887	$736	$4,836	$737
Years of Experience	4.610	5.442	11.865	9.386
No degree	0.027	0.161	0.006	0.074
MA	0.137	0.344	0.217	0.413
Ph.D.	0.006	0.079	0.005	0.074
Certified in:				
Mathematics	0.026	0.160	0.077	0.267
Science	0.028	0.164	0.068	0.251
Bilingual/ESL	0.040	0.196	0.097	0.296
Special Education	0.043	0.203	0.131	0.338
Any teaching certificate	0.404	0.491	0.872	0.335
New hire	0.621	0.485	0.165	0.372
Teaching Assignment:				
Mathematic	0.246	0.430	0.209	0.406
Science	0.231	0.422	0.186	0.389
Special Education	0.028	0.166	0.056	0.231
Health and Physical Education	0.111	0.314	0.117	0.322
Language arts	0.277	0.448	0.256	0.437
Coach	0.012	0.109	0.082	0.275
Number of Observations		14,660		1,215,715
AECs of Choice				
FTE Monthly Salary	$3,685	$706	$4,973	$762
Years of Experience	5.460	6.927	13.753	10.289
No degree	0.034	0.180	0.011	0.102
MA	0.146	0.353	0.295	0.456
Ph.D.	0.010	0.098	0.014	0.116
Certified in:				
Mathematics	0.055	0.228	0.166	0.372
Science	0.055	0.229	0.146	0.353
Bilingual/ESL	0.026	0.158	0.017	0.131
Special Education	0.086	0.281	0.157	0.364
Any teaching certificate	0.411	0.492	0.877	0.328
New hire	0.632	0.482	0.156	0.363
Teaching Assignment:				
Mathematic	0.204	0.403	0.182	0.386
Science	0.188	0.391	0.152	0.360
Special Education	0.066	0.248	0.045	0.208
Health and Physical Education	0.112	0.316	0.094	0.292
Language arts	0.251	0.434	0.254	0.435
Coach	0.000	0.016	0.020	0.139
Number of Observations		3,894		7,011

Source: PEIMS.

Figure A2: The Hedonic Model of Teacher Salaries, 2007-2011

	Baseline Coefficient	**Charter Interaction Term**
Salary Index Variables		
OE Charter School		-0.229***
		(0.0134)
Alternative Education Campus	0.0312***	-0.0729***
	(0.00212)	(0.00848)
Percent Economically Disadvantaged Students	0.00959***	
	(0.000883)	
Percent LEP Students	0.0130***	
	(0.00138)	
Percent Special Education Students	0.0175***	
	(0.00307)	
Campus Enrollment (log)	0.0147***	
	(0.000429)	
Elementary School	0.00622***	
	(0.00182)	
Middle School	0.0106***	
	(0.00177)	
Secondary School	0.00785***	
	(0.00176)	
Comparable Wage Index	0.423***	
	(0.0398)	
Fair Market Rent (log)	0.126***	
	(0.00819)	
Unemployment Rate	0.0105***	
	(0.00219)	
CWI*Fair Market Rent (log)	-0.0608***	
	(0.00568)	
CWI*Unemployment Rate	0.00523***	
	(0.000440)	
Fair Market Rent (log)*Unemployment Rate	-0.00260***	
	(0.000387)	
Teacher Demographics		
Years of Experience (log)	-0.0349***	0.187***
	(0.00107)	(0.0181)
Log Experience, squared	0.0404***	-0.0500***
	(0.000567)	(0.00621)
First-year Teacher	-0.0271***	0.0867***
	(0.000690)	(0.0110)
No Degree	0.00178	-0.0418**
	(0.00170)	(0.0184)
MA	0.0245***	0.00258
	(0.000377)	(0.00717)

	Baseline Coefficient	Charter Interaction Term
Ph.D.	0.0323***	0.0107
	(0.00387)	(0.0217)
Mathematics Certified	0.000967	0.0242***
	(0.000593)	(0.00878)
Science Certified	-0.000794	-0.00762
	(0.000600)	(0.0105)
Bilingual/ ESL Certified	0.00277***	0.0274***
	(0.000370)	(0.00942)
Special Education Certified	0.00128***	0.00474
	(0.000415)	(0.00804)
Certified Teacher	0.00270***	0.00871**
	(0.000239)	(0.00355)
New Hire	-0.00221***	-0.00571**
	(0.000204)	(0.00286)
Teaching assignment		
Mathematics	0.000248	0.00182
	(0.000271)	(0.00492)
Science	8.10e-05	-0.00140
	(0.000280)	(0.00507)
Special Education	0.00105***	-0.00522
	(0.000327)	(0.0109)
Health and P.E.	0.00342***	-0.00483
	(0.000324)	(0.00515)
Language Arts	-0.000936***	-0.00203
	(0.000196)	(0.00431)
Coach	-0.0290***	0.0134
	(0.000659)	(0.0150)
Observations	1,241,172	
Number of teachers	369,699	
R-squared	0.714	

Note: Robust standard errors in parentheses. The model also includes individual teacher fixed effects, metropolitan area fixed effects and year fixed effects. The asterisks indicate a coefficient that is statistically significant at the ** 5%; *** significant at 1%
Source: Authors' calculations from PEIMS.