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The Intersection between School Efficiency and Student Individual Differences

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THE INTERSECTION BETWEEN SCHOOL EFFICIENCY AND STUDENT INDIVIDUAL DIFFERENCES

By

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ABSTRACT

The relationship between school spending and academic performance is one that is constantly being assessed and evaluated. More rarely however, is the evaluation of how efficiently that spending is taking place. This paper used a method known as Data Envelopment Analysis (DEA), to examine how efficiently Florida elementary schools were spending their funds to produce student gains in reading achievement. This paper found that schools (*n=1,446)* were performing on average at an approximate 61% relative efficiency level for the 2009-2010 school year. This paper then used OLS regression and various school-level demographic characteristics to see if school efficiency is able to be predicted, finding that student race, free and reduced lunch status, presence of exceptionalities, and school size to all be significant predictors of school-level efficiency. Finally, this paper examined the relationship between these differing efficiency scores and student individual differences, using a sample of *n=677,386* Florida public elementary school students. In doing so, significant interactions between school efficiency and a student's exceptionality and free and reduced lunch status were found, indicating the negative impact of having an exceptionality or being free and reduced lunch status to be further increased in lower efficiency schools.

THE INTERSECTION BETWEEN SCHOOL EFFICIENCY AND STUDENT INDIVIDUAL DIFFERENCES

Since *Brown v. Board of Education,* the issue of providing truly equal education and opportunities to children has been present and contentiously discussed. Since the landmark case, researchers and policymakers have pointed to numerous factors as potential causes for inequity, and similarly as potential areas for intervention. One of the most common factors these individuals point to is in school funding. Although extreme inequality in school funding existed between schools of varying demographic backgrounds for a long time, decades of funding reform and efforts at the state and federal level have removed much of said inequality, with some studies showing schools in both rich and poor communities seeing relatively equal levels of funding (Urban Institute, 2017). Still however, funding disparities and gaps in achievement and school quality between schools and individuals with different demographics background persist. The persistence of these gaps indicates that although school funding is becoming more equal it may not be equitable, and that funding may still hold the key to understanding and solving this issue. The major problem this paper aims to investigate is the role that funding plays in contributing to these disparities in educational quality, and the potential role that it could play in fixing them.

Study Aims and Questions

In order to get to the true role that school funding has in this, this paper aims to answer several questions. First, how efficiently are schools spending funds to promote student success? Although equal funding has been achieved in many areas of the country, equal funding does not necessarily mean equally appropriate or efficient use of these funds. Understanding the extent to which schools differ in their efficiency in spending is an integral step to understanding the overall role that funding plays, and identifying those schools that are inefficient allows for further questions about those schools to be explored. This paper will utilize a method known as Data Envelopment Analysis (DEA) to evaluate all elementary schools in the state of Florida on their in spending their provided funds, and in doing so will assign an efficiency score to each school that will allow further questions to be answered. This will be done by setting benchmarks for each school given what other schools with similar levels of spending are able to achieve, and measuring each school's ability to meet said benchmark. This process will be explained in deeper detail in a section to follow.

The second question this paper will explore is what school-level characteristics do efficient and inefficient schools differ by? If several characteristics are indicative of levels of inefficiency, then policymakers will be able to identify schools that are more at-risk of inefficient spending. Through identifying these schools early on, interventions and consulting on expenditure in the beginning of the year could help to improve those schools' overall efficiency and quality of education they are providing their students. Characteristics that these schools will be compared on will be a school's overall demographic composition (race, socio-economic status, English language proficiency), school attendance, school size, and percentage of students with a disability. Ordinary least squares regression will be utilized to examine these differences and their ability to predict a school's efficiency.

The third question of interest is what effect does a school's overall efficiency have on student performance, and how do these effects differ for students of different races, socio-economic status, disability status, or English language proficiency? Although, studies have been done looking at school's overall efficiency using funding and student achievement data, no research has been done exploring the impact inefficiency has on students and how these effects contribute to individual differences. Taking an individual differences approach and further analyzing funding impacts at the student-level will help to identify potential causes for school inefficiency and areas for improvement and intervention. Additionally, exploring this will show if schools simply are inefficient in teaching their students overall, or if instead inefficient schools are struggling to reach certain populations of students within their school. If it is the case that schools are failing to reach certain populations, then this will be identified as a potential cause of inefficiency and area for potential intervention. OLS regression will again be used with particular attention being placed on the interactions between a school's efficiency score and student individual difference characteristics.

LITERATURE REVIEW

School Funding and its Predictors

Due to the heterogeneity of the student population throughout the United States, school funding formulas have become more complex and more specialized in attempts to best reach this diverse population. The path of change that these formulas have taken have varied widely from state to state, and have in no way been linear. Guthrie (1983) attempted to make sense of the major changes in education reform by specifying specific eras of different reform efforts from 1955-1980, but still recognized that the non-linearity and variance between and within states limits the practical use of these eras. From 1955-1965, equity and equal opportunity were the focus of most educational reforms, and funding efforts were aimed on equalizing funding levels between primarily black and white schools. From 1965-1975, efforts were focused on increasing school accountability and efficiency, with funding efforts focused on getting the most achievement out of each dollar spent. Finally, from 1975-1980 the focus of education reform was in school choice, and funding efforts took the form of voucher programs and tax credit plans. Since 1980, countless attempts at reforming the education system and its funding have taken place with the common themes of equity, accountability, and choice. In 1991, Minnesota passed the first law enabling charter schools, an innovative idea seen by many as the solution to all of the past problems (Schroeder, 2004). Despite the promising idea of charter schools, their success has been highly variable and at this point is just another chapter in the book of continually changing educational and funding reform efforts.

Through all of these efforts, the United States has arrived at its current state of educational funding. This current system is one that varies between and within states to a large degree, with states placing differing levels of decision-making power at the district and local levels. Because of this variance in school funding formulas, school funding levels based on demographic characteristics also vary widely from state to state and in turn are of particular interest. Although the Urban Institute Report (2017) has stated that school-level funding has become far more equal, other articles have found that significant differences in funding equality across districts arise when examining schools based off their percentage of students coming from low-SES, racial minority, or low English language proficiency backgrounds (Payne & Biddle, 1999; Arroyo, 2007). Arroyo (2007), found that funding varied significantly on the basis of race and SES. They found that in districts with high populations of low-SES students, 14 states spent significantly more on average per student than in districts with low populations of low-SES students, 21 states spent significantly less, and 14 states there was no significant difference of per student spending between districts with high and low populations of low-SES students (Arroyo, 2007). On the basis of race, similar patterns arose with 18 states spending significantly more per student in districts with high percentages of minority students, 16 states spent significantly less in these districts, and in 15 districts there was no significant difference between the two populations (Arroyo, 2007).

The extent to which within- and between-district school funding varies on the basis of these factors makes it an important factor for predicting a school's efficiency in spending funds. In addition to SES and race, presence of English language learners (ELL's) also plays a significant role in determining school funding. As of 2017, 46 states have efforts in place that grant additional funding to schools with ELL's (Millard, 2017). Despite this, the level of additional funding granted is highly variable within and between each state making percentage of ELL's an interesting variable when predicting how efficiently schools spend their funds. Another major area that impacts a school's level of funding is the number of students they serve with disabilities. Thanks to the Individual with Disabilities Education Act (1975) all students with disabilities in the United States are entitled to a free and appropriate public education. However, the way this policy is carried out is different between states and districts, and in turn results in further differences in school funding (Griffith, 2015). Again, these differences make the presence of students with disabilities an important variable to consider when predicting a school's efficiency. One final area where funding levels differ greatly is among schools with different numbers of students. Funding in this area is of particular interest as school size often skews the interpretation of per-student funding. Differences in school size, but similar levels of overhead and indirect costs often make schools with smaller amounts of students appear to have far greater levels of per-student expenditures (Necochea & Cline, 1996). Additionally, changes to formulas that do not take this into consideration often have far different impacts based off of a school's size (Thomas & Bullock, 1992). These facts make this a final variable of interest when predicting a school's level of efficiency.

The Link between Funding and Achievement

Extensive research has been conducted on the relationship between school funding and student academic success. Both the Coleman report (Coleman et al., 1966) and the Jencks' report (Jencks, 1972) identify educational funding as a potential source for intervention, yet both state that its potential for impact is likely limited. In the decades since these reports, empirical analyses and meta-analyses have been conducted, nearly all concluding that the effect of funding is widely variable and calls for better methods of how funding can be distributed and spent by schools (Sebold & Dato, 1981; Hanushek, 1997; Hedges, Laine & Greenwald, 1994, Borman et al., 2003). These papers indicate that funding does have its place, but simply increasing a school's funding alone is not the solution. Rather, better funding paradigms, identification of schools that need additional funding, and more informed decision making on how additional funds be spent, is needed.

Other countries and even some regions within the United States have heeded this advice and turned to other methods to get the most out of their school funding. One such alternative method that has become extremely popular in the Netherlands is a system known as weighted-student funding (WSF). This method of funding allocation focuses on funding that follows students regardless of school choice, and aims to support students coming from more typically at-risk backgrounds such as minorities, low socioeconomic status, students with disabilities, etc. (Ladd & Fiske, 2011). Due to large achievement gaps and segregation in their school system, the Netherlands transitioned to this form of funding in the 1970's and saw significant reductions in their educational achievement gaps (Ladd, Fiske, & Ruij, 2011). Within the United States, several cities including Cincinnati, Ohio and Houston, Texas have used similar systems of weighted funding to achieve some success in closing achievement gaps (Baker, 2009), and the recently implemented Every Student Succeeds Act has plans to pilot a similar program it refers to "Flexibility for Equitable Per-Pupil Funding" (ESSA, 2015). Although this funding method is starting to gain traction in the United States, little research has been done on its effectiveness within the country, or on the appropriate weights to give each student.

School Spending Efficiency

Although extensive research has examined the impact of school funding on overall student achievement, the research on efficiency in utilizing said funds is far more limited. For this article and the subsequent articles cited, efficiency will be defined as a school's ability to optimally use its funds to produce some output. Efficiency will be measured relatively as a percentage based on how much the school actually produced compared to the optimal amount they could have produced given their funding level. One study examined 100 New Jersey high schools, and found that on average schools were performing at an 81% efficiency level, with vast differences in efficiency found between the wealthiest and poorest schools (Noulas & Ketkar, 1998). The same study also found that socioeconomic factors were significant predictors of said inefficiency. This study is evidence not only of inefficient utilization of funding, but of certain indicators being predictive of the level of efficiency that can be expected at a given school. Another study that examined Georgia public high schools found slightly higher levels of average efficiency, with schools operating at an average 90% efficiency level (Denaux, 2007). Despite higher levels of efficiency compared to the New Jersey sample, this study also found that county size, county adult education levels, and county race levels were the most significant predictors of school (in)efficiency (Denaux, 2007). At the national level, one study by Hanushek (1989) found that between the late 1960's and late 1980's per pupil expenditures rose at an average inflation-controlled rate of around 3% per year, with declines in student performance still persisting. Additionally, Hanushek (1989) also claims that most schools receiving increased funds used these increases ineffectively by mainly focusing on decreasing class size while ignoring other evidence-based practices. These increases in funding without increases in achievement are further indication of widespread inefficiency in school spending.

Data Envelopment Analysis (DEA) as a Measure of School Efficiency

Originally developed by Charnes, Cooper, and Rhodes (1978) as a method for distinguishing between various types of efficiency within an organization, or what they refer to as decision making units, DEA as a method has now made its way to the public sector and has been of particular interest in evaluating school's efficiency in producing achievement outcomes. To assess efficiency, DEA uses a method known as linear-programming or linear-optimization to compute efficiency of decision-making units (DMU's) relative to one another. Relative efficiency relies on the assumption that all DMU's should be able to achieve the same level of outputs if they utilize the same resources. Going off of this assumption, DEA uses data from all DMU's in a given set to establish benchmarks for the highest attainable level of output given any set of inputs. Several studies have successfully used this method to evaluate schools on their efficiency compared to one another (Bessent & Bessent, 1980; Ruggiero & Vitaliano, 1999; Tyagi, Yadav & Singh, 2009). By using DEA in this way, each school's individual inputs and outputs were taken into account and compared to every other school in the set. This method results in one relative efficiency score calculated for each individual school, ranging from 0 to 1, with 1 representing 100% relative efficiency. Some studies have taken this a step further and combined DEA with other methods, such as Tsakiridou and Stergiou (2014), who used linear regression and school characteristics to predict efficiency scores in Greek public schools, and Denaux (2007) using county-level variables to predict Georgia high school efficiency levels.

Achievement Gap

At the student level, several demographic variables will be considered as predictors of student achievement. The inclusion of these variables will be based off prior research, indicating the presence and significant impact of academic achievement gaps based on student race, ethnicity, socioeconomic status, English language proficiency, and ability. The presence of academic achievement gaps between these various demographic groups have been documented and explored for decades. On the basis of socioeconomic status, research has shown that students from low socioeconomic status backgrounds score significantly worse on measures of achievement regardless of differences in ethnicity or race (Lacour & Tissington, 2011). Specifically, one longitudinal study found that, at the beginning of Kindergarten, low socioeconomic status students scored on average 0.47 and 1.17 standard deviations lower than middle-class and high socioeconomic status students respectively (Lee & Burkham, 2002). Furthermore, despite the nation's best efforts, this gap has increased over the past few decades. According to Reardon (2011), the achievement gap between low and high income for students born in the year 2001 increased between 30% and 40% over the course of the previous 25 years.

Beyond socioeconomic status, several achievement gaps are present throughout the nation. A minority or black-white achievement gap is something that has been well documented and under high scrutiny since the times of *Plessy v. Ferguson*. Extensive research on this area has been conducted that has found that not only do black students score lower on average than white students, but that when controlling for socioeconomic status and other related factors the gap still is statistically significant (Willie, 2006; Bohrnstedt et al., 2015). In addition to the black-white gap, gaps between English language learners (ELL's) and students with English as their primary language as well as gaps based off student ability also exist. According to the National Education Association, NAEP data from 2013 indicated that students with disabilities were on average 20% less proficient at reading and 27% less proficient compared to their peers without disabilities (National Education Association, 2018). For ELL's, even larger gaps are seen with 73% of 4th grade ELL's scoring below the basic level on reading, and 46% scoring below the basic level on math (National Center for Educational Statistics, 2005). Beyond standardized testing, teacher biases and attributions were found to have a significant negative effect on achievement outcomes for students with disabilities (Clark, 1997).

This paper aims to expand the areas of research presented above by answering the questions "how efficiently are schools spending funds to promote student success," "what school-level characteristics do efficient and inefficient schools differ by," and "what effect does a school's overall efficiency have on student performance, and how do these effects differ for students of different races, socioeconomic status, disability status, or English language proficiency?" The research conducted in this paper will help to expand the current research related to the first two research questions by examining the elementary schools within the state of Florida, and by utilizing a larger sample of schools to gain deeper insights into the possible predictors of school efficiency. The third research question is one that has not been explored, and utilizing the combination of school and student level data this paper aims to observe the deeper implications that inefficiency has on the individual student. Although no prior research has been done looking at the direct effect of efficiency on individual students, I would hypothesize that significant interactions might be found between the demographic variables and the school-level efficiency. These interactions would likely take the form of inefficiency having an additional negative impact on student performance for students who are members of these at-risk demographic groups, such as English Language Learners, students with exceptionalities or on free and reduced lunch, or students in racial groups typically associated with lower performance such as black or Hispanic students.

METHODS AND DATA ANALYSIS

Data Management and Preparation

Data was collected from multiple different sources and combined through the use of school specific identification numbers. Transformation and recoding of variables are described below. Since this project utilized human subjects, IRB approval was needed. IRB approval was granted by the Human Subjects Committee at Florida State University

Participants. To best assess each school's efficiency and attempt to answer all of the proposed research questions, data on schools throughout the entire state of Florida and inclusive of students in grades K-5 were used.

Schools. All public elementary schools in Florida were used, across all 67 school districts. A total of 1,446 schools were included in the analysis.

Students. All students in grades K-5 in Florida public elementary schools that have completed the state standardized reading comprehension test were used. A total of 677,386 students were used. Students were 48.5% female and 51.5% male. Broken down by grade, students evenly came from grades 1-5 with 19.9% in grade 1, 19.9% in grade 2, 22.1% in grade 3, 19.1% in grade 4, and 18.9% in grade 5. No students from grade K met the necessary criteria for inclusion.

School-level Characteristics

School per pupil expenditure. School-level spending for the 2009-2010 school year was gathered using Florida Department of Education's Program Cost Analysis Series Reports (http://webapps01.fldoe.org/transparencyreports/CostReportSelectionPage.aspx). Funding is reported as a school's per pupil expenditure, and is weighted according to grade level. Weighted funds are weighted to reflect higher costs of instruction and program delivery for different grade levels and were chosen over non-weighted funds in order to neither penalize nor reward schools based on the number of students in any given grade. In addition to using total expenditure per pupil by the schools, spending is broken down into the following categories: salaries, employee benefits, purchase services, materials and supplies, other expenditures, capital outlay, school indirect costs, and district level direct costs. For the efficiency analysis section of this paper, funds will be separated into the following categories:

Salaries and benefits (SB)- This includes employee salary and benefits.

Other direct costs (ODC)- This includes purchase services, materials and supplies, capital outlay, and other expenditures.

School indirect costs (SIC)- This includes only school indirect costs.

Districts indirect costs (DIC)- This includes only district level indirect costs.

School-level attendance and school size. School attendance rates and school average daily attendance are reported and recorded by the Florida Department of Education and are made publicly available through their website (http://www.fldoe.org/accountability/data-sys/edu-info-accountability-services/pk-12-public-school-data-pubs-reports/archive.stml). Average daily attendance is reported as a percentage of students that attend school per day. School size was computed for the year, by aggregating the student data available in the PMRN.

Demographic and achievement variables. School-level demographic characteristics were computed using the student-level data from 2009-2010 provided by the Florida Progress Monitoring and Reporting Network (PMRN). School values included student population breakdowns by race, free or reduced lunch status, English language proficiency, and presence of a disability. Further descriptions of these variables are provided in the Student-level characteristics section below. School-level achievement was also computed using student-level data from the PMRN, aggregated by school. Further description of this process is included in the student-level characteristics section below.

Student-level Characteristics

PMRN. In order to calculate a school's overall efficiency score, individual student achievement data was used from the 2009-2010 school year from the Florida Progress Monitoring and Reporting Network (PMRN). PMRN provides data on student demographics and achievement, as well as the school the student attended for each part of the school year. PMRN provides end-of-the-year Florida Comprehensive Assessment Test (FCAT) scores, as well as 3 testing points, or "waves," of reading performance throughout the year for progress monitoring. This study utilized this progress monitoring data, specifically the Florida Assessment for Instruction in Reading (FAIR) Reading Comprehension raw scale scores to measure student ability in reading comprehension for students in grades K-5. If a student had not completed the FAIR Reading Comprehension test, then that student was removed from analysis. In order to best assess a school's ability to educate its students and to ensure schools were neither penalized nor rewarded for prior student performance, residualized change scores were calculated using Wave 1 – measured in Autumn of the school year – and Wave 3 – measured in Spring of the school year –data on reading comprehension. One aggregated reading comprehension residualized change score was computed for each school, which was used for school-level analyses. Residualized change scores for each individual student was also calculated and used for student-level analyses.

In addition to achievement data, the PMRN reports student demographic characteristics, including student race, disability status, English language proficiency, and free or reduced lunch status. These measures were again aggregated to provide school-level demographic data as well as individual student data. Variables were recoded and dichotomized when appropriate in the following ways:

Race- Race and ethnicity were reported with the following options: Non-Hispanic White, Non-Hispanic Black, Hispanic, Asian or Pacific Islander, Native American or Alaskan Native, or Multiracial.

Free or reduced lunch status- In order to measure socioeconomic status, free and reduced lunch status was used. Free and reduced lunch status is reported with the following options: "did not apply for free or reduced lunch,, "applied for free or reduced-price lunch but is not eligible," "student is eligible for free lunch," "student is eligible for reduced price lunch," and "student is enrolled in a USDA-approved Provision Z school." This variable was dichotomized into low-SES and non-low-SES with students who did not apply for free or reduced lunch status and students who were not eligible being classified as non-low-SES, and the remaining students being classified as low-SES.

Disability- Disability is reported as status of having any exceptionality including orthopedic impairments, speech impairments, language impairments, deaf or hard of hearing, visual impairments, emotionally handicapped, specific learning disabilities, gifted, hospital/homebound, dual-sensory impairments, autistic, traumatic brain injuries, developmental delays, established conditions, other health impairments, intellectual disabilities, and a not applicable option for typically developing students. One drawback of this reporting measure in the PMRN is that only one exceptionality can be reported for each student, indicating that there may be students with multiple disabilities that are not reported. In order to best control for this, this variable was dichotomized into those students not having a disability – for those students reported as gifted and not applicable – and students having any of the other exceptionalities will be classified as having a disability.

English language proficiency- English language proficiency is reported as English language learner status. This variable is reported with the following options: LY -"Limited English Proficient and enrolled in classes designed for ELL students," LN - "Limited English Proficient and not enrolled in classes designed for ELL students," LF - "Student is being followed up after exiting ESOL program two years ago," LZ - "student has been followed up after completing ESOL program two years ago," LP - "student is proficient in some aspects but awaiting assessment in other areas," and ZZ - "Not applicable." This variable was dichotomized into ELL's and non-ELL's with LF, LZ, and ZZ classified as non-ELL's, and LY, LN, and LP as ELL's.

Analyses

School-level descriptive statistics and correlations. Descriptive statistics at the school-level were computed. Particular statistics of interest were measures of central tendency and variance for each variable, as well as measures of normality. School per-pupil expenditure, school attendance, school demographic, and school achievement data are the variables of most interest. Following the examination of descriptive statistics, correlation tables were computed for the same variables.

Data envelopment analysis: measure of school efficiency (Research Question #1). When applying data envelopment analysis as a method for determining efficiency, it is important to distinguish between the input-oriented and output-oriented approaches. Input oriented traditionally focuses on achieving the same level of outputs while reducing inputs, whereas output-oriented focuses on maximizing outputs given any set of inputs. For this paper, the output-oriented approach will be taken, and the relative efficiency of each school's ability to maximize outputs given their funding inputs will be calculated. Using this method, schools were be assigned an efficiency score ranging from 0 to 1, with 0 being completely inefficient and 1 being the most efficient. This score is a measure of each school's relative efficiency to all other schools in the dataset. This is done using DEA by observing what the level of gains in achievement each school is able to achieve with their own individual set of inputs. This relies on the assumption that if one school is able to gain a certain Y level of outputs given an X level of inputs, then another school with the same X level of inputs should likewise be able to achieve that same Y level of outputs. The extent to which the second school is not able to reach the same level of input as the higher achieving school with the same level of inputs is what is represented by the efficiency score. Utilizing all the schools in the dataset, DEA identifies the highest level of achievable outputs given any set of X inputs. This is done by a system of assigning weights to each school's inputs and outputs, resulting in what are known as virtual inputs and virtual outputs.

Virtual inputs are the result of weighting and linearly aggregating all of the inputs or outputs being examined. Virtual inputs are calculated using the following formula.

$$\textit{Virtual Input} = I = \sum_{i=1}^{I} u_i x_i$$

Where x_i is a given input, u_i is the specific weight assigned to said input, where weights are values between 0 and 1. Virtual outputs are computed using the following formula.

$$\textit{Virtual Output} = J = \sum_{j=1}^{J} v_j y_j$$

Where y_j is a given output, v_j is the weight assigned to said output, where weights are values between 0 and 1. Efficiency is now calculated as a function of the virtual inputs and virtual outputs, with the constraint that efficiencies must lie between 0 and 1.

$$Efficiency = \frac{J}{I} = \frac{\sum_{j=1}^{J} v_j y_j}{\sum_{i=1}^{I} u_i x_i}$$

At this point, specific inputs and outputs for each school are known, but the specific weights assigned to each are not. Rather than assigning one set weight for each input and output specifically, DEA is highly flexible and allows each school to have its own unique set of weights for all inputs and outputs. Allowing each school to have its own set of weights allows DEA to take each school's unique situation into account and assign weights that will maximize each school's efficiency score with the constraint that each efficiency score must lie between 0 and 1. Taking this into account, the formula for efficiency for a school is now as follows.

$$Efficiency = Maximize\ \frac{J}{I} = Maximize\ \frac{\sum_{j=1}^{J} v_j y_j}{\sum_{i=1}^{I} u_i x_i}$$

Utilizing this formula, DEA is able to calculate the specific weights that maximize each school's individual efficiency given their own set of inputs and outputs. However, without constraints this formula will result in an optimal efficiency score of 1 for every single school. Let's now recall that DEA calculates efficiency as relative to all other schools in a set. In order to arrive at a true relative efficiency score that will not result in all schools being perfectly efficient, DEA constrains the above formula so that a set of weights is only possible when those weights can be assigned to every single school in the set and result in efficiency scores between 0 and 1. This process begins by determining the best set of weights for the first school and assessing the viability of these weights for the other schools in the set. Now, if this set of weights is optimal for this school but results in an efficiency score outside of the bounds of 0 and 1 for any other school, that set of weights is no longer deemed possible and the next best set of weights is calculated until the optimal set of weights that satisfies the constraints for the other schools is found. This continues until every school arrives at the set of weights that both maximizes its own efficiency and results in realistic efficiency scores when applied to every other unit in the set. Once this point has been reached, what is known as the efficiency frontier is now built as all of the values that would result in an efficiency score of 1. In other words, this frontier represents the optimal output values for all sets of inputs and can be used to easily calculate a school's relative efficiency score.

It is important to note that this frontier does not necessarily represent the truly optimal level of achievement, but rather is a relatively optimal one determined by the highest achieving school for each funding level. Once the frontier has been established and maximal output values are benchmarked for every set of input, schools are then compared to the value that most closely resembles their own set of X inputs. The extent to which the school's output then differs from the maximal achievable output represented by the frontier is the school's efficiency score. Using this method, a score of 1 shows that the school is achieving the highest possible maximal value as represented by the efficiency frontier, and lower scores representing further distance away from the frontier. In this sense, a score of 0.50 would represent that a school is performing at a 50% efficiency level, or only achieving half the level it should given its inputs. For this analysis, salary and benefits (SB), other direct costs (ODC), school indirect costs (SIC) and district indirect costs (DIC) will serve as the inputs, and school achievement, operationalized as the school's aggregated residualized change will be the output. This school-level efficiency score will then be directly assigned as a new variable describing each student within a school.

OLS regression: predictors of school efficiency (Research Question #2). After completing data envelopment analysis and computing efficiency scores for each school, ordinary least squares regression was used to estimate the predictability of these school-level efficiency scores using school-level demographic and attendance variables. This regression analysis is of particular interest as highly significant predictability of inefficiency could indicate potential areas for early policy intervention for at-risk schools.

Student-level descriptive statistics and correlations. The analyses now shifted focus from school-level to student-level characteristic. Descriptive statistics at the student-level were computed and reported. Particular statistics of interest will be measures of central tendency and variance for each variable, as well as measures of normality. Breakdowns of demographic distributions as well as achievement scores were of particular interest. Following, correlations were presented with specific attention placed on relationships between demographic characteristics and achievement. Correlations between school-efficiency scores, demographic characteristics, and achievement at the student-level were also reported.

OLS regression: effect of inefficiency on student achievement (Research Question #3). The final analysis was conducted on the student-level and again utilized ordinary least squares regression. This time, regression was used to estimate the impact that efficiency scores have on a student's achievement. Residualized change scores were again used to measure student achievement and served as the dependent variable of interest. Two models were examined in order to measure the effect that school level efficiency has on a student's performance. First, student achievement was regressed on school level efficiency and demographic variables including free or reduced lunch status, disability status, race, and English language proficiency (model 1). Afterwards, the model was again run (model 2), this time including the following interactions: school level efficiency*free or reduced lunch status, school level efficiency*race, school level efficiency*disability, and school level efficiency*English language proficiency. Through modeling this way, significant interaction effects indicate added burden placed on traditionally at-risk students by attending an inefficiently performing school. It was hypothesized that these interactions would likely look like a widening or narrowing of the gap between at-risk students depending on the efficiency level of the school they attend. Additionally, this indicates to some extent that inefficient schools are less able to meet the needs of specific at-risk student populations than others. If inefficiency impacts all student populations equally, then models should show significant impacts for school level efficiency alone on student achievement but not for the interaction effects. Comparisons of model 1 and model 2 will be discussed in findings.

RESULTS

School-level Descriptive Statistics and Correlations

Presented below is a table representing the school-level descriptive statistics for variables related to residualized gains, school demographics, school funding, school size, and school attendance rates. There was a total of 1,446 schools in the dataset. All demographic variables appeared to be fairly normally distributed at the school-level, with the main exceptions of certain student races, and English Language proficiency which showed slight signs of abnormal skewness and kurtosis. For school funding variables, the data again appeared normally distributed with the exception of the school indirect costs and the district indirect costs which showed signs of significant positive skewness. This is to be expected as majority of schools are in urban settings, and as a result have larger populations of students for indirect costs to be spread out amongst. In contrast, a small number of rural schools will have fewer students making the indirect costs per student appear much higher and skew the overall distribution in the positive direction.

Table 1

Measures of central tendency, deviation, and normality at the school-level

	Mean/ Percentage	Median	Min.	Max.	Standard Deviation	Skewness	Kurtosis
Residualized change (1)	-1.338	0.210	-64.31	48.53	13.021	-0.599	0.659
Race							
White (2)	43.4%	46.9%	0.00%	96.98%	0.285	-0.098	-1.271
Black (3)	25.0%	15.5%	0.00%	99.34%	0.263	1.411	0.915
Hispanic (4)	24.6%	15.2%	0.00%	98.95%	0.246	1.448	1.266
Asian (5)	2.3%	1.5%	0.00%	21.04%	0.027	2.422	7.677
Native American (6)	0.3%	0.2%	0.00%	29.22%	0.009	25.349	823.157
Multiracial (7)	4.1%	3.9%	0.00%	21.88%	0.029	0.696	1.333
Lunch status (8)	34.6%	30.6%	0.00%	93.70%	0.239	0.539	-0.663
ESE (9)	83.9%	84.2%	62.02%	98.92%	0.052	-0.488	0.672
ELL (10)	88.2%	93.8%	18.24%	100.00%	0.141	-1.654	2.383

Table 1 - continued

	Mean/ Percentage	Median	Min.	Max.	Standard Deviation	Skewness	Kurtosis
Total school costs (11)	7451	7207	4,835	14,800	1288.206	1.185	2.287
Salaries and benefits (12)	4638	4528	3,056	8,863	754.97	1.044	2.122
Other direct costs (13)	427.5	390.5	101	1,469	195.915	0.992	1.596
School indirect costs (14)	2385	2286	858	7,815	650.509	1.749	7.373
District indirect costs (15)	359.9	334.0	141	1,007	136.396	1.489	3.168
School size (Number of students) (16)	644.34	636.82	37	1,799	208.7	0.543	1.551
Average daily attendance (17)	94.76	94.80	87.70%	98.50%	1.0811	-0.598	2.158

Note: For demographic characteristics, average percentage of students identified as demographic group are presented for mean statistics: Race- average percentage of students identifying as each race within schools, Lunch status- average percentage of students not on free and reduced lunch, ESE- average percentage of students without an exceptionality, ELL- average percentage of students with high English language proficiency. n=1,446.

In Table 2 (pg. 25), correlation values are presented for the same school-level variables. Nearly all correlations were statistically significant at $p<0.05$, and several interesting trends emerged. Relationships between school achievement as measured by the residualized change and demographic variables closely resembled what past research has shown, this is that higher English Language proficiency, less students on free and reduced lunch, and less students identified as having an exceptionality are all tied to higher overall achievement scores. Additionally, correlations among achievement and race mirror what past research has shown, with white, Asian, and multiracial students being the only groups positively correlated with higher achievement scores. Funding variables all appeared to be negatively correlated with higher levels of student achievement, indicating that higher levels of funding do not necessarily lead to higher achievement. Following from this logic, it can be hypothesized that simple increases in funding will not necessarily lead to increased performance. Funding variables were also negatively correlated with student’s free and reduced lunch status, showing that schools with high levels of low-income students actually appear to be spending more per student than schools with high levels of high-income students.

Data Envelopment Analysis (Research Question 1)

Figure 1 below shows a histogram of the results for the Data Envelopment Analysis. For this dataset, schools were performing on average at a 61.7% efficiency level, indicating an average underperformance of 38.3% given individual levels of funding. Efficiency scores were normally distributed with a skewness of 0.089 and a kurtosis value of 0.202. 33 schools had an efficiency score of 1 and were identified as performing at their relatively optimal level of performance. For these school, the only path to higher levels of achievement will be increased funds as these schools are those that are achieving the most possible given their funding levels. Per pupil expenditures varied widely for the top 10% most efficiently performing schools ranging between $5303.00 and $9265.00 showing that efficiency can be found at several points throughout the funding distribution.

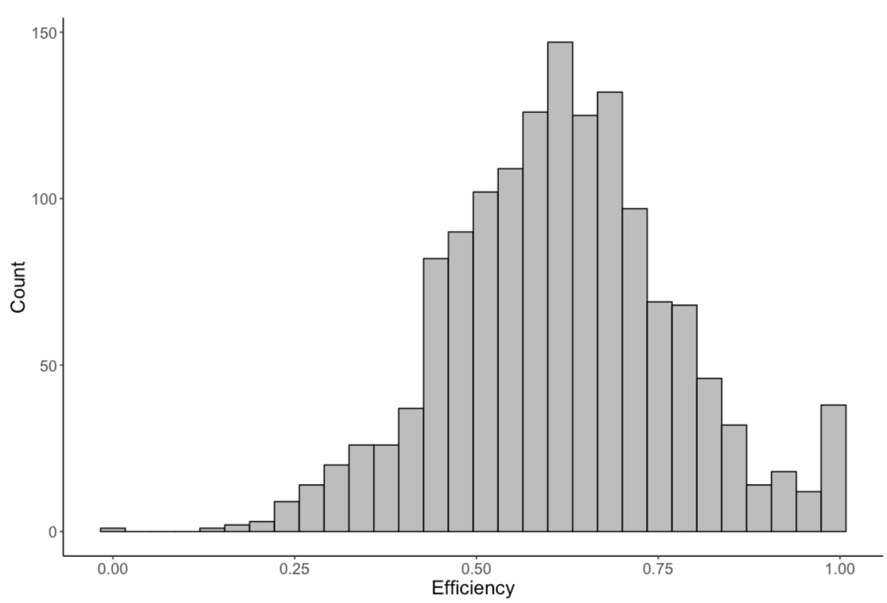

Figure 1: Distribution of school efficiency ratings.

Table 2

Correlation table for school-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Residualized change (1)																
White (2)	0.57															
	(0.000)															
Black (3)	-0.54	-0.63														
	(0.000)	(0.000)														
Hispanic (4)	-0.16	-0.55	-0.29													
	(0.000)	(0.000)	(0.000)													
Asian (5)	0.31	0.17	-0.19	-0.13												
	(0.000)	(0.000)	(0.000)	(0.000)												
Native American (6)	0.04	0.04	-0.07	-0.02	0.06											
	(0.131)	(0.093)	(0.008)	(0.369)	(0.016)											
Multiracial (7)	0.32	0.36	-0.22	-0.32	0.25	0.03										
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.201)										
Lunch status (8)	0.65	0.72	-0.54	-0.33	0.44	0.01	0.26									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.789)	(0.000)									
ESE (9)	0.03	-0.25	0.08	0.21	0.13	-0.00	-0.19	0.02								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.480)								
ELL (10)	0.26	0.60	0.09	-0.84	0.12	-0.04	0.33	0.45	-0.26							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
Total school costs (11)	-0.34	-0.42	0.42	0.09	-0.24	-0.03	-0.17	-0.51	-0.16	-0.14						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.336)	(0.000)	(0.000)	(0.000)	(0.000)						
Salaries and benefits (12)	-0.19	-0.29	0.21	0.14	-0.16	-0.06	-0.09	-0.32	-0.24	-0.14	0.86					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Other direct costs (13)	-0.25	-0.25	0.28	0.01	-0.18	0.02	-0.03	-0.48	-0.09	-0.07	0.41	0.13				
	(0.000)	(0.000)	(0.000)	(0.768)	(0.000)	(0.399)	(0.303)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
School ind. costs (14)	-0.37	-0.44	0.51	0.01	-0.24	0.01	-0.22	-0.5	-0.02	-0.10	0.86	0.51	0.37			
	(0.000)	(0.000)	(0.000)	(0.721)	(0.000)	(0.639)	(0.000)	(0.000)	(0.378)	(0.000)	(0.000)	(0.000)	(0.000)			
District ind. costs (15)	-0.03	0.14	0.03	-0.19	-0.13	-0.02	0.09	-0.11	-0.28	0.23	0.11	0.16	0.25	-0.05		
	(0.311)	(0.000)	(0.000)	(0.000)	(0.000)	(0.284)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)		
School size (16)	0.18	0.11	-0.36	0.24	0.16	0.18	0.03	0.28	0.17	-0.16	-0.53	-0.32	-0.28	-0.59	-0.17	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.50)	(0.207)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Attendance (17)	0.25	-0.01	-0.16	0.18	0.18	-0.01	-0.133	0.40	0.31	-0.12	-0.20	-0.12	-0.34	-0.17	-0.28	0.24
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.750)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values presented in parentheses.

OLS Regression: Predictors of School Efficiency (Research Question 2)

The table below shows the results for the OLS Regression model that examined the predictability of school efficiency scores based off of different demographic variables, school size, and school attendance rates. Effect sizes indicate how the percentage of any given demographic variable affects the expected efficiency score between 0 and 1. For example, a school with 50% of its students not on free and reduced lunch status is expected to have an efficiency score 0.084 less than a school with 75% of its students not on free and reduced lunch. This is found by simply multiplying the difference in their percentage of students on free and reduced lunch (-0.25) times the overall effect having students on free and reduced lunch has on efficiency (0.336), resulting in a difference of 0.084 or 8.4% lower efficiency. Results from the model show a significant relation between all variables measured and school efficiency, with the exception of number of English Language Learners and average daily attendance rates. Although all other statistics were statistically significant, the impact of some variables is much larger than others. Percentage of ESE and students on Free and Reduced Lunch proved to be the most substantively impactful variables on a school's efficiency, with the school's having the least number of students on free and reduced lunch expected to perform 33.6% more efficiently than those schools with the highest number of these students. Racial breakdown also proved to be substantively significant, though at a far lesser degree than the prior mentioned variables. Still, these results reflect the relationships we would expect, with schools with high percentages of black and Hispanic students expected to perform less efficiently than schools with larger populations of white, Asian, or multiracial students. The model overall had an R-squared value of 0.5677, indicating a large percentage of the overall variance in school efficiency to be explained by these variables. The model overall was significant at $p<0.01$, with an F-statistic of $F(11, 1{,}434)=171.2$.

Table 3

OLS Regression predicting school-level efficiency from demographic characteristics.

	School Efficiency	
Variable	B	95% CI
Intercept	2.35**	[0.629, 4.069]
ELL	-0.059	[-0.137, 0.018]
ESE	0.263***	[0.146, 0.379]
Lunch Status	0.336***	[0.289, 0.383]
White	-2.199**	[-3.795, -0.601]
Asian	-2.131*	[-3.753, -0.508]
Black	-2.353**	[-3.952, -0.753]
Hispanic	-2.30**	[-3.898, -0.703]
Multiracial	-1.779*	[-3.401, -0.158]
Native American	-2.053*	[-3.766, -0.340]
School Size (Every 100 students)	0.003*	[0.001, 0.004]
Average Daily Attendance	-0.002	[-0.001, 0.001]
R-Squared	0.568	
Adjusted R-Squared	0.564	
F	171.2**	

*Note: 95% Confidence intervals presented in brackets. *=p<0.05, **=p<0.01, ***=p<0.0001. n=1,446.*

Student-level Descriptive Statistics and Correlations

The table below shows descriptive statistics for the dataset at the student-level. A mean score, as well as standard deviation, and skewness are presented for achievement scores. For demographic variables, the percentage of students identified by each characteristic is reported. The statistics at the student level closely reflect what was seen at the school level, which is to be expected given that our school-level variables were all fairly normally distributed. The same relationships between variables and achievement are again seen at this level, with being on free and reduced lunch, being an English Language Learner, or being identified as having an exceptionality being negatively related to achievement. By race, similar relationships were again found, with only white, Asian, and multiracial students being positively correlated with higher levels of achievement.

Table 4

Descriptive statistics and correlations for student-variables.

	Mean/ Percentage	Std. Dev.	Skew	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residualized change (1)	0.29	69.67	-0.061									
White (2)	46.07%			0.098 (0.000)								
Black (3)	21.66%			-0.101 (0.000)	0.000 (0.000)							
Asian (4)	2.49%			0.033 (0.000)	0.000 (0.000)	0.000 (0.000)						
Hispanic (5)	25.04%			-0.035 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)					
Native American (6)	0.33%			0.000 (0.549)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)				
Multiracial (7)	4.27%			0.012 (0.000)	-0.195 (0.000)	-0.111 (0.000)	-0.034 (0.000)	-0.122 (0.000)	-0.012 (0.000)			
ELL (8)	11.9%			0.072 (0.000)	0.307 (0.000)	0.107 (0.000)	-0.045 (0.000)	-0.467 (0.000)	0.002 (0.149)	0.057 (0.000)		
ESE (9)	15.8%			0.115 (0.000)	-0.032 (0.000)	-0.005 (0.000)	0.033 (0.000)	0.027 (0.000)	0.000 (0.727)	0.006 (0.000)	-0.017 (0.000)	
Lunch status (10)	62.6%			0.129 (0.000)	0.381 (0.000)	-0.257 (0.000)	0.069 (0.000)	-0.224 (0.000)	-0.003 (0.017)	0.004 (0.003)	0.197 (0.000)	0.053 (0.000)

Note: For demographic characteristics, percentage of students identified as demographic group are presented for mean statistics: Race- percentage of students identifying as each race within schools, Lunch status- percentage of students not on free and reduced lunch, ESE- percentage of students without an exceptionality, ELL- percentage of students with high English language proficiency. For correlations, p-values provided in parentheses. n=677,386.

OLS Regression: Effect of Inefficiency on Student Achievement (Research Question 3)

Results of the OLS Regression models predicting student achievement based off the demographic variables presented above and each student's school-level efficiency are presented in Table 5 below. Model 1, shows the results with no interaction effects modeled, whereas Model 2, shows results with said interactions added in. In order to control for multiple comparisons and the testing of several different variables, a Bonferroni correction was used. To use the correct, the traditional significance level of $\alpha=0.05$ was transformed to take into account the 19 unique variables that were tested, resulting in a new significance threshold of $\alpha=0.0026$. This is due to the fact that by testing a large number of variables, we would expect at least one variable to be significant at $\alpha=0.05$ simply by random chance.

Table 5

OLS Regression predicting student residualized change scores from student demographic characteristics and school efficiency scores.

	Student Residualized Change			
	Model 1		Model 2	
Variable	B	95% CI	B	95% CI
Intercept	-79.137***	[-84.886, -73.387]	-96.593***	[-119.297, -73.889]
White	17.729***	[12.076, 23.383]	23.437*	[1.005, 45.868]
Black	7.565**	[1.899, 13.231]	5.449	[-17.035, 27.933]
Asian	24.509***	[18.759, 30.259]	32.375**	[9.385, 55.360]
Hispanic	17.255***	[11.588, 22.921]	16.009	[-6.492, 38.512]
Native American	15.999***	[9.584, 22.413]	20.692	[-5.954, 47.339]
Multiracial	17.007***	[11.295, 22.719]	24.488*	[1.721, 47.253]
ELL	12.355***	[11.703, 13.006]	12.623***	[9.815, 15.435]
ESE	21.744***	[21.248, 22.241]	38.120***	[35.981, 40.257]
Lunch status	8.089***	[7.676, 8.501]	12.055***	[10.109, 14.000]
Efficiency	48.406***	[47.131, 49.681]	75.278***	[40.316, 110.239]
White*Efficiency			-7.829	[-42.335, 26.677]
Black*Efficiency			5.093	[-29.515, 39.702]
Asian*Efficiency			-10.801	[-46.021, 24.420]
Hispanic*Efficiency			2.884	[-31.742, 37.510]
Native American *Efficiency			-6.630	[-47.280, 34.019]
Multiracial*Efficiency			-10.717	[-45.693, 24.259]
ELL*Efficiency			-0.691	[-5.305, 3.921]
ESE*Efficiency			-25.558***	[-28.809, -22.306]
Lunch Status*Efficiency			-5.639***	[-8.492, -2.787]
R-Squared	0.047		0.048	
Adjusted R-Squared	0.047		0.048	
F	2828***		1510***	

*Note: 95% Confidence intervals presented in brackets. *=p<0.05, **=p<0.01, ***=p<0.0001*

In Model 1, all variables are statistically significant even when considering the Bonferroni correction, however substantive significance varies. For race, although each different race is statistically significant, all races except black and Asian have nearly the same exact effect size. Indicating little difference between races in expected achievement with the exception of black students expected to achieve approximately 0.16 SD's lower than average, and Asian students expected to achieve approximately 0.11 SD's higher than average. For students with exceptionalities, on free and reduced lunch, or English Language Learners, achievement scores are significantly lower than their counterparts, with students with exceptionalities having the largest difference of 0.356 SD's lower than students with no identified exceptionality. School efficiency had the largest effect size overall, with the difference between a student at an optimally performing school versus a school with an efficiency near 0 equal to 0.80 SD's. The overall model was significant at $p<0.001$ with an F-statistic of $F(10, 573{,}858)=2{,}828$.

For Model 2, several of the variables that were statistically significant in the first model were no longer found to be significant after including interaction effects. For race, after including interactions only white, Asian, and multiracial were now statistically significant. However, after using the Bonferroni correction these variables no longer passed the significance test. Further, their effects more closely reflected what was seen in the correlations. ELL status, presence of exceptionalities, and free and reduced lunch status were again found to be significant even with the corrections, this time however with exceptionalities and lunch status having much larger effect sizes. Efficiency again was found to be statistically significant, with a much larger effect size of a 1.23 SD's difference between the highest and lowest efficiency schools. The overall model was significant at $p<0.001$ with an F-statistic of $F(19, 573{,}849)=1510$.

For the interaction effects, only 2 interactions were found to be statistically significant – efficiency interacting with free and reduced lunch status, and efficiency interacting with students with exceptionalities. These interactions are presented in figures 2 and 3 below, with the expected residualized change presented on the y-axis given a student's ESE or Free and reduced lunch status, and the level of efficiency for the school they attend on the x-axis. It should be noted that both figures have the same control values. This is because due to the way variables were measured the default or control student in the model both has an exceptionality and is on free and reduced lunch.

Figure 2: Expected residualized change for ESE and non-ESE students in schools with varying efficiencies.

Figure 3:Expected residualized change for students on and not on Free and reduced lunch in schools with varying efficiencies.

For students with exceptionalities, this shows a far greater difference between students with exceptionalities at low efficiency schools versus those at high efficiency schools. Students with exceptionalities at the lowest efficiency schools are expected to perform 0.62 SD's worse than students with no exceptionality at the same school. This is in comparison to a difference of only 0.21 SD's at the highest achieving schools, or a difference of 0.41 SD's. Similar results are found for the interaction between lunch status and efficiency, with a larger gap between students on and not on free and reduced lunch in lower efficiency schools than high efficiency schools. The difference for these groups is far smaller than that presented for students with exceptionalities, but still shows an overall difference of 0.09 SD's.

DISCUSSION

The results of this study aimed to answer three primary research questions: how efficiently are schools spending funds to promote student growth, what school-level characteristics do efficient and inefficient schools differ by, and what effect does a school's overall efficiency have on student performance, and how do these effects differ for students of different races, socio-economic status, disability status, or English language proficiency?

The first of these research questions was answered via the method of Data Envelopment Analysis. Results of this first level of analysis indicated that on average schools in the state of Florida for the 2009-2010 school year were operating at a 61% relatively optimal level of efficiency. This indicates that given current levels of spending, the average school could be expected to produce student growth approximately 40% greater than it currently is. This result, coupled with the negative correlations results found between funding and achievement, strongly indicate that simply increasing funds available will not lead to increased performance. Rather, interventions targeted on best usage of said funds in order to maximize each school's performance and get them closer to their respective achievement benchmarks would be more effective at seeing student growth gains. However, the exact process and method of intervening for these schools is still a question yet to be answered. At this point in the analysis, the major benefit is that we are now able to identify which schools are and are not performing efficiently, and are able to assign a specific individual rating to each school that was not possible before. In order to identify best routes for intervention, this first step of identifying those struggling schools is necessary. Now that both high and low efficiency schools have been identified, researchers can further examine what exactly leads to high schools performing well and low schools failing to reach their benchmarks. Both quantitative and qualitative research designs will be useful in identifying the differences between these schools. Future research should focus on differences within administration, teaching, locus of spending, and overall school policies. Results from these future studies can help lead to specific intervention strategies for those schools that are performing sub-optimally.

The second research question was answered via the first OLS regression model. This model indicated that nearly 60% of the variance in efficiency among schools in this set could be explained by only 6 demographic characteristics. Understanding that efficiency scores are highly predictable based on these characteristics is important in that it allows us to identify schools for being at-risk of low efficiency before the school year even begins. Early identification of these schools will help lead to earlier – and in turn more effective – interventions. Additionally, understanding the role that these demographic variables play in efficiency can help shape future focal points of research when going into schools to examine causes of low and high efficiency. If free and reduced lunch status and students with exceptionalities are key predictors of a school's efficiency, then examining the practices related to these students in both high and low efficiency schools will likely help to understand some of the causes for these differences in efficiency. Additionally, examining schools with high percentages of these students, but still high efficiency scores can help identify some best practices and shape specific interventions for schools that may have their efficiency limited by not being able to meet the needs of these students within their own schools. Combining the results from research questions 1 and 2, we now know not only which schools are and are not performing efficiently, but we also have a way of predicting how efficiently schools will perform in the upcoming school years and have some understanding of how demographics relate to efficiency. Additionally, some light is now being shed some on the different groups of students that may be impacted the most by this inefficiency within schools.

The final question was answered utilizing the final two regression models. Prior to this, the first two research questions looked specifically at efficiency at the school-level. This research question shifted focus to how this efficiency directly affects the individual students within these schools. The first model included only the demographic characteristics of the students and the school's efficiency. In this model, nearly all variables were statistically significant. Results from this model help to identify in general what factors put students at-risk of falling behind their peers. The second model retested the same variables, this time however including interactions between all variables and the school-level efficiency. These interactions were to test whether or not certain subpopulations of students were not having their needs met by lower efficiency schools. Two interactions were found with significant implications. These interactions found that the gaps between students on and not on free and reduced lunch and students with and without exceptionalities were significantly larger in low-efficiency schools than in high-efficiency schools. Additionally, these gaps were lowest in the high-efficiency schools where their needs were being more adequately met. In low-efficiency schools, these gaps were higher, indicating that an additional risk for these students beyond that which is present simply from having one of these qualities or being in a low efficiency school is present. This also shows that high-efficiency schools appear to be engaging in practices that mitigate risks associated with being on free and reduced lunch or having an exceptionality. This relates back to the idea of identifying school's best practices for meeting the needs of these typically at-risk students. If we can identify what policies and methods high efficiency schools are using to minimize this gap, then we can further understand what interventions will be most effective for reproducing these results in low-efficiency schools. These significant interactions at the student-level should also be used to shape research questions and designs when going into those schools identified as high or low-efficiency. This also shows that the effects of inefficiency at the school-level extend beyond the school as a whole, and have differential impacts on the individual students. Further, this seems to indicate that failing to meet these individual student needs is one potential cause for inefficiency. If interventions could help to minimize the gap in between these subpopulations of students in low-efficiency schools in the same way as is being done in high-efficiency schools, then overall school performance would increase leading to not only better student outcomes, but also higher overall efficiency scores for these schools.

All of this information together helps to show the state of school efficiency in the state of Florida during the 2009-2010 school year. It not only helps to see the current level at which these schools are operating, but helps to identify which schools may be in need of the most intervention. The final research question additionally shows specific student populations that these at-risk schools could focus on in order to boost their efficiency. Limitations in reporting for specific types of exceptionalities or more in-depth measures of student socioeconomic status limit the potential for truly measuring the impact of efficiency on the student-level, however this study is a step in the right direction and just show significant trends among these broader populations. Future research should seek to further break down these student populations by specific exceptionality or other measures of socioeconomic status beyond free and reduced lunch status in order to best understand the way that efficiency is affecting each subtype. Additionally, both qualitative and quantitative research within high and low efficiency schools, administration, and staff could help to better understand what exactly is leading to disparities in efficiency and in turn identify the best possible interventions.

APPENDIX A

IRB APPROVAL MEMORANDUM

Office of the Vice President for Research
Human Subjects Committee
Tallahassee, Florida 32306-2742
(850) 644-8673 · FAX (850) 644-4392

APPROVAL MEMORANDUM

Date: 04/17/2019
To: Jeffrey Shero
Address:
Dept.: Psychology Department

From: Thomas L. Jacobson, Chair

Re: Use of Human Subjects in Research
The intersection between school efficiency and student individual differences

The application that you submitted to this office in regard to the use of human subjects in the proposal referenced above have been reviewed by the Secretary, the Chair, and two members of the Human Subjects Committee. Your project is determined to be Expedited per 45 CFR § 46.110(7) and has been approved by an expedited review process.

The Human Subjects Committee has not evaluated your proposal for scientific merit, except to weigh the risk to the human participants and the aspects of the proposal related to potential risk and benefit. This approval does not replace any departmental or other approvals, which may be required.

If you submitted a proposed consent form with your application, the approved stamped consent form is attached to this approval notice. Only the stamped version of the consent form may be used in recruiting research subjects.

If the project has not been completed by No Expirat you must request a renewal of approval for continuation of the project. As a courtesy, a renewal notice will be sent to you prior to your expiration date; however, it is your responsibility as the Principal Investigator to timely request renewal of your approval from the Committee.

You are advised that any change in protocol for this project must be reviewed and approved by the Committee prior to implementation of the proposed change in the protocol. A protocol change/amendment form is required to be submitted for approval by the Committee. In addition, federal regulations require that the Principal Investigator promptly report, in writing any unanticipated problems or adverse events involving risks to research subjects or others.

By copy of this memorandum, the chairman of your department and/or your major professor is reminded that he/she is responsible for being informed concerning research projects involving human subjects in the department, and should review protocols as often as needed to insure that the project is being conducted in compliance with our institution and with DHHS regulations.

This institution has an Assurance on file with the Office for Human Research Protection. The Assurance Number is IRB00000446.

Cc: Sara Hart , Advisor
HSC No. 2019.27121

REFERENCES

Arroyo, C. (2008). The funding gap. *Washington, DC: Educational Trust Fund.*

Bessent, A. M., & Wailand Bessent, E. (1980). Determining the comparative efficiency of schools through data envelopment analysis. *Educational Administration Quarterly*, *16*(2), 57–75. https://doi.org/10.1177/0013161X8001600207

Bohrnstedt, G., Kitmitto, S., Ogut, B., Sherman, D., and Chan, D. (2015). School composition and the black–white achievement gap (NCES 2015-018). U.S. Department of Education, Washington, DC: National Center for Education Statistics.

Borman, G. D., Hewes, G. M., Overman, L. T., & Brown, S. (2003). Comprehensive school reform and achievement: A Meta-Analysis. *Review of Educational Research*, *73*(2), 125–230. https://doi.org/10.3102/00346543073002125

Charnes A., Cooper W. W.,, & Rhodes, E. (1978). Measuring efficiency of decision making units. *Euro J Oper Res, (2)429–444.*

Clark, M. D. (1997). Teacher response to learning disability: A test of attributional principles. *Journal of Learning Disabilities, 30(1), 69–79.* https://doi.org/10.1177/002221949703000106

Coleman, J. S., Campbell, E., Hobson, C., McPartland, J.,. Mood, A., Weinfeld, F. & York, R. (1966). Equality of Educational Opportunity, Washington, DC: Government Printing Office.

Denaux, Z. (2007). Determinants of technical efficiency: Urban and rural public schools in the state of Georgia. *Southwestern Economic Review, 36(1)*, 105-115.

ESSA (2015). Every Student Succeeds Act of 2015, Pub. L. No. 114-95 § 114 Stat. 1177 (2015-2016).

Griffith, M. (2015). A look at funding for students with disabilities. *The Progress of Education Reform, 16(1).*

Guthrie, J. W. (1983). United states school finance policy, 1955–1980. *Educational Evaluation and Policy Analysis, 5(2), 207–230.* https://doi.org/10.3102/01623737005002207

Hanushek, E. A. (1989). Expenditures, efficiency, and equity in education: The federal government's role. *The American Economic Review, 79(2), 46-51.*

Hanushek, E. A. (1997). Assessing the effects of school resources on student performance: An update. *Educational Evaluation and Policy Analysis*, *19*(2), 141–164. https://doi.org/10.3102/01623737019002141

Hedges, L. V., Laine, R. D., & Greenwald, R. (1994). An exchange: Part I: Does money matter? A meta-analysis of studies of the effects of differential school inputs on student outcomes. *Educational Researcher*, *23*(3), 5–14. https://doi.org/10.3102/0013189X023003005

Jencks, C. (1972) Inequality: A reassessment of the effect of family and schooling in america. New York: Basic Books.

Lacour, M. and Tissington, L. (2011). The effects of poverty on academic achievement. *Educational Research and Reviews,* 6 (7), 522-527.

Ladd, H. F., & Fiske, E. B. (2011). Weighted student funding in the netherlands: A model for the u.s.?. *Journal of Policy Analysis and Management, 30,* 3, 470-498.

Ladd, H.F., Fiske, E.B., Ruijs, N. (2011). Does parental choice foster segregated schools: Insights from the Netherlands. In Berends, M., Cannata, M., Goldring, E.B. (Eds.), School choice and school improvement. Cambridge, MA: Harvard Education Press, 233–254.

Lee, V.E. & Burkham, D.T. (2002). Inequality at the starting gate. Washington, DC: Economic Policy Institute.

Millard, M. (2017). State funding mechanisms for english language learners. *Eric, ED556739.*

National Center for Education Statistics. (2005). The Nation's Report Card Mathematics 2005, NCES 2006-453, August, Washington, D.C.: NCES.

National Education Association. (2018). Understanding the gaps: Who are we leaving behind -- and how far? *Backgrounder.* Retrieved from https://www.nea.org/assets/docs/18021-Closing_Achve_Gap_backgrndr_7-FINAL.pdf

Necochea, J. & Cline, Z. (1996). A case study analysis of within district school funding inequities. *Equity and Excellence in Education, 29(2), 69-77.* doi:10.1080/1066568960290208

Noulas, A. & Ketkar, K. (1998). Efficient utilization of resources in public schools: a case study of new jersey. *Applied Economics, 30, 1299-1306.*

Payne, K. J., & Biddle, B. J. (1999). Poor school funding, child poverty, and mathematics achievement. *Educational Researcher*, *28(6), 4-13*. https://doi.org/10.3102/0013189X028006004

Reardon, S.F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. In R. Murnane & G. Duncan (Eds.), Whither Opportunity? Rising Inequality and the Uncertain Life Chances of Low-Income Children. New York: Russell Sage Foundation Press.

Ruggiero, J. & Vitaliano, D. (1999). Assessing the efficiency of public schools using data envelopment analysis and frontier regression. *Contemporary Economic Policy,* 17(3), 321-31. *https://doi.org/10.1111/j.1465-7287.1999.tb00685.x*

Schroeder, J. (2004). Ripples of innovation: Charter schooling in minnesota, the nation's first charter school state. *Washington D.C., Progressive Policy Inst.*

Sebold, F. D., & Dato, W. (1981). School funding and student achievement: An empirical analysis. *Public Finance Quarterly*, *9*(1), 91–105. https://doi.org/10.1177/109114218100900108

Thomas, H., & Bullock, A. (1992). School size and local management funding formulae. *Educational Management & Administration,* 20(1), 30–38. https://doi.org/10.1177/174114329202000103

Tsakiridou, H., and K. Stergiou. (2014). Explaining the efficiency differences in primary school education using data envelopment analysis. *Journal of Education, Psychology and Social Sciences* 2, 89–96.

Tyagi, P., Yadav, S., & Singh, S. (2009). Efficiency analysis of schools using dea: A case study of uttar pradesh state in india. Department of Mathematics, IIT.

Urban Institute. (2017). School funding: Do poor kids get their fair share? Retrieved from http://apps.urban.org/features/school-funding-do-poor-kids-get-fair-share/

Willie, C. V. (2016). The contextual effects of socioeconomic status on student achievement test scores by race. *Urban Education, 36(*4), 461-478.

BIOGRAPHICAL SKETCH

At the time of the completion of this document, Jeffrey Shero is a 2nd year doctoral student in the Developmental Psychology program at Florida State University. Prior to attending Florida State University, Jeffrey completed his Bachelor of Science in Human Development and Family Sciences (2016), and his Master of Public Administration (2018) with a focus on educational policy from The Ohio State University. Jeffrey's research focuses on how contextual and environmental factors such as socioeconomic status, student exceptionalities, or race affect individuals' development. He is also interested in how public policies could better reflect our current understandings of the ways in which these contextual factors impact student growth and development, specifically within school settings. Finally, Jeffrey has a strong interest in advanced methodologies and bringing innovative methodologies to the Psychological and Educational fields to help further advance the research taking place in each field.