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How Large are District Effects on Student Attendance? Implications for School Funding Based on Average Daily Attendance

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Greater attendance rates in the K-12 grades demonstrate motivation and discipline and contribute to other desired educational outcomes such as cognitive development. A growing number of states incentivize school districts to increase attendance by allocating funding based on the average number of students in attendance, or average daily attendance (ADA). Using statewide data from Texas, we assess the proportion of variation in student attendance not explained by student characteristics. We then estimate district effects on attendance and compare them to school, teacher, and student effects. We find that observed and unobserved student characteristics explain the vast majority of variation in student attendance and that districts have only minor effects on attendance. These results imply that school funding systems based on ADA may unfairly penalize high-poverty school districts.

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Abstract

Greater attendance rates in the K-12 grades demonstrate motivation and discipline and contribute to other desired educational outcomes such as cognitive development. A growing number of states incentivize school districts to increase attendance by allocating funding based on the average number of students in attendance, or average daily attendance (ADA). Using statewide data from Texas, we assess the proportion of variation in student attendance not explained by student characteristics. We then estimate district effects on attendance and compare them to school, teacher, and student effects. We find that observed and unobserved student characteristics explain the vast majority of variation in student attendance and that districts have only minor effects on attendance. These results imply that school funding systems based on ADA may unfairly penalize high-poverty or otherwise low-attendance school districts.

Keywords: attendance, HLM, teacher effects, school effects, district effects

Improving student attendance remains a critical objective in K-12 education because attendance is linked to the development of character skills such as motivation and self-discipline (Gershenson, 2016; Heckman et al., 2006; Liu et al., 2021). These skills, often referred to as non-cognitive, sociobehavioral, or soft skills, are highly demanded in today's labor market (Kraft & Grace, 2016; Weinberger, 2014). Greater attendance is also linked to improved cognitive development (Gershenson et al., 2015), lower rates of grade retention and drug use (Hallfors et al. 2002; Nield & Balfanz 2006), and greater school readiness and long term educational attainment (Rumberger & Thomas, 2000; Ehrlich et al., 2018).

A number of potential policy levers exist for improving student attendance, such as setting minimum attendance rates as course requirements, implementing physical and mental health interventions, expanding meal programs, improving personnel hiring and retention, and including attendance in state accountability plans (Bartanen, 2020; Borman et al., 2019; Cohen et al., 2021; Eklund et al., 2022; Epstein & Sheldon, 2002; Holt & Gershenson, 2019; Jacob, 2017; Liu & Loeb, 2021; Magzamen et al., 2008). One approach that states have used to promote higher attendance is to tie school district funding to student attendance rates. While most states distribute funding to school districts based on the number of students enrolled, a growing number of states allocate funding based on the average number of students in attendance, or average daily attendance (ADA), as a way to incentivize school districts to improve and maintain student attendance (Baker & Corcoran, 2012; Ely & Fermanich, 2012).

Policy reforms targeted at the district level presume that variation in district practice influences student attendance. Yet little research exists on the impacts of school districts on student outcomes generally, and student attendance in particular. One recent analysis of district effects on student achievement found that districts have small but policy-relevant impacts on standardized test scores (Chingos, Whitehurst, and Gallagher, 2015). Less is known about district-level impacts on student attendance. Despite the use of ADA-based funding in seven states that represent 35 percent of all students nationally (Baker, 2014), no prior research examines the extent to which districts have influence over student attendance.

The purpose of this study is to estimate the extent to which school districts vary in their effects on student attendance.[1] We draw on student-level longitudinal attendance data from Texas, which provide a unique opportunity to measure the effects of teachers, schools, and districts on student attendance rates. Data on statewide standardized test scores allow us to compare teacher, school, and district effects on attendance to that of student achievement, which are more established in the literature. Although past research has evaluated specific school or district interventions aimed at improving student attendance, and other studies have estimated variation in the impact of teachers on student attendance (Gershenson, 2016), this study is the first to quantify the variation in attendance explained at the district level and provides the first evidence of the size of district effects on student attendance. Our two overarching research questions are: (a) w*hat proportion of variation in student attendance is explained at the district level?* And (b) *to what extent are there statistically significant associations between individual districts' efforts to improve student attendance and actual observed district-level attendance rates, after controlling for student background characteristics?* The second question asks, in short, how large are district effects on student attendance and are those effects statistically significant?

[1] Our models estimate variation in student attendance not explained by student background characteristics. These models are not causal; however, to avoid awkward phrasing, we often use causal language, for example, referring to "district effects" on student attendance.

We answer the first question using hierarchical linear modeling (HLM). We find that districts account for very little – between 0.98 and 1.05 percent – of the total variation in student attendance, after controlling for student background characteristics. We find that districts account for a slightly greater proportion of the variation in student achievement (about 1.30 percent), depending on the grade level and subject area. We answer the second question using value-added models with district fixed effects. We find minimal evidence of statistically significant associations between individual districts and attendance rates in Texas, after controlling for student background characteristics. Our results show that a one standard deviation (SD) increase in district effectiveness, as measured by value-added to student attendance, increases student attendance rates by between 0.09 and 0.13 standard deviations (SD), or between 0.64 and 0.88 days, depending on the grade level.[2] District effects on math and English language arts (ELA) achievement are larger than effects on attendance, whereas schools and teachers have larger effects on both achievement and attendance than school districts. District effects on attendance are stable over time and moderately correlated with district effects on achievement.

These findings suggest that holding districts accountable for attendance through school finance formulae – without including adjustments for student background – may not be an equitable mechanism for increasing student attendance. In particular, the data show that districts in Texas serving greater proportions of low-income students, students of color, and lower-performing students have lower attendance rates. In other words, use of ADA in the Texas

[2] These estimates are based on models that predict the percent of days a student is present out of the number of instructional days in her or his district. We convert the attendance rate back to the number of days present (for purposes of interpretability) by multiplying the percent of days a student is present by 180, the approximate number of instructional days in a school year. However, the number of instructional days in each district varies because Texas defines a school year as 75,600 instruction minutes, with one day defined as at least 420 minutes.

school finance system disproportionately reduces funding for high-need districts. Even if districts identified practices to improve attendance, such improvements are not likely to close attendance gaps. Moving from the 50th percentile of district effectiveness (measured by value-added to student attendance) to the 90th percentile would increase a district's overall attendance rate by 0.32 percentage points, or about 0.58 days. Policy simulations suggest that the highest-poverty districts would receive an additional 7.2 percent state and local funding (compared to 4.9 percent for low-poverty districts) if Texas based funding on enrollment rather than attendance.

Five states currently use ADA throughout the school year and two other states use ADA calculated over a specific period of the school year (see Appendix Table A1). The current study suggests that states should consider whether their enrollment count mechanism unfairly penalizes high-poverty districts. In the following section, we discuss prior studies that estimate district effects on student outcomes and outline a theory of action for how districts may influence student attendance. The subsequent sections describe, in turn, the study's data and methods, findings, implications, and conclusions.

Background Literature

We review past literature from two broad areas that address our research questions. The first subsection below draws on literature exploring school and non-school factors that influence student attendance. Research on school-related factor affecting student attendance provides the basis for a theory of action that describes how districts (as well as schools and teachers) may differ in their effects on student attendance. We then synthesize research on district effects on other student outcomes.[3]

[3] As noted above, we use causal language to avoid awkward phrasing about how districts might influence student attendance; however, we take extra care to clarify that our models show relationships that are not necessarily causal.

Factors Influencing Student Attendance

Despite the ubiquitous reliance on test scores as an outcome measure in educational research, there is broad consensus that non-cognitive outcomes, such as attendance, are important and more deserving of attention (e.g., Heckman et al., 2006). Factors influencing student attendance are not necessarily the same as those influencing achievement. We divide factors that affect student attendance into school-related and non-school related.

School factors influencing student attendance. Individual teachers, schools, and districts all play a role in determining student attendance rates. Several studies estimate teacher effects on non-tested subjects including student attendance (Backes & Hansen, 2015; Blazar & Kraft, 2017; Liu & Loeb, 2021; Redding, 2019). A recent study shows that teachers have relatively large effects on attendance that persist over time and increase with additional years of experience (Gershenson, 2016). That study finds that teacher effects on attendance are approximately as large as teacher effects on achievement. A one standard deviation increase in attendance-based teacher effects is associated with an increase in attendance of between 0.33 and 0.48 standard deviations, depending on the model and data source.[4] However, the two measures were weakly correlated within individual teachers, suggesting that teachers who are effective at raising achievement may not be the same as those who are effective at increasing student attendance. Beyond teachers, studies show school counselors and principals play active roles in promoting student attendance (Bartanen, 2020; Pincus et al., 2020).

Other studies identify the effects of school-, district-, or community-level interventions on student attendance (Borman et al., 2019; Hamlin, 2021; Reid, 2008; Schwartz et al., 2021). Programs implemented at these higher levels of the education system (beyond individuals) have

[4] Gershenson (2016) also reports smaller teacher effects on attendance (0.07 standard deviations) when estimates are adjusted using methods described in Kane & Staiger (2008).

been successful at promoting attendance. Studies find positive effects on attendance associated with initiatives that provide free meals (Cohen et al., 2021), promote better health and exercise (Davison et al., 2008; Magzamen et al., 2008; Slater et al., 2013), provide child care and work-release programs (Epstein & Sheldon, 2002; Prevatt & Kelly, 2003; Sheldon, 2007), and coordinate community messaging about the importance of school attendance (Wiseman & Dawson, 2015; Robinson et al., 2018; Rogers & Feller, 2018). In contrast, several studies find null or negative effects associated with student rewards for perfect attendance (Robinson et al., 2018).

A plausible theory of action for how districts may vary in their impact on student attendance is as follows. Districts may conduct a self-study of how to improve student outcomes and some may focus specifically on improving attendance (e.g., Beutner et al., 2017; Smith, 2018; Vance, 2016). Those districts would then identify specific interventions that may help increase student attendance. In 2011, for example, the Los Angeles Unified School District implemented the Attendance Improvement Plan, which aimed to improve attendance among kindergarten students through a set of evidence-based interventions (Godinez & Garoupa, 2017). A central motivating factor for implementing this strategy was to address projected budget deficits (Anguiano et al., 2015). Beginning the 2017-18 school year, Fort Worth Independent School District in Texas launched a districtwide program offering students incentives for reducing absenteeism in part to generate more state funding (Smith, 2018). While evaluations of these types of programs exist, prior studies do not explore the extent to which school districts differentially affect student attendance rates in general. The theory of action described here suggests that some districts may identify effective interventions to improve attendance, and therefore, school districts in general may vary in their impact on student attendance.

Similarly, schools and teachers may differ in their effects on attendance. In some cases, interventions that promote student attendance are implemented at the school, rather than district level (e.g., Sheldon, 2017). More broadly, particular principals may be more effective at promoting student attendance (Bartanen, 2020; Grissom & Loeb, 2011), and this trend would likely manifest as differences in "school effects" on attendance (Branch et al., 2009). Finally, Gershenson (2016) argues that individual teachers may be more or less effective at increasing attendance. Under this theory of action, certain teachers may use pedagogical practices that increase attendance among students in their classrooms. These behaviors would expand differences in teacher effects on student attendance. In many cases, district effects are mediated through schools or classrooms (Hallinger & Heck, 2011). For example, districts might affect student attendance through superior recruitment of teachers and principals, or by encouraging teachers or principals to adopt particular behaviors that support student attendance.[5]

Non-school factors influencing student attendance. Although prior research establishes a reasonable theory of action for how school-related factors may be related to attendance rates, extant literature suggests that out-of-school factors are the primary determinants of student attendance (e.g., Baker, 2014; Balfanz & Byrnes, 2012; Bonilla et al., 2005). Non-school factors that affect student attendance include high rates of air pollution that contribute to asthma and other illnesses (Magzamen et al., 2008); family emergencies or home and work obligations (Sheldon, 2007); and neighborhood and student poverty. Poverty might influence attendance through a number of interrelated factors that are outside the control of schools, including the factors mentioned above (Ladd, 2012). A recent study of absenteeism in Texas echo these findings, highlighting acute and chronic illnesses and family emergencies as the most common

[5] In our empirical work, these district-level efforts manifest as district effects to the extent that teachers or principals in a given district have larger effects on attendance, on average, compared to other districts.

non-school factors cited for student absences (Wiseman & Dawson, 2015). The extant research suggests that student background characteristics included in most administrative datasets, such as family income and race/ethnicity, are not likely to fully account for student-level variation in attendance. Even when models control for prior year attendance, much of the student-level variation in attendance may be unexplained if illnesses or family emergencies are not highly correlated with previous attendance records.

Districts Effects on Student Outcomes

Few studies examine variation in the impact of school districts on student outcomes. Most studies focus on the practices of one or a small number of high-performing school districts, rather than studying districts that span the broad distribution of effectiveness (see Bowers, 2010 and Trujillo, 2013 for reviews of this work). For example, Waters and Marzano (2006) summarize quantitative studies of district effectiveness and argue that school district leadership is an important predictor of student outcomes. However, most of the studies included in their meta-analysis involve simple correlations between various district-level student outcome measures and the survey responses of school district leaders. These studies do not include measures of individual students' prior achievement or commonly included student demographic characteristics. As a result, estimates of district characteristics associated with effectiveness are likely biased. That is, districts that enroll higher-achieving students may be more likely to adopt particular leadership practices, and this sorting of students across districts may bias estimates of district effectiveness. Moreover, these prior studies do not consider how much variation in student outcomes exists at the district level, after accounting for student background characteristics. For example, prior research suggests that most of the variation in student achievement is *within* schools rather than *between* schools or districts (Konstantopoulos, 2005;

Raudenbush, 2005). In other words, there may be little variation in student achievement across districts after accounting for prior achievement and student background characteristics.

One notable exception that addresses the common limitations of the district effectiveness literature is Chingos et al. (2015). The authors draw on statewide student-level data from Florida and North Carolina to estimate variation in district effects on student achievement. Consistent with a long-standing literature (Coleman et al., 1966; Ladd, 2012; Rivkin et al., 2005), they find that student background characteristics explain the vast majority of differences in student achievement. Among school-related factors, teachers accounted for approximately one to four percent of variation in student achievement, schools explained zero to one percent, and school districts accounted for less than one percent of differences in student achievement in models that included prior year achievement. Results were fairly consistent across the two states examined and between math and reading scores. The authors note that despite accounting for less than one percent of differences in achievement, school districts may still have significant influence over student achievement. Indeed, their results suggest that a one-standard deviation increase in district effectiveness in Florida and North Carolina is associated with a 0.10 and 0.14 standard deviation increase in math standardized test scores, respectively (Chingos et al., 2015). In other words, school districts have a small but educationally significant impact on student achievement. The study provides insight into the extent to which differences in school district practices – separate from individual teachers or schools – may impact student outcomes.

In the section below, we provide additional background on student count mechanisms for funding purposes used across states and then describe how ADA is used in Texas, the setting of our study.

Policy Context

Student Count Mechanisms

The majority of states allocate funding to school districts based on fall enrollment levels (Baker, 2014). This approach makes sense conceptually because districts make staffing decisions for the school year annually, based on fall enrollment levels. As noted in Baker (2014), schools are required to have resources for all enrolled students because all students will attend for some portion of the school year. Schools therefore require funding that covers all students, rather than the average number in attendance on a given day. Setting funding levels based on ADA may also introduce perverse incentives to school districts. For example, under ADA-based funding, districts may be more likely to cancel school in the case of inclement weather if poor weather is associated with low attendance (Baker, 2014).

At the same time, ADA-based funding may be an effective means for improving attendance. In states that use attendance-based funding, districts are well aware that increases in student attendance lead to increases in funding (Anguiano et al., 2015). As noted earlier, districts with particularly low attendance rates may be more likely to adopt policies aimed at improving attendance if such improvements will lead to greater funding. New Jersey Education Commissioner proposed a transition to ADA-based funding, arguing that this change would encourage “districts to do everything in their power to get kids to attend class” (Method, 2012). State legislative office reports and research or advocacy groups encourage states to transition to ADA funding on the basis that this approach may incentivize districts to increase attendance. A Washington State Senate staffing report states “The rationale for exploring an ADA-based student count is to provide districts with a financial incentive to maintain students’ enrollment after the September count has been completed” (Roe & Greef, 2011, p. 1). A report to the

Nevada Department of Education recommends that the state "create incentives to promote student attendance" including "counting students on the basis of average daily attendance" (Chambers et al., 2012, p. 111). Finally, an Oregon-based advocacy group argues that "a transition to an alternative student count, Average Daily Attendance (ADA), would explicitly encourage schools to emphasize attendance where the current fiscal system does not" (Grubbs et al., 2011, p. 1).

Seven states currently use ADA to determine funding levels and these states – California, Idaho, Illinois, Kentucky, Mississippi, Missouri, and Texas – represent one third of all students nationally (see Appendix Table A1). Some researchers argue that the use of ADA to determine funding levels disproportionately penalizes high-poverty and high-need districts (Baker, 2014; Baker & Corcoran, 2012). Most obviously, districts serving a greater proportion of students in poverty have lower attendance in part because of factors outside the control of school districts (e.g., higher rates of illness related to poverty, lack of transportation, or familial responsibilities). Second, because ADA measures typically employ weighting formulae, absenteeism in high-poverty districts reduces funding by more per student because each student generates more funding than in districts that serve more advantaged student populations. For example, in Texas, district funding levels are calculated based on weighted average daily attendance (WADA), where students in special enrollment classifications (low-income, special education, etc.) are weighted more heavily than students without these classifications. Lower rates of attendance for districts serving more heavily weighted students reduces funding by a greater amount per absence than in districts serving students without these classifications. Finally, in most states, including Texas, centrally distributed state funding increases only up to a basic foundation level.[6]

[6] The Texas school finance system includes a basic foundation program and a guaranteed tax base. Districts are free to raise taxes beyond the basic foundation level to increase total revenues and the state matches local tax revenues

Due to a lower property tax base, high-poverty districts typically receive a greater proportion of their funding from the state. The use of ADA to allocate state aid may further disadvantage high-need districts.

Attendance Rates Across Districts in Texas

Table 1 displays attendance rates for districts and students in Texas, a state that uses ADA to distribute funding to school districts. The top panel of Table 1 shows summary statistics for student attendance and student subgroups, for school year 2015-16. The first row shows the average number of days attended, standard deviation, and the average attendance rate, across grades. Average attendance rates for each student are calculated based on the number of days attended, divided by the number of instructional days at that student's school, usually around 180 days. Students in grade four attend 96.8 percent of instructional days on average, corresponding to approximately 5.76 days absent (excused or unexcused), for a 180-day school year. Students in upper elementary and middle school grades have slightly lower attendance rates, but there is also more variation (larger standard deviations) in the upper grades. The standard deviation for grade four is 5.9 days compared to 9.6 days among grade eight students.

Differences in attendance across student race/ethnicity are small; Black and Hispanic students have slightly higher attendance in elementary grades and slightly lower attendance in middle grades. Low-income (FRL) students have slightly lower attendance than non-FRL students and that gap increases in upper grades. However, as shown in Panel B of Table 2, districts have a wide range of average attendance rates. Districts in the highest quintile of attendance have average attendance rates of 96.9 percent, whereas the average attendance rate for districts in the lowest quintile is 94.7 percent. In other words, the absentee rate in low-

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for lower-wealth districts up to a statutory level. However, all funding amounts are based on each district's ADA, not fall enrollment levels.

attendance districts (5.3 percent) is 71 percent greater than in high-attendance districts, where the absentee rate is 3.1 percent. Districts with the lowest attendance rates are also lower achieving and serve a larger proportion of Black, Hispanic, and low-income students. The modeling strategies that we describe in the next section are intended to shed light on the extent to which lower attendance in some districts can be attributed to differences in district practices or to differences in student background characteristics.

Data and Analytic Approach

Data

We draw on student-level longitudinal data that include information on all students in Texas from 2012-13 to 2015-16. We use this older dataset due to data availability. Linked datasets from the Texas Education Agency Public Education Information Management System are provided through the Education Research Center at the University of Texas at Austin. Student data include demographic information (race/ethnicity, gender, English language status, special education identification, and eligibility for free/reduced price lunch) linked to standardized assessment and attendance records.

Beginning in the 2011-12 school year, all students in grades three through eight take the math and ELA portions of the State of Texas Assessment of Academic Readiness (STAAR) standardized exams. We link test score data with student attendance records, which include the number of instructional days each individual student was recorded as present and the number of instructional days per year in each student's school. Unique class identifiers allow us to link teachers to individual students for school years 2011-12 to 2015-16. We merge these student- and teacher-level data with district-level finance information from the National Center of Education Statistics (F-33 survey), the U.S. Census Bureau Small Area Income and Poverty

Estimates, and the Education Comparable Wage Index dataset (Taylor & Fowler, 2006).

Our analytic sample focuses on four school years, from 2012-13 through 2015-16 because current and prior year STAAR results are available in all four of those years. Because we are interested in comparisons between attendance and achievement effects at the district, school, and teacher levels, we further limit the sample to grades four through eight.[7] In grades nine to eleven, standardized assessments are distributed at the end of designated courses rather than by grade level, and the vertical scaling of these exams introduces additional considerations beyond the scope of our analyses. For the same reasons, we omit the 2011-12 school year because all lagged test score data would be based on the Texas Assessment of Knowledge and Skills (TAKS), which was administered from 2002-03 to 2010-11. The final analytic sample includes 7,816,154 student-year records for school years 2012-13 through 2015-16, grades four through eight, and 90,212 teacher-year records. For 2015-16, the most recent year of data, the analytic sample includes 1,966,391 unique student observations for grades four through eight (an average of 393,287 per grade statewide) and 51,335 unique teacher observations across 6,471 schools and 1,181 school districts.[8]

Methods

Our two research questions are what proportion of variation in student attendance is explained at the district level? And how large are district effects on student attendance? We use

[7] Although standardized test scores are available for students in grade three, we control for lagged achievement which limits the sample to students in grades four through eight.

[8] These numbers reflect the "math achievement sample," which includes all students in grades 4-8 with complete records for current and prior year math test scores and attendance rate, prior year ELA scores, demographic information, and teacher, school, and district assignment. This sample restriction allows us to estimate models predicting math achievement and attendance rates using the same sample. We create a separate sample to predict ELA achievement, and estimate separate models that predict attendance that are based on the "ELA achievement sample." Thus, when we report district, school, and teacher effects on ELA achievement, we also report effects on attendance based on the ELA achievement sample. The samples include many of the same students: 98 percent of students in the math achievement sample are in the ELA achievement sample, and 97 percent of students in the ELA achievement sample are in the math achievement sample.

hierarchical linear models (HLM) to address the first question and value-added models with fixed effects to address the second question.

Methods for research question 1. For the first research question, we conduct a variance decomposition analysis of student attendance using HLM. For comparison, we conduct the same analysis for math and ELA achievement. These models take into account the nesting of students within teachers, schools, and districts. We estimate three models: a reduced form model with no controls, a model with student demographic controls and peer effects at the classroom, school, and district level, and a fully articulated model that adds prior-year test scores and attendance. Following the methods described in Chingos et al. (2015), we include student-level indicators for race/ethnicity, eligibility for free or reduced-price lunch (FRL), English language learner status (ELL), gender, special education status, and talented and gifted status. In the fully articulated model, we include prior achievement in math and reading and prior year attendance. Achievement values are standardized within year, grade level, and test form. To measure attendance rates, we use the percent of instructional school days the student was present, standardized within year and grade level, so that variation in attendance and achievement are comparable (a similar strategy used in Gershensen, 2014). In specification checks, we use the log of the number of days attended, the log of the percent of days absent, and a dichotomous indicator of whether the student misses more than 18 days of class (i.e., a “chronically absent” student, corresponding to roughly 10 percent of the school year). Classroom-level student demographics include race/ethnicity, FRL, and ELL status. At the school level, we control for FRL, ELL, and student race/ethnicity. Finally, district level controls include FRL and student race/ethnicity. All control variables are mean-centered at their respective levels (e.g., the percent of FRL students in the classroom is mean-centered at the classroom level).

Following the notation suggested in Raudenbush et al. (2011), we estimate the following four-level HLM, predicting attendance (A_{ijkl}), indexing for students (i), classrooms (j), schools (k), and districts (l):

Level 1 (students): $A_{ijkl} = \pi_{0jkl} + \Sigma_{p=1}^{P} \pi_{pjkl}\alpha_{pijkl} + e_{ijkl}$ (1)

Level 2 (classrooms): $\pi_{pjkl} = \beta_{p0kl} + \Sigma_{q=1}^{Q_p} \beta_{pqkl}X_{qjkl} + r_{pjkl}$ (2)

Level 3 (schools): $\beta_{pqjkl} = \gamma_{pq0} + \Sigma_{s=1}^{S_{pq}} \gamma_{pqsl}W_{skl} + u_{pqkl}$ (3)

Level 4 (districts): $\gamma_{pqsl} = \delta_{pqs0} + \Sigma_{g=1}^{G_{pqs}} \delta_{pqsg}Z_{gl} + \nu_{pqsl}$ (4)

At level 1, π_{0jkl} is the constant, π_{pjkl} is a set of level-1 coefficients, α_{pijkl} is a set of level-1 predictors mentioned above (student background characteristics, lagged attendance, and lagged achievement), and e_{ijkl} is the level-1 random error. At level 2, we regress the level-1 coefficients, π_{pjkl}, on level-2 predictors (X_{qjkl}) mentioned above (classroom-level averages of student characteristics). β_{pokl} and β_{pqkl} is the level 2 constant and a set of level-2 coefficients, respectively, and r_{pjkl} represent level-2 random effects. Similarly, the level-3 equation predicts level-2 coefficients included in β_{pqkl}, based on W_{skl}, the level-3 predictors, where γ_{pq0} is the level-3 constant, γ_{pqsl} is a set of level-3 coefficients, and u_{pqkl} are the level-3 random effects. Finally, the level 4 equation follows the pattern of the lower level specifications.[9] These straightforward models allow us to partition the variance in student attendance and achievement at each of the four levels described above. We estimate separate models at individual grade levels and identical models for math and reading achievement. We note that the variance decomposition and associated point estimates that result from the HLM do not warrant a causal interpretation.

[9] Our modeling approach replicates the 4-level models used in Chingos et al. (2015). We considered a 5-level model that includes attendance rates within students over time, but determined that this analysis was outside the scope of our work.

Methods for research question 2. The second research question asks how large are district effects on student attendance? Despite our finding (described in the introduction) that student characteristics explain the vast majority of variation in outcomes, there remains the possibility that districts, schools, and teachers have significant variation in their fixed effects estimates. This second research question allows our findings to more easily be compared to the broader value-added literature on district, school, and teacher effectiveness (e.g., Chingos et al., 2015; Gershenson; 2016). We include a similar set of covariates as described above, this time using fixed effects models that are aligned with value-added literature (e.g., Hanushek & Rivkin, 2010). In separate models, we estimate district, school, and teacher fixed effects, pooling the data over the four years. The first model includes district fixed effects with student and classroom covariates. District fixed effect models estimate the value-added effects of school districts on student attendance. The second model drops the district fixed effects and includes instead school fixed effects. Finally, a third model exchanges the school fixed effects with teacher fixed effects to estimate individual teacher effects on student achievement. This model is identical to the one used in Gershenson (2016) and elsewhere (e.g., Goldhaber, Strunk, Brown, Knight & 2016; Strunk, Goldhaber, Knight & Brown, 2018). We use these fixed effects models to align our analyses with prior research on variation in teacher and school value-added measures of effectiveness (e.g., Chingos et al., 2015; Hanushek & Rivkin, 2010).

We begin with the district effects model, which predicts student attendance, A_{iklt}, based on lagged attendance, achievement, and other student and classroom covariates, indexing for student i, school k, district l, and year t. We estimate the following model separately for each grade level, pooled over school years 2012-13 through 2015-16:

$$A_{iklt} = \beta_0 + \beta_1 X_{iklt} + \beta_3 C_{klt} + \varphi_l + \delta_t + \upsilon_{ikt}. \quad (5)$$

In equation 5, φ_l represents district fixed effects and δ_t represents year fixed effects. The vectors X_{iklt} and C_{klt} are student and classroom covariates, including students' prior attendance and achievement, race/ethnicity, income level, and gender. This model is identical to the district fixed effects models estimated in Chingos et al. (2015), except that we use attendance (rather than achievement) as the outcome measure and control for lagged attendance.[10] We then estimate similar models exchanging the district fixed effect with school and teacher fixed effects. We estimate the same set of fixed effects models based on math achievement and (in separate models) ELA achievement. As noted earlier, to allow for comparisons between attendance and achievement effects, we convert both outcome measures into student-level standard deviations, standardized within grade and year. Because this measure of attendance is skewed left, we create alternate measures students' attendance that are more normally distributed (e.g., log absentee rate) and also estimate models predicting chronic absenteeism.

Based on prior work from the value-added literature (Chetty, Friedman & Rockoff, 2014; Koedel & Betts, 2007; Koedel, Mihaly, & Rockoff, 2015; McCaffrey, Sass, Lockwood, & Mihaly, 2009; Rothstein, 2010), our specification tests of this model include one-year district fixed effects models, pooled models that omit classroom-level covariates, and models that include students' twice-lagged student achievement and attendance. Our estimates of the size of district effects on attendance, based on standard deviations of district effectiveness measures, are similar for models that include twice-lagged outcomes and for models that drop classroom covariates, but slightly larger for one-year models. The findings we describe below are robust to these alternate value-added specifications and these results are available from the authors upon

[10] Note that the fixed effects models presented in Chingos et al. (p. 387, 2015), which estimate the size of district effects on achievement, do not include classroom-level covariates. We include classroom-level covariates to more closely match with our HLM analysis; however, results that exclude classroom-level covariates are nearly identical.

request.

Findings

Findings are reported in Tables 2-4. We first discuss our HLM results, which decompose the variance in student attendance to the district, school, teacher, and student level (research question 1). We then describe estimates of the magnitude of district effects on attendance, based on district fixed effects models (research question 2). We report results for grade four as a representative grade and note that our results for other grades follow similar patterns. In each section, we compare results for attendance to those of student achievement on state standardized exams.

Variance Decomposition

Table 2 shows the variance decomposition for attendance and math achievement for grade 4 students for the 2015-16 school year.[11] The first column shows the variance of the random effects at the district, school, teacher, and student level, for a null model that does not include any covariates. We also report the percent of the random effects at each level as a share of the total variance in student attendance. The first row shows that the district random effects have a total variance of 0.019 standard deviations (SD), or 1.9 percent of the total variance in fourth grade attendance. Approximately the same proportion of variance exists at the school level, the teacher level includes 2.6 percent of the variance, and the remaining proportion of variance, 93.7 percent, is unexplained variance at the student level.

If students are non-randomly assigned to teachers, schools, or districts, then part of the variance in attendance that is explained at the teacher, school, or district level may simply reflect differences in average student background characteristics across these groups. To that end,

[11] Results for each individual year from 2012-13 to 2014-15 are almost identical and are available from the authors upon request.

Model 2 includes controls at each level as described in the methods section. When these additional controls are added, the share of variance in attendance explained at the district level decreases to 1.3 percent, and the school and teacher levels decrease to 1.2 percent and less than 0.1 percent, respectively. Finally, Model 3, shown in the third column of Table 2, includes controls for prior year student attendance and achievement. The proportion of variance explained at each level decreases when lagged outcome measures are included. For example, districts explain 0.3 percent, schools explain 0.4 percent, and teachers explain less than 0.1 percent.[12] The student background variables explain 43.8 percent of the variation in attendance, whereas 55.4 percent of the variance in attendance is unexplained variation at the student level. As shown in columns 4-6, teachers, schools, or districts account for a slightly larger share of the variation in math achievement compared to student attendance. Column 6 shows the variance decomposition of grade 4 math achievement when student controls and lagged outcomes are included. The proportion of variance explained at the district, school, teacher, and student level are 1.3, 2.3, 2.9, and 31.6 percent, respectively, and student controls account for 61.9 percent of the variance in achievement.[13] The variance in achievement at each level reported in Table 2 is somewhat consistent with identical models run for Florida and North Carolina (reported in Chingos et al., 2015). Districts, schools, teachers, and students in Florida account for 0.1, 0.7, 3.7, and 24.1

[12] Many elementary schools only have one section per grade level (i.e., one grade four teacher), which limits the amount of variation in attendance explained at the teacher level (after removing variation at the school level). We therefore specify alternative models restricting the sample to schools with 4 or more grade level teachers and our results are qualitatively similar.

[13] Results in Table 2 lump all controls into a single category (reported in row five). We find that the controls for student background at the student and classroom level were largely consistent with the literature. At the student level, as expected, prior year achievement is the strongest predictor of current year achievement, followed by gifted and talented designation, race and ethnicity, and ELL status. Similarly, prior year attendance is the strongest predictor of current year attendance, followed by ELL status, indicators of race and ethnicity, and free and reduced price lunch designation. At the school and teacher levels, the control variable for special education status accounted for the largest portion of variance explained, while neither of the control variable variances exceeded the residual variance at the district level. We found this pattern to be repeated in the attendance models. For models that omit lagged outcomes, income status is the strongest predictor of current year outcomes.

percent of the variance in upper elementary math achievement, respectively. In North Carolina, the same figures are 0.3, 1.1, 3.3, and 24.1 percent, respectively. Our results for other grades and for ELA achievement are qualitatively similar except that districts, schools, and teachers account for slightly less of the variation in ELA achievement compared to math achievement.

Magnitude of District Effects

Table 3 shows the standard deviation (SD) of district, school, and teacher effects on student attendance and math achievement, based on pooled-year value-added models. The first two columns show the standard deviations of districts effects. For both fourth and fifth grade students, a one-SD increase in district effectiveness, as measured by value-added to student attendance, is associated with a 0.11 SD increase in attendance. Effects are larger in grade six, but smaller in grades seven and eight. District effects on math (and ELA) achievement are larger in all grades. For example, the SD of grade four district effects on math achievement is 0.19 (column 2), which is roughly consistent with (although somewhat larger than) those identified in Chingos et al. (2015). That study found districts effects on fourth and fifth grade math achievement of 0.10 SD in Florida and 0.14 SD in North Carolina. As shown in Appendix Table A2, the SD of districts effects on ELA are smaller than math (0.12 for grade four), which is consistent with Chingos et al. (in which ELA achievement effects range from 0.07 to 0.11 SD). Districts effects on achievement may be larger in Texas in part because districts are significantly smaller, with average enrollment of approximately 5,000 in Texas, compared to 40,000 in Florida and 13,000 in North Carolina.

Columns 3 and 4 of Table 3 show *school* effects on student attendance and math achievement, respectively, and Columns 5 and 6 show *teacher* effects on the same two outcomes. For grades four and five, school effects on attendance are similar in magnitude to district effects on attendance, but teacher effects are larger than school or district effects. For example, a one-SD increase in district, school, and teacher effectiveness (based on grade 4 attendance) is associated with an increase in student attendance of 0.11, 0.11, and 0.17 SD, respectively. In grades six, seven, and eight, school effects on attendance are larger than district effects and approximately the same size as teacher effects. Across all grade levels, teacher effects on attendance are larger than district effects, and (with some exceptions), effects are generally larger moving from districts, to schools, and teachers. For all grade levels, districts, schools, and teachers all have larger effects on math achievement than on student attendance. Additionally, effects on math achievement follow a consistent pattern across grade levels: district effects are smallest, followed by school effects, and then teacher effects (which are largest). For example, a one-SD increase in district, school, and teacher effectiveness (based on grade 4 math achievement) is associated with an increase in student achievement of 0.19, 0.19, and 0.28 SD, respectively. Our results using one-year fixed effects models and for other subjects are qualitatively similar. These values are roughly consistent with estimates of teacher fixed effects reported elsewhere (e.g., Hanushek & Rivken, 2010).

Our estimated district effects on attendance are shown in Figure 1, which includes all districts with at least 100 fourth grade students over the four years upon which the pooled models are based (N = 901, 86.0 percent of the 1,146 districts present in all years from 2012-13 to 2015-16). Figure 1a shows district effects on attendance and Figure 1b shows district effects on math achievement, for fourth grade students.[14] Of the 901 districts, 130 (14.4 percent) have fixed effects estimates for attendance that are statistically significantly negative, while 128 (14.2 percent) have fixed effects estimates for attendance that are significantly positive. Importantly,

[14] Point estimates of fixed effect shown in Figure 1 have been adjusted using empirical Bayesian methods.

most districts (71 percent) do not have statistically significant fixed effects estimates on student attendance, either positive or negative. A larger number of districts have statistically significant fixed effects estimates on achievement. We find that 72 percent of districts have statistically significant effects on grade four math achievement (positive or negative), whereas only 28 percent have 95 percent confidence intervals that include zero. Results are qualitatively similar for other grades and for ELA achievement. These results differ from those based on data from Florida and North Carolina. Chingos et al. (2015) find that 15 percent of districts in Florida are statistically significantly above average and 12 percent are statistically significantly below average. In North Carolina, the comparable figures are 16 percent above and 16 percent below. The larger proportion of districts with statistically significant effects in our sample may result from larger overall sample size (increasing precision), or from the fact that districts are smaller on average and may therefore exhibit greater variation in local practices.[15]

Finally, Table 4 shows correlations across measures of district effectiveness based on pooled fixed effects models (Panel A) and year-to-year correlations of one-year fixed effects estimates (Panel B). We find that district effects on attendance are correlated with district effects on math and ELA achievement at 0.21 and 0.20, respectively, based on weighted correlations. The correlations are slightly lower when districts are not weighted by district size, implying that the correlation between effectiveness based on attendance and achievement is greater in larger districts (which we confirmed by running similar correlations for small, medium, and large districts). Interestingly, district effects on math and ELA achievement are correlated at 0.59,

[15] Note that because we use the tfxreg user command in STATA, the standard errors of fixed effects are calculated based on the ordinary least squares method for the effect (McCaffrey, Lockwood, Mihaly, Sass, 2010). We find that district enrollment is negatively correlated with the standard error of district fixed effect estimates (r = -0.43) and positively correlated with district effects on attendance. That is, larger districts have smaller standard errors and, on average, larger (more positive) effects on attendance.

which is roughly consistent with estimates of the correlation in measures of teacher effectiveness measured by contributions to math and ELA achievement (e.g., Goldhaber, Walch, & Gabele, 2014). Panel B of Table 4 shows that district effects on attendance are only moderately stable over time. For example, the correlation between district effects on attendance in one year and district effects on attendance in the prior year is 0.23. Measures of district effectiveness based on achievement are more stable over time compared to those based on attendance (the year-to-year correlations for district effects on math and ELA achievement are both 0.53).

Specification and Robustness Checks

We describe here analyses of the sensitivity of our model specification to alternate approaches. We include as additional specification checks: (a) alternate approaches to transforming the attendance variable to satisfy the assumption of linearity; and (b) prediction of the dichotomous indicator identifying chronically absent students. We also extent our work by examining the potential role of migrant students for models predicting student attendance.

As noted above, in our preferred model, we follow Gershenson (2016), who uses the standardized values of students' attendance rate, measured as the number of days attended, divided by the number of instructional days at the student's school. Standardizing attendance rates allows for more straightforward comparison between models based on attendance and those based on test scores. However, as shown in Appendix Figure A1, attendance rates are not normally distributed. If we use absentee rates multiplied by 100, and take natural log of this variable, we obtain a measure of student attendance that is more normally distributed (see Appendix Figure A1). Findings based on this measure of attendance are qualitatively similar to our main findings, showing that districts account for only a small percent of variation in student attendance, while schools and teachers explain a slightly greater proportion, and student background characteristics account for the far majority of variation in attendance. Value-added estimates of district effects on attendance are highly correlated with our preferred specification (above 0.95 in each year). While this transformation more closely satisfies the assumption of linearity, the transformed variable has the disadvantage of being less sensitive to changes in the outcome measure for students with lower levels of attendance (or high levels of absenteeism).[16] Given that interventions to increase attendance typically focus on chronically absent students, a superior transformation might be more sensitive to changes in attendance at lower attendance rates.

To that end, we also specify models predicting the likelihood that a given student is chronically absent. We define chronically absent students as those who are absent for more than 10 percent of the school year, or 18 instructional days for students in schools with 180 instructional days. We estimate generalized HLM using the logit link function that predicts the likelihood a student is chronically absent. In addition to addressing the non-normal distribution of attendance rates, this specification has the added benefit of assessing whether teachers, schools, or districts affect attendance for students with excessive absenteeism. The proportion of variation explained at each level for this outcome measure follow a similar pattern to our preferred HLM results.

Finally, we conduct robustness checks that examine the potential role of students' immigrant status. First, we explicitly control for migrant status in our HLM variance decomposition. We exclude this variable from our preferred model as a way to better align our models to extant literature. We find that inclusion of the migrant status variable has almost no

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[16] For example, moving a student from a 98 percent to a 99 percent attendance rate shifts the natural log of the absentee rate multiplied by 100 by 0.29, from 1.10 to 1.39, whereas moving a student from a 90 percent to a 91 percent attendance rate shifts the natural log of the absentee rate multiplied by 100 by only 0.10, from 2.20 to 2.30.

change on the proportion of variation in attendance explained at each level. The migrant status variable in our dataset is based on students' reported participation in the state's Migratory Agricultural Worker program and may exclude immigrant students not participating in this program. Thus, a second approach we use is to include a dummy variable at level 2 in the HLM for whether the district is in a county that shares a border with Mexico, where larger concentrations of migrant families reside (Texas Education Agency, 2018). We find that these results are similar to our overall findings.

Discussion

Increasingly, states are enacting policy to hold districts accountable for student attendance by tying attendance rates to funding. New Jersey recently enacted a form of ADA funding and other states including Colorado and Virginia have considered doing so (Baker & Green, 2005; Groginsky, 2010). The analysis described here demonstrates that, similar to student achievement, the large majority of variation in student attendance is explained at the student level. Higher institutional levels of the education system – from classrooms up to schools and districts – explain smaller and smaller proportions of the variation in attendance. In other words, similar to what prior research has shown with student achievement, a student's attendance rate is primarily a factor of his or her own observed and unobserved background characteristics. The teacher and school to which a student is assigned is the next best predictors, while districts appear to have limited predictive power for student attendance. For example, our district fixed effects models show that a one-SD increase in district effectiveness increases student attendance by less than one day, but increases student achievement by as much as 0.19 SD, corresponding to approximately two months of learning (Lee, Finn & Liu, 2017). Results from HLM models suggest that the variation attributed to differences at the district level account for 0.32 percent of one school day, compared to the variation in math achievement at the district level, which corresponds to 8.25 weeks.[17]

A few caveats of this analysis are noteworthy. First, our analyses do not provide causal analysis of district effects on attendance, nor do they evaluate the effectiveness of ADA funding as an incentive to increase attendance. Second, our models are designed to examine variation in district effects on student attendance. If all districts engage in similar practices that, for example, increase the average rate of attendance by 20 school days, this impact would not be observed in our models. Yet, by setting school calendars, coordinating student transportation, determining local attendance policies, and disseminating information to parents and the community, districts likely do play a larger role in overall attendance than our models reflect. However, to the extent that districts engage in different activities to encourage student attendance, or engage in similar activities to varying degrees of quality or intensity, our models measure differences in the effects of those activities on student attendance. Importantly, the policy-relevant variation in district effects on attendance is the effects districts have on attendance over and above the "main effects" which are produced through provision of basic services. Lastly, districts in Texas face incentives to increase attendance because the state uses ADA-based funding. Our study does not address how district might influence student attendance in states that do not use ADA funding.

Most analyses of school finance systems focus on how base funding rates are determined or how finance systems distribute per-student funds to school districts (e.g. Baker et al., 2017; Knight, 2017). An often-overlooked feature of state school finance systems is how states

[17] We convert district-level variation in attendance from the HLM results to days of attendance by taking the square root of the variance associated with the district level and multiplying by the number of days absent in one standard deviation of absences. Following Chingos et al. (2015), we calculate the achievement value by dividing the square root of the district variance by the average learning gain for fourth grades students in math (Hill et al., 2008) and multiplying by 36, the number of weeks in a 180-day school year. To convert standard deviations of achievement to months, based on fixed effects models, we use the methods outlined in Lee et al. (2017).

determine total student enrollment for funding purposes. Although districts have relatively small effects on student attendance, seven states currently hold districts directly accountable for the level of student attendance through ADA-based funding. By basing funding levels on a district's ADA, without adjustments for student background characteristics, states effectively punish districts that serve students who, due to factors outside the control of schools, have lower attendance rates.

To gain a sense of the extent to which districts in Texas are financially penalized by the use of ADA and the extent to which those financial penalties disproportionately fall on high-need districts, we interviewed several Chief Financial Officers in large school districts in the El Paso and Dallas-Fort Worth areas. Each of these district administrators described methods for calculating the amount of lost funding associated with the use of ADA funding, as opposed to fall membership. The Texas school finance formula is based on two tiers of funding, both of which are allocated primarily on the basis of the district's "weighted" ADA, or WADA, where students with special enrollment classification such as low-income, English learner, or special education receive greater weights for funding purposes. The finance formula includes several add-on funds in addition to Tier 1 and Tier 2 funding, which are based on WADA, ADA, or other district factors.[18] To calculate the amount of funding lost as a result of the use of ADA-funding, we separate each district's per-student state and local funding rate into three components: (a) the component determined by ADA, (b) the component determined by WADA, and (c) other components not determined by student attendance. The amount of funding lost

[18] All of Tier 1 and 2 funding is allocated based on WADA except the following: high school students, students in new instructional facilities, the supplemental staff salary allotment, the transportation allotment, the technology and instructional materials allotment, and the Available School Fund distribution (Pace, 2018). Funding for high school students, new instructional facilities, instructional materials, and the Available School Fund are all based on ADA, whereas the transportation allotment is based on the number of square miles per student and the staff salary allotment is based on the number of professional employees ($500 per full time professional staff).

from the first component is the per-student funding amount multiplied by the difference between fall enrollment and ADA. The funding lost from the second component is the same, except we also multiply by the ratio of WADA to ADA. No funding is lost from the third component as a result of the use of ADA-based funding. Most of a district's funding, 87 percent on average across districts, is determined by funding that is based on WADA (Pace, 2018).

We find that the average district receives approximately $2.7 million less state and local funding (4.1%), or about $501 less per student, on average, when ADA is used to determine funding instead of fall enrollment. Were the amount of lost funding per student the same for all districts, it would not be particularly consequential in the sense that, in determining the basic allocation for each district, state legislators may take into account the reduced funding resulting from ADA-based calculations. However, not surprisingly, this difference in funding does not affect all districts equally. Districts that lose the greatest share of funding are those with low attendance rates and those whose students have greater weights within the funding system. Districts with 87% or more low-income students (i.e., the roughly 100 districts that fall at or above the 90th percentile of poverty rate) lose 7.2 percent of funding whereas those with 22 percent or fewer low-income students (the 10th percentile of poverty rate) lose 4.9% of per-pupil funding. Districts in the 90th percentile of funding reduction associated with ADA-funding lose an average of 10.3% of funding while those in the bottom 10th percentile lose 4.2%. Edgewood Independent School District (ISD), for example, receives $9,328 for each of its 11,000 students and has an attendance rate of 92.2 percent and a ratio of WADA to ADA of 1.42 (implying that the average student is weighted at 1.42 students). The district loses $1,025 per student as a result of not having perfect attendance, about 11 percent of its funding. Alamo Heights ISD, a low-poverty district in the same county with a 96.0 percent attendance rate, loses 4.7 percent of funding as a result of ADA-based (instead of enrollment-based) funding. Yet estimates of district effectiveness for each of these two districts are not statistically significantly different from each other, implying that these districts have, roughly the same effect on student attendance.

ADA funding is accomplishing the goal of punishing districts with high absenteeism while rewarding districts with high attendance, effectively allocating, on average, an additional $582 per student for districts with the highest attendance.[19] However, this differential funding exacerbates disparities in funding levels that already exist as a result of differences in the property tax base. Importantly, as we highlight throughout this study, the primary determinant of student attendance is student background characteristics, of which districts have little control. Ranking districts by their estimated fixed effects on student attendance shows that moving from the bottom to the top of the distribution of effectiveness would do little to improve attendance. Using our grade four estimates, a district at the 10th percentile of district effects on attendance increases student attendance by 0.65 days fewer than the median district.[20] A district at the 90th percentile of district effects on attendance increases student attendance by 0.58 days more than the median district. Thus, our estimates suggest that districts that make dramatic improvements in their “impact” on attendance – moving from the 10th to the 90th percentile in effectiveness – would increase attendance by only 1.23 days.[21] In contrast, districts at the 90th percentile of effects on grade four math achievement increase achievement by 0.22 SD more than the median

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[19] Districts in the highest decile of attendance lose, on average, 4.8% of funding, whereas those in the lowest decile of attendance lose an average of 9.2%, corresponding to per-pupil amounts of $648 and $1229, respectively. In other words, high-attendance districts receive an additional $582 per student more than low-attendance districts.

[20] When we rank districts by their effect on student attendance, the district at the 10th percentile, Rains ISD, has a district effect on attendance of -0.109 SD. The standard deviation of grade four attendance rate is 0.033, so multiplying these numbers implies that this district increases attendance by 0.359 percentage points less than the median district. Multiplying this number by 180 days implies that this district increases attendance by 0.65 fewer days than the median district.

[21] As noted earlier, our value-added district fixed effects models are not causal. We use causal language in some cases to avoid awkward phrasing.

districts, which corresponds to about between 3.5 to 4 months of learning (just over one third of a school year), depending on the conversion from standard deviations to learning time (Cremata et al, 2013; Lee et al., 2017). Again, these results are somewhat larger than those reported in Chingos et al. (2015), who find that districts at the 84th percentile contribute an additional one quarter to one third of a school year of learning in North Carolina and about one-fifth of a school year in Florida.

More broadly, this study adds to the literature on districts effects. Prior work is based on Florida and North Carolina, two states with relatively large districts (Chingos et al., 2015). That study found that district effects were somewhat larger in North Carolina, where there are smaller districts on average. The authors suggest that in states with smaller school districts, districts may exhibit larger effects on student outcomes, and our study provides additional evidence of this pattern. Smaller districts may allow superintendents and other district leaders to more directly influence district practice. Greater variation in practice likely leads to greater variation in district effectiveness, either positive or negative, which increases estimates of districts' overall impact on student outcomes. While our results for district effects on achievement could be generalized to other states, especially those with similar average district size, the state's use of ADA to determine funding may alter the observed variance decomposition and estimates of district effects on attendance. Placing higher stakes on attendance rates could alter district efforts to improve attendance, but it's not clear whether that would increase or decrease variance explained at the district level, or estimates of district effects on attendance.

Conclusion

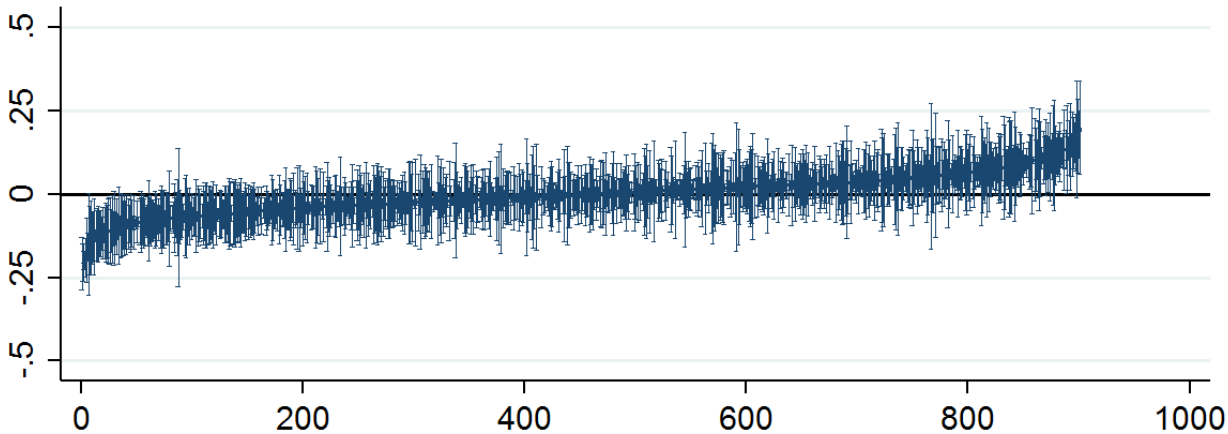
States use ADA-based funding as a way to incentivize districts to increase student attendance. However, this policy assumes that districts have significant control over absenteeism.

Our results show that (a) districts have only minor effects on their actual attendance rates, relative to student background characteristics; and (b) disadvantaged districts are more likely to be harmed by funding policies that use ADA. That said, whether districts actually respond to incentives to increase attendance – and whether ADA funding actually increases student attendance – remains an open question. What is clear is that states using ADA funding may need to consider the importance of student background characteristics in determining average student attendance and the resulting funding levels.

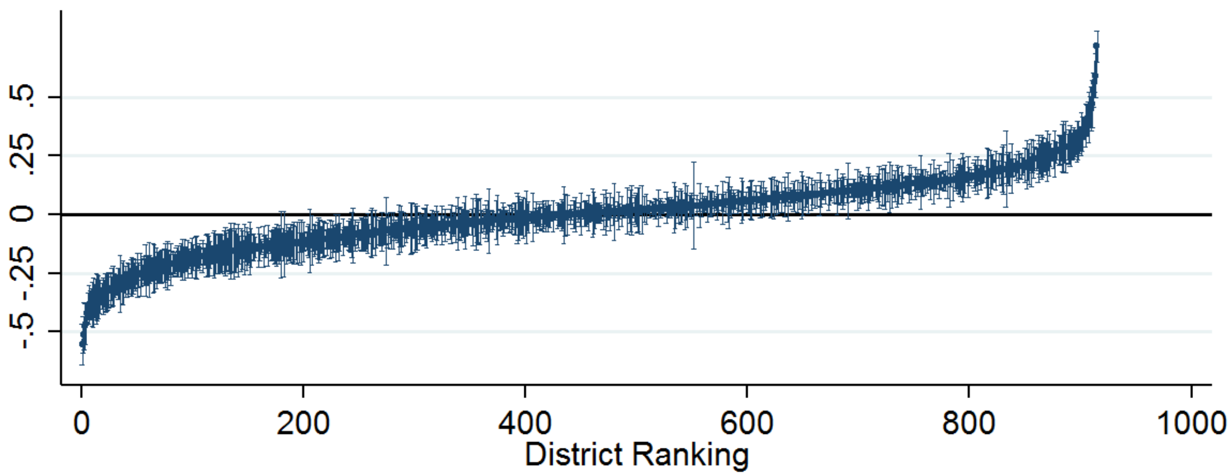
FIGURE 1

Estimated district effects on grade four attendance and math achievement with 95% confidence intervals, based on a pooled-year value-added model, 2012-13 to 2015-16

Panel A. Attendance



Panel B. Math achievement



Note. Each dot and confidence interval represents a school district (n = 901). The sample is limited to districts with at least 100 fourth grade students present in the 4-year pooled sample. Values have been adjusted using empirical Bayes methods to account for inflated standard errors in the tails of the distributions and centered at the mean. School districts are ranked by their estimated fixed effect on student attendance (1a) and achievement (1b) in ascending order.

TABLE 1

Summary statistics for average attendance across school districts, elementary schools, 2015-16

Panel A. Student-level summary statistics

	Percent of all students	Attendance rates				
		Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
All students (days attended, SD, % attended)	100%	174.24 (5.94) 96.8%	174.23 (6.12) 96.8%	173.70 (7.02) 96.5%	172.98 (8.10) 96.1%	172.62 (9.54) 95.9%
Black	12.7%	96.7%	96.8%	96.3%	95.9%	95.8%
Hispanic	51.7%	96.8%	96.9%	96.5%	96.0%	95.7%
White	30.5%	96.6%	96.5%	96.4%	96.2%	95.9%
FRL	49.0%	96.6%	96.6%	96.2%	95.7%	95.4%
EL	20.7%	97.5%	97.5%	97.0%	96.4%	96.0%
SPED	8.4%	95.8%	95.8%	95.3%	94.8%	94.4%

Panel B. District-level summary statistics, by quintile of attendance rate

	All districts	Highest quintile	4th quintile	3rd quintile	2nd quintile	Lowest quintile
Number of districts	1,150	230	230	230	230	230
Average attendance	95.9%	96.9%	96.4%	96.0%	95.6%	94.7%
Elementary	96.2%	97.0%	96.5%	96.2%	96.0%	95.2%
Middle	96.3%	97.2%	96.6%	96.3%	95.9%	95.2%
High	95.4%	96.7%	96.1%	95.6%	94.9%	93.6%
Average achievement	0.000	0.601	0.218	0.064	-0.045	-0.645
Average enrollment	4,922	3,598	3,817	6,653	5,618	4,717
% African American	9.0%	9.9%	8.8%	7.2%	7.6%	11.4%
% Latina/o	39.8%	34.4%	34.4%	38.0%	40.3%	51.9%
% White	47.4%	50.4%	52.6%	51.1%	48.7%	34.3%
% FRL	57.7%	50.9%	53.7%	56.2%	60.6%	66.9%

Note. In row 1, we report the mean number of days attended, the standard deviation of this measure, and the average attendance rate. FRL stands for free and reduced-price lunch; SPED stands for special education, and EL stands for English learners. Panel A data are based on all students in grades 4-8 in 2015-16 (n = 1,966,391) across 6,471 schools and 1,181 school districts. Panel B includes all K-12 students from districts with attendance and achievement data (n = 5,371,521 students, 1,146 districts).

TABLE 2

Variance decomposition of grade four student attendance and math achievement, 2015-16

	Attendance			Math Achievement		
	(1)	(2)	(3)	(4)	(5)	(6)
District level	0.019 1.88%	0.013 1.33%	0.003 0.30%	0.056 5.78%	0.058 6.00%	0.012 1.26%
School level	0.018 1.85%	0.012 1.21%	0.004 0.38%	0.081 8.36%	0.056 5.83%	0.023 2.34%
Teacher level	0.025 2.55%	0.000 0.00%	0.000 0.00%	0.090 9.34%	0.039 4.04%	0.028 2.84%
Student level (unobserved residual)	0.933 93.72%	0.896 90.10%	0.552 55.49%	0.740 76.52%	0.616 63.68%	0.306 31.65%
Controls		0.073 7.37%	0.436 43.83%		0.198 20.45%	0.599 61.90%
Total variance	0.995	0.995	0.995	0.967	0.967	0.967
Demographic controls	No	Yes	Yes	No	Yes	Yes
Prior-year scores / attendance	No	No	Yes	No	No	Yes

Note. n = 429,919 grade four students in 1,181 school districts.

TABLE 3

Standard deviation of district, school, and teacher effects on student attendance and math achievement, 2012-13 to 2015-16

	District effects		School effects		Teacher effects	
	Attendance	Math achievement	Attendance	Math achievement	Attendance	Math achievement
Grade 4	0.109	0.186	0.110	0.190	0.171	0.284
Grade 5	0.108	0.165	0.125	0.174	0.170	0.250
Grade 6	0.125	0.181	0.204	0.193	0.209	0.238
Grade 7	0.094	0.139	0.209	0.143	0.195	0.206
Grade 8	0.089	0.167	0.186	0.184	0.184	0.246

Note. Each cell represents the standard deviation of estimate value-added effects of teachers, schools, or districts on student attendance or achievement. Value-added models are based on pooled year fixed effects models. Results for one-year fixed effects models are similar (and are available from the authors upon request).

TABLE 4

Correlations across measures of district effectiveness and year-to-year correlations of fixed effects estimates, grade 4, 2012-13 to 2015-16

	Weighted			Unweighted		
	Effects on Attendance	Effects on Math ach.	Effects on ELA ach.	Effects on Attendance	Effects on Math ach.	Effects on ELA ach.
Panel A: Correlations across measures of district effectiveness						
Effects on Attendance	1			1		
Effects on Math ach.	0.208*	1		0.182*	1	
Effects on ELA ach.	0.199*	0.590*	1	0.204*	0.535*	1
Panel B: Lagged effects						
Lagged effects on Attendance	0.225*			0.103*		
Lagged effects on Math achievement		0.534*			0.420*	
Lagged effects on ELA achievement			0.532*			0.353*

Note. Correlations across measures of district effectiveness are based on pooled models with district fixed effects. Year-to-year correlations of fixed effects are based on one-year district fixed effects models. * p< .05.

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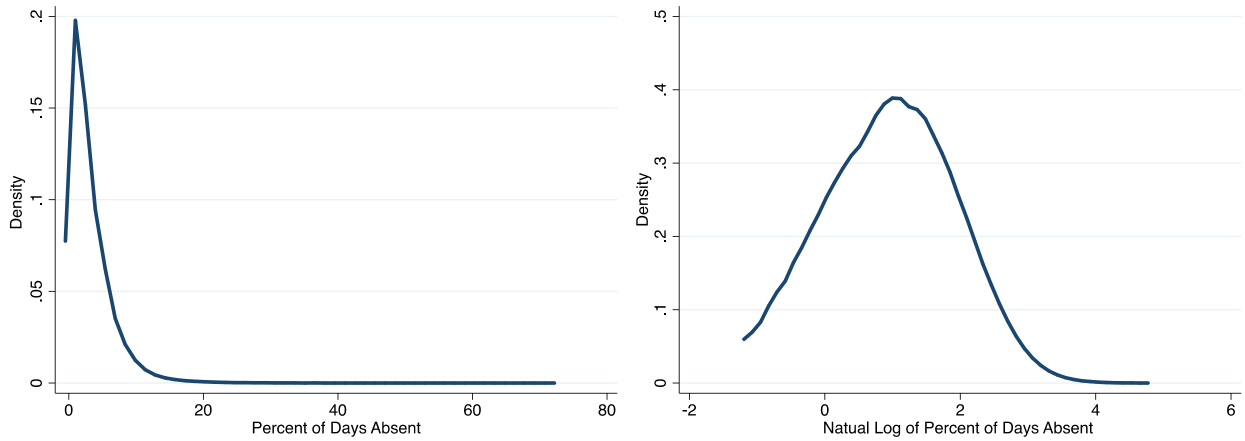
APPENDIX FIGURE A1

Kernel density plots of percent of days absent, grade 4 students, 2015-16



Note. Percent of days absent is multiplied by 100 (with possible values ranging from 0 to 100). Other grades and years show similar distributions. Our preferred model uses the standardized value of the percent of instructional days that each student attends, ranging from 0 to 1 (i.e., attendance rate), whereas the above graphs show *absentee* rates multiplied by 100 (left panel) and the natural log of absentee rates multiplied by 100 (right panel). Density plots are shown with bandwidth equal to 5.

APPENDIX TABLE A1

Mechanisms for determining student enrollment for funding purposes

State	Total enrollment	Percent of U.S. enrollment
States using a form of average daily attendance		
California	5,994,549	12.6%
Idaho	272,713	0.6%
Illinois	2,032,163	4.3%
Kentucky	688,475	1.4%
Mississippi	474,022	1.0%
Missouri	892,499	1.9%
Texas	5,000,322	10.5%
Total	15,354,743	32.2%
States using a count mechanism other than average daily attendance		
All other states	32,375,274	67.8%

Note. Two states using ADA allow for some weighting of the best weeks of attendance during select periods of time. Specifically, Idaho equally weights ADA during the fall semester and the best 28 weeks overall. Illinois uses the best three months of the year.

APPENDIX TABLE A2

Standard deviation of district, school, and teacher effects on student attendance and ELA achievement, 2012-13 to 2015-16

	Districts effects		Campus effects		Teacher effects	
	Attendance	ELA achievement	Attendance	ELA achievement	Attendance	ELA achievement
Grade 4	0.104	0.117	0.105	0.127	0.174	0.203
Grade 5	0.113	0.104	0.119	0.114	0.170	0.184
Grade 6	0.116	0.118	0.202	0.130	0.201	0.180
Grade 7	0.094	0.095	0.188	0.108	0.191	0.161
Grade 8	0.088	0.082	0.199	0.095	0.189	0.164

Note. Each cell represents the standard deviation of estimated value-added effects of teachers, schools, or districts on student attendance or achievement. Value-added models are based on pooled year fixed effects models. Results for one-year fixed effects models are similar (and are available from the authors upon request). Estimated effects for attendance differ slightly from those reported in Table 3 because the underlying samples differ. Table 3 is based on a sample of students with current year attendance and math achievement data, whereas this table is based on a sample of students with current year attendance and ELA achievement data. All students in both samples have lagged attendance data, lagged math and ELA achievement data, demographic information, and teacher, school and district assignment data.