Engaging Teachers

Measuring the Impact of Teachers on Student Attendance in Secondary School

Jing Liu
Susanna Loeb

ABSTRACT

On average, secondary school students in the United States are absent from school three weeks per year. For this study, we are able to link middle and high school teachers to the class-attendance of students in their classrooms and create measures of teachers' contributions to student class-attendance. We find systematic variation in teacher effectiveness at reducing unexcused class absences. These differences across teachers are as stable as those for student achievement, but teacher effectiveness on attendance only weakly correlates with their effects on achievement. A high value-added to attendance teacher has a stronger impact on students' likelihood of finishing high school than does a high value-added to achievement teacher. Moreover, high value-added to attendance teachers can motivate students to pursue higher academic goals. These positive effects are particularly salient for low-achieving and low-attendance students.

*Jing Liu is an assistant professor in education policy at the College of Education, University of Maryland (jliu28@umd.edu). Susanna Loeb is director of the Annenberg Institute and a professor in education and international and public affairs, Brown University.**Jing Liu thanks the National Academy of Education/Spencer Dissertation Fellowship and the Karr Family Fellowship at Stanford's Center for Education Policy Analysis for financial support. The authors are grateful for the substantial help received from Ben Backes, Lindsay Fox, Dan Goldhaber, Demetra Kalogrides, Emily Penner, Sean Reardon, Jane Rochmes, Jonah Rockoff, Min Sun, Monica Vasquez, Camille Whitney, and participants in the Family and Education Workshop, AEFP, APPAM, and seminars at Stanford, Harvard, University of Kentucky, and University of California at Irvine. In addition, they extend deep gratitude to several individuals at the school district; they do not mention them by name in order to protect district anonymity. All errors are those of the authors. The analysis uses confidential student-level data obtained from an anonymous district in California, which cannot be publicly shared. The authors are willing to provide guidance on how to obtain the data to interested researchers (jliu28@umd.edu).*
[Submitted December 2016; accepted June 2019]; doi:10.3368/jhr.56.2.1216-8430R3
JEL Classification: I21, J44, and J45

Supplementary materials are freely available online at: http://uwpress.wisc.edu/journals/journals/jhr-supplementary.html

I. Introduction

On average, secondary school students in the United States are absent from school three weeks per year (Snyder and Dillow 2013). Besides the well-established correlations between low attendance and less learning (Goodman 2014; Gottfried 2009, 2010, 2011), drug and alcohol use (Henry and Thornberry 2010) and crime (Allensworth and Easton 2007; Balfanz, Herzog, and Mac Iver 2007), absenteeism is among the strongest predictors of long-term outcomes, such as high school dropout, net of other factors including achievement and suspensions (Balfanz and Byrnes 2012). Chronic absenteeism is particularly pronounced for Black, Hispanic, and low-income students, aggravating the achievement gaps. Due to the prevalence of absences and their adverse consequences, policymakers have doubled their efforts to combat absenteeism in recent years. While a variety of individual and family factors can lead students to miss school, such as student illness (Romero and Lee 2007) and residential mobility (Hanushek, Kain, and Rivkin 2004), factors within the purview of schools, such as a positive and safe school environment and an effective, supportive and engaging teacher, are also likely to influence absences.

Teachers are among the most important educational inputs at school (Rivkin, Hanushek, and Kain 2005). Despite the critical role of regular school attendance for student long-run success, research is surprisingly sparse in teachers' impact on reducing absences, especially at the secondary school level, a stage that directly feeds into students' college enrollment. Even less is known about whether teachers who reduce absenteeism have long-term effects on student success, particularly for at-risk students, who tend to accrue large amounts of absences and drop out of high school. With this study, we are among the first to estimate teachers' contributions to student class attendance in secondary school. We then evaluate several important statistical properties of this new measure, including how stable this measure is over time and how it correlates with teachers' contribution to student test scores. Finally, and most substantively, we link this measure to several student long-run outcomes, including high school graduation and Advanced Placement (AP) course-taking. We then examine both the average long-run effects of having a high value-added to attendance teacher and also the nonlinearities and heterogeneities on student subgroups. Teachers who are effective at reducing absenteeism may be particularly beneficial for the most disengaged students, and, as such, we assess heterogeneity in the long-run effects of high value-added to attendance teachers by students' prior absenteeism and prior achievement.

Overall, we find that teachers have large effects on student attendance. A student would have approximately 44 percent fewer unexcused absences in math classes (that is, 4.4 class meetings for a student who is expected to miss ten class meetings) and 54 percent fewer in English classes, if they had a teacher who is one standard deviation above the average in value-added to attendance than if they had an average teacher, holding other variables constant. Compared with value-added to achievement, value-added to attendance is similarly stable across years, and, yet, value-added to attendance is weakly correlated with value-added to achievement. Compared with having a high value-added to achievement teacher, a high value-added to attendance teacher has stronger effects on a student's opportunity to graduate from high school and meaningful effects on students' pursuit of higher academic goals, such as taking more AP courses.

Specifically, having a teacher whose value-added to attendance is one standard deviation above an average teacher can increase a student's likelihood of graduation by 0.7 percentage points. Notably, the effects of value-added to attendance are particularly strong for students with lower prior achievement, lower prior attendance, and high predicted probability of dropping out, while showing little impact on students who are at the top of these distributions.

Our study builds on the extensive literature of teacher effectiveness. Prior work has convincingly documented that effective teachers have large impacts on student test score gains in math and reading in the year in which the teacher teaches the student (for example, Clotfelter, Ladd, and Vigdor 2007; Goldhaber 2007; Rivkin, Hanushek, and Kain 2005), and they can have long-term impacts on college attendance, income, and other adult outcomes (Chetty, Friedman, and Rockoff 2014). However, a large portion of teacher effects on student long-term outcomes, like college attendance, is not explained by teacher effects on student achievement (Chamberlain 2013), suggesting that good teachers not only increase students' test scores, but also impact other capacities. An emerging literature is beginning to shed light on teachers' impact on students' nonachievement outcomes (for example, Gershenson 2016; Jackson 2018; Kraft 2019).[1] For example, Jackson (2018), using data from North Carolina, estimates ninth-grade teachers' effects on a composite measure of student GPA, on-time grade completion, suspensions, and full-day attendance and shows that this nonachievement dimension of teacher effectiveness can contribute to students' long-run success above and beyond the teachers' impact on student test scores. Our study extends Jackson (2018) by focusing on teachers' contribution to student class attendance in secondary school.

This work makes five main contributions to the literature. First, we focus on attendance at the secondary school level rather than the elementary level. Since during secondary school students themselves rather than their parents are likely to make the decision to attend classes, attendance in secondary school is more likely to be affected by the student's own perceptions of the teacher than it is in elementary school and is therefore likely a key setting for estimating "teacher effects" on absences. Absenteeism is also higher in secondary school (Whitney and Liu 2017). Gershenson (2016) focuses on elementary grades, and although Jackson (2018) studies ninth-graders, ours is the first study that examines both middle and high school students (Grades 7–11). Second, the detailed administrative data that we use provide information on whether a student missed each class of each day for either an excused or unexcused reason. Gershenson (2016) and Jackson (2018), as well as other research on student absence, focus on full-day absences as the outcome measure. Because middle and high school students attend classes with multiple teachers, attributing full-day absences to individual teachers is potentially problematic. Class-level absence greatly improves the precision of measuring absenteeism and estimating teacher effects. Moreover, focusing on unexcused rather than the combination of excused and unexcused absences allows us to isolate the

1. An emerging literature sheds light on teachers' impact on students' nonachievement outcomes (for example, Gershenson 2016; Jackson 2018; Kraft 2019). Most of these studies focus on the elementary or middle school level, examining a range of outcomes, including psychological traits like growth mindset and grit (Kraft and Grace 2015), self-reported self-efficacy and happiness (Blazar and Kraft 2017), academic motivation (Ruzek et al. 2015), teacher-reported measures of children's social and behavior skills (Jennings and DiPrete 2010), and full-day absences (Gershenson 2016; Ladd and Sorensen 2017).

types of absences that are more likely a reflection of the student's perceptions of the teacher. A recent study of middle and high school student attendance in one urban school district finds that approximately one-half of all absences from class were due to class skipping on days that students attended rather than to full-day absences (Whitney and Liu 2017). Third, unlike existing studies that treat absences as a continuous variable despite the fact that absences are a discrete count variable (that is, 0, 1, 2, 3, etc.) and have excessive zeros, we employ a two-level negative binomial model to estimate teacher effects on absences, a method specifically designed for estimation of count variables (Ellison and Swanson 2016).[2] Fourth, using high school graduation, dropout, and AP course-taking data, we test whether teacher value-added to attendance has predictive power for student long-term outcomes above and beyond teachers' impact on student test scores. Only Jackson (2018) has looked at longer-run outcomes by using teacher effects on non-test score outcomes. Finally, we also ask whether subgroups of students respond differently to each dimension of teacher effectiveness. Given at-risk students are likely to have particularly high absenteeism rates, they might benefit more from teachers who are capable of keeping students at school. We directly test the heterogeneity of multidimensional teacher effects based on several student characteristics, an aspect rarely examined in the literature.

The paper proceeds as follows. First, we summarize related literature to motivate the importance of attendance and how teachers can influence student class attendance. We then describe our data and show which student and class characteristics predict absences. In the methods section, we present our identification strategy of estimating teacher effects on student attendance, as well as on test scores. Finally, we describe our approaches for answering the other research questions, present results and robustness checks, and conclude with a discussion of the implications.

II. Background

Prior research has documented the critical role of noncognitive skills for a host of long-term socioeconomic outcomes (Heckman, Stixrud, and Urzua 2006; Cunha, Heckman, and Schennach 2010). While latent noncognitive skills may be difficult to measure, behaviors, such as attendance and class disruptions, are correlated with well-known psychological measures, such as the "Big Five"[3] personality traits, and may serve as good proxies for them (Heckman and Kautz 2013). School attendance is particularly valuable because it can be measured relatively easily and objectively. Psychologists find attendance positively associated with conscientiousness (Duckworth et al. 2007) and negatively associated with neuroticism and low levels of agreeableness (Lounsbury et al. 2003), among other character skills that are valued in the labor market (Heckman, Pinto, and Savelyev 2013).

Quasi-experimental research consistently shows a negative relationship between absences and test scores. Gottfried (2009, 2010, 2011) uses data from the School District

2. We also replicate all the results using an OLS model. See the "Robustness Checks" section for details.
3. The "Big Five" character skills include openness, conscientiousness, extraversion, agreeableness, and neuroticism.

of Philadelphia to examine several facets of the relationship between student absences and achievement. Using proximity from students' homes to their school to instrument for attendance and controlling for school fixed effects, Gottfried (2010) finds a positive relationship between attendance and both grade point average and test scores. Gottfried (2011), alternatively, uses family fixed effects on a longitudinal sample of siblings to control for unobserved heterogeneity in the family environment, which might affect both absences and school performance. He finds a negative relationship between absences and achievement even within families. In a more recent study, Goodman (2014) uses snow days as an instrumental variable and finds that each absence induced by moderate snowfall reduces student math achievement by 0.05 standard deviations. Goodman (2014) also finds evidence that absences can cause lower achievement even among nonabsent students. The teacher is likely to have a "coordination problem" because when absent students return to school, the teacher may need to allocate instructional time to catching up students on what they missed (Goodman 2014).

The prior literature has hypothesized about the role of teachers in encouraging or discouraging absences, though very little empirical work has addressed this relationship directly. Monk and Ibrahim (1984), for example, hypothesize that "if a teacher is weak, or a class is unruly and a student is not learning, the student may respond by being excessively absent." Ladd and Sorensen (2017), similarly, hypothesize that "effective teachers do more for students on a daily basis than simply imparting a narrow set of reading or math skills…such teachers cultivate character, discipline, and curiosity, and a variety of other capacities."

Recent research includes a few studies estimating teacher effects on student social and behavioral outcomes, including attendance (Backes and Hansen 2015; Blazar and Kraft 2017; Gershenson 2016; Jackson 2018; Jennings and DiPrete 2010; Kraft 2019; Kraft and Grace 2015; Ladd and Sorensen 2017; Ruzek et al. 2015). Of these, Gershenson (2016) is the only study that focuses specifically on teachers' impacts on student attendance. The author uses data for third- to fifth-graders from North Carolina and an aggregated measure of absences that does not differentiate excused and unexcused reasons. He finds teacher effects on student attendance that are of approximately the same magnitude in terms of standard deviations as effects on achievement. In a similar vein, Blazar and Kraft (2017) estimate teacher effects for fourth- and fifth-grade teachers on a range of student self-reported measures, including self-efficacy in math and happiness. They find that the magnitudes of teacher effects on these measures are similar to that for test scores. These studies find weak or moderate correlations between teacher effects on non-test score outcomes and their effects on test scores, indicating that teaching is likely to be a multifaceted activity that cannot be captured well by a single outcome measure for students.

The only study looking at nonachievement measures for high school teachers, Jackson (2018), estimated Grade 9 teachers' effects on a composite measure of student GPA, on-time grade completion, suspensions, and full-day attendance in North Carolina. Jackson (2018) distinguishes his work from similar studies not only by examining high school students but also by directly testing how teacher effects on noncognitive outcomes affect students' long-run success. He finds that teacher effects on these outcomes have stronger predictive power than their effects on test scores on student educational attainment, such as high school graduation, SAT taking, and intended college-going. Effects of teachers on these nontest outcomes are key to explaining their effects on long-run outcomes, particularly for English teachers.

Our study extends Jackson (2018) by focusing on class-attendance for the entire secondary grades (except for 12th grade) and how this new dimension of teacher effectiveness predicts student long-run outcomes. In addition, we extend the literature on the long-run effects of multidimensional teacher effectiveness by paying particular attention to the nonlinearities and heterogeneities. In the value-added to achievement literature, there is evidence showing that teachers can be somewhat more effective with one group of students than others (Aaronson, Barrow, and Sander 2007; Lockwood and McCaffrey 2009; Loeb, Soland, and Fox 2014), but less is known about differences in teacher effects across students for long-run outcomes and for alternative teacher effectiveness measures.

Specifically, we pose the following research questions:

Research Question 1: Variance. To what extent do teachers vary in their contribution to student class-attendance?

Research Question 2: Stability. How well does a teacher's value-added to attendance in the current year predict his or her future value-added to attendance, and how does this cross-year relationship compare to that for value-added to achievement?

Research Question 3: Similarity. To what extent are teachers who contribute most to student attendance the same ones who contribute most to student test performance?

Research Question 4: Effects. Does attending classes with a teacher who has high value-added to attendance benefit students in the long run, especially those students with low attendance, low achievement, and high propensity to drop out?

III. Data

Longitudinal administrative data for the study, including school years 2003–2004 through 2013–2014, come from a medium-sized urban school district in California. We focus on students in Grades 7–11, excluding 12th-graders for two reasons. First, 12th-graders do not take standardized tests, so we cannot estimate teachers' value-added to test performance for that grade. Second, 12th-graders are about to graduate and thus have weaker motivation to attend class compared to students in prior grades (that is, so-called "senioritis"), making 12th-graders a special population that deserves separate analyses.

The most unusual feature of this data set is that it has student attendance records for each class on each day and the reasons for absence. During the school years we examine, teachers used a paper scantron to mark a student as absent, tardy, or present in each class. For an absent student, a clerk in the school office would mark the student as excused absent if they received a phone call from a parent or guardian providing reasons for absence; otherwise, the student was identified as unexcused absent for that class. According to interviews with several administrators in the district, teachers had incentives to report absences accurately. The school did not want them to overreport absences because funding was tied to average daily attendance (ADA); however, if a student was recorded as in class when they had a discipline issue or were found to be outside of school, that difference could create problems for the school and the teacher. Thus, deliberate misreporting was not perceived as a problem, although a teacher might make mistakes when tracking student attendance. Whitney and Liu (2017) conduct several validity checks to assess the classification of part-day and full-day absence using the same data set.

Such detailed class-level attendance data are rarely available for researchers. As a result, nearly all the current studies of student attendance use full-day absences, with just a few exceptions and none addressing teacher effects.[4] Since part-day absences account for more than half of total class absences (Whitney and Liu 2017), ignoring part-day absences may result in significant error for estimating days when students do not attend particular classes and may bias estimates of value-added to attendance, as well as result in less reliable measures, especially when part-day absences are nonrandomly distributed among students with different characteristics. Class-level attendance data also allow us to estimate directly teacher effects on the specific student absences for which they are responsible. Since we have information on whether absences are excused or unexcused, we are able to focus on unexcused absences that are more discretionary for students and thus more likely to be affected by teachers.

We combine several databases to construct our final sample. First, we match classes in the attendance data set to their corresponding subject area. We focus our analysis on five core subjects—math, English language arts (ELA), science, social studies, and foreign languages—because noncore subjects like physical education have relatively fewer teachers. Second, we link student attendance data to a rich set of student demographic variables, including race/ethnicity, gender, English learner status (EL), special education status, and gifted status. Third, we add in student test scores from California Standards Tests (CST). Students in Grades 2–11 were required to take these state-mandated tests during the years of our study. Although we also have test scores for science and history, we only use math and ELA test scores in this study because science and history were not tested in each grade. We link teachers to students using a combination of class identifier, school, grade, period, and teacher ID, which in turn allows us to construct classroom-level covariates. For our last research question, we merge in student high school graduation status, whether they dropped out before 12th grade,[5] and their AP course-taking behavior.

In secondary school, a student can have multiple teachers and classes in a subject but only one test score in that specific subject area, which creates a problem for how to construct samples for estimating value-added scores. For the main analysis, we estimate value-added to attendance and achievement for math and English teachers on the same sample, which we fully describe below, though we run specification checks using a range of other samples. We choose this restricted sample so that we can compare value-

4. One prior study of absences uses the average number of absences for each class but does not examine effects of teachers on this measure (Cortes, Bricker, and Rohlfs 2012).

5. The district gave us these long-term outcomes up to school year 2014–2015. For later cohorts (for example, those who were seventh-graders in 2012–2013) for whom we do not have data to observe their graduation and dropout, we assign missing values to these outcomes. For all seventh-graders we can observe in our sample, 56.51 percent graduated from high school, and 28.39 percent dropped out before 12th grade. These numbers are 59.30 percent and 22.50 percent for eighth-graders, 68.40 percent and 16.51 percent for ninth-graders, 81.39 percent and 8.27 percent for tenth-graders, and 91.18 percent and 3.37 percent for 11th-graders. For those who neither graduated nor dropped out, some are transitional school students (Grades 8–9) who did not return to the district and did not submit a school enrollment application for the subsequent year.

added measures on attendance and achievement without the concern that these two measures are estimated using different samples. To create this sample, we constrain the data in several ways. We begin with observations at the student–class-period–semester level. We use only students who have one teacher in a subject for the entire school year. This restriction cuts nearly a quarter (22.6 percent) of our sample[6] but removes the difficulty of disentangling teacher effects on student test scores when multiple teachers are present. This restriction reduces the generalizability of our sample somewhat, though it fits with our purpose of understanding value-added to attendance. We also drop student–class-period–semester observations if one is absent from more than 50 percent of their total classes because students with extremely high absence rates are likely to be absent due to reasons beyond a teacher's control. We thus also drop observations when the student has less than ten valid attendance marks in a class per semester.[7] We also exclude classes with fewer than five students because we would lack precision when estimating teacher effects for such small classes. For the comparison of value-added to achievement and value-added to attendance, we limit the sample to teachers for which we can compute both measures. These restrictions drop an additional 12 percent of the sample.

Table 1 reports the descriptive statistics at the student, classroom, and school level. The first four columns report characteristics of students in all five subjects for both the full sample and the restricted sample,[8] while the next set are math specific, and the last set are for ELA. Overall, we lose about 20 percent of student–year observations using our analytical sample, resulting in 185,000 student-by-year observations and 8,900 teacher-by-year observations. Compared with the full sample, the analytical sample has slightly lower percentages of Black and Hispanic students. The average test scores are higher, and the number of absences are lower, suggesting that we are using a slightly more advantaged group of students, though overall, the samples are quite similar. Our analytical sample includes slightly more male students than females.

One salient feature is that students are racially diverse. About 50 percent of the students are Asian, slightly more than 20 percent are Hispanic, and about 10 percent are Black. The racial composition for math and ELA classes is similar to the whole analytical sample, with slightly more Asian students in math classes. Given this racial composition, it is not surprising that the percentage of EL is about 20 percent. The classroom-level and school-level statistics are similar to those at the individual level.

On average, students have 3.04 unexcused absences for a math class and 2.96 unexcused absences for an ELA class per school year,[9] accounting for 3.96 percent and 3.84 percent of the total class meetings, respectively. For both subjects, the average excused absences are about one-half of the unexcused absences for a class. The

6. 24.21 and 15.54 percent of students have more than one teacher in English and math, respectively.

7. Invalid attendance marks refer to those classes that are inactive, have no record of attendance, or have attendance marks that are miscoded.

8. We constrain this sample using the same criteria as what we do for the sample used to estimate both value-added to attendance and value-added to achievement; that is, every student has only one teacher in a specific subject–year, each class has more than five students, and each student has less than 50 percent of total class absences.

9. Students might take multiple classes in a subject in a school year. We report the averages across all class-periods in the corresponding subject in a school year.

Table 1
Descriptive Statistics

Variable	Full Sample		Analytical Sample					
	All Subjects		All Subjects		Math		ELA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Student								
Female	0.484		0.486		0.483		0.484	
White	0.081		0.081		0.077		0.080	
Black	0.113		0.103		0.091		0.094	
Hispanic	0.218		0.209		0.203		0.197	
Asian	0.498		0.519		0.540		0.537	
EL	0.205		0.197		0.178		0.142	
Excused absences	1.724	(2.821)	1.693	(2.577)	1.602	(2.502)	1.634	(2.518)
Unexcused absences	3.765	(7.000)	3.373	(5.200)	3.040	(4.962)	2.959	(4.901)
Total class meetings	75.069	(17.305)	76.155	(13.918)	76.768	(14.196)	77.132	(13.494)
Math score	0.026	(0.999)	0.058	(0.977)	0.080	(0.948)	0.072	(0.928)
ELA score	0.008	(0.998)	0.044	(0.973)	0.080	(0.925)	0.110	(0.901)
Class-period								
White	0.081	(0.088)	0.082	(0.090)	0.080	(0.095)	0.084	(0.100)
Black	0.111	(0.140)	0.102	(0.140)	0.097	(0.151)	0.100	(0.149)
Hispanic	0.218	(0.211)	0.208	(0.208)	0.203	(0.224)	0.198	(0.215)
Asian	0.502	(0.250)	0.521	(0.249)	0.531	(0.274)	0.526	(0.254)
EL	0.189	(0.014)	0.189	(0.036)	0.188	(0.037)	0.188	(0.036)
Excused absences	1.731	(1.090)	1.708	(1.061)	1.689	(1.176)	1.725	(1.163)
Unexcused absences	3.785	(3.661)	3.970	(3.667)	3.923	(4.249)	3.943	(3.992)

(*continued*)

Table 1 (*continued*)

Variable	Full Sample		Analytical Sample					
	All Subjects		All Subjects		Math		ELA	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total class meetings	75.348	(16.151)	74.209	(16.983)	74.417	(17.574)	74.419	(17.459)
Math score	–0.006	(0.670)	0.010	(0.684)	0.037	(0.754)	–0.004	(0.701)
ELA score	–0.025	(0.726)	–0.009	(0.727)	0.009	(0.755)	–0.026	(0.773)
School								
White	0.084	(0.069)	0.084	(0.070)	0.083	(0.068)	0.081	(0.070)
Black	0.111	(0.093)	0.105	(0.094)	0.102	(0.093)	0.102	(0.093)
Hispanic	0.214	(0.174)	0.206	(0.171)	0.204	(0.171)	0.203	(0.171)
Asian	0.503	(0.201)	0.517	(0.200)	0.523	(0.199)	0.525	(0.199)
EL	0.204	(0.149)	0.200	(0.150)	0.197	(0.151)	0.198	(0.149)
Excused absences	1.745	(0.767)	1.644	(0.711)	1.640	(0.701)	1.633	(0.695)
Unexcused absences	3.677	(2.574)	3.097	(1.878)	3.003	(1.694)	3.061	(1.672)
Total class meetings	75.436	(15.402)	76.673	(12.179)	77.207	(11.864)	76.924	(11.927)
Math score	0.002	(0.499)	0.032	(0.474)	0.016	(0.401)	–0.002	(0.368)
ELA score	–0.013	(0.528)	0.018	(0.509)	0.008	(0.417)	–0.009	(0.377)
Observations								
Student by year	230,686		184,976		136,540		124,800	
Teacher by year	11,372		8,893		2,510		2,606	
School by year	367		367		367		367	

Notes: Data are for all students in Grades 6–11 from school year 2003–2004 through 2012–2013, as we use school year 2002–2003 to generate prior achievement and attendance. Characteristics are calculated using the final matched data sets at student–year level. "All subjects" includes math, ELA, science, social studies, and foreign languages. At the student level, absences and total class meetings are averages across all class-periods taken in the corresponding subject in a school year. To construct the analytical sample, we drop observations when a student has more than one teacher in a subject for the entire school year, is absent from more than 50 percent of classes, has less than ten valid attendance marks in a class per semester, and classes have fewer than five students.

standard deviations are much bigger than the means for both excused and unexcused absences, indicating highly skewed distributions for both variables.[10]

Both student and class characteristics can influence students' decision to attend a class. To better inform our value-added estimation, we use regression analysis to examine how these factors predict unexcused absences.[11] Table 2 synthesizes the results. The dependent variable is the rate of unexcused absences for a class. In the first two columns, we report results using data for all subjects. In Columns 3–6, we report results of separate analyses for math and ELA. The first model contains only the reported variables, while the second includes school-by-year fixed effects, so that the comparison of students and classes are within schools in a given year.

Across different subjects and model specifications, female students have significantly fewer unexcused absences than do males, but the size of the differences are small at about 0.002–0.003. Differences across ethnic groups, in contrast, are quite substantial. Compared with Asian students (the group left out of the model for comparison), Black students have an average unexcused absences rate 6.3 percentage points higher, according to the most conservative estimate. Hispanic students have substantially lower unexcused absence rates than do Black students but exceed the rates for white students and students from other ethnic groups, each of whom have higher average rates than Asian students. Unexcused absences also differ by grade level. Higher grade levels generally have more unexcused absences, with a large jump between Grades 8 and 9 and then relative stability between Grades 9 and 11.

Class characteristics also predict student attendance. For example, attendance varies by the timing of the class. Most schools have seven periods per day, while a few also have a zero or eighth period. We group those periods as a separate group. Students skip the first class in a day more than later ones and are second-most absent from their seventh-period class. The number of unexcused absences varies less by class subject. ELA classes have significantly fewer unexcused absences than do math, science, social studies, and foreign language classes, but the differences are small.

To facilitate constructing our value-added measures, we aggregate our data from the student–class-period–semester level to the student–teacher–year level, which allows us to estimate teacher effects on both test scores and attendance using the same data set. Although a student has only one test score in a subject in a year, students can take more than one class-period with a teacher in a subject, so we aggregate absences for each student–teacher–subject–year combination.[12] This method allows students to have different *exposure times* or total class meetings with a teacher, and, thus, the total number of absences after aggregation are not directly comparable among students. In what follows, we provide a detailed explanation on how our model addresses this issue. For class-level controls, we calculate the average classroom characteristics for all class-periods a student took with a teacher in a certain subject in a year.

10. We calculate total class meetings for each student–class-period cell by aggregating all the unexcused, excused, tardy, and present attendance marks. Classes on average have about 76 meetings in a semester, a 15-week span, assuming students met every day. While the school year is 180 days, some classes do not meet every day, particularly at schools with nontraditional schedules. In addition, on some days students in a class may not meet due to special activities such as school-wide assemblies.

11. For a more comprehensive examination, see Whitney and Liu (2017).

12. If counting one class-period–semester as a class (so Algebra 1 in fall and Algebra 2 in spring are counted as two classes), 33.22 percent students have just one class with a teacher in a subject in a year, and 63.50 percent have two classes.

Table 2
Characteristics Predicting Unexcused Class Absence Rate

	All Subjects		Math		ELA	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	–0.003**	–0.002**	–0.002**	–0.002**	–0.002**	–0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.020**	0.021**	0.021**	0.022**	0.019**	0.021**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black	0.074**	0.063**	0.073**	0.063**	0.070**	0.063**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	0.045**	0.039**	0.045**	0.039**	0.042**	0.037**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other	0.025**	0.023**	0.026**	0.023**	0.025**	0.023**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
English language learner	0.014**	0.010**	0.014**	0.011**	0.014**	0.012**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Grade 8	0.002**	0.002**	0.003**	0.002**	0.003**	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Grade 9	0.031**	0.010**	0.032**	0.015**	0.034**	–0.003
	(0.000)	(0.002)	(0.001)	(0.005)	(0.001)	(0.005)
Grade 10	0.032**	0.010**	0.032**	0.016**	0.032**	–0.004
	(0.000)	(0.002)	(0.001)	(0.005)	(0.001)	(0.005)
Grade 11	0.030**	0.010**	0.032**	0.017**	0.029**	–0.006
	(0.000)	(0.002)	(0.001)	(0.005)	(0.001)	(0.005)
Period 2	–0.009**	–0.009**	–0.008**	–0.008**	–0.008**	–0.008**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Period 3	–0.012**	–0.012**	–0.011**	–0.010**	–0.010**	–0.010**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Period 4	–0.010**	–0.011**	–0.007**	–0.009**	–0.010**	–0.010**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Period 5	–0.010**	–0.010**	–0.009**	–0.009**	–0.008**	–0.008**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Period 6	–0.007**	–0.007**	–0.007**	–0.006**	–0.007**	–0.006**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Period 7	–0.004**	–0.002**	–0.001	–0.000	–0.001	–0.002*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)

(*continued*)

Table 2 (*continued*)

	All Subjects		Math		ELA	
	(1)	(2)	(3)	(4)	(5)	(6)
Other periods	–0.022**	–0.004**	–0.022**	–0.002	–0.012**	–0.008**
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)
Math	0.001**	0.002**				
	(0.000)	(0.000)				
Science	0.001**	0.003**				
	(0.000)	(0.000)				
Social studies	0.001+	0.002**				
	(0.000)	(0.000)				
Foreign language	–0.003**	0.001**				
	(0.000)	(0.000)				
School by year FE		X		X		X
Observations	1,197,741	1,197,741	262,993	262,993	253,235	253,235

Notes: Robust standard errors in brackets are adjusted for clustering at class-period level. $^{**}p<0.01$, $^{*}p<0.05$, $+p<0.10$. The dependent variable is unexcused absence rate at class-period level. "All subjects" includes math, ELA, science, social studies, and foreign languages. The reference group for the race/ethnicity variable is Asian students. The reference group for the period variable is the first period. The reference group for the subject variable is English classes.

IV. Empirical Strategy

A. Estimating Value-Added to Attendance

We estimate a two-level negative binomial regression model (NBRM) to construct value-added measures for teachers' impact on student attendance and estimate the variance in this measure across teachers. Prior studies that use student test scores as outcome variables generally employ an ordinary least squares (OLS) model with teacher or teacher-by-year fixed effects to estimate value-added. The NBRM is better suited than OLS to model teacher effects on attendance given that attendance is a count variable and has excessive zeros, though in some cases NBRM and OLS provide similar results even with count data. We test the relative merits of the approaches for our data by replicating the analyses using OLS models and find that OLS performs worse than NBRM, which we explain in detail in the "Robustness Checks" section. As Figure 1, Panel A shows, the distribution of unexcused absences is extremely skewed. Around 40 percent of the values are zeros at the student–class-period level for math classes. A similar pattern holds for the percentage of unexcused absences over total class meetings for all five subjects at the student–school-year level, for the class-period level, and for the teacher-year level.

The NBRM belongs to the family of models that deal with counts as dependent variables. The NBRM is an extension of the Poisson regression model, adding one more

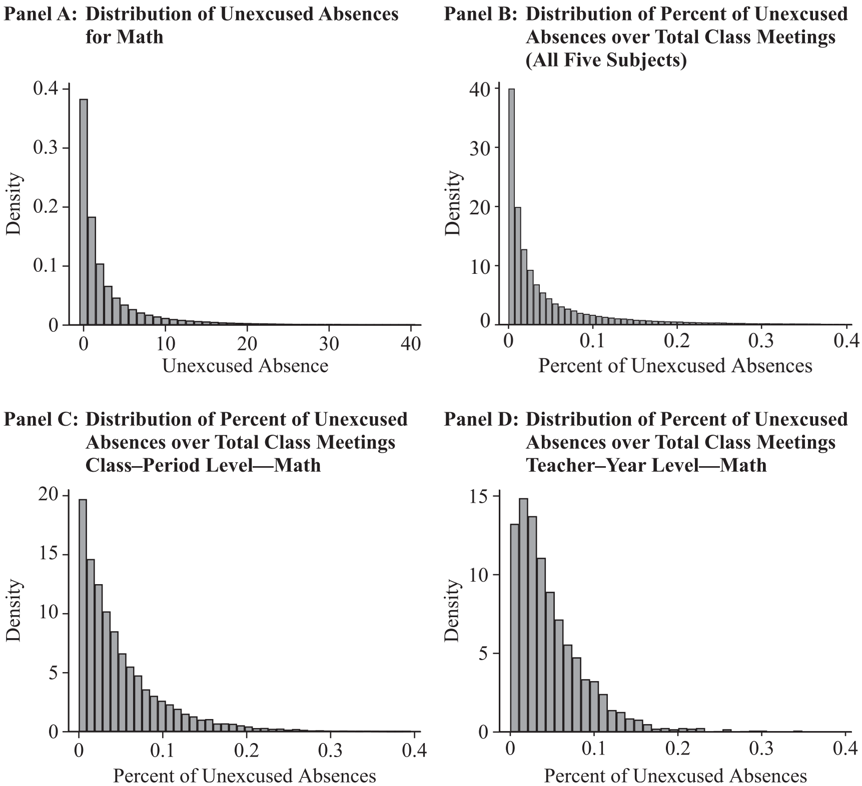


Figure 1

Distribution of Unexcused Absences

Notes: Panel A uses the restricted data at the student–class-period–semester level. Panel B uses the restricted data that have all five subjects at the student–school year level. Panel C uses data collapsed at the class-period level for all math classes during school years 2002–3003 to 2012–2013. Panel D uses data collapsed at the teacher level for all math classes during school years 2002–3003 to 2012–2013. The data are truncated at 40 percent of unexcused absences to show the bulk of the distribution.

parameter to account for overdispersion in the dependent variable, which allows the variance to exceed the mean.[13] The NBRM allows the number of events to have different exposure times and thus can account for students who have the same teacher for different meeting times in a year. We embed the NBRM into a two-level random intercept framework to estimate teacher effects. A two-level random intercept model estimates the

13. We run a simple test to show that the NBRM outperforms the PRM in our setting. We regress student unexcused absences on basic student, class, and school covariates with both models. Then we predict the expected number of unexcused absences given the results of these two models. If there is a smaller difference between the observed value and predicted value for the NBRM compared with the PRM, it suggests the NBRM fits the data better.

variance of value-added directly and provides empirical Bayes estimates of individual teacher effects (McCaffrey et al. 2004).[14]

The greatest challenge to estimating teacher effects is that students may not randomly sort to teachers. Several studies show that controlling for student prior test scores eliminates most of the sorting bias when creating measures of value-added to test performance (Chetty, Friedman, and Rockoff 2014; Kane and Staiger 2008). To reduce the possibility of bias from within-school sorting, we control for student prior absence rates in the same subject, as well as in other subjects, in addition to controlling for student prior test scores. Unlike when calculating teacher effects using data on elementary and middle school students, simply controlling for prior test scores and absences may not fully eliminate selection bias at the high school level because of academic tracks and unobserved track-level treatments (Jackson 2014). The school district we study does not use formal academic tracking. However, students in secondary school chose which math courses to take and, as a result, take different math tests at the end of the year. We use interactions of grade and the test the students took in that grade, as well as in the prior year, to control for possible selection of teachers and students into different courses. Following Jackson (2018), we formally test selection on both observables and nonobservables to further assess whether our controls sufficiently remove bias due to sorting. We do not find evidence of substantive bias for value-added to attendance, as we discuss in the "Robustness Checks" section.

We pool all grades together and estimate the following models separately by subject:

Level 1:

$$E(Abs_{ijt}) = \mu_{ijt} = \exp[X'_{ijt}\beta + \theta_{jt} + \varepsilon_{ijt} + \ln(ET_{ijt})]$$

where $Abs_{ijt} \mid \mu_{ijt} \sim Poisson(\mu_{ijt})$, and $\exp(\varepsilon_{ijt}) \mid \theta_{jt} \sim Gamma(r_{ijt}, p_{ijt})$, and $Cov(X_{ijt}, \theta_{jt}) = 0$, and $Cov(X_{ijt}, \varepsilon_{ijt}) = 0$.

r_{ijt} and p_{ijt} are two parameterizations of conditional overdispersion. Specifically,

$$r_{ijt} = 1/\alpha \text{ and } p_{ijt} = \frac{1}{1 + \alpha * \exp(X'_{ijt}\beta + \theta_{jt})}$$

Level 2:

$$\theta_{jt} = \gamma_{00} + u_{jt}$$

where $u_{jt} \sim N(0, \psi)$.

In this model, the variation driving the estimation comes from teachers who taught students who share similar achievement, attendance, and demographic characteristics and were in the same types of courses, adjusting for differences across grade levels and years. In Level 1, $E(Abs_{ijt})$ or μ_{ijt} indicate student i's expected unexcused absences with teacher j in school year t. X_{ijt} represents a variety of student, classroom, and school

14. A common debate in the value-added literature is whether teacher effects should be treated as fixed or random. In our case, although Hausman, Hall, and Griliches (1984) propose a conditional likelihood method for negative binomial regression with fixed effects, Allison and Waterman (2002) show that it does not qualify as true fixed effects because time-invariant covariates are allowed in their model and can result in a nonzero coefficient on those covariates. This problem arises because the model allows for individual-specific variation in the dispersion parameter instead of in the conditional mean (Rabe-Hesketh and Skrondal 2012). We thus choose to embed the NBRM into a two-level random intercept framework to estimate teacher effects.

characteristics. Online Appendix A gives a full list of controls. θ_{jt} is a random effect for teacher j in year t, which is the teacher-by-year value-added estimate of interest. Alternatively, we estimate value added on the teacher level by replacing θ_{jt} with θ_j, which directly provides variance estimates across teachers. ε_{ijt} is a random error that results in overdispersion, the reason for choosing the NBRM model. ET_{ijt} indicates the exposure time (that is, total class meetings), for student i with teacher j in school year t. By adding this exposure variable, we control for differences in exposure times, with the coefficient constrained to one (Long and Freese 2014). In Level 2, our teacher-by-year effect θ_{jt} follows a normal distribution with mean equal to zero.[15]

In our preferred model, we do not include school fixed effects, although we also run a version of the model with school fixed effects to compare their performance. First, the inclusion of school fixed effects reduces stability and creates additional noise in value-added estimates because only teachers who move between schools identify the school effects (Mihaly et al. 2013; Mansfield 2015). In our case, only about 8.5 percent of teachers switched between schools within the district during the period we examine, which creates much noise in the value-added scores. Second, the literature on teacher effects on achievement finds that once controlling for prior performance, adding school fixed effects does little to further remove bias (Koedel, Mihaly, and Rockoff 2015). Nevertheless, school-level policy might influence student attendance and teachers' ability to reduce student absences. Thus, while we estimate the value-added model without school fixed effects, we include school fixed effects in models estimating how value-added to attendance affects student short- and long-run outcomes. Thus, these estimates use only within-school variation.

Given the nonlinear nature of the model, we can interpret teacher effects as the percentage change of the expected number of unexcused absences. By computing the equation below, we get the percentage change in the expected number of unexcused absences for a student with a teacher who has a value-added of one standard deviation above the average, compared with the result assuming the student has an average teacher, holding other variables constant.

$$\frac{E(Abs_{ijt} \mid X_{ijt}, \psi^{1/2})}{E(Abs_{ijt} \mid X_{ijt}, 0)} = \exp(\psi^{1/2})$$

The result is given by $100 \times [\exp(\psi^{1/2}) - 1]$.

We predict the Empirical Bayes (EB) estimates of the teacher–year effects by using the means of the empirical posterior distribution with the estimated model parameters including $\hat{\beta}$, $\hat{\alpha}$, and the variance components of ψ.[16] We then standardize these EB

15. The variance of u_{jt} (that is, ψ) is a $q \times q$ variance matrix Σ. The conditional distribution of $Abs_{jt} = \{Abs_{1jt}, \ldots, Abs_{njt}\}'$ given random effects u_{jt} and the conditional overdispersion parameter α is

$$f(Abs_{jt} | u_{jt}, \alpha) = \Pi \frac{\Gamma(Abs_{ijt} + r_{ijt})}{\Gamma(Abs_{ijt} + 1)\Gamma(r_{ijt})} p_{ijt}^{r_{ijt}} (1 - p_{ijt})^{Abs_{ijt}}.$$

The likelihood function for teacher j in year t is

$$\mathcal{L}_{jt}(\beta, \Sigma, \alpha) = (2\pi)^{\frac{1q}{2}} |\Sigma|^{-\frac{1}{2}} \int f(Abs_{jt} | u_{jt}, \alpha) \exp(-u'_{jt}\Sigma^{-1}u_{jt}/2) du_{jt}.$$

16. For a complete introduction of this procedure, see Rabe-Hesketh and Skrondal (2012).

estimates to have a mean of zero and a standard deviation of one. Since the dependent variable is unexcused absences, a bigger value in these EB estimates indicates a bigger effect on increasing unexcused absences. To ease interpretation, we convert them to *value-added to attendance* by multiplying all the EB estimates by −1.

We test the robustness of our results using excused absence as an outcome variable to conduct a form of a placebo test. In theory, students need legitimate reasons, such as sickness, to have an excused absence, which should be free from a teacher's influence. In practice, excused absences may be fungible, for example, if students are more likely to feign sickness or to schedule doctors' appointments or other appointments during classes in which they are not engaged. Nonetheless, unexcused absences are likely to be more affected by teachers than are excused absences, and, thus, the estimated variance of value-added to unexcused absences should be larger than that for excused absences.

B. Estimating Value-Added to Achievement

We estimate value-added to achievement so that we can examine how the two measures of teacher effectiveness correlate and compare their stability. We adopt a widely used strategy that estimates teacher or teacher-by-year fixed effects, accounting for student math and reading test scores in the prior year. An experimental study shows that this model outperforms other models of teachers' value added to student test scores (Guarino et al. 2015). We compute empirical Bayes estimates after running the fixed-effects model by summarizing the estimated standard errors to estimate the sampling error variance and then shrinking the estimates by a signal-to-noise ratio based on this sampling error variance.

V. Results

A. Variance

By running NBRM separately for each subject, we obtain a standard deviation of value-added to attendance for each of math, ELA, science, social studies, and foreign languages.[17] Table 3 gives the results, reporting both teacher-level and teacher-by-year-level estimates since both come into play in subsequent analyses. The first column shows the raw standard deviations. Predictably, teacher-level estimates have smaller variances than teacher-by-year estimates for each subject.

Because we use the number of unexcused absences as dependent variables, these standard deviations do not provide an intuitive interpretation of the magnitude, nor can we compare them directly to value-added to achievement. Instead, in Column 2 of Table 3, we report the incidence rate ratio (IRR) of one standard deviation of value-added to attendance, which has a multiplicative interpretation. For example, a student would have 44.3 percent fewer unexcused absences in math classes if they had a teacher who was one standard deviation above the average than they would if they had an

17. In OnlineAppendix B, we report the regression results for estimating math teachers' value-added to attendance. In Online Appendix C, we report both the variances and the stability of value-added estimates after adding school fixed effects to our base specification. As expected, value-added to attendance has a much smaller variance and is less stable after adding school fixed effects.

Table 3
Magnitude of Teacher and Teacher-by-Year Effects on Student Absences

		SD	Incidence Rate Ratio
Teacher	Math	0.366	1.443
	ELA	0.433	1.541
	Science	0.422	1.525
	Social studies	0.402	1.495
	Foreign languages	0.403	1.496
Teacher by Year	Math	0.447	1.564
	ELA	0.478	1.612
	Science	0.479	1.615
	Social studies	0.467	1.595
	Foreign languages	0.409	1.505

Notes: Standard deviations are directly estimated from two-level negative binomial models. Incidence rate ratio is calculated using exp(SD).

average teacher, holding other variables constant. To make the magnitude more intuitive, consider a typical math class that has 77 class meetings a semester (Table 2). For a chronically absent[18] student who has an expected absence rate of 10 percent (that is, 7.7 class meetings for this math class), the magnitude equals a reduction of 3.4 unexcused absences. The incidence rate ratio is greater, 54.1 percent, for English classes.[19]

As expected, we find that the magnitude of the variance of value-added to attendance when using excused absence is smaller than for unexcused absences. Specifically, the standard deviation is 0.23 for math (compared with 0.37 for unexcused absence) and 0.24 for ELA (compared with 0.43 for unexcused absence), suggesting that unexcused absence is more malleable and that teachers have a greater impact on it.

B. Stability

To investigate the stability of value-added to attendance, we conduct two analyses. First, we generate transition matrixes to examine how teachers' quintile rankings change from the first two years we observe them to their third through fifth years. We compute teachers' quintile ranking by taking the average of each teacher's first two years' value added and also the following three years. If a large proportion of teachers stay where

18. The U.S. Department of Education defines chronic absenteeism as missing 15 or more days of school per year (U.S. Department of Education, Office of Civil Rights 2018), but many reports and research studies use 10 percent of school days. Because we have class-level attendance data, following Whitney and Liu (2017), we choose to use total class meetings as the denominator instead of school days.

19. We also estimate a model controlling for school fixed effects, so we are only comparing teachers within schools, though, as discussed above, the approach has drawbacks. The standard deviation is 0.282 (IRR = 1.326) for math teachers and 0.348 (IRR = 1.417) for English teachers, both slightly smaller than the results without school fixed effects. Because school fixed-effects models identify school effects through the relatively small sample of movers, we prefer a model without school fixed effects and focus on this preferred model in this paper.

they are initially in their third through fifth years or move very little, we have evidence to say that value-added to attendance is a relatively stable measure. Although transition matrixes provide an intuitive way to measure the stability of value-added to attendance, they do not offer a succinct measure of how well early value-added predicts future value-added. Moreover, they do not capture variation within the quintiles. Thus, we conduct a second analysis that regresses teachers' value added for a future year (three, four, or five) on their first two years of value added. The adjusted R-squared statistics measure how much variation is explained by teachers' early years' effectiveness (Atteberry, Loeb, and Wyckoff 2015). To benchmark the results, we do the same analysis on value-added to achievement so that we can compare the measures. Throughout these two analyses, we limit our analytical sample to teachers who have at least five years of value-added to attendance and to achievement.

We find substantial stability in value-added measures for teachers over time. Table 4, Panel A reports the quintile transition matrixes for value-added to class attendance.[20] About 67 percent of teachers who are in the lowest quintiles in terms of their average value-added to attendance during the first two years we observe them (the least effective ones) stay in the bottom two quintile in the following three years, and 78 percent of the initially top teachers stay in the top two quintiles. For comparison, Table 4, Panel B gives the corresponding transition matrixes for value-added to achievement.[21] Value-added to achievement is approximately as stable as value-added to attendance, with 70 percent of the lowest quartile teachers remaining in the lowest two quintiles and 79 percent of the highest quartile teachers remaining in the highest two quintiles.

For further evidence of stability, Table 5 reports the adjusted R-squared from regression analyses that measure how teachers' early years' effectiveness predicts future years' performance. The first row of the table reports the adjusted R-squared when we regress value-added to attendance in Years 3, 4, and 5 and the average of all three years on the first year and/or second year of available value-added measures. Panel A shows results from using value-added to attendance, and Panel B shows results from using value-added to achievement. In keeping with the transition matrixes, the regression analyses show substantial predictive power for the value-added to attendance measures. This predictive power is similar to that for value-added to achievement. The first two years of value-added to math attendance explains 39.7 percent of the variance in the average value-added in Years 3–5. This figure for attendance is 22.6 percent for English teachers. In comparison, the percent explained for achievement is 36.3 percent for math and 28.0 percent for English.

C. Similarity

Our third research question asks how correlated measures of value-added to attendance are to measures of value-added to achievement. We use both Pearson correlation and Spearman rank correlation to examine this question. We disattenuate the Pearson correlations by dividing the correlations by the square root of the product of the reliabilities of each value-added measure in each subject. We expect to see a stronger correlation

20. We compute teachers' ranking quintiles by subject, but in those transition matrixes we combine math and English teachers into one table.

21. After adjusting for measurement error, the true standard deviation of value-added to achievement is 0.17 for math and 0.10 for English.

Table 4
Transition Matrix: Value-Added to Attendance and Achievement

		Quintile of Future Performance					
Initial Quintile		Q1	Q2	Q3	Q4	Q5	Row
Panel A: Value-Added to Attendance							
Q1	*n*	35	18	13	12	1	79
	(row %)	(44.30)	(22.78)	(16.46)	(15.19)	(1.27)	(100.00)
Q2	*n*	24	12	20	13	8	77
	(row %)	(31.17)	(15.58)	(25.97)	(16.88)	(10.39)	(100.00)
Q3	*n*	10	22	18	19	9	78
	(row %)	(12.82)	(28.21)	(23.08)	(24.36)	(11.54)	(100.00)
Q4	*n*	6	19	20	12	20	77
	(row %)	(7.79)	(24.68)	(25.97)	(15.58)	(25.97)	(100.00)
Q5	*n*	4	6	7	21	39	77
	(row %)	(5.19)	(7.79)	(9.09)	(27.27)	(50.65)	(100.00)
Column total		79	77	78	77	77	388
Panel B: Value-Added to Achievement							
Q1	*n*	36	19	11	11	2	79
	(row %)	(45.57)	(24.05)	(13.92)	(13.92)	(2.53)	(100.00)
Q2	*n*	24	21	18	12	2	77
	(row %)	(31.17)	(27.27)	(23.38)	(15.58)	(2.60)	(100.00)
Q3	*n*	8	14	25	18	13	78
	(row %)	(10.26)	(17.95)	(32.05)	(23.08)	(16.67)	(100.00)
Q4	*n*	7	17	18	16	19	77
	(row %)	(9.09)	(22.08)	(23.38)	(20.78)	(24.68)	(100.00)
Q5	*n*	4	6	6	20	41	77
	(row %)	(5.19)	(7.79)	(7.79)	(25.97)	(53.25)	(100.00)
Column total		79	77	78	77	77	388

Notes: Only using teachers who have at least five years' observations in our sample. Bottom quintiles represent those who are least effective in reducing unexcused absences. We combine math and English teachers together, though we calculate their quintiles by subject.

when using teacher value added than using teacher-by-year value added because the teacher-level estimates use information from multiple cohorts of students and will be less prone to measurement error.

Alternatively, we run a joint multilevel model to estimate our two value-added measures simultaneously so that we can estimate the covariance directly. Previous research has used a similar approach to examine whether the same teacher has differential effects when teaching different subjects (Fox 2016) or different types of students (Loeb, Soland,

Table 5
Adjusted R-Squared Using Early Year Value-Added to Predict Future Performance

Early Year VA Predictor(s)	VA in Y3	VA in Y4	VA in Y5	Mean(VA_{Y3-5})
Panel A: Outcome (Attendance)				
Math				
Math VA in Y1 Only	0.222	0.205	0.076	0.226
Math VA in Y2 Only	0.260	0.312	0.172	0.355
Math VA in Y1 & Y2	0.319	0.349	0.174	0.397
ELA				
ELA VA in Y1 Only	0.282	0.108	0.078	0.216
ELA VA in Y2 Only	0.309	0.140	0.088	0.251
ELA VA in Y1 & Y2	0.222	0.205	0.076	0.226
Panel B: Outcome (Achievement)				
Math				
Math VA in Y1 Only	0.216	0.260	0.098	0.280
Math VA in Y2 Only	0.315	0.176	0.094	0.282
Math VA in Y1 & Y2	0.352	0.289	0.123	0.363
ELA				
ELA VA in Y1 Only	0.112	0.130	0.066	0.209
ELA VA in Y2 Only	0.148	0.148	0.088	0.265
ELA VA in Y1 & Y2	0.216	0.260	0.098	0.280

Notes: Only using teachers who have at least five years' observations in our sample. All entries are adjusted *R*-squared.

and Fox 2014). Although this model does not allow us to use a NBRM framework anymore, it has the benefit of reducing sampling errors. Online Appendix D gives a more detailed description of this model.

Overall, the correlations between value-added to attendance and value-added to achievement are small, though a bit stronger for math than for ELA. At the teacher level, after adjusting for reliabilities,[22] the Pearson correlation is 0.115 for math and 0.082 for ELA. Correspondingly, the Spearman rank correlation for math teachers is 0.132 and for English teachers 0.012.[23] Figure 2 provides a visual description of these correlations. We further test these results by using a joint model to directly estimate the covariance of the two value-added scores. The resulting correlation is 0.063 for math and 0.070 for ELA. As a reference, Gershenson (2016) reports near zero correlations (Spearman rank correlation is 0.04 for math teachers and 0.02 for English teachers) for

22. The reliability of value-added to attendance is 0.82 for math and 0.79 for ELA. The reliability of value-added to achievement is 0.89 for math and 0.70 for ELA.
23. If we use value-added measures from a model with school fixed effects, the correlations are similar to the results here. Specifically, after adjusting for measurement error, the Pearson correlation is 0.135 for math and 0.015 for ELA. Correspondingly, the Spearman rank correlation for math teachers is 0.174 and for English teachers is 0.015.

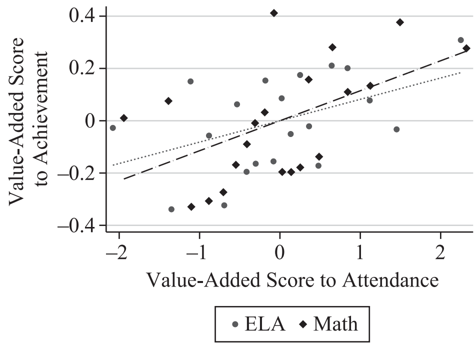


Figure 2
Binned Scatter Plot: Teacher Effects on Attendance versus Teacher Effects on Achievement

elementary teachers. Pooling together both math and ELA, Jackson (2018) reports a Pearson correlation of 0.097 for ninth grade teachers.[24] Our results are consistent with the literature in terms of showing teacher effectiveness as multidimensional, as suggested by the low correlations across measures.

Another approach to answering this question is to regress student outcomes (that is, test score and rate of unexcused absence) on value-added to achievement and value-added to attendance.[25] If these two measures capture distinct dimensions of teacher ability, we would expect to see no impact of value-added to achievement on attendance and value-added to attendance on test scores. To avoid "mechanical endogeneity" of our value-added measures, as discussed by Chetty, Friedman, and Rockoff (2014) and Jackson (2018), we estimate "leave-year-out" value added by using all data except the year when the focal student has the teacher (that is, Jackknife estimates). We standardize those value-added estimates using the "true" standard deviations of teacher effects estimated in RQ 1 and RQ 2.[26] The standard deviation of value-added to achievement is 0.17 for math and 0.10 for ELA. The standard deviation of value-added to attendance is 0.37 for math and 0.44 for ELA. In these models, we include school fixed effects in order to eliminate the time-invariant factors within schools that could affect both measures of teacher effectiveness and student outcomes.

Table 6 presents the results. As Columns 1 and 5 show, the leave-year-out estimates of teacher effects for one outcome strongly predict that outcome. A one standard deviation increase in value-added to achievement improves student test scores by 0.08 standard

24. Both Gershenson (2016) and Jackson (2018) originally report negative cross-domain correlations because they do not convert teacher effects on absence to teacher effects on attendance. We change the direction here to ease comparison.
25. To ease interpretation, we run linear regressions for both outcomes, though we use a nonlinear model to estimate value-added to attendance.
26. For the two-level negative binomial model, the variance of teacher value-added to attendance is directly estimated. For the fixed-effects model used to estimate value-added to achievement, the true variance equals the observed variance minus the variance of errors.

Table 6
Effects of Out of Sample Teacher Effects on Current Outcomes

	Test Scores			Unexcused Absence Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Test score VA	0.08161** (0.00154)		0.08160** (0.00155)	–0.00046** (0.00013)		0.00011 (0.00013)
Attendance VA		0.00946** (0.00183)	0.00013 (0.00182)		–0.00790** (0.00016)	–0.00791** (0.00016)
Observations	223,623	223,623	223,623	223,623	223,623	223,623
Adjusted R^2	0.657	0.653	0.657	0.428	0.434	0.434

Notes: Each column reports coefficients from an OLS regression, with standard errors clustered at both student and teacher level to account for correlation between observations. The columns are estimated using the stacked sample that pools together both math and ELA for students in Grades 7–11. Dependent variables are current test scores and unexcused absence rates. All columns control for the baseline student-, class-, and school-level characteristics, which include lagged math and English scores, absence rates, suspension, and demographic composition; tests students took in both previous and current year interacted with grade; year fixed effects; subject fixed effects; and school fixed effects. Value-added scores are "leave-year-out" estimates standardized using "true" standard deviations of teacher effects estimated using all years of data. $^{**}p < 0.01$, $^{*}p < 0.05$, $+p < 0.10$.

deviation (p-value < 0.01), and a one standard deviation increase of value-added to attendance reduces a student's unexcused absence rate by 0.79 percentage points (p-value < 0.01). Columns 2 and 4 indicate that a teacher who is more effective in increasing student test scores can also reduce student absences, and vice versa, although the magnitude is much smaller than those from Columns 1 and 5. This result is expected given the weak but positive correlation between the two measures of teacher effects. When including both value-added estimates in the same regression, conditional on value-added to achievement, value-added to attendance does not demonstrate an impact on test scores, and both the magnitude and significance of value-added to achievement stay approximately the same. Similar results hold when using the unexcused absence rates as the outcome. These results further confirm the weak correlation of our two measures of teacher effects, which measure largely distinct dimensions of teacher ability.

D. Effects

To examine the effects of high value-added to attendance teachers on longer-run outcomes, we use as outcome measures high school graduation, dropping out of high school before 12th grade, and the total number and credits earned for AP courses in 12th grade.[27] The two sets of measures—one focused on completion and one on higher-level

27. In our sample, 53.36 percent of AP courses are taken in 12th grade, and 37.97 percent are taken in 11th grade. We only use AP courses taken in 12th grade to avoid mechanical endogeneity since we are using seventh- to 11th-grade teachers.

course-taking—allow us to examine outcomes for students at different parts of the academic distribution. The completion margin is more salient for students who are marginally engaged with schools and, on average, are likely to have lower achievement and attendance, while AP taking is more salient for highly engaged students who are choosing between more and less challenging coursework but, on average, have higher achievement and attendance.

To construct this data set, we pool math and ELA classes for all students in Grades 7–11. Under this data structure, each student has one outcome but multiple observations (because of multiple subjects and grades). We account for the correlation of observations by clustering the standard errors at both student and teacher levels. We regress our dependent variables on the standardized leave-year-out value-added to achievement and value-added to attendance separately and then together. Of particular interest is whether adding value-added to attendance affects student outcomes in the long run, after controlling for value-added to achievement. In all the models, we control for baseline covariates as what we did in RQ 1, including student demographics, lagged test scores and attendance, lagged and current academic "tracks" (test types), and classroom and school characteristics. In addition, we include school fixed effects to account for time-invariant school characteristics that could independently affect value-added and student outcomes.

Table 7 presents the first set of results, pooling data for math and ELA for students in Grades 7–11. Panel A of Table 7 reports results using high school graduation and dropout as the outcome variables. Teachers with high value-added to attendance increase students' probability of graduating from high school and reduce their chance of dropping out before Grade 12, independent of their effectiveness in increasing student test scores. Although value-added to achievement has a positive coefficient for high-school graduation, it is insignificant. In contrast, value-added to attendance shows significant impact on high-school graduation. Specifically, a one standard deviation increase in value-added to attendance improves a student's probability of high-school graduation by 0.7 percentage points. When both measures are in the same regression, the coefficients maintain similar magnitude and significance. The results for value-added to attendance are similar when using dropout as the outcome variable. A one standard deviation increase in value-added to attendance reduces a student's probability of dropping out before 12th grade by 0.3 percentage points, with no discernable effect of test-score value added with or without value-added to attendance in the regression.

The story is somewhat different when using AP course-taking as outcomes (Table 7, Panel B). Value-added to achievement and value-added to attendance both have significant and positive estimated effects on the number and earned credits of AP courses. Here, however, the estimated effects are smaller for value-added to attendance. Specifically, a one standard deviation increase in value-added to achievement increases the number of AP courses taken by 0.02 and AP credits by 0.10. These numbers are 0.01 and 0.06, respectively, for value-added to attendance.

To investigate potential nonlinearity of teacher effectiveness, we examine long-term outcomes by classifying teachers into deciles based on their value-added to attendance and value-added to achievement. We then run a semiparametric model using teachers who are in the fifth decile as the reference group, as these are the "median" teachers. These analyses provide insights into whether the effects on longer-term outcomes of variation among low value-added teachers are stronger than the effects among higher

Table 7
Effects of Out-of-Sample Teacher Effects on Long-Term Outcomes

	Graduation			Dropout Before 12th Grade		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Graduation and Dropout						
Test score VA	0.00117 (0.00109)		0.00055 (0.00111)	–0.00050 (0.00076)		–0.00024 (0.00077)
Attendance VA		0.00710** (0.00126)	0.00702** (0.00128)		–0.00293** (0.00086)	–0.00289** (0.00088)
Observations	197,639	197,639	197,639	197,639	197,639	197,639
Adjusted R^2	0.208	0.208	0.208	0.107	0.107	0.107
	Number of AP Courses			Credits of AP Courses		
Panel B: AP Course-Taking						
Test score VA	0.02272** (0.00239)		0.02168** (0.00239)	0.11314** (0.01189)		0.10771** (0.01189)
Attendance VA		0.01470** (0.00310)	0.01172** (0.00310)		0.07561** (0.01541)	0.06082** (0.01542)
Observations	197,639	197,639	197,639	197,639	197,639	197,639
Adjusted R^2	0.306	0.306	0.306	0.305	0.305	0.305

Notes: Each column, within panels, reports coefficients from an OLS regression, with standard errors clustered at both the student and teacher level to account for correlation between observations. The columns are estimated using the stacked sample that pools together both math and ELA for students in Grades 7–11. Both the number and credits earned for AP courses include only those taken in 12th grade to avoid mechanical endogeneity. All columns control for the baseline student-, class-, and school-level characteristics, which include lagged math and English scores, absence rates, suspension, and demographic composition; tests students took in both previous and current year interacted with grade; year fixed effects; subject fixed effects; and school fixed effects. Value-added scores are "leave-year-out" estimates standardized using "true" standard deviations of teacher effects estimated using all years of data. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.10$.

value-added teachers and whether these patterns differ for the two dimensions of teacher effectiveness. Figures 3A and 3B plot the coefficients and standard errors of all the deciles relative to the fifth decile. The detailed results are reported in Online Appendix Table E1.

We find, as described by Figure 3A, that the impact of value-added to attendance on graduation increases steadily from decile 1 to decile 6, but then levels off for the higher deciles. That is, the effects of teachers' value-added to attendance on high school graduation are driven primarily by the negative effects of particularly ineffective teachers. This pattern does not hold for the other outcome measures. In particular, while the

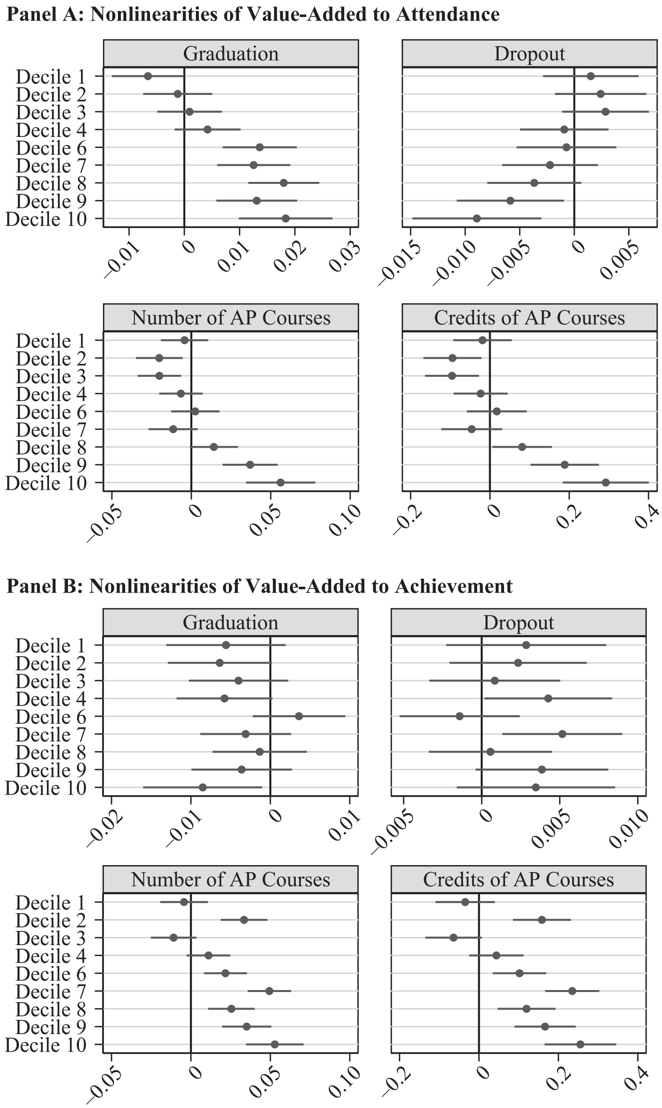


Figure 3

Nonlinearities of Value-Added to Attendance and Achievement

Notes: Panels are based on Online Appendix Table E1. Each subgraph is from a separate regression. Reference groups are teachers who are in the fifth decile.

results provide some evidence that low value-added to attendance teachers discourage students from AP course-taking, high value-added to attendance teachers more clearly help students to pursue higher academic goals, especially teachers in the top two deciles. So, for the AP outcome measures, the effects are more driven by variation among the high value-added to attendance teachers. We find less evidence of nonlinearities for value-added to achievement. Teachers' value-added to achievement does not appear to affect students' graduation or dropout behavior at any part of the value-added distribution. The effects on AP course-taking are positive but are relatively linear across the distribution of teachers' value-added to achievement. Given the variation in these relationships across the outcomes, the results are suggestive but not definitive for either value-added to attendance or value-added to achievement.

To examine the potential heterogeneous effects across students, we categorize students by their prior year's attendance, prior year's math test scores, and probability of graduating from high school. We also use chronic absenteeism status to classify students, as this is a widely used indicator in school accountability systems.[28] Specifically, we run separate regressions for students who are in the bottom, middle, and top thirds of the first three measures. Similarly, for chronic absenteeism status, we run regressions for those who are and who are not chronically absent (Table 8). These analyses provide insights, for example, into whether students who are on the margin of dropping out benefit more from teachers who can keep them at school, while students who are already academically advanced need teachers with a different skillset to motivate them to pursue higher learning goals, such as AP courses. We report the results in Online Appendix Table E2 and the first two columns in Table E3 and visually show them in Figure 4A–4D.

Figure 4A plots the results for using prior attendance to classify students into subgroups. Heterogeneity is evident. Teachers' value-added to achievement has little effect on graduation or dropping out for any of the student groups, but teachers' value-added to attendance does, and it is particularly important for low attenders. For example, a one standard deviation increase in value-added to attendance improves a student's probability of high school graduation by 1.13 percentage points. Since high-attendance students are not missing a lot of school and likely have a low risk of dropping out, it is not surprising that we observe little relationship between either type of value added and graduation or dropout of high-attendance students. For outcomes related to AP course-taking, test-score value-added has a positive effect for all students, but the effects are strongest in the top of the prior attendance distribution. The results are largely opposite for value-added to attendance, for which the teacher effectiveness measure has no effect for students at the top of the prior attendance distribution, but positive effects for students with worse prior attendance. Overall, a teacher's value-added to attendance is more important for less engaged students, while a teacher's value-added to achievement is more important for more engaged students.

We find largely consistent effects if we use prior math scores (Figure 4B) and predicted probability of graduation (Figure 4C) to classify students into tertiles. For students in the bottom tertile of both measures, their teachers' value-added to attendance predicts greater longer-run outcomes across measures. For students in the top tertile of

28. We predict the probability of high school graduation by using lagged math and English scores, absence rates, suspension, and demographic. Chronic absenteeism status is defined as missing at least 10 percent of total class meetings in the previous year.

Table 8
Heterogeneity of Teacher Effects on Long-Term Outcomes: By Chronic Absenteeism Status, Gender, and Race

	Chronically Absent (1)	Nonchronically Absent (2)	Female (3)	Male (4)	Black/Hispanic (5)	White/Asian (6)
Panel A: Graduation						
Test score VA	0.00024	0.00064	0.00559*	–0.00150	0.00166	0.00020
	(0.00150)	(0.00162)	(0.00240)	(0.00122)	(0.00308)	(0.00114)
Attendance VA	0.00678**	0.00819**	0.00977**	0.00816**	0.01218**	0.00584**
	(0.00173)	(0.00186)	(0.00326)	(0.00132)	(0.00420)	(0.00128)
Adjusted R^2	0.198	0.215	0.191	0.123	0.194	0.154
Panel B: Dropout before 12th Grade						
Test score VA	–0.00035	–0.00006	–0.00248	0.00097	–0.00010	–0.00040
	(0.00106)	(0.00111)	(0.00185)	(0.00073)	(0.00243)	(0.00073)
Attendance VA	–0.00328**	–0.00258*	–0.00349	–0.00393**	–0.00565+	–0.00163+
	(0.00119)	(0.00127)	(0.00243)	(0.00081)	(0.00317)	(0.00084)
Adjusted R^2	0.101	0.113	0.111	0.054	0.136	0.070
Panel C: Number of AP Courses						
Test score VA	0.02503**	0.02071**	0.01234**	0.02596**	0.00721*	0.02417**
	(0.00360)	(0.00317)	(0.00275)	(0.00350)	(0.00308)	(0.00284)
Attendance VA	0.00564	0.01543**	0.00595	0.00005	0.02290**	0.00372
	(0.00458)	(0.00417)	(0.00372)	(0.00425)	(0.00448)	(0.00355)
Adjusted R^2	0.306	0.299	0.184	0.302	0.201	0.300

(*continued*)

Table 8 (*continued*)

	Chronically Absent (1)	Nonchronically Absent (2)	Female (3)	Male (4)	Black/Hispanic (5)	White/Asian (6)
Panel D: Credits of AP Courses						
Test score VA	0.12328**	0.10404**	0.06007**	0.12879**	0.03422*	0.12060**
	(0.01793)	(0.01578)	(0.01349)	(0.01745)	(0.01499)	(0.01415)
Attendance VA	0.03272	0.07761**	0.03036+	0.00239	0.11184**	0.02172
	(0.02284)	(0.02072)	(0.01828)	(0.02120)	(0.02196)	(0.01768)
Adjusted R^2	0.306	0.297	0.181	0.301	0.198	0.299
Observations	96,317	101,322	52,063	127,302	35,540	162,099

Notes: Each column, within panels, reports coefficients from an OLS regression, with standard errors clustered at both student and teacher level to account for correlation between observations. The columns are estimated using the stacked sample that pools together both math and ELA for students in Grades 7–11. Both number and credits of AP courses include only those taken in 12th grade to avoid mechanical endogeneity. All columns control for the baseline student-, class-, and school-level characteristics, which include lagged math and English scores, absence rates, suspension, and demographic composition; tests students took in both previous and current year interacted with grade; year fixed effects; and subject fixed effects. Value-added scores are “leave-year-out” estimates standardized using “true” standard deviations of teacher effects estimated using all years of data. $^{**}p < 0.01$, $^{*}p < 0.05$, $+p < 0.10$.

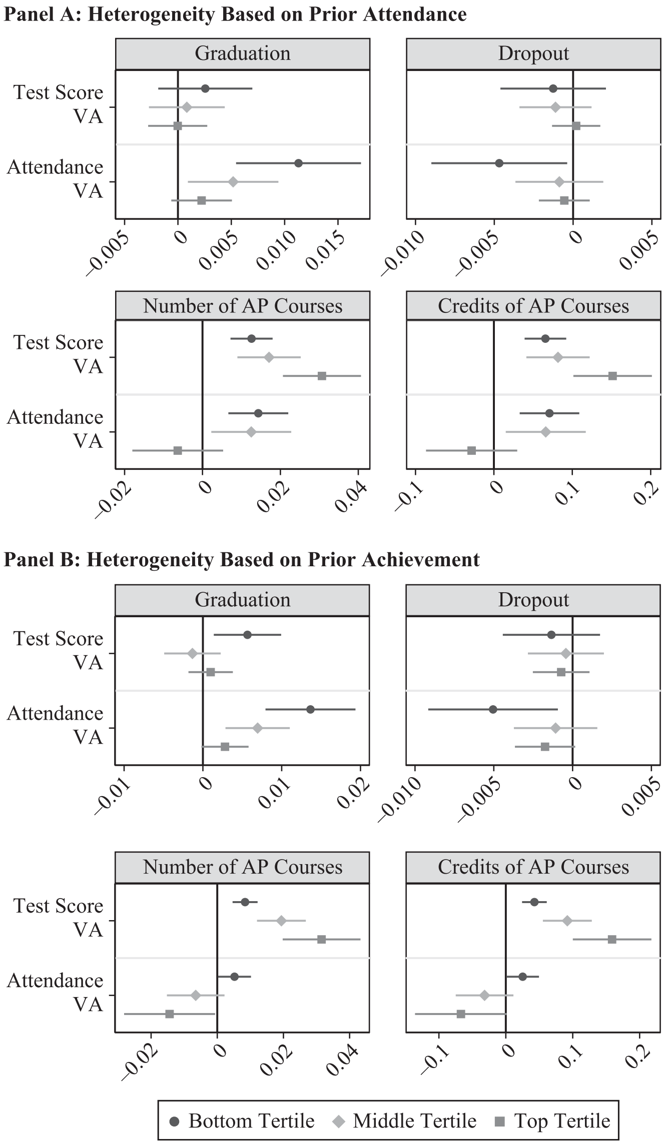
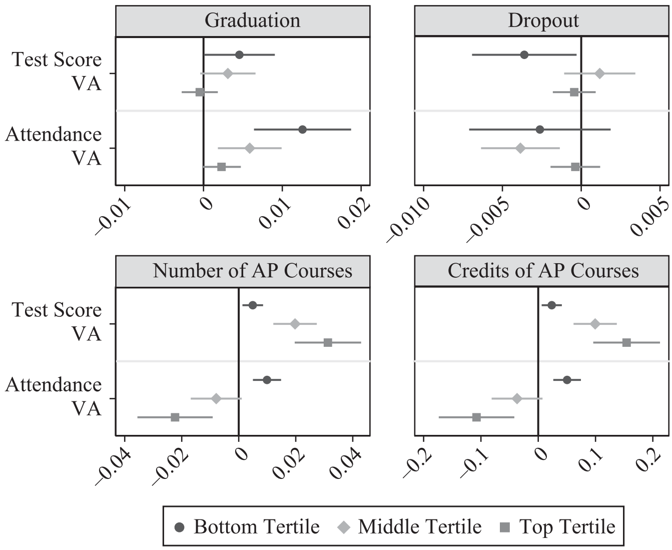


Figure 4

Heterogeneity Based on Prior Attendance, Achievement, Predicted Probability of Graduation, and Chronic Absenteeism Status

Notes: Panels A, B, and C are based on Online Appendix Table E2, and each subgraph is from a separate regression. Panel A: Tertiles are based on student prior attendance. Panel B: Tertiles are based on student prior achievement. Panel C: Tertiles are based on students' predicted probability of high school graduation. Panel D is based on Online Appendix Table E3, and each subgraph is from a separate regression. Chronic absenteeism is defined as missing at least 10 percent of total class meetings in the previous year.

Panel C: Heterogeneity Based on Predicted Probability of Graduation



Panel D: Heterogeneity Based on Chronic Absenteeism Status

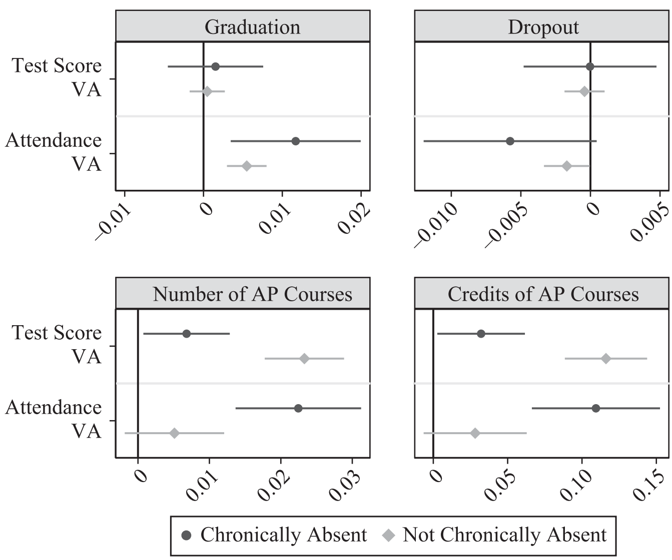


Figure 4 (*continued*)

the measures, value-added to attendance has no effect on AP course behaviors, but value-added to achievement does. Value-added to achievement also has a stronger effect on these students than on students with less positive priors. The results are similar if we classify students using their chronic absenteeism status in the previous year (Figure 4D), with chronically absent students benefiting substantially more from high value-added to attendance teachers.

We also examine heterogeneity by gender and race. Online Appendix Table E3 presents the results. We do not find significant differences by race and gender for value-added to attendance on almost all the outcomes, but value-added to achievement has a substantially bigger effects on AP courses for white and Asian students compared with black and Hispanic students, a group on average academically weaker than their white and Asian peers.

Taken as a whole, our results confirm the multidimensional nature of teacher effectiveness. A teacher who has high value-added to attendance is likely able to engage students in class and motivate the student to pursue higher academic goals, and this impact is more salient for students with low attendance, low achievement, low probability of graduation and who tend to be chronically absent. In contrast, teachers with high value-added to achievement are likely to help students to pursue higher academic goals. They are especially impactful for those students who are academically more advanced, but do little to improve graduation and reduce dropout for students prone to missing classes.

E. Robustness Checks

First, we check the difference between OLS and the two-level NBRM. The two-level NBRM accounts for the count nature of attendance and, as a result, can work with excessive zeros in the outcome variable. Nonetheless, OLS is robust to substantial nonnormality in the dependent variable. If OLS is able to accurately estimate value-added measures in this context, it would be a simpler approach. We check by rerunning all analyses using similar value-added measures based on OLS regression and mirroring our value-added to achievement measures. While many of the results from NBRM hold up using OLS, some do not. Intuitively, an OLS prediction always generates a negative residual for zero values, while NBRM does not. As a result, some teachers with many students with zero absences who receive positive value-added scores in NBRM end up with negative scores in OLS. To check whether this drawback of OLS leads to the differences, we eliminate these teachers who are sensitive to the modeling procedure and rerun the model. The results using OLS and NBRM are consistent (see Online Appendix F for the details). The results of these analyses indicate that NBRM indeed outperforms OLS for this context.

We next test for omitted variables bias. In keeping with value-added measures in prior studies, our value-added measures for both attendance and achievement are based on models that adjust for selection of students into teachers using controls for observables. Given this approach, bias from selection on both observables and unobservables is possible. The assumption of our analyses is that conditional on the controls in our specification, students are not systematically sorted to teachers. To test the validity of this assumption, following Chetty, Friedman, and Rockoff (2014) and Jackson (2018), we first use twice-lagged student characteristics to predict all the long-term outcomes.[29] Using predicted outcomes and conditional on all student, class, and school characteristics, excluding those used in the prediction, we should not observe any significant association between the estimated teacher value-added (leave-year-out estimates) and the predicted outcomes. As shown in Online Appendix Table G1, the significances of value-added to attendance disappear for predicted graduation and dropout, providing some evidence that the main model adjusted successfully for the observables. Although the coefficients are significant for predicted number of AP courses and earned AP credits, the magnitudes are so small that they suggest very little selection in our model. For value-added to achievement, we observe significant coefficients for predicted graduation and dropout, but the directions suggest underestimation, instead of overestimation, of effects. Similar to the coefficients on value-added to attendance, the coefficients on value-added to achievement for predicted AP courses are very small and only marginally significant. Overall, the results provide evidence that our strategy largely eliminates selection on observables.

We cannot directly test whether our estimates are biased due to selection on unobservables. However, following Jackson (2018), we can assess selection on unobservables by comparing estimates based on two distinct sources of variation. The first strategy relies on school-by-cohort fixed effects. Since Jackson (2018) uses only ninth-graders, he uses school-by-year fixed effects. Here we modify his approach by using school-by-cohort fixed effects. This approach should be robust to any school-level policies and shocks that affect all students in a school cohort, since our estimating variation comes from within school–cohort. The second strategy uses a two-stage least squares estimator, using variation in average estimated teacher value-added scores across cohorts within a school. This instrumental variable approach is robust to student selection to teachers within a school but is susceptible to selection across schools. If these two distinct identification strategies provide similar results, then we have some additional evidence that our estimation strategy is not biased due to unobservables. As shown in Online Appendix Table H1, the overall magnitude and significance is remarkably consistent with Table 7, especially for value-added to attendance. We find no evidence of bias due to selection on unobservables.

VI. Discussion and Conclusion

Students in secondary school skip many classes even when they are in the school. Approximately one-half of the days in which they are not in a specific class, they attend other classes (Whitney and Liu 2017). In this study, we create measures of middle and high school teachers' individual contribution to student engagement as measured by student class-by-class attendance, asking to what extent teachers vary in their ability to get students to come to class, and how much this variation also leads to differential long-run outcomes for students. An extension of Jackson (2018), our study is only the second study that is able to estimate teachers' effect on student non-test score

29. This approach effectively limits our sample to students who have twice-lagged controls and only students in Grades 8–11. The student characteristics used here include test scores and absence rates for both math and ELA classes, days of suspension, race, gender, special education status, gifted status, and English learner status.

outcomes and then link this measure to student longer-run outcomes, and it is probably the first study that examines how subgroups of students, especially those on the margin, benefit from multidimensional teacher effectiveness.

We find substantial variation across teachers in their effectiveness at increasing student attendance, on par with the variation in teacher effectiveness at raising student test performance. We also find that a teacher's ability to reduce unexcused absences contributes strongly to students' probability of completing high school and affects AP course-taking. Value-added to attendance measures are as stable over time as are measures of teachers' value-added to test performance. Yet, value-added to attendance and achievement are distinct. Many teachers excel at one but not at the other. While teachers who are more effective at engagement tend to be more effective at raising achievement, this relationship is weak.

Our results provide evidence of the multidimensional nature of teaching effectiveness and that teachers require different skillsets to help different students succeed. A teacher who has high value-added to attendance can engage students in class and motivate the student to pursue higher academic goals. Not surprisingly, benefits from these teachers are much more salient for students with low prior attendance, low prior achievement, low probabilities of graduating from high school, and who tend to be chronically absent. In contrast, teachers with high value-added to achievement do little to improve graduation and reduce dropout for students prone to missing class, but they can help students pursue higher academic goals.

Our analyses build on the prior literature. While other studies have assessed teachers' contribution to attendance and find a distinction between teachers who contribute to attendance and those who contribute to achievement, ours is the first along a number of dimensions. First, we use data that identifies class-by-class unexcused absences instead of full-day absences across all middle and high school grade levels. Prior work has not looked at this grade range, where unexcused absences are the most common and teachers' effects on absences likely the greatest. Moreover, prior studies have used all absences instead of distinguishing unexcused absences, which, as we demonstrate, teachers are more likely to affect. Second, we use the NBRM model, an approach that is more appropriate than OLS for dealing with count data like attendance. Finally, and most substantively, we are able to assess the longer-run effects of teacher value-added to attendance, with a thorough heterogeneity analysis by student demographics, demonstrating both the predictive validity of the measure and the importance of this dimension of teacher effectiveness for students' academic accomplishments.

Our results, particularly in conjunction with other recent papers (Gershenson 2016; Jackson 2018), confirm that teacher effectiveness is multidimensional. Effectiveness at improving student test performance does not fully capture the qualities of teachers that benefit students in the long run. Moreover, the results provide evidence that teachers' ability to engage students in class (that is, have them show up for class), in particular, is an important dimension of teacher effectiveness, especially for boosting students' likelihood of graduating from high school. From a policy perspective, a teacher evaluation system that fails to consider value-added to attendance might discourage teachers who are capable of helping at-risk students persist. Finally, the importance of engaging teachers, combined with the substantial extent of unexcused class skipping, points more broadly to the importance of better engaging students, whether that is done by teachers or by other experiences in or out of school.

References

Allensworth, Elaine, and John Easton. 2007. "What Matters for Staying On-Track and Graduating in Chicago Public High Schools: A Close Look at Course Grades, Failures, and Attendance in the Freshman Year. Research Report." Consortium on Chicago School Research.

Allison, Paul D., and Richard P. Waterman. 2002. "Fixed-Effect Negative Binomial Regression Models." *Sociological Methodology* 32(1):247–65.

Aaronson, Daniel, Lisa Barrow, and William Sander. 2007. "Teachers and Student Achievement in the Chicago Public High Schools." *Journal of Labor Economics* 25(1):95–135.

Atteberry, Allison, Susanna Loeb, and James Wyckoff. 2015. "Do First Impressions Matter? Predicting Early Career Teacher Effectiveness." *AERA Open* 1(4):2332858415607834.

Backes, Ben, and Michael Hansen. 2015. "Teach For America Impact Estimates on Nontested Student Outcomes." Working Paper 146. National Center for Analysis of Longitudinal in Education Research.

Balfanz, Robert, and Vaughan Byrnes. 2012. "The Importance of Being in School: A Report on Absenteeism in the Nation's Public Schools." *Education Digest* 78(2):4.

Balfanz, Robert, Liza Herzog, and Douglas J. Mac Iver. 2007. "Preventing Student Disengagement and Keeping Students on the Graduation Path in Urban Middle-Grades Schools: Early Identification and Effective Interventions." *Educational Psychologist* 42(4):223–35.

Blazar, D., and M.A. Kraft. 2017. "Teacher and Teaching Effects on Students Attitudes and Behaviors." *Educational Evaluation and Policy Analysis* 39(1):146–70.

Chamberlain, Gary E. 2013. "Predictive Effects of Teachers and Schools on Test Scores, College Attendance, and Earnings." *Proceedings of the National Academy of Sciences of the United States of America* 110(43):17176–82.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood." *American Economic Review* 104(9):2633–79.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2007. "Teacher Credentials and Student Achievement: Longitudinal Analysis with Student Fixed Effects." *Economics of Education Review* 26(6):673–82.

Cortes, Kalena E., Jesse Bricker, and Chris Rohlfs. 2012. "The Role of Specific Subjects in Education Production Functions: Evidence from Morning Classes in Chicago Public High Schools." *B.E. Journal of Economic Analysis and Policy* 12(1):1–36.

Cunha, F., J.J. Heckman, and S.M. Schennach. 2010. "Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Econometrica* 78(3):883–931.

Duckworth, A.L., C. Peterson, M.D. Matthews, and D.R. Kelly. 2007. "Grit: Perseverance and Passion for Long-Term Goals." *Journal of Personality and Social Psychology* 92(6):1087–101.

Ellison,Glenn, and Ashley Swanson. 2016. "Do Schools Matter for High Math Achievement?" *American Economic Review* 106(6):1244–77.

Fox, L. 2016. "Playing to teachers' Strengths: Using Multiple Measures of Teacher Effectiveness to Improve Teacher Assignments." *Education Finance and Policy* 11(1):70–96.

Gershenson, Seth. 2016. "Linking Teacher Quality, Student Attendance, and Student Achievement." *Education Finance and Policy* 11(2):125–49.

Goldhaber, Dan D. 2007. "Everyone's Doing It, but What Does Teacher Testing Tell Us about Teacher Effectiveness?" *Journal of Human Resources* 42(4):765–94.

Goodman, Joshua. 2014. "Flaking Out: Student Absences and Snow Days as Disruptions of Instruction Time." NBER Working Paper w20221. Cambridge, MA: NBER.

Gottfried, Michael A. 2009. "Excused Versus Unexcused: How Student Absences in Elementary School Affect Academic Achievement." *Educational Evaluation and Policy Analysis* 31(4): 392–415.

———. 2010. "Evaluating the Relationship Between Student Attendance and Achievement in Urban Elementary and Middle Schools: An Instrumental Variables Approach." *American Educational Research Journal* 47(2):434–65.
———. 2011. "The Detrimental Effects of Missing School: Evidence from Urban Siblings." *American Journal of Education* 117(2):147–82.
Guarino, Cassandra, Mark Reckase, Brian Stacy, and Jeffrey Wooldridge. 2015. "A Comparison of Student Growth Percentile and Value-Added Models of Teacher Performance." *Statistics and Public Policy* 2(1):1–11.
Hanushek, Eric A., John F. Kain, and Steven G. Rivkin. 2004. "Disruption versus Tiebout Improvement: The Costs and Benefits of Switching Schools." *Journal of Public Economics* 88(9–10):1721–46.
Hausman, J.A., Bronwyn H. Hall, and Z. Griliches. 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52(4):909–38.
Heckman, J.J., and T. Kautz. 2013. "Fostering and Measuring Skills: Interventions that Improve Character and Cognition. NBER Working Paper w19656. Cambridge, MA: NBER.
Heckman, J., R. Pinto, and P. Savelyev. 2013. "Understanding the Mechanisms through which an Influential Early Childhood Program Boosted Adult Outcomes." *American Economic Review* 103(6):2052–86.
Heckman, J.J., J. Stixrud, and S. Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24(3):411–82.
Henry, K.L., and T.P. Thornberry. 2010. "Truancy and Escalation of Substance Use during Adolescence." *Journal of Studies on Alcohol and Drugs* 71(1):115–24.
Jackson, C. Kirabo. 2014. "Teacher Quality at the High School Level: The Importance of Accounting for Tracks." *Journal of Labor Economics* 32(4):645–84.
———. 2018. "What Do Test Scores Miss? The Importance of Teacher Effects on Non-Test Score Outcomes." *Journal of Political Economy* 126(5):2072–107.
Jennings, Jennifer L., and Thomas A. DiPrete. 2010. "Teacher Effects on Social and Behavioral Skills in Early Elementary School." *Sociology of Education* 83(2):135–59.
Kane, Thomas J., and Douglas O. Staiger. 2008. "Estimating Teacher Impacts on Student Achievement: An Experimental Evaluation." NBER Working Paper w14607. Cambridge, MA: NBER.
Koedel, C., K. Mihaly, and J.E. Rockoff. 2015. "Value-Added Modeling: A Review." *Economics of Education Review* 47:180–95.
Kraft, Matthew A. 2019. "Teacher Effects on Complex Cognitive Skills and Social-Emotional Competencies." *Journal of Human Resources* 54(1):1–36.
Kraft, Matthew A., and Sarah Grace. 2015. "Teaching for Tomorrow's Economy? Elementary Teacher Effects on Complex Tasks, Grit, and Growth Mindset." Working Paper. Providence, RI: Brown University.
Ladd, Helen F., and Lucy C. Sorensen. 2017. "Returns to Teacher Experience: Student Achievement and Motivation in Middle School." *Education Finance and Policy* 12(2):241–79.
Lockwood, J.R. and Daniel F. McCaffrey. 2009. "Exploring Student–Teacher Interactions in Longitudinal Achievement Data." *Education Finance and Policy* 4 (4):439–67.
Loeb, Susanna, James Soland, and Lindsay Fox. 2014. "Is a Good Teacher a Good Teacher for All? Comparing Value-Added of Teachers with Their English Learners and Non-English Learners." *Educational Evaluation and Policy Analysis* 36 (4):457–75.
Long, J. Scott, and Jeremy Freese. 2014. *Regression Models for Categorical Dependent Variables Using Stata*. College Station, TX: Stata Press Books.
Lounsbury, J.W., E. Sundstrom, J.M. Loveland, and L.W. Gibson. 2003. "Intelligence, 'Big Five' Personality Traits, and Work Drive as Predictors of Course Grade." *Personality and Individual Differences* 35(6):1231–39.

Mansfield, R.K. 2015. “Teacher Quality and Student Inequality.” *Journal of Labor Economics* 33(3)”751–88.
McCaffrey, D.F., J.R. Lockwood, Daniel Koretz, Thomas A. Louis, and Laura Hamilton. 2004. “Models for Value-Added Modeling of Teacher Effects.” *Journal of Educational and Behavioral Statistics* 29(1):67–101.
Mihaly, K., D. McCaffrey, T.R. Sass, and J.R. Lockwood. 2013. “Where You Come from or Where You Go? Distinguishing between School Quality and the Effectiveness of Teacher Preparation Program Graduates.” *Education Finance and Policy* 8(4):459–93.
Monk, D.H., and MA. Ibrahim. 1984. “Patterns of Absence and Pupil Achievement.” *American Educational Research Journal* 21(2):295–310.
Rabe-Hesketh, Sophia, and Anders Skrondal. 2012. *Multilevel and Longitudinal Modeling Using Stata*. Third Edition. College Station, TX: Stata Press.
Rivkin, Steven G., Eric A. Hanushek, and John F. Kain. 2005. “Teachers, Schools, and Academic Achievement.” *Econometrica* 73(2):417–58.
Romero, Mariajose, and Young-Sun Lee. 2007. “The Influence of Maternal and Family Risk on Chronic Absenteeism in Early Schooling.” New York: National Center for Children in Poverty.
Ruzek, Eric A., Thurston Domina, AnneMarie M. Conley, Greg J. Duncan, and Stuart A. Karabenick. 2015. “Using Value-Added Models to Measure Teacher Effects on Students’ Motivation and Achievement.” *Journal of Early Adolescence* 35(5–6):852–82.
Snyder, Thomas D., and Sally A. Dillow. 2013. “Digest of Education Statistics 2012.” NCES 2014-015. Washington, DC: National Center for Education Statistics.
U.S. Department of Education, Office of Civil Rights. 2018. “2015–16 Civil Rights Data Collection.” Washington, DC: U.S. Department of Education, Office of Civil Rights.
Whitney, Camille R., and Jing Liu. 2017. “What We’re Missing: A Descriptive Analysis of Part-Day Absenteeism in Secondary School.” *AERA Open* 3(2):2332858417703660.