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Engaging Teachers: Measuring the Impact of Teachers on Student Attendance in Secondary School

AUTHORS

Jing Liu
Stanford University

Susanna Loeb
Stanford University

ABSTRACT

Both anecdotal and systematic evidence points to the importance of teachers for students' long run success. Previous research on effective teachers has focused almost exclusively on student test score gains in math and reading. For this study we are able to link middle and high school teachers to the class-attendance of students in their classrooms, and to create measures of teachers' contributions to student attendance. Student absence is a growing concern for policy makers. On average, secondary students in the United States are absent from school three weeks per year (Snyder & Dillow, 2013), and even when they are in school, they miss many classes. We find systematic variation in teacher effectiveness at reducing class absences. These differences across teachers are as stable as those for student achievement. While positively correlated with teachers' value-added to achievement, teachers' value-added to attendance is clearly different and contributes independently and approximately equally to long run student outcomes including high school graduation.

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Engaging Teachers:

Measuring the Impact of Teachers on Student Attendance in Secondary School

Jing Liu and Susanna Loeb

Stanford University

January, 2017

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Abstract: Both anecdotal and systematic evidence points to the importance of teachers for students' long run success. Previous research on effective teachers has focused almost exclusively on student test score gains in math and reading. For this study we are able to link middle and high school teachers to the class-attendance of students in their classrooms, and to create measures of teachers' contributions to student attendance. Student absence is a growing concern for policy makers. On average, secondary students in the United States are absent from school three weeks per year (Snyder & Dillow, 2013), and even when they are in school, they miss many classes. We find systematic variation in teacher effectiveness at reducing class absences. These differences across teachers are as stable as those for student achievement. While positively correlated with teachers' value-added to achievement, teachers' value-added to attendance is clearly different and contributes independently and approximately equally to long run student outcomes including high school graduation.

JEL Codes: I21, J44, J45

Key words: teacher evaluation; value added; attendance; non-cognitive outcomes.

Introduction

Both anecdotal and systematic evidence points to the importance of teachers for students' long run success. Previous research on effective teachers has focused almost exclusively on student test score gains in math and reading in the year in which the teacher teaches the student. This research has shown that a high value-added teacher improves student short-term achievement (e.g.,Clotfelter, Ladd, & Vigdor, 2007; Goldhaber, 2007; Rivkin, Hanushek, & Kain, 2005) and can have long-term impacts on college attendance, income and other adult outcomes (Chetty, Friedman, & 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 outcomes. As one example, teachers may affect students' school engagement, which can have long-term benefits even if it does not improve test scores in the short run. Ignoring the non-test-score effects of teachers may be even more problematic in middle and high schools where the tested material may not align with the coursework and thus measures based solely on test performance may miss a large part of teachers' contribution to students.

A few prior studies have estimated teachers' effects on student outcomes beyond test performance (Backes & Hansen, 2015; Blazar & Kraft, 2016; Gershenson, 2016; Jackson, 2016; Jennings & DiPrete, 2010; Kraft & Grace, 2015; Ladd & Sorensen, 2016; Ruzek, Domina, Conley, Duncan, & Karabenick, 2015). Most of those studies focus on elementary or middle school level, and examine a range of outcomes including psychological traits such as growth mindset and grit (Kraft & Grace, 2015), self-reported self-efficacy and happiness (Blazar & Kraft, 2016), academic motivation (Ruzek et al., 2015), teacher-reported measures of children's social and behavior skills (Jennings & DiPrete, 2010), and full-day absences (Gershenson, 2016; Ladd & Sorensen, 2016). The only study looking at non-achievement measures for high school teachers, Jackson (2016), estimated 9th grade teachers' effects on a composite measure of student GPA, on-time grade completion, suspensions and full-day attendance.

Absence from school, particularly unexcused absence, is a compelling outcome to look at given its prevalence, especially for older students and for students with other indicators of low school engagement (Whitney & Liu, 2016). Student absence is also a growing concern for policy makers and education researchers. On average, secondary students are absent from school an average of three weeks per year (Snyder & Dillow, 2013). Research provides some evidence that lower attendance results in less learning (Goodman, 2014; Gottfried, 2009, 2010, 2011). In addition, absence predicts long-term outcomes such as high school dropout, net of other factors such as achievement (Allensworth & Easton, 2007; Balfanz & Byrnes, 2012; Balfanz, Herzog, & Mac Iver, 2007; Gottfried, 2011). Absence is also a critical indicator of student risk such as drug use and crime, particularly unexcused absence and chronic absence (Henry, 2007; Henry & Thornberry, 2010; Lochner & Moretti, 2004; Pérez et al., 2010; Vaughn et al., 2013). While a variety of individual and family factors can lead students to miss school, like student illness (Romero & Lee, 2007) and residential mobility (Hanushek, Kain, & Rivkin, 2004), absences are also likely to be influenced by factors within the purview of schools such as a positive and safe school environment and an effective, supportive and engaging teacher.

Because middle and high school students attend classes with multiple teachers, it is difficult to attribute full-day absences to individual teachers. For this study we are able to link teachers to the class-attendance of students in their classrooms, and to create measures of teachers' contributions to student attendance, which we then examine for key validity issues.

While full day attendance does predict longer run outcomes, it misses much of students' actual school absence. For example, a recent study of middle and high school student attendance in one urban school district found that approximately half of all absences from class were due to class skipping on days attended rather than to full day absences (Whitney & Liu, 2016). Individual teachers within schools may be able to attract students to attend their classes even when other teachers in their schools cannot.

This paper makes four main contributions to this literature, building on the two prior studies that examined teacher effects on student attendance (Gershenson, 2016; Jackson, 2016). 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 of attending classes, attendance in secondary school is more likely to be affected by the student's own perceptions of the teacher than in elementary school, and is therefore a more appropriate setting for estimating "teacher effects" on absences. In contrast, Gershenson (2016) focuses on elementary grades and, although Jackson (2016) studies 9th graders, ours is the first study that examines both middle and high school students (7th to 11th graders). Second, the detailed administrative data that we use allows us to know whether a student missed each class of each day for either an excused or unexcused reason. Gershenson (2016) and Jackson (2016), as well as other research on student absence, instead focus on full-day absences as the outcome measure. Class-level absence greatly improves the precision of measuring absenteeism, as well as the estimation of teacher effects. Focusing on unexcused rather than excused absences also allows us to isolate the types of absences that are more likely a reflection of the student's perception of the teacher. Third, unlike existing studies that unambiguously treat absences as a continuous variable despite the fact that absences are a discrete count variable (i.e. 0, 1, 2, 3, etc.), we employ a two-level negative binomial model to estimate teacher effects on absences. OLS can be biased and inefficient when using counts as a dependent variable (Long & Freese, 2014), while the negative binomial model is designed for estimation of count variables. Finally, using high school graduation and dropout data, we are able to directly test whether teacher value-added to attendance has predictive power on student long-term outcomes above and beyond teachers' impact on student test scores.

Specifically, this paper answers the following research questions:

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

Research Question 2: 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: To what extent are teachers who contribute most to student attendance the same ones who contribute most to student test performance?

Research Question 4: Does attending class with a teacher who has high value-added to attendance benefit students in the long run?

This paper proceeds as follows. First, we summarize related literature to motivate the importance of attendance and how teachers can influence student class attendance. Then we describe our data and show which student and class characteristics are associated with class absences. In the methods section, we present our identification strategy of estimating teacher effects on student attendance, as well as our approaches for answering the other research questions. Lastly we present results and conclude with a discussion of the implications.

Overall, we find that teachers have large effects on student attendance. A student would have about 45 percent fewer unexcused absences in math classes, and 55 percent fewer in English classes, if she had a teacher who is one standard deviation above the average in value added to attendance than if she had an average teacher, holding other variables constant. Compared with value-added to achievement, value-added to attendance is similarly stable across years. While in general value-added to attendance is weakly correlated with value-added to achievement, the correlation is relatively stronger for math (Spearman rho = 0.127) than for English (Spearman rho = 0.069). Having a high value-added to attendance teacher improves a student's opportunity to graduate from high school and reduces her probability of dropping out before 12th grade, net of the teacher's contribution to student test score.

Background

Quasi-experimental research consistently shows a negative relationship between absences and test scores. Gottfried (2009, 2010, 2011) uses data from the School District 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. In another study, Gottfried (2011) uses family fixed effects on a longitudinal sample of siblings to control for unobserved heterogeneity in the family environment which might be related to 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 find that each absence induced by moderate snowfall reduces student math achievement by 0.05 standard deviation.

Goodman (2014) also finds evidence that absences can cause lower achievement even among non-absent students. The teacher is likely to have a "coordination problem" because when an absent student returns to school, the teacher may need to allocate instructional time to catching the student up on what they missed (Goodman, 2014).

Beyond estimating the effects of absences, prior literature has also explored the role of the teacher in encouraging or discouraging absences. When the teacher lacks instructional effectiveness or struggles with classroom management, students may respond with absences to the class (Monk & Ibrahim, 1984). Teachers might also affect attendance directly through efforts such as calling parents at home when students are absent. Teachers differ in their ability to connect with students, engage them in learning, and foster a positive learning environment, as well as in their effort and effectiveness in directly encouraging attendance. Thus, teachers likely differ in their effects on student attendance. However, while teachers' influence on student test performance is well documented, only a few studies examine teacher effects on attendance.

Recent research has begun to shed light on teacher effects on student social and behavioral outcomes including attendance. Jennings and DiPrete (2010) find substantial teacher effects on the development of students' social and behavioral skills in addition to their cognitive skills using the Early Childhood Longitudinal Survey-Kindergarten Cohort (ECLS-K). Jackson (2016) estimates teacher effects on an aggregated measure of full-day absences, suspensions, grades, and on-time grade progression for 9th graders in North Carolina. Many teachers may contribute simultaneously to students' development of those non-cognitive outcomes but he uses multiple robustness checks to isolate teacher-specific effects. Jackson finds that teacher effects on these outcomes have extra predictive power on student educational attainment beyond their effects on test scores. In a similar vein, Blazar & Kraft (2016) estimate teacher effects for 4th and

5th 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 on test scores. All three studies find weak or moderate at best correlations between teacher effects on non-test score outcomes and their effects on test scores, indicating that teaching is likely to be a multi-faceted activity that cannot be captured just by a single outcome measure for students.

Gershenson (2016) is the only study that focuses specifically on teachers' impacts on student attendance. The author uses data for 3rd to 5th graders from North Carolina, and an aggregated measure of absences that does not differentiate excused and unexcused reasons. He finds a similar magnitude of teacher effects on student attendance compared to achievement. Quite surprisingly, given prior literature finding at least a weak correlation between teacher effects on non-cognitive outcomes and on achievement, Gershenson (2016) finds no correlation (cross domain spearman rank correlation is close to zero) between teachers' effects on attendance and on test scores.

The current study differs from Gershenson (2016) by focusing on secondary rather than elementary students. Secondary grades are a more suitable setting for examining teacher effects on attendance. Given their age, secondary students are often autonomous enough to decide whether to stay or leave school, and thus are more likely to respond to teachers by increasing or decreasing attendance. According to anecdotal reports from employees of the district in this study, many parents claim they are unable to control their children's attendance beginning as early as 6th or 7th grades. A recent descriptive paper by Whitney and Liu (2016) focuses on the district in this study and finds that the average proportion of absences that were unexcused to a class increased from 2.43 in 6th grade to 7.65 in 12th grade, indicating either a growing disengagement of schooling when students become older or a growing ability to act on that disengagement. At the same time, unlike elementary students who remain in the same classroom the whole school day, secondary students move between classrooms within a school day, allowing us to more easily distinguish teacher effects from out-of-school factors which would be expected to affect absences across all teachers roughly equally. Whitney and Liu (2016) show that about half of class absences are on days when students attend at least one other class. Given this large amount of variation in attendance across different classes during the school day, class-level absence is likely to be a useful metric for examining teacher effects on attendance as a proxy for teachers' effects on student engagement more broadly.

Data

We use longitudinal administrative data including school years 2003-2004 through 2013-2014 from a medium-sized urban school district in California. We focus on 7th to 11th graders. We do not include 12th graders for two reasons. First, 12th graders do not take standardized tests so we would not be able to estimate teachers' value-added to test performance. Second, 12th graders are about to graduate and thus have weaker motivation to attend class compared to students in prior grades, making 12th graders a special population that deserves separate analyses.

The most unusual feature of this dataset 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 or present in each class. For an absent student, a clerk in the school office would mark the student as excused absent if he or she received a phone call from a parent or guardian providing reasons for absence, otherwise the student was identified as unexcused absent for that class.[1] Such detailed 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 address teacher effects.[2] 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 non-randomly distributed among students with different characteristics. Moreover, since we have information on whether absences are excused or unexcused, we are able to focus on unexcused absences which 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 dataset to their corresponding subject area. In this paper we focus our analysis on five core subjects – math, English language arts (ELA), science, social studies, and foreign languages – because non-core 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 (ELL), special education status, and gifted status. Third, we add in student test scores from California Standards Tests (CST). Students in grades two to eleven 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

[1] According to our interview with several administrators in the district, attendance records may bias toward presence due to the funding of Average Daily Attendance (ADA), but this measurement error is on our dependent variable and should not bias our results.

[2] One prior study uses the average number of absences to each class but does not examine effects of teachers on attendance (Cortes, Bricker, & Rohlfs, 2012).

turn allows us to construct classroom level covariates. For our last research question, we merge in student high school graduation status and whether they dropped out before 12th grade.[3]

For the main analysis we estimate value-added to attendance and achievement for math and English teachers on the same sample, though we run specification checks using a range of other samples. We choose this restricted sample so that we can compare value-added measures on attendance and achievement without the concern that differences are due to different samples. To create this sample, we constrain the data in several ways. We begin with observations at the student-class period-semester level. To simplify our estimation, we only use students who have one teacher in a subject for the entire school year. This restriction cuts nearly a quarter of our sample (math and English)[4] but it is important when estimating value-added to achievement because it is difficult to disentangle teacher effects on student test scores when multiple teachers are present. However, this restriction does reduce the generalizability of our sample somewhat. We also drop student-class period-semester observations if one is absent from more than 50 percent of their classes because students with extremely high absence rates are very likely to be absent due to reasons beyond a teacher's control. We also thus drop observations when the

[3] The district gave us those long-term outcomes up to school year 2014-2015. For later cohorts (e.g., those who were 7th graders in 2012-2013) that we do not have data to observe their graduation and dropout, we assign missing values to these outcomes. For all 7th graders we can observe in our sample, 56.51% graduated from high school, and 28.39% dropped out before 12th grade. These numbers are 59.30% and 22.50% for 8th graders, 68.40% and 16.51% for 9th graders, 81.39% and 8.27% for 10th graders, and 91.18% and 3.37% for 11th graders. For those who neither graduated nor dropped out, some are transitional school level students (8th to 9th grade) who did not return to the district and did not submit a school enrollment application for the subsequent year.

[4] 24.21 and 15.54 percent of students have more than one teacher in English and math, respectively.

student has less than ten valid attendance marks[5] in a class per semester. Classes with fewer than five students are also excluded from our sample 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 11.85 percent of the whole sample.

Table 1 reports the basic descriptive statistics at the student, classroom, and school level. The first two columns report characteristics of our full sample which contains all five subjects, while the next set are math specific and the last set are for ELA. Overall, we have about 185,000 student-by-year observations and 8,900 teacher-by-year observations. In our analytical sample, there are slightly more male students than females. One salient feature is that students are racially diverse. About 50 percent of the students are Asian, slightly over 20 percent are Hispanic, and about 10 percent are black. The racial composition is very similar for math and ELA classes compared with the whole sample, with slightly more Asian students in math classes. Given this racial composition, it is not surprising that the percentage of ELL is about 20 percent. Since we eliminate students with more than 50 percent of unexcused absences as well as those with multiple math or ELA classes in the same semester, who tend to be academically weaker than other students, the average (standardized) test scores on both math and ELA in our sample are slightly higher than zero. The classroom level and school level statistics are similar to those at the individual level.

On average, students have 3.04 unexcused absences for math per semester and 2.96 unexcused absences for ELA per semester, accounting for 3.96 percent and 3.84 percent of the

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

total class meetings, respectively. For both subjects, the average excused absences are about half of unexcused absences for a class. The standard deviations are much bigger than the means for both excused and unexcused absences, suggesting highly skewed distributions for both variables.[6]

[Table 1 here]

Both student and class characteristics can influence students' decision to attend a class. To better inform our VA estimation, we use regression analysis to examine how these factors predict unexcused absences.[7] Table 2 synthesizes the results. The dependent variable here is the rate of unexcused absences for a class. In the first two columns, we report results using data for all subjects. In columns three to six, we conduct 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 males, but the size of the differences are quite small at about .002 to .003. Differences between ethnic groups, in contrast, are quite substantial. Compared with Asian students (the group left out of the model for comparison as it is the largest in the district), 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

[6] 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 non-traditional schedules. In addition, on some days students in a class may not meet due to special activities such as school-wide assemblies.

[7] For a more comprehensive examination, see Whitney & Liu (2016).

rates than 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 school grades generally have more unexcused absences, with a large jump between grades 8 and 9 and then relatively stable rates between grades 9 and 11.

Class characteristics also predict student attendance. One important factor is the timing of class. Here we use dummy variables indicating class periods. Most schools have seven total periods, while a few have a zero or eighth period because different schools have various bell schedules in the time span we examine. We group those periods as a separate group. As expected, students skip the first class in a day more than later ones. Class subject is less important to the number of unexcused absences. Our results show that ELA classes have significantly fewer unexcused absences than math, science, social studies and foreign language, but the differences are small.

[Table 2 here]

To facilitate constructing our value-added measures, we aggregate our data from student-class period-semester level to student-teacher-year level, which allows us to estimate both teacher effects to test scores and attendance using the same dataset. Although a student probably only has 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.[8] 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 between students anymore. In the following section, we provide a detailed

[8] 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% students have just one class with a teacher in a subject in a year. 63.50% have two classes.

explanation on how our model solves 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.

Methods

RQ1: To what extent do teachers vary in their contribution to student class attendance? To answer this research question we create a value-added to attendance measure for each teacher and in the process estimate the variance in this measure across teachers.

Estimating Value-Added to Attendance: We estimate a two-level negative binomial regression model (NBRM) to construct value-added measures for teacher's impact on student attendance. Prior studies that use student test scores as outcome variables generally employ an Ordinary Linear Square (OLS) model with teacher or teacher-by-year fixed effects to estimate value-added. In the small amount of literature which examines teacher effects on student absences, researchers often treat absence as if it is a continuous variable (Gershenson, 2016). However, our dependent variable, unexcused absences, is a count variable instead of a continuous one. It indicates the discrete number of class meetings from which the student was unexcused absent. Graph 1 shows a histogram of unexcused absences for math classes. The distribution is strongly positively skewed, with zero unexcused absences among 20 percent of student-by-year observations. As a result, using OLS estimation methods would likely result in inconsistent, inefficient, and biased estimates since OLS assumes a continuous, normal distribution that is not truncated (Long & Freese, 2014). Another possible solution is to do a logarithmic transformation to constrain the high end of the distribution, which is employed by Jackson (2016). Given a fair amount of zeroes in our dependent variable, we need to add a small constant to be able to do the logarithm transformation, but the choice of the constant is arbitrary and there is no obvious reason to prefer one constant over another (Nichols, 2010).

[Graph 1 here]

The NBRM belongs to the family of models which deal with counts as dependent variables. The most well know model in this category is the Poisson regression model (PRM), where the probability of a count is determined by a Poisson distribution. One assumption of the PRM is that the conditional mean equals the conditional variance. This assumption is often violated in practice and is violated in our data as well. The NBRM is an extension of the PRM by adding one more parameter to account for over-dispersion in the dependent variable, which allows the variance to exceed the mean. Another feature of a count model is that it allows the number of events to have different amount of exposure times and thus can account for students who have the same teacher for different meeting times in a year.

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[9] 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. Graph 2 presents the results. It is clear that for both math and ELA, NBRM has much smaller observed-predicted differences than PRM at different absent counts.

After showing that the NBRM is more appropriate to estimate class absences, we need to choose between treating teacher effects as fixed or random, which is a common debate in the

[9] Covariates include gender, race, whether the student is gifted, whether the student is English language learner, whether the class is an honor class, whether the class is AP flag, lagged absence rate in ELA and math, and corresponding class-level and school-level variables.

value-added literature. We choose to embed the NBRM into a two-level random intercept framework to estimate teacher effects for the following reasons. First, although Hausman, Hall, & Griliches (1984) propose a conditional likelihood method for negative binomial regression with fixed effects, Allison & Waterman (2002) show that it does not qualify as a true fixed effects because time-invariant covariates are allowed in their model and can result in a non-zero 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 & Skrondal, 2008). Second, a two-level random intercept model estimates the variance of value-added directly, which is more efficient than estimating the variance from the fixed effects, and provides empirical Bayes estimates of individual teacher effects (McCaffrey, Lockwood, Koretz, Louis, & Hamilton, 2004).

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, & Rockoff, 2014; Kane & 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 high school level because of academic tracks and unobserved track-level treatments (Jackson, 2014). We thus use interactions of grade and different types of tests students took in that grade to control for possible selection of teachers and students into different courses.

Specifically, we pool all grades together and estimate models separately by subject:

Level 1:

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

where $\qquad Abs_{ijt}|\mu_{ijt} \sim Poisson(\mu_{ijt})$

and $\qquad \exp\,(\varepsilon_{ijt})|\theta_{jt} \sim Gamma(r_{ijt}, p_{ijt})$

and $\qquad Cov(X_{ijt}, \theta_{jt}) = 0$

and $\qquad Cov(X_{ijt}, \varepsilon_{ijt}) = 0.$

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

In level one, $E(Abs_{ijt})$ or μ_{ijt} indicates student i's expected unexcused absences with teacher j in school year t. X_{ijt}represents a variety of student, classroom, and school characteristics. A full list of controls is given in the Appendix A. θ_{jt} is a random effect for teacher j in year t, which is the teacher-by-year value-added we are estimating. 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 over-dispersion, the reason for choosing the NBRM model. ET_{ijt} indicates the exposure time, i.e. 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 & Freese, 2014). In level 2, our teacher-by-year effect θ_{jt} follows a normal distribution with mean equal to 0.

Finally, the likelihood function is

$$L(\beta|Abs_{ijt}, \mu_{ijt}) = \prod \frac{\Gamma(Abs_{ijt}+r_{ijt})}{\Gamma(Abs_{ijt}+1)\Gamma(r_{ijt})} p_{ijt}^{r_{ijt}} (1 - p_{ijt})^{Abs_{ijt}}$$

Given the nonlinear nature of our non-linear 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.

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

The result is given by 100 x $(\exp(\psi^{1/2}) - 1)$. To ease interpretation, after estimating teacher effects on absences using NBRM, we convert them to *value-added to attendance* by multiplying all the estimates by -1.

RQ 2: 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? To investigate how stable value-added to attendance is, we conduct two analyses. First, we generate transition matrices to examine how teachers' quintile rankings change from the first two years *we observe them* to their third through fifth years. Specifically, 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 they are initially in their third to fifth years or move very little, we have evidence to say that value-added to attendance is a relatively stable measure. Although the transition matrices provide us an intuitive way to measure how stable value-added to attendance is and has more policy relevancy, it offers little information on exactly how early value-added can explain the variation of future value-added. Thus, we conduct a second analysis which regress value added of a future year (3, 4, or 5) on their first 2 years' value added. The adjusted R-squared statistics can inform us about how much variation is explained by teachers' early years' effectiveness (Atteberry, Loeb, & Wyckoff, 2015). To benchmark the results, we do the same analysis on value-added to achievement so that we can compare these two different measures. Throughout these two analyses, we limit our analytical sample to teachers who have at least five years' value-added on attendance as well as achievement.

Estimating Value-Added to Achievement: In addition to estimating value-added to attendance, we also estimate value-added to achievement so that we can examine how these two different measures of teacher effectiveness correlate with each other, and their differences in terms of stability. To estimate teacher effects on student achievement, we adopt a widely used strategy which 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 value added models on student test scores (Guarino, Reckase, Stacy, & Wooldridge, 2015). We also compute empirical Bayes estimates after running the fixed effects model.

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

Another way of answering this question is to directly regress student outcomes (i.e., test score and rate of unexcused absence) on value-added to achievement and value-added to attendance.[10] 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 et al. (2014) and Jackson (2016), we estimate "leave-year-out" value added by using all data but not the year when the focal student has the teacher (Jackknife estimates). Then we standardize those value-added estimates using the "true" standard deviations[11] of teacher effects estimated in RQ 1 and RQ 2.

RQ 4: Does attending class with a teacher who has high value-added to attendance benefit students in the long run? To examine this question, we use both high school graduation and dropping out from high school before 12th grade as long run outcomes. To construct this dataset, we pool together math and ELA classes for all 7th to 9th graders.[12] 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. After preparing the measures, we regress our dependent variables on the standardized leave-year-out value-added to achievement and value-added to

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[10] To ease interpretation, we run linear regressions for both outcomes, though we use a non-linear model to estimate value-added to attendance.

[11] 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 minuses the variance of errors.

[12] We only use 7th to 9th graders because less than 10 percent of students dropped out before 12th grade conditional on being a 10th grader.

attendance separately, and then using both together. We are especially interested in 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, classroom and school characteristics. Lastly, we estimate the same strand of models for math and ELA separately, aiming for comparing subject effects.

Results

RQ1: To what extent do teachers vary in their contribution to student class attendance?

First we ask how much teachers vary in their contribution to student attendance. The two level NBRM estimates the variance of teacher effects directly.[13] Because we run this model 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. Table 3 gives the results, reporting both teacher level and teacher-by-year level estimates since both come into play in subsequent research questions. The first column shows the raw standard deviations. Teacher level estimates have smaller variances than teacher-by-year estimates for each subject. Since teacher level estimates should be more precise, we focus on them in this section.

English teachers have a larger variance compared with their math colleagues. If we compare all five subjects, English teachers have the largest standard deviation while foreign languages teachers have the smallest. 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. In column 2, we

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[13] The full results of estimating teacher level value-added to attendance are in Appendix B.

report the incidence rate ratio (IRR) of one standard deviation of value-added to attendance. The magnitude is large. For example, a student would have 45.4 percent less unexcused absences in math classes if she has a teacher with one standard deviation above the average than she would have been with an average teacher, holding other variables constant. This number jumps to 54.8 percent for English classes.[14]

[Table 3 here]

RQ 2: 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? We find substantial stability in value-added measures for teachers over time. Table 4.1 reports the quintile transition matrices for value-added to class attendance.[15] About 70 percent of teachers who are in the lowest quintiles in terms of their average value-added to attendance of the first two years we observe them (the least effective ones), stay in the bottom two quintile in the following three years. 77 percent of the initially top teachers stay in the top two quintiles.

Table 4.2 gives the corresponding transition matrices for value-added to achievement.[16] 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 76 percent of the

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[14] We also estimate a model controlling for school fixed effects, so we are only comparing teachers within schools. 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 assume the average teacher quality is the same between schools, we prefer a model without school fixed effects, and focus on this preferred model in this paper.

[15] We compute teachers' ranking quintiles by subject, but in those transition matrices we combine math and English teachers into one table.

[16] After adjusting for measurement error, the true standard deviation of value-added to achievement is 0.18 for math, and 0.13 for English.

highest quartile teachers remaining in the highest two quintiles (compared with 70 percent and 77 percent for attendance).

[Table 4 here]

Transition matrices have drawbacks as measures of stability because they do not capture variation within the quintiles. Given the number of teachers is not large in our case, even a small change of ranking may reduce stability. To further measure stability, we use regression analysis to measure how early years' effectiveness predicts future years' performance. Table 5 reports the adjusted R-squared from different specifications. The first row of the table reports the adjusted R-squared when we regress value-added to attendance in year 3, 4, 5 and the average of all three years on the first year of available value-added measures. The upper half of the table shows results using value-added to attendance, and the lower half is for 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 stronger than for value-added to achievement for math teachers, but not for English teachers. The first two years of value-added to math attendance explains 41.6 percent of the variance in the average value-added in years three through five. This figure for attendance is 27.0 percent for English teachers. In comparison, the percent explained for achievement is 36.2 percent for math and 31.1 percent for English.

[Table 5 here]

RQ 3: To what extent are teachers who contribute most to student attendance the same ones who contribute most to student test performance? Here we report correlations between value-added to attendance and value-added to achievement. We have both teacher and teacher-by-year measures but we prefer the teacher level since it is less vulnerable to measurement error.

While overall the correlations are small, it is a bit stronger for math than for ELA. After adjusting for reliabilities[17], the Pearson correlation is 0.117 for math, and 0.087 for ELA. Correspondingly, the Spearman rank correlation for math teachers is 0.127 and for English teachers 0.069.[18] 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 elementary teachers. Pooling together both math and ELA, Jackson (2016) reports a Pearson correlation of 0.097 for 9th grade teachers, which is more similar to ours.[19] Our results are consistent with the literature in terms of showing teacher's effectiveness as multi-dimensional, as suggested by those small correlations, but it is likely that some teachers tend to be both effective in increasing student achievement and reducing unexcused absences, especially for math.

To further answer this question, we directly regress student current outcomes on both value-added to achievement and value-added to attendance. These value-added measures are out-of-sample estimates to avoid "mechanical endogeneity". They are also standardized by the "true" standard deviations of teacher effects estimated using all years of data we have. Specifically, the standard deviation of value-added to achievement is 0.18 for math, and 0.13 for ELA. The standard deviation of value-added to attendance is 0.37 for math, and 0.44 for ELA. Table 6 presents the results. As columns (1) and (5) show, our leave-year-out estimates of teacher effects

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[17] The reliabilities of value-added to attendance in both math and ELA are 0.85. The reliability of value-added to achievement is 0.80 for math, and 0.64 for ELA. For comparison, when we control for school fixed effects, 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 0.87 for math, and 0.59 for ELA.

[18] 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.

[19] Both Gershenson (2016) and Jackson (2016) 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.

on one outcome have a strong impact on that outcome. A one standard deviation increase of value-added to achievement improves student test scores by 0.108 standard deviation (p-value<0.01), and a one standard deviation increase of value-added to attendance reduces a student's unexcused absence rate by 0.440 percentage points (p-value<0.01). Interestingly, columns (2) and (4) indicate that a more effective teacher in increasing student test scores can also reduce student absences, and vice versa, though the magnitude is much smaller compared with those from columns (1) and (5). This result is expected given the weak positive correlation between the two measures of teacher effects. After putting two value-added estimates in the same regression, conditional on value-added to achievement, value-added to attendance does not show any impact on test scores, but value-added to achievement still has the same magnitude and significance on test scores. Similar results hold when using 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.

[Table 6 here]

RQ 4: Does attending class with a teacher who has high value-added to attendance benefit students in the long run? We find that teachers with high value-added to attendance increase student probability of graduating from high school and reduce their chance of dropping out before grade 12, above and beyond their effectiveness in increasing student test scores. Table 8 presents the first set of results, pooling data of both math and ELA for 7^{th} to 9^{th} graders. The first three columns of table 7 report results using high school graduation as the outcome variable. Both value-added to achievement and value-added to attendance have positive effects on high school graduation, as shown in the first two columns. A one standard deviation increase on value-added to achievement improves a student's probability of high school graduation by 0.4 percentage points. The effects of value-added to attendance is somewhat smaller, at about 0.3 percentage points and only marginally significant. When putting both measures in the same regression, both coefficients drop a little, with value-added to attendance losing its marginal significance but holding a similar magnitude and the right sign. The results are stronger when using dropout as the outcome variable. A one standard deviation increase on value-added to achievement or to attendance reduces a student's probability of dropping out before 12th grade by 0.4 percentage points when entered separately. After putting two measures in the same equation, the coefficients remain approximately the same in magnitude and significance.

[Table 7 here]

To further investigate the differential effects of math and English teachers, we examine long-term outcomes by subject. Table 8 provides the results. We find that English teachers have a much stronger impact on student long-run outcomes than do math teachers, working though both their value-added to achievement and their value-added to attendance. All the coefficients for English teachers are positive and significant at traditional levels, but only value-added to attendance for math teachers is marginally significant. Having an English teacher with value-added to attendance that is one standard deviation above the average teacher improves a student's probability of graduation by 0.5 percentage points. This estimate holds constant the somewhat larger effect of teachers' value-added to achievement.

[Table 8 here]

Discussion and Conclusion

In this paper we have created measures of individual middle and high school teachers' contribution to student engagement as measured by student class-by-class attendance. We find substantial variation in this measure of teacher effectiveness across teachers, on par with the variation in teacher effectiveness at raising student test performance. This teacher value-added to attendance measure is also as stable over time as are measures of value-added to test performance. While teachers who are more effective at engagement tend to be more effective at raising achievement, this relationship is weak. Many teachers excel at one but not at the other. We find that both teacher abilities contribute to students' probability of completing high school and that these effects are driven largely by English teachers and not by math teachers. This differential effect by subject is consistent with prior research which finds that variation across English language arts teachers is more important than variation across math teachers in affecting students' long-run success (Chetty et al., 2014; Master, Loeb & Wyckoff, 2015).

Our results, particularly in conjunction with other recent papers (Gershenson, 2016; Jackson, 2016) confirm that teacher effectiveness is multi-dimensional. Effectiveness at improving student test performance does not fully capture the dimensions of teacher effectiveness that benefit students in the long run. Conditional on value-added to achievement, a teacher with high value-added to attendance boosts student long-run outcomes. The importance engaging teachers more broadly points to the importance of engaging students, whether that is done by teachers or by other school or out of school experiences.

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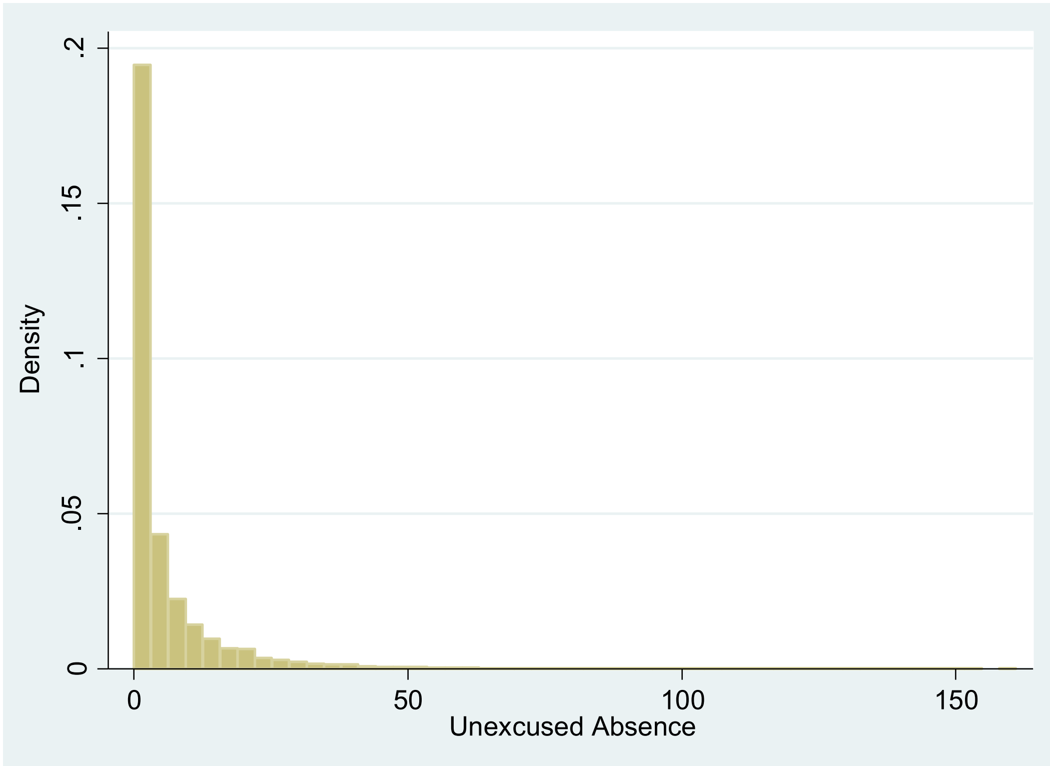
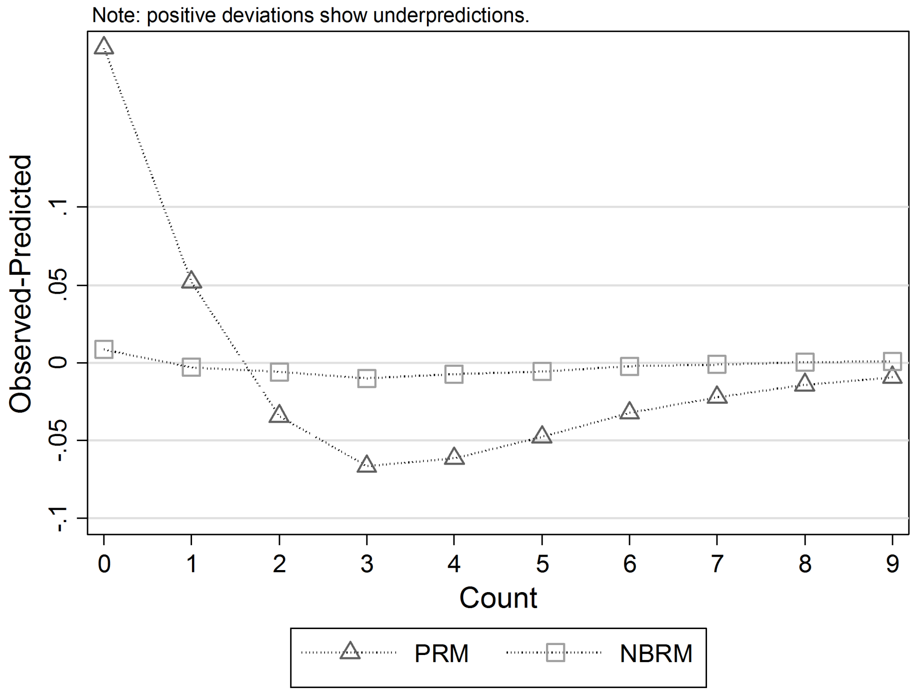
Graph 1: Distribution of Unexcused Absences for Math

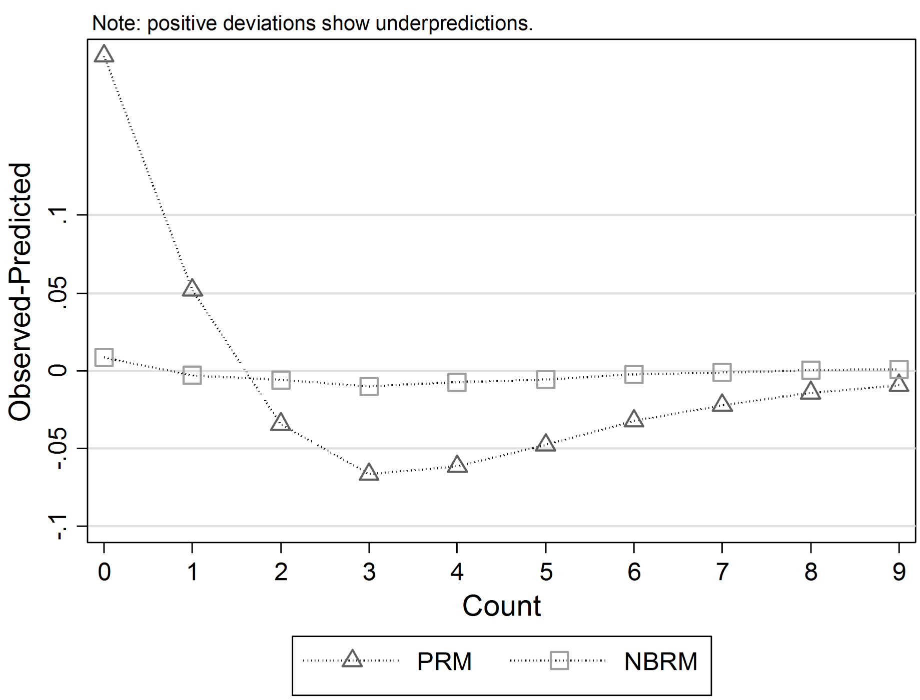


Note: This distribution is using the raw data before implementing any restriction described in the data section.

Graph 2.1: NBRM Versus. PRM: Math



Graph 2.2: NBRM Versus. PRM: ELA



Graph 3: Binned Scatter Plot: Teacher Effects on Attendance Versus. Teacher Effects on Achievement

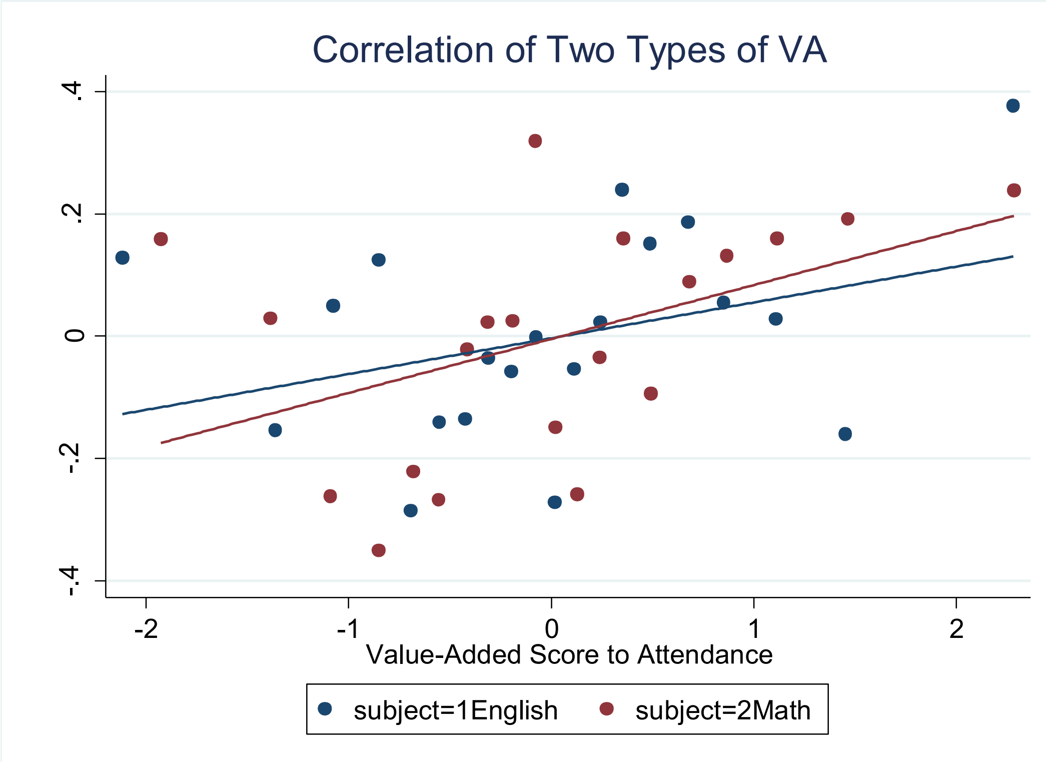


Table 1 Descriptive Statistics

Variable	All Subjects		Math		ELA	
	Mean	SD	Mean	SD	Mean	SD
Student						
Female	0.486		0.483		0.484	
White	0.081		0.077		0.080	
Black	0.103		0.091		0.094	
Hispanic	0.209		0.203		0.197	
Asian	0.519		0.540		0.537	
ELL	0.197		0.178		0.142	
Excused Absences	1.693	(2.577)	1.602	(2.502)	1.634	(2.518)
Unexcused Absences	3.373	(5.200)	3.040	(4.962)	2.959	(4.901)
Total Class Meetings	76.155	(13.918)	76.768	(14.196)	77.132	(13.494)
Math Score	0.058	(0.977)	0.080	(0.948)	0.072	(0.928)
ELA Score	0.044	(0.973)	0.080	(0.925)	0.110	(0.901)
Class-period						
White	0.082	(0.090)	0.080	(0.095)	0.084	(0.100)
Black	0.102	(0.140)	0.097	(0.151)	0.100	(0.149)
Hispanic	0.208	(0.208)	0.203	(0.224)	0.198	(0.215)
Asian	0.521	(0.249)	0.531	(0.274)	0.526	(0.254)
ELL	0.189	(0.036)	0.188	(0.037)	0.188	(0.036)
Excused Absences	1.708	(1.061)	1.689	(1.176)	1.725	(1.163)
Unexcused Absences	3.970	(3.667)	3.923	(4.249)	3.943	(3.992)
Total Class Meetings	74.209	(16.983)	74.417	(17.574)	74.419	(17.459)
Math Score	0.010	(0.684)	0.037	(0.754)	-0.004	(0.701)
ELA Score	-0.009	(0.727)	0.009	(0.755)	-0.026	(0.773)
School						
White	0.084	(0.070)	0.083	(0.068)	0.081	(0.070)
Black	0.105	(0.094)	0.102	(0.093)	0.102	(0.093)
Hispanic	0.206	(0.171)	0.204	(0.171)	0.203	(0.171)
Asian	0.517	(0.200)	0.523	(0.199)	0.525	(0.199)
ELL	0.200	(0.150)	0.197	(0.151)	0.198	(0.149)
Excused Absences	1.644	(0.711)	1.640	(0.701)	1.633	(0.695)
Unexcused Absences	3.097	(1.878)	3.003	(1.694)	3.061	(1.672)
Total Class Meetings	76.673	(12.179)	77.207	(11.864)	76.924	(11.927)
Math Score	0.032	(0.474)	0.016	(0.401)	-0.002	(0.368)
ELA Score	0.018	(0.509)	0.008	(0.417)	-0.009	(0.377)
Observations						
Student by Year	184976		136540		124800	
Teacher by Year	8893		2510		2606	

Note: Data are from school year 2002-2003 through 2012-2013. Characteristics are calculated using the final matched data sets at student-year level. "All subjects" include math, ELA, science, social studies and foreign languages. At student level, absences and total class meetings are averages across all classes taken in the corresponding subject in a school year.

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)
2nd Period	-0.009**	-0.009**	-0.008**	-0.008**	-0.008**	-0.008**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
3rd Period	-0.012**	-0.012**	-0.011**	-0.010**	-0.010**	-0.010**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
4th Period	-0.010**	-0.011**	-0.007**	-0.009**	-0.010**	-0.010**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
5th Period	-0.010**	-0.010**	-0.009**	-0.009**	-0.008**	-0.008**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
6th Period	-0.007**	-0.007**	-0.007**	-0.006**	-0.007**	-0.006**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
7th Period	-0.004**	-0.002**	-0.001	-0.000	-0.001	-0.002*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
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	1197741	1197741	262993	262993	253235	253235

Note: 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 include 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 1st period. The reference group for the subject variable is English classes.

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

		Standard Deviation	Incidence Rate Ratio
Teacher	Math	0.374	1.454
	ELA	0.437	1.548
	Science	0.422	1.525
	Social Studies	0.402	1.495
	Foreign Languages	0.403	1.496
Teacher by Year	Math	0.458	1.581
	ELA	0.494	1.639
	Science	0.479	1.615
	Social Studies	0.467	1.595
	Foreign Languages	0.409	1.505

Note: Standard deviations are directly estimated from two-level Negative Binomial models. Incidence rate ratio is calculated using $\exp(SD)$.

Table 4.1 Transition Matrix: VA to Attendance

Initial Quintile		*Quintile of Future Performance on Attendance* Q1	Q2	Q3	Q4	Q5	Row
Q1	n	38	17	14	9	1	79
	(row %)	(48.10)	(21.52)	(17.72)	(11.39)	(1.27)	(100)
Q2	n	21	19	18	13	6	77
	(row %)	(27.27)	(0.25)	(0.23)	(0.17)	(0.08)	(100)
Q3	n	9	21	19	17	12	78
	(row %)	(11.54)	(0.27)	(0.24)	(0.22)	(0.15)	(100)
Q4	n	7	13	20	19	18	77
	(row %)	(9.09)	(0.17)	(0.26)	(0.25)	(0.23)	(100)
Q5	n	4	7	7	19	40	77
	(row %)	(5.19)	(0.09)	(0.09)	(0.25)	(0.52)	(100)
Column Total		79	77	78	77	77	**388**

Note (same for Table 4.2): 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.

Table 4.2 Transition Matrix: VA to Achievement

Initial Quintile		*Quintile of Future Performance on Achievement* Q1	Q2	Q3	Q4	Q5	Row
Q1	n	34	21	15	6	3	79
	(row %)	(43.04)	(26.58)	(18.99)	(7.59)	(3.80)	(100)
Q2	n	18	23	19	11	6	77
	(row %)	(23.38)	(0.30)	(0.25)	(0.14)	(0.08)	(100)
Q3	n	12	15	19	18	14	78
	(row %)	(15.38)	(0.19)	(0.24)	(0.23)	(0.18)	(100)
Q4	n	11	12	17	21	16	77
	(row %)	(14.29)	(0.16)	(0.22)	(0.27)	(0.21)	(100)
Q5	n	4	6	8	21	38	77
	(row %)	(5.19)	(0.08)	(0.10)	(0.27)	(0.49)	(100)
Column Total		79	77	78	77	77	**388**

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

	Outcome (Attendance)			
Early Year VA Predictor(s)	VA in Y3	VA in Y4	VA in Y5	Mean(VA_{Y3-5})
Math				
Math VA in Y1 Only	0.234	0.230	0.094	0.259
Math VA in Y2 Only	0.259	0.331	0.172	0.361
Math VA in Y1 & Y2	0.323	0.374	0.181	0.416
ELA				
ELA VA in Y1 Only	0.141	0.118	0.059	0.148
ELA VA in Y2 Only	0.284	0.129	0.094	0.243
ELA VA in Y1 & Y2	0.298	0.163	0.101	0.270
	Outcome (Achievement)			
Early Year VA Predictor(s)	VA in Y3	VA in Y4	VA in Y5	Mean(VA_{Y3-5})
Math				
Math VA in Y1 Only	0.112	0.204	0.152	0.231
Math VA in Y2 Only	0.267	0.219	0.152	0.311
Math VA in Y1 & Y2	0.270	0.277	0.198	0.362
ELA				
ELA VA in Y1 Only	0.129	0.101	0.102	0.183
ELA VA in Y2 Only	0.172	0.119	0.111	0.218
ELA VA in Y1 & Y2	0.230	0.167	0.161	0.311

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
		Test Scores			Unexcused Absence Rate	
Test Score VA	0.10782**		0.10799**	-0.00077**		-0.00016
	(0.00170)		(0.00172)	(0.00015)		(0.00015)
Attendance VA		0.00950**	-0.00126		-0.00440**	-0.00439**
		(0.00136)	(0.00135)		(0.00012)	(0.00012)
Observations	223623	223623	223623	223623	223623	223623

Note: 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 7^{th} to 11^{th} graders. 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; 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)
		Graduation			Dropout Before 12th Grade	
Test Score VA	0.00410*		0.00381*	-0.00365**		-0.00318**
	(0.00166)		(0.00167)	(0.00119)		(0.00121)
Attendance VA		0.00265+	0.00230		-0.00391**	-0.00361**
		(0.00139)	(0.00140)		(0.00099)	(0.00100)
Observations	108364	108364	108364	105580	105580	105580
Adjusted R-squared	0.192	0.192	0.192	0.107	0.107	0.107

Note: 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. 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. R-squared-within is R-squared without fixed effects, which provides a better interpretation on how adding different value-added scores change the predictive power of the model on longer term outcomes. ** p<0.01, * p<0.05, + p<0.10.

Table 8. Effects of Out of Sample Teacher Effects on Longer-Term Outcomes: by Subject

	(1)	(2)	(3)	(4)
	Graduation		Dropout Before 12th Grade	
	English	Math	English	Math
Test Score VA	0.01371**	0.00056	-0.00975**	-0.00117
	(0.00323)	(0.00213)	(0.00240)	(0.00153)
Attendance VA	0.00509*	-0.00014	-0.00476**	-0.00263+
	(0.00204)	(0.00194)	(0.00145)	(0.00139)
Observations	51411	56953	50156	55424

Note: 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 subject-specific data pooling across 7th-9th grades. 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.

Appendix A: List of covariates included in models

Prior math test score (standardized)
Prior ELA test score (standardized)
Prior absence rate in math
Prior absence rate in ELA
Black
Hispanic
Asian
Female
English learner status
Special education status
Gifted education status
Prior suspensions
Current math test
Prior math test
Class average prior math test score
Class average prior reading test score
Class average prior absence rate
Class average prior suspensions
Class percentage black
Class percentage Hispanic
Class percentage Asian
Class percentage English learners
Class in first period
School percentage black
School percentage Hispanic
School percentage Asian
School percentage English learners
School average prior absence rate
School average prior suspensions

Appendix B: Regression results of estimating value-added to attendance for math teachers

	Coefficient		Standard Error
% Any absence_math_lag	1.500	**	0.103
% Any absence_ELA_lag	1.734	**	0.098
Any absence_lag	4.982	**	0.102
Test score_math_lag (standardized)	-0.170	**	0.006
Test score_ELA_lag (standardized)	-0.039	**	0.006
Suspension days_lag	0.020	**	0.004
Black	0.159	**	0.014
Hispanics	0.099	**	0.011
Asian	-0.356	**	0.009
Female	-0.067	**	0.006
Special Education	-0.113	**	0.014
Gifted	-0.027	**	0.009
ELL	0.046	**	0.011
Class black	0.129	*	0.064
Class Hispanics	-0.059		0.053
Class Asian	-0.087	+	0.047
Class ELL	3.424	**	0.763
Class math test score_lag	-0.244	**	0.018
Class ELA test score_lag	-0.020		0.017
Class absence_lag	-0.083		0.148
Class suspension_lag	-0.005		0.015
School black	-0.553	*	0.232
School Hispanics	-0.508	**	0.173
School Asian	-0.388	*	0.160
School ELL	0.335	**	0.104
School absence_lag	2.776	**	0.441
School suspension_lag	-0.188	**	0.054
grade = 8	0.018		0.017
grade = 9	0.586	**	0.057
grade = 10	0.294	**	0.072
grade = 11	0.378	**	0.075
Period = 2	-0.304	**	0.012
Period = 3	-0.345	**	0.012
Period = 4	-0.313	**	0.012
Period = 5	-0.268	**	0.013
Period = 6	-0.190	**	0.012

Period = 7	0.010		0.016
Period = 8	-0.048		0.059
Constant	-4.631	**	0.195
ln(total)	1.000		(exposure)
/lnalpha	-0.217		0.006
var(_cons)	0.200		0.007