# Chronic Absenteeism in the Classroom Context: Effects on Achievement 

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#### Abstract

Though educational policy makers uphold that chronic absenteeism (missing 10\% or more of the school year) is damaging to students' schooling outcomes, there is little empirical research to match. This study considers the role of spillover effects of chronic absenteeism on classmates' achievement. It does so by utilizing a large-scale administrative urban district dataset of elementary schoolchildren - a sample of students where the rates of chronic absenteeism are expected to be higher compared to the national average. The results show that students suffer academically from having chronically absent classmates - as exhibited across both reading and math testing outcomes. Chronic absenteeism not only had a damaging effect on those individuals missing excessive school days, but also has the potential to reduce outcomes for others in the same educational setting.


Key words: peer effects; school attendance; achievement

## Chronic Absenteeism in the Classroom Context: Effects on Achievement

While it is has been established that greater numbers of school absences are linked to a range of negative schooling outcomes (Dryfoos, 1990; Finn, 1993; Gottfried, 2009; Lehr et al., 2004; Neild \& Balfanz, 2006; Rumberger, 1995; Silverman, 2012; Steward et al., 2008;

Stouthamer-Loeber \& Loeber, 1988; Tobin, 2014), little work has focused specifically on the effects of chronic absenteeism. Rather, research has focused on comparing students with higher versus lower rates of absenteeism rather than examining the effects of being chronically absnt. Though this issue has not been fully disentangled, education policy dialog surrounding student absences been charging forward with rhetoric pertaining to the negative effects of chronic absenteeism and how to reduce it (see e.g., Harris, et al., 2013). Additional research in chronic absenteeism is needed to support these policy conversations and at the most fundamental level, to better document and monitor those students in particular who might be at a potentially much higher risk of educational failure from the act of missing excessive amounts of school.

It is understandable why policy makers have begun to turn their attention towards chronic absenteeism. Chronic absenteeism is dramatic - it is an extreme form of missing school which often is defined as missing at least 18 days or more of a given academic year (i.e., approximately $10 \%$ of the school year; Balfanz \& Byrnes, 2012). Descriptive research indicates that between 10 and $15 \%$ of U.S. students would be considered chronically absent under this Balfanz \& Byrnes (2012) definition. In our nation's largest cities, this rate of chronic absenteeism is even higher (Nauer, Mader, Robinson, \& Jacobs, 2014) for reasons described below. Therefore, in addition to other challenges that students in our largest schools systems often face - lower-SES, higher dropout rates, lower parental involvement, fewer social services, and greater teacher turnover -
students in our nation's largest school districts also face the challenges associated with extremely high rates of of absenteeism.

Moreover, descriptive research has found that chronic absenteeism is extremely prevalent in elementary school, both at the national level and also when examining urban school districts (Balfanz \& Byrnes, 2012; Chang \& Romero, 2008; Connolly \& Olson, 2012; Romero \& Lee, 2007). In addition to descriptive findings, two studies have examined the causal mechanism of chronic absenteeism for elementary school students. Gershenson et al. (2014) find that chronic absentees tend to have $0.05 \sigma$ to $0.11 \sigma$ lower test scores compared to average absentees; that said, they do not define chronic absentees according to the more commonly-supported definition put forth by Balfanz and Byrnes (2012), as mentioned above. Using these more-established definitions, Gottfried (2014) found a negative effect of chronic absenteeism on a students' academic and socio-emotional outcomes in kindergarten. Both of these studies used nationaland/or state-level samples. Nonetheless, there is initial evidence that chronic absenteeism persists in U.S. schools, that it exists even among our youngest students, and that there are a range of negative individual-level ramifications of this behavior.

Compounding these negative individual effects, however, is the fact that chronic absenteeism does not occur in a vacuum - rather, there is the potential for negative spillover effects of chronic absenteeism onto other classmates. To conceptualize this, it is first necessary to describe the negative individual academic and behavioral ramifications of those students missing great amounts of school time. Academically, it has been established that highly absent students receive fewer hours of instruction and are consequently more likely to require significant remediation when returning to school (Chen \& Stevenson, 1995; Connell, Spencer, \& Aber, 1994; Finn, 1993). Behaviorally, it has also been established that absenteeism causes
students to feel a greater sense of alienation from their classmates, teachers, and schools and may have larger frequencies of negative interactions and social disengagement when returning to school (Ekstron, Goertz, Pollack, \& Rock, 1986; Finn, 1989; Gottfried, 2014; Johnson, 2005; Newmann, 1981). In tandem, these negative individual-level academic and behavioral consequences have the potential to spillover on the outcomes of other students.

Specifically, as teachers respond to needs of absent students upon their return to school, then other members of the classroom might be negatively impacted as the pace of instruction slows in order to remediate those absentees. While this may occur with any degree of absenteeism, it is hypothesized that extreme rates of absenteeism might further impede regularlypaced instruction and slow academic progress for all students. As absences increase individuallevel school disengagement or alienation (Gottfried, 2014) and as these behaviors in turn produce further social problems in school (Finn, 1989; Gottfried, 2014), then absent students might also be creating also non-instructional (i.e., behavioral) disruptions when in the classroom setting (Reid, 1984). Just like academic disruptions, behavioral disruptions also might slow the learning process for non-absent peers, as teachers must devote their time and resources to classroom management rather than to instruction. Again, while this may occur for any degree of absenteeism, it is hypothesized that chronically absent students might invoke even greater academic and behavioral disruptions.

This negative spillover effect has theoretical underpinnings in Lazear (2001). He put forth that teacher time, resources, and instruction can be thought of as a public good - i.e., something that is 'consumed' by all students in the classroom. Therefore, when students are chronically absent, there may be congestion effects exist on this teacher's time and resources based on chronically-absent students' disruptions upon return to school (either academic or
behavioral). As chronic absentees have been shown to exhibit greater frequencies of disruptive behavior (Gottfried, 2014), teachers must spend more of their time and resources in ways from which other students may not benefit. In essence, chronically absent students produce both an individual effect by decreasing their own learning and increasing social disengagement from having missed excessive amounts of school, and also a congestion effect on the public good by frequently slowing instruction and reducing the educational outcomes for others in the class when actually present in the classroom.

There is some evidence of the existence of this classroom mechanism - Gottfried (2011) found students perform worse in classrooms with higher average rates of absenteeism. That said, Gottfried (2011) relied on average classroom rates of absenteeism and did not focus exclusively on the effect of having chronically absent classmates (partly as a function of the fact that chronic absenteeism had not yet fully entered into the policy dialogue). Average rates of absenteeism certainly have utility, as they provide a diagnosis for the occurrence of the frequency of this behavior in classrooms. However, average absenteeism rates might be underestimating the extent to which a student might be affected by chronically absent classmates. For instance, in classroom A, it is possible that each day, a different subset of the students is absent, such that over the course of the entire school year, each student would only be missing a few days of school. Therefore, the academic and behavioral risks faced by each student in this classroom are not extreme, as no student is missing a great amount of in-school time. In this classroom, there may be little need for academic remediation or behavioral management associated with chronic absenteeism. Theory would then suggest that congestion effects would be lower on teacher instruction, compared to classrooms containing a greater number of chronic absentees.

On the other hand, classroom B might ostensibly have the same average absence rate as classroom A. However, in classroom B, it is possible that the absence rate is driven by a single set of students, who are alternating (within this one subset) being absent. This latter classroom faces chronic absentee issues. Therefore, even if both classrooms A and B have the same absence rate on record, issues pertaining to absenteeism might be exacerbated in this second classroom, where there are students missing a much greater proportion of the school year. Due to having chronic absentees in this setting, academic remediation might be extremely high in classroom B , as might be behavioral management. Theory would suggest that the congestion effects on instruction and teacher time would be much higher here than in classroom A, given the presence of students missing excessive amounts of school. Consequently, the peer effects of chronic absenteeism would be much higher as well, and the academic performance of all students might consequently suffer. It might only be in this classroom B where other non-absentee students might suffer as instruction slows. Clearly, having more detail on the role of classmate chronic absenteeism (as opposed to average absence rates) could better inform policy and practice efforts to reduce the negative individual effects and the potentially detrimental peer effects.

Given the general lack of research focusing on chronic absenteeism coupled with the movement forward of this issue in educational policy dialogue, this study asks the following two research questions:

1. In urban elementary schools, do chronically absent classmates influence the achievement outcomes of other students in the same classroom?
2. Do these effects differ based on different individual characteristics?

As described below, these two questions will be addressed using a large-scale longitudinal dataset of elementary school children from one large urban school district. Relying on this
dataset is critical for three key reasons. First, because of detailed record keeping, district data makes it possible to link students to classrooms (and hence classmates). By having official records of absences for each student over time, this study can identify both individual and classmate chronic absenteeism and can measure the effects on achievement test scores.

Second, focusing on these issues for a sample of elementary school students is also critical. Unlike high school students, elementary school students are generally taught within the same classroom throughout the school day and academic year. Empirically, then, studying elementary school students allows for the precise documentation of chronically absent classmates in a given school year. Also, given that chronic absenteeism rates are documented as being high in elementary school (Balfanz \& Byrnes, 2012), it is necessary to identify how this behavior is detrimental to schooling outcomes in early schooling years. In doing so, it will be possible to develop policy and support interventions for students at-risk of educational decline from this behavior at the start of education rather than delaying and taking action later on.

Third, the research questions focus specifically on chronic absenteeism in urban schools - and this is critical, as explained below. But first it is necessary to frame 'urban' schools. In this study, the definition of urban schooling aligns with research and policy. Relying on a taxonomy from Milner (2012), urban schools in this study are defined as "urban intensive," meaning those schools that are concentrated in the largest metropolitan areas in the U.S. This also corresponds with definitions from policy - the U.S. Department of Education defines the sample of students in this study as being in the most urban district ("city-large") as based on a taxonomy developed by the Office of Management and Budget (2000). Urban education in this study, then, pertains to those students being educated in our nation's largest cities.

As mentioned above, students in urban districts face an array of challenges, including lower financial resources, lower parental involvement, higher odds of high school dropout, and fewer academic and social support systems (Conchas, Lin, Oseguera, \& Drake, 2014). Many of these challenges are linked directly to absenteeism. For instance, students from families with fewer resources tend to have parents with higher rates of depression and mobility, both of which have been directly linked to absenteeism (Chang \& Romero, 2008; Claessens, Engel \& Curran, in review; Ready, 2010). Also, students in large urban schools often face greater health challenges, and health has been linked to absenteeism (Allen, 2003). For these reasons and others, it is often the case that parents in urban schools do not have the adequate resources to address going to school regularly, whether that pertains to school-going logistics like transportation (Chang \& Romero, 2008), health issues (Allen, 2003; Hughes \& Ng, 2003; Romero \& Lee, 2007), or negative attitudes about school (Chang \& Romero, 2008). Thus, students in urban schools tend to face higher rates of chronic absenteeism. Indeed, low resources has been shown to be a more significant factor of chronic absenteeism than race (Chang \& Romero, 2008).

Given this prevalence of higher rates of chronic absenteeism in large urban districts due to limited opportunities and fewer resources (Nauer, Mader, Robinson, \& Jacobs, 2014), it is key to focus on the experiences of students in these large school systems, as schools and families might not have the supports necessary to address and mitigate this harmful school-going behavior. Parents and schools in urban districts might have a greater number of challenges to face when addressing school-going behavior, as mentioned in the previous paragraph. These same students then also face greater challenges and have fewer resources when addressing the consequences of being chronically absent. Therefore, in contrast to higher-resourced families and
schools, those in urban schools might face potentially worsened schooling consequences as a result of excessive absenteeism due to a lack of necessary supports and services to prevent or address the consequences of this negative school-going behavior (Balfanz \& Legters, 2004; Fine, 1994; Orfield \& Kornhaber, 2001). Understanding the extent to which chronic absenteeism impedes outcomes for a population of students facing great challenges in our largest districts will better inform researchers, policy makers, and practitioners as to how to make adjustments and guide policy to address specific needs for those students with limited opportunities.

Method

## Descriptive Statistics

Dataset overview. This study utilizes an administrative dataset from a large urban district to address the role of chronic absenteeism on student achievement. For each year of collected data, the dataset contains records of absence for every student (critical to this study) as well as student demographic and academic information and teacher and classroom measures. These data were obtained directly from the School District of Philadelphia via the District's Office of Student Records and through the District's Personnel Office. Using this dataset is unique because it is longitudinal, non-selective, and comprehensive of entire cohorts within a single, large district. Therefore, the results derived from employing these data may be representative of those needs facing urban schoolchildren in other similar districts.

Overall, the analytic sample $N=23,386$ consists of third and fourth grade students within 175 public, neighborhood schools with elementary grades over five contiguous academic years. The sample is restricted to third and fourth grade observations over this period because students could only be included in the analyses if data exist on their current and previous year's standardized achievement test scores. Students in the dataset only have standardized testing
information for second, third, and fourth grades; therefore, only third and fourth grade observations could be used in the analyses, as each model requires a lagged outcome from the previous school year. Furthermore, in order to be included in the sample, data must also exist for the other independent measures, as described below.

Chronic absenteeism. The key measure in this study is the percentage of a student's classmates who are chronically absent in a given school year. As mentioned, the advantage of relying on a sample of elementary school students is that children are contained in a single classroom throughout the day and year thereby allowing for a clear identification of classmates (Gottfried, 2012). Additionally, with this dataset, it was possible to identify student absences sourced directly from school records - this may not be the case in survey datasets or nationallyrepresentative datasets where absence information might be based on predetermined response ranges ( $0-5,6-10$, etc.). Here, precise total absences are available for each child across every classroom.

The strongest definition of chronic absenteeism is one where a student misses 18 days of school or more per year (Balfanz \& Byrnes, 2012; Gottfried, 2014). This is the definition utilized in this study. When it comes to chronic absenteeism, the precise reason designated for missing school is not the critical feature; rather, missing any excessive amount of school days, regardless of reason, becomes the defining characteristic (Gottfried, 2014). This definition of chronic absenteeism is applied to this present study - any student who misses 18 days or more of school in a given year is considered a chronic absentee. Approximately $22 \%$ of the sample would be considered a chronic absentee. Note that $99.5 \%$ of the sample missed between 0 and 70 days of school in any given year.

Once controlling for an individual's own chronic absenteeism and hence controlling for the individual effect of chronic absenteeism in the analytic models described below, the key measure of interest in this study is the percentage of a student's classmates who are chronic absentees. Students can be grouped unambiguously into classrooms because school and classroom assignment information is found on each student's record. Therefore, for each student in every year, it is possible to determine the exact percentage of classmates who are chronic absentees. Importantly, this measure for student $i$ does not include student $i$ 's own chronic absentee designation. In other words, the key feature of this peer measure (which again highlights the value of relying on large-scale district data) is that it identifies the rates of chronic absenteeism for any given student's set of classmates. That is, this measure 'picks up' the classroom context as experienced by each individual student. As such, students in a single classroom will have slightly different values for the percentage of chronically-absent classmates, depending on whether or not he/she is also chronically absent.

Outcomes. Table 1 presents the mean and standard deviation of all outcomes as well as all other measures employed in this study. The dependent variables are the normal curve equivalent scores (NCE) for the Stanford Achievement Test (SAT9). The NCEs are the generally preferred measurement for methodological reasons - they have statistical properties that allow for evaluating achievement over time (Balfanz \& Byrnes, 2006). Normal curve equivalents range in value from 1 to 99 .

Student data. For each student in every school year, the dataset contains demographic and academic characteristics. This study includes information on gender, race, as well as yearly indicators for special education status, English language learner (ELL) status, free lunch status,
and whether or not the student has a behavior issue, determined by his or her behavior grade from the end of previous academic year.

Insert Table 1 about here

Classmate data. Given individual-level student data, it is possible to construct a wide range of additional classmate measures by aggregating individual-level observations into classroom percentages. Except for class size (which would have no variation by student in a single classroom), all classroom measures are constructed as 'classmate' variables, as consistent with the construction of the percentage of chronically-absent classmates. These variables describe the characteristics of a set of classmates for each student. Accounting for classmate variables in this regard avoids confounding issues, where the classmate effect would be intertwined with an individual effect if conducted as the total percentage of students in classroom rather than the percentage of one's classmates.

The average class size is approximately 28 students (i.e., each student has 27 classmates on average). Average classmate reading and math achievement are both constructed based on the previous year's testing outcomes for a student's classmates in his/her classroom. Student $i$ 's lagged test outcome is not included in the average class score. Therefore, each student has a slightly different average classmate ability observation in a given school year.

The remaining classmate variables are the percentage of a student's classmates who embody certain characteristics. Each classmate variable mirrors the student-level characteristics utilized as control measures in this study. Here, this includes the percentage of a student's
classmates who are boys, Black, hold special education status, hold ELL status, receive free lunch, and have behavioral issues.

Teacher data. Data on teachers are sourced from student records and from the District's Personnel Office. A student record provides the name of the teacher assigned to a student's classroom in a given academic year. In addition, a teacher dataset was obtained from the District's Personnel Office. For each teacher, basic characteristics include race and gender. Also, a binary variable indicates whether a teacher had a Master's degree, based on the record which provides detail on which graduate school the teacher had attended.

Correlations. Table 2 presents partial correlation coefficients between a series of chronic absentee measures and the set of control measures selected in this study. Partial correlations were selected intentionally, as they derive the correlation between each pair of variables (each row * each column) while controlling for the joint influence of all other measures. All variables running down the rows are from the current academic year.

Insert Table 2 about here

The first set of chronic absentee measures focuses on the individual - each column indicates if a student was a chronic absentee in the previous year or the current year, respectively. The intention of examining these correlation coefficients is to determine if there are any systematic patterns between individual chronic absenteeism and individual- and classroomlevel characteristics. For instance, a hypothetically higher correlation between being a chronic absentee in the previous year and this year's set of classroom variables might suggest some degree of matching between student and classroom that might bias the estimates to follow.

The coefficients for these first two columns, however, suggest zero to very weak correlations between having been (or being) a chronic absentee student and the measures running down the rows. As for the student data, nothing stands out as being systematically related to being a chronic absentee. Certain students are no more or less likely to be chronic absentees (by demographic traits in the dataset). Importantly, the correlation coefficients between chronic absenteeism and classmate and teacher variables also approximate a value of 0 or are extremely weak. Notably, when it comes to looking at the relationship between having been a chronic absentee last year and a student's classroom and teacher characteristics in the present year, nothing stands out as presenting any sort of systematic pattern between student and classroom.

The latter group of two columns presents a similar interpretation. These final columns examine the correlations between the percentage of chronically absent classmates and the student, classmate, and teacher variables running down the rows. As before, there are no systematic relationships between the percentage of chronically absent classmates and individual student measures. That is, certain types of students are not more/less likely to have a greater or lower percentage of chronically absent classmates. Importantly, classroom and teacher characteristics are also not systematically related to the percentage of chronically absent classmates. Prior research examining the assignment of students to classrooms in this dataset suggests a lack of intentional matching between student and classroom and student and teacher (Gottfried, 2014). The evidence in Table 2 present consistent findings.

## Analytic Approach

Baseline model. To address the relationship between chronically absent classmates and individual-level outcomes, this study first employs a baseline empirical specification as follows:

$$
\begin{equation*}
Y_{i j k t}=\beta_{0}+\beta_{1} A_{i j t}+\beta_{2} Y_{i j k(t-1)}+\beta_{3} S_{i j k t}+\beta_{4} C_{k t}+\beta_{5} T_{k t}+\delta_{t}+\varepsilon_{i j k t} \tag{1}
\end{equation*}
$$

where $Y$ is achievement (reading or math: evaluated separately to follow) for student $i$ in classroom $j$ in school $k$ in year $t$.

The key term is A, which contains the percentage of chronically absent classmates in student $i$ 's classroom $j$ in school $k$ in year $t$. Additionally, the individual-level indicator for whether or not a student is chronically absent is included in this term, such that the analysis can parse out the individual effect from the classmate effect.

At the student level, other sets of independent variables include the following. First, $Y_{i j k(t-1)}$ represents a one-year lagged measure of achievement, such that the outcome measured during this year is not confounded with omitted prior characteristics (Gottfried, 2010). Second, $S_{i j k t}$ is a term that represents student data in Table 1. At the classroom level, $C_{k t}$ are classroom characteristics, and $T_{k t}$ are teacher characteristics. The model also accounts school year $t$ in $\delta_{t}$, which are year indicators. This way, each model examines within-year effects, which removes any spurious effects from having multiple student observations (i.e., students in grade three in year one move to grade 4 in year two of the dataset).

The error term $\varepsilon$ includes all unobserved determinants of achievement. Empirically, this component is estimated with robust standard errors, adjusted for classroom clustering. Because students are nested in schools by classroom and hence share common but unobservable characteristics and experiences, clustering student data by classroom is one approach that provides for a corrected error term given this non-independence of individual-level observations within a single classroom. Note that consistent with prior research, the error remains clustered at the classroom level, as the 'treatment' of the percentage of chronically absent classmates is a classroom-level measure.

School heterogeneity. Table 2 indicates little systematic patterning between being a chronic absentee and the other measures in the model or the percentage of chronically absent classmates and the other measures in the model. Hence, while there is no evidence that bias may exist in this domain, it might be speculated that unobserved school-level factors or practices are correlated with the key predictor variable as well as with the outcome given that absence patterns may be a function of school-level policies. For instance, some schools may have administrators with extremely strict attendance policies; these same types of administrators would most likely be making additional investments to boost achievement. Therefore, students in these schools may appear to have a greater boost from a lower percentage of chronically absent classmates, though it may have been driven by unobserved school influences. Alternatively, holding all else constant, one school may have aggregately low parental involvement, in which parents are not invested to ensure their children attend school. These same parents would not be as involved in ensuring academic success as parents in other schools might be. Given that this aggregate parental involvement may potentially influence both achievement outcome and percent of chronically absent classmates, any negative effect of the latter may be overestimated. With the multitude of hypothetical school-level scenarios that relate to higher/lower absences (and peers as such) as well as achievement, a school fixed effects model is employed to account for these aggregate school factors:

$$
\begin{equation*}
Y_{i j k t}=\beta_{0}+\beta_{1} A_{i j t}+\beta_{2} Y_{i j k(t-1)}+\beta_{3} S_{i j k t}+\beta_{4} C_{k t}+\beta_{5} T_{k t}+\delta_{t}+\delta_{s}+\varepsilon_{i j k t} \tag{2}
\end{equation*}
$$

Here, $\delta_{s}$ represents school fixed effects. This new term in Equation 2 represents is a set of binary variables that indicates if a student had attended a particular school (for each school variable in the dataset, 1 indicates yes, and 0 indicates no). The estimation process of including school
indicator variables leaves out one school as the reference group (this process is analogous to creating indicator variables for race, where one racial category is left out as the reference group).

The importance of school fixed effects is that they control for all unobserved school-level influences and characteristics because they hold constant omitted all school-specific factors, such as curriculum, school neighborhood, educational investments, organization, hiring practices, aggregate parental involvement, absence policies, and so forth. In doing so, the primary source of variation used to identify the classmate effect occurs across classrooms within each school (in addition to controlling for school year). Note that alternative fixed effects models are examined as tests of validity, as described in the results section.

## Results

## Baseline Findings

Table 3 presents empirical specifications of Equation 1, where the effect of the percentage of chronically absent classmates predicts reading and math achievement, controlling for all else. The estimates in the table are unstandardized coefficients with robust standard errors adjusted for classroom clustering in parentheses. Recall that the sample includes all third and fourth grade students, and the model controls for year.

Insert Table 3 about here

The key predictors in this study are found in the first section of results: the individual measure of being a chronic absentee, followed by the percentage of chronically absent classmates. Looking across both testing subjects, the results suggest that there is both an individual and classroom effect of chronic absenteeism. Beginning with the individual effect,
chronically absent students tend to have lower reading and math scores compared to other students, holding all else constant. The effect size utilized throughout this study is the standardized beta - a common metric utilized in non-experimental studies using large-scale datasets (e.g., Datar, 2006; McEwan, 2003). The effect sizes of these individual effects are approximately $-0.08 \sigma$ for reading and $-0.10 \sigma$ for math. Note that these individual effects are consistent with the chronic absentee effects sizes in Gershenson et al. (2014), and that they are approximately double the effect sizes found when considering the effect of average student absence rates without taking chronic absenteeism into account (e.g., Gottfried, 2011).

Of key interest in this study is the role of classmate chronic absenteeism. The second line of findings presents the estimates of this measure, which recall is the percentage of a student $i$ 's classmates who are chronically absent in the current school year. Controlling for a student's own chronic absenteeism as well as all other student, classmate, and teacher measures, the results suggest a negative relationship between the percentage of chronically absent classmates and individual reading and math achievement.

The effect sizes here are $-0.04 \sigma$ in reading and $-0.05 \sigma$ in math. In context, these are approximately the same size as the free lunch recipient/nonrecipient test gap and slightly smaller than the gender test gap (in reading) in this model. Moreover, what this does show is the effect experienced by every student in the classroom, given the construction of this classmate variable as the effect of the classmates that each student individually experiences in a given year. Hence, there is potential for large classroom effects when considering that the result pertains to all students in the classroom.

The baseline models provide formative evidence that having a greater proportion of chronically absent classmates is associated with lower achievement, across both reading and
math. The fact that the findings and effect sizes are similar across subjects suggests a robustness in the empirical specification selected in this study and that the findings are not necessarily domain specific to one outcome. Moreover, for those students who are chronically absent, there is the potential for larger negative effects as a result from chronic absenteeism. This would arise from the combination of a negative individual effect compounded with any negative peer effect associated with having chronically absent classmates. In other words, the negative 'chronic absenteeism effect' may be exacerbated by both individual and peer effects. Hence, including measures for both individual and classmate chronic absenteeism portrays a more complete story of the ramifications of this behavior rather than considering simply an individual effect in isolation.

## School Fixed Effects

Table 4 builds upon previous findings by presenting results from the school fixed effects models delineated in Equation 2. As in Table 3, the estimates are unstandardized coefficients. Below each coefficient are robust standard errors adjusted for classroom clustering.

Insert Table 4 about here

As a general interpretation of these findings, the results suggest a consistency between baseline and school fixed effects models. Chronically absent students tend to have lower reading and math achievement scores. Thus, there persists a negative individual effect. In the context of the classroom, having a higher percentage of chronically absent classmates also remains linked to lower achievement, as before. Given these findings, there remains the potential for both negative individual and classmate effects of chronic absenteeism. That said, even if an individual
student is not a chronic absentee per se, there is still the potential for a loss in achievement given any chronic absenteeism of his/her classmates.

It is apparent that the inclusion of school fixed effects does little to veer from the conclusion that chronic absenteeism (at both student and classroom levels) is associated with lower achievement. In fact, the unstandardized coefficients and effect sizes of the chronically absence measures in Table 4 are slightly larger than what was presented in Table 3. Thus, there is evidence of a slight degree of underestimation in the detrimental relationship between when not accounting for school-level processes and policies. Accounting for these unobserved schoollevel factors proves to be critical in defining the negative role of chronic absenteeism on student outcomes.

## Tests of Robustness

The consistency between baseline and school fixed effects models is reassuring of the empirical framework in this study. That said, there are potentially several other additional processes and policies that might be biasing the results. Each is tested here.

First, it is possible that time-varying unobserved school-level factors may be influencing the estimate of the percentage of chronically absent classmates. For example, if there were an increased emphasis on accountability in a given school year, the estimated effect of the key predictor and outcome may be biased. To account for these potential time-varying school confounds, a second revision to the baseline specification includes school-by-year fixed effects.

Second, it might be possible that grade- and school-specific factors might be influencing the estimates. A third revision will be to employ school-by-grade fixed effects. The rationale behind this particular model, then, is that school-by-grade fixed effects account for systematic grade-by-grade differences in a particular school that may affect the chronic absenteeism as well
as achievement, such as grade-specific policies (e.g., in some schools, grading policies change between third and fourth grades). Third, there is the possibility that time-varying unobserved factors may be influencing schools and grades in particular years, such as grade-specific policies under new school administration. To account for such school-grade differences over time, a model will include school-by-grade-by-year fixed effects.

Finally, in addition to biases on the estimates that may arise from unobserved school factors, there may also be unobserved individual-level biases. For instance, principals might place low motivated students in the same classroom with a greater percentage of students known to be chronically absent as a way of sorting/tracking. Although unobserved to the researcher, student motivation might be biasing the percentage of chronically absent classmates that he/she has as well as achievement. Given the potential student-level biases that may not be accounted for by school fixed effects, a student fixed effects model is tested. Analogous to the school fixed effect model, the student fixed effect model holds constant all unit-specific variation such all unobserved confounders that remain constant over time (e.g., individual motivation). What remains in the equation are solely time-varying factors, such as 'this year's' percentage of chronically absent classmates.

Insert Table 5 about here

Table 5 presents the findings from these tests of robustness. The testing outcome is presented in each row, and the tests of robustness are indicated by the column heading. For the sake of clarity given the number of tests in this table, only chronically absent classmate measures are presented as these are they key covariates in this study. First are the classmate measures from

Tables 3 and 4, provided in the table for comparison to these additional tests. The overall findings from the school-by-year, school-by-grade, school-by-grade-by-year, and student fixed effects models are quite similar to those from Table 4. While there was potential for a change in the estimates based on the scenarios driving the need for these four additional threats to validity, the findings here instead show a great deal of consistency between estimation approaches. In the end, the models continue to indicate a negative relationship between an increase in the percentage of chronically absent classmates and both reading and math outcomes. This is evident reading for either testing outcome, or for any test of robustness.

## Heterogeneity in Effects

Given the consistent findings of a negative effect of a greater percentage of chronically absent classmates (in addition to a negative individual effect of being a chronically absent student), it may be of interest to school leaders and policy makers to determine how these findings may differ based on individual characteristics. In doing so, it will be possible to determine what groups of students might be put at higher risk from having a greater percentage of chronically absent classmates.

Table 6 focuses on the differential effects of the percentage of chronically absent classmates. Each cell represents the result from a unique regression, with the sample from that regression delineated by the row heading and the outcome delineated by the column heading. In this way, it is possible to determine if there are differences in effects by specific subgroup. The models are those using school fixed effects, and the chronically absent classmate estimates from Table 4 are presented first for comparability.

Overall, the results suggest some heterogeneity by student characteristic. First, girls are slightly more negatively influenced by having a higher percentage of chronically absent
classmates compared to boys (effect sizes: available upon request in this section). The difference is larger in math. Academically, the differences in the effect of a greater percentage of chronically absent classmates are generally not delineated by individual ability - as seen in Table 5, the coefficients are fairly consistent (with perhaps a very slightly higher effect experienced by higher ability students).

Insert Table 6 about here

As for students with academic/demographic needs, there is evidence that special education and ELL students are generally not being affected by a higher percentage of chronically absent classmates, though the lack of statistical significance may have been driven by a small sample size in these subgroups given district demographics. Therefore, this current study would encourage further investigation in a district where these subgroups may hold a larger share of the student population.

Finally, as for additional student measures, there is evidence that students that receive free lunch at school (i.e., one potential proxy for relatively lower-income families) may be more negatively influenced by a higher percentage of chronically absent classmates compared to those students who do not receive lunch at school (i.e., a proxy for relatively higher-income families). Students without behavioral issues tend to be more negatively affected by having a higher percentage of chronically absent classmates.

While the differences within each demographic subgroup displayed here are not exceedingly large, they do suggest two overall conclusions. First, it does appear for the most part that students across the board have negative relationships with a greater percentage of
chronically absent classmates. That said, further exploration is required to test for differences in special education and ELL populations. Second, it does appear that the slight differences that do arise place students who were at a disadvantage (receipt of free lunch, behavioral issue) are put at greater risk with a higher percentage of chronically absent classmates compared to their less disadvantaged counterparts.

## Discussion

While much more is known about the effects of average rates of absenteeism, little work has examined the effects of chronic absenteeism - i.e., those students who miss approximately $10 \%$ or more of the academic year. Moreover, little work has assessed the role of absences in the context of the classroom. To address this research gap, this study explored the influence of having chronically-absent classmates on individual-level outcomes. Examining classroom chronic absenteeism (as opposed to average rates of absenteeism) has provided a more detailed portrait of risk, as average rates of classroom absenteeism might be masking a more dangerous absenteeism problem. Moreover, examining classmate effects in elementary school has proved to be significant - as research has found that chronic absenteeism pervades outcomes for even the youngest of students in the U.S. Additionally, evaluating these issues for a sample of students in a large urban school district is critical, given that students in these districts often face additional challenges often not faced by students in non-urban settings. Understanding these dynamics of individual- and classroom-level chronic absenteeism yields significant insight into how to best address attendance issues and how to reduce chronic absenteeism in our nation's schools where there are heighted incidence rates and worsened effects.

There are several noteworthy findings. First, although not a direct focus of this study, students who are chronically absent have lower achievement outcomes, as demonstrated in

Tables 3 and 4. Across both reading and math tests, the effect sizes are consistent with prior findings on the role of student chronic absenteeism on achievement, and they are much larger than the effect sizes pertaining to average absenteeism. Hence, these findings in this present study confirm the presence of a detrimental effect of individual-level chronic absenteeism on individual-level outcomes - one that is larger than what was previously established regarding average rates of absenteeism.

Second and central to this study, there is evidence of a negative spillover effect, as motivated by the guiding framework laid-out in the introduction of this article. Across both reading and math outcomes, students in classrooms with a higher percentage of chronic absentees have lower test scores. These findings were robust to multiple testing outcomes and multiple methodological approaches. There appears to both individual and classmate effects stemming from chronic absenteeism behavior. Chronic absentees themselves tend to have lower achievement outcomes, and the contribution of this study is that it shows that the act of chronically missing school imposes onto the learning outcomes of others. Even if students themselves are not chronic absentees, they may still be at-risk of educational decline based on the chronic absenteeism of others in the same classroom.

Finally, these results were somewhat differentiated by individual characteristics. There were slight differences that do arise place non-chronically-absent students (receipt of free lunch, behavioral issue) at a further risk when faced with a greater rate of classmate chronic absenteeism. Thus, those facing additional challenges may be placed at even greater risk for academic decline when considering the role of classmates' chronic absences. Nonetheless, the findings do indicate that all students are negatively affected by this behavior.

Taken together, these three sets of findings contribute to a more refined understanding of factors contributing to schooling risk. First, being a chronic absentee certainly serves as a first indicator of individual risk for that student engaging in this behavior. Second, however, this study shows that engagement in negative school-related behaviors affects others. Thus, there is an additional risk associated with absenteeism, based on the actions of one's classmates. Though this study assessed chronic absenteeism in particular, this interpretation of this finding generalizes to how there are both first- and second-order effects resultant from risk-related actions. The first-order effect in this study was the act of missing school and the effect that it had on that individual. As perhaps expected, negative actions impose negative consequences for the person engaging in this at-risk behavior. However, this study shows that there is also a secondorder effect - namely, a negative externality. The findings in this study therefore develop a more nuanced portrayal of student risk: individual actions impose negative outcomes on others. Firstand second-order effects of risky behaviors are fairly prevalent beyond the scope of education. Here, the same patterning of effects has arisen in educational research through absenteeism. Therefore, what this study has identified is not simply how individual actions affect individual outcomes; rather, students' risky behaviors negatively impact others as well.

Moreover, this study shows that first- and second-order indictors of risk can be exacerbated by specific individual-level characteristics. Both first- and second-order effects of at-risk schooling behavior may become worsened for certain students. This might actualize as a differentiation between urban versus non-urban students. However, this study also showed within-group differences the effects of student absenteeism, as depicted in the discussion of heterogeneous effects. All-in-all, then, this study expands our knowledge of what individual schooling behaviors contribute to risk, in what capacity and for whom.

With this more complete depiction of the negative implications of missing school and a more developed interpretation of how absenteeism exemplifies how first- and second-order risks detract from student attainment, it becomes easier to facilitate recommendations for policy and practice. One key straightforward implication speaks directly to data analysis and risk measurement. The fact remains that public school performance is still generally evaluated based on averages, such as an average daily attendance rate or average daily absence rate (Sheldon, 2007). It would appear that on the whole, policy might encourage schools to access and assess the appropriate data when it comes to evaluating risk data associated with absenteeism. While average absence measures do provide some contextual insight onto the status of a school-specific absentee problem, this study demonstrates that average absence data does not provide as strong of a metric. Whereas average rates of absenteeism may provide insights into the functioning of a school (e.g., high attending versus low attending schools), it does not depict who is most at-risk from this negative school-going behavior. More so, average attendance rates provide less detail on second-order effects of risk behavior; knowing the number of chronically-absent classmates provides much richer detail regarding the interconnectedness of at-risk schooling behaviors than do average classroom attendance rates. As previously referenced, two classrooms with the same average daily absence rate may have vastly different absentee issues, and thus two very different risk profiles. By focusing on average absence rates in addition to chronic absenteeism, schools can better evaluate the sources of school-wide absence measures and better identify those students (and classmates) at greatest risk of educational decline. For instance, if school-level absence rates are driven by repeated absences by the same set of students, it may be most effective for administrators to employ individually targeted interventions. If school-wide absence trends are based on patterns in the overall student body, practitioners could enact more general
school policies to reduce absences. Therefore, it would behoove policy makers to encourage or induce schools and districts to collect, assess, and address average absence data as well as chronic absence data.

A second implication for policy is that the detrimental effect of chronic absenteeism on achievement was found to be multilevel - the first- and second-order effects were individual and classroom, respectively. This provides insight into the role of within-school, between-classroom variation in chronic absenteeism - the key contribution of this study. For policy makers and practitioners to identify whether there is within-school variation in classroom chronic absenteeism allows for even greater detection and diagnosis of absenteeism issues (springboarding from the issues raised in the previous paragraph). For instance, a lack of withinschool variation in chronic absence patterns might suggest more widespread school-level issues need to be addressed. Perhaps there are school-wide gaps in attendance policies or in parental involvement - both hypothetical examples. A high degree of within-school, between-classroom variation in chronic absenteeism rates might have alternative implications, demanding further investigation as to what might be driving such high rates of chronic absenteeism in particular classrooms and to make adjustments accordingly.

A third implication for policy is grounded in the fact that this study focused on schoolchildren in a large urban district. Approximately $22 \%$ of the sample was classified as chronically absent based on the Balfanz and Byrnes (2012) definition of chronic absenteeism. If chronic absenteeism on a national scale occurs at a rate of 10 to 15 percent, then this behavior could potentially be interpreted as double the size in urban districts. This study certainly urges research and policy to continue focusing on chronic absenteeism at national and state levels, much as Gottfried (2014) has done regarding the former and much as Harris et al. (2013) has
done regarding the latter. However, it is imperative that policy also focus specifically on issues of chronic absenteeism in large urban school districts, as exemplified by the findings in this study.

As mentioned, elementary school students in large urban districts face a number of challenges that might inhibit them from regularly attending school, including health issues and parental involvement. Therefore, chronic absenteeism is particularly salient to address in large urban districts for two reasons. First, students in these districts do not have the supports and resources to attend school on a regular basis, which may not necessarily be the case for nonurban youth. Policy must therefore address what specific factors (beyond very general constructs) are inhibiting students in urban districts from attending school in the first place. For instance, perhaps a lack of parental involvement in getting their children to school stems specifically from logistics or transportation issues. Or perhaps health issues stem specifically from chronic illnesses. This study calls for policy and practice to more effectively narrow down the specific drivers of chronic absenteeism so that we can not only establish the effects of this school-going risk behavior but what specific supports and services are required. Thus, policy must address how to rectify negative these first-order effects of individual chronic absenteeism on individual outcomes. Second, because of the documented spillover effect found in this study and because of the challenges that students in urban schools often face in general (Conchas et al., 2014), the spillover effects of chronic absenteeism may be compounding the challenges faced by other students who do not necessarily engage in chronic absenteeism themselves. As chronic absenteeism is highest in large urban districts as are additional challenges, it is crucial to develop policy that addresses not only how to identify and reduce chronic absenteeism for the individual
engaging in this behavior but also provide supports and services for classmates who may face other risks of educational decline.

As a final policy implication, the findings in this study demonstrate that chronic absenteeism has detrimental effects for students and their classmates as early as in elementary school. It might be an at older age when rhetoric surrounding chronic absenteeism gains momentum as 'truancy,' as policy makers and practitioners become concerned about the activities in which older students engage if they are not attending school (for non-health reasons). For older students, these activities are often correlated with other high-risk behaviors, and thus truancy among older students often takes the spotlight in this arena. It is certainly necessary to prevent truancy among older students. However, this study among others demonstrate that patterns of chronic absenteeism begin early (Balfanz \& Byrnes, 2012), that the effects of early chronic absenteeism affect achievement and development as early as in kindergarten (Gottfried, 2014) and that there are implications for both individual and peers throughout elementary school as shown in this study. These negative school-going behaviors in early years can therefore have a damaging effect early on. Therefore, reducing these negative school-going behaviors early in schooling is essential, and this study supports the policies, practices, and interventions geared at addressing chronic absenteeism in early schooling. Previous efforts at school interventions that try to mitigate absences and stimulate engagement, such as Check \& Connect (Lehr et al., 2004) would be supported as critical. Further interventions that address both individual and group effects are necessary.

These interventions may take many forms in practice. For instance, in addition to targeting specifically those students with high rates of chronic absenteeism, programs that target entire classrooms may be another effective strategy to address classroom-level chronic absence
issues. After-school programming that focused on engaging all students in a classroom at once (in contrast to, say, a pull-out program that might only have the capacity to address individual student needs at any given time) might lead to a more system-wide and efficient reduction in classroom chronic absenteeism. One option might be classroom-wide participation in afterschool sports, as prior research has shown extracurricular participation to be positively related to school attendance (Marvul, 2012; Whitley, 1995). Importantly, these types of interventions would rely on large districts collecting appropriate measures on both absenteeism as well as chronic absenteeism, as described earlier, in order to identify which students and classrooms face the greatest challenges from chronic absenteeism. Therefore, the capacity for data collection and analysis by large districts with high rates of chronic absenteeism hence directly maps onto to the capacity to support students and classrooms.

A second intervention in practice may arise as attendance monitoring. Prior research has found a link between increased monitoring and absenteeism reduction in urban schools (Marvul, 2012), and the findings in this present study would support continued efforts in this area. It may be possible to build upon these prior intervention efforts by developing monitoring interventions that incorporate classroom-level issues. For instance, in the introduction of this article, two example classrooms were presented (A versus B) in which only one of these classrooms actually had a chronic absenteeism problem. By tracking data and subsequently creating real-time early warning systems of classrooms where there does appear to be high rates of chronic absenteeism in particular, it would be possible to notify teachers, administrators, and parents of the increased risks in specific classrooms over the duration of the school year. From this, structured classroomlevel outreach programs could be developed in a way that a variety of stakeholders can address
that classroom's chronic absenteeism issues in addition to individual student issues on a very tangible and immediate basis.

As a third implication for practice, this study would support an increase in parental engagement and awareness regarding the negative ramifications of chronic absenteeism. However, to do so, it is imperative to understand what specific factors connect parental involvement to lowered chronic absenteeism and which do not, as mentioned previously in this discussion. From this, it will be possible to develop intervention programs that address specific issues relating to chronic absenteeism rather than relying on more general notions of 'parental involvement.' In other words, what is necessary to move forward with the reduction of chronic absenteeism in urban schools is the identification of precise factors inhibiting young children from attending school, whether that pertains to logistics, health, attitudes, or perceptions. Thus, this study calls for interventions to be based on very specific, tangible aspects of engagement and awareness in order to make changes to rates of chronic absenteeism. One final point, however, is that in addition to those traditional outreach interventions focusing on the individual student, additional interventions pertaining to how chronic absenteeism also hurts their child's classmates may also serve as an effective strategy. That is, we need practices that reduce chronically-absent children from engaging in this behavior not only because it puts themselves at risk, but also hurts their peers.

## Conclusion

In sum, being chronically absent has negative implications not only for the individual student, but also for a chronic absentee's classmates. If the classroom environment can be conceptualized as a public good as Lazear (2001) has suggested, then any deviance from regular instruction caused by one student can be interpreted as a strain exerted onto his or her
classmates. In this study, this negative strain materialized as a decline in academic performance based on missing excessive amounts of school.

There are limitations that can be used to direct future research. First, this study focused solely on reading and math achievement. Future research may entail evaluating the effects of chronically-absent classmates on non-testing academic outcomes, such as nonpromotion. With a longitudinal dataset spanning primary and secondary grades, it might even be possible to examine the effects on dropout. In this way, schools could more efficiently evaluate how individual and classroom chronic absenteeism places students at risk, and develop policies and programs to target specific students and settings.

Second, as with most district datasets, the focus was exclusively on academic outcomes. That said, recent empirical research has documented the role of chronic absenteeism on socioemotional outcomes (e.g., Gottfried, 2014). With non-administrative data, such as a survey study, future research might examine metrics of academic motivation and engagement. Doing so would provide an even richer picture of the effect of chronic absenteeism.

Finally, though this study examined chronic absenteeism as a key input, equally as critical would be determining what drives this. Future research might consider assessing what factors at what level (student, family, classroom, etc.) might predict higher rates of individual and classroom chronic absenteeism. Doing so will continue efforts at identifying what mediates high rates of chronic absenteeism and how to prevent it and its associated damaging effects.

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Table 1: Descriptive Statistics

|  | Mean | $S D$ |
| :---: | :---: | :---: |
| Outcomes |  |  |
| Reading achievement | 42.68 | 14.89 |
| Math achievement | 56.52 | 19.11 |
| Chronic absenteeism |  |  |
| Chronic absentee | 0.22 | 0.42 |
| Percent of chronic absentee classmates | 0.23 | 0.11 |
| Student data |  |  |
| Boy | 0.49 | 0.50 |
| White | 0.18 | 0.38 |
| Black | 0.68 | 0.47 |
| Latino | 0.10 | 0.30 |
| Asian | 0.04 | 0.20 |
| Other | 0.00 | 0.04 |
| Special education | 0.03 | 0.17 |
| English language learner | 0.03 | 0.17 |
| Free lunch | 0.53 | 0.50 |
| Behavior issues | 0.09 | 0.29 |
| Classmate data |  |  |
| Class size | 28.78 | 2.94 |
| Average reading achievement (prior year) | 22.99 | 10.90 |
| Average math achievement (prior year) | 36.46 | 14.09 |
| Percent of classmates: boys | 0.49 | 0.08 |
| Percent of classmates: black | 0.67 | 0.35 |
| Percent of classmates: special education | 0.03 | 0.04 |
| Percent of classmates: English language learner | 0.04 | 0.09 |
| Percent of classmates: free lunch | 0.51 | 0.21 |
| Percent of classmates: behavioral issues | 0.09 | 0.08 |
| Teacher data |  |  |
| Male | 0.01 | 0.11 |
| White | 0.49 | 0.50 |
| Black | 0.48 | 0.50 |
| Latino | 0.02 | 0.15 |
| Asian | 0.01 | 0.08 |
| Holds Master's degree | 0.02 | 0.13 |
| n | 23,386 |  |

Table 2: Correlation Coefficients with Chronic Absence Measures

|  | Student is a Chronic Absentee |  | Percent of Chronic Absentee Classmates |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Previous <br> Year | Current Year | Previous <br> Year | Current Year |
| Current year student data |  |  |  |  |
| Prior year's reading achievement | -0.02 | 0.00 | -0.01 | 0.00 |
| Prior year's math achievement | -0.06 | -0.05 | -0.03 | -0.04 |
| Boy | 0.01 | -0.01 | 0.01 | 0.01 |
| White | -0.01 | -0.01 | 0.03 | 0.00 |
| Black | -0.01 | -0.02 | 0.02 | 0.00 |
| Latino | -0.01 | -0.02 | 0.03 | 0.00 |
| Asian | -0.02 | -0.03 | -0.02 | -0.01 |
| Special education | 0.00 | 0.00 | -0.02 | 0.00 |
| English language learner | -0.01 | 0.00 | -0.02 | 0.01 |
| Free lunch | 0.12 | 0.10 | 0.02 | 0.00 |
| Behavior issues | 0.05 | 0.05 | -0.01 | -0.01 |
| Current year classmate data |  |  |  |  |
| Class size | 0.02 | 0.01 | 0.01 | 0.02 |
| Average reading achievement (prior year) | -0.03 | 0.00 | -0.01 | -0.03 |
| Average math achievement (prior year) | -0.01 | -0.03 | 0.08 | -0.07 |
| Percent of classmates: boys | 0.00 | 0.00 | -0.03 | -0.06 |
| Percent of classmates: black | -0.02 | 0.00 | -0.09 | -0.01 |
| Percent of classmates: special education | 0.00 | 0.00 | -0.02 | 0.03 |
| Percent of classmates: English language learner | -0.01 | 0.00 | -0.01 | -0.01 |
| Percent of classmates: free lunch | 0.01 | -0.02 | 0.03 | 0.03 |
| Percent of classmates: behavioral issues | 0.00 | -0.01 | 0.04 | 0.01 |
| Current year teacher data |  |  |  |  |
| Male | 0.01 | 0.02 | -0.02 | 0.02 |
| Black | 0.01 | 0.02 | -0.03 | 0.02 |
| Latino | 0.00 | 0.00 | 0.01 | 0.00 |
| Asian | 0.00 | 0.00 | -0.02 | 0.00 |
| Holds Master's degree | 0.00 | 0.00 | -0.01 | 0.00 |

Table 3: Baseline Estimates of Effects of Chronic Absenteeism on Achievement

|  | Reading | Math |
| :---: | :---: | :---: |
| Chronic absentee | $-1.15{ }^{* * *}$ | $-1.92{ }^{* * *}$ |
|  | (0.18) | (0.27) |
| Percent of chronic absentee classmates | -5.67*** | -8.85 *** |
|  | (1.10) | (1.84) |
| Student demographic/academic data |  |  |
| Prior year's outcome | 0.69 *** | $0.66{ }^{* * *}$ |
|  | (0.01) | (0.01) |
| Male | -1.08 ${ }^{* * *}$ | 0.02 |
|  | (0.14) | (0.16) |
| Black | $-2.56{ }^{* * *}$ | $-3.55{ }^{* * *}$ |
|  | (0.25) | (0.32) |
| Latino | $-1.22^{* * *}$ | -1.80*** |
|  | (0.35) | (0.54) |
| Asian | $0.67{ }^{*}$ | $2.96{ }^{* * *}$ |
|  | (0.37) | (0.53) |
| Other | -2.10 | 1.11 |
|  | (1.74) | (2.45) |
| Special education | $-1.62^{* * *}$ | -0.80 |
|  | (0.47) | (0.59) |
| English language learner | -1.50 *** | -2.61 *** |
|  | (0.45) | (0.79) |
| Free lunch | -0.73 *** | $-1.47{ }^{* * *}$ |
|  | (0.14) | (0.18) |
| Behavior issues | $-0.87{ }^{* * *}$ | -1.14 ${ }^{* *}$ |
|  | (0.22) | (0.30) |


|  | Reading | Math |
| :---: | :---: | :---: |
| Classroom data |  |  |
| Class size | 0.00 | 0.00 |
|  | (0.04) | (0.08) |
| Average reading achievement (prior year) | 0.07 | $0.18{ }^{* * *}$ |
|  | (0.04) | (0.07) |
| Average math achievement (prior year) | -0.05 | $0.14{ }^{* * *}$ |
|  | (0.03) | (0.05) |
| Percent of classmates: boys | $-2.45{ }^{* * *}$ | -2.46 |
|  | (1.39) | (1.83) |
| Percent of classmates: Black | -0.84 | -3.41 *** |
|  | (0.53) | (0.70) |
| Percent of classmates: special education | -2.86 | 0.95 |
|  | (3.64) | (4.50) |
| Percent of classmates: English language learner | 0.80 | -2.21 |
|  | (1.36) | (2.20) |
| Percent of classmates: free lunch | $-3.10{ }^{* * *}$ | -1.72 |
|  | (0.68) | (1.29) |
| Percent of classmates: behavioral issues |  |  |
|  | (1.81) | (2.49) |
| Teacher data |  |  |
| Male | 0.98 | 0.60 |
|  | (0.78) | (0.93) |
| Black | -0.61 | $-1.66{ }^{* *}$ |
|  | (0.56) | (0.78) |
| Latino | -4.64 * | -4.06 |
|  | (1.87) | (3.69) |
| Asian | 1.21 | 0.96 |
|  | (2.81) | (4.04) |
| Master's degree | 0.51 | $2.37{ }^{* *}$ |
|  | (0.56) | (0.93) |
| n | 23,458 | 23,393 |
| $\mathrm{R}^{2}$ | 0.56 | 0.53 |

Note: *** $p<0.01,{ }^{* *} p<0.05,{ }^{*} p<0.01$
Robust Huber-White standard errors adjusted for clustering within classrooms are in partentheses.
Note that all models include control for school year.
All regressions include a constant.

Table 4: School Fixed Effects Estimates of Effects of Chronic Absenteeism on Achievement

|  | Reading | Math |
| :---: | :---: | :---: |
| Chronic absentee | $-1.22^{* * *}$ | $-2.05{ }^{* * *}$ |
|  | (0.18) | (0.25) |
| Percent of chronic absentee classmates | -6.63 *** | $-10.05{ }^{* *}$ |
|  | (1.30) | (1.97) |
| Student demographic/academic data |  |  |
| Prior year's outcome | $0.68{ }^{* * *}$ | $0.64{ }^{* * *}$ |
|  | (0.01) | (0.01) |
| Male | -1.11 ${ }^{* * *}$ | 0.02 |
|  | (0.13) | (0.16) |
| Black | -2.73 *** | -3.77 *** |
|  | (0.25) | (0.23) |
| Latino | $-1.58{ }^{* * *}$ | $-2.05{ }^{* * *}$ |
|  | (0.28) | (0.39) |
| Asian | 0.83 ** | 3.09 *** |
|  | (0.34) | (0.51) |
| Other | -2.58 | -0.34 |
|  | (1.83) | (2.38) |
| Special education | $-1.69{ }^{* * *}$ | -1.06 * |
|  | (0.47) | (0.60) |
| English language learner | -1.43 *** | -2.31 ${ }^{* * *}$ |
|  | (0.48) | (0.83) |
| Free lunch | $-0.76{ }^{* * *}$ | $-1.51{ }^{* * *}$ |
|  | (0.13) | (0.18) |
| Behavior issues | -0.96 *** | -1.29 *** |
|  | (0.21) | (0.29) |


|  | Reading | Math |
| :---: | :---: | :---: |
| Classroom data |  |  |
| Class size | $\begin{array}{r} 0.01 \\ (0.05) \end{array}$ | $\begin{array}{r} 0.02 \\ (0.07) \end{array}$ |
| Average reading achievement (prior year) | $\begin{array}{r} 0.03 \\ (0.05) \end{array}$ | $\begin{gathered} 0.16{ }^{* *} \\ (0.07) \end{gathered}$ |
| Average math achievement (prior year) | $\begin{array}{r} -0.05 \\ (0.03) \end{array}$ | $\begin{aligned} & 0.17 \\ & (0.05) \end{aligned}$ |
| Percent of classmates: boys | $\begin{array}{r} -2.03 \\ (1.45) \end{array}$ | $\begin{array}{r} -1.30 \\ (2.19) \end{array}$ |
| Percent of classmates: Black | $\begin{array}{r} -2.20 \\ (1.78) \end{array}$ | $\begin{gathered} -4.66 \\ (2.70) \end{gathered}$ |
| Percent of classmates: special education | $\begin{array}{r} -5.61 \\ (3.45) \end{array}$ | $\begin{array}{r} -2.12 \\ (4.89) \end{array}$ |
| Percent of classmates: English language learner | $\begin{array}{r} 2.33 \\ (1.90) \end{array}$ | $\begin{array}{r} -0.37 \\ (3.12) \end{array}$ |
| Percent of classmates: free lunch | $\begin{array}{r} -2.41 \\ (1.42) \end{array}$ | $\begin{array}{r} -2.08 \\ (2.19) \end{array}$ |
| Percent of classmates: behavioral issues | $\begin{gathered} -2.89 \\ (1.70) \end{gathered}$ | $\begin{array}{r} -1.54 \\ (2.47) \end{array}$ |
| Teacher data |  |  |
| Male | $\begin{array}{r} 1.13 \\ (0.87) \end{array}$ | $\begin{array}{r} 0.42 \\ (1.04) \end{array}$ |
| Black | $\begin{array}{r} -0.57 \\ (0.58) \end{array}$ | $\begin{gathered} -1.81^{* *} \\ (0.86) \end{gathered}$ |
| Latino | $\begin{array}{r} -3.26 \\ (1.58) \end{array}$ | $\begin{array}{r} -2.51 \\ (2.90) \end{array}$ |
| Asian | $\begin{array}{r} 0.85 \\ (1.94) \end{array}$ | $\begin{array}{r} 2.11 \\ (3.53) \end{array}$ |
| Master's degree | $\begin{array}{r} 0.46 \\ (0.62) \end{array}$ | $\begin{array}{r} 1.67^{*} \\ (0.95) \end{array}$ |
| n | 23,458 | 23,393 |
| $\mathrm{R}^{2}$ | 0.58 | 0.56 |

Note: *** $p<0.01,{ }^{* *} p<0.05,{ }^{*} p<0.01$
Robust Huber-White standard errors adjusted for clustering within classrooms are in partentheses. Note that all models include control for school year.
All regressions include a constant.

|  | Table 3 | Table 4 | School-year FE | School-grade FE | School-gradeyear FE | Student FE |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Reading | $\begin{gathered} -5.67^{* * *} \\ (1.10) \end{gathered}$ | $\begin{aligned} & -6.633^{* *} \\ & (1.30) \end{aligned}$ | $\begin{aligned} & -6.65{ }^{* * *} \\ & (1.24) \end{aligned}$ | $\begin{aligned} & -6.08{ }^{* * *} \\ & (1.17) \end{aligned}$ | $\begin{aligned} & -6.38^{* * *} \\ & (1.18) \end{aligned}$ | $\begin{aligned} & -6.41{ }^{* * *} \\ & (1.60) \end{aligned}$ |
| Math | $\begin{aligned} & -8.85^{* * *} \\ & (1.84) \end{aligned}$ | $\begin{aligned} & -10.05{ }^{* * *} \\ & (1.97) \end{aligned}$ | $\begin{aligned} & -11.39^{* * *} \\ & (2.00) \end{aligned}$ | $\begin{aligned} & -10.31 * * \\ & (1.94) \end{aligned}$ | $\begin{aligned} & -10.14^{* * *} \\ & (1.90) \end{aligned}$ | $\begin{aligned} & -10.31 \text { *** } \\ & (2.39) \end{aligned}$ |

Note: ${ }^{* * *} p<0.01,{ }^{* *} p<0.05,{ }^{*} p<0.01$
Robust Huber-White standard errors adjusted for clustering within classrooms are in partentheses.
Note that all models include control for school year.
All regressions include a constant.

Table 6: Heterogeneity in the Effects of Chronically Absent Classmates

|  | Reading | Math |
| :---: | :---: | :---: |
| Estimates from Table 4 | $-6.63{ }^{* * *}$ | $-10.05^{* * *}$ |
|  | (1.30) | (1.97) |
| Boys | $-6.38{ }^{* * *}$ | $-8.76{ }^{* * *}$ |
|  | (1.58) | (2.06) |
| Girls | $-7.01{ }^{* * *}$ | $-11.53{ }^{* * *}$ |
|  | (1.43) | (2.28) |
| Below average ability | -4.94 ** | -9.58*** |
|  | (2.13) | (2.52) |
| Above average ability | $-6.85{ }^{* * *}$ | -9.99 ** |
|  | (1.38) | (2.01) |
| Special education | -7.05 | 1.76 |
|  | (6.44) | (8.31) |
| Not special education | $-6.56{ }^{* * *}$ | $-10.51{ }^{* * *}$ |
|  | (1.37) | (2.03) |
| ELL | $-10.28{ }^{* *}$ | -8.49 |
|  | (4.63) | (8.95) |
| Not ELL | $-6.59{ }^{* * *}$ | -10.09 *** |
|  | (1.31) | (2.00) |
| Free lunch | $-7.04{ }^{* * *}$ | -10.44 *** |
|  | (1.53) | (2.33) |
| Non free lunch | $-5.79{ }^{* * *}$ | -9.64 *** |
|  | (1.53) | (2.22) |
| Behavioral issue | -6.71 * | $-12.35{ }^{* * *}$ |
|  | (3.27) | (4.18) |
| No behavioral issue | $-6.70{ }^{* * *}$ | $-9.75{ }^{* * *}$ |
|  | (1.28) | (1.97) |

Note: ${ }^{* * *} p<0.001,{ }^{* *} p<0.01,{ }^{*} p<0.05,+p<0.10$.
Robust Huber-White standard errors adjusted for clustering within classrooms are in partentheses.
Each cell represents a separate regression, which includes the same control variables as in Tables 3 and 4.

