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ABSTRACT

Quantile Regression Estimates of the Effect of Student Absences on Academic Achievement

Credible evidence from a variety of contexts suggests that student absences harm academic achievement. However, extant studies focus entirely on the average effects of student absences, and how those average effects vary by student, school, and absence type. This paper enhances our understanding of the nature of the causal relationship between absences and achievement by estimating quantile regressions that identify the impact of student absences on the full distribution of achievement, not just its mean. Somewhat surprisingly, the harmful effects of student absences are approximately constant across the achievement distribution. This suggests that cost-benefit analyses of interventions designed to improve attendance can use previously-estimated average effects to predict benefits. Moreover, it suggests that interventions that target all students would neither increase nor decrease the variance in test scores.

JEL Classification: I2

Keywords: student attendance, chronic absence, education production function, quantile regression

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1. Introduction

A series of recent rigorous academic studies document the harm that student absences inflict on student achievement (Aucejo & Romano, 2016; Gershenson et al., 2017; Goodman, 2014; Gottfried, 2009, 2010, 2011). Evidence of a causal relationship between absences and achievement has motivated educators, school administrators, and policymakers to reassess and create both proactive and reactive interventions that might lessen the consequences of student absences. It has also led policy makers to explicitly consider attendance as an indicator of school and student success (Bauer et al., 2018; Gottfried & Hutt, 2019).

However, the extant research base that motivates such interventions and policies focuses exclusively on the identification and estimation of the average effects of student absences. While average effects are interesting and add to our understanding of the education production function, they overlook potential variation across the achievement distribution in the relationship between absences and student achievement. The limitations of focusing solely on average effects has been discussed in the context of instructional time and school vouchers (Bitler et al., 2015; Eide & Showalter, 1998; Hayes & Gershenson, 2016), but this nuance has yet to be considered in the case of student absences.

Understanding the extent to which the impact of absences varies across the achievement distribution has important implications for policy makers seeking to either close achievement gaps or improve the achievement of schools' lowest performing students. For example, if the impact of absences varies across the achievement distribution, policies that reduce absences have the potential to either increase or decrease achievement gaps. The former constitutes an unintended consequence of such policies that would go undetected by analyses that focus solely on constant, average effects. Similarly, knowledge of the impact of student absences on the distribution of achievement gains would facilitate more nuanced cost-benefit analyses of absence-reducing interventions.

We address this gap in the literature by extending the quasi-experimental methods used in past research on the harmful effects of student absences (e.g., Gershenson et al., 2017) to the quantile regression context.[1] Quantile regressions model conditional quantiles in similar fashion to how linear regressions model conditional means (Koenker & Hallock, 2001). Specifically, we use student-level data on first and third graders who participated in the Tennessee STAR class-size reduction experiment to estimate value-added quantile regressions that relate student absences to student achievement at each decile of the achievement distribution. Consistent with previous research in other settings (e.g., Gershenson et al., 2017), we first replicate the basic result that, on average, a one standard deviation (SD) increase in absences (6.3) reduces achievement by 0.03 to 0.04 test score SD. Our novel contribution, though, is showing that the harmful effects of student absences are actually fairly constant across the achievement distribution. This means that the extant literature's focus on the average effects of student absences is appropriate and not missing significant nuances in the relationship between absences and achievement.

We proceed as follows: Section 2 describes the STAR data and compares it to data used in previous analyses of student absences. Section 3 describes the identification strategy and quantile regression method. Section 4 presents the main results. Section 5 concludes.

[1] An abbreviated version of this working paper (Gershenson et al., 2019) is forthcoming in an edited volume (Hutt & Gottfried, 2019).

2. Data

Tennessee's Project STAR (Student Teacher Achievement Ratio) was a seminal field experiment in education, designed to identify the impact of class size on student achievement (Krueger, 1999; Schanzenbach, 2006). Project STAR began in 1985-1986, when it randomly assigned kindergarten students and teachers in participating schools to either small- or regular-sized classrooms. The experiment continued over the next three years, randomly assigning students from the 1986 kindergarten cohort to small- and regular-sized classrooms in grades 1-3, while also refreshing the analytic sample in each year with new entrants to participating schools. Small classes significantly improved student performance on standardized tests. Subsequent analyses document long-run effects of random assignment to a small classroom on educational attainment (Dynarski et al., 2013). Tran and Gershenson (2018) show that a ten-student reduction in class size lowers the probability of being chronically absent by about three percentage points (21%).

While Project STAR influenced debates over the efficacy of class-size reductions, other researchers recognized that the random assignment of students and teachers to classrooms could be leveraged to study other questions. For example, scholars have leveraged the random classroom assignments generated by the STAR experiment to estimate the impacts of having a same-race teacher on test scores, the long-run effects of high-quality kindergarten classrooms on earnings, peer effects, and the impact of classroom characteristics on attendance (Chetty et al., 2011; Dee, 2004; Graham, 2008; Tran & Gershenson, 2018). We similarly use Project STAR data to address a question unrelated to class size: how do student absences affect the distribution of test scores?

We do not directly exploit the random assignment of students and teachers to classrooms. Intuitively, the reason is that student absences were not randomly assigned to students (and indeed doing so would be both unethical and impossible). Nor is our goal to estimate the impact of classroom characteristics, which were randomly assigned, on student outcomes. Nonetheless, Project STAR's random assignment does alleviate some concerns common to research on student absences. First, random assignment mitigates the concern that students with past attendance issues are assigned to particularly effective teachers, as previous research shows that teachers affect student attendance (Gershenson, 2016). Second, we might worry that students prone to attendance issues sort into classrooms with students who have similar attendance (and related behavioral) issues, in which case the effect of absences might be confounded with classroom-level peer effects. We further address these and other identification concerns in Section 3.

To our knowledge the relationship between attendance and achievement has yet to be studied in the public-use Project STAR data. Thus, documenting the impact of absences on achievement in the Project STAR schools adds to the generalizability of extant evidence on the harmful effects of student absences and is a secondary contribution of this paper.

The empirical analysis focuses on the relationship between absences and achievement in grades 1 and 3. The reason is that while the STAR experiment covered a single cohort of students as they progressed from kindergarten to third grade, attendance data was not collected in second grade and the lag-score value-added models described in Section 3 cannot be estimated for the kindergarten year because there is no lagged measure of achievement. Accordingly, we summarize the first- and third-grade analytic samples in Table 1. Here, we see that the average STAR student was absent about seven times, which is similar to the average absence rates observed in the nationally representative ECLS-K survey and statewide administrative data from North Carolina (Gershenson et al., 2017). The chronic absence rate among STAR students of 6 to 7 percent is similar in magnitude to those in the ECLS-K and North Carolina (Balfanz & Byrnes, 2001). We define "chronically absent" as being absent 18 or more times during the year because this commonly used definition of chronic absence corresponds to about 10 percent of school days. Figure 1 reports a histogram and kernel density estimate of the distribution of student absences.

Figures 2 and 3 motivate the analysis by plotting the distribution of test scores separately for students who were and were not chronically absent. Figure 2 does so for math. Two points merit attention. First, the vertical bars show that the average score of chronically absent students is significantly lower than that of students who were not chronically absent. This is consistent with previous research documenting the achievement gap between more- and less-absent students. Second, the distribution of math scores for chronically absent students is decidedly to the left of the non-chronically-absent distribution. However, the distributions have different shapes, suggesting that the effect of absences might vary at different points of the distribution. Figure 3 shows similar patterns for reading (ELA) score distributions. We investigate this question formally using the quantile regressions described in Section 3.

3. Methodology

Following Gershenson et al. (2017), we investigate the relationship between student absences and academic achievement by including absences as a contemporaneous input in value-added models (VAMs) of the education production function. Intuitively, VAMs exploit longitudinal student data by using lagged test scores to proxy for the unobserved histories of educational and familial inputs received by each child. Accordingly, our baseline model of the spring test score (y) of student i, in classroom j, in grade g is

$$y_{ijg} = \alpha\, y_{i,g-1} + f\,(A_{ig}) + \boldsymbol{\beta}\mathbf{x}_{ig} + \eta_j + u_{ijg}\,, \tag{1}$$

where $\mathbf{x}$ is a vector of student and household characteristics summarized in Table 1, some of which vary over time; η is a classroom fixed effect (FE); and u is a composite error term that contains student i's time-invariant unobserved ability and idiosyncratic shocks to achievement.[2] We let absences (A) enter the model linearly because Gershenson et al. (2017) show that the effect is approximately linear. However, we also estimate specifications that replace A with a "chronically absent" indicator that equals one if the student was absent 18 or more times during the year, and zero otherwise.

The year, grade, teacher, and school FE commonly included in VAMs are subsumed by the classroom FE, which are crucial to our identification strategy. Specifically, classroom FE control for non-random sorting of teachers across schools and classrooms, classroom-specific shocks that jointly influence both absences and achievement (e.g., a flu epidemic or a particularly effective teacher) (Gershenson, 2016), and potential differences across classrooms in how absences are coded. As a result, our estimates of absences' effects on performance rely on within-classroom variation in student absences, holding past achievement constant. Intuitively, this means that all estimates are generated by comparisons between the current outcomes of students who were in the same classroom and had the same test score in the previous year. Because students in the same classroom are exposed to the same peers, same teacher, same broader school climate, same grading standards, and same absence-recording procedures, this strategy effectively eliminates all potential school- and classroom-level confounders.

We begin by estimating equation (1) by OLS, essentially replicating past research using a different dataset. The OLS estimates of a linear model such as equation (1) provide evidence of absences' effects on the conditional mean of achievement; that is, *on average*, how does an additional absence affect achievement, net of prior achievement, student background, and so on.

[2] We refer to grades rather than years because the STAR experiment follows a cohort of students, so grades are perfectly collinear with years. The classroom FE directly control for issues of test timing and testing conditions, since all students in a classroom take the test on the same day.

This is not say that all students are affected in the exact same way. Indeed, some individual students may be harmed more and some may be harmed less by an additional absence. But the OLS estimate tells us the average of these individual effects. Average effects are appealing for two main reasons. First, everyone is familiar with the concept of averages so there is no new terminology to explain. Second, the average effect is a single parameter that is easily reported and interpreted.

There is rarely a free lunch, of course, and the case of OLS is no exception: the simplicity and elegance of OLS estimation of average effects comes with two main costs, or limitations. First, OLS estimates (and averages in general) are susceptible to the influence of outlying (extreme) observations. Second, by assuming a constant average effect for every student in the sample, the OLS estimate necessarily ignores the possibility that student absences affect the entire distribution of student achievement, whether or not the mean of the distribution remains the same. Accordingly, we address these shortcomings by estimating quantile regressions that take the right hand side of equation (1) as the linear index.

As their name suggests, quantile regressions estimate the effect of independent variables (e.g., student absences) on specific quantiles of the outcome distribution. This means that we no longer think about what, on average, will happen to a specific individual, but rather about what will happen to the distribution of outcomes for individuals who receive the treatment. To fix ideas, consider the binary treatment of "chronic absence." In the linear regression case, the OLS estimate identifies the average difference in an outcome, say test scores, between students who were and were not chronically absent (i.e., treated). In the quantile regression case, for the 50th quantile (i.e., the median), the quantile regression coefficient estimate represents the difference between the median scores of those who were, and were not, chronically absent. We similarly estimate a unique coefficient (effect) for each quantile (i.e., percentile). We do so by estimating the impact of student absences on each quintile of the achievement distribution. Standard errors are clustered at the school level and computed via 500 bootstrap replications. Finally, conditioning on fixed effects (FE) in a quantile regression model is nontrivial. We proceed by implementing the non-additive quantile FE estimator proposed by Powell (2016).

4. Results

It is easiest to report, compare, and interpret quantile regression estimates visually. Accordingly, the OLS estimates (average effects) and quantile-regression estimates (distributional effects) of students' absences' effects at each decile of the math score distribution are reported in Figure 4. Panel A reports estimates for first graders and panel B does so for third graders. Figure 5 does the same for the effect of being chronically absent (relative to not). All estimates come from the linear- and quantile-regression versions of equation (1).

4.1 Math Achievement

The solid horizontal lines in Figure 4 represents the OLS estimate of the average harm associated with one additional absence in third grade on the standardized third-grade math test. The dashed horizontal lines are represent the 95% confidence interval, which excludes zero, indicating that the estimated effect is statistically significantly different from zero at the 0.05 level in both grades, though the harm is slightly greater in first grade. The OLS point estimate in third grade of -0.007 is identical to the corresponding point estimate in North Carolina reported in Gershenson et al. (2017), who also study third graders, suggesting that the harmful effects of absences are approximately constant across time and locale. Specifically, the point estimate of

0.007 indicates that, on average, 10 additional absences reduce achievement by about 7% of a test-score SD.

The key innovation of the current study is to also report quantile regression estimates that reflect the impact of absences on different parts of the achievement distribution. The red dots in Figure 4 represent the quantile regression estimate of the effect of an absence on each decile of the distribution. The associated error bars are bootstrapped 95% confidence intervals. The error bars generally exclude zero, indicating that the quantile regression estimates are also statistically significant at traditional confidence levels. Interestingly, the nine quantile coefficients bounce around the OLS line in no discernible pattern and mostly lie within the OLS confidence interval. This suggests that the marginal effect of an absence on each decile is approximately the same as the OLS (average) estimate. Overall, then, Figure 4 provides no evidence that absences change the shape or spread of the math achievement distribution and instead shift it to the left.

Two slight exceptions to this interpretation are observed in the tails of the distribution, the 10th and 90th percentiles, though the patterns reverse from first to third grade. In first grade, absences pull down the bottom of the distribution, but have no impact on the top. The reverse is true in third grade, where there is no significant difference in the tenth percentile score of students who do and do not experience one additional absence. The effect is about half as large as the OLS estimate and statistically indistinguishable from zero. However, we caution against making too much of these results, as both estimates are relatively imprecise and are not significantly different from the OLS estimate.

Figure 5 presents the same set of estimates for a model that operationalized absences' role in the educational process as a binary indicator for chronic absence. The reason is that, although Gershenson et al. (2017) finds that the average effect of absences is linear, it is possible that there are nonlinearities in the effect of absences across the achievement distribution. Figure 5 makes immediately clear that there are no such nonlinearities, as the quantile estimates all fall within the OLS confidence interval and bounce around the OLS point estimate. Moreover, these estimates are exactly what we would expect to see if the effects were additively linear: they are about 20 times the linear estimate, since being chronically absent means being absent about 20 times. Like the linear model reported in Figure 4, Figure 5 again suggests that the harmful effects of student absences on math performance are approximately constant across the achievement distribution.

4.2 Reading Achievement

Figures 6 and 7 report the same set of analyses for reading scores. Figure 6 reports estimates of the marginal harm attributable to one absence, which is generally similar to that for math. Specifically, like for math, the OLS estimates are negative, statistically significant, and larger in first than in third grade. The quantile estimates display a similar pattern as well, in both grades, bouncing around the OLS point estimate and almost entirely falling within the OLS 95% confidence interval. Figure 7 shows similar results for the impact of chronic absence, with the quantile estimates falling within the OLS 95% confidence interval and often right on the OLS point estimate. Again, the average effect is larger in first than in third grade, where the latter is not significantly different from zero. That absences in third grade have a greater effect of math than on reading is consistent with past research (e.g., Gershenson et al., 2017), perhaps because students are more apt to develop reading skills at home.

5. Conclusion

The extant literature on the impact of absences on student achievement focuses entirely on average effects estimated via linear-in-parameters regression models. While this focus is a natural starting point for the study of any educational input, it necessarily overlooks the possibility that student absences alter the shape and spread of the achievement distribution in ways that linear estimators such as OLS miss. The current study fills this gap in knowledge by estimating quantile regressions that examine whether the impact of absences on student achievement varies across the achievement distribution.

We find no evidence that student absences alter the shape or spread of the achievement distribution. Rather, student absences reduce achievement by simply shifting the achievement distribution to the left. Accordingly, at least in the case of the relationship between absences and student achievement, OLS estimates of the average effects of student absences adequately capture the policy-relevant relationship of interest.

Ruling out the presence of nuanced distributional impacts of student absences is useful for policy discussions surrounding student absences for two main reasons. First, it means that attendance advocates can focus on a simple, easy to interpret number: the average effect of chronic absence. This number can be used in cost-benefit analyses of interventions and in selling the importance of attendance, and associated interventions, to parents, students, schools, teachers, and policy makers. Second, that the effect is constant and shifts the entire achievement distribution to the left means that increasing attendance is good for everyone, and therefore an easy policy and intervention to rally behind. Attendance can be a bi-partisan cause relevant to schools in all parts of the country and to schools serving students of all socio-demographic backgrounds.

The quantile regression analyses presented here fill one of the few remaining holes in the research literature on the harmful effects of student attendance. Rigorous studies have now documented an arguably causal impact of student absences that is remarkably constant across schools, students, and geographic locales. Moreover, this effect is approximately linear in the number of absences and approximately constant across the achievement distribution. That the harm caused by student absences is fairly constant across schools and students of differing backgrounds and linearly additive in the number of absences suggests that the precise definition of chronic absence used in school accountability policies is relatively unimportant. A student who is absent 15, 18, or 20 times per year will score about 10 to 15% of a SD lower than an otherwise similar student who misses only a handful of days per year. These results suggest that educators' and policymakers' valuable but limited bandwidth can be focused on implementing interventions that boost attendance and help students catch up following an absence, rather than get mired in technical debates about the exact threshold used to define chronic absence. It also suggests that while all students would benefit from such interventions, targeted interventions provide an opportunity to close achievement gaps, as students of color and students from low-income households are absent more frequently than their white and more advantaged counterparts.

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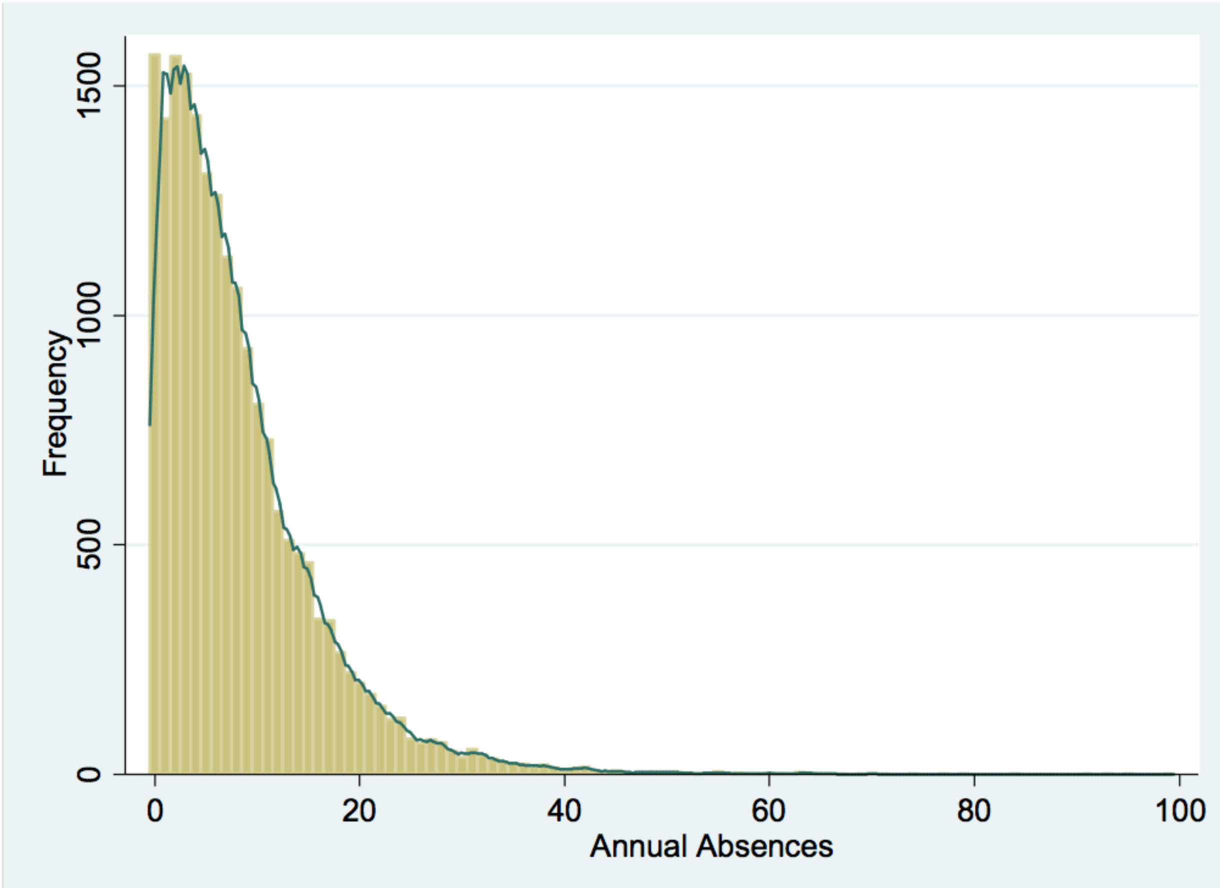
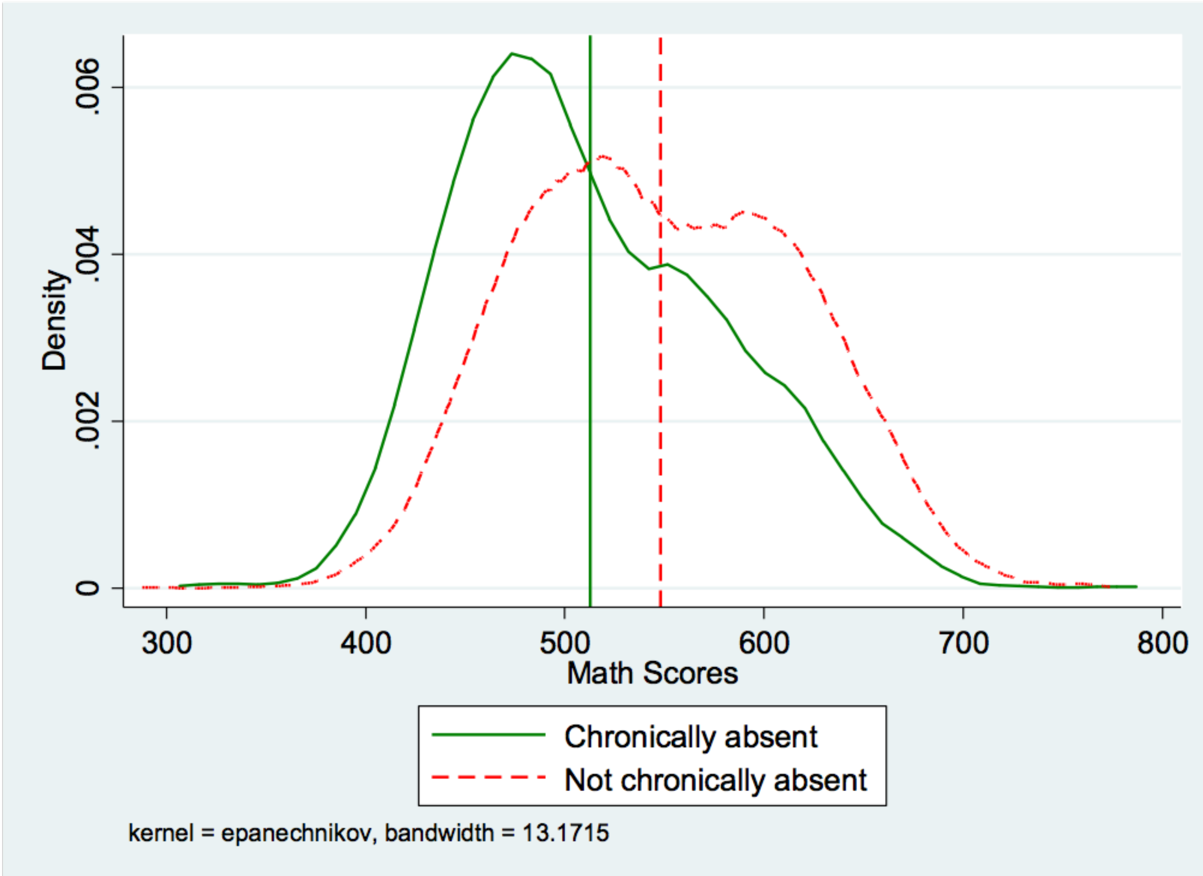
Figure 1. Distribution of Total Annual Absences



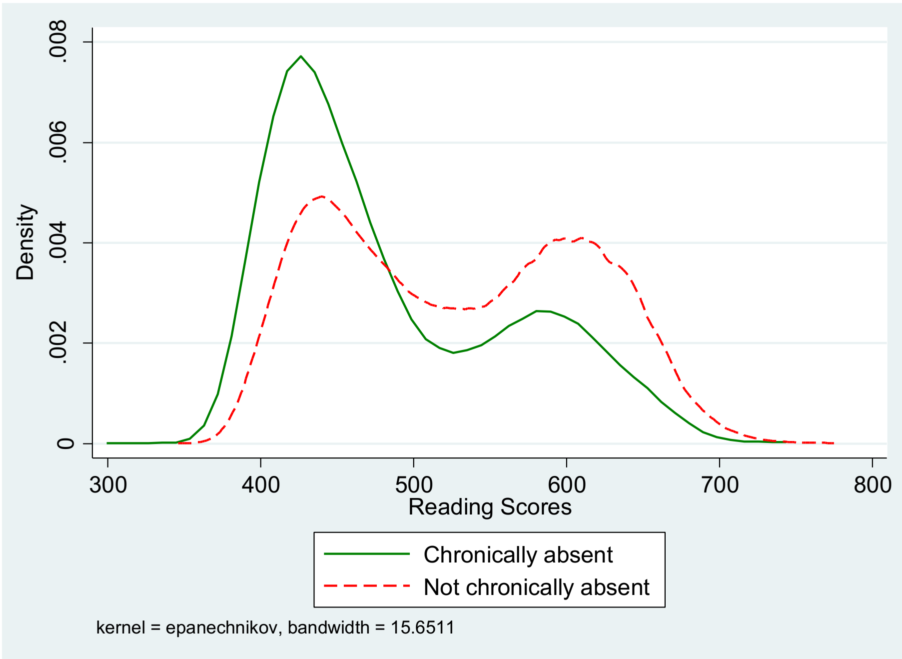
Notes: Bars represent histogram (one absence bins). Line is kernel density plot.

Figure 2. Math Score Distributions of Chronically-Absent and Non-Chronically-Absent Students



Note: Distributions are kernel density plots. Vertical bars represent mean scores.

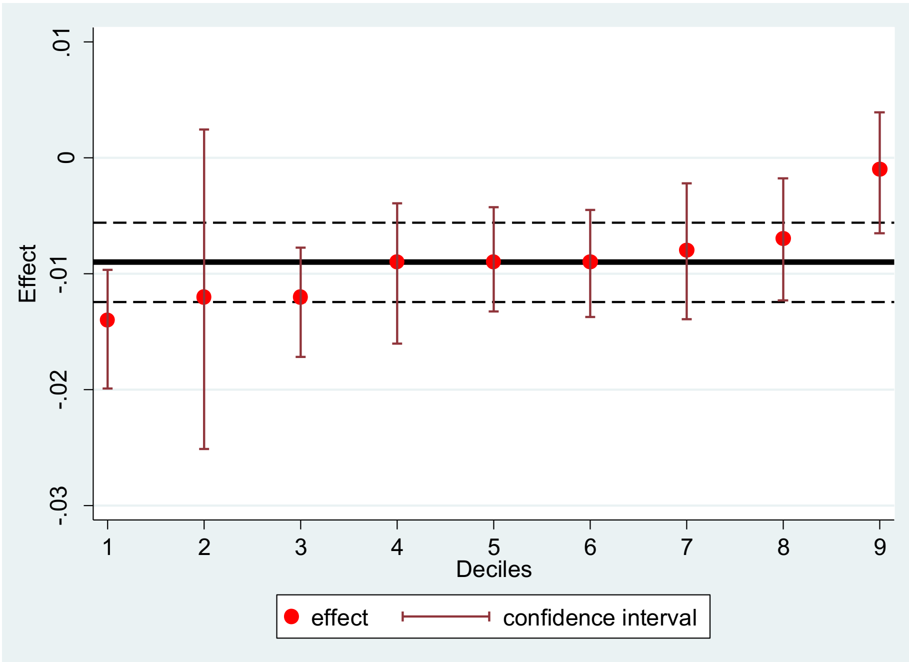
Figure 3. ELA Score Distributions of Chronically-Absent and Non-Chronically-Absent Students



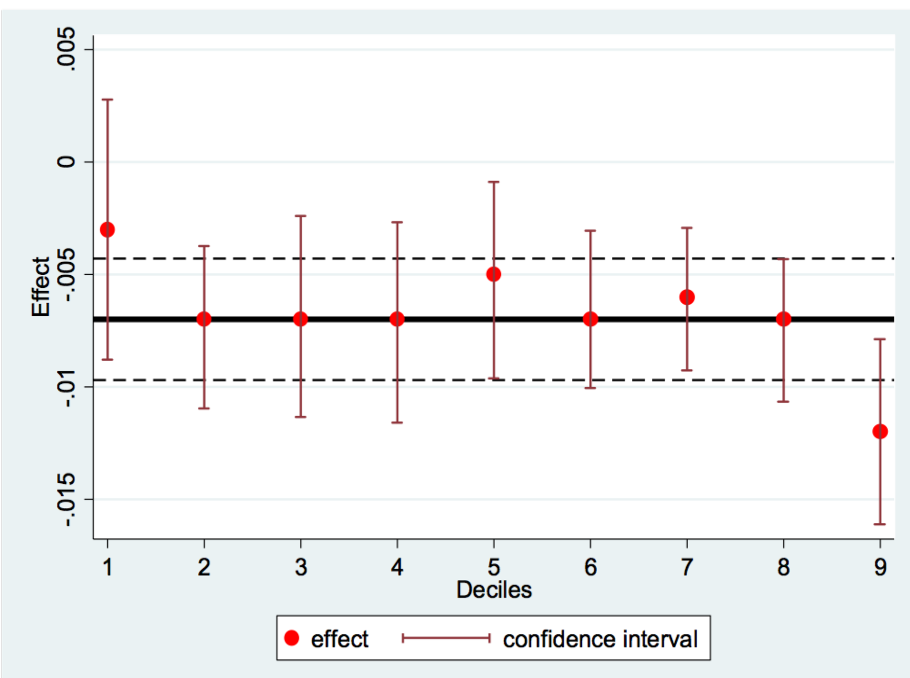
Notes: Chronically-absent students' mean ELA (English Language Arts) score: 485.47. Chronically-absent students' median reading score: 457. Non-chronically-absent students' mean reading score: 529.31. Non-chronically-absent students' median reading score: 527.

Figure 4. Marginal effect of one absence on math scores in grades 1 and 3

4.A Grade 1



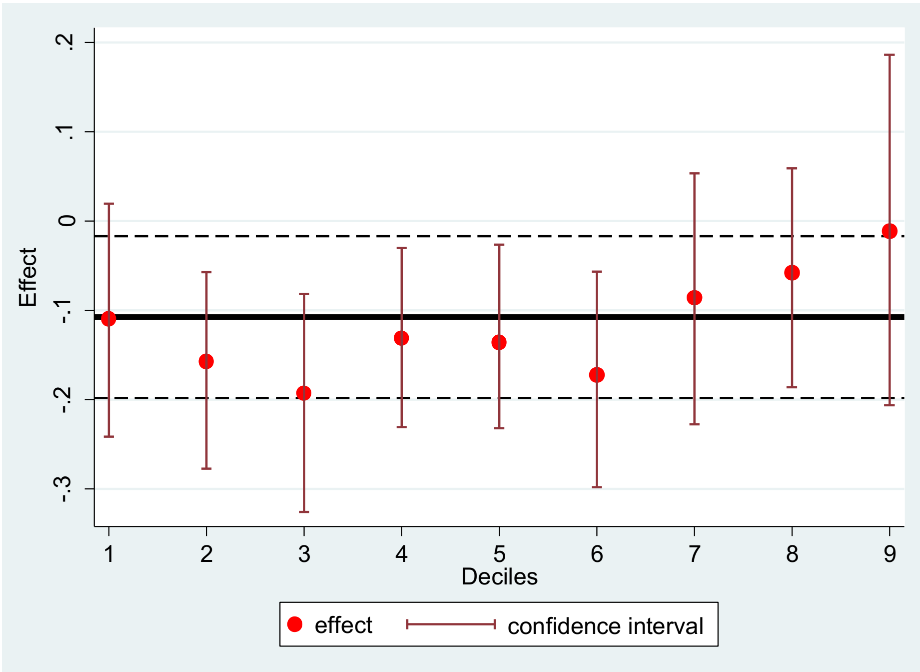
4.B Grade 3



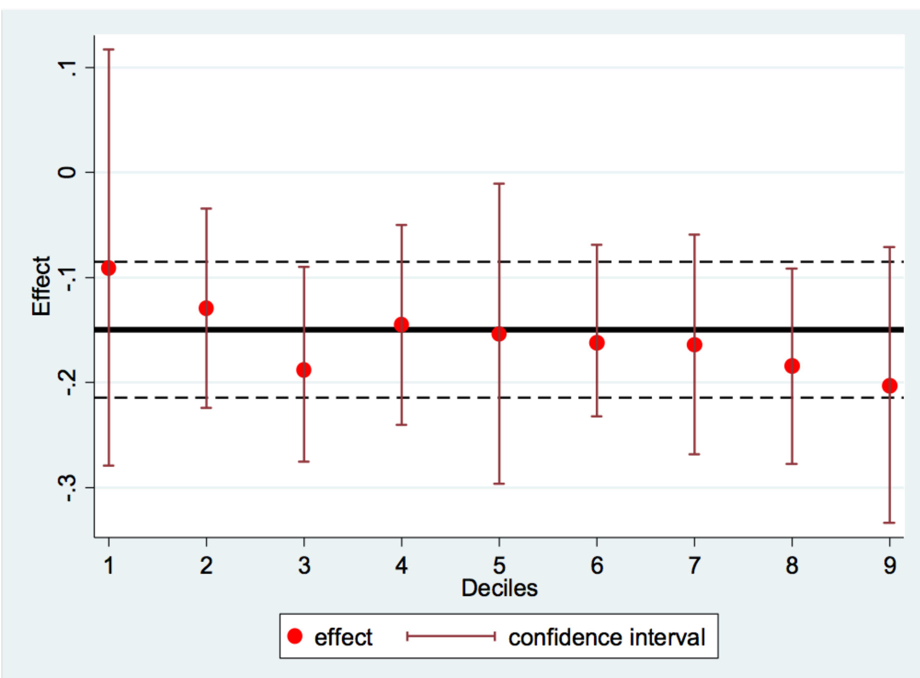
Notes: The solid line and the circles represent the OLS and quantile regression coefficient estimates, respectively. The dashed lines and the error bars represent the corresponding 95% confidence intervals.

Figure 5. Effect of chronic absence on math scores in grades 1 and 3

5.A Grade 1



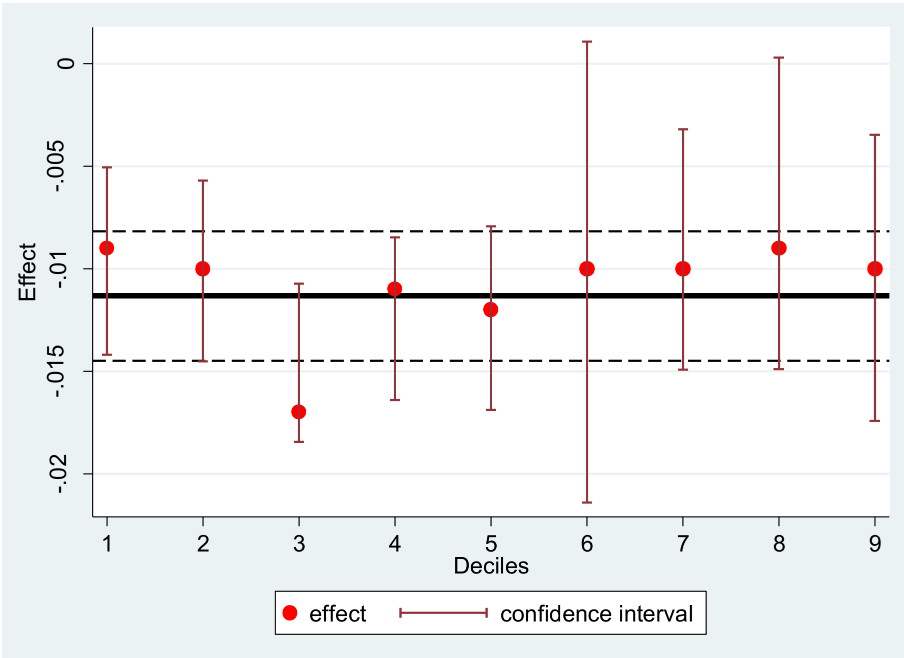
5.B Grade 3



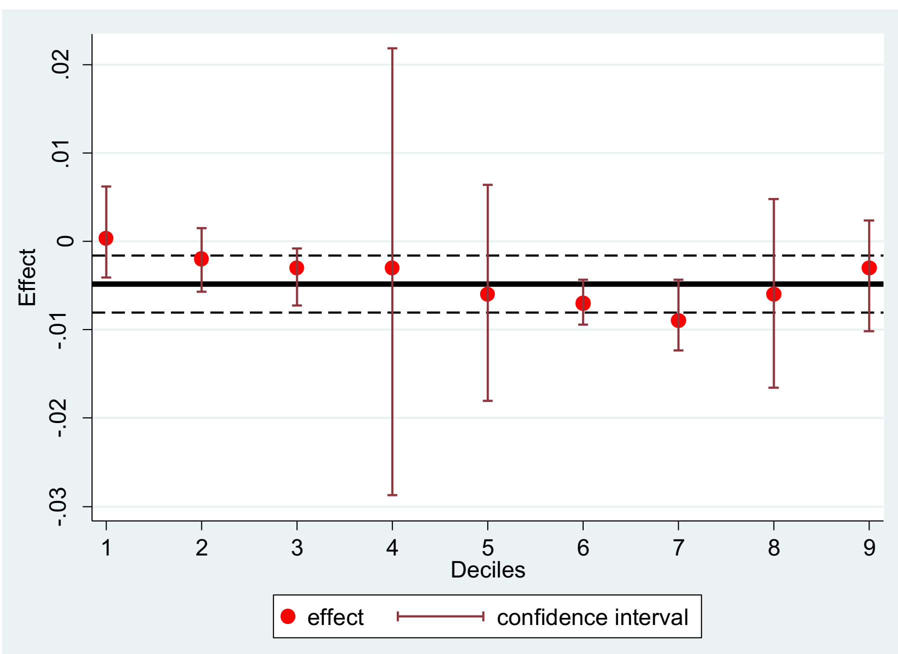
Notes: The solid line and the circles represent the OLS and quantile regression coefficient estimates, respectively. The dashed line and the error bars represent the corresponding 95% confidence intervals. Chronic absence indicator equals one if 18 or more absences, zero otherwise.

Figure 6. Marginal effect of one absence on ELA scores in grades 1 and 3

6.A Grade 1



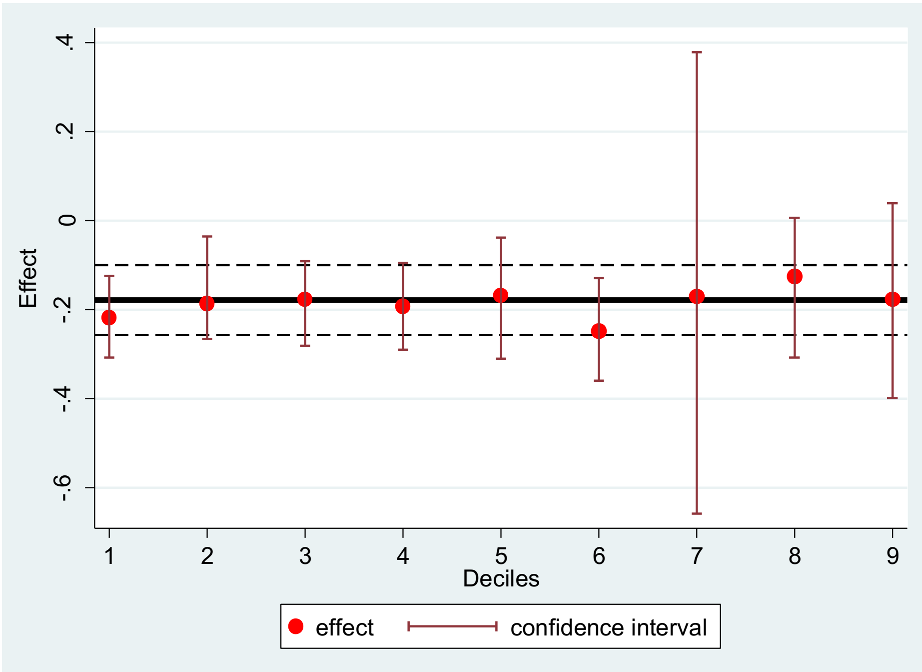
6.B Grade 3



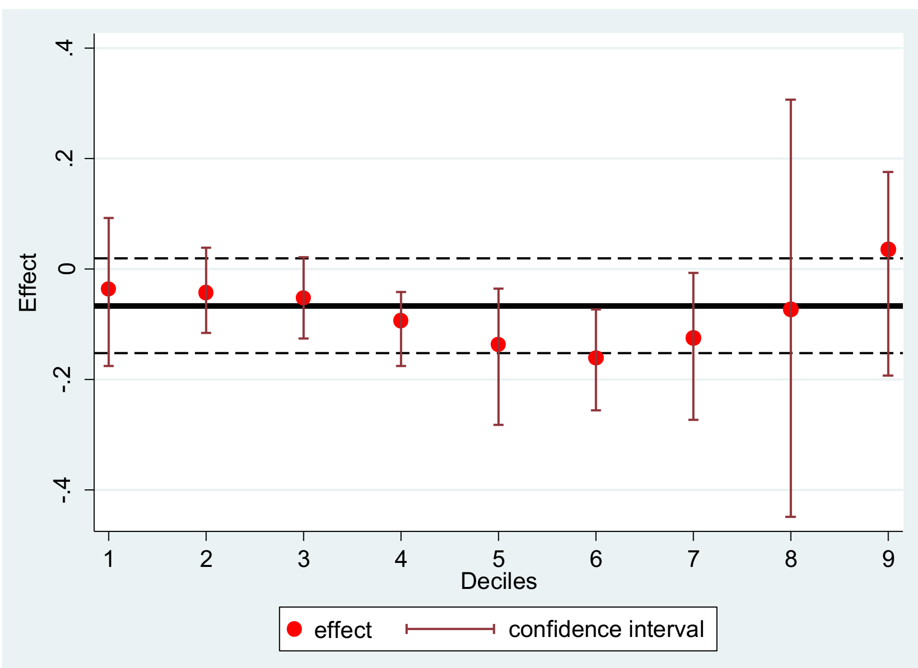
Notes: The solid line and the circles represent the OLS and quantile regression coefficient estimates, respectively. The dashed lines and the error bars represent the corresponding 95% confidence intervals.

Figure 7. Effect of chronic absence on ELA scores in grades 1 and 3

7.A Grade 1



7.B Grade 3



Notes: The solid line and the circles represent the OLS and quantile regression coefficient estimates, respectively. The dashed line and the error bars represent the corresponding 95% confidence intervals. Chronic absence indicator equals one if 18 or more absences, zero otherwise.