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Experimental Estimates of the Student Attendance Production Function

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ABSTRACT

Experimental Estimates of the Student Attendance Production Function

Student attendance is both a critical input and intermediate output of the education production function. However, the malleable classroom-level determinants of student attendance are poorly understood. We estimate the causal effect of class size and observable teacher qualifications on student attendance rates by leveraging the random classroom assignments made by Tennessee's Project STAR (Student/Teacher Achievement Ratio) class size experiment. A ten-student increase in class size raises the probability of being chronically absent by about three percentage points (21%). For black students, random assignment to a black teacher reduces the probability of chronic absence by 3.1 percentage points (26%). These suggest that a small, but nontrivial, share (about 5%) of class-size and race-match effects on student achievement are driven by changes in students' attendance habits.

JEL Classification: I2

Keywords: education production function, student attendance, chronic absence, class size

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1. Introduction

There is a growing consensus that student attendance is a critical input in the education production function, an important intermediate outcome influenced by teachers and other school-based interventions, and a type of non-cognitive skill valued in the labor market (Gershenson, 2016; Gottfried & Hutt, 2019). Accordingly, education policy increasingly uses student attendance as a performance metric with which to hold schools and teachers accountable (Bauer et al., 2018; Gottfried & Hutt, 2019). Holding schools and teachers accountable for student attendance, however, only makes sense if policy levers can improve student attendance. Recent quasi-experimental research suggests that teachers influence student attendance (Gershenson, 2016; Holt & Gershenson, 2017; Jackson, 2018; Ladd & Sorenson, 2017; Liu & Loeb, 2017). An emerging experimental literature suggests that light-touch information interventions can also improve student attendance (Bergman & Chan, 2017; Robinson et al., 2018; Rogers & Feller, 2018; Smythe-Leistico & Page, 2018). However, the extent to which other classroom-level inputs affect student attendance is unclear and teachers' effects on student attendance have yet to be studied in an experimental setting.

We address these gaps in the literature by leveraging the experimental variation in classroom assignments created by the Tennessee Project STAR (Student/Teacher Achievement Ratio) class size experiment to address three research questions:

1. To what extent do classrooms vary in their aggregate impacts on student attendance?
2. How do specific classroom-level inputs such as class size, teacher qualifications, and peer composition affect attendance?
3. To what extent is increased attendance a channel through which classroom inputs improve students' academic achievement?

We find that classrooms vary significantly in their effects on student absenteeism. Several observed classroom-level characteristics, most notably assignment to a small class size or an own-race teacher, significantly reduce student absences. This is true whether attendance is operationalized as the count of absences or an indicator for chronic absence. Finally, about 5% of the impact of both class-size and student-teacher race match on test scores can be explained by improved attendance.

The paper proceeds as follows: Section 2 provides a brief background on student absences, Section 3 describes the Project STAR experiment and data, Section 4 presents the main results, Section 5 presents a series of sensitivity analyses, Section 6 presents a simple mediation analysis that isolates attendance as a mechanism through which class size and student-teacher race match affect achievement, and Section 7 concludes.

2. Background

2.1. Student absences matter

Student absences are important for several reasons. First, arguably causal evidence suggests that student absences harm achievement (Aucejo & Romano, 2016; Gershenson et al. 2017, 2019; Goodman, 2014; Gottfried, 2009, 2010, 2011). For example, using both nationally-representative survey data and rich administrative data from North Carolina, Gershenson et al. (2017) show that a one standard deviation (SD) increase in absences is associated with statistically significant decreases in reading and math achievement of 0.02 and 0.04 test-score SD, respectively. These effects are practically significant as well, on par with those of a one-SD increase in teacher absences (Herrmann & Rockoff, 2012) or a 0.33 SD increase in teacher effectiveness (Hanushek & Rivkin, 2010). Second, absenteeism predicts high-school dropout and risky behaviors such as drug and alcohol use (Allensworth et al., 2007; Balfanz & Byrnes, 2012; Henry & Huizinga, 2007; Henry & Thornberry, 2010). Finally, attendance is an objectively measurable correlate of several "Big Five" character skills and highly valued in the labor market (Duckworth et al. 2007; Heckman and Kautz 2013; Lerman 2013; Lounsbury et al. 2004). Indeed, researchers often proxy for character skills with attendance (Jackson, 2018; Jacob, 2002)

Given the consequences of student absences and the disproportionate level of absences among socioeconomically-disadvantaged students, student attendance has been a growing concern for policy makers. Recent education policy, notably the Every Student Succeeds Act (ESSA), uses chronic absence rates as an outcome for which schools and teachers can be held accountable (Bauer et al., 2018; Gottfried & Hutt, 2019). Such policies implicitly assume that there are school- or classroom-level policy levers available that can increase student attendance. While a handful of interventions have recently shown promise, the general classroom-level characteristics that might shape student attendance patterns remain underexplored. The current paper addresses this gap by investigating classroom-level determinants of student attendance, including class size and observed teacher characteristics.

2.2. Classroom-level determinants of student attendance

Student attendance is certainly influenced by numerous factors outside the purview of schools, such as student health, household stability, and environmental pollution (Currie et al., 2009; Gottfried & Gee, 2017; Morrissey et al. 2014; Ready, 2010; Romero & Lee, 2008). This does not mean that schools cannot reduce absenteeism, of course, and a variety of interventions are currently being piloted and rigorously evaluated. For example, light-touch "nudges" that use text messages to communicate with parents about the importance of attendance have been shown to reduce chronic absence (Robinson et al., 2018; Rogers & Feller, 2018; Smythe-Leistico & Page, 2018) and class-specific absences in the middle and high school setting (Bergman & Chan, 2017). Interestingly, Bennet and Bergman (2018) show that because students are often absent together, these interventions can have spill-over effects on students' friends. Indeed, a student's classmates, and classroom culture, might influence attendance habits (Gottfried et al., 2016).

Traditional school-based inputs can affect attendance as well, as teachers might increase student attendance by fostering a passion for learning, increasing student engagement, building a sense of community in the classroom, changing norms, and stressing the importance of regular attendance (Gershenson, 2016; Baker et al., 2010; Kelly, 2012; Ladd & Sorensen 2014; Monk & Ibrahim, 1984). Primary school teachers also can affect their students' attendance by shifting parents' and other household adults' attitudes, expectations, and practices regarding their children's attendance, in similar fashion to the information interventions described above. Similarly, Dee and West (2011) describe several channels through which class size might affect non-cognitive skills such as attendance (e.g., by making it easier for teachers to intervene when there is a problem, communicate with parents, and reallocate instructional time from academic lessons to building social and emotional skills).

Indeed, an emerging literature uses value-added models to document teachers' impacts on student attendance. Using longitudinal administrative data on the population of public primary school students in North Carolina, Gershenson (2016) finds that teachers affect student absences and that they are not always the same teachers who boost test scores. Liu and Loeb (2017) find similar results in middle and high schools in a large urban school district in California. Teacher characteristics such as teaching experience and student-teacher racial match have also been shown to reduce student absenteeism (Gershenson, 2016; Holt & Gershenson, 2017; Ladd &

Sorenson, 2017). Similarly, Dee and West (2011) show that eight-grade class size affects school engagement, which is a correlate of attendance.

The current study contributes to this literature in two ways. First, we examine the impact of previously unexplored classroom characteristics on student attendance such as class size and classroom peer composition. Second, we replicate the earlier teacher studies, which rely on observational data, using experimental data in which both students and teachers were randomly assigned to classrooms. We do so in the same spirit as previous research that exploited the STAR experiment to estimate the impacts of kindergarten classroom quality, class size, class composition, teacher characteristics, and student-teacher race match on educational achievement and attainment (Chetty et al., 2011; Dee, 2004; Gershenson et al., 2017; Graham, 2008; Krueger, 1999; Krueger & Whitmore, 2001; Penney 2017; Sojourner 2013).

3. Data and Methodology

3.1. Project STAR

We investigate classroom-level inputs' effects on student attendance using publicly available data from Tennessee's Project STAR, a seminal large-scale field experiment in education that was designed to identify the impact of class size on student achievement (Krueger, 1999; Schanzenbach, 2006). Funded by the Tennessee legislature at a total cost of about $12 million, project STAR randomly assigned kindergarten students and teachers in 79 participating public schools in Tennessee to either small-size classes (13 to 17 students) or regular-size classes (22 to 25 students) within their schools in the 1985-1986 school year. Project STAR intentionally recruited schools serving relatively disadvantaged populations, so the sample is not representative of the state's public-school population (Schanzenbach, 2006). The experiment continued over the next three years, following the 1986 kindergarten cohort to third grade while also refreshing the analytic sample each year by randomly assigning new entrants to the STAR cohort to small- or regular-size classrooms. All told, 11,600 students and 1,330 teachers participated in the experiment. Randomization was achieved, at least in students' first year in a STAR school, and small classes improved student achievement (Krueger, 1999).

While Project STAR was designed to assess the effectiveness of class-size reductions, many researchers have recognized that its within-school random assignment of students and teachers to classrooms could be leveraged to study other research questions. For instance, scholars have leveraged the random assignments created by Project STAR to estimate the effects of having an own-race teacher on academic achievement and attainment (Dee, 2004; Gershenson et al., 2017; Penney, 2017), the long-run impacts of classroom quality on educational attainment and future earnings (Chetty et al., 2011), and peer effects on academic achievement (Graham, 2008; Sojourner, 2013). In the same vein, we leverage the experimental variation in classroom assignments created by Project STAR to estimate the student attendance production function.

3.2. Data

Table 1 summarizes the analytic sample separately by student race, gender, and free/reduced lunch (FRL) status. Project STAR did not record absences in second grade, so the analytic sample contains only grades K, 1, and 3. The main dependent variable is a binary indicator of whether a student was chronically absent, though we show that our main results are robust to instead using a simple count of annual absences. We define "chronically absent" as 18 or more absences during the school year (i.e., about 10 percent of school days) because this is the most commonly used definition of chronic absence and is consistent with many state's definitions (Balfanz & Byrnes, 2012; Bauer et al., 2018). Table 1 shows that 14 percent of students in the analytic sample were chronically absent and that the average student was absent about 9.5 times. Absence rates are higher for white, female, and FRL students. The average absence and chronic absences rates of FRL STAR students are quite similar to those of similarly-aged, low-income students in the nationally representative ECLS-K (Gershenson et al., 2017).

Independent variables of interest include *Class Size* (i.e., the count of students in class), observable teacher qualifications that have been shown to affect student achievement such as *Same-Race* and *Experience* (Dee, 2004; Wiswall, 2013), and the classroom's sociodemographic composition. Only 43 percent of black students had a same-race teacher, compared to 95 percent of white students. The average teacher had about 10 years of experience, and this is similar for both black and white students, and for FRL and non-FRL students. The peer-composition variables show that classrooms are fairly segregated by race and FRL receipt.

As for the demographics of the analytic sample, 35 percent of students in the sample were black, 47 percent were female, and 54 percent were FRL eligible. Again, the relative disadvantage of the sample is due to Project STAR's focus on disadvantaged schools.

3.3. Distribution of Classroom Effects

We document variation in aggregate classroom and school effects on student absence rates using straightforward multilevel models of the attendance production function. Specifically, these models include both school and classroom random effects (REs), where classrooms are nested in schools and the REs are assumed to be normally distributed. Interest lies in the estimated variance of the REs, specifically the classroom RE, as zero variance indicates a lack of classroom effects. Specifically, we model the absences of student i in classroom j in school k as

$$Y_{ijk} = \beta \boldsymbol{x}_{ij} + \gamma_j + \theta_k + u_{ijk}, \quad (1)$$

where $\boldsymbol{x}$ is a vector of observed student and classroom characteristics, γ and θ are REs, and u is an idiosyncratic error term. We sometimes restrict β to see how much variation in the estimated classroom effects is explained by observable characteristics. We estimate both logistic and linear versions of equation (1), for chronic absence and absence counts, respectively.

3.4 Student Attendance Production Function

We estimate the causal effect of specific inputs on student absences by modifying equation (1) in two ways. First, we replace the classroom RE with observed classroom inputs, including class size, teacher characteristics, and peer characteristics, which are the independent variables of interest. Second, we replace the school RE with a school-by-cohort fixed effect (FE) (Krueger & Whitmore, 2001). The school-by-cohort FE means that estimates are identified by within-school, within-cohort variation in classroom characteristics, which is important because random assignment occurred within schools, and students entering a school in later grades may be systematically different from students who entered the school in kindergarten. This effectively controls for any non-random sorting of teachers and students across schools, as well as any school- and grade-specific characteristics such as the way student absences were administratively recorded, school-level leadership, different lengths of academic calendars, and policy changes.

Specifically, the model for student i, in classroom j, school k, and cohort g is

$$Y_{ijkg} = \beta_1 \boldsymbol{x}_i + \beta_2 \boldsymbol{z}_j + \beta_4 C_j + \omega_{kg} + u_{ijkg}, \quad (2)$$

where $\boldsymbol{x}$ is a vector of observed student characteristics, $\boldsymbol{z}$ is a vector of observed teacher and peer characteristics, C is class size, ω is the school-by-cohort FE; and u is an idiosyncratic error term. We estimate both linear probability model (LPM) and FE-Logit (Chamberlain, 1980) versions of equation (2). We prefer the former, as it allows for the inclusion of FE and the identification of average partial effects, though FE-Logit provides similar results. Standard errors are clustered by classroom, as this is level of random assignment and the level at which treatment varies (Abadie et al., 2017), though clustering by school-cohort or school yields similar inferences.

Three final points about estimation of equation (2) merit mention. First, Project STAR randomly assigned student entrants to three dichotomous classroom types: small, regular, and regular plus aide. Actual class size *C* could (and does) vary within these groups, and that variation might be endogenous. Accordingly, we estimate equation (2) by 2SLS, using the randomly assigned "classroom type" indicators as instruments for *C* (Krueger, 1999). As expected, and consistent with Krueger (1999), the first-stage is strong. Of course, we can also replace *C* with the set of classroom-type indicators and estimate equation (2) by OLS. Second, to account for the existence of both nonrandom attrition from the STAR sample and noncompliance in students' second, third, and fourth years in STAR, we estimate equation (2) using only data from students' first years in STAR, when attrition and noncompliance were of no concern (Krueger, 1999). We then further restrict the sample to the kindergarten cohort and find similar results. Finally, to test for heterogeneity, we estimate equation (2) separately by student type.

4. Results

4.1. Distribution of Classroom Effects

Table 2 presents the estimated standard deviations (SD) of the classroom and school random effects from equation (1). Columns 1 and 2 report estimates from the mixed logit model predicting chronic absence, with and without the classroom controls. The SD of the classroom RE is strongly significant in both specifications, suggesting that there is significant variation in chronic absence rates across classrooms. The similarity between specifications further suggests that this is largely due to unobserved classroom differences, specifically differences in unobserved teacher quality: controlling for observed classroom size, student composition, and teacher qualifications reduced the SD by 0.006, or 2.3%. Columns 3 and 4 do the same for the mixed linear model of annual absences and paint a similar picture: controlling for observed classroom characteristics only reduces the classroom effect SD by 0.004, or 1%. These results are consistent with the value-added literature on teacher effectiveness, which finds large variation in teachers' and classrooms' effects on student achievement and attendance that cannot be explained by observed characteristics (Gershenson, 2016; Staiger & Rockoff, 2010).

4.2. Student Attendance Production Function

Table 3 presents baseline LPM estimates of equation (2) for chronic absence. Column 1 reports estimates for the full analytic sample and finds that class size significantly increases chronic absenteeism. Specifically, reducing class size by 10 students would decrease the probability of chronic absence by three percentage points, or 21%. The other observed classroom characteristics did not have a significant impact on student attendance in the full sample.

Columns 2 to 7 of Table 3 report estimates separately by student race, gender, and FRL status.[1] A few results are worth noting. First, the class-size effect is approximately constant for each sociodemographic subgroup, suggesting that class size affects the attendance of students from all backgrounds. Second, column 3 shows that having an own-race teacher significantly decreased chronic absence rates for black students by about 3.1 percentage points, or 26.5%. The

[1] Following Dynarski et al. (2013), in estimates available upon request, we estimate the model separately by FRL tercile, but find not systematic differences by school socioeconomic status.

own-race effects are negative in the other subgroups, but not precisely estimated. That the race-match effect is more pronounced for black students is consistent with evidence of race-match effects on student achievement in STAR (Dee, 2004) and on achievement and attendance in other contexts (Fairlie et al., 2014; Holt & Gershenson, 2017). Still, this effect is about twice as large as that for nonwhite students observed in North Carolina (Holt & Gershenson, 2017). Third, like in the full sample, the other observed teacher qualifications do not strongly predict student absences in the various student subgroups. This is consistent teacher qualifications in the STAR data having weak, if any, effect on student achievement (Krueger, 1999).

Finally, that FRL students are more likely to be chronically absent is not surprising and consistent with the socioeconomic gaps in attendance observed in other contexts and samples (e.g., Gershenson et al., 2017). However, that black students are less likely to be chronically absent than their white peers is perhaps surprising at first blush, though likely explained by the fact that white students in integrated schools are likely to be more disadvantaged than their black peers along both observable and unobservable dimensions, for reasons having to do with discrimination in the housing market (Alba et al., 2000). Indeed, a within-school black advantage is observed in college-going among STAR students as well (Gershenson et al., 2018).

5. Sensitivity Analyses

This section reports the results of several robustness checks and sensitivity analyses of the main findings that (i) small classes reduce chronic absence among all students, (ii) same-race teachers reduce chronic absence among black students, and (iii) other observed classroom characteristics do not systematically influence chronic absence rates. Because these findings are remarkably robust, we relegate these checks to Appendix A. Each check is essentially a variant of the baseline specification given by equation (2) and presented in the format of Table 3.

First, in Appendix Table A.1, we change the outcome measure of attendance from a binary indicator for chronic absence to a simple count of annual absences. Here, we see that a ten-student reduction in class size leads to about one fewer absence per year, or a 9.4% reduction. Similarly, for black students, having a same-race teacher leads to about one fewer absence per year, or a 13.5% reduction in annual absences.

Second, in Appendix Table A.2, we replace the independent variable *Class Size* with an indicator for random assignment to a small class (so the omitted reference group includes regular classes with and without aides), and re-estimate equation (2) by OLS. Once again, the main findings are robust to this modeling choice, as students randomly assigned to a small class are about two percentage points less likely to be chronically absent. This effect size lines up with the baseline estimates, as the average difference between small and regular classes is about 7 or 8 students (Krueger, 1999). We group regular classes with and without aides together because previous research finds no effect of aides on achievement (Krueger, 1999). We confirm that this is so in the absences case in Appendix Table A.3, where the small indicator is replaced by indicators for the two types of regular-size classrooms. These indicators are positive, jointly statistically significant, and statistically indistinguishable from one another in the full sample.

Third, in Appendix Tables A.4 and A.5, we re-estimate the chronic-absence and absence-count models, respectively. We do so using nonlinear logit and poisson regressions that account for the binary and count natures of the dependent variables, respectively. We use a randomly assigned small-class indicator in place of *Class Size*, as in Appendix Table A.2, to avoid the complication of instrumenting for an endogenous variable in a nonlinear panel model. Once again, the same qualitative results are observed: random assignment to a small class has a significant effect on the attendance habits of students from all backgrounds and having a same-race teacher significantly improves the attendance habits of black students. For example, while proper average partial effects comparable to the LPM estimates cannot be computed because the distribution of the FE are not recovered by the FE-logit estimator (Wooldridge, 2010), approximate scale factors map the FE-logit coefficients on small class and same-race teacher in columns 1 and 3 into approximate partial effects of 0.019 and 0.037, respectively, which are nearly identical to the analogous LPM estimates reported in Appendix Table A.2.[2] This implies that the results are not driven by the linear functional form assumed in equation (2).

Finally, following Dee (2004) and Krueger (1999), we re-estimate the baseline model (equation 2 and Table 3) for only the kindergarten-entry cohort, which was not subject to potential noncompliance or attrition concerns and necessarily did not change schools from the previous year. These results are presented in Appendix Table A.6 and once again the main results prove to be quite robust: they are nearly indistinguishable from those based on all cohorts reported in Table 3. Thus the main results are not compromised by lack of experimental fidelity in later years of Project STAR nor by later entrants being systematically different from cohort 1.

6. Explaining Classroom Inputs' Effects on Student Achievement

To this point we have leveraged experimental variation in classroom assignments in Project STAR to document causal effects of class size and exposure to same-race teachers on student attendance. These results are consistent with quasi-experimental results obtained in other

[2] The scale factors are computed as Pr(y = 1)*[1 – Pr(y = 1)]. Using the means reported in Table 1, these factors are 0.14*0.86 = 0.1204 and 0.12*0.88 = 0.1056, respectively.

contexts (Dee & West, 2011; Holt & Gershenson, 2017). They are also consistent with previous research, from Project STAR and elsewhere, that these same classroom characteristics affect student achievement (Angrist & Lavy, 1999; Dee, 2004; Fairlie et al., 2014; Krueger, 1999). This suggests that student attendance is a mechanism through which class-size and race-match effects on student achievement operate. We pursue this idea below.

The odd columns of Table 4 replicate the basic classroom-input effects on achievement of Krueger (1999) and Dee (2004) in our analytic sample. Here, we see an overall effect of a ten-student increase in class size of 0.024 math-score SD and a race-match effect among black students of 0.12 math-score SD. Estimates from the same Project STAR data suggest that one absence and chronic absence lower math achievement by about 0.0075 and 0.15 SD, respectively (Gershenson et al., 2019). The even columns report a simple mediation analysis in which the achievement models control for chronic absence, the potential mediator. Doing so causes the estimated coefficient on class size to drop by 0.001, or 4.2%, in the full sample. Similarly, the estimated coefficient on own-race teacher drops by about 0.007, or 5.7%, in the black sample. These mediation exercises suggest that a small, but nontrivial, share of the class-size and race-match effects on student achievement are driven by changes in students' attendance habits.

7. Conclusion

Student attendance is both an important input and intermediate output of the education production function. Attendance improves academic achievement, predicts a variety of long-run socioeconomic outcomes, is correlated with several types of character and socio-emotional skills, and is highly valued in the labor market. Accordingly, schools are increasingly being held accountable for student attendance. However, the malleable school inputs that affect student attendance are poorly understood. This study provides novel, causal evidence on the classroom-level inputs that affect student attendance. We do so by exploiting the random assignment of both students and teachers to classrooms in the Project STAR class size experiment. We use publicly available Project STAR data to estimate the student attendance production function.

The main findings are that: (1) classrooms vary significantly in their effects on student absenteeism, mostly along unobserved dimensions; (2) class size reductions significantly reduce the frequency of chronic absence and the level of annual absences, for students of all socio-demographic groups; (3) having a same-race teacher significantly reduces the probability of chronic absence and the level of annual absences among black students; (4) other observed classroom characteristics, such as teacher qualifications and classroom sociodemographic composition, do not systematically affect student attendance habits; and (5) class-size and race-match effects on attendance explain a small, but nontrivial, share of those inputs' effects on academic achievement (about 5%). Our results are consistent with quasi-experimental evidence that small classes boost student engagement (Dee & West, 2011), teachers affect student attendance (Gershenson, 2016; Lie & Loeb 2017), and variation in teacher effects is not well explained by observable teacher characteristics (Staiger & Rockoff, 2010).

For policymakers and educational administrators, these results suggest that a limited number of classroom-level policy levers can be used to improve student attendance. However, the modest effect sizes and costliness of class-size reductions at scale also highlight the limits of relying on traditional educational inputs to improve student attendance and reduce socio-economic achievement and attendance gaps. Recently piloted, light-touch, behavioral interventions that provide parents with information on both student attendance records and the importance of regular attendance may prove more cost effective (Bergman & Chan, 2017;

Robinson et al., 2018; Rogers & Feller, 2018; Smythe-Leistico & Page, 2018). Such interventions can be targeted and deployed at scale relatively easily. It would be particularly interesting for future research to investigate the complementarities between such interventions and the traditional classroom inputs studied here.

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Table 1: Summary statistics

Variable	All (1)	White (2)	Black (3)	Male (4)	Female (5)	FRL (6)	Non-FRL (7)
Chronic absence	0.14	0.15	0.12	0.13	0.15	0.16	0.12
Absent days	9.46	10.05	8.38	9.33	9.60	10.09	8.73
(SD)	(9.13)	(9.13)	(8.32)	(9.02)	(9.26)	(9.90)	(8.10)
(within-school SD)	(8.74)	(8.94)	(8.38)	(8.73)	(8.76)	(8.92)	(8.54)
(within-classroom SD)	(8.03)	(8.17)	(7.77)	(7.96)	(8.10)	(8.14)	(7.89)
Class size	20.84	20.63	21.22	20.87	20.80	21.05	20.59
(SD)	(4.00)	(4.00)	(3.96)	(4.00)	(4.00)	(4.04)	(3.94)
Own-race teacher	0.76	0.95	0.43	0.77	0.76	0.66	0.88
Black teacher	0.19	0.05	0.43	0.18	0.19	0.26	0.10
Teacher experience	10.42	10.55	10.19	10.37	10.49	10.44	10.40
(SD)	(7.38)	(6.63)	(8.57)	(7.39)	(7.37)	(7.95)	(6.65)
Post-graduate teacher	0.36	0.39	0.30	0.36	0.36	0.33	0.38
Class black rate	0.35	0.09	0.82	0.34	0.35	0.50	0.17
(SD)	(0.41)	(0.15)	(0.30)	(0.41)	(0.41)	(0.44)	(0.28)
Class female rate	0.48	0.48	0.49	0.46	0.51	0.49	0.48
(SD)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)
Class FRL rate	0.51	0.38	0.74	0.50	0.51	0.66	0.33
(SD)	(0.29)	(0.21)	(0.29)	(0.29)	(0.29)	(0.26)	(0.20)
Black student	0.35	0	1	0.35	0.36	0.54	0.13
Female student	0.47	0.47	0.48	0	1	0.48	0.47
FRL student	0.54	0.38	0.83	0.53	0.54	1	0
N (Students)	9,588	6,201	3,387	5,036	4,552	5,139	4,449

Notes: Standard deviations (SDs) are reported in parentheses under the means for non-categorical variables.

Table 2: Standard deviation of classroom and school random effects

Outcome:	Chronic Absence		Absent Days	
	(1)	(2)	(3)	(4)
Classroom RE	0.430***	0.424***	0.439***	0.435***
	(0.058)	(0.059)	(0.014)	(0.0013)
School RE	0.313***	0.310***	0.079***	0.070***
	(0.055)	(0.056)	(0.028)	(0.030)
Observations	9,558	9,558	9,558	9,558
Student controls	Yes	Yes	Yes	Yes
Classroom controls	No	Yes	No	Yes

Notes: Standard errors in parentheses. Columns 1 and 2 come from a multilevel mixed logit model. Columns 3 and 4 come from a multilevel mixed linear model. Chronic absence is an indicator of 18 or more absences in a given school year. Absent days is the count of annual absences. Student controls include student race, sex, FRL status, and entry cohort. Classroom controls include class size, class composition, and observed teacher qualifications.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3: LPM estimates of classroom inputs' effects on likelihood of chronic absence

Variable	All (1)	White (2)	Black (3)	Male (4)	Female (5)	FRL (6)	Non-FRL (7)
Class size	0.003***	0.003**	0.003	0.003**	0.002	0.002	0.003**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Own-race teacher	-0.018	-0.018	-0.031***	-0.023	-0.009	-0.020	-0.005
	(0.013)	(0.028)	(0.011)	(0.017)	(0.017)	(0.021)	(0.015)
Black teacher	-0.006			0.008	-0.033*	-0.016	0.012
	(0.014)			(0.017)	(0.019)	(0.022)	(0.018)
Teacher experience	0.000	-0.000	0.000	-0.000	0.001	0.001	-0.001**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-graduate teacher	-0.012	-0.005	-0.026*	-0.005	-0.023*	-0.029**	-0.001
	(0.008)	(0.009)	(0.014)	(0.011)	(0.012)	(0.013)	(0.010)
Class black rate	0.006	-0.041	0.060	-0.092	0.130	-0.079	0.112
	(0.058)	(0.075)	(0.094)	(0.087)	(0.088)	(0.098)	(0.077)
Class female rate	0.007	-0.018	0.066	0.015	-0.022	-0.031	0.045
	(0.033)	(0.040)	(0.056)	(0.048)	(0.049)	(0.056)	(0.042)
Class FRL rate	-0.017	-0.015	0.001	0.005	-0.061	-0.001	-0.022
	(0.032)	(0.041)	(0.049)	(0.044)	(0.048)	(0.053)	(0.041)
Black student	-0.067***			-0.076***	-0.060***	-0.083***	-0.050***
	(0.015)			(0.021)	(0.021)	(0.024)	(0.019)
Female student	0.011	0.009	0.011			0.017*	0.006
	(0.007)	(0.009)	(0.011)			(0.010)	(0.010)
FRL student	0.084***	0.088***	0.057***	0.076***	0.094***		
	(0.009)	(0.011)	(0.013)	(0.012)	(0.014)		
Observations	9,588	6,201	3,387	5,036	4,552	5,139	4,449
R-squared	0.071	0.087	0.076	0.084	0.095	0.090	0.083
E[chronic absence]	0.140	0.153	0.117	0.134	0.148	0.162	0.115

Notes: 2SLS linear probability model (LPM) estimates where *Class Size* is instrumented by the indicators for the randomly assigned classroom type. All models include school-by-cohort fixed effects. Standard errors are clustered by classroom. The outcome, chronic absence, is an indicator of 18 or more absences in a given school year.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Mediation analysis of classroom inputs' effects on math achievement

Variable	All (1)	All (2)	White (3)	White (4)	Black (5)	Black (6)
Class size	-0.024***	-0.023***	-0.021***	-0.020***	-0.029***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
Own-race teacher	0.123***	0.121***	0.103	0.101	0.123**	0.116*
	(0.042)	(0.042)	(0.084)	(0.084)	(0.061)	(0.061)
Black teacher	-0.000	-0.002				
	(0.055)	(0.055)				
Teacher experience	0.005**	0.005**	0.004	0.004	0.006*	0.006*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Post-graduate teacher	0.005	0.003	-0.012	-0.013	0.037	0.031
	(0.032)	(0.032)	(0.036)	(0.036)	(0.054)	(0.054)
Class black rate	-0.128	-0.126	-0.204	-0.211	0.017	0.038
	(0.325)	(0.323)	(0.357)	(0.356)	(0.509)	(0.508)
Class female rate	0.289*	0.298*	-0.001	0.005	0.781***	0.798***
	(0.158)	(0.157)	(0.182)	(0.181)	(0.275)	(0.274)
Class FRL rate	-0.138	-0.143	-0.272*	-0.277*	0.105	0.103
	(0.147)	(0.147)	(0.163)	(0.162)	(0.282)	(0.281)
Black student	-0.283***	-0.297***				
	(0.045)	(0.044)				
Female student	0.072***	0.074***	0.066***	0.068***	0.076**	0.078**
	(0.018)	(0.019)	(0.024)	(0.024)	(0.030)	(0.030)
FRL student	-0.365***	-0.345***	-0.380***	-0.359***	-0.274***	-0.262***
	(0.022)	(0.022)	(0.027)	(0.027)	(0.041)	(0.041)
Chronic absence		-0.235***		-0.228***		-0.243***
		(0.025)		(0.032)		(0.042)
Constant	0.007	0.042	0.103	0.165	-0.508	-0.531
	(0.261)	(0.264)	(0.278)	(0.281)	(0.420)	(0.417)
Observations	8,881	8,881	5,744	5,744	3,137	3,137
R-squared	0.271	0.277	0.210	0.216	0.318	0.324
Adj. R-squared	0.251	0.257	0.182	0.189	0.279	0.286

Notes: 2SLS estimates where *Class Size* is instrumented by the indicators for the randomly assigned classroom type. The outcome, math score, is standardized by year to have mean 0 and standard deviation 1. All models include school-by-cohort fixed effects. Standard errors are clustered by classroom. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.1: 2SLS estimates of classroom inputs' effects on annual absences

	(All) (1)	(White) (2)	(Black) (3)	(Male) (4)	(Female) (5)	(FRL) (6)	(Non-FRL) (7)
Class size	0.089***	0.100***	0.075*	0.066*	0.109***	0.090**	0.078**
	(0.027)	(0.033)	(0.042)	(0.035)	(0.039)	(0.041)	(0.033)
Own-race teacher	-0.279	0.452	-1.138***	-0.339	0.010	-0.334	-0.021
	(0.320)	(0.629)	(0.315)	(0.423)	(0.407)	(0.519)	(0.370)
Black teacher	-0.802**			-0.337	-1.667***	-0.982*	-0.477
	(0.336)			(0.459)	(0.446)	(0.531)	(0.491)
Teacher experience	0.010	0.010	0.012	0.007	0.019	0.030	-0.017
	(0.012)	(0.016)	(0.017)	(0.018)	(0.019)	(0.018)	(0.017)
Post-graduate teacher	-0.340	-0.281	-0.425	-0.200	-0.572*	-0.817**	-0.005
	(0.214)	(0.262)	(0.383)	(0.280)	(0.315)	(0.328)	(0.263)
Class black rate	0.779	-0.497	2.855	0.562	1.790	1.719	1.073
	(1.748)	(2.374)	(2.595)	(2.410)	(2.301)	(2.790)	(2.173)
Class female rate	-0.640	-1.248	0.758	0.069	-1.856	-0.743	-0.854
	(0.892)	(1.185)	(1.349)	(1.315)	(1.271)	(1.424)	(1.113)
Class FRL rate	-0.087	-0.003	0.306	2.134	-2.721**	0.836	-0.925
	(1.024)	(1.335)	(1.579)	(1.344)	(1.277)	(1.578)	(1.144)
Black student	-2.260***			-2.449***	-1.864***	-2.705***	-1.712***
	(0.397)			(0.520)	(0.522)	(0.610)	(0.467)
Female student	0.185	0.092	0.281			0.168	0.285
	(0.182)	(0.236)	(0.293)			(0.280)	(0.242)
FRL student	2.635***	2.614***	2.366***	2.551***	2.688***		
	(0.233)	(0.284)	(0.341)	(0.324)	(0.354)		
Observations	9,588	6,201	3,387	5,036	4,552	5,139	4,449
R-squared	0.105	0.117	0.095	0.124	0.128	0.113	0.133
Average absent days	9.461	10.053	8.378	9.335	9.601	10.094	8.731

Notes: 2SLS estimates where *Class Size* is instrumented by indicators for the randomly assigned classroom type. All models include school-by-cohort fixed effects. Standard errors are clustered by classroom. The outcome is a count of annual absences. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.2: OLS estimates of small-class effects on chronic absence

Variable	(All) (1)	(White) (2)	(Black) (3)	(Male) (4)	(Female) (5)	(FRL) (6)	(Non-FRL) (7)
Small class	-0.019**	-0.021**	-0.018	-0.023**	-0.012	-0.016	-0.019*
	(0.007)	(0.009)	(0.012)	(0.010)	(0.011)	(0.012)	(0.010)
Same race	-0.018	-0.016	-0.032***	-0.023	-0.009	-0.019	-0.005
	(0.013)	(0.028)	(0.011)	(0.017)	(0.017)	(0.022)	(0.015)
Black teacher	-0.007			0.007	-0.034*	-0.017	0.011
	(0.014)			(0.018)	(0.020)	(0.023)	(0.018)
Experience	0.000	-0.000	0.000	-0.000	0.001	0.001	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-graduate	-0.012	-0.006	-0.026*	-0.005	-0.023*	-0.029**	-0.002
	(0.008)	(0.009)	(0.014)	(0.011)	(0.012)	(0.013)	(0.010)
Class black rate	0.012	-0.035	0.069	-0.085	0.136	-0.076	0.119
	(0.059)	(0.076)	(0.097)	(0.089)	(0.090)	(0.100)	(0.079)
Class female rate	0.005	-0.019	0.062	0.014	-0.025	-0.034	0.044
	(0.033)	(0.040)	(0.057)	(0.049)	(0.051)	(0.057)	(0.043)
Class FRL rate	-0.017	-0.013	-0.002	0.005	-0.059	-0.001	-0.021
	(0.033)	(0.041)	(0.051)	(0.045)	(0.049)	(0.054)	(0.042)
Black student	-0.067***			-0.075***	-0.060***	-0.083***	-0.050**
	(0.016)			(0.021)	(0.022)	(0.024)	(0.020)
Female student	0.011	0.009	0.011			0.017	0.006
	(0.007)	(0.009)	(0.011)			(0.010)	(0.010)
FRL student	0.084***	0.088***	0.057***	0.076***	0.094***		
	(0.009)	(0.011)	(0.014)	(0.012)	(0.014)		
Constant	0.236***	0.354***	0.010	0.283***	0.195***	0.372***	0.147*
	(0.040)	(0.067)	(0.069)	(0.054)	(0.063)	(0.065)	(0.088)
Observations	9,588	6,201	3,387	5,036	4,552	5,139	4,449
R-squared	0.071	0.087	0.076	0.084	0.095	0.090	0.083

Notes: OLS estimates of impact of random assignment to a small-class on chronic absence (relative to assignment to a regular-sized class, with or without an aide). All models include school-by-cohort fixed effects. Standard errors are clustered by classroom. The outcome, chronic absence, is an indicator of 18 or more absences in a given school year.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.3: LPM estimates of classroom type's effects on chronic absence

Variable	All (1)	White (2)	Black (3)	Male (4)	Female (5)	FRL (6)	Non-FRL (7)
Small class	Reference	-	-	-	-	-	-
Regular class	0.013*	0.012	0.021*	0.028**	-0.005	0.012	0.014
	(0.008)	(0.010)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)
Regular class with aide	0.024***	0.030***	0.015	0.018	0.029**	0.019	0.023**
	(0.008)	(0.011)	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)
Own-race teacher	-0.018	-0.019	-0.032***	-0.022	-0.011	-0.020	-0.005
	(0.013)	(0.028)	(0.011)	(0.017)	(0.017)	(0.022)	(0.015)
Black teacher	-0.006			0.006	-0.031	-0.017	0.012
	(0.014)			(0.018)	(0.019)	(0.023)	(0.018)
Teacher experience	-0.000	-0.000	0.001	-0.000	0.000	0.001	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-graduate teacher	-0.012	-0.006	-0.027*	-0.005	-0.023*	-0.029**	-0.002
	(0.008)	(0.009)	(0.014)	(0.011)	(0.012)	(0.013)	(0.010)
Class black rate	0.013	-0.035	0.068	-0.086	0.139	-0.073	0.117
	(0.059)	(0.077)	(0.097)	(0.089)	(0.090)	(0.100)	(0.080)
Class female rate	0.007	-0.014	0.060	0.010	-0.019	-0.033	0.047
	(0.033)	(0.040)	(0.058)	(0.049)	(0.050)	(0.057)	(0.043)
Class FRL rate	-0.018	-0.016	-0.001	0.006	-0.063	-0.002	-0.022
	(0.033)	(0.041)	(0.050)	(0.045)	(0.049)	(0.054)	(0.042)
Black student	-0.067***			-0.075***	-0.062***	-0.084***	-0.050**
	(0.016)			(0.021)	(0.022)	(0.024)	(0.020)
Female student	0.011	0.009	0.011			0.017	0.006
	(0.007)	(0.009)	(0.011)			(0.010)	(0.010)
FRL student	0.084***	0.088***	0.058***	0.075***	0.094***		
	(0.009)	(0.011)	(0.014)	(0.012)	(0.014)		
Constant	0.218***	0.336***	-0.008	0.259***	0.185***	0.357***	0.130
	(0.040)	(0.066)	(0.066)	(0.054)	(0.061)	(0.064)	(0.089)
H_0: Reg = Aide = 0 (*p*)	0.017	0.014	0.240	0.050	0.005	0.330	0.130
H_0: Reg = Aide (*p*)	0.134	0.048	0.588	0.270	0.002	0.504	0.412
Observations	9,588	6,201	3,387	5,036	4,552	5,139	4,449
R-squared	0.072	0.087	0.076	0.084	0.096	0.090	0.083

Notes: OLS estimates of randomly assigned classroom type on chronic absence. All models include school-by-cohort fixed effects. Standard errors are clustered by classroom. The outcome, chronic absence, is an indicator of 18 or more absences in a given school year.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.4: FE-Logit coefficient estimates for effect of small class assignment

Variable	All (1)	White (2)	Black (3)	Male (4)	Female (5)	FRL (6)	Non-FRL (7)
Small class	-0.161**	-0.174**	-0.163	-0.202**	-0.096	-0.111	-0.192*
	(0.071)	(0.085)	(0.137)	(0.101)	(0.102)	(0.094)	(0.114)
Same race	-0.176	-0.142	-0.338**	-0.219	-0.089	-0.179	0.012
	(0.113)	(0.226)	(0.151)	(0.157)	(0.171)	(0.152)	(0.236)
Black teacher	-0.082			0.029	-0.310	-0.154	0.170
	(0.128)			(0.178)	(0.194)	(0.170)	(0.271)
Experience	0.001	-0.000	0.004	-0.002	0.005	0.009	-0.015
	(0.005)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.010)
Post-graduate	-0.119	-0.058	-0.298*	-0.052	-0.217*	-0.212*	-0.035
	(0.081)	(0.095)	(0.166)	(0.116)	(0.117)	(0.109)	(0.128)
Class black rate	0.286	-0.146	1.290	-0.813	1.498	-0.548	1.752
	(0.794)	(0.947)	(1.614)	(1.156)	(1.101)	(1.058)	(1.242)
Class female rate	0.013	-0.143	0.540	0.080	-0.228	-0.316	0.519
	(0.343)	(0.415)	(0.629)	(0.494)	(0.485)	(0.447)	(0.557)
Class FRL rate	-0.077	-0.043	-0.001	0.080	-0.345	0.014	-0.106
	(0.343)	(0.403)	(0.686)	(0.495)	(0.489)	(0.466)	(0.561)
Black student	-0.578***			-0.670***	-0.496**	-0.625***	-0.633**
	(0.143)			(0.199)	(0.213)	(0.177)	(0.296)
Female student	0.092	0.071	0.106			0.128	0.057
	(0.062)	(0.075)	(0.114)			(0.081)	(0.100)
FRL student	0.700***	0.669***	0.692***	0.643***	0.759***		
	(0.076)	(0.082)	(0.202)	(0.106)	(0.110)		
N (Students)	8,937	5,578	2,984	4,414	3,904	4,674	3,669
N (School-cohort FE)	188	140	83	162	153	172	111

Notes: FE-Logit coefficient estimates of impact of random assignment to a small-class on chronic absence (relative to assignment to a regular-sized class, with or without an aide). All models include school-by-cohort fixed effects. The outcome, chronic absence, is an indicator of 18 or more absences in a given school year.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.5: FE-Poisson coefficient estimates for effect of small class assignment

	All	White	Black	Male	Female	FRL	Non-FRL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Small class	-0.063***	-0.069**	-0.059	-0.049*	-0.075**	-0.055*	-0.062**
	(0.023)	(0.029)	(0.036)	(0.030)	(0.035)	(0.031)	(0.030)
Same race	-0.038	0.049	-0.143***	-0.044	-0.003	-0.047	-0.006
	(0.033)	(0.056)	(0.044)	(0.047)	(0.042)	(0.047)	(0.044)
Black teacher	-0.095***			-0.043	-0.193***	-0.103**	-0.065
	(0.036)			(0.057)	(0.045)	(0.050)	(0.057)
Experience	0.001	0.001	0.001	0.001	0.002	0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Post-graduate	-0.040	-0.031	-0.062	-0.027	-0.064	-0.080**	-0.004
	(0.028)	(0.031)	(0.053)	(0.036)	(0.042)	(0.039)	(0.038)
Class black rate	0.125	-0.010	0.459	0.108	0.213	0.220	0.164
	(0.204)	(0.279)	(0.337)	(0.268)	(0.312)	(0.300)	(0.279)
Class female rate	-0.085	-0.128	0.056	-0.009	-0.215	-0.099	-0.094
	(0.114)	(0.135)	(0.216)	(0.171)	(0.149)	(0.178)	(0.146)
Class FRL rate	0.010	0.020	0.024	0.238	-0.249	0.087	-0.090
	(0.131)	(0.161)	(0.245)	(0.163)	(0.157)	(0.171)	(0.170)
Black student	-0.243***			-0.270***	-0.191***	-0.271***	-0.226***
	(0.047)			(0.058)	(0.065)	(0.062)	(0.060)
Female student	0.019	0.009	0.033			0.016	0.032
	(0.020)	(0.024)	(0.038)			(0.028)	(0.028)
FRL student	0.269***	0.249***	0.314***	0.263***	0.269***		
	(0.024)	(0.027)	(0.041)	(0.031)	(0.035)		
N (Students)	9,588	6,198	3,355	5,035	4,550	5,134	4,434
N (School-cohort FE)	229	181	134	228	226	222	199

Notes: FE-Poisson coefficient estimates of impact of random assignment to a small-class on count of annual absences (relative to assignment to a regular-sized class, with or without an aide). All models include school-by-cohort fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A.6: Baseline LPM chronic absence estimates, Kindergarten cohort only

Variable	All (1)	White (2)	Black (3)	Male (4)	Female (5)	FRL (6)	Non-FRL (7)
Class size	0.003***	0.004**	0.004*	0.004**	0.003*	0.004*	0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Own-race teacher	-0.014	-0.050	-0.026*	-0.024	-0.001	-0.001	-0.011
	(0.019)	(0.042)	(0.016)	(0.024)	(0.023)	(0.034)	(0.020)
Black teacher	0.004			0.047*	-0.052*	-0.016	0.018
	(0.021)			(0.026)	(0.028)	(0.037)	(0.025)
Teacher experience	-0.000	-0.000	-0.001	-0.002	0.001	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-graduate teacher	-0.014	-0.004	-0.037**	0.009	-0.040***	-0.028	-0.006
	(0.011)	(0.012)	(0.018)	(0.016)	(0.015)	(0.019)	(0.012)
Class black rate	0.036	-0.005	0.118	-0.173	0.305***	-0.164	0.221**
	(0.081)	(0.100)	(0.134)	(0.116)	(0.112)	(0.144)	(0.096)
Class female rate	0.033	0.005	0.094	0.039	0.013	0.001	0.053
	(0.039)	(0.045)	(0.069)	(0.057)	(0.055)	(0.070)	(0.049)
Class FRL rate	-0.024	-0.015	-0.004	0.042	-0.127**	0.007	-0.049
	(0.044)	(0.051)	(0.070)	(0.063)	(0.060)	(0.077)	(0.051)
Black student	-0.087***			-0.094***	-0.082***	-0.102***	-0.051*
	(0.023)			(0.031)	(0.028)	(0.036)	(0.027)
Female student	0.007	0.008	0.001			0.007	0.007
	(0.009)	(0.012)	(0.015)			(0.014)	(0.013)
FRL student	0.092***	0.103***	0.041**	0.085***	0.102***		
	(0.013)	(0.015)	(0.017)	(0.017)	(0.018)		
Constant	0.162***	0.279***	-0.057	0.221***	0.096	0.319***	0.080
	(0.052)	(0.086)	(0.083)	(0.067)	(0.074)	(0.085)	(0.092)
Observations	6,172	4,144	2,028	3,176	2,996	3,003	3,169
R-squared	0.057	0.065	0.063	0.064	0.078	0.075	0.061

Notes: 2SLS linear probability model (LPM) estimates where *Class Size* is instrumented by the indicators for the randomly assigned classroom type. All models include school-by-cohort fixed effects, which in this case reduce to school fixed effects, because the analytic sample is retricted to the kindergarten entry cohort. Standard errors are clustered by classroom. The outcome, chronic absence, is an indicator of 18 or more absences in a given school year.
*** p<0.01, ** p<0.05, * p<0.1.