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Abstract

This paper provides evidence that student behavior issues contribute to teacher turnover among U.S. middle school teachers. Using detailed administrative data on student behavior, discipline, and teacher movement in North Carolina middle schools, I show that when teachers experience an increase in reported disciplinary offenses at their school–or among the students in the grade they teach–they are more likely to leave the school or the profession. Among first-year teachers, these effects are largest for more effective teachers. I measure student behavior using only offenses that require mandatory reporting to the state, suggesting that differential reporting by teachers or schools is not driving the results. Further, I compare teachers to others at their school using school and school-by-year fixed effects models, suggesting that school-level changes in student composition are not driving the results. I also show that a more punitive disciplinary response to student offenses does not lead to higher teacher turnover for most teachers. These findings suggest that schools and teacher preparation programs should focus on strategies to help teachers manage student behavior issues.

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1 Introduction

Schools' failure to retain effective teachers is common and costly. Prior to the COVID-19 pandemic in 2020, about 16% of K–12 teachers in the U.S. left their school in a given year.[1] At high-poverty schools and among first-year (novice) teachers, more than 20% left each year, an issue that is more acute in some places since 2020 (Bruno, 2022). The cost of replacing teachers is high, both in terms of direct costs (e.g., recruitment, hiring, and training) (Barnes, Crowe, & Schaefer, 2007) and indirect costs (e.g., lower student achievement when losing high-quality teachers) (Chetty, Friedman, & Rockoff, 2014). Further, teacher attrition–leaving the teaching profession altogether–is particularly costly for school systems, as teaching effectiveness grows with experience (Wiswall, 2013).

Extensive survey evidence suggests that poor school climate and administrative support are major reasons why teachers leave a school (Carver-Thomas & Darling-Hammond, 2019; Ingersoll, 2001; Nguyen, Pham, Crouch, et al., 2020). However, the exact factors that contribute to school climate are less clear. One understudied factor suggested by teacher surveys is student behavior: teachers who report behavioral problems at their school are more likely to leave teaching (Kukla-Acevedo, 2009; Nguyen, Pham, Crouch, et al., 2020). Behavior issues may be particularly problematic for novice teachers, who typically receive minimal classroom management training before becoming teachers. While teachers can improve their classroom management abilities, novice teachers who struggle with classroom management are more likely to leave teaching early in their career (Bartanen, Bell, James, et al., 2023).

However, existing evidence linking student behavior to teacher attrition or mobility (moving to another school) may be biased by using unreliable measures of student behavior. Teachers' perceptions, while important in individual decision-making, may not objectively reflect differences across classrooms or schools. Meanwhile, administrative data on reported offenses in schools, collected by many states, are an incomplete record of student behavior. These data include offenses reported to principals and added to the state database, but reporting policies vary by state and school. In North Carolina, the setting for this study, many offenses–such as disruptive behavior, dress code violations, cutting class, and insubordination–require reporting only

[1] The latest nationally-representative data are from the 2012–13 school year (U.S. Department of Education, 2019). Teachers who leave the profession (attrition) account for roughly half of overall turnover while teachers who move to another school (mobility) account for the other half.

if they result in an out-of-school suspension. If teachers who are more (less) likely to report these discretionary offenses leave at higher (lower) rates, descriptive evidence comparing reported offenses and teacher turnover will overstate (understate) the effect of student behavioral offenses (Feng, 2009).[2]

In this paper, I use administrative panel data from North Carolina on student behavior, discipline, and teacher turnover in public middle schools from 2009–2019 to show whether student behavior affects teacher turnover. I measure student behavior both at the school and in the grade that a teacher is assigned, allowing me to rule out many other potential explanations for the relationship between student behavior and teacher retention, and to limit the influence of individual teachers on recorded behavior. Because student behavior is correlated with other school-level factors that determine teacher turnover, I estimate models with both school and school-by-year fixed effects to control for school-level factors that contribute to differences in teacher turnover. Additionally, I control for a rich set of student demographics and achievement variables at the school, grade, and classroom-level, as well as teacher characteristics, to control for other factors driving teacher turnover.

To measure student behavior consistently across grades and schools, I use data on offenses that are consistently reported in the administrative data. In North Carolina, state and federal laws mandate that all of a subset of "reportable" offenses that occur in the school are reported to the state administrative data system.[3] These "mandatory offenses" include both more serious offenses–such as assault and drug possession–and less serious offenses–including property damage and bullying. I measure student behavior using only mandatory offenses, limiting the potential for discretionary reporting by teachers or administrators to affect my results. Additionally, because I observe offenses regardless of the consequences applied, I measure the severity of offenses empirically, categorizing offenses as "low severity", "middle severity", or "high severity" based on the average length of suspensions given for each offense type statewide.

Given the importance of student behavior, I also assess the potential for the disciplinary response to student offenses to affect teacher turnover. Because a disciplinary event reflects both the occurrence and severity of a student offense and how punitive a school chooses to be when responding, I measure disciplinary

[2]Hayes, Liu, and Gershenson (2023) find that disciplinary reporting rates vary by some teacher characteristics, such as experience, that impact teacher turnover rates.

[3]Schools are also required to report all offenses that result in an out-of-school suspension. Additionally, many schools choose to report other offenses, even if they do not result in an out-of-school suspension.

punitiveness by calculating a school's "propensity to remove" (PTR), as proposed by Sorensen, Bushway, and Gifford (2022), who show that a more punitive discipline policy leads to negative outcomes for students. By conditioning on a detailed description of the offense, PTR measures a school's response to offenses instead of the severity of the underlying behavior. To separate the effect of discipline from the effect of student behavior, I control for the number and severity of offenses in a teacher's school or grade.

This analysis builds on the mixed existing evidence on the effect of school discipline policy on teacher turnover, which does not control for student behavior. Penner, Liu, and Ainsworth (2023) find that when schools discipline a higher percentage of students, they have higher teacher turnover but do not control for student behavior. Pope and Zuo (2023), studying a district-wide policy to lower suspension rates, find that higher suspension rates lead to lower teacher turnover but do not investigate whether changes in suspension policy also lead to changes in student behavior that may affect teacher turnover. In this paper, I show whether schools' disciplinary choices affect teacher turnover while controlling directly for a rich set of student behavior measures.

I find that higher levels of student offenses in a given year lead to higher teacher turnover. In particular, a one standard deviation (SD) increase in offenses per student leads to a 0.5–0.8 percentage point (p.p.) increase in teacher turnover. These effects are driven by low- and middle-severity offenses, not the most severe offenses. An additional SD in middle-severity or low-severity offenses leads to a 1.1–1.3 p.p. increase in turnover, accounting for 6%–7% of annual turnover. Among novice teachers, more high-severity offenses lead to higher turnover, particularly among novice teachers with above-median value added and among novice female teachers.[4]

In contrast to previous work, I find that, on average, a more punitive discipline policy is not related to teacher turnover. Among all teachers, an additional SD in disciplinary punitiveness leads to at most a 0.5 p.p. decrease in turnover or a 0.7 p.p. increase in turnover. However, these average effects do not hold for all teachers. Among novice male teachers, a more punitive discipline policy leads to higher mobility but lower attrition. This suggests that changing discipline policies may create tradeoffs in the characteristics of teachers retained.

[4]Value added is a measure of teacher effectiveness, as measured using standardized assessments, that controls for student characteristics and prior achievement. See section Appendix D for details.

My results provide evidence that the relationship documented in previous literature that compares student behavior and teacher turnover cannot be explained by school-level factors related to both student behavior and teacher turnover. My identification strategy rules out many alternative explanations–including differences in school student body characteristics and teacher selection of schools based on average characteristics. As I show in Section 4.7.2, failure to control for all school-level factors–as in the existing descriptive literature–likely overstates the effect of student behavior on teacher turnover.

This research contributes to our understanding of the factors that determine teacher mobility and attrition. Previous research has documented various aspects of school climate and working conditions that teachers cite as reasons for leaving their school, including working conditions such as class sizes, workload, facility quality, and peer teacher quality as well as principal leadership and perceptions of autonomy and pay structure.[5] I contribute to this literature by showing the relationship between teacher mobility and attrition and two measures of school working conditions—student behavior and discipline policy—that have not been studied in detail but are cited by teachers as reasons for leaving their school (Kukla-Acevedo, 2009; Nguyen, Pham, Crouch, et al., 2020). My findings–that worse student behavior leads to higher turnover–complements literature on teacher turnover and student body characteristics–showing that teachers leave schools at higher rates after reassignment of more low-achieving or minority students to their schools (C. K. Jackson, 2009; Karbownik, 2020).

One study, Feng (2009), looks at novice teacher mobility and attrition among Florida teachers as a function of teacher, school, and classroom characteristics, including the number of formally reported student disciplinary offenses. Using data on middle school teachers in North Carolina, I match the finding in Feng (2009) that more offenses in a teacher's classroom are associated with higher mobility and build on this work in multiple ways. First, using measures of student behavior for offenses with mandatory reporting requirements, I provide evidence that the relationship between student behavior and teacher attrition is not the result of differences in reporting across teachers or schools. Second, using school fixed effects in addition to the district and year fixed effects included in analyses by Feng (2009), I provide evidence that the relationship between student behavior and teacher attrition cannot be explained by differences in teacher characteristics or stu-

[5]See Donaldson and Johnson (2011), Feng and Sass (2017), and Loeb and Luczak (2013) for an analysis of general working condition factors that affect teacher retention. Grissom (2011), Ingersoll and May (2012), Johnson, Kraft, and Papay (2012), and Ladd (2011) study the importance of principals and organizational context. Biasi (2021) studies the effect of incentive pay.

dent behavior across schools. However, I show that estimates from regressions that do not control for all school-level factors likely overstate the relationship between student behavior and teacher attrition. Third, I use school- and grade-level instead of classroom-level student behavior measures, reducing the potential for bias from unobserved confounding variables. As I show in section 4.7.3, student and teacher characteristics are much less correlated with school- and grade-level behavior measures than with classroom-level measures. Finally, I show that the relationship between student behavior and teacher attrition differs by severity: among novice teachers, higher turnover is driven by the most severe offenses.

This research also contributes to the literature on school discipline policy. Recent literature finds that receiving a suspension has negative effects on a variety of academic and life outcomes.[6] However, little is known about the impacts of changing discipline policy on the ability of schools to retain teachers. Two studies–Penner, Liu, and Ainsworth (2023) and Pope and Zuo (2023)–find mixed results of changing discipline policy; however, neither controls for changes in student behavior that I show have a separate effect on teacher retention. I contribute to this research by showing that when controlling for student behavior, a more punitive discipline policy has no average effect on retention but does affect certain teacher subgroups.

The rest of this paper proceeds as follows. Section 2 describes the data and measurement of student behavior, discipline, and teacher mobility and attrition. Section 3 provides details on my empirical strategy. Section 4 presents the results of the analysis, including a detailed analysis of the effects on novice teachers. Finally, Section 5 concludes.

2 Data and Measurement

To estimate the relationship between student behavior and disciplinary punitiveness on teacher turnover, I use data from the North Carolina (NC) Education Research Data Center. In particular, I use student-level data on student misconduct and suspension and teacher-level data on employment in NC public schools, education and experience, and pay.

[6] See Anderson, Ritter, and Zamarro (2019); Bacher-Hicks, Billings, and Deming (2019); Chu and Ready (2018); D. Jackson, Testa, Todić, et al. (2021); Lacoe and Steinberg (2019); Noltemeyer, Ward, and Mcloughlin (2015); Sorensen, Bushway, and Gifford (2022); Wolf and Kupchik (2017)

2.1 Sample

I create a sample of 37,781 teachers at 618 NC public middle schools in 112 school districts between the 2008–09 and 2018–19 school years.[7] My main specifications use 141,435 teacher-by-year observations. I focus on middle schools because issues of behavior and discipline are most frequent at the middle and high school levels, and because students in middle schools are consistently given standardized tests that can be used to control for student academic performance.[8] I assign teachers to a school each year based on the school where they are employed the most hours per week in that school year, and; if hours are unavailable, I assign teachers to the school in which they earn the highest salary.

2.2 Student Behavior

I create variables measuring student behavior each year at both the school level and in the grade(s) each teacher is assigned to teach in that year. While a teacher might be most responsive to student behavior among the students they teach, they also have the most direct control over the behavior of these students and the reporting of offenses committed by these students. Therefore, I measure behavior at a higher level: among students in the grade(s) they are assigned or at their school. In Section 4.7.3, I assess the sensitivity of my results to this choice.

To measure school behavior, I use incident-level data on student infractions and the resulting discipline assigned. These data include records for all offenses requiring mandatory reporting by state or federal law, any offenses resulting in an out-of-school suspension or, in rare cases, an expulsion[9], and any additional incidents that each school chooses to record.

To create consistent measures across schools, I focus on mandatory offenses, which schools are required to record according to state or federal law. Appendix C lists the offenses recorded in the data and whether they are mandatory under state or federal law. Offenses with required reporting under state law consist of more serious offenses such as assault and firearm possession while offenses with required reporting only under federal law are somewhat less serious, such as possession of tobacco and property damage. As I show in

[7] Charter schools are counted as a separate "district."

[8] Figure A1 shows the frequency of student offenses by school level. Middle and high schools have higher levels of student offenses than elementary schools.

[9] In my analysis, I group out-of-school suspensions and expulsions.

Section 2.2.1, there is significant variation in the severity of discipline applied to each mandatory offense. To include both more serious offenses and less serious offenses, I measure student behavior using the number of offenses per student requiring mandatory reporting under either state or federal law.

2.2.1 Measuring Offense Severity

There is significant variation in the severity of discipline applied to each offense. Table B1 shows the percentage of incidents in each offense category that result in an out-of-school suspension. The most common offense–fighting–results in an out-of-school suspension in 84% of incidents, while the third most common offense–bullying–results in an out-of-school suspension in only 43% of incidents. There is also variation in the average length of out-of-school suspensions: the average out-of-school suspension length for fighting is 4 days, while the average out-of-school suspension length for bullying is 1 day.

To categorize offenses by severity, I use statewide variation in the length of out-of-school suspensions applied in each incident, controlling for each student's disciplinary history. The length of a suspension is a function of how severe a principal believes a certain offense to be, a student's prior offense history, and how punitive a principal wants to be. Therefore, before categorizing offenses, I control for a student's disciplinary history as well as year fixed effects to control for year-to-year variation in discipline policy and grade fixed effects to control for average differences in suspension policy by grade and average differences in the severity of offenses within categories by grade.

In particular, I estimate incident-level models

$$d_{ijkt} = \phi H_{it} + \theta_g + \theta_t + \theta_k + \varepsilon_{ijkt} \tag{1}$$

where d_{ijkt} is an indicator for whether an out-of-school suspension was applied in the incident j involving student i (each student may have more than one offense in a year) for offense type k in year t.[10] H_{it} is a vector of the student's prior disciplinary record–the number of mandatory offenses in the current year and the number of offenses in the prior year–and θ_t and θ_g are year and grade fixed effects, respectively. The parameters of interest–θ_k–are offense fixed effects, which capture the conditional average out-of-school suspension length for each offense type.

I designate "low", "medium", and "high" severity offenses based on terciles of the estimated offense fixed effects. Figure 1 shows the percentage of offenses in each category that result in an out-of-school suspension. The lowest severity offenses result in an out-of-school suspension in 43% of incidents, medium severity offenses result in an out-of-school suspension in 70% of incidents, and high severity offenses result in an out-of-school suspension in 82% of incidents. The average out-of-school suspension length–conditional on receiving a suspension–for low-severity offenses is 3 days, for medium-severity offenses is 6 days, and for high-severity offenses is 5 days.

2.3 Descriptive Statistics on Student Behavior

There is significant variation in student behavior across schools. Table 1 shows descriptive statistics on the number of mandatory offenses per student and the number of offenses in each severity category per student at a teacher's school in each year. The average teacher is at a school with 12 mandatory offenses per 100 students, with 4 low severity offenses, 8 medium severity offenses, and 1 high severity offense per 100 students. However, teachers in the 90th percentile of exposure to student infractions are at schools with approximately twice as many offenses: 23 mandatory offenses per 100 students, 8 low severity offenses, 15 medium severity offenses, and 2 high severity offenses per 100 students. Teachers in the 10th percentile of exposure to student infractions are at schools with only 4 mandatory offenses per 100 students, with less than 1 low severity offense, fewer than 2 medium severity offenses, and almost no high severity offenses per 100 students.

By construction, the average number of offenses per 100 students in a teacher's grade(s) is similar to the school-level averages; however, there is more variation across teachers at the grade level than at the school level. Table 1 shows the number of offenses per 100 students in the grade(s) a teacher is assigned to teach in each year overall and by offense severity. The standard deviation in the number of mandatory offenses at the grade level is 16, higher than the standard deviation in the number of mandatory offenses at the school level (9). The standard deviations in the number of low-, medium-, and high-severity offenses in a teacher's grade(s) are also higher than the school-level standard deviations.

[10] Recorded incidents can include more than one offense code. In this regression, I use the first offense code recorded for each incident. To assign each incident a severity measure, I use the offense code with the highest severity.

2.4 Disciplinary Policy

I measure student discipline policy based on the probability of a suspension being applied in each incident. The discipline assigned in a particular incident reflects both the severity of student behavior and a student's behavioral history as well as how punitive a school chooses to be for a given incident. Therefore, I measure school discipline policy conditional on both a student's prior offenses and the offense type.

In particular, I adapt Sorensen, Bushway, and Gifford (2022), who estimate principal-specific punitiveness, by estimating a school's "propensity to remove" (PTR) using incident-level regressions

$$r_{ijkt} = \mu_{kst} + \phi H_{it} + \theta_g + \theta_t + \varepsilon_{ijkt} \tag{2}$$

where r_{ijkt} is an indicator for whether a student received an out-of-school suspension for the incident j involving student i (each student may have more than one offense in a year) for offense-type k in year t. H_{it} is a vector of the student's prior disciplinary record (the number of mandatory offenses in the current year and the number of offenses in the prior year) and θ_g and θ_t are grade and year fixed effects respectively. The parameters of interest–μ_{kst}–are a vector of offense-school-year fixed effects, along with their standard errors. These fixed effects estimate the conditional probability that an out-of-school suspension is applied for a given offense type in a given year.[11]

To reduce the influence of offense fixed effects that are estimated with low precision, I adjust these estimates using empirical Bayes weights, which place more weight on offense fixed effects that are estimated with more precision. Specifically, I use the following empirical Bayes estimator:

$$\eta_{kst} = \left(1 - \frac{\widehat{\sigma_{skt}}^2}{\widehat{\sigma_{skt}}^2 + V(\widehat{\mu_{kst}})}\right)\widehat{\mu_{kst}} + \frac{\widehat{\sigma_{skt}}^2}{\widehat{\sigma_{skt}}^2 + V(\widehat{\mu_{kst}})}\overline{\mu_{kt}} \tag{3}$$

where $\widehat{\sigma_{kst}}$ is the estimated standard error of the school-year-offense fixed effects, $\overline{\mu_{kt}}$ is the average school-year-offense effect, and $V(\widehat{\mu_{kst}})$ is the variance of the set of estimated fixed effects.

[11] Sorensen, Bushway, and Gifford (2022) use a similar strategy to estimate static principal-specific punitiveness using principal-offense fixed effects instead of school-year-offense fixed effects.

Finally, to ensure that PTR estimates are not biased by the mix of offenses in each school, I create a single PTR measure for each school-by-year combination by weighting the individual offense-level estimates based on the sample proportion of offenses faced by all schools in a given year. Specifically, I calculate the following weighted average:

$$\widehat{P_{st}} = \sum_k \eta_{kst} \frac{n_{kt}}{n_t} \tag{4}$$

where n_{kt} is the number of offenses of type k across all schools in year t and n_t is the total number of offenses in year t. As shown in Table 1, the standard deviation in PTR is 0.12.

2.5 Teacher Outcomes

I measure teacher turnover as whether a teacher is not employed at the same school in the next year. Movement can be the result of mobility–moving to a new school–or attrition–no longer teaching in NC public schools.[12] As shown in Table 1, 9% of teachers in my sample change schools and 10% leave teaching each year. Similar to national statistics, mobility and attrition account for a similar proportion of overall turnover in my sample; however, overall turnover in my sample is somewhat higher than national statistics.

2.6 Student Achievement

To control for the effect of student achievement on teacher turnover, I use student-level data on standardized Math and Reading assessments. I use each student's score on the end-of-grade (EOG) Math and Reading assessments for students in grades 6–8.[13] I standardize each student's score relative to other students in the same grade and year. Because teachers may have preferences for achievement levels at different points in the achievement distribution, I measure the 10th, 25th, 50th, 75th, and 90th percentiles of achievement separately in Math and Reading. I also measure achievement at the classroom-, grade-, and school-level.

[12] I cannot distinguish teaching outside of NC public schools from not teaching at all.

[13] To calculate teacher value added, I also use scores on end-of-course Math and Reading assessments for students in grade 5 to control for prior student performance. See Appendix Appendix D.

2.7 Teacher Characteristics

To control for individual teacher characteristics that affect mobility and attrition rates and to assess heterogeneity by teacher characteristics, I use data on teacher age, experience (number of years since they first appeared in my pay data), gender, and race. For descriptive statistics on teacher characteristics, see Table 1. To assess heterogeneity by teacher quality, I also calculate estimates of teacher value added on standardized Math and Reading assessment (see Appendix D for details).

3 Empirical Strategy

To understand how student behavior and school discipline affect teacher outcomes, I leverage variation within schools using school fixed effects models to control for average differences across schools. I then use grade-level student behavior measures and school-by-year fixed effects models to compare student behavior and teacher retention for teachers at the same school in the same year.

3.1 School Fixed Effects

Using teacher-level data on mobility and attrition and school-level measures of student behavior and discipline, I estimate school fixed effects models

$$y_{igt} = \beta_1 S_{st} + \beta_2 D_{st} + \beta_3 X_{st} + \beta_4 X_{gst} + \beta_5 X_{it} + \alpha_s + \alpha_{dt} + \alpha_g + \varepsilon_{igt} \tag{5}$$

where y_{igt} is the outcome (attrition/mobility) for teacher i in year t who teaches grade g; S_{st} is a measure of student behavior (or a vector of measures of student behavior by offense severity) for the school that teacher i teaches at in year t; D_{st} is school-year PTR; X_{st}, X_{gst}, and X_{it} are a set of classroom-, grade-, and school-level demographic covariates, teacher characteristics; and α_s and α_{dt} are school and district-by-year fixed effects respectively.[14] α_g is a set of indicators for the grades taught. The coefficients of interest, β_1, estimate the effect of more student offenses at a school on the probability of attrition or mobility after the current year, and β_2 estimates the effect of higher school PTR. In some specifications, I replace the school-level student behavior measures in equation 5 with grade-level behavior measures. Standard errors are clustered at the district level.

The main identification assumption is that changes in student behavior or discipline at a school are unrelated to other factors driving teacher retention. This is plausible since most schools have little control over the students they enroll. Indeed, while student behavior and discipline are strongly correlated with student body characteristics *across* schools, they are less strongly correlated with these characteristics *within* schools over time. As shown in Table 2, schools with more offenses have more male, economically disadvantaged, and non-white students; and lower median Math and Reading test scores. However, these correlations are much weaker when looking at within-school variation over time. Similar patterns hold for PTR. However, some correlation between behavior and student body characteristics persists within schools over time, potentially biasing my estimates. To limit the ability of this correlation to affect my results, I control for a rich set of school, grade, and classroom-level covariates and, in some specifications, a detailed set of controls for student achievement.

School fixed effects also rule out the potential for bias from teacher selection of schools based on their preferences for average behavior. As shown in Table 2, schools with more student offenses have teachers who are younger and more likely to be Black. However, teachers likely select schools based on average characteristics and not in anticipation of changes in behavior in the coming year. Indeed, after removing across-school variation using school fixed effects, teacher characteristics are not related to the quartile of student behavior or PTR.

3.2 School-by-Year Fixed Effects

Because unobserved time-varying school-level variables could still explain the relationship between student behavior and teacher attrition, I also use grade-level measures of student behavior to isolate within-school variation in student behavior using school-by-year fixed effects models

[14] Demographic covariates include percentage of female stduents, percentage of economically disadvantaged students, percentage of Black students, percentage of Hispanic students, and percentage of Asian students. Teacher characteristics include teacher experience (novice, 1 – –2 years, 3 – –4 years, or 5 – –10 years), age (five-year bins from age 20 – –65 and an indicator for 65 or older), gender, and race.

$$y_{igt} = \beta_1 S_{gt} + \beta_3 X_{gst} + \beta_4 X_{it} + \alpha_{st} + \alpha_g + \varepsilon_{igt} \quad (6)$$

where S_{gt} is the measure of student behavior for the grade that teacher i teaches in year t and α_{st} is a school-by-year fixed effect. Because disciplinary punitiveness varies at only the school level, I exclude school-level PTR from this specification.

The main identification assumption in school-by-year fixed effects specifications is that changes in student behavior in a grade–relative to other grades at the same school–are unrelated to unobserved factors that determine teacher retention. Since most school policies–including student discipline–are implemented at the school level, they are likely to affect all teachers at the same school. However, as shown in Table 2, after controlling for school-by-year fixed effects, there is still some correlation between the number of mandatory offenses per student in a teacher's grade and average student characteristics–including student achievement–in that student's grade. To limit the possibility that this correlation biases my results, I control for a rich set of grade- and classroom-level covariates and, in some specifications, a detailed set of controls for student achievement.

School-by-year fixed effects also rule out teacher selection on time-varying school characteristics. Further, because teachers are primarily assigned to teach grades based on their qualifications and experience–not their time-varying preferences for students–making it unlikely that teachers' preferences for student behavior determine their grade assignments in a particular year. Indeed, as shown in Table 2, teacher characteristics are unrelated to grade-level student behavior after controlling for school-level variation in student behavior using school-by-year fixed effects.

4 Results

4.1 Student Behavior

Student offenses lead to higher teacher turnover rates among middle school teachers. Table 3 shows results from regressions of teacher mobility, attrition, or any turnover, on measures of student behavior and school

PTR and school and district-year fixed effects (see equation 5). On average, I find that changes in the number of mandatory offenses are associated with higher overall turnover: as shown in column 1, an additional mandatory offense per student is associated with 8.6 p.p. higher turnover. This magnitude is significant: an additional standard deviation (SD) in the number of mandatory offenses per student is associated with 0.8 percentage points (p.p.) higher turnover, or 4% of annual turnover. Estimates of the effect of offenses on attrition are more precisely estimated than estimates of the effect of offenses on mobility; however, I cannot rule out an effect on mobility of a similar magnitude.

The relationship between the number of mandatory offenses per student and teacher turnover persists when using grade-level measures of student behavior and when including school-by-year fixed effects to control for all school-level confounding variables. Column 4 of Table 3 shows estimates from regressions of teacher turnover on the number of mandatory offenses per student in the grade that a teacher is assigned (along with school and district-year fixed effects, see equation 5). I find that an additional mandatory offense per student in the grade that a teacher is assigned is associated with 3 p.p. higher turnover. This is similar in magnitude to the effect of an additional mandatory offense per student in the school: an additional SD in the number of mandatory offenses per student in the grade that a teacher is assigned is associated with 0.5 p.p. higher mobility. However, this estimate is less precisely estimated than the estimate using school-level student behavior and I cannot rule out a null effect. In column 5 of Table 3, I present estimates of the relationship between the number of mandatory offenses per student in a teacher's grade and teacher turnover when including school-by-year fixed effects. Estimates of the effect on overall turnover are similar in magnitude to estimates in column 4 that do not include school-by-year fixed effects but are less precisely estimated.

Offense Severity

Increases in teacher turnover from school-level student behavior are driven by middle- and low-severity offenses. In columns 2 and 6 of Table 3, I present results from regressions of teacher turnover on student behavior by offense severity and student discipline. An additional SD in middle severity offenses at a school is associated with 1.1 p.p. higher turnover, accounting for 6% of overall turnover. As with the overall effect of mandatory offenses, this effect is most precisely estimated for teacher attrition–an additional SD in middle-severity offenses per student at a school is associated with 0.5 p.p. higher attrition–but estimates for mobility are similar in magnitude. However, in estimates that measure student behavior in the grade that a teacher is assigned and including school-by-year fixed effects–as shown in column 6–low-severity offenses–but not middle- or high-severity offenses–are associated with higher turnover. An additional SD in low-severity offenses in a teacher's grade is associated with 1.3 p.p. higher turnover, accounting for 6% of overall turnover. For middle-severity offenses in a teacher's grade, I can rule out effects larger than 0.8 p.p. This evidence suggests that both middle- and low-severity offenses are associated with higher teacher turnover but I cannot differentiate between the importance of measuring behavior at the school- or grade-level and the importance of school-level confounding variables.

4.2 Student Discipline

Despite the importance of student behavior for teacher turnover, I find limited evidence that a more punitive discipline policy affects teacher turnover independently of student behavior. As shown in Table 3, an additional SD in a school's PTR is associated with 0.1 p.p. higher overall turnover. This estimate is statistically insignificant and precise enough to rule out effects larger than 0.7 p.p. and smaller than −0.5 p.p. (across all specifications in Table 3). Estimates are particularly small for attrition: an additional SD in a school's PTR is associated with at most a 0.3 p.p. increase or decrease in attrition.

4.3 Controls for Student Achievement

My main specifications control for school-level changes in student composition that may drive both changes in student behavior and discipline in addition to teacher turnover, but do not fully control for all classroom- or grade-level student characteristics. While I include controls for a rich set of student demographics at the school-, grade-, and classroom-level, unmeasured changes in student composition may still be correlated with changes in student behavior and discipline. For example, changes in academic achievement have an independent effect on teacher turnover (Karbownik, 2020) that may not be accounted for by changes in the school-level student body or classroom-level student demographics.

To investigate whether changes in student achievement are driving my results, I estimate my main specifications while adding a rich set of controls for student achievement. In particular, I add controls for school-, grade-, and classroom-level student achievement on end-of-grade Math and Reading assessments. Because teachers may react differently to the achievement levels of the best, worst, and average students in their class, grade, or school, I include controls for the test scores of students at the 10th, 25th, 50th, 75th, and 90th percentiles of a teacher's classroom, grade, and school.

Controls for student achievement have a minimal effect on my overall results. In columns 3 and 7 of Table 3, I present estimates from regressions including student achievement controls. Estimates are close to estimates from regressions that do not include controls for student achievement, suggesting that my results are not driven by correlated changes in student achievement.

4.4 Heterogeneity by Teacher Experience

First-year (novice) teachers react differently to student behavior than the average teacher. Table 4 shows estimates from my main school-level and grade-level specifications separately by teacher experience levels. In contrast to the average teacher, novice teachers are most responsive to high-severity offenses and not low- or middle-severity offenses. Among novice teachers, an additional SD in high-severity offenses in their school is associated with 1.8 p.p. higher turnover, in contrast to estimates for teachers with more experience. This effect accounts for 6% of the 30% overall turnover rate among novice teachers. Among novice teachers, this effect is driven by teacher mobility and not attrition: an additional SD in high-severity offenses in their school is associated with 1.2 p.p. higher mobility and only 0.7 p.p. higher attrition (an estimate that is statistically insignificant). This suggests that novice teachers are more likely to move schools in response to high-severity offenses but are not more likely to leave the profession. On average, novice teachers are not responsive to changes in school PTR.

While informative of teacher's decisions, comparisons of the effect of student behavior on teacher turnover by teacher experience level should be interpreted with caution due to the high level of overall turnover and attrition. Just 70% of teachers in my sample remain in their first school after one year and 14% leave the profession. Because novice teachers are more likely to move schools due to high-severity offenses, the remaining teachers may be less responsive to high-severity offenses not because of their teaching experience but because they were initially less responsive to high-severity offenses and thus did not previously change schools or leave teaching. Therefore, my results should not be interpreted as showing that teaching experience changes how teachers react to student behavior issues. In Section 4.6, I focus on novice teachers, who are least affected by potential selection out of teaching.

My overall results are driven by teachers with prior teaching experience. Among teachers with at least three years of experience, an additional SD in middle-severity offenses at their school is associated with 1.2–1.6 p.p. higher turnover. Among teachers with fewer than three years of experience, I find no statistically significant relationship between school-level middle-severity offenses and teacher turnover. Similarly, grade-level estimates show that the relationship between grade-level student behavior and teacher turnover is driven by teachers with 1–2 years of experience: among these teachers, an additional SD in low-severity offenses in their grade is associated with 3.8 p.p. higher turnover, accounting for 15% of turnover among that group. Among teachers with no experience or more than 2 years of experience, I find no statistically significant relationship between grade-level middle-severity offenses and teacher turnover.

4.5 Heterogeneity by Gender

Teachers differ in their reactions to student behavior based on gender. Despite having similar levels of overall turnover, estimates of the effect of student behavior on teacher turnover are generally larger for male teachers than for female teachers. Table 5 shows estimates from my main school-level and grade-level specifications separately by teacher gender. Among male teachers, an additional SD in middle-severity offenses per student at their school is associated with 1.7 p.p. higher turnover while among female teachers, an additional SD is associated with only 0.7 p.p. higher turnover. For male teachers, this effect is driven by mobility: an additional SD in middle-severity offenses at their school is associated with 1.2 p.p higher mobility and 0.6 p.p. higher attrition. Among female teachers, estimated effects are smaller but driven by attrition: an additional SD in middle-severity offenses is associated with 0.7 p.p. higher turnover, 0.4 p.p. higher attrition, and 0.3 p.p. higher mobility (not statistically significant).

Male teachers are also more responsive–in terms of mobility–to low-severity offenses in the grade they are assigned. An additional SD in low-severity offenses in a male teacher's grade is associated with 1.7 p.p. higher mobility, accounting for 19% of overall mobility for male teachers. Similar estimates for female teachers are small and statistically insignificant.

4.6 Novice Teachers

As I show in Section 4.4, novice teachers are most responsive to high-severity student offenses; however, these results are driven by female teachers and by teachers with above-median effectiveness. Table 6 shows estimates of my main specifications for novice teachers overall, and separately by teacher gender and teacher effectiveness (value-added). While an additional SD in high-severity offenses is associated with 1.8 p.p. higher turnover among novice teachers, among novice female teachers an additional SD in high-severity offenses is associated with 2.6 p.p. higher turnover. In contrast, high-severity offenses are not associated with higher turnover among novice male teachers.

Among novice teachers with above-median value added (compared to other novice teachers), an additional SD in high-severity offenses is associated with 3.9 p.p. higher turnover. Among teachers with below-median value added, I find no statistically significant relationship between high-severity offenses and turnover. This effect is driven by mobility and not attrition: among novice teachers with above-median effectiveness, an additional SD in high-severity offenses is associated with 3.6 p.p. higher mobility and not higher attrition. This suggests that effective novice teachers are more likely to move schools in response to high-severity offenses but are not more likely to leave the profession.

While novice teachers are on average not responsive to school discipline, I find evidence that male teachers have higher mobility–but lower attrition–when schools are more punitive. Among novice male teachers, an additional SD in PTR is associated with 2.4 p.p. higher mobility. However, an additional SD in PTR is also associated with 2.4 p.p. lower attrition, offsetting the effect of mobility on overall turnover. This suggests that student discipline affects the composition of novice teachers who remain at their school or in the profession but does not affect the overall level of turnover.

4.7 Comparison to Previous Research

My analysis diverges from the existing literature on the relationship between student behavior and teacher turnover in three primary ways. First, I measure student behavior using only offenses requiring mandatory reporting, while Feng (2009) uses all offenses. Second, I include school or school-by-year fixed effects to control for school-level confounding variables while Feng (2009) includes only district and year fixed effects. Third, to limit the influence of teachers on behavior and offense reporting, I measure student behavior at the school and grade level. This contrasts with Feng (2009), who uses administrative data from Florida, finding that more student offenses at the classroom level are associated with higher attrition. In this section, I investigate the sensitivity of my results to these choices.

4.7.1 Mandatory vs. Discretionary Offenses

Using a specification similar to Feng (2009), I confirm that the number of mandatory and discretionary offenses in a teacher's classroom is associated with higher attrition. In column 1 of Table 7, I show these results, which are from regressions of teacher attrition and mobility on classroom-level measures of student behavior that include both mandatory and discretionary offenses, PTR, district and year fixed effects, as well as a rich set of controls included in my primary specifications.[15] Consistent with Feng (2009), I find that additional offenses are associated with higher attrition and, in contrast to Feng (2009), find that it is also associated with higher mobility.

This relationship persists when limiting behavior measures to offenses requiring mandatory reporting. In column 2 of Table 7, I show estimates from regressions that measure classroom-level behavior using only mandatory reporting offenses. As with estimates that include discretionary offenses, the estimates are positive and statistically significant. However, the magnitude of estimates from specifications measuring behavior using only offenses requiring mandatory reporting should not be compared directly to estimates from specifications measuring behavior using both mandatory and discretionary offenses. Excluding discretionary offenses primarily removes offenses–such as dress code violations, cutting class, and insubordination–that are less severe than the offenses with mandatory reporting requirements, meaning that an additional mandatory offense is likely to represent a more severe offense than an additional offense in specifications that include discretionary offenses.[16] In column 3, I include measures separately for both mandatory and discretionary offenses. Estimates for both are smaller in magnitude than in specifications that do not include both but are still positive and statistically significant, except for the effect of discretionary offenses on mobility.

[15] A "classroom" is defined as the set of students assigned to a teacher in a given year.

[16] Due to data limitations, I do not directly estimate severity for non-mandatory offenses types. As described in Section 2.2.1, I measure severity using the average discipline applied to each offense type, which relies on observing offenses for which discipline

4.7.2 School Fixed Effects

Next, I show that estimates are sensitive to the inclusion of school fixed effects. In columns 4 and 5 of Table 7, I add school and district-by-year fixed effects to the specifications in columns 2 and 3. Estimates for the effect of mandatory offenses are somewhat smaller than in specifications without school and district-by-year fixed effects and–for attrition–no longer statistically significant. Estimates for the effect of discretionary offenses are similar in magnitude to estimates in column 3, while estimates for the effect of mandatory offenses is smaller in specifications that include school and district-by-year fixed effects. In columns 6 and 7, I include school-by-year fixed effects instead of school and district-by-year fixed effects. For mandatory offenses, these estimates are smaller in magnitude than estimates from specifications with district and year fixed effects. This suggests that it is important to fully control for school-level confounding variables.

4.7.3 Classroom-level Behavior

Finally, I investigate whether my estimates are sensitive to measuring behavior at the school or grade level instead of the classroom level. While teachers may be most responsive to the behavior of students they teach, they also have the most direct control over the behavior of students in their classroom and greater control over the reporting of individual incidents to the administration. This dynamic may create a spurious correlation between teachers' ability to manage classroom behavior or their propensity to report offenses and teacher turnover. Indeed, there is a stronger correlation between classroom-level behavior and student and teacher characteristics than between school-level behavior and classroom characteristics. Table B2 shows average student and teacher characteristics by quartile of classroom behavior. Classroom-level behavior is highly correlated with grade, classroom, and teacher characteristics, even within schools and years. In contrast, as discussed in Section 3, school- and grade-level behavior are less correlated with student and teacher characteristics within school and year. Additionally, as shown in Table B3, while school- and grade-level behavior measures are correlated with classroom-level student characteristics, they are less correlated than classroom-level behavior measures.

My estimates are sensitive to measuring behavior at school and grade level instead of the classroom level.

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is not applied. However, for non-mandatory offenses, I only observe the offense if it results in an out-of-school suspension or if the school chooses to report the offense.

In Table 7, I show estimates from regressions of teacher attrition and mobility on classroom-, school-, and grade-level measures of student behavior separately for mandatory and discretionary offenses. In columns 4 and 5, I show estimates from regressions using classroom-level behavior without and without discretionary offenses and including school and district-by-year fixed effects. In columns 8 and 9, I show estimates from regressions using school-level behavior and the same fixed effects. Estimates using classroom-level behavior are somewhat smaller, particularly when not including measures for discretionary offenses. Similarly, in columns 6 and 7, I show estimates from regressions using classroom-level behavior with and without discretionary offenses and including school-by-year fixed effects. In columns 10 and 11, I show estimates from regressions using grade-level behavior and the same fixed effects. Estimates using classroom-level behavior are somewhat larger and estimates using grade-level measures of mandatory offenses are statistically insignificant. These results suggest that my estimates are sensitive to measuring behavior at the classroom level instead of at the school or grade level.

5 Conclusion

The retention of effective teachers is a critical issue for education policy, with significant equity considerations created by the movement of experienced teachers away from high-poverty schools (Boyd, Grossman, Lankford, et al., 2008). While poor school climate and administrative leadership are often cited as major reasons for teacher turnover, student characteristics also play a significant role (C. K. Jackson, 2009; Karbownik, 2020). In this paper, using detailed administrative data from North Carolina, I show that more student offenses lead to higher teacher turnover. Among novice teachers–who have the high turnover rates–this effect is driven by the high-severity offenses, while among more experienced teachers, the effect is driven by middle- and low-severity offenses. These results suggest that schools and teacher preparation programs need to focus on strategies to support teachers in responding to student behavior issues. Existing evidence suggests that training teachers on effective classroom management strategies can reduce attrition but more evidence is needed to show whether these programs can scale (Bartanen, Bell, James, et al., 2023).

When faced with student behavior issues, many schools have adopted more punitive discipline policies. While there is limited evidence that these policies reduce student offenses (Sorensen, Bushway, & Gifford, 2022), they may also have effects on teacher turnover. However, I find that a more punitive discipline policy does not lead to higher or lower teacher turnover among most teachers. In light of extensive evidence showing that more punitive discipline policies have adverse effects on student outcomes (Bacher-Hicks, Billings, & Deming, 2019; Sorensen, Bushway, & Gifford, 2022), this suggests that efforts aimed at reducing the use of out-of-school suspensions will have limited direct effect on teacher turnover. However, given that I find that more student offenses lead to higher teacher turnover, schools should still be mindful of the effects of promising alternative discipline strategies–such as restorative justice–on student behavior and teacher turnover (Davison, Penner, & Penner, 2019).

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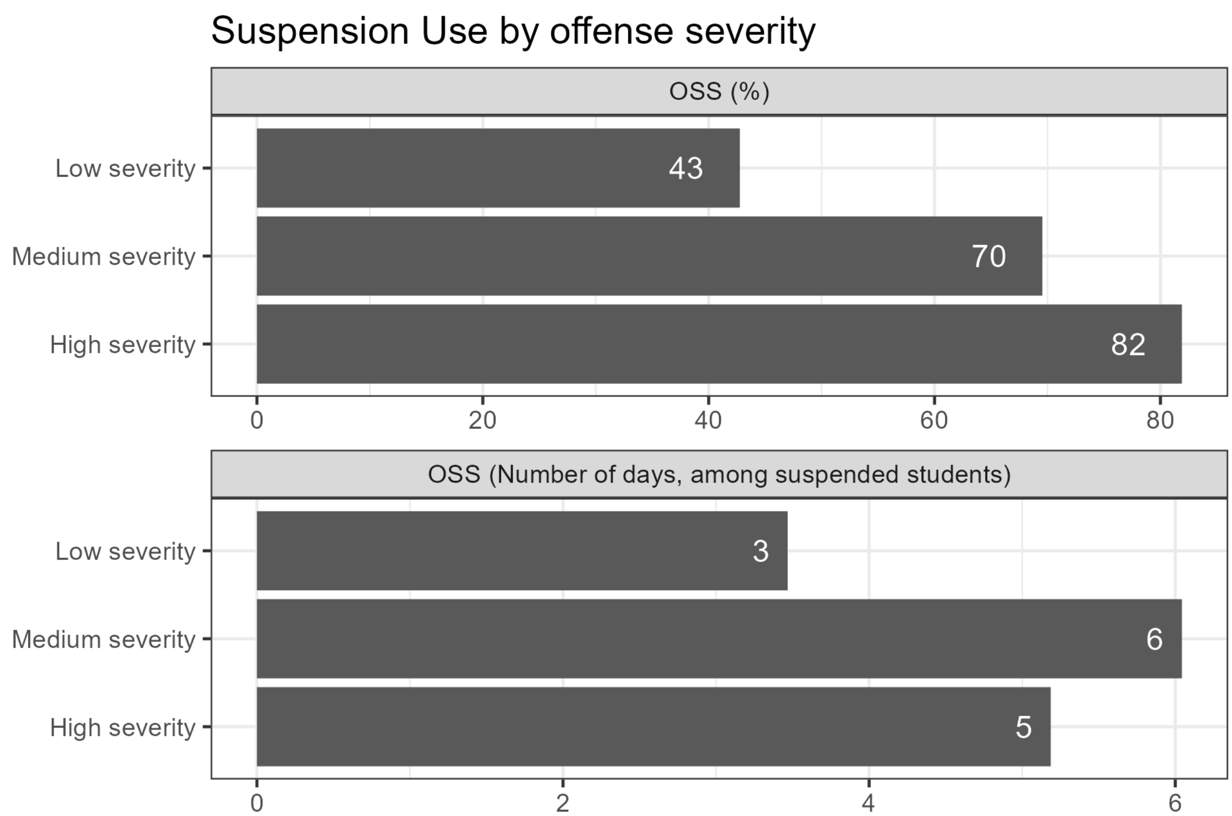
Figures

Figure 1



Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Tables

Table 1: Descriptive statistics

	Mean	SD	Percentile 10th	Percentile 90th
Dependent variables				
Attrition	0.10	0.30	–	–
Mobility	0.09	0.29	–	–
Any turnover	0.19	0.39	–	–
Independent variables: school-level				
Mandatory offenses per student	0.12	0.09	0.0	0.2
Offenses per student: low severity	0.04	0.04	0.0	0.1
Offenses per student: middle severity	0.08	0.06	0.0	0.2
Offenses per student: high severity	0.01	0.01	0.0	0.0
School-year PTR	0.03	0.12	−0.1	0.1
Independent variables: grade-level				
Mandatory offenses per student	0.13	0.16	0.0	0.2
Offenses per student: low severity	0.04	0.08	0.0	0.1
Offenses per student: middle severity	0.08	0.10	0.0	0.2
Offenses per student: high severity	0.01	0.02	0.0	0.0
School characteristics				
Female students	0.48	0.04	0.5	0.5
Non-white students	0.49	0.25	0.2	0.9
Economically disadvantaged students	0.47	0.16	0.2	0.7
Teacher characteristics				
Age	41.46	11.00	27.0	57.0
Female	0.75	0.43	–	–
Black	0.17	0.37	–	–
White	0.79	0.40	–	–
Hispanic	0.02	0.13	–	–

"SD" represents the sample standard deviation for each measure. Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).
Source: North Carolina Education Research Data Center (NCERDC) and author's calculations.

Table 2: Average school characteristics by measures of student behavior and discipline

	Quartile				Wald statistics		
	1st (lowest)	2nd	3rd	4th (highest)	Across schools	Within schools	Within school by year
School: number of mandatory offenses per student							
School Characteristics							
Female students	0.49	0.49	0.48	0.47	12.59***	0.60	
Non-white students	0.38	0.43	0.50	0.65	60.03***	3.24**	
Economically disadvantaged students	0.36	0.43	0.49	0.58	48.87***	3.86***	
Median Math score (z-score)	0.16	0.15	0.13	0.07	28.23***	8.07***	
Median Reading score (z-score)	0.16	0.15	0.13	0.06	32.28***	9.00***	
Grade Characteristics							
Female students	0.49	0.49	0.48	0.47	17.39***	1.67	
Non-white students	0.38	0.43	0.50	0.65	59.19***	2.55*	
Economically disadvantaged students	0.36	0.43	0.49	0.58	50.07***	3.39**	
Median Math score (z-score)	0.16	0.15	0.13	0.07	25.74***	8.77***	
Median Reading score (z-score)	0.16	0.15	0.13	0.06	29.76***	7.53***	
Teacher Characteristics							
Age	42.00	41.59	41.32	40.92	4.81***	0.28	
Female	0.74	0.76	0.75	0.74	12.59***	0.60	
Black	0.09	0.13	0.17	0.28	24.54***	1.93	
White	0.87	0.83	0.80	0.67	24.89***	0.53	
Hispanic	0.02	0.02	0.01	0.02	4.94***	2.44*	

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Table 2, continued

	Quartile				Wald statistics		
	1st (lowest)	2nd	3rd	4th (highest)	Across schools	Within schools	Within school by year
Grade: number of mandatory offenses per student							
School Characteristics							
Female students	0.49	0.49	0.48	0.47	12.79***	0.92	
Non-white students	0.38	0.43	0.50	0.64	53.61***	5.17***	
Economically disadvantaged students	0.37	0.44	0.49	0.58	47.66***	3.97***	
Median Math score (z-score)	0.16	0.15	0.13	0.07	31.16***	2.03	
Median Reading score (z-score)	0.16	0.15	0.13	0.06	35.57***	1.30	
Grade Characteristics							
Female students	0.49	0.49	0.49	0.47	21.41***	7.61***	10.77***
Non-white students	0.39	0.43	0.50	0.64	54.95***	6.18***	5.46***
Economically disadvantaged students	0.36	0.43	0.48	0.58	52.46***	8.07***	3.51**
Median Math score (z-score)	0.16	0.15	0.13	0.07	32.94***	7.09***	11.11***
Median Reading score (z-score)	0.16	0.15	0.13	0.06	38.14***	2.79**	8.07***
Teacher Characteristics							
Age	41.91	41.59	41.44	40.90	3.90***	0.86	1.44
Female	0.75	0.75	0.75	0.75	12.79***	0.92	0.00
Black	0.10	0.13	0.17	0.27	15.21***	0.69	2.04
White	0.86	0.84	0.79	0.68	16.75***	1.07	2.21*
Hispanic	0.02	0.02	0.02	0.02	4.61***	1.11	0.82

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Table 2, continued

	Quartile				Wald statistics		
	1st (lowest)	2nd	3rd	4th (highest)	Across schools	Within schools	Within school by year
	School-year propensity to remove						
School Characteristics							
Female students	0.48	0.48	0.48	0.48	1.29	2.80**	
Non-white students	0.41	0.46	0.52	0.56	13.94***	1.13	
Economically disadvantaged students	0.44	0.46	0.48	0.49	2.07	0.33	
Median Math score (z-score)	0.13	0.13	0.13	0.12	0.33	0.96	
Median Reading score (z-score)	0.13	0.12	0.12	0.12	1.25	2.13*	
Grade Characteristics							
Female students	0.49	0.49	0.48	0.48	1.91	3.96***	
Non-white students	0.41	0.46	0.52	0.56	13.94***	1.11	
Economically disadvantaged students	0.44	0.46	0.48	0.49	2.12*	0.49	
Median Math score (z-score)	0.14	0.13	0.13	0.13	0.18	0.67	
Median Reading score (z-score)	0.13	0.12	0.12	0.12	0.76	1.11	
Teacher Characteristics							
Age	41.49	41.49	41.42	41.43	0.12	0.75	
Female	0.75	0.75	0.75	0.75	1.29	2.80**	
Black	0.11	0.15	0.19	0.22	10.78***	0.11	
White	0.86	0.82	0.77	0.73	10.46***	0.23	
Hispanic	0.01	0.02	0.02	0.02	1.10	0.28	

Note: Wald statistics test the null hypothesis that indicators for quartile of each measure of student behavior or discipline are equal to zero. The within-school estimates come from regressions with school and district-year fixed effects and indicators for the grade taught. The within-school by year estimates come from regressions with school-year fixed effects and indicators for the grade taught.
Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).
*p<0.10; **p<0.05; ***p<0.01

Table 3: Main regression results: school- and grade-level student behavior

	School-level behavior			Grade-level behavior			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mobility							
Mandatory offenses per student	0.048			0.017	0.006		
	(0.036)			(0.016)	(0.022)		
School-year PTR	0.014	0.011	0.011	0.012			
	(0.016)	(0.017)	(0.017)	(0.017)			
Offenses per student: low severity		−0.041	−0.047			0.087**	0.087*
		(0.047)	(0.051)			(0.043)	(0.044)
Offenses per student: middle severity		0.090	0.094*			−0.029	−0.029
		(0.055)	(0.055)			(0.029)	(0.029)
Offenses per student: high severity		0.227	0.226			0.014	0.001
		(0.150)	(0.154)			(0.118)	(0.116)
Attrition							
Mandatory offenses per student	0.038**			0.014*	0.038**		
	(0.018)			(0.008)	(0.019)		
School-year PTR	−0.002	−0.004	−0.004	−0.003			
	(0.013)	(0.013)	(0.013)	(0.012)			
Offenses per student: low severity		−0.029	−0.023			0.078	0.072
		(0.043)	(0.043)			(0.053)	(0.052)
Offenses per student: middle severity		0.084***	0.078***			0.020	0.023
		(0.026)	(0.025)			(0.036)	(0.034)
Offenses per student: high severity		0.028	0.046			0.040	0.028
		(0.128)	(0.134)			(0.114)	(0.118)
Any turnover							
Mandatory offenses per student	0.086***			0.031*	0.044		
	(0.030)			(0.016)	(0.031)		
School-year PTR	0.013	0.007	0.007	0.009			
	(0.023)	(0.024)	(0.023)	(0.023)			
Offenses per student: low severity		−0.070	−0.070			0.165**	0.159**
		(0.055)	(0.057)			(0.063)	(0.063)
Offenses per student: middle severity		0.174***	0.172***			−0.009	−0.006
		(0.055)	(0.056)			(0.050)	(0.048)
Offenses per student: high severity		0.255	0.272			0.054	0.029
		(0.183)	(0.191)			(0.165)	(0.166)
Obs.	141,435	141,435	141,435	141,435	141,435	141,435	141,435
School FE	X	X	X	X			
District-year FE	X	X	X	X			
School-year FE					X	X	X
School-level controls	X	X	X	X			
Grade-level controls	X	X	X	X	X	X	X
Classroom-level controls	X	X	X	X	X	X	X
Teacher demographic controls	X	X	X	X	X	X	X
Grade taught indicators	X	X	X	X	X	X	X
School-level achievement controls			X				
Grade-level achievement controls			X				X
Classroom-level achievement controls			X				X

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).
Standard errors clustered at the district level in parentheses.
*p<0.10; **p<0.05; ***p<0.01

Table 4: Heterogeneity by experience level

	School-level					Grade-level				
	Novice	1–2 years	3–4 years	5–10 years	>= 10 years	Novice	1–2 years	3–4 years	5–10 years	>= 10 years
Mobility										
Offenses per student: low severity	0.203	0.175	−0.035	−0.128*	−0.029	0.363	0.208	0.266*	0.106	−0.124
	(0.159)	(0.111)	(0.149)	(0.069)	(0.080)	(0.219)	(0.143)	(0.151)	(0.079)	(0.085)
Offenses per student: middle severity	−0.014	−0.071	0.220*	0.075	0.103*	−0.019	0.067	−0.066	−0.089*	0.047
	(0.159)	(0.102)	(0.120)	(0.080)	(0.058)	(0.132)	(0.076)	(0.105)	(0.047)	(0.046)
Offenses per student: high severity	1.070**	−0.268	0.441	0.064	0.366	−0.116	−0.073	0.274	−0.215	0.286
	(0.464)	(0.411)	(0.553)	(0.234)	(0.229)	(0.512)	(0.486)	(0.335)	(0.211)	(0.256)
School-year PTR	0.076	0.025	0.023	−0.003	0.006					
	(0.058)	(0.042)	(0.045)	(0.021)	(0.019)					
Average mobility	0.14	0.12	0.11	0.08	0.07	0.14	0.12	0.11	0.08	0.07
Attrition										
Offenses per student: low severity	−0.015	0.030	−0.119	−0.013	−0.004	−0.071	0.297**	−0.281	0.109	0.081
	(0.152)	(0.133)	(0.141)	(0.059)	(0.067)	(0.235)	(0.146)	(0.191)	(0.082)	(0.088)
Offenses per student: middle severity	0.051	0.053	0.038	0.126*	0.066	0.210	−0.028	−0.001	0.004	0.014
	(0.111)	(0.073)	(0.069)	(0.071)	(0.062)	(0.130)	(0.113)	(0.108)	(0.057)	(0.039)
Offenses per student: high severity	0.598	0.519	−0.189	0.025	−0.059	−0.103	−0.148	−0.061	−0.043	0.153
	(0.725)	(0.364)	(0.553)	(0.173)	(0.291)	(0.607)	(0.301)	(0.429)	(0.232)	(0.241)
School-year PTR	−0.080	−0.012	0.006	−0.004	0.011					
	(0.059)	(0.031)	(0.038)	(0.020)	(0.018)					
Average attrition	0.16	0.14	0.11	0.08	0.08	0.16	0.14	0.11	0.08	0.08
Any turnover										
Offenses per student: low severity	0.188	0.205*	−0.155	−0.141	−0.033	0.292	0.505**	−0.015	0.215*	−0.043
	(0.232)	(0.123)	(0.179)	(0.090)	(0.098)	(0.251)	(0.195)	(0.232)	(0.120)	(0.112)
Offenses per student: middle severity	0.037	−0.017	0.258*	0.201**	0.168**	0.191	0.039	−0.066	−0.085	0.061
	(0.162)	(0.123)	(0.141)	(0.079)	(0.085)	(0.135)	(0.147)	(0.156)	(0.079)	(0.072)
Offenses per student: high severity	1.668**	0.251	0.252	0.089	0.307	−0.219	−0.221	0.212	−0.258	0.439
	(0.663)	(0.530)	(0.777)	(0.284)	(0.367)	(0.775)	(0.482)	(0.447)	(0.308)	(0.421)
School-year PTR	−0.004	0.013	0.029	−0.007	0.017					
	(0.094)	(0.058)	(0.070)	(0.032)	(0.025)					
Average turnover	0.30	0.26	0.22	0.16	0.15	0.30	0.26	0.22	0.16	0.15
Obs.	11,884	19,689	15,687	52,577	41,598	11,884	19,689	15,687	52,577	41,598
School FE	X	X	X	X	X					
District-year FE	X	X	X	X	X					
School-year FE						X	X	X	X	X
School-level controls	X	X	X	X	X					
Classroom-level controls	X	X	X	X	X	X	X	X	X	X
Grade-level controls	X	X	X	X	X	X	X	X	X	X
Grade taught indicators	X	X	X	X	X	X	X	X	X	X
Teacher demographic controls	X	X	X	X	X	X	X	X	X	X

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Standard errors clustered at the district level in parentheses.

*p<0.10; **p<0.05; ***p<0.01

Table 5: Heterogeneity by gender

	School-level		Grade-level	
	Male	Female	Male	Female
Mobility				
Offenses per student: low severity	0.033	−0.063	0.223**	0.023
	(0.079)	(0.050)	(0.106)	(0.056)
Offenses per student: middle severity	0.184**	0.048	−0.123**	−0.011
	(0.091)	(0.054)	(0.060)	(0.035)
Offenses per student: high severity	0.017	0.294	0.284	−0.041
	(0.173)	(0.219)	(0.184)	(0.176)
School-year PTR	−0.004	0.014		
	(0.023)	(0.018)		
Average mobility	0.09	0.09	0.09	0.09
Attrition				
Offenses per student: low severity	−0.113	0.026	−0.060	0.094
	(0.069)	(0.043)	(0.088)	(0.060)
Offenses per student: middle severity	0.102*	0.071**	0.119*	−0.002
	(0.059)	(0.032)	(0.066)	(0.035)
Offenses per student: high severity	0.046	0.024	0.156	−0.029
	(0.219)	(0.147)	(0.191)	(0.132)
School-year PTR	−0.026	0.005		
	(0.025)	(0.013)		
Average attrition	0.10	0.10	0.10	0.10
Any turnover				
Offenses per student: low severity	−0.080	−0.037	0.162	0.117
	(0.080)	(0.061)	(0.136)	(0.079)
Offenses per student: middle severity	0.286***	0.119**	−0.004	−0.013
	(0.106)	(0.050)	(0.100)	(0.051)
Offenses per student: high severity	0.063	0.318	0.439*	−0.071
	(0.284)	(0.202)	(0.247)	(0.237)
School-year PTR	−0.030	0.019		
	(0.034)	(0.026)		
Average turnover	0.19	0.19	0.19	0.19
Obs.	35,453	105,982	35,453	105,982
School FE	X	X		
District-year FE	X	X		
School-year FE			X	X
School-level controls	X	X		
Classroom-level controls	X	X	X	X
Grade-level controls	X	X	X	X
Grade taught indicators	X	X	X	X
Teacher demographic controls	X	X	X	X

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Standard errors clustered at the district level in parentheses.

*p<0.10; **p<0.05; ***p<0.01

Table 6: Novice teachers

	School-level					Grade-level				
		VA		Gender			VA		Gender	
	All	Below-median	Above-median	Male	Female	All	Below-median	Above-median	Male	Female
Mobility										
Offenses per student: low severity	0.203	0.565	−0.458	0.174	0.172	0.178	0.129	0.363	−0.422	0.493
	(0.159)	(0.396)	(0.626)	(0.306)	(0.183)	(0.547)	(0.252)	(0.219)	(0.609)	(0.583)
Offenses per student: middle severity	−0.014	−0.370	0.139	0.119	0.012	0.305	0.071	−0.019	0.394	−0.162
	(0.159)	(0.424)	(0.339)	(0.294)	(0.184)	(0.278)	(0.155)	(0.132)	(0.299)	(0.392)
Offenses per student: high severity	1.070**	−0.148	3.104*	1.209	0.925	1.938*	−0.830	−0.116	−1.860	−1.603
	(0.464)	(1.316)	(1.747)	(0.973)	(0.884)	(1.102)	(0.577)	(0.512)	(1.351)	(1.280)
School-year PTR	0.076	0.081	−0.029	0.219**	0.059					
	(0.058)	(0.194)	(0.116)	(0.107)	(0.067)					
Average mobility	0.14	0.15	0.13	0.14	0.14	0.14	0.15	0.13	0.14	0.14
Attrition										
Offenses per student: low severity	−0.015	0.152	0.150	−0.121	0.103	−0.035	0.273	−0.071	−0.428	−0.232
	(0.152)	(0.414)	(0.517)	(0.259)	(0.249)	(0.784)	(0.312)	(0.235)	(0.638)	(0.699)
Offenses per student: middle severity	0.051	0.002	−0.053	0.366*	−0.047	−0.035	0.047	0.210	0.246	−0.438
	(0.111)	(0.248)	(0.224)	(0.194)	(0.164)	(0.326)	(0.158)	(0.130)	(0.311)	(0.295)
Offenses per student: high severity	0.598	1.775	0.264	−1.891	1.315	−3.193**	1.172	−0.103	1.124	1.224
	(0.725)	(1.635)	(2.771)	(1.690)	(0.982)	(1.354)	(0.743)	(0.607)	(1.203)	(1.115)
School-year PTR	−0.080	−0.212	−0.180	−0.199*	−0.025					
	(0.059)	(0.131)	(0.137)	(0.120)	(0.079)					
Average attrition	0.16	0.15	0.13	0.18	0.15	0.16	0.15	0.13	0.18	0.15
Any turnover										
Offenses per student: low severity	0.188	0.716	−0.308	0.053	0.275	0.143	0.402	0.292	−0.850	0.260
	(0.232)	(0.558)	(0.551)	(0.398)	(0.331)	(0.921)	(0.329)	(0.251)	(0.784)	(0.870)
Offenses per student: middle severity	0.037	−0.368	0.086	0.485*	−0.035	0.270	0.118	0.191	0.640*	−0.600
	(0.162)	(0.396)	(0.361)	(0.288)	(0.212)	(0.326)	(0.207)	(0.135)	(0.354)	(0.467)
Offenses per student: high severity	1.668**	1.628	3.368**	−0.682	2.240***	−1.256	0.342	−0.219	−0.736	−0.379
	(0.663)	(1.990)	(1.521)	(1.689)	(0.770)	(1.327)	(0.897)	(0.775)	(1.734)	(1.433)
School-year PTR	−0.004	−0.131	−0.210	0.019	0.034					
	(0.094)	(0.225)	(0.198)	(0.174)	(0.115)					
Average turnover	0.30	0.30	0.26	0.32	0.29	0.30	0.30	0.26	0.32	0.29
Obs.	11,884	2,617	2,617	3,278	8,606	11,884	2,617	2,617	3,278	8,606
School FE	X	X	X	X	X					
District-year FE	X	X	X	X	X					
School-year FE						X	X	X	X	X
School-level controls	X	X	X	X	X					
Classroom-level controls	X	X	X	X	X	X	X	X	X	X
Grade-level controls	X	X	X	X	X	X	X	X	X	X
Grade taught indicators	X	X	X	X	X	X	X	X	X	X
Teacher demographic controls	X	X	X	X	X	X	X	X	X	X

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Standard errors clustered at the district level in parentheses.

*p<0.10; **p<0.05; ***p<0.01

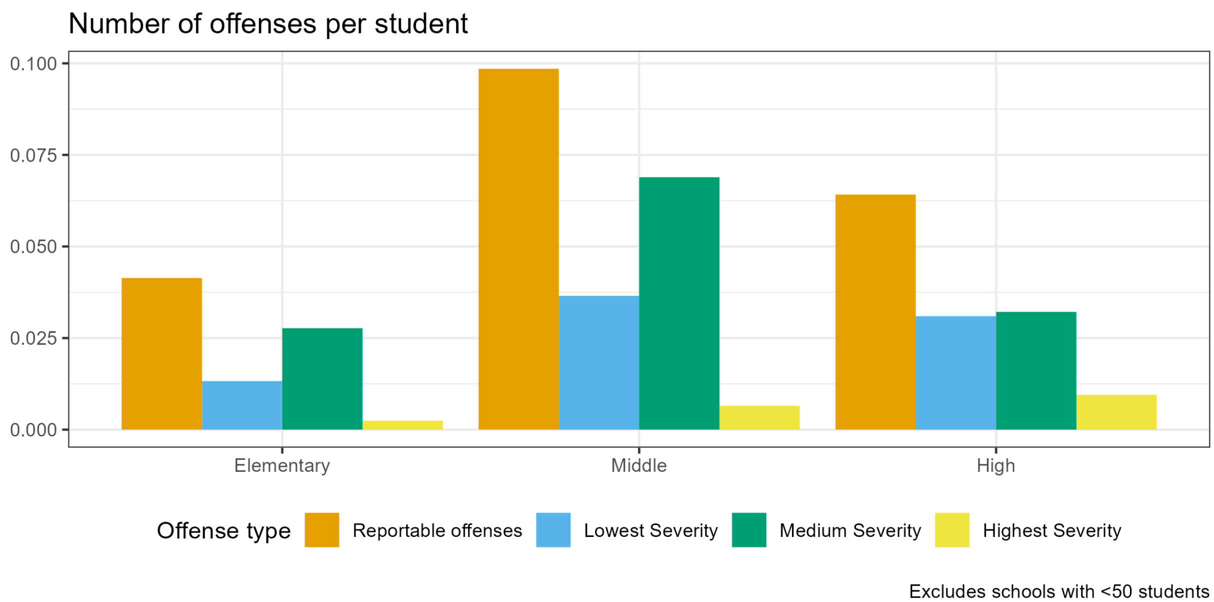
Table 7: Alternative specifications

	Classroom-level behavior							School-level behavior		Grade-level behavior	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mobility											
Mandatory and discretionary offenses per student	0.004***										
	(0.001)										
School-year PTR	−0.009	−0.010	−0.010	0.015	0.014			0.016	0.014		
	(0.011)	(0.011)	(0.011)	(0.017)	(0.017)			(0.016)	(0.016)		
Mandatory offenses per student		0.042***	0.041***	0.032***	0.037***	0.020**	0.036***	0.036	0.048	−0.006	0.006
		(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.037)	(0.036)	(0.023)	(0.022)
Discretionary offenses per student			0.001	0.002		0.007***		0.004***		0.009**	
			(0.001)	(0.002)		(0.002)		(0.001)		(0.005)	
Attrition											
Mandatory and discretionary offenses per student	0.006***										
	(0.001)										
School-year PTR	0.002	−0.002	0.002	0.000	−0.002			0.001	−0.002		
	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)			(0.013)	(0.013)		
Mandatory offenses per student		0.030***	0.019***	0.008	0.021***	0.003	0.022***	0.022	0.038**	0.016	0.038**
		(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.019)	(0.018)	(0.020)	(0.019)
Discretionary offenses per student			0.005***	0.006***		0.008***		0.006***		0.017***	
			(0.001)	(0.001)		(0.002)		(0.001)		(0.005)	
Any turnover											
Mandatory and discretionary offenses per student	0.010***										
	(0.002)										
School-year PTR	−0.007	−0.012	−0.008	0.016	0.012			0.018	0.013		
	(0.014)	(0.015)	(0.015)	(0.024)	(0.024)			(0.023)	(0.023)		
Mandatory offenses per student		0.072***	0.059***	0.040***	0.058***	0.023*	0.057***	0.058*	0.086***	0.010	0.044
		(0.014)	(0.014)	(0.013)	(0.012)	(0.012)	(0.013)	(0.032)	(0.030)	(0.032)	(0.031)
Discretionary offenses per student			0.005**	0.008***		0.015***		0.011***		0.026***	
			(0.002)	(0.002)		(0.003)		(0.002)		(0.007)	
Obs.	141,435	141,435	141,435	141,435	141,435	141,435	141,435	141,435	141,435	141,435	141,435
District FE	X	X	X								
Year FE	X	X	X								
School FE				X	X			X	X		
District-year FE				X	X			X	X		
School-year FE						X	X			X	X
School-level controls	X	X	X	X	X	X	X	X	X	X	X
Classroom-level controls	X	X	X	X	X	X	X	X	X	X	X
Grade-level controls	X	X	X	X	X	X	X	X	X	X	X
Teacher demographic controls	X	X	X	X	X	X	X	X	X	X	X
Grade taught indicators	X	X	X	X	X	X	X	X	X	X	X

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).
Standard errors clustered at the district level in parentheses.
*p<0.10; **p<0.05; ***p<0.01

Appendix A Appendix Figures

Figure A1: Offenses and Suspensions by School Level



Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.
School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Appendix B Appendix Tables

Table B1: Offense severity by offense category

Offense	% Suspended	Suspension Days	Suspension Days (Avg. > 0)	N
Highest severity				
Assault involving a weapon	89	25	31	812
Assault on school personnel not resulting in an injury	83	9	11	15,083
Assault resulting in an injury	84	20	26	1,025
Bomb threat	77	23	32	1,106
Controlled substance use or possession	89	11	13	54,361
Distribution of a controlled substance	83	15	20	3,383
Possession of a firearm	90	9	10	14,433
Possession of a weapon (non-firearm)	83	10	13	29,685
Robbery without a dangerous weapon	91	17	19	1,376
Medium severity				
Alcohol use or possession	87	7	9	13,069
Assault not resulting in an injury	72	4	6	120,745
Communicating threats of attack with a firearm	72	5	7	866
Communicating threats of attack with a weapon (non-firearm)	69	4	6	1,117
Extortion	76	4	6	663
Fighting	84	4	4	606,904
Gang activity	78	7	10	13,737
Posession of drug paraphernalia	87	7	8	8,966
Possession of another's prescription drug	85	9	12	4,418
Sexual Assault	81	7	10	2,403
Lowest severity				
Bullying	43	1	3	93,513
Communicating threats	71	4	6	81,401
Communicating threats of attack without a weapon	55	2	4	5,925
Discrimination	36	1	3	1,205
Harrassment - other	46	2	3	2,993
Possession of tobacco	51	1	3	52,916
Property damage	44	2	4	53,020
Sexual Harassment	71	3	4	36,958
Tobacco use	44	1	3	59,864
Verbal harassment	43	1	3	44,838

Includes offenses with at least 100 observations.

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Table B2: Average student and teacher characteristics by classroom-level measures of student behavior and discipline

	Quartile				Wald statistics		
	1st (lowest)	2nd	3rd	4th (highest)	Across schools	Within schools	Within school by year
Classroom: number of mandatory offenses per student							
School Characteristics							
Female students	0.49	0.49	0.48	0.47	14.43***	1.25	
Non-white students	0.41	0.44	0.50	0.60	35.92***	6.76***	
Economically disadvantaged students	0.39	0.44	0.49	0.55	42.80***	6.03***	
Median Math score (z-score)	0.15	0.15	0.13	0.09	20.53***	1.55	
Median Reading score (z-score)	0.14	0.15	0.12	0.08	23.68***	0.63	
Grade Characteristics							
Female students	0.49	0.49	0.49	0.47	20.48***	7.39***	9.12***
Non-white students	0.42	0.44	0.50	0.60	36.65***	8.28***	9.39***
Economically disadvantaged students	0.39	0.44	0.49	0.55	45.52***	7.99***	6.37***
Median Math score (z-score)	0.15	0.16	0.13	0.09	22.54***	4.07***	7.22***
Median Reading score (z-score)	0.14	0.15	0.12	0.08	25.22***	2.40*	5.98***
Classroom Characteristics							
Female students	0.49	0.49	0.48	0.43	176.41***	238.71***	257.80***
Non-white students	0.40	0.44	0.51	0.63	58.67***	27.86***	34.17***
Economically disadvantaged students	0.38	0.43	0.50	0.60	126.88***	89.02***	131.18***
Median Reading score (z-score)	−0.57	0.09	0.01	−0.24	114.39***	94.13***	91.42***
Median Math score (z-score)	−0.51	0.10	0.01	−0.28	116.23***	103.28***	98.50***
Teacher Characteristics							
Age	42.12	41.39	41.11	41.20	22.65***	13.49***	12.09***
Female	0.78	0.74	0.74	0.75	14.43***	1.25	0.00
Black	0.10	0.13	0.17	0.27	16.99***	15.43***	14.44***
White	0.85	0.83	0.79	0.69	18.76***	16.56***	16.88***
Hispanic	0.02	0.02	0.01	0.02	3.92***	9.57***	8.66***

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Note: Wald statistics test the null hypothesis that indicators for quartile of each measure of student behavior or discipline are equal to zero. The within-school estimates come from regressions with school and district-year fixed effects and indicators for the grade taught. The within-school by year estimates come from regressions with school-year fixed effects and indicators for the grade taught. "N" presents the number of teacher-year observations used in each calculation.

*p<0.10; **p<0.05; ***p<0.01

Table B3: Average classroom characteristics by measures of student behavior and discipline

	Quartile				Wald statistics		
	1st (lowest)	2nd	3rd	4th (highest)	Across schools	Within schools	Within school by year
School: number of mandatory offenses per student							
Classroom Characteristics							
Female students	0.48	0.48	0.47	0.46	17.65***	1.96	
Non-white students	0.39	0.44	0.50	0.65	54.39***	1.81	
Economically disadvantaged students	0.38	0.44	0.50	0.59	49.27***	3.41**	
Median Reading score (z-score)	−0.12	−0.15	−0.18	−0.24	4.41***	0.09	
Median Math score (z-score)	−0.12	−0.15	−0.18	−0.24	4.45***	0.24	
Grade: number of mandatory offenses per student							
Classroom Characteristics							
Female students	0.48	0.48	0.47	0.46	20.99***	11.13***	13.05***
Non-white students	0.39	0.44	0.50	0.65	50.31***	3.82***	4.14***
Economically disadvantaged students	0.38	0.45	0.50	0.59	51.68***	5.81***	2.96**
Median Reading score (z-score)	−0.10	−0.15	−0.21	−0.24	9.01***	0.56	1.11
Median Math score (z-score)	−0.10	−0.15	−0.20	−0.23	9.57***	0.40	1.47

Note: Offense variables include only offenses requiring mandatory reporting under state or federal law. Severity categories are based on the average days of out-of-school suspensions applied to each offense type. See Section 2.2.1 for details.

School-year PTR is the school-year propensity to remove (see Section 3 for details.).

Note: Wald statistics test the null hypothesis that indicators for quartile of each measure of student behavior or discipline are equal to zero. The within-school estimates come from regressions with school and district-year fixed effects and indicators for the grade taught. The within-school by year estimates come from regressions with school-year fixed effects and indicators for the grade taught. "N" presents the number of teacher-year observations used in each calculation.

*p<0.10; **p<0.05; ***p<0.01

Appendix C List of Offenses

Offenses Requiring Reporting Under State Law

Alcohol use or possession
Assault involving a weapon
Assault on school personnel not resulting in an injury
Assault resulting in an injury
Bomb threat
Burning of a school building
Controlled substance use or possession
Death by other than natural causes
Distribution of a controlled substance
Distribution of a prescription drug
Homicide
Kidnapping
Posession of a controlled substance
Posession of a firearm
Posession of a weapon (non-firearm)
Possession of a firearm
Possession of a weapon (non-firearm)
Possession of another's prescription drug
Rape
Robbery with a dangerous weapon
Robbery without a dangerous weapon
Sexual Assault

Offenses Requiring Reporting Under Federal Law (and not State Law)

Assault not resulting in an injury
Bullying
Communicating threats
Communicating threats of attack with a firearm
Communicating threats of attack with a weapon (non-firearm)
Communicating threats of attack without a weapon
Discrimination
Extortion
Fighting
Gang activity
Harrassment - other
Posession of drug paraphernalia
Possession of tobacco
Property damage
Sexual Harassment
Tobacco use
Verbal harassment

Offenses Not Requiring Reporting

Aggressive behavior
Alcohol intoxication
Being in an unauthorized area
Bus misbehavior
Cell phone use
Controlled substance intoxication
Cutting class
Dangerous acts
Discipline action violation
Disorderly conduct
Disrespect of faculty/staff
Disruptive behavior
Dress code violation
Excessive display of affection
Excessive tardiness
False fire alarm
Falsification of information
Gambling
General rule violation
Hazing
Honor code violation
Inappropriate behavior
Inappropriate items on school property
Indecent exposure
Insubordination
Intimidation
Misuse of technology
Mututal sexual contact between students
No immunization
Other
Physical Exam
Posession of own prescription drug
Possession of counterfeit items
Possession of drug paraphernalia
Profanity
Staff Offense
Theft
Threats
Truancy
Unlawfully setting a fire
Use of counterfeit items

Appendix D Teacher Value Added Estimation

To assess heterogeneity by teacher quality, I estimate teacher value added (VA) on standardized Math and ELA exams following Chetty, Friedman, and Rockoff (2014). These estimates use student scores from end-of-course Math and Reading assessments for the students each teacher is assigned.

I estimate teacher VA using the following steps. First, I capture residuals from the following teacher fixed effects regression:

$$a_{ijt} = \eta_i + \eta_t + \eta_g + \upsilon_1 X_{jt} + \upsilon_2 X_{it} + \varepsilon_{ijt} \tag{7}$$

where a_{ijt} is the Math or Reading test score for student j assigned to teacher i (students are assigned to more than one teacher) in year t, standardized relative to other students in that subject, grade, and year. η_i, η_t, and η_g are teacher, year, and grade fixed effects respectively. X_{jt} is a vector of one-year-lagged student test score controls in both Math and Reading. X_{it} is a vector of classroom-, grade-, and teacher-level controls for student demographics.

Second, I create "modified residuals" for each observation, ignoring the teacher fixed effects in equation 7:

$$\widetilde{\varepsilon_{ijt}} = a_{ijt} - (\widehat{\upsilon_1} X_{jt} + \widehat{\upsilon_2} X_{it} + \widehat{\eta_i} + \widehat{\eta_t} + \widehat{\eta_g}) \tag{8}$$

Third, I average these residuals by teacher and year, weighted by the number of students assigned to each teacher in each year.

Finally, I estimate teacher VA in each year using fitted values from the following (linear) jackknife forecast separately for each teacher and year T:

$$\widehat{\widetilde{\varepsilon_{ijt}}} = \beta_0 + \beta_1 t + \varphi_{ijt}, \ for \ t \neq T \tag{9}$$

Because much of my analysis focuses on the attrition of novice teachers, I estimate VA for novice teachers using a modified version of equation 9 that includes only the constant term. Additionally, I create an "overall" teacher VA variable that averages the Math and Reading VA estimates for each teacher in each year (when available).