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DISCUSSION PAPER SERIES

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ABSTRACT

Disruptive Peers and Academic Performance: Short- and Long-Term Outcomes*

How do disruptive peers shape academic and career paths? We examine this question by leveraging the random assignment of students to classrooms in Greece and identifying the effects of peer disruptiveness on academic performance and career paths. Using suspension hours as a measure of disruptiveness, we find that students assigned to more disruptive classrooms have lower academic achievement, a higher risk of grade retention, and reduced likelihood of graduating from high school on time. They are also less likely to pursue competitive STEM fields or enroll in selective postsecondary programs. The adverse effects are more pronounced for students from low-income areas, in larger classrooms, or with fewer female peers. Using a lab-in-the-field experiment, we find that exposure to multiple disruptors, compared to just one, reduces students' study motivation, college aspirations, and readiness for science studies and careers, especially for those seated closer to disruptive peers.

JEL Classification: I24, I26, J16, J24

Keywords: disruption, suspension, random classroom assignment, high school graduation, STEM careers, lab-in-the-field experiment

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* The survey-based RCT experiment received ethics approval by Stanford University (eProtocol Number 66665) and has also been preregistered at the AEA RCT Registry with RCT ID number AEARCTR-0010090. Rigissa Megalokonomou acknowledges research support from Monash University, Monash Establishment Grant (No: 1755774).

1 Introduction

Students with behavioral misconduct often exhibit lower academic outcomes, yet relatively little is known about how such behaviors spill over to affect their peers. While the literature extensively examines cognitive spillover effects, the impact of noncognitive peer characteristics—such as disruptive behavior stemming from misconduct—remains underexplored. Disruptive students' negative externalities can profoundly impact the learning environment. Their behavior often creates a chaotic and distracting atmosphere, making it harder for students to focus, engage, and absorb material. Frequent interruptions or disciplinary actions directed at disruptive students reduce instructional time and overall learning productivity. Research shows that classrooms with higher levels of disruptive behavior experience lower overall academic performance (Kinsler, 2013; Carrell, Hoekstra, and Kuka, 2018). These disruptions affect both high- and low-achieving students by fostering a negative classroom climate, diminishing motivation and engagement, and ultimately hindering academic progress across subjects. Understanding the effects of peers' disruptiveness is crucial, as it has significant implications for fostering equitable access to high-quality education for all students.

Two main empirical challenges arise when investigating the effect of disruptive peers on classmates. First, the self-selection of students in learning environments makes it difficult to disentangle the effect of disruptiveness from broader contextual influences. This issue is particularly pronounced in disadvantaged settings, where the prevalence of disruptive peers tends to be higher. Second, measures of disruptive behavior are rare and often indirect (Carrell and Hoekstra, 2010; Kristoffersen, Kraegpot, Nielsen, and Simonsen, 2015; Carrell, Hoekstra, and Kuka, 2018; Carneiro, Cruz-Aguayo, Salvati, and Schady, 2024). These measures often capture aspects of the family environment, making it difficult to separate personality or behavioral traits from family conditions.

This paper investigates the effects of peer disruptiveness on short- and longer-term student outcomes and choices. We combine exogenous variation in peer group formation with novel administrative data. We exploit a setting in which students at the start of high school (grade 10) are quasi-randomly assigned to classrooms based on the alphabetical order of their surnames. Having prior measures of disruptiveness along with the exogenous variation in peer group formation mitigate the reflection problem (Manski, 1993). Specifically, students are grouped with classmates who display varying levels of prior disruptive behavior, a trait that exhibits strong serial correlation (Segal, 2008). Our identification approach compares outcomes of students across classrooms within the same school cohort, controlling for student and classroom characteristics. The key assumption is that prior peer disruptiveness is uncorrelated with unobserved student characteristics within school cohorts. This empirical investigation draws motivation from a theoretical model that explains how disruptive classmates affect student outcomes. The model links individual scholastic outcomes to peers' disruptive behavior. At equilibrium, classroom disruptiveness reduces the effort students invest, ultimately harming their academic performance.

We use novel, detailed student-level data from a representative school sample, which captures student outcomes and behavior across grades. We merge this dataset with administrative data from the Ministry of Education, which covers national exams, university applications, and admissions for all students between 2000 and 2011. A key feature of these data is that they include student-level suspension hours (from 2^{nd} semester of grade 9) and classroom identifiers for grade 10—the first year of senior high school—where students are randomly assigned to classrooms. We measure classroom disruptiveness using prior-semester student suspension hours, which reflect disciplinary actions for rule violations such as disruptive behavior, violence, or bullying. These suspensions, initiated by teachers or principals, serve as indicators of negative behavior and help schools enforce corrective measures. We use two metrics: (1) the leave-out mean of classroom peers' suspension hours, and (2) the proportion of students with over 20 baseline suspension hours (the 75^{th} percentile of the suspension hours distribution). We focus on several key outcomes: exam performance, study choices, academic probation (grade retention and exam retaking), university applications, and enrollment. These outcomes are linked with human capital formation, and life and career success. We also design and implement a lab-in-the-field experiment to gain insights into the role of mechanisms underlying the effects of peer disruptiveness on student outcomes, focusing on motivation, aspirations, and readiness for science study and careers.

Our analysis reveals that classroom peer disruptiveness has significant and persistent negative effects on academic outcomes. An 1 standard deviation (SD) increase in baseline suspension hours among peers, roughly equivalent to an additional 4 suspension hours, is associated with a decline of 0.03 SD in test scores by the end of grade 10 and 0.05 SD by the end of grade 11. These results are economically significant. An 1 SD increase in baseline suspension hours among peers has a detrimental effect on students' performance comparable to a decrease in teacher quality by more than one-quarter of the SD (Rivkin, Hanushek, and Kain, 2005) or an increase in the class size by two students out of 20 (Angrist and Lavy, 1999). The detrimental influence of disruptiveness is consistent across all subjects, with no significant differences between STEM and non-STEM fields, underscoring its broad impact on academic achievement. We then examine whether peer disruptiveness affects student future specialization decisions. We find that students assigned to more disruptive classmates reduce their likelihood of enrolling in the competitive science track by 2.3 percentage points and raises the likelihood of enrolling in the less competitive professional IT track by 3.4 percentage points. This has important implications for student human capital formation, since this is the first instance of student specialization and determines future outcomes. Our findings also suggest that students assigned to more disruptive classroom peers face higher risks of failing a grade, having to retake exams, and not graduating from high school on time. These effects have long-term implications for professional development and lifetime earnings. We find that students assigned to more disruptive peers in grade 10 are applying to and enrolling in less competitive university departments and fields 3 years later.

Our findings reveal that the adverse effects of peer disruptiveness are widespread, affecting various groups and contexts, with some notable heterogeneous effects. While both disruptive and non-disruptive students experience negative impacts, the adverse effects are slightly more pronounced for non-disruptive students. To further explore these effects, and given that a student's own disruptiveness is typically correlated with prior performance, we then examine heterogeneity based on prior test scores. We find that high-performing students are particularly vulnerable to classroom disruption, facing larger adverse effects than their lower-performing counterparts. We then examine whether fewer resources and weaker support systems may mitigate the negative effects of disruption. We examine heterogenous effects in terms of resources and find that the negative impacts of classroom disruptiveness are more severe in schools located in lower-income neighborhoods, underscoring the vulnerability of students in less affluent areas. Also, our analysis shows that students in larger classrooms or classrooms with a lower share of female peers experience stronger adverse effects from disruptiveness. These findings suggest that policymakers should prioritize disruption-management strategies in these settings to mitigate the broader impacts on learning environments.

Our analysis reveals a nonlinear relationship between peer disruptiveness and student performance, with significantly greater negative impacts for students in the middle and top tertiles of suspension hours and disruptive peers compared to those in the bottom tertile. Also, we perform a simulation exercise, demonstrating the potential benefits of redistributing disruptive peers more evenly across classrooms. Equalizing the share of disruptive students within school cohorts reduces variance in classroom disruptiveness and improves student performance, particularly for low-performing students. The share of students performing above the median increases from 50.88% to 53.22%, illustrating the value of balanced classroom compositions in mitigating the negative externalities of disruptive peers. These findings highlight the potential for targeted allocation strategies to improve educational outcomes.

To ensure the validity of our findings, we conduct placebo and robustness checks. For the placebo tests, we first examine whether conditions unrelated to disruptiveness, such as sickness-related absences, affect student test scores. We find no significant relationship, which suggests that health-related absences do not impact academic outcomes. We also assess the influence of disruptiveness levels among peers outside a student's classroom and again find no significant effect, which demonstrates that our results are not driven by unobserved factors. For robustness, we test different thresholds for defining disruptive students, adjusting suspension hours to vary from 15 to 25 hours (instead of 20 hours, which corresponds to the 75$^{\text{th}}$ percentile). Across these definitions, the negative impact of disruptive peers remains consistent, and thus confirms that our findings are robust to variations in defining disruptiveness. Our results are not solely driven by extremely disruptive students or by specific classrooms.

Understanding the mechanisms through which disruptive environments affect students' educational outcomes is crucial in designing mitigating strategies. We combine insights from a survey-based randomized experiment and our administrative data. In a lab-in-the-field experiment, we survey 644 high school students from 31 classrooms in five public schools, exposing them to randomized scenarios featuring either a single disruptive peer or one-third of their classmates causing disruption. Students rated the perceived impact of these disruptors on their study motivation, college aspirations, science study and career readiness on a 0–100 scale. We find that exposure to multiple disruptive peers, as opposed to a single disruptor, significantly decreases students' perceived study motivation, college aspirations, readiness to study science, and career readiness. These effects are more pronounced for students seated closer to disruptive peers, underscoring the role of physical proximity in amplifying the adverse impacts of classroom disruption.

We then explore whether classroom disruptiveness affects instructional time or triggers contagion effects (i.e., other students attempt to imitate disruptive students and become disruptive themselves) using our administrative data. Our analysis reveals no evidence that exposure to disruptive peers increases student suspension hours, class attendance, or the likelihood of students becoming disruptive themselves. This suggests that the negative impact of disruptiveness operates primarily through reductions in motivation and readiness rather than through a loss of instructional time or contagion effects.

This study goes beyond prior research in several ways. First, we introduce a direct measure of disruptiveness. This measure is based on observed, prior student suspension hours, which result from disciplinary actions for rule violations such as disruptive behavior, violence, or bullying. These suspensions, initiated by teachers or principals, reflect negative behaviors and enable schools to monitor absenteeism and implement corrective measures. Other studies relied on indirect measures of disruptiveness: some use children exposed to domestic violence (Carrell and Hoekstra, 2010; Carrell, Hoekstra, and Kuka, 2018), others focus on children whose parents were investigated for abuse or neglect (Santavirta and Sarzosa, 2024) or those with divorced parents or parents convicted of crimes (Kristoffersen, Kraegpot, Nielsen, and Simonsen, 2015; Bayer, Hjalmarsson, and Pozen, 2009), children exposed to pollutions (Billings and Schnepel, 2018; Gazze, Persico, and Spirovska, 2024), and others focus on how disadvantage environment affect students educational and life outcomes (Black, Devereux, and Salvanes, 2013; Chetty, Hendren, and Katz, 2016; Chyn and Katz, 2021,0; Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, et al., 2022; Collinson, Humphries, Mader, Reed, Tannenbaum, and Van Dijk, 2024). As a recent example, Carneiro, Cruz-Aguayo, Salvati, and Schady (2024) use teacher-reported lists of students exhibiting the most severe behavioral issues and learning difficulties. However, these teacher-reported measures may be susceptible to biases, including those related to race or gender. A few papers employ more direct measures, such as diagnosing children with attention-deficit disorders or special needs (Aizer, 2008; Kristoffersen, Kraegpot, Nielsen, and Simonsen, 2015; Hwang and Domina, 2021; Balestra, Eugster, and Liebert, 2022). Direct measures of disruptiveness focus on student behavior rather than family influences, reducing measurement error and improving the reliability of the results.

Second, unlike prior work, we use two distinct transformations of our disruptiveness measure. The first metric, the leave-out mean of classroom peers' suspension hours, captures the intensity of peer disruptiveness by reflecting the average severity of negative behavior. The second metric, the proportion of students with over 20 baseline suspension hours, captures the prevalence of peer disruptiveness by indicating how widespread disruptive behavior is. Together, these metrics provide rich variation, improve the robustness and depth of the findings, and provide a more nuanced understanding of classroom disruptiveness and its effects. Third, we contribute to the growing literature on the causal impact of classroom disruptiveness on student outcomes (Carrell, Hoekstra, and Kuka, 2018; Verma and Meiselman, 2022; Carneiro, Cruz-Aguayo, Salvati, and Schady, 2024). Armed with a conceptual model that provides conceptual structure, our study is the first to account for year-level influences and to rely on the disruptiveness of all peers in the classroom, rather than focusing on a small subset of students.

Fourth, we contribute to the evidence on the longer-term effects of classroom disruptiveness by leveraging rich and novel data to examine a wide range of outcomes beyond test scores, a distinction shared only with Carrell, Hoekstra, and Kuka (2018). Specifically, we analyze scholastic outcomes such as grade retention, timely high school graduation, and the choice of competitive specialization tracks, as well as longer-term achievements like university admissions exam scores and postsecondary education applications and enrollment. By incorporating multiple outcomes, our analysis provides a more robust and comprehensive understanding of the impact of disruptiveness. Moreover, early academic indicators such as retention and academic probation not only shape long-term life and career trajectories but also serve as critical warning signs, enabling teachers and principals to identify at-risk students and take timely actions to mitigate potential negative effects.

Fifth, our study provides valuable insights into the mechanisms through which classroom disruptiveness affects student outcomes, addressing a key gap in the literature. Our administrative data allow us to exclude the potential influence of classroom disruptiveness on students' own levels of disruptive behavior or instructional time. Using a lab-in-the-field experiment, we find that increased classroom disruption diminishes students' study motivation, college aspirations, and readiness for science study and careers. Furthermore, we provide unique evidence that these adverse effects are more pronounced for students seated closer to disruptive peers, underscoring the spatial and behavioral dimensions of disruptiveness in shaping student outcomes.

Our study suggests that targeted interventions to reduce classroom disruption are vital for equitable learning. We find that the negative effects of disruptiveness are more pronounced in larger classrooms, those with a lower proportion of female students, and in economically disadvantaged neighborhoods, highlighting the importance of tailoring strategies to these contexts. Key policy tools include smoothing disruptiveness by re-allocating disruptive students more evenly across classrooms and implementing seating arrangement strategies to minimize the impact on peers seated close to disruptive students. Additional measures include early identification and support for disruptive students through behavioral interventions, social and emotional learning (SEL) programs, and counseling, particularly in lower-income schools. Broadly, this study contributes to our understanding of how peers' noncognitive personality traits affect academic performance, study choices, and college admission.[1] By identifying additional channels of peer influence, we expand the range of policy levers available to improve educational and career trajectories.

2 Data and Institutional Framework

The Greek education system is highly centralized (OECD, 2018), with over 90% of students attending traditional public schools. Students are typically assigned to high schools based on their residential zones (Goulas and Megalokonomou, 2021; Megalokonomou, Goulas, and Zhang, 2024). Since students come from various elementary schools, the majority of classmates in grade 10 are unfamiliar with each other.

2.1 Data

We examine the impact of peer disruptiveness on educational outcomes by combining data from multiple administrative sources. First, we use administrative data gathered from 10 representative public high schools across Greece,[2] which includes information on $5,013$ students who attended these schools between 2000 and 2011. Figure A1 in the Online Appendix shows the municipalities in which the sampled schools are located. From these schools, we collected comprehensive records, including attendance data, student demographics, transcripts, classroom assignments, and class enrollment information for each term in grades 10 through 12. Moreover, we obtained attendance and transcript data for the second semester of grade 9 for students in our sample (our baseline measures). Attendance data include sickness-related absences and suspension hours, both measured in school hours. The baseline student test scores reflect outcomes on comparable school exams based on the same curriculum, with grading standards unified across classrooms.[3]

Second, we obtained information on student performance on national exams and their university admission records from the Ministry of Education for all sampled students in the graduating cohorts between 2003 and 2011. This dataset includes detailed student-level information on national exam performance, university enrollment status, admissions scores, and the specific postsecondary

[1] Other papers have demonstrated that students' noncognitive behaviors, such as personality (Golsteyn, Non, and Zölitz, 2021) or propensity to move schools (Hanushek, Kain, and Rivkin, 2004), have a significant effect on peers' educational performance.

[2] Online Table A1 presents a comparison of student and school characteristics between our study sample and all high schools nationwide, drawing on national exam data from the Ministry of Education for 2003 to 2011. Our analysis shows that the characteristics of students and schools in our sample are statistically equivalent to the national averages across all high schools.

[3] Teaching faculty in each subject and grade collaborate to design the final exam and share grading responsibilities. The principal reviews and approves the exam questions and graded papers, records the scores in the school log and computer system, and ensures that teachers adhere to grading guidelines provided by the Ministry of Education Goulas and Megalokonomou (2020a).

programs (university and degree) students are admitted to. We also obtained household income data for the postcodes of the sampled schools from the Ministry of Economy and Finance. We mapped the postcode income data to school locations and use this information as a proxy for neighborhood household income and local economic conditions.

2.2 The Greek Education System

The Greek education system is highly centralized (OECD, 2018). Students are assigned to high schools based on proximity to their residential address. Grade 10 is the first year of high school, and students come from different elementary schools. As a result, each student is placed in a classroom in which most of their classmates are new to them. Students are quasi-randomly assigned to classrooms at the beginning of grade 10. This assignment is based on alphabetical order based on surnames (Goulas, Griselda, and Megalokonomou, 2022; Goulas, Gunawardena, Megalokonomou, and Zenou, 2024; Goulas and Megalokonomou, 2020b). Students remain in the same classroom until the end of grade 10 and for compulsory subjects until the end of high school. Students enroll in one of three specialization tracks in grade 11: competitive science, professional information technology (IT), or classics. All schools offer these tracks, and students must select their track by the end of grade 10.[4] Each track features a distinct set of subjects, but all students within a track must take the same subjects.

Tables 1 and A2 present summary statistics of student baseline characteristics and outcomes, respectively. Table 1 shows that 55% of students are female, with an average age of around 16 years. On average, students have 13.7 hours of suspension hours from class (roughly equivalent to 2 school days) and about 7 hours of sickness-related absences. The average class size is 23 students, with 27% of students being classified as disruptive in the classrooms. Online Table A2 shows that 23%, 35%, and 41% of students enroll in the competitive science, professional IT, and classics track. 6% of students repeat at least one grade.

Postsecondary education in Greece is tuition-free. Students take standardized national exams at the end of grade 12, which are the most important determinant for college admissions.[5] After students take these exams, they submit a list of their preferred postsecondary programs to the Ministry of Education, in which they list their preferred degree in order of preference. Students have no restrictions on how many degrees they can list, but they obtain a single offer.[6] We also consider four variables that capture how selective the admitted degree is: whether the admitted degree is within the top 10% or 20% of departments and two continuous measure of degree selectivity. If a postsecondary degree is within the top 10% or 20% based on a ranked list of degree admissions cutoffs (i.e., the minimum scores of the lowest-ranked enrolled student for each university degree), then the

[4]Although students can theoretically switch tracks between grades 11 and 12, most remain on the same track in grade 12 (Goulas, Griselda, and Megalokonomou, 2022).

[5]National exams are externally graded and proctored.

[6]For the majority of students, this is the enrolled degree (Bizopoulou, Megalokonomou, and Simion, 2024).

respective indicator is equal to 1 and 0 otherwise. We measured the selectivity of postsecondary degrees by ranking all degrees based on the average performance of enrolled students in each program.

2.3 Randomized Classroom Assignment

To investigate the impact of classroom disruptiveness, we leverage a quasi-random assignment of students (and teachers) to classrooms at the start of high school (grade 10).[7] This assignment process is strictly regulated by a law that mandates classroom allocation based on the alphabetical order of students' surnames (Goulas, Griselda, and Megalokonomou, 2022; Goulas, Gunawardena, Megalokonomou, and Zenou, 2024; Goulas, Megalokonomou, and Zhang, 2023).[8] Each school has at least two classrooms in grade 10, and students with last names starting earlier in the alphabet are assigned to classrooms with lower numbers; those with last names later in the alphabet are assigned to higher-numbered classrooms. Students are not allowed to switch classrooms based on personal preferences and must remain in their assigned classroom for the duration of high school. This alphabetical assignment at the beginning of grade 10 creates exogenous peer groupings, which means that a student's classroom peers, including those with specific characteristics such as disruptiveness or academic performance, are assigned independent of the student's own characteristics. Below, we demonstrate that students' baseline characteristics are uncorrelated with their peers' characteristics at the point of classroom assignment, which is crucial for addressing the reflection and selection issues raised by Manski (1993).

3 Absenteeism and Peer Disruptiveness

3.1 Types of Absenteeism

We have information on two types of school attendance data: *hours of suspensions from class* and *sickness-related (or excused) hours of absence*. Suspension hours result from disciplinary actions taken by the school in response to rule violations, leading to the temporary removal of a student from the classroom (for 1 or more hours) or the school (for 1 or more days). Suspensions are typically driven by behavioral issues such as disruptive conduct, violence, or bullying that disrupt the learning environment. Either the principal or a teacher has the authority to suspend a student, and parents or doctors cannot excuse these suspensions.[9] These hours reflect disruptive behavior that can negatively impact the classroom climate, and schools track them to monitor absenteeism and implement necessary interventions. We refer to these as *hours of suspension*.

[7]For evidence of the random assignment of teachers to classrooms in this context, see Lavy and Megalokonomou (2024a) and Lavy and Megalokonomou (2024b). Teachers rotate between classrooms based on their subject expertise, and students take a variety of standardized compulsory courses alongside their classmates.

[8]See Government Gazette of the Hellenic Republic 167 A/1566/1985.

[9]A key challenge in identifying the exogenous influence of peer disruptiveness on student outcomes is that teachers may have varying levels of tolerance for disruptiveness before suspending a student. Our context mitigates this issue through the random assignment of teachers to classrooms and a common training program in classroom management practices.

In contrast, *excused hours of absence* refer to periods when students are permitted to miss class for valid reasons, such as illness, medical appointments, or family emergencies, without facing penalties. These absences are authorized by a doctor or parent. Since they are unrelated to behavioral issues, we use them as a placebo measure, because they are not expected to have direct external effects on classmates, aside from potential indirect ones.

3.2 Measures of Peer Disruptiveness

As discussed above, we use suspension hours as a direct measure of student *disruptiveness*. Due to the quasi-random assignment of peer groups, some classrooms inevitably are allocated more disruptive peers than others. A genuinely disruptive student is likely to exhibit persistent disruptive behavior across different classroom settings (Segal, 2008). We construct two measures of peer disruptiveness based on students' observed baseline suspension hours. The first measure captures the average baseline suspension hours of students assigned to each classroom in grade 10, using suspension data for all students in that classroom except student i. In other words, our first treatment variable is peer disruptiveness measured by classroom peers' ($j \neq i$) baseline suspension hours, excluding the suspension hours of student i. We refer to this as the *baseline peers' suspension hours*, calculated as follows:

$$\text{Baseline (Classroom) Peers' Suspension Hours}_i = \frac{\sum_{j \neq i} \text{Suspension Hours}_j}{\text{Classroom Size} - 1}. \tag{1}$$

This measure captures the *intensity* of classroom disruptiveness. Figure 1D shows this distribution, and Figure 1C shows classroom peers' sickness-related absences distribution.[10] There is substantial variation in disruptiveness across classrooms, primarily driven by the random assignment of students, which renders this variation exogenous to both student and classroom baseline characteristics.

Next, we classify students as disruptive or non-disruptive based on how disruptive they are in the classroom. We classify students with *more than 20 hours of baseline suspensions* (in the 75^{th} percentile) as "*disruptive*."[11] Our second measure of peer disruptiveness is the *share of disruptive peers* in a classroom, which captures a different aspect of classroom disruptiveness intensity by

[10] Figure 1B shows the student-level distribution of *suspension hours* and the distribution of student-level sickness-related absences (Figure 1A). While both distributions peak around zero, the suspension hours distribution is notably more spread out, which indicates that students accumulate more suspension hours than sickness-related absences. Table 1 further supports this, showing that the mean of baseline peers' suspension hours are nearly double those of sickness-related hours—about 14 hours vs. 7 hours.

[11] We aim to understand the profiles of students who are more likely to be disruptive. Online Table A3 examines the relationship between suspension hours (column 1) or disruptive student status (column 2) and various student characteristics. Older students, those with lower academic performance, higher sickness-related absences, and residing in less affluent areas are more likely to accumulate more suspension hours and be classified as disruptive. In Table A4 we compare student outcomes for disruptive and non-disruptive students. Columns 1 and 2 show the means of various student outcomes for non-disruptive and disruptive students, column 3 shows the mean differences, and column 4 the p-values of the differences. Disruptive students consistently show significantly lower performance across all subjects. They are more likely to enroll in the professional IT track and less likely to enroll in the competitive science or classics track. Disruptive students are also significantly more likely to repeat a grade, are less likely to complete high school on time, have a higher likelihood of being at risk of retention—which requires re-taking exams—have lower university admissions exam scores, and are less likely to enroll in postsecondary education and gain admission to higher-quality programs than their non-disruptive counterparts.

focusing on the presence of disruptive students. This measure is defined as follows:

$$\text{Share of Disruptive (Classroom) Peers}_i = \frac{\sum_{j \neq i} \mathbb{1}(\text{Suspension Hours}_j \geq P_{75})}{\text{Classroom Size} - 1}. \tag{2}$$

Figure 2A illustrates the distribution of the number of disruptive students per classroom and shows that 90% of students have fewer than nine disruptive peers, while 25% have just three disruptive peers. To account for class size, we divide the number of disruptive students in a classroom by the total number of students and exploit the random variation in the classroom-level share of disruptive peers, excluding the student in question. The distribution of our second measure of peer disruptiveness (i.e., share of disruptive peers) is shown in Figure 2B. There is substantial variation in the share of disruptive peers across classrooms, which is expected given the random assignment of students to classrooms.

4 Do Suspension Hours Capture Disruptive Behavior?

In this section, we describe a survey we designed and distributed in September 2022, which aimed to gain deeper insights into the aspects of student behavior that suspensions capture and how these behaviors may influence the learning environment. Based on this survey, we are able to assess whether absences due to suspensions are linked to classroom disruption levels and explore the underlying reasons for student suspensions. We then turn to our administrative data to investigate which students are more likely to accumulate suspension hours. Specifically, we analyze whether students with different prior academic performance and gender exhibit varying levels of disruptiveness, and we assess whether our findings align with established research in the literature.

4.1 Survey Data Evidence

We supplemented the administrative and school archive data with a survey questionnaire that involved approximately 700 high school students. The survey was administered to students in 31 classrooms across grades 10, 11, and 12 in five public schools in September 2022. We collected information on students' perceptions regarding whether they had observed disruptive peers receiving absences as a penalty for their behavior and the types of behavior that led to unexcused absences. We focus on two key questionnaire items that provide insights into how unexcused absences (i.e., suspension hours) are used in the classroom and the reasons teachers expel students.

Figure 3 is based on a questionnaire item that asked students "Have you witnessed the use of hourly unexcused absences as a penalty for disruptive students?" Students could respond with "Yes" or "No." A significant 89.37% of students reported having seen disruptive students receive absences as a penalty (Panel a) and responses were consistent across both male and female students (Panels b and c). This confirms our belief that unexcused absences or suspensions are commonly used by teachers as a disciplinary measure for disruptive behavior in the classroom. Figure 4A reports survey responses by students to the following questionnaire item: "In what way can a student in your classroom behave to receive unexcused absences as a penalty?" Students could select multiple options, including "Disrupting Others' Attention," "Making Noise," and "Being Disengaged." The results show that 92.14% of students reported that "Making Noise" was a common reason for unexcused absences; 62.68% cited "Disrupting Others' Attention"; and 11.48% chose "Disengagement." Responses were consistent across male and female students, as shown in Figures 4B and Figure 4C. These findings suggest that suspensions are primarily used to mitigate the negative externalities caused by disruptive students in the classroom, and particularly behaviors such as making noise and disrupting other students' attention.

4.2 Administrative Data Evidence

Using our administrative data, we examine the association between low-achieving students and disruption in the classroom, as identified in previous studies (e.g., Lavy, Paserman, and Schlosser, 2011). Figures 5 and 6 display histograms of baseline suspension hours by student performance at student and classroom levels. Figure 5A shows the distribution of suspension hours for students above (gray) and below (light green) the median baseline performance. The distribution for lower-achieving students is shifted to the right, which indicates that they are suspended more frequently than higher achievers. A similar pattern emerges in Figure 5B, in which we plot the same distributions for students in the top 25% and bottom 25% of baseline performance. A large share of high achievers are never suspended, whereas low-achieving students are frequently suspended. We then plot the same distributions at classroom level. Both Figures 6A and 6B reveal the same pattern: Low achievers in a classroom are suspended much more frequently than high achievers, on average. This demonstrates that low-performing students are significantly more likely to accumulate suspension hours compared with their high-performing peers, which suggests that suspension hours may be indicative of truancy-related behaviors.[12]

We next examine whether there are differences in suspension hours by student gender. Previous studies have found that boys tend to be more disruptive than girls (Lavy and Schlosser, 2011; Goulas, Megalokonomou, and Zhang, 2023). Panel A of Online Figure A4 plots the distribution of student-level suspension hours for males and females. While the pattern is not stark, there is some evidence that boys accumulate more hours of suspension at high levels of suspension compared with girls. We also perform t-tests for these gender differences: Boys are suspended approximately 1.2 hours more than girls (14.39 vs. 13.18 hours, with an SE of the difference = 0.290). Panel B of Online Figure A4 presents the share of disruptive peers in the classroom by gender. The share of disruptive peers is

[12]While a high number of suspension hours is clearly associated with lower performance, this association is weaker when considering sickness-related absences. Figure 7 illustrates the association between students' sickness-related *absences* and baseline performance (Figure 7A), and between suspension hours and performance (Figure 7B). As sickness-related absences increase, median performance remains relatively stable. In contrast, students with a significant number of suspension hours have lower median baseline performance compared with those with fewer than 5 hours of suspension. Figures A2 and A3 show histograms of baseline sickness-related absences by student baseline performance at both student and classroom levels, respectively.

calculated as the percentage of students with more than 20 suspension hours at baseline, divided by the total number of students in the classroom. While the histograms do not reveal a clear pattern, a t-test shows that about 30% of males are classified as disruptive, compared with only 25% of females (t-stat = 4.97).[13]

These findings align with prior literature in economics, which highlights the fact that low-achieving students and boys tend to exhibit more disruptive behavior.

5 Theoretical Framework

5.1 Baseline Model

We present a theoretical framework to guide the empirical analysis of how disruptive students impact their peers' educational outcomes. Consider a population of n students in a classroom with n^D disruptive and n^{ND} non-disruptive students, with $n = n^D + n^{ND}$. N^D and N^{ND} refer to the set of disruptive and non-disruptive students, respectively. We denote the (leave-out) mean of suspension hours in the classroom c by q_c^{-i}. In the data, q_c^{-i} captures our first measure of disruptiveness: the baseline average suspension hours (see equation (1)). Also, q_c^{-i} can alternatively represent our second measure of disruptiveness defined in (see equation (2)): the share of disruptive students in the classroom (those with more than 20 hours of baseline suspensions), excluding the student in question. In this model, we take q_c as given, an assumption we relax in the following subsection.

Consider equation (2). Define the $(n \times 1)$ vector $\mathbf{q}_c$, where the first n^{ND} entries, corresponding to non-disruptive students in the classroom, are set to zero, and the following n^D entries, representing disruptive students, are set to one. Then, the share of disruptive students in classroom c is equal to

$$q_c = \frac{1}{n}\mathbf{q}_c^{\mathrm{T}}\, \mathbf{1}_n, \tag{3}$$

where $\mathbf{1}_n$ represent the $(n \times 1)$ vector of ones, and let $\mathbf{x}^{\mathrm{T}}$ denote the transpose of vector $\mathbf{x}$. Define $\mathbf{q}_{[-i]c}$ as the $(n \times 1)$ vector obtained by setting the i-the entry to zero while leaving all other entries unchanged. The *leave-out* share of disruptive students in classroom c is defined as

$$q_c^{-i} = \begin{cases} \frac{1}{n}\mathbf{q}_c^{\mathrm{T}}\, \mathbf{1}_n & \text{if} \quad i \in N^{ND} \\ \frac{1}{n}\mathbf{q}_{[-i]c}^{\mathrm{T}}\, \mathbf{1}_n & \text{if} \quad i \in N^D \end{cases} \tag{4}$$

Using definition (1), we can similarly define q_c^{-i} in terms of baseline average suspension hours by inserting hours in place of individuals. Education outcomes y_c^i (e.g., test scores, long-term outcomes)

[13] Online Figure A5 shows the distribution of excused (sickness-related) absences by gender. We observe no significant differences in sickness-related absences between males and females. On average, males receive 6.82 hours of sickness-related absences at baseline, while females receive 6.71 hours (a difference of 0.114 hours with an SE of 0.301). Following an approach similar to the previous analysis, we calculate the share of peers with frequent sickness-related absences, defined as those with more than 11 hours of excused absences at baseline (75$^{\text{th}}$ percentile). This share is then divided by the total number of students in the classroom. We find no significant differences in this category: 25.04% of males are identified as frequently sick, compared with 25.5% of females (a difference of -0.005 with an SE of 0.01).

for student i in classroom c are modeled as follows:

$$y_c^i = a_c^i + \theta q_c^{-i} + \rho s_c^i + \varepsilon_c^i, \tag{5}$$

where s_c^i represents the study effort chosen by student i, a^i is a fixed parameter that captures the student's baseline education outcomes (e.g., test scores), and ε_c^i is an unobserved error term. We assume that $\theta < 0$, meaning that a higher share of disruptive peers or a higher mean of suspension hours (q_c^{-i}) leads to lower education outcomes,and $\rho > 0$, meaning that greater study effort (s_c^i) results in improved test scores.

Each student i chooses their effort s_c^i to maximize the following utility function:

$$u_c^i = b_c^i \, y_c^i - \frac{1}{2}\left(s_c^i\right)^2 + \phi \, y_c^i \, \overline{y}_{0,c}^{-i}, \tag{6}$$

where $\overline{y}_{0,c}^{-i}$ is classroom peers' average baseline performance, excluding student i (the subscript 0 refers to baseline). For q_i^{-i}, we define

$$\overline{y}_{0,c}^{-i} = \frac{1}{n}\mathbf{y}_{0,[-i]c}^{\mathrm{T}}\mathbf{1}_n, \tag{7}$$

where $\mathbf{y}_{0,[-i]c}$ is the $(n \times 1)$ vector derived from the vector of test scores $\mathbf{y}_c = (y_i^c)$ by setting the i-th entry to zero while keeping all other entries unchanged. In equation (6), $\phi > 0$ represents the intensity of spillover effects, which implies that the higher the average ability in the classroom, the greater the marginal benefit of student i's own test score for their utility. Here, b_c^i denotes the marginal private benefit of test scores for student i, composed of both observable characteristics (e.g., gender, parents' income) represented by $\mathbf{x}^i\beta$ and unobservable characteristics ξ_c^i. Specifically, $b_c^i = \mathbf{x}^i\beta + \xi_c^i$. In this utility function, student i derives utility from their educational outcomes y_c^i but must incur a cost in terms of the effort s_c^i.

The utility function (6) consists of two parts. The first term, $b_c^i \, y_c^i - \frac{1}{2}\left(s_c^i\right)^2$, represents the utility of exerting s_c^i units of effort when there is *no interaction* with other students. The second term, $\phi \, y_c^i \overline{y}_{0,c}^{-i}$, captures the *spillover effects* that student i experiences from the baseline average ability of classmates. This implies that the higher the $\overline{y}_{0,c}^{-i}$—the (baseline) average ability in the classroom—the higher the marginal utility of exerting effort y_i^c.

Each student chooses study effort s_c^i to maximize their utility (6). Using the outcome equation (5), the first-order condition for utility maximization is given by

$$s_c^i = \rho b_c^i + \phi\rho\overline{y}_{0,c}^{-i}. \tag{8}$$

From (5), we also have

$$s_c^i = \frac{y_c^i - a_c^i - \theta q_c^{-i} - \varepsilon_c^i}{\rho}. \tag{9}$$

Substituting this expression into the first-order condition yields

$$y_c^i = \rho^2 b_c^i + a_c^i + \phi\rho^2 \overline{y}_{0,c}^{-i} + \theta q_c^{-i} + \varepsilon_c^i,$$

or equivalently

$$y_c^i = a_c^i + \theta q_c^{-i} + \widetilde{\phi}\, \overline{y}_{0,c}^{-i} + \widetilde{b}_c^i + \varepsilon_c^i, \tag{10}$$

where

$$\widetilde{b}_c^i := \rho^2 b_c^i \text{ and } \widetilde{\phi} := \phi\rho^2.$$

In particular, since $b_c^i = \mathbf{x}_c^i \beta + \xi_c^i$, the term $\widetilde{b}^i$ depends on both observable $\mathbf{x}^i\beta$ and unobservable ξ^i characteristics.

We can solve the Nash equilibrium of this game for all students. By writing (10) in matrix form, we obtain

$$\mathbf{y}_c = \mathbf{a}_c + \theta\, q_c^{-i} \mathbf{1}_n + \widetilde{\phi}\, \overline{y}_{0,c}^{-i}\, \mathbf{1}_n + \widetilde{\mathbf{b}}_c + \boldsymbol{\varepsilon}_c,$$

where q_c^{-i} is given by (4), $\overline{y}_{0,c}^{-i}$ by (7), $\mathbf{a}_c$ is the $(n \times 1)$ vector of a_i^c, $\widetilde{\mathbf{b}}_c$ is the $(n \times 1)$ vector of $\widetilde{b}_c^i$, and $\boldsymbol{\varepsilon}_c$ is the $(n \times 1)$ vector of ε_c^i. Since these equations are independent, there clearly exists a unique interior equilibrium given by (10).

This simple model describes students' optimal study effort as a function of a convex combination of their observable and unobservable characteristics, as well as the (leave-out) average test score in the classroom (see equation (8)). This effort, in turn, impacts their educational outcomes, such as test scores (see equation (10)). Specifically, educational outcomes are influenced by individual study effort and the intensity of classroom disruptiveness—a relationship we will empirically examine in the following sections.

5.2 Modeling Peer Disruptiveness

In the model presented in Section 5.1, we assume $\theta < 0$, meaning that q_c, the share of disruptive students, negatively affects student test scores. In this section, rather than simply assuming this relationship, we aim to derive it, providing insights into the underlying structure. Consider utility (6), but now assume it is defined by the following expression:

$$u_c^i = b_c^i y_c^i - \frac{1}{2}\left(s_c^i\right)^2 + \phi\, y_c^i\, \overline{y}_c^{-i}, \tag{11}$$

where $\overline{y}_c^{-i}$ represent the actual, rather than the baseline (leave-out), average test score in classroom c. Since our goal is to derive q_c, outcome equation (5) can be rewritten as follows:

$$y_c^i = a_c^i + \overline{y}_{0,c}^{-i} + \rho s_c^i + \varepsilon_c^i. \tag{12}$$

By plugging (12) into (11), we obtain

$$\begin{aligned} u_c^i &= b_c^i y_c^i - \frac{1}{2}\left(s_c^i\right)^2 + \phi\, y_c^i\, \overline{y}_c^{-i} \\ &= b_c^i\left(a_c^i + \overline{y}_{0,c}^{-i} + \rho s_c^i + \varepsilon_c^i\right) - \frac{1}{2}\left(s_c^i\right)^2 + \phi\,\left(a_c^i + \overline{y}_{0,c}^{-i} + \rho s_c^i + \varepsilon_c^i\right)\overline{y}_c^{-i}. \end{aligned}$$

Each student chooses s_i^c that maximizes this utility function. The first-order condition is given by

$$s_c^i = \rho b_c^i + \phi\,\rho\,\overline{y}_c^{-i} \tag{13}$$

Note that from (12), we have

$$s_c^i = \frac{y_c^i - a_c^i - \overline{y}_{0,c}^{-i} - \varepsilon_c^i}{\rho}$$

Plugging this value of s_i^c into (13) yields

$$y_c^i = \widetilde{b}_c^i + \overline{y}_{0,c}^{-i} + \widetilde{\phi}\,\overline{y}_c^{-i}, \tag{14}$$

where

$$\widetilde{b}_c^i := \rho^2 b_c^i + a_c^i + \varepsilon_c^i,$$

and

$$\widetilde{\phi} := \phi\,\rho^2$$

In order to gain additional intuition from the model and derive closed-form solutions to the equilibrium of this game, we assume that all disruptive students have the same characteristics (that is, the same b_c^i, the same a_c^i, and the same ε_c^i); i.e., $\widetilde{b}_c^i = \widetilde{b}_c^D$ for all disruptive students and all non-disruptive students have the same characteristics—i.e., $\widetilde{b}_c^i = \widetilde{b}_c^{ND}$ for all non-disruptive students.[14] We also assume that they have the same baseline average ability—i.e., $\overline{y}_{0,c}^{-i} = \overline{y}_{0,c}^{-D}$ for all $i \in N^D$, and $\overline{y}_{0,c}^{-i} = \overline{y}_{0,c}^{-ND}$ for all $i \in N^{ND}$. Under these assumptions, there are only two study effort levels, s_c^D and s_c^{ND}, and thus two test scores for the n^{ND} non-disruptive students and the n^D disruptive students, denoted by y_c^{ND} and y_c^D. The average test score in the classroom can then be written as

$$\overline{y}_c = q_c y_c^D + (1-q_c) y_c^{ND},$$

where $q_c = n^D/n$ is the fraction of disruptive students in the classroom. This implies that

$$\overline{y}_c^{-i} = \begin{cases} q_c y_c^D + (1-q_c) y_c^{ND} - \frac{y_c^D}{n} & \text{for} \quad i \in N^D \\ q_c y_c^D + (1-q_c) y_c^{ND} - \frac{y_c^{ND}}{n} & \text{for} \quad i \in N^{ND} \end{cases} \tag{15}$$

[14]This assumption is obviously relaxed in the empirical section.

The first-order condition (14) can then be written as

$$y_c^i = \begin{cases} \widetilde{b}_c^D + \overline{y}_{0,c}^{-D} + q_c y_c^D + (1-q_c) y_c^{ND} - \frac{y_c^D}{n} & \text{for} \quad i \in N^D \\ \widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND} + q_c y_c^D + (1-q_c) y_c^{ND} - \frac{y_c^{ND}}{n} & \text{for} \quad i \in N^{ND} \end{cases}$$

This leads to

$$y_c^D = \frac{\widetilde{b}_c^D + \overline{y}_{0,c}^{-D} + (1-q_c) y_c^{ND}}{1 + (1-q_c)\, n} n,$$

$$y_c^{ND} = \frac{\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND} + q_c y_c^D}{1 + q_c n} n.$$

By solving these two equations, we can compute the unique equilibrium quantities of test scores as follows:

$$y_c^D = \frac{\left(\widetilde{b}_c^D + \overline{y}_{0,c}^{-D}\right)(1 + q_c n)\, n + \left(\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND}\right)(1-q_c) n}{\left(1 + (1-q_c)\, n\right)(1 + q_c n) - (1-q_c) q_c n}, \tag{16}$$

and

$$y_c^{ND} = \frac{\left(\widetilde{b}_c^D + \overline{y}_{0,c}^{-D}\right) q_c n + \left(\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND}\right)\left(1 + (1-q_c)\, n\right) n}{\left(1 + (1-q_c)\, n\right)(1 + q_c n) - q_c (1-q_c) n}. \tag{17}$$

We have thus derived a relationship between test scores and the share q_c of disruptive students in the classroom, a relation that was assumed in equation (5). Thus,

$$\frac{y_c^{ND}}{y_c^D} = \frac{\left(\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND}\right)\left(1 + (1-q_c)\, n\right) n + \left(\widetilde{b}_c^D + \overline{y}_{0,c}^{-D}\right) q_c n}{\left(\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND}\right)(1-q_c) n + \left(\widetilde{b}_c^D + \overline{y}_{0,c}^{-D}\right)(1 + q_c n)\, n}.$$

This implies that

$$y_c^{ND} > y_c^D \text{ iff } \left(\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND}\right) \frac{(1 - 2q_c)\, n}{\left(q_c\,(n-1) + 1\right)} > \widetilde{b}_c^D + \overline{y}_{0,c}^{-D}.$$

Proposition 1 *Assume that $q_c \leq 1/2$ (the majority of students are not disruptive). Then, for a given n and q_c, $y_c^{ND} > y_c^D$ if and only if $\widetilde{b}_c^{ND} + \overline{y}_{0,c}^{-ND} > \widetilde{b}_c^D + \overline{y}_{0,c}^{-D}$—that is, non-disruptive students tend to have, on average, higher baseline test scores and characteristics that lead them to exert more effort.*

Figure 2B illustrates that, in most cases, fewer than 50% of students are non-disruptive, while Table A4 indicates that non-disruptive peers perform better than disruptive ones. A higher q_c negatively affects the classroom's average test score, $\overline{y}c^{-i}$ (see equation (15)), by assigning greater weight to the lower test scores of disruptive students. Due to spillover effects (see utility equation (11)), an increase in q_c reduces $\overline{y}c^{-i}$, thereby lowering the marginal utility of study effort. As a result, students in more disruptive classrooms decrease their study effort, leading to a decline in their test scores (see equation (12)). This model can also be extended by using an alternative measure of classroom disruptiveness—namely, baseline peers' suspension hours.

6 Effect of Disruptive Peers on Academic Performance

6.1 Identifying Variation

We exploit quasi-random variation in classroom composition within school cohorts that results from the alphabetical assignment of students to classrooms. This random assignment of students to classrooms within school cohorts produces exogenous variation in our peer disruptiveness measures. In other words, our identification strategy compares students with the same baseline individual and classroom characteristics. These students may be exposed to different peer disruptiveness because they are assigned to classrooms with peers who exhibit different levels of disruptive behavior. This identification strategy allows us to account for average classroom characteristics that could confound our estimates of interest. Variation in peer disruptiveness measures stems from differences in the disruptive behavior of *random* classroom peers in the same school-cohort. We plot the distribution of the leave-out mean of classroom-level absences due to suspensions (Figure 8A) and the distribution of the share of disruptive peers in one's classroom (Figure 8B), and remove influences at school-cohort level. Figure 8 reveals considerable variation in both disruptiveness measures.[15]

Our setup allows for the impact of peers' disruptiveness to be identified separately from traditional peer effects. Traditional ability peer effects refer to the direct overall influence of one's classroom peers' average baseline ability on his/her outcomes while accounting for one's own baseline ability. Traditional peer effect investigations do not consider the influence of one's peers' noncognitive characteristics, which may vary within baseline ability level. Our empirical approach in this study accounts for traditional peer ability influences by directly controlling for the baseline performance of peers.

6.2 Empirical Strategy

We aim to estimate the effect of *classroom disruptiveness* (measured by either the baseline average suspension hours or the share of disruptive peers) on students' outcomes using equation (10). The econometric equivalent of this equation is

$$y^i_{cst} = \alpha + \theta q^{-i}_{cst} + \widetilde{\phi}\, \overline{y}^{-i}_{0,cst} + \gamma X^i_{cst} + \delta Z_{cst} + \lambda_{st} + \varepsilon^i_{cst}, \tag{18}$$

where the subscripts cst refer to classroom c, school s, and time/cohort t. In this model, q^{-i}_{cst} represents either the (leave-out) fraction of disruptive students or the (leave-out) mean of suspension hours; $\overline{y}^{-i}_{0,cst}$ denotes the average ability in the classroom, which is the leave-out classroom mean of student

[15] For approximately one-quarter of the students, the average baseline suspension time of their peers is below 11 hours. For another quarter of students, the average baseline suspension time of their peers exceeds 16 hours. When examining the proportion of disruptive classroom peers, one-quarter of students are in classrooms in which less than 17% of their peers are disruptive, while another quarter of students are in classrooms with 35% or more disruptive peers.

baseline test scores (average baseline performance on language and math);[16] X_{icst} includes student-level characteristics, such as gender (a binary indicator equal to 1 for females and 0 otherwise), age, an indicator for being born in the first quarter of the year, baseline performance (average baseline scores in language and math), baseline suspension hours, and baseline sickness-related absences; and Z_{cst} is a vector of classroom-level controls, including the classroom peers' average baseline performance (excluding student i), number of students in classroom c, classroom leave-out mean of sickness-related absences, classroom leave-out mean of age, the leave-out mean proportion of female peers, and the leave-out mean proportion of students born in the first quarter (excluding student i). The regression includes school-by-cohort fixed effects (λ_{st}) to control for potential confounding factors, particularly the endogenous sorting of students across schools in a given year. We use robust standard errors to account for heteroskedasticity.[17]

Our identification strategy exploits the variation in peer disruptiveness across classrooms within the same school. The basic idea is to compare the outcomes and educational choices of students from different classrooms within the same school year, who share similar characteristics (including baseline performance) and experience the same school environment. The key difference is that some students are randomly assigned to more disruptive peers than others. Since there is no significant variation in students' observed characteristics and abilities across classrooms within the same school, this approach allows us to isolate the impact of peer disruptiveness on student outcomes.

6.3 Validity of the Identification Strategy

The estimate of θ in equation (18) represents the causal effect of being assigned to disruptive peers or a classroom with a high number of suspension hours, under the assumption that the share of disruptive peers or the number of suspension hours among classmates is uncorrelated with student i's characteristics. This is conditional on classmates' performance, sickness-related absences, and the inclusion of student- and class-level controls. This assumption holds if students are randomly allocated to classrooms. As discussed in Section 2.3, classroom assignments in Greece are strictly mandated by law.

We empirically test the validity of the random assignment of students to classrooms in two ways. First, we examine whether assigning students to classrooms based on alphabetical order can be considered effectively random. In each school, students are allocated to classrooms in alphabetical order, with those at the beginning of the alphabet assigned to class 1, followed by students assigned to classes 2, 3, and so on. To assess the validity of this assignment process, we evaluate whether classroom number is correlated with classroom-level characteristics. Online Table A5 shows that classroom numbers are not systematically associated with classroom characteristics. Specifically, we find that classrooms have similar average baseline performance (both overall and in compulsory subjects), comparable numbers of suspension and sickness-related absences, and similar proportions of

[16]Student baseline performance is measured during the second semester of grade 9.

[17]The results remain robust if we cluster standard errors at classroom level.

disruptive peers. Furthermore, there are no significant differences in classroom size or the proportion of female students, the average age of students, or the proportion of students born in the first quarter of the year.

Second, we examine whether the number of classroom peers' suspension hours and the proportion of disruptive peers within a classroom (both measured excluding the student in question) are correlated with observable student characteristics. This analysis ensures that students are not systematically sorted into classrooms based on attributes such as gender or prior academic performance. Table 2 presents results for the average number of suspension hours in the classroom (Panel A) and the proportion of disruptive peers (Panel B). We find no statistically significant association between the proportion of disruptive peers and individual student characteristics. These findings support the assumption that the distribution of disruptive peers across classrooms is exogenous.

Overall, these investigations reinforce the validity of our identification strategy and confirm that the proportion of disruptive peers is not correlated with classroom or student characteristics. This mitigates concern regarding the randomness of classroom assignment.

7 Results

7.1 Baseline Results

Impact on Test Scores. Table 3 presents our baseline estimated effects of classroom disruptiveness on students' test scores in grades 10 and 11. In Panels A and B, we show the estimated effects of the baseline average suspension hours and the share of disruptive peers on student test scores, respectively. In column 1, we show the effects on standardized end-of-year performance across all subjects, while columns 2 and 3 report the effects on performance in STEM-related and non-STEM-related subjects, respectively.[18] We standardize raw test scores, which range from 0 to 20, by school, grade, and year.

We find that students assigned to classrooms with 1 additional baseline average suspension hour experience a statistically significant drop in their end-of-grade 10 and 11 overall performance by 0.009 and 0.013 standard deviations (SD), respectively. Given that 3.78 hours of suspension corresponds to a 1 SD increase (see Panel B, Table 1), our estimates suggest that a 1 SD increase in the baseline suspension hours of classroom peers is associated with a decrease of approximately 0.03 SD (0.009 $\times$ 3.78) in student test scores at the end of grade 10 and 0.05 SD (0.013 $\times$ 3.78) in student test scores at the end of grade 11.[19] We use a similar approach in interpreting the estimated coefficient of the share of disruptive peers in Panel B. An increase in the share of disruptive peers in the classroom from 0 to 100% reduces overall end-of-grade performance in grades 10 and 11 by 0.230 and

[18]STEM-related subjects include the average standardized performance in math and physics. Non-STEM-related subjects include the average standardized performance in language and history. Math, physics, language and history are compulsory subjects.

[19]These findings are in line with those of Carneiro, Cruz-Aguayo, Salvati, and Schady (2024), who find that having one or more poorly behaving student reduces classmates' performance by 0.019 SD.

0.280 SD, respectively. This implies that a 1 SD increase in the share of disruptive peers leads to a reduction in student test scores of about 0.03 SD (0.230 × 0.13) by the end of grade 10 and grade 11. This calculation is based on information from Panel B in Table 1, which shows that a 1 SD increase in the share of disruptive peers corresponds to 0.13. We find statistically significant effects of our disruptiveness measures on student performance in both STEM and non-STEM subjects, with comparable impacts across the two fields. Our effect size of peer disruptiveness is comparable to the effect of other educational inputs. For instance, the negative effect on test scores is comparable to the positive impact of hiring a teacher whose quality is approximately 0.6-1 SD above the average (Lavy and Megalokonomou, 2024a; Chetty, Friedman, and Rockoff, 2014; Bau and Das, 2020).

Impact on Track Specialization. Next, we present results on the impact of peer disruptiveness on student track specialization decisions at the end of grade 10. There are three specialization options available at every school: competitive science, professional IT, and classics. This is the first specialization decision students make in their school career. Panel A of Table 4 shows that a 1 SD increase in baseline classroom peers' suspension hours reduces the likelihood of enrolling in the most competitive science track by 2.3 (0.006 × 3.78) percentage points (column 1), and raises the likelihood of enrolling in the less competitive professional IT track by 3.4 (0.009 × 3.78) percentage points (column 2). Panel B of Table 4 shows that a 1 SD increase in the share of disruptive peers (Panel B) increases the likelihood of enrolling in the professional IT track by 2 (0.157 × 0.13) percentage points (column 2), while the effect on the likelihood of enrolling in the most competitive science track is negative but imprecise (column 1). The effect on the decision to enroll in the classics track is smaller and imprecise (column 3).

Impact on Retention and Timely High School Graduation. Grade repetition, timely high school graduation, and exam retaking may be critical in shaping students' both immediate and future academic trajectories. Panel A of Table 5 indicates that a 1 SD increase in peer disruptiveness, measured by baseline classroom peers' suspension hours, increases the probability of grade repetition by 1.1 (0.003 × 3.78) percentage points (column 1), decreases the likelihood of graduating from high school on time by 1.1 (0.003 × 3.78) percentage points (column 2), and increases the risk of failing grades 10 and 11 by 1.5 (0.004 × 3.78) percentage points (columns 3 and 4, respectively). When using the share of disruptive students to measure classroom disruptiveness (Panel B), we observe a similar pattern to that in Panel A. Specifically, a 1 SD increase in the proportion of disruptive peers raises the likelihood of grade repetition by approximately 0.7 (0.056 × 0.13) percentage points (column 1) and reduces the probability of timely high school graduation by 0.8 (-0.061 × 0.13) percentage points (column 2). Moreover, a 1 SD increase in the share of disruptive peers raises the likelihood of having to retake exams by about 1 (0.077 × 0.13) and 1.6 (0.125 × 0.13) percentage points in grade 10 (column 3) and grade 11 (column 4), respectively. These findings highlight the consequences of peers' disruptiveness, revealing its role in increasing the risk of academic probation—a critical warning sign linked to students' chances of graduating high school and has far-reaching implications for their future lives and careers (Angrist and Keueger, 1991; Machin, Marie, and Vujić, 2011; Hjalmarsson, Holmlund, and Lindquist, 2015; Cook and Kang, 2016).

Impact on Longer-term Student Outcomes. Next, we examine whether classroom peers' disruptiveness affects student university admissions outcomes, measured 3 years after exposure to peer disruptiveness in grade 10.[20] Table 6 indicates that baseline peers' disruptiveness reduces longer-term outcomes. Panel A of Table 6 shows that a 1 SD increase in the baseline classroom peers' suspension hours in grade 10 reduces performance on national exams taken in grade 12 by 0.053 SD (0.014×3.78), decreases the probability of enrolling in postsecondary education by 2.3 (0.006×3.78) percentage points, lowers the preference rank of the degree to which students are admitted to by more than one place (0.004×3.78), lowers the likelihood that a student is admitted to a top 10 or top 20 department by 1.5 (0.004×3.78) percentage points, and lowers the degree quality students are admitted to by 1.7 (0.438×3.78) percentiles. Panel B of Table 6 shows that when we measure classroom disruptiveness using the share of disruptive peers, the pattern aligns with that observed when using baseline peers' suspension hours as the measure of disruptiveness.This further reinforces the robust effect peers' disruptive behavior on longer-term university outcomes.

Online Table A7 presents evidence on the effects of peer disruptiveness on students' university aspirations and readiness for university attendance. University aspirations are reflected in their preferences during the application process, while readiness is measured by the competitiveness of the degree program they ultimately enroll in. The outcome variables are binary indicators for whether a student applied for or was admitted to a less or more competitive department. We classify departments as less competitive if the average university admissions score for admitted students is below the median, and as more competitive if the score is above the median. Less competitive departments typically include fields such as humanities, economics, professional studies, and business. In contrast, more competitive disciplines often include STEM and health-related fields.

Panel A of Online Table A7 shows that a 1 SD increase in baseline average suspension hours leads to an increase in the likelihood of submitting a college application for a less competitive department by approximately 3.8 (0.010×3.78) percentage points (column 1) and has a close-to-zero effect on the probability of submitting a college application to a more competitive department (column 2). Students exposed to more disruptive classmates are more likely to target less competitive departments in their applications and less likely to gain admission to relatively competitive ones if they do apply. Panel B of Table A7 presents results based on the share of disruptive peers as a measure of classroom disruptiveness, showing a pattern consistent with the findings in Panel A. A 1 SD increase in the share of disruptive peers increases the likelihood of submitting a college application to a less competitive

[20] We present summary statistics of the long-term outcomes in Online Table A6.

department by approximately 3.1 (0.240 × 0.130) percentage points (column 1). It also increases the likelihood of admission to a less competitive department by 2.2 (0.167 × 0.130) percentage points (column 3). At the same time, a 1 SD increase in the share of disruptive peers reduces the likelihood of admission to a more competitive department by 2.5 (0.189 × 0.130) percentage points (column 4).

Classroom peers' disruptiveness increases the likelihood of students applying to or enrolling in less competitive departments, while steering them away from more competitive ones. This pattern aligns with findings in Table 4, where students in disruptive classrooms shift from competitive to less competitive tracks in high school. These results suggest that disruptiveness may diminish students' motivation or aspirations to pursue ambitious, competitive studies. The channels driving these effects are explored in Section 9.

7.2 Robustness Checks

In the main analysis, we define disruptive students as those with baseline suspension hours exceeding 20, a threshold corresponding to the 75$^{\text{th}}$ percentile of suspension hours. This section investigates the robustness of our main results to alternative definitions of disruptive students and demonstrates that varying these definitions produces results consistent with our baseline findings. This section shows evidence that different definitions for disruptive students produce results similar to our main results. The baseline definition for a disruptive student is when their baseline suspension hours are above 20. The reasoning behind this choice was that it corresponds to the to the 75$^{\text{th}}$ percentile of suspension hours.

Panel A of Figure 9 plots the distribution of the share of disruptive peers in the classroom when we set the threshold at 15 (light green), 20 (gray), or 25 hours (red). The distribution for the share of disruptive peers shifts to the right when we lower the baseline suspension hours threshold. Importantly, we observe sufficient variation in the share of disruptive peers across classrooms under all three definitions. Panel B of Figure 9 replicates our main analysis using alternative definitions of disruptive students. Our results consistently show a negative impact on overall performance, regardless of how disruptive students are defined. The effect ranges from -0.3 to -0.1 when disruptive peers are defined as those with over 25 and 15 suspension hours, respectively, reinforcing the robustness of our main findings. These checks demonstrate that the choice of threshold for defining disruptive students does not affect the results, as the adverse effects of peer disruptiveness on test scores remain consistent across reasonable thresholds. We also demonstrate that the main results remain robust when excluding students with suspension hours above the 90$^{\text{th}}$ percentile (Online Table A8) or when randomly dropping 10% of classrooms (Online Figure A6). This indicates that our results are not driven by extreme values in student suspension hours or by specific classrooms.

7.3 Placebo Exercises

One may worry that the observed effects of peer disruptiveness on student performance may be driven by unobserved factors or spurious correlations. To address this, we conduct two placebo tests. First, we use a placebo attendance variable—sickness-related absences—and include it in the main specification alongside the primary treatment variable (peer disruptiveness). Since sickness-related absences typically reflect parent-approved absences related to health rather than disruptive classroom behavior, we expect no significant effect of this variable on student outcomes. This helps validate that our findings are not confounded by unrelated attendance patterns. In Panel A of Online Table A9, we simultaneously include the main treatment variable (baseline peers' suspension hours) and the placebo variable (baseline peers' sickness-related hours). In Panel B, we simultaneously include the main treatment variable (share of disruptive peers) and the placebo variable (share of sick peers). The estimated coefficients of the placebo variables are practically zero, while the estimated effects of the main treatment variables remain almost unchanged.[21] These results indicate that the estimated effects of classroom disruption on student outcomes may not be driven by other attendance channels.

Second, one may worry that the observed effects may be influenced by students in other classrooms rather than their own classroom peers. To address this, we conduct a placebo test by replacing our main variables of interest with measures of disruption from peers within the same school but assigned to different classes and cohorts. Since classroom disruption primarily occurs within the student's own classroom, we expect no significant effect of disruptive behavior from peers in other classrooms on outcomes within their classroom. Online Table A10 shows no statistically significant effects from disruptive behavior of peers in other classrooms. Only one out of 12 coefficients is significant at the 10% significance level, which provides further evidence that disruption has a localized adverse effect within the classroom in which disruptors are present. Overall, these results provide strong evidence that our main findings are not driven by random correlations or unobserved confounding factors, reinforcing the validity of our analysis.

8 Heterogeneous and Non-Linear Effects

8.1 Heterogeneous Effects

In order to gain further insight into the effects of classroom disruptiveness on student outcomes we conduct a series of heterogeneity analyses.

Heterogeneity by Subject. Online Table A11 explores the estimated effect of classroom disruptiveness on performance on different compulsory subjects: physics, language, math, and history. We also present estimated effects on aggregated STEM subjects (physics and math) and non-STEM sub-

[21] Our specifications control for sickness-related absences throughout.

jects (language and history). The adverse effects of peer disruptive behavior are consistent across all subjects, with no significant differences between STEM and non-STEM fields; this underscores the broad detrimental effect of classroom disruption on academic achievement. The pattern is consistent across both Panels A and B.

Heterogeneity by Gender and Baseline Performance. We then examine the potential heterogeneity of the main results by student gender and baseline performance. Column 1 of Online Table A12 reports the baseline estimated effects, while columns 2 and 3 show the estimates for male and female students, respectively. Despite potential differences in learning environments and peer interactions between genders, disruptive behavior negatively impacts both genders in comparable ways. Columns 4 and 5 of Online Table A12 report heterogeneous disruptiveness effects for students stratified by the median baseline standardized performance (median equals 0.17). The adverse effects of disruption are slightly more pronounced among students with performance above the median compared with those below in both Panels A and B. These findings suggest that higher-performing students may be more sensitive to disruptive environments.

Disruptive vs. Non-disruptive Students. In this section, we aim to gain a deeper understanding of how classroom disruptiveness differentially impacts non-disruptive and disruptive students. Online Table A13 shows the effects of classroom disruptiveness on test scores by students' own disruptive status. We find that the impact of disruptiveness is evident for both groups and is, in most instances, slightly larger for non-disruptive students.[22] This highlights the broader implications of classroom disruptiveness, revealing that it not only harms those who exhibit disruptive behavior but also significantly affects their non-disruptive peers.

Heterogeneity by Neighborhood Income. Socio-economic background can play a key role in moderating disruption by amplifying or buffering the adverse impact of disruptive behavior on student performance. Columns 1 and 2 of Online Table A14 present the results for samples stratified by neighborhood household income.[23] We find that the adverse effect of peer disruptiveness is more pronounced in schools located in below-median-income neighborhoods compared with above-median-income neighborhoods. This pattern is clear in both Panels A and B. This suggests that students in less affluent schools are more vulnerable to the negative externalities of peer disruptions compared with those in more affluent areas.[24]

[22] Online Figure A7 illustrates an alternative approach by graphically examining the classroom-level association between disruptiveness and overall performance at the end of grade 10 for both disruptive and non-disruptive students. We find that the negative association is slightly more consistent for non-disruptive students' performance compared with that for disruptive students.

[23] The median household income is 18,414 euros, based on 2009 values.

[24] This differential impact may stem from several factors, including limited resources and weaker institutional support in lower-income neighborhoods. These schools often have fewer counselors, teaching assistants, and extracurricular or academic intervention programs, making it harder to manage and mitigate classroom disruption. At the same

Heterogeneity by Classroom Characteristics. We examine whether aspects of the classroom environment moderate the effects of disruption. We focus on two features: class size and the share of female classmates. Columns 3 and 4 of Online Table A14 report the estimated effects for students in classrooms with below-median and above-median class sizes, respectively. The median class size is 24 students. The adverse effect of peer disruptiveness is more pronounced in *larger classrooms* (above-median size, column 4) than in smaller classrooms (below-median size, column 3). This finding suggests that classroom disruption has amplified negative impacts in larger classes, highlighting the importance of targeting disruption-management strategies to these settings for policymakers. Also, columns 5 and 6 of Online Table A14 show the adverse of peer disruptiveness among students with below- and above-median share of female classmates, respectively. The majority of the results suggest that peer disruptiveness has a more detrimental effect on student test scores in classrooms with a lower share of female classmates compared with those with a higher share. This aligns with studies showing that a higher share of females in a peer group improves classroom learning by creating a less disruptive environment (Lavy and Schlosser, 2011; Goulas, Megalokonomou, and Zhang, 2023). Our findings highlight the role of gender dynamics in classroom behavior and peer interactions, emphasizing the importance of considering gender composition when addressing the effects of peer disruptiveness.

8.2 Nonlinear Effects

In this section, we examine whether the effect of peer disruptiveness on student performance intensifies or diminishes at higher levels, rather than following a linear trajectory. Understanding this relationship is crucial for identifying thresholds or tipping points where disruptive behavior has disproportionately larger impacts. This insight enables policymakers and educators to allocate students and resources more effectively, design targeted interventions, and promote greater equity in educational outcomes. Specifically, we replace our continuous treatment variable (baseline peers' suspension hours or share of disruptive peers) with a set of tertile indicators. By omitting the bottom tertile from the regression, we compare the mean outcomes of students in the middle and top tertiles of disruptiveness to those in the bottom tertile.[25]

Panel A of Table 7 presents the estimated effects of classroom disruptiveness, measured by peers' suspension hours, across tertiles. Specifically, we compare students in the middle and top tertiles of suspension hours to those in the bottom tertile. The results reveal significantly larger negative

time, students in lower-income neighborhoods often face compounded disadvantages, including household stressors like financial insecurity and less access to academic resources, such as tutoring or educational technology. For these students, classroom disruption adds to an already heavy burden, further limiting their academic progress (Morsy and Rothstein, 2015).

[25]The mean baseline peers' suspension hours are 9.83 in the bottom tertile, 14.02 in the middle tertile, and 18.01 in the top tertile. The mean share of disruptive peers is 13% in the bottom tertile, 28% in the middle tertile, and 43% in the top tertile.

effects on overall performance for students in the middle and top tertiles relative to the bottom tertile of peers' suspension hours. Furthermore, the negative impact is more pronounced for students in the top tertile compared with those in the middle tertile. Largely similar patterns are observed for both STEM and non-STEM performance. Panel B of Table 7 reports the estimated effects of the share of disruptive peers on student performance across tertiles. Consistent with Panel A, we find greater negative impacts on overall performance, STEM performance, and non-STEM performance for students in the middle and top tertiles of the share of disruptive peers compared with those in the bottom tertile. The negative impact is more pronounced for students in the top tertile than for those in the middle tertile. These findings highlight a nonlinear relationship, where even moderate levels of peer disruptiveness have substantial negative effects on student outcomes, and these effects intensify further as disruptiveness increases. The nonlinear relationship between classroom disruption and student performance suggests that redistributing students more efficiently across classrooms could help balance disruptiveness within tolerable thresholds.

We conduct a simulation exercise to evaluate how much student performance could improve through a more efficient distribution of disruptive students across classrooms. Specifically, we simulate a counterfactual distribution of classroom disruptiveness by reassigning an equal number of disruptive peers to each classroom within the same school cohort. This approach ensures a balanced distribution of disruptive students across classrooms. Panel A in Online Figure A8 shows the distribution of the proportion of disruptive peers across classrooms under both the observed data and the simulated assignments. In the observed data, classrooms exhibit considerable variation in the share of disruptive peers, whereas the simulated scenario results in a distribution with significantly reduced variance, reflecting the more equal allocation of disruptive students across classrooms.

Using the simulated proportion of disruptive peers, we predict student performance under a counterfactual scenario. Panel B of Online Figure A8 compares the distributions of actual and predicted student performance at the end of grade 10 under the original and simulated classroom assignments. The simulated distribution indicates an improvement in the performance of low-performing students, with the share of students above the median performance level increasing from 50.88 to 53.22 percent. This highlights the benefits of a more balanced allocation of disruptive peers. The simulation exercise provides valuable insights into the potential advantages of alternative strategies for allocating disruptive students within school cohorts. Our findings suggest that the negative effects of classroom disruptiveness on student performance can be significantly reduced under more balanced classroom compositions, effectively mitigating the externalities associated with disruptive peers.

9 Mechanisms Behind the Impact of Peer Disruptiveness

The theoretical framework in Section 5 describes how classroom disruptiveness affects students' utility through its impact on performance. This approach allows us to consider an indirect effect through reduced study effort, which we investigate in the Subsection 9.1. Specifically, classroom disruption may distract students, impairing their concentration and shaping negative attitudes toward learning. Over time, this can decrease motivation, reduce engagement, and diminish confidence or aspirations about their potential achievements (Finn and Zimmer, 2012; Blank and Shavit, 2016; Felkey, Dziadula, and Chiang, 2023). We investigate this channel in Section 9.1 using a lab-in-the-field experiment we conducted to gain deeper insights into the underlying mechanisms. In Subsection 9.2, we explore an additional framework, which suggests that peer disruptiveness generates behavioral spillover effects, influencing students to adopt more disruptive behaviors when surrounded by disruptive peers.

9.1 Changes in Motivation and Readiness Outcomes

9.1.1 Theoretical Insights

Section 5 provided a conceptual framework for the direct impact of peer disruptiveness in the education production function. An additional key channel may operate through student motivation. Specifically, students in contexts with higher disruptiveness levels may be less motivated to exert study effort. To incorporate this mechanism, we extend the benchmark model from Section 5.1 by modifying the utility function (6) as follows:

$$u_c^i = b_c^i y_c^i - \frac{1}{2}\left(s_c^i - \theta_s q_c^{-i}\right)^2 + \phi y_c^i \overline{y}_{0,c}^{-i}, \tag{19}$$

where $\theta_s < 0$.

The primary implication of this new utility function is that, for a given test score y_c^i, the cross-effect of q_c^{-i} and s_c^i on utility u_c^i is negative and given by:

$$\frac{\partial^2 u_c^i}{\partial s_c^i \partial q_c^{-i}} = \theta_s < 0. \tag{20}$$

Previously, with the utility function in (6), this cross-effect was zero. This new formulation implies that a higher fraction of disruptive students in classroom c reduces the utility derived from study effort s_c^i (i.e., motivation). In other words, a higher fraction of disruptive students discourages individual students from exerting greater study effort. We assume the production function remains unchanged, as specified in (5), with θ replaced by θ_y.

Each student chooses their study effort s_c^i to maximize utility (19). Using the outcome equation (5), the first-order condition for utility maximization is:

$$s_c^i = \rho b_c^i + \phi \rho \overline{y}_{0,c}^{-i} + \theta_s q_c^{-i}. \tag{21}$$

Compared with (8), the equilibrium study effort is now *directly* (and negatively) influenced by q_c^{-i}, the fraction of disruptive students in classroom c. By assuming $\theta := \theta_s + \theta_y$, we derive the same equation (10) to determine the equilibrium test score y_c^i.

The implication of this simple model is that as the proportion of disruptive students rises, the utility students gain from their study efforts diminishes (see equation (20)). Thus, students, aiming to maximize their utility, reduce their study efforts, reflecting a declined study motivation as q_c^{-i} increases.

9.1.2 Lab-in-the-Field Experimental Design

We conducted a survey-based randomized experiment in which students were randomly exposed to different scenarios of disruption levels. We administered the survey instrument to 693 students across 31 classrooms in grades 11 and 12 in five public schools in October 2022. Participation was voluntary and anonymous. Forty-nine students either did not report their gender or failed to respond to at least one of the randomized scenario questions, which results in a final analytic sample of 644 students.

The study was designed and conducted in close collaboration with local school authorities, school principals, and head teachers. The experiment took place during the first hour of the school day, aligning with students' routine educational activities. Each classroom's teacher remained unobtrusive at the back of the room while the research team introduced and supervised the survey. Students completed the survey at their usual desks using traditional paper-and-pencil methods. The process lasted approximately five minutes. Paper copies were generated using a computer-based randomization process to ensure that scenarios were randomly assigned to participating students.

The experiment included two basic scenarios: having one disruptive student in the classroom or having one-third of the classmates being disruptive. The scenario that involved one class disruptor is framed as follows: "Imagine the following scenario: You are a grade 10 student. In your class, last week, 1 student in your classroom was suspended because they interrupted the lesson. Do you believe that exposure to this disruptive peer in your classroom, regardless of their performance, would affect you in terms of." The scenario that involved multiple class disruptors is the following: "Imagine the following scenario: You are a grade 10 student. In your class, last week, one-third of your classmates were suspended because they interrupted the lesson. Do you believe that exposure to this disruptive peer in your classroom, regardless of their performance, would affect you in terms of."

Participants were asked to rate the perceived or expected impact of peer disruptiveness on various noncognitive outcomes using a 0-100 scale, where 0 indicated no influence and 100 represented the highest possible influence. We examine four potential response outcomes that represent channels through which disruptive students may influence their peers: changes in study motivation, career aspirations, readiness to study science, and career readiness. Within each treatment condition, students were randomly assigned one of two prompts specifying whether the disruptive student(s) was/were seated physically close to them in the classroom or far away. The full questionnaire is available in both English and Greek in the Online Appendix.

At the start of the survey-experiment, participating students provided consent and demographic information, including their gender, the grade they are in, and their chosen high school study track. Students were then asked about their perceptions of unexcused absences and disruptive behavior in the classroom (described in Section 4.1). Online Table A15 presents summary statistics for survey participants' main characteristics. The results indicate balance in the characteristics of respondents exposed to the different disruptor profiles.[26]

9.1.3 Results

We investigate four potential mechanisms that may explain the adverse effects of classroom disruptiveness on students' outcomes: decreased perceived/expected study motivation, college aspiration, readiness to study science and career readiness when exposed to multiple, compared with a single, class disruptor. To explore these channels, we estimate a regression specification for each mechanism, using an indicator variable that captures whether a respondent was exposed to the multiple disruptor scenario relative to the single disruptor scenario, conditional on controls. All mechanisms are standardized with a mean of 0 and a standard deviation of 1. Controls include an indicator for the respondent's gender (female), a STEM track choice indicator, an indicator for whether the disruptor(s) were physically close to the respondent in the scenario, grade fixed effects, and class fixed effects. Table 8 shows that students exposed to the multiple class disruptors scenario, compared with the single disruptor scenario, report a 14% of an SD decrease in perceived study motivation, a 16% of an SD decrease in perceived college aspiration, an 11% of an SD decrease in perceived science study readiness, and a 14% of an SD decrease in perceived career readiness. All estimates are precisely measured, except for the effect on study motivation, which is less precise. These results suggest that higher levels of classroom disruption are associated with decreased motivation and lower student perceptions of their potential achievements. These effects may help explain the main findings presented in Section 7.1. This table also provides empirical support for equation (21).

We then examine whether the results vary based on the physical proximity of the disruptive student to the respondent. This analysis is presented in Table 9, where we estimate the same regression as in Table 8 using two subsamples: students seated physically close to the disruptive peers and those seated farther away. Columns 1-4 report the estimated effects of having multiple class disruptors compared with a single disruptor for students seated close to the disruptors, while columns 5-8 present the corresponding effects for students seated farther away. The results in Table 9 suggest that the effects of classroom disruption are more pronounced for students seated near disruptive peers. These students report decreases in perceived study motivation and college aspirations by

[26] We compare the characteristics of respondents who were exposed to one class or multiple class disruptors. In columns (1)-(3), we present summary statistics (mean, standard deviation, and number of observations) for the full sample. In columns (4)-(6) and (7)-(9), we focus on respondents who were exposed to the one class disruptor scenario and the multiple class disruptor scenario, respectively. Columns (10) and (11) report the differences in means and the P-value of the differences between individuals assigned to scenarios of one compared with multiple class disruptors, respectively. Online Table A16 shows balance in respondents' characteristics exposed to the secondary treatment—i.e., being physically close or distant from the disruptive peer.

2.4% and 2.6% of an SD, respectively, and declines in science study readiness and career readiness by 2.8% and 1.7% of an SD, respectively. Our results underscore the role of seating arrangements in mitigating classroom disruption. Targeted interventions for disruptive students and teacher training in classroom management can help mitigate the negative impact on classmates' motivation and readiness and ultimately foster a more supportive learning environment. Such low-cost interventions may be particularly effective in disadvantaged settings, in which disruptions are frequent and reducing them has shown significant benefits (Goulas, Megalokonomou, and Zhang, 2023).

Our investigation into mechanisms reveals that the number of classroom disruptors is negatively associated with students' motivation, aspirations, and readiness for academic and career pursuits, which is in line with the predictions of the model in Section 9.1.1. These adverse effects are more pronounced for students seated closer to disruptive peers. Additionally, peer disruptiveness may indirectly affect student outcomes by shifting teachers' focus from instruction to behavior management, and thus potentially reduce the quality of instruction and support provided to students.[27]

9.2 Disruptiveness and Instructional Time

There is growing evidence highlighting the critical role of instructional time in shaping students' outcomes (Rivkin and Schiman, 2015; Lavy and Megalokonomou, 2024b; Caetano, Kinsler, and Teng, 2019; Goulas, Megalokonomou, and Zhang, 2023; Lavy, 2015). Disruptive students can influence their peers by triggering a contagion effect, where others adopt similar disruptive behaviors. This dynamic increases peers' suspension hours, reduces instructional time, and hinders their ability to grasp key concepts or complete assignments, ultimately leading to lower test scores. In Table A17, we examine whether classroom peers' disruptiveness affects student outcomes, including end-of-year suspensions in grade 10 (columns 1-2), end-of-year sickness-related absences in grade 10 (columns 3-4), and the likelihood of becoming disruptive (having suspension hours in the 75$^{\text{th}}$ percentile or higher) at the end grades 10 and 11 (columns 5-6). We find no evidence that exposure to more disruptive peers is associated with changes in student suspension hours, sickness-related absences, or the likelihood of being classified as disruptive. This pattern remains consistent across Panels A and B. Overall, we find no evidence of changes in instructional time or contagion effects due to peer disruptiveness.

10 Conclusion

Measuring the extent to which students' noncognitive attributes affect their classroom peers has been difficult due to data limitations and methodological issues. This study combines a novel theoretical framework, direct measures of student disruptiveness, quasi-random peer group formation, and a lab-in-the-field experiment to study how disruptive students impact their peers' performance, choices, and career prospects. Specifically, we leverage a natural experiment that randomly assigns students

[27] A recent study finds no difference in teacher effectiveness by class size, which suggests that high-quality teachers can effectively manage classes of varying sizes (Lavy and Megalokonomou, 2024a).

to classrooms and new administrative data that allow us to measure student disruptiveness with prior-semester class suspensions. The panel structure of our data further allows us to control for school-by-year fixed effects and identify externalities by comparing classrooms with varying levels of student disruptiveness within the same school cohort. This setup allows us to estimate the impact of peer disruptiveness on student outcomes while mitigating the reflection problem that has complicated previous studies.

We find that students exposed to more disruptive classrooms experience lower academic achievement in both the short and the longer term. We also find that students assigned to more disruptive classrooms face a higher risk of grade retention, a lower likelihood of graduating from high school on time, and are less likely to pursue competitive STEM fields, or enroll in selective postsecondary programs. We also demonstrate that these adverse effects are amplified in larger classrooms, poorer neighborhoods, and classrooms with a lower proportion of female students. Our lab-in-the-field experiment indicates that peer disruptiveness decreases motivation for study effort, college study aspirations, and science study and career readiness.

The negative impact of disruptive students on their peers' educational outcomes has important policy implications for school administrators and policymakers. A key takeaway is the need for targeted interventions to minimize classroom disruptions and ensure an equitable learning environment. Policies that focus on early identification and support for disruptive students—such as behavioral interventions, counseling, or alternative disciplinary approaches like social and emotional learning (SEL) programs[28]—can benefit not only the disruptive students but also their peers by mitigating the adverse effects of disruptiveness. Schools in lower-income areas, where these impacts are often more pronounced, may require additional resources such as smaller class sizes, specialized staff, or increased access to mental health services. Our study highlights key policy tools, such as redistributing disruptive students more evenly across classrooms and adopting seating arrangements that minimize the impact on peers seated near disruptive students.

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[28]Although De Chaisemartin and Navarrete (2023) do not find effects of SEL programs on targeted disruptive students in Chile, the broader literature suggests these programs are effective in reducing disruptiveness, particularly in high-income countries (Payton, Weissberg, Durlak, Dymnicki, Taylor, Schellinger, and Pachan, 2008).

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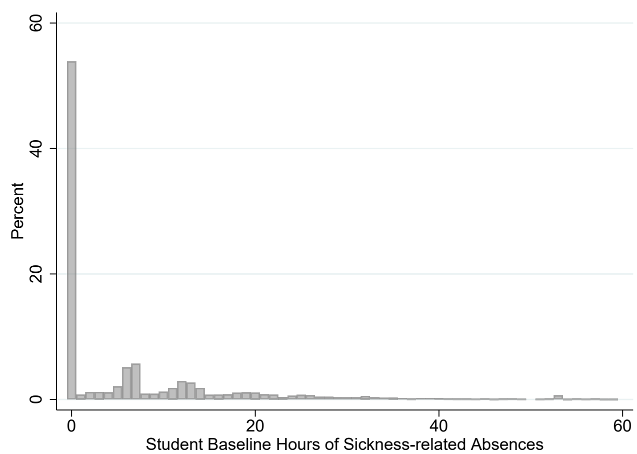
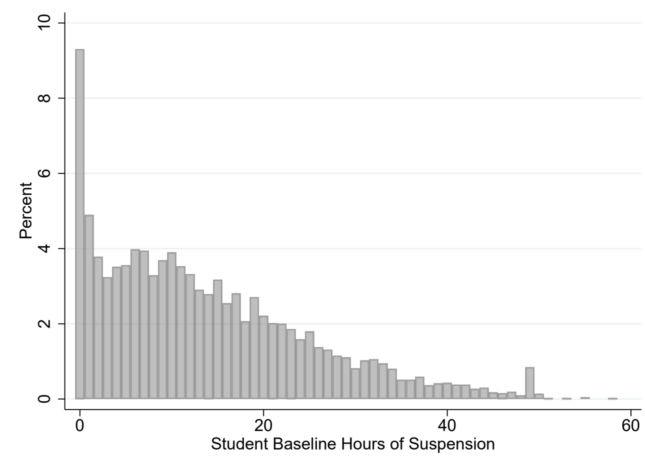
Main Figures and Tables

Figure 1: Distribution of Sickness-related and Suspensions Absences at Student and Classroom Level

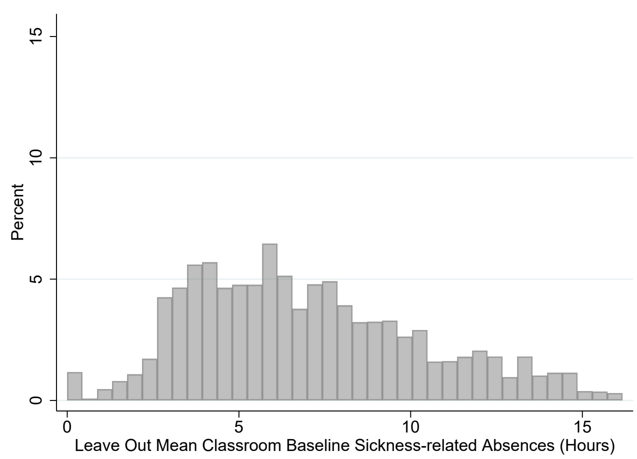
(A) Baseline Sickness-related Absences



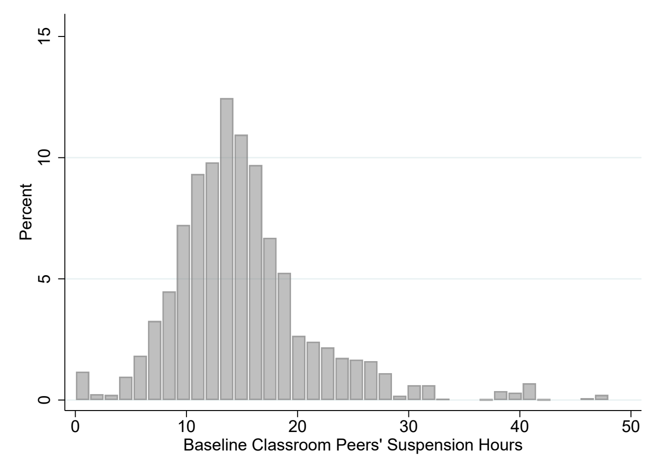
(B) Baseline Hours of Suspension



(C) Average Class Sickness-related Absences



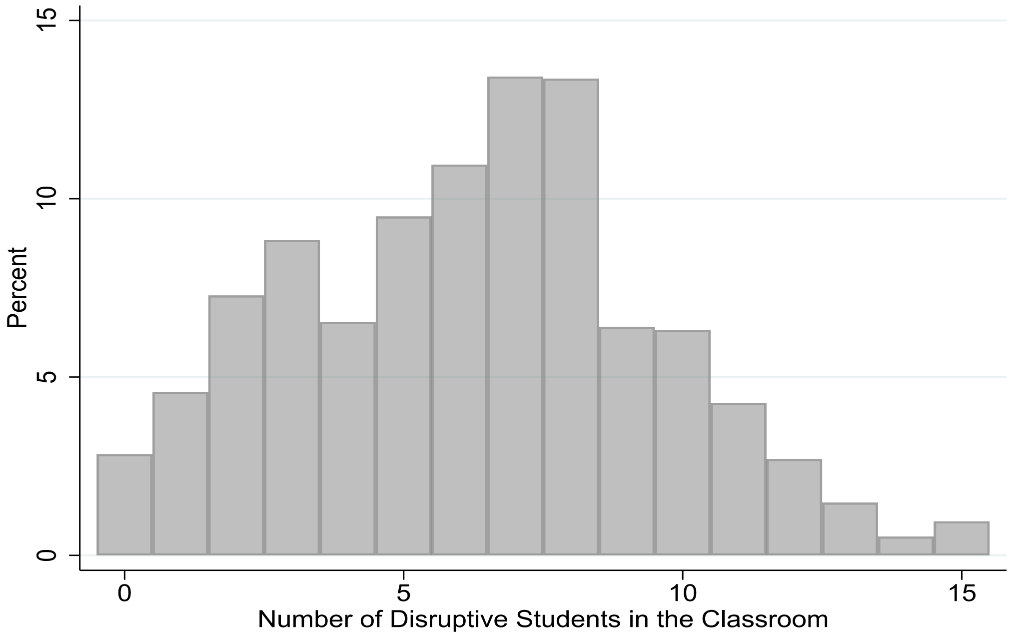
(D) Baseline Classroom Peers' Suspension Hours



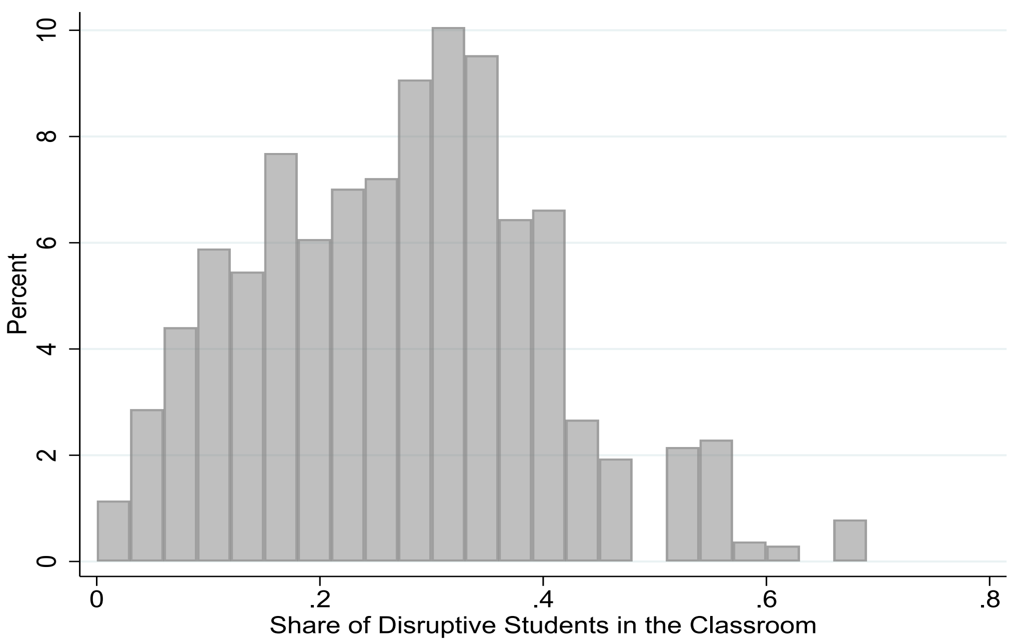
Notes: The figure plots the distribution of student-level (top panels) and class-level (bottom panels) hours of baseline absences due to sickness (Panels A and C) and hours due to suspensions (Panels B and D). Panels (A) and (B) show student-level histograms, while in Panels (C) and (D) class average absences are computed as leave-out mean.

Figure 2: Distribution of Number and Share of Disruptive Peers

(A) Number of Disruptive Students in the Classroom



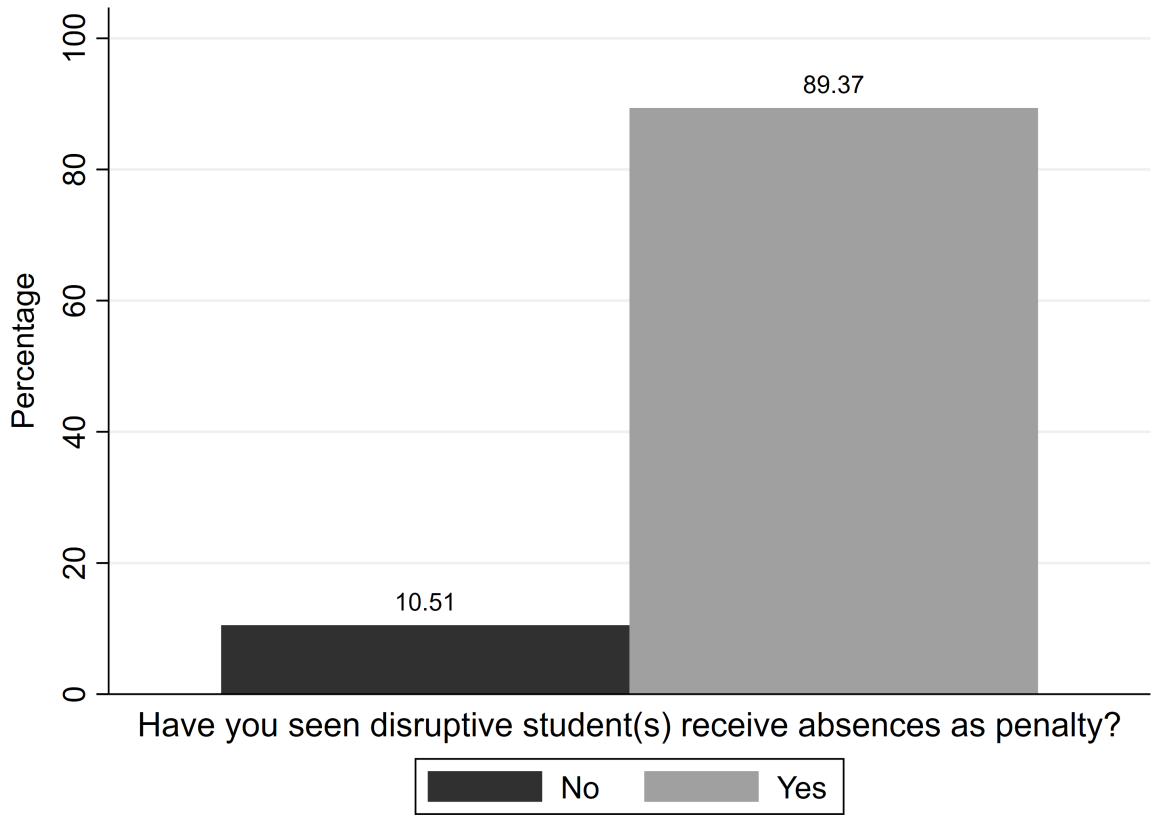
(B) Share of Disruptive Students in the Classroom



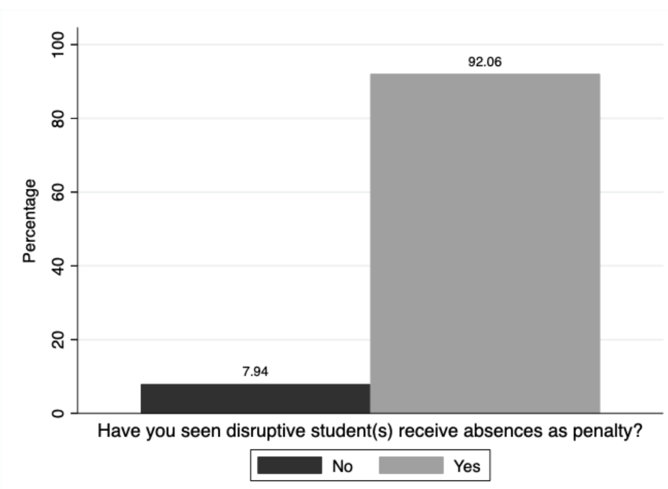
Notes: Figure (A) plots the number of disruptive students in the classroom. Figure (B) plots the share of disruptive students in the classroom. Disruptive students are defined as students with a number of baseline hours of absences due to suspensions above 20 (the 75^{th} percentile).

Figure 3: Association Between Disruptiveness and Absences, Overall and By Gender

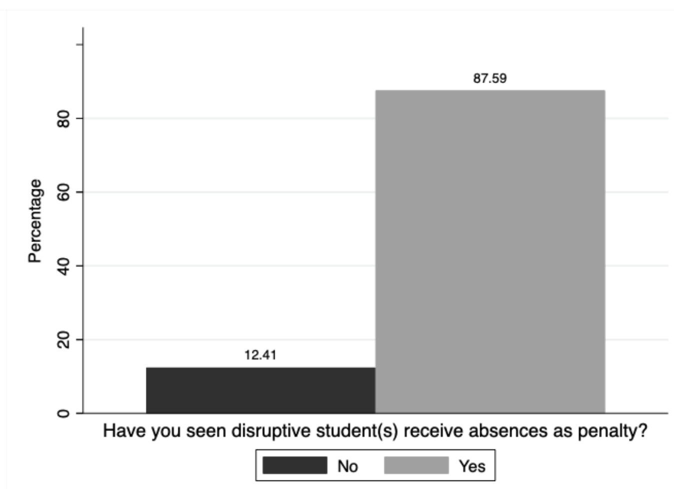
(A) All Students



(B) Male Students



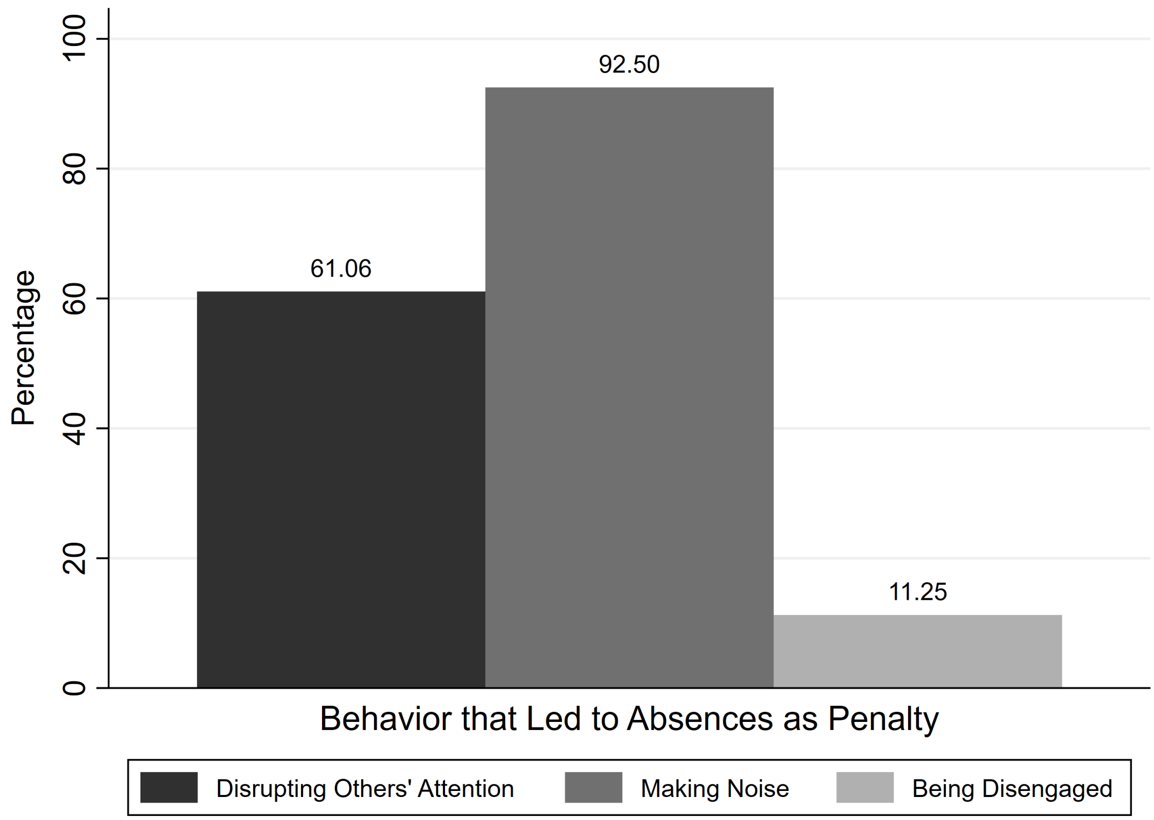
(C) Female Students



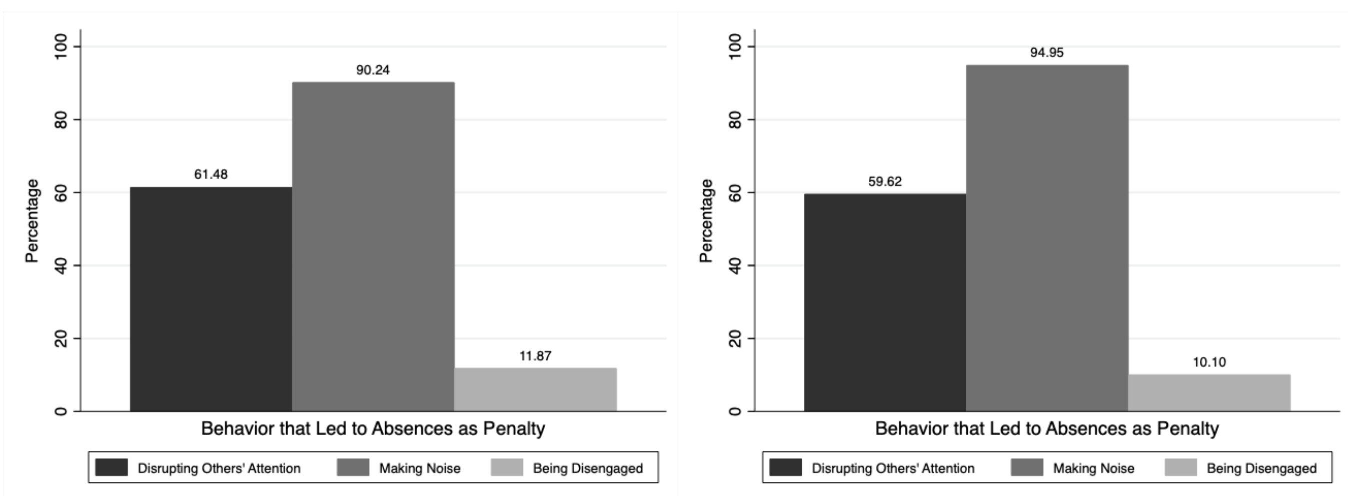
Notes: The figure shows survey responses from high school students on whether they have witnessed students receiving hours of suspension as a penalty for disruptive behavior. The survey was administered in 2022 as part of a field experiment in 6 high schools. The relevant questionnaire item was "Have you witnessed the use of hourly unexcused absences as a penalty for disruptive students?" Students responded to the question with "Yes" or "No." Figure (A) shows the responses of all students, Figure (B) only the responses of male students, and Figure (C) only the responses of female students.

Figure 4: Survey Evidence that Unexcused Absences are Used as a Punishment for Disruption and Noise, Overall and By Gender

(A) All Students



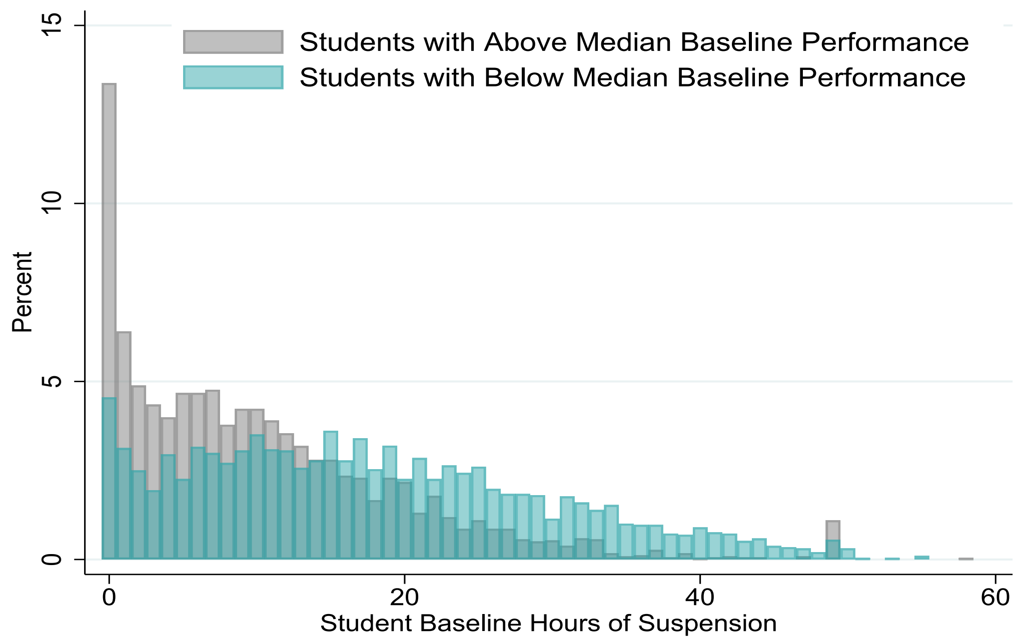
(B) Male Students (C) Female Students



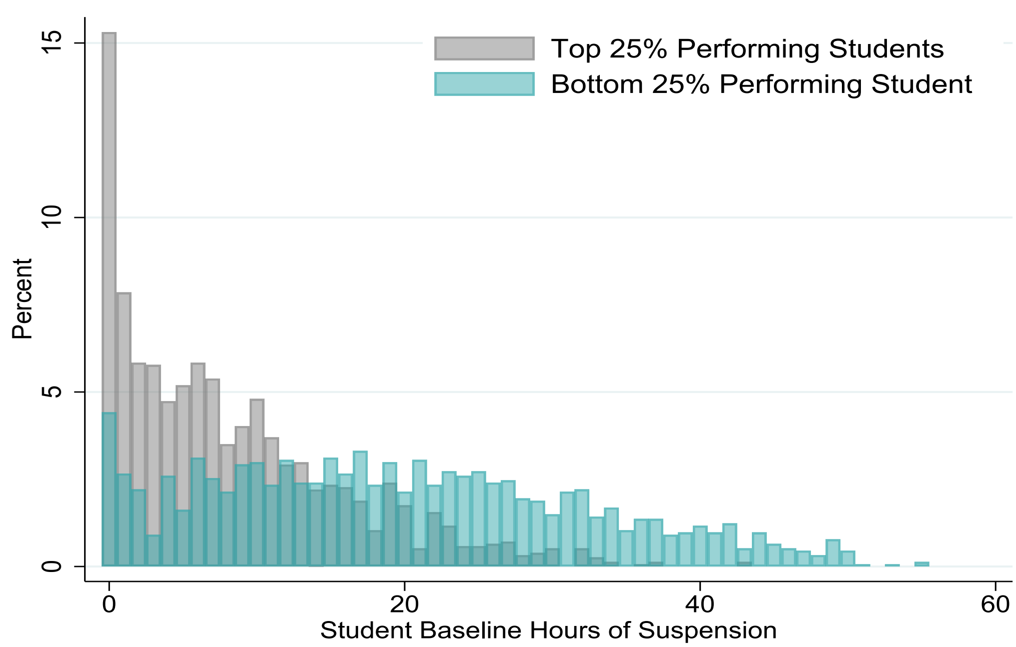
Notes: The figure shows high school students' survey responses regarding which behavior leads students to receive unexcused absences as a penalty for disruptive behavior. The figure uses student responses to the following questionnaire item "In which way can a student in your classroom behave and receive unexcused absences as a penalty." Students have the following options to choose from "Disrupting Others' Attention," "Making Noise," and "Being Disengaged." This is a multiple-choice question. Figure (A) shows the responses of all students, Figure (B) only the responses of male students, and Figure (C) only the responses of female students.

Figure 5: Distribution of Absences due to Suspension Hours by Student Baseline Performance

(A) Above and Below Median of Baseline Performance



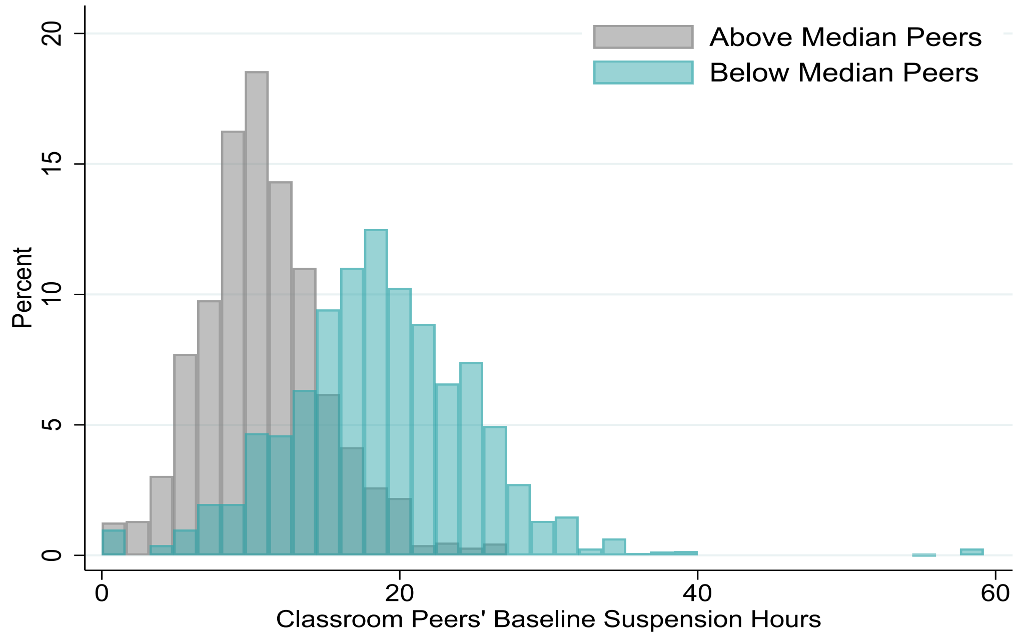
(B) Top 25% and Bottom 25% of Baseline Performance



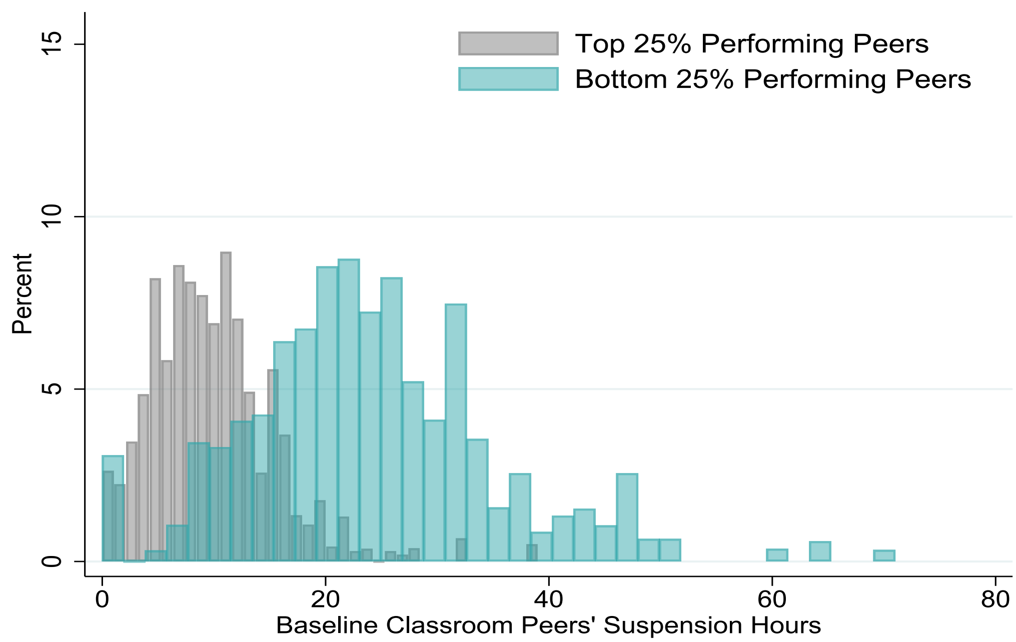
Notes: The figure shows the distribution of student-level hours of absences due to suspensions by student baseline performance. Figure (A) shows the distributions for students above and below median baseline performance. Figure (B) shows the distributions for students in the top 25% and bottom 25% of baseline performance.

Figure 6: Distribution of Peers' Absences due to Suspension Hours

(A) Above and Below Median of Baseline Performance



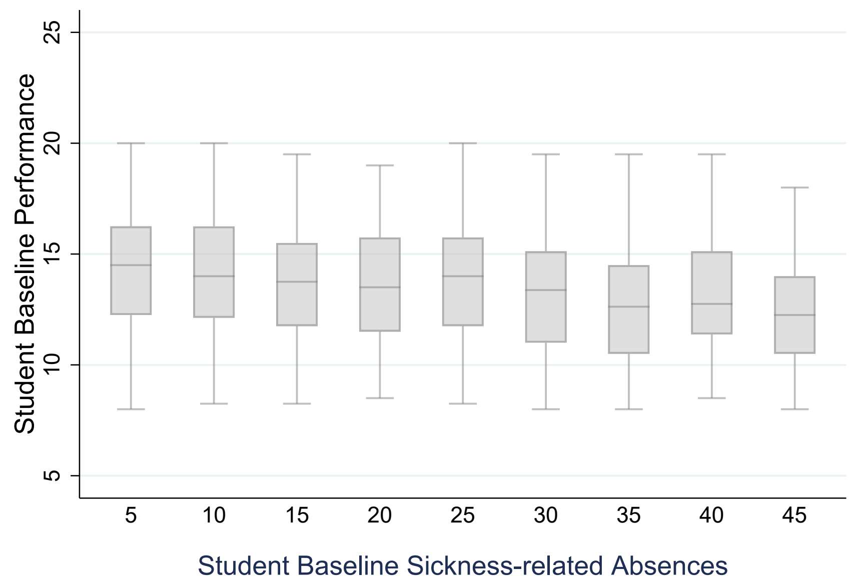
(B) Top 25% and Bottom 25% of Baseline Performance



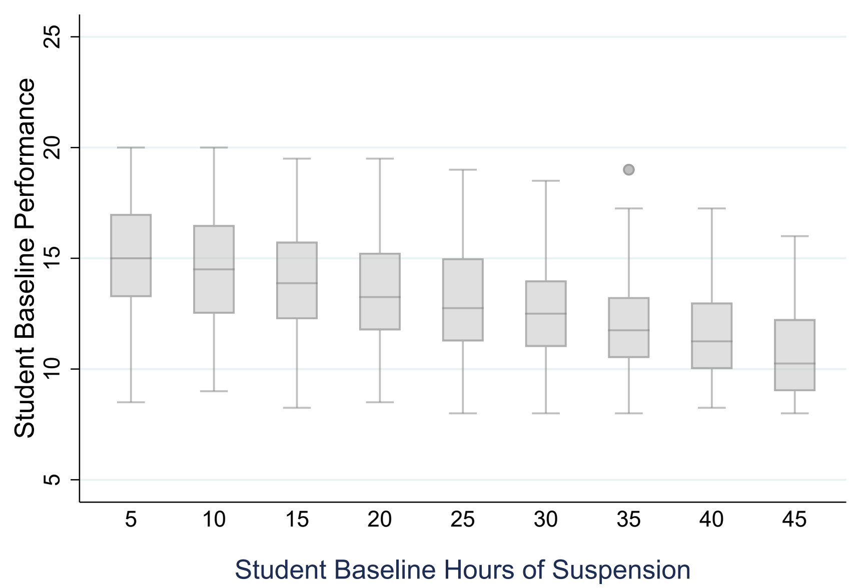
Notes: The figure shows the distribution of classroom peers' (leave-out mean) absences due to suspensions by student baseline performance. Figure (A) shows the distributions for students above and below median baseline performance. Figure (B) shows the distributions for students in the top 25% and bottom 25% of baseline performance.

Figure 7: Association between Student Baseline Performance and Different Types of Absenteeism

(A) Baseline Performance and Sickness-related Absences



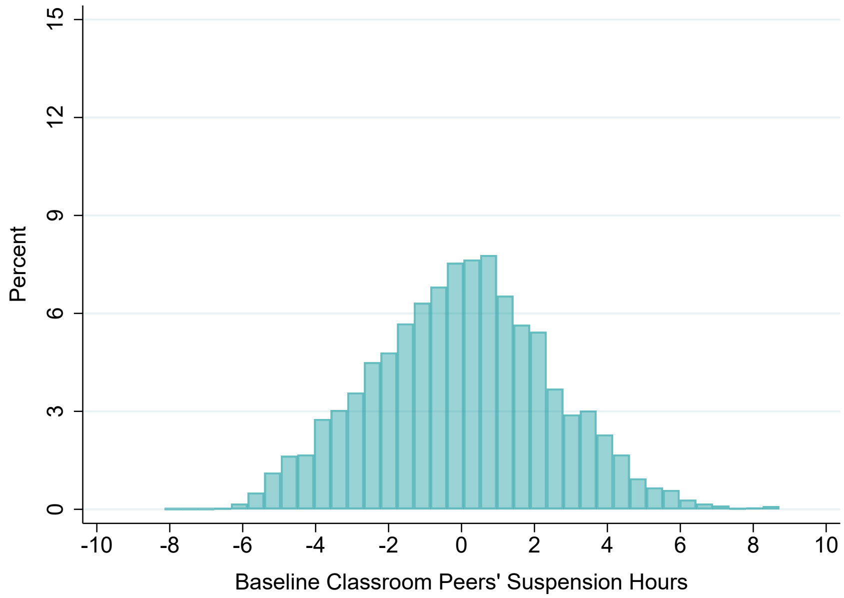
(B) Baseline Performance and Hours of Suspension



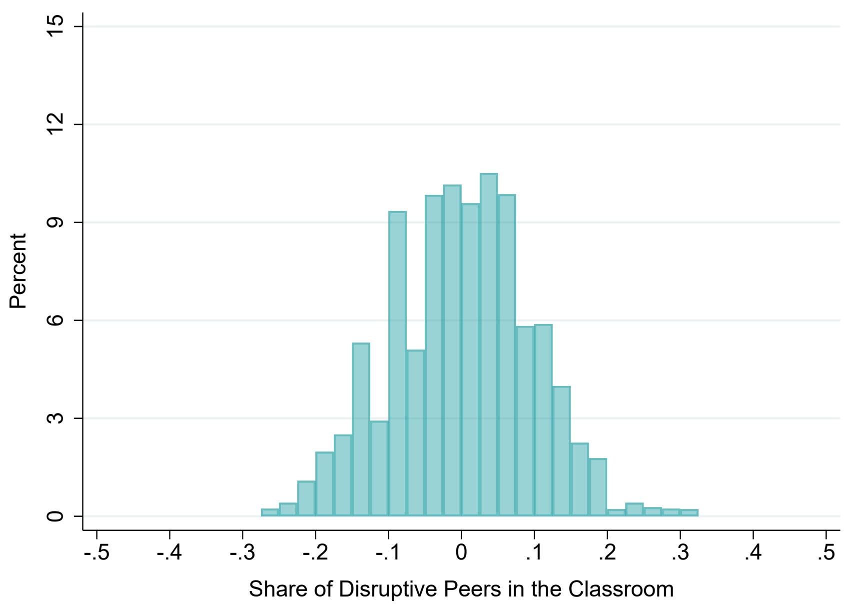
Notes: These figures depict the association between students' baseline types of absences and performance. The box plots display the distribution of student performance across different levels of sickness-related absences (Figure A), and suspension hours (Figure B). Each box represents the interquartile range (IQR), which captures the middle 50% of the data, with the line inside the box indicating the median (50th percentile). Whiskers extend to 1.5 times the IQR, demonstrating the spread of the data, while any points outside the whiskers represent outliers. Figure (A) shows that as sickness-related absences increase, the median performance remains relatively stable, with few outliers. Figure (B) highlights the fact that higher suspension hours are associated with lower median performance and a broader spread of lower scores, along with more frequent outliers, which indicates the negative impact of suspensions on academic outcomes.

Figure 8: Distributions of Disruptiveness Measures Conditional on School-Year FE

(A) Baseline Classroom Peers' Suspension Hours



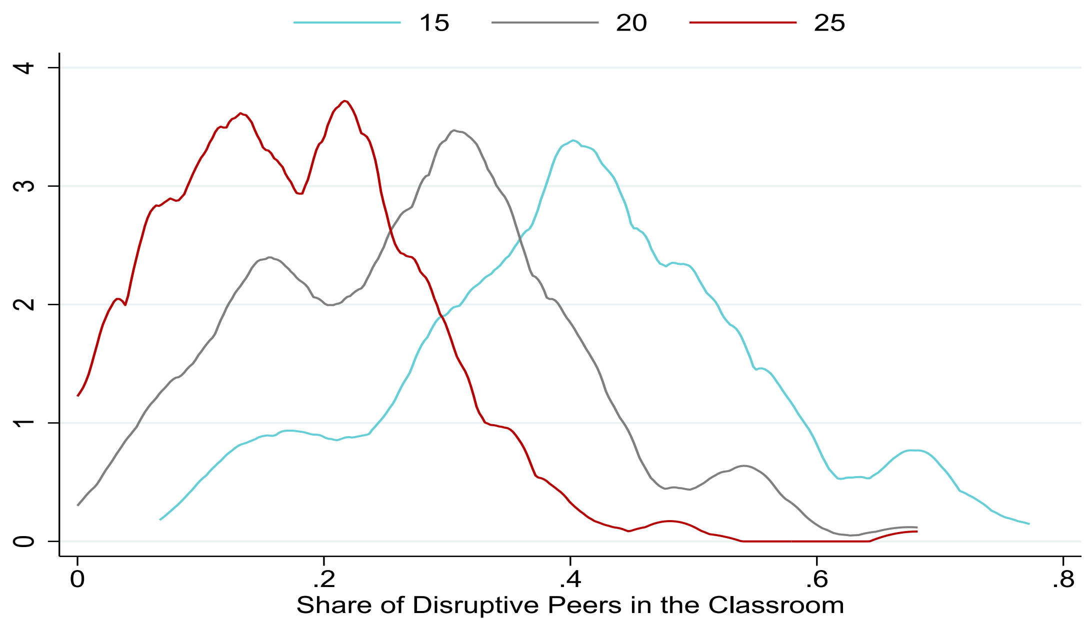
(B) Share of Disruptive Peers



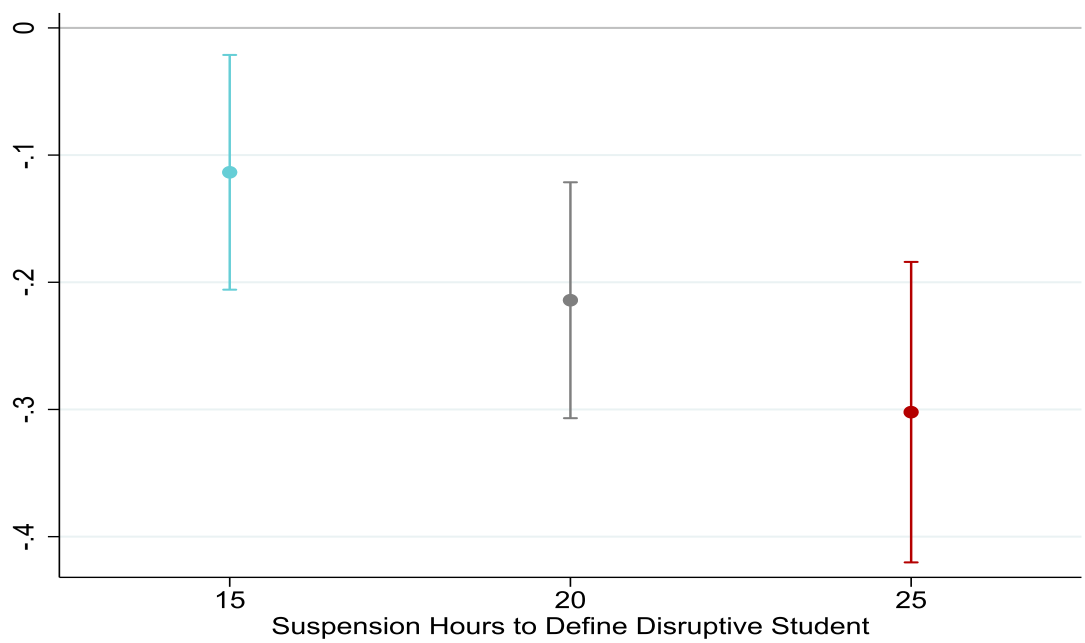
Notes: The figure shows the distribution of disruptiveness measures. Figure (A) shows the distribution of classroom peers' (leave-out mean) absences due to suspensions, adjusted for school-by-year influences. Figure (B) shows the distribution of the share of disruptive peers in the classroom, regression-adjusted for school-by-year influences. This is the exact variation we use in the identification strategy.

Figure 9: Robustness Exercise Using Different Definitions of Disruptive Students

(A) Distributions of Share of Disruptive Peers For Different Suspension Hour Thresholds



(B) Estimated Effects for Different Suspension Hour Thresholds



Notes: Figure (A) presents the share of disruptive peers in the classroom when we use different suspension hour thresholds to define disruptive students. Our main analysis considers disruptive students as those who are in the 75$^{\text{th}}$ percentile of unexcused absences—i.e., students who obtain more than 20 suspension hours at the baseline. Figure (A) shows how the share of disruptive peers changes when we use 15 and 25 suspension hours to define disruptive students (instead of 20). Light green, gray and red lines represent the share of disruptive peers when we classify as *disruptive* students with at least 15, 20, and 25 suspension hours, respectively. Figure (B) plots the estimated effects of the different shares of disruptive peers in the classroom (when baseline suspension hour thresholds are defined as 15, 20 and 25) on standardized overall student performance when using different suspension hour thresholds to define disruptive peers, as in Equation (18).

Table 1: DESCRIPTIVE STATISTICS OF STUDENT, CLASSROOM, AND SCHOOL CHARACTERISTICS

	Mean	SD	Min	Max	N
Panel A: Student Characteristics					
Age	15.98	0.49	8	20	5,013
Born in 1st Quarter of Year	0.09	0.29	0	1	5,013
Female	0.55	0.50	0	1	5,013
Student Baseline Hours of Suspension	13.70	11.03	0	55	5,013
Student Baseline Sickness-related Absences	6.76	10.63	0	58	5,013
Student Baseline Performance	14.40	2.58	8	20	5,013
Panel B: Peer Characteristics (Leave-out Means)					
Age	16.00	0.20	15	17	5,013
Born in 1st Quarter of Year	0.09	0.11	0	0	5,013
Baseline Peers' Sickness-related Hours	6.76	3.10	1	16	5,013
Baseline Peers' Suspension Hours	13.94	3.78	3	25	5,013
Share of Disruptive Peers (Excluding Top 10% Disruptors)	0.27	0.13	0	1	5,013
Share of Sick Peers	0.25	0.12	0	1	5,013
Average Class Baseline Performance	14.28	0.97	11	18	5,013
Panel C: Classroon Characteristics					
Prop. of Females in Class	0.55	0.13	0.17	0.96	5,013
Class Size	23.47	3.59	14.00	32.00	5,013
Panel D: School Characteristics					
Postcode Income (in 2009 Thousand Euros, Annual)	18,976	2,114	14,267	26,586	5,013

Notes: The table reports descriptive statistics for student characteristics (Panel A), classroom peers' characteristics (i.e., leave-out means; Panel B), classroom characteristics (Panel C), and school characteristics (Panel D). Baseline test scores are measured based on the earliest exam students take at the very beginning of grade 10. "Enrolled in Top 20% STEM Degree" is a binary indicator that takes the value of 1 if a student enrolls in a STEM Degree with the top 20%. Raw exam scores range from 0 to 20 and are increasing in performance.

Table 2: Tests for The Disruptiveness of Peers at the Individual Level

	Panel A: Baseline Classroom Peers' Suspension Hours					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.064					
	(0.071)					
Age		0.041				
		(0.082)				
Born in 1st Quarter of Year			-0.124			
			(0.129)			
Student Baseline Performance (Std.)				0.047		
				(0.053)		
Student Baseline Hours of Suspension					0.004	
					(0.003)	
Student Baseline Sickness-related Absences						-0.004
						(0.003)
Observations	5,013	5,013	5,013	5,013	5,013	5,013
	Panel B: Share of Disruptive Peers					
Female	0.002					
	(0.003)					
Age		0.004				
		(0.003)				
Born in 1st Quarter of Year			-0.005			
			(0.005)			
Student Baseline Performance (Std.)				0.000		
				(0.002)		
Student Baseline Hours of Suspension					0.000	
					(0.000)	
Student Baseline Sickness-related Absences						-0.000
						(0.000)
Observations	5,013	5,013	5,013	5,013	5,013	5,013

Notes: Columns (1)-(6) report school × year fixed-effects estimates from separate regressions with independent variables for each student characteristic. Outcome variables are the baseline classroom peers' suspension hours (Panel A) and the share of disruptive classroom peers (Panel B). In column (7) we include all control variables simultaneously in the regression and report the joint significance of those variables. We also control for the share of female students in the class and class size in all regressions. The outcome variable, baseline classroom peers' disruptiveness, has a mean of 13.95 hours and a standard deviation of 3.78 hours. The outcome variable baseline share of disruptive peers has a mean of 0.27 and a standard deviation of 0.13. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: Effects of Peers' Disruptiveness on Student Performance

	Overall Performance	STEM (Math and Physics)	Non-STEM (Language and History)
	(1)	(2)	(3)
	Panel A		
	Final Exam Performance in Grade 10 (Std.)		
Baseline Peers' Suspension Hours	-0.009***	-0.007**	-0.010***
	(0.002)	(0.003)	(0.003)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Baseline Peers' Suspension Hours	-0.013***	-0.012***	-0.014***
	(0.003)	(0.004)	(0.003)
Observations	4,138	4,138	4,138
Mean X	13.95	13.95	13.95
St Dev X	3.78	3.78	3.78
	Panel B		
	Final Exam Performance in Grade 10 (Std.)		
Share of Disruptive Peers	-0.230***	-0.154**	-0.306***
	(0.049)	(0.067)	(0.063)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Share of Disruptive Peers	-0.288***	-0.295***	-0.282***
	(0.069)	(0.093)	(0.085)
Observations	4,138	4,138	4,138
Mean X	0.27	0.27	0.27
St Dev X	0.13	0.13	0.13
School $\times$ Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports estimated effects of peer disruptiveness on student test scores. The outcome variables are standardized performance scores: overall performance (column 1), performance on STEM compulsory subjects (column 2), and performance on non-STEM compulsory subjects (column 3) in grades 10 and 11. The treatment variable is baseline peers' suspension hours in Panel A and the share of disruptive peers in Panel B. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: Effects of Classroom Disruptiveness on Track Specialization Decisions

	Track Choice at the End of Grade 10		
	Competitive Science Track	Professional IT Track	Classics Track
	(1)	(2)	(3)
	Panel A		
Baseline Peers' Suspension Hours	-0.006**	0.009***	-0.003
	(0.003)	(0.003)	(0.003)
	Panel B		
Share of Disruptive Peers	-0.096	0.157**	-0.056
	(0.067)	(0.074)	(0.078)
Observations	4,138	4,138	4,138
Mean Y	0.22	0.36	0.41
St Dev Y	0.41	0.48	0.49
School × Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports the estimated effects of peer disruptiveness on students' longer-term university admissions outcomes. The outcome variable in column (1) is the standardized (at cohort level) performance on the national exam at the end of high school. The outcome variable in column (2) is a binary indicator for whether the student enrolls in some postsecondary institution (and 0 otherwise). Outcome variables in columns (3) and (4) are binary indicators that take the value of 1 if a student is admitted to a top 10 or top 20 degree (based on the academic performance of admitted students) and 0 otherwise. The outcome variable in column (5) is the rank of the institution attended on the student's degree preference list. Lower rank is associated with less preferred degrees. We report the estimated coefficient of peer disruptiveness on the rank of the attended institution by reversing the regression sign. The outcome variables in columns (5) and (6) are the percentile quality rank measures of the postsecondary degree students are admitted to. "Postsecondary Degree Quality" captures the rankings of the admitted postsecondary program measured by the mean national exam performance of enrolled students in each postsecondary program. In our sample, we have information on college admissions for 3,160 students (of those, 2,454 are admitted). All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Effects of Classroom Disruptiveness on Academic Probation

	Grade Retention	Timely Graduation	At Risk (Re-taking Exams) End Grade 10	At Risk (Re-taking Exams) End Grade 11
	(1)	(2)	(3)	(4)
		Panel A		
Baseline Peers' Suspension Hours	0.003**	-0.003**	0.004*	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
		Panel B		
Share of Disruptive Peers	0.056*	-0.061*	0.077	0.125**
	(0.034)	(0.035)	(0.053)	(0.061)
Observations	5,013	5,013	5,013	4,138
School × Year FE	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓
Classroom-level Controls	✓	✓	✓	✓

Notes: The table reports the estimated nonlinear effects of disruptiveness on student academic probation. The outcome variables are binary indicators for whether students had to repeat a grade during the 3 years of high school (column 1) and whether they completed high school within 3 years (column 2). The outcome variables in columns (3)–(4) are binary indicators for whether students were at risk of retention and required to retake exams at the end of grades 10 and 11, respectively. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Effects of Disruptiveness on Student Longer-Term Outcomes

		University Outcomes				
	(1) National Exam Performance Grade 12	(2) College Admission	(3) Admitted to Top 10 Department	(4) Admitted to Top 20 Department	(5) Institution Rank on Preference List	(6) PostSecondary Degree Quality
			Panel A			
Baseline Peers' Suspension Hours	-0.014***	-0.006**	-0.004***	-0.004**	-0.152*	-0.438**
	(0.005)	(0.003)	(0.001)	(0.002)	(0.087)	(0.212)
			Panel B			
Share of Disruptive Peers	-0.449***	-0.103	-0.090**	-0.117**	-5.542**	-14.763***
	(0.132)	(0.069)	(0.036)	(0.049)	(2.367)	(5.650)
Observations	3,160	3,160	3,160	3,160	2,454	2,454
School $\times$ Year FE	✓	✓	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓	✓	✓
Classsroom-level Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports the estimated effects of peer disruptiveness on students longer-term university admissions outcomes. The outcome variable in column (1) is the standardized (at the cohort level) performance on the national exam at the end of high school. The outcome variable in column (2) is a binary indicator for whether the student enrolls in some postsecondary institution (and 0 otherwise). The outcome variables in columns (3) and (4) are binary indicators for whether a student is admitted to a top 10 or top 20 degree, based on the academic performance of admitted students. The outcome variable in column (5) is the rank of the institution attended on the student's degree preference list. Lower rank is associated with more preferred degrees. We report the estimated coefficient of peer disruptiveness on the rank of the attending institution by reversing the regression sign. "Postsecondary Degree Quality" is the percentile quality rank of the postsecondary program student enroll in. In our sample, we have information on college admission for 3160 students. Of those, 2454 are admitted. We have information on the quality of the departments he was admitted to for these students. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Nonlinear Effects of Peers' Disruptiveness on Student Performance

	Overall Performance	STEM (Math and Physics)	Non-STEM (Language and History)
	(1)	(2)	(3)
		Panel A	
		Final Exam Performance in Grade 10 (Std.)	
Middle Tertile	-0.039***	-0.027	-0.050***
	(0.013)	(0.018)	(0.017)
Top Tertile	-0.049***	-0.027	-0.071***
	(0.016)	(0.021)	(0.021)
		Final Exam Performance in Grade 11 (Std.)	
Middle Tertile	-0.058***	-0.055**	-0.062***
	(0.018)	(0.024)	(0.023)
Top Tertile	-0.074***	-0.073***	-0.075***
	(0.021)	(0.028)	(0.026)
Mean X in Bottom Tertile	9.83	9.83	9.83
Mean X in Middle Tertile	14.02	14.02	14.02
Mean X in Top Tertile	18.01	18.01	18.01
		Panel B	
		Final Exam Performance in Grade 10 (Std.)	
Middle Tertile	-0.031**	-0.014	-0.048***
	(0.013)	(0.018)	(0.017)
Top Tertile	-0.049***	-0.009	-0.088***
	(0.015)	(0.020)	(0.019)
		Final Exam Performance in Grade 11 (Std.)	
Middle Tertile	-0.055***	-0.071***	-0.040*
	(0.018)	(0.024)	(0.023)
Top Tertile	-0.086***	-0.089***	-0.084***
	(0.021)	(0.028)	(0.026)
Mean X in Bottom Tertile	0.13	0.13	0.13
Mean X in Middle Tertile	0.28	0.28	0.28
Mean X in Top Tertile	0.43	0.43	0.43
Observations	4,138	4,138	4,138
School × Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports the estimated nonlinear effects of disruptiveness on student performance. The model replaces the single treatment variable with a set of tertile indicators for measures of disruptiveness. The omitted category is the bottom tertile, in which disruptiveness is the smallest possible. Outcome variables are the standardized overall performance (column 1), performance on STEM compulsory subjects (column 2), and performance on compulsory non-STEM subjects (column 3). All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Mechanism Investigation: Effects of Disruptiveness on Perceived Peer's Noncognitive Characteristics, Lab-in-the-field Experiment

	Study Motivation (1)	College Aspiration (2)	Science Study Readiness (3)	Career Readiness (4)
Multiple Class Disruptors vs. One	-0.138	-0.157**	-0.114*	-0.139**
	(0.065)	(0.039)	(0.045)	(0.041)
Observations	644	644	644	644
Mean of Y	26.963	7.634	8.374	8.244
SD of Y	33.772	20.555	21.365	22.068
Controls	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Class FE	✓	✓	✓	✓

Notes: The table reports estimated coefficients of the perceived influence of disruptive peers on study motivation, college aspirations, willingness to pursue a competitive science career, and career readiness. Participating students are in either grade 11 or 12. All student outcomes have been standardized to have a mean equal to 0 and a standard deviation equal to 1. Controls include a binary indicator that takes the value of 1 if the respondent was female (and 0 otherwise), an indicator that takes the value 1 if the scenario stated that the disruptor/(s) are close physically to the survey respondent, the share of females in the classroom, the share of students who chose a STEM track in grade 11 in the classroom, and an indicator that takes the value of 1 if the student chose a STEM track at the beginning of grade 11 (and 0 otherwise). Standard errors clustered at the school level are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9: Perceived Effect of Peer Disruptiveness on Outcomes by Type of Peers

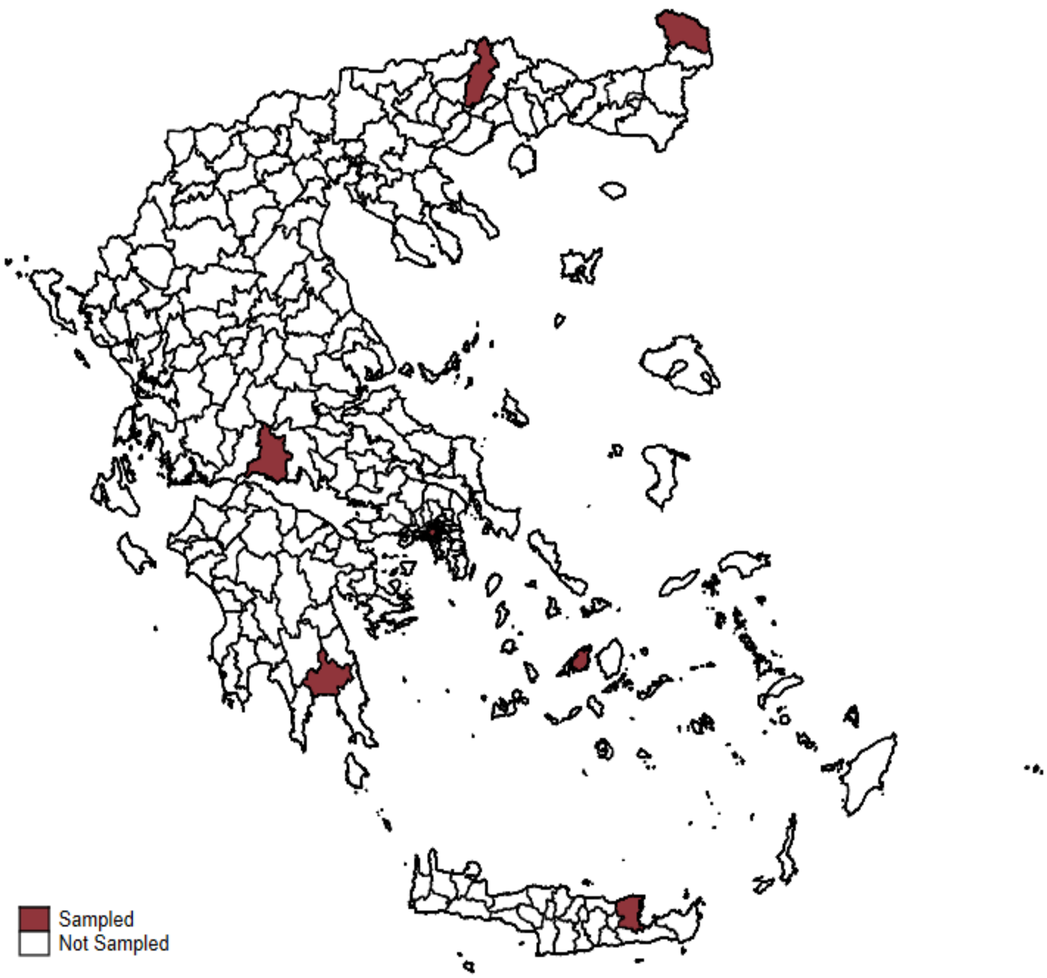
	Physically Close Peers				Physically Distant Peers			
	Study Motivation (1)	College Aspiration (2)	Science Study Readiness (3)	Career Readiness (4)	Study Motivation (5)	College Aspiration (6)	Science Study Readiness (7)	Career Readiness (8)
Multiple Class Disruptors vs. One	-0.240*	-0.258*	-0.284***	-0.174	-0.069	0.031	-0.034	-0.089
	(0.108)	(0.094)	(0.024)	(0.089)	(0.097)	(0.037)	(0.059)	(0.058)
Observations	317	317	317	317	324	324	324	324
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓
Class FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports estimated coefficients of being exposed to multiple class disruptors in the scenario, compared with one class disruptor, on various outcomes. The outcome variables are the standardized mechanism variables and the student's perceived influence of peer disruptiveness on study motivation, college aspirations, science study readiness, and career readiness. Columns (1)-(4) refer to the perceived impact of peer disruptiveness in the case of peers who were described in the scenario as being seated physically close to the participating student. Columns (5)-(8) refer to the perceived impact of peer disruptiveness in the case of peers who were described in the scenario as being seated physically distant from the participating student. Controls include an indicator that takes the value of 1 if the respondent was female (and 0 otherwise), the leave-out mean of the share of females in the classroom (excluding the survey respondent's gender), the leave-out mean of the share of students who chose a STEM track in grade 11 in the classroom (excluding the track choice of the own survey respondent), and an indicator that takes the value of 1 if the student chose a STEM track at the beginning of grade 11 (and 0 otherwise). Standard errors clustered at the school level are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Online Appendix:

Additional Tables and Figures

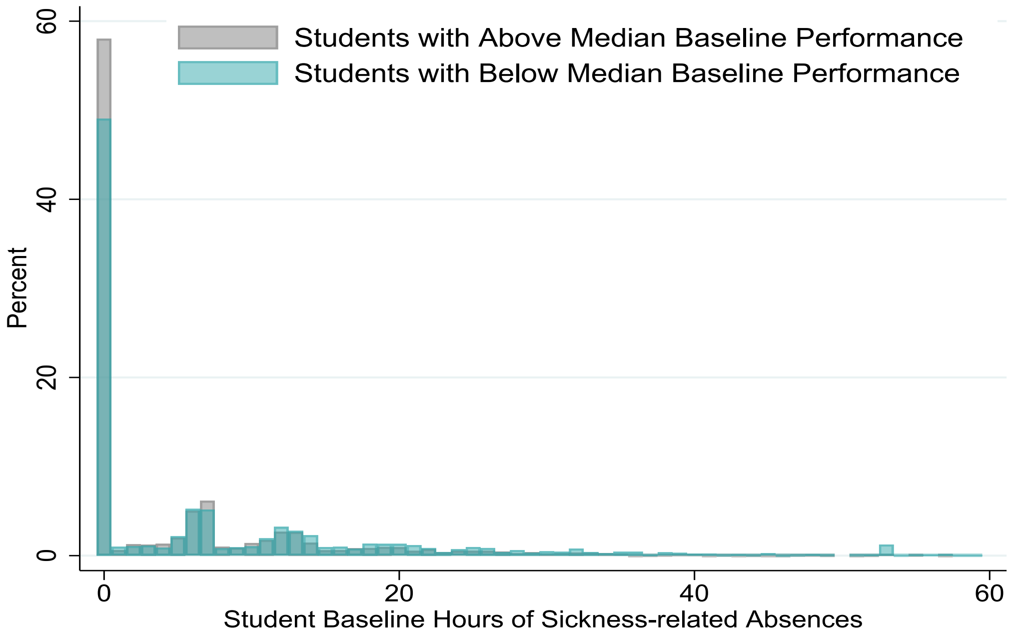
Figure A1: Map of Schools in the Sample



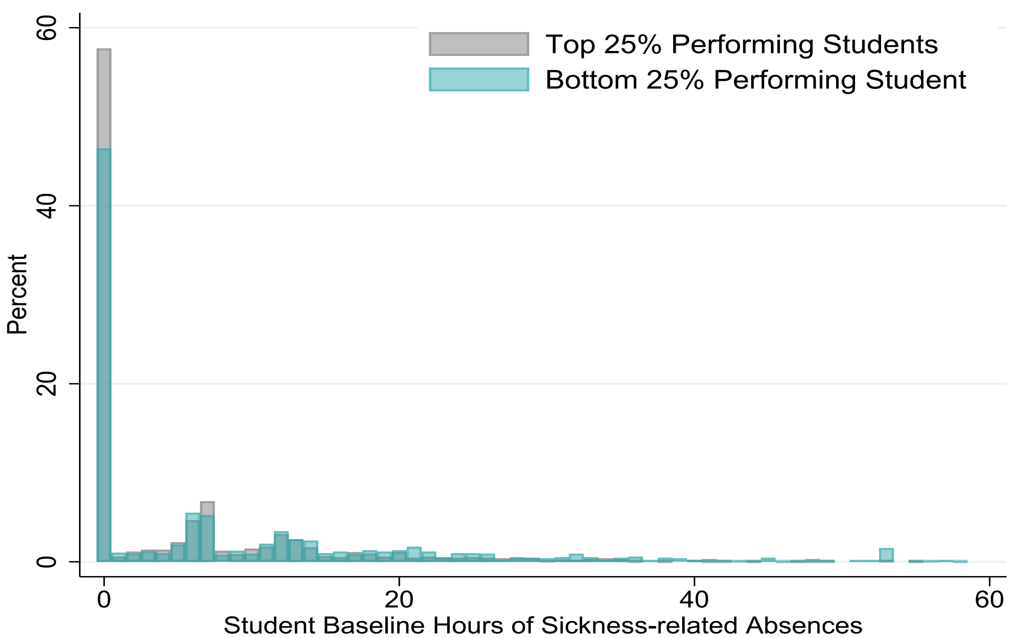
Notes: The figure shows the municipalities in which sampled schools are located.

Figure A2: Distribution of Sickness-related Absences by Student Baseline Performance

(A) Above and Below Median of Baseline Performance



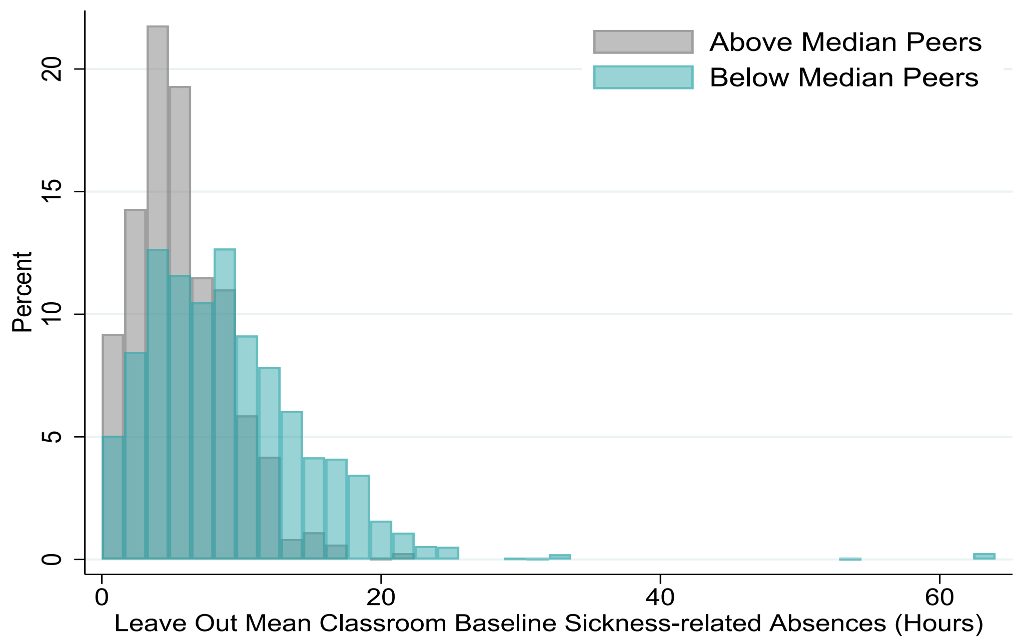
(B) Top 25% and Bottom 25% of Baseline Performance



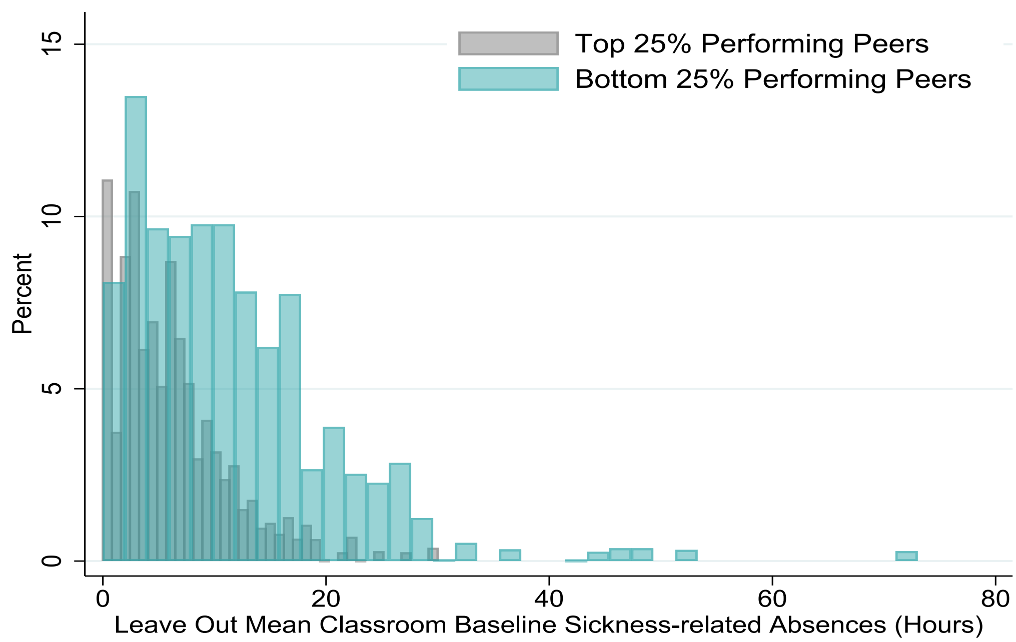
Notes: The figure shows the distribution of student-level sickness-related absences by student baseline performance. Figure (A) shows the distributions for students above and below median baseline performance. Figure (B) shows the distributions for students in the top 25% and bottom 25% of baseline performance.

Figure A3: Distribution of Classroom Peers' Sickness-related Absences

(A) Above and Below Median of Baseline Performance



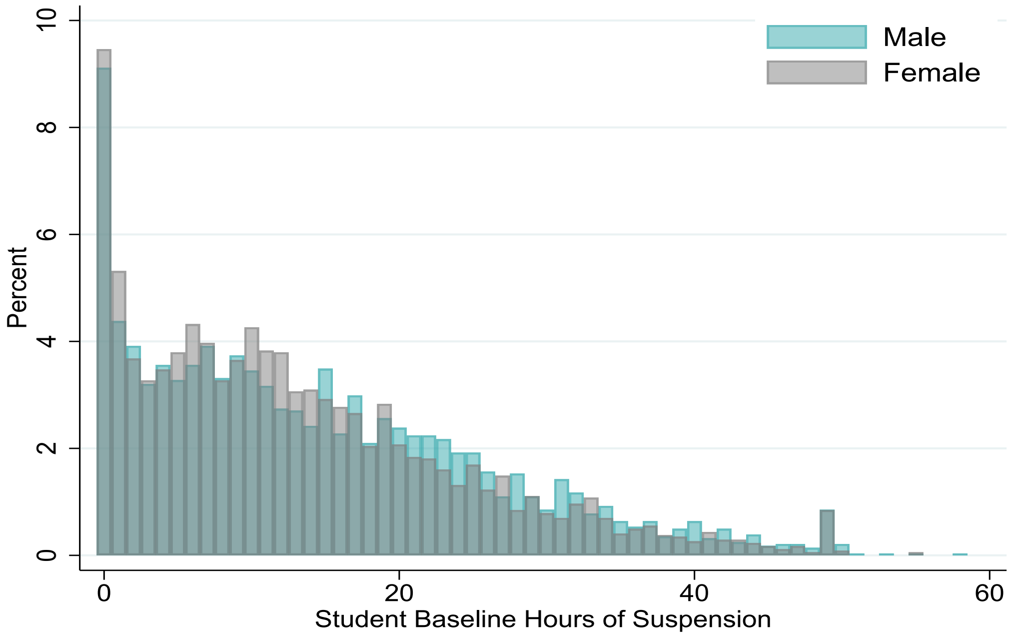
(B) Top 25% and Bottom 25% of Baseline Performance



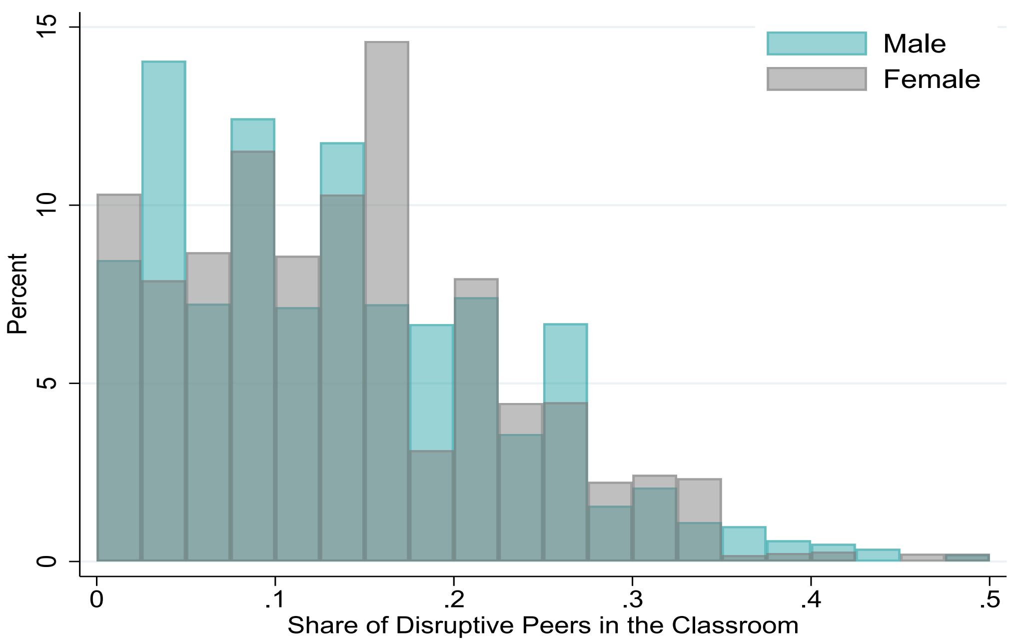
Notes: The figure shows the distribution of classroom peers' (leave-out mean) sickness-related absences by student baseline performance. Figure (A) shows the distributions for students above and below median baseline performance. Figure (B) shows the distributions for students in the top 25% and bottom 25% of baseline performance.

Figure A4: Distribution of Suspension Hours and Share of Disruptive Students, by Gender

(A) Baseline Suspension Hours for Males and Females



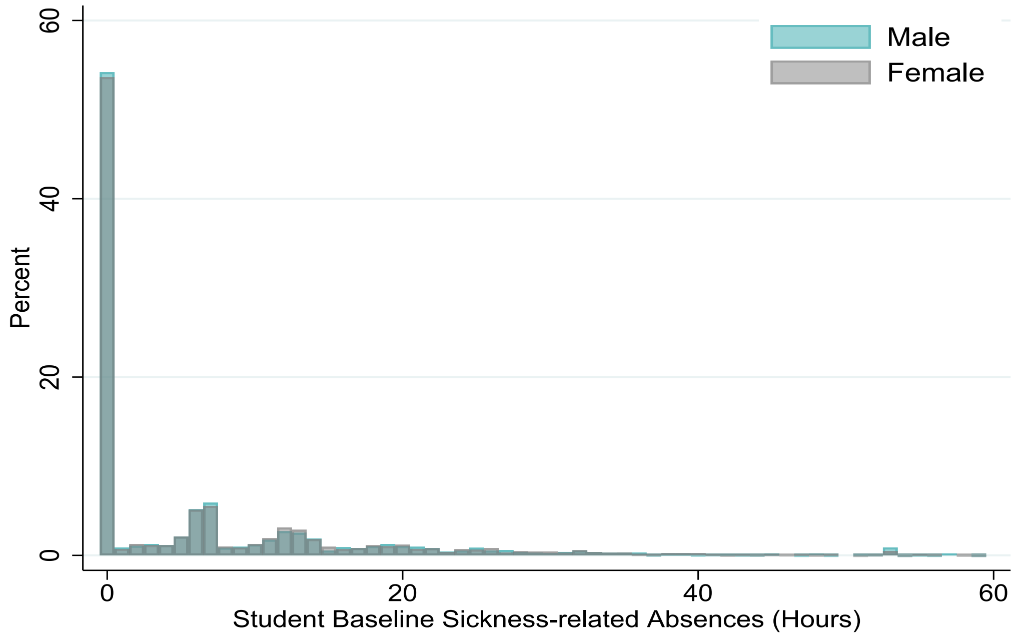
(B) Share of Disruptive Male and Female Peers



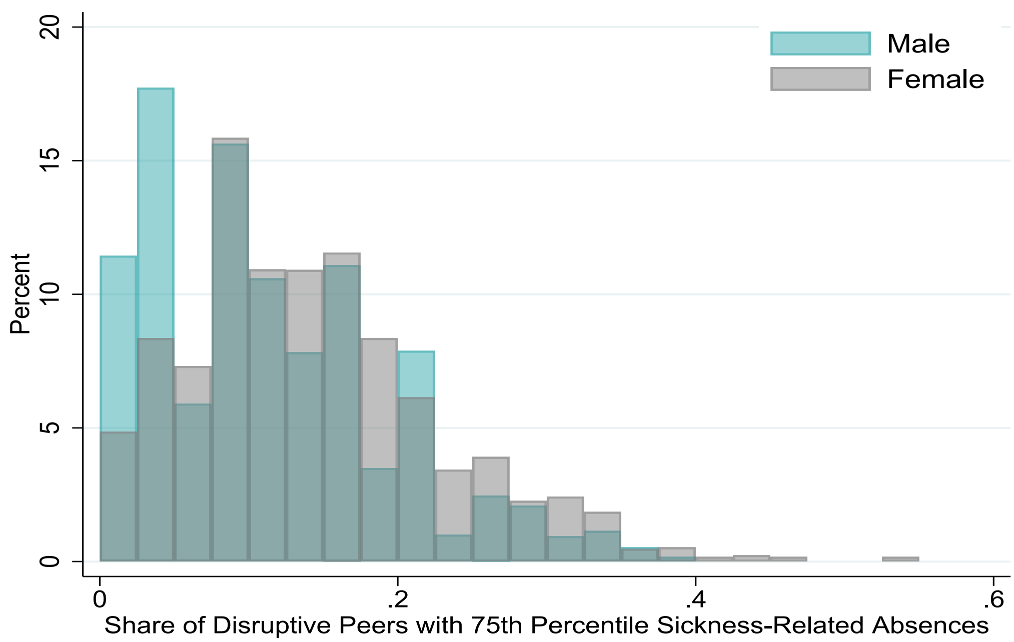
Notes: Figure (A) shows the distribution of student-level suspension hours for males and females. Figure (B) shows the distribution of the share of disruptive peers in the classroom for males and females. A disruptive peer is defined as a student who has more than 20 suspension hours at the baseline (the 75$^{\text{th}}$ percentile). To calculate the share of disruptive peers in the classroom, we calculate the share of students with more than 20 suspension hours at the baseline divided by the total number of students in the classroom.

Figure A5: Distribution of Excused Hours of Absence and Share of Students with Sickness-related Absences in 75$^{\text{th}}$ Percentile, by Gender

(A) Baseline Hours of Sickness-related Absences, for Males and Females

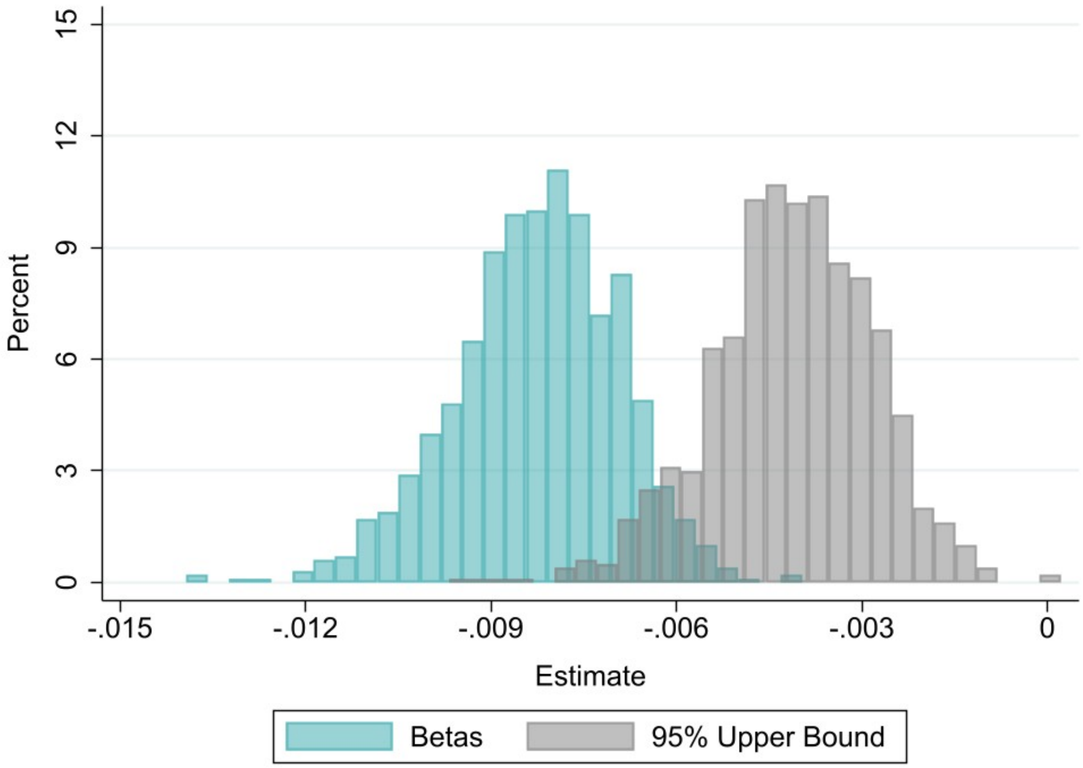


(B) Share of Male and Female Peers with Excused Absence in the 75$^{\text{th}}$ Percentile



Notes: Figure (A) shows the distribution of student-level hours of excused absences for males and females. Figure (B) shows the distribution of the share of peers with excused absences in the 75th percentile in the classroom, for males and females. To calculate the share of disruptive peers in the classroom, we calculate the share of students with more than 11 hours of excused absences at the baseline divided by the total number of students in the classroom.

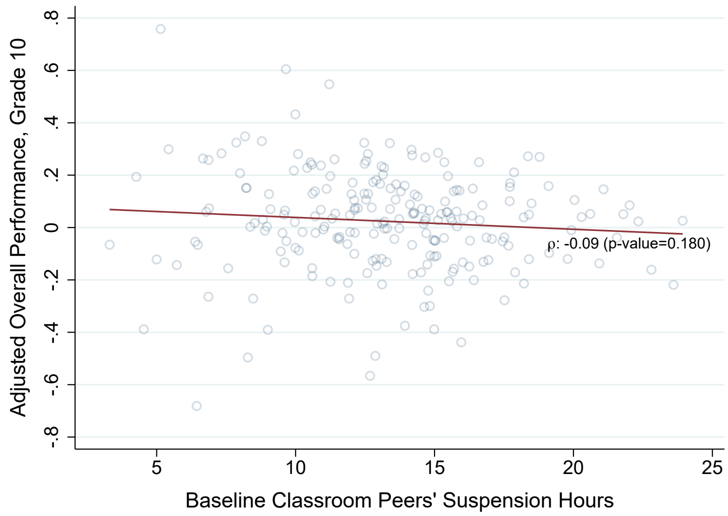
Figure A6: Simulation Exercise of Predicted Performance When Randomly Dropping 10% of Classrooms



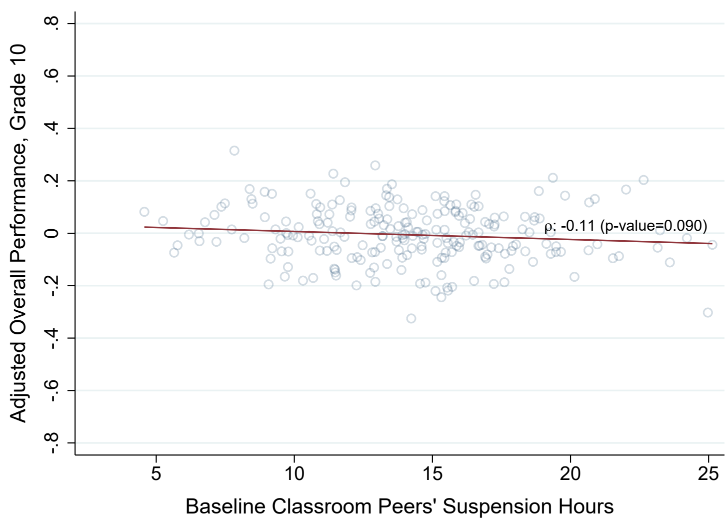
Notes: The figure presents the point estimates and the 95% upper bounds of the effect of peers' baseline suspension hours on overall performance at the end of grade 10. These estimates are derived by iteratively and randomly excluding 10% of classrooms in each iteration, repeated 1,000 times.

Figure A7: Impact of Classroom Peers' Disruptiveness on Disruptive and Non-disruptive Students

(A) Disruptive Students



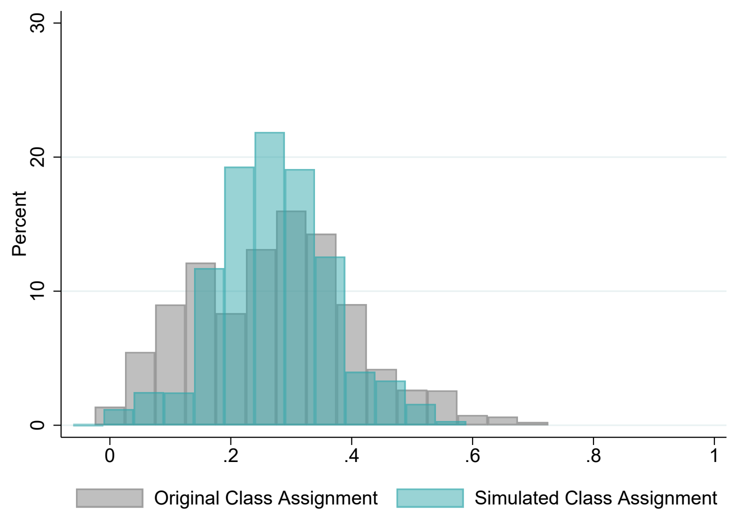
(B) Non-disruptive Students



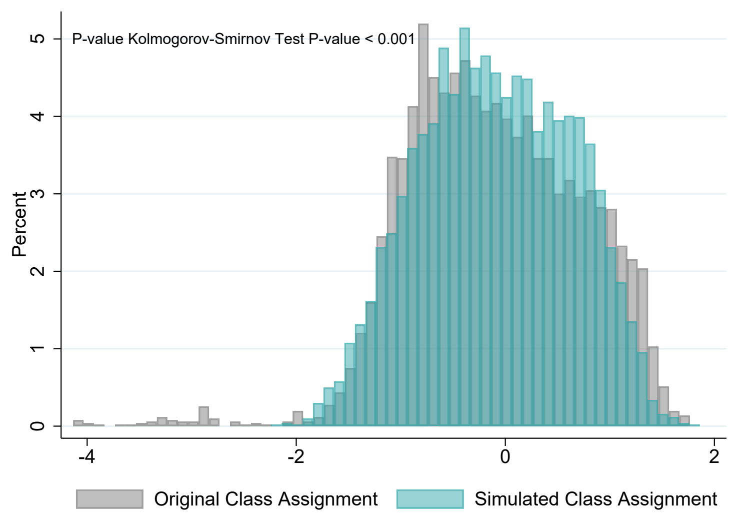
Notes: Figure (A) investigates the association between classroom peers' disruptiveness and overall performance at the end of grade 10 for disruptive students. Figure (B) investigates the association between classroom peers' disruptiveness and overall performance at the end of grade 10 for non-disruptive students. Overall performance at the end of grade 10 has been regression-adjusted for controls. Controls include school-by-year fixed effects, student controls and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means).

Figure A8: Simulation Exercise: Actual and Predicted Performance Under Simulated Classroom Assignments

(A) Distributions of Disruptive Peers Across Classroom



(B) Distributions of Grade 10 Final Exam Performance (Std.)



Notes: Figure (A) illustrates the distribution of disruptive peers across classrooms in the observed data (gray) and a simulated scenario where an equal number of disruptive students are allocated to each classroom within the same school-cohort (light green). Figure (B) depicts the actual distribution of standardized final exam performance in grade 10 (gray) and the predicted distribution of student performance under the simulated reallocation of disruptive peers (light green).

Table A1: Representativeness of Sampled High Schools

	Sample (10 Schools) Mean	Population (1,199 Schools) Mean	Difference (s.e.)
Student Characteristics			
Female (%)	0.56	0.56	0.001
			(0.012)
Age (Yrs)	17.91	17.88	-0.026
			(0.014)
Born in 1st Quarter of Year (%)	0.13	0.15	0.016
			(0.011)
Graduation Cohort Size	58.44	73.01	14.563
			(13.545)
College Admission (%)	0.75	0.77	0.019
			(0.014)
Admitted to Higher Educational Institutions (%)	0.53	0.51	-0.022
			(0.024)
Apply to STEM Degree Programs (%)	0.62	0.61	-0.008
			(0.008)
University Admission Score (/20,000)	13,326.34	13,417.79	91.442
			(158.373)
Track Choice (%):			
Classics Track	0.43	0.41	-0.021
			(0.020)
Competitive Science Track	0.12	0.13	0.005
			(0.017)
Professional IT Track	0.45	0.47	0.016
			(0.016)
School Characteristics			
Postcode Income (in 2009 Euros, Annual)	19,308.90	18,955.63	-353.270
			(1043.320)
Urban (1=yes)	0.76	0.90	0.140
			(0.101)

Notes: The table reports differences in student and school characteristics between the schools in the sample used in this analysis (column 1) and all remaining schools in Greece (column 2), along with standard errors for the significance of these differences. *"Graduation Cohort Size"* refers to the final grade school cohort. The population includes all traditional public schools; evening, experimental, and private schools are excluded.

Table A2: Descriptive Statistics of Student Outcomes in High School

	Mean	SD	Min	Max	N
Performance					
Overall Performance, Grade 10	13.16	3.31	0	20	5,013
STEM Performance, Grade 10	12.25	3.81	0	20	5,013
Non-STEM Performance, Grade 10	14.08	3.28	0	20	5,013
Overall Performance, Grade 11	13.10	3.29	0	20	4,138
STEM Performance, Grade 11	12.24	4.08	0	20	4,138
Non-STEM Performance, Grade 11	13.96	3.15	0	20	4,138
Track Choice					
Competitive Science Track, Grade 11	0.23	0.42	0	1	4,138
Professional IT Track, Grade 11	0.35	0.48	0	1	4,138
Classics Track, Grade 11	0.41	0.49	0	1	4,138
Academic Probation					
Grade Retention	0.06	0.23	0	1	5,013
Timely Graduation	0.94	0.24	0	1	5,013
Re-taking Exams, Grade 10	0.38	0.49	0	1	5,013
Re-taking Exams, Grade 11	0.39	0.49	0	1	4,138

Notes: The table reports descriptive statistics for student-level outcome variables. Raw exam scores range from 0 to 20 and are increasing in performance. Three tracks are available in school: competitive science, professional IT, and classics. Timely Graduation is a binary indicator that takes the value of 1 if a student graduates from high school on time and 0 otherwise. *Re-taking Exams* are binary indicators that take the value of 1 if a student scores below the required threshold of raw performance (which is 10/20) on the final exams in each of the grades. These students must retake the supplementary exams to meet the grade threshold and progress to the next grade.

Table A3: Association between Student Baseline Suspension Hours or Disruptive Behavior and Students' Observable Characteristics

	Student Baseline Hours of Suspension		Disruptive Student (At Least 20 Hours of Suspension)	
	(1)	(2)	(3)	(4)
Female	-0.048	-0.003	-0.011	-0.009
	(0.284)	(0.277)	(0.012)	(0.012)
Age	1.228*	1.047*	0.046**	0.043**
	(0.643)	(0.621)	(0.020)	(0.020)
Born in 1st Quarter of Year	0.378	0.207	0.000	-0.006
	(0.782)	(0.792)	(0.028)	(0.029)
Student Baseline Sickness-related Absences	0.164***	0.158***	0.005***	0.005***
	(0.015)	(0.015)	(0.001)	(0.001)
Student Baseline Performance	-1.655***	-1.714***	-0.054***	-0.055***
	(0.058)	(0.058)	(0.002)	(0.002)
Postcode Income (in 2009 Euros, Annual)	-0.237***		-0.009***	
	(0.061)		(0.003)	
Observations	5,013	5,013	5,013	5,013
Mean Y	13.94	13.94	0.27	0.27
St Dev Y	11.38	11.38	0.44	0.44
School x Year FE	No	Yes	No	Yes

Notes: The table reports estimates from an OLS regression, with student baseline suspension hours as the dependent variable in columns (1) and (2) and a dummy variable indicating whether a student is classified as disruptive (defined as students with more than 20 suspension hours) in columns (3) and (4). Columns (2) and (4) include school-year FE. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: Summary Statistics of Outcome Variables, Disruptiveness vs. Non-disruptive Students

	Non-Disruptive Student (Less than 20 Suspension Hours)	Disruptive Student (At Least 20 Suspension Hours)	Difference	*P-value*
	(1)	(2)	(3)	(4)
Performance				
Overall Performance, Grade 10	13.859	10.925	-2.934	0.000
STEM Performance, Grade 10	12.958	10.006	-2.952	0.000
Non-STEM Performance, Grade 10	14.761	11.845	-2.916	0.000
Overall Baseline Performance, Grade 11	15.140	13.344	-1.796	0.000
STEM Baseline Performance, Grade 11	14.957	13.047	-1.910	0.000
Non-STEM Baseline Performance, Grade 11	15.323	13.641	-1.682	0.000
Overall Performance, Grade 11	13.645	11.312	-2.333	0.000
STEM Performance, Grade 11	12.841	10.274	-2.567	0.000
Non-STEM Performance, Grade 11	14.450	12.350	-2.100	0.000
Track Choice				
Competitive Science Track, Grade 11	0.250	0.159	-0.091	0.000
Professional IT Track, Grade 11	0.323	0.453	0.130	0.000
Classics Track, Grade 11	0.414	0.377	-0.037	0.038
Academic Probation				
Grade Retention	0.023	0.167	0.144	0.000
Timely Graduation	0.973	0.816	-0.157	0.000
Re-taking Exams, Grade 10	0.292	0.633	0.341	0.000
Re-taking Exams, Grade 11	0.320	0.642	0.322	0.000
National Exam Performance, Grade 12	12.767	10.962	-1.805	0.000
College Admission	0.801	0.669	-0.132	0.000
Institution Rank on Preference List	8.415	8.988	0.573	0.301
Admitted to Top 10 Department	0.051	0.016	-0.034	0.000
Admitted to Top 20 Department	0.091	0.048	-0.043	0.001
Post-Secondary Degree Quality	40.654	32.399	-8.255	0.000

Notes: The table reports summary statistics for the outcome variables for non-disruptive (defined as students with less than 20 suspension hours, corresponding to the 75^{th} percentile) and disruptive students (defined as students with more than 20 suspension hours), in columns (1) and (2), respectively; the difference between columns (2) and (1) in column (3); and p-values for the t-test on the difference in column (4).

Table A5: Balancing Exercise at the Classroom Level

	Classroom's Mean Baseline GPA	Classroom's Mean Baseline Performance in Core Subjects	Classroom's Mean Sick-related Absences	Classroom's Mean Baseline Hours of Suspension	Classroom's Mean Number Disruptive Peers	Proportion of Females in Class	Classroom Size	Classroom's Mean Age	Proportion Born in 1st Quarter in Class
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Class 2	0.013	-0.002	-0.659	0.343	0.003	-0.035	0.156	-0.003	-0.009
	(0.028)	(0.036)	(0.453)	(0.516)	(0.020)	(0.025)	(0.265)	(0.023)	(0.009)
Class 3	0.033	-0.013	-1.250**	-0.437	-0.019	0.023	0.548*	-0.000	-0.001
	(0.031)	(0.039)	(0.499)	(0.567)	(0.022)	(0.027)	(0.292)	(0.025)	(0.010)
Class 4	0.030	0.019	-0.484	-0.181	-0.013	0.068*	0.081	0.012	-0.006
	(0.040)	(0.050)	(0.641)	(0.729)	(0.028)	(0.035)	(0.375)	(0.032)	(0.012)
Class 5	0.116*	0.168**	0.396	0.184	-0.011	0.028	-0.772	-0.000	-0.002
	(0.066)	(0.083)	(1.059)	(1.205)	(0.047)	(0.058)	(0.619)	(0.053)	(0.020)
Class 6	-0.078	0.006	1.653	1.862	0.049	-0.031	-1.964***	-0.038	-0.007
	(0.075)	(0.095)	(1.204)	(1.370)	(0.053)	(0.066)	(0.704)	(0.061)	(0.023)
Class 7	0.084	0.069	-0.687	-0.636	-0.060	0.082	-1.200	-0.066	0.001
	(0.090)	(0.114)	(1.445)	(1.644)	(0.064)	(0.079)	(0.845)	(0.073)	(0.028)
Observations.	222	222	222	222	222	222	222	222	222
Mean of Y	0.26	0.19	6.90	13.90	0.27	0.55	22.86	16.01	0.09
School x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat. for joint significance	1.17	0.84	1.81	0.74	0.58	1.91	2.71	0.24	0.24
P-value for joint significance	0.33	0.52	0.11	0.59	0.72	0.09	0.02	0.94	0.94

Notes: The table presents the estimated coefficients of binary indicators for different class numbers on a variety of outcomes. For instance, *Class 2* is a binary indicator that takes the value of 1 if the class average of the relevant variable comes from class 1 and 0 otherwise. Class number 1 is omitted from the regression as the reference category. The unit of observation is the class. Outcome variables are reported in column headings and have been averaged at class level. In particular, we regress the binary indicators for classroom numbers on average class baseline GPA (column 1), average class baseline test score for compulsory subjects (column 2), average class baseline suspension hours (column 3), average class share of females (column 4), classroom size (column 5), and average share of students born in 1st quarter in class (column 6). F-statistics for the joint significance of the regressors and the related P-value are also reported. These suggest that class numbers are not associated with differences in class-level averages. The mean of each outcome variable at the class level is also reported (*Mean of Y*). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A6: Descriptive Statistics of Student Longer-Term Outcomes

	Mean	SD	Min	Max	N
National Exam Performance, Grade 12	12.43	4.07	2	20	3,160
College Admission	0.78	0.42	0	1	3,160
Admitted to Top 10 Department	0.04	0.21	0	1	3,160
Admitted to Top 20 Department	0.08	0.28	0	1	3,160
Institution Rank on Preference List	8.51	10.20	1	100	2,454
Post-Secondary Degree Quality	39.29	30.32	0	99	2,454

Notes: The table reports descriptive statistics for student-level longer-term outcome variables. All university applicants take the national exams. "Admitted to a Top 10 Department" and "Admitted to a Top 20 Department" are binary indicators that take the value of 1 if a student enrolls in a degree that is within the top 10% or 20% of departments and 0 otherwise.

Table A7: Effects of Disruptiveness on Postsecondary Applications and Admissions

	Applied for		Admitted to	
	Less Competitive Departments	More Competitive Departments	Less Competitive Departments	More Competitive Departments
	(1)	(2)	(3)	(4)
	Panel A			
Baseline Peers' Suspension Hours	0.010***	-0.001	0.005	-0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
Observations	4,138	4,138	4,138	4,138
	Panel B			
Share of Disruptive Peers	0.236***	-0.088	0.167**	-0.189***
	(0.073)	(0.063)	(0.074)	(0.070)
Observations	4,138	4,138	4,138	4,138
School × Year FE	✓	✓	✓	✓
Track FE	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓
Classroom-level Controls	✓	✓	✓	✓

Notes: The table reports the estimated effects of disruptiveness on postsecondary degree applications and admissions. We categorize departments into two groups: less competitive (columns 1 and 3) and more competitive (columns 2 and 4). Less competitive departments are those with an average university admissions score of admitted students below the median, and more competitive departments are those with average university admissions scores of admitted students above the median. Less competitive departments include humanities, economics, and business-related fields. In contrast, more competitive disciplines include STEM and health-related fields. In columns (1) and (2) the outcomes are binary indicators for whether a student applied for a department with average admissions scores below (less competitive departments) and above the median (more competitive departments). In columns (3) and (4) the outcomes are binary indicators for whether a student was admitted to a department with average admissions scores below (less competitive departments) and above the median (more competitive departments). All regressions include school-by-year fixed effects, specialization track fixed effects, student controls and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A8: Robustness Effects of Disruptiveness on Student Performance, Excluding Top 10% Most Disruptive Students

	Overall Performance	STEM (Math and Physics)	Non-STEM (Language and History)
	(1)	(2)	(3)
	Panel A		
	Final Exam Performance in Grade 10 (Std.)		
Baseline Peers' Suspension Hours (Excluding Top 10% Disruptors)	-0.008***	-0.005	-0.011***
	(0.003)	(0.004)	(0.003)
Observations	4,554	4,554	4,554
	Final Exam Performance in Grade 11 (Std.)		
Baseline Peers' Suspension Hours (Excluding Top 10% Disruptors)	-0.011***	-0.010**	-0.011**
	(0.004)	(0.005)	(0.005)
Observations	3,844	3,844	3,844
Mean X	13.95	13.95	13.95
St Dev X	3.78	3.78	3.78
	Panel B		
	Final Exam Performance in Grade 10 (Std.)		
Share of Disruptive Peers (Excluding Top 10% Disruptors)	-0.194***	-0.086	-0.302***
	(0.056)	(0.079)	(0.073)
Observations	4,554	4,554	4,554
	Final Exam Performance in Grade 11 (Std.)		
Share of Disruptive Peers (Excluding Top 10% Disruptors)	-0.189**	-0.186*	-0.193*
	(0.083)	(0.111)	(0.101)
Observations	3,844	3,844	3,844
Mean X	0.27	0.27	0.27
St Dev X	0.13	0.13	0.13
School × Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports the estimated effects of the baseline peers' suspension hours in Panel A, and share of disruptive peers in Panel B. We use the exact same specification as in main Table 3, with the only difference that we exclude students who have hours of baseline suspensions over 90^{th}. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A9: Placebo Effects of Disruptiveness and Sickness of Peers on Student Performance

	(1) Overall Performance	(2) STEM (Math and Physics)	(3) Non-STEM (Language and History)
	Panel A		
	Final Exam Performance in Grade 10 (Std.)		
Baseline Peers' Suspension Hours	-0.009***	-0.007**	-0.010***
	(0.002)	(0.003)	(0.003)
Baseline Peers' Sickness-related Hours	-0.000	-0.004	0.003
	(0.002)	(0.003)	(0.003)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Baseline Peers' Suspension Hours	-0.013***	-0.012***	-0.014***
	(0.003)	(0.004)	(0.003)
Baseline Peers' Sickness-related Hours	0.003	-0.004	0.009**
	(0.003)	(0.004)	(0.004)
Observations	4,138	4,138	4,138
	Panel B		
	Final Exam Performance in Grade 10 (Std.)		
Share of Disruptive Peers	-0.227***	-0.140**	-0.314***
	(0.049)	(0.068)	(0.064)
Share of Sick Peers	0.046	0.209	-0.117
	(0.101)	(0.131)	(0.130)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Share of Disruptive Peers	-0.287***	-0.295***	-0.278***
	(0.070)	(0.094)	(0.086)
Share of Sick Peers	0.021	0.002	0.041
	(0.135)	(0.175)	(0.179)
Observations	4,138	4,138	4,138
School × Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports the estimated effects of baseline peers' suspension hours and baseline peers' sickness-related hours in Panel A and share of disruptive peers and share of sick peers in Panel B. We use the exact same specification as in main Table 3, with the only difference that we have now added one placebo variable in each panel, as shown in the Table.*Baseline Peers' Sickness-related Hours* are calculated as the average number of baseline sickness-related hours of absence in the classroom. The *Share of Sick Peers* is calculated as the share of classmates with baseline sickness-related hours of absence in the $75\hat{th}$ percentile of the baseline sickness-related absences. This is equivalent to 11 hours of baseline sickness-related hours. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A10: Placebo Effects of the Disruptiveness of Peers Not in the Same Classroom

	(1) Overall Performance	(2) STEM (Math and Physics)	(3) Non-STEM (Language and History)
	Panel A		
	Final Exam Performance in Grade 10 (Std.)		
Baseline Peers' Suspension Hours of:			
Peers in Same School, but not in the Same Class	-0.000	-0.011	0.011
	(0.123)	(0.159)	(0.161)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Baseline Peers' Suspension Hours of:			
Peers in Same School, but not in the Same Class	-0.262	-0.174	-0.349*
	(0.163)	(0.214)	(0.207)
Observations	4,138	4,138	4,138
	Panel B		
	Final Exam Performance in Grade 10 (Std.)		
Share of Disruptive Peers:			
in Same School, but not in the Same Class	-1.918	-1.845	-1.990
	(2.778)	(3.731)	(3.720)
Observations	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)		
Share of Disruptive Peers:			
in Same School, but not in the Same Class	-2.344	-0.344	-4.344
	(4.105)	(5.368)	(5.137)
Observations	4,138	4,138	4,138
School $\times$ Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports the estimated effects of disruptiveness on student outcomes, in which the main treatment effects are replaced with placebo effects. These placebo variables are calculated for all classrooms within the school, excluding the classroom that the student attends. In Panel A, we show the estimated effect of the baseline average suspension hours of students in all other classrooms, excluding the student's own classroom. In Panel B, we show the estimated effect of the share of disruptive peers in all other classrooms, again excluding the student's own classroom. The outcome variables are the standardized performance: overall (column 1); in STEM compulsory subjects (column 2); and non-STEM compulsory subjects (column 3) in grades 10 and 11. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A11: Effects of the Disruptiveness of Peers on Student Performance, By Subject

	(1) Math	(2) Physics	(3) Language	(4) History	(5) STEM (Math and Physics)	(6) Non-STEM (Language and History)
	Panel A					
	Final Exam Performance in Grade 10 (Std.)					
Baseline Peers' Suspension Hours	-0.001	-0.012***	-0.008***	-0.013***	-0.007**	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	5,013	5,013	5,013	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)					
Baseline Peers' Suspension Hours	-0.011***	-0.013***	-0.015***	-0.013***	-0.012***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	4,138	4,138	4,138	4,138	4,138	4,138
	Panel B					
	Final Exam Performance in Grade 10 (Std.)					
Share of Disruptive Peers	-0.021	-0.288***	-0.117*	-0.495***	-0.154**	-0.306***
	(0.072)	(0.079)	(0.071)	(0.084)	(0.067)	(0.063)
Observations	5,013	5,013	5,013	5,013	5,013	5,013
	Final Exam Performance in Grade 11 (Std.)					
Share of Disruptive Peers	-0.299***	-0.291***	-0.261***	-0.302***	-0.295***	-0.282***
	(0.097)	(0.102)	(0.098)	(0.099)	(0.093)	(0.085)
Observations	4,138	4,138	4,138	4,138	4,138	4,138
Mean Y in Grade 10	-0.14	-0.05	-0.17	-0.11	-0.15	-0.08
St. Dev. Y in Grade 10	0.88	1.01	0.84	0.92	0.84	0.91
Mean Y in Grade 11	-0.13	-0.03	-0.14	-0.09	-0.14	-0.06
St. Dev. Y in Grade 11	0.84	0.91	0.82	0.85	0.80	0.83
School × Year FE	✓	✓	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓	✓	✓
Classroom-level Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports the estimated effects of disruptiveness on student outcomes by subject. We consider math (column 1), physics (column 2); language (column 3); and history (column 4); STEM (column 5, as the average between math and physics); and non-STEM (column 6, as the average between Language and history). All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A12: Heterogeneous Effects of the Disruptiveness of Peers by Gender and Prior Performance

	Student Gender		Student Baseline Performance	
	Male	Female	Above Median	Below Median
	(1)	(2)	(3)	(4)
	Panel A			
	Final Exam Performance in Grade 10 (Std.)			
Baseline Peers' Suspension Hours	-0.011***	-0.006**	-0.008***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2,236	2,777	2,693	2,320
	Final Exam Performance in Grade 11 (Std.)			
Baseline Peers' Suspension Hours	-0.013***	-0.012***	-0.014***	-0.009**
	(0.004)	(0.003)	(0.004)	(0.004)
Observations	1,798	2,339	2,382	1,756
	Panel B			
	Final Exam Performance in Grade 10 (Std.)			
Share of Disruptive Peers	-0.205***	-0.239***	-0.232***	-0.169**
	(0.076)	(0.065)	(0.064)	(0.068)
Observations	2,236	2,777	2,693	2,320
	Final Exam Performance in Grade 11 (Std.)			
Share of Disruptive Peers	-0.195*	-0.327***	-0.336***	-0.189**
	(0.113)	(0.088)	(0.093)	(0.096)
Observations	1,798	2,339	2,382	1,756
School × Year FE	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓
Classroom-level Controls	✓	✓	✓	✓

Notes: The table reports estimated effects of peer disruptiveness on student outcomes by student gender and student prior performance. Columns 1 and 2 present the estimated effects of disruptiveness for male and female students. Columns 3 and 4 present the estimated effects of disruptiveness for students with prior performance above and below the median. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A13: Effects of Peers' Disruptiveness on Student Performance, Disruptive vs. Non-disruptive Students

	Overall Performance	STEM (Math and Physics)	Non-STEM (Language and History)
	(1)	(2)	(3)
	Panel A: Baseline Classroom Peers' Suspension Hours		
	Final Exam Performance in Grade 10 (Std.)		
Disruptive	-0.007***	-0.004	-0.009***
	(0.002)	(0.003)	(0.003)
Non-disruptive	-0.009***	-0.008***	-0.011***
	(0.002)	(0.003)	(0.003)
	Final Exam Performance in Grade 11 (Std.)		
Disruptive	-0.013***	-0.011***	-0.015***
	(0.003)	(0.004)	(0.004)
Non-disruptive	-0.013***	-0.012***	-0.014***
	(0.003)	(0.004)	(0.003)
	Panel B: Share of Disruptive Peers		
	Final Exam Performance in Grade 10 (Std.)		
Disruptive	-0.185***	-0.078	-0.292***
	(0.063)	(0.084)	(0.083)
Non-disruptive	-0.245***	-0.180***	-0.310***
	(0.050)	(0.069)	(0.064)
	Final Exam Performance in Grade 11 (Std.)		
Disruptive	-0.315***	-0.277**	-0.354***
	(0.090)	(0.119)	(0.113)
Non-disruptive	-0.281***	-0.300***	-0.263***
	(0.070)	(0.095)	(0.086)
Observations	4,138	4,138	4,138
School × Year FE	✓	✓	✓
Student Controls	✓	✓	✓
Classroom-level Controls	✓	✓	✓

Notes: The table reports estimated effects of peer disruptiveness on student test scores for disruptive and non-disruptive students. The outcome variables are standardized performance scores: overall performance (column 1), performance on STEM compulsory subjects (column 2), and performance on non-STEM compulsory subjects (column 3) in grades 10 and 11. The treatment variable is baseline peers' suspension hours in Panel A and the share of disruptive peers in Panel B. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A14: Heterogeneous Effects of Peer Disruptiveness, by Household Income and Class Environment

	Below Median Income	Above Median Income	Below Median Class Size	Above Median Class Size	Below Median Prop. of Female	Above Median Prop. of Female
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
			Final Exam Performance in Grade 10 (Std.)			
Baseline Peers' Suspension Hours	-0.011***	-0.006**	-0.010***	-0.014***	-0.008**	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Observations	2,510	2,503	2,831	2,182	2,521	2,492
			Final Exam Performance in Grade 11 (Std.)			
Baseline Peers' Suspension Hours	-0.014***	-0.008*	-0.004	-0.023***	-0.018***	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Observations	2,209	1,929	2,269	1,869	2,022	2,116
			Panel B			
			Final Exam Performance in Grade 10 (Std.)			
Share of Disruptive Peers	-0.335***	-0.077	-0.227***	-0.465***	-0.145	-0.209**
	(0.065)	(0.078)	(0.071)	(0.080)	(0.089)	(0.081)
Observations	2,510	2,503	2,831	2,182	2,521	2,492
			Final Exam Performance in Grade 11 (Std.)			
Share of Disruptive Peers	-0.330***	-0.091	-0.047	-0.609***	-0.542***	-0.090
	(0.091)	(0.116)	(0.095)	(0.114)	(0.141)	(0.112)
Observations	2,209	1,929	2,269	1,869	2,022	2,116
School × Year FE	✓	✓	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓	✓	✓
Classroom-level Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports estimated effects of peer disruptiveness on student outcomes by household income, class size, and share of female classmates. Columns 1 and 2 present the estimated effects of disruptiveness for students living in areas with income levels below and above the median. Columns 3 and 4 report the estimated effects for students assigned to classrooms with class sizes below and above the median. Columns 6 and 7 show the estimated effects for students assigned to classrooms with a share of female classmates below and above the median. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A15: Balance of Characteristics Across Main Treatment Groups, Lab-in-the-Field Experiment

	Full Sample			One Class Disruptors			Multiple Class Disruptors				
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff. (4) − (7)	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Female Student (1=yes)	0.54	0.50	644	0.54	0.50	331	0.55	0.50	313	-0.01	0.83
STEM Track (1=yes)	0.70	0.46	644	0.72	0.45	331	0.69	0.46	313	0.03	0.42
School 1	0.22	0.42	644	0.23	0.42	331	0.22	0.42	313	0.01	0.85
School 2	0.24	0.43	644	0.25	0.44	331	0.23	0.42	313	0.02	0.48
School 3	0.14	0.35	644	0.14	0.34	331	0.15	0.36	313	-0.01	0.61
School 4	0.18	0.38	644	0.16	0.37	331	0.20	0.40	313	-0.04	0.21
School 5	0.21	0.41	644	0.22	0.42	331	0.20	0.40	313	0.02	0.49
Grade 11	0.48	0.50	644	0.49	0.50	331	0.48	0.50	313	0.01	0.79
Grade 12	0.52	0.50	644	0.51	0.50	331	0.52	0.50	313	-0.01	0.79
Physically Close Peers	0.49	0.50	644	0.48	0.50	331	0.50	0.50	313	-0.02	0.59

Notes: The table shows summary statistics of the pretreatment characteristics of participants in the survey experiment, along with the differences between the main scenario treatments (i.e., being exposed to multiple vs. one class disruptor). "Female Student (1=yes)" is a binary indicator that takes the value of 1 if the survey participant was a female and 0 otherwise. "STEM Track (1=yes)" is a binary indicator that takes the value of 1 if the survey participant chose a STEM track at the beginning of grade 11 and 0 otherwise. "Physically Close Peers" is a binary indicator that takes the value of 1 if the survey participant was assigned to a scenario in which multiple or one disruptive peer is seated next to them and 0 otherwise. Students in grades 11 and 12 participated in the experiment.

Table A16: Balance of Characteristics Across Secondary Treatment Groups, Lab-in-the-Field Experiment

	Full Sample			Physically Close Peers			Physically Distant Peers				
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff. (4) – (7)	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
One Class Disruptor											
Female Student (1=yes)	0.54	0.50	331	0.51	0.50	171	0.56	0.50	160	-0.05	0.38
STEM Track (1=yes)	0.72	0.45	331	0.73	0.44	171	0.70	0.46	160	0.03	0.53
School 1	0.23	0.42	331	0.22	0.42	171	0.23	0.42	160	-0.01	0.85
School 2	0.25	0.44	331	0.27	0.44	171	0.24	0.43	160	0.03	0.51
School 3	0.14	0.34	331	0.13	0.34	171	0.14	0.35	160	-0.00	0.94
School 4	0.16	0.37	331	0.16	0.37	171	0.16	0.37	160	-0.00	0.91
School 5	0.22	0.42	331	0.22	0.41	171	0.23	0.42	160	-0.01	0.75
Grade 11	0.49	0.50	331	0.50	0.50	171	0.47	0.50	160	0.02	0.69
Grade 12	0.51	0.50	331	0.50	0.50	171	0.53	0.50	160	-0.02	0.69
Many Class Disruptors											
Female Student (1=yes)	0.55	0.50	313	0.56	0.50	155	0.53	0.50	158	0.03	0.60
STEM Track (1=yes)	0.69	0.46	313	0.70	0.46	155	0.67	0.47	158	0.03	0.54
School 1	0.22	0.42	313	0.20	0.40	155	0.24	0.43	158	-0.04	0.39
School 2	0.23	0.42	313	0.23	0.42	155	0.23	0.42	158	0.00	0.93
School 3	0.15	0.36	313	0.14	0.35	155	0.16	0.37	158	-0.02	0.69
School 4	0.20	0.40	313	0.21	0.41	155	0.18	0.39	158	0.03	0.52
School 5	0.20	0.40	313	0.21	0.41	155	0.19	0.39	158	0.02	0.61
Grade 11	0.48	0.50	313	0.45	0.50	155	0.51	0.50	158	-0.06	0.28
Grade 12	0.52	0.50	313	0.55	0.50	155	0.49	0.50	158	0.06	0.28

Notes: The table shows summary statistics of the pretreatment characteristics of participants in the survey experiment, along with the differences between treatments. "Female Student (1=yes)" is a binary indicator that takes the value of 1 if the survey participant was a female and 0 otherwise. "STEM Track (1=yes)" is a binary indicator that takes the value of 1 if the survey participant chose a STEM track at the beginning of grade 11 and 0 otherwise. Students in grades 11 and 12 participated in the experiment.

Table A17: Mechanism Investigation: Effects of Disruptiveness on Peers' Attendance

	Suspension Hours End of Grade 10	Suspension Hours End of Grade 11	Sickness-related Absences End of Grade 10	Sickness-related Absences End of Grade 11	New Disruptive Status End of Grade 10	New Disruptive Status End of Grade 11
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
Baseline Peers' Suspension Hours	0.003	0.080	0.016	0.056	-0.002	-0.001
	(0.107)	(0.054)	(0.074)	(0.085)	(0.003)	(0.003)
			Panel B			
Share of Disruptive Peers	-1.760	0.353	-0.422	2.376	-0.069	-0.048
	(1.840)	(1.343)	(1.799)	(2.237)	(0.070)	(0.065)
Observations	5,013	4,138	5,013	4,138	5,013	4,138
Mean Y	14.19	16.48	0.28	0.27	9.23	13.03
St Dev Y	20.62	10.21	0.45	0.44	12.16	14.30
School × Year FE	✓	✓	✓	✓	✓	✓
Student Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports the estimated effects of peer disruptiveness on student end-of-year attendance. The outcome variables in columns (1) and (2) are the hours of suspension a student obtains at the end of grades 10 and 11. The outcome variables in columns (3) and (4) are the sickness-related hours of absence a student receives at the end of grades 10 and 11. The outcome variables in columns (5) and (6) are binary indicators for whether a student receives suspensions that would cause them to fall into the 75^{th} percentile of suspensions. All regressions include school-by-year fixed effects, student controls, and classroom-level controls. Student controls include controls for student age (in years), an indicator that takes the value 1 if a student is born in the first quarter of the calendar year (and 0 otherwise), an indicator that takes the value 1 if a student is female (and 0 otherwise), student baseline average performance on compulsory subjects, student baseline sickness-related absences, and student-level hours of suspension. Classroom-level controls include average age, average baseline sickness-related absences, average baseline peers' baseline performance on compulsory subjects, share of peers born in the first quarter of the year, and share of female peers (all calculated as leave-out means). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Online Appendix:

Questionnaire in English

Invitation to Participate in Research Study

The researchers Dr. Rigissa Megalokonomou and Dr. Sofoklis Goulas invite you to participate in a research study about the role of peers in school. Participation in the study is voluntary and takes no longer than 5 minutes. You are not at any risk from participating or not participating in this study. Your confidentiality is guaranteed.

If you have any questions regarding the questionnaire, you can contact the researchers via email at **r.megalokonomou@uq.edu.au** or **goulas@stanford.edu**.

If you are not satisfied with the way the study is being conducted or have any questions, complaints, or concerns about the research or your rights as a participant, please contact the Stanford Institutional Review Board (IRB) to speak with someone independent from the research team at 650-723-2480, or by mail at Stanford IRB, Stanford University, 1705 El Camino Real, Palo Alto, CA 94306.

The GDPR regulation guarantees certain rights concerning your data, including the right (1) to request access, correct, or delete your data, (2) to withdraw or restrict the processing of your data, and (3) to request the transfer or copying of your data to another entity. You may also withdraw your consent at any time. If you withdraw your consent or request the deletion of your data, we may still collect or use your data up until the point at which you withdraw your consent or request deletion. Even if you withdraw your consent, we may still use anonymized data by removing information that could potentially identify you. We may also use pseudonymized data by removing information that could identify you, as defined by law. Your anonymized or pseudonymized data may be used for (a) public health purposes, (b) scientific, historical, or statistical analysis as defined by the laws of the EU member states, and (c) the storage of important public interest information. We will retain your data in an identifiable form if required by law. There is no time limit on the retention of your data for scientific research purposes. We will retain your data for as long as it remains useful or until you withdraw your consent. You consent to the collection, use, and transfer of your data for the purposes of scientific research, and you are aware that you may withdraw your consent at any time, and we will cease processing your data as described above.

If you agree to participate in the study, please select "I Agree."

- I Agree
- I Disagree

If you selected "I Disagree," you may exit the questionnaire without answering any further questions.

Survey Questions

[The following questions are displayed for all participants.]

Q1. What is your gender?

☐ Male

☐ Female

☐ Non-binary

☐ Prefer not to answer

Q2. Which track of specialization have you chosen?

☐ Humanities

☐ Science

Q3. Have you witnessed the use of hourly unexcused absences as a penalty for disruptive students?

☐ Yes

☐ No

Q4. In what ways can one or more students typically disrupt the class and be sent out? (Multiple answers possible)

☐ Distracting other students in class

☐ Making noise

☐ Being indifferent or disengaged during the lesson

☐ Other: _________________

[TREATMENT BLOCKS]

[In the treatment block, participants receive a random treatment in which only the questions related to the allocated treatment are displayed. A participant receives only one treatment.]

[Beginning of Treatment 1]

Q5. Imagine the following scenario:

You are a 10th-grade student. Last week, **one student** in your class was sent out of the lesson for disruptive behavior.

Do you think the behavior of these peers, regardless of their academic performance, would affect you in terms of:

*Rate from **0** to **100**, where 0 means no influence, and 100 means maximum influence.*

Study Motivation	
Aspiration for university studies	
Readiness for science studies	
Readiness for career preparation	

[End of Treatment 1]

[Beginning of Treatment 2]

Q5. Imagine the following scenario:

You are a 10th-grade student. Last week, **one-third** of the students in your class was sent out of the lesson for disruptive behavior.

Do you think the behavior of these peers, regardless of their academic performance, would affect you in terms of:

*Rate from **0** to **100**, where 0 means no influence, and 100 means maximum influence.*

Study Motivation	
Aspiration for university studies	
Readiness for science studies	
Readiness for career preparation	

[End of Treatment 2]

[Beginning of Treatment 3]

Q5. Imagine the following scenario:

You are a 10th-grade student. Last week, **a student** who was **sitting next to you** in class was sent out of the lesson for disruptive behavior.

Do you think the behavior of these peers, regardless of their academic performance, would affect you in terms of:

*Rate from **0** to **100**, where 0 means no influence, and 100 means maximum influence.*

Study Motivation	
Aspiration for university studies	
Readiness for science studies	
Readiness for career preparation	

[End of Treatment 3]

[Beginning of Treatment 4]

Q5. Imagine the following scenario:

You are a 10th-grade student. Last week, **one-third** of the students in your class **sitting next to you** were sent out of the lesson for disruptive behavior.

Do you think the behavior of these peers, regardless of their academic performance, would affect you in terms of:

*Rate from **0** to **100**, where 0 means no influence, and 100 means maximum influence.*

Study Motivation	
Aspiration for university studies	
Readiness for science studies	
Readiness for career preparation	

[End of Treatment 4]

Q6. Can you describe an incident where one or more students were disruptive and sent out of the class?

Q7. Who is the person in your life whose opinion you value the most when they speak?

Q8. What was your final grade in 10th grade? _____________

Q9. What grade do you expect to finish with in the current academic year? ______________

Q10. If you would like to participate in our next research study, please provide your email address below.

Thank you very much.

____

Questionnaire in Greek

<u>Πρόσκληση για Συμμετοχή σε Έρευνα</u>

Οι ερευνητές Δρ. Ρήγισσα Μεγαλοκονόμου και Δρ. Σοφοκλής Γούλας σας προσκαλούν στην έρευνα για το ρόλο των συμμαθητών στο σχολείο. Η συμμετοχή στην έρευνα είναι προαιρετική και δεν διαρκεί πάνω από 5 λεπτά. Δεν διατρέχετε κανέναν κίνδυνο από τη συμμετοχή σας ή μη στη μελέτη αυτή. Το προσωπικό απόρρητο διασφαλίζεται.

Αν έχετε οποιαδήποτε απορία σχετικά με το ερωτηματολόγιο, μπορείτε να επικοινωνήσετε με τους ερευνητές μέσω email στις διευθύνσεις r.megalokonomou@uq.edu.au ή goulas@stanford.edu.

Αν δεν είστε ικανοποιημένοι με τον τρόπο που διεξάγεται η μελέτη αυτή ή έχετε απορίες, παράπονα ή ερωτήσεις σχετικά με την έρευνα ή με τα δικαιώματά σας ως συμμετέχοντες, παρακαλώ επικοινωνήστε με το Stanford Institutional Review Board (IRB) για μιλήσετε με κάποιον ανεξάρτητο από την ερευνητική ομάδα στο τηλέφωνο 650-723-2480 ή ταχυδρομικά στη διεύθυνση Stanford IRB, Stanford University, 1705 El Camino Real, Palo Alto, CA 94306.

Ο κανονισμός GDPR κατοχυρώνει ορισμένα δικαιώματα ως προς τα δεδομένα σας, συμπεριλαμβανωμένων το δικαίωμα (1) να ζητήσετε πρόσβαση, να διορθώσετε ή να διαγράψετε τα δεδομένα σας, (2) να αποσύρετε ή να περιορίσετε την επεξεργασία των δεδομένων σας, και (3) να ζητήσετε τη μεταφορά ή αντιγραφή των δεδομένων σας σε άλλο φορέα. Μπορείτε επίσης να αποσύρετε τη συγκατάθεσή σας οποιαδήποτε στιγμή. Αν αποσύρετε τη συγκατάθεσή σας ή ζητήσετε τη διαγραφή των δεδομένων σας, εξακολουθούμε να μπορούμε να συλλέξουμε ή να χρησιμοποιήσουμε τα δεδομένα σας μέχρι τη στιγμή που αποσύρετε τη συγκατάθεσή σας ή ζητήσετε τη διαγραφή των δεδομένων σας. Ακόμα και αν αποσύρετε τη συγκατάθεσή σας, εξακολουθούμε να μπορούμε να χρησιμοποιήσουμε ανωνυμοποιημένα στοιχεία σας αφαιρώντας πληροφορίες που πιθανόν σας ταυτοποιούν. Μπορούμε επίσης να χρησιμοποιήσουμε ψευδωνυμοποιημένα δεδομένα σας αφαιρώντας πληροφορίες που πιθανόν σας ταυτοποιούν όπως ορίζει ο νόμος. Τα ανωνυμοποιημένα ή ψευδωνυμοποιημένα δεδομένα σας μπορούν να χρησιμοποιηθούν στα πλαίσια (α) δημόσιας υγείας, (β) επιστημονικής, ιστορικής ή στατιστικής ανάλυσης όπως ορίζουν οι κατά χώρα νόμοι των μελών της ΕΕ, και (γ) την αποθήκευση σημαντικών πληροφοριών δημοσίου συμφέροντος. Θα διατηρήσουμε τα δεδομένα σας σε ταυτοποιήσιμη μορφή αν το απαιτεί ο νόμος. Δεν υπάρχει χρονικό όριο στη διατήρηση των δεδομένων σας επιστημονική έρευνα. Θα διατηρήσουμε τα δεδομένα σας για όσο καιρό παραμένουν χρήσιμα ή μέχρι να αποσύρετε τη συγκατάθεσή σας. Παραχωρείτε συγκατάθεση για τη συλλογή, χρήση και μεταφορά των δεδομένων σας για τους σκοπούς επιστημονικής έρευνας και γνωρίζετε ότι μπορείτε να αποσύρετε τη συγκατάθεσή σας οποιαδήποτε στιγμή και θα παύσουμε την επεξεργασία των δεδομένων σας όπως περιγράφεται ανωτέρω.

Αν συμφωνείτε να συμμετάσχετε στη μελέτη, επιλέξτε "Συμφωνώ".

☐ Συμφωνώ

☐ Διαφωνώ

Αν επιλέξατε "Διαφωνώ" μπορείτε να τερματίσετε το ερωτηματολόγιο χωρίς να απαντήσετε τις επόμενες ερωτήσεις

Ερωτήσεις Έρευνας

[The following questions are displayed for all participants.]

Q1. Ποιο είναι το φύλο σας;

- ☐ Άρρεν
- ☐ Θήλυ
- ☐ Μη δυαδικό
- ☐ Δεν επιθυμώ να απαντήσω

Q2. Τι ομάδα προσανατολισμού έχετε επιλέξει;

- ☐ Ανθρωπιστικών Σπουδών
- ☐ Θετικών Σπουδών

Q3. Έχετε δει περιστατικά ωριαίων αποβολών όταν ένας/μια μαθητής/μαθήτρια διέκοπτε το μάθημα;

- ☐ Ναι
- ☐ Όχι

Q4. Με ποιους τρόπους ένας ή περισσότεροι μαθητές μπορούν συνηθώς να διακόψουν το μάθημα και να πάρουν απουσία; (πολλαπλές απαντήσεις)

- ☐ Απασχολώντας άλλους μαθητές στην τάξη
- ☐ Κάνοντας φασαρία
- ☐ Μένοντας αδιάφοροι και αμέτοχοι στο μάθημα
- ☐ Άλλο:____

[TREATMENT BLOCKS]

[In the treatment block, participants receive a random treatment in which only the questions related to the allocated treatment are displayed. A participant receives only one treatment.]

[Beginning of Treatment 1]

Q5. Φανταστείτε το εξής σενάριο:

Είστε μαθητής/μαθήτρια της Α' Λυκείου. Στην τάξη σας την προηγουμένη εβδομάδα, **ένας μαθητής** πήρε απουσία επειδή διέκοπτε το μάθημα.

Πιστεύετε πως η συμπεριφορά των συμμαθητών αυτών που πήραν απουσία, ανεξάρτητα της επίδοσής τους, σας επηρεάζει ως προς τη/την:

*Βαθμολογείστε από το **0** μέχρι το **100**. **0** σημαίνει μηδενική επιρροή και **100** σημαίνει μέγιστη επιρροή*

Όρεξη για Διάβασμα	
Φιλοδοξία για Πανεπιστημιακες Σπουδές	
Ετοιμότητα για Σπουδές σε Θετικές Επιστήμες	
Ετοιμότητα για Επαγγελματική Σταδιοδρομία	

[End of Treatment 1]

[Beginning of Treatment 2]

Q5. Φανταστείτε το εξής σενάριο:

Είστε μαθητής/μαθήτρια της Α' Λυκείου. Στην τάξη σας την προηγουμένη εβδομάδα το **ένα τρίτο της τάξης,** πήρε απουσία επειδή διέκοπτε το μάθημα.

Πιστεύετε πως η συμπεριφορά των συμμαθητών αυτών που πήραν απουσία, ανεξάρτητα της επίδοσής τους, σας επηρεάζει ως προς τη/την:

*Βαθμολογείστε από το **0** μέχρι το **100**. **0** σημαίνει μηδενική επιρροή και **100** σημαίνει μέγιστη επιρροή*

Όρεξη για Διάβασμα	
Φιλοδοξία για Πανεπιστημιακες Σπουδές	
Ετοιμότητα για Σπουδές σε Θετικές Επιστήμες	
Ετοιμότητα για Επαγγελματική Σταδιοδρομία	

[End of Treatment 2]

[Beginning of Treatment 3]

Q5. Φανταστείτε το εξής σενάριο:

Είστε μαθητής/μαθήτρια της Α' Λυκείου. Στην τάξη σας την προηγουμένη εβδομάδα, **ένας μαθητής που καθόταν κοντά σας** πήρε απουσία επειδή διέκοπτε το μάθημα.

Πιστεύετε πως η συμπεριφορά των συμμαθητών αυτών που πήραν απουσία, ανεξάρτητα της επίδοσής τους, σας επηρεάζει ως προς τη/την:

*Βαθμολογείστε από το **0** μέχρι το **100**. **0** σημαίνει μηδενική επιρροή και **100** σημαίνει μέγιστη επιρροή*

Όρεξη για Διάβασμα	
Φιλοδοξία για Πανεπιστημιακες Σπουδές	
Ετοιμότητα για Σπουδές σε Θετικές Επιστήμες	
Ετοιμότητα για Επαγγελματική Σταδιοδρομία	

[End of Treatment 3]

[Beginning of Treatment 4]

Q5. Φανταστείτε το εξής σενάριο:

Είστε μαθητής/μαθήτρια της Α' Λυκείου. Στην τάξη σας την προηγουμένη εβδομάδα το **ένα τρίτο της τάξης που καθόταν κοντά σας,** πήρε απουσία επειδή διέκοπτε το μάθημα.

Πιστεύετε πως η συμπεριφορά των συμμαθητών αυτών που πήραν απουσία, ανεξάρτητα της επίδοσής τους, σας επηρεάζει ως προς τη/την:

*Βαθμολογείστε από το **0** μέχρι το **100**. **0** σημαίνει μηδενική επιρροή και **100** σημαίνει μέγιστη επιρροή*

Όρεξη για Διάβασμα	
Φιλοδοξία για Πανεπιστημιακες Σπουδές	
Ετοιμότητα για Σπουδές σε Θετικές Επιστήμες	
Ετοιμότητα για Επαγγελματική Σταδιοδρομία	

[End of Treatment 4]

Q6. Μπορείτε να περιγράψετε ένα περιστατικό όπου ένας ή περισσότεροι μαθητές διέκοπταν το μάθημα και πήραν ωριαία αποβολή.

____

Q7. Ποιος είναι ο άνθρωπος στη ζωή σας που όταν μιλάει ακούτε;

____

Q8. Με τι βαθμό τελειώσατε την Α' Λυκείου;____________________

Q9. Με τι βαθμό περιμένετε να τελειώσετε τη σχολική χρονιά που μόλις άρχισε;
____

Q10. Αν θα θέλατε να συμμετάσχετε σε επομένη ερευνά μας, παρακαλώ συμπληρώστε παρακάτω τη διεύθυνση ηλεκτρονικής σας αλληλογραφίας (email).

Σας ευχαριστούμε.

____