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Veering off track in U.S. high schools? Redirecting student trajectories by disrupting punishment and math course-taking tracks

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ABSTRACT

Students in punishment "tracks" are rarely in advanced course-taking "tracks" in high school. Yet, there is little research that demonstrates the relationships *between* punishment and advanced course-taking, nor research that demonstrates how punishment and advanced course-taking *together* can impact long-term student trajectories. Using multi-level modeling with a national longitudinal study of high school students, we observed reciprocal disruptions. Advanced math courses significantly impacted future suspensions when accounting for prior suspensions, while suspensions significantly impacted future advanced math course-taking when accounting for prior math courses. We also observed that both suspensions and advanced math courses significantly influenced dropout status and college attendance. As baseline measures often maintained a strong relationship with their respective outcomes, disadvantages appeared to accumulate when students were excluded both from advanced math courses and through suspensions. Nevertheless, while we cannot undo the harms of previous disadvantages in punishment, our findings suggest that we can facilitate potential turning points in students' lives by opening up new opportunities in math. By doing so, we can redirect students towards college. We conclude with a discussion of implications for policy and practice.

1. Introduction

Advanced courses in high school can have long-term impacts on students' lives. For example, students who take advanced science, technology, engineering, and math (STEM) courses in high school are more likely to major in a STEM subject in college and secure a STEM job in the labor market (Engberg & Wolniak, 2013). Conversely, punitive discipline practices can also have long-term impacts on students' lives. Students who have been suspended are more likely to drop out of school and become involved in the criminal justice system (Fabelo, Thompson, Plotkin, Carmichael, Marchbanks, & Booth, 2011, p. xii). Thus, early engagement with STEM courses can propel students along trajectories of *inclusion*—inclusion in selective STEM classrooms, college majors, and career fields, while early exposure to punishment can propel students along trajectories of *exclusion*—exclusion from classrooms (in-school suspension), schools (out-of-school suspension), formal education (dropping out), and society (incarceration).

Unsurprisingly, students in punishment "tracks" are rarely in advanced course-taking "tracks" in high school, especially in math (Schneider, Swanson, & Riegle-Crumb, 1997). Nevertheless, there is little research that demonstrates the relationships *between* punishment and advanced math course-taking, nor research that demonstrates how punishment and advanced math courses *together* can impact long-term student trajectories. By filling this gap, we believe that we will be able to pinpoint pivotal turning points in high school that may be able to redirect student trajectories away from negative life outcomes, such as dropping out of high school, and towards more positive ones, such as attending college.

Furthermore, when considering the relationship between advanced math courses and the U.S.'s under-developed STEM workforce (PCAST, 2010), as well as the fact that innovation from STEM workers creates more new jobs for non-STEM workers than any other sector (National Research Council, 2011), advanced math course-taking can be seen as a potential driver of economic prosperity. Conversely, when considering the relationship between punitive disciplinary practices and the U.S.'s over-populated prison population (Fowler, 2011), as well as its large social costs to families, children, and community members (Pettus-Davis, Brown, Veeh, & Renn, 2016), suspensions can be seen as a current driver of social vulnerability.

Moreover, as Black students are often *underrepresented* in advanced math courses (Riegle-Crumb & Grodsky, 2010) and *over-represented* in punitive disciplinary practices (Anyon et al., 2014), advanced math course-taking and suspensions can also be seen as drivers of economic and social inequity as well. While just 13 percent of engineers were Black or Hispanic in 2015 (Pew Research Center, 2018b), the combined percentage of Black and Hispanic individuals who were incarcerated was 56 percent (Pew Research Center, 2018a). Thus, redirecting students away from the school-to-prison pipeline and towards the STEM pipeline represents an important area of interest convergence for the broader U.S. economy and society.

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In our study, we observed reciprocal disruptions: advanced math courses significantly impacted future suspensions when accounting for prior suspensions, while suspensions significantly impacted future advanced math course-taking when accounting for prior math courses. In terms of long-term student trajectories, we observed that both suspensions and advanced math courses significantly influenced dropout status and college attendance.

2. Literature background

2.1. School tracks and student trajectories in the life course

In his discussion of the life course Pallas (2003) defines a *pathway* as an attribute of a social systems and a *trajectory* as an attribute of individuals. While pathways are structural in nature, trajectories involve both structural conditions and individual agency *within* these structural conditions (2003). Similarly, we define "tracks" as attributes of schools that are structural in nature and trajectories as attributes of students that involve both structural conditions *and* individual agency.

While tracks and trajectories related to advanced course-taking and punishment can start long before 9th grade, we focus on high schools, as they encompass opportunity structures with greater levels of stratification, as well as greater levels of individual agency (see Pettit & Western, 2004; Bottia, Stearns, Mickelson, Moller, & Parker, 2015). For example, high schools often have more structured academic tracks (e.g. vocational tracks, college preperatory tracks, etc.) (Gamoran & Mare, 1989), as well as more structured punishment processes (e.g. school resource officers, in-school suspension rooms, etc.) (Kupchik, 2010). At the same time, students in high school are often offered a wider variety of math and science courses and are legally allowed to permanently drop out.

We focus on high school tracks that ideally offer continued *access* to advanced knowledge and skills, such as the advanced math track (Oakes, 1985), as well as tracks that commonly offer continued *exposure* to exclusionary discipline practices, such as the punishment track (Hirschfield, 2008). Entrance and persistence within these tracks create positional advantages and disadvantages in schools, which can accumulate over time, signal status, and ultimately increase or decrease future opportunities related economic mobility, social mobility, and attainment (see Blau & Duncan, 1967). In this study, we focus on trajectory indicators related to educational attainment—specifically *dropping out* of high school and *attending college*. Based on previous literature, dropping out can be seen as a trajectory indicator associated with the punishment track (Fabelo et al., 2011), while and attending college can be seen as a trajectory associated with the advanced math track (Finkelstein & Fong, 2008).

We operationalize the advanced math track as a structure of educational opportunity that continually includes students in increasingly exclusive and advanced math courses (Schneider et al., 1997). Given course sequencing guidelines, students' freshman year math courses are highly predictive of the number of math credits, and ultimately, their senior year math courses (Cortes, Goodman, & Nomi, 2015). In addition to impacting a student's decision to pursue a STEM major in college (Tyson, 2011), advanced math course-taking has also been associated with general college attendance (Finkelstein & Fong, 2008).

While we recognize the possibility that some punishments can have a positive impact on the learning environment for non-punished students (see Kinsler, 2013), we instead focus on the educational opportunities of *punished* students. In doing so, we operationalize the punishment track as a structure of educational *in*opportunity that continually excludes students from learning environments through increasingly frequent and severe measures of surveillance and punishment (Kupchik et al., 2009). Given school discipline policies and practices, once students are brought to the attention of school authorities, they can be strictly surveilled and constantly "tracked" for further missteps (Morrison, Anthony, Storino, & Dillon, 2001). In addition to impacting future involvement with the criminal justice system (Mowen & Brent, 2016), suspensions have also been associated with higher levels of dropping out and lower level of attending college (Rosenbaum, 2018).

2.2. Reciprocal disruptions and turning points in the life course

Our conceptualization of reciprocal disruptions between punishment and advanced math tracks and their impact on student trajectories builds on the "life course" perspective (Elder, Johnson, & Crosnoe, 2003). Within the life course perspective, we combine Thornberry's (1987) interactional theory with Sampson and Laub's (1993) "turning points" theory. Starting with interactional theory, Thornberry, Lizotte, Krohn, Farnworth, and Jang (1994) have demonstrated that there is a reciprocal relationship between students' behavior and their commitment to school that increases in intensity over the life course. Here, initially weak bonds to school can lead to greater opportunities for delinquency to be learned, performed, and reinforced, which can further weaken bonds to school (Thornberry, 1987, p. 883). As a result, initial disadvantages across discipline and academics can accumulate over time. Moving on to "turning points" theory, Sampson and Laub (1993) have demonstrated that certain life points can "separate the past from the present" and in doing so redirect trajectories (p. 304). In relation to education, turning points can "reorder the life course by opening or closing off conventional opportunity structures" (Mowen & Brent, 2016, p. 634).

In combining these theories, we conceptualize that the reciprocal relationships between students' behavior and their commitment to school can be disrupted by specific turning points and that these turning points can redirect students' long term trajectories. As seen in Fig. 1 below, advanced math courses may "open up" new opportunity structures for students who have previously been suspended and direct them towards college attendance. Conversely, suspensions may "close off" opportunity structures for students who have previously taken advanced math courses and direct them towards dropping out.

While previous research has not been able to demonstrate reciprocal disruptions and their impact on long-term student trajectories in this way, it has revealed some of the important relationships between punishment and achievement. Using data from a large school district in Florida, Arcia (2006) demonstrated that students who were removed from learning environments through suspensions tended to have lower academic achievement prior to their removal, made fewer achievement gains after they returned, and were often suspended again (see Arcia, 2006). In a meta-analysis of 24 studies, Noltemeyer, Ward, and Mcloughlin (2015) found that suspensions were negatively associated with academic achievement. However, as the majority of these studies did not control for academic achievement measures that occurred prior to suspensions, many of these studies were unable to disentangle the impact of being suspended from the underlying factors that may have lead students to be suspended in the first place, such as low academic achievement (see Anderson, Ritter, & Zamarro, 2019). Noting these shortcomings, Anderson et al.'s (2019) analysis of suspensions, math achievement scores, and student retention rates included prior academic achievement measures, controlled for behavioral infractions, and tested the differences among more and less-exclusionary responses. While the authors found that more exclusionary practices were associated with worse outcomes, the authors ultimately concluded that their results may still be influenced by selection bias (2019).

2.3. Social background influences, student attachment, and school climate

In order to best understand educational trajectories in the life course, social background influences must be considered, as these influences not only "structure the choices that individuals make, but also shape the structures in which individuals can exercise choice" (Pallas, 2003, p. 168). For example, Schiller and Hunt (2011) found that

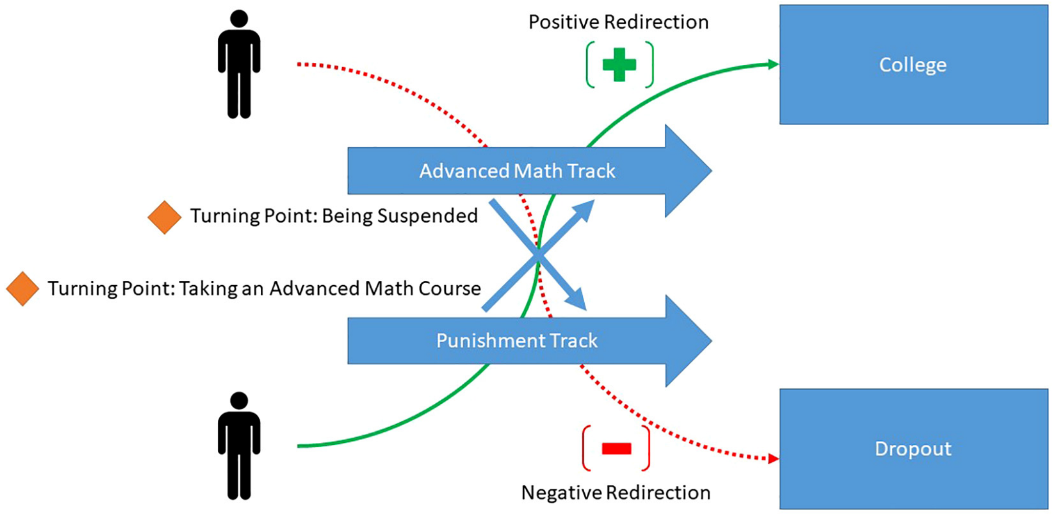

Fig. 1. Redirecting Student Trajectories through Turning Points.

students from less advantaged backgrounds were more likely to deviate from common course sequences in math and thus were less likely to progress through the full math curriculum by the end of high school (p. 87). Conversely, for students from less advantaged backgrounds, prior knowledge of their academic marks and behavioral sanctions led to poor perceptions of their current behaviors, which then led to an increase in punishments (Bowditch, 1993; Gregory & Weinstein, 2008). In each case, initial disadvantages stemming from students' social backgrounds were accumulated.

Unsurprisingly, some of the same social background characteristics that were positively related to math were negatively related to punishments. This was especially true for racial and ethnic demographic classifications. For example, while students who were racialized as White tended to have higher levels of math achievement than Black and Hispanic-identified students (Reardon & Galindo, 2009; Vanneman, Hamilton, Anderson, & Rahman, 2009), Black and Hispanic students tended to receive more frequent and harsher punishments than White students for identical problem behaviors (Skiba et al., 2011). Black and Hispanic students were also more likely to drop out of high school (McFarland, Cui, Rathbun, & Holmes, 2018) and less likely to graduate college than white students (Musu-Gillette, Robinson, McFarland, KewalRamani, & Zhang, 2016). For gender, the reciprocal relationships were slightly more complicated: males were more likely to be suspended than females (Losen & Skiba, 2010; Skiba, Michael, Nardo, & Peterson, 2002), but while more females took moderately advanced math courses, such as Pre-Calculus, more males took highly advanced math courses, such as Calculus (Riegle-Crumb, King, Grodsky, & Muller, 2012). Males were also more likely to drop out and less likely to attend college than females (McFarland, Hussar, Zhang, Wang, Wang, Hein, Diliberti, Forrest Cataldi, Bullock Mann, & Barmer, 2019). Additionally, as both student and school-level factors have been associated with punishment (Hemphill, Plenty, Herrenkohl, Toumbourou, & Catalano, 2014; Theriot, Craun, & Dupper, 2010) and math attainment (Kelly, 2009), we include school-level demographic characteristics in our models as well.

Finally, student attachment and school climate have also been strongly associated with math, suspensions, and educational attainment. For example, student engagement measures have been positively associated with math achievement (Sciarra & Seirup, 2008) and college attendance rates (Hill & Wang, 2015), as well as negatively associated with suspensions (Costenbader & Markson, 1998; Marks, 2000) and dropping out (Ream & Rumberger, 2008). At the school-level, teacher expectations of students' abilities have been positively associated with math achievement (Hinnant, O'Brien, & Ghazarian, 2009) and college attendance (Boser, Wilhelm, & Hanna, 2014), as well as negatively associated with suspensions (Hinojosa, 2008) and dropping out (Jia, Konold, & Cornell, 2016). Conversely, school problems have been positively associated with suspensions (Christle, Nelson, & Jolivette, 2004) and dropout status (Christle, Jolivette, & Nelson, 2007), as well as a well as negatively associated with math achievement (Milam, Furr-Holden, & Leaf, 2010) and college attendance (Grogger, 1997).

2.4. Present study

In previous research, Schneider et al. (1997) demonstrated that students in in more advanced math tracks had fewer behavior problems in high school and that students with behavior problems were less likely to be in more advanced math tracks. They also found that advanced math tracks were positively related to high school graduation and college enrollment, while behavior problems were negatively related to high school graduation and college enrollment. We add to this foundational study in three important ways. First, we use multi-step modeling in order to first establish tracks and trajectories, and then see how they might be disrupted and influenced. This also allows us to understand whether the strength of the original tracks and trajectories weaken when they are disrupted and influenced. Second, we include both student and school-level demographic characteristics, as well student attachment and school climate measures. This allows us to understand the factors that "structure the choices that individuals make," as well as the factors that "shape the structures in which individuals can exercise choice" (Pallas, 2003, p. 168). Third, given the importance of school-level characteristics in predicting suspensions and math attainment, we perform multi-level modeling. This allows us to isolate within-school relationships while simultaneously understanding how these relationships vary between-schools. Finally, we fill more recent gaps in the literature by accounting for baseline measures for each of the outcomes, by demonstrating reciprocal disruptions between punishment and advanced math tracks, and by modeling educational attainment trajectories as a function of both punishment and advanced academics. We ask the following questions:

I. How do advanced math courses disrupt punishment tracks?
II. How do suspensions disrupt advanced math tracks?
III. How is dropout status influenced by both suspensions and advanced math course-taking?
IV. How is college attendance influenced by both suspensions and advanced math course-taking?

3. Data and methods

3.1. Population: high school students

Given our interest in school tracks and student trajectories over time, our analyses utilized the most recent national longitudinal study of high school students. The High School Longitudinal Study of 2009 (HSLS) was administered by U.S. Department of Education. In the two-stage stratified random sampling design of the HSLS, an average of 27 ninth-graders at each of the 944 schools were selected for a total of 25,206 eligible students (Ingels, Pratt, Herget, Bryan, Fritch, Ottem, Rogers, & Wilson, 2015). As we are interested in student *and* school-level influences on student trajectories, we utilized student, parent, teacher, counselor, and administrator questionnaire data from the Base Year (fall of 9th grade), First Follow-Up (spring of 11th grade), 2013 Update (spring of 12th grade), and the 2013 High School Transcript Study. Student surveys were conducted online, while parent, teacher, counselor and administrator surveys were conducted online, as well as on the phone (2015). Students who had dropped out of high school were followed and included in this study.

The use of multiple waves of data created the expected problem of participant non-responses across and within waves. Although 15,188 students participated in four questionnaire waves, only 8,619 of these students had parent, administrator, counselor, and math teacher questionnaires completed. Nevertheless, the NCES did provide both school-level and student-level analytic weights to account for these instances of non-response, as well as instances of sampling inefficiencies that are inherent to a stratified sampling approach (Ingels et al., 2015). Additionally, in order to account for the conditional probability of students selected within schools, the overall student-level weight was rescaled so that the weights summed to the effective sample size of each student's corresponding school.

With the exception of the administrator scale of school problems, which was missing 15% of the responses in the dataset, all other independent variables had less than 10% of their responses missing, with the majority missing less than 5% of their responses. To recover these missing values, we used multiple imputation with chained equations (MICE) to impute 5 sets of missing values. Missing values for dependent variables were *not* imputed. All other responses that were missing were dropped from the analyses. Finally, in order to utilize all of the information made available by the imputation process, principle components were created *after* missing values were imputed. While our decision to not impute all missing values resulted in some list-wise deletion, our weighted analytic samples had properties that were very similar, but not exactly representative of the U.S. population of high school students.

3.2. Measures

For the punishment track, *in-school suspension (ISS)* consisted of a binary measure of receiving an *ISS* collected in the in the spring of 11th grade and occurring within the last six months (1 = yes, 0 = no). A binary measure of *suspension history* (1 = yes; 0 = no), which was recorded by parents and indicated whether or not a student had been suspended prior to the fall of 9th grade, was used as a baseline measure for in-school suspension. For the advanced course-taking track, we created a measure of advanced math course-taking that was defined as students who took *pre-calculus* (or a more advanced math course) during their senior year of high school. This decision was informed by Burkam and Lee's (2003) widely accepted scale of math course levels, which was used in HSLS and defines pre-calculus as a moderately advanced course within the math course-taking pipeline (as opposed to calculus, which is defined as a highly advanced math course). As pre-calculus is also less prone to student prerequisites in middle school and preferences in high school (see Assouline & Lupkowski-Shoplik, 2005; Riegle-Crumb et al., 2012), it is an ideal measure for access to advanced math knowledge and skills. As an outcome measure it was coded as having taken pre-calculus (1 = yes; 0 = no); as a model predictor, it was coded as having *not* taken pre-calculus (1 = no; 0 = yes) in order to allow for more appropriate interpretations of model intercepts. Not taking *algebra* in 9th grade (1 = no; 0 = yes) was used as a baseline measure for taking pre-calculus in 12th grade.

For student trajectories *dropout status* was defined as students who were dropped out of high school during the spring semester of 12th grade (1 = yes; 0 = no). As we are primarily interested in students who are pushed out of the standard learning environment through early suspensions and math course-taking, this measure also included students who were seeking an alternative route to high school completion, such as pursuing a GED. A binary measure of *dropout history* (1 = yes; 0 = no), which was recorded by parents and indicated whether or not a student had stopped attending school for at least one month—for reasons other than illness, injury, or vacation—prior to the fall of 9th grade, was used as a baseline measure for dropout status. This aligns with recent research that has demonstrated the link between previous school departures and dropping out (see Aratani & Cooper, 2015). Conversely, full-time *college attendance* was recorded during the fall that followed students' last year of high school (1 = yes; 0 = no). A binary measure of *college expectations* indicated whether or not a student expected to complete a bachelor's degree or higher (1 = yes; 0 = no/don't know) was recorded during the fall of 9th grade and was used as a baseline measure for full-time college attendance. This aligns with previous research that has demonstrated the link between initial college expectations and college attendance (see Eccles, Vida, & Barber, 2004). Finally, in order to ensure temporal precedence, as well as to maintain similar samples for trajectory analyses and their associated track analyses, the samples for second and fourth analyses did *not* include students who took pre-calculus (or a more advanced math course) during their junior year of high school. With the expected exception that fewer students took pre-calculus *or higher* in 12th grade in the restricted sample, the samples were very similar.

Informed by our literature review, student and school demographic characteristics, as well as student attachment-related measures and school climate-related measures, were also included in each analysis. Student demographic characteristics included *gender* (1 = female; 0 = male), *Black* race/ethnicity (1 = yes; 0 = no), *Hispanic* race/ethnicity (1 = yes; 0 = no), and *socio-economic-status* (SES). SES created by the NCES through principal component and standardized to a mean of 0 and a standard deviation of 1 (alpha = 0.65). It was derived from parent education, parent occupation, and family income. School demographic characteristics were centered at the grand mean in the analyses in order to allow for accurate estimates of the intercepts, which is important in multilevel modeling (Luke, 2019); all other variables were either standardized by the NCES or had a meaningful zero. These school demographic characteristics included mean-centered measures of the *level of Black student enrollment*, the *level of Hispanic student enrollment*, and the level of enrollment of *students eligible for free or reduced lunch*. Each of these measures was categorized by NCES in the following manner: '0′= 0%; '1′ > 0%; '2′ > /= 10%; '3′ > /= 20%; '4′ > /= 30%; '5′ > /= 40%; '6′ > /= 50%; '7′ > /= 60%; '8′ > /= 70%; '9′ > /= 80%; '10′ > /= 90%; and '11′ > /= 100%.

Also informed by our literature review, we operationalized student attachment-related measures through *9th grade school belonging* and *9th grade school engagement* and operationalized school climate-related measures through *staff expectations* and *school problems.* Both *9th grade school belonging* and *9th grade school engagement* were created by the NCES through principal components and were standardized to a mean of 0 with a standard deviation of 1 (alpha = 0.65). The continuous measure of *school belonging* was derived from the following items: feeling safe and proud, feeling like the student has someone that they could talk about their problems with, not feeling that school was a waste of time, and feeling that good grades were important. The continuous measure of *school engagement* was derived from the following items: being prepared with homework, having the necessary materials, and being on time. The administrator measure of school problems was also created by the NCES through principal components and was standardized to a mean of 0 with a standard deviation of 1 (alpha = 0.65). It was derived from the following items: student tardiness, absenteeism, truancy, dropping out, apathy, preparedness, health, parental involvement, and teacher resources. Finally, the measure of *staff expectations* was created from the first principal component of a counselor's perceptions of teacher, administrator, and other counselor expectations of students. This measure accounted for 77% of the overall variance of a counselor's perceptions of teacher, administrator, and other counselor expectations of students (eigenvalue = 2.30). Similar to the other measures, these continuous measures were created by the NCES through principal components and were standardized to a mean of 0 with a standard deviation of 1 (alpha = 0.65). Each measure was derived from the following items: working hard to make sure all students learn, setting high standards for teaching and learning, setting clear goals for students, believing that all students can do well, giving up on some students, caring only about smart students, and expecting very little from students. Survey weighed statistics for each variable can be found in Table 1.

3.3. Analytic approach

Because policies, practices, and course offerings related to punishment and math can vary across schools, it is important to account for and partition out the variance in the outcomes at the school-level. By doing so, we are better able to understand the student-level relationships in each of the models. We therefore used Multilevel Modeling (MLM) with random intercepts to estimate these effects. This method allows the intercepts of the outcomes to vary between schools, which allows for the proper estimation of both within-school and between-school relationships (Snijders & Bosker, 2012). After ensuring all assumptions for multilevel modeling and logistic regression were met, each analysis fit a series of two-level random intercept models using STATA's melogit program (StataCorp, 2013).

Table 1
Descriptive Statistics.

	Models 1 and 3		Models 2 and 4	
Variable	Mean(sd)	Percentage	Mean(sd)	Percentage
Gender: Female		50.17%		50.11%
Race/Ethnicity: Black		10.08%		11.82%
Race/Ethnicity: Hispanic		12.04%		11.63%
Socioeconomic Status	0.05(0.77)		−0.05(0.73)	
School Belonging	0.15(0.98)		0.09(0.99)	
School Engagement	0.16(0.93)		0.09(0.95)	
School Enrollment Level: Black	1.52(1.71)		1.56(1.83)	
School Enrollment Level: Hispanic	1.63(1.91)		1.49(1.74)	
School Enrollment Level: F/R Lunch	3.97(2.61)		4.01(2.61)	
School Problems	−0.22(0.96)		−0.18(0.96)	
Staff Expectations	0.08(1.45)		0.03(1.41)	
Suspension History		9.09%		11.22%
In-School Suspension (11th Gd.)		8.51%		9.88%
Algebra: Not Taken (9th Gd.)		13.56%		15.81%
Pre-Calculus: Not Taken (12th Gd.)		60.03%		71.70%
Dropout History		1.88%		1.98%
Dropout Status (12th Gd.)		3.54%		4.19%
College Expectations		59.41%		54.85%
College Attendance		72.68%		68.94%

Note: Models 2 and 4 restrict the sample to students who have not taken Pre-calculus in 11th grade.

We employed an analytic approach that first isolates punishment and achievement tracks (separately) and then disrupts them by adding a predictor from the opposing track. These reciprocal disruptions—math course level in punishment track and suspensions in the course-taking track—occur *after* the original tracks are established. For dropout status and college attendance we temporally ordered the addition of suspension and math course-taking predictors in order to best demonstrate these trajectories over time. Additionally, we block-added student demographic characteristics, student attachment-related measures, school demographic characteristics, and school climate-related measures to measure their impact on the outcomes and see if the original tacks and trajectories, as well as disruptions and other influences, alter in the presence of these constructs. Finally, we included Wald model test estimates in order to demonstrate how models differred when we added new "blocks" of predictors.

4. Results

4.1. Disrupting the punishment track

Our first analysis explored how math-course-taking can disrupt punishment tracks by modeling the impact of 9th grade math course-taking on 11th grade in-school suspension (ISS) (see Table 2). Starting with student-level predictors in Model 1a, we first isolated the suspension track, finding that being suspended prior to 9th grade was associated with increased odds of receiving an ISS in 11th grade (OR = 7.64; $p < 0.001$). We then disrupted this track by adding a math predictor in Model 1b, finding that not taking algebra by 9th grade was associated with increased odds of receiving an ISS in 11th grade (OR = 2.91; $p < 0.001$). This model addition also marginally lessened the original relationship among suspensions (suspension history: OR = 6.28; $p < 0.001$). Next, we added student demographic characteristics in Model 1c, finding that both identifying as female (OR = 0.36; $p < 0.001$) and socio-economic status (OR = 0.45; $p < 0.001$) were negatively associated with ISS. This model addition also moderately lessened the original relationship among suspensions (suspension history: OR = 4.40; $p < 0.001$) and marginally lessened the influence of 9th grade math course-taking (OR = 2.21; $p < 0.001$). In Model 1d we added student attachment-related measures, finding that both student belonging (OR = 0.73; $p < 0.05$) and student engagement (OR = 0.81; $p < 0.05$) were negatively associated with ISS. This model addition also marginally lessened the original relationship among suspension (suspension history: OR = 3.86; $p < 0.001$) and the influence of 9th grade math-course-taking (OR = 1.97; $p < 0.01$).

Moving on to school-level predictors, we added school demographic characteristics in Model 1e, finding that an increase in the school enrollment level of Hispanic students was negatively associated with ISS (OR = 0.86; $p < 0.05$), while an increase in the school enrollment level of free/reduced lunch students was positively associated with ISS (OR = 1.22; $p < 0.001$). This model addition also marginally lessened the original relationship among punishment (suspension history: OR = 3.48; $p < 0.001$). In Model 1f we added school climate-related measures, but neither school problems nor staff expectations were significantly associated with ISS. Finally, it is important to note that with the exception of Model 1f, all other model additions were significantly different from the previous nested model.

4.2. Disrupting the advanced math track

Our second analysis explored how suspensions can disrupt math course-taking tracks by modeling the impact of 11th grade in-school suspension (ISS) on 12th grade math course-taking (see Table 3). Starting with student-level predictors in Model 2a, we first isolated the math course-taking track, finding that not taking algebra by 9th grade was associated with decreased odds of taking pre-calculus in 12th grade (OR = 0.03; $p < 0.001$). We then disrupted this track by adding a

Table 2
The Impact of 9th Grade Math Course-Taking on 11th Grade In-School Suspension (ISS).

	(Model 1a)	(Model 1b)	(Model 1c)	(Model 1d)	(Model 1e)	(Model 1f)
Dependent Variable	ISS	ISS	ISS	ISS	ISS	ISS
Fixed Effects: Student Level Predictors						
Suspension History	7.64(1.61)***	6.28(1.45)***	4.40(0.95)***	3.86(0.88)***	3.48(0.78)***	3.46(0.77)***
Algebra: Not Taken (9th)		2.91(0.72)***	2.21(0.54)**	1.97(0.51)**	1.98(0.48)**	1.97(0.48)**
Gender: Female			0.36(0.08)***	0.38(0.09)***	0.37(0.09)***	0.37(0.09)***
Race/Ethnicity: Black			1.25(0.24)	1.32(0.26)	0.96(0.19)	0.96(0.19)
Race/Ethnicity: Hispanic			1.27(0.59)	1.21(0.56)	1.57(0.85)	1.56(0.79)
Socio-Economic Status			0.45(0.05)***	0.46(0.06)***	0.57(0.08)***	0.57(0.08)***
School Belonging				0.73(0.09)*	0.74(0.09)*	0.74(0.09)*
School Engagement				0.81(0.08)*	0.82(0.08)*	0.82(0.08)*
Fixed Effects: School Level Predictors						
School Enrollment Level: Black					1.04(0.05)	1.04(0.05)
School Enrollment Level: Hispanic					0.86(0.06)*	0.86(0.06)*
School Enrollment Level: F/R Lunch					1.22(0.04)***	1.21(0.05)***
School Problems						1.00(0.06)
Staff Expectations						1.02(0.12)
Intercept	0.05(0.01)***	0.04(0.01)***	0.07(0.01)***	0.06(0.01)***	0.06(0.01)***	0.06(0.01)***
Random Effects						
Random Intercept Variance	0.56(0.21)**	0.56(0.21)**	0.33(0.16)*	0.41(0.16)*	0.22(0.14)	0.22(0.15)
Model Differences						
Wald Test	89.60***	18.90***	20.79***	7.58***	14.88***	0.02
Observations	8,310	8,310	8,310	8,310	8,310	8,310

Notes: For Fixed Effects, Odds Ratios are Provided Followed by Robust Standard Errors in Parentheses.
Also, the Unconditional Model (not shown) had a Significant Random Intercept Variance Component of 0.77(0.25)**.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

punishment predictor in Model 2b, finding that receiving an ISS in 11th grade was associated with decreased odds of taking pre-calculus in 12th grade (OR = 0.15; $p < 0.001$). Next, we added student demographic characteristics in Model 2c, finding that SES (OR = 1.85; $p < 0.001$) was positively associated with taking pre-calculus in 12th grade. In Model 2d we added student attachment-related measures, finding that both student belonging (OR = 1.24; $p < 0.05$) and student engagement (OR = 1.25; $p < 0.01$) were positively associated with taking pre-calculus in 12th grade.

Moving on to school-level predictors, we added school demographic characteristics in Model 2e and school climate-related measures in 2f, but none of these predictors were significantly associated with taking pre-calculus in 12th grade. Unsurprisingly, these model additions were not statistically different from previous nested models. Finally, it is important to note the influence of 9th grade math course level and 11th grade ISS on taking pre-calculus in 12th grade remained practically unchanged with all subsequent model additions.

4.3. *Influencing dropout trajectories*

Our third analysis explored the influence of early suspensions and advanced math courses on dropout trajectories (see Table 4). Starting

Table 3
The Impact of 11th Grade In-School Suspension on 12th Grade Math Course-Taking.

	(Model 2a)	(Model 2b)	(Model 2c)	(Model 2d)	(Model 2e)	(Model 2f)
Dependent Variable	Pre-Calculus	Pre-Calculus	Pre-Calculus	Pre-Calculus	Pre-Calculus	Pre-Calculus
Fixed Effects: Student Level Predictors						
Algebra: Not Taken (9th)	0.03(0.01)***	0.03(0.02)***	0.04(0.02)***	0.04(0.02)***	0.05(0.02)***	0.05(0.02)***
In-School Suspension (11th)		0.15(0.05)***	0.16(0.06)***	0.18(0.06)***	0.17(0.06)***	0.17(0.06)***
Gender: Female			0.94(0.10)	0.87(0.10)	0.86(0.10)	0.86(0.10)
Race/Ethnicity: Black			0.91(0.21)	0.95(0.22)	0.79(0.16)	0.79(0.16)
Race/Ethnicity: Hispanic			0.91(0.25)	0.95(0.24)	0.90(0.23)	0.90(0.23)
Socio-Economic Status			1.85(0.21)***	1.84(0.21)***	1.89(0.22)***	1.88(0.22)***
School Belonging				1.24(0.11)*	1.25(0.11)*	1.24(0.11)*
School Engagement				1.25(0.11)**	1.26(0.11)**	1.26(0.11)**
Fixed Effects: School Level Predictors						
School Enrollment Level: Black					1.12(0.10)	1.12(0.10)
School Enrollment Level: Hispanic					1.05(0.07)	1.05(0.07)
School Enrollment Level: F/R Lunch					1.02(0.05)	1.03(0.06)
School Problems						0.93(0.13)
Staff Expectations						0.97(0.07)
Intercept	0.40(0.05)***	0.45(0.06)***	0.46(0.07)***	0.43(0.07)***	0.47(0.06)***	0.46(0.06)***
Random Effects						
Random Intercept Variance	1.56(0.36)***	1.59(0.38)***	1.58(0.37)***	1.61(0.37)***	1.54(0.34)***	1.55(0.34)***
Model Differences						
Wald Test	60.92***	28.56***	7.66***	11.75***	1.02	0.23
Observations	6,430	6,430	6,430	6,430	6,430	6,430

Notes: For Fixed Effects, Odds Ratios are Provided Followed by Robust Standard Errors in Parentheses.
Also, the Unconditional Model (not shown) had a Significant Random Intercept Variance Component of 1.16(0.26)***.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 4
The Impact of Suspension History and 9th Grade Math Course-Taking on 12th Grade Dropout Status.

	(Model 3a)	(Model 3b)	(Model 3c)	(Model 3d)	(Model 3e)	(Model 3f)	(Model 3 g)
Dependent Variable Dropout Status	Dropout Status	Dropout Status	Dropout Status	Dropout Status	Dropout Status	Dropout Status	
Fixed Effects: Student Level Predictors							
Dropout History	3.33(2.08)	1.83(1.30)	1.44(1.13)	1.20(1.01)	1.30(1.02)	1.41(1.09)	1.27(1.01)
Suspension History		11.62(3.62)***	8.64(2.98)***	8.15(2.61)***	7.31(2.17)***	6.79(1.98)***	6.52(1.89)***
Algebra: Not Taken (9th)			6.64(1.73)***	5.54(1.63)***	5.11(1.57)***	5.28(1.56)***	5.12(1.50)***
Gender: Female				0.91(0.27)	0.96(0.28)	0.96(0.28)	0.96(0.27)
Race/Ethnicity: Black				0.29(0.11)**	0.31(0.12)**	0.16(0.06)***	0.17(0.06)***
Race/Ethnicity: Hispanic				0.76(0.83)	0.71(0.27)	0.59(0.22)	0.57(0.21)
Socio-Economic Status				0.38(0.07)***	0.39(0.07)***	0.45(0.09)***	0.46(0.09)***
School Belonging					0.81(0.20)	0.80(0.19)	0.81(0.20)
School Engagement					0.84(0.13)	0.84(0.13)	0.85(0.13)
Fixed Effects: School Level Predictors							
School Enrollment Level: Black						1.18(0.09)*	1.17(0.09)*
School Enrollment Level: Hispanic						1.06(0.09)	1.07(0.09)
School Enrollment Level: F/R Lunch						1.09(0.09)	1.03(0.10)
School Problems							1.45(0.29)
Staff Expectations							1.08(0.12)
Intercept	0.02(0.005)***	0.01(0.004)***	0.01(0.002)***	0.01(0.003)***	0.01(0.003)***	0.01(0.004)***	0.01(0.004)***
Random Effects							
Rand. Int. Var.	2.01(0.67)*	1.10(0.37)*	1.39(0.48)**	1.38(0.53)**	1.46(0.58)*	1.28(0.56)*	1.20(0.56)*
*Model Differences*Wald Test	3.68	62.06***	52.73***	8.90***	2.54	2.88*	1.79
Observations	8,170	8,170	8,170	8,170	8,170	8,170	8,170

Notes: For Fixed Effects, Odds Ratios are Provided Followed by Robust Standard Errors in Parentheses
Also, the Unconditional Model (not shown) had a Significant Random Intercept Variance Component of 2.03(0.66)**
*$p < 0.05$ **$p < 0.01$ ***$p < 0.001$

Table 5
The Impact of 11th Grade In-School Suspension and 12th Grade Math Course-Taking on College Attendance.

	(Model 4a)	(Model 4b)	(Model 4c)	(Model 4d)	(Model 4e)	(Model 4f)	(Model 4 g)
Dependent Variable	College	College	College	College	College	College	College
Fixed Effects: Student Level Predictors							
College Expectations	3.98(0.52)***	3.82(0.45)***	3.28(0.40)***	2.69(0.34)***	2.48(0.30)***	2.48(0.30)***	2.46(0.30)***
In-School Suspension (11th)		0.14(0.03)***	0.17(0.03)***	0.22(0.04)***	0.24(0.04)***	0.26(0.05)***	0.27(0.05)***
Pre-Calculus: Not Taken (12th)			0.32(0.06)***	0.38(0.07)***	0.40(0.08)***	0.39(0.07)***	0.39(0.07)***
Gender: Female				1.59(0.19)***	1.57(0.19)***	1.59(0.19)***	1.58(0.19)***
Race/Ethnicity: Black				1.15(0.25)	1.16(0.27)	1.53(0.40)	1.52(0.39)
Race/Ethnicity: Hispanic				1.08(0.20)	1.10(0.22)	1.07(0.28)	1.07(0.27)
Socio-Economic Status				2.49(0.26)***	2.47(0.26)***	2.26(0.25)***	2.22(0.24)***
School Belonging					1.22(0.09)*	1.21(0.09)*	1.21(0.09)*
School Engagement					1.08(0.09)	1.07(0.08)	1.07(0.08)
Fixed Effects: School Level Predictors							
School Enrollment Level: Black						0.93(0.03)	0.94(0.03)
School Enrollment Level: Hispanic						1.02(0.05)	1.02(0.05)
School Enrollment Level: F/R Lunch						0.92(0.03)*	0.95(0.03)
School Problems							0.82(0.06)**
Staff Expectations							0.92(0.05)
Intercept	1.02 (0.11)	1.30(0.14)*	3.31(0.56)***	2.70(0.53)***	2.69(0.54)***	2.65(0.55)***	2.57(0.53)***
Random Effects							
Rand. Int. Var.	0.62(0.12)***	0.53(0.11)***	0.51(0.11)***	0.31(0.10)**	0.31(0.11)**	0.28(0.11)*	0.25(0.09)**
Model Differences							
Wald Test	110.60***	112.52***	33.36***	24.14***	5.03**	5.14**	5.04**
Observations	6,290	6,290	6,290	6,290	6,290	6,290	6,290

Notes: For Fixed Effects, Odds Ratios are Provided Followed by Robust Standard Errors in Parentheses.
Also, the Unconditional Model (not shown) had a Significant Random Intercept Variance Component of 0.65(0.13)***.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

with student-level predictors in Model 3a, we first attempted to isolate the dropout trajectory, finding that having dropped out prior to 9th grade *approaches* a significant positive association (OR = 3.33; p-value = 0.059) with dropout status. We then attempted to disrupt this trajectory by adding a punishment predictor in Model 3b, finding that being suspended prior to 9th grade was associated with increased odds of dropping out (OR = 11.62; $p < 0.001$). We further attempted to isolate this trajectory by adding a math predictor in Model 3c, finding that not taking algebra by 9th grade was associated with increased odds of dropping out (OR = 6.64; $p < 0.001$). This model addition also moderately lessened the influence of suspension history (OR = 8.64; $p < 0.001$). In Model 3d we added student demographic characteristics, finding that identifying as Black (OR = 0.29; $p < 0.01$) and socio-economic status (OR = 0.38; $p < 0.001$) were negatively associated with dropout status. This model addition also marginally lessened the influence of suspension history (OR = 8.15; $p < 0.001$) and 9th grade math course-taking (OR = 5.54; $p < 0.001$). In Model 3e we added student attachment-related measures, but neither student belonging nor student engagement were significantly associated with dropping out.

Moving on to school-level predictors, we added school demographic characteristics in Model 3f, finding that an increase in the school enrollment level of Black students was positively associated with dropping out (OR = 1.18; $p < 0.05$). This model addition marginally lessened the influence of suspension history (OR = 6.89; $p < 0.001$) and 9th grade math course-taking (OR = 5.28; $p < 0.001$), while increasing the influence of being Black (OR = 0.16; $p < 0.05$). In Model 3g we added school climate-related measures, but neither school problems nor staff expectations were significantly associated with dropout status. Finally, as expected, model additions with no significant added predictors (i.e. Models 3a, 3e, and 3g) were not statistically different from previous nested models.

4.4. Influencing college-going trajectories

Our fourth analysis explored the influence of later suspensions and advanced math courses on college-going trajectories (see Table 5). Starting with student-level predictors in Model 4a, we first isolated the college-going trajectory, finding that 9th grade college expectations were positively associated with college attendance (OR = 3.98; $p < 0.001$). We then disrupted this trajectory by adding a punishment predictor in Model 4b, finding that receiving an ISS in 11th grade was associated with decreased odds of attending college (OR = 0.14; $p < 0.001$). We further disrupted this trajectory by adding a math predictor in Model 4c, finding that not taking pre-calculus by 12th grade was associated with decreased odds of attending college (OR = 0.32; $p < 0.001$). This model addition also marginally lessened the original relationship among college-going (college expectations: OR = 3.28; $p < 0.001$) and the influence of 11th grade ISS (OR = 0.17; $p < 0.001$). In Model 4d we added student demographic characteristics, finding that both identifying as female (OR = 1.59; $p < 0.001$) and socio-economic status (OR = 2.49; $p < 0.001$) were positively associated with attending college. This model addition also marginally lessened the original relationship among college-going (college expectations: OR = 2.66; $p < 0.001$), as well as the influence of 11th grade ISS (OR = 0.22; $p < 0.001$) and 12th grade math course-taking (OR = 0.38; $p < 0.001$). In Model 4e we added student attachment-related measures, finding that student belonging was positively associated with attending college (OR = 1.22; $p < 0.05$). This model addition was also associated with a marginal decrease in the original relationship among college-going (college expectations: OR = 2.48; $p < 0.001$).

Moving on to school-level predictors, we added school demographic characteristics in Model 4e, finding that an increase in the school enrollment level of free/reduced lunch students (OR = 0.92; $p < 0.05$) was negatively associated with attending college. In Model 4 g we added school climate-related measures, finding that school problems was negatively associated with attending college (OR = 0.82; $p < 0.01$). Here, it is important to note that the influence of the school enrollment level of free/reduced lunch students lost significance when school climate-related measures were added in Model 4 g. Finally, with significant added predictors in each model addition, it was unsurprising that each model addition was statistically different from previous nested models.

4.5. Between-school effects

In models 1, 3 and 4 the variance components for the random intercepts experienced an overall decrease. In fact, when school-level predictors were added in Model 1e the random intercept variance component (σ_u^2) no longer remained significant. Nevertheless, the random intercept variance components (σ_u^2) did remain statistically significant in Models 2, 3, and 4, indicating that a significant amount of variation was left unexplained at the school-level—even after accounting for all other explanatory variables in each of these models. Still, these explanatory variables—both at the student and school-level—did decrease the overall amount of between-school variation in Models 3 and 4. When comparing the final models to the unconditional models, approximately 41% of the school variation in dropout status was explained by the explanatory variables in Model 3 and approximately 72% of the school variation in college attendance was explained by the explanatory variables in Model 4. Nevertheless, in Model 2, the opposite occurred. When comparing the final model to the unconditional model, the overall amount of between-school variation actually *increased* by 25%. A closer look reveals that the amount of between-school variation in Model 2 tended to increase with the addition of student-level predictors and decrease with the addition of school-level predictors.

5. Discussion

5.1. Disrupting tracks and redirecting student trajectories

In both the first and second analyses, we observed significant disruptions in punishment and advanced math tracks. When controlling for prior suspensions in the first analysis, less-advanced math course-taking was associated with an increase in suspensions in 11th grade; when controlling for prior math course-taking in the third analysis, being suspended was associated with a decrease in more advanced math course-taking in 12th grade. While Anderson et al. (2019) refer to the relationship between discipline and academic outcomes as a "vicious cycle," our focus on advanced math course-taking may signal that this cycle is less about student agency and more about academic opportunity structures. Furthermore, advanced math course-taking only marginally lessened the strength of the original punishment track, while suspensions had no discernable impact on the original math course-taking track. Thus, while these opportunity structures are fundamentally related, the original tracks are difficult to change.

In the third and fourth analyses, we again observed significant influences of punishment and math achievement. All else considered, being suspended prior to high school was associated with an 87% chance of dropping out of high school during senior year, while being suspended in 11th grade was associated with a 21% chance of attending college following senior year. Conversely, not taking algebra during 9th grade was associated with an 84% chance of dropping out of high school during senior year, while not taking pre-calculus during 12th grade was associated with a 28% chance of attending college following senior year. These influences, along with the original trajectory indicators, remained strong in the presence of additional model predictors. Thus, for students who have *not* been in advanced math courses *and* who have been suspended, the relationships between opposing opportunity structures can be seen as creating *additional* forms of stratification and marginalization—not *substitutions* for other forms. Here, disadvantages appeared to accumulate when students were both excluded from advanced knowledge through math course-taking *and* excluded from the general learning environment through suspensions. While these findings support theories of accumulated disadvantage within the life-course perspective (Thornberry, 1987), these findings also support theories of turning points (Sampson & Laub, 1993). By opening up new opportunities, the significant disruptions and influences we have demonstrated here may operate as turning points in students' lives, which ultimately may be able to redirect students away from dropout trajectories and towards college-going trajectories. For example, while advanced math course-taking may not be able to *undo the harm* of prior suspensions, it may be able to redirect students away from dropping out and towards attending college.

Finally, previous research has pointed to labeling theory as a possible explanation for the *mechanisms* of these disruptions and their impacts on the life course (Becker, 1963). After a negative turning point, such as a suspension, a label may be applied, and the ensuing stigma may prevent the student from accessing advanced math courses. As stigma represents "the extent to which a particular stratified location in the schooling system confers a devalued social identity on a student" (Pallas, 2003, p. 169), it is not surprising that exclusion from the learning environment through suspensions may lead to other forms of exclusion, such as exclusion from advanced academic opportunities in math. As noted by Mowen and Brent (2016), stigma can limit opportunities both through internal mechanisms (e.g. a student adopting a low self-concept) or external mechanisms (e.g. a teacher having low expectations). Nevertheless, labels and stigma are often evident in student attachment-related measures and teacher expectations (see Lee, Menard, & Bouffard, 2014; Shifrer, 2013), and yet the key relationships involving suspensions and advanced math course-taking held with the addition of student attachment-related measures and staff expectations. Thus, while the removal mechanism (i.e. missed opportunities to learn) may explain how punishment disrupts advanced math tracks and their related trajectories (see Welsh & Little, 2018), more research is needed to better understand the mechanism by which advanced math courses disrupt punishment tracks and their related trajectories.

5.2. Social background influences, student attachment, and school climate

Overall, the impacts and influences of suspensions and math-courses remained mostly unaffected by the addition of student demographic characteristics, school demographic characteristics, student attachment-related measures, and school climate-related measures. Thus, we can infer that the relationships between punishment and math, as well as their relationships with dropout status and college attendance, were not adequately explained by gender, race/ethnicity, social class, attachment or climate—at either the student or school-level.

However, these measures did have significant impacts on the outcomes *net* of punishment, math courses, and each outcome's baseline measure. Focusing on demographic influences, we found that—when we controlled for all other model predictors, Male students were less likely to attend college, Black students were less likely to drop out, and higher-SES students were less likely to be suspended and drop out. Higher SES students were also more likely to take more advanced math courses and attend college. As expected, student belonging and engagement were negatively associated with suspension and positively associated with advanced math course-taking, while school belonging was also associated with college attendance. At the school-level, the enrollment level of Black students was positively associated with dropout status, while the enrollment level of Hispanic students was negatively associated with suspensions. Finally, while the enrollment level of free and reduced lunch students were positively associated with suspensions and negatively associated with college attendance, the impact of free and reduced lunch students on college attendance dissipated when school problems, which was negatively associated with college attendance, was added to the model. Here, the relationship among school social class and college attendance may partially represent an artifact of school climate-related measures, such as behavioral problems.

In regards to race these findings reveal an interesting paradox: at the individual-level being identified as a Black student is negatively related to dropout status, while at the school-level, attending a school with a higher proportion of Black students is positively related to dropout status. While the majority of Black students did not attend majority-Black schools in this study, these paradoxes suggest that the structure of opportunity is different in schools where Black students are in greater numbers. Here, higher proportions of Black students within schools, which may represent racial segregation, can be seen as depriving students in these schools of the greater educational achievement (i.e. completing high school) that might otherwise be obtained in less segregated contexts. When considering Blalock's (1967) racial threat hypothesis, which holds that as the relative size of a racial minority group increases, members of the majority racial group feel threatened and increase their institutional forms of social control (that may *push* students out of school), this phenomenon becomes more plausible. Nevertheless, future research is needed to determine the levels of Black enrollment where the odds of dropout status are likely to differ or become non-linear.

5.3. Between-school effects

When considering between-school results, we have both expected and unexpected results. As expected each unconditional model had a significant random intercept. As schools have different policies and practices related to math course-taking and suspensions, we expect that a significant portion of the outcomes varies between schools. We also expect the amount of between school variation to decrease when we account for additional model predictors—as it did in Models 1, 3, and 4. Here, as we explain more of the variation in the outcomes within schools, there is less variation left unexplained between schools. For example, when we accounted for student demographic characteristics in Model 1, less of the differences in suspension were due to differences between schools. As previous research has demonstrated that some schools may be more likely to suspend minority students (see Anderson & Ritter, 2017), it is likely that some of the differences in suspensions between schools might actually be due to a student's race or ethnicity. There were also fewer differences in the outcomes between schools when we accounted for demographic characteristics at the school level in Model 1, which again is supported by previous literature that has found that Black students tend to attend higher suspending schools (Jabbari & Johnson, 2020; Johnson, Jabbari, Williams, & Marcucci, 2019).

We were initially surprised to find that the overall amount of between-school variation increased in Model 2. However, a closer look revealed that the amount of between-school variation in Model 2 tended to increase with the addition of student-level predictors and decrease with the addition of school-level predictors. In fact, the majority of the increase in between-school variation occurred when we added predictors to our unconditional model (moving from a 'variance-components model' to a 'random intercept model'). When we accounted for initial math course-taking, the between-school variation in 12th grade math-course taking increased, suggesting that there was a *negative* correlation between initial math course-taking within schools and the variation in 12th grade math course-taking between schools. One potential explanation is that in schools with very high proportions of students taking advanced math courses in 12th grade, students' 9th grade math course could become slightly less important in predicting their future math attainment, as there may be greater efforts to increase a student's potential regardless of the level that he or she begins at. Here, there may be slightly less students taking a more advanced course in 9th grade than we would expect in schools with a high proportion of students taking advanced math courses in 12th grade, which may bring down the average likelihood of students taking pre-calculus in these schools—when initial math course-taking is not accounted for. Thus, these schools may appear less extreme. Alternatively, in schools with very low proportions of students taking advanced math courses in 12th grade, students' 9th grade math course could become slightly less important in predicting their future math attainment, as there may be fewer efforts to increase a student's potential regardless of the level that he or she begins at. Here, there may be slightly more students taking a more advanced course in 9th grade than we would expect in schools with a low proportion of students taking advanced math courses in 12th grade, which may bring up the average likelihood of students taking pre-calculus in these schools—when initial math course-taking is not accounted for. Thus, these schools may also appear less extreme. In both of these cases 12th grade math course-taking would appear more similar across all schools *before* we account for initial math course-taking within each school. This would explain why the overall amount of between-school variation increased *after* we accounted for initial math course-taking in Model 2.

Conversely, when we account for additional sources of variation at the school-level in advanced math course-taking—specifically race/ethnicity and social class, the amount of between-school variation decreases in Model 2. Even though these school-level additions did not represent a statistically different model change for advanced math course-taking, a similar trend was found in the other models. Thus, this decrease in the random intercept variance component suggests that part of the variation in math course-taking between schools can be explained by differences involving school characteristics, such as school racial/ethnic and social class composition. Here, less segregated schools may lead to more equitable opportunity structures between schools in regards to advanced math course-taking, as well as suspensions, dropout status, and college attendance. As we are interested in accounting for these between-school differences and isolating these relationships within schools, random intercept models are essential in our study and other studies that explore similar relationships.

Finally, when considering that the random intercepts remained significant in Models 2, 3 and 4—even after all of student and school characteristics were added to these models, we recognize that there may be other student and school characteristics leading to inequitable opportunity structures and trajectories between schools. Future research should continue to explore these relationships with additional model predictors to understand the point at which between school variation dissipates completely.

5.4. Implications for policy and practice

Our findings lead us to four important implications for policy and practice. First, given the strength of the punishment and math course-taking tracks—even in the presence of other disruptions, we conclude that once students enter high school, it is difficult to stop students in their tracks. However, while we cannot undo the harms of previous involvement in punishment and achievement, we can redirect students away from punishment trajectories and towards academic trajectories. When considering that pre-HS suspensions and 9th grade math course level were two of the strongest predictors for many of the outcomes, *early* interventions that focus on both punishment *and* achievement should be pursued. Second, when we account for early punishment and math achievement, we find that Black students are *less* likely to dropout. Given their relatively high rates of dropping out (U.S. Department of Education, National Center for Education Statistics, 2019), increased efforts should be made to decrease Black students' suspension rates before high school, as well as to increase advanced math course-taking during their freshman year of high school. Third, given that Black enrollment rates are positively related to dropout status and negatively related to college attendance, reducing racial segregation in schools may be key in decreasing instances of dropping out and increasing rates of college attendance. Finally, it is important to note that even after we account for the influence of punishment and achievement, as well as student and school attachment/climate-related measures, key demographic characteristics still remained significant predictors of the outcomes. Thus, while policies aimed at decreasing suspensions and increasing math achievement should rightfully be pursued, more must be done to ensure reductions in gender, racial/ethnic, and social class inequalities across suspensions, math course-taking, dropout status, and college attendance.

While we recognize the need for safe schools, we believe that many suspensions can be avoided by seeking healthy alternatives, such as restorative justice (see Johnson et al., 2019). Rather than separating the offending students from their classroom communities, restorative justice seeks to reintegrate them through peer mediations (González, 2012). This reintegration can build students' problem solving skills (2012), increase their sense of belonging and engagement, and ultimately, prevent future transgressions (Eisenberg, 2016). It is unsurprising that schools adopting restorative justice philosophies, policies, and practices see a reduction in suspension rates (Anyon et al., 2014) and an increase in academic achievement and graduation rates (Eisenberg, 2016). Similarly, the adoption of Positive Behavior and Interventions Supports (PBIS) systems, which focus on teaching, modeling, and monitoring expected behaviors—while offering students a continuum of supports—have been associated with a reduction in suspension rates as well (Cruz & Rodl, 2018). Additionally, research has found that schools with highly structured and highly supportive environments are less likely to suspend students (Huang & Cornell, 2018) and less likely to have large racial discipline gaps (Gregory, Cornell, & Fan, 2011). Thus, efforts aimed at creating environments like these should also be pursued. Finally, recent research by Cortes et al. (2015) found that an intensive math instructional program for 9th grade students—known as "Double-dosage Algebra"— increased students' total math credits and test scores, as well as their high school graduation and college enrollment rates. Programs like this should be pursued as well.

6. Limitations

Future research on this topic should be mindful of this study's limitations. While this study has focused on opportunity structures related to math, we recognize that there are other important opportunity structures both within and beyond STEM that should be explored as well. We also recognize that in addition to access and course-taking, achievement in these courses should also be explored. Furthermore, while we while we include demographic categories related to gender, race, and social class, future studies should also explore interactions with and among these categories. For example, Ibrahim and Johnson (2019) included race-gender intersectional identities in their exploration of suspensions and math achievement, while Marcucci (2019b) explored how parental involvement moderated the relationship between race and suspensions. Furthermore, studies that explore school responses to race should also be pursued, as institutional racism and implicit bias may impact the relationships among punishment and achievement as well (Marcucci, 2019a).

Additionally, while we focus on high school students, we recognize that these trajectories can often start long before high school. For example, Yang, Harmeyer, Chen, and Lofaso (2018) found that early and persistent predictors of suspension can begin in kindergarten and first grade, while Wang and Goldschmidt (2003) found that math tracks can begin in middle school. Finally, because we use population subsamples and imputation techniques, we recognize that our findings may not be completely generalizable to the US population of high school students.

7. Conclusion

By using a multi-step and multi-level modeling process, as well as by (1) accounting for baseline measures for each of the outcomes, (2) demonstrating reciprocal disruptions between opposing opportunity structures, and (3) modeling educational attainment trajectories as a function of both punishment and advanced academics, we have filled important gaps in the research literature. Furthermore, by demonstrating how advanced math course-taking can disrupt punishment tracks, how punishments can disrupt advanced math tracks, and how together these disruptions can impact long-term students trajectories related to educational attainment, we have pinpointed potential "turning points" for high school students. These turning points may be able to redirect student trajectories away from negative life outcomes, such as dropping out, and towards more positive ones, such as attending college. Moreover, given the nation's concern for international competitiveness in STEM, the increasing demand for college-educated workers, and the large and inequitable pipeline of students who are first suspended, then pushed out of school, and eventually directed towards prisons, these efforts should be promptly pursued.

Additionally, when considering our findings alongside current racial inequities in the STEM and school-to-prison (STP) pipelines, there is much promise in potential reforms. Black students who take advanced math and science courses are just as likely as White students to pursue

STEM degrees (Tyson, Lee, Borman, & Hanson, 2007). Conversely, Black students who graduate college have lowered incarceration rates that are similar to White college graduates (Sum, Khatiwada, McLaughlin, & Palma, 2009). Finally, even if students are able to exit the STP pipeline, but not fully enter the STEM pipeline, there are still important spillover effects. For example, 11.5 million of the 11.6 million (99%) jobs created since the recession have gone to individuals with at least some college education (Carnevale, Jayasundera, & Gulish, 2016, p. 1). As college graduates earn on average $32,000 (134%) more than individuals with a high school diploma (Trostel, 2015) and are expected to pay $273,000 more in lifetime tax contributions, while receiving $81,000 less in lifetime tax benefits (Carnevale et al., 2016), it is clear that we all benefit from disrupting punishment tracks and redirecting students towards college.

8. Author note

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CRediT authorship contribution statement

Jason Jabbari: Conceptualization, Investigation, Methodology, Formal analysis, Writing - original draft. **Odis Johnson:** Funding acquisition, Supervision, Methodology, Writing - review & editing.

Declaration of Competing Interest

The Authors declare that there are no conflicts of interest in submitting this manuscript to Children and Youth Services Review.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.childyouth.2019.104734.

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