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Multiplying Disadvantages in U.S. High Schools: An Intersectional Analysis of the Interactions Among Punishment and Achievement Trajectories

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We examined recent process models of accumulated disadvantage with an intersectional lens in order to provide a more complete picture of how disadvantages across punishment and math trajectories can accumulate over time and disparately affect marginalized race-gender groups. Using structural equation modeling (SEM) with a nationally representative longitudinal study of high school students (HSLS-09), we found that punishment trajectories were influenced by math and vice versa, as well as that these relationships differed across math performance and various aspects of math attitudes, including efficacy, utility, and identity. Furthermore, we found that gender, race, and race-gender groups experienced significantly different relationships. When considering the intersection of punishment and math disadvantages, these differences appear to not only accumulate disadvantages within punishment and math trajectories but also across them for marginalized race-gender groups. This was especially true for Black males. We conclude with a discussion of implications for policy and practice.

Keywords: *disparities, educational policy, gender studies, mathematics education, punishment, race, social stratification, structural equation modeling*

Racial and gender disparities in educational achievement tend to accumulate as students progress through school (Hanushek & Rivkin, 2009; Lee, 2002). The culmination of these accumulated disparities in high school results in higher proportions of Black, Hispanic, and male students dropping out when compared to White and female students (McFarland et al., 2018), which can lead to higher rates of unemployment (McFarland et al., 2018) and increased rates of incarceration (Sum et al., 2009).

While decades of previous research have demonstrated the importance of both punishment and academic trajectories in educational attainment (Suh et al., 2007; Werblow et al., 2013), only recently has research began to explore how these trajectories are related in such a way that disadvantages not only accumulate *within* these trajectories but also *across* them. Here, it is not only that early disadvantages in punishment lead to increased disadvantages in later punishment, but also that early disadvantages in punishment lead to increased disadvantages in later math, and vice versa. For example, suspended students may miss out on core math instruction, which may make it difficult for them to catch up to their nonsuspended peers; unable to catch up, these students may become disengaged or labeled—or both, leading to further suspensions and more missed math instruction. Some authors have referred to this relationship as a "vicious cycle" (Anderson et al., 2019). Thus, from a longitudinal perspective, the accumulation of disadvantages can "cycle" students through increasing trajectories of punishment and academics—with each turn making it more difficult for a student to alter their respective paths. Indeed, with a particular focus on exclusionary discipline and math, recent research has demonstrated that students are cycled across punishment and math achievement trajectories—the former representing academic exclusion and the latter representing academic inclusion—in such a way that eventually cycles students out of school altogether (Jabbari & Johnson, 2022).

When considering how various facets of identity operate within and across these trajectories, this research has noted the importance of gender and race at the individual level (Jabbari & Johnson, 2020, 2022, 2023), as well as race at the school level (Johnson & Jabbari, 2021). Nevertheless, previous research suggests that it is the *intersections* of these identities that can provide the most comprehensive insights into the ways in which these trajectories interact to accumulate disadvantages (Ferguson, 2000; Johnson & Jabbari, 2022; Morris, 2007). The salience of intersectional identities can be especially true in high school (see Bradley & Renzulli, 2011; Sutton et al., 2018).

We, therefore, extend previous work by critically exploring the ways in which marginalized identities interact to accumulate disadvantages within and across punishment and math trajectories for particular race-gender groups. As both race and gender can operate uniquely within and across punishment and achievement trajectories over time, an intersectional analysis of this type can (a) illuminate the educational experiences of multiplicatively disadvantaged students; (b) demonstrate the accumulation of disadvantages across multiple inequitable structures; and (c) provide policy-makers with a blueprint for targeted reform efforts that span across multiple groups (race, gender, and race-gender), time points (eighth grade, freshman year, and junior year), and domains (punishment and math). This endeavor is particularly important when considering that many of the same race-gender groups that are *overrepresented* in suspensions (Skiba et al., 2014) and the criminal justice system (Pettit & Western, 2004) are also *underrepresented* in math achievement and the science, technology, engineering, and math (STEM) workforce. For example, despite making up 13% of the total population, Black males made up only 3% of scientists and engineers in 2013 (National Science Foundation, 2013) but over 37% of incarcerated males in 2013 (Carson, 2013). Thus, by generating knowledge on the reciprocal relationships among punishment and math achievement trajectories, we will inform future efforts seeking to drain the school-to-prison (STP) pipeline and fill the STEM pipeline.

Similar to previous research (Jabbari & Johnson, 2022), we use a structural equation modeling (SEM) framework to conceptualize the mediating relationships among punishment and math over time. Specifically, we conceptualize that the relationship between early and later punishment is partially explained (i.e., mediated) through math achievement and, conversely, that the relationship between early and later math achievement is partially explained (i.e., mediated) through punishment. While basic mediation models tend to follow a cause ("X"), mediator ("M"), effect ("Y") structure, because we focus on both punishment and math trajectories, we have multiple mediators in our model, which leads to multiple mediation effects, as seen in Figure 1. Furthermore, in order to explore the moderating roles of gender, race, and race-gender, we use a multigroup strategy, which tests the degree to which relationships vary across particular gender, race, and race-gender groups. Unlike previous work using SEM, we do not create latent constructs for math attitudes. Instead, we separate out the various aspects of attitudes, including efficacy, utility, and identity, as these may not only alter the relationships with punishment but also vary across gender, race, and race-gender. We make the following hypotheses:

1. *Mediation*: Punishment trajectories will be influenced by math, and math trajectories will be influenced by punishment.
   a. These relationships will differ across math performance and various aspects of math attitudes, including math efficacy, math utility, and math identity.
2. *Moderation*: Gender, race, and race-gender intersections will alter these relationships.

We proceed with a triangulated theoretical orientation. First, we follow previous research (Jabbari & Johnson, 2022) and conceptualize the relationships among punishment and math through a turning points framework. Second, we review the research on accumulated advantages and consider how the relationships among punishment and math may accumulate disadvantages across the life course. Finally, we consider how these accumulation effects may differ across gender, race, and race-gender groups through a critical quantitative intersectional lens.

Background

Turning Points and Trajectories

Within the life-course perspective (Elder et al., 2003), Laub and Sampson (1993) demonstrate that certain points in one's life can "separate the past from the present" and, in doing so, redirect their trajectories (p. 304). In an educational context, both suspensions (Mowen & Brent, 2016) and math achievement (Schneider et al., 1997) can act as important "turning points." By operating as public labels of deviance (see Farrington, 1977) or intelligence (Thompson, 2014), suspensions and math achievement can either lower or raise individuals' self-concepts (Lemert, 1951), as well as the conceptions of others (Liberman et al., 2014). Ultimately, these turning points can "reorder the life course by opening or closing off conventional opportunity structures . . . [and] set in motion a sequence of reinforcing conditions" (Mowen & Brent, 2016, p. 631). Through this sequence of reinforcing conditions, disadvantages and advantages can start to accumulate over the life course.

For example, research on punishment trajectories has demonstrated that students who have been suspended have a higher risk of dropping out in the future (Suh et al., 2007) and that students who have dropped out have a higher risk of being arrested in the future (Christle et al., 2005). Here, students on punishment trajectories are successively excluded from classrooms (e.g., suspensions), formal education (e.g., dropout/pushout), and ultimately society (e.g., incarceration)—with each successive level of exclusion resulting in a further removal from opportunity for a longer period of time

(Jabbari & Johnson, 2020). Conversely, research on math achievement trajectories has demonstrated how students with high levels of math ability (Wai et al., 2009), math efficacy (Wang, 2013), math utility (Harackiewicz et al., 2012), and math identity (Hazari et al., 2010) often have higher rates of completing high school, attending college, majoring in a STEM subject, and securing a STEM job (see Finkelstein & Fong, 2008; Rose & Betts, 2001; Tai et al., 2006; Tyson et al., 2007). As a result, disadvantages and advantages in the punishment and math achievement trajectories are often considered to be *cumulative*.

Accumulated Disadvantage

Accumulated (i.e., more consequential) *disadvantage* refers to the extent that disadvantaged students experience larger setbacks in the future because "second chances" are not available to them in the same way they may be for more advantaged peers (Hannon, 2003). Alternatively, accumulated *advantage*—often referred to as "The Matthew Effect"—refers to the extent to which advantaged students experience larger gains in the future. The gains of accumulated advantages may be a product of one's reputation (student labels), resources (school opportunity structures), or both (see Kerckhoff & Glennie, 1999). Conversely, disadvantages and advantages can also be *saturated* (i.e., less consequential). Here, disadvantaged students could experience smaller setbacks because they have "less to lose" (Hannon, 2003), while advantaged students could experience smaller gains because they have already reaped much of the rewards.

Building on DiPrete and Eirich's (2006) main conception of a *path-dependent process of cumulative advantage*—where initial achievement directly and causally impacts subsequent achievement—Baumert et al. (2012) demonstrate the importance of time periods and status groups. Noting that some time periods in the life course can be more influential than others, Baumert et al. (2012) suggest a *time-dependent process of cumulative advantage*. For example, recent research has stressed the importance of students' time in high school, which can entail opportunity structures with greater levels of stratification, as well as agency (Jabbari & Johnson, 2022). Stemming from Blau and Duncan's (1967) work on status groups, Baumert and his colleagues (2012) also demonstrate a *status-dependent process of cumulative advantage* in which some status groups can experience different accumulation effects within similar path-dependent processes. Here, Baumert and his colleagues (2012) found that status-dependent cumulative effects increased social class disparities in elementary school math achievement over time.

While much of the research on accumulated disadvantage focuses on singular trajectories, such as punishment (Mowen & Brent, 2016) and, separately, math achievement (Schiller & Hunt, 2011; Baumert et al., 2012), some research has explored how disadvantages can be accumulated across multiple trajectories and populations. In this regard, Hannon (2003) found that disadvantages in delinquency were saturated on academic achievement for students living in poverty, such that early delinquency did not lead to larger setbacks in later academic achievement for poor students. Alternatively, Jabbari and Johnson (2022) found that disadvantages in achievement were accumulated on punishment, such that early poor math achievement did lead to larger setbacks in later punishment. Nevertheless, when considering status-driven accumulation effects for intersectional groups, there is a large gap in the research. For example, given that Jabbari and Johnson (2022) found accumulated math disadvantages on dropout status for low-SES and Black and Hispanic students, as well as accumulated discipline disadvantages on HS suspensions, later math achievement, and dropout status for males, exploring the accumulation effects of Black males may be particularly insightful.

Intersectionality and the Process of Pushing Out

When considering status-driven accumulation processes, we recognize that students experience opportunity structures in punishment and achievement differently, often due to varied institutional responses to their multiple and intersecting identities. Stemming from Black feminist thought, intersectionality theory holds that systems of oppression work to marginalize individuals along multiple dimensions of identity (Crenshaw, 1990; Collins, 1990). This can compound experiences for racialized and gendered populations based upon their various facets of identity (Crenshaw, 1990; Collins, 1990). For example, recent research has found that individuals occupying multiple socially disadvantaged identities incur far greater penalties than those occupying a single socially disadvantaged identity *and* that these disadvantages exponentially increase over the life course (Woodhams et al., 2015).

A full understanding of how intersectional groups accumulate disadvantages leads us to utilize a critical quantitative intersectionality (CQI) framework (Jang, 2018). This framework acknowledges that because punishment and math achievement can be conditioned on the social construction of students' race and gender, these opportunity structures may represent forms of institutionalized and structural oppression. By increasing exposure to punishment and limiting access to achievement, race and gender not only "structure the choices that individuals make, but also shape the structures in which individuals can exercise choice" (Pallas, 2003, p. 168).

As intersecting power dynamics can vary both within and across opportunity structures (see Jang, 2018), intersectionality is especially important in research conditions where (a) exhibiting advantages within opportunity structures are not uniformly experienced across broader identity dimensions; (b) varying intersections of identity respond differently to distinct facets of opportunity structures; and (c) competing advantages among identities vary across opportunity structures. These conditions are particularly prevalent in research on race and gender across punishment and math achievement trajectories.

When considering race separately, it is clear that there is an inverse relationship between punishment and math achievement. For example, Black students are more likely than White students to be referred to an administrator's office and tend to receive harsher punishments for similar problem behaviors (Skiba et al., 2011). At the same time, Black students are less likely to have higher math achievement scores (Vanneman et al., 2009). Moreover, in both cases, these racial trends are not due to social class differences within punishment (Wallace et al., 2008) or math achievement (Lubienski, 2002); in other words, there is a distinct relationship between race and punishment and math achievement that cannot be explained by social class. When we consider gender separately, there is not an inverse relationship between punishment and math achievement. Rather, males are more likely to be suspended than females (Skiba et al., 2002) and also more likely to have higher math achievement (Ercikan et al., 2005).

However, when we intersect race with gender it becomes clear that certain advantages within opportunity structures are not uniformly experienced across broader identity dimensions. For example, while the male gender can operate as a source of advantage in STEM (Good et al., 2008), Black males have been shown to face unique barriers in both STEM education (Riegle-Crumb & King, 2010) and the STEM labor market (Bidwell, 2015). Conversely, while the female gender can operate as a source of advantage in school discipline and the criminal justice system, Black females are often disproportionately targeted for suspensions (Losen & Skiba, 2010) and criminal offenses (Bush-Baskette, 1998). In fact, the punishment gap between Black and White students is often largest among females (Morris & Perry, 2017). Together, these findings suggest that Black females may not receive the social benefits of their gender in disciplinary matters while also incurring a social cost for their race in academic matters. Moreover, race-gender differences can also emerge across various aspects of punishment and math achievement. For example, Black females are more likely to be suspended for subjective reasons, while White females are more likely to be suspended for objective reasons (Annamma et al., 2016). Furthermore, observing math performance *in the absence of* math attitudes may predict STEM persistence for White male students but not White female students; conversely, observing math attitudes *in the absence of* math performance may predict STEM persistence for White male students but not Black male students (Riegle-Crumb et al., 2011).

Data, Measures, and Methods

Data

The analyses in this article utilized restricted-use data from the High School Longitudinal Study of 2009 (HSLS). In the 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 & Dalton, 2013). The analyses in this article utilized student and parent data from the base year (fall of 9th grade) and first follow-up (spring of 11th grade). While instances of nonresponse occurred both within waves (for different questionnaire types) and across waves, the National Center of Education Statistics (NCES) did provide analytic weights to account for these instances of nonresponse, as well as instances of sampling inefficiencies that are inherent to a stratified sampling approach. In particular, we utilized the W2W1PAR weight, which accounts for instances of nonresponse between waves one and two, as well as instances of nonresponse for the parent questionnaire.

Out of the 25,206 eligible students, 21,444 students responded to the first wave of the survey. A total of 5,015 participants were removed because they lacked parent respondents; 1,508 participants were removed because they did not take a math course during the fall of freshman year; and 1,388 participants were removed because they did not participate in the follow-up survey. As our sample focused on White and Black students,[1] an additional 4,381 respondents were removed, resulting in 9,153 respondents. All study variables had less than 5% missing. Listwise deletion resulted in a final analytic sample of 7,822.[2]

Measures

Punishment variables consisted of a parent-reported binary measure indicating whether or not heir student had been suspended or expelled prior to high school—referred to as *pre-HS suspension* (0 = no; 1 = yes),[3] as well as a student-reported measure collected during the spring of junior year indicating the amount of times the student had received an in-school suspension within the last 6 months—referred to as *HS suspension* (0 = zero times; 1 = one to two times; 2 = three to six times; 3 = seven to nine times; 4 = ten or more times).[4] While the latter measure does not capture all suspension types nor does it capture all suspension instances, it serves as an appropriate proxy for involuntary involvement in exclusionary discipline later in high school commonly used in research of this type (Jabbari & Johnson, 2022).

Math variables consisted of math performance, math efficacy, math utility, and math identity. These variables represent snapshots of both early and later math achievement and attitudes during high school. *Math performance* measures algebraic reasoning skills, and it was collected from a 72-item test administered by the NCES during the fall of freshman year of high school and a 118-item test administered in the spring of junior year of high school. It consists of a continuous, norm-referenced standardized performance (theta) score with a mean of 50 and a standard deviation of 10. Standardized theta scores represent a transformation of ability estimates derived from item-response theory (IRT). *Math efficacy* was derived from four Likert-scale questions that consider the extent to which a student is confident that they can do an excellent job in math assignments (S1MASSEXCL[5]) and tests (S1MTESTS), that they can understand the most difficult material presented in their math textbook (S1MTEXTBOOK), and that they can master the skills being taught in their math courses (S1MSKILLS) (Cronbach's alpha = 0.90). *Math utility* was derived from a series of questions that consider the extent to which a student sees their math courses as useful for everyday life (S1MUSELIFE), college (S1MUSECLG), and future careers (S1MUSEJOB) (Cronbach's alpha = 0.78). Finally, *math identity* was derived from a series of questions that consider the extent to which a student sees him or herself as a math person (S1MPERSON1), as well as the extent to which others see him or her as a math person (S1MPERSON2) (Cronbach's alpha = 0.84). For all of these times, Likert scales consisted of four levels, ranging from strongly agree to strongly disagree. The NCES created these variables through principal component factor analysis. These variables were standardized to a mean of 0 and had a standard deviation of 1.

Methods

In order to test our hypotheses, we construct a series of moderated-mediated path models under an SEM framework to test the relationship between punishment and math performance, efficacy, utility, and identity. SEM is ideal for testing hypothesized relationships over time and is unique in that it allows both mediation and moderation to be explored in a single model (Kline, 2015). First, as seen in Figure 1, we construct a series of four-time-point multivariate path models in which (a) math observed at time-point one mediates the relationship between punishment at time points one and two and (b) punishment at time-point two mediates the relationship between math at time points one and two. In particular, path #1 estimates the relationship between early suspension and early math; path #2 estimates the relationship between early suspension and later suspension; path #3 estimates the relationship between early math and later suspension; path #4 estimates the relationship between early math and later math; and path #5 estimates the relationship between later suspension and later math. These paths are estimated through a maximum likelihood function.[6] This creates a series of multiple mediation models between punishment and math achievement by which: (a) indirect effects from early suspension to later suspension (S1→M1→S2) are measured by multiplying paths 1 and 3; (b) indirect effects from early math to later math (M1→S2→M2) are measured by multiplying paths 3 and 5; and (c) indirect effects from early suspension to later math (S1→M1→S2→M2) are measured by adding the multiplied paths of 1, 3, and 5; 1 and 4; and 2 and 5.

Then, through multigroup modeling, we construct a series of models across gender, race, and race-gender. By constraining paths to be similar across groups and comparing the constrained model to the unconstrained model (where paths are allowed to vary across groups), we are able to test a particular path for group invariance. When models with constrained paths are significantly different from models with unconstrained paths, these paths are deemed noninvariant and thus estimated separately for each group; all other paths are deemed invariant and are constrained to be equal across groups. The parameters that are allowed to vary across groups demonstrate a moderating effect of the group on a particular path (Bowen & Guo, 2011). To account for nested data, we use STATA's survey package for analyzing complex data, which takes into account sampling weights, primary sampling units, and stratas.

Results

Descriptive Statistics

As seen in Table 1, the proportion of males who experienced pre-high school suspension was nearly three times that of females (14.1% vs. 5.5%), while a proportion of Black students who experienced pre-high school suspension was nearly three times that of White students (23.1% vs. 7.9%). When considering race-gender intersections, the proportion of students who experienced pre-high school suspension was highest for Black males (31.3%), followed by Black females (15%), White males (11.6%), and White females (4.2%). Similarly, the average measure of high school suspensions experienced by males was over twice that of females (0.154 vs. 0.069), while the average measure of high school suspensions experienced by Black students was nearly twice that of White students (0.185 vs. 0.10).[7] When considering race-gender intersections, the average measure of high school suspensions was highest for Black males (0.246), followed by White males (0.14), Black Females (0.123), and White females (0.061).

Concerning math, while performance was nearly identical across gender at both time points, White students outperformed Black students by roughly 5 points each time (representing over a half standard deviation advantage). When considering race-gender intersections, most differences occurred between race and not gender: White males had roughly a half-point advantage in math performance over White females, while Black Females had roughly a half-point advantage in math performance over Black males. For math efficacy, males had slightly higher levels when

TABLE 1
Descriptive Statistics

	Total		Gender				Race				Race-Gender								Total	
			Male		Female		White		Black		White male		White Female		Black male		Black female			
Variable	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Min	Max
Pre-HS suspension	0.097		0.141		0.055		0.079		0.231		0.116		0.042		0.313		0.15		0	1
HS suspension	0.111	*0.42*	0.154	*0.497*	0.069	*0.32*	0.1	*0.41*	0.185	*0.47*	0.14	*0.488*	0.061	*0.31*	0.246	*0.55*	0.123	*0.38*	0	4
Math 1 performance	53.383	*9.41*	53.526	*9.842*	53.244	*8.96*	54.027	*9.28*	48.829	*9.04*	54.242	*9.711*	53.818	*8.84*	48.528	*9.29*	49.129	*8.78*	24.1	82.19
Math 2 performance	53.344	*9.74*	53.587	*10.23*	53.107	*9.23*	53.977	*9.69*	48.864	*8.83*	54.327	*10.17*	53.638	*9.19*	48.417	*9.09*	49.307	*8.56*	26.66	84.91
Math 1 efficacy	0.103	*0.97*	0.202	*0.957*	0.007	*0.98*	0.087	*0.98*	0.22	*0.92*	0.184	*0.969*	-0.008	*0.98*	0.327	*0.85*	0.113	*0.96*	-2.92	1.62
Math 2 efficacy	0.068	*1*	0.189	*0.973*	−0.05	*1.01*	0.046	*1.01*	0.228	*0.94*	0.172	*0.977*	-0.077	*1.02*	0.311	*0.94*	0.146	*0.93*	-2.5	1.73
Math 1 utility	−0.039	*0.98*	0.012	*0.998*	−0.088	*0.96*	−0.077	*0.98*	0.233	*0.97*	-0.025	*0.994*	-0.127	*0.95*	0.271	*0.98*	0.195	*0.96*	-3.51	1.31
Math 2 utility	−0.01	*1*	0.056	*1.018*	−0.074	*0.98*	−0.038	*1*	0.191	*0.96*	0.034	*1.024*	-0.109	*0.98*	0.209	*0.97*	0.173	*0.95*	-3.94	1.21
Math 1 identity	0.116	*1*	0.186	*0.99*	0.048	*1*	0.12	*1*	0.088	*0.99*	0.195	*0.99*	0.048	*1*	0.125	*0.98*	0.052	*1*	-1.73	1.76
Math 2 identity	0.087	*1.03*	0.191	*1.017*	−0.014	*1.04*	0.089	*1.03*	0.071	*1.02*	0.197	*1.022*	-0.016	*1.03*	0.145	*0.98*	-0.002	*1.06*	-1.54	1.82
Observations	7,822		3,857 (49.31%)		3,965 (50.69%)		6,853 (87.61%)		969 (12.39%)		3,374 (43.13%)		3,479 (44.48%)		483 (6.17%)		486 (6.21%)			

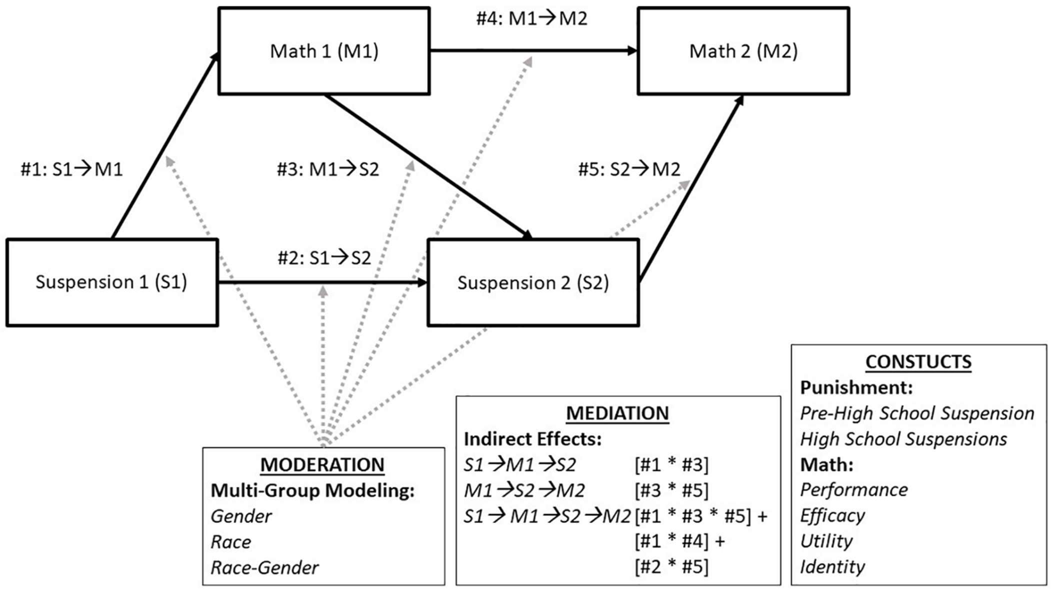

FIGURE 1. *Conceptual figure.*

compared to females at each time-point, whereas Black students had slightly higher levels when compared to White students at each time point. When considering race-gender intersections, Black males had the highest levels of math efficacy, followed by White males, Black females, and White females. Similar gender and race patterns were observed for math utility; however, White males no longer maintained an advantage over Black females whose math utility nearly rivaled that of Black males. Finally, while males had higher levels of math identity than females, the pattern reversed for race: White students had higher levels of math identity than Black students. When considering race-gender intersections, White males had the highest levels of math identity, followed by Black males, while Black females and White females had nearly identical levels.

Path Analyses

Math Performance. Starting with math performance, our empirical model supports our hypothesized model: being suspended prior to high school was significantly associated with a decrease in early math performance (S1→M1: B = −7.659***) and an increase in high school suspensions (S1→S2: B = 0.337***), whereas early math performance was significantly associated with a decrease in high school suspensions (M1→S2: B = −0.006***) and an increase later math performance (M1→M2: B = 0.744***). Additionally, high school suspensions were significantly associated with a decrease in later math performance (S2→M2: B = −2.05***). Unsurprisingly, being suspended prior to high school was indirectly associated with a significant increase in high school suspensions *through early math performance* (S1→M1→S2: B = 0.043***), while early math performance was indirectly associated with a significant increase in later math performance *through high school suspensions* (M1→S2→M2: B = 0.012***). Finally, being suspended prior to high school was indirectly associated with a significant decrease in later math performance *through early math performance and high school suspensions* (S1→M1→S2→M2: B = -6.475***).

When considering differences across gender and race, we find multiple instances of group moderation. As seen in Table 2, some coefficients are estimated separately for each group, representing instances of group noninvariance or moderation effects. In doing so, the size of the coefficients can be compared across the groups. Here, a larger coefficient represents a larger effect of a given construct on another construct along a particular path.[8] First, we find that males exhibit larger paths from early math performance to high school suspensions (M1→S2) and later math performance (M1→M2). Second, we find that Black students exhibit larger paths from pre-high school suspension to early math performance (S1→M1), while White students exhibit larger paths from early math performance to later math performance (M1→M2). Subsequently, the indirect effects from pre-high school suspension to high school suspensions (S1→M1→S2) and later math performance (S1→M1→S2→M2), as well from early math performance to later math performance (M1→S2→M2), were larger for males, while the indirect effect from pre-high school suspension to later math performance (S1→M1→S2→M2) was larger for White students.

TABLE 2

Path Coefficients by Gender, Race, and Race-Gender

	Total	Gender (Group Invariant Paths)		Race (Group Invariant Paths)		Race-Gender (Group Invariant Paths)			
		Male (Noninvariant Paths)	Female (Noninvariant Paths)	White (Noninvariant Paths)	Black (Noninvariant Paths)	White Male (Noninvariant Paths)	White Female (Noninvariant Paths)	Black Male (Noninvariant Paths)	Black Female (Noninvariant Paths)
Performance									
Direct effects									
S1→M1	−7.659***(0.753)	−7.809***(0.754)		−5.795***(0.734)	−5.891***(1.417)	*−6.542***(0.918)*	*−4.476**(1.29)*	*−6.956***(1.765)*	*−4.351*(1.877)*
S1→S2	0.337***(0.065)	0.241***(0.062)		0.345***(0.065)		*0.42***(0.105)*	*0.128*(0.06)*	*0.442***(0.125)*	*0.146(0.121)*
M1→S2	−0.006***(0.001)	−0.008***(0.002)	−0.004**(0.001)	−0.006***(0.001)		−0.007***(0.002)	−0.006***(0.001)	−0.004(0.005)	−0.003(0.005)
M1→M2	0.744***(0.021)	0.782***(0.027)	0.702***(0.028)	0.756***(0.021)	0.597***(0.054)	0.778***(0.029)	0.73***(0.025)	0.616***(0.056)	0.561***(0.078)
S2→M2	−2.05***(0.43)	−2.042***(0.422)		−2.048***(0.431)		−1.96***(0.404)			
Indirect effects									
S1→M1→S2	0.043***(0.009)	0.066***(0.017)	0.035**(0.01)	0.035***(0.007)	0.035**(0.01)	0.045**(0.014)	0.025**(0.008)	0.027(0.038)	0.014(0.02)
M1→S2→M2	0.012***(0.003)	0.017***(0.004)	0.009**(0.003)	0.012***(0.003)		0.013***(0.004)	0.011***(0.003)	0.008(0.01)	0.006(0.009)
S1→M1→S2→M2	−6.475***(0.627)	−6.732***(0.672)	−6.042***(0.576)	−5.158***(0.614)	−4.298***(1.035)	−6.003***(0.806)	−3.57***(0.983)	−5.203***(1.219)	−2.755*(1.229)
Efficacy									
Direct effects									
S1→M1	−0.233**(0.083)	−0.273**(0.082)		−0.424***(0.096)	−0.01(0.16)	−0.477***(0.122)	−0.477**(0.154)	−0.124(0.239)	0(0.205)
S1→S2	0.373***(0.065)	0.278***(0.062)		0.38***(0.083)	0.355**(0.106)	0.439***(0.103)	0.139*(0.06)	0.46***(0.125)	0.16(0.11)
M1→S2	−0.033*(0.013)	−0.063*(0.025)	−0.017(0.011)	−0.033**(0.012)		−0.055*(0.024)	−0.029**(0.01)	−0.068(0.056)	0.021(0.036)
M1→M2	0.365***(0.022)	0.356***(0.021)		*0.385***(0.022)*	*0.254**(0.073)*	0.35***(0.022)			
S2→M2	−0.084(0.056)	−0.12*(0.059)		*−0.104(0.066)*	*−0.019(0.126)*	−0.149†(0.084)	−0.104(0.092)	−0.315*(0.145)	0.213(0.193)
Indirect effects									
S1→M1→S2	0.008†(0.004)	0.017†(0.009)	0.005(0.003)	0.014*(0.007)	0(0.005)	0.026†(0.015)	0.014*(0.007)	0.008(0.015)	0(0.004)
M1→S2→M2	0.003(0.002)	0.008†(0.004)	0.002(0.002)	0.003(0.002)	0.001(0.004)	0.008(0.005)	0.003(0.003)	0.021(0.021)	0.005(0.006)
S1→M1→S2→M2	−0.117**(0.039)	−0.133***(0.037)	−0.131***(0.036)	−0.204***(0.048)	−0.009(0.063)	−0.236***(0.062)	−0.183**(0.059)	−0.191(0.137)	0.034(0.085)
Utility									
Direct effects									
S1→M1	−0.006(0.092)	−0.033(0.106)	0.004(0.169)	−0.32**(0.095)	0.058(0.168)	−0.317**(0.119)	−0.456**(0.149)	0.097(0.167)	−0.006(0.254)
S1→S2	0.381***(0.065)	0.288***(0.062)		0.392***(0.084)	0.355**(0.105)	0.459***(0.105)	0.15*(0.061)	0.474***(0.129)	0.16(0.111)
M1→S2	−0.006(0.012)	*−0.018(0.023)*	*0.002(0.01)*	−0.007(0.011)		−0.017(0.023)	−0.007(0.009)	−0.052(0.06)	0.024(0.022)
M1→M2	0.313***(0.026)	0.312***(0.027)		0.296***(0.023)		0.292***(0.023)			
S2→M2	−0.016(0.057)	−0.023(0.056)		−0.031(0.058)		−0.034(0.058)			
Indirect effects									
S1→M1→S2	0(0.001)	0.001(0.002)	0(0)	0.002(0.004)	0(0.001)	0.006(0.008)	0.003(0.004)	−0.005(0.011)	0(0.006)
M1→S2→M2	0(0)	0(0.001)	0(0)	0(0.001)		0.001(0.001)	0(0.001)	0.002(0.004)	−0.001(0.002)
S1→M1→S2→M2	−0.008(0.036)	−0.017(0.036)	−0.006(0.055)	−0.107**(0.035)	0.006(0.057)	−0.109*(0.043)	−0.138**(0.046)	0.013(0.061)	−0.007(0.075)

(continued)

TABLE 2. **(CONTINUED)**

	Total	Gender (Group Invariant Paths)		Race (Group Invariant Paths)		Race-Gender (Group Invariant Paths)			
Identity									
Direct effects									
S1→M1	−0.446***(0.088)	−0.469***(0.089)		−0.493***(0.094)	−0.377*(0.169)	−0.454***(0.109)	−0.721***(0.17)	−0.402*(0.204)	−0.333(0.242)
S1→S2	0.372***(0.065)	0.277***(0.062)		0.384***(0.084)	0.347**(0.105)	0.455***(0.107)	0.139*(0.06)	0.461***(0.13)	0.153(0.112)
M1→S2	−0.02†(0.011)	−0.04†(0.021)	−0.011(0.01)	−0.02†(0.011)		−0.02*(0.008)			
M1→M2	0.582***(0.022)	0.579***(0.022)		0.58***(0.022)		0.614***(0.029)	0.579***(0.027)	0.491***(0.097)	0.512***(0.078)
S2→M2	−0.103*(0.046)	−0.124**(0.046)		−0.099*(0.046)		−0.122*(0.047)			
Indirect effects									
S1→M1→S2	0.009†(0.005)	0.019†(0.011)	0.005(0.005)	0.01†(0.006)	0.008(0.005)	0.009*(0.005)	0.015*(0.007)	0.008(0.005)	0.007(0.005)
M1→S2→M2	0.002†(0.001)	0.005†(0.003)	0.001(0.001)	0.002†(0.001)		0.002†(0.001)			
S1→M1→S2→M2	−0.299***(0.053)	−0.308***(0.053)	−0.306***(0.053)	−0.325***(0.058)	−0.254*(0.1)	−0.335***(0.073)	−0.437***(0.101)	−0.255*(0.117)	−0.19(0.118)
Observations	7,822	3,857	3,965	6,853	969	3,374	3,479	483	486

Note. Unstandardized estimates presented, followed by standard errors in parentheses.
Centered coefficients represent group-invariant paths, which are the same for each group.
Italicized coefficients represent cases of marginal group invariance (i.e., $p < 0.1$).
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.1$.

Additionally, we consider the differences across race-gender groups, again, noticing multiple instances of group moderation. For example, the path from pre-high school suspension to early math performance (S1→M1) was largest for Black males, followed closely by White males and more distantly by White females and Black females. Similarly, the path from pre-high school suspension to high school suspensions (S1→S2) was largest for Black males, followed closely by White males and more distantly by White females; however, this relationship was insignificant for Black females. In each case, these group differences represent cases of marginal moderation, as the unconstrained paths were only marginally (i.e., $p<0.1$)[9] different from the constrained paths. Furthermore, the path from early math performance to high school suspensions (M1→S2) was slightly larger for White males when compared to White females; however, this relationship was not significant for Black males or Black females. Moreover, the path from early math performance to later math performance (M1→M2) was largest for White males, followed sequentially by White females, Black males, and Black females. Subsequently, the indirect effects from pre-high school suspension to high school suspensions (S1→M1→S2) were substantially larger for White males when compared to White females, while the indirect effects of early math performance to later math performance (M1→S2→M2) were only slightly larger for White males when compared to White Females. In both cases, these indirect effects were insignificant for Black males and Black females. Finally, the indirect effect from pre-high school suspension to later math performance (S1→M1→S2→M2) was largest for White males, followed sequentially by Black males, White females, and Black females.

Math Efficacy. Moving onto math efficacy, our empirical model mostly supports our hypothesized model: being suspended prior to high school was significantly associated with a decrease in early math efficacy (S1→M1: B = −0.233**) and an increase in high school suspensions (S1→S2: B = 0.373***), while early math efficacy was significantly associated with a decrease in high school suspensions (M1→S2: B = -0.033*) and an increase in later math efficacy (M1→M2: B = 0.365***). However, high school suspensions were not significantly associated with later math efficacy. Subsequently, being suspended prior to high school was indirectly associated with a marginally significant increase in high school suspensions *through early math efficacy* (S1→M1→S2: B = 0.008†), whereas early math efficacy was not indirectly associated with later math efficacy. Finally, being suspended prior to high school was indirectly associated with a significant decrease in later math efficacy *through early math efficacy and high school suspensions* (S1→M1→S2→M2: B = −0.117**).

When considering differences across gender and race, we, again, find multiple instances of group moderation. First, we find that males exhibit a significant path from early math efficacy to high school suspensions (M1→S2), a path that is insignificant for females, while White students exhibit a significant path from pre-high school suspension to early math efficacy (S1→M1), a path that is insignificant for Black students. White students also exhibit a slightly larger path from pre-high school suspension to high school suspensions (S1→S2), as well as a larger marginally significant path from early math efficacy to later math efficacy (M1→M2). Subsequently, the indirect effects from pre-high school suspension to high school suspensions (S1→M1→S2), as well from early math efficacy to later math efficacy (M1→S2→M2), were only marginally significant for males, while the indirect effect from pre-high school suspension to later math efficacy (S1→M1→S2→M2) was slightly larger for males. Finally, the indirect effect from pre-high school suspension to high school suspensions (S1→M1→S2), as well as the indirect effect from pre-high school suspension to later math efficacy (S1→M1→S2→M2), was only significant for White students.

Additionally, we consider the differences across race-gender groups, again, noticing multiple instances of group moderation. For example, the path from pre-high school suspension to early math efficacy (S1→M1) was identical for White males and White females and insignificant for Black males and Black females. Similar to the math performance model, the path from pre-high school suspension to high school suspensions (S1→S2) was largest for Black males, followed closely by White males and more distantly by White females; this path was not significant for Black females. Furthermore, the path from early math efficacy to high school suspensions (M1→S2) was larger for White males when compared to White females; however, this path was not significant for Black males or Black females. Moreover, the significant path from high school suspensions to later math efficacy (S2→M2) was larger for Black males when compared to the marginally significant path for White males; this path was not significant for White females or Black females. Subsequently, the indirect effects from pre-high school suspension to high school suspensions (S1→M1→S2), as well as from pre-high school suspension to later math efficacy (S1→M1→S2→M2), was larger for White males when compared to White females. Here, it is important to note that indirect effects from pre-high school suspension to high school suspensions were only marginally significant for White males. In both cases, these indirect effects were nonsignificant for Black males and Black females.

Math Utility. Moving onto math utility, our empirical model only partially supports our hypothesized model: being suspended prior to high school was, again, significantly associated with an increase in high school suspensions (S1→S2: B = 0.381***), while early math utility was significantly associated with an increase in later math utility (M1→M2: B = 0.313***). However, none of the other paths were significant. Unsurprisingly, there were no significant indirect paths in this model.

When considering differences across gender and race, we find few instances of group moderation with significant relationships. Pertaining to race, we find that White students exhibit a significant path from pre-high school suspension to early math utility (S1→M1)—a path that is insignificant for Black students. In line with previous models, we also find that White students exhibit a slightly larger path from pre-high school suspension to high school suspension (S1→S2). Subsequently, the indirect effect from pre-high school suspension to later math utility (S1→M1→S2→M2) was only significant for White students.

Additionally, we consider the differences across race-gender groups, again, finding only a few instances of group moderation with significant relationships. For example, the path from pre-high school suspension to early math utility (S1→M1) was moderately larger for White females when compared to White males; this path was insignificant for Black males and Black females. Similar to previous models, the path from pre-high school suspension to high school suspension (S1→S2) was largest for Black males, followed closely by White males and more distantly by White females; this path was insignificant for Black females. Subsequently, the indirect effects from pre-high school suspension to later math utility (S1→M1→S2→M2) was slightly larger for White females when compared to White males; this effect was insignificant for Black males and Black females.

Math Identity. Closing with math identity, our empirical model mostly supports our hypothesized model: being suspended prior to high school was significantly associated with a decrease in early math identity (S1→M1: B = −0.446***) and an increase in high school suspensions (S1→S2: B = 0.372***), while early math identity was marginally associated with a decrease in high school suspensions (M1→S2: B = −0.02†) and significantly associated with an increase in later math identity (M1→M2: B = 0.582***). Additionally, high school suspensions were significantly associated with a decrease in later math identity (S2→M2: B = −1.03***). Subsequently, being suspended prior to high school was indirectly associated with a marginally significant increase in high school suspensions *through early math identity* (S1→M1→S2: B = 0.009†), whereas early math identity was indirectly associated with a marginally significant increase in later math identity *through high school suspensions* (M1→S2→M2: B = 0.002†). Finally, being suspended prior to high school was indirectly associated with a significant decrease in later math identity *through early math identity and high school suspensions* (S1→M1→S2→M2: B = −0.299***).

When considering differences across gender and race, we find some instances of group moderation. For example, we find that males exhibited a marginally significant path from early math identity to high school suspensions (M1→S2)—a path that was insignificant for females. Alternatively, White students exhibited larger paths from pre-high school suspension to early math identity (S1→M1) and high school suspensions (S1→S2). Subsequently, the indirect effects from pre-high school suspension to high school suspensions (S1→M1→S2), as well from early math identity to later math identity (M1→S2→M2), was only marginally significant for males, while the indirect effect from pre-high school suspension to later math identity (S1→M1→S2→M2) was slightly larger for males when compared to females. Alternatively, the indirect effect from pre-high school suspension to high school suspension (S1→M1→S2) was only marginally significant for White students, while the indirect effect from pre-high school suspension to later math identity (S1→M1→S2→M2) was larger for White students when compared to Black students.

Additionally, we consider the differences across race-gender groups, again, finding some instances of group moderation. For example, the path from pre-high school suspension to early math identity (S1→M1) was moderately larger for White females when compared to White males, followed closely by Black males; this path was insignificant for Black females. Similar to previous models, the path from pre-high school suspension to high school suspension (S1→S2) was largest for Black males, followed closely by White males and more distantly by White females; this path was not significant for Black females. Furthermore, the path from early math identity to later math identity (M1→M2) was largest for White males, followed by White females, Black females, and Black males. Subsequently, the indirect effect from pre-high school suspension to high school suspension (S1→M1→S2) was slightly larger for White females when compared to White males; this effect was insignificant for Black males and Black females. Finally, the indirect effect from pre-high school suspension to later math identity (S1→M1→S2→M2) was largest for White females, followed sequentially by White males and Black males; this effect was insignificant for Black females.

Discussion

Previous research has demonstrated the general relationships among punishment and math over time, while noting the importance of gender and race at the individual level as well as race at the school level (Jabbari & Johnson, 2020, 2022, 2023; Johnson & Jabbari, 2021). Through a variety of treatments (e.g., in-school suspensions, high suspension schools, high surveillance schools, etc.), outcomes (e.g., math achievement, math efficacy, math attitudes, dropout/pushout status, and college attendance, etc.), modeling strategies (e.g., structural equation modeling, propensity score weighting, multi-level modeling, etc.), and theoretical orientations (e.g., social control, life course, turning points, accumulated disadvantage, etc.), previous research has demonstrated how the relationships among punishment and math can push Black students and males away from STEM and toward prisons (Jabbari & Johnson, 2022; Johnson & Jabbari, 2022). Nevertheless, a critical approach to this quantitative work requires a deeper look into the ways in which marginalized identities interact to place particular race-gender groups on certain punishment and math trajectories. Similar to previous work, we conceptualize the relationships among punishment and math as mediating influences where punishment may represent departures in math trajectories and vice versa. We therefore use a multivariate path model under an SEM framework. Then, in order to explore the moderating roles of gender, race, and race-gender, we use a multigroup strategy, again, under an SEM framework. However, unlike previous work using SEM, we do not create latent constructs for math attitudes; rather, we separate out the various aspects of attitudes, as these may vary across gender, race, and race-gender.

Summary of Findings

Our findings yield several important insights on the role of gender, race, and race-gender in punishment and math trajectories. First, when considering descriptive statistics, we find that it is the intersection of gender and race that marginalize students in punishment: Black males enter high school with punishment histories that are over seven times that of White females (31.3% vs. 4.2%). Moreover, gender does not appear to protect Black females from punishment prior to high school who have punishment histories that are greater than that of White males (15% vs. 11.6%). However, high schools appear to further marginalize males in punishment, as White males surpass Black females in high school suspensions (0.140 vs. 0.123).

Concerning math, we find that gender, race, and race-gender patterns differ substantially across performance and different facets of attitudes. For example, math performance gaps are primarily driven by race with very little differences observed across gender. However, despite disadvantages in math performance, Black students demonstrated higher levels of math efficacy, which differed by gender. Together, the intersection of race and gender placed Black males at a distinct advantage over White females with regards to math efficacy. Yet, White males still maintained an advantage over Black females in math efficacy. Similar patterns were observed for math utility; however, White males no longer maintained an advantage over Black females whose math utility rivaled that of Black males. While males had higher levels of math identity than females, the pattern reversed for race: White students had higher levels of math identity than Black students—ultimately placing White males at a distinct advantage and Black females at a distinct disadvantage. Here, we can infer that despite lower performance, Black students have higher levels of efficacy and utility than White students and that while gender further marginalizes Black females in their beliefs about their math abilities, it doesn't stop them from believing that math can be beneficial in the future. Nevertheless, advantages in efficacy and utility don't translate into advantages in identity, where Black males and Black females remain relatively disadvantaged when compared to White males.

To uncover why and how these advantages and disadvantages relate to each other, we turn to our path analyses. Starting with math performance, our empirical model supports our hypothesized model: being suspended prior to high school places students on a path of decreased math performance (S1→M1) and increased suspensions (S1→S2). Indeed, the indirect model effects demonstrate significant mediation within trajectories, suggesting that part of why students remain on punishment trajectories is because they perform worse in math (S1→M1→S2), and conversely, that part of why students remain on math performance trajectories is because they are suspended less in high school (M1→S2→M2). We also find a substantial accumulation effect: being suspended prior to high school leads to a decrease in junior-year math performance (S1→M1→S2→M2) that represents almost two-thirds of a standard deviation drop.

However, the effects of math performance on high school suspensions and future math performance tend to be larger for males, and while the effect of pre-high school suspension on early math performance is slightly larger for Black students, the effect of early math performance on later math performance is moderately larger for White students. Taken together, it is unsurprising that White males—who have the highest levels of early math performance—maintain their advantage by demonstrating the largest path from early to later math performance. Furthermore, it is unsurprising that Black males—who have the highest proportion of pre-high school suspensions—maintain these disadvantages in punishment by demonstrating the largest path from pre-high school suspension to early math performance. As Black females demonstrate the only insignificant path from pre-high school suspension to high school suspension, it is also unsurprising that they are the only race-gender group who experience a decline in their punishment standing, falling below White males in high school. Moreover, as the direct effect of early math performance on high school suspensions is not significant for Black males and Black females, we are unsurprised to find that the indirect effects from pre-high school to high school suspension, as well as the indirect effects from early to later math performance were insignificant for these groups. Nevertheless, even though these indirect effects did not cross trajectories for Black males and

Black females, the combination of disadvantages from punishment and math performance trajectories was still strong enough to accumulate disadvantages from pre-high school suspension to later math performance for Black males and Black females.

Moving on to math efficacy, our empirical model mostly supports our hypothesized model: being suspended prior to high school places students on a path of decreased math efficacy and increased suspensions, with one exception—high school suspensions were not significantly associated with later math efficacy. Here, the effect of suspensions on math efficacy may be more salient earlier in one's high school career, whereas suspensions may hinder students' math performance *throughout* one's high school career, potentially through missed learning opportunities. As a result, there is only a marginally significant indirect effect within the punishment trajectory and no significant indirect effect within the math efficacy trajectory. Nevertheless, we do find a significant accumulation effect: being suspended prior to high school leads to a decrease in junior-year math efficacy. However, this effect—representing roughly a 10% standard deviation drop in efficacy—pales in comparison to the indirect effect of pre-high school suspension on junior-year math performance.

For students with more high school suspensions than others, the lack of significance from high-school suspensions to later math efficacy may be advantageous, as it doesn't allow their punishments to bring down their efficacy levels. Nevertheless, this was not the case for Black males who demonstrated the largest and most significant path from high school suspensions to later math efficacy. This is somewhat peculiar when considering that the path from pre-high school suspension to early math efficacy was insignificant for Black students, suggesting that punishment takes a toll on Black students' math efficacy later in high school but not earlier. Here, it could be the case that freshman year represents a fresh start for Black students who don't let their punishment histories influence their efficacy levels, whereas by junior year labeling and other socializing practices may cause lower efficacy levels for Black students who experience punishment. Similar to math performance, the path from early math efficacy to high school suspensions was only significant for White males and White females. Thus, the advantages that Black students had in math efficacy were not able to protect them from future suspensions.

Considering math utility, our empirical model only partially supports our hypothesized model: while within-trajectory paths were significant (i.e., the path from pre-high school to high school suspensions and the path from early to later math utility), there were no significant cross-trajectory paths for math utility. Unsurprisingly, there were no significant indirect effects. Unlike math performance and math efficacy, suspensions did not appear to be related to math utility. As math utility is less connected to an individuals' beliefs about oneself, like efficacy, and more connected to one's perceptions of the broad benefits of math, these patterns appear to make sense. However, this was not the case for both Black and White students, as there was a significant path from pre-high school suspension to early math utility for White students. As Black students have higher rates of pre-high school suspension, this finding—potentially suggesting that the disadvantage that Black students experience in punishment may not translate into lower levels of math utility—may partially explain Black students' higher rates of math utility when compared to White students. Although there were no significant gender differences in math utility, slightly larger direct and indirect paths from pre-high school suspension to early and later math utility were observed for White females when compared to White males, potentially suggesting that the disadvantage that male students experience in punishment may not translate into lower levels of math utility; this may partially explain male students' higher rates of math utility when compared to female students.

Closing with math identity, our empirical model almost entirely supports our hypothesized model: with the exception of one of the paths only being marginally significant, being suspended prior to high school places students on a path of decreased math identity and increased suspensions. As a result, there are only marginally significant indirect effects within punishment and math identity trajectories. Similar to math efficacy, we do find a significant accumulation effect: being suspended prior to high school leads to a decrease in junior year math identity. This effect—representing roughly a 30% standard deviation drop in identity—is much larger than the drop in math efficacy.

Similar to the math efficacy model, male students demonstrated a (marginally) significant path from early math identity to high school suspensions, whereas White students demonstrated larger paths from pre-high school suspension to early math identity, and high school suspensions. While White females demonstrated the largest path from pre-high school suspension to early math identity because they had the lowest rates of pre-high school suspension, their math identity levels may not have been negatively impacted as much as other race-gender groups. White males, on the other hand, who had the highest levels of early math identity experienced the largest path from early to later math identity, which may explain how they were able to maintain their advantages in math identity.

Altogether, our results demonstrate that the relationships among punishment and math vary across performance and different facets of math attitudes and that these relationships, in turn, vary across gender, race, and race-gender. These variations depict accumulations and saturations of both advantages and disadvantages. Despite having the highest levels of math efficacy and utility, Black males had the lowest levels of math performance and trailed behind White males in math identity. At the same time, Black males have the highest rates of both pre-high school and high school suspensions. As our models demonstrate, these trends are deeply related. For example, Black males had the largest paths from pre-high school suspension to early math performance and high school suspension, which demonstrates an accumulation of disadvantages both across punishment and math trajectories and within punishment trajectories. While the lack of significance from pre-high school suspension to early math efficacy and utility may have partially protected Black males' efficacy and utility levels, the significant path from pre-high school suspension to early math identity may explain why Black males trail White males in this regard. Moreover, as the path from early math efficacy to high school suspensions was only significant for White males and White females, the advantages that Black male students had in math efficacy were not able to protect them from future suspensions, representing a saturation of advantage. Alternatively, White males—who have the highest levels of early math performance—accumulate their advantage by demonstrating the largest path from early to later math performance. White males also have the highest levels of math identity and demonstrate the strongest path from early to later math identity—again, suggesting an accumulation of advantage. Finally, it is worth noting that almost all model paths that were moderated by race-gender were insignificant for Black females. While the lack of significance may have protected Black females' math efficacy and utility levels from the negative effects of increased suspensions, potentially representing a saturation of disadvantage, more must be done to explore these relationships. Indeed, the lack of significance could signal other factors influencing punishment and math for this group.

Implications

Theories of cumulative disadvantage are based on the premise that initial disadvantages accumulate over time. Conversely, those who suffer the most initially may also benefit the most from early interventions. Thus, given our findings, more of a focus should be placed on alleviating these initial disadvantages. Here, perspectives from the "Matthew effect," which extends from the biblical adage that the rich get richer and the poor get poorer and is often applied to theories of educational achievement (Stanovich, 2009), can be combined with perspectives from the "Heckman equation" (Heckman, 2012), which demonstrates the importance of early investments in children and youth. Applied to our study, schools should both reduce early engagement with punishment trajectories and increase early access to math trajectories, and this should be done both before and during high school. Moreover, given the reciprocal relationships between punishment and math, efforts to decrease punishment trajectories should simultaneously consider boosting math performance, efficacy, and identity, while efforts to increase math trajectories should also consider reducing exclusionary punishment.

Furthermore, these efforts should be specifically tailored for particularly marginalized groups. Given our descriptive findings around relative disadvantage, early punishment interventions should be developed for Black males while early math performance interventions should be developed for both Black males and Black females. Moreover, extending from a strength-based perspective, stakeholders should also consider ways to leverage Black males' relatively high levels of math efficacy, as well as Black males' and Black females' relatively high levels of math utility, to both increase math achievement trajectories and decrease punishment trajectories. In addition to highlighting relative disadvantages, our study also sheds light on cumulative disadvantages, which can also guide intervention design. In this regard, early math performance interventions should be tailored toward male students, while the early punishment interventions should be tailored toward Black students. While these accumulation trends suggest that White males should also be considered in punishment interventions, these trends also reveal the unique cumulative disadvantages that Black males face at the intersection of race and gender. Indeed, our research on cumulative disadvantages reiterates the importance for stakeholders to consider Black males in punishment and math interventions. Nevertheless, given the lack of significance for many of the cross-trajectory relationships involving Black females, it is possible that other factors not included in this model are affecting their trajectories, too; exploration of these potential factors will be an important next step for future research.

In line with Gregory et al.'s (2017) framework, programs that provide supportive relationships, bias awareness, academic rigor, culturally relevant and responsive pedagogy, and opportunities for learning and correcting behavior may prevent disciplinary incidents from occurring, while strategies that rely on equitable data inquiries, emphasize problem-solving approaches to discipline, include student and family voices in causes and solutions to conflicts, and reintegrate students after conflicts may increase equity when discipline incidents occur (p. 255). Here, multitiered systems of support can serve as both a prevention and intervention method (2017). However, as noted by Cruz and her colleagues (2021a), more research must be done to determine the extent to which these efforts actually decrease discipline disproportionality or if they merely represent "color-evasive" approaches to overall reductions in punitive discipline (Annamma et al., 2017). Indeed, Gregory et al. (2018) found that participating in a restorative justice intervention reduced overall rates of suspension but only slightly narrowed the Black vs. White suspension gap. Concerning math, research has demonstrated the importance of algebra instruction. For example, work by Cortes and her colleagues (2015) demonstrates the importance of double-dosage algebra in ninth grade. Research has also demonstrated the effectiveness of algebra interventions that focus on elementary grades (Blanton et al., 2019). Nevertheless, similar to discipline interventions, future research should explore how these programs pertain to race, gender, and other dimensions of identity.

Limitations

The use of path analysis in this study is designed to test a hypothesized longitudinal mediation model and determine how it is moderated by gender, race, and race-gender groups. Without an instrument that accounts for selection into punishment or a robust set of student- and school-level controls that one might find in a typical regression model, we cannot establish causal relationships within our modeling framework or rule out potential confounders. For example, as seen in our correlation table (Table A1), many of the math constructs are significantly related to each other. Furthermore, socioeconomic status, which can often be significantly related to race in these contexts, is also not included in these models. Moreover, other tests of cognitive ability, which are often related to math, are also not included. Here, it is important to note that we are primarily interested in these math and demographic categories as a whole. Thus, we do not employ an analytic strategy that seeks to pull apart the influences of race and social class, nor the influence of cognitive ability and math. Nevertheless, future research should continue to explore how these constructs relate to each other and operate together in the context of high school trajectories. Our study is also confined by the particular measures we use, which is only available up to eleventh grade. Therefore, future research should consider additional data sources to leverage data across a longer period of time. Future research should also explore how these relationships extend to related life outcomes, such as dropout/pushout status and college entry and completion. Indeed, these measures may allow for a more robust understanding of how disadvantages in punishment and math accumulate to produce disadvantages in other life outcomes. A final limitation is the generalizability of our findings. While NCES weights help account for sample attrition, which is inherent in a study of this type, and our analytic sample appears fairly representative of the original sample, we recognize that our findings may not be representative of all students in U.S. high schools.

Conclusion

In this study, we explored "multiplicatively disadvantaged" groups. These are groups in which multiple dimensions of a group's identity are simultaneously placed at a disadvantage in both discipline and math. In doing so, we found that advantages and disadvantages weren't additive but rather multiplicative. For example, based on suspension rates and math performance levels, White females can be considered to exist at the intersection of advantage, while Black males can be considered to exist at the intersection of disadvantage. Here, the advantage for White females in discipline was far greater than what we would expect if we had simply "added" the effects of being White and female together. Conversely, the disadvantages in discipline were far worse for Black males than what we would expect if we had simply "added" the effects of being Black and male together. Moreover, these facets of disadvantage did not dissipate over time. Indeed, Black males led all groups in suspensions both before and during high school; Black males also maintained the lowest levels of math performance in both freshman and junior year of high school. As these disadvantages in punishment and math have led to later life outcomes associated with the school-to-prison (e.g. dropout/pushout, involvement with police, incarceration) and STEM (e.g. college entrance and persistence) pipelines, these persistent disadvantages can be seen as accumulating over time. However, this accumulation does not only occur *within* punishment and math trajectories, but also *across* them, as we consistently see significant relationships among punishment and math over time. These insights are made possible by looking deeper into the ways in which marginalized identities interact to place particular race-gender groups on punishment and math trajectories through a critical lens. However, this is only the start. As demonstrated by Cruz and her colleagues (2021b), future critical quantitative work should continue to explore the ways in which marginalized identities interact in ways that can multiply disadvantages in education.

Appendix

TABLE A1
Spearman's Rank Correlation Coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Pre-HS suspension	1.000									
(2) HS Suspension	0.226*	1.000								
(3) Math 1 performance	−0.197*	−0.200*	1.000							
(4) Math 2 performance	−0.212*	−0.229*	0.746*	1.000						
(5) Math 1 efficacy	−0.045*	−0.061*	0.303*	0.304*	1.000					
(6) Math 2 efficacy	−0.051*	−0.082*	0.276*	0.320*	0.379*	1.000				
(7) Math 1 utility	0.015	0.013	0.011	0.008	0.353*	0.178*	1.000			
(8) Math 2 utility	−0.004	−0.030*	0.124*	0.166*	0.225*	0.396*	0.301*	1.000		
(9) Math 1 identity	−0.079*	−0.086*	0.414*	0.408*	0.569*	0.355*	0.308*	0.272*	1.000	
(10) Math 2 identity	−0.062*	−0.087*	0.406*	0.455*	0.415*	0.591*	0.187*	0.437*	0.580*	1.000

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Open Practices Statement

The data for “Multiplying Disadvantages in U.S. High Schools: An Intersectional Analysis of the Interactions among Punishment and Achievement Trajectories” are not publicly accessible, but information on how to obtain the data is found at: https://www.openicpsr.org/openicpsr/project/197221/version/V1/view.
The code for this study is publicly accessible at: https://www.openicpsr.org/openicpsr/project/195001/version/V1/view.
There is no preregistration for this study.

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Notes

1. Students’ race (not parents’ race) was used to identify Black and White students. To narrow our focus, we specifically identified non-Hispanic Black and non-Hispanic White students.

2. We chose not to impute our data based on empirical tests for whether or not the data was missing at random, as well as evidence supporting the stability of our nonimputed results. Specifically, we conduct Little’s test of data missing at random (Li, 2013), as missing randomness is often an assumption for imputation. In doing so, we found that our data are not missing at random; due to the complexities of imputation when data is not missing at random, we did not impute our data. Additionally, to better understand the stability of our non-imputed data, we compared the results with multiple imputed data, but did not observe substantial changes across our models. Similarly, we tested the stability of the NCES weights, finding that our results did not substantially change across models that included and did not include NCES analytic weights; following NCES suggestions and previous research, we did utilize the provided weights. Finally, it is also worth noting that—in terms of our main demographic characteristics of interest—our sample appears fairly representative of the original survey. For example, in the main (i.e. base year student survey) sample of Black and White students 51% of participants are male, 82% are white, 27% live in cities, 36% live in suburbs, 13% live in towns, and 24% live in rural areas; 12% of participants are in the lowest quintile of socioeconomic status (SES), and 28% are in the highest quintile of SES; and the average high schools size of participants is 1,126 students. Similarly, in our analytic sample, 49% of participants are male, 88% are white, 28% live in cities, 35% live in suburbs, 13% live in towns, and 23% live in rural areas; 10% of participants are in the lowest quintile of socioeconomic status (SES), and 35% are in the highest quintile of SES; and the average size of high school participants is 1,120 students. Moreover, in the main sample participants attended schools in all 50 states, while in the analytic sample participants attended schools in 49 states.

3. Although not differentiated in the NCES question stem, this item may include both in-school and out-of-school, as well as both short-term and long-term, suspensions.

4. The NCES chose to capture an ordinal measure of in-school suspensions in their student survey, potentially to simplify the survey question and avoid recall bias that could result from a count variable being captured in a retrospective survey of this type. In our analytic sample, 7.17% of participants were suspended one to two times, 1.35% were suspended 3–6 times; 0.25% were suspended 7–times; and 0.35% were suspended 10 or more times. Given our focus on accumulation effects, we chose to retain the ordinal measure in our analyses (e.g., as opposed to collapsing into a binary measure). Future research should consider leveraging administrative data to better understand the accumulation effects of multiple

suspensions; doing so can limit the types of measurement errors that are common in retrospective surveys that capture information across prolonged periods of time.

5. NCES variable names are provided, which can be looked up in the online codebook (https://nces.ed.gov/datalab/onlinecodebook) for further description of items.

6. Given binary independent and ordinal dependent measures, an asymptotic distribution free (ADF) estimation method was also used; however, results were nearly identical in the full sample, so ML was retained, which allowed for model convergence to be achieved in multigroup models.

7. Here, it is important to note that these comparisons reflect the ordinal measure of the suspension and not the observed number of suspensions.

8. Similar to an average marginal effect model resulting from a linear regression approach with a significant interaction term, groups with larger coefficients can be seen as having a larger effect of a given predictor variable on an outcome variable.

9. While some scholars caution the use of presenting marginally significant (i.e., $p < 0.1$) findings, as authors may use this strategy to achieve post-hoc flexibility (Olsson-Collentine et al., 2019), other scholars question the sacredness of the $p < 0.05$ significant level (Engman, 2013). As multigroup structural equation models can rely on samples of different sizes, which can affect significance levels, we chose to present both, but we note what is marginally significant and what is fully significant.

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