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The Process of "Pushing Out": Accumulated Disadvantage across School Punishment and Math Achievement Trajectories

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Abstract

Students drop out of school for a variety of reasons, yet are "pushed out" when they exhibit traits that are deemed undesirable to school officials, such as misbehavior and academic failure. While much of the previous research on pushouts views the phenomenon as a discrete occurrence often attributed to either misbehavior or academic failure, we recognize the underlying relationships between punishment and achievement, and therefore conceptualize pushing out as a process of both disciplinary involvement and academic exclusion over time. Using structural equation modeling (SEM) with a nationally representative longitudinal study of high school students (HSLS-09), we find that significant relationships among punishment and math achievement (including math attitudes, ability, and course-taking) have the effect of pushing students out of high school over time. We note the importance of race and ethnicity within these relationships and close with a discussion of policy implications.

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While students drop out of school for a variety of reasons, students are "pushed out" when they exhibit traits that are deemed undesirable to school officials, such as misbehavior and academic failure (Stearns & Glennie, 2006). Here, dropping out can be seen as an act done *by* the student (often by their own will), while pushing out can be seen as an act done *to* the student (often against their own will). Within the pushout literature, scholars often point to the importance of retentions (Stearns et al., 2007), suspensions (Bowditch, 1993), and even arrests (Hirschfield, 2009). Yet, while academic achievement dimensions, such as motivation (Fan & Wolters, 2014), ability (Foley et al., 2014), and course-taking (Long et al., 2012), are often viewed as predictors of dropping out, these dimensions are rarely viewed as predictors of being pushed out. Nevertheless, recent research has demonstrated the relationships among pushout predictors and academic achievement—especially in relation to suspensions. For example, Jabbari and Johnson (2020) found that suspensions were significantly related to later course-taking patterns when accounting for prior course-taking patterns. Thus, even when students may appear to drop out as a result of *current* low academic achievement, it may be the case that students are actually being pushed out as a result of *previous* punishments that ultimately led to their low academic achievement.

While recent research has begun to explore the relationships among punishment, achievement, and pushout status (see Jabbari & Johnson, 2020), their analyses relied on a series of separate disciplinary and academic models, and thus they were not able to empirically establish accumulation effects in a continuous, (i.e., multi-time point) path model. Without understanding this *process*, stakeholders and policymakers may fail to recognize some of the underlying mechanisms that push students out of school, and as a result, offer remedies that only address problems at the surface and in the moment of the pushout occurrence. We therefore extend the previous research on pushouts by conceptualizing and analyzing pushing out as a process of *both* disciplinary involvement *and* academic exclusion over time. As a result, our findings will allow us to identify key leverage points for early interventions that can redirect vulnerable student groups away from punishment trajectories and towards math achievement trajectories and, in doing so, curb the process of pushing out.

Background

Accumulated Disadvantage across the Life Course

Our conceptualization of the process of pushing out builds on the "life course" perspective (Elder et al., 2003). Within this perspective, we focus on Laub and Sampson's (1993) "turning points" theory in which certain life points can "separate the past from the present" and in doing so redirect individuals' trajectories (p. 304). In the context of schools, suspensions can act as important turning point (see Mowen & Brent, 2016, p. 631). By operating as public labels of deviance (see Farrington, 1977), suspensions can lower individuals' expectations (see Lemert, 1951), as well as the expectations of others (Liberman et al., 2014). Moreover, as reciprocal relationship between punishment and students' commitment to school tend to increase in intensity over time (Thornberry et al., 1994), suspensions, 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). In our study, we hypothesize that suspensions can "close off" opportunity structures in math, which can then (1) increase the likelihood of future suspensions, (2) further increase achievement deficits in math, and (3) eventually push students out of school entirely. In doing so, disadvantages in punishment can accumulate over time.

While prior studies have highlighted how a variety of factors can contribute to being pushed out of school, previous research has not been able to demonstrate the pushout process through a continuous (multi time-point) path model. For example, Stearns and Glennie (2006) found that pushout rates were highest in ninth grade and lowest in 12th grade and that younger students were more likely to be pushed out for disciplinary reasons, while older students are more likely to be pushed out for academic reasons. However, for students who are suspended in ninth grade and initially remain in school, the disadvantages associated with early disciplinary involvement may accumulate across both punishment and achievement trajectories *and* ultimately push these students out of school in 12th grade. Until now, this phenomenon has not yet been empirically explored. Furthermore, in a meta-analysis of 24 studies, Noltemeyer et al. (2015) found that suspensions were negatively associated with academic achievement and positively associated with dropout status. Nevertheless, 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 on achievement and dropout status from the underlying factors that may have lead students to be suspended in the first place (see Anderson et al., 2019).

In an attempt to fill this gap, Jabbari and Johnson (2020) used a nationally representative sample of high school students, finding that advanced math course-taking in ninth grade significantly decreased 11th grade suspensions and that 11th grade suspensions significantly decreased advanced math course-taking in 12th grade. Jabbari and Johnson (2020) also found that disciplinary and academic baseline measures often maintained a strong relationship with their respective outcomes and that both suspensions and advanced math course-taking significantly influenced dropout status and college attendance. As a result, Jabbari and Johnson (2020) concluded that disadvantages may actually *accumulate* when students are excluded *both* from suspensions and advanced math courses. Nonetheless, in order to empirically establish this accumulation process, a continuous multi-time point path model is necessary.

Punishment and Achievement Trajectories

In his discussion of the life course Pallas (2003) defines a trajectory as an attribute of individuals that involve both structural conditions and individual agency. We focus on high school trajectories that offer continued exposure to exclusionary discipline practices, such as the punishment trajectory (Hirschfield, 2008), as well as trajectories that offer continued access to advanced knowledge and skills, such as the math achievement trajectory (Oakes, 1985). Entrance and persistence within these trajectories can create advantages and disadvantages, which can accumulate over time by either pushing students out of school or into college.

Starting with punishment trajectories, students who have been suspended have a higher risk of being pushed out in the future (Suh et al., 2007), and students who have been pushed out have a higher risk of being arrested in the future (Christle et al., 2005). Thus, students on punishment trajectories are successively excluded from classrooms (in-school suspension), schools (out-of-school suspension), formal education (premature departure), and society (incarceration)—with each successive level of exclusion often having a substantially longer duration and larger impact on the individual.

Moving on to math achievement trajectories, students who have demonstrated high levels of math achievement, for example, have higher rates of taking advanced STEM courses, 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). Recent research has suggested that among the strongest predictors of persistence in STEM are math attitudes, such as identity (Hazari et al., 2010), efficacy (Wang, 2013), and utility (Harackiewicz et al., 2012), math ability (Wai et al., 2009), and advanced math course-taking in high school (Engberg & Wolniak, 2013). Additionally, students in math achievement trajectories appear to have lowered odds of premature school departure that exist beyond behavioral infractions (see Jabbari & Johnson, 2020)—implying that math achievement trajectories can not only be thought of as an increasing trajectory of inclusion in selective STEM classrooms, college majors, and career fields, but also inclusion in formal educational institutions themselves.

Finally, in order to best understand educational trajectories in the life course, it is also important to consider social background characteristics, which—by limiting access to achievement and increasing exposure to punishment—can not only "structure the choices that individuals make, but also shape the structures in which individuals can exercise choice" (Pallas, 2003, p. 168). Unsurprisingly, there is an inverse relationship among social background characteristics across punishment and math achievement trajectories—especially in regards to race and ethnicity. Within punishment trajectories Black and Hispanic students have been found to be more likely than their White peers to be referred to an administrator's office and receive harsher punishments for similar problem behaviors (Skiba et al., 2011). Within math achievement trajectories, Black and Hispanic have been found to be severely underrepresented among those with higher math test scores (Vanneman et al., 2009). Furthermore, when considering how these two phenomena are related, Morris and Perry (2016) found that school suspensions account for approximately one-fifth of Black-White differences in school performance. Given these trends, it is unsurprising to find that Black and Hispanic students were also more likely to be pushed out of high school (Bradley & Renzulli, 2011; McFarland et al., 2018). However, it is important to note that when punishment and math achievement are accounted for, Black students are far less likely to be pushed out (Jabbari & Johnson, 2020).

Current Study

In order to best understand the process of pushing out over the course of students' entire high school experience, we focus on students who drop out during 12th grade. Moreover, in order to best explore the various mechanism within this process, we focus on three different dimensions of achievement—attitudes, ability, and course-taking. While there are likely multiple aspects of disciplinary involvement and academic exclusion that, together, can push students out of schools, we follow Jabbari and Johnson (2020) and focus on suspensions and math achievement, whose trajectories can represent important pieces of larger opportunity structures in society, such as the School-to-Prison (STP) pipeline and the science, technology, engineering, and math

(STEM) pipeline. Additionally, as many of the same groups of students that are underrepresented in math achievement and the STEM workforce are also overrepresented in suspensions (Skiba et al., 2002) and the criminal justice system (Pettit & Western, 2004), our analysis also focuses on race/ethnicity. Finally, as behavior can play an important role within the process of pushing out, we include an initial measure of misbehavior in all of our models. We ask the following questions:

I. What are the long-term relationships across punishment and math achievement trajectories in high school and how do they relate to being pushed out?
II. How do the relationships among punishment, math achievement, and pushout status differ across achievement dimensions of attitudes, ability, and course-taking?
III. How do the relationships among punishment, math achievement, and pushout status moderate the relationships that these constructs have with race and ethnicity?

Data and Methods

We used structural equation modeling (SEM) in our analyses, which is able to simultaneously test the significance and strength of multiple hypothesized relationships over time with both latent and observed variables (Kline, 2015). Specifically, we employed a three-step process in our analytic approach. First, confirmatory factor analysis (CFA) was used to create a valid latent construct of math attitudes at two time points. Second, we used a multiple indicator multiple cause (MIMIC) modeling approach to account for model covariates. Third, we used a multiple mediation structural equation model to test the long-term relationships among punishment and math achievement trajectories and how they relate to the process of pushing out.

Data

The analyses in this article relied on a subset of restricted-use data from the High School Longitudinal Study of 2009 (HSLS). From this sample, we used data from the first four waves, which included student and parent data from the Base Year (fall of ninth grade), student data from the First Follow-Up (spring of 11th grade) and 2013 Update (spring of 12th grade), and transcript data from High School Transcript Study (collected in 2014). Within-wave attrition (due to both parent and student questionnaires being used), across-wave attrition (due to Base Year, First Follow Up, 2013 Update, and High

School Transcript studies being used), and list-wise deletion (due to our focus on students who took math during ninth grade and our decision not to impute missing information in our outcome measure), resulted in a final analytic sample of 11,267 participants (out of the original 21,444 survey participants). Additional sample attrition information is available upon request.

Nevertheless, the National Center of Education Statistics (NCES) did provide analytic weights to account for these instances of non-response both within and across waves, as well as instances of sampling inefficiencies that are inherent to a stratified sampling approach. Thus, we were able to retain much of the external reliability in our sample. Finally, we used multiple imputation with chained equations (MICE) to impute five sets of missing values based on core demographic characteristics (e.g., gender, race/ethnicity, and SES) to impute values for a small proportion (<6%) of observations that remained missing among our model independent variables (see Von Hippel, 2007; White et al., 2011).

Measures

Latent constructs of math attitudes were created from continuous math identity, math efficacy, and math utility measure collected during the fall of freshman year of high school and spring of junior year of high school. *Math identity* was variable derived from the extent to which a student sees him or herself as a math person, as well as the extent to which others see him or her as a math person; *math efficacy* was derived from the extent to which a student is confident that they can do an excellent job in math assignments and tests, that they can understand the most difficult material presented in their math textbook, and that they can master the skills being taught in their math courses; *math utility* was derived from the extent to which a student sees their math courses as useful for everyday life, college, and future careers. The NCES created these variables through principal components factor analysis (alpha = 0.65) that were standardized to a mean of 0 and had a standard deviation of 1.

Math ability was also collected during the fall of freshman year of high school and spring of junior year of high school. It consisted of a continuous, norm-referenced standardized ability (theta) score on a test that focused on algebraic reasoning (mean = 50; *SD* = 10). These scores "provide a summary measure of achievement and are recommended by NCES to capture gains in algebraic reasoning ability over time" (Barr, 2015, p. 30).

Informed by Burkam and Lee's (2003) widely accepted scales of math course levels, *math course level* consisted of two binary measures—one measure depicting whether or not a student took algebra by the end of ninth grade

(1 = yes; 0 = no) and another measure depicting whether or not a student took pre-calculus by the end of 12th grade (1 = yes; 0 = no).

Punishment variables consisted of a parent reported binary measure indicating whether or not a their student had been suspended or expelled prior to the fall of ninth grade—referred to as *pre-high school suspension* (1 = yes; 0 = no), as well as a student reported binary measure collected during the spring of junior year indicating whether or not the student had received an in-school suspension or an out-of-school suspension (for students not currently in school) within the last 6 months—referred to as *high school suspension* (1 = yes; 0 = no). *Pushout status* was defined as students who had dropped out of high school (or were seeking an alternative route to high school completion) by the spring semester of 12th grade, but did *not* include students who dropped out prior to 12th grade (1 = yes; 0 = no). As students who had been pushed out by the spring of 12th grade are unlikely to graduate high school, this measure can be seen as representing students who exit early from formal, secondary education without graduating. Moreover, as this measure was collected during the spring semester of 12th grade, we are still able to observe fall 12th grade math courses for students who were eventually pushed out.

Finally, model covariates consisted of race/ethnicity, which was divided into five groups (White, Black, Hispanic, Asian, and Other), as well as a measure of misbehavior. Misbehavior was collected from parents in the fall of ninth grade and consisted of the level of behavior problems (e.g., acting out, fighting, bullying, arguing, etc.) relative to other students (0 = no difficulty with behavior problems; 1 = a little difficulty with behavior problems; 2 = a lot of difficulty with behavior problems). The correlation matrix is available upon request.

Methods

Developing a latent construct of math attitudes. The latent construct of math attitudes—derived from math identity, efficacy, and utility variables—can be described as a longitudinal, two time-point construct. Following the procedures outlined by Muthén and Muthén (2017) for complex surveys and analyses involving both observed and latent variables, we use the mean and variance adjusted weighted least squares (WSLMV) estimator, which provides probit regression coefficients. In order to identify the construct, the math utility factor loading was fixed to 1.0. Because of the longitudinal nature of the data, factor loadings at time-point one were correlated with factor loadings at time-point two. All factor loadings were statistically significant and had standardized values ranging from 0.041 to 0.83, which exceeds the 0.4 threshold recommended by Stevens (1992). Additionally, the model contained excellent fit statistics, as the Root Mean Square Error of Approximation (RMSEA = 0.031) and Confirmatory Fit Index (CFI = 0.989) exceeded the thresholds recommended by Hu and Bentler (1999). Factor loadings, residual variances, and correlations are available upon request.

Developing a multiple indicator multiple causes model. In a multiple indicator multiple cause model (MIMIC) approach, endogenous latent and observed variables are regressed on model covariates. In our models, the endogenous variables—early math achievement, high school suspension, later math achievement, and pushout status—were regressed on race/ethnicity and misbehavior variables both before and after our SEM model paths were estimated. This allows us to isolate the main phenomenon—the longitudinal relationships among punishment, math achievement, and pushout status—while also allowing us to understand how this phenomenon moderates prior relationships among our endogenous variables and our covariates.

Developing a mediation model of suspensions, math achievement, and dropout status. In testing the long-term relationships across punishment and math achievement trajectories and their relationship to pushout status, three longitudinal mediation models were constructed that represent five temporally ordered time-points: (1) pre-high school suspension—"S1"; (2) early math achievement—"M1"; (3) high school suspension—"S2"; (4) later math achievement—"M2"; and (5) pushout status—"PO". In all three models, the punishment trajectory is represented by pre-HS and HS suspensions. In model 1, the math achievement trajectory is represented by early and later math attitudes; in model 2, the math achievement trajectory is represented by early and later math ability; in model 3, the math achievement trajectory is represented by early and later math course-taking. All three models have excellent levels of fit (RMSEA < 0.05; CFI > 0.95).

Findings

Descriptive Statistics

As seen in Table 1, a small proportion of students received suspensions prior to and during high school; however, these suspensions were not equally distributed. White and Asian students were often suspended the least, while Black, Hispanic, and Other students were often suspended the most. A similar pattern emerged for pushout status. Similarly, White and Asian students often had the highest levels of achievement while Black, Hispanic, and Other students often had the lowest levels of achievement. The one exception was math identity in which Black students had higher rates of efficacy and utility than White students. Finally, while the suspension disparities tended to decrease over time across racial/ethnic groups, the math achievement gaps did not; while attitude and ability gaps maintained the same, course-taking gaps substantially increased.

MIMIC Models

As seen in Table 2, the addition of structural paths in the SEM model moderated the relationship among identifying as White and later math ability in the MIMIC model, which was no longer significant. The addition of these structural paths also moderated the relationships among identifying as Asian and later math attitudes and pushout status. Furthermore, the addition of these structural paths moderated the relationships among identifying as Black and later math attitudes and ability. However, in the math ability SEM model, identifying as Black was now associated with a decrease in dropout status—meaning that when we account for math ability, Black students are actually less likely to be pushed out of school.

SEM Models

As seen in Figure 1, the SEM results generally demonstrated continual mediations across punishment and math achievement trajectories and a significant convergence at pushout status. When following the structural paths from start to finish, receiving a suspension prior to high school decreases early math achievement, which then increases the likelihood of receiving a suspension in high school, which then decreases later math achievement; together, these experiences increase the likelihood of being pushed out. However, there was one exception: later suspensions were *not* significantly related to later math attitudes.

As seen in Table 3, important trends emerged when comparing the paths and constructs within our models. First, within-trajectory paths tended to be stronger than cross-trajectory paths (e.g., in the math attitudes model the impact of M1 on M2 was significant, while the impact of S2 on M2 was non-significant). Second, when within-trajectory paths were absent, cross-trajectory paths tended to be stronger (e.g., in all models the impact of S1 on M1 was stronger than the impact of S2 on M2 because M2 was also predicted by M1). Third, the indirect effects of a given variable tended to be relatively small when compared to the direct effects of that same variable (e.g., in the math ability model the indirect effect of S2 on PO made up only 6% of the

Table 1. Descriptive Statistics.

	Full sample		White		Black		Hispanic		Asian		Other		Full sample	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Min	Max
Pre-high school suspension	0.094		0.071		0.244		0.103		0.030		0.128		0	1
High school suspension	0.083		0.072		0.161		0.104		0.024		0.096		0	1
Behavior (fall ninth)	0.113	0.364	0.103	0.345	0.141	0.415	0.127	0.387	0.059	0.269	0.166	0.441	0	2
Pushout status (spring 12th)	0.043		0.042		0.055		0.053		0.014		0.056		0	1
Math course 1 (ninth grade)	0.902		0.906		0.857		0.888		0.966		0.883		0	1
Math course 2 (12th grade)	0.460		0.472		0.310		0.363		0.770		0.414		0	1
Math ability 1 (fall ninth)	53.486	9.720	54.080	9.258	48.335	9.151	50.693	9.120	60.399	10.354	53.130	9.370	24.10	82.19
Math ability 2 (spring 11th)	53.657	9.947	54.169	9.580	48.563	8.793	50.799	9.346	61.351	9.965	53.211	9.711	22.24	84.91
Math identity 1 (fall nith)	0.128	0.992	0.112	0.994	0.091	0.999	0.010	0.972	0.530	0.870	0.102	1.019	−2.43	2.76
Math efficacy 1 (fall ninth)	0.122	0.967	0.096	0.975	0.212	0.919	0.027	0.957	0.409	0.882	0.100	0.996	−3.13	2.85
Math utility 1 (fall ninth)	−0.015	0.977	−0.086	0.972	0.250	0.974	0.046	0.967	0.086	0.957	0.006	0.984	−3.51	2.63
Math identity 2 (spring 11th)	0.121	1.022	0.095	1.032	0.075	1.010	0.045	0.994	0.549	0.930	0.092	1.009	−2.83	2.83
Math efficacy 2 (spring 11th)	0.093	0.998	0.058	1.002	0.194	0.944	0.057	0.990	0.330	0.941	0.073	1.048	−2.74	3.11
Math utility 2 (spring 11th)	0.036	0.987	−0.032	0.994	0.208	0.964	0.072	0.968	0.241	0.948	0.080	0.979	−3.94	3.15
N	11,267		6,714		1,023		1,576		878		1,076		11,267	

Table 2. Model Covariates and Constructs.

	Math attitudes model				Math ability model				Math courses model			
	Math 1	Susp. 2	Math 2	Pushout	Math 1	Susp. 2	Math 2	Pushout	Math 1	Susp. 2	Math 2	Pushout
Empty (MIMIC) model												
Covariate coefficients												
Behavior	−0.11***	0.49***	−0.11***	0.66***	−4.01***	0.49***	−4.76***	0.66***	−0.52***	0.49***	−0.67***	0.66***
	(0.02)	(0.07)	(0.03)	(0.06)	(0.40)	(0.07)	(0.38)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
White	−0.001	−0.11	0.001	−0.09	1.36*	−0.11	1.14*	−0.09	0.08	−0.11	0.31***	−0.09
	(0.02)	(0.09)	(0.03)	(0.10)	(0.53)	(0.09)	(0.50)	(0.10)	(0.09)	(0.09)	(0.07)	(0.10)
Black	0.10**	0.52***	0.09**	0.09	−5.41***	0.52***	−5.36***	0.09	−0.16	0.52***	−0.16	0.09
	(0.03)	(0.15)	(0.04)	(0.15)	(0.68)	(0.15)	(0.77)	(0.15)	(0.13)	(0.15)	(0.10)	(0.15)
Hispanic	−0.03	0.08	−0.01	−0.08	−1.64*	0.08	−2.47***	−0.07	0.09	0.08	0.02	−0.08
	(0.02)	(0.11)	(0.03)	(0.10)	(0.83)	(0.11)	(0.79)	(0.10)	(0.13)	(0.11)	(0.08)	(0.10)
Asian	0.14***	−0.76***	0.16**	−0.58**	7.94***	−0.76***	8.84***	−0.58**	0.79***	−0.75***	1.13***	−0.58**
	(0.03)	(0.20)	(0.05)	(0.19)	(0.64)	(0.20)	(0.74)	(0.19)	(0.13)	(0.20)	(0.12)	(0.19)
Construct variances												
Residuals	0.14***		0.23***		82.85***		86.17***					
	(0.01)		(0.01)		(1.75)		(1.99)					
R^2 (%)	2.6	9.4	1.6	7.9	11.2	9.5	12.6	7.9	6.7	9.4	12.7	7.9

(continued)

Table 2. (continued)

	Math attitudes model				Math ability model				Math courses model			
	Math 1	Susp. 2	Math 2	Pushout	Math 1	Susp. 2	Math 2	Pushout	Math 1	Susp. 2	Math 2	Pushout
Full (MIMIC + SEM) model												
Covariate coefficients												
Behavior	−0.09***	0.29***	−0.03	0.38***	−3.04***	0.24***	−1.41***	0.33***	−0.39***	0.26***	−0.33***	0.21*
	(0.02)	(0.07)	(0.03)	(0.07)	(0.47)	(0.06)	(0.40)	(0.07)	(0.07)	(0.06)	(0.09)	(0.08)
White	−0.01	−0.04	0.001	−0.02	1.04*	−0.01	0.14	−0.001	0.03	−0.03	0.31**	0.13
	(0.02)	(0.09)	(0.02)	(0.13)	(0.49)	(0.10)	(0.30)	(0.13)	(0.10)	(0.09)	(0.10)	(0.15)
Black	0.10**	0.49**	0.02	0.24	−4.89***	0.33*	−1.02	−0.37*	−0.08	0.45**	0.08	−0.26
	(0.03)	(0.16)	(0.03)	(0.19)	(0.69)	(0.16)	(0.55)	(0.18)	(0.13)	(0.15)	(0.18)	(0.20)
Hispanic	−0.03	0.12	0.004	−0.14	−1.91*	0.08	−1.11*	−0.19	0.07	0.14	−0.01	−0.12
	(0.02)	(0.11)	(0.03)	(0.14)	(0.78)	(0.11)	(0.43)	(0.13)	(0.14)	(0.11)	(0.12)	(0.14)
Asian	0.13***	−0.63**	0.06	−0.18	7.68***	−0.48*	2.43***	−0.04	0.73***	−0.55**	0.69***	0.23
	(0.03)	(0.20)	(0.04)	(0.25)	(0.65)	(0.21)	(0.53)	(0.24)	(0.14)	(0.20)	(0.18)	(0.26)
Construct variances												
Residuals	0.14***		0.15***		81.18***		43.30***					
	(0.01)		(0.01)		(2.10)		(2.98)					
R^2 (%)	3.0	16.0	34.1	32.1	12.8	19.5	56.5	32.4	10.0	16.6	45.3	45.2

Note. Unstandardized estimates are followed by standard errors in parentheses.
$^{*}p \leq .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 3. Model Path Coefficients.

	Math affect				Math ability				Math courses			
	STD	STDY	STDYX	REG	STD	STDY	STDYX	REG	STD	STDY	STDYX	REG
Direct effects												
S1→M1	−0.20***	**−0.20*****	−0.07***	−0.08***	−3.82***	**−0.40*****	−0.13***	−3.82***	−0.62***	**−0.58*****	−0.19***	−0.62***
	(0.06)	**(0.06)**	(0.02)	(0.02)	(0.06)	**(0.06)**	(0.02)	(0.60)	(0.09)	**(0.08)**	(0.03)	(0.09)
S1→S2	0.75***	**0.69*****	0.23***	0.75***	0.68***	**0.61*****	0.20***	0.68***	0.67***	**0.61*****	0.20***	0.67***
	(0.11)	**(0.09)**	(0.03)	(0.11)	(0.12)	**(0.10)**	(0.03)	(0.12)	(0.10)	**(0.09)**	(0.03)	(0.10)
M1→S2	−0.15***	−0.13***	**−0.13*****	−0.38***	−0.03***	−0.25***	**−0.25*****	−0.03***	−0.17**	**−0.17****	−0.17**	−0.17**
	(0.04)	(0.03)	**(0.03)**	(0.10)	(0.003)	(0.03)	**(0.03)**	(0.003)	(0.06)	**(0.05)**	(0.05)	(0.06)
M1→M2	0.58***	0.58***	**0.58*****	0.73***	0.68***	0.66***	**0.66*****	0.68***	0.62***	**0.49*****	0.49***	0.62***
	(0.02)	(0.02)	**(0.02)**	(0.04)	(0.03)	(0.02)	**(0.02)**	(0.03)	(0.06)	**(0.04)**	(0.04)	(0.06)
S2→M2	0.02	**0.02**	0.02	0.01	−1.13***	**−0.13*****	−0.13***	−1.13***	−0.32***	**−0.26*****	−0.26***	−0.32***
	(0.03)	**(0.03)**	(0.03)	(0.01)	(0.19)	**(0.02)**	(0.02)	(0.19)	(0.06)	**(0.04)**	(0.04)	(0.06)
S2→PO	0.56***	**0.50*****	0.50***	0.56***	0.45***	**0.42*****	0.42***	0.45***	0.38***	**0.31*****	0.31***	0.38***
	(0.06)	**(0.04)**	(0.04)	(0.06)	(0.06)	**(0.04)**	(0.04)	(0.06)	(0.07)	**(0.05)**	(0.05)	(0.07)
M2→PO	−0.17***	−0.14***	**−0.14*****	−0.36***	−0.03***	−0.24***	**−0.24*****	−0.03***	−0.48***	**−0.48*****	−0.48***	−0.48***
	(0.04)	(0.03)	**(0.03)**	(0.09)	(0.01)	(0.04)	**(0.04)**	(0.01)	(0.06)	**(0.04)**	(0.04)	(0.06)

(continued)

Table 3. (continued)

	Math affect				Math ability				Math courses			
	STD	STDY	STDYX	REG	STD	STDY	STDYX	REG	STD	STDY	STDYX	REG
Indirect effects												
S1→M1→S2				0.03**				0.11***				0.11**
				(0.01)				(0.02)				(0.03)
M1→S2→M2				−0.004				0.03***				0.06**
				(0.01)				(0.01)				(0.02)
S1→M1→S2→M2→PO				0.000				0.004***				0.02**
				(0.000)				(0.001)				(0.01)
M1→S2→M2→PO				0.001				0.001***				−0.03**
				(0.002)				(0.000)				(0.01)
S2→M2→PO				−0.004				0.03***				0.15***
				(0.01)				(0.01)				(0.03)
S1→S2→PO				0.42***				0.31***				0.25***
				(0.07)				(0.06)				(0.05)
M1→M2→PO				−0.26***				−0.02***				−0.30***
				(0.07)				(0.003)				(0.04)
Model fit statistics												
RMSEA				0.014				0.021				0.016
CFI				0.980				0.991				0.990

Note. Estimates are followed by standard errors in parentheses. Bold values represent recommended standardizations: STDY standardization for binary independent variables (change in *Y* standard deviation units when *X* changes from 0 to 1) and STDYX standardization for continuous independent variables (change in *Y* standard deviation for a one standard deviation change in *X*).
$^{**}p < .01$. $^{***}p < .001$.

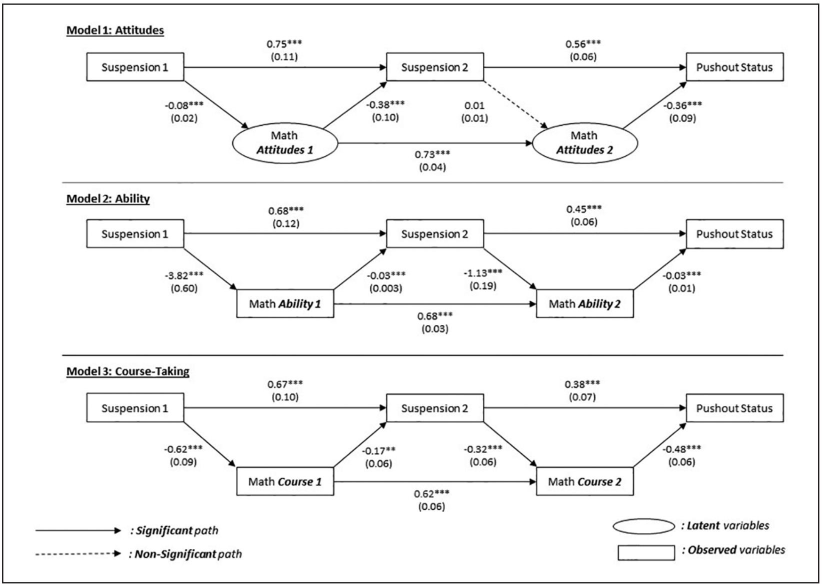

Figure 1. SEM models.
Note. Unstandardized estimates shown with standard errors in parentheses. MIMIC indicators not shown for the purpose of visual clarity.

total effect of S2 on PO). Fourth, indirect effects that crossed trajectories tended to be relatively weak when compared to similar effects that did not cross trajectories (e.g., the effect of S1→M1→S2→M2→PO was smaller than the effect of S1→ S2→PO), as well as when compared to the indirect effects of later trajectory junctures (e.g., the effect of S1→M1→S2→M2→PO was smaller than the effect of S2→M2→PO).

When making comparisons across models, additional trends also emerged. First, when considering that the percent of variance explained in pushout status was smallest in the math attitudes model and largest in the math course-taking model, we can assume that math course-taking has the largest impact on pushout status, followed by math ability and math attitudes. Second, when considering that the percent of variance explained in high school suspension was smallest in the math attitudes model and largest in the math ability model, we can assume that math ability has the largest impact on suspensions followed by math course-taking and math attitudes. Third, when considering that the proportion of the indirect effect from early to later math achievement was larger in the math course-taking model when compared to the math ability model, we can assume that suspensions have a larger impact on math course-taking.

Additionally, when considering that early and later math achievement were both predicted by suspensions, yet the percent of variance explained in later math achievement was far greater than the percent of variance explained in early math achievement, we can infer that prior math achievement, which also predicted later math achievement, explains a larger proportion of the variance than prior suspensions. Finally, when comparing the (larger) percent of variance explained in later math achievement with the (smaller) percent of variance explained in HS suspensions—despite both being predicted by early suspensions and math achievement, we can infer that more variance is explained in academic achievement than disciplinary involvement across our models.

Discussion

Together, these findings have implications for theory, research, and practice. Pertaining to theory, the general results confirm our theoretical model based on the life course—that *inclusion* in punishment trajectories has a reciprocal relationship with *exclusion* in the math achievement trajectories and that these relationships can accumulate disadvantages over time and perpetuate the process by which students are pushed out of school. Operating as turning points, suspensions appear to "close off" opportunity structures in math, which can then (1) increase the likelihood of future suspensions, (2) further increase achievement deficits in math, and (3) eventually push students out of school entirely.

However, punishment does not operate consistently with different dimensions of math achievement within this process. For example, later math attitudes were not directly impacted by prior suspensions—demonstrating that these attitudes may be less prone to change later in the course of high school as a result of punishments. When considering that this was not the case for math ability or course-taking, we can assume that some students who are suspended in high school may still have more positive attitudes towards math, yet don't have the opportunities to pursue it, and thus, get pushed out of school. Concerning "labeling" theories, we can also assume that suspensions may operate more through missed opportunities to learn and less through attitudes.

Moreover, when considering race and ethnicity, we see evidence of accumulation effects. For example, from our descriptive statistics, we see widening disparities in advanced math course-taking among Black students despite relatively positive attitudes towards math. This confirms part of Schiller and Hunt's (2011) earlier work that found disadvantages were often accumulated within math. Here, the sequential nature of math curriculum may place initially disadvantaged students further behind. Furthermore, from our MIMIC models we see that when we account for later suspensions and math ability, Black students are less likely to be pushed out, while Asian students no longer experience and advantage here.

Moving on to research, these findings extend Jabbari and Johnson's (2020) previous work and empirically establish long-term mediations across both punishment and math achievement trajectories in a continuous, multi-time point path model. In doing so, these findings demonstrate the need to include within-trajectory influences when estimating cross-trajectory influences —and vice-versa—in order to avoid inflated estimates.

Closing with implications for practice, given the relative weakness of early trajectory junctures on pushout status—especially when considering the effects of the junctures that cross trajectories, our findings suggest that it is rarely too late to implement interventions within either trajectory. Furthermore, given the significant effects both within and across-trajectories, our findings suggest that interventions should be implemented in both trajectories simultaneously; however, given stronger within-trajectory effects, interventions that target specific outcomes should prioritize trajectory-specific programs. Moreover, our findings suggest that a reduction in suspensions *alone* may not be the *most* effective strategy for reducing the rate of pushouts. Rather, an increase in math achievement should simultaneously accompany a decrease in suspensions—especially when considering that more variance was explained in later math achievement than punishment in our models.

Additionally, with math course-taking and ability explaining a larger amount of variation in pushout status, stakeholders should prioritize interventions that increase early algebra coursework and skills. Specifically, stakeholders should consider programs like *double-dosage algebra*—an intensive math program for ninth grade students that has been demonstrated to increase students' math credits and test scores, as well as student's high school graduation and college enrollment rates (Cortes et al., 2015). Finally, when considering the detrimental impacts of punishment and their disparate rates across racial/ethnic groups, stakeholders should also explore practices that decrease punitive discipline measures, such as those found within restorative justice. Recent research has demonstrated that schools adopting restorative justice philosophies, policies, and practices see a drastic reduction in suspension rates, as well as an increase in academic achievement and graduation rates (Eisenberg, 2016). As schools with larger proportions of racial minority students have been less likely to implement restorative justice practices (see Payne & Welch, 2015), implementing restorative justice in these schools should be prioritized.

Limitations

When considering internal validity, we do include an initial measure of misbehavior, which has been associated with punishments—both as causes and effects (see Mowen et al., 2020; Rosenbaum, 2020). However, due to data availability, we are not able to include additional measures of misbehavior over time. Thus, while we can explore the relationships among punishment, math achievement and dropout status that exist *beyond* initial levels of misbehavior, we are unable to see how a change in misbehavior may alter these relationships. Nevertheless, because our misbehavior measure is collected in ninth grade—*after* previous suspensions had occurred, we are likely picking up some of the effects of suspensions on misbehavior, and yet we still find that suspensions have a significant impact on achievement, future suspensions, and pushout status. Furthermore, given the fact that multiple suspensions may have a "cumulative" effect on future outcomes, our binary measures suspension may dampen some of the effects in our models. Thus, future research should explore data sets with more comprehensive measures of both behavior and punishment.

Moreover, while temporality can easily be established in the math attitude and ability models, there are some limitations in the course-taking model. Although rare, it could be the case that the reported suspension occurred after the course in question began. For example, some students could have taken algebra in eighth grade and the parent could be reporting a suspension in that same year; similarly some students could have taken pre-calculus in the fall of 11th grade and the student could have recieved a suspension in that same semester. Therefore, we performed a robustness check by rerunning the analysis and removing individuals who were currently enrolled in calculus during their junior year (and thus likely enrolled in pre-calculus sophomore year). These individuals represented less than 5% of our analytic sample. Our results did not change in any meaningful way, and thus we can confirm their robustness to most issues concerning temporality.

Additionally, when considering external validity, our survey weights are able to account for much of the sample attrition that occurred through our use of multiple stakeholders (student and parent), waves (ninth grade, 11th grade, 12th grade), and instruments (surveys and transcripts). However, it is important to note that it may not be completely representative of the US population of high school students, as we did not include those who didn't take a math class freshman year ($N=1{,}507$), nor did we impute missing information for pushout status ($N=388$). Nevertheless, we further explored this attrition through full information maximum likelihood (FIML) estimates, which relied on all available data at each time point (including students who would otherwise be dropped from the sample), and we did not find any discernable differences. Future studies should further explore ways to use alternative estimation techniques that can retain larger samples within SEM.

Finally, while we focus on students who are pushed out of school at the end of high school, we acknowledge that there are many re-entry points within both discipline and math achievement trajectories, as well as formal schooling (see Boylan & Renzulli, 2017; Xie & Shauman, 2003), that deserve the attention of future research. The simultaneous roles that race/ethnicity, gender, social class, language, and immigration status can play in the process of pushing out should also be further explored (see Bradley & Renzulli, 2011; Ibrahim & Johnson, 2020).

Conclusion

In closing, it is important to note that suspensions, math achievement, and their convergence at high school completion represent important pieces of larger opportunity structures, such as the school-to-prison and STEM pipelines. Thus, by perpetuating a process of continued involvement in punitive discipline and exclusion from opportunities to learn math, we are not only pushing students out of high school. Rather, we are also pushing students away from careers in STEM and towards cells in prisons. Furthermore, given our overpopulated prison population with roughly 1.4 million individuals recently incarcerated (Gramlich, 2019) and our undeveloped STEM workforce with over 3 million recent jobs left unfilled (New American Economy Research Fund, 2017), we believe that curbing the process of pushing out can benefit us all.

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