Interacting the School-to-Prison and STEM Pipelines: A Multiple Method Exploration of the Relationships among Exclusionary Discipline and Math

Jason F. Jabbari
Washington University in St. Louis

Follow this and additional works at: https://openscholarship.wustl.edu/art_sci_etds

Recommended Citation
https://openscholarship.wustl.edu/art_sci_etds/1811

This Dissertation is brought to you for free and open access by the Arts & Sciences at Washington University Open Scholarship. It has been accepted for inclusion in Arts & Sciences Electronic Theses and Dissertations by an authorized administrator of Washington University Open Scholarship. For more information, please contact digital@wumail.wustl.edu.
Interacting the School-to-Prison and STEM Pipelines:
A Multiple Method Exploration of the Relationships among Exclusionary Discipline and Math
by
Jason Jabbari

A dissertation presented to
The Graduate School
of Washington University in
partial fulfillment of the
requirements for the degree
of Doctor of Philosophy

May 2019
St. Louis, Missouri
# Table of Contents

List of Figures...........................................................................................................v
List of Tables...............................................................................................................vi
Acknowledgments.....................................................................................................vii
Abstract of the Dissertation......................................................................................x

## Chapter 1: Introduction

1.1 Background...........................................................................................................5
1.2 Gaps in the Literature.........................................................................................7
1.3 Objectives............................................................................................................9
1.4 Theoretical Perspectives......................................................................................10
  1.4.1 Interactional Theories......................................................................................11
  1.4.2 Intersectional Theories...................................................................................11
  1.4.3 Social Control.................................................................................................12
1.5 Research Context.................................................................................................13
1.6 Research Terms...................................................................................................14
1.7 Data.....................................................................................................................15
1.8 Research Questions............................................................................................16
1.9 Methods...............................................................................................................17
1.10 Findings..............................................................................................................18
1.11 Significance........................................................................................................18
References................................................................................................................19

## Chapter 2: Two Sides of the Same Coin? A Multilevel Analysis of STEM and Disciplinary Trajectories in U.S. High Schools over Time

2.1 Literature Review...............................................................................................26
  2.1.1 Oppositional Opportunity Structures and Divergent Student Trajectories...26
  2.1.2 Interactions among Discipline and Academics............................................39
2.2 Data and Methods.............................................................................................30
  2.2.1 High School Students...................................................................................30
  2.2.2 Measures.....................................................................................................32
2.3 Analytic Strategy...............................................................................................36
2.4 Results...............................................................................................................37
  2.4.1 The Influence of In-School Suspension on Advanced Math Course-taking...37
  2.4.2 The Influence of Math Achievement on Dropout Status..........................38
  2.4.3 Between-School Effects..............................................................................40
2.5 Discussion..........................................................................................................43
2.6 Conclusion..........................................................................................................46
References.................................................................................................................48
Chapter 3: The Process of ‘Pushing Out’: An Intersectional Analysis of the Interactions among School-to-Prison and STEM Pipelines

3.1 Literature Review

3.1.1 Academic and Disciplinary Pipelines

3.1.2 Interactional and Intersectional Theories of Discipline and Academics

3.2 Research Gaps, Objectives, and Questions

3.3 Data

3.4 Measures

3.5 Methods and Results

3.5.1 Parameterization, Estimation, and Standardization Techniques

3.5.2 Developing a Latent Construct of Math Achievement

3.5.3 Group Differences

3.5.4 The Short-Term Impact of Suspensions on Math Achievement

3.5.5 The Long-Term Interactions among the STP and STEM Pipelines

3.6 Discussion

3.7 Conclusion

References

Chapter 4: The Collateral Damage of In-School Suspensions: A Counterfactual Analysis of High-Suspension Schools, Math Achievement and College Attendance

4.1 Literature Review

4.1.1 Exclusionary Discipline

4.1.2 Collateral Damages

4.2 Research Objectives and Questions

4.3 Data and Measures

4.3.1 Data

4.3.2 Treatments

4.3.3 Covariates in the Propensity Score Estimation Models

4.3.4 Outcomes

4.3.5 Covariates in the Analysis Models

4.4 Methodological Approach

4.4.1 Counterfactual Modeling

4.4.2 Propensity Score Analysis

4.5 Results

4.5.1 Math Achievement Models

4.5.2 College Attendance Models

4.5.3 Sensitivity Analysis

4.6 Discussion

4.7 Conclusion and Directions for Future Policy and Practice

References

Chapter 5: Conclusion
List of Figures

Figure 1.1 Workers in Science and Engineering Occupations........................................1
Figure 1.2 STEM Jobs Advertised for each Unemployed STEM Worker..........................2
Figure 1.3 Racial/Ethnic representations in U.S. Prisons..................................................3
Figure 1.4 Incarceration Rates by Countries........................................................................3
Figure 3.1 CFA Model........................................................................................................79
Figure 3.2 Latent Variable Means Comparisons for Black-Females.................................81
Figure 3.3 Latent Variable Means Comparisons for Black-Males ....................................81
Figure 3.4 Latent Variable Means Comparisons for White-Females.................................82
Figure 3.5 Latent Variable Means Comparisons for White-Males....................................82
Figure 3.6 Observed Variable Proportions by Race and Gender.......................................83
Figure 3.7 Observed Variable Proportions by Race-Gender Intersections.........................83
Figure 3.8 LDS Model.........................................................................................................84
Figure 3.9 SEM Model........................................................................................................85
Figure 3.10 STP Within-Pipeline Effects by Race and Gender..........................................88
Figure 3.11 STP Within-Pipeline Effects by Race-Gender Intersections............................88
Figure 3.12 STEM Within-Pipeline Effects by Race and Gender......................................89
Figure 3.13 STEM Within-Pipeline Effects by Race-Gender Intersections........................89
Figure 3.14 Cross-Pipeline Effects by Race and Gender....................................................90
Figure 3.15 Cross-Pipeline Effects by Race-Gender Intersections ......................................90
Figure 3.16 The Impact of HS Suspension on Dropout Status by Race and Gender............91
Figure 3.17 The Impact of HS Suspension on Dropout Status by Race-Gender Intersections..91
Figure 3.18 The Impact of Math 2 on Dropout Status by Race-Gender Intersections............92
Figure 3.19 The Impact of Math 2 on Dropout Status by Race-Gender Intersections............92
Figure 3.20 STP Pipeline Indirect Effects on Dropout Status by Race and Gender.............93
Figure 3.21 STP Pipeline Indirect Effects on Dropout Status by Race-Gender Intersections..93
Figure 3.22 STEM Pipeline Indirect Effects on Dropout Status by Race and Gender...........94
Figure 3.23 STEM Pipeline Indirect Effects on Dropout Status by Race-Gender Intersections..94
Figure 3.24 The Indirect Effect of S2 on Dropout Status by Race and Gender....................95
Figure 3.25 The Indirect Effect of S2 on Dropout Status by Race-Gender Intersections........95
Figure 3.26 Percent of Variance Explained by Race and Gender........................................96
Figure 3.27 Percent of Variance Explained by Race-Gender Intersections........................96
Figure 4.1 Boxplot of propensity scores.............................................................................139
Figure 4.2 Histogram of propensity scores weights for High-Suspension group...............140
Figure 4.3 Histogram of propensity scores weights for Low-Suspension group................140
Figure 5.1 Racial Earnings Gaps in STEM.......................................................................174
List of Tables

Table 1.1 Descriptive Statistics........................................................................................................35
Table 1.2 Mixed Effects Logistic Regression on the Influences of Student Discipline on Advanced Math Course-taking ........................................................................................................41
Table 1.3 Mixed Effects Logistic Regression on the Influences of Math Achievement on Dropout Status .........................................................................................................................42
Table 3.1 Longitudinal Invariance ......................................................................................................70
Table 3.2 Race and Gender Group Invariance ......................................................................................71
Table 3.3 Race-Gender Group Invariance ............................................................................................71
Table 3.4 Mean Comparisons of Math Achievement Constructs.....................................................80
Table 3.5 Structural Equation Model Path Coefficients ......................................................................86
Table 3.6 Structural Equation Model Indirect Effects ........................................................................87
Table 4.1 Descriptive Statistics ..........................................................................................................136
Table 4.2 Comparison of Treatment Selection Variables before Propensity Score Weighting ....137
Table 4.3 Comparison of Treatment Selection Variables after Propensity Score Weighting ......138
Table 4.4 Unconditional Outcome Models .........................................................................................146
Table 4.5 Continuous Regressions of the Impact of High-Suspension Schools on Math Achievement .................................................................................................................................146
Table 4.6 Null Models: Logistic Regressions of the Impact of Treatment Covariates and Outcome Covariates on College Attendance ..................................................................................147
Table 4.7 Treatment Models: Non-Propensity Score Weighted Logistic Regressions of the Impact of High-Suspension Schools on College Attendance ..............................................................148
Table 4.8 Selection Models: Propensity Score Weighted Logistic Regressions of the Impact of High-Suspension Schools on College Attendance ........................................................................149
Table 4.9 Sensitivity Results ...............................................................................................................150
Acknowledgments

First, I would like to thank the National Science Foundation Division of Engineering Education and Centers (#1619843 & #1800199) for sponsoring this work. I would also like to thank Professor Odis Johnson, Jr. for chairing this dissertation, serving as a collaborative co-author on the works included, and for being an outstanding advisor and mentor over the past four years. Without the challenges he has set for me and the encouragement he has offered me, this dissertation would not be possible. I would like to thank Professor Garrett Albert Duncan for helping me find my voice in my writing and for reminding me of my purpose as an educational researcher. In addition, I would also like to thank Dean William F. Tate, for helping me see the larger picture in my research and for helping me make the connections between research and policy. Furthermore, I would like to thank Professor Shenyang Guo, for teaching me how to do quantitative research and for advising me on the statistical methods employed in this dissertation. Moreover, I would like to thank Professor Sheretta Butler-Barnes, for helping me understand the lived experiences of the students in my research. Finally, I would like to thank the faculty, staff, and students in the Department of Education for helping to make this dissertation possible.

In closing, I would like to thank my family. Starting with my parents, I would like to thank my father, Farhad, who taught me the value of hard work and determination. I would also like to thank my mother, Barbara, who taught me that we make a life not by what we receive, but by what we give. I am also grateful for my sister, Amanda, who has been working overtime as an amazing aunt for the past 4 years and an outstanding sister for the past 34 years. Finally, I would like to thank my wife, JoAnn, my two boys, John and Zach, and my dog Tux, for making me the luckiest man on the face of the earth…I could not have done this without their love and support.

Jason Jabbari
For my students, who showed me that anything is possible.
ABSTRACT OF THE DISSERTATION

Interacting the School-to-Prison and STEM Pipelines:
A Multiple Method Exploration of the Relationships among Exclusionary Discipline and Math

by

Jason Jabbari

Doctor of Philosophy in Education
Washington University in St. Louis, 2019

Professor Odis Johnson, Jr., Chair

Despite the belief that the discipline and academics are fundamentally related, opposing student opportunity structures, such as the School to Prison (STP) pipeline and the Science, Technology, Engineering, and Math (STEM) pipeline, are often studied as separate phenomena. As a result, previous research has been limited in its ability to explore problems and seek solutions to the overrepresentation of students of color in the STP pipeline and the underrepresentation of students of color in the STEM pipeline. By examining these phenomena in concert with each other, this three-article dissertation provides important insights into both the individual and institutional factors that impact a student’s entrance and persistence into each respective pipeline. Using a recent national longitudinal study of high school students, this dissertation demonstrates, a) how suspensions can influence outcomes related to the STEM pipeline, as well as how math achievement can influence outcomes related to the STP pipeline, b) how the interactions among suspension and math achievement are uniquely experienced by different race-gender intersections of identity, and c) how the impacts of suspensions on math achievement and college entrance can be experienced indirectly through attendance in high-suspension schools.
Findings from this dissertation demonstrate that discipline and academics are deeply interrelated. First, through multilevel regression modeling in article one, results demonstrate reciprocal relationships: suspensions significantly influenced outcomes related to the STEM pipeline, while math achievement significantly influenced outcomes related to the STP pipeline. Nevertheless, in both cases, within-pipeline influences remained strong and only marginally lessened the impact of cross-pipeline influences in some cases. Highlighting the varying roles of race—both at the student and school-level—in each pipeline, we conclude article one with a discussion of implications for policy and practice. Next, through latent difference score and structural equation modeling in article two, results demonstrate that suspensions significantly decreased math achievement and that the significant interactions among the STP and STEM pipelines have the effect of “pushing” students out of high school over time. Moreover, the strength of these structural interactions was different for advantaged and disadvantaged race-gender groups within and across each respective pipeline. The accumulation and saturation of these advantages and disadvantages inform our concluding discussion of policy implications in article two. Last, through propensity score weighting in article three, results demonstrate that when controlling for an individual’s suspensions, as well as a school’s overall level of social disorder, attending a high-suspension high school significantly decreases a student’s math test scores during their junior year of high school, while also decreasing a student’s odds of attending college full-time. Significant race interactions inform our discussion of policy implications at the conclusion of article three.
Chapter 1: Introduction

As a society, we're failing. In so many ways. Such high incarceration rates of underrepresented minorities ultimately means we're missing out on great potential from Black and Latino communities. Yes, there's immense talent brewing even within the most impoverished neighborhoods. Talent is universal, but opportunity is not.

– Christine Tsai, Founder of “500 Startups”

Equal opportunity is currently complicated by two divergent yet interrelated realities in the United States. The first reality is that the country has struggled to increase the number of science, technology, engineering, and mathematics (STEM) professionals from underrepresented backgrounds. Despite efforts to broaden the participation of racial/ethnic groups in STEM, the workforce remains “no more diverse than it did 14 years ago” (Bidwell, 2015). The disproportionate distribution of racial/ethnic groups in STEM can be seen in Figure 1.1 below.

Figure 1.1. Workers in Science and Engineering Occupations (NSF, 2015)
However, the problem in STEM is not only one of diversity, but also one of total numbers and global competitiveness. In 2012, the President’s Council of Advisors on Science and Technology (PCAST) concluded that the U.S. needed approximately 1 million more STEM workers than it was currently able to produce in order to maintain its global competitive advantage in science and technology. Moreover, when considering recent research from The New American Economy Research Fund (2017), the need for STEM workers has likely increased since PCAST’s 2012 projection. As seen in the Figure 1.2 below, thirteen STEM jobs were advertised online for every one unemployed STEM worker in 2016. This translates to roughly 3 million more STEM jobs in 2016 than the available number of STEM workers (2017). As innovation from STEM workers creates more new jobs for non-STEM workers than any other sector (NRC, 2011), the need for a larger, more diverse STEM workforce extends beyond the ability for the U.S. to maintain its global competitive advantage in science and technology.

![Figure 1.2. STEM Jobs Advertised for each Unemployed STEM Worker (NAERF, 2017)](image-url)
The second reality is that the same groups that have been underrepresented in STEM have been overrepresented in the criminal justice system. For example, while just 11 percent of science and engineering professionals were Black or Hispanic in 2015 (NSF, 2015), as seen in Figure 1.3 below, the combined percentage of Black and Hispanic individuals who were incarcerated was 56 percent (Pew Research Center 2018). Similar to STEM, the problem in the criminal justice system is not only one of representation, but also one of total numbers and global standing. As seen in Figure 1.4 below, the U.S. leads the world in incarceration rates by incarcerating 655 individuals for every 100,000 persons (Pew Research Center, 2018). Here, recent research by Pettus-Davis, Brown, Veeh, and Renn (2016) demonstrates that when accounting for the social costs to families, children, and community members, current incarceration rates costs the US one trillion dollars, which translates to 6% of our Gross Domestic Product; alternatively, this money could be used to invest in education and technology.

**Figures 1.3 (Left).** Racial/Ethnic representations in U.S. Prisons (Pew Research Center, 2018)  
**Figure 1.4 (Right).** Incarceration Rates by Countries (Pew Research Center, 2018)
Unsurprisingly, both of these realities mirror the state of education across U.S. high schools. There is a disproportionately smaller percentage of Black, Hispanic, and low-income students, as well as an overall shortage, experiencing high achievement in STEM subjects (NRC, 2011)—despite the fact that more Black students than White students believe that they need to do well in science in order to get the job they want (Anderson, 2017). At the same time, there is a disproportionately larger percentage of Black, Hispanic, and low-income students, as well as an overall excess, experiencing exclusionary discipline practices (Skiba et al., 2014)—despite the fact that Black students misbehave at similar rates as White students (Skiba, Michael, Nardo, and Peterson, 2002). Moreover, when considering identity intersections, gender parallels between STEM and exclusionary discipline are also apparent, as males of color are often underrepresented in STEM, but overrepresented in suspensions, even in preschool (U.S. Dept. of Education 2014). Thus, given the demographic makeup of both STEM achievement and exclusionary discipline in U.S. school systems, one way to increase the number of native STEM workers is to decrease the number of individuals involved in the criminal justice system.

The connection between these two realities in educational settings appears more likely once we consider that a significant number of individuals with criminal records are now first introduced to the justice system in the same place where STEM talent is developed: schools. For example, between 2005 and 2014, law enforcement in San Bernardino, CA arrested 6,923 minors on streets, but over 30,000 while in schools (Ferriss, 2015). It is also within schools where the relationship among poor academic preparation, especially in math and science, and exclusionary discipline can converge in such a manner that prematurely pushes students out of formal education settings altogether. Unlike ‘dropout’, the term ‘pushout’ involves a systematic process by which schools—through the absence of high quality academic opportunities and the over-
reliance on exclusionary discipline measures—push students out who they deem undesirable; these students are often low-income students and students of color (Mission, 2018). Similar to mass incarcerations, being pushed out not only negatively impacts those who prematurely leave formal education settings, but also negatively impacts the larger economies and societies in which these individuals are embedded in. For example, when considering lost wages and tax revenues, as well as welfare and criminal justice expenses, Alverez et al. (2009) estimated that the total social cost of dropouts and pushouts—for a single Texas cohort—totaled between $5.4 billion and $9.6 billion. Here, when opportunities are missing for the development of STEM talent with low-income students and students of color, and these students are instead placed on the criminal justice track and eventually pushed out of schools, we all suffer.

The tendency for academic opportunities and exclusionary discipline practices to negatively impact many of the same students has caused Gregory, Skiba, and Noguera (2010) to conclude that the achievement gap and the discipline gap may represent “two sides of the same coin.” Nevertheless, nearly a decade after their call for research to address the relationships among academics and discipline, we have little empirical evidence that demonstrates how academic achievement, especially in STEM, is impacted by exclusionary school discipline—and vice versa. Generating knowledge as to how academic achievement in STEM and exclusionary discipline are related would reveal the potential human capital cost to STEM fields that are masked by school attempts to maintain order through exclusionary discipline, as well as the social costs of mass incarceration that are hidden in poor academic preparation in STEM.

1.1 Background

Schools structure opportunity in multiple ways, which can include access to learning (Oakes, 1985; Gamoran, 1987; McNeil, 1988), as well as exposure to discipline (Tuzzolo &
Hewitt, 2006). These opportunities can ultimately place students on different pathways or “pipelines,” such as the STEM pipeline or the STP pipeline. In turn, these pipelines can significantly impact the trajectory of students’ lives, as well as the larger societies and economies in which they are embedded in. Here, highly stratified learning opportunities for prized areas of knowledge, such as STEM, can be used to afford students mobility within educational institutions and eventually be allocated into prized economic positions in a highly stratified labor market (Blau & Duncan, 1967). At the same time, schools also provide “opportunities” for students to fill carceral roles in our society, such as those found in the prison industrial complex (Hirschfield, 2008).

Specifically, recent research has demonstrated that students who have demonstrated high levels of math ability, affect, and attainment, have higher rates of attending college, majoring in a STEM subject, and securing a STEM job (see Pajares & Miller, 1995, Rose & Betts 2001, Tai, Liu, Maltese, & Fan, 2006). On the other hand, recent research has demonstrated that students who have been suspended in high school have a higher risk of dropping out in the future (Skiba, Simmons, Staudinger, Rausch, Dow, & Feggin 2003) and that students who have dropped out have a higher risk of being incarcerated (Christle, Jolivette, & Nelson, 2005). As a result, the STEM pipeline can be thought of as an increasing trajectory of inclusion—inclusion in selective STEM classrooms, college majors, and career fields, while the STP pipeline can be thought of as an increasing trajectory of exclusion—exclusion from classrooms (suspension), schools (dropping out), and society (incarceration).

Thus, while certain opportunities and structures in math and science education can prepare some students for futures that involve creativity, problem-solving, and teamwork (Anyon, 1980), like those found in STEM careers, exclusionary discipline measures can prepare
other students for futures that involve conformity, repetition, and isolation (Wald & Losen, 2003), like those found in prison cells. This is especially true for students from underserved groups. Here, while educational opportunities and structures in STEM have been found to pull a select subset of students from underserved groups towards meaningful futures in STEM careers (Means, Wang, Young, Peters, & Lynch, 2016), exclusionary discipline measures have been found to push many more less-fortunate students from these same groups towards futures in the criminal justice system (Skiba, Arredondo & Williams, 2014). Finally, it is important to note that like many other opportunity structures, the stratification of STEM and exclusionary discipline “opportunities” can occur both within-schools and between-schools, which allows students from underrepresented groups to be easily excluded in STEM and targeted in discipline.

1.2 Gaps in the Literature

While much of the research on these pipelines has been confined to within-pipeline analyses—disciplinary factors influencing disciplinary outcomes and academic factors influencing academic outcomes, some research has begun to analyze the relationships between discipline and academics. In terms of STEM, Lacoe and Steinberg (2018) found that suspensions were related to lower math achievement, while Martin, Martin, Gibson, and Wilkins (2007) found that an increase in math achievement was significantly related to a decrease in suspensions. Beyond STEM, Arcia (2006) found that students who were suspended had significantly lower pre-suspension reading achievement, made fewer academic gains in reading after being suspended, and were more likely to dropout afterwards. Nevertheless, current research remains unclear about the extent to which the influence of discipline on academics remains after accounting for prior academic influences—and vice-versa.
Furthermore, when considering the tendency for these pipelines to be studied in isolation, outcomes that stem from both pipelines, like dropout status, are often viewed as separately derived phenomena; this tendency can “squeeze out complexity” in inherently complex phenomena (see Cannady, Greenwald, & Harris, 2014; McGrew, 2016). For example, the underlying process by which students are pushed out of schools is often portrayed as a product of either academic or disciplinary forces, rather than a culmination of their interactions over time. This portrayal ultimately limits our ability to not only comprehend this phenomenon, but also to combat it. Moreover, previous research has been unable to address how the accumulation and saturation of advantages and disadvantages—stemming from different dimensions and intersections of identity—operates within and across academic and disciplinary pipelines over time. Again, this gap in the literature has ultimately limited our ability to tailor appropriate group-level interventions within and across both academic and disciplinary domains.

Finally, as exclusionary discipline trends have signaled a move towards more coercive measures of control (Kupchik, Green, & Mowen, 2015), researchers are beginning to recognize not only the direct consequences of these practices, but also the indirect consequences of this heightening ‘culture of control’ (Garland, 2001). Similar to the research on the collateral damage of mass imprisonment (Mauer & Chesney-Lind, 2002), which has emphasized the negative effects of incarceration on non-incarcerated individuals (Clear, 2007), research on the collateral damage of mass suspensions tends to emphasize the negative effects of high-suspension schools on non-suspended individuals. Here, it is believed that it is not only components of destabilization (movement in and out of classrooms) that negatively affects non-offending students, but also components of anxiety stemming from the threat of unfair punishment (Kupchik, 2010). For example, punishments that appear excessive or discriminatory, which are
common in suspensions, are likely to be viewed as unfair and immoral by students (Arum, 2003; Perry & Morris, 2014). This view can ultimately undermine a school’s institutional authority and lead to alienation and resistance of its students—“affecting both well and poorly behaved students alike” (2014, p. 5). However, even though previous research has demonstrated the adverse effects of exclusionary discipline on non-suspended students (2014), this research has often relied on localized samples; been unable to control for selection of students within schools; been unable to demonstrate both short and long-term indirect effects; and has overlooked the indirect effect of the more common form of exclusionary discipline—in-school-suspensions.

1.3 Objectives

In an attempt to fill some of the most important gaps within the literature on the relationships among academics and discipline, this dissertation will have three primary objectives. First, this dissertation will seek to understand how cross-pipeline impacts operate in the presence of within-pipeline impacts. Specifically, article one will demonstrate the relationship between in-school suspension and advanced math course-taking, as well as the relationship between early math achievement and dropout status—and how these relationships change as social background characteristics, attachment-related measures, prior math achievement, discipline history, and school-level features are taken into consideration. Second, this dissertation will seek to understand significance and strength of multiple hypothesized structural relationships among the STP and STEM pipelines simultaneously, how these relationships are related to process by which students are pushed out of school, and how these relationships operate differently for unique race-gender intersections of identity. Specifically, article two will demonstrate the short-term impact of suspensions on a latent construct of math over time, as well as the long-term interactions among the STP and STEM pipelines in high
school and how these interactions relate to dropout status for different dimensions and intersections of racial/ethnic and gender identity. Finally, as the vast majority of students do not receive suspensions, some may still question whether the use of suspensions does, in fact, ensure the learning of non-offending students by removing those who are perceived to be misbehaving from classrooms (see Kinsler, 2013). As a result, this dissertation will seek to understand the indirect effects of suspensions on the STEM pipeline. Specifically, the article three will test the indirect effects of attending a high-suspension high school on math achievement and college attendance that are net of school-level disorder and student-level sanctioning—when controlling for selection into schools.

In three separate articles, this dissertation will demonstrate a) how the STP and STEM pipelines are interrelated—when considering both within and cross-pipeline impacts at the student and school-level, b) how the interactions among the STP and STEM pipelines influence the process by which students are pushed out of high school—when considering different intersections of identity, and c) how the impacts of suspensions on the STEM pipeline can be experienced indirectly—when controlling for selection into schools. With a comprehensive conclusion at the end, this dissertation will progress in the following manner: Chapter 2—Article One; Chapter 3—Article Two; Chapter 4—Article Three; and Chapter 5—Conclusion. Finally, it is important to note that all three articles are co-authored with Dr. Odis Johnson. As the first author in all three articles, I have designed the studies, completed the analysis, and written the initial draft of each article. In addition to making general edits and revisions, as well as tightening the introductions and conclusions, the theoretical framing of all three articles have received important input from my advisor and co-author, Dr. Odis Johnson.

1.4 Theoretical Perspectives
Meeting the objectives of this dissertation will require an understanding of interactional (Thornberry, 1987), intersectional (Collins, 2002), and social control (Durkheim, 1961) theories. Together, these theories will inform the development of the analyses, the interpretation of the findings, and the consideration of the implications.

1.4.1 Interactional Theories

An interactional theory of discipline and academics was first put forth by Thornberry (1987), which posited that delinquency was subject to reciprocal effects of interrelated social factors, such as commitment to schools, and that these effects are capable of impacting individuals over the life course. Highlighting the importance of the interactive processes among multiple, interrelated pathways in producing student outcomes over time, Thornberry noted that initially weak bonds to school can lead to greater allowances for delinquency to be learned, performed, and reinforced in the presence of peers, which can further weaken conventional bonds to school (p. 883). Here, delinquent peers, values, and behaviors can be seen as forming a “mutually reinforcing causal loop that leads towards increasing delinquency involvement over time” (Thornberry, 1987, p. 886). While the underlying interactive process is supported by Thornberry, Lizotte, Krohn, and Farnworth (1994), much of interactional theory focuses on the reciprocal effects of misbehavior and academics. Thus, our research will expand upon this premise and instead focus on sanctions to misbehavior (as mechanisms of formal social control) and the reciprocal relationship of these sanctions to students’ pursuit of STEM—and vice-versa. Finally, as Thornberry (1987) suggests that race, gender, and class are systematically related to the interactions among discipline and academics, it is important to also consider intersectional theories.

1.4.2 Intersectional Theories
Stemming from Black feminist thought, intersectionality holds that as multiple systems of power work to oppress multiple dimensions of identity, those that simultaneously hold multiple dimensions of oppressed identities exist in uniquely oppressed societal spaces (Collins, 1990; Crenshaw, 1991). As intersecting power dynamics can vary both within and across opportunity structures (see Jang, 2018), the simultaneous consideration of multiple social dimensions paints a more complete picture of oppression than considering those same attributes separately. Intersectionality is especially important in research on interactions among academic and disciplinary pipelines, as different dimensions of identities can operate inconsistently within and across divergent structures of opportunity. For example, while the male gender can act as a source of privilege in math and science, Black males have been shown to face unique barriers in both STEM education, as well as the STEM labor market (Bidwell, 2015). Conversely, while the female gender can act as a source of privilege in school discipline and the criminal justice system, Black females have been specifically targeted for suspensions (Losen & Skiba, 2010) and criminal offenses (Bush-Baskette, 1998).

1.4.3 Social Control

Finally, as this dissertation focuses more on the response to delinquency, rather than delinquency itself, theories of social control will also be essential in framing this research. Formal social control sanctions were originally theorized to reduce anti-social behavior, maintain social order, and—by doing so—provide opportunities to learn (Durkheim, 1961). However, the overly severe and overly abundant use of sanctions relative to misbehavior, as well as the disproportionate targeting of low-income students and students of color, can undermine social cohesion (1961), which can ultimately render these sanctions ineffective. Thus, given the recent increase in the severity (Skiba & Knesting, 2001), rate (Losen & Martinez, 2013), and
disproportionality of sanctioning (Skiba, Chung, Trachok, Baker, Sheya, & Hughes, 2014), despite decreasing (Muschert, Henry, Bracy, & Peguero, 2014; Johnson, 2015) and relatively proportional (Skiba, Michael, Nardo, & Peterson, 2002) rates of misbehavior, the use of formal social control sanctions appear to have gone beyond merely maintaining social order; rather, “punishment has become an end in itself, not an occasional means to an end of normative social order” (Perry & Morris, 2014, p. 5). When considering these trends, which signal a move towards more coercive measures of control (Kupchik, Green, & Mowen, 2015), as well as the fact that students do not only experience these sanctions directly, but also indirectly (Perry & Morris, 2014), it is imperative to understand the effects of these sanctions on learning. This is especially important for learning that appears antithetical to high levels of coercive control, like STEM, which often requires high levels of creativity, problem-solving, and teamwork (Adams & Hamm, 2010).

1.5 Research Context

The central focus of this dissertation will be on the context of high schools. The approach to understanding these pipelines within this context is driven by the belief that high schools represent a crucial period of time after which students take increasingly concrete steps within either pipeline (see Pettit & Western, 2004; Bottia, Stearns, Mickelson, Moller, & Parker, 2015). Additionally, high schools offer greater differentiation in terms of STEM and discipline, as students in high school have the ability to take a variety of math and science courses and are legally allowed to permanently drop out.

Nevertheless, it is important to note that formal education is one of many contexts that affects the STP and STEM pipelines, and high schools represent only one segment of this formal education context. Moreover, and perhaps more importantly, high schools are not the first
segment of this formal education context. Indeed, neither STEM preparation, nor involvement with exclusionary discipline start in the 9th grade. For example, researchers have often noted the importance algebraic concepts—and the detrimental effects associated with misconceptions—in middle school (see Bush & Karp, 2013), as well as the importance of building foundational algebra skills, such as relational thinking, in elementary schools (see Carpenter, Franke, Levi, & Zeringue, 2005). As success in algebra is a primary indicator of STEM preparation and persistence, these foundational knowledge and skill areas are essential in preparing students for STEM in high school and beyond. Yet, while early interventions in algebra have been proven effective (see Blanton, Stephens, Knuth, Gardiner, Isler, & Kim, 2015), comparative proficiency levels and persistent racial/ethnic gaps in algebra performance demonstrate that these interventions have yet to be broadly implemented. The same can be said of exclusionary discipline. For example, the Center for American Progress—using data from the National Survey of Children’s health—reported that over 50,000 preschoolers were suspended in 2016. Similarly, interventions, such as moratoriums on elementary suspensions for non-violent offenses, like the one instituted in California in 2014, have been shown to decrease the discipline gap within racial/ethnic groups. Unfortunately, similar to math interventions, these disciplinary interventions are often the exception and not the rule. Thus, while this dissertation seeks to explore ways to redirect students from the STP pipeline to the STEM pipeline in the context of high schools, it is important to keep in mind that this task might be less arduous if these persistent problems were more effectively tackled in pre-K, elementary, and middle schools.

1.6 Research Terms

Even though the ultimate destinations of these respective pipelines might eventually become mutually exclusive, student experiences in high school do not only occur within each
pipeline, but also across them. Here, it is students’ interactions among academic and disciplinary opportunity structures that propel them along STEM and STP pipelines. Thus, the research in this dissertation will be based on the premise that students can not only cross over from one pipeline to the other at any point in time, but also that students can occupy parts of both pipelines at once. Pipeline persistence during high school does not designate the final destination for students, but rather represents a temporary move towards one pipeline’s end point, which often—but not always—is accompanied by temporary move away from the other pipeline’s end point. As a result, this research will allow for multiple entrance and exit points, as well as multiple directional flows, both within and across these divergent, yet interacting pipelines. In doing so, this dissertation will provide important insights into both the individual and institutional factors that impact a student’s entrance and persistence into each respective pipeline during high school, which may therefore limit their opportunities to persist in the other pipeline.

1.7 Data

The analyses in this paper used the restricted-use data from High School Longitudinal Study of 2009 (HSLS). Access to this data has been obtained through the National Center for Education Statistics (NCES). The HSLS employed a stratified, two-stage random sampling design with schools randomly selected at the first stage, followed by students randomly selected from these schools at the second stage (Ingels, Pratt, Herget, Burns, Dever, Ottem, Rogers, Jin & Leinwand, 2011). In doing so, an average of 27 ninth-graders at each of the 944 schools were selected for a total of 25,206 eligible students (Ingels et al., 2011). The analyses in this paper utilized all currently available waves, which included Base Year data (fall of 9th grade), First Follow-Up data (spring of 11th grade), 2013 Update (spring of 12th grade), and HS Transcripts.
1.8 Research Questions

Article One: “Two Sides of the Same Coin? A Multilevel Analysis of STEM and Disciplinary Trajectories in U.S. High Schools over Time.”

I. What is the relationship between in-school suspension and advanced math course-taking and how does it change as social background characteristics, attachment-related measures, prior math achievement-related measures, and school-level features are taken into consideration?

II. What is the relationship between math achievement-related measures and dropout status and how does it change as social background characteristics, discipline history, attachment-related measures, in-school suspensions, and school-level features taken into consideration?

III. How does race—both at the student and school-level—operate in each trajectory?


I. What is the short-term impact of receiving a suspension on math achievement?

II. What are the long-term interactions among the STP and STEM pipelines in high school and how do they relate to the process of pushing students out of school?

III. How do the long-term interactions among the STP and STEM pipelines compare across different dimensions and intersections of identity, specifically race and gender?

Article Three: “The Collateral Damage of In-School Suspensions: A Counterfactual Analysis of High-Suspension Schools, Math Achievement and College Attendance.”
I. What are the short-term (math achievement) and long-term (college attendance) impacts associated with attending a high-suspension high school and how are these impacts related?

II. How do the effects associated with directly receiving a suspension differ from the indirect effects associated with attending a high-suspension high school?

III. How do student background characteristics interact with high-suspension schools and math when predicting college attendance?

1.9 Methods

In the first article, multilevel modeling (MLM) was utilized, which allows for nested data structures, such as students within school buildings, to be statistically accounted for and measured (see Snijders & Bosker, 2012). Specifically, multilevel regression analyses within random intercept models were used, which allows intercepts to vary across clusters (Rabe-Hesketh & Skrondal, 2014). In doing so, these models allowed student-level outcomes to vary across schools in the analyses, which provides an estimation of between-school effects (random effects). In the second article, a two-step process was utilized (Kline, 2015), which first uses confirmatory factor analysis to test the validity of the latent construct of math achievement and then uses latent difference score and structural equation modeling to test the relationships among the latent construct of math achievement and exclusionary discipline over time. Finally, the third article utilizes propensity score weighting (Guo & Fraser, 2014), which limits the selection bias associated with the impact that attending a high-suspension school has on secondary and post-secondary achievement. Together, these three methods allow for a) an estimation of both fixed and random effects; b) an understanding of structural relationships that are mediated by latent constructs; and c) an estimate of school-level “treatments” that are void of selection bias.
1.10 Findings

Findings from this dissertation demonstrate that there are significant interactions among the STP and STEM pipelines. First, accounting for student and school-level demographic, achievement, and attachment-related variables, suspensions significantly influenced STEM trajectories, while early math achievement significantly influenced disciplinary trajectories. Second, noting nuances among race-gender groups, significant interactions among the STP and STEM pipelines had the effect of pushing students out of high school over time. Finally, demonstrating indirect effects, students attending high-suspension high schools had lower math achievement and, as a result, were less likely to attend college.

1.11 Significance

If we assume that high schools have played an important role in directing underserved students towards the prison pipeline—and therefore away from the STEM pipeline—then we may also assume that schools have the ability to play an important role in redirecting underserved students towards the STEM pipeline—and therefore away from the prison pipeline—in the future. By operationalizing these pipelines within high schools and demonstrating student’s direct and indirect interactions within and across these pipelines for various race and gender groups, stakeholders can gain a more comprehensive understanding of how students navigate complex opportunity structures in both academics and discipline. These findings can eventually lead to policies and practices that can decrease exposure to the STP pipeline, while increasing access to the STEM pipeline. Ultimately, this may lead to a significant redirection from the school-to-prison pipeline to the STEM pipeline for underserved students and the communities they live in.
References


high school STEM learning experiences and students’ intent to declare and declaration of a STEM major in college. *Teachers College Record*, 117(3), 1-46.


education, 135-155.


Equal opportunity in the United States is currently complicated by two important and intertwined realities. While the U.S. has struggled to increase the number of science, technology, engineering, and mathematics (STEM) professionals from underrepresented groups, many of the same groups who have been underrepresented in STEM have been overrepresented in the criminal justice system. While just 13 percent of engineers were Black or Hispanic in 2015 (Pew Research Center, 2018b), the combined percentage of Black and Hispanic individuals who were incarcerated was 56 percent (Pew Research Center, 2018a). Unsurprisingly, both of these realities mirror the state of education in many U.S. high schools. The same students that are underrepresented in successful STEM education are often overrepresented in exclusionary discipline practices. The tendency for academic opportunities and exclusionary discipline practices to marginalize many of the same students has caused Gregory, Skiba, and Noguera (2010) to conclude that the achievement gap and the discipline gap may represent “two sides of the same coin.”

Nevertheless, nearly a decade after their call for research that addresses the relationships among academics and discipline, we have little empirical evidence that demonstrates how students operate within and across these trajectories over time. Generating knowledge as to how these trajectories—and the opportunity structures that underlie them—are related would not only reveal the human capital cost to STEM fields that are hidden in school attempts to “maintain order” through exclusionary discipline, but would also inform future efforts seeking to redirect
students away from disciplinary trajectories, such as those related to the school-to-prison (STP) pipeline, and towards academic trajectories, such as those related to the STEM pipeline.

On this point, our findings demonstrate a reciprocal relationships: suspensions significantly influenced STEM trajectories, while math achievement significantly influenced disciplinary trajectories. Nevertheless, within-trajectory influences were strong and only marginally lessened the impact of cross-trajectory influences in some cases. Highlighting the varying roles of race—both at the student and school-level—in each trajectory, we conclude with a discussion of implications for policy and practice.

2.1 Literature Review

2.1.1 Oppositional Opportunity Structures and Divergent Student Trajectories

Schools structure opportunity in multiple ways, which can include access to learning (Oakes, 1985), as well as exposure to discipline (Hirschfield, 2008). Engagement with these opportunity structures can ultimately propel students along divergent trajectories in life. For example, students who have demonstrated high levels of math achievement, are more likely to take advanced STEM courses, major in a STEM subject in college, and secure a STEM job in the labor market (see Engberg & Wolniak, 2013). Conversely, students who have been suspended are more likely to depart school prematurely and become involved with the criminal justice system (Fabelo et al., 2011, p. xii). Here, STEM trajectories operate as a continuum of *inclusion* in selective STEM classrooms, college majors, and career fields, while disciplinary trajectories operate as a continuum of *exclusion* from classrooms (in-school suspension), schools (out-of-school suspension), formal education (dropping out), and society (being incarceration). As high school represents a critical juncture during which students take increasingly concrete steps towards futures involving STEM (Bottia, Stearns, Mickelson, Moller, & Parker, 2015) and the
criminal justice system (Pettit & Western, 2004), we have decided to focus on early math achievement and advanced math course-taking as proxies for academic opportunity structures and trajectories related to STEM involvement. Conversely, we have focused on in-school-suspension and dropout status as proxies for disciplinary opportunity structures and trajectories related to involvement with the criminal justice system.

**STEM Trajectories.** STEM trajectories are influenced both by student characteristics and school-level features. Starting with student characteristics, STEM trajectories are influenced by early math achievement, which can consist of performance (Updegraff, Eccles, Barber, O’Brien, 1996), ability (Veenstra, Dey, & Herrin, 2009), and course-taking (Tyson, 2011). Furthermore, math attitudes, which can consist of math identity (Hazari, Sonnert, Sadler, & Shanahan, 2010), interest (Maltese & Tai, 2011), utility (Harackiewicz, Rozek, Hulleman, & Hyde, 2012), and self-efficacy (Wang, 2013), can also influence STEM trajectories. Moreover, extracurricular activities can influence STEM trajectories as well (VanMeter-Adams, Frankenfeld, Bases, Espina, & Liotta, 2014). Moving on to the school-level, math course offerings and enrollments (Main, Darolia, Koedel, Yan, & Ndashimye, 2017), as well as teacher and staff expectations of student abilities (Cherng, 2017) can also influence STEM trajectories. As a result, we consider the influence that all of these features have on students’ advanced mathematics course-taking, which remains one of the strongest predictors of a student’s decision to pursue a STEM major in college (Engberg & Wolniak, 2013).

**Disciplinary Trajectories.** While suspensions remain the first and most common influence on disciplinary trajectories (Fabelo, et al., 2011), suspensions are often accompanied by other attachment-related measures. For example, suspensions have been associated with decreased interest (Costenbader & Markson, 1998) and engagement (Marks, 2000) in school, as
well as increased alienation (Moyer & Motta, 1982) and absenteeism (Brown, 2007). Additionally, suspensions have also been associated with lower expectations for college (Berends, 1995). Finally, at the school-level, higher staff expectations for students were associated with a decrease in suspensions, while greater instances of overall student violations were associated with an increase in suspensions (Christle, Nelson, & Jolivette, 2004). Thus, we consider the influence that all of these features have on students’ dropout status, which remains one of the strongest predictors of a future incarceration (Christle, Jolivette, & Nelson, 2005).

**Social Background Influences.** Many of the same social background characteristics that influence STEM trajectories are inversely related to disciplinary trajectories. For example, while White students tend to have higher levels of math achievement than Black students (Vanneman, Hamilton, Anderson, & Rahman, 2009), Black students tend to receive more frequent and harsher punishments than White students for identical problem behaviors (Skiba et al., 2011). Similar inverse relationships between math achievement and suspensions were found among poor students (see Herbers et al., 2012; Sullivan, Klingbeil, & Norman, 2013), as well as students from single-parent households (see Pong, 1997; Manning & Lamb, 2003). However, in terms of gender, there was no inverse relationship among math and disciplinary trajectories. While boys were often suspended more than girls, they also misbehaved more (Skiba, Michael, Nardo, & Peterson, 2002). Conversely, while girls often demonstrated math abilities that were similar to boys, they also had less interest and confidence in math (Catsambis, 1994).

Additionally, many of these social background characteristics have been found to be significant at the school-level as well. For instance, while school poverty has been associated with lower math achievement (Payne & Biddle, 1999), punishments were often more frequent and severe in schools that had high proportions of low-income students (Ramey, 2015).
However, while punishments were also more frequent and severe in schools that had high proportions of Black students (Skiba, et al., 2014), the relationships between race and math is not as straightforward at the school-level. Rather, due to the inclusive nature of these schools, students were often more likely to take advanced math courses in predominantly Black schools (Kelly, 2009).

### 2.1.2 Interactions among Discipline and Academics

Our conceptualization of interactions among disciplinary and academic trajectories builds on one of the primary premises of Thornberry’s (1987) interactional theory, which posits that there is a reciprocal relationship between students’ behavior and their commitment to school. However, while much of the work on interactional theory focuses on the reciprocal effects of students’ misbehavior and general academic trajectories, we instead focus on the sanctions to perceived misbehavior (i.e. suspensions) and their reciprocal relationship to student’s academic trajectories in STEM.

Despite Thornberry’s belief that the interactions among discipline and academics can drive students towards increasingly divergent trajectories over the life course, much of the research on these trajectories has been confined to within-trajectory analyses—disciplinary factors influencing disciplinary outcomes and, conversely, academic factors influencing academic outcomes. However, some research has begun to analyze the relationships between discipline and academics. In terms of STEM, Lacoe and Steinberg (2018) found that suspensions were related to lower math achievement, while Martin, Martin, Gibson, and Wilkins (2007) found that an increase in math achievement was related to a decrease in suspensions. More broadly, Arcia (2006) found that students who were suspended had significantly lower pre-
suspension achievement, made fewer academic gains after suspension, and were more likely to dropout afterwards.

Nevertheless, current research remains unclear about the extent to which the influence of discipline on academics remains after accounting for prior academic influences (and vice-versa). As a result, the primary objective of this research will be to test reciprocal relationships between disciplinary and academic trajectories throughout high school in models that simultaneously include both cross-trajectory and within-trajectory and influences—at both the student and school-level. Only through these kinds of analyses can we gain information that reveals how students operate within and across disciplinary and academic trajectories over time. Paying close attention to race, which often plays an inverse relationship among these trajectories, we ask the following research questions:

I. What is the relationship between in-school suspension and advanced math course-taking and how does it change as social background characteristics, attachment-related measures, prior math achievement-related measures, and school-level features are taken into consideration?

II. What it the relationship between math achievement-related measures and dropout status and how does it change as social background characteristics, discipline history, attachment-related measures, in-school suspensions, and school-level features taken into consideration?

III. How does race—both at the student and school-level—operate in each trajectory?

### 2.2 Data and Methods

#### 2.2.1 High School Students
Our analyses utilized The High School Longitudinal Study of 2009 (HSLS), which is the U.S. Department of Education’s most recent comprehensive study of high school students. 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, et al., 2015). We utilized all currently available waves, which included student, parent, teacher, counselor, and administrator questionnaire data from the Base Year (fall of 9th grade), First Follow-Up (spring of 11th grade), 2013 Update (spring of 12th grade), and the 2013 High School Transcript Study.

The use of multiple waves of data created the expected problem of participant non-responses across and within waves. Although 15,188 students participated in four questionnaire waves, only 8,619 of these students had parent, administrator, counselor, and math teacher questionnaires completed. Nevertheless, the NCES did provide analytic weights to account for these instances of non-response, as well as instances of sampling inefficiencies that are inherent to a stratified sampling approach. WISCHOOL was used as the school-level weight, and W3W1W2STUTR was used as the student-level weight. Additionally, in order to account for the conditional probability of students selected within schools, W3W1W2STUTR, which represents the overall student-level weight, was re-scaled so that the weights summed to the effective sample size of each student’s corresponding school.

With the exception of the administrator scale of school problems, which was missing 15% of the responses in the dataset, all other independent variables had less than 10% of their responses missing, with the majority missing less than 5% of their responses. To recover these missing values, multiple imputation with chained equations (MICE) were used to impute 5 sets of missing values. However, missing values for dependent variables, as well as key independent variables (including ISS and 9th grade math class), were not imputed. Finally, in order to utilize
all of the information made available by the imputation process, principal components were created after missing values were imputed. While our decision to not impute all missing values resulted in some list-wise deletion, our weighted analytic samples of 6,918 and 6,005 students had properties that were very similar, but not exactly representative of the U.S. population of high school students.

2.2.2 Measures

Dependent variables. For the first analysis, advanced math course-taking (AMCT) was defined as students who had taken trigonometry or higher (1 = yes; 0 = no) at some point during high school. Trigonometry—defined as ‘advanced’ by Burkam and Lee (2003)—was found to represent the stage where heightened interests in math and science “kicks in”, leading to increased intentions to pursue math and science in college. As almost all high schools offer trigonometry on site, this measure ensures that a student’s specific high school course offerings did not limit their ability to take this advanced math course. For the second analysis, Dropout Status was defined as students who had dropped out of high school during the spring semester of 12th grade (1 = yes; 0 = no), which did include students who were seeking an alternative route to high school completion, such as pursuing a GED.

Independent variables. Variables that were not standardized or did not have a meaningful zero were centered at the grand mean in order to allow for accurate estimates of the intercepts, which is important in multilevel modeling. In the first analysis, a mean-centered measure of a student’s 9th grade math course level, which ranged from taking no math at all to taking pre-calculus, was used as a primary control for advanced math course-taking. In the second analysis, a binary measure of dropout history (1 = yes; 0 = no), which indicated whether or not a student had previously stopped attending school for one at least month—for reasons
other than illness, injury, or vacation—starting in kindergarten, was used as a primary control for dropout status.

Additionally, based on what has been considered in previous research, each analysis also included social background, math, and attachment-related variables as added measures of control. Student-level social background variables included being female (1 = female; 0 = male), being Black (1 = yes; 0 = no), being Hispanic (1 = yes; 0 = no), being from a single-parent household (1 = yes; 0 = no), as well as a continuous measure socio-economic-status (SES). School-level social background variables, on the other hand, included mean-centered measures of the percentage of Black students, the percentage of Hispanic students, and the percentage of students eligible for free or reduced lunch. Each of these measures was categorized by NCES in the following manner: ‘0’ = 0%; ‘1’ > 0%; ‘2’ >/= 10%; ‘3’ >/= 20%; ‘4’ >/= 30%; ‘5’ >/= 40%; ‘6’ >/= 50%; ‘7’ >/= 60%; ‘8’ >/= 70%; ‘9’ >/= 80%; ‘10’ >/= 90%; and ‘11’ >/= 100%.

At the student-level, variables related to math achievement included mean-centered algebra I grades (scaled 1-5 with 1 indicating the highest letter grade), mean-centered, norm-referenced 9th grade math test scores (focused on algebraic reasoning), a binary measure of 9th grade extracurricular math/science participation (1 = no; 0 = yes), which included math and science clubs, competitions, camps, study groups, and tutoring programs, and a continuous measure of 9th grade math attitude. Here, math attitude was created using the first principal component of math identity, math utility, math efficacy, and math interest, which explained 60% of the overall variance (eigenvalue = 2.39; KMO = 0.76). At the school-level, math variables included a continuous measure of math teacher’s perceptions about the expectations of other math teachers at his or her school provided by the NCES (subcomponents include working hard to make sure all students learn, setting high standards for teaching and learning, setting clear
goals for students, believing that all students can do well, giving up on some students, caring only about smart students, and expecting very little from students), as well as a mean-centered measure of a school’s *average highest math course taken* by its students (ranging from taking no math at all to taking AP/IB calculus).

Student-level attachment-related variables included a binary measure of *student expectations for completing a bachelor’s degree or higher* (1 = yes; 0 = no/don’t know), a continuous measure of *9th grade school belonging*, a continuous measure of *9th grade school engagement*, mean-centered measures of *classes skipped* and *absences* within the last six months (both scaled 1-5: 1 = never; 2 = one-two times; 3 = three-six times; 4 = seven-nine times; 5 = ten or more times), and a binary measure of *receiving ISS* within the last six months (1 = yes, 0 = no). Additionally, continuous measures of *school belonging* and *school engagement* were each provided by the NCES. School belonging was created from the following items: feeling safe and proud, feeling like the student has someone that they could talk about their problems with, not feeling that school was a waste of time, and feeling that good grades were important. The school engagement measure, on the other hand, was created from the following items: being prepared with homework, having the necessary materials, and being on time.

Finally, school-level attachment-related variables included a continuous administrator measure of *school problems* and a continuous counselor measure of *staff expectations*. The administrator measure of school problems was provided by the NCES and created from the following items: student tardiness, absenteeism, truancy, dropping out, apathy, preparedness, health, parental involvement, and teacher resources. Here, higher values represented more positive assessments of the school’s problems. The counselor measure of staff expectations was created from the first principal component of a counselor’s perceptions of teacher, administrator,
and other counselor expectations of students. This measure accounted for 77% of the overall variance (eigenvalue = 2.30; KMO = 0.72). Similar to math teacher expectations, these continuous measures were provided by the NCES and created from the following items: working hard to make sure all students learn, setting high standards for teaching (only for the teacher measure) and learning, setting clear goals for students, believing that all students can do well, giving up on some students, caring only about smart students, and expecting very little from students. Summary statistics for each variable can be found in Table 1.1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adv. Math Course-Taking</td>
<td>0.62</td>
<td>0.49</td>
</tr>
<tr>
<td>Dropout Status</td>
<td>0.03</td>
<td>0.18</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>0.52</td>
<td>0.5</td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.09</td>
<td>0.29</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.11</td>
<td>0.32</td>
</tr>
<tr>
<td>SES</td>
<td>0.06</td>
<td>0.76</td>
</tr>
<tr>
<td>Single-Parent Household</td>
<td>0.21</td>
<td>0.41</td>
</tr>
<tr>
<td>9th Grade Math Course</td>
<td>4.22</td>
<td>1.38</td>
</tr>
<tr>
<td>Lower Algebra I Grade</td>
<td>1.85</td>
<td>0.93</td>
</tr>
<tr>
<td>9th Grade Math Test</td>
<td>51.56</td>
<td>9.13</td>
</tr>
<tr>
<td>No Extracurricular Math Part.</td>
<td>0.83</td>
<td>0.38</td>
</tr>
<tr>
<td>9th Grade Math Attitudes</td>
<td>0.07</td>
<td>1.53</td>
</tr>
<tr>
<td>Dropout History</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>Student Expectations</td>
<td>0.60</td>
<td>0.49</td>
</tr>
<tr>
<td>9th School Belonging</td>
<td>0.14</td>
<td>1.01</td>
</tr>
<tr>
<td>9th School Engagement</td>
<td>0.17</td>
<td>0.92</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>1.17</td>
<td>0.54</td>
</tr>
<tr>
<td>Absences</td>
<td>2.49</td>
<td>1.02</td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.08</td>
<td>0.27</td>
</tr>
<tr>
<td>Percent of School Black</td>
<td>1.45</td>
<td>1.68</td>
</tr>
<tr>
<td>Percent of School Hispanic</td>
<td>1.62</td>
<td>1.93</td>
</tr>
<tr>
<td>Percent Free Lunch</td>
<td>3.91</td>
<td>2.58</td>
</tr>
<tr>
<td>Math Teacher’s Expectations</td>
<td>0.22</td>
<td>0.91</td>
</tr>
<tr>
<td>Highest Math Course Taken</td>
<td>7.87</td>
<td>1.55</td>
</tr>
<tr>
<td>Staff Expectations</td>
<td>0.13</td>
<td>1.44</td>
</tr>
<tr>
<td>School Problems</td>
<td>-0.25</td>
<td>0.96</td>
</tr>
</tbody>
</table>
2.3 Analytic Strategy

As the factors that influence each pipeline consist of both student and school-level factors, we are interested in both within and between-school effects. We therefore used multilevel regression analyses within random intercept models to estimate these effects, which appropriately accounts for nested data structures, such as students within schools (see Snijders & Bosker, 2012). In doing so, the intercepts of the binary student-level outcomes (advanced math course-taking in analysis 1 and dropout status in analysis 2) were allowed to vary across schools, which then allows for the estimation of between-school effects.

After running unconditional models with the outcome, significant random intercept variance components demonstrated that multilevel modeling (MLM) was indeed appropriate for both analyses (not shown). Subsequently, each analysis fit a series of two-level random intercept logistic regression models using STATA’s melogit program (StataCorp, 2017). The following equation was used for the combined level 1 (student-level) and level 2 (school-level) model. Here, X represents student-level variables, while Z represents school-level variables:

\[
\log(\pi_{ij}/1-\pi_{ij}) = \beta_0 + \beta_1X_{1ij} + \beta_2X_{2ij} + \ldots + \beta_iZ_{ij} + u_j
\] (2.1)

After checking for multicollinearity and ensuring that all models were statistically significant, normality tests of residuals were performed to visually ensure that the residuals were normally distributed. All assumptions for multilevel modeling and logistic regression in each analysis were met.

With these models, we employed an analytic approach that isolates in-school-suspension (ISS) in the first analysis, while block-adding student and school-level social background, math, and attachment-related variables. This is done because ISS serves as the main student-level indicator of school discipline in the first analysis. Alternatively, in the second analysis, since
there were no specific math variables that warranted isolation, all math-related variables were added simultaneously, while social background, discipline, and attachment-related student variables were block-added. In doing so, each analysis allowed for greater clarity in identifying the influence of discipline on math, as well as the influence of math on discipline.

2.4 Results

2.4.1 The Influence of In-School Suspension on Advanced Math Course-taking

Our first analysis explores the relationship between in-school suspension (ISS) and advanced math course-taking (AMCT), and how it changes as social background characteristics, attachment-related measures, prior math achievement-related measures, and school-level features are taken into consideration. Starting with student-level variables, model 1a demonstrated the direct relationship between ISS and advanced math course-taking (AMCT). Here, students that experienced ISS had their odds of AMCT lowered to a ratio of 0.19 to 1 when compared to students that did not experience ISS. Next, model 1b added student social background characteristics to the previous model. In doing so, SES was found to be a positive predictor of AMCT. Moreover, in the presence of student social background characteristics, the odds of AMCT associated with ISS slightly weakened.

In model 1c student math achievement-related measures were added to the previous model. The strongest math predictor was students’ 9th grade math course-level, which was related to increased odds of AMCT. Additionally having a lower algebra I grade was related to decreased odds of AMCT, while having a higher 9th grade math test score was related to increased odds of AMCT. Also, it is important to note that in model 1c significant racial differences emerged, as being Black was related to an increase in the odds of AMCT when compared to all other students. At the same time, the odds of AMCT associated with SES
substantially weakened, while the odds of AMCT associated with ISS slightly weakened. In model 1d student-level school attachment-related variables were added to the previous model. Of these variables, student expectations of graduating college and school engagement were positive predictors of AMCT. Conversely, classes skipped was negatively related to AMCT. Again, the odds of AMCT associated with ISS slightly weakened in the presence of these added variables.

The final three models added school-level features. In model 1e we considered the racial and social class composition of schools. While a school’s composition of Black students became a positive predictor of AMCT, the odds associated with being Black at the student-level became insignificant. Also, the percent of a student’s school that qualified for free and reduced lunch was negatively related to AMCT. In model 1f we considered school-level measures of math teacher expectations, as well as the average highest math course taken. While math teacher expectations was not a significant predictor of AMCT, the average math course of students in each school was significantly related with an increase in the odds of AMCT. Also, with the addition of these math variables, the odds of AMCT associated with the percentage of students who qualify for free and reduced lunch no longer remained significant. In model 1g we considered school-level attachment variables, but neither staff expectations nor school problems were found to be significant predictors of AMCT. Finally, it is important to note that the odds of AMCT associated with ISS did not substantially alter with the inclusion of any school-level variables.

2.4.2 The Influence of Math Achievement on Dropout Status

Turning our attention to the second research question concerning the relationship between early math achievement and dropout status (DS), we estimated a series of models that were similar to analysis 1, except with the relationship between discipline and math reversed. Model 2a represents the relationship between math predictors and DS. Here, multiple measures
related to math achievement were found to be significant predictors of DS: a one unit increase in 9th grade math course was related to a decrease in the relative odds of DS to a ratio of 0.64 to 1; a one letter drop in algebra I grades was related to an increase in the relative odds of DS to a ratio of 2.8 to 1; and not participating in any extracurricular math or science activities was related to an increase in the odds of DS to a ratio of 11.58 to 1 when compared to students to did participate in extracurricular math and science activities. In model 2b we added student social background variables. Again, SES was found to be significantly related to DS, proving to be a negative predictor of the outcome. Also, the odds associated with not participating in any extracurricular math or science activities slightly weakened.

In model 2c ISS and student-level school attachment-related variables were added to the previous model. Considering the variables that would reduce students’ exposure to instruction first, both ISS and classes skipped were found to be positive predictors of DS. Among the other variables related to school attachment, only student expectations of college was significantly related to DS, proving to be a negative predictor of the outcome. Moreover, while the odds associated with having a lower algebra 1 grade slightly weakened model 2c, the odds associated with positive math attitudes became significant—a one unit increase in math attitudes was associated with a decrease in the relative odds of DS to a ratio of 0.76 to 1.

Moving on to school-level features, model 2d added school social background variables. Of these variables, only the percent of a student’s school composition that was Black was found to be significantly related to DS, proving to be a positive predictor of the outcome. However, when these variables were added, being Black at the student-level became a significant negative predictor of DS. In model 2e school-level math variables were added to the previous model. In doing so, an increase in the school average for students’ highest math course was significantly
related to a decrease in the odds of DS. In the final model (2f), a measure of staff expectations and school problems were added to the previous model but, again, were not found to be significant predictors of the outcome. Nevertheless, it is important to note that when these variables were added, the odds associated with the school average for students’ highest math course taken no longer remained a significant predictor of DS. Similar to the first analysis, it is important to note that the odds of DS associated with significant student-level math achievement predictors did not substantially alter with the inclusion of any school-level variables.

2.4.3 Between-School Effects

The variance component for the random intercept experienced an overall decrease from models 1a to 1g in the first analysis, as well as in models 2a to 2f in the second analysis. Here, as blocks of outcome predictors were added to the models, the overall amount of between-school variation in each outcome decreased. Approximately 29% of the school variation in AMCT was explained by the added variables in the first analysis (when comparing model 1g to 1a), while 13% of the school variation in DS was explained by the added variables in the second analysis (when comparing model 2f to 2a). However, while we would expect the variability of schools to decrease with the addition of student and school-level predictors in the models, the random intercept variance components (σ_u^2) still remained relatively large and statistically significant throughout these model progressions—indicating a substantial amount of variation is left unexplained at the school-level after accounting for all other explanatory variables in each model. In the final model of analysis 1, after accounting for all other variables, the between-school variance in a student’s propensity to take an advanced math course had a significant log-odds value of 1.87 with a standard error of 0.44. In contrast, the log-odds of dropout status was 2.54 with a standard error of 1.14. Results can be found in Tables 1.2 and 1.3.
Table 1.2. Mixed Effects Logistic Regression on the Influences of Student Discipline on Advanced Math Course-taking

<table>
<thead>
<tr>
<th>Fixed Effects: Student Level</th>
<th>Model 1a</th>
<th>Model 1b</th>
<th>Model 1c</th>
<th>Model 1d</th>
<th>Model 1e</th>
<th>Model 1f</th>
<th>Model 1g</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender: Female</td>
<td>1.08(0.11)</td>
<td>0.92(0.14)</td>
<td>0.82(0.19)</td>
<td>0.82(0.13)</td>
<td>0.81(0.12)</td>
<td>0.81(0.12)</td>
<td></td>
</tr>
<tr>
<td>Race: Black</td>
<td>1.2(0.33)</td>
<td>2.26(0.63)**</td>
<td>2.1(0.59)**</td>
<td>1.39(0.36)</td>
<td>1.39(0.36)</td>
<td>1.42(0.36)</td>
<td></td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.88(0.19)</td>
<td>1.21(0.28)</td>
<td>1.26(0.28)</td>
<td>1.21(0.26)</td>
<td>1.12(0.25)</td>
<td>1.13(0.25)</td>
<td></td>
</tr>
<tr>
<td>SES</td>
<td>2.72(0.27)***</td>
<td>1.73(0.18)***</td>
<td>1.58(0.17)***</td>
<td>1.5(0.16)***</td>
<td>1.43(0.16)**</td>
<td>1.44(0.16)**</td>
<td></td>
</tr>
<tr>
<td>Single-Parent Household</td>
<td>0.8(0.11)</td>
<td>0.85(0.13)</td>
<td>0.89(0.14)</td>
<td>0.89(0.14)</td>
<td>0.89(0.14)</td>
<td>0.88(0.14)</td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Course</td>
<td>2.6(0.39)***</td>
<td>2.56(0.39)***</td>
<td>2.49(0.36)***</td>
<td>2.3(0.32)***</td>
<td>2.27(0.31)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower Algebra I Grade</td>
<td>0.43(0.04)***</td>
<td>0.45(0.04)***</td>
<td>0.44(0.04)***</td>
<td>0.44(0.04)***</td>
<td>0.44(0.04)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Test</td>
<td>1.09(0.01)***</td>
<td>1.08(0.01)***</td>
<td>1.09(0.01)***</td>
<td>1.08(0.01)***</td>
<td>1.08(0.01)***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Mth/Sci Extracurricular(s)</td>
<td>1.15(0.45)</td>
<td>1.13(0.44)</td>
<td>1.16(0.44)</td>
<td>1.11(0.38)</td>
<td>1.09(0.37)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Attitudes</td>
<td>1.12(0.07)</td>
<td>1.04(0.06)</td>
<td>1.04(0.06)</td>
<td>1.05(0.06)</td>
<td>1.04(0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th Student Expectations</td>
<td>2.09(0.35)***</td>
<td>2.09(0.35)***</td>
<td>2.05(0.34)***</td>
<td>2.05(0.34)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th School Belonging</td>
<td>1.11(0.11)</td>
<td>1.09(0.11)</td>
<td>1.07(0.11)</td>
<td>1.07(0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th School Engagement</td>
<td>1.23(0.13)*</td>
<td>1.23(0.13)*</td>
<td>1.24(0.13)*</td>
<td>1.24(0.13)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.62(0.1)***</td>
<td>0.61(0.1)***</td>
<td>0.62(0.1)***</td>
<td>0.62(0.1)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absences</td>
<td>0.96(0.08)</td>
<td>0.97(0.08)</td>
<td>0.97(0.08)</td>
<td>0.96(0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.19(0.05)***</td>
<td>0.27(0.06)***</td>
<td>0.38(0.11)***</td>
<td>0.47(0.14)***</td>
<td>0.47(0.14)*</td>
<td>0.48(0.14)*</td>
<td></td>
</tr>
</tbody>
</table>

Fixed Effects: School Level

| Percent School Black        | 1.58(0.15)*** | 1.39(0.16)** | 1.37(0.14)** |
| Percent School Hispanic     | 1.1(0.08) | 1.1(0.07) | 1.0(0.07) |
| Percent School Free Lunch   | 0.83(0.06)** | 1.01(0.08) | 0.98(0.08) |
| Math Teacher's Expectations | 1.06(0.13) | 1.09(0.13) |
| Highest Math Course (Avg.)  | 2.33(0.3)*** | 2.43(0.31)*** |
| Staff Expectations          | 0.92(0.1) |
| School Problems             | 1.29(0.2) |
| Intercept                   | 2.14(.31)*** | 2.14(0.34)*** | 2.11(0.86) | 1.28(0.57) | 1.76(0.75) | 2.39(0.95)* | 2.57(1.04)* |

Random Effects

| Random Intercept Variance   | 2.43(0.5)*** | 2.08(0.42)*** | 3.18(0.69)*** | 3.52(0.73)*** | 2.99(0.62)*** | 1.94(0.47)*** | 1.87(0.44)*** |
| Observations                | 6918         | 6918         | 6918         | 6918         | 6918         | 6918         | 6918         |

Note: Odds Ratios followed by Robust Standard Error in Parentheses

*p <.05  **p <.01  ***p <.001
### Table 1.3. Mixed Effects Logistic Regression on the Influences of Math Achievement on Dropout Status

<table>
<thead>
<tr>
<th>Fixed Effects: Student Level</th>
<th>Model 2a</th>
<th>Model 2b</th>
<th>Model 2c</th>
<th>Model 2d</th>
<th>Model 2e</th>
<th>Model 2f</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender: Female</td>
<td>0.74(0.25)</td>
<td>0.88(0.32)</td>
<td>0.88(0.32)</td>
<td>0.89(0.32)</td>
<td>0.91(0.32)</td>
<td></td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.47(0.26)</td>
<td>0.52(0.28)</td>
<td>0.24(0.12)**</td>
<td>0.28(0.13)**</td>
<td>0.28(0.13)**</td>
<td></td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.73(0.42)</td>
<td>0.69(0.43)</td>
<td>0.53(0.36)</td>
<td>0.6(0.39)</td>
<td>0.61(0.39)</td>
<td></td>
</tr>
<tr>
<td>SES</td>
<td>0.41(0.1)***</td>
<td>0.49(0.13)**</td>
<td>0.53(0.13)**</td>
<td>0.53(0.12)**</td>
<td>0.54(0.12)**</td>
<td></td>
</tr>
<tr>
<td>Single-Parent Household</td>
<td>0.95(0.38)</td>
<td>0.87(0.36)</td>
<td>0.83(0.32)</td>
<td>0.84(0.32)</td>
<td>0.82(0.32)</td>
<td></td>
</tr>
<tr>
<td>Dropout History</td>
<td>0.94(0.9)</td>
<td>0.96(0.94)</td>
<td>0.94(0.94)</td>
<td>0.91(0.89)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th Student Expectations</td>
<td>0.44(0.15)*</td>
<td>0.45(0.16)*</td>
<td>0.46(0.16)*</td>
<td>0.45(0.15)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th School Belonging</td>
<td>1.29(0.25)</td>
<td>1.25(0.23)</td>
<td>1.28(0.23)</td>
<td>1.28(0.23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th School Engagement</td>
<td>0.98(0.19)</td>
<td>1.0(0.19)</td>
<td>1.01(0.19)</td>
<td>1.02(0.19)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>1.92(0.41)**</td>
<td>1.9(0.39)**</td>
<td>1.88(0.38)**</td>
<td>1.87(0.38)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absences</td>
<td>1.11(0.22)</td>
<td>1.14(0.23)</td>
<td>1.16(0.22)</td>
<td>1.15(0.22)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>4.32(1.81)**</td>
<td>3.94(1.64)**</td>
<td>3.71(1.54)**</td>
<td>3.77(1.56)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Course</td>
<td>0.64(0.1)****</td>
<td>0.66(0.1)****</td>
<td>0.66(0.11)*</td>
<td>0.68(0.11)*</td>
<td>0.67(0.11)*</td>
<td></td>
</tr>
<tr>
<td>Lower Algebra I Grade</td>
<td>2.8(0.47)***</td>
<td>2.69(0.44)***</td>
<td>2.38(0.38)***</td>
<td>2.29(0.36)***</td>
<td>2.27(0.36)***</td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Test</td>
<td>0.98(0.02)</td>
<td>0.99(0.02)</td>
<td>1.0(0.03)</td>
<td>1.01(0.02)</td>
<td>1.01(0.02)</td>
<td></td>
</tr>
<tr>
<td>9th Grade Math Attitudes</td>
<td>0.79(0.1)</td>
<td>0.79(0.1)</td>
<td>0.76(0.09)*</td>
<td>0.75(0.09)*</td>
<td>0.75(0.09)*</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effects: School Level</th>
<th>Model 2a</th>
<th>Model 2b</th>
<th>Model 2c</th>
<th>Model 2d</th>
<th>Model 2e</th>
<th>Model 2f</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent School Black</td>
<td>1.29(0.15)*</td>
<td>1.34(0.16)*</td>
<td>1.33(0.16)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent School Hispanic</td>
<td>1.12(0.15)</td>
<td>1.15(0.15)</td>
<td>1.15(0.15)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Free Lunch</td>
<td>1.03(0.15)</td>
<td>0.93(0.14)</td>
<td>0.91(0.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Math Teacher’s Expectations</td>
<td>0.81(0.23)</td>
<td>0.83(0.24)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highest Math Course (Average)</td>
<td>0.67(0.12)*</td>
<td>0.69(0.13)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Staff Expectations</td>
<td>0.98(0.15)</td>
<td>0.98(0.15)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Problems</td>
<td>1.25(0.31)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0006(.0004)***</td>
<td>0.0007(.0005)***</td>
<td>0.0008(.0006)***</td>
<td>0.001(.0008)***</td>
<td>0.0008(.0007)***</td>
<td>0.0009(.0007)***</td>
</tr>
</tbody>
</table>

**Random Effects**

<table>
<thead>
<tr>
<th></th>
<th>Model 2a</th>
<th>Model 2b</th>
<th>Model 2c</th>
<th>Model 2d</th>
<th>Model 2e</th>
<th>Model 2f</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Intercept Variance</td>
<td>2.91(1.17)*</td>
<td>3.04(1.17)**</td>
<td>3.1(1.21)*</td>
<td>2.82(1.12)*</td>
<td>2.52(1.12)*</td>
<td>2.54(1.14)*</td>
</tr>
<tr>
<td>Observations</td>
<td>6,005</td>
<td>6,005</td>
<td>6,005</td>
<td>6,005</td>
<td>6,005</td>
<td>6,005</td>
</tr>
</tbody>
</table>

*Note: Odds Ratios followed by Robust Standard Error in Parentheses

* p < .05  ** p < .01  *** p < .001
In regards to our first question, after all other student and school-level features were considered, students who received ISS in grade 11 were associated with a 32% chance of taking an advanced mathematics course by the end of 12th grade. Given the nation’s concern for international competitiveness in STEM, as well as the increasing demand for STEM workers that routinely exceeds the labor supply, we view 32% as a dismal recovery of an ever expanding segment of our school-age population—suspended students. Indeed, there are large human capital costs to STEM fields that are hidden in school attempts to “maintain order” through exclusionary discipline. Moreover, it is important to note that while the influence of ISS marginally lessened with the addition of student-level characteristics, it remained practically unchanged with the addition of school-level features.

Moving on to our second question, after all other student and school-level features were considered, students who demonstrated high levels of early math achievement—specifically, taking a higher level math course in 9th grade, receiving a higher Algebra 1 course grade, participating in an extracurricular math activity, and having more positive attitudes towards math—were less likely depart school before graduating. Given the decreasing rates of employment and increasing rates of incarceration for students that don’t graduate high school—and the social costs associated with these students, we view early math achievement as a prime opportunity for avoiding this hazard. Additionally, with the exception of 9th grade math course, which remained practically unchanged, and math attitudes, which became significant with the addition of student discipline and attachment-related measures, the influence of early math achievement-related measures experienced a slight overall decrease with the addition of student and school-level features. Finally, besides extracurricular math activities, ISS had the strongest
influence on dropout status: students who received an ISS in 11th grade were associated with a 79% chance of dropping out by the end of 12th grade.

In both cases, within-trajectory influences were strong in the presence of cross-trajectory influences. Thus, while decreasing suspensions can increase math attainment, it cannot erase the influence of low early math achievement; conversely, while increasing early math achievement can decrease premature school departure, it cannot erase the influence of prior suspensions. Moreover, the addition of within-trajectory influences only marginally lessened the impact of cross-trajectory influences (and only did so in some cases for math achievement). Thus, high early math achievement cannot buffer the full effect of suspensions on math attainment, nor can good discipline buffer the full effect of low early math achievement on premature school departure. As a result, current disciplinary reforms that seek to reduce suspensions might increase the likelihood that students would complete school, as well as the likelihood that students would take advanced math courses. However, even with a reduction of suspensions, students who experience early setbacks in math still may be unable to avoid premature school departure. Moreover, even if these students were able to complete high school, they may be unable to do so with having taken advanced math courses. On the other hand, current math reforms that seek to increase early math achievement might increase the likelihood that students would take advanced math courses, as well as the likelihood that students would complete school. However, even with an increase of early math achievement, students who receive suspensions may still be unable to take advanced math courses. Moreover, even if these students were able to take advanced math courses, they may be unable to obtain a high school diploma that would afford them the greatest opportunity to take advantage of these courses in future educational and occupational markets.
Finally, in regards to our last question, our analysis also revealed some important results regarding race. First, Black students appeared more likely to take advanced math courses until school features were considered in our models, after which point, there was little significant variation in advanced math course-taking along the dimension of students’ race. In contrast, at the school-level, the proportion of Black students did appear positively related to students’ advanced math course-taking, which is consistent with prior literature on homogenous school contexts. Here, the average advantage that individual Black students had in advanced math course-taking may have extended from school-level Black enrollment rates.

Additionally, Black students had the most significantly reduced odds of dropout status among racial groups once school features were considered, underscoring the importance of school conditions in investigations of Black students’ rates of dropping out. However, as we observed that Black students had significantly reduced odds of dropping out, paradoxically, students in schools with higher percentages of Black students appeared to have significantly increased odds of dropping out. While the majority of Black students did not attend majority-Black schools in this study (only 13% of the Black students in our sample attended a school where over 50% of the school population was Black), this paradox suggests that the structure of opportunity is different in schools where Black students are in greater numbers. Here, higher proportions of Black students within schools, which may represent racial segregation, can be seen as depriving students in these schools of the greater educational attainment (i.e. completing high school) that might otherwise be obtained in less segregated contexts, while simultaneously placing these students in schools where they are more likely to take advanced math courses. Future research is needed to determine at what levels of Black enrollment are the odds of dropout status and advanced math course-taking likely to differ or become non-linear. Thus, when
considering school-level features, the structure of school opportunity in math and discipline seemed to be most consequential to Black students, while the other aspects of the math achievement, and to a lesser degree—suspensions—seemed resilient to school features.

2.6 Conclusion

When considering implications for policy and practice, our findings lead us to three important conclusions. First, given the significance of within-trajectory influences—even in the presence of cross-trajectory influences, we conclude that interventions must work across both academics and discipline. Here, decreasing suspensions and increasing early math achievement must both occur in order to redirect students away from disciplinary trajectories and towards STEM trajectories. Second, while ISS was initially conceptualized as a less-severe and more productive alternative to out-of-school suspension, its impacts revealed in this study do not reflect these intentions. Thus, school systems that implement moratoriums on out-of-school suspensions should be cautious if they replace these sanctions with in-school suspensions. Third, our findings suggest that reducing racial segregation in schools is key to decreasing instances of dropping out, but also antithetical to maximizing the participation in advanced math course-taking for students within predominantly Black schools. Thus, while reducing racial segregation between schools should be accompanied with measures for integrating advanced classrooms within these schools, targeting predominantly Black schools with suspension-reducing reforms could increase the number of students that these schools can direct toward higher math attainment.

Finally, while interacting both sides of the coin demonstrated the reciprocal relationships among discipline and academics—often highlighting the pitfalls that many of our most marginalized students are prone to, there is much promise in potential reforms. Black students
who take advanced math and science courses are just as likely as White students to pursue STEM degrees (Tyson, Lee, Borman, & Hanson, 2007). Additionally, Black students who graduate college have lowered incarceration rates that are similar to White college graduates (Sum, Khatiwada, McLaughlin, & Palma, 2009). Thus, efforts to increase equity within and across schools by both reducing suspensions and increasing early math achievement have the potential to redirect students away from disciplinary trajectories and towards STEM trajectories. These combined efforts should therefore be a priority for all stakeholders.
References


Teachers College Record, 115(1), 1–27.


Chapter 3: The Process of ‘Pushing Out’: An Intersectional Analysis of the Interactions among School-to-Prison and STEM Pipelines

According to the Current Population Survey (CPS) of 2014, the dropout rate in the US was 6.5%, with Black (7.4%), Hispanic (10.6%), Male (7.1%), and low-income (11.6%) students demonstrating the highest rates dropping out (Mcfarland, Cui, & Stark, 2018). As the US economy increases its demands for science, technology, engineering, and math (STEM) workers (Fayer, Lacey, & Watson, 2017), dropping out has an increasingly important impact on employment. For example, in 2014 only 44.7% of individuals who dropped out were employed, which was 8.3% less than the percent of dropouts who were employed just ten years earlier in 2004 (Mcfarland, Cui, & Stark, 2018). Furthermore, employment rates for Black students who dropped out were far worse—31.2% according the CPS of 2008 (Sum, Khatiwada, McLaughlin, & Palma, 2009). Moreover, dropping out not only decreases rates of employment, but also increases rates of incarceration. According to the 2006-2007 American Community Survey (ACS), 6.3% of dropouts were institutionalized (93% of whom were in correctional facilities), which again, was more common among students of color, especially those who are male: 22.9% of Black-male dropouts were institutionalized (Sum et al., 2009). Of course, dropping out not only has a negative impact on the individuals directly impacted, but also on the larger economies and societies in which these individuals are embedded. For example, Alvarez et al. (2009) estimated that the total social cost of dropouts for a single Texas cohort—when considering lost wages and tax revenues, as well as welfare and criminal justice expenses—totaled between $5.4 billion and $9.6 billion.
While students drop out for a variety of reasons, Bradley and Renzulli (2011) note that students are pushed out of school when they exhibit traits that are deemed undesirable to school officials. Here, pushing out involves a process of convergence among academic and disciplinary school components that tend to target low-income students and students of color, such as limited access to high-quality academic opportunities and an over-reliance on exclusionary discipline practices (Mission, 2018). While there are many aspects of high-quality academic opportunities that when absent can have the effect of pushing students out of schools, STEM learning opportunities are uniquely important, as they prepare students—especially those from underserved groups—for both college and high-skilled employment (Trusty & Niles, 2003; Tyson, Lee, Borman, & Hanson, 2007). Moreover, the convergence of the STEM and school-to-prison (STP) pipelines in the pushout phenomenon are emblematic of how divergent opportunity structures that begin in schools can be carried out to the detriment of both individuals and the larger societies that they are embedded in. Finally, mirroring the demographic makeup of pushouts, many of the same groups that are underrepresented in STEM are also overrepresented in suspensions (Skiba, Chung, Trachok, Baker, Sheya, Hughes, 2014) and, ultimately, the criminal justice system (Pettit & Western, 2004). For example, while just 13% of engineers were Black or Hispanic in 2015 (Pew Research Center, 2018b), the combined percentage of these individuals who were incarcerated was 56% (Pew Research Center, 2018a).

While these trends suggest that altering the process of pushing students out of school may involve both filling the STEM pipeline and draining the school-to-prison (STP) pipeline, there is little research that measures how these pipelines are related both to each other and to the larger phenomenon of pushouts. Generating knowledge as to how these two opportunity structures interact in perpetuating the process of pushing students out of school would inform future efforts
seeking to redirect students from the school-to-prison pipeline to the STEM pipeline and, ultimately, reduce the number of pushouts.

In this article we demonstrate that suspensions significantly decrease math achievement and that the significant interactions among the school-to-prison (STP) and STEM pipelines have the effect of pushing students out of high school over time. Moreover, we demonstrate that the accumulation and saturation of advantages and disadvantages within and across these pipelines is different for unique race and gender identities and intersections. We conclude with a discussion of how these findings can inform future policies and practices.

3.1 Literature Review

3.1.1 Academic and Disciplinary Pipelines

Science, Technology, Engineering, and Math (STEM) Pipeline. More than a metaphor, the STEM pipeline consists of formal learning opportunities that allow students to gain prized forms of highly stratified knowledge (Gamoran, 1987). This knowledge can then be used to afford students mobility within secondary and post-secondary educational institutions and eventually be allocated into economic opportunities in the labor market (Blau & Duncan 1967). Here, students who have demonstrated high levels of math course-taking, ability, and attitudes, have higher rates of taking advanced STEM courses, attending college, majoring in a STEM subject, and securing a STEM job (see Pajares & Miller, 1995, Rose & Betts 2001, Tai, Liu, Maltese, & Fan, 2006). Furthermore, as evidenced by the widening NAEP mathematics test-score gap across grade groups (Musu-Gillette et al., 2017) and the much lower number of students that complete post-secondary STEM training compared to those that start (NSF, 2014), inequality in the STEM pipeline grows over time. Additionally, as STEM achievement is also related to a decrease in dropout status that is net of behavioral infractions (Jabbari & Johnson,
the STEM pipeline can be thought of as an increasing trajectory of inclusion—not only in selective STEM classrooms, college majors, and career fields, but also in formal educational institutions. Finally, in terms of its contents, recent research has suggested that among the strongest predictors of persistence in the STEM pipeline are advanced math and science course-taking in high school (Engberg & Wolniak, 2013), math ability (Wai, Lubinski, & Benbow, 2009), and math attitudes, which are closely related to math identity (Hazari, Sonnert, Sadler, & Shanahan, 2010).

**School to Prison (STP) Pipeline.** As a primary institution of social reproduction (Bourdieu & Passerson, 1977), schools not only provide “opportunities” for students to fill occupational roles in our society, such as those found in STEM (Thomasian, 2011), but also to fill carceral roles in our society, such as those found in the prison industrial complex (Hirschfield, 2008). The socialization process that prepares certain segments of the population—often poor students of color—for prison includes a variety of surveillance and punishment strategies that together operate as a continuum of educational exclusion. Here, students who have been suspended have a higher risk of dropping out in the future (Skiba, Simmons, Staudinger, Rausch, Dow, & Feggins, 2003; Suh, Suh, & Houston, 2007), and students who have dropped out have a higher risk of being arrested in the future (Christle, Jolivette, & Nelson 2005). Thus, students on the criminal justice “track” are successively excluded from classrooms (in-school suspension), schools (out-of-school suspension), formal education (being pushed out), and society (incarceration)—with each successive level of exclusion often having a substantially longer duration and larger impact on the individual. Finally, recent research has confirmed this continuum of educational exclusion by demonstrating that these successive junctures within the educational exclusion continuum all share direct connections with suspensions, which often
operates as the gateway to the STP pipeline. For example, in a comprehensive study in Texas, 10% of the students who were suspended or expelled between 7th and 12th grade were pushed out; 59% of students with multiple suspensions did not graduate; and students who were suspended or expelled for discretionary violations, which made up the majority of all suspensions, were nearly three times as likely to be in contact with the juvenile justice system the following year (Fabelo, et al., 2011, p. xii).

3.1.2 Interactional and Intersectional Theories of Discipline and Academics

**Interactional theory.** Our conceptualization of cross-pipeline dynamics and their contribution to pushouts builds on Thornberry’s (1987) interactional theory of delinquency. Supported by Thornberry, Lizotte, Krohn, Farnworth, and Jang’s (1994) research, interactional theory asserts that weaker social constraints resulting from decreased commitment to schools can lead to greater allowances for delinquency to be learned, performed, and reinforced, which can ultimately lead to increasing trajectories of delinquency over the life course. While much of the work on interactional theory focuses on the reciprocal effects of misbehavior, we follow Jabbari & Johnson, 2019) and instead focus on the sanctions to perceived misbehavior. In doing so, we are able uncover how disciplinary opportunity structures, such as suspensions, interact with academic opportunity structures, such as STEM, which may ultimately perpetuate the process of pushing students out of school.

**Interactions among the STEM and STP pipelines.** Starting with STEM trajectories, suspensions have been negatively associated with math achievement (Lacoe and Steinberge, 2018) and advanced math course taking (Jabbari & Johnson, 2019) in high schools. Beyond STEM, suspensions have been associated with decreased interest in schools (Costenbader & Markson, 1998) and decreased rates of college enrollment (Balfanz, Byrnes, & Fox, 2015).
Moving on to disciplinary trajectories, Martin, Martin, Gibson, and Wilkins (2007) found that increased math achievement was related to decreased discipline referrals and suspensions. Beyond STEM, Arcia (2006) found that students who were suspended had substantially lower reading levels before suspension.

**Intersectional Theory.** As Thornberry (1987) suggests that race/ethnicity, gender, and class are systematically related to the interactions among discipline and academics, intersectional theories must also be considered. Stemming from Black feminist thought, intersectionality holds that as multiple systems of power work to oppress multiple dimensions of identity, those that simultaneously occupy multiple dimensions of oppressed identities operate in uniquely oppressed spaces in society (Collins, 1990). Here, the simultaneous consideration of multiple social dimensions provides a more complete depiction of oppression than considering those same attributes separately. 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 privileges 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 privileges among identities vary across opportunities structures.

These conditions are particularly prevalent in research on race/ethnicity and gender across STEM and discipline. For example, when considering how privileges within opportunity structures may not be uniformly experienced across broader identity dimensions, the male gender can operate as a source of privilege in STEM, yet Black-Males have been shown to face unique barriers in both STEM education and the STEM labor market (Bidwell, 2015); conversely, the female gender can operate as a source of privilege in school discipline and the criminal justice
system, yet Black-females are often targeted for suspensions (Losen & Skiba, 2010) and criminal offenses (Bush-Baskette, 1998). Additionally, when considering how varying intersections of identity can respond differently to distinct facets of opportunity structures, observing math course-taking or ability in the absence of math attitudes may predict STEM pipeline persistent for White-male students, but not White-female students; conversely, observing math attitudes in the absence of math course-taking or ability may predict STEM pipeline persistent for White-male students, but not Black-male students (Riegle-Crumb, Moore, & Ramos-Wada, 2011).

Finally, when considering how competing privileges among identities can vary across opportunities structures, Black-females may not receive the social benefits of their gender in disciplinary matters, while also incurring a social cost for their race/ethnicity in academic matters.

Specifically, we will use intersectionality to understand how the effects associated with advantages and disadvantages that stem from intersectional identities—in relation to both the discipline and academics—are either “accumulated” or “saturated.” In the context of discipline and academics, accumulated effects refer to the extent to which multiply disadvantaged students experience larger effects from setbacks because they cannot afford “second chances” in the same way that multiply advantaged students can (Hannon, 2003). Conversely, saturated effects refer to the extent to which multiply disadvantaged students experience smaller effects from setbacks because they have “less to lose” than multiply advantaged students do (2003). While Hannon (2003) found that greater potential obstacles and fewer possible opportunities had a saturating effect on the impact of delinquency on academics, Schiller and Hunt (2011) found that disadvantages were accumulated within math.
Intersections of race/ethnicity and gender among the STP and STEM pipelines.

Students’ involvement within the STP pipeline implicates relationships with and among race/ethnicity and gender that are inversely related to the STEM pipeline. For example, Black 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, Horner, Choong-Geun, Rausch, May, & Tobin, 2011). At the same time, the gap between Black and White students in math achievement has been significantly increasing since 1990 (Vanneman, Hamilton, Anderson, & Rahman, 2009). In both cases, it is important to note that these racial differences were not due to social class differences within suspensions (Wallace, Goodkind, Wallace, and Bachman, 2008) or math achievement (Lubienski, 2002).

Furthermore, while gender does not appear to share a similar inverse relationship among these pipelines, as male students are often overrepresented in both the STP (Skiba, Michael, Nardo, and Peterson, 2002; Federal Bureau of Prisons, 2018) and STEM pipelines (Ercikan, McCreith, LaPointe, 2005; Good, Aronson, Harder, 2008), some of the intersections of race/ethnicity and gender do share inverse relationships among these pipelines. For example, when compared to White-males, Black-males are often overrepresented in suspensions in both middle (Losen & Skiba, 2010) and high schools (Mendez & Knoff, 2003). At the same time, Black males often receive lower returns on early math courses (Riegle-Crumb, 2006), while demonstrating lower levels of STEM achievement despite similar STEM aspirations (Riegle-Crumb, Moore, & Ramos-Wada, 2011). Finally, when comparing intersectional trends in the literature among these competing pipelines, nuances emerged that deserve further exploration. For example, while Mendez and Knoff (2003) found that Black-females had higher rates of
suspension than White-males, Hanson (2004) demonstrated that Black-females also had more positive attitudes towards and higher interests in science than White-females.

### 3.2 Research Gaps, Objectives, and Questions

While prior research has theorized the link between discipline and academics (Gregory, Skiba, & Noguera, 2010), their structural relationships both in the short and long-term have not previously been tested. Rather, the impacts of discipline on academics and vice-versa—*when tested*—have mostly been researched in a recursive, as opposed to a reciprocal, manner. Furthermore, when considering the multifaceted nature of academic achievement trajectories, which—as seen in the STEM pipeline—can include course-taking, ability, and attitudes, previous research has also been unable to account for the inherent intricacy found within academic achievement and its relationship with discipline. Moreover, when considering the tendency for these trajectories to be studied in isolation, shared outcomes, such as dropout status, are often viewed as separately derived phenomena, which can “squeeze out complexity” in intrinsically complex phenomena (see Cannady, Greenwald, & Harris, 2014; McGrew, 2016). Unsurprisingly, given the inability for previous research to demonstrate the reciprocal structural relations among discipline and a comprehensive measure of academic achievement over time, previous research has also been unable to address how the accumulation and saturation of advantages and disadvantages—stemming from various dimensions and intersections of identity—operates within and across disciplinary and academic trajectories.

As the combination of interactional and intersectional theories require that we examine the interactions among discipline and multiple facets of academic opportunity structures for multiple identities and identity intersections, the analysis of reciprocal structural relationships with latent variables for population subsamples becomes necessary. Thus, we will utilize latent
difference score and structural equation models, which are able test the impact of an observed variable on a latent construct over time, as well as ascertain the significance and strength of multiple hypothesized structural relationships simultaneously for multiple groups (Kline, 2015). As a result, we will be able to demonstrate the short-term impact of discipline on a latent construct of math achievement, as well as the long-term interactions among the STP and STEM pipelines—and how these interactions continually and differentially perpetuate the process by which students from various dimensions and intersections of identity are pushed out of school. In doing so, we pose the following questions:

I. What is the short-term impact of receiving a suspension on math achievement?

II. What are the long-term interactions among the STP and STEM pipelines in high school and how do they relate to the process of pushing students out of school?

III. How do the long-term interactions among the STP and STEM pipelines compare across different dimensions and intersections of identity, specifically race and gender?

### 3.3 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, Pratt, Herget, Burns, Dever, Ottem, Rogers, Jin & Leinwand, 2011). The analyses in this article utilized all currently available waves, which included student and parent data from the Base Year (fall of 9th grade), First Follow-Up (spring of 11th grade), 2013 Update (spring of 12th grade), and High School Transcript. While instances of non-response occurred both within waves (for different questionnaire types) and across waves, the NCES did provide analytic weights to account for these instances of non-response, as well as instances of sampling inefficiencies that
are inherent to a stratified sampling approach. Specifically, the W3W1W2STUTR weight was used in all analyses, which accounts for all four waves. The inclusion of this sample weight can be seen as a corrective measure for retaining much of the sample’s original representation.

Finally, the confirmatory factor analysis (CFA) and latent difference score (LDS) models relied on full-information maximum likelihood (FIML) estimators, which utilized all information present for each subject when arriving at an estimate. While this resulted in the full sample being retained in the LDS model (N = 25,206), because the CFA model did not include all of the variables used in the LDS model, the sample experienced a slight decrease (N = 23,485).

Conversely, the structural equation model (SEM) relied on a mean and variance-adjusted weighted least squares (WSLMV) estimator, which did utilize multiply imputed data. With all study variables having less than 5% of their responses missing, multiple imputation using chained equations (MICE) were used to impute 5 sets of missing values (White, Royston, & Wood, 2011). Here, it is important to note that within-wave attrition (due to both parent and student questionnaires being utilized), across-wave attrition (due to all four survey waves being utilized), as well as list-wise deletion (due to our decision not to impute outcome and key demographic variables), resulted in a sample of 16,510 students in the Structural Equation Model.

### 3.4 Measures

Latent constructs of math achievement were created from math identity, math test score, and math course level variables in order to represent snapshots of both early and later math achievement during high school. Collected during the fall of freshman year of high school and spring of junior year of high school, math identity was a continuous 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 (ranging from -1.73 to 1.76 during freshman year and from -1.54 to 1.82 during junior year). Similarly, math test score consisted of a continuous, norm-referenced theta value depicting performance on a test that focused on algebraic reasoning (ranging from -2.58 to 3.03 during freshman year and from -2.60 to 4.50 during junior year). Finally, math course level was a continuous variable that represented the highest level math course taken by the end of a student’s 9th and 12th grade school years—originally ranging from 0 (no math) to 13 (AP/IB Calculus), this variable was standardized to match other construct variables and prevent the possibility of ill-scaling.

Additionally, suspension variables consisted of a parent reported binary measure of whether or not a their student had been suspended prior to high school (1 = yes; 0 = no), as well as a student reported binary measure—collected during the spring of junior year—of whether or not the student had received an in-school suspension within the last 6 months (1 = yes; 0 = no). While the latter measure does not capture all suspension types nor does it capture all suspension instances since the start of high school, it can serve as an appropriate proxy for a more common exclusionary discipline sanction that occurs before students’ later math achievement. Dropout status was defined as students who had dropped out of high school during the spring semester of 12th grade (1 = yes; 0 = no). This variable was created from the 2013 Update, and included students who were seeking an alternative route to high school completion, such as pursuing a GED. As students who drop out during 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.

Finally, demographic variables consisted of race/ethnicity—specifically being Black or Hispanic (1 = Black or Hispanic; 0 = not Black and not Hispanic), gender—specifically being
female (1 = female; 0 = male), and low social class (1 = bottom two SES quintiles; 0 = top three SES quintiles).

3.5 Methods and Results

In order to understand the short-term impacts of exclusionary discipline sanctions on math achievement, as well as the long-term interactions among the STP and STEM pipelines, how these interactions relate to the process of pushing out, and how these interactions vary for different intersections of identity, a variety of methodological steps were taken. First, confirmatory factor analysis (CFA) was used to create a valid latent construct of math achievement at two time points, which was then tested for measurement invariance; mean differences among groups were also tested. Second, latent difference score (LDS) modeling was used to test the short-term impacts of exclusionary discipline sanctions on this latent construct of math achievement. Finally, structural equation modeling (SEM) was used to test the long-term interactions among the STP and STEM pipelines, how these interactions related to the process of pushing out, and how they varied for different intersections of identity.

3.5.1 Parameterization, Estimation, and Standardization Techniques

All of our analytic steps utilized the ‘COMPLEX’ function in Mplus, which takes into account the cluster and stratification information found in the HSLS survey. While the CFA and LDS models utilized the delta parameterization technique, which does not allow for residual variances to be free parameters, the SEM models—because they contained categorical dependent variables that both influence and are influenced by observed dependent and latent variables—utilized a theta parameterization technique, which does allow for residual variances to be free parameters (Muthen & Muthen, 2017). This parameterization technique can be especially beneficial in longitudinal models (2017), such as the SEM model used in this article.
Furthermore, due to the different parametrization techniques in each process, it is important to note that the estimators were also different. In the CFA and LDS models, a Robust Maximum Likelihood (MLR) estimator was used (specifically, FIML), which employs a “sandwich” technique to compute standard errors and is robust to both non-normality and non-independence of observations (Muthen & Muthen, 2017). Conversely, in the structural equation model, the mean and variance-adjusted weighted least squares WSLMV estimator was used, which involves both diagonal and full weight matrixes to compute standard errors and is robust to categorical measures (2017). As a result, probit regression was utilized for the categorical outcomes in the SEM model, which relies on underlying continuous variables (2017).

Moreover, in terms of path coefficients, Muthen and Muthen (2017) recommend using the STDY standardization for binary independent variables (interpreted as the change in standard deviation units in Y when X change from 0 to 1) and STDYX standardization for continuous independent variables (interpreted as the change in standard deviation units of Y for a one standard deviation change in X). However, when comparing path coefficients across groups, it is recommended that unstandardized coefficients are used, as groups may have different variances on both latent and observed variables (2017).

Finally, for assessing power, we utilized MacCallum, Browne, and Sugawara’s (1996) ‘non close-fit’ power formula, which provides a conservative estimate of power. Results for our latent difference score and structural equation model analyses, as well as all identity intersection subsample analyses, had a power value of 1.0, which is excellent.

3.5.2 Developing a Latent Construct of Math Achievement

The latent construct of math achievement—derived from math identity, test score, and course level variables—can be described as a longitudinal, two time-point construct. Because of
the longitudinal nature of the data, factor loadings at time-point one were correlated with factor loadings at time-point two (Figure 3.1). All factor loadings were statistically significant and had standardized values above 0.4, which exceeds the threshold recommended by Stevens (1992). Additionally, the model contained excellent fit statistics in term of Root Mean Square Error of Approximation (RMSEA) and Confirmatory Fit Index (CFI). Here the RMSEA value of 0.005 and the CFI value of 1.0 exceeds the thresholds recommended by Hu and Bentler (1999).

Invariances Testing. After identifying the measurement model, two types of invariance tests were performed—longitudinal invariance and group invariance. Testing the longitudinal invariance of our measurement model involved testing the difference between a freely estimated model derived from the same set of factor loadings across time (the configural model), a model where the factor loadings from time points one and two were constrained to be equal (the metric model), and a model where the factor loadings and item intercepts from time points one and two were constrained to be equal (scalar model). Because we utilized an MLR estimator in developing our latent construct of math achievement, we were provided with a scaling correction factor, which we used in calculating Satorra-Bentler Chi-Square difference tests for measurement invariance. While the metric and scalar models were both statistically different from the configural model, it is important to note that chi-square tests can be vulnerable to large samples (see Byrne, 2013). On this point, Chung & Rensvold (2002), among others, argue that models with CFI values within +/- 0.01 points from nested models are practically similar. Therefore, because the CFI value of the metric model (0.99) was within +/- 0.01 points of the configural model (1.00), we consider it to be longitudinally invariant in this case. Conversely, because the CFI value of the scalar model (0.94) was considerably beyond +/- 0.01 points of the configural model, we consider it longitudinally non-invariant in this case. When considering the nature of
these item intercepts, it is unsurprising that their starting values differ at time points one and two. Thus, while the latent constructs of math achievement can be considered to have the same meaning across time, mean comparisons of math achievement constructs over time is not appropriate in this study.

Next, group invariance of our measurement model was tested using Mplus’s ‘CONFIGURAL METRIC SCALAR’ command. We tested group invariance for race/ethnicity (Black vs. White students), gender (females vs. males), and racial/ethnic-gender intersectional groups (Black-Females, Black-Males, White-Females, and White-Males). Results demonstrate that all groups were found to have statistical metric invariance (equivalent factor loadings), but no groups were found to have statistical scalar invariance (equivalent item intercepts). However, for race/ethnicity and gender, the CFI values for scalar models (0.99) were within +/- 0.01 of the configural model (1.00), which indicates practical scalar invariance. Nevertheless, for intersectional groups, the CFI value for the scalar model (0.98) was slightly beyond +/- 0.01 points of the configural model (1.00). As a result, we used the modification indexes to select the minimum amount of item intercept parameters to free in order to increase our CFI value to within +/-0.01 of the configural model. Increasing our CFI value to 0.99 entailed freeing the math identity intercept for White-Females in math achievement at time-points one and two. This partially invariant scalar model allowed for mean comparisons on math achievement among intersectional groups. Results of invariance tests can be found in Tables 3.1-3.3.
Table 3.1
*Longitudinal Invariance for Math 1 and Math 2*

<table>
<thead>
<tr>
<th></th>
<th>Chi-Square</th>
<th>DF</th>
<th>P-Value</th>
<th>Scaling Correction</th>
<th>RMSEA</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Math 2 : Math 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Configural Model</td>
<td>6.20</td>
<td>5</td>
<td>0.287</td>
<td>4.36</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Metric Model</td>
<td>119.92</td>
<td>7</td>
<td>0.000</td>
<td>4.71</td>
<td>0.03</td>
<td>0.99</td>
</tr>
<tr>
<td>Scalar Model</td>
<td>694.66</td>
<td>9</td>
<td>0.000</td>
<td>4.65</td>
<td>0.06</td>
<td>0.94</td>
</tr>
<tr>
<td>Metric to Configural</td>
<td>96.29 (Δ)</td>
<td>2 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Configural</td>
<td>639.03 (Δ)</td>
<td>4 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Metric</td>
<td>600.30 (Δ)</td>
<td>2 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2
*Race and Gender Group Invariance for Math 1 and Math 2*

<table>
<thead>
<tr>
<th></th>
<th>Chi Square</th>
<th>DF</th>
<th>P-Value</th>
<th>Scaling correction</th>
<th>RMSEA</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Female : Male</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Configural Model</td>
<td>7.68</td>
<td>10</td>
<td>0.660</td>
<td>4.32</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Metric Model</td>
<td>12.26</td>
<td>14</td>
<td>0.585</td>
<td>4.21</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Scalar Model</td>
<td>110.56</td>
<td>18</td>
<td>0.000</td>
<td>4.42</td>
<td>0.02</td>
<td>0.99</td>
</tr>
<tr>
<td>Metric to Configural</td>
<td>4.68 (Δ)</td>
<td>4 (Δ)</td>
<td>0.322</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Configural</td>
<td>100.59 (Δ)</td>
<td>8 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Metric</td>
<td>85.25 (Δ)</td>
<td>4 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Black : White</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Configural Model</td>
<td>14.99</td>
<td>10</td>
<td>0.133</td>
<td>4.93</td>
<td>0.01</td>
<td>1.00</td>
</tr>
<tr>
<td>Metric Model</td>
<td>19.75</td>
<td>14</td>
<td>0.138</td>
<td>4.67</td>
<td>0.01</td>
<td>1.00</td>
</tr>
<tr>
<td>Scalar Model</td>
<td>107.45</td>
<td>18</td>
<td>0.000</td>
<td>4.74</td>
<td>0.02</td>
<td>0.99</td>
</tr>
<tr>
<td>Metric to Configural</td>
<td>4.56 (Δ)</td>
<td>4 (Δ)</td>
<td>0.335</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Configural</td>
<td>96.63 (Δ)</td>
<td>8 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scalar to Metric</td>
<td>83.37 (Δ)</td>
<td>4 (Δ)</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.3

<table>
<thead>
<tr>
<th>Race-Gender Group Invariance for Math 1 and Math 2 across Black-Females, Black-Males, White-Females and White-Males</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race-Gender (Original)</td>
</tr>
<tr>
<td>Configural Model</td>
</tr>
<tr>
<td>Metric Model</td>
</tr>
<tr>
<td>Scalar Model</td>
</tr>
<tr>
<td>Metric to Configural</td>
</tr>
<tr>
<td>Scalar to Configural</td>
</tr>
<tr>
<td>Scalar to Metric</td>
</tr>
<tr>
<td>Race-Gender (Partial)</td>
</tr>
<tr>
<td>Scalar Model</td>
</tr>
<tr>
<td>Scalar to Configural</td>
</tr>
<tr>
<td>Scalar to Metric</td>
</tr>
</tbody>
</table>

*Note: The Partial Scalar Model Freely Estimated Math Identity for White-Females in Math 1 and Math 2.*
3.5.3 Group Differences

**Latent Variable Means.** Latent mean comparisons involved constraining the mean of the comparison group to equal zero, while allowing the mean(s) of the other group(s) to be freely estimated. While there was not a significant difference between females and males, Black students had significantly lower math achievement than White students. Alternating the reference group for intersectional comparisons, we found that there were no significant differences between White-females and White-males, and a relatively small difference between Black-females and Black-males—with Black-females having slightly higher math achievement than Black-males. The largest differences were across race/ethnicity, as White-females and White-males had (similar) higher math achievement than Black-females and—to a slightly greater extent—Black-males. Finally, it is important to note that even though these intersectional mean comparisons were conducted with partially invariant math achievement constructs, the results were nearly identical to comparisons with the original constructs. While we can assume that the small differences in model fit (CFI) did not substantially impact mean comparisons, future work should further explore the role of math identity for White-females, as the relationship between the starting values of these item intercepts and their latent constructs were slightly different from other intersectional groups. Latent variable mean comparisons can be found in Table 3.4, as well as figures 3.2-3.5.

**Observed Variable Proportions.** Black students experienced pre-HS suspension at over twice the rate as White students, and male students experienced pre-HS suspension at twice the rate as female students. While the relative size of the gap in suspensions slightly decreased in HS among both racial/ethnic and gender groups, for dropout status these gaps further decreased within racial/ethnic groups but remained the same within gender groups. For intersectional
groups, Black-males experienced the highest rates of pre-HS suspension, especially when compared to White-females, who had the lowest rates of pre-HS suspension; Black-females had slightly higher rates of pre-HS suspension when compared to White-males. All racial/ethnic and gender gaps in pre-HS suspension decreased among intersectional groups in HS suspension. However, for dropout status, when compared to other intersectional groups, Black-males experienced a relatively large increase, while Black-females experienced a relatively large decrease—so much to the point that White-males surpassed Black-females in their rate of dropping out. Thus, the maintenance of the gender gap in dropout status was in large part due to relatively high number of Black-male dropouts when compared to Black-female dropouts. Results can be found in Figures 3.6 and 3.7.

3.5.4 The Short-Term Impact of Suspensions on Math Achievement

A latent difference score (LDS) model was used to test the short-term impact of suspension on math achievement (McArdle, 2001; Kenny, 2014). In our LDS model, a latent construct of math achievement at time-point one causes math achievement at time-point two, and this causal effect is constrained to equal one; at the same time, suspensions cause the disturbance in math achievement at time-point two. Here, it is important to note that math achievement at time-point one is correlated with both suspensions and the disturbance in math achievement at time-point two. Additionally, in order to control for race/ethnicity, gender, and social class, MIMIC Modeling was used, which entailed regressing the disturbance variable on race/ethnicity, gender, and social class (Figure 3.8).

In order to test the added influence of suspension, a null model was run first, which only included race/ethnicity, gender, and social class. Results indicated that both having a low social class (STDY b = -0.13) and being Black or Hispanic (STDY b = -0.07) significantly decreased
math achievement, accounting for 3% of the variance explained in the difference. When suspension was added to the model, it too, significantly decreased math achievement (STDY b = -0.17). In doing so, the effect of both social class (STDY b = -0.11) and race/ethnicity (STDY b = -0.06) slightly decreased, while the variance explained increased to 6%. Finally, it is important to note that the fit results were excellent for our LDS model: RMSEA = .024 (90% CI: 0.022-0.026); CFI = 0.97; Degrees of Freedom (DF) = 23.

3.5.5 The Long-Term Interactions among the STP and STEM Pipelines

In testing the long-term interactions between the STP and STEM pipelines, a longitudinal mediation model was constructed that represents five temporally ordered time-points: (1) suspension prior to high school—“S1”; (2) fall freshman year math achievement—“M1”; (3) fall/spring junior year suspensions—“S2”; (4) spring junior year/fall senior year math achievement—“M2”; and (5) spring senior year dropout status—“DS”. Here, the STP pipeline is represented by pre-high school suspension and high school suspension, while the STEM pipeline is represented by math achievement at time-points one and two. Similar to the latent difference score model, a MIMIC modeling approach was employed, which regressed the endogenous variables (M1, S2, M2, and DS) on race, gender, and social class control variables. Initially, two mediation models were fit and compared—a partially mediated model and a fully mediated model. The fully mediated model had relatively poor levels of fit (RMSEA 0.04; CFI 0.85; DF = 35) when compared to the partially mediated model (RMSEA = 0.02; CFI = 0.96; DF = 32), so the partially mediated model was used (Figure 3.9), which also fit better with our underlying theory of interactions in this article. Correlations for the CFA and SEM models can be found in Appendix B.
**General Population Results.** For the overall model, the standardized effect of S1 on M1 was significant and negative (STDY b = -0.63), while the effect of S1 on S2 was significant and positive (STDY b = 0.52). Additionally, the standardized effect of M1 on S2 was significant and negative (STDYX b = -0.28), while the effect of M1 on M2 was significant and positive (STDYX b = 0.87). Conversely, the standardized effect of S2 on M2 was significant and negative (STDY b = -0.11), while the effect of S2 on DS was significant and positive (b = 0.29). Finally, the standardized effect of M2 on DS was significant and negative (STDYX b = -0.48).

In addition, five tests of indirect effects were performed using the ‘MODEL INDIRECT’ command from Mplus. The first indirect test involved the effect of S1 on DS through all mediating variables (referred to as “S1 Indirect”), which was positive, significant, and relatively small (STDY b = 0.01). The second indirect test involved the effect of M1 on DS through S2 and M2 (referred to as “M1 Indirect”), which was negative, significant and relatively small (STDYX b = -0.02). The third indirect test involved the effect of S2 on DS through M2 (referred to as “S2 Indirect”), which was positive, significant and also relatively small (STDY b = 0.05). The fourth indirect test involved the effect of S1 on DS through S2 (referred to as “STP Indirect”), which was positive, significant and considerably larger (STDY b = 0.15) than previous indirect tests. The final indirect test involved the effect of M1 on DS through M2 (referred to as “STEM Indirect”), which was negative, significant and also considerably larger (STDYX b = -0.41) than previous indirect tests.

**Racial/Ethnic and Gender Identity and Intersectional Groups.** All subgroup analyses had excellent levels of fit (RMSEA < 0.04; CFI > 0.94). In utilizing the MIMIC modeling approach to isolate group characteristics in the subgroup analyses, the endogenous variables were regressed on (a) social class and gender in models that sought to isolate race/ethnicity; (b)
social class and race/ethnicity in models that sought to isolate gender; and (c) social class in
models that sought to isolate race/ethnicity-gender intersections. In terms of structural paths, it is
important to note that the direction—detonating either a positive or negative relationship among
variables and constructs—remained the same as the direction for the general population for all
significant model paths of the identity and intersectional groups. Thus, our primary concern is
the relative strength or weakness of these paths for various identity and intersectional groups.

For within-pipeline effects (as seen in Figures 3.10 through 3.13), STP paths (S1 $\rightarrow$ S2)
were substantially stronger for White and—to a slightly lesser degree—male students when
compared to female students, while the path for Black students was non-significant.
Intersectional results reveal that Black-females account for the weaker path for female students,
as well as the non-significant path for Black students. For STEM paths (M1 $\rightarrow$ M2) male students
demonstrated the strongest path, followed closely by White, Black, and female students (in that
order). Intersectional results reveal that White-males account for the slightly stronger path for
male students, while Black-males account for the slightly weaker path for Black students. Here,
Black-females experienced slightly stronger paths than White-females.

For cross-pipeline effects (as seen in Figures 3.14-3.15), the negative path between S1
and M1 was slightly stronger for female students, followed closely by male and White students
(who had identical paths), who were then followed closely by Black students. Additionally, the
negative path between M1 and S2 was substantially stronger for Black students, who were
followed closely by male, female, and White students (in that order). Finally, the negative path
between S2 and M2 was identical for White and male students and non-significant for Black and
female students. Intersectional results reveal that White-females account for the relative strength
of the path between S1 and M1, as well as the relative weakness of the path between M1 and S2,
for female students. On the other hand, Black-males account for the relative weakness of the path between S1 and M1, as well as the relative strength of the path between M1 and S2, for Black students—especially when considering that this path was non-significant for Black-females. Moreover, given their non-significant path from S2 to M2, Black-females also account for the non-significant paths between S2 and M2 for Black and female students.

For direct effects on the final outcome (as seen in Figures 3.16-3.19), male students had the strongest (positive) path from S2 to DS, who were followed closely by White, female, and Black students (in that order). Intersectional results—in which Black-males and Black-females had non-significant paths—reveal that White-males account for the relative strength of the path for males. Conversely, the negative path between M2 and DS was substantially stronger for Black students and—to a lesser degree—female students when compared to White and male students. Intersectional results—in which Black-males had the strongest paths by far, followed by White-females, Black-females, and White-males—reveal that Black-males account for the overall strength of the path for Black students, while White-females account for the relative strength of the path for female students. A similar pattern was observed for the STP and STEM within-pipeline indirect effects on DS for identity and intersectional groups (as seen in Figures 3.20-23).

When considering indirect effects that crossed pipelines, White and male students demonstrated identical, positive indirect effects of S2 on DS, while Black and female students demonstrated non-significant effects. Intersectional results—in which Black-males demonstrated the strongest effects, followed by White-females and White-males—reveal that Black-males account for the overall strength of the effect for male students, while White-females account for the relative strength of the path for White students (as seen in Figures 3.24-3.25). Additionally,
when considering the indirect effects of S1 and M1 on DS, paths were similar for White and male students and non-significant for Black and female students; intersectional results reveal that Black-males and Black-females account for the non-significant effects for Black and female students.

Finally, it is important to note that while differences in the percent of variance explained across race and gender groups were relatively small, larger differences, overall, occurred across intersectional groups (as seen in Figures 3.26-3.27). Starting with M1, Black-males, followed closely by Black-females, had the highest R-squared values; here, it is important to note that the relationship within race/ethnicity held for White students as well, as White-males had slightly higher R-squared values than White-females. For S2, the relationships within race/ethnicity also remained the same—both Black-males and White-males had higher R-squared values than their respective female counterparts; however, across race, the relationship was reversed—both White-males and White-females had higher R-squared values than their respective gender counterparts. While, again, the relationship within race/ethnicity was replicated in M2, the relationship across race/ethnicity was slightly altered. Similar to S2, in M2 White-males had the highest R-squared values overall, while Black-females had the lowest R-squared values overall; however, while White-females had R-squared values that were lower than Black-males in S2, in M2 White-females had R-squared values that were identical to Black-males. Finally, for DS Black-males had the highest R-squared values overall, while Black-females had the lowest R-squared values overall; for White students, this relationship within race/ethnicity reversed, as White-females had higher R-squared values than White-males. Group results can be found in Tables 3.5 and 3.6.
Figure 3.1. CFA Model (N = 23,485)
Note: Unstandardized estimates of variances (no arrows), residual variances (short, single-sided arrow), factor loadings (long, single-sided arrow), and correlations (long, double-sided arrow) are provided, followed by standard errors in parentheses.
Table 3.4
Mean Comparisons of Math Achievement Constructs

<table>
<thead>
<tr>
<th></th>
<th>Math 1</th>
<th>Std. Math 1</th>
<th>Math 2</th>
<th>Std. Math 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female : Male (ref. grp.)</td>
<td>+0.01</td>
<td>+0.02</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td>Black : White (ref. grp.)</td>
<td>-0.29***</td>
<td>-0.75***</td>
<td>-0.27***</td>
<td>-0.78***</td>
</tr>
<tr>
<td>Black-Male : Black-Female (ref. grp.)</td>
<td>-0.08*</td>
<td>-0.19*</td>
<td>-0.07*</td>
<td>-0.20*</td>
</tr>
<tr>
<td>White-Female : Black-Female (ref. grp.)</td>
<td>+0.26***</td>
<td>+0.59***</td>
<td>+0.23***</td>
<td>+0.51***</td>
</tr>
<tr>
<td>White-Male : Black-Female (ref. grp.)</td>
<td>+0.25***</td>
<td>+0.53***</td>
<td>+0.24***</td>
<td>+0.47***</td>
</tr>
<tr>
<td>Black-Female : Black-Male (ref. grp.)</td>
<td>+0.08*</td>
<td>+0.20*</td>
<td>+0.07*</td>
<td>+0.21*</td>
</tr>
<tr>
<td>White-Male : Black-Male (ref. grp.)</td>
<td>+0.33***</td>
<td>+0.69**</td>
<td>+0.31***</td>
<td>+0.62***</td>
</tr>
<tr>
<td>White-Female : Black-Male (ref. grp.)</td>
<td>+0.34***</td>
<td>+0.76**</td>
<td>+0.31***</td>
<td>+0.67***</td>
</tr>
<tr>
<td>White-Male : White-Female (ref. grp.)</td>
<td>+0.003</td>
<td>+0.01</td>
<td>+0.02</td>
<td>+0.03</td>
</tr>
<tr>
<td>Black-Female : White-Female (ref. grp.)</td>
<td>-0.26***</td>
<td>-0.67***</td>
<td>-0.23***</td>
<td>-0.65***</td>
</tr>
<tr>
<td>Black-Male : White-Female (ref. grp.)</td>
<td>-0.33***</td>
<td>-0.79***</td>
<td>-0.30***</td>
<td>-0.81***</td>
</tr>
<tr>
<td>White-Female : White-Male (ref. grp.)</td>
<td>+0.01</td>
<td>+0.01</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td>Black-Male : White-Male (ref. grp.)</td>
<td>-0.35***</td>
<td>-0.92***</td>
<td>-0.34***</td>
<td>-0.97***</td>
</tr>
<tr>
<td>Black-Female : White-Male (ref. grp.)</td>
<td>-0.26***</td>
<td>-0.65***</td>
<td>-0.24***</td>
<td>-0.68***</td>
</tr>
</tbody>
</table>

Notes: Mean comparisons are conducted with partially invariant Math Achievement factors. However, these results are nearly identical to comparisons with original factors. Estimates are followed by standard errors in parentheses below.

*p =/≤ .05   **p < .01   ***p < .001
Figure 3.2. Latent Variable Means Comparisons for Black-Females (Reference Group)

Figure 3.3. Latent Variable Means Comparisons for Black-Males (Reference Group)
Figure 3.4. Latent Variable Means Comparisons for White-Females (Reference Group)
Notes: Gradient fill for White-Males denotes a non-significant mean difference. Also, the bar for White-Males in the Math 1 comparison has been enlarged for visual clarity.

Figure 3.5. Latent Variable Means Comparisons for White-Males (Reference Group)
Note: Gradient fill for White-Females denotes a non-significant mean difference.
Figure 3.6. Observed Variable Proportions by Race and Gender

Figure 3.7. Observed Variable Proportions by Race-Gender Intersections
Figure 3.8. LDS Model (N = 25,206)
Notes: Correlations among demographic controls not shown for the purpose of visual clarity. Unstandardized estimates of variances (no arrows), residual variances (short, single-sided arrow), path coefficients (long, single-sided arrow), and correlations are provided (long, double-sided arrow), followed by standard errors in parentheses.
Figure 3.9. SEM Model
Notes: Demographic controls not shown for the purpose of visual clarity. Unstandardized estimates of residual variances (short, single-sided arrow), path coefficients (long, single-sided arrow), and correlations are provided (long, double-sided arrow), followed by standard errors in parentheses.
### Table 3.5
**Structural Equation Model Path Coefficients**

<table>
<thead>
<tr>
<th></th>
<th>Pre-HS Susp.</th>
<th>HS Susp.</th>
<th>Drop. Status</th>
<th>RMSEA Path: S1→M1</th>
<th>Path: S1→S2</th>
<th>Path: M1→S2</th>
<th>Path: M1→M2</th>
<th>Path: S2→M2</th>
<th>Path: S2→DS</th>
<th>Path: M2→DS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Sample</strong></td>
<td>14%</td>
<td>11%</td>
<td>6%</td>
<td>0.02</td>
<td>-0.31***</td>
<td>0.59***</td>
<td>-0.64***</td>
<td>0.85***</td>
<td>-0.05***</td>
<td>0.34***</td>
</tr>
<tr>
<td>(N = 16510)</td>
<td></td>
<td></td>
<td></td>
<td>(0.03)</td>
<td>(0.10)</td>
<td>(0.08)</td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.06)</td>
<td>(0.12)</td>
</tr>
<tr>
<td><strong>STDYX</strong></td>
<td></td>
<td></td>
<td></td>
<td>-0.22***</td>
<td>0.18***</td>
<td>-0.28***</td>
<td>0.87***</td>
<td>-0.11***</td>
<td>0.29***</td>
<td>-0.48***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.03)</td>
</tr>
<tr>
<td><strong>STDY</strong></td>
<td></td>
<td></td>
<td></td>
<td>-0.63***</td>
<td>0.52***</td>
<td>-0.28***</td>
<td>0.87***</td>
<td>-0.11***</td>
<td>0.29***</td>
<td>-0.48***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.09)</td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.03)</td>
</tr>
<tr>
<td><strong>White</strong></td>
<td>11%</td>
<td>10%</td>
<td>5%</td>
<td>0.03</td>
<td>-0.31***</td>
<td>0.63***</td>
<td>-0.56***</td>
<td>0.87***</td>
<td>-0.07***</td>
<td>0.34***</td>
</tr>
<tr>
<td>(N = 12,457)</td>
<td></td>
<td></td>
<td></td>
<td>(0.03)</td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.04)</td>
<td>(0.01)</td>
<td>(0.06)</td>
<td>(0.11)</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>28%</td>
<td>19%</td>
<td>8%</td>
<td>0.02</td>
<td>-0.26***</td>
<td>0.37</td>
<td>-0.84**</td>
<td>0.84***</td>
<td>-0.01</td>
<td>0.25*</td>
</tr>
<tr>
<td>(N = 2,525)</td>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.26)</td>
<td>(0.31)</td>
<td>(0.12)</td>
<td>(0.03)</td>
<td>(0.13)</td>
<td>(0.46)</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>19%</td>
<td>14%</td>
<td>7%</td>
<td>0.02</td>
<td>-0.31***</td>
<td>0.62***</td>
<td>-0.70***</td>
<td>0.90***</td>
<td>-0.07***</td>
<td>0.36***</td>
</tr>
<tr>
<td>(N = 8,422)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.05)</td>
<td>(0.01)</td>
<td>(0.08)</td>
<td>(0.14)</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>9%</td>
<td>08%</td>
<td>4%</td>
<td>0.02</td>
<td>-0.34***</td>
<td>0.44**</td>
<td>-0.59***</td>
<td>0.83***</td>
<td>-0.02</td>
<td>0.31**</td>
</tr>
<tr>
<td>(N = 8,228)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.16)</td>
<td>(0.12)</td>
<td>(0.05)</td>
<td>(0.02)</td>
<td>(0.09)</td>
<td>(0.19)</td>
</tr>
<tr>
<td><strong>White-Male</strong></td>
<td>15%</td>
<td>13%</td>
<td>6%</td>
<td>0.03</td>
<td>-0.30***</td>
<td>0.62***</td>
<td>-0.66***</td>
<td>0.90***</td>
<td>-0.07***</td>
<td>0.36***</td>
</tr>
<tr>
<td>(N = 6,228)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.05)</td>
<td>(0.02)</td>
<td>(0.08)</td>
<td>(0.14)</td>
</tr>
<tr>
<td><strong>White-Female</strong></td>
<td>6%</td>
<td>6%</td>
<td>4%</td>
<td>0.03</td>
<td>-0.33***</td>
<td>0.50***</td>
<td>-0.46***</td>
<td>0.82***</td>
<td>-0.06**</td>
<td>0.28**</td>
</tr>
<tr>
<td>(N = 6,229)</td>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.13)</td>
<td>(0.11)</td>
<td>(0.05)</td>
<td>(0.02)</td>
<td>(0.10)</td>
<td>(0.21)</td>
</tr>
<tr>
<td><strong>Black-Male</strong></td>
<td>36%</td>
<td>23%</td>
<td>10%</td>
<td>0.02</td>
<td>-0.26***</td>
<td>0.57**</td>
<td>-0.84*</td>
<td>0.78***</td>
<td>-0.05*</td>
<td>0.23</td>
</tr>
<tr>
<td>(N = 1,288)</td>
<td></td>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.22)</td>
<td>(0.33)</td>
<td>(0.15)</td>
<td>(0.03)</td>
<td>(0.18)</td>
<td>(0.81)</td>
</tr>
<tr>
<td><strong>Black-Female</strong></td>
<td>22%</td>
<td>16%</td>
<td>5%</td>
<td>0.02</td>
<td>-0.29***</td>
<td>0.10</td>
<td>-0.74</td>
<td>0.86***</td>
<td>0.03</td>
<td>0.21</td>
</tr>
<tr>
<td>(N = 1,237)</td>
<td></td>
<td></td>
<td></td>
<td>(0.07)</td>
<td>(0.31)</td>
<td>(0.39)</td>
<td>(0.19)</td>
<td>(0.03)</td>
<td>(0.15)</td>
<td>(0.42)</td>
</tr>
</tbody>
</table>

**Notes:** Unstandardized estimates—unless otherwise noted—are followed by standard errors in parentheses. Bold values represent recommended values to interpret for standardized effects. More detailed information on RMSEA CI’s can be found in Appendix #2.

*p =/> .05  **p < .01  ***p < .001
<table>
<thead>
<tr>
<th></th>
<th>S1 Indirect</th>
<th>M1 Indirect</th>
<th>S2 Indirect</th>
<th>STP Indirect</th>
<th>STEM Indirect</th>
<th>R-Square Math 1</th>
<th>R-Square HS Susp.</th>
<th>R-Square Math 2</th>
<th>R-Square Drop. Status</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Sample</strong></td>
<td>0.01***</td>
<td>-0.04***</td>
<td>0.06***</td>
<td>0.20***</td>
<td>-1.12***</td>
<td>0.18</td>
<td>0.23</td>
<td>0.84</td>
<td>0.44</td>
</tr>
<tr>
<td><strong>STDYX</strong></td>
<td>0.003***</td>
<td><strong>-0.02</strong>*</td>
<td>0.05***</td>
<td><strong>0.05</strong>*</td>
<td><strong>-0.41</strong>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>STDY</strong></td>
<td><strong>0.01</strong>*</td>
<td><strong>-0.02</strong>*</td>
<td><strong>0.05</strong>*</td>
<td><strong>0.15</strong>*</td>
<td><strong>-0.41</strong>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>White</strong></td>
<td>0.01***</td>
<td>-0.04***</td>
<td>0.08***</td>
<td>0.22***</td>
<td>-0.97***</td>
<td>0.14</td>
<td>0.22</td>
<td>0.87</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>0.01</td>
<td>-0.02</td>
<td>0.02</td>
<td>0.09</td>
<td>-1.68***</td>
<td>0.20</td>
<td>0.17</td>
<td>0.76</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.08)</td>
<td>(0.45)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>0.02***</td>
<td>-0.05***</td>
<td>0.08***</td>
<td>0.23***</td>
<td>-0.99***</td>
<td>0.20</td>
<td>0.22</td>
<td>0.88</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.13)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>0.01</td>
<td>-0.02</td>
<td>0.03</td>
<td>0.14*</td>
<td>-1.40***</td>
<td>0.19</td>
<td>0.19</td>
<td>0.80</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.18)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>White-Male</strong></td>
<td>0.01***</td>
<td>-0.04***</td>
<td>0.07***</td>
<td>0.23***</td>
<td>-0.79***</td>
<td>0.15</td>
<td>0.22</td>
<td>0.88</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.06)</td>
<td>(0.13)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>White-Female</strong></td>
<td>0.02**</td>
<td>-0.05**</td>
<td>0.10**</td>
<td>0.17*</td>
<td>-1.41***</td>
<td>0.13</td>
<td>0.15</td>
<td>0.81</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.07)</td>
<td>(0.19)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Black-Male</strong></td>
<td>0.03</td>
<td>-0.12</td>
<td>0.14*</td>
<td>0.13</td>
<td>-1.95**</td>
<td>0.19</td>
<td>0.20</td>
<td>0.81</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.12)</td>
<td>(0.67)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Black-Female</strong></td>
<td>-0.01</td>
<td>0.03</td>
<td>-0.05</td>
<td>0.02</td>
<td>-1.22**</td>
<td>0.18</td>
<td>0.12</td>
<td>0.66</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(0.41)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Unstandardized estimates—unless otherwise noted—are followed by standard errors in parentheses. Bold values represent recommended values to interpret for standardized effects.

*p =/.05   **p < .01   ***p < .001
Figure 3.10. STP Within-Pipeline Effects by Race and Gender

Figure 3.11. STP Within-Pipeline Effects by Race-Gender Intersections
Note: Dotted lines represent non-significant paths.
Figure 3.12. STEM Within-Pipeline Effects by Race and Gender

Figure 3.13. STEM Within-Pipeline Effects by Race-Gender Intersections
Figure 3.14. Cross-Pipeline Effects by Race and Gender
Note: Dotted lines represent non-significant paths.

Figure 3.15. Cross-Pipeline Effects by Race-Gender Intersections
Note: Dotted lines represent non-significant paths.
Figure 3.16. The Impact of HS Suspension on Dropout Status by Race and Gender
Note: Dotted lines represent non-significant paths.

Figure 3.17. The Impact of HS Suspension on Dropout Status by Race-Gender Intersections
Note: Dotted lines represent non-significant paths.
Figure 3.18. The Impact of Math 2 on Dropout Status by Race-Gender Intersections

Note: Minor adjustments have been made to differentiate overlapping lines.

Figure 3.19. The Impact of Math 2 on Dropout Status by Race-Gender Intersections
Figure 3.20. STP Pipeline Indirect Effects on Dropout Status by Race and Gender
Note: Dotted lines represent non-significant paths.

Figure 3.21. STP Pipeline Indirect Effects on Dropout Status by Race-Gender Intersections
Note: Dotted lines represent non-significant paths.
Figure 3.22. STEM Pipeline Indirect Effects on Dropout Status by Race and Gender

Figure 3.23. STEM Pipeline Indirect Effects on Dropout Status by Race-Gender Intersections
Figure 3.24. The Indirect Effect of S2 on Dropout Status by Race and Gender

Notes: Dotted lines represent non-significant paths. Also, minor adjustments have been made to differentiate overlapping lines.

Figure 3.25. The Indirect Effect of S2 on Dropout Status by Race-Gender Intersections

Note: Dotted lines represent non-significant paths.
Figure 3.26. Percent of Variance Explained by Race and Gender

Figure 27. Percent of Variance Explained by Race-Gender Intersections
3.6 Discussion

I. What is the short-term impact of receiving a suspension on math achievement?

In the LDS model, while being Black or Hispanic and having a low social class background were negative predictors of math achievement, gender was not, which affirms findings from the means analysis of the latent construct of math achievement. Moreover, when suspension was added to the model, it was found to have similar effects and explain the same amount of variation as these two significant demographic variables combined. Thus, while suspensions have a negative impact on math achievement, it can also be inferred that students from underserved demographic groups—particularly poor students of color—may be doubly disadvantaged when suspended.

II. What are the long-term interactions among the STP and STEM pipelines in high school and how do they relate to the process of pushing students out of school?

**General Population Patterns.** General SEM model results demonstrated continual interactions among exclusionary discipline and math achievement and their significant convergence at dropout status. Broadly, junctures in each pipeline negatively impacted the other pipeline, while the final juncture in each pipeline had a significant impact on dropout status; specifically, suspensions were negatively related to math achievement constructs and positively related to dropout status, while math achievement constructs were negatively related to suspensions and dropout 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 dropping out. These findings confirm our theoretical model—that interactions among the STP and STEM pipelines,
which at an institutional level might represent that an over-reliance on exclusionary discipline practices in concert with limited access to high-quality academic opportunities in math, can perpetuate the process by which students are pushed out of school.

Additional findings emerged that highlight how this process occurs for the general population of students. Starting with the interactions among the STP and STEM pipelines, as well as the direct effects on dropout status, three important findings emerged: first, within-pipeline paths tended to be stronger than cross-pipeline paths; second, when early within-pipeline paths were absent, early cross-pipeline paths were stronger than later cross-pipeline paths (that exist in the presence of within-pipeline paths), yet the variance explained was substantially less (e.g. the impact of S1 on M1 was stronger than the impact of S2 on M2 because M2 was also predicted by M1); and third, the direct effect of the last STP pipeline juncture on dropout status was considerably weaker in magnitude than the direct effect of the last STEM pipeline juncture on dropout status. Three important findings also emerged when considering the indirect effects of these pipelines on dropout status: first, effects stemming from early pipeline junctures tended to be relatively weak when compared to similar effects that did not cross pipelines (e.g. the indirect effect of S1 vs. the indirect effect of STP), as well as when compared to the direct effects of later pipeline junctures (e.g. the indirect effect of S1 vs. the direct effect of S2); second, indirect effects tended to make up a substantially smaller portion of the total effects on dropout status than direct effects; and third, the indirect effects of the STP pipeline on dropout status were considerably weaker in magnitude than the indirect effects of the STEM pipeline.

**General Population Implications.** Together, these findings have implications for theory, research, and practice. Pertaining to theory, these findings support a reciprocal relationship among the STP and STEM pipelines, which—by their continual interactions and their significant
convergence at dropout status, can be seen as perpetuating the process by which students are pushed out of school. Pertaining to research, these findings demonstrate the need to include within-pipeline paths when estimating cross-pipeline paths—and vice-versa—in order to avoid inflated impacts within and across disciplinary and academic trajectories. Pertaining to practice, these findings have multiple implications. First, given the relative weakness of early pipeline junctures on dropout status—especially when considering the effects of these junctures that cross pipelines (e.g. indirect effects of S1 and M1), it can be inferred that it is never too late to implement interventions within either pipeline. Second, given the significant effects both within and across-pipelines, it can be inferred that interventions should be implemented in both pipelines simultaneously; however, given stronger within-pipeline effects, interventions that target specific outcomes should prioritize pipeline-specific programs. Finally, these findings suggest that a reduction in suspensions alone may not be the most effective strategy for reducing the rate of dropouts. Rather, an increase in math achievement must simultaneously accompany a decrease in suspensions. Thus, when considering the relatively stronger effects of math achievement on dropout status, these findings suggest that the best way to move away from the long-term destinations commonly associated with the STP pipeline—dropout status in this case—is to move towards the STEM pipeline.

III. How do the long-term interactions among the STP and STEM pipelines compare across different dimensions and intersections of identity?

Identity and Intersectional Group Patterns. In understanding how the interactions among the STP and STEM pipelines compare across different dimensions and intersections of identity, it is important to consider our initial findings. Based on observed variable rates and latent variable means, Black and male students can be considered disadvantaged in discipline,
while Black students can also be considered disadvantaged in math achievement. When considering race-gender intersections, Black-males can be considered the most disadvantaged among all intersectional groups in terms of both discipline and math achievement—followed closely by Black-females. When compared to White-females, White-males can be considered disadvantaged in discipline. We also consider the findings of previous literature, which demonstrate that disadvantages in discipline are often weakened or “saturated”, while disadvantages in academics are often strengthened or “accumulated.” In doing so, we find that our identity and intersectional results not only confirm the trends of previous literature, but also provide important new insights and nuances regarding the process by which a variety of student groups are differentially pushed out of school. Specifically, four trends emerged.

First, disadvantages in discipline appear to be substantially saturated within the STP pipeline, while advantages in math achievement appear to be minimally accumulated within the STEM pipeline. In both cases, these saturation and accumulation effects were caused or “activated” by gender—meaning that these saturation and accumulation effects were most prominent when gender was intersected with the identities that were considered disadvantaged or advantaged in discipline and math. Here, as Black students had higher rates of suspension than White students, and Black-females had the weakest paths from pre-HS suspension to HS suspension, it can be inferred that being female activated the saturation of racial/ethnic disadvantage within discipline for Black students. Conversely, as White students had higher math achievement means than Black students, and White-males had the strongest paths from early math achievement to later math achievement, if can be inferred that being male activated the accumulation of racial/ethnic advantage within math for White students.
Second, racial/ethnic and gender advantages within discipline, as well as racial/ethnic advantages within math were often accumulated when students crossed from the STP pipeline to STEM pipeline, yet saturated when students crossed from the STEM pipeline to STP pipeline. Here, White-females, who exist at the intersection of advantage for both discipline and math, had the strongest paths when crossing from the STP pipeline to STEM pipeline and the weakest paths when crossing from the STEM pipeline to STP pipeline. The opposite was true for racial/ethnic and gender disadvantages within discipline, as well as racial/ethnic and gender disadvantages within math. Here, Black-males, who exist at the intersection of disadvantage for both discipline and math, had the weakest paths when crossing from the STP pipeline to STEM pipeline and the strongest paths when crossing from the STEM pipeline to STP pipeline.

Third, when considering the direct and indirect effects of STP and STEM pipeline junctures on dropout status, disadvantages, again, appear to be saturated within discipline, yet accumulated within math. Starting with discipline, the intersection of race/ethnicity and gender activated the saturation of racial/ethnic disadvantages within discipline, as Black-males and Black-females demonstrated non-significant direct effects of suspension on dropout status—despite all racial/ethnic and gender groups demonstrating significant effects when not intersected with each other. Here, Black students demonstrate saturated effects of suspension on dropout status only when their racial/ethnic group is intersected with gender. Thus, in the relationship between suspensions and dropout status for Black students there is something unique that exists at the intersection of race/ethnicity and gender that does not exist when these dimensions of identity are considered separately. For the direct effect of math on dropout status, gender—specifically, being male—appears to activate the accumulation of disadvantage within math for Black students, while activating the saturation of advantage within math for White students, as
Black-males had the strongest paths from later math achievement to dropout status, while White-males had the weakest paths.

Fourth, while similar patterns were observed for the indirect effects on dropout status that traveled separately through STP and STEM pipeline junctures, for indirect effects that crossed pipelines, new patterns emerged. Most notably, while there was no direct effect of suspensions on dropout status for Black-males, there was an indirect effect of suspensions on dropout status through math achievement for this group. Thus, it is indirectly through math achievement in which suspensions can significantly impact dropout status for Black-males—indicating another accumulation of disadvantage. Nevertheless, as cross-pipeline effects on dropout status that included multiple junctures in a given pipeline were non-significant for Black-males and Black-females, we can conclude that racial disadvantages stemming from early discipline and early math achievement are ultimately saturated on dropout status when these effects cross pipelines with multiple junctures.

**The Process of Pushing Out for Black Males.** For Black-males, the introduction to exclusionary discipline often occurs before they begin high school, as 36% of them—more than any other intersectional group—enter 9th grade having previously been suspended. While the relationship between pre- HS suspension and early math achievement is slightly weaker for Black-males when compared to other intersectional groups, the impact of pre- HS suspension explains a larger proportion of variance in early math achievement for Black-males than it does for any other group. Thus, their rate of pre- HS suspension certainly contributes to Black-males having the lowest levels of early math achievement among all intersectional groups. Moreover, pre- HS suspension not only impacts the level early math achievement for Black-makes, but also their likelihood of being suspended in high school. While the relationship between pre- HS
suspension and HS-suspension for Black-males is slightly weaker than the same relationship for White-males and White-females, again, Black-males lead all intersectional groups in their rate of HS-suspension, as 23% are suspended during their 11th grade year. Here, Black-males cannot escape the lingering effects of early disciplinary involvement.

However, it is not only pre-HS suspension that may be contributing to this trend, but also early math achievement, as Black-males demonstrate stronger relationships between early math achievement and HS-suspension than any other intersectional group. As a result, it is unsurprising that the proportion of variance explained in HS-suspension for Black-males is among the largest of all intersectional groups (with only White-males having a slightly larger proportion of variance explained). Furthermore, the impacts of poor early math achievement are compounded for Black-males, as this group, again, demonstrates one of the strongest relationships of early math achievement on later math achievement (with only White-males demonstrating a slightly stronger impact). Even with a slightly weaker impact of early math achievement on later math achievement among intersectional groups, as well as a slightly weaker impact of HS-suspension on later math achievement (when compared to White-males and White-females), significant relationships among these paths render Black-males with the lowest levels of later math achievement among all intersectional groups. Unsurprisingly, Black-males have one of the largest proportions of variance explained in their later math achievement (with only White-males having a slightly larger proportion of variance explained). Thus, similar to early disciplinary involvement, Black-males have a difficult time escaping the lingering effects of poor early math achievement.

Finally, Black-males demonstrate the strongest relationship between later math achievement and dropout status among all intersectional groups. Even with a non-significant
relationship between HS-suspension and dropout status, Black-males have more variance
explained in their dropout status than any other group. Here, it is important to note that even
though the direct effect of HS suspension on dropout status was non-significant for Black-males,
the indirect effect of HS suspension on dropout status (through later math achievement) was both
significant and stronger for Black-males than any other group. It is also worth noting that
although the STP indirect effect on dropout was non-significant for Black-males, the STEM
indirect effect on dropout status was both significant and stronger for Black-males than any other
group. Thus, it is unsurprising that Black-males dropped, or more appropriately, were pushed out
more than any other group at a rate of 10%.

Thus, the intersection of race and gender, places Black-males at a uniquely tragic space
of oppression when considering the both discipline and academics. Within this space of
oppression, Black-males are weaved across both disciplinary and academic opportunity
structures in a manner that often accumulates disadvantages along the way. From start to finish,
Black-males are more likely to be suspended prior to HS, which decreases their early math
performance, which makes them more likely to be suspended during HS, which further decreases
their later math performance, which—ultimately—makes them more likely to drop out. While it
is true that—when compared to other intersectional groups—disadvantages in discipline were
slightly saturated for Black-males, it is also true that disadvantages in math achievement were
substantially accumulated. This, however, is not meant to diminish the important role of
exclusionary discipline in the process by which Black-males are pushed out of school, but rather
to emphasize the importance of math achievement in keeping Black-males on the path to
graduation.
**The Process of Pushing Out for Black Females.** Similar to Black-males, the introduction to exclusionary discipline often occurs before Black-females begin high school, as 22% of them enter 9th grade having previously been suspended. While the relationship between pre-HS suspension and early math achievement is slightly weaker for Black-females than it is for White-females and White-males, this relationship explains a larger proportion of the variance in early math achievement for Black-females than it does for White-females and White-males. Thus, their rate of pre-HS suspension certainly contributes to Black-females having lower levels of math achievement than White-females and White-males. Similar to Black-males, Black-females cannot escape the lingering effects of early disciplinary involvement.

However, unlike Black-males, there is not a significant relationship between pre-HS suspension and HS suspension for Black-females. In fact, despite having higher suspension rates and lower math achievement than both White-females and White-males, neither pre-HS suspension nor early math achievement have a significant relationship with HS suspension for Black-females. Unsurprisingly, Black-females have the smallest proportion of variance explained in HS-suspension among all other intersectional groups. Clearly, there are other factors impacting HS-suspension for Black-females.

Conversely, the impacts of poor early math achievement are compounded for Black-females, as these students demonstrate one of the strongest relationships between early math achievement and later math achievement (with only White-males demonstrating a slightly stronger relationship). This may explain their maintenance of math disadvantages when compared to White-females and White-males. However, with a non-significant relationship between HS-suspension and later math achievement, Black-females are left with the lowest
proportion of variance explained in later math achievement among all intersectional groups. Similarly, there are other factors impacting later math achievement for Black-females.

Additionally, while Black-females demonstrate stronger relationships between later math achievement and dropout status when compared to White-males, these relationships were weaker when compared to White-females and Black-males. Finally, like Black-males, Black-females also did not demonstrate a significant relationship between HS-suspension and dropout status; however, unlike Black-males, Black-females did not demonstrate a significant indirect effect of HS suspension on dropout status (through later math achievement). Rather, the only significant indirect effect for Black-females was the STEM indirect effect, which was weaker than the STEM indirect effect for both White-females and Black-males. Thus, it is unsurprising that Black-females had the smallest proportion of variance explained in dropout status among all other intersectional groups. When considering that Black-females drop out more often than White-females, not being able to adequately account for the variance in dropout status with discipline and academics is particularly troubling.

Similar to Black-males, the combination of race and gender, also places Black-females at a uniquely tragic space of oppression when considering both discipline and academics. When considering math achievement means, Black-females face academic disadvantages that are universal across their race/ethnicity when compared to White students. However, when considering suspensions and dropout rates, it becomes clear that Black-females do not receive the benefits of their gender in discipline. Furthermore, the manner in which Black-females are weaved across both disciplinary and academic opportunity structures in high school is both similar and different from Black-males. Similar to Black-males, when considering the impact on later math achievement, the disadvantages of Black-females in early math achievement are
accumulated—to a slightly stronger degree than Black-males; when considering the impact on dropout status, the disadvantages of Black-females in later math achievement are also accumulated—only this time to a slightly lesser degree than Black-males. Also, when taking into account the one significant indirect effect on dropout status for Black-females, which only involves math achievement measures, it becomes clear that math achievement is most crucial in preventing Black-females from being pushed out of school. Conversely, when taking into account the multiple non-significant indirect effects on dropout status for Black-females, which all involve suspension measures, it becomes clear that suspensions are less crucial in preventing Black-females from being pushed out of school. Thus, unlike Black-males, suspensions—especially those occurring during high school—play a less significant role in the manner in which Black-females are weaved across both disciplinary and academic opportunity structures in high school.

**Intersectional Population Interpretations.** It is first important to consider the interpretation of accumulated and saturated disadvantages from a policy perspective. Accumulated disadvantages demonstrate that future consequences are more devastating for students that are more disadvantaged initially. As a result, more of our focus should be placed on improving these initial disadvantages. Here, we can assume that for an inclusive intervention that targets accumulated disadvantages, those that suffer the most, may also benefit the most. Saturated disadvantages, on the other hand, demonstrate that future consequences are less devastating for students that are mode disadvantaged initially. As a result, *relative to accumulated disadvantages*, less of our focus should be placed on improving these initial disadvantages. Here, we can assume that for an inclusive intervention that targets saturated disadvantages, those that suffer the most, may not benefit the most. However, when determining
where and when to focus our attention, it is important to consider both the frequency of the initial disadvantages, as well as the level of the outcome that these disadvantages are impacting. For example, while Black-males have a relatively saturated impact of pre-HS suspension on early math achievement, because they are suspended the most and have the lowest level of early math achievement, Black-males, overall, may actually benefit the most—in terms of their early math achievement—from a reduction of pre-HS suspensions. Nevertheless, it is important to draw a distinction between relative and absolute saturation. For example, when considering the impact of HS suspension on later math achievement, Black-females not only have a relatively saturated impact, but also an absolutely saturated impact, as the actual relationship is non-significant. Thus, even though Black-females have high rates of suspension and low levels of math achievement, Black-females may not benefit at all—in terms of their later math achievement—from a reduction in HS suspensions.

**Intersectional Population Implications.** In total, multiple systems of power—both within discipline and math—work to simultaneously oppress multiple dimensions and intersections of racial/ethnic and gender identity within schools. This impacts the ways in which uniquely oppressed groups, such as Black-males and Black-females, are weaved across structures of opportunity in a process that ultimately pushes them out of school altogether. In each part of this process, it was often the intersection of racial/ethnic and gender identities that amplified the saturation of disadvantages in discipline and the accumulation of disadvantages in math; rarely, were these saturation and accumulation effects as prominent when considering these dimensions of identity separately.

With this in mind, when considering the consistent saturation of racial/ethnic-gender intersectional disadvantages in discipline, combined with the consistent accumulation of
racial/ethnic-gender intersectional disadvantages in math, group-tailored interventions for multiply disadvantaged students—Black-males and Black-females in this case—should focus increasing math achievement. While decreasing suspensions would also be beneficial both before and during high school for Black-males, our findings demonstrate that that reducing suspensions will be most beneficial for Black-females before HS; once in HS, increasing math achievement will be most beneficial for these students. Finally, as evidenced by the non-significant indirect effects of both pre-HS suspension and early math achievement on dropout status for Black-males and Black-females, we can also infer that even after freshman year of high school, it is not too late to positively intervene. Nevertheless, given the relatively low percentage of variance explained in many of the model’s constructs for Black-females, as well as the relative and absolute saturation of many of the study’s relationships for these students, other factors should be explored to better understand the process in which Black-females prematurely depart schools. In addition to factors that “push” Black-females out of school, factors that “pull” Black-females out of school should also be considered.

3.7 Conclusion

In summary, we have demonstrated that the short-term impact of suspensions on math achievement, as well as the long-term interactions among the STP and STEM pipelines—and their relationship to pushouts, are both significant and substantial. Furthermore, through intersectional analyses, which demonstrated how racial and gender advantages and disadvantages can either be accumulated or saturated within and across these pipelines, we have been able to provide key leverage points for targeted interventions. Thus, while dropping out of school appears at the apex of disciplinary and academic trajectories, the interactions that are related to this phenomenon suggest a deeper process by which students are “pushed” out of school. Here,
students are continually and differentially—based on their race/ethnicity, gender, social class, and, in particular, their race/ethnicity-gender intersections—weaved across the structures of opportunity within the STP and STEM pipelines leading up to and during high school. When considering the institutional nature of an over-reliance on exclusionary discipline practices (see Welch & Payne, 2010; Payne & Welch, 2015), as well as access to high-quality academic opportunities in math (see McFarland, 2006)—and how both of these factors can work together to disparately impact underserved students—our findings suggest that dropping out may have more to do with the underlying structures of opportunity within schools than a student’s individual desire to drop out. Indeed, the process of pushing students out is perpetuated, at least in part, by disciplinary and academic structures within schools.
References


Jang, S. T. (2018). The Implications of Intersectionality on Southeast Asian Female Students’


Tyson, W., Lee, R., Borman, K., & Hanson, M. (2007). Science, technology, engineering, and mathematics (STEM) pathways: High school science and math coursework and
postsecondary degree attainment. *Journal of Education for Students Placed at Risk*, 12(3), 243-270


Chapter 4: The Collateral Damage of ISS: A Counterfactual Analysis of High-Suspension Schools, Math Achievement and College Attendance

Since the onset of zero tolerance policies in the early 1990s, U.S. schools have increased their mechanisms of surveillance, as well as their menu of punishments (Kafka, 2011). In doing so, many schools have adopted an authoritarian approach to discipline that—through social exclusion—has pushed some students further away from academic achievement and closer toward the criminal justice system (Fabelo, et al., 2011). Mirroring the research on mass incarceration, scholars have begun to not only demonstrate the negative direct effects of mass suspensions on students who receive them, but also the negative indirect effects of mass suspensions on their classmates (Perry & Morris, 2014). As a result, grassroots movements, such as the “Solutions Not Suspensions” movement, has called for a moratorium on out-of-school suspensions (Take Action, 2019).

However, given recent suspension trends, we fear that a decrease in out-of-school suspensions may be coupled with an increase in a similar alternative—in-school suspensions. While recent research has demonstrated that in-school suspensions have direct effects that are similar to the direct effects of out-of-school suspensions (Jabbari & Johnson 2019a; 2019b), little is known about the indirect effects of in-school suspensions. Understanding whether ISS is being used as a tool that replicates the indirect effects of OSS, while shielding the harmful impacts of this exclusionary discipline practice from public scrutiny, is a policy development worthy of
concern. Finding adverse indirect or “collateral” effects associated with ISS would suggest that the original policy alternative might, in fact, need a policy alternative of its own.

In-school suspension (ISS) was initially conceived as a less-exclusionary alternative to out-of-school suspension (OSS). It was originally designed to remove disruptive students from classrooms in order to provide a secluded setting where the behavior of offending students could be reformed, while also ensuring the learning of their classmates (Sheets, 1996). This would ideally result in a reduction of recidivism and an increase in academic achievement—both for the disciplined student and his or her classmates. Nevertheless, recent research by Jabbari and Johnson (2019a; 2019b) has demonstrated that the intents of ISS do not match its reality: when controlling for the attitudes and behaviors associated with disciplinary sanctions, directly receiving an ISS was found to be significantly related to a decrease in academic achievement and an increase in premature school departure.

However, as the vast majority of students do not receive suspensions, some may still question whether the use of ISS does, in fact, ensure the learning of non-offending students by removing those who are perceived to be misbehaving from classrooms (see Kinsler, 2013). Since more serious infractions may still warrant the removal of students from classrooms, one way to understand some of the indirect effects of ISS is to analyze their usage rates between schools. As the use of exclusionary discipline practices has been found to significantly vary across school contexts (Rausch & Skiba, 2004; Skiba, Chung, Trachok, Baker, Sheya, & Hughes, 2014; Ritter & Anderson, 2018), analyzing the impact of schools’ greater reliance on ISS is essential in moving towards more equitable educational systems.

In filling these gaps, we found that when controlling for selection into schools, students attending high-suspension high schools were associated with lower math achievement scores
during their junior year of high school and were less likely to attend college—even when accounting for school-level social order and student-level sanctioning. Moreover, we found that the effect associated with attending a high-suspension high school was similar and in some cases greater than the effect associated with directly receiving a suspension when not accounting for attendance into high-suspension schools. We close with a discussion of how these findings can inform future policies and practices, especially as they relate to race.

4.1 Literature Review

Whether discipline has been enacted within groups or communities to achieve internal group regulation (informal social control), or externally through the actions of state agents (formal social control), social control has been theorized to reduce anti-social behavior, maintain social order, and ultimately, enhance the safety and wellbeing of societies, communities and institutions (see Durkheim, 1961; Kirk, 2009). Within schools, discipline takes on the added purpose of socializing youth toward adult roles and responsibilities, as well as ensuring the process of learning (Durkheim, 1961).

This study considers a particular kind of discipline—exclusionary discipline—and relates it to mathematics and college attendance. Here, while the potentially problematic role of exclusionary discipline in exacerbating the school-to-prison pipeline has become an area of national concern (Skiba, Arredondo, & Williams, 2014), recent research (see Jabbari & Johnson, 2019b) has begun to demonstrate that the demographic groups with the highest rates of exclusionary discipline (Hispanics and Black Americans) are also most underrepresented in advanced mathematics achievement. College attendance is also considered because the STEM pipeline often “leaks” as the merits of students’ high school performance are used to access post-secondary educational opportunities.
4.1.1 Exclusionary Discipline

Given these specific research interests, we found the literature on suspensions to be large, but heavily concentrated on out-of-school suspension (OSS). Much of this work revealed that OSS has a variety of negative impacts on students. For example, students who are suspended out of school are more likely to demonstrate lower academic achievement gains (Arcia, 2006; Beck & Muschkin, 2012; Lacoe and Steinberg, 2018), while also being more likely to drop out (Skiba, Simmons, Staudinger, Rausch, Dow, & Feggin 2003; Suh, Suh, & Houston, 2007). Additional research has shown that suspended students demonstrate decreased rates of college attendance and graduation, as well as increased rates of arrests and incarcerations (Shollenberger, 2015).

Furthermore, while there is a focus on academics in the studies of Arcia (2006), Beck and Muschkin (2012), Perry and Morris (2014), and Lacoe and Steinberg (2018), only Perry and Morris (2014) and Lacoe and Steinberg (2018) considered mathematics in high school.

Research has also consistently revealed that students with traditionally underserved backgrounds shoulder the burdens of exclusionary discipline, as it is often low-income students and students of color who are most frequently exposed to and impacted by these practices (Sullivan, Klingbeil, & Van Norman, 2013; Skiba, Chung, Trachok, Baker, Sheya, & Hughes, 2014), especially in urban areas (Shedd, 2015). For example, research has uncovered racial bias in teachers’ expectations and assessments of student misbehavior (Ferguson, 2001; Downey & Pribesh, 2004; Fenning & Rose, 2007; Okonofua & Eberhardt, 2015), while also uncovering that punishments are often more severe in schools that have relatively higher proportions of low-income (Ramey, 2015) and minority students (Skiba & Knesting, 2001; Losen & Martinez, 2013; Skiba, Chung, Trachok, Baker, Sheya, & Hughes, 2014).
Of course, exclusion does not only entail being removed from schools, but also from classrooms, as seen in ISS. In fact, the use of ISS has recently surpassed its predecessor—OSS: 2,710,924 students received an ISS in the 2013-2014 school year, while 2,635,743 received OSS (US Department of Education, Office for Civil Rights, 2014). Originally intended for less-severe infractions that were disruptive to the learning environment, ISS would ideally include academic support services, such as tutoring and goal-setting, as well as activities to improve students' self-esteem, communication, and problem-solving skills (Sheets, 1996). However, previous research on ISS has shown that it is often applied inequitably according race/ethnicity, gender, and cultural styles, such as students’ dress (see Morris, 2005; DaCosta, 2006) and hairstyles (Lattimore, 2017). Moreover, more recent work has begun to measure the impact of ISS on mathematics and dropout status (Jabbari & Johnson, 2019a), reporting that ISS significantly lowered the odds of taking advanced math courses, while increasing the odds of dropping out. Outside of these studies, there has been little empirical evidence demonstrating whether ISS is primarily used for the purpose of removing disruptive students, whether there are support services within ISS programs, and whether ISS provides opportunities for students to learn the material covered in missed classes. Thus, the effectiveness of ISS in supporting the academic wellbeing of ISS recipients and their peers remains largely unknown.

4.1.2 Collateral Damages

Our interests in a school-level quality, such as high suspension rates, led us to consult the literature on the mechanisms by which schools become high suspension schools, as well as how—within these schools—disciplinary actions taken against individual students may present “ecological consequences” (see Johnson, 2008) for all students. Although our methodological approach bounds the impacts of schools into treatment effects, we nonetheless believe it is
important to explore the specific mechanisms by which disciplinary actions could come to characterize schools, and in turn, have effects that extend beyond the direct recipient of punishment.

Initially, we must consider the possibility that high suspension schools may arise in response to higher than average levels of student offending. While student misbehavior on a number of measures has been declining for decades (Robers et al., 2014), an uneven distribution of students with behavioral problems across schools might lead some schools to have relatively high rates of suspensions. High-suspension schools would therefore appear as such due to the higher levels of social disorder that they must address, as well as possible student responses to the disciplinary actions taken by these schools, which could further increase social disorder and the need for disciplinary actions. For example, some researchers have speculated that suspensions may actually reinforce stigma and anti-social behaviors because it increases the amount of time a student spends with other delinquent peers (Ferguson 2001; Skiba and Knesting 2001). In this case, suspensions could increase the chance that students will find solidarity in disobedience and re-offend, which would in turn increase a school’s rate of suspensions. Due to these possibilities, it is important to consider a school’s average level of social order and students’ non-random school selection into schools, as our analysis does, when estimating the impacts associated with high-suspension schools.

Alternatively, high suspension schools may arise from differences in detection practices rather than differential rates of offending. Here, Ditton’s (1979) classic concept of control waves posits that increases in crime and punishment might be due to changes in formal social control practices rather than increases in social disorder. For example, as seen in Morrison, Anthony, Storino, and Dillon’s (2003) study of middle school students receiving ISS, aggressive
infractions were the most common transgressions for first-time offenders, while attitudinal infractions were the most common transgressions for repeat offenders. Here, the authors conclude that “it appears once a student comes to the attention of school officials through aggression, they are watched closely for additional acts of defiance. Office referrals and suspensions are then used repeatedly for these less dangerous, attitudinal transgressions” (p. 290).

Hence, rather than an actual escalation in student misconduct, schools can become high-suspension schools when the threshold for which a suspension is triggered gets lowered to include less serious and more subjective offenses.

In either scenario, the consequences of attending a high versus a low-suspension school are not limited to the students directly receiving suspensions (see Rausch & Skiba, 2004; Lee, Cornell, Gregory, & Fan, 2011; Peguero, Varela, Marchbanks, Blake, & Eason, 2018). As a result, we speculate that these indirect or “collateral” effects might occur in the following ways.

Considering high-suspension schools first, discriminatory or excessive disciplinary sanctions may be viewed by student observers as unjust, unfair, or simply pointless (Costenbader & Markson, 1998; Arum, 2003; Perry & Morris, 2014), and could consequently increase anxiety from the threat of undeserved punishment for all students (Kupchik, 2010). Additionally, when “punishment becomes an end in itself, [and] not an occasional means to an end of normative social order” (Perry & Morris, 2014, p. 5), the institutional authority of schools may be undermined, which can lead to student alienation, resistance and lowered academic performance—“affecting both well and poorly behaved students alike” (Perry & Morris 2014, p. 5). Criminological research describes this as a process in which “negative vicarious experiences” with authority permeate groups and communities, which can have a particularly salient impact on historically oppressed populations that share a sense of “linked fate” and a common outlook.
rooted in a shared history of discriminatory surveillance and punishment (Brunson & Miller, 2006). Taking into consideration race/ethnicity and social class, as we do in this analysis, is therefore essential to understanding the ecological effects of high-suspension schools.

Nevertheless, public scrutiny of schools’ overreliance on suspensions may have tacitly advanced a potentially erroneous conclusion that schools at the other extreme of the suspension continuum may not pose harmful collateral consequences for learning as well. Here, low-suspension schools may be overly lenient, and allow unchecked misbehavior to impact the learning of all students—in effect, having collateral consequences of their own. The prevention of these “negative spillover effects” has been the stated aim of most school safety strategies, and recent research has suggested that permissive schools may exacerbate inequalities in school outcomes as well (Peguero, Varela, Marchbanks, Blake, & Eason, 2018).

4.2 Research Objectives and Questions

These theoretical mechanisms and the advances made by previous research on the collateral effects of exclusionary school discipline led us to pose a similar hypothesis: that suspensions will be associated with adverse effects on non-suspended students “above and beyond the overall level of student offending” (Perry & Morris, 2014, p. 5), especially in high-suspension schools. We nonetheless do so noting that many policy relevant questions have been left unanswered by previous research. For example, since much of the research uses localized samples we do not know under what circumstances the effects of suspensions might apply more broadly to schools throughout the nation. Given the focus of these studies on OSS (or measures that aggregate all suspension types), existing research cannot inform the consequences of the current shift, from the use of OSS to ISS, in many school systems. Additionally, a focus on outcomes at a single time in time within existing work has not revealed the duration of
educational consequences that extend from exposure to these social control extremes. We also do not know whether these effects persist when methodologies are used that limit selection bias by addressing the issue of non-random selection of students into schools.

In extending the previous literature, we (a) rely on students from a nationally representative sample; (b) establish the impacts of less-severe exclusionary policies through measures of ISS; (c) explore both the short-term (math achievement) and long-term (college attendance) impacts associated with high and low-social control contexts and demonstrate how these impacts are related; (d) limit bias associated with selection into schools that vary in ISS rates by using a counterfactual model based on propensity scores; (e) explore the difference between the direct and indirect effects of ISS; (f) explore the interactions of gender, race, and class variables with suspensions, high-suspension schools, and academic predictors of the outcomes. In doing so, we pose the following questions:

IV. What are the short-term (math achievement) and long-term (college attendance) impacts associated with attending a high-suspension high school and how are these impacts related?

V. How do the effects associated with directly receiving a suspension differ from the indirect effects associated with attending a high-suspension high school?

VI. How do student background characteristics interact with high-suspension schools and math when predicting college attendance?

4.3 Data and Measures

4.3.1 Data

The analyses in this paper 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
The analyses in this paper utilized student, parent, and administrator questionnaire data from the Base Year (fall of 9th grade), First Follow-Up (spring of 11th grade), and the 2013 High School Transcript study. The NCES did provide analytic weights to account for instances of non-response that occurred both within waves (for different questionnaire types) and across waves, as well as instances of sampling inefficiencies that are inherent to a stratified sampling approach.

This study involved two series of longitudinal analyses, spanning across two unique sets of waves. The first series of analyses, which tests the impact of attending a high-suspension high school on math achievement, spans across the first wave and (9th grade) and the second wave (11th grade) and therefore utilized the W2W1STU weight. The second series of analyses, which tests the impact of attending a high-suspension high school on college attendance, spans across the first wave (9th grade), second wave (11th grade), and fourth wave (freshman year of college) and therefore utilized the W3W1W2STUTR weight.

With the exception of the administrator scale of school social order, which was missing 23% of the responses in the original dataset, all other independent variables had less than 5% of their responses missing. Not including key demographic and dependent variables, which were not imputed, multiple imputation using chained equations (MICE) were used to impute five sets of missing values (White, Royston, & Wood, 2011).

4.3.2 Treatments

The treatment variable in this study is attending a high-suspension high school—as opposed to attending a low-suspension high school. This treatment variable was derived from a student-level, self-reported measure of in-school suspension within the previous six months that occurs on the following scale: 1 = never suspended; 2 = suspended one to two times; 3 =
suspended three to six times; 4 = suspended seven to nine times; and 5 = suspended ten or more times. Using the base-year student weight (W1STUDENT), a weighted mean of suspensions was created for each individual high school. This created a school-level measure of in-school suspensions that was representative of both schools and the students attending them. Based on this measure, high schools were broken down into five quintiles of equal distributions, creating a range of school typologies based on suspensions. The highest quintile (192 schools with 5,041 students) was operationalized as high-suspension high schools, while the lowest quintile (233 schools with 5,971 students) was operationalized as low-suspension high schools (1 = high-suspension school; 0 = low-suspension school).

4.3.3 Covariates in the Propensity Score Estimation Models

Since we are unable to assume that selection into these treatments occurs randomly, a set of observed covariates that are theoretically related to selection into the treatments, as well as the underlying treatment mechanisms, and ultimately, the outcomes associated with the treatments in this study, were used in the propensity score estimation model. The inclusion of these variables in the propensity score estimation models will not only limit potential biases in treatment assignment (high and low-suspension schools), but will also balance students’ pre-dispositional characteristics related to the underlying treatment mechanisms (suspensions), as well as the characteristics that are known to impact the outcomes under study (high school math achievement and college attendance). Variables that occurred before treatment assignment were utilized in order to meet the temporal assumption that the treatment occurred before the outcome.

Stemming from the literature on high social control schools, which demonstrates that the overuse of suspensions often manifests itself in schools that predominantly serve low-income and students of color, this study included the following demographic variables as treatment
covariates in the propensity score estimation model: SES quintile (created by NCES and derived from parent education, parent occupation, and family income; ranging from 1 to 5 with 1 representing the lowest quintile and 5 representing the highest quintile), household structure (1 = two parent/guardian household; 0 = single parent/guardian household), Black race/ethnicity (1 = yes; 0 = no), Hispanic race/ethnicity (1 = yes; 0 = no), and female (1 = yes; 0 = no).

Additionally, in order to balance covariates that are also related to suspensions, this study included pre-treatment behavioral and academic variables in the propensity score estimation model. The inclusion of these variables, which again, stemmed from the literature on suspensions, consisted of two separate four-point scales depicting how often parents were contacted about their child’s perceived misbehavior, as well as their child’s poor academic performance, during their eighth grade year (1 = never; 2 = once or twice; 3 = three or four times; 4 = more than four times). Finally, in order to balance covariates that are also related to the main outcomes, pre-treatment math achievement and college attendance variables were included in the propensity score estimation model. This included a scale of advanced math course-taking during students’ 8th grade year—ranging from 1 (“Math 8”) to 9 (“Other advanced math course such as pre-calculus or calculus”), as well as a scale of grades received in these math courses during students’ 8th grade year (1 = “A”; 2 = “B”; 3 = “C”; 4 = “D”; 5 = “below D”); a measure of parental expectations for their students’ college attainment was also included (1 = child will receive a bachelor’s degree; 0 = child will not receive a bachelor’s degree).

4.3.4 Outcomes

The short-term outcome variable consisted of a norm-referenced math achievement test score taken during the spring of 11th grade (ranging from 22.24-84.91), which focused primarily on algebraic reasoning and contained more difficult items than a similar test taken in 9th grade.
Here, it is important to note that this math assessment was developed by the NCES to reflect growth in math achievement and preparedness for college STEM programs (Ingels et al., 2011). The long-term outcome variable consisted of full-time college attendance recorded during the fall of a student’s freshman year of college (1 = yes; 0 = no).

4.3.5 Covariates in the Analysis Models

In order to isolate the impact of the school type, 11th grade math achievement test scores were bound by a student’s initial (fall of 9th grade) math achievement test scores (ranging from 24.02-82.19). Similarly, full-time college attendance was bound by a student’s initial (9th grade) expectation for graduating college (1 = student does not expect to receive a bachelor’s degree; 0 = student expects to receive a bachelor’s degree). Moreover, in order to further operationalize high and low-suspension school types each analysis also included a school measure of social order. This continuous measure (ranging from -4.22 to 1.97 with higher values representing higher levels of social order) was provided by the NCES and derived from administrator frequency ratings of the following activities: physical conflicts, robberies, vandalism, drug use, alcohol use, drug sales, weapon possessions, physical abuse of teachers, racial tensions, bullying, verbal abuse of teachers, in-class misbehavior, disrespect towards teachers, and gang activities.

Furthermore, our analysis includes students’ suspension histories in order to establish that the effects of attending a high suspension school are net of individual-level disciplinary experiences. Moreover, as schools might have the strongest impact on individuals who attend them most regularly, the amount of student absences (0 = no absences; 1 = one or two absences; 2 = three to six times absences; 3 = seven to nine absences; 4 = ten or more absences) and classes skipped (0 = no classes skipped; 1 = one or two classes skipped; 2 = three to six classes skipped; 3 = seven to nine classes skipped; 4 = ten or more classes skipped) were also included in each
analysis. Given our interest in race/ethnicity, gender, and social class, indicators for Black, Hispanic, female, and SES quintiles were included as model covariates to ensure robustness of the treatment impacts (see Bang & Robins, 2005), as well as to provide insight into how these factors impact the outcome after we account for the extremes of the distribution of suspensions across schools.

Finally, it is important to note that out of the 11,012 original students from the high and low-suspension schools in the sample, attrition across the three waves left 8,856 students in the final treatment and control groups. Some additional students were also lost due to attrition across the three types of questionnaires used (student, parent, and administrator), which resulted in sample sizes ranging from 7,680 to 7,920 students in the subsequent analyses. It is also important to note that while the variables remained in their original form in the propensity score estimation model, variables that were not standardized or did not have a meaningful zero were centered at the grand mean (or appropriately rescaled to include a meaningful zero) in order to allow for accurate estimates of the intercepts in the outcome models. Descriptive statistics can be found in Table 4.1.

4.4 Methodological Approach

4.4.1 Counterfactual Modeling

In testing the impacts associated with attending high and low-suspension high schools, it is first important to recognize that attendance in these high schools is not random. Thus, estimating treatment effects without adjusting for students’ non-random selection into these high schools can yield biased results. We therefore employed a counterfactual framework where treatment and non-treatment participants have potential outcomes in both states: the state in which they are observed and the state in which they are not observed (Rubin, 2005: Johnson &
Thus, the average treatment effect (ATE) in this study can be considered the difference in the potential outcomes associated with attending either high or low-suspension schools for all students. By examining both treatments and meeting key statistical assumptions, counterfactual modeling can allow researchers to make inferences that can approach causality. However, in our analyses—due to the fact that the initial measure of math achievement test scores occurred within the treatment duration, as well as the fact that there was not an exact pre-treatment measure of college attendance—the nature of our counterfactual models do not allow for true causal claims, but rather associational claims that are less prone to selection bias.

**Assumptions.** The strongly ignorable treatment assignment (SITA) assumption is the first of these assumptions, and requires that conditional on observed covariates, treatment assignment is independent of potential outcomes (Rosenbaum & Rubin, 1983). By utilizing observed covariates of both the treatment and the outcome in the propensity score estimation model, as well as the main analytical models, we can reasonably assume that we will control for most major confounding variables. A second assumption, the stable unit value treatment assumption (SUTVA), requires that “observation on one unit should be unaffected by the particular assignment of treatments to the other units” (Cox, 1958). In this regard, we can reasonably assume that there are few interactions between students that receive different treatments, as their treatments occur in different physical spaces (schools) that are often separated by substantial physical distances.

**Strategy.** We employed a counterfactual strategy based on propensity scores in order to limit selection bias in the estimation of treatment effects associated with attending high and low-suspension high schools. Propensity scores define the conditional probability of being assigned to a treatment based on a set of observed covariates (Rosenbaum & Rubin, 1983). In doing so,
propensity scores can be seen as balancing property: “conditional on the propensity score, the
distribution of observed baseline covariates will be similar between treated and untreated
subjects” (Austin, 2011). Specifically, propensity score weighting was used in this study, which
uses the inverse probability for receiving the treatment (that the subject actually received) to
weight these observations from a given sample (2011). Thus, in following Guo’s (2014) notation,
the ATE weights for cases in the first treatment group (low-suspension schools) becomes \( w_i = 1/p(x_i) \), while the ATE weights for cases in the second treatment group (high-suspension schools)
becomes \( w_i = 1/(1-p(x_i)) \).

4.4.2 Propensity Score Analysis

Similar to other propensity score strategies, propensity score weighting consists of a
multi-step process. First, a propensity score is estimated based on the observed covariates of a
specific treatment. Second, an inverse probability treatment weight is created based on the
propensity score, which is then multiplied by the necessary survey weights. Third, balance and
diagnostic checks are completed to ensure that the observed covariates are properly balanced and
that the propensity scores—and their resulting weights—are adequately overlapped and
distributed. Finally, after the main analyses are run a sensitivity analysis is performed to ensure
that previous analyses are not vulnerable to the impacts of unobserved confounders (Guo, 2014).

Propensity Score Estimation Model. Since model misspecification errors have been
shown to bias estimates of treatment effects, especially in analyses with binary outcomes (see
Drake, 1993; Freedman & Berk, 2008), we utilized generalized boosted modeling (GBM) to
estimate propensity scores. Nonparametric modeling approaches, such as GBM, have been
shown to reduce the chance of these errors (McCaffrey, Ridgeway, & Morral, 2005).
Specifically, GBM utilizes automated, data adaptive modeling algorithms to “predict treatment
assignment from a large number of pretreatment covariates while also allowing for flexible, non-linear relationships between the covariates and the propensity score” (p. 3). As a result, in estimating the propensity score weights for the treatment, this study utilized the TWANG—Toolkit for Weighting and Analysis of Non-equivalent Groups—package (Ridgeway, McCaffrey, Morral, Burgette, & Griffin, 2014) in R and STATA. Using TWANG’s default settings, we generated and assessed both mean effect sizes and the Kolmogorov-Smirnov (KS) statistics for covariate balance. In addition to the number of observations used in the propensity score estimation, TWANG also provides the comparable sample sizes for both treatments—known as the effective sample size (ESS) (McCaffrey et al., 2005). Finally, as recommended by DuGoff, Schuler, and Stuart (2014) for inferences on populations (as opposed to samples), we used TWANG to multiply the propensity score weights by the provided survey weights.

**Propensity Score Estimation Results.** Results of the propensity score estimation models demonstrate that all treatment covariates were properly balanced (Tables 4.2 and 4.3). Additionally, propensity scores for both treatment and control groups shared an adequate region of common support (Figure 4.1), which was also the case when looking at the distribution of propensity score weights (Figures 4.2 and 4.3). These checks ensure that participants with similar treatment covariates have a positive theoretical probability of being in either the treatment or control group (Rosenbaum & Rubin, 1983).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Math Achievement Models</th>
<th>College Attendance Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treatment Group</td>
<td>Control Group</td>
</tr>
<tr>
<td>College Attendance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low College Expectation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Social Order</td>
<td>-0.17</td>
<td>0.39</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>0.11</td>
<td>0.15</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>0.50</td>
<td>0.51</td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.23</td>
<td>0.22</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.20</td>
<td>0.19</td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.34</td>
<td>0.00</td>
</tr>
<tr>
<td>Absences</td>
<td>1.55</td>
<td>1.44</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.36</td>
<td>0.25</td>
</tr>
<tr>
<td>Freshman Year Math Score</td>
<td>-0.90</td>
<td>0.22</td>
</tr>
<tr>
<td>Junior Year Math Score</td>
<td>-1.73</td>
<td>0.84</td>
</tr>
<tr>
<td>Observations</td>
<td>3,890</td>
<td>3,800</td>
</tr>
</tbody>
</table>

Note: Due to slight differences between W2W1STU weights (Math Achievement Models) and W3W1W2STUTR weights (College Attendance Models), variable means and standard deviations have been listed separately. Also, unweighted population statistics, such as the number of observations, have been rounded to the nearest ten to comply with our restricted use data license agreement.
Table 4.2
Comparison of Treatment Selection Variables before Propensity Score Weighting

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Suspension School</th>
<th>Low-Suspension School</th>
<th>Standardized Difference</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race: Black</td>
<td>0.33</td>
<td>0.14</td>
<td>0.45</td>
<td>0.00</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.22</td>
<td>0.21</td>
<td>0.03</td>
<td>0.46</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>0.48</td>
<td>0.52</td>
<td>-0.09</td>
<td>0.01</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>2.64</td>
<td>3.53</td>
<td>-0.62</td>
<td>0.00</td>
</tr>
<tr>
<td>Two Parent Household</td>
<td>0.67</td>
<td>0.83</td>
<td>-0.35</td>
<td>0.00</td>
</tr>
<tr>
<td>High Parental College Expectations</td>
<td>0.63</td>
<td>0.79</td>
<td>-0.34</td>
<td>0.00</td>
</tr>
<tr>
<td>8&lt;sup&gt;th&lt;/sup&gt; Grade Behavior</td>
<td>1.52</td>
<td>1.25</td>
<td>0.37</td>
<td>0.00</td>
</tr>
<tr>
<td>8&lt;sup&gt;th&lt;/sup&gt; Grade Performance</td>
<td>1.45</td>
<td>1.31</td>
<td>0.20</td>
<td>0.00</td>
</tr>
<tr>
<td>8&lt;sup&gt;th&lt;/sup&gt; Grade Math Course</td>
<td>3.27</td>
<td>3.48</td>
<td>-0.11</td>
<td>0.00</td>
</tr>
<tr>
<td>8&lt;sup&gt;th&lt;/sup&gt; Grade Math Grade</td>
<td>2.25</td>
<td>1.92</td>
<td>0.33</td>
<td>0.00</td>
</tr>
<tr>
<td>Observations</td>
<td>4,150</td>
<td>4,710</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS</td>
<td>2,052.88</td>
<td>1,949.67</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Above results from Multiple Imputation set #1. Due to space limitations results from other Multiple Imputation sets were not included. However, it is worth noting that their results were nearly identical.
Table 4.3
Comparison of Treatment Selection Variables after Propensity Score Weighting

<table>
<thead>
<tr>
<th>Variable</th>
<th>High-Suspension School</th>
<th>Low-Suspension School</th>
<th>Standardized Difference</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race: Black</td>
<td>0.24</td>
<td>0.22</td>
<td>0.03</td>
<td>0.45</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.21</td>
<td>0.21</td>
<td>0.00</td>
<td>0.99</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>0.50</td>
<td>0.49</td>
<td>0.01</td>
<td>0.72</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>3.06</td>
<td>3.11</td>
<td>-0.04</td>
<td>0.26</td>
</tr>
<tr>
<td>Two Parent Household</td>
<td>0.75</td>
<td>0.75</td>
<td>0.00</td>
<td>0.91</td>
</tr>
<tr>
<td>High Parental College Expectations</td>
<td>0.72</td>
<td>0.73</td>
<td>-0.04</td>
<td>0.34</td>
</tr>
<tr>
<td>8th Grade Behavior</td>
<td>1.37</td>
<td>1.37</td>
<td>0.01</td>
<td>0.86</td>
</tr>
<tr>
<td>8th Grade Performance</td>
<td>1.36</td>
<td>1.38</td>
<td>-0.02</td>
<td>0.70</td>
</tr>
<tr>
<td>8th Grade Math Course</td>
<td>3.36</td>
<td>3.35</td>
<td>0.00</td>
<td>0.88</td>
</tr>
<tr>
<td>8th Grade Math Grade</td>
<td>2.08</td>
<td>2.08</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Observations</td>
<td>4,150</td>
<td>4,710</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS</td>
<td>2,027.64</td>
<td>1,405.51</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Above results from Multiple Imputation set #1. Due to space limitations results from other Multiple Imputation sets were not included. However, it is worth noting that their results were nearly identical.
Figure 4.1. Boxplot of propensity scores.
Figure 4.2. Histogram of propensity scores weights for High-Suspension (treatment) group.

Figure 4.3. Histogram of propensity scores weights for Low-Suspension (control) group.
4.5 Results

Each weighted analysis used STATA’s SVY program (StataCorp, 2013), which is designed for the analysis of complex surveys. After demonstrating the unconditional treatment effects associated with the outcomes (Table 4.4), we created conditional models that allowed us to understand the difference between directly receiving a suspension and attending a high-suspension school. Here, we started with two main “null” models—one model that estimated the effect associated with ISS on math achievement and another model that estimated the effect associated with ISS on college attendance. These models were then juxtaposed with similar “treatment” models, which added the treatment of attending either a high or low-suspension school—without controlling for selection into these schools. Additionally, “selection” models were run, which controlled for selection into high and low-suspension high schools with the inclusion of propensity score weights. Finally, to empirically test the relationships between the short and long-term outcomes, two additional sets of models were created for predicting college attendance—one model set that included an additional control measure of freshman year math achievement and another model set that included both freshman and junior year math achievement.

4.5.1 Math Achievement Models (Table 4.5)

Null model findings (Model 1). In a sample that contains students attending both extremes of the distribution of ISSs across schools, directly receiving an ISS had one of the largest impacts on junior year math achievement for all students. For a one-unit increase in ISS, junior year math achievement scores were associated with a 1.17 point decrease. The only factor that had a larger impact on math achievement scores was race—specifically being Black, which was associated with a 1.20 point decrease in junior year math achievement scores. Other
significant factors were freshman year math achievement scores (the primary control for the outcome) and SES quintile, which were both positively related to junior year math achievement; additionally, absences was also negatively related to junior year math achievement.

**Treatment model findings (Model 2).** When the treatment—attending either a high or low-suspension high school—was added to the previous model, the direct effect of receiving an ISS substantially weakened. In fact, the indirect effect of attending a high suspension school was over twice size of the direct effect of receiving an ISS. Here, attending a high-suspension high school was associated with a 1.81 point decrease in junior year math achievement scores, while a one unit increase in directly receiving an ISS was associated with a 0.78 point decrease in math achievement scores. While other covariates remained similar (even gender, despite its slight change in significance), the impact of race slightly weakened.

**Selection model findings (Model 3).** When controlling for selection into high and low-suspension schools with propensity score weights, the impact of attending a high-suspension school weakened. Specifically, attending a high-suspension school went from being associated with a 1.81 point decrease in math achievement scores in the previous treatment model to now being associated with a 1.45 point decrease in the current selection model. While other covariates remained similar (even gender, despite its change in slight significance again), the impact of directly receiving an ISS and being Black slightly strengthened.

### 4.5.2 College Attendance Models

**Null model findings (Table 4.6).** In the first null model predicting college attendance—in which neither freshman nor junior year math achievement was included (Model 4), directly receiving a suspension was negatively related to college attendance. Here, a one unit increase in ISS was associated with a decrease in the relative odds of attending college to a ratio of 0.58 to
1. The only factors that had a larger impact on college attendance were low-college expectations (the primary control for the outcome) and SES quintile, which was also a significant predictor in the math achievement null model (Model 1). Furthermore, unlike the math achievement null model (Model 1), being Black was not a significant predictor of college attendance; however, gender—specifically being female—was a significant predictor of college attendance in this model. Moreover, absences and classes skipped were both negatively related to college attendance in this model. Additionally, it is important to note that when freshman year math achievement scores were added in Model 5, which turned out to be a significant predictor of college attendance (a one unit increase in math achievement scores were associated with an increase in the relative odds of college attendance to a ratio of 1.05 to 1), the strength the other significant predictors of college attendance—with the exception of gender, which experienced a slight increase in strength—slightly weakened. Finally, with the exception of classes skipped, which experienced a slight increase in strength, as well as freshman year math achievement, which no longer remained significant, the pattern of coefficient changes in Model 5 was replicated when junior year math achievement was added in Model 6.

**Treatment model findings (Table 4.7).** In the first treatment model predicting college attendance—in which neither freshman nor junior year math achievement was included (Model 7), the treatment—attending a high or low-suspension school—was associated with a decrease in the odds of college attendance to a ratio of 0.56 to 1. Similar to the math achievement treatment model (Model 2), when the treatment was added in Model 7, the direct effect of receiving an ISS weakened from its effect in this model’s equivalent null model (Model 4) and was now less impactful than the indirect effect of attending a high-suspension school (in Model 7 a one unit increase in ISS was now associated with a decrease in the relative odds of attending college to a
Additionally, it is important to note that the other covariates in Model 7 were similar in size and significance to this model’s equivalent null model (Model 4). Finally, when compared to their equivalent null models (Models 5 and 6, respectively), similar patterns among covariates were observed when freshman year math scores were added in Model 8, as well as when freshman and junior year math scores were added in Model 9.

**Selection model findings (Table 4.8).** In the first selection model predicting college attendance—in which neither freshman nor junior year math achievement was included (Model 10), propensity score weights were used to control for selection into high and low-suspension schools. Similar to the math achievement selection model (Model 3), the impact of attending a high-suspension school weakened from its impact in this model’s equivalent treatment model (Model 7). In Model 10 attending a high-suspension school was now associated with a decrease in the relative odds of attending college to a ratio 0.76 to 1. While other covariates remained similar to Model 10’s equivalent treatment model (Model 7), there were two noteworthy changes. First, unlike the math achievement selection model (Model 3), which demonstrated a stronger impact of directly receiving an ISS than its treatment model (Model 2), the impact of directly receiving an ISS slightly weakened in Model 10 when compared to its equivalent treatment model (Model 7). Second, while the impact of being Black slightly increased in the math achievement selection model (Model 3) when compared to its equivalent treatment model (Model 2), the impact of being Black changed from being non-significant in Model 7 to being significant in Model 10. Here, being Black was now associated with a decrease in the odds of attending college to a ratio of 0.75 to 1 in Model 10. However, when freshman year math achievement scores were added in Model 11, being Black no longer remained significant. Moreover, when both freshman and junior year math scores were added in Model 12, neither the
impact of attending a high-suspension high school, nor the impact of directly receiving an ISS, remained significant. Finally, it is important to note that in both Models 11 and 12, the other covariates demonstrated patterns that were similar to their equivalent treatment models (Models 7 and 8, respectively).

4.5.3 Sensitivity Analysis (Table 4.9)

In order to check the extent to which these analyses were sensitive to unobserved—and possibly confounding—treatment covariates, analyses were replicated with all observed covariates deliberately removed from the propensity score estimation models on separate occasions. When these variables were removed, outcomes were nearly identical to the main analyses. However, one exception was SES; when this variable was removed from the propensity score estimation model a slight change occurred in the treatment’s coefficient and standard error, which resulted in the treatment no longer remaining a significant predictor of college attendance. Nevertheless, when considering that this variable was a composite of multiple indicators for social class, this change is to be expected. Moreover, as it is unlikely that another variable containing a similar set of information exists outside of the variables already included in our propensity score estimation models, the potential for an unobserved confounder of this importance is low. As a result, the overall results of the sensitivity analysis provide further support for the robustness of our estimation of treatment effects. Thus, while our propensity score estimation model may not contain all treatment-related variables, our sensitivity analysis ensures that the ensuing analyses are likely to be insensitive to treatment-related variables that are unobserved.
### Table 4.4

*Unconditional Outcome Models*

<table>
<thead>
<tr>
<th></th>
<th>Math Achievement:</th>
<th>Math Achievement:</th>
<th>College Attendance:</th>
<th>College Attendance:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treatment Model</td>
<td>Selection Model</td>
<td>Treatment Model</td>
<td>Selection Model</td>
</tr>
<tr>
<td>High-Suspension School</td>
<td>-6.67(0.58)*****</td>
<td>-2.57(0.64)*****</td>
<td>0.31(0.04)*****</td>
<td>0.67(0.09)****</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.81(0.43)*****</td>
<td>0.84(0.47)</td>
<td>3.61(0.34)*****</td>
<td>2.36(0.25)*****</td>
</tr>
<tr>
<td>Observations</td>
<td>7,830</td>
<td>7,830</td>
<td>7,900</td>
<td>7,920</td>
</tr>
</tbody>
</table>

*Notes: For Math Achievement Models, coefficients are provided, which are followed by robust standard errors in parentheses. For College Attendance Models, odds ratios are provided, which also are followed by robust standard errors in parentheses.*

* *p < .05  **p < .01  ***p < .001

### Table 4.5

*Continuous Regressions of the Impact of High-Suspension Schools on Math Achievement*

<table>
<thead>
<tr>
<th></th>
<th>Model 1 (Null Model)</th>
<th>Model 2 (Treatment Model)</th>
<th>Model 3 (Selection Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-Suspension School</td>
<td>-1.17(0.24)*****</td>
<td>-1.81(0.37)*****</td>
<td>-1.45(0.38)*****</td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.31(0.16)</td>
<td>0.11(0.16)</td>
<td>0.09(0.17)</td>
</tr>
<tr>
<td>School Social Order</td>
<td>0.66(0.02)*****</td>
<td>0.66(0.02)*****</td>
<td>0.66(0.02)*****</td>
</tr>
<tr>
<td>Freshman Year Math Score</td>
<td>0.73(0.10)*****</td>
<td>0.63(0.11)*****</td>
<td>0.59(0.11)*****</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>-0.44(0.23)</td>
<td>-0.46(0.23)*</td>
<td>-0.45(0.26)</td>
</tr>
<tr>
<td>Race: Black</td>
<td>-1.20(0.32)*****</td>
<td>-0.97(0.31)*****</td>
<td>-1.13(0.36)*****</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>-0.02(0.40)</td>
<td>-0.10(0.40)</td>
<td>-0.32(0.46)</td>
</tr>
<tr>
<td>Absences</td>
<td>-0.65(0.12)*****</td>
<td>-0.64(0.11)*****</td>
<td>-0.68(0.12)*****</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.12(0.17)</td>
<td>0.07(0.17)</td>
<td>0.08(0.17)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.32(0.28)*****</td>
<td>2.18(0.33)*****</td>
<td>2.16(0.39)*****</td>
</tr>
<tr>
<td>Observations</td>
<td>7,680</td>
<td>7,680</td>
<td>7,680</td>
</tr>
</tbody>
</table>

*Note: Coefficients Followed by Robust Standard Errors in Parentheses*  

* *p < .05  **p < .01  ***p < .001
### Table 4.6: Null Models: Logistic Regressions of the Impact of Treatment Covariates and Outcome Covariates on College Attendance

<table>
<thead>
<tr>
<th></th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-School Suspension</td>
<td>0.58(0.08)***</td>
<td>0.64(0.08)***</td>
<td>0.68(0.08)**</td>
</tr>
<tr>
<td>School Social Order</td>
<td>1.12(0.07)</td>
<td>1.10(0.07)</td>
<td>1.08(0.07)</td>
</tr>
<tr>
<td>Low College Expectation</td>
<td>0.36(0.03)***</td>
<td>0.43(0.04)***</td>
<td>0.46(0.05)***</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>1.67(0.06)***</td>
<td>1.55(0.05)***</td>
<td>1.51(0.05)***</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>1.30(0.12)**</td>
<td>1.34(0.13)**</td>
<td>1.42(0.14)***</td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.84(0.10)</td>
<td>1.00(0.12)</td>
<td>1.09(0.13)</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.95(0.14)</td>
<td>0.94(0.14)</td>
<td>0.95(0.14)</td>
</tr>
<tr>
<td>Absences</td>
<td>0.74(0.04)***</td>
<td>0.74(0.04)***</td>
<td>0.76(0.04)***</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.81(0.07)*</td>
<td>0.83(0.07)*</td>
<td>0.82(0.07)*</td>
</tr>
<tr>
<td>Freshman Year Math Score</td>
<td></td>
<td>1.05(0.01)***</td>
<td>1.01(0.01)</td>
</tr>
<tr>
<td>Junior Year Math Score</td>
<td></td>
<td></td>
<td>1.07(0.01)***</td>
</tr>
<tr>
<td>Intercept</td>
<td>5.06(0.60)***</td>
<td>5.54(0.56)***</td>
<td>4.17(0.52)***</td>
</tr>
<tr>
<td>Observations</td>
<td>7,900</td>
<td>7,900</td>
<td>7,900</td>
</tr>
</tbody>
</table>

*Note: Odds Ratios Followed by Robust Standard Errors in Parentheses*

*p < .05  **p < .01  ***p < .001*
Table 4.7
Treatment Models:
Non-Propensity Score Weighted Logistic Regressions of the Impact of High-Suspension Schools on College Attendance

<table>
<thead>
<tr>
<th></th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-Suspension High School</td>
<td>0.56(0.07)***</td>
<td>0.60(0.07)***</td>
<td>0.67(0.08)**</td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.67(0.08)**</td>
<td>0.72(0.08)**</td>
<td>0.75(0.09)*</td>
</tr>
<tr>
<td>School Social Order</td>
<td>1.05(0.07)</td>
<td>1.04(0.07)</td>
<td>1.04(0.07)</td>
</tr>
<tr>
<td>Low College Expectation</td>
<td>0.36(0.03)***</td>
<td>0.42(0.04)***</td>
<td>0.45(0.05)***</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>1.62(0.06)***</td>
<td>1.52(0.05)***</td>
<td>1.48(0.05)***</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>1.30(0.12)***</td>
<td>1.34(0.13)***</td>
<td>1.42(0.13)***</td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.93(0.11)</td>
<td>1.09(0.13)</td>
<td>1.16(0.15)</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.91(0.13)</td>
<td>0.91(0.13)</td>
<td>0.93(0.14)</td>
</tr>
<tr>
<td>Absences</td>
<td>0.75(0.04)***</td>
<td>0.74(0.04)***</td>
<td>0.76(0.04)***</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.80(0.07)**</td>
<td>0.82(0.07)*</td>
<td>0.82(0.07)*</td>
</tr>
<tr>
<td>Freshman Year Math Score</td>
<td>1.05(0.01)***</td>
<td>1.01(0.01)</td>
<td>1.06(0.01)***</td>
</tr>
<tr>
<td>Junior Year Math Score</td>
<td></td>
<td>1.06(0.01)***</td>
<td>1.06(0.01)***</td>
</tr>
<tr>
<td>Intercept</td>
<td>6.73(0.90)***</td>
<td>5.84(0.78)***</td>
<td>5.10(0.71)***</td>
</tr>
<tr>
<td>Observations</td>
<td>7,900</td>
<td>7,900</td>
<td>7,900</td>
</tr>
</tbody>
</table>

Note: Odds Ratios Followed by Robust Standard Errors in Parentheses
*p < .05         **p < .01       ***p < .001
Table 4.8
Selection Models:
Propensity Score Weighted Logistic Regressions of the Impact of High-Suspension Schools on College Attendance

<table>
<thead>
<tr>
<th></th>
<th>Model 10</th>
<th>Model 11</th>
<th>Model 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-Suspension High School</td>
<td>0.76(0.09)*</td>
<td>0.78(0.11)*</td>
<td>0.84(0.11)</td>
</tr>
<tr>
<td>In-School Suspension</td>
<td>0.75(0.09)*</td>
<td>0.79(0.09)*</td>
<td>0.84(0.10)</td>
</tr>
<tr>
<td>School Social Order</td>
<td>1.11(0.08)</td>
<td>1.11(0.08)</td>
<td>1.11(0.08)</td>
</tr>
<tr>
<td>Low College Expectation</td>
<td>0.36(0.04)***</td>
<td>0.42(0.04)***</td>
<td>0.45(0.05)***</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>1.66(0.06)***</td>
<td>1.53(0.06)***</td>
<td>1.50(0.05)***</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>1.32(0.12)**</td>
<td>1.34(0.13)**</td>
<td>1.41(0.13)***</td>
</tr>
<tr>
<td>Race: Black</td>
<td>0.75(0.10)*</td>
<td>0.88(0.13)</td>
<td>0.95(0.13)</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>0.91(0.12)</td>
<td>0.89(0.12)</td>
<td>0.92(0.13)</td>
</tr>
<tr>
<td>Absences</td>
<td>0.76(0.04)***</td>
<td>0.75(0.04)***</td>
<td>0.77(0.04)***</td>
</tr>
<tr>
<td>Classes Skipped</td>
<td>0.77(0.06)***</td>
<td>0.80(0.06)***</td>
<td>0.79(0.07)***</td>
</tr>
<tr>
<td>Freshman Year Math Score</td>
<td>1.05(0.01)***</td>
<td>1.01(0.01)</td>
<td>1.01(0.01)</td>
</tr>
<tr>
<td>Junior Year Math Score</td>
<td>1.06(0.01)***</td>
<td>1.06(0.01)***</td>
<td>1.06(0.01)***</td>
</tr>
<tr>
<td>Intercept</td>
<td>5.59(0.75)***</td>
<td>5.09(0.73)***</td>
<td>4.50(0.65)***</td>
</tr>
<tr>
<td>Observations</td>
<td>7,920</td>
<td>7,920</td>
<td>7,920</td>
</tr>
</tbody>
</table>

Note: Odds Ratios Followed by Robust Standard Errors in Parentheses

*p < .05  **p < .01  ***p < .001
Table 4.9  
*Sensitivity Results*

<table>
<thead>
<tr>
<th>Removed Treatment Covariate</th>
<th>Comparison</th>
<th>Outcome</th>
<th>Sensitivity Results</th>
<th>Original Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race: Black</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.39(0.37)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>Race: Black</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.77(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.45(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>Race: Hispanic</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.44(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>Gender: Female</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.19(0.38)**</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>SES Quintile</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.83(0.10)</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>Two Parent Household</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.46(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>Two Parent Household</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.77(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>High Parental College Expectations</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.46(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>High Parental College Expectations</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>8th Grade Performance</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.45(0.37)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>8th Grade Performance</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>8th Grade Behavior</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.44(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>8th Grade Behavior</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.74(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>8th Grade Math Course</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.52(0.37)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>8th Grade Math Course</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
<tr>
<td>8th Grade Math Grade</td>
<td>Model #3</td>
<td>Math Achievement (coefficient)</td>
<td>-1.53(0.38)***</td>
<td>-1.45(0.38)***</td>
</tr>
<tr>
<td>8th Grade Math Grade</td>
<td>Model #10</td>
<td>College Attendance (odds ratio)</td>
<td>0.76(0.09)*</td>
<td>0.76(0.09)*</td>
</tr>
</tbody>
</table>
4.6 Discussion

I. What are the short-term (math achievement) and long-term (college attendance) impacts associated with attending a high-suspension high school and how are these impacts related?

When controlling for selection, students that attend high-suspension high schools were associated with lower math achievement test scores in high school (Model 3) and were less likely to attend college full time (Model 12)—even when accounting for school-level social order and student-level sanctions. These effects were not only statistically significant, but also practically significant: students who attend a high-suspension school have only a 43% chance of attending college full-time—compared to a 57% chance for students attending a low-suspension school.

In regards to the relationship among these short and long-term impacts, when junior year math scores were added in the college attendance selection model (Model 12), both the indirect effects associated with attending a high-suspension high school, as well as the direct effects associated with receiving an ISS no longer remained significant predictors of college attendance. The salience of math in rendering the impacts of high-suspension schools and suspensions moot in the college attendance selection models allow for two plausible interpretations. First, based on the negative impact that high-suspension schools have on math achievement scores, it can be inferred that attending a high-suspension school decreases some students’ junior year math achievement scores to the extent that the actual impact of the school no longer remains a significant predictor of college attendance. This implies that the long-term collateral effects of attending high suspension schools may be channeled through their impacts on academic subjects, such as math. Second, it can be also be inferred that higher junior year math achievement may act as a protective factor for other students—shielding them from the negative indirect and direct effects associated with suspensions. For these students, later math achievement may serve as a
way to achieve mobility in high-suspension contexts. Of course, these interpretations are not mutually exclusive. In fact, based on the range of junior year math achievement scores within schools, it is likely that both phenomena are occurring at the same time. In either interpretation, we can infer that the negative impact that attending a high-suspension school has on college attendance is significantly mediated by later math achievement, which demonstrates the overall importance of math in these contexts.

Finally, it is important to note that when junior year math scores were added in the college attendance treatment model (Model 9), both the indirect effects associated with attending a high-suspension school, as well as the direct effects associated with receiving an ISS remained significant predictors of college attendance. Thus, when selection is not controlled for, the significant effects associated with attending a high-suspension school, as well as directly receiving a suspension, are strong enough to withstand the impacts of later math achievement. Here, we can infer that students who naturally “select” into high-suspension schools may be more susceptible to the negative effects of them and that these negative effects might not be significantly mediated through later academic achievement. Thus, for students that naturally select into these schools, lower junior year math achievement may not completely account for the impact of attending a high-suspension school; alternatively, higher junior year math achievement may not be able to buffer the negative impact of attending a high-suspension school either.

II. How do the effects associated with directly receiving a suspension compare to the indirect effects associated with attending a high-suspension high school?

In the null models for both math achievement (Model 1) and college attendance (Model 4), directly receiving an ISS was associated with a large and significant negative effect on each
respective outcome. In order to understand whether or not ISS also acted as an indirect effect, we added a measure of attending a high or low-suspension school in the treatment models for both math achievement (Model 2) and college attendance (Model 7). In each model, the indirect effect associated with attending high or low-suspension school surpassed the direct effect associated with receiving an ISS (as demonstrated by a one unit increase in ISS), which had weakened with the inclusion of the treatment. While the indirect school-level impacts of ISS can be seen as absorbing a small portion of the direct student-level impacts of ISS in these treatment models (that included both measures), it is important to note that the indirect effects associated with ISS in the treatment models were also stronger than direct effects associated with ISS in the null models. Furthermore, even though the indirect effects associated with attending a high-suspension school slightly weakened in the selection models for math achievement (Model 3) and college attendance (Model 10), these effects still remained stronger than the direct effects associated with receiving an ISS in the selection model. Moreover, while the indirect effect associated with attending a high-suspension school in the college attendance selection model (Model 10) was slightly less than—although still similar to—the direct effect associated with receiving an ISS in its equivalent null model (Model 4), the indirect effect associated with attending a high-suspension school in the math achievement selection model (Model 3) was greater than the direct effect associated with receiving an ISS in its equivalent null model (Model 1). Thus, when we account for the extremes of the distribution of ISSs across schools, the indirect effects associated with attending a high-suspension school on college attendance and math achievement are similar—and at times—stronger than the direct effects associated with receiving a suspension when not accounting for attendance within these school types.
III. How do student background characteristics interact with high-suspension schools and math when predicting college attendance?

In the college attendance models we found a significant interaction between race and high-suspension schools, as well as a significant interaction between race and math. When we controlled for selection into high-suspension schools in the college attendance model (Model 10), Black students were significantly associated with decreased odds of attending college. This change in the selection model implies that racial/ethnic inequality in college entry exists net of school levels of social control. Moreover, this type of racial/ethnic inequality may be masked in studies that do not attempt to account for potential selection effects. We can conclude from this finding that even if school suspension rates were equalized across high and low suspension schools, Black students would likely face other significant obstacles in their pursuit of post-secondary educational opportunities. One of these additional obstacles may be early math preparation and performance. Here, when freshman year math achievement scores were included in the college attendance selection model (Model 11), significant differences in college entrance no longer remained for Black students. This underscores the importance of math course-taking and algebra preparation in the first year of high school for Black students in high-suspension schools.

4.7 Conclusion and Directions for Future Policy and Practice

In total, the differences in the results between the treatment and selection models tells us that the distribution of achievement across social control categories—specifically high and low-suspension schools—is unequal. Perhaps more important, however, is the change in the magnitude of the effect-sizes of high-suspension schools once non-random school selection is addressed. This tells us that the effects appearing in the majority of research about school social
control may be overstated by proportions that should not be ignored (see Table 4.4). Therefore, counterfactual models and other strategies that are able to adjust for non-random selection into schools are needed in limiting the biases associated with their effects.

In this study we have demonstrated that even the least severe forms of exclusion, such as ISS, are associated with detrimental short and long-term effects on students that do not directly receive them, but—by no fault of their own—merely attend schools that overuse them. While a low-suspension school may be prone to some collateral consequences of their own, our study demonstrates that it is far worse to attend a high-suspension school. Attending a high-suspension school can lower students’ math achievement scores and, ultimately, decrease their ability to access post-secondary educational opportunities. Adding to previous research, these findings demonstrate that the relationships among the school-to-prison and STEM pipelines do not only occur directly, but also indirectly, which provides several implications for practitioners, policymakers, and members of the public who are concerned about the school-to-prison pipeline, the STEM pipeline, and their interrelation.

In light of this study’s findings, the rationale that a greater reliance on exclusionary discipline sanctions might mitigate school disruptions and by doing so increase the overall learning of non-offending students, appears to be unfounded. Rather, a greater reliance on ISS provides an additional mechanism of educational stratification, and by doing so, further exacerbates inequities between schools. As further research is necessary to understand how the mechanisms of exclusionary discipline operate within high social control educational environments, these findings support the need future explorations of crime wave and negative vicarious experience theories within schools. Thus, while ISS has been thought of as an
alternative to out-of-school suspensions, this study has demonstrated that ISS might need an alternative as well.

In seeking an alternative to ISS, recent research has indicated that restorative justice might offer a viable solution. Rather than separating the offending individuals from their classroom communities, restorative justice seeks reintegration (Gonzalez, 2012). In doing so, restorative justice builds students’ problem-solving skills (2012), while also increasing their sense of belonging and engagement—ultimately, making transgression less likely to occur in the first place (Eisenberg, 2016). Therefore, it is unsurprising 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). However, while the positive effects of restorative justice have been found to extend to even the most marginalized student groups (Anyon et al., 2014; Anyon et al., 2016), schools with a higher proportion of minority and low-income students have been found less likely to implement these policies (Welch & Payne 2010; Payne & Welch, 2015).

In addition to ensuring that restorative justice policies extend to all schools, our work suggests that stakeholders should also focus on increasing math achievement in high-social control contexts. As this study has demonstrated, math—especially algebraic reasoning—may represent an alternative access point for interventions that seek to curb the collateral effects of suspensions. Here, research by Cortes, Goodman, and Nomi (2015), found that an intensive math instructional policy for 9th grade students—known as “Double-dosage Algebra”—increased students’ math credits and test scores, as well as student’s high school graduation and college enrollment rates. Based on our findings, interventions of this kind may be especially impactful for Black students.
In closing, it is important to note that even after we account for the extremes of the distribution of ISSs across schools, key demographic variables still remained significant predictors of the outcomes. Inequality in math performances remained a reality for Black students; increases in college attendance were evident only for female students; and Higher-SES students remained significantly related to an increase in both math achievement and college attendance. Thus, while policies aimed at decreasing exclusionary discipline practices, as well as increasing math achievement, should rightfully be pursued, more must be done to ensure the short and long-term reductions in test-score inequality and college attendance disparities. Moreover, as more and more jobs in the knowledge-based economy are requiring mathematical and technological skills, as well as college degrees, creating more equitable schools in this regard would not only meet the needs of these specific students, but also the needs of the larger economy and our society as a whole.
References


discipline the role of school policy. *Urban Education, 42*(6), 536-559.


Kinsler, J. (2013). School discipline: A source or salve for the racial achievement


StataCorp. 2013. *Stata: Release 13. Statistical Software*. College Station, TX: StataCorp LP.


the influence of sociodemographics and school characteristics on students' risk of suspensions. *School Psychology Review, 42*(1).


Chapter 5: Conclusion

Education then, beyond all other devices of human origin, is the great equalizer of the conditions of men, the balance-wheel of the social machinery. – Horace Mann

Since the publication of the *A Nation at Risk* report in 1983, improving STEM education as a means of ensuring both national and individual economic success has been a central goal of U.S. education policy (Mehta, 2013). However, today there is not only a disproportionately smaller percentage of Black, Hispanic, and low-income students engaged in successful STEM education, but also an overall shortage. Unsurprisingly, these trends are also reflected in the STEM workforce. When considering the history of school desegregation in America coupled with the of unequal structuring of opportunities-to-learn STEM within and across schools and neighborhoods, access to high quality STEM education can be considered a civil right (Tate, 2001). Thus, STEM education policy in the U.S. has fallen short of its goals, not only for the national prosperity, but also for individual equity.

Furthermore, at the same time that policy-makers were calling for a broad increase in the STEM workforce, there was a targeted increase in the prison population. Alexander (2012), among others, has argued that certain educational and criminal justice policies beginning in the 1980s, such as zero tolerance policies in schools and the war on drugs in neighborhoods, increasingly targeted Black, Hispanic, and low-income individuals. This caused a disproportionate spike for these populations within exclusionary school discipline practices, and ultimately, prisons. Moreover, similar to STEM, the problem in prisons is not only one of disproportionality, but also one of total numbers, as many scholars, including Pettus-Davis, Brown, Veeh, and Renn, (2016), argue that in addition to an unequal amount of individuals incarcerated, there is also an overall excessive amount of individuals incarcerated.
Placing these two realities in concert with each other, the disproportionality in each pipeline can be seen as currently complementing the other. Here, underrepresented groups in STEM tend to be overrepresented in exclusionary discipline measures and prisons, while overrepresented groups in STEM tend to be underrepresented in exclusionary discipline measures and prisons. Therefore, we are unlikely to increase the overall size of the STEM workforce—with individuals currently living in the U.S.—by focusing our efforts on those that are already overrepresented in STEM, nor are we likely to decrease the overall size of the prison population by focusing our efforts on those that are already underrepresented in prisons. Rather, we must focus on increasing the number of underrepresented students in the STEM pipeline, which would likely decrease the number of overrepresented students in the STP pipeline, while at the same time focus on decreasing the number of overrepresented students in the STP pipeline, which would likely increase the number of underrepresented students in the STEM pipeline. Thus, in order for education move closer the ideal of being the “great equalizer” that it was intended to be, efforts in both areas must occur concurrently.

Nevertheless, previous research has been limited in its ability to comprehensively address the complex nature of opposing student opportunity structures and their resulting pipelines in a manner that both explores problems and seeks solutions through interactions between academics and discipline. Consequently, as neither the STEM nor the STP pipeline—studied in isolation—can explain the complex relationship between math and exclusionary discipline in high schools over time (or point to possible interventions), I have used this dissertation to analyze both pipelines in concert with each other.

5.1 Summary
Findings from this dissertation demonstrate that there were significant interactions among the STP and STEM pipelines. In article one results demonstrate a reciprocal relationship among exclusionary discipline and math: suspensions significantly influenced outcomes associated with the STEM pipeline, while math achievement significantly influenced outcomes associated with the STP pipeline. Nevertheless, within-pipeline influences were strong and only marginally lessened the impact of cross-pipeline influences in some cases. Thus, while decreasing suspensions can increase math attainment, this would not erase the impact of low early math performance; similarly, while increasing early math performance can decrease dropout cases, this would not erase the impact of prior suspensions.

In article two results demonstrate that suspensions significantly decreased a latent construct of math achievement and that the significant interactions among the school-to-prison (STP) and STEM pipelines had the effect of pushing students out of high school over time. Furthermore, findings from article two demonstrate that the accumulation and saturation of advantages and disadvantages within and across these pipelines were different for unique race and gender identities and intersections. Specifically, the effects of initial disadvantages in discipline—according to race and gender—often weakened over time (or were “saturated”), while the effects of initial disadvantages in academics often strengthened over time (or were “accumulated”). Here, weaker effects of discipline on academics for disadvantaged groups may be due to the fact that students within these groups have “less to lose” in terms of their math achievement. Conversely, stronger effects of academics on discipline for disadvantaged groups may be due to the fact that math knowledge is developed sequentially and thus prone to exponentially detrimental effects when there is less of it to lose for students within these groups.
Finally, in article three results demonstrate that when controlling for selection into schools, students attending high-suspension high schools were associated with a relative decrease in junior year math achievement and were less likely to attend college—even when accounting for school-level social order and student-level sanctioning. Moreover, findings from article three demonstrate that the indirect effect associated with attending a high-suspension high school was similar and in some cases greater than the direct effect associated with receiving a suspension when not accounting for attendance into high-suspension schools.

5.2 Implications

In the first article, given the significance of within-trajectory influences—even in the presence of cross-trajectory influences, it was affirmed that interventions must work across both discipline and academics. Here, decreasing suspensions and increasing early math achievement must both occur in order to redirect students away from the STP pipeline and towards the STEM pipeline. This assertion was reaffirmed in the second article, which demonstrated that the interactions among math and discipline had the effect of pushing students out of school altogether, as well as the third article, which found that suspensions were indirectly associated with a decrease in math achievement and, ultimately, college attendance. Additionally, in the third article, the rationale that a greater reliance on exclusionary discipline measures might mitigate school disruptions and by doing so increase the overall learning of non-offending students, appears to be unfounded. Rather, a greater reliance on exclusionary discipline measures decreases the overall learning of non-offending students, and ultimately provides an additional mechanism of educational stratification between schools.

Furthermore, in terms of race, findings from the first article suggest that reducing racial segregation in schools is key to decreasing instances of dropping out, but also antithetical to
maximizing the participation in advanced math course-taking for students within predominantly Black schools. Thus, reducing racial segregation between schools should be accompanied with measures for integrating advanced classrooms within schools; at the same time, targeting predominantly Black schools with suspension-reducing reforms should also be pursued, as it could increase the number of students that these schools can direct towards advanced math course-taking. In the second article, our findings suggest that when considering the consistent saturation of racial/ethnic and gender disadvantages within discipline, combined with the consistent accumulation of racial/ethnic disadvantages within math, group-tailored interventions for multiply disadvantaged students, which in this case are Black males, should emphasize increasing math achievement. Also, given the relatively low percentage of variance explained in many of the study’s constructs for Black females, as well as the saturation of many of the study’s effects for these students, other factors should be explored for decreasing the rate of dropping out for these particular students. Here increasing math achievement, even if accompanied by suspension-reducing reforms may not be enough to significantly disrupt the process of pushing out for Black females. Finally, in the third article our findings suggest that even after we account for the extremes of the distribution of ISSs across schools, certain demographic groups still remained significant predictors of the math achievement and college enrollment. Thus, while policies aimed at decreasing exclusionary discipline practices across schools should rightfully be pursued, more must be done to ensure the short and long-term math achievements of disadvantaged student groups, such as Black students, male students, and low-income students.

5.3 Interventions

In-school suspension (ISS) was initially conceived as a less-exclusionary alternative to out-of-school suspension (OSS)—originally designed to remove disruptive students from
classrooms in order to provide a secluded setting where the behavior of offending students could be reformed, while also ensuring the learning of their classmates (Sheets, 1996). This would likely result in a reduction of recidivism and an increase in academic achievement—both for the disciplined student and his or her classmates. However, this dissertation has demonstrated that the original intents of ISS do not match its current reality: it was found to be directly and indirectly related to a decrease in math achievement, directly related to an increase in premature school departure, and indirectly related to a decrease in the odds of college attendance.

In seeking an alternative to ISS, recent research has indicated that restorative justice might offer a viable solution. Rather than separating the offending individuals from their classroom communities, restorative justice seek reintegration (Gonzalez, 2012). In doing so, restorative justice build students’ problem solving skills (2012), while also increasing their sense of belonging and engagement (Eisenberg, 2016). As a result, restorative justice can be seen as improving the overall climate of classrooms and schools, which ultimately makes student transgressions less likely to occur in the first place (2016). Hence, it is unsurprising 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). However, while the positive effects of restorative justice have been found to extend to even the most marginalized student groups (Anyon et al., 2014; Anyon et al., 2016), schools with a higher proportion of minority and low-income students have been found less likely to implement these policies (Welch & Payne 2010; Payne & Welch, 2015). Thus, while stakeholders should seek to ensure that restorative justice policies extend to all schools, stakeholders should also focus on increasing math achievement in high-social control contexts.
Additionally, as this dissertation has demonstrated, math—especially algebraic reasoning—may represent an alternative access point for interventions that seek to curb the negative effects of suspensions. Here, research by Cortes, Goodman, and Nomi (2015), found that an intensive math instructional policy for 9th grade students—known as “Double-dosage Algebra”—increased students’ math credits and test scores, as well as student’s high school graduation and college enrollment rates for all students.

5.4 Limitations

While this dissertation has been able to demonstrate the interactions among math and school discipline in a variety of ways, the scope of this dissertation—which has focused mainly on math and suspensions within the context of high schools—has limited its reach. For example, while the relationship among suspensions, math, dropout status, and college enrollment was confirmed throughout this dissertation, it is possible that the patterns presented in this dissertation may extend beyond the specific variables and constructs employed in the analyses. Rather, these patterns may also represent a larger phenomenon across multiple forms of disciplinary and academic domains. Moreover, these patterns may have unique impacts on a variety of racial/ethnic groups that were not explicitly explored in these analyses. Thus, future studies in this area should include other academic areas, such as science, as well as other measures of exclusionary discipline, such as out-of-school suspensions—and do so paying close attention to other racial/ethnic groups, such as Asian-Americans. Furthermore, the interactions among STEM and discipline should also be explored both prior to and after high school, which will allow for a more robust proxy of both the STEM and STP pipelines, as well as a more comprehensive understanding of the longitudinal nature of each pipeline. Finally, while this dissertation was able to demonstrate the interactions among discipline and STEM, the specific
mechanisms that underlie these interactions remain somewhat unknown—especially when considering the potential psychological and sociological constructs at play. Thus, future research should also consider such aspects like stereotype threat and labeling theory.

5.5 Strengths

This dissertation has led to important breakthroughs in the knowledge, theories, and methods surrounding the research of discipline and academics, which can ultimately have a positive impact on both educational and criminal justice systems in the U.S. Starting with knowledge, findings from this dissertation allow stakeholders to understand 1) how STP and STEM cross-pipeline impacts operate in the presence of within-pipeline impacts—when considering both student and school-level characteristics, 2) how the interactions among the STP and STEM pipelines relate to the process by which students are pushed out of school for unique race-gender intersections of identity, and 3) how indirect exposure to the STP pipeline can impact access to the STEM pipeline—both within and beyond high schools. In total, this new knowledge provides acute access points for decreasing exposure to the STP pipeline, while increasing access STEM pipeline in high schools.

Moving on to theory, the new knowledge generated by this dissertation has expanded 1) interactional theories—by exploring interactions among academics and sanctions to misbehavior; 2) intersectional theories—by exploring how intersections of identities can operate differently within and across opposing structures of opportunity in which advantages and disadvantages are not uniformly experienced among identities; and 3) social control theories—by exploring the collateral damages of less severe exclusionary discipline practices, like in-school suspensions. By expanding these theories in the research on math and suspensions, scholars will gain a more
comprehensive perspective on the interactions among discipline and academics and how these interactions can impact educational outcomes for underserved students.

Furthermore, in terms of methods, this dissertation has expanded on previous analyses pertaining to academics and discipline by 1) removing biases associated with missing-ness through multiple imputation in multi-level logistic regression models, while accounting for both student and school-level weights; 2) employing multiple-indicator, multiple causes (MIMIC) modeling techniques with latent difference score and structural equation models in order to remove biases associated with missing demographic variables; and 3) limiting selection bias into school-level treatments with propensity score weighting through optimized general boosted regression machine learning techniques. By expanding these the methods previously used in the research on academics and discipline, scholars will be able to further remove biases in the estimation of school-level, structural, and treatment effect models when dealing with complex survey data in the future. Moreover, by using methods that account for student and school-level variability (MLM), measure structural relationships over time (SEM), and estimate treatment effects (PSA), this dissertation provides stakeholders with a better understanding of 1) how the interactions between math and suspensions occur both within and between schools; 2) how these interactions occur over time for different intersections of identity; and 3) how these interactions occur both directly and indirectly through treatments.

By filling these gaps in the knowledge, theories, and methods surrounding discipline and academics, stakeholders are better positioned to design and implement the interventions needed to meet the academic, behavioral, and social-emotional needs of underserved students.

5.6 Conclusions
While interacting the STP and STEM pipelines demonstrated the reciprocal relationships among suspensions and math—often highlighting the pitfalls that many of our most underserved students are prone to, there is much promise in potential reforms. Black students who take advanced math and science courses are just as likely as White students to pursue STEM degrees (Tyson, Lee, Borman, & Hanson, 2007). Additionally, Black students who graduate college have lowered incarceration rates that are similar to White college graduates (Sum, Khatiwada, McLaughlin, & Palma, 2009). Moreover, when considering that racial/ethnic earning gaps tend to narrow in the STEM workforce (as seen in Figure 5.1 left), redirecting students away from the STP pipeline and towards the STEM pipeline has the ability to increase equity—not only in education and occupation—but also in earnings and wealth. Thus, efforts to reduce suspensions and increasing early math achievement should be a priority for all stakeholders.

*Figure 5.1. Racial Earnings Gaps in STEM (Pew Research Center, 2018)*

Additionally, it is important to note that even if students are able to exit the STP pipeline, but not fully enter the STEM pipeline, there are still important spillover effects for students that graduate high school and attend college. For example, in a 2013 report Carnevale, Smith, & Strohl (2013) predicted that by year 2020 sixty-five percent of all jobs in the U.S. economy
would require at least some form of postsecondary education; in a subsequent report Carnevale, Jayasundera, and Gulish, (2016) suggest that these earlier predictions may have underestimated the importance of a college degree, as 11.5 million of the 11.6 million (99%) jobs created since the recession have gone to individuals with at least some college education (p. 1). Furthermore, college graduates earn on average $32,000 (134%) more than individuals with a high school diploma (Trostel, 2015) and are expected to pay $273,000 more in lifetime tax contributions, while receiving $81,000 less in lifetime tax benefits (Carnevale, Jayasundera, & Gulish, 2016). Here, it is important to note that importing highly skilled labor from abroad does not have the same impact as developing talent in our current citizenry.

In total, by understanding the various ways in which the STP and STEM pipelines interact—especially for underserved students, stakeholders will be able to use these findings to guide targeted reforms in both discipline and STEM in order to create more equitable opportunity structures in schools that will benefit both underserved students and the larger U.S. economy and society. Thus, if the goal in education is not only to halt students’ progress on a perilous path, but also to redirect students to a more prosperous one, then this research is vital—both for individuals and the communities they are embedded in.

5.7 Future Work

While my dissertation research has demonstrated the significant interactions among these pipelines within schools, research has yet to explore these interactions within social networks and neighborhoods, which—given the social nature of the STEM and STP pipelines—may prove to be promising contexts for reforms. In filling this gap, my future research will explore how social network and neighborhood characteristics—including the geospatial location of friends, classmates, and schools—can impact students’ interactions within and across STEM and STP
pipelines over time, especially for underrepresented race, class, and gender identities and intersections. In doing so, this research has the potential lead to policies and programs that work synergistically across network, neighborhood, and school contexts in order to more comprehensively decrease exposure to the STP pipeline, while increasing access to the STEM pipeline.
References


Finally, it is important to note that all of the analyses in this paper relied on multiple imputation techniques for missing data. Following Rubin’s (1987) formula for efficiency, we utilized 5 imputed data sets for each analysis (with the exception of those using FIML), which, as Schafer and Olsen (1998) note, is sufficient for an efficient analysis of imputed data. However, more recent research has demonstrated that while 5 imputed data sets may be efficient for point estimates, more imputed data sets may be needed for efficient estimates of standard errors (see White, Royston, & Wood, 2011). As a result, White, Royston, and Wood (2011), among others, recommend that the number of imputations should be similar to the percentage of cases that are missing. For most imputed variables, this was the case in our analyses. However, there were a few variables where the percentage of cases that were missing exceeded the number of imputations we used (5). While we acknowledge this as a potential limitation, we also note that additional analyses that relied on more imputations (10), produced similar results.
# Appendix B: CFA and SEM Correlation Tables

## Correlation of Variables used in CFA Model

<table>
<thead>
<tr>
<th></th>
<th>Identity 1</th>
<th>Score 1</th>
<th>Course 1</th>
<th>Identity 2</th>
<th>Score 2</th>
<th>Course 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identity 1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Score 1</td>
<td>0.37</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course 1</td>
<td>0.18</td>
<td>0.37</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Identity 2</td>
<td>0.54</td>
<td>0.35</td>
<td>0.16</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Score 2</td>
<td>0.36</td>
<td>0.74</td>
<td>0.34</td>
<td>0.38</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Course 2</td>
<td>0.31</td>
<td>0.56</td>
<td>0.48</td>
<td>0.33</td>
<td>0.61</td>
<td>1</td>
</tr>
</tbody>
</table>

## Correlation of Endogenous Variables used in SEM Model

<table>
<thead>
<tr>
<th></th>
<th>Math 1</th>
<th>Math 2</th>
<th>HS Susp.</th>
<th>Drop. Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Math 1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Math 2</td>
<td>0.91</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HS Susp.</td>
<td>-0.38</td>
<td>-0.44</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Drop. Status</td>
<td>-0.53</td>
<td>-0.60</td>
<td>0.49</td>
<td>1</td>
</tr>
</tbody>
</table>
## Appendix B: RMSEA Confidence Intervals (90%)

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Sample</td>
<td>0.024</td>
<td>0.022</td>
<td>0.027</td>
</tr>
<tr>
<td>(N = 16510)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0.034</td>
<td>0.032</td>
<td>0.037</td>
</tr>
<tr>
<td>(N = 12,457)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>0.019</td>
<td>0.012</td>
<td>0.027</td>
</tr>
<tr>
<td>(N = 2,525)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.023</td>
<td>0.019</td>
<td>0.027</td>
</tr>
<tr>
<td>(N = 8,422)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.022</td>
<td>0.018</td>
<td>0.026</td>
</tr>
<tr>
<td>(N = 8,228)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White-Male</td>
<td>0.032</td>
<td>0.027</td>
<td>0.036</td>
</tr>
<tr>
<td>(N = 6,228)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White-Female</td>
<td>0.032</td>
<td>0.028</td>
<td>0.037</td>
</tr>
<tr>
<td>(N = 6,229)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black-Male</td>
<td>0.020</td>
<td>0.002</td>
<td>0.033</td>
</tr>
<tr>
<td>(N = 1,288)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black-Female</td>
<td>0.020</td>
<td>0.000</td>
<td>0.033</td>
</tr>
<tr>
<td>(N = 1,237)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>