The Impact of Discrimination on Mental Health

Regression Analysis of the Effects and Moderating Factors in Adolescents

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The Impact of Discrimination on Mental Health: Regression Analysis of the Effects and Moderating Factors in Adolescents

Abstract

In recent decades, mental health has become an increasingly prevalent issue in adolescents. Discrimination, in particular, can be a major cause of mental health symptoms for adolescents belonging to minority racial groups. In this study, we used generalized linear regression models and propensity scoring methods to quantify the relationship between perceived racial discrimination and mental health and to investigate factors that modify the effect of discrimination. These methods were applied using data from the Substance Use and Risk Factor (SURF) project and the Massachusetts Department of Elementary and Secondary Education (DESE).

Through both cross-sectional and longitudinal analysis of high school students, we found a significant positive association between perceived racial discrimination and mental health that was robust to various sensitivity analyses including different model specifications, imputation methods, and non-parametric testing. Moreover, the effect of discrimination was found to differ based on individual demographic factors such as gender, sexuality, and U.S. birth status, as well as school characteristics such as enrollment size and attendance rate. Discrimination from peers had a particularly strong negative impact on mental health. Additionally, discrimination with respect to other identity types including gender, sexuality, religion, disability, and money were also predictive of mental health with varying degrees of magnitude. Our results highlight the need for mental health support targeted toward adolescents who report experiences of discrimination and indicate several directions for future research that could better inform interventions for addressing the impact of discrimination on mental health in adolescents.

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Acknowledgments

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1 Introduction

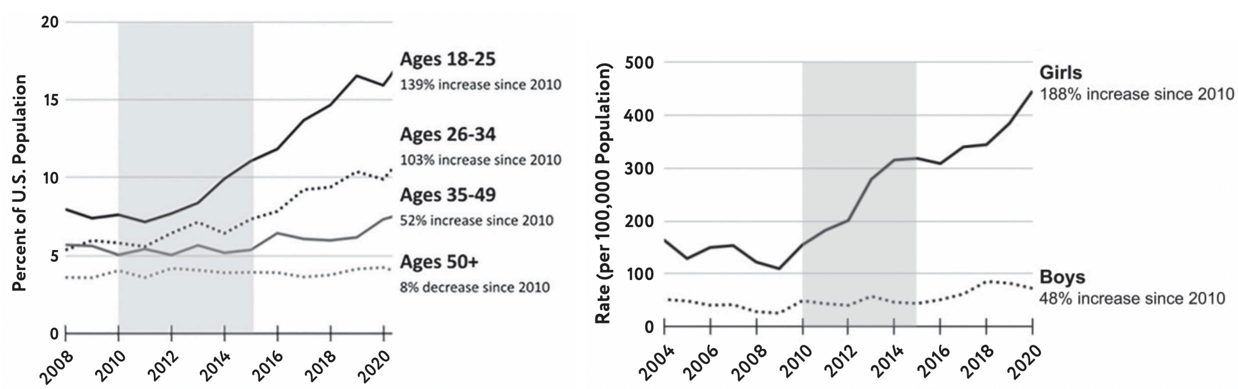
1.1 Overview

In recent decades, mental health has become an increasingly prevalent issue, especially among adolescents. Mental health symptoms are becoming increasingly common, with depression being the leading cause of disability-adjusted life years lost in 10-19-year-olds worldwide [36].

In particular, discrimination can be a major cause of mental health issues for adolescents belonging to minority groups. In the United States, due to social and political events such as the 2016 election, incidents of racial discrimination have spiked in recent years [3] [11]. Other events such as the Black Lives Matter protests and the COVID-19 pandemic in 2020 highlighted ongoing issues of discrimination and systemic inequality both nationally and internationally [20] [28]. Adolescents are especially vulnerable to discriminatory incidents, since exposure to racial discrimination in adolescence can have long-lasting impacts on development into adulthood, affecting both physical and mental health [39]. Therefore, the connection between discrimination and mental health outcomes in adolescents is an important and relevant issue to investigate.

In this study, we used generalized linear regression models and propensity scoring methods to quantify the relationship between perceived racial discrimination and mental health and to investigate factors that modify the effect of discrimination. We performed both cross-sectional and longitudinal analysis of data from the Substance Use and Risk Factor (SURF) project, a survey conducted annually in Massachusetts middle and high schools. While adolescence is generally defined as ages 10-19, we only analyzed high school students because the discrimination questions were not administered to middle school students. Although the survey data only captures self-reported information, we will typically refer to "perceived discrimination" as "discrimination" throughout this paper for simplicity. For additional variables on school characteristics, we also use auxiliary data from the Massachusetts Department of Elementary and Secondary Education (DESE).

1.2 Recent Trends in Mental Health and Discrimination



(a) Percent of adults reporting high levels of anxiety by age group

(b) The rate of adolescents (ages 10–14) being treated in emergency rooms for nonfatal self-injury

Figure 1.2.1: From *The Anxious Generation*, reports of anxiety and self-harm in the U.S. (sources: U.S. National Survey on Drug Use and Health, U.S. Centers for Disease Control, National Center for Injury Prevention and Control)

Self-reports of mental health symptoms and incidents of self-harm have increased for all age groups over the past decade, but the prevalence in adolescents is particularly prominent (Figure 1.2.1). The adolescent mental health crisis has been largely attributed to social media, which has led young people to spend increasingly more time online instead of socializing in person [22]. Young people themselves also recognize the impact that social media has on their mental health, citing how comparison to peers and cyberbullying on social media platforms negatively impacts their stress and anxiety [1] [25].

Social media has also opened the door to discrimination online. One of the earliest studies of online teen chat rooms in 2004 found at least one racial or ethnic utterance in 37 out of 38 of the half-hour transcripts they studied [47]. Increased political polarization and extremist content on the internet has also led to a rise in online hate activity in the past decade, further contributing to depressive symptoms and anxiety in adolescents [48].

The COVID-19 pandemic has further exacerbated both racial discrimination and mental health. By forcing social activity online, the pandemic induced significant lifestyle changes and increased isolation, worsening mental health challenges for children and adolescents [41]. Violence against Asian Americans and healthcare inequities during the pandemic also highlighted the ongoing issue of racial prejudice and stereotyping in the United States [44]. Although most pandemic restrictions have been lifted, the effects of the pandemic on mental health and discrimination are likely long-lasting.

1.3 Related Works

1.3.1 Race, Discrimination, and Mental Health

Findings from academic research on racial and ethnic disparities in mental health have been inconsistent. For instance, cross-sectional studies of the National Survey on Drug Use and Health from 2011-2018 found that racial and ethnic minorities seem to experience fewer mental health symptoms [36] [37]. However, due to cultural and social factors, these individuals are also less likely to report mental health issues or seek mental health services, leaving many cases undiagnosed.

Although the relationship between race and mental health is inconsistent, several previous studies have identified a significant association between racial discrimination and mental health [6] [32] [33] [46] [51]. In a study of children and youth aged 6-17 from a nationally representative survey, Weeks and Sullivan (2019) found that racial discrimination relates to both internal outcomes, such as worse mental health, and external outcomes, which include behavioral disorders [51]. Similar results were found in a longitudinal analysis of young adults in the Panel Study of Income Dynamics, the longest-running American panel survey [33]. In this study, the authors considered many types of discrimination including racism, sexism, ageism, and physical appearance discrimination, which were all significantly related to both internal and external outcomes, and the results were robust to sensitivity analysis of different encodings of the discrimination variables.

Studies that specifically analyze responses from people of color also find similar results. In their survey of Chicago public schools, Tobler et. al. (2013) found that 73% of racial or ethnic minority adolescents report having experienced racial or ethnic discrimination, and even occasional incidents can contribute to maladaptive behavioral and mental health outcomes [46]. Similarly, a four-year longitudinal study of black high school students conducted by Hurd et. al. (2014) suggests that perceived racial discrimination contributes to elevated anxiety symptoms, depressive symptoms, and alcohol use during the transition into adulthood [29]. Moreover, adolescents who deeply internalize their experiences of racism through reflection or activism may have an even stronger association between discrimination and mental health [15].

During COVID-19, while mental health symptoms were elevated among all adolescents, those who experienced racial or ethnic discrimination had disproportionately higher odds of having suicidal ideation, making a suicide plan, and attempting suicide [6]. Additionally, new experiences of discrimination may have had a particularly outsized impact on mental health. For instance, Yang (2024) conducted a study on Chinese American middle and high school students in the United States and found that those who had previously experienced bullying with respect to their race were less impacted by COVID-related discrimination than students who did not have much previous exposure to discrimination [52].

Discrimination may also have disparate effects in different identity groups. Several studies have found that sexual and gender minority youth report mental health symptoms at higher rates [6] [9] [18], suggesting that the effect of racial discrimination on mental health might vary across different dimensions of identity. In their study of black young adults, Hurd et. al. (2014) did not find a significant difference between black men and black women in how perceived racial discrimination impacted their mental health [29]. However, there are limited additional studies, especially in other minority racial groups, that consider potential differences in the effect of racial discrimination in intersectional identities. Moreover, different minority groups are prone to experiencing different types of discrimination [39]. For example, Fisher et. al. (2000) found that Asian adolescents were more likely to experience discrimination from peers while African American and Hispanic teenagers were more likely to experience institutional discrimination in stores or by police [17].

1.3.2 Moderating Effects

A strong sense of identity can moderate the impact of discrimination on mental health. A survey study of Middle Eastern and North African adults found that ethnic identity, which the authors define as "psychological, social, and behavioral affiliation with one's familial ethnicity and cultural heritage," negatively correlates with mental health symptoms [40]. Moreover, multiple meta-studies have found that race and affiliation to one's race can mediate the negative impacts of discrimination on both internal and external outcomes [53] [32]. Due to their minority status, individuals from marginalized identity groups tend to have a stronger ethnic identity. This implies that while minority racial groups may experience more discrimination, when majority group members *do* experience racial discrimination, they might be more impacted. In practice, however, this is not always the case. Weeks and Sullivan (2019), for example, found that non-Hispanic Black children who had experienced discrimination were more likely than non-Hispanic White children to have anxiety-related problems [51].

Schools can also impact adolescents' mental health by either mitigating or exacerbating the effect of discrimination. Negative school experiences can increase students' likelihood of having mental health conditions [36]. More specifically, the discrimination they experience from teachers or peers can severely impact their well-being [39]. Black students who attend schools where staff and peers are not representative of their background tend to report more discriminatory feelings [19]. In schools with high academic pressure, they may experience less discriminatory incidents, but there is still a strong impact on their mental health, and they may be less likely to seek help from mental health services [19].

1.4 Motivation

The numerous factors driving the recent rise in both racial discrimination and mental health issues, especially in adolescents, highlights the need to investigate the relationship between these two variables. Given the difficulty of diagnosing mental health in minority youth, reports of discrimination could serve as a proxy for identifying adolescents with mental health problems. Therefore, a better understanding of how discrimination relates to mental health can elucidate how to best identify students who are the most at risk for anxiety, depression, or other mental health conditions. Furthermore, experiences of discrimination do not need to be objectively real to have an effect on mental health [51], indicating that self-reported discrimination metrics, such as those in the SURF survey, can still serve as meaningful predictors.

This study extends the existing literature on discrimination and mental health in adolescents in several ways. We considered the problem in a new dataset, the Substance Use Risk Factor (SURF) survey, in which the discrimination variables have not been analyzed extensively yet. Specifically, we analyzed the 2022 and 2023 survey waves, which would reflect recent post-pandemic developments in adolescent discrimination and mental health trends. Although the schools included in the survey change each year, there are some students who have been longitudinally linked, which allowed for both cross-sectional and longitudinal study. Similar to the previously mentioned studies, our survey is also observational. However, we introduced propensity score methods, allowing for a more causal interpretation of the results. This statistical approach is relatively novel for cross-sectional studies of the impact of discrimination on mental health.

We were able to explore several subtopics because of how discrimination was encoded in the SURF data. Our measure of perceived racial discrimination was the Adolescent Discrimination Distress Index (ADDI), which captures self-reported exposure and distress from 15 discriminatory experiences. Therefore, in addition to discrimination exposure, we also analyzed students' self-reports of how upset they were by discriminatory experiences. While previous studies of discrimination typically focus on interpersonal discrimination from peers and teachers, the ADDI questions cover three racial discrimination subtypes - including peer, educational, and institutional discrimination, so we investigated potential differences in these discrimination subtypes.

The complexity of how social factors affect the way adolescents internalize discrimination highlights the need for additional research across multiple identity groups. Administered in the Boston area, the SURF survey includes a large sample size of students across several demographic groups, which allowed us to consider how individual characteristics influence the impact of discrimination. By linking the SURF data to public data from the Massachusetts Department of Elementary and Secondary Education (DESE), we studied school effects on discrimination and mental health as well.

2
Data Overview

2.1 Substance Use and Risk Factor Survey

The Substance Use and Risk Factor (SURF) survey, conducted annually by the Center for Addiction Medicine at Massachusetts General Hospital, collects data on substance use and mental health from Massachusetts middle and high schools. The sample each year includes students from middle and high schools in Massachusetts that agree to administer the survey that year. Within participating schools, parents have the option of having their child opt out of taking the survey. While the survey has been administered since 2016, the sample size remained relatively small until 2022. Therefore, this study will only include analysis of the 2022 and 2023 survey waves. In the 2023 survey, there were a total of 21,231 high school participants from 62 schools, and in 2022, there were 19,951 high school participants from 53 schools.

The SURF survey questions span several categories including demographic information, substance use, mental health, school experiences, and discrimination. Several previous studies have analyzed data from the SURF survey to understand the relationship between adolescent substance use and mental health, such as Liu et. al. [34] and Tervo-Clemmens et. al. [45]. This study will focus specifically on the questions about discrimination, which have not been extensively studied in this dataset, and the relationship of discrimination with students' mental health as measured by the PHQ-4. The discrimination questions are only administered to high school students, so our analysis is limited to students in grades 9, 10, 11, and 12.

2.2 Measures of Discrimination

The main measure of discrimination in the SURF survey is the Adolescent Discrimination Distress Index (ADDI) created by Fisher et. al. (2000) [17]. The ADDI consists of 15 true or false questions that indicate whether a participant has ever had a certain discriminatory experience with respect to their racial or ethnic identity. For each question where the participant responds "true," a follow-up question asks how much the experience upset them on a Likert scale ranging from 1 (not at all) to 5 (extremely). Figure 2.2.1 shows the full list of questions that comprise the ADDI.

	Have you experienced this?	If you had this experience, did it upset you?				
	Yes / No	**1**	**2**	**3**	**4**	**5**
		not at all	slightly	moderately	considerably	extremely
1. You were discouraged from joining an advanced level class.	Yes / No	1	2	3	4	5
2. You were wrongly disciplined or given after-school detention.	Yes / No	1	2	3	4	5
3. You were given a lower grade than you deserved.	Yes / No	1	2	3	4	5
4. You were discouraged from joining a club.	Yes / No	1	2	3	4	5
5. Others your age did not include you in their activities.	Yes / No	1	2	3	4	5
6. People expected more of you than they expected of others your age.	Yes / No	1	2	3	4	5
7. People expected less of you than they expected of others your age.	Yes / No	1	2	3	4	5
8. People assumed your English was poor.	Yes / No	1	2	3	4	5
9. You were hassled by police.	Yes / No	1	2	3	4	5
10. You were hassled by a store clerk or store guard.	Yes / No	1	2	3	4	5
11. You were called racially insulting names.	Yes / No	1	2	3	4	5
12. You received poor service at a restaurant or store.	Yes / No	1	2	3	4	5
13. People acted as if they thought you were not smart.	Yes / No	1	2	3	4	5
14. People acted as if they were afraid of you.	Yes / No	1	2	3	4	5
15. You were threatened.	Yes / No	1	2	3	4	5

Figure 2.2.1: Adolescent Discrimination Distress Index (ADDI) questions from Fisher et al. 2000

In Fisher et. al. (2000), the ADDI was defined as a sum of scores for the 15 questions, where for each question, individuals who responded "no" receive a score of 0 and those who responded "yes" receive a score 1-5 based on how upset they were. In this study, we will consider both the sum of the 15 indicator questions, which we will define as the *ADDI Total*; the original metric that incorporates how upset the respondent was, which we will define as *ADDI Distress*; and an indicator of discrimination exposure, which we will define as $ADDI\ Binary = I(ADDI\ Total > 0)$. Defining the metrics in this way allows us to separately analyze the effect of exposure to discrimination and the effect of distress from discrimination.

The 15 questions can also be divided into subindices for three different types of discrimination – educational, institutional, and peer. From Figure 2.2.1, questions 1, 2, 3, and 6 contribute to the educational discrimination subindex, questions 7, 9, 10, 12, 13, and 14 contribute to the institutional discrimination subindex, and questions 4, 5, 8, 11, and 15 contribute to the peer discrimination subindex. The ADDI subindices are calculated by finding the average of the questions corresponding to that subindex. Separating these aspects of discrimination is important as different minority groups typically experience different types of discrimination. In particular, Asian students tend to experience more peer discrimination while African American students tend to experience more institutional discrimination compared to other racial minority groups [17].

The ADDI is only intended to measure discrimination based on a participant's racial and ethnic identity. To capture exposure to discrimination on demographic dimensions other than race or ethnicity, the SURF survey includes an additional "check all that apply" question where students can indicate whether they have experienced discrimination related to gender, sexuality, religion, disability, or money in the past year. Students also have the option of selecting "other" and providing a free response answer of another aspect of their identity for which they have experienced discrimination. While the main focus of this study will be racial and ethnic discrimination, we will also explore interaction effects with these additional discrimination indicators.

2.3 Measures of Mental Health

Several mental health measures are included in the SURF survey. This study will focus only on the Four-Item Patient Health Questionnaire (PHQ-4), a scale that screens for depression and anxiety [31], which has the highest base rate among the mental health measures in SURF, allowing for greater statistical power.

The PHQ-4 is calculated by asking participants how often they have been bothered over the last 2 weeks by anxiety, worry, depression, and anhedonia. The exact phrasing for these four questions can be found in Table 2.3.1. For each of the questions, participants can answer not at all, several days, more than half the days, or nearly every day which are recoded as integers from 0-3. The *PHQ-4 Total* is the sum of all four questions, which is an integer ranging from 0-12. Similarly, the anxiety subscale is the sum of the responses on anxiety and worry, and the depression subscale is the sum of the responses on depression and anhedonia. There is also an ordinal version of the PHQ-4 where 2 or less is considered "normal," 3 to 5 is "mild," 6 to 8 is "moderate," and 9 or greater is "severe."

Over the last 2 weeks, how often have you been bothered by:	Not at all	Several days	More than half the days	Nearly every day
Feeling nervous, anxious or on edge	0	1	2	3
Not being able to stop or control worrying	0	1	2	3
Feeling down, depressed, or hopeless	0	1	2	3
Little interest or pleasure in doing things	0	1	2	3

Table 2.3.1: The Four-Item Patient Health Questionnaire (PHQ–4) for Anxiety and Depression

2.4 Massachusetts Department of Education Data

For additional characteristics on schools, public data from the Massachusetts Department of Elementary and Secondary Education (DESE) was linked to the SURF data. Metrics taken from the DESE database (https://profiles.doe.mass.edu/statereport/) include total enrollment; enrollment by race, gender, English as a Second Language (ELL), disability, high needs, and low income status; graduation rates and cohort size; college attendance rate; attendance and chronic absence rates; churn, intake, and stability percentages; teacher retention rates; and number of teachers by race and gender. Since the 2023 SURF survey was conducted in the fall of 2023, DESE data from the 2023-2024 school year was used, except for college attendance rates, which only had data available for the 2022-2023 school year.

A few additional variables were derived from the DESE data. Using the enrollment by race and the number of teachers by race, we calculated a same-race teacher-student ratio for each student, which is intended to measure racial representation that a student would have among the adult role models at their school. Additionally, a counselor-student ratio was calculated to capture school-level mental health support.

2.5 Exploratory Data Analysis and Data Cleaning

2.5.1 SURF Summary Statistics

Table 2.5.1 shows the distribution of demographic characteristics in the 2022 and 2023 SURF survey data. The majority of students identify as white, but there are also more than 1,000 students from both survey years identifying in each of the Black, Asian, multiracial, or other racial categories. Among those that responded “other” for their race, nearly 95% in 2023 and nearly 90% in 2022 identified as Hispanic or Latino(a).

For gender and sexuality, the large majority of students identify with gender-conforming, heterosexual groups. Therefore, in order to increase statistical power, some minority groups were combined. For the gender variable, non-binary, transgender, another gender, and not sure were combined into one label of “other.” For the sexuality variable, unsure, questioning, and haven’t thought about it were combined together into a single category of “unsure,” while pansexual, queer, asexual, and something else were combined into a single category of “something else.”

One notable aspect of the data is that grades 9 and 10 are overrepresented, especially in 2023. This is because as part of the SURF project, there are around 40 schools involved in a clinical trial, and these schools were only required to submit data for 9th and 10th grade students. To adjust for this imbalance, we made sure to include grade as a co-varying factor in downstream analyses.

Taking a closer look at the components of the discrimination index, we find that certain experiences of racial and ethnic discrimination are more common than others. Overall agreement to ADDI questions is higher in 2023 compared to 2022 (Figure 2.5.1). This is likely due to the fact that there are more students of color represented in the 2023 survey wave compared to the 2022 survey wave (Table 2.5.1). Accordingly, when we look at the

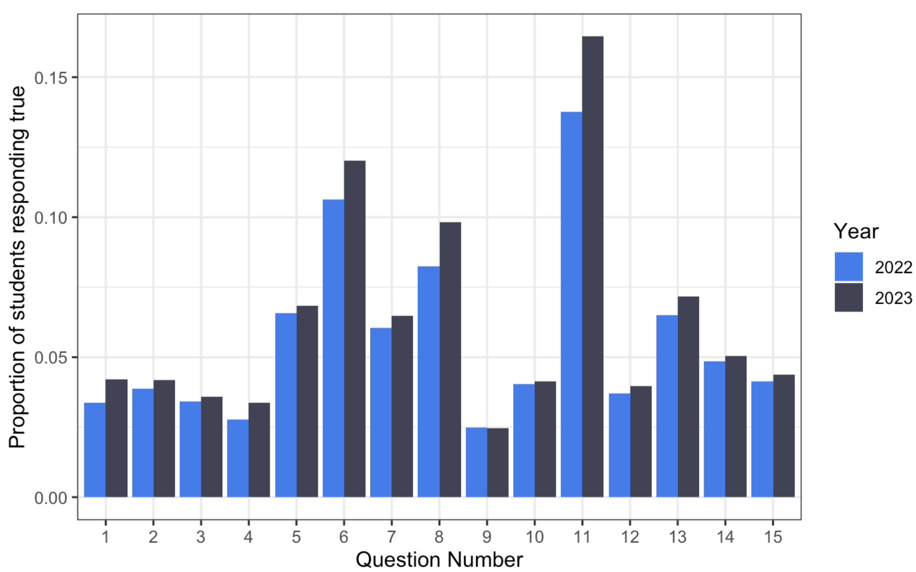


Figure 2.5.1: Proportion of students agreeing with each individual ADDI question

Variable	2022 Frequency (N = 19951)	2022 Percent (%)	2023 Frequency (N=21231)	2023 Percent (%)
Race				
White	14,421	72.28	13,393	63.08
Haitian, Black or African American	1,288	6.46	1,683	7.93
Asian	1,166	5.84	1,593	7.50
Middle Eastern/North African	233	1.17	309	1.46
American Indian/Alaska Native	78	0.39	136	0.64
Hawaiian or Other Pacific Islander	34	0.17	71	0.33
Multiracial	1,404	7.04	1,623	7.64
Other	1,020	5.11	1,734	8.17
Missing	307	1.54	689	3.25
Ethnicity				
Hispanic / Latino(a)	3,787	18.98	5,395	25.41
Not Hispanic / Latino(a)	15,905	79.72	15,389	72.48
Missing	259	1.30	447	2.11
Gender				
Boy/man/male	9,050	45.36	9,781	46.07
Girl/woman/female	9,572	47.98	10,024	47.21
Non-binary, genderqueer, or not exclusively male/female	621	3.11	494	2.33
Transgender male	151	0.76	175	0.82
Transgender female	75	0.38	64	0.30
Another gender	34	0.17	63	0.30
Not sure	179	0.90	157	0.74
I don't want to say	168	0.84	196	0.92
Missing	101	0.51	277	1.30
Sexuality				
Straight or heterosexual	14,856	74.46	16,229	76.44
Bisexual	1,770	8.87	1,538	7.24
Gay or Lesbian	615	3.08	552	2.60
Pansexual	553	2.77	482	2.27
Queer	285	1.43	205	0.97
Asexual	240	1.20	193	0.91
Something else	59	0.30	–	–
Unsure	848	4.25	–	–
Questioning or still figuring it out	–	–	542	2.55
Haven't thought about it or don't know what this question means	–	–	275	1.30
I don't want to say	560	2.81	776	3.66
Missing	165	0.83	350	1.65

Table 2.5.1: Distributions of demographic variables for 2022 and 2023 SURF high school students

Variable	2022 Frequency (N = 19951)	2022 Percent (%)	2023 Frequency (N=21231)	2023 Percent (%)
Age				
$\leq$13	30	0.15	17	0.08
14	3,378	16.93	3,746	17,64
15	5,249	26.31	6,281	29.58
16	4,792	24.02	5,210	24.54
17	4,423	22.1	3,910	18.42
18	1,701	8.53	1,475	6.95
$\geq$19	147	0.75	180	0.86
Missing	231	1.16	412	1.94
Grade				
9	5,702	28.58	6,472	30.48
10	5,139	25.76	6,746	31.77
11	4,745	23.78	4,349	20.48
12	4,365	21.88	3,664	17.26
Born USA				
Yes	17,831	89.37	18,162	85.54
No	1,976	9.90	2,764	13.02
Missing	144	0.72	305	1.44
Class Performance				
Mostly A's	8,701	43.61	8,183	38.54
Mostly B's	4,175	20.93	4,084	19.24
Mostly C's	715	3.58	822	3.87
Mostly D's	166	0.83	242	1.14
Mostly F's	102	0.51	138	0.65
Mixed grades that range from A's and B's to C's and D's	1,977	9.91	2,255	10.62
None of these grades	52	0.26	55	0.26
Not sure	300	1.50	366	1.72
Missing	3,763	18.86	5,086	23.96
Sports Participation				
Yes	9,008	45.15	8,582	40.42
No	7,106	35.62	7,479	35.23
Missing	3,837	19.23	5,170	24.35

Table 2.5.1: Distributions of demographic variables for 2022 and 2023 SURF high school students (continued)

Variable	Number of Observations	Mean	SD	Min	Max	% Missing
2022						
ADDI Total	16,442	0.821	1.999	0	15	17.59
ADDI Distress	16,442	2.523	7.398	0	75	17.59
ADDI Binary	16,442	0.265	0.441	0	1	17.59
ADDI Education	17,117	0.0528	0.146	0	1	14.20
ADDI Peer	17,005	0.0703	0.170	0	1	14.77
ADDI Institutional	17,042	0.0453	0.144	0	1	14.58
PHQ-4 Total	16,225	3.227	3.379	0	12	18.68
PHQ-4 Anxiety	16,291	1.832	1.957	0	6	18.34
PHQ-4 Depression	16,316	1.399	1.690	0	6	18.22
2023						
ADDI Total	16,947	0.920	2.059	0	15	20.18
ADDI Distress	16,947	2.678	7.335	0	75	20.18
ADDI Binary	16,947	0.299	0.458	0	1	20.18
ADDI Education	17,861	0.059	0.153	0	1	15.87
ADDI Peer	17,720	0.081	0.178	0	1	16.54
ADDI Institutional	17,797	0.048	0.144	0	1	16.17
PHQ-4 Total	17,845	2.932	3.323	0	12	15.95
PHQ-4 Anxiety	17,898	1.637	1.904	0	6	15.70
PHQ-4 Depression	17,911	1.299	1.673	0	6	15.64

Table 2.5.2: Summary statistics for the ADDI and PHQ-4 totals and subscales for 2022 and 2023 SURF data. *ADDI Binary* is an indicator for a participant responding true at least one of the ADDI questions.

average *ADDI Total* by race, the values in 2023 are no longer higher (Figure 2.5.4a). On average, students have a higher index for peer discrimination (2023 mean = 0.081) than for educational (0.059) or institutional (0.048) discrimination (Table 2.5.2).

At the level of the individual questions comprising the ADDI, we further find differential rates of agreement (Figure 2.5.1). In particular, students experience question 11 (You were called racially insulting names, 16.45% in 2023), question 6 (People expected more of you than they expected of others your age, 12.02%), and question 8 (People assumed your English was poor, 9.81%) the most across both years. Questions also differed in the amount of distress they caused (Figure 2.5.2). For example, most (28%) students who have been called racially insulting names (question 11) were not distressed at all by the experience, while students who were hassled by police (question 9) were often extremely upset (39%).

Figure 2.5.3 shows the proportion of students experiencing discrimination with respect to

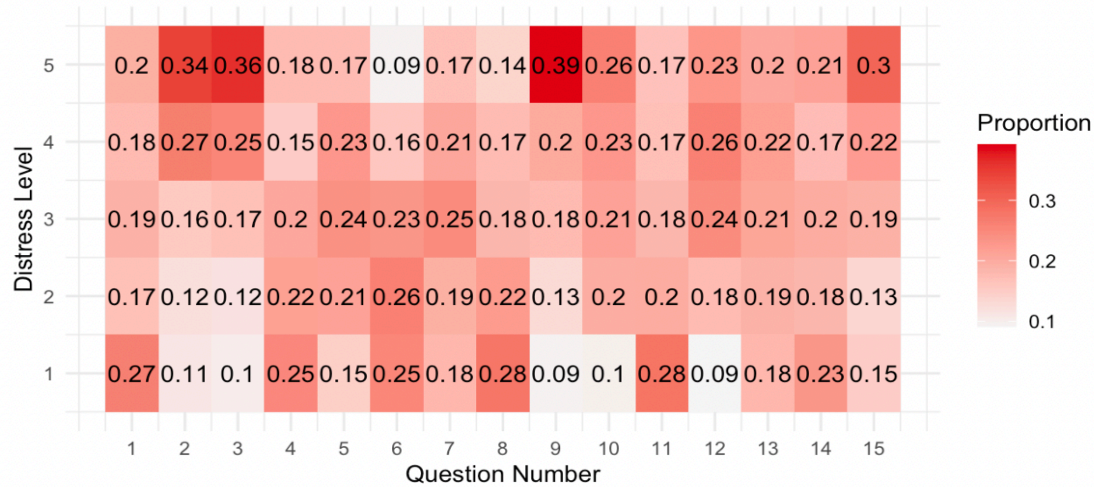


Figure 2.5.2: Distress distribution for students who had experienced each ADDI question in 2023

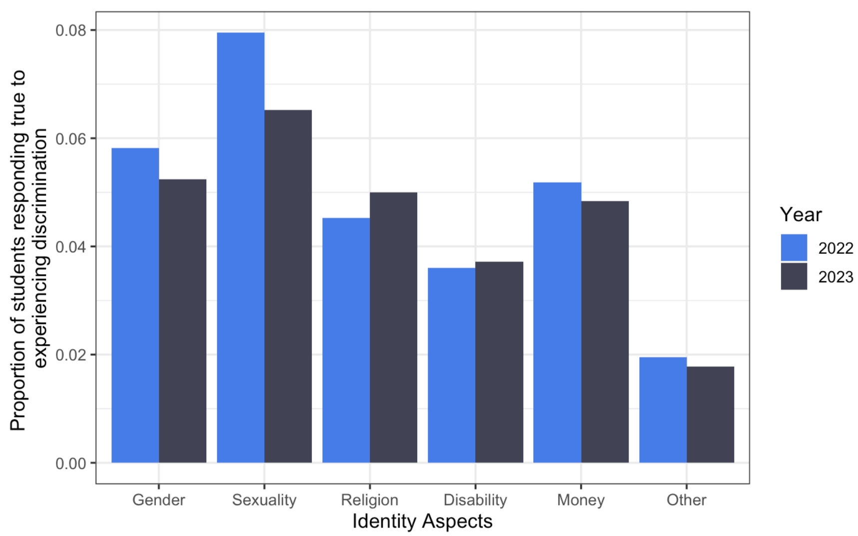
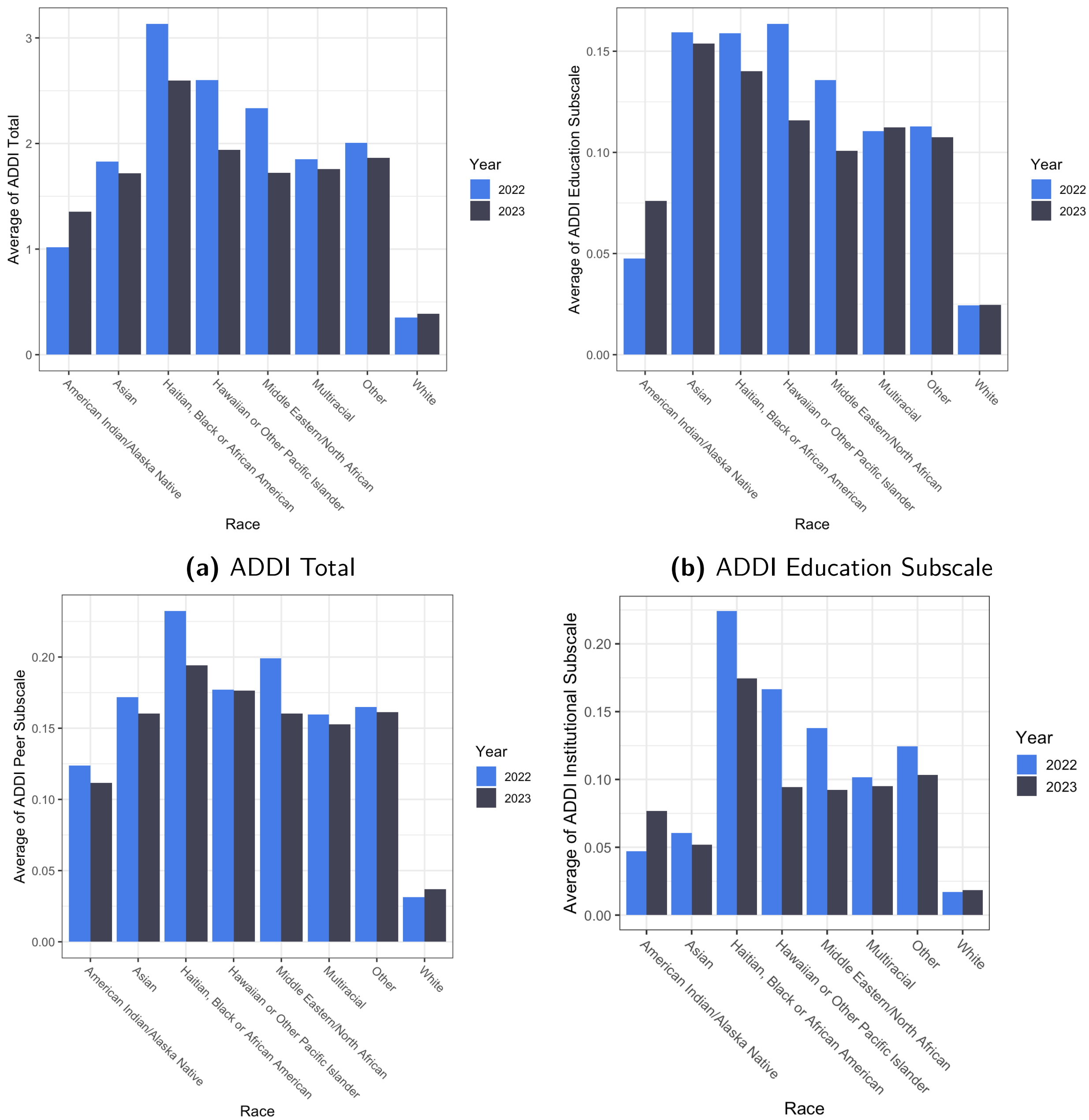


Figure 2.5.3: Proportion of the students experiencing discrimination due to identities other than race

identity aspects other than race. Among these categories, discrimination with respect to gender and sexuality are particularly common. Within the "other" category, many students reported experiences of discrimination related to their physical appearance such as weight and physique. There were also a few students who mentioned mental health and mental or learning disabilities as sources of discrimination.

2.5.2 Relationships between the ADDI, PHQ-4, and demographic variables

Unsurprisingly, *ADDI Total* differs by racial group. Students of color have a much higher average *ADDI Total* than white students (Figure 2.5.4). Moreover, Black students



(a) ADDI Total

(b) ADDI Education Subscale

(c) ADDI Peer Subscale

(d) ADDI Institutional Subscale

Figure 2.5.4: ADDI Total and subscale averages by racial group

experience peer and institutional discrimination more than other minority groups while Asian students experience more educational discrimination, particularly in the 2023 data, reflecting the findings of Fisher et. al. (2000) [17].

Unlike the discrimination index, PHQ-4 does not seem to differ much between racial groups (Figure 2.5.5). However, a higher PHQ-4 does seem to be associated with a higher *ADDI Total* (Figure 2.5.6). Interestingly, PHQ-4 levels are generally lower in 2023 compared to 2022 despite higher ADDI averages and the positive relationship between ADDI and PHQ-4. Both of these observations justify a deeper investigation into the

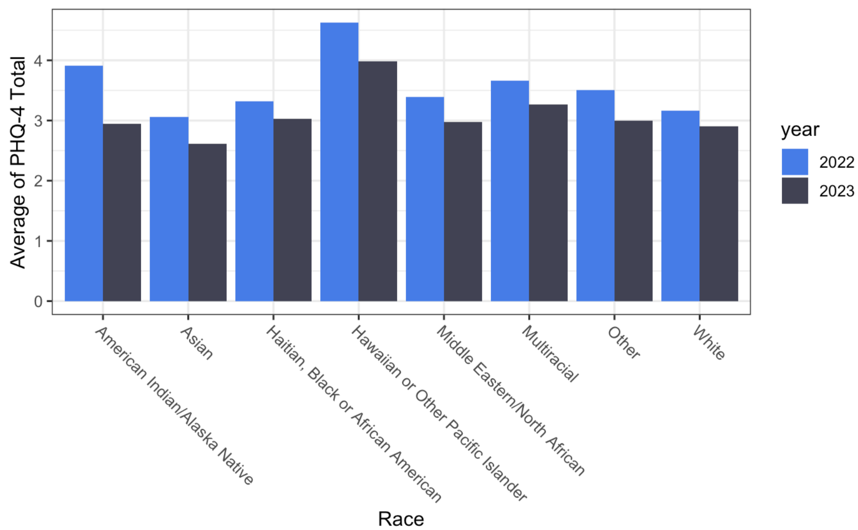


Figure 2.5.5: Average PHQ-4 score by racial group

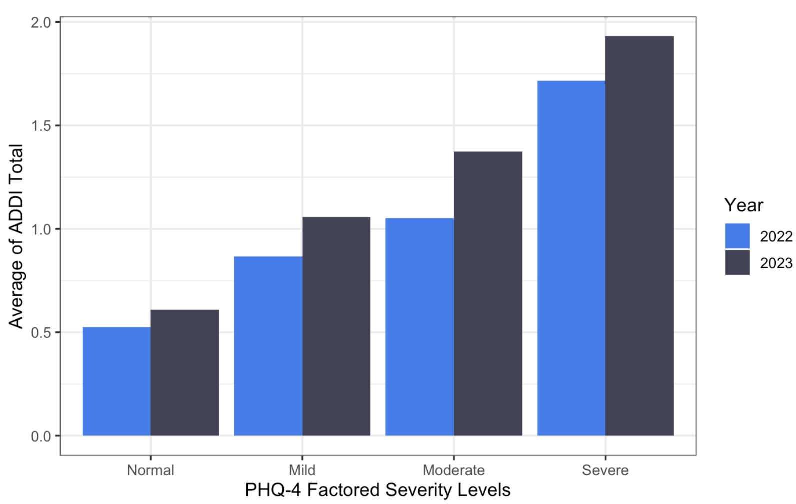
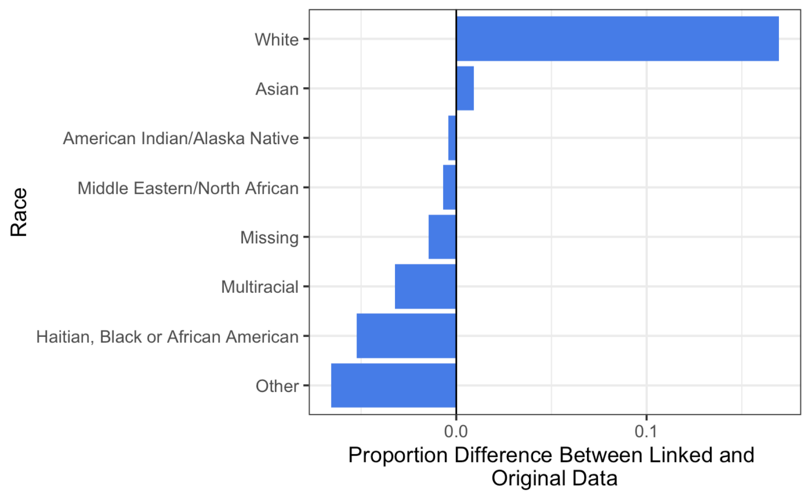


Figure 2.5.6: Average ADDI Total by PHQ-4 severity level categorization

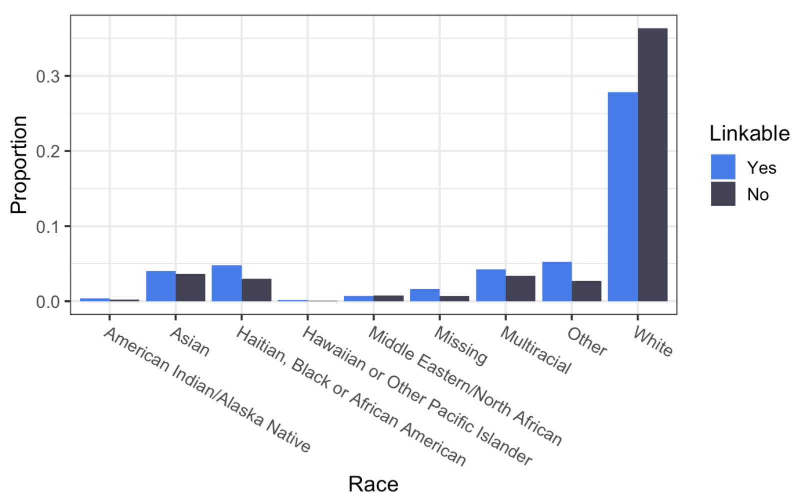
relationship between discrimination, mental health, and potential confounding factors or effect modifiers.

2.5.3 Longitudinally Linked Survey Data

The SURF survey also includes questions that can be used to longitudinally link students across years without using their name or other personal identifiers [14]. Between 2022 and 2023, among the 27 high schools that administered the survey both years, there were 3,141 students across 22 schools who were linked. There are 474 9th grade students in the linked



(a) Difference in racial group proportions



(b) Average race proportions in linked and non-linked schools from 2023 data

Figure 2.5.7: Comparison of racial distributions in longitudinally linked and non-linked data

dataset, who do not have ADDI responses from 2022 since the ADDI questions are only administered to high school students, leaving 2,667 data points for our analysis. Students of color are underrepresented in the linked students compared to the overall data (Figure 2.5.7a). This is likely due to the school-clustered survey design, as schools that were included in both survey years had a higher proportion of white students on average than schools that were only included in one year of the SURF survey (Figure 2.5.7b).

2.5.4 Missing and Inaccurate Responses

Because of the length of the survey, some students do not complete the full survey. In particular, students who have more experiences with substance use or mental health are asked more follow-up questions than students with fewer experiences, making them less likely to finish the survey (Figure 2.5.8). As a result, questions that are asked at the beginning of the survey, such as demographic information, have lower rates of missingness compared to questions asked near the end of the survey, including the ADDI and PHQ-4 questions.

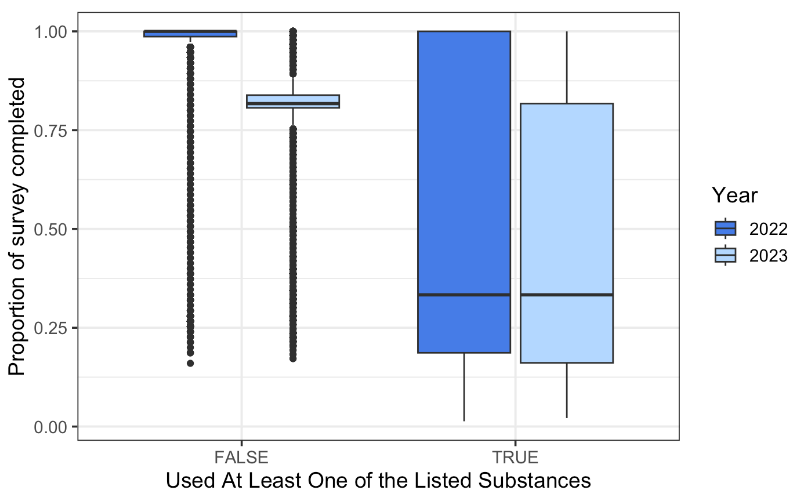


Figure 2.5.8: Distribution of Survey Completion by Substance Usage

Past work with the SURF data has typically dropped students who complete less than 60% of the survey, which is approximately 20% of the participants (Table 2.5.3). However, for some variables of interest, students who complete a low proportion of the overall survey may still fill out a large portion of the relevant variables for this study. Therefore, instead of removing participants based on their completion rate of the survey, we added an additional "missing" category to categorical variables and only dropped participants with

	Survey Year	
Metric	2022	2023
At Least 60% Complete Survey (%)	81.59	79.66
At least One Correct Attention Check (%)	98.69	98.30
All Correct Attention Checks (%)	96.98	95.91

Table 2.5.3: Completion level and attention check correctness among high school participants in the SURF survey

missingness in numeric data, with the exception of an imputation sensitivity analysis where the effects of other imputation methods were explored.

Even when data is not missing, students may also misrepresent their data by answering questions dishonestly. For most questions, there is no way of knowing whether a given response is honest. However, the survey does contain attention checks such as "Please select option 4 below." In both 2022 and 2023, more than 98% of high school participants responded correctly to at least one attention check, and around 96% responded correctly to all of them (Table 2.5.3). Students who did not respond correctly to at least one attention check were removed from all analyses after exploratory data analysis. This reduced the 2023 sample size to 20,524 across 57 schools and the 2022 sample size to 19,514 across 49 schools.

2.5.5 School Characteristics

The positive relationship between PHQ-4 and ADDI also seemed to hold at the school level (Figure 2.5.9). However, even among schools with similar average ADDI levels, there is some variation in the average PHQ-4. In analyzing the role of schools, our goal was to determine what school characteristics cause this variation and, therefore, how schools play a role in the relationship between discrimination exposure and mental health.

Table 2.5.4 shows the summary statistics of variables from DESE for all Massachusetts high schools in the DESE database and for high schools represented in the 2023 SURF survey. For almost all variables, the range represented in the SURF data is smaller, which should be expected since it is unlikely that outliers would be captured in the sample. Overall, the schools in the SURF data appear to be larger than the typical school in Massachusetts. The average and median enrollment, graduation cohort, graduation rate,

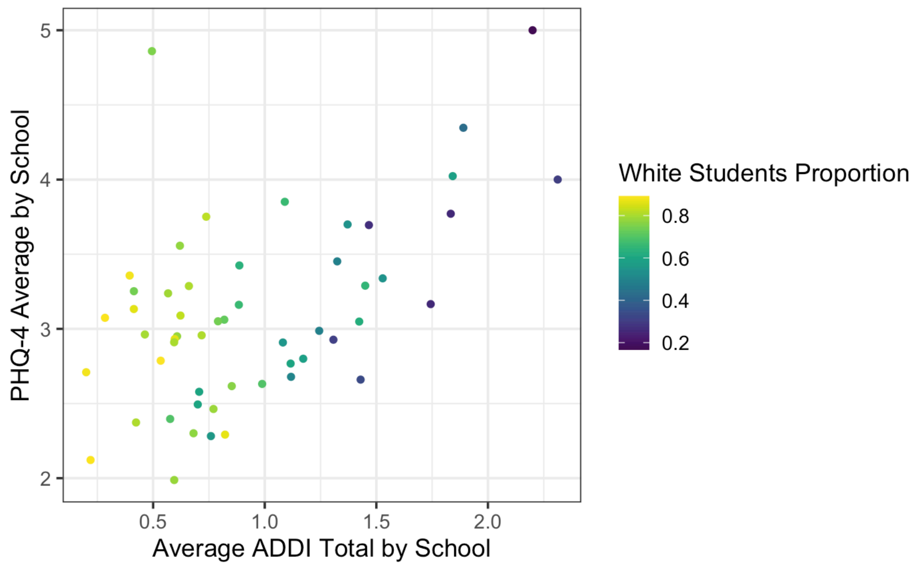


Figure 2.5.9: Scatterplot of average ADDI and average PHQ-4 by school for 2023 data

attendance rate, stable enrollment rate, and college attendance rate are all higher in the SURF data. Additionally, schools in the SURF dataset seem to be less racially diverse with respect to both teachers and students. The mean and median number of white students and teachers are higher than the overall DESE data while the mean number of students and teachers of color is lower.

2.6 A Note on Survey Weights

Given the discrepancy between the school characteristics in the SURF data and those of all high schools in the Massachusetts DESE data, we should consider the possibility of bias in estimates derived from the SURF data. Typically in survey statistics, bias is addressed using survey weights, which adjust for an observation's probability of being included in the sample. However, because the SURF survey is a convenience sample, the true inclusion probabilities are unknown. While post-hoc survey weights have been created by calibrating the data to race and grade-level population numbers from DESE, these weights were not correlated with the key variables of interest, the ADDI and PHQ-4. Since this study focuses on regression, survey weights are less crucial than when estimating population proportions or totals. In fact, some research suggests that unnecessary weighting in regression analysis can create inefficient estimators without reducing bias [8] [42]. Therefore, we have opted not to use survey weights in our data analysis.

	All DESE Schools (N=416)				2023 SURF Schools (N=57)			
School characteristics	Mean	Min	P50	Max	Mean	Min	P50	Max
Enrollment Metrics								
Total student enrollment (#)	792.9	8	654	3679	1202	14	1064	2566
Asian (%)	4.96	0	2.2	63.0	6.79	0	2.9	31.1
Black or African American (%)	11.54	0	4.7	87.9	5.175	0	4.0	26.0
Hispanic (%)	24.93	0.2	14.85	98.7	21.89	2.3	11.1	81.7
Native American (%)	0.296	0	0.1	9.1	0.231	0	0.2	0.7
Pacific Islander (%)	0.106	0	0	3.8	0.105	0	0	0.7
Multiracial (%)	3.833	0	3.3	15.8	3.229	0	2.7	10.3
White (%)	54.33	0	64.0	96.9	62.57	7.8	67.5	92.6
Female (%)	47.44	0	48.8	73.1	48.58	43.1	49.3	60.7
Male (%)	52.14	26.9	51.0	100	51.06	37.5	50.4	56.8
Non-binary (%)	0.421	0	0.2	6.0	0.37	0	0.3	1.8
English Language Learner (%)	9.01	0	3.35	100	8.012	0	3.0	36.6
Disability (%)	22.89	0	18.2	100	17.19	9.8	16.4	92.9
High Needs (%)	57.27	2.0	54.9	100	45.86	18.5	38.0	92.9
Low Income (%)	46.67	2.0	43.05	100	35.03	6.4	25.7	83.1
Teacher Demographics								
Total Full-Time Teachers (#)	56.88	0	49	223	80.88	4	74	166
Total Counselors (#)	3.82	0	3	20	5.38	0	5	13
Asian Teachers (#)	1.43	0	1	23	1.384	0	1	10
African American Teachers (#)	2.56	0	0	45	1.342	0	0	12
Hispanic Teachers (#)	2.90	0	1	61	3.87	0	2	25
Native American Teachers (#)	0.05	0	0	2	0.089	0	0	1
Pacific Islander Teachers (#)	0.04	0	0	1	0.040	0	0	1
Multiracial Teachers (#)	0.40	0	0	8	0.399	0	0	2
White Teachers (#)	49.5	0	45	183	73.76	4	69	137
Female Teachers (#)	33.29	0	29	132	48.52	3	45	111
Male Teachers (#)	23.56	0	21	90	32.34	1	32	58
Graduation Metrics								
Graduation cohort size (#)	178	6	139	876	289	19	264	666
Graduation rate (%)	85.5	0	92.6	100	91.26	26.3	94.4	100
College attending (%)	61.39	5.40	64.20	91.80	65.93	35.6	71.3	89.5
Other Student Characteristics								
Attendance rate (%)	89.53	35.1	92.6	98.6	91.92	66.2	92.6	95.6
Chronically absent (%) (missing ≥10% of school days)	28.94	0	21.9	100	23.74	5.1	21.6	82.0
Stable enrollment percent (%)	89.9	40	94.25	100	94.03	66.9	95.5	98.8
Churn rate (%)	15.4	0	8.4	82.6	9.086	1.6	6.6	42.9
Intake rate (%)	9.26	0	4.1	62.5	4.963	0.2	3.0	38.1
Other School Characteristics								
Student-teacher Ratio	12.43	2.1	11.2	224	12.04	4.3	12.1	15.1
Teacher retention rate (%)	81.58	0	85.0	100	86.98	33.3	87.9	97.1
Experienced teacher (%)	78.99	0	83.9	100	82.62	40.8	86.3	100
Teaching infield (%)	83.95	0	90.4	100	91.57	44.4	93.9	100
District per pupil expenditure (in thousands of USD)	22.28	11.2	21.04	38.93	20.85	16.46	21.08	26.53

Table 2.5.4: Summary statistics for school characteristics in DESE and 2023 SURF high schools

2.7 Data Processing Summary

Figure 2.7.1 shows a summary of the data processing steps and the number of students and schools in the data at each stage of the process. For the majority of the analysis, we used the subset of data that has been filtered for students who incorrectly answered all attention checks and for missingness in the ADDI and PHQ-4. However, for some analyses, the data was further filtered or modified as summarized in the diagram.

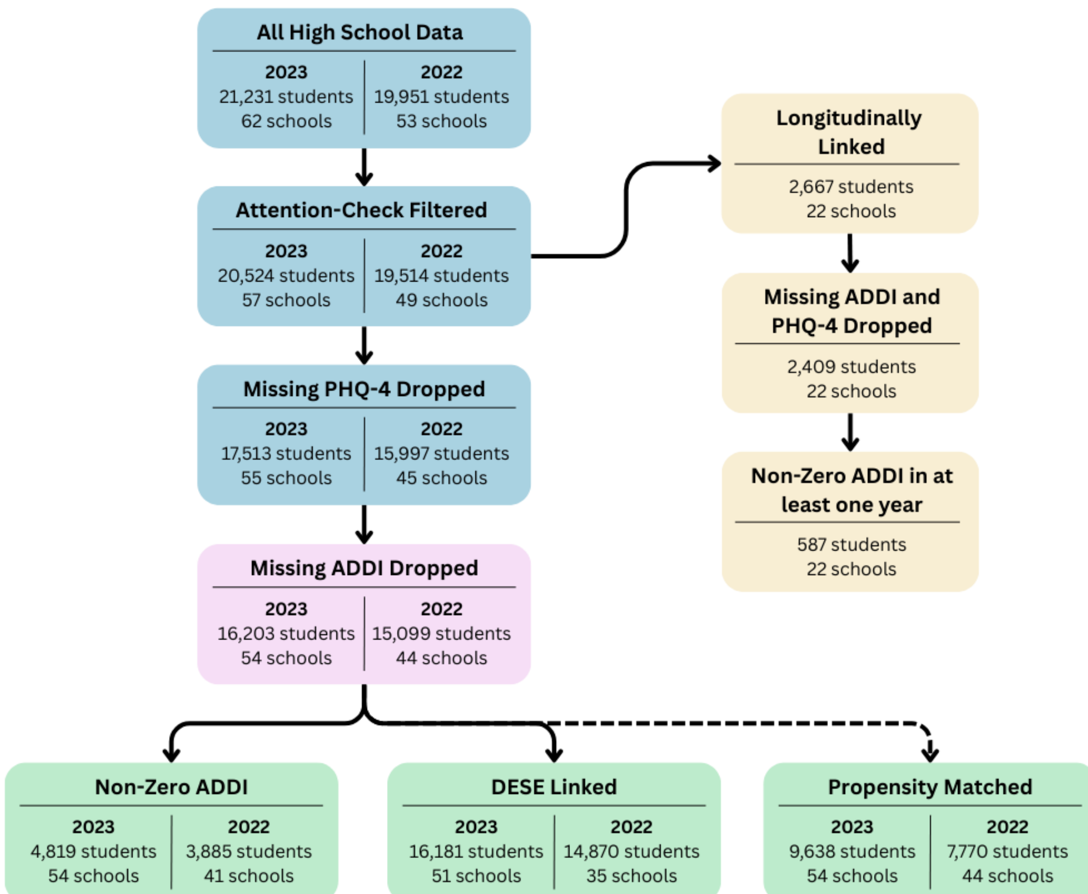


Figure 2.7.1: Data processing summary: Sample sizes for each of the data subsets created during data cleaning and for different analysis purposes. The propensity matched dataset was created through modeling.

3
Methods

3.1 Racial Discrimination Exposure and Mental Health

3.1.1 Preliminary Modeling

We started by testing several generalized linear models using *ADDI Total* as the sole predictor of *PHQ-4 Total*, our response variable. Even though the data likely does not meet all the model assumptions, our focus will be limited to generalized linear models to maintain model interpretability. Starting with standard linear regression, the model follows the form below:

$$y_i = \beta_0 + \beta_1 \cdot x_i$$

with the assumption that the data is normally distributed:

$$Y_i|(X_i = x_i) \overset{i.i.d.}{\sim} \mathcal{N}(\beta_0 + \beta_1 x_i, \sigma^2)$$

where in our case, y represents the PHQ-4 score, and x represents the ADDI. β_0 and β_1 are the intercept and ADDI coefficient respectively, which are estimated by minimizing squared errors.

However, our response variable is discrete and positive, so standard linear regression, which assumes an unbounded continuous outcome, is unlikely to be the best parameterization. Although the *PHQ-4 Total* is not strictly a count variable, since it is a score that only takes on positive integer values, a model designed for count data could be more appropriate.

One example is the negative binomial model, in which the data is assumed to follow a negative binomial distribution $Y_i|X_i \sim NBin(r, p)$. The distribution can be thought of as counting the number of failures until a set number r of successes, and p is the probability of success on each trial. The mean and variance of $Y_i|X_i$ are $\mu = \frac{r(1-p)}{p}$ and $\sigma = \frac{r(1-p)}{p^2}$ respectively. The regression models the log of the expected value of Y_i as:

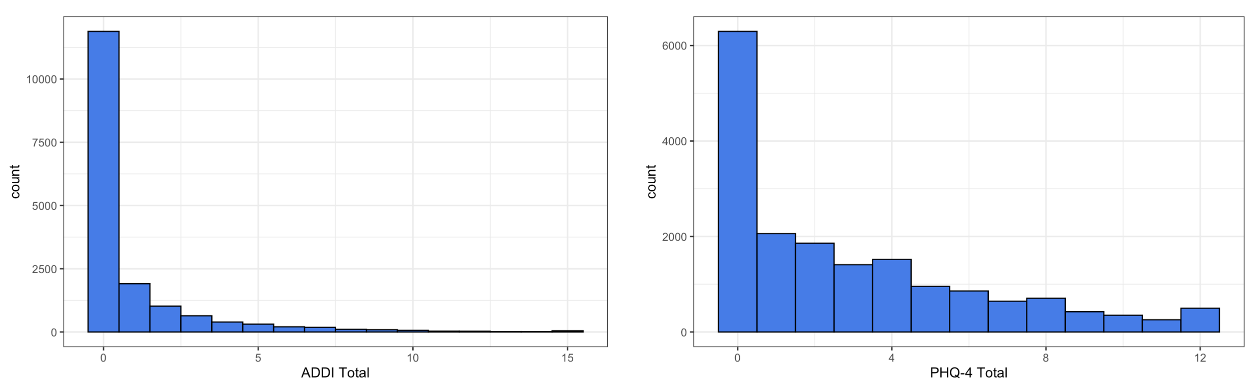
$$\log y_i = \beta_0 + \beta_1 \cdot x_i$$

or exponentiating both sides:

$$y_i = e^{\beta_0 + \beta_1 \cdot x_i} = e^{\beta_0} \cdot e^{\beta_1 \cdot x_i}$$

There is also an extra dispersion parameter θ estimated during model fitting that allows for the variance and mean of the outcome variable to differ. In standard linear regression, β_1 represents the change in the expected value of the outcome y given a one unit increase in x. In negative binomial regression, β_1 can instead be interpreted as the change in expected log-count of the outcome corresponding to a one-unit increase in x. Alternatively, the exponentiated coefficient e^{β_1} can be interpreted as the multiplicative effect on y from a one-unit increase in x.

Aside from linear and negative binomial regression, other generalized linear models we considered in this preliminary analysis included polynomial regression of orders 2 through



(a) ADDI Total

(b) PHQ-4 Total

Figure 3.1.1: Distributions of key variables in 2023 SURF data

5, binomial regression, and Poisson regression. We compared these models based on their AIC (Akaike Information Criterion), which is defined as:

$$AIC = -2 \log \mathcal{L} + 2k$$

where $\mathcal{L}$ is the likelihood of the model and k is the number of model parameters. Model selection based on AIC optimizes model fit while penalizing the number of parameters to prevent overfitting. The negative binomial model had the lowest AIC, so we chose to use it as the primary model in subsequent analysis. We also continued to use linear regression as a simpler model for comparison.

Both the ADDI and the PHQ-4 are very right-skewed, as seen from both the summary statistics (Table 2.5.2) and their histograms (Figure 3.1.1). Because of this, we also tested the same preliminary models using $x = \log(ADDI\ Total + 1)$ as the predictor to see whether the model fit significantly improved after a log-transformation. We did not transform the PHQ-4 since the negative binomial model already models the log of the response variable.

3.1.2 Demographic Variables as Confounders

Using both negative binomial and linear regression, we added demographic variables as additional predictors to determine possible confounders. The set of demographic variables were race, ethnicity, gender, sexuality, grade, born USA, class performance, and sports participation. The reference category for each of the categorical variables is shown in Table 3.1.1. In total, we compared five model specifications for predicting PHQ-4:

1. ADDI and all demographic variables as predictors
2. ADDI as well as all demographic variables and their interactions with each other as predictors
3. Predictors selected through backward stepwise selection starting from model 2
4. A random-effects model with a school-varying intercept (no demographic variables)
5. A random-effects model with a school-varying intercept and demographic variables as additional fixed effects

With the addition of more variables, the regression formula from the previous section becomes:

$$\log(y_i) = x_i^T \cdot \boldsymbol{\beta}, \qquad y_i = x_i^T \cdot \boldsymbol{\beta}$$

for negative binomial and linear regression respectively, where x_i is now a vector of the intercept and predictor variables.

Backward stepwise selection is implemented by iteratively removing the least significant predictor from the model, until removing another variable no longer improves AIC based on the methods described in Hastie and Pregibon (1992) [24].

In the random-effects models, we assume that the intercept is no longer fixed and instead varies by school according to a normal prior distribution. Therefore, the (linear) regression setup is:

$$y_{ij} = \alpha_j + x_i^T \boldsymbol{\beta}$$

$$Y_{ij} | (X_i = x_i), \alpha_j \sim \mathcal{N}(\alpha_j + x_i^T \boldsymbol{\beta}, \sigma^2)$$

$$\alpha_j \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2)$$

where i indexes an individual and j indexes their school. The negative binomial regression is analogous, with $\log(y_{ij})$ replacing y_{ij}. This mixed-effects model specification better reflects the sampling design of the survey, which has a hierarchical structure where individual students are nested within sampled schools.

We compared the ADDI coefficient and its 95% confidence interval from each of these models to evaluate how the inclusion of demographic variables in the model affects the relationship between ADDI and PHQ-4. Standard errors were cluster-adjusted by school as implemented by `vcovCL()` from the `sandwich` package in R [54], which helps to reduce bias for estimating standard errors in cluster sampling designs [2] [7], such as the school-based convenience sampling of the SURF survey. Cluster-adjustment was not applied to the random effects models, as the varying intercept accounts for cluster effects. Similar to the previous section, AIC was also used to compare model quality.

Variable	Reference Group
Race	White
Ethnicity	Non-Hispanic
Gender	Boy/man/male
Sexuality	Straight or heterosexual
Class Performance	Mostly A's

Table 3.1.1: Reference groups for categorical demographic variables

3.1.3 Demographic Variables as Effect Modifiers

Next, we introduced interaction terms between *ADDI Total* and demographic variables to identify potential effect modifiers, continuing to use negative binomial and linear regression.

We considered four effect modifiers in total: race/ethnicity, gender, sexuality, and born USA. For each of these variables, we used ANOVA to test whether the variable was a significant effect modifier. Two models were fitted for each variable, one where the variable is a confounder with ADDI and one where the variable is an effect modifier. For example, the linear regression confounder model would take the form:

$$PHQ4 = \beta_0 + \beta_1 \cdot ADDI\ Total + \vec{\beta_2} \cdot EM$$

where EM is the effect modifier. $\vec{\beta_2}$ is a vector since the effect modifiers are all categorical, so there will be one coefficient per category. Similarly, the linear regression effect modifier model would be:

$$PHQ4 = \beta_0 + \beta_1 \cdot ADDI\ Total + \vec{\beta_2} \cdot EM + \vec{\beta_3} \cdot ADDI\ Total \cdot EM$$

The confounder model is nested within the effect modifier model, so by using ANOVA, our goal was to determine whether the larger effect modifier model is significantly more predictive of the response variable than the smaller confounder model. Specifically, we conducted an ESS F-test where the null hypothesis is that the additional predictors do not add explanatory power to the model, or in this case, that $\vec{\beta_3} = \vec{0}$. The F-test statistic for comparing linear regression models is

$$F = \frac{(SSE_1 - SSE_2)/k}{SSE_2/df_2}$$

where SSE_1 and SSE_2 are the sum of squared errors for the smaller and larger model respectively, k is the number of extra parameters in the larger model, and df_2 is the residual degrees of freedom in the larger model. F follows the F-distribution with df_2 degrees of freedom, which is used to determine the p-value for the test. We will reject the null hypothesis for $p < 0.05$.

For negative binomial models, ANOVA testing involves a likelihood ratio test instead of an F-test. The test statistic for comparing negative binomial models is

$$LR = -2(\log \mathcal{L}_1 - \log \mathcal{L}_2) \sim \chi^2_{df_2}$$

where $\mathcal{L}_1$ and $\log \mathcal{L}_2$ are the likelihoods of the smaller and larger model, respectively.

For the effect modifiers deemed significant, we will use forest plots to compare the ADDI coefficient and confidence intervals of different identity groups to investigate which groups are more impacted by discrimination.

3.1.4 Imputation Sensitivity Analysis

To investigate the issue of missingness in the data, we conducted a sensitivity analysis to test whether different imputation methods affect the results. The following imputation methods were applied to the predictors in the data both with and without missingness indicators for each imputed variable:

1. Median and mode imputation for numeric and categorical variables respectively
2. Regression imputation implemented using the `mice` package in R [50] with 5 iterations
3. Hotdeck imputation implemented using the `VIM` package in R [30] using `Race` as the domain variable. This means that missing values are imputed from a randomly drawn donor with the same race.
4. kNN imputation implemented using the `VIM` package in R with $k = 5$

For each imputation method, we refit a model with *ADDI Total* and demographic variables as predictors of PHQ-4, and compared the ADDI coefficient and 95% confidence intervals. We also looked at the coefficients of the missingness indicators, to see if missingness in any of the variables was associated with the response variable.

The PHQ-4, the response variable, was not imputed to avoid artificially introducing correlations between the predictors and the response. Instead, we created exploratory visualizations of demographic variables to investigate whether there are major differences between responders and non-responders.

3.1.5 Non-parametric Testing

In the analyses of previous sections, the standard error estimates assumed normality. However, given that both the ADDI and the PHQ-4 are very skewed (Figure 2.5.4), it is possible that the coefficient is not normally distributed. To address this issue, we used bootstrapping with 5,000 iterations to approximate a distribution for the ADDI coefficient using a negative binomial model with *ADDI Total* and demographic variables as predictors of PHQ-4. A permutation test that shuffles the ADDI column with 5,000 iterations was also used to check whether the significance of the coefficient changes when normality is no longer assumed. To decrease computation time, the dispersion parameter θ was fixed at the θ estimated from the model with demographic covariates fit in the analysis of confounders (Section 3.1.2).

3.2 Re-parameterizing Discrimination

3.2.1 Racial Discrimination Distress

In addition to exposure to racial discrimination, the ADDI survey questions also ask participants how upsetting an experience was. Distress due to discrimination might have a stronger effect on mental health than exposure alone. To test this possibility, we refit the negative binomial and linear models but using the *ADDI Distress* variable instead of the *ADDI Total* to predict *PHQ-4 Total* with demographic covariates. Using AIC, we compared whether the model that includes *ADDI Distress* or *ADDI Total* was more predictive of PHQ-4. Due to the extreme skewness of *ADDI Distress*, we also repeated this procedure with the log-transformed variables $\log(ADDI\ Total + 1)$ and $\log(ADDI\ Distress + 1)$.

We also fit linear and negative binomial models with both *ADDI Total* and *ADDI Distress* included as predictors, as well as demographic variables, to determine whether the effects change when accounting for both discrimination exposure and distress together. We performed an ANOVA test between the models with and without *ADDI Distress* to see whether adding distress yielded a significantly more predictive model.

3.2.2 Racial Discrimination Subtypes

The ADDI can also be separated into three sub-indices for educational, peer, and institutional discrimination. To determine whether these discrimination subtypes have different effects on mental health, we refit the negative binomial and linear models with demographic covariates but using the three discrimination subtype variables instead of the combined *ADDI Total*.

Since different minority groups are more prone to experiencing different racial discrimination subtypes [17], we also looked at the effect modification of race on each of the three subtypes, following a procedure similar to section 3.1.3.

3.2.3 Discrimination for Other Identity Aspects

In addition to the ADDI, we also have indicator variables for whether students have experienced discrimination with respect to other aspects of their identity. For both negative binomial and linear regression, we fit a model using $ADDI\ Binary = I(ADDI\ Total > 0)$ and the other discrimination indicator variables to predict PHQ-4, in order to compare the effects of different types of discrimination on mental health. Since the other discrimination variables are all indicators, we used the binary ADDI instead of *ADDI Total* for greater comparability. Then, to see how different types of discrimination interact, we introduced the two-way interactions between the variables into the model. Finally, we refit the models with demographic variables as additional predictors to see if the effects change when controlling for demographic information.

3.3 Re-parameterizing Mental Health

PHQ-4 Total, the response variable we have been using in previous sections, combines survey responses relating to anxiety and depression into one index. However, the relationship of discrimination with anxiety and depression could be different. To test for this possibility, we refit separate linear and negative binomial regression models with demographic variables and *ADDI Total* as predictors but using the anxiety and depression subscales as outcomes.

As described in section 2.3, the numeric PHQ-4 score also factors into severity levels ranging from normal to severe. To determine whether ADDI has a predictive effect on the factored PHQ-4 scale, we used ordinal logistic regression to predict the categorical PHQ-4 using *ADDI Total* and demographic variables as predictors. In a typical logistic regression model, the outcome follows a Bernoulli distribution, $Y \sim Bern(p)$, and the probability p is modeled with:

$$P(Y_i = 1|X_i = x_i) = \frac{1}{1 + e^{-x_i^T \boldsymbol{\beta}}}$$

This can also be rewritten in terms of the log-odds:

$$\log\left(\frac{P(Y_i = 1|X_i = x_i)}{P(Y_i = 0|X_i = x_i)}\right) = \text{logit}(p_i) = x_i^T \boldsymbol{\beta}$$

where $p_i = P(Y_i = 1|X_i = x_i)$

Ordinal logistic regression extends this model for an outcome Y that takes on ordered, discrete values $0, 1, ..., k$. In this case, $k = 3$ as we have four PHQ-4 levels: normal, mild, moderate, and severe. Instead of modeling the probability of being equal to a category, ordinal logistic regression models the probability $p_j = P(Y_i \leq j|X_i = x_i)$ with:

$$\text{logit}(p_j) = \beta_{0j} + x_i^T \boldsymbol{\beta}$$

In other words, each level j has a different intercept β_{0j} that represents the baseline odds of being at or below that level. The remaining coefficients in $\boldsymbol{\beta}$ can be interpreted as the expected increase in the log-odds of moving to a higher category of the response variable when the corresponding predictor increases by one unit.

Ordinal logistic regression assumes proportional odds, which in our case implies that the effect of ADDI on the probability of being in a higher PHQ-4 severity level is the same for each level. To test this assumption, we conducted a brant test [10].

3.4 Propensity Scoring

Since discrimination and exposure cannot be randomly assigned, the previous analyses were all predictive. To answer a more causal question about the relationship between discrimination and mental health, we used propensity scores. Propensity score methods have been shown to reduce bias when working with observational data as they help to balance the covariate distributions between control and treatment groups [27] [38]. These methods are typically used on binary treatments, so we used *ADDI Binary* as the "treatment" in this analysis.

To create the propensity scores, we fit a logistic regression model using the demographic variables race, ethnicity, gender, sexuality, born USA, grade, class performance, and sports participation to predict *ADDI Binary*. We made sure to include a wide range of predictors without any variable selection methods in the logistic regression because several simulation studies have shown that including as many variables associated with both the exposure and outcome as possible reduces bias the most [5] [49].

The propensity score for an individual i is their predicted probability of discrimination exposure:

$$p_i = P(ADDI\ Binary = 1) = \frac{1}{1 + e^{-x_i^T \hat{\boldsymbol{\beta}}}}$$

where $\hat{\boldsymbol{\beta}}$ is the vector of coefficient estimates from the logistic regression. Using the propensity scores, each participant in the treatment group will be matched with a participant in the control group. The `MatchIt` package in R [26] will be used to calculate propensity scores and to match participants with similar scores from the exposed and unexposed groups. Matching will be done using the "optimal" method to create 1:1 pairings without replacement while minimizing the average absolute distance between scores across all the matched pairs [23].

Using the matched data, we performed g-computation, a method that predicts potential outcomes to estimate an average treatment effect in the treated (ATT). G-computation is advantageous for estimating effects after propensity score matching because it is not dependent on the outcome variable type or the model specification [21]. First, we fit a linear regression model to predict PHQ-4 using the binary ADDI and the covariates that were used in the logistic regression for creating the propensity scores. We then used the `marginaleffects` package in R [4] to perform g-computation and estimate the ATT of racial discrimination exposure on the PHQ-4, specifying the matched pairs as clusters to create cluster-robust standard errors.

Although matching is the most popular propensity score method, inverse probability of treatment weighting (IPTW) is also common and may reduce bias and variance more than matching [12]. Thus, we also used the propensity scores to estimate the effect of the binary ADDI on PHQ-4 in a weighted linear regression using IPTW weights. For each individual i, their IPTW weight was defined as:

$$w_i = \begin{cases} \frac{1}{p_i} & \text{if } ADDI\ Binary = 1 \\ \frac{1}{1-p_i} & \text{if } ADDI\ Binary = 0 \end{cases}$$

In the weighted regression, instead of minimizing the sum of squared errors, we minimize the sum of the squared weighted errors:

$$\sum_i \left[w_i(y_i - x_i^T \boldsymbol{\beta}) \right]^2$$

The coefficient for *ADDI Binary* can be thought of as the estimated average treatment effect (ATE) of discrimination exposure on PHQ-4.

Using a forest plot, we compared the ATT from g-computation and propensity score matching and the ATE from IPTW regression to the result of a baseline, unweighted linear regression with the same model specification as the IPTW regression.

3.5 Modeling the Role of Schools

We explored how schools influence the relationship between discrimination and mental health from both predictive and causal perspectives.

From a predictive point of view, we started by investigating school characteristics that predict exposure to discrimination. We fit a logistic regression model with a school-varying intercept, using demographic variables and school characteristics as predictors of *ADDI Binary*. The school characteristics included in the model are listed in Table 3.5.1. Looking at the coefficients and their significance, we evaluated which school characteristics, if any, are predictive of students experiencing racial discrimination. The intraclass correlation coefficient (ICC) for the model was calculated to quantify how much variance in discrimination exposure is explained by schools. The ICC is defined as:

$$ICC = \frac{\sigma_\alpha}{\sigma_\alpha + \sigma_r}$$

where σ_α is the variance of the school-varying intercepts, and σ_r is the residual variance in the model.

Similarly, to explore how school characteristics relate to mental health, we also fit a random-effects linear regression model with a school-varying intercept and ADDI coefficient, using *ADDI Total*, demographic variables, and school characteristics as predictors of PHQ-4. By comparing the ADDI coefficient and its confidence intervals from this model with results from earlier sections, we aim to determine whether school characteristics confound the relationship between ADDI and PHQ-4. Additionally, the variance of the ADDI coefficient will reveal whether there are major differences across schools in the effect of ADDI on mental health. The ICC for this model was calculated as well.

Then, to determine how school characteristics modify the effect of discrimination on mental health, we followed a procedure similar to Section 3.1.3, substituting the

Variable	Description
enrollment	Total student enrollment
ell_pct	Percent students who are English language learners
disability_pct	Percent of students with disabilities
high_needs_pct	Percent of students considered high needs
low_income_pct	Percent of students who are low income
graduation_rate	Graduation rate
college_attendance_rate	Percent of students attending college
attendance_rate	School attendance rate
chronic_absent_pct	Percent of students absent $> 10\%$ of days
stability_pct	Percent of students enrolled from previous year
teacher_pct_retained	Teacher retention rate
experienced_teacher_pct	Percent of teachers experienced
per_pupil_expenditure	District per pupil expenditure in thousands
student_teacher_ratio	Overall student-teacher ratio
counselor_student_ratio	Number of counselors and student enrollment ratio
same_race_teacher_student_ratio	Teacher-student ratio for student's race

Table 3.5.1: List of school characteristic variables to be used for modeling

demographic variables with school characteristics.

For a more causal approach, we stratified students into quintiles based on their propensity scores (Section 3.4). Therefore, students in the same strata have similar demographic backgrounds but may attend different types of schools. For each stratum, we fit a logistic regression to predict discrimination exposure in order to assess whether schools impact the probability of students experiencing discrimination differently based on their likelihood of experiencing it due to their demographics. We also repeated the effect modification procedure within each stratum to explore whether schools buffer the impact of discrimination differently depending on students' propensity for discrimination exposure.

3.6 Longitudinal Analysis

For the longitudinal analysis, we used the subset of students linked between 2022 and 2023 who were in high school for both survey waves. To understand how ADDI and PHQ-4 evolve over time, we fit a paired differences linear regression model using the change in ADDI to predict the change in PHQ-4 between the two years, including demographic variables from the 2022 responses as confounders. This was repeated excluding students with $ADDI\ Total = 0$ in both years to see whether the effect is different for students who actually reported experiencing racial discrimination in at least one of the two years.

Additionally, to investigate whether ADDI is predictive of new onset of mental health, we conducted a case-control study, comparing participants who had a "normal" PHQ-4 score (0-2) to those who changed from normal to a more severe level. Specifically, we compared the mean *ADDI Total* in each year and the mean change in ADDI for the two groups. We also fit a logistic regression using the change in ADDI to predict whether PHQ-4 switches from normal to non-normal, including demographic variables as covariates.

4

Results

This section presents the results from our analysis, with additional supplementary figures and tables provided in Appendix A. Unless specified, the results for the cross-sectional analyses in this section are derived from the 2023 dataset. 2022 results will only be included in this section when there are major differences from the 2023 results. The remaining figures and tables from the 2022 data can be found in Appendix B.

4.1 Racial Discrimination Exposure

4.1.1 Preliminary Models

The results of the preliminary models for predicting *PHQ-4 Total* with *ADDI Total* as the sole predictor are displayed in Table 4.1.1. For all of the models tested, the ADDI coefficients were positive and significant above the 95% confidence level, indicating that a higher ADDI total predicts a higher PHQ-4 score (Figure 4.1.1). Results using the log-transformed ADDI were similar (Appendix Table 6.1.1).

The model with the lowest AIC was the negative binomial model, which had a coefficient of 0.0967. This indicates that a one-unit increase in ADDI is associated with a 0.0967 increase in the log count of the PHQ-4, or equivalently, a multiplicative effect of

Model Type	AIC	ADDI Coefficient	Standard Error	95% CI
Linear	84011.19	0.3485	0.0168	(0.3157, 0.3814)
2nd Order Polynomial	83982.56	0.4912	0.0467	(0.3998, 0.5826)
3rd Order Polynomial	83975.65	0.6231	0.0695	(0.4868, 0.7593)
4th Order Polynomial	83976.79	0.6876	0.1100	(0.4721, 0.9032)
5th Order Polynomial	83978.23	0.7651	0.1734	(0.4253, 1.1049)
Poisson	93858.53	0.0872	0.0040	(0.0793, 0.0951)
Negative Binomial	71395.93	0.0967	0.0046	(0.0876, 0.1057)
Binomial	112000.07	0.1360	0.0066	(0.1230, 0.1490)

Table 4.1.1: Results for preliminary models using ADDI Total to predict PHQ-4 Total in 2023 data. Standard errors are adjusted for clustering by school.

$e^{0.0967} = 1.102$ on the PHQ-4.

Model diagnostics for the linear and negative binomial models using both the log-transformed and untransformed ADDI Total both indicated violations of homoskedasticity and normality of the residuals (Appendix Figures 6.2.1 and 6.2.2). While the log-transformation slightly improved the model fit, there did not appear to be a major difference. Because of this, we primarily used the untransformed predictor in subsequent analyses.

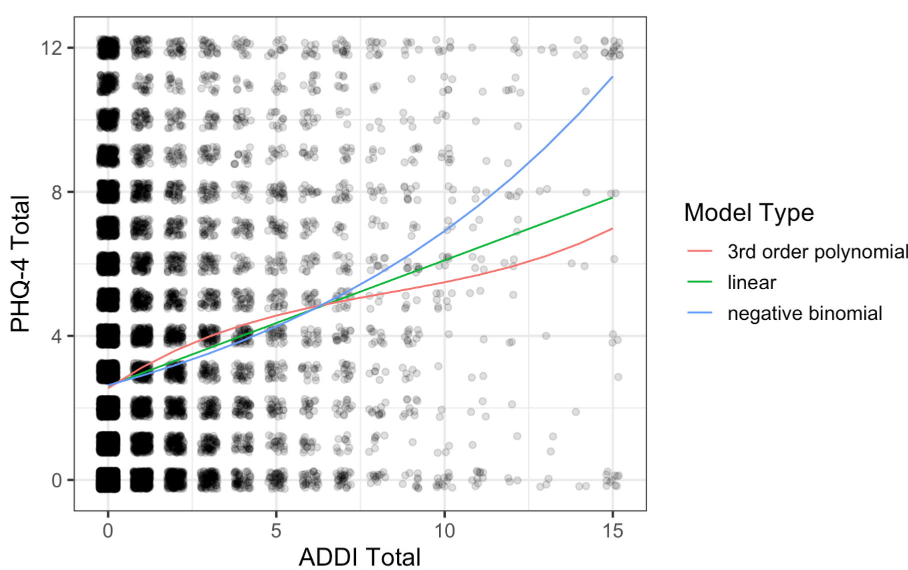


Figure 4.1.1: Predictions of select model types for predicting PHQ-4 with ADDI

4.1.2 Confounders

Adding demographic variables as covariates created models that fit the data better with respect to AIC (Table 4.1.2). In particular, backward stepwise selection and random effects with demographic variables as confounders had the lowest AIC for both negative binomial and linear regression. The lower AIC of the random-effects models demonstrates that controlling for school, in addition to individual characteristics, further helped to improve the model fit.

	AIC	
Model	Negative Binomial	Linear
No Confounders	71395.93	84011.19
Demographic Variables	69453.89	81174.80
Demographic Variables and Interactions	69737.55	81307.14
Backward Stepwise	69398.57	81117.52
Random Effects	71256.49	83807.76
Random Effects with Demographics	69332.83	81088.21

Table 4.1.2: AIC of various model specifications with confounders

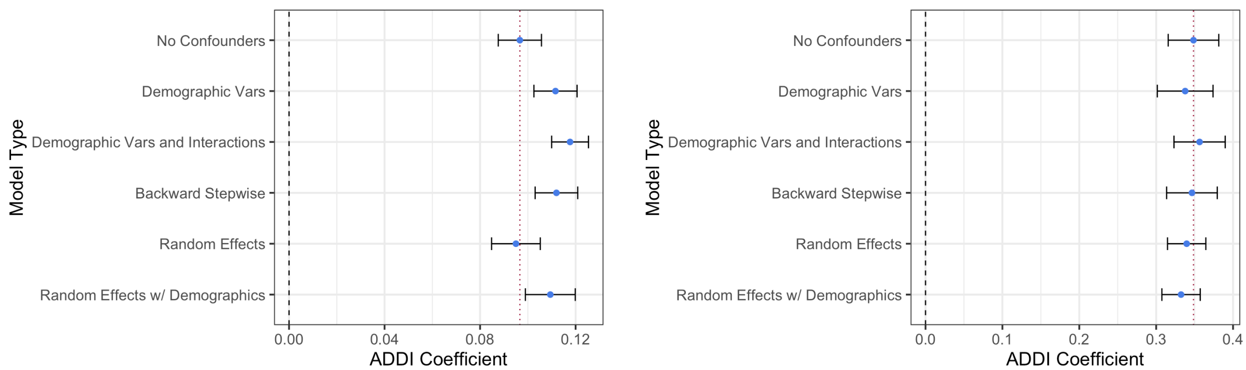
In all of the models, the ADDI coefficient continued to be significant, indicating that ADDI continues to have a positive effect on PHQ-4 even when controlling for demographic characteristics (Figure 4.1.2). For linear regression, adding additional variables to the model did not noticeably change the ADDI coefficient. On the other hand, for negative binomial regression, adding additional variables increased the ADDI coefficient, suggesting that some of the demographic variables may be collinear with both ADDI and the response variable.

In the 2022 data, however, adding the confounders did not have any noticeable impact on the effect of ADDI (Appendix Figure 7.0.1). The effect of ADDI on the log-count of PHQ-4 in 2022 (Appendix Table 7.0.2) was also smaller in magnitude for all models compared to 2023 (Table 4.1.3). The difference between years was significant. For instance, in the negative binomial models with demographic variables, the ADDI effect in 2022 was 0.080 (CI = [0.069, 0.091]) compared to 0.112 (CI = [0.103, 0.121]) in 2023.

Aside from ADDI, several of the confounders were also significantly associated with PHQ-4 in the negative binomial models (Table 4.1.3). In particular, coefficients for almost all gender and sexuality groups were positive and significant in each of the models that included demographic variables, indicating that individuals who do not identify as male

	Negative Binomial Models Predicting PHQ4 Total			
	Demographic variables	*Full Interactions*	*Backward Stepwise*	*Mixed-Effects w/ demographics*
ADDI Total	0.112***	0.118***	0.112***	0.109***
RaceNative	−0.074	−2.404*	−0.101	−0.076
RaceAsian	−0.289***	0.263	−0.071	−0.255***
RaceBlack	−0.248***	0.414	−0.113	−0.260***
RacePacific Islander	0.035	−2.542	0.649*	0.034
RaceMiddle Eastern	−0.008	−0.180	0.040	−0.007
RaceMultiracial	−0.079**	−0.921**	−0.131	−0.086**
RaceOther	−0.160***	0.266	−0.050	−0.178***
EthnicityHispanic	−0.046	−0.325	−0.110***	−0.064**
GenderGirl/ woman/ female	0.516***	1.062***	1.115***	0.521***
GenderI don't want to say	0.431***	1.044	2.027**	0.450***
GenderOther	0.583***	1.294**	1.431***	0.585***
SexualityBisexual	0.577***	0.848**	0.375***	0.562***
SexualityGay or Lesbian	0.564***	1.505**	0.629***	0.560***
SexualityI don't want to say	0.206***	0.071	−0.016	0.200***
SexualitySomething else	0.561***	1.409***	0.437***	0.558***
SexualityUnsure	0.447***	0.117	0.084	0.439***
Grade	0.037***	0.095**	0.080***	0.039***
BornUSA	0.017	0.165	0.026	0.022
ClassPerformanceBs	0.060**	0.079	0.065***	0.076***
ClassPerformanceCs	0.263***	0.087	0.267***	0.251***
ClassPerformanceDs	0.486***	1.018	0.488***	0.474***
ClassPerformanceFs	0.529***	−0.644	0.525***	0.498***
ClassPerformanceMixed	0.240***	0.412	0.247***	0.236***
ClassPerformanceNone	0.393**	2.425	0.391**	0.362**
ClassPerformanceUnsure	−0.120	1.329	−0.126	−0.099
Sports	−0.183***	−0.457**	−0.346***	−0.184***
RaceNative * BornUSA		−0.035	0.096	
RaceAsian * BornUSA		−0.238**	−0.270***	
RaceBlack * BornUSA		−0.139	−0.172*	
RacePacific Islander * BornUSA		−0.996*	−0.788*	
RaceMiddle Eastern * BornUSA		−0.005	−0.038	
RaceMultiracial * BornUSA		0.057	0.045	
RaceOther * BornUSA		−0.143	−0.128	
EthnicityHispanic * Sports		0.141**	0.148***	
GenderGirl/ woman/ female * Grade		−0.061***	−0.069***	
GenderI don't want to say * Grade		−0.085	−0.155	
GenderOther * Grade		−0.072	−0.091**	
GenderGirl/ woman/ female * Sports		0.172***	0.227***	
GenderI don't want to say * Sports		−0.092	−0.126	
GenderOther * Sports		0.110	0.225**	
SexualityBisexual * BornUSA		0.126	0.227*	
SexualityGay or Lesbian * BornUSA		−0.202	−0.076	
SexualityI don't want to say * BornUSA		0.223	0.273**	
SexualitySomething else * BornUSA		−0.069	0.143	
SexualityUnsure * BornUSA		0.372**	0.420***	
BornUSA * Sports		0.020	0.009	
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.1.3: Coefficients and significance of confounders in negative binomial models. Interaction terms that were removed in backward selection are not shown.



(a) Negative Binomial Model

(b) Linear Model

Figure 4.1.2: ADDI coefficients across confounder model types. The red dotted line indicates the coefficient when no confounders are included.

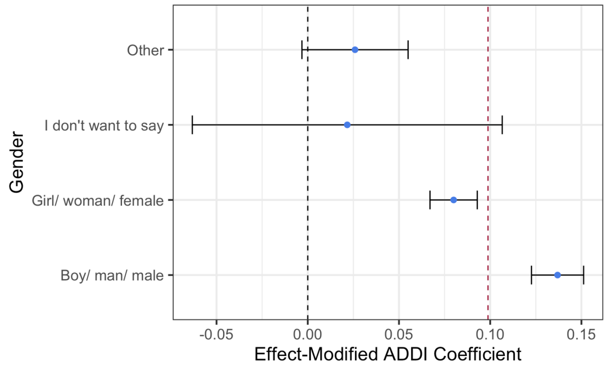
and straight have a higher PHQ-4 score. Class performance was also significantly associated with PHQ-4. Students who do not receive mostly As have higher PHQ-4 scores on average than those that do, with lower grades (Ds and Fs) having a larger negative effect than relatively higher grades (Bs and Cs). Sports were negatively associated with PHQ-4, indicating that students who participate in sports have less frequent mental health symptoms. Results from the linear regression models were very similar, although the set of interaction terms retained in backward selection were slightly different (Appendix Table 6.1.2).

4.1.3 Effect Modifiers

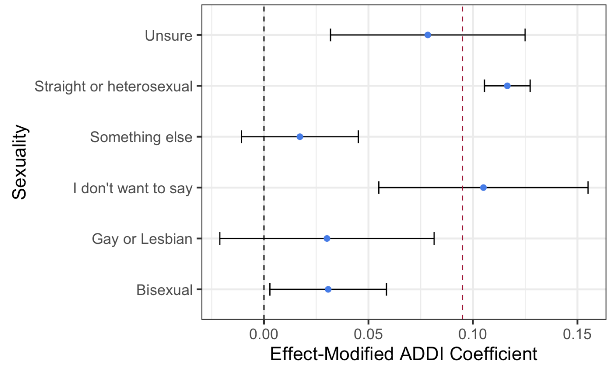
In the negative binomial models, gender, sexuality, and born USA were significant effect modifiers (Table 4.1.4). The effect of ADDI on mental health was smaller for girls and non-gender conforming individuals than for boys (Figure 4.1.3a). In terms of sexuality, the effect of ADDI on non-straight individuals was statistically significantly lower than for straight individuals (Figure 4.1.3b). Those who were unsure or who did not want to

		Negative Binomial		Linear Regression	
Effect Modifier	df	Likelihood Ratio stat.	p-value	F stat.	p-value
Race	39	49.65	0.118	1.591	0.011
Gender	4	54.61	<0.001	6.502	<0.001
Sexuality	6	62.64	<0.001	10.615	<0.001
Born USA	2	12.84	0.0016	13.535	<0.001

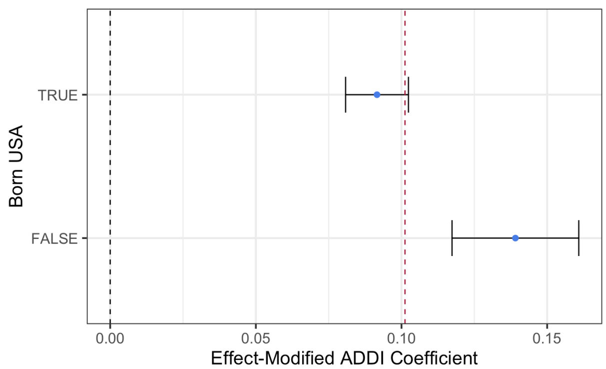
Table 4.1.4: Effect modifier ANOVA tests



(a) Gender



(b) Sexuality

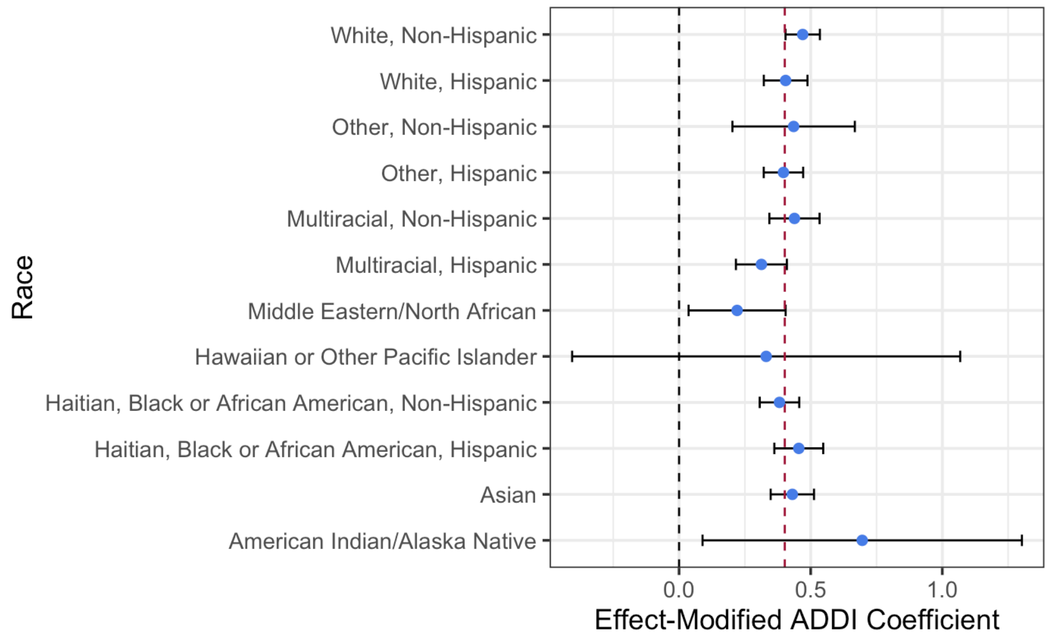


(c) Born USA

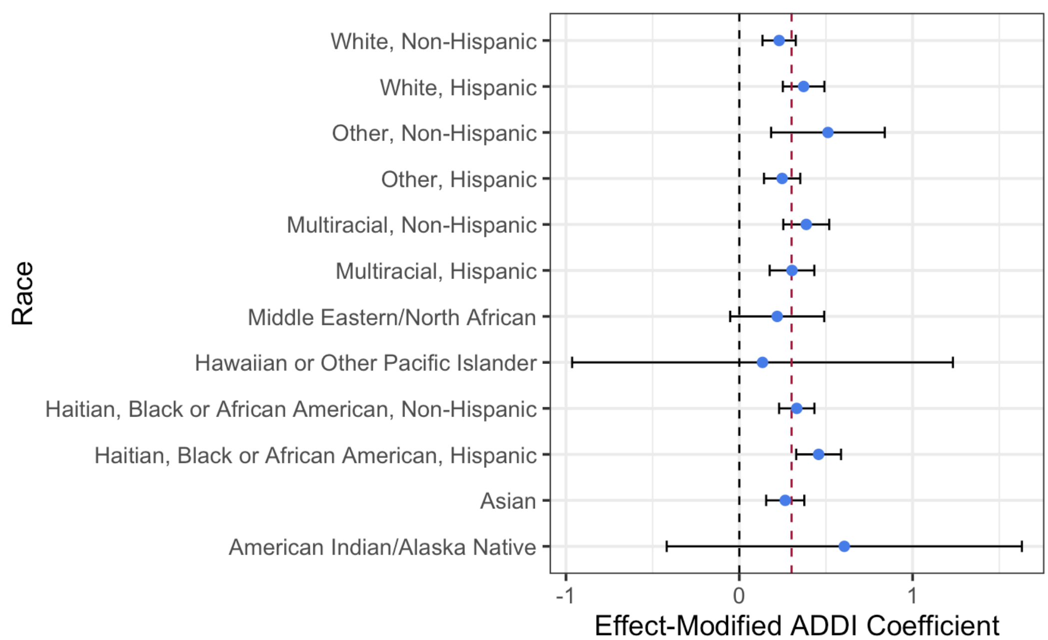
Figure 4.1.3: Effect modification forest plots for gender, sexuality, and USA birth status in negative binomial models. Red dashed lines indicate the ADDI coefficient in the model with the variable as a confounder but not an effect modifier.

disclose their sexuality did not have estimates statistically significantly different from the ADDI coefficient without effect modification. Finally, ADDI had a greater effect on those who were not born in the US than those who were (Figure 4.1.3c).

For the linear regression model, all of the effect modifiers we considered were significant in ANOVA testing (Table 4.1.4). The results for gender, sexuality, and born USA were similar to the negative binomial (Appendix Figure 6.1.1). Within each racial and ethnic identity groups, ADDI still had a significant effect on PHQ-4, other than Pacific Islanders and American Natives, which had small sample sizes (Figure 4.1.4). In the full sample, the effect of ADDI on PHQ-4 was lower for almost all minority racial groups compared to white non-Hispanic students. However, when we look instead at the effect modification of race in only individuals who have experienced racial discrimination (ADDI Total > 0), most minority racial groups experience more of an effect than non-Hispanic whites.



(a) Full Sample



(b) Subset experiencing discrimination (*ADDI Total* > 0)

Figure 4.1.4: Effect modification forest plots for race in the full sample (a) and in the subset of individuals who have experienced discrimination (b) in linear regression models (2023 data).

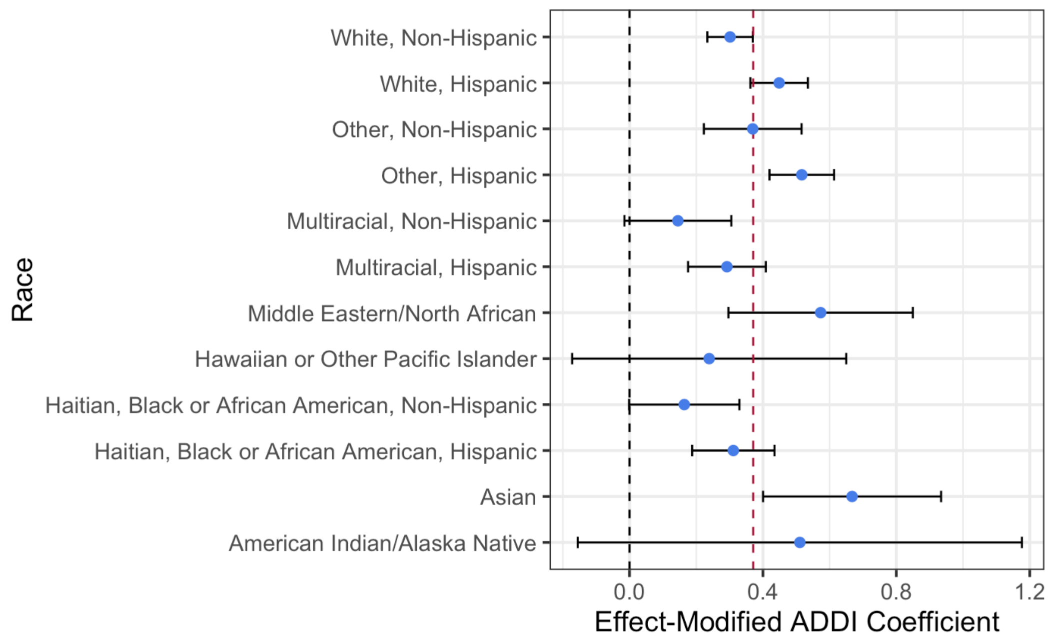


Figure 4.1.5: Effect modification forest plot for race in a linear regression model for (2022 data).

In the 2022 data, for most racial groups, the effect modification in the linear model was comparable to the 2023 results (Figure 4.1.5). For Asians, however, the effect modification was insignificant in 2023, while in 2022, the effect of ADDI on PHQ-4 for Asians was significantly greater than the baseline effect of ADDI without effect modifiers.

4.1.4 Imputation Sensitivity

Figure 4.1.6 shows the forest plot of ADDI coefficients for each of the imputation methods. Most of the imputation methods yielded lower point estimates for the ADDI coefficient than the imputation method used in our other analyses, which was adding a "missing" category for all categorical variables. This suggests that there may be some sensitivity to imputation, but the differences are not statistically significant. The results from linear regression were similar (Appendix Figure 6.1.2).

Including missingness indicators led to increased estimates of the ADDI coefficient for all imputation methods where having missingness indicators was applicable. Most missingness indicators were not consistently predictive of PHQ-4, except for the ADDI missingness indicator, which was positively correlated with PHQ-4 in all methods and statistically significant in median/mode, hotdeck, and kNN imputation (Table 4.1.5). Results from linear regression were similar (Appendix Table 6.1.3). This result could be explained by ADDI and PHQ-4 both appearing after the substance use questions in the survey, and as

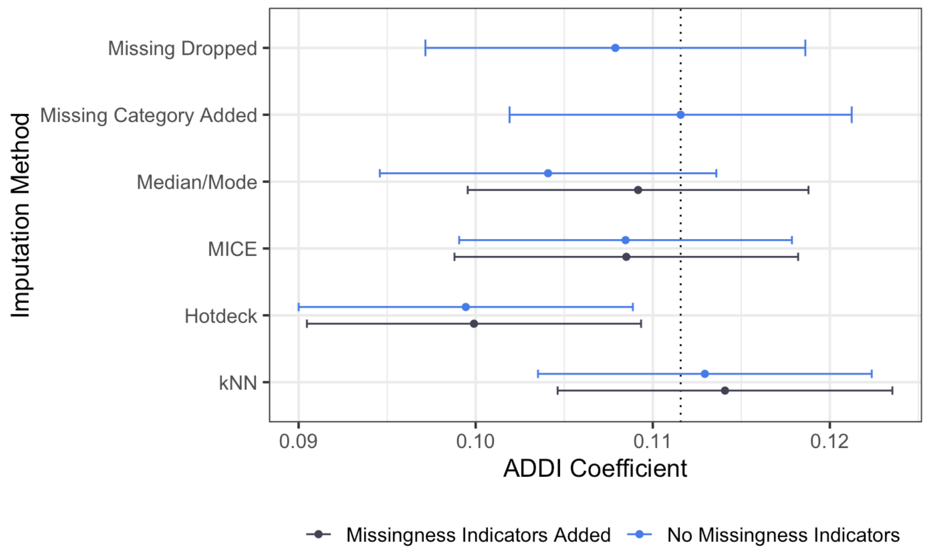


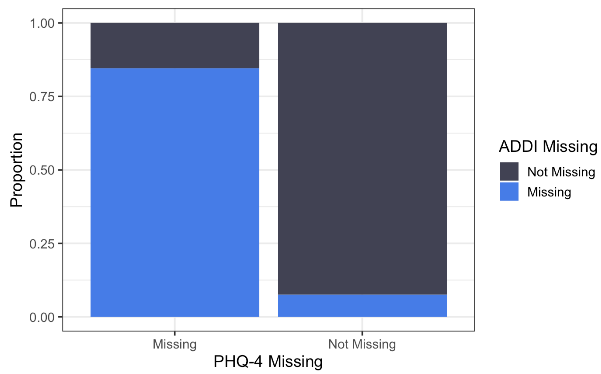
Figure 4.1.6: Forest plot of the ADDI coefficient in a negative binomial model for various imputation methods

such, their missingness is highly correlated (Figure 4.1.7a). By contrast, the demographic questions appear at the beginning of the survey, so we should not expect their missingness to be closely correlated with PHQ-4.

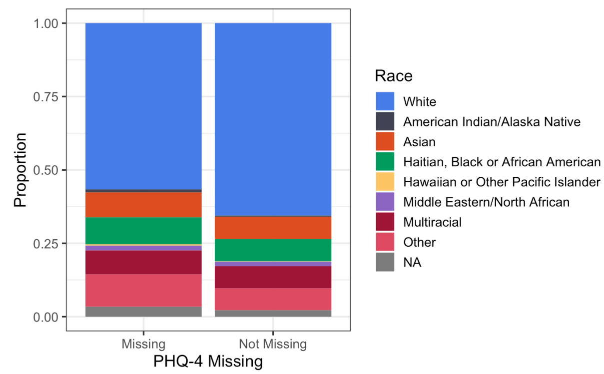
PHQ-4, the response variable, was not imputed. However, there are noticeable differences between responders and non-responders. Among those who responded to the PHQ-4 questions, a larger proportion are white compared to those who did not respond

	Imputation Method				
Missing Indicator	Missing Category	Median/Mode	MICE	Hotdeck	kNN
ADDI Total	–	0.173053 ***	0.03203	0.06512*	0.09449***
Race	-0.12088*	-0.09534	-0.02314	–	-0.05723
Ethnicity	-0.00567	-0.03086	-0.01655	-0.05587	-0.02055
Gender	0.19803	-0.26376 *	-0.03995	-0.00450	-0.01958
Sexuality	-0.04366	-0.02171	-0.08970	-0.15056	-0.14126
Born USA	-0.18675	-0.17084	-0.19840	-0.28018	-0.19507
Class Performance	0.15390	0.11150	-0.04215	0.04280	0.01778
Sports	-0.190951	0.04674	-0.07069	-0.05256	-0.04674
Note:					*p<0.1; **p<0.05; ***p<0.01

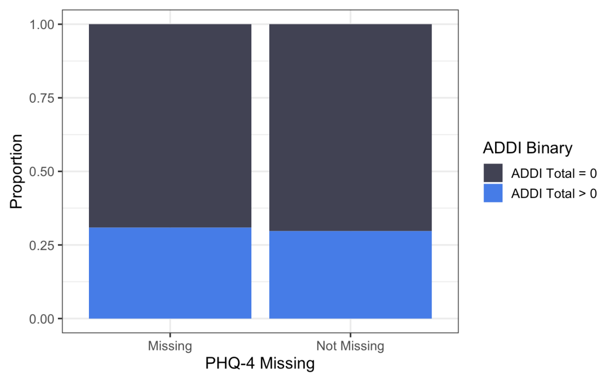
Table 4.1.5: Coefficients of missingness indicators in the negative binomial model for various imputation methods



(a) ADDI Missingness



(b) Race



(c) Discrimination Exposure (ADDI Binary)

Figure 4.1.7: Distribution of (a) ADDI missingness, (b) race, and (c) discrimination exposure for responders vs. non-responders of PHQ-4

(Figure 4.1.7b). These discrepancies indicate that PHQ-4 is not missing at random. Since the ADDI questions appear in a similar part of the survey, it is likely that ADDI is also not missing at random, potentially introducing bias into our estimates. Despite this, the level of discrimination exposure was similar between non-responders and responders of PHQ-4 (Figure 4.1.7c).

4.1.5 Non-parametric testing

The bootstrap coefficients for the negative binomial model had a mean of 0.1118, and the 95% quantile confidence interval was [0.103, 0.121]. The coefficients appear to be roughly symmetrically distributed around the original coefficient of 0.1116 (Figure 4.1.8). The standard deviation of the bootstrap coefficients was 0.004575, which is closer to the cluster-adjusted standard error of 0.004612 than the non-cluster-adjusted standard error of 0.004928 of the original model.

The permutation test coefficients were also roughly symmetrically distributed (Figure

4.1.9). They were centered around 0, and there were no iterations where the estimated coefficient was as large as 0.1116, the coefficient of the original model, indicating a p-value of <0.0002 for the estimated coefficient.

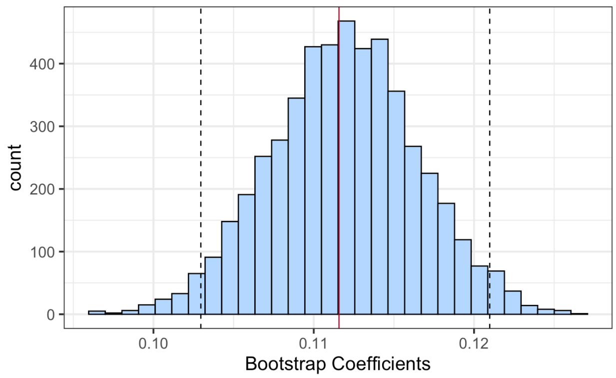


Figure 4.1.8: Histogram of bootstrap ADDI coefficients for the negative binomial model. The solid red line marks the original coefficient and the black dashed lines indicate the 95% quantile confidence interval.

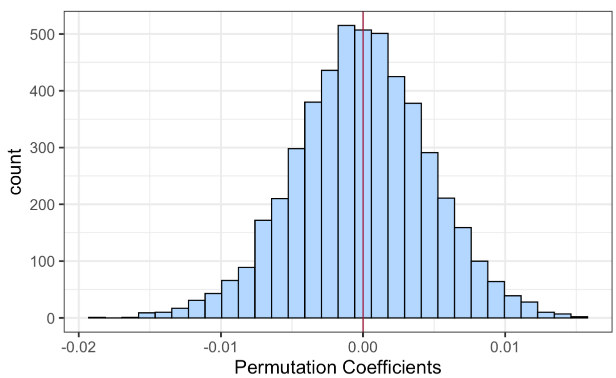


Figure 4.1.9: Histogram of permutation coefficients of ADDI for the negative binomial model

4.2 Re-Parameterizing Discrimination

4.2.1 Racial Discrimination Distress

When replacing *ADDI Total* with *ADDI Distress* in both the negative binomial and linear models, AIC was lower for the model with *ADDI Total* as the predictor than for the model with *ADDI Distress*. Since the ADDI metrics are highly skewed, we also compared models that use the log-transformed *ADDI Total* and *ADDI Distress*, in which case the model with *ADDI Distress* had the lower AIC instead (Table 4.2.1).

When adding *ADDI Distress* as an extra predictor in the model, for the negative binomial, the ANOVA test of adding *ADDI Distress* was only significant when the ADDI variables were log-transformed (Table 4.2.2). In the linear models, the ANOVA test was significant for both the log-transformed and untransformed cases.

The coefficients from the models with and without *ADDI Distress* are shown in Table 4.2.3 for the negative binomial models Table 4.2.4 for the linear regression models. Compared to a model with only *ADDI Total*, adding *ADDI Distress* to the model generally decreased the magnitude of the coefficient for *ADDI Total*. For instance, in the negative binomial models with log-transformed ADDI variables, the *ADDI Total* coefficient without distress was 0.405, while the coefficient in the model with distress was 0.155. This change is likely due to the collinearity of the variables, since *ADDI Distress* is derived from *ADDI Total* by design. Adding distress to the model generally did not have a major impact on the coefficients for any of the demographic covariates.

Both *ADDI Total* and *ADDI Distress* are positive and significant in most of the models, indicating that exposure and distress are both important predictors of mental health even when controlling for each other. The model with the lowest AIC was the negative binomial model with log-transformed predictors. Figure 4.2.1 shows PHQ-4 predictions from this

	AIC	
ADDI Variable	Negative Binomial	Linear
ADDI Total	69453.89	81174.80
ADDI Distress	69541.28	81228.10
$\log(ADDI\ Total + 1)$	69328.85	81066.76
$\log(ADDI\ Distress + 1)$	69318.41	81016.11

Table 4.2.1: AIC comparison of models using ADDI Total vs. ADDI Distress as the predictor

	ANOVA test statistic	
	Negative Binomial	Linear
Untransformed ADDI variables	1.19 ($p = 0.275$)	9.81 ($p = 0.002$)
Log-transformed ADDI variables	16.6 ($p < 0.001$)	50.9 ($p < 0.001$)

Table 4.2.2: Results of ANOVA tests between models with and without *ADDI Distress*

	Exposure only	*With Distress*	*Log Exposure*	*Log with distress*
ADDI Distress		−0.004		
ADDI Total	0.112***	0.125***		
log(ADDI Total + 1)			0.405***	0.155**
log(ADDI Distress + 1)				0.167***
RaceNative	−0.074	−0.074	−0.104	−0.112
RaceAsian	−0.289***	−0.291***	−0.384***	−0.390***
RaceBlack	−0.248***	−0.248***	−0.292***	−0.299***
RacePacific Islander	0.035	0.034	0.012	0.007
RaceMiddle Eastern/North African	−0.008	−0.010	−0.059	−0.057
RaceMissing	−0.121*	−0.123*	−0.155**	−0.157**
RaceMultiracial	−0.079**	−0.079**	−0.127***	−0.134***
RaceOther	−0.160***	−0.161***	−0.201***	−0.202***
EthnicityHispanic	−0.046	−0.047*	−0.075***	−0.074***
EthnicityMissing	−0.006	−0.006	−0.011	−0.012
GenderGirl/ woman/ female	0.516***	0.518***	0.518***	0.511***
GenderI don't want to say	0.431***	0.430***	0.449***	0.456***
GenderMissing	0.198	0.196	0.217	0.223
GenderOther	0.583***	0.585***	0.592***	0.586***
SexualityBisexual	0.577***	0.577***	0.567***	0.564***
SexualityGay or Lesbian	0.564***	0.566***	0.569***	0.561***
SexualityI don't want to say	0.206***	0.206***	0.206***	0.205***
SexualityMissing	−0.044	−0.043	−0.029	−0.026
SexualitySomething else	0.561***	0.561***	0.556***	0.553***
SexualityUnsure	0.447***	0.447***	0.438***	0.436***
Grade	0.037***	0.037***	0.038***	0.037***
BornUSAMissing	−0.187	−0.187	−0.170	−0.165
BornUSA	0.017	0.017	0.031	0.031
ClassPerformanceBs	0.060**	0.060**	0.060**	0.060**
ClassPerformanceCs	0.263***	0.262***	0.253***	0.254***
ClassPerformanceDs	0.486***	0.486***	0.489***	0.491***
ClassPerformanceFs	0.529***	0.531***	0.578***	0.587***
ClassPerformanceMissing	0.154	0.154	0.166	0.167
ClassPerformanceMixed	0.240***	0.240***	0.237***	0.238***
ClassPerformanceNone	0.393**	0.392**	0.434***	0.442***
ClassPerformanceUnsure	−0.120	−0.120	−0.109	−0.108
Sports	−0.183***	−0.183***	−0.185***	−0.183***
SportsMissing	−0.191*	−0.192*	−0.202*	−0.200*
Constant	0.173*	0.169*	0.122	0.132
Akaike Inf. Crit.	69453.89	69454.70	69328.85	69314.25
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.2.3: Coefficients of negative binomial models with and without discrimination distress

	Exposure only	*With Distress*	*Log Exposure*	*Log with distress*
ADDI Distress		0.027^{***}		
ADDI Total	0.338^{***}	0.248^{***}		
log(ADDI Total + 1)			1.182^{***}	0.088
log(ADDI Distress + 1)				0.735^{***}
RaceNative	−0.205	−0.208	−0.282	−0.317
RaceAsian	-0.794^{***}	-0.780^{***}	-1.008^{***}	-1.033^{***}
RaceBlack	-0.674^{***}	-0.676^{***}	-0.777^{***}	-0.805^{***}
RacePacific Islander	0.275	0.280	0.214	0.193
RaceMiddle Eastern	−0.165	−0.151	−0.319	-0.331^{*}
RaceMissing	-0.284^{*}	−0.273	-0.354^{**}	-0.347^{**}
RaceMultiracial	-0.258^{***}	-0.258^{***}	-0.368^{***}	-0.398^{***}
RaceOther	-0.436^{***}	-0.426^{***}	-0.515^{***}	-0.520^{***}
EthnicityHispanic	-0.188^{***}	-0.182^{***}	-0.266^{***}	-0.270^{***}
EthnicityMissing	−0.161	−0.163	−0.154	−0.158
GenderGirl/ woman/ female	1.237^{***}	1.227^{***}	1.241^{***}	1.211^{***}
GenderI don't want to say	1.073^{***}	1.090^{***}	1.112^{***}	1.149^{***}
GenderMissing	0.366	0.388	0.438	0.462
GenderOther	1.985^{***}	1.971^{***}	2.012^{***}	1.985^{***}
SexualityBisexual	2.154^{***}	2.150^{***}	2.120^{***}	2.098^{***}
SexualityGay or Lesbian	1.741^{***}	1.731^{***}	1.751^{***}	1.720^{***}
SexualityI don't want to say	0.563^{***}	0.561^{***}	0.557^{***}	0.545^{***}
SexualityMissing	−0.041	−0.044	0.009	0.002
SexualitySomething else	1.969^{***}	1.964^{***}	1.973^{***}	1.954^{***}
SexualityUnsure	1.447^{***}	1.451^{***}	1.422^{***}	1.414^{***}
Grade	0.072^{***}	0.071^{***}	0.075^{***}	0.072^{***}
BornUSAMissing	−0.538	−0.541	−0.488	−0.459
BornUSATRUE	0.013	0.011	0.042	0.037
ClassPerformanceBs	0.200^{***}	0.201^{***}	0.202^{***}	0.204^{***}
ClassPerformanceCs	0.712^{***}	0.717^{***}	0.691^{***}	0.699^{***}
ClassPerformanceDs	1.487^{***}	1.491^{***}	1.484^{***}	1.500^{***}
ClassPerformanceFs	2.089^{***}	2.077^{***}	2.331^{***}	2.390^{***}
ClassPerformanceMissing	0.388	0.388	0.408	0.413
ClassPerformanceMixed	0.714^{***}	0.715^{***}	0.703^{***}	0.707^{***}
ClassPerformanceNone	1.292^{***}	1.278^{***}	1.421^{***}	1.440^{***}
ClassPerformanceUnsure	-0.348^{*}	-0.351^{*}	−0.289	−0.269
Sports	-0.452^{***}	-0.450^{***}	-0.446^{***}	-0.443^{***}
SportsMissing	-0.483^{*}	-0.477^{*}	-0.498^{*}	-0.497^{*}
Constant	1.046^{***}	1.072^{***}	0.916^{***}	0.968^{***}
Akaike Inf. Crit.	81174.80	81166.97	81016.11	81017.81
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.2.4: Coefficients of linear regression models with and without discrimination distress

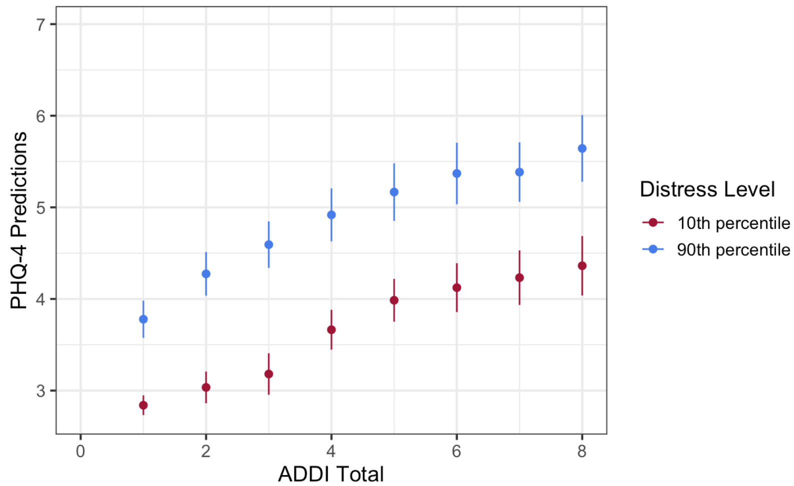


Figure 4.2.1: PHQ-4 predictions from a negative binomial model with ADDI predictors log-transformed at low and high distress levels for various discrimination exposure levels

model at a low (10th percentile) and high (90th percentile) distress level for varying levels of *ADDI Total*. The PHQ-4 predictions are larger for higher levels of distress at every exposure level, and the predictions also increase as exposure increases.

4.2.2 Racial Discrimination Subtypes

All three of the discrimination subtypes had positive coefficients in a negative binomial model with demographic covariates, indicating that more exposure to discrimination is associated with increased mental health symptoms for all racial discrimination subtypes (Figure 4.2.2). Peer and educational discrimination were significant predictors of PHQ-4 while institutional discrimination was not. Furthermore, peer discrimination had the highest point estimate coefficient among all three discrimination types. Results from linear regression were similar (Appendix Figure 6.1.3).

Since the discrimination subtype indices are on a scale of 0-1, they can be interpreted as the predicted change in PHQ-4 for someone who has not encountered any of the experiences comprising that discrimination subtype and someone who has experienced all of them. For peer discrimination, the effect is a 0.9986 increase in log-count or $e^{0.9986} = 2.714$ multiplicative increase of the PHQ-4, while for educational discrimination, the predicted effect is a $e^{0.4307} = 1.538$ multiplicative increase.

The ANOVA tests between a model having race as a confounder and a model having race as an effect modifier were insignificant for all three discrimination subtypes, indicating that race was not a significant effect modifier.

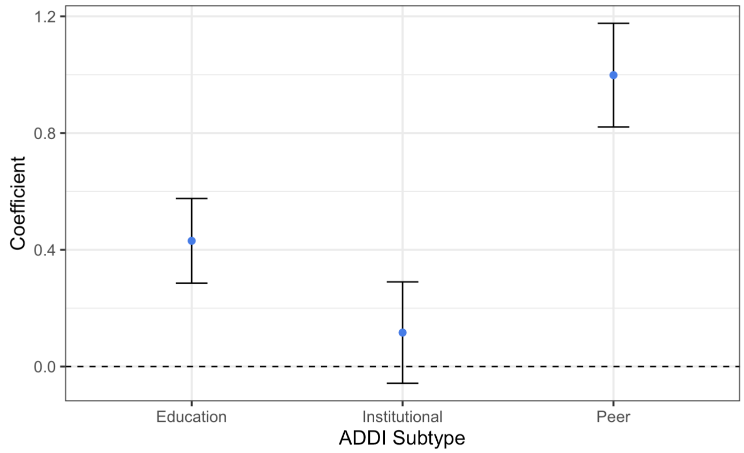


Figure 4.2.2: Discrimination subtype coefficients for predicting PHQ-4 in a negative binomial model with demographic covariates

4.2.3 Discrimination for Other Identity Aspects

Coefficients in the negative binomial model for all the discrimination variables were positive and significant both with and without confounders (Table 4.2.5). The results for linear regression were similar (Appendix Table 6.1.4). In other words, discrimination with respect to all identity types predicted an increase in PHQ-4, holding all other discrimination and demographic variables constant. Discrimination due to religion seemed to have a smaller effect on mental health than the other discrimination types measured in the survey, as the coefficient of *DISC.Religion* was the smallest in all model specifications.

When interaction terms were added, the coefficients of the discrimination variables themselves generally increased in magnitude, while the coefficients of the interaction terms were mostly negative (Table 4.2.5). Because these variables are indicators, the coefficients of the non-interaction terms can be interpreted as a first effect. For example, the coefficient of *ADDI Binary* is 0.349 in the model with interactions, indicating that when an individual who has experienced none of the discrimination types is exposed to racial discrimination, the expected increase in the log-count of their PHQ-4 is 0.349. The discrimination indicators for sexuality (0.701), gender (0.632), and disability (0.631) have the largest coefficients in the model with interactions, indicating that as a first exposure to discrimination, they have the largest impact on mental health. The negative coefficients of the interaction terms indicate that additional exposure to discrimination related to a different identity type is not expected to increase PHQ-4 as much as the first effect.

When demographic variables were added as additional covariates, some of the coefficients of the discrimination variables change in magnitude. Specifically, the coefficient for *ADDI*

	Model Type		
	Discrimination Variables Only	*With Interactions*	*With Interactions and Demographics*
ADDI.Binary	0.305***	0.349***	0.445***
DISC.Gender	0.351***	0.632***	0.357***
DISC.Sexuality	0.481***	0.701***	0.338***
DISC.Religion	0.113**	0.320***	0.336***
DISC.Disability	0.369***	0.631***	0.536***
DISC.Money	0.356***	0.578***	0.485***
DISC.Other	0.317***	0.493***	0.418***
ADDI.Binary * DISC.Gender		−0.123**	−0.077
ADDI.Binary * DISC.Sexuality		−0.144*	−0.118
ADDI.Binary * DISC.Religion		−0.212***	−0.219**
ADDI.Binary * DISC.Disability		−0.130**	−0.150
ADDI.Binary * DISC.Money		−0.108	−0.049
ADDI.Binary * DISC.Other		−0.178*	−0.086
DISC.Gender * DISC.Sexuality		−0.333***	−0.220**
DISC.Gender * DISC.Religion		−0.141*	−0.092
DISC.Gender * DISC.Disability		−0.128**	−0.072
DISC.Gender * DISC.Money		−0.217***	−0.155
DISC.Gender * DISC.Other		0.131	0.078
DISC.Sexuality * DISC.Religion		0.032	0.027
DISC.Sexuality * DISC.Disability		−0.319***	−0.291**
DISC.Sexuality * DISC.Money		−0.150***	−0.153
DISC.Sexuality * DISC.Other		−0.345***	−0.278
DISC.Religion * DISC.Disability		0.055	0.010
DISC.Religion * DISC.Money		−0.184***	−0.119
DISC.Religion * DISC.Other		0.164	−0.062
DISC.Disability * DISC.Money		−0.090	−0.015
DISC.Disability * DISC.Other		−0.240*	−0.132
DISC.Money * DISC.Other		−0.153*	−0.157
Akaike Inf. Crit.	70,622.060	70,537.170	69,121.750
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.2.5: Coefficients of negative binomial models predicting PHQ-4 using all discrimination variables. All significance indicators reflect cluster-adjusted standard errors, and p-values of the seven discrimination variables are additionally Bonferroni adjusted.

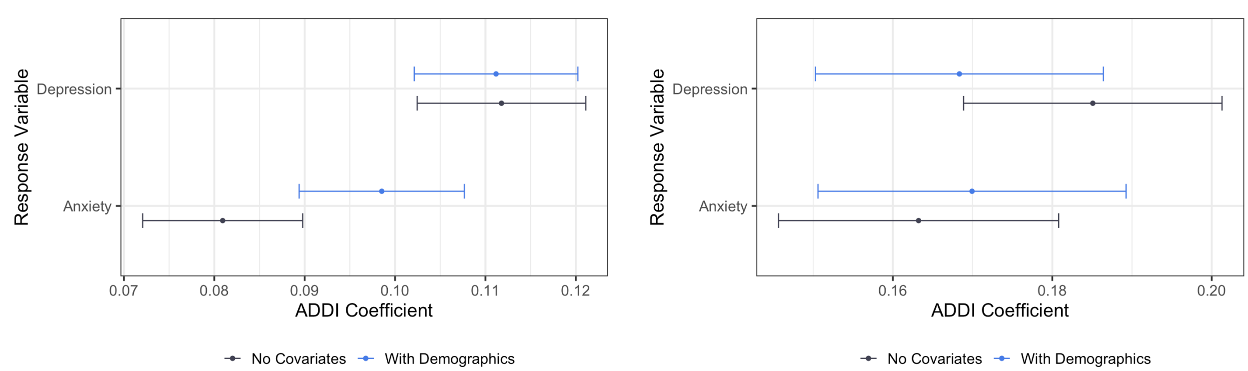
Binary noticeably increases in magnitude, and the coefficients for *DISC.Gender* and *DISC.Sexuality* decrease in magnitude. Race, gender, and sexuality are explicitly encoded in the demographic variables measured in the survey, while the other identity aspects - religion, disability, and money - are not, which may explain why certain coefficients were more impacted by the demographic confounders than others.

4.3 Re-Parameterizing Mental Health

4.3.1 Separating Anxiety and Depression

In all of the models predicting anxiety and depression, the estimated coefficient for ADDI was positive and significant. In the negative binomial models, *ADDI Total* seemed to be more predictive of depression than anxiety. The point estimate of the coefficient in the model with depression as the response variable was larger (Figure 4.3.1a), and the AIC was lower in the model predicting depression model both with and without confounders (Table 4.3.1). Adding the demographic variables as confounders in the model increased the estimated effect of ADDI on anxiety, but had no impact on the estimated effect on depression (Figure 4.3.1a).

In the linear regression models, the estimated effect of ADDI on anxiety and depression were more similar. The point estimate of the ADDI coefficient was only noticeably larger for depression when demographic confounders were not included, but the difference was not significant (Figure 4.3.1b). Similar to the negative binomial results, the AIC was also lower for the linear models predicting depression (Table 4.3.1).



(a) Negative Binomial

(b) Linear regression

Figure 4.3.1: Coefficients of predicting anxiety and depression subscales separately.

Response	Negative Binomial		Linear	
	No Covariates	w/ Demographics	No Covariates	w/ Demographics
Anxiety	56619.52	54451.41	66465.93	63695.76
Depression	50398.28	48794.82	61762.29	59613.73

Table 4.3.1: AIC comparison of models using anxiety and depression as the response variable

4.3.2 Categorical PHQ-4

The coefficient for *ADDI Total* was 0.1827 in the ordinal logistic regression for predicting categorical PHQ-4, and the effect was significant (Table 4.3.2). This indicates that a one-unit increase in ADDI is associated with a 0.1827 increase in the log-odds of moving to a higher level of the categorical PHQ-4 scale. When demographic confounders were added to the model, the ADDI coefficient increased to 0.1978.

The brant test results with respect to ADDI were insignificant at the $\alpha = 0.05$ level for both the model without confounders ($p = 0.2$) and with confounders ($p = 0.58$), indicating that the proportional odds assumption of the model was met.

Model	ADDI Coefficient	Cluster-adjusted Standard Error	Brant Test p-value
Without Covariates	0.1827***	0.00955	0.20
With Demographics	0.1978***	0.01066	0.58
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 4.3.2: Ordinal regression results for predicting categorical PHQ-4 with ADDI Total. Standard errors are cluster-adjusted for school.

4.4 Propensity Scoring

4.4.1 Matching Diagnostics

During propensity score matching, each of the 4819 participants with non-zero ADDI (treatment) were matched with one of 4819 participants with an ADDI of 0 (control), leaving 6565 unmatched control group units. The unmatched control group observations all had low-propensity scores (Figure 4.4.1).

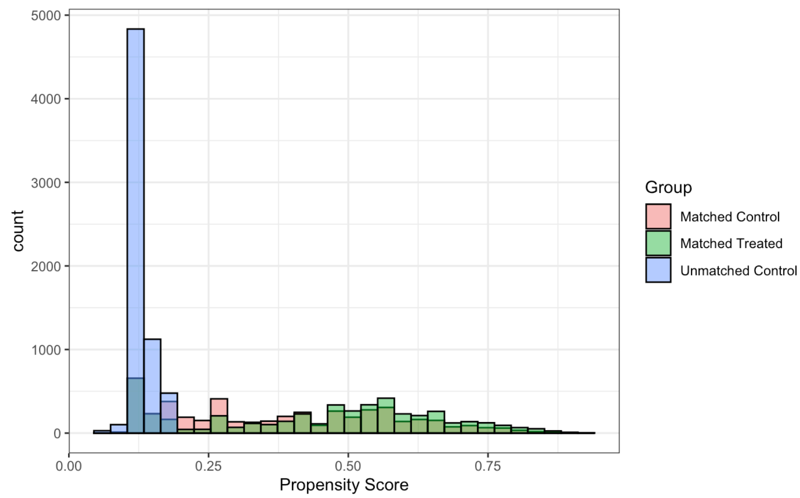
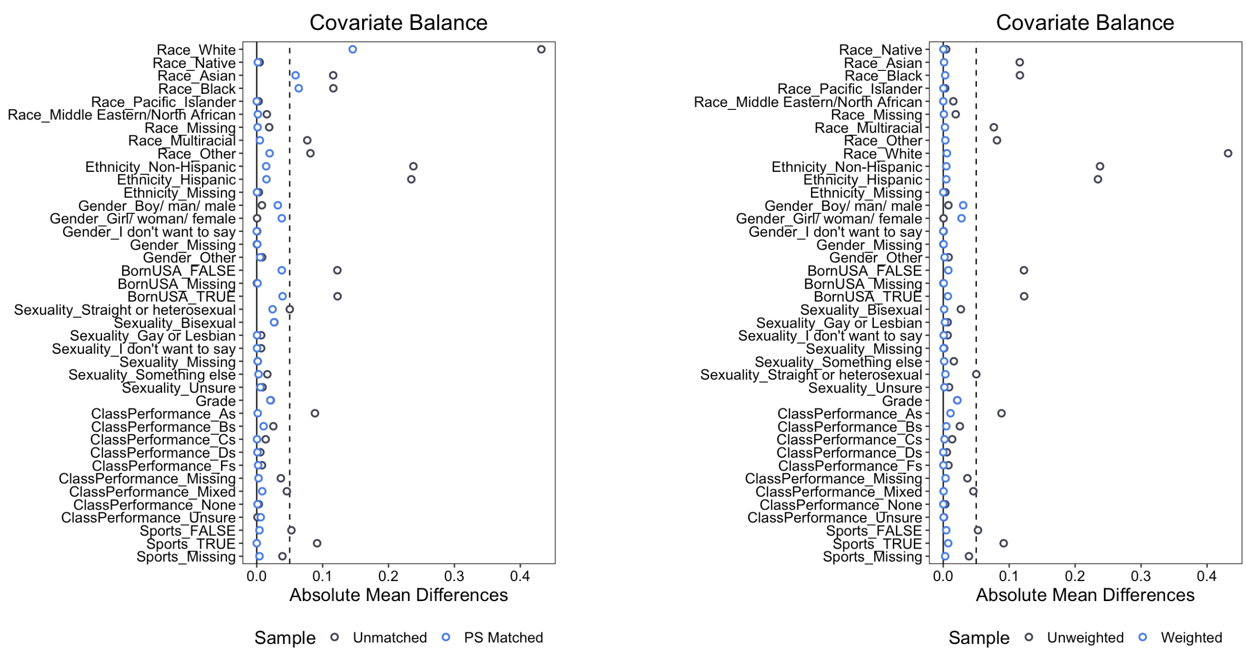


Figure 4.4.1: Distribution of propensity scores based on treatment status (ADDI Binary) and propensity matching status



(a) 1:1 Matching **(b)** Inverse Probability Treatment Weighting

Figure 4.4.2: Standardized mean differences for unadjusted and propensity-score adjusted data

Matching improved covariate balance but not perfectly. For most variables, such as race, ethnicity, class performance, and sports, the distribution of treatment and control groups became more similar after matching (distribution comparisons can be found in Appendix Figures 6.3.1-6.3.7). When covariate balance is achieved, the difference in standardized means should be close to 0 for all variables. However, in this case, there were still a few variables where the absolute standardized mean difference was larger than 0.05, particularly for a few of the race subcategory variables, indicating that racial groups were not perfectly balanced between the control and treatment groups (Figure 4.4.2a).

Inverse probability treatment weighting (IPTW) seemed to fully resolve covariate imbalance, as all the weighted standardized mean differences were less than 0.05 (Figure 4.4.2b).

4.4.2 Regression Results

In a baseline linear regression using *ADDI Binary* to predict PHQ-4, the estimated coefficient was 1.393. The results from both of the propensity score methods were similar (Figure 4.4.3). The IPTW linear regression yielded an ATE estimate of 1.416, and the g-computation ATT estimated from the propensity-matched pairs was 1.366. These estimates suggest that the effect of discrimination on mental health in the overall population is similar to the effect on those actually exposed to discrimination.

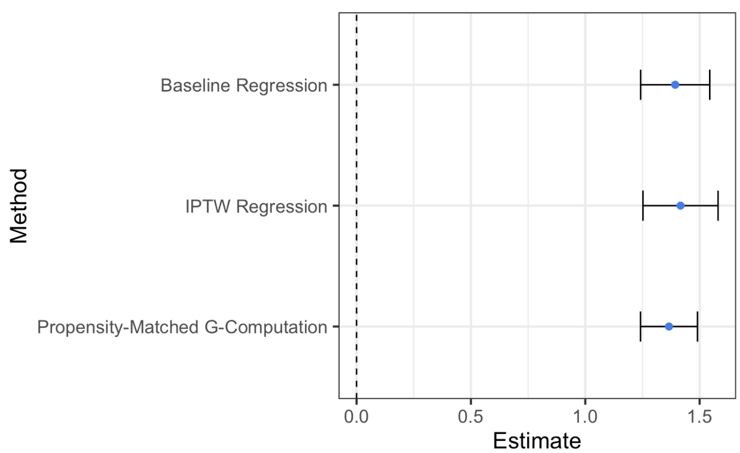


Figure 4.4.3: Propensity method estimates of the effect of *ADDI Binary* on PHQ-4

4.5 The Role of Schools

4.5.1 Predictive Modeling

Table 4.5.1 shows the coefficients of the school characteristics in the mixed-effects logistic regression model with school-varying intercepts to predict *ADDI Binary.* Most of the coefficients were insignificant at the 95% confidence level, suggesting that for students with the same demographic variables, most of these school characteristics do not affect their probability of exposure to racial discrimination. The only exceptions were total enrollment and the same-race teacher-student ratio, which were both positively associated with the probability of discrimination exposure. Based on the ICC, only 1.2% of the variation in *ADDI Binary* is explained by the difference between schools.

When predicting PHQ-4 in a mixed-effects linear regression with school-varying intercepts and ADDI coefficients, most of the school characteristics coefficients were also not statistically significant, except for the same-race teacher-student ratio, which was positively associated with PHQ-4 (Table 4.5.1). The ICC was low for this model as well, with only 2.1% of the variation in the response variable being explained by the difference between schools. The overall ADDI coefficient continued to be significant with an estimated coefficient of 0.325, which is similar to the estimated coefficient of 0.332 in the random effects linear model where school characteristics were not included (Appendix Table 6.1.2). However, there was some variation between schools for the effect of ADDI on PHQ-4 (Appendix Figure 6.1.4). The standard deviation of the school-varying ADDI coefficients was 0.09285 with the estimated effect ranging from 0.1627 to 0.4382 across schools.

Although school characteristics did not seem predictive of discrimination exposure or mental health, many of them were significant effect modifiers of ADDI including total enrollment, percentages of high needs students, low income students, ELL students, and chronically absent students, and the percentage of experienced teachers (Figure 4.5.1). The

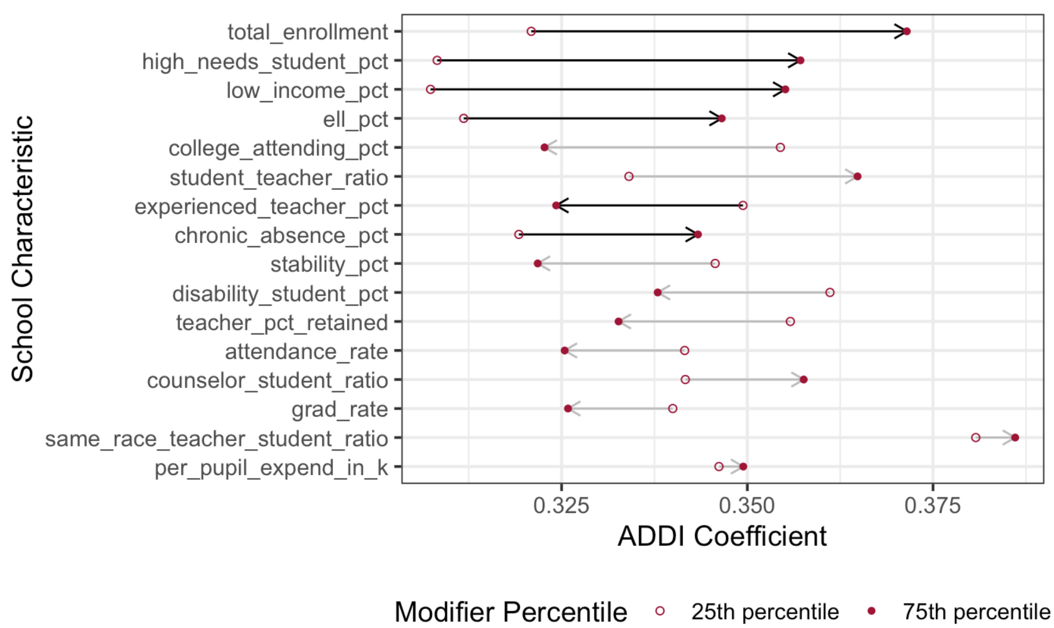


Figure 4.5.1: School characteristic effect modifiers: differences in the estimated effect of ADDI on PHQ-4 between the 25th and 75th percentile of school characteristics. Black arrows indicate variables that were significant effect modifiers in ANOVA testing.

	Dependent variable:	
	ADDI Binary	PHQ4 Total
	generalized linear mixed-effects	*linear mixed-effects*
ADDI Total		0.325*** (0.020)
total_enrollment	0.0004*** (0.0001)	−0.0001 (0.0002)
ell_pct	−0.020 (0.018)	−0.016 (0.031)
disability_student_pct	−0.037 (0.026)	−0.0003 (0.046)
high_needs_student_pct	0.047 (0.043)	0.027 (0.073)
low_income_pct	−0.023 (0.036)	−0.012 (0.061)
grad_rate	−0.018 (0.014)	−0.038 (0.024)
college_attending_pct	0.006 (0.006)	0.009 (0.010)
attendance_rate	−0.060 (0.099)	−0.088 (0.164)
chronic_absence_pct	−0.033 (0.021)	−0.026 (0.036)
stability_pct	−0.012 (0.020)	0.016 (0.032)
teacher_pct_retained	0.015 (0.013)	0.005 (0.020)
experienced_teacher_pct	0.004 (0.008)	0.002 (0.014)
per_pupil_expend	−0.032 (0.021)	0.004 (0.036)
student_teacher_ratio	−0.043 (0.037)	−0.038 (0.062)
counselor_student_ratio	2.471 (33.106)	−23.202 (52.257)
same_race_teacher_student_ratio	1.664*** (0.477)	1.884*** (0.620)
Intraclass Correlation Coefficient	0.012	0.021
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.5.1: Coefficients for school-varying intercept models using school characteristics as predictors. Coefficients of demographic covariates are omitted.

percentage of experienced teachers had a negative effect modification, suggesting that having a higher proportion of experienced teachers buffers the effect of ADDI on PHQ-4. For the remaining significant effect modifiers, the effect modification was positive, meaning that in schools with larger enrollment, more chronic absence, and higher percentages of low income, high needs, and ELL students, ADDI had a larger estimated effect on PHQ-4.

4.5.2 Propensity Score Analysis

Table 4.5.2 shows the propensity score cutoffs and size of each stratum. The strata are not equal size due to some students having the exact same score.

Significant predictors of discrimination exposure (*ADDI Binary*) differed between strata (Table 4.5.3). Specifically, in the two highest propensity score strata, a greater number of

Propensity Stratum	Min	Max	Number of Students
Quintile 1	0.0545	0.1243	3720
Quintile 2	0.1243	0.1352	2777
Quintile 3	0.1352	0.2765	3231
Quintile 4	0.2765	0.5400	3241
Quintile 5	0.5401	0.9207	3234

Table 4.5.2: Propensity score strata information

school characteristics were statistically significant compared to the other strata, suggesting that for students who are the most prone to experiencing racial discrimination, school characteristics are particularly important for determining whether they actually experience discrimination.

For most of the school characteristics, the sign of coefficient for predicting *ADDI Binary* within strata was the same as the sign in the full sample. However, the same-race teacher-student ratio, which was positively associated with discrimination exposure in the full sample model, was negatively associated with discrimination exposure in all of the strata with $p < 0.01$.

The effect modifiers also differed between strata (Table 4.5.4). In analysis of the 2023 data, several significant effect modifiers were identified in quintiles 1 and 5, while in middle quintiles, very few, if any, school characteristics were deemed significant effect modifiers at the 0.05 level. However, in analysis of the 2022 data, the middle strata had more significant effect modifiers instead.

Similar to the trends in the overall data, ADDI had a greater effect on PHQ-4 in schools with a higher percentage of ELL, high-needs, and low-income students. Larger enrollment and higher student-teacher ratios also seemed to exacerbate the impact of ADDI. On the other hand, having better attendance, stable enrollment, and graduation rates moderated the impact of ADDI.

	Strata				
	(1)	(2)	(3)	(4)	(5)
total_enrollment	0.0001**	0.0001***	0.0002***	0.0001***	0.00005
ell_pct	−0.005	−0.004	−0.005	−0.002	−0.008*
disability_student_pct	−0.018***	−0.008	−0.012**	−0.012*	−0.020***
high_needs_student_pct	0.019**	0.019*	0.017*	0.016*	0.030***
low_income_pct	−0.010	−0.010	−0.006	−0.007	−0.018**
grad_rate	0.001	−0.001	−0.003	−0.005	−0.012***
college_attending_pct	0.002*	0.003*	0.005***	0.005***	0.004***
attendance_rate	−0.045**	−0.052**	−0.039*	−0.051**	−0.134***
chronic_absence_pct	−0.010**	−0.015***	−0.012**	−0.015***	−0.034***
stability_pct	−0.005	−0.001	−0.006	−0.002	0.014**
teacher_pct_retained	0.005*	0.005*	0.0003	0.004	0.003
experienced_teacher_pct	−0.0002	−0.001	0.003	−0.001	−0.001
per_pupil_expend_in_k	0.002	−0.010*	−0.009**	−0.010**	−0.012**
student_teacher_ratio	−0.001	−0.017	−0.026***	−0.026***	−0.017**
counselor_student_ratio	8.080	2.520	−8.846	−1.850	6.612
same_race_teacher_student_ratio	−1.840***	−1.982***	−2.166***	−2.301***	−2.102***
Constant	4.297**	5.113**	4.723**	5.637**	12.859***
Observations	3,714	2,771	3,226	3,239	3,231
Akaike Inf. Crit.	4,407.852	3,289.770	3,629.431	3,667.143	3,417.108
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 4.5.3: Model results for predicting racial discrimination (*ADDI Binary*) exposure using school characteristics by propensity score strata

Effect Modifier	Strata (1)	(2)	(3)	(4)	(5)
2023					
total_enrollment	0.0657				
ell_pct	0.0540	0.0472			0.0450
disability_student_pct		-0.2691			
high_needs_student_pct	0.0515				0.0727
low_income_pct	0.0502				0.0723
grad_rate	-0.0712				
college_attending_pct	-0.0481				
stability_pct					-0.1156
student_teacher_ratio	0.0571	0.0761			
counselor_student_ratio					0.0625
attendance_rate	-0.1154				-0.1247
chronic_absence_pct	0.0731				0.0795
2022					
total_enrollment		0.0721			
ell_pct		0.0574		0.0937	0.0553
disability_student_pct		-0.0696	-0.0405		
high_needs_student_pct				0.0805	
low_income_pct				0.0791	
grad_rate			0.1871		
college_attending_pct				-0.1049	
stability_pct			0.0531		
student_teacher_ratio		0.0514			
counselor_student_ratio		0.1301		-0.0687	-0.0725
per_pupil_expend		0.0758			
teacher_pct_retained		0.0748			
same_race_teacher_student_ratio		0.1645			

Table 4.5.4: School effect modifiers by strata: Interaction term coefficients for standardized school characteristics that were significant modifiers of the effect of ADDI on PHQ-4 within propensity score strata.

4.6 Longitudinal Analysis

In the paired differences linear regression, the change in ADDI was associated with a positive change in PHQ-4 (Figure 4.6.1). The effect of a one-unit change in ADDI on the change in PHQ-4 was around 0.24 and significant at the 95% confidence level for the models both with and without confounders and for the models fit on both the full sample and the sample restricted to those with non-zero ADDI in at least one of 2022 or 2023. Model diagnostics for the paired regression models on the full longitudinal sample are shown in Appendix Figure 6.2.3.

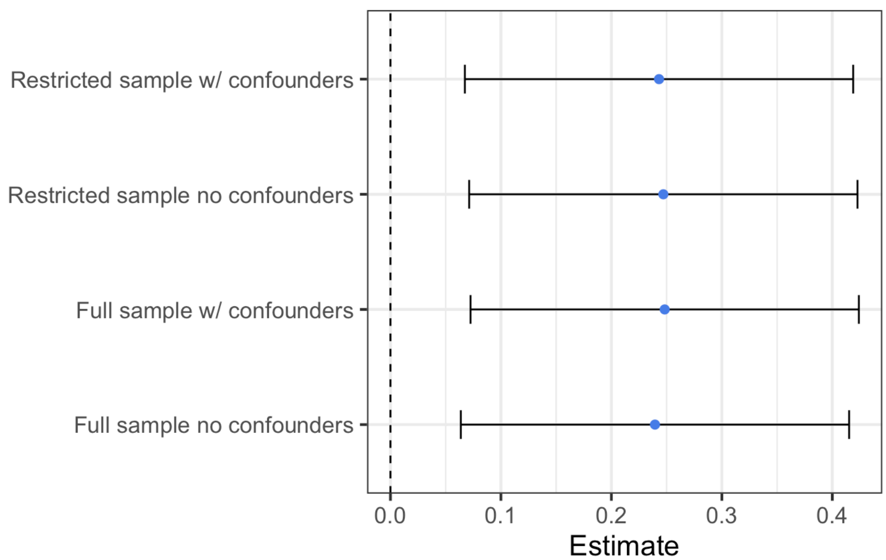
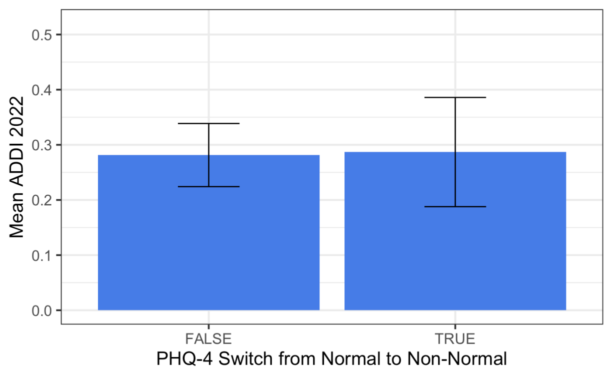


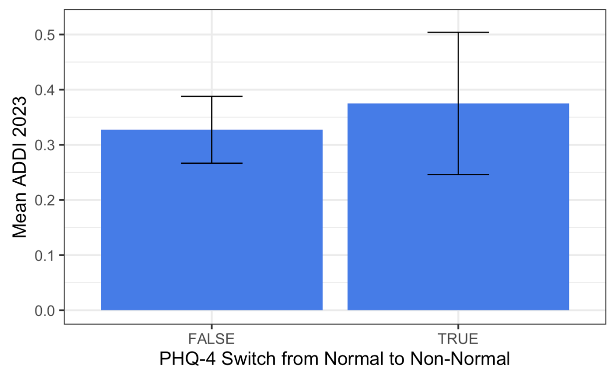
Figure 4.6.1: Coefficient estimates for longitudinal paired differences regression of PHQ-4 on ADDI. Standard errors are cluster-adjusted for school

Among the longitudinally linked students, there were 1,424 who had a PHQ-4 within the normal range (0-2) in 2022. Of this subset of students, 1,160 students remained in the normal range in 2023, 258 students had a PHQ-4 that increased beyond the normal range (188 to mild, 49 to moderate, and 21 to severe), and 6 students did not report PHQ-4 in 2023.

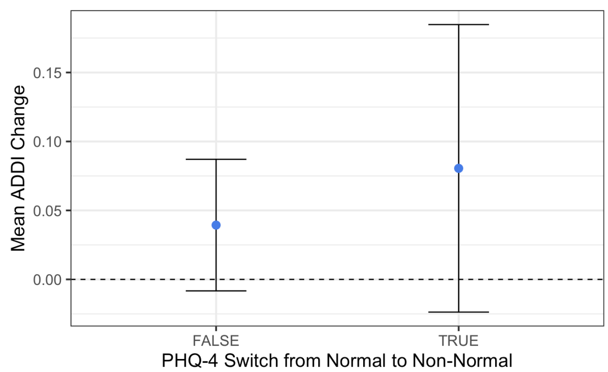
The students who had worsened PHQ-4 status in 2023 had a larger average increase in ADDI, but the difference was not significant (Figure 4.6.2). In the logistic regression predicting whether PHQ-4 switched from normal to non-normal, the estimated effect of the change in ADDI was 0.05388 (SE = 0.075901), a positive effect that was also not significant.



(a) 2022 Mean ADDI



(b) 2023 Mean ADDI



(c) Mean Change in ADDI

Figure 4.6.2: Case-control results: ADDI comparison of students with "normal" PHQ-4 in both 2022 and 2023 and those who switched from normal to non-normal

5 Discussion

5.1 Summary of Results

Overall, we found a significant positive association between perceived racial discrimination and mental health, aligning with the findings of existing literature [6] [32] [33] [46] [51]. In the 2023 SURF data, the estimated coefficient of *ADDI Total* predicting *PHQ-4 Total* in a negative binomial model with covariates was 0.112 (cluster-adjusted 95% CI = [0.103, 0.121]), indicating that a one-unit increase in the discrimination index was associated with a multiplicative effect of $e^{0.112} = 1.119$ on the PHQ-4, controlling for demographic variables (Table 4.1.3). This effect was robust to various sensitivity analyses including multiple model specifications such as backward selection, mixed-effects models with a school-varying intercept, and ordinal regression (Sections 4.1.2 and 4.3.2); different imputation methods such as MICE, hotdeck, and kNN (Section 4.1.4); and non-parametric testing (Section 4.1.5).

The results from propensity score methods were similar to that of a baseline regression without propensity score adjustments (Figure 4.4.3). This suggests that the observed relationship between racial discrimination and PHQ-4 in the original data is robust to potential selection bias that could have been introduced by the convenience sampling design of the survey and the fact that discrimination cannot be randomly assigned.

Additionally, the longitudinal analysis showed that ADDI and PHQ-4 also evolve together over time. In the paired differences regression, a one-unit increase in an individual's ADDI from 2022 to 2023 was associated with an increase of 0.24 in their PHQ-4 (Figure 4.6.1).

Our analysis on effect modifiers suggests that the effect of discrimination on mental health differed across identity groups (Section 4.1.3). In particular, minority sexuality and gender groups had a lower estimated effect of discrimination. Students who are willing to report belonging to a minority identity group may have a stronger sense of identity. Therefore, one explanation for these individuals having a lower estimated effect of racial discrimination might be the moderating effect of a strong sense of identity that was found in previous work [32] [40] [51] [53].

Race did not seem to be a major effect modifier, but U.S. birth status was. For participants who were not born in the United States, discrimination had a greater effect on mental health than those who were born in the United States. Previous research on the impact of COVID-related discrimination in Asian youth found that students who had experienced discrimination before were less affected by the impact of COVID-related discrimination [52]. Similarly, the discrepancy between U.S. born and non-U.S. born students in our data might suggest that immigrants are less accustomed to experiencing discrimination, and therefore, their mental health is more impacted than non-immigrants when they are exposed to racial discrimination. Compared to students born in the U.S., a larger proportion of the students born outside the U.S. are non-white (Figure 5.1.1). As such, students born outside the U.S. may have originated from a country where they were not a racial minority, and thus, they did not experience much racial discrimination until

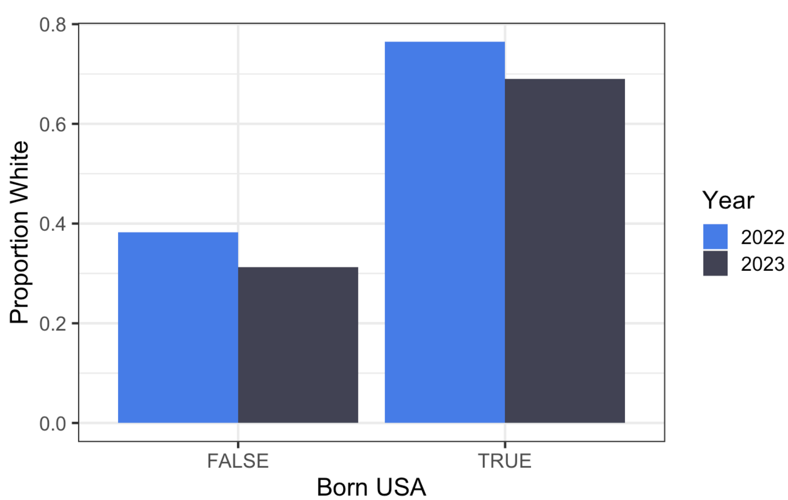


Figure 5.1.1: Proportion of students identifying as white by U.S. birth status

moving to the U.S.

In the 2022 data, the estimated effect of discrimination on mental health was smaller (Table 7.0.2). In the negative binomial model with demographic covariates, the coefficient for ADDI was 0.080 (cluster-adjusted 95% CI = [0.069, 0.091]), which was significantly smaller in magnitude than 2023.

There are several potential reasons for the difference between years. One explanation is the convenience sampling design, which may have caused the 2022 and 2023 samples to be inherently different from each other. Since the 2022 sample has disproportionately more white students compared to 2023 (Table 2.5.1), the estimated effect for each year may reflect different populations.

Another explanation is that there is a true difference in the discrimination effect between years. In our exploratory data analysis, PHQ-4 scores were generally higher in 2022 than in 2023 (Table 2.5.2, Figure 2.5.5). The same pattern was also found in the longitudinally linked data, where the average PHQ-4 in 2022 was 3.013 compared to 2.694 in 2022. There may have been other confounding factors outside of our data that negatively impacted students' mental health in 2022 more than 2023, causing discrimination to have less predictive power in the earlier year. One possibility is that the broader mental health effects of the COVID-19 pandemic, which would have been more prominent in 2022 than in 2023, diluted the specific impact of discrimination. However, further investigation would be needed to determine whether students who are exposed to discrimination were affected by the pandemic differently compared to those who are not.

Comparing the effect modification results between 2022 and 2023 also suggests a potential COVID effect. For most racial groups, race had a similar pattern of effect modification between 2022 and 2023. However, for Asians, the pattern differed between the two years. In 2023, the effect of discrimination on mental health for Asians was not significantly different from the estimate without effect modification (Figure 4.1.4). On the other hand, in 2022, which was closer to the onset of the pandemic, the effect of racial discrimination on mental health was higher for Asians than any other racial group, and the estimate was significantly greater than the estimate without effect modification (Figure 4.1.5). Given the targeted nature of Asian discrimination during the pandemic, this result suggests that students may internalize their experiences of discrimination more intensely during periods of broader increased prejudice targeted toward their identity groups.

Our analysis also suggests that not all discrimination types have equal influence on mental health. In addition to discrimination exposure, distress from discrimination was also predictive of mental health even when controlling for exposure (Figure 4.2.1). Therefore, students may need more mental health support when they report being particularly upset by discriminatory experiences. Moreover, mental health in adolescents is especially connected to the quality of their peer relationships [35]. Accordingly, in our analysis, peer discrimination had a much higher estimated impact on mental health compared to educational and institutional discrimination (Figure 4.2.2).

Discrimination with respect to other identity types including gender, sexuality, religion, disability, and money were also all found to be predictive of PHQ-4 with varying degrees of magnitude (Table 4.2.5). After controlling for demographic variables, discrimination related to disability, money, and race appeared to have the largest effect on mental health. The coefficients of the interaction terms between different types of discrimination were mostly negative, indicating that the effect of experiencing multiple types of discrimination is not necessarily additive. Instead, there appears to be a diminishing effect where initial exposure to discrimination has the greatest effect on mental health, and each additional exposure becomes less impactful.

When we modeled the effect of discrimination on anxiety and depression separately, rather than the combined PHQ-4 metric, discrimination had a significant relationship with both disorders but seemed to be more predictive of depression (Section 4.3.1). The point estimate of the coefficient for ADDI was larger in the model predicting depression, and this model also had a lower AIC. Anxiety is more prevalent among students, with 26.27% of students in 2023 having anxiety based on the PHQ-4 anxiety subscale compared to 19.72% for depression. Because of its higher prevalence, anxiety likely has more contributing factors than depression, which may explain why discrimination has a comparatively smaller predictive effect.

While school characteristics were not very predictive of discrimination exposure when modeling with the full sample (Table 4.5.1), there were several school characteristics that were significant predictors of discrimination exposure in the propensity score-based strata (Table 4.5.3). The top two propensity score quintiles had more school characteristics that were significant predictors of discrimination exposure, suggesting that for students who are the most likely to experience discrimination, the school characteristics become more important for whether they actually experience discrimination. Total enrollment was positively associated with discrimination exposure in both the full sample and in four out of the five quintiles, indicating that students in larger schools are more likely to experience discrimination. Other factors that were significantly associated with discrimination exposure in the multiple strata include lower attendance rates and higher student-teacher ratio.

The same-race teacher-student ratio was also a significant predictor of discrimination exposure. However, while the metric was positively associated with *ADDI Binary* in the

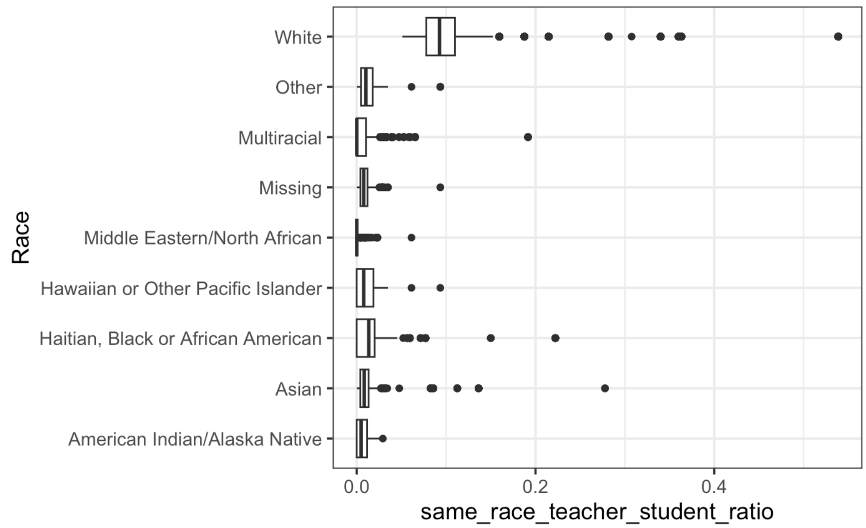


Figure 5.1.2: Same-race teacher-student ratio by race

full sample model (Table 4.5.1), it was negatively associated with *ADDI Binary* in the models for each of the five quintiles (Table 4.5.3). The same-race teacher-student ratio differs substantially by race, with white students having a much higher ratio on average (Figure 5.1.2). Therefore, this could be a case of Simpson's Paradox [43] where the same-race teacher-student ratio reflects other school-level or individual-level factors that might lead to a positive relationship with discrimination exposure in the full sample. However, when controlling for students' propensity scores for discrimination exposure, having a higher same-race teacher-student ratio appears to protect students against experiencing discrimination.

There were also several school characteristics that appeared to be effect modifiers in the relationship between discrimination and mental health (Figure 4.5.1). Overall, it seemed that the effect of discrimination on mental health was estimated to be smaller in schools with better attendance, higher graduation rates, and lower percentages of low income, ELL, and high-needs students. Socioeconomic status, English proficiency, and high-needs status were not explicitly measured by the demographic variables we included in our models, so these school characteristics might actually reflect individual-level factors that contribute to discrimination and mental health. There were some differences in significant effect modifiers between propensity score quintiles (Table 4.5.4), but there were no clear patterns, and these differences may simply be due to the arbitrary significance level of 0.05 and randomness from data sampling.

5.2 Limitations

5.2.1 Methodological Limitations

Throughout this study, we focused on generalized linear models, specifically negative binomial and linear regression. However, these models do not necessarily capture the true underlying relationship between ADDI and PHQ-4. Moreover, the negative binomial was selected by comparing preliminary models that used ADDI as the sole predictor of PHQ-4, but this does not necessarily mean that the negative binomial remains the best model when other predictors are introduced into the model.

The survey only includes observational data, and although we considered causal methods such as propensity scoring and longitudinal analysis, these adjustments are not perfect substitutes for random assignment. Similarly, the relationship of school characteristics to discrimination and mental health cannot be interpreted causally since students are not randomly assigned to schools, and there are many confounding factors, such as socioeconomic status or location of residence, that could influence which school a student attends. Additionally, although our analysis is framed with discrimination as the predictor of mental health, the true direction of causality may be reversed.

5.2.2 Data Limitations

The survey design introduces several sources of bias. Due to the convenience sampling structure, the survey sample was not perfectly representative of the population. The schools included in the survey had disproportionately large enrollment and high proportions of white students and teachers (Table 2.5.4).

Additionally, our results may be biased because of missing data. Although the imputation sensitivity analysis showed minimal variation in the coefficient estimates, there was a systematic difference between students who completed the survey and those who did not. Due to the length of the survey, some students run out of time, particularly those who reported higher rates of substance use as they are asked more follow-up questions. Questions related to mental health and discrimination appear after the substance use questions, directly impacting the analysis in this study. Some schools may allocate more time for students to complete the survey than others, introducing even more bias. Furthermore, students may choose to intentionally skip certain questions or may have been opted out of the survey entirely by their parents. Since there are two potential sources of non-response bias – one from students never reaching certain questions and one from students intentionally skipping certain questions – it is difficult to assess the direction of bias from non-response.

The survey relies entirely on self-reporting, so bias could also be introduced from students failing to recall certain experiences or intentionally misreporting their answers. For instance, the ADDI questions asks students, “tell us if you have experienced each of the following types of discrimination because of your race or ethnicity,” implying an indefinite range of time. Therefore, we should not expect ADDI to ever decrease for an individual, and yet, in the paired longitudinal data, there were several students with a negative change in ADDI. Participants may also have different perceptions of what is considered a discriminatory incident or a mental health symptom, so all analyses reflect only individuals’ perceived experiences.

Although the survey captures a fairly diverse group of students, given that the survey is limited to Massachusetts schools, the results may not be generalizable to other populations. ADDI and PHQ-4, the proxies for discrimination and mental health in our analysis, are also limited in the information they capture. For example, the 15 questions that comprise the ADDI were all treated equally in our analysis even though experiences of racial discrimination differ in pervasiveness and severity.

5.3 Future Directions

Within the SURF data, there are several extensions of this project that could be explored. We could model the effect of individual questions comprising the ADDI to determine which specific incidents of discrimination are the most impactful. Our analysis focused on anxiety and depression, but there are many other aspects of mental health in the SURF survey that may be related to discrimination as well such as suicidality, the Adolescent Psychotic-like Symptom Screener (APSS), the Emotional Reactivity Scale (ERS), and ADHD symptoms. Behavioral outcomes such as students’ substance use could also be explored. We could also investigate whether effect modifiers based on the response variable given that previous work such as Weeks and Sullivan (2019) found that race moderated the effect between discrimination and anxiety, but not discrimination and depression [51].

The SURF survey is primarily designed for the purpose of studying substance use. Therefore, designing or analyzing a different survey that specifically targets the topics of discrimination and mental health could address many of the limitations mentioned previously. Such a survey might include additional questions about discrimination for identity types other than race and ethnicity, allowing for deeper investigation into the interactions between discrimination types. We could also include measures for both discrimination and mental health that do not depend entirely on self-reporting in order to avoid the problems of response bias.

An explicitly longitudinal survey design could also provide additional insights. The sample size for longitudinal analysis was quite small in our analysis, since the schools included in the SURF survey change from year to year. Studying students over a longer period of time would allow us to better understand how the relationship between discrimination and mental health evolves over multiple years during and beyond high school. Further analysis could also be performed to investigate how the effect of new discriminatory incidents differs from the effect of ongoing experiences of discrimination. A longitudinal survey could also provide a more robust analysis of factors that might buffer the effect of discrimination on mental health.

To better investigate the role of schools, an experimental approach would be more suitable. For example, we could compare students just above and below the acceptance benchmark for college-preparatory schools, following a quasi-experimental design similar to Moving to Opportunity or Harlem Children's Zone experiments [13] [16]. By focusing on specific schools, this approach would allow us to measure more school characteristics than public education data and would allow us to create causal conclusions about whether school characteristics with a predictive effect in our study, such as attendance rate and enrollment size, have a causal effect on moderating discrimination impacts on mental health.

5.4 Conclusion

In our analysis, we found a strong association between perceived discrimination and mental health that was robust to various sensitivity analyses. Our results highlight the need for mental health support targeted toward adolescents who report experiences of discrimination, whether related to race or other aspects of their identity. In particular, peer and educational discrimination had the strongest negative impact on mental health, suggesting that schools can play an important role in reducing mental health issues by creating inclusive environments for their students. Several demographic and school characteristics were identified as effect modifiers, such as gender, sexuality, U.S. birth status, enrollment size, attendance levels, and school-level percentages of high needs, low income, and ELL students. Based on these differences mental health resources could be directed toward individuals or schools where discrimination has the greatest effect. Our results suggest several directions for future research including analyzing additional response variables, longitudinal impacts of discrimination, and the causal role of schools - all of which could inform better interventions for addressing the impact of discrimination on mental health in adolescents during this critical period of development into adulthood.

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6

Appendix A: 2023 Additional Results

6.1 Additional Modeling Results

Model Type	AIC	ADDI Coefficient	Standard Error	95% CI
Linear	83985.97	1.121392	0.054912	(1.0138, 1.229)
2nd Order Polynomial	83973.87	0.700198	0.181668	(0.3441, 1.0563)
3rd Order Polynomial	83973.73	1.070433	0.334328	(0.4151, 1.7258)
4th Order Polynomial	83975.71	1.154086	0.766434	(-0.3482, 2.6564)
5th Order Polynomial	83976.56	3.144839	2.274117	(-1.3127, 7.6024)
Poisson	93543.60	0.324642	0.016318	(0.2927, 0.3566)
Negative Binomial	71346.88	0.258422	0.014583	(0.2298, 0.2870)
Binomial	111737.46	0.461334	0.022812	(0.4166, 0.5060)

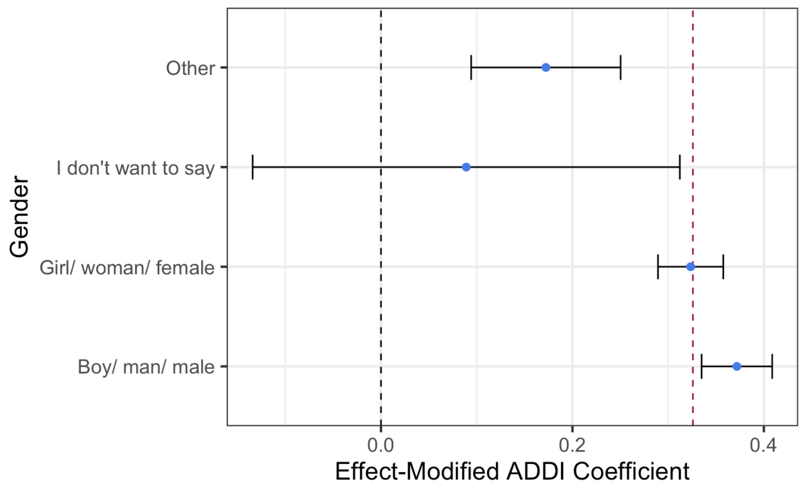
Table 6.1.1: Results for preliminary models using the log-transformed ADDI Total to predict PHQ-4 Total in 2023 data. Standard errors are adjusted for clustering by school.

	Linear Models Predicting PHQ-4 Total			
	Demographic variables	*Full Interactions*	*Backward Stepwise*	*Mixed-Effects w/ demographics*
ADDI Total	0.338***	0.356***	0.347***	0.332***
RaceNative	−0.205	−6.745**	−6.659**	−0.076
RaceAsian	−0.794***	0.791	−0.035	−0.255***
RaceBlack	−0.674***	1.487	0.630	−0.260***
RacePacific Islander	0.275	−5.128	−0.696	0.034
RaceMiddle Eastern	−0.165	−0.096	−0.027	−0.007
RaceMultiracial	−0.258***	−3.189***	−2.936***	−0.086**
RaceOther	−0.436***	0.625	−0.679	−0.178***
EthnicityHispanic	−0.188***	−0.752	−0.423***	−0.064**
GenderGirl/ woman/ female	1.237***	1.976***	2.342***	0.521***
GenderI don't want to say	1.073***	1.885	4.446	0.450***
GenderOther	1.985***	3.208**	4.477***	0.585***
SexualityBisexual	2.154***	2.317**	1.758***	0.562***
SexualityGay or Lesbian	1.741***	5.960***	3.247***	0.560***
SexualityI don't want to say	0.563***	0.491	0.100	0.200***
SexualitySomething else	1.969***	5.883***	2.138***	0.558***
SexualityUnsure	1.447***	−0.305	0.462	0.439***
Grade	0.072***	0.146	0.139***	
BornUSA	0.013	0.215	−0.134	0.022
ClassPerformanceBs	0.200***	−0.288	0.055	0.076***
ClassPerformanceCs	0.712***	−0.198	0.646***	0.251***
ClassPerformanceDs	1.487***	1.928	1.294***	0.474***
ClassPerformanceFs	2.089***	−7.237**	2.374***	0.498***
ClassPerformanceMixed	0.714***	0.438	0.490***	0.236***
ClassPerformanceNone	1.292***	5.871	1.621***	0.362**
ClassPerformanceUnsure	−0.348*	0.211	−0.060	−0.099
Sports	−0.452***	−0.831	−0.486***	−0.184***
RaceNative * Hispanic		1.168	1.137*	
RaceAsian * Hispanic		0.217	−0.019	
RaceBlack * Hispanic		0.777***	0.833***	
RacePacific Islander * Hispanic		1.193	2.165**	
RaceMiddle Eastern * Hispanic		1.376**	1.516***	
RaceMultiracial * Hispanic		0.173	0.137	
RaceOther * Hispanic		0.476	0.545	
RaceNative * Grade		0.619*	0.567**	
RaceAsian * Grade		−0.071	−0.077	
RaceBlack * Grade		−0.165*	−0.158*	
RacePacific Islander * Grade		0.519	−0.050	
RaceMiddle Eastern * Grade		−0.060	−0.035	
RaceMultiracial * Grade		0.271***	0.263***	
RaceOther * Grade		−0.063	−0.014	
Note:				*p<0.1; **p<0.05; ***p<0.01

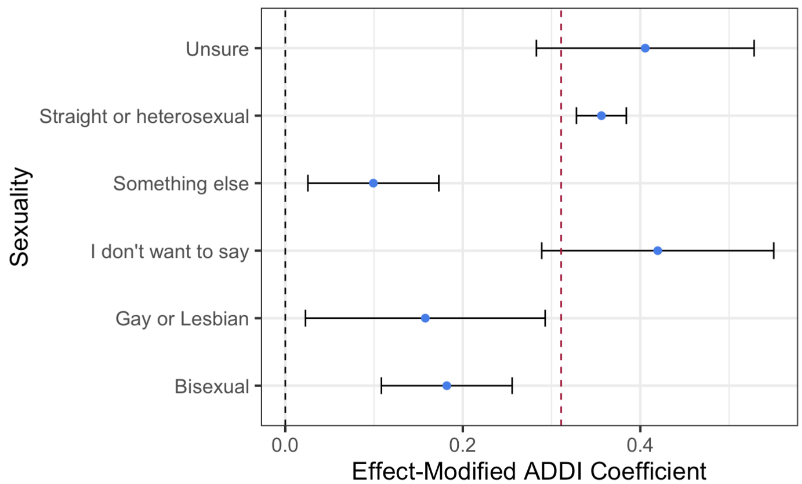
Table 6.1.2: Coefficients and significance of confounders in linear regression models. Interaction terms that were removed in backward selection are not shown.

	Linear Models Predicting PHQ-4 Total	
	Full Interactions	*Backward Stepwise*
Hispanic * SexualityBisexual	−0.498*	−0.499**
Hispanic * SexualityGay or Lesbian	−0.463	−0.850**
Hispanic * SexualityI don't want to say	0.141	−0.001
Hispanic * SexualitySomething else	−0.921**	−0.957***
Hispanic * SexualityUnsure	−0.632*	−0.560*
Hispanic * Sports	0.331**	0.327***
GenderGirl/ woman/ female * Grade	−0.095**	−0.119***
GenderI don't want to say * Grade	−0.205	−0.350
GenderOther * Grade	−0.139	−0.225**
GenderGirl/ woman/ female * ClassPerformanceBs	0.249**	0.311**
GenderI don't want to say * ClassPerformanceBs	1.147	1.860**
GenderOther * ClassPerformanceBs	−0.996***	−0.355
GenderGirl/ woman/ female * ClassPerformanceCs	0.255	0.106
GenderI don't want to say * ClassPerformanceCs	−0.446	−0.620
GenderOther * ClassPerformanceCs	0.550	0.606
GenderGirl/ woman/ female * ClassPerformanceDs	1.130**	0.676
GenderI don't want to say * ClassPerformanceDs	0.598	0.349
GenderOther * ClassPerformanceDs	−0.353	−0.840
GenderGirl/ woman/ female * ClassPerformanceFs	−0.429	−0.114
GenderI don't want to say * ClassPerformanceFs	10.631**	5.953**
GenderOther * ClassPerformanceFs	−3.793***	−2.255**
GenderGirl/ woman/ female * ClassPerformanceMixed	0.473***	0.453***
GenderI don't want to say * ClassPerformanceMixed	−0.571	−0.049
GenderOther * ClassPerformanceMixed	−0.414	−0.068
GenderGirl/ woman/ female * ClassPerformanceNone	1.732	−0.115
GenderI don't want to say * ClassPerformanceNone		−5.392*
GenderOther * ClassPerformanceNone	0.500	−2.110
GenderGirl/ woman/ female * ClassPerformanceUnsure	−0.460	−0.422
GenderI don't want to say * ClassPerformanceUnsure	−1.702	−0.557
GenderOther * ClassPerformanceUnsure	−2.358**	−1.029
SexualityBisexual * BornUSA	0.335	0.553
SexualityGay or Lesbian * BornUSA	−1.816***	−1.433**
SexualityI don't want to say * BornUSA	0.531	0.594*
SexualitySomething else * BornUSA	−0.692	0.106
SexualityUnsure * BornUSA	1.246***	1.332***
Note:		*p<0.1; **p<0.05; ***p<0.01

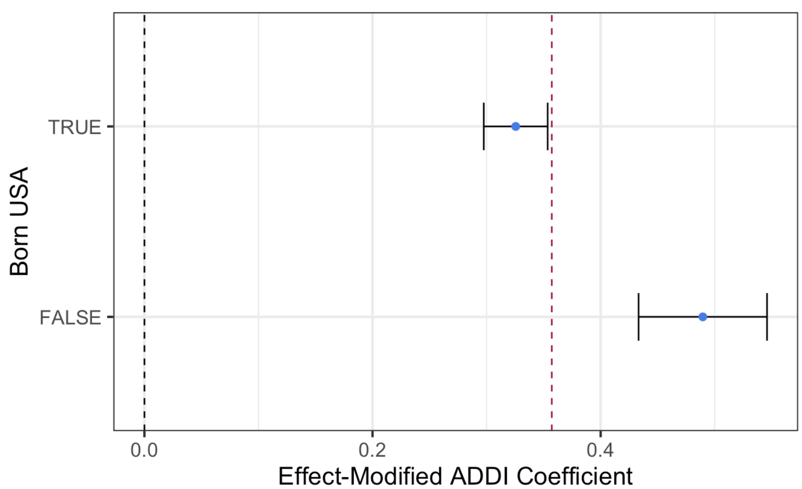
Table 6.1.2: (Continued from previous page) Coefficients and significance of confounders in linear regression models. Interaction terms that were removed in backward selection are not shown.



(a) Gender



(b) Sexuality



(c) Born USA

Figure 6.1.1: Effect modification in linear regression models for gender, sexuality, and born USA

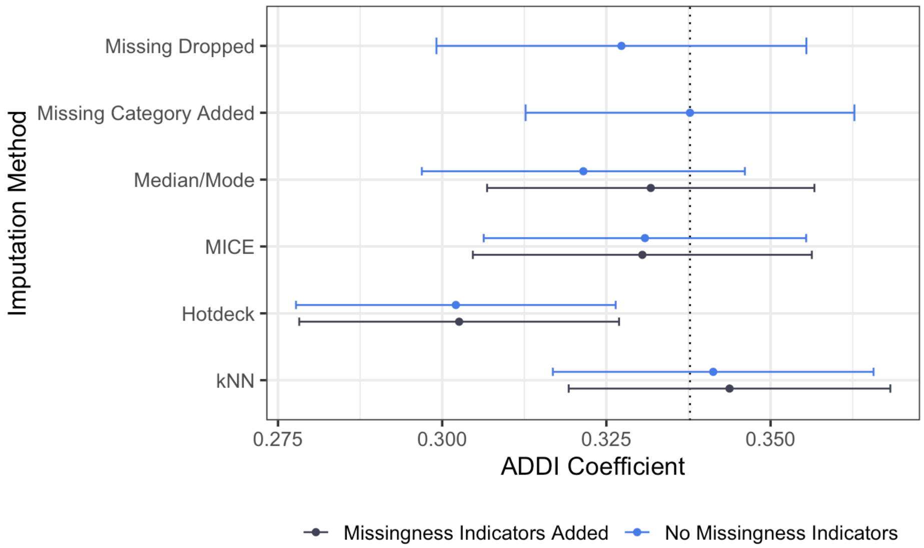


Figure 6.1.2: Imputation sensitivity in linear regression

	Imputation Method				
Missing Indicator	Missing Category	Median/Mode	MICE	Hotdeck	kNN
ADDI Total	–	0.41063***	0.04632	0.04477	0.23946***
Race	-0.28358	-0.21473	0.00099	–	-0.07435
Ethnicity	-0.16119	-0.25429	-0.19018	-0.30842	-0.09638
Gender	0.36649	-0.75326**	-0.06251	-0.27166	-0.00139
Sexuality	-0.04065	0.02141	-0.15395	-0.45708	-0.13712
Born USA	-0.53840	-0.45114	-0.50724	-0.64659*	-0.47491
Class Performance	0.38830	0.29738	-0.08601	0.09262	0.05605
Sports	-0.48335*	0.09004	-0.22346	-0.17716	-0.10081
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6.1.3: Coefficients of missingness indicators in the linear regression model for various imputation methods

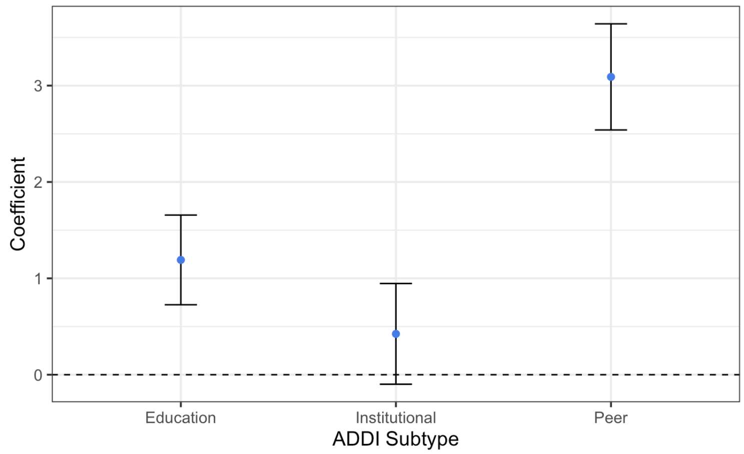


Figure 6.1.3: Linear regression discrimination subtype coefficients

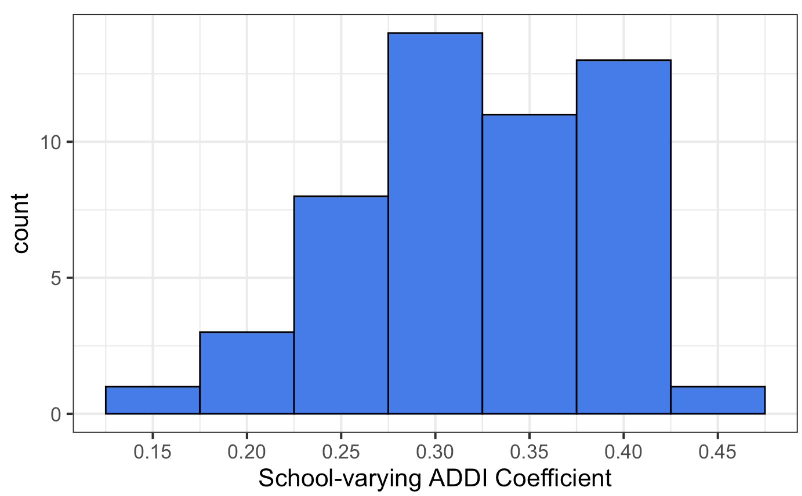
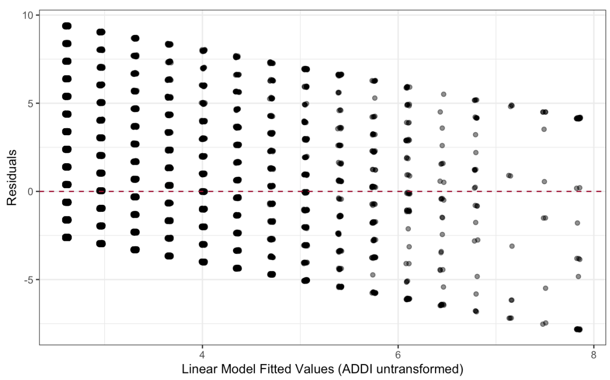


Figure 6.1.4: Distribution of school-varying ADDI coefficients for the random-effects model predicit-ing PHQ-4 with demographic and school characteristics

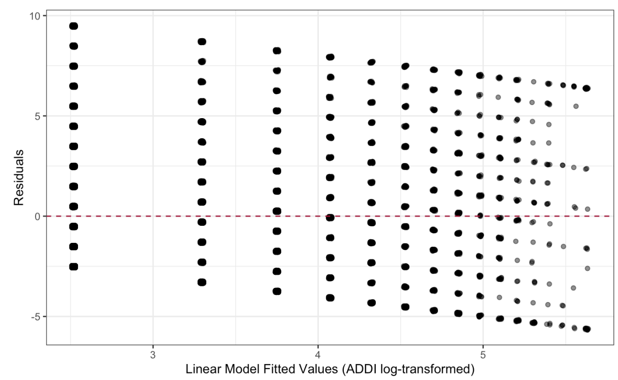
	Model Type		
	Discrimination Variables Only	*With Interactions*	*With Interactions and Demographics*
ADDI.Binary	0.860***	0.931***	1.075***
DISC.Gender	1.367***	2.292***	1.279***
DISC.Sexuality	1.918***	2.438***	1.153***
DISC.Religion	0.350***	0.914***	0.905***
DISC.Disability	1.526***	2.285***	1.873***
DISC.Money	1.405***	1.981***	1.623***
DISC.Other	1.009***	1.486***	1.274***
ADDI.Binary * DISC.Gender		−0.396	−0.241
ADDI.Binary * DISC.Sexuality		−0.243	−0.179
ADDI.Binary * DISC.Religion		−0.578**	−0.572**
ADDI.Binary * DISC.Disability		−0.316	−0.302
ADDI.Binary * DISC.Money		−0.081	0.109
ADDI.Binary * DISC.Other		−0.295	−0.151
DISC.Gender * DISC.Sexuality		−0.886***	−0.511**
DISC.Gender * DISC.Religion		−0.756*	−0.490
DISC.Gender * DISC.Disability		−0.382	−0.300
DISC.Gender * DISC.Money		−0.884*	−0.567*
DISC.Gender * DISC.Other		0.900	0.710
DISC.Sexuality * DISC.Religion		0.487	0.388
DISC.Sexuality * DISC.Disability		−1.014***	−0.813**
DISC.Sexuality * DISC.Money		−0.384	−0.343
DISC.Sexuality * DISC.Other		−1.440**	−1.110**
DISC.Religion * DISC.Disability		0.347	0.242
DISC.Religion * DISC.Money		−0.760**	−0.508
DISC.Religion * DISC.Other		0.995	0.451
DISC.Disability * DISC.Money		−0.016	0.171
DISC.Disability * DISC.Other		−1.695**	−1.392
DISC.Money * DISC.Other		−0.561	−0.616*
Akaike Inf. Crit.	82,483.410	82,358.590	80,544.220
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6.1.4: Coefficients and significance of linear regression models predicting PHQ-4 using all discrimination variables

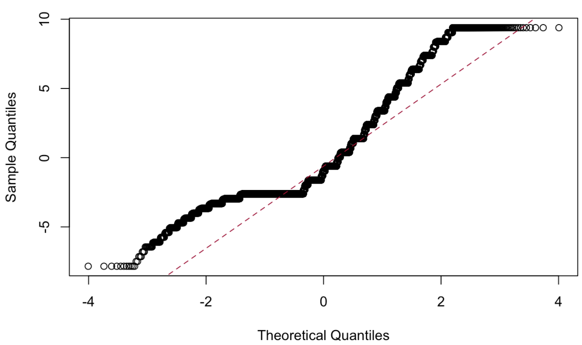
6.2 Preliminary Model Diagnostics



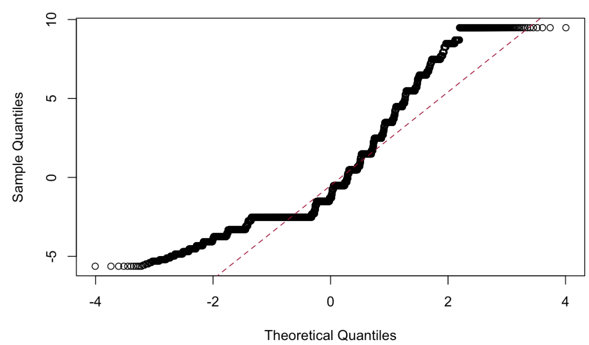
(a) Residuals vs. fitted values for untransformed ADDI



(b) Residuals vs. fitted values for log-transformed ADDI

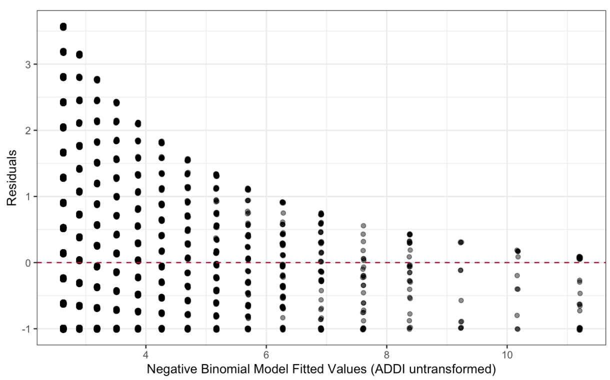


(c) Residuals QQ-plot for untransformed ADDI

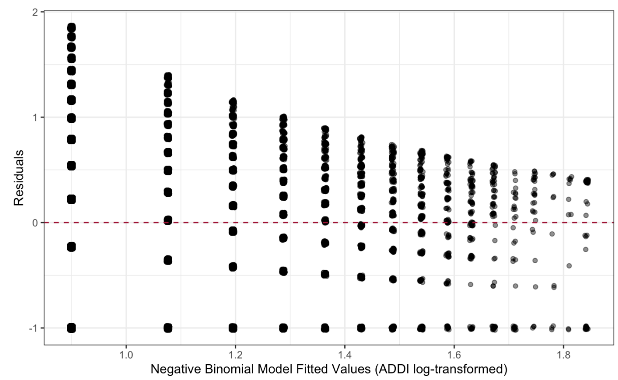


(d) Residuals QQ-plot for log-transformed ADDI

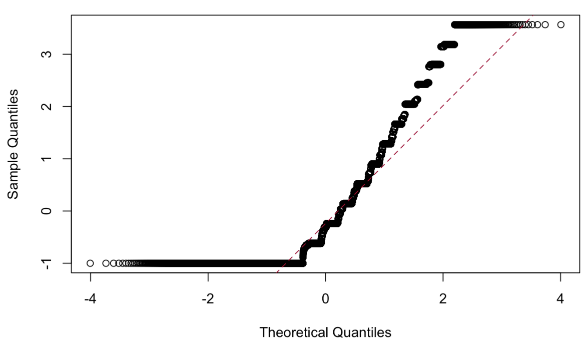
Figure 6.2.1: Model diagnostics for the preliminary linear models



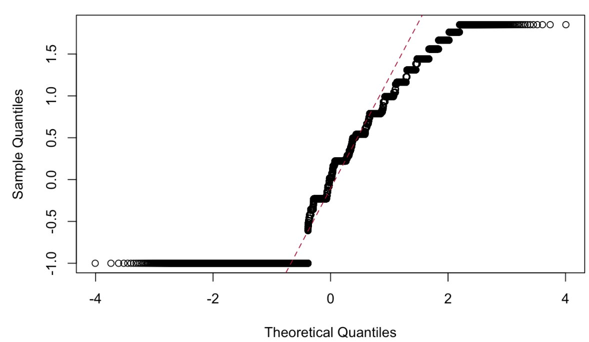
(a) Residuals vs. fitted values for untransformed ADDI



(b) Residuals vs. fitted values for log-transformed ADDI

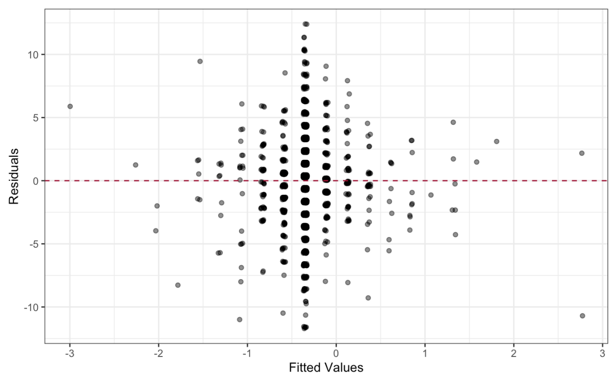


(c) Residuals QQ-plot for untransformed ADDI

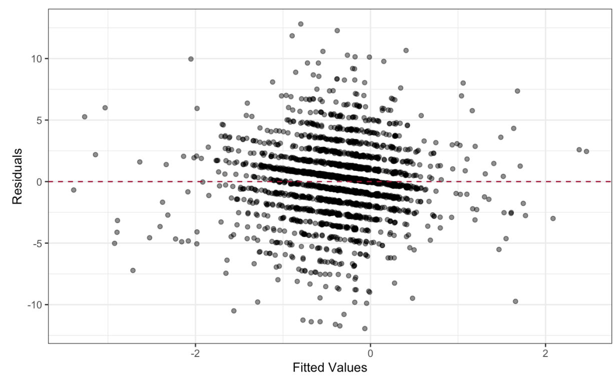


(d) Residuals QQ-plot for log-transformed ADDI

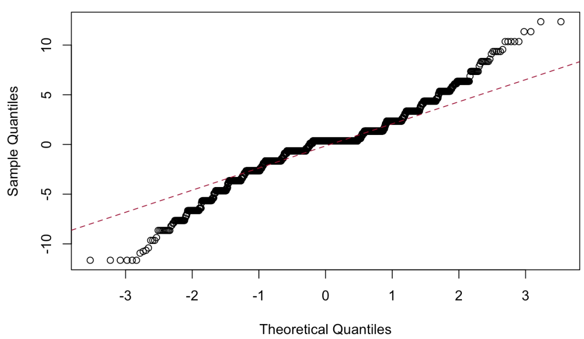
Figure 6.2.2: Model diagnostics for the preliminary negative binomial models



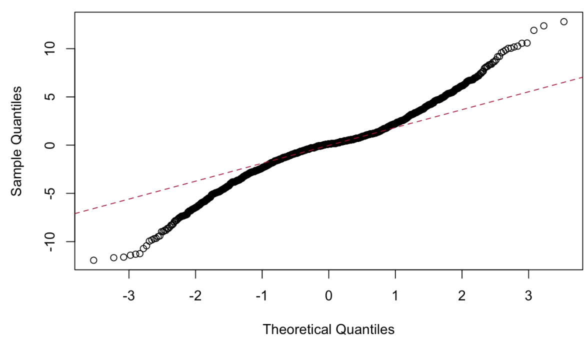
(a) Residuals vs. fitted values for the model without confounders



(b) Residuals vs. fitted values for the model with confounders



(c) Residuals qq-plot for the model without confounders



(d) Residuals qq-plot for the model with confounders

Figure 6.2.3: Model diagnostics for paired differences linear regression models in the longitudinal analysis

6.3 Additional Propensity Scoring Balancing Diagnostics

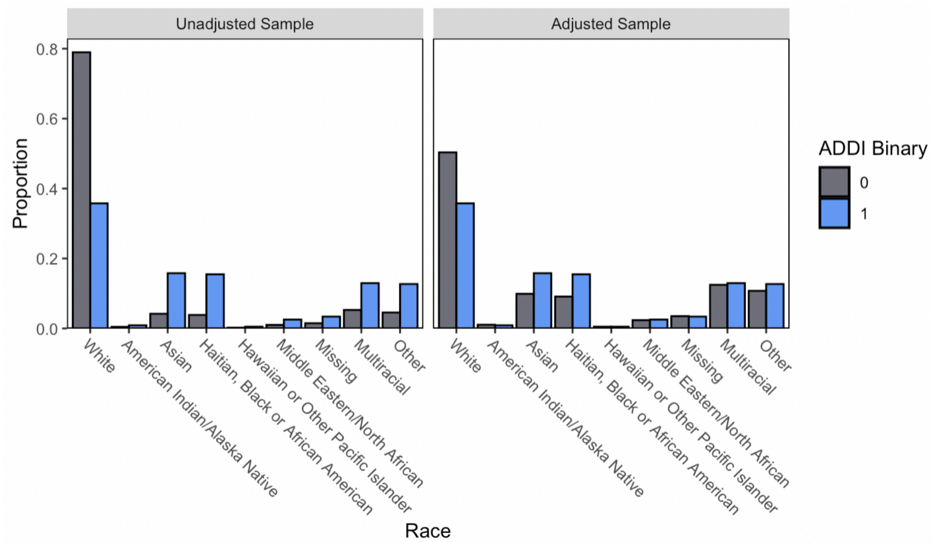


Figure 6.3.1: Race distribution in unmatched vs. propensity-matched samples

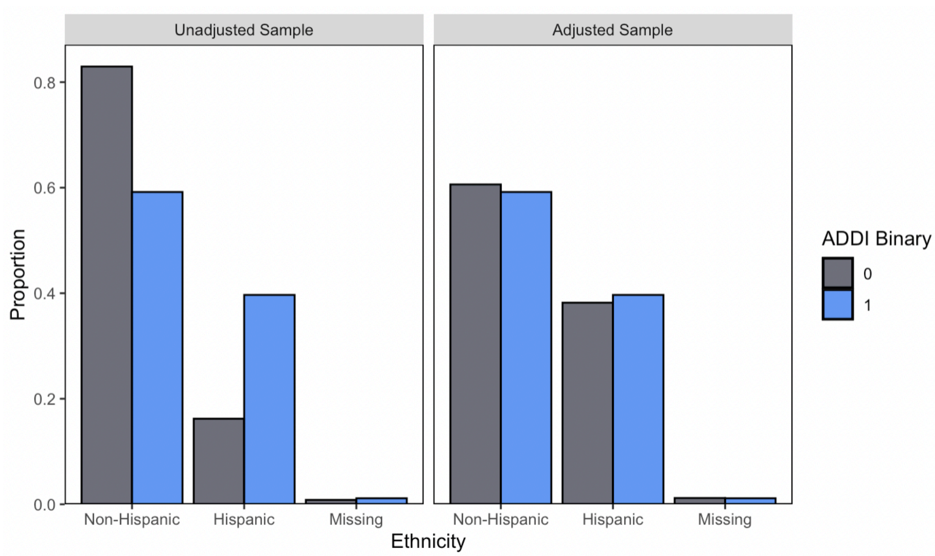


Figure 6.3.2: Ethnicity distribution in unmatched vs. propensity-matched samples

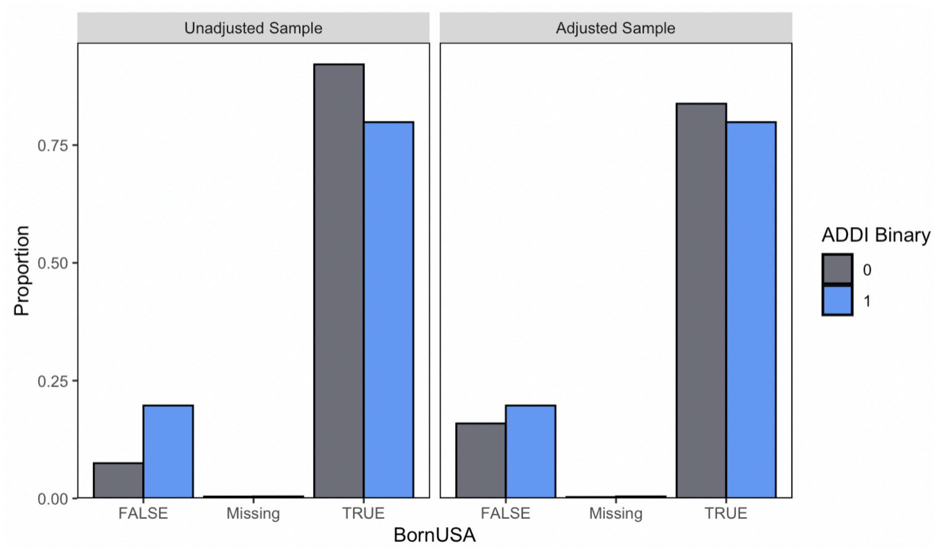


Figure 6.3.3: Born USA distribution in unmatched vs. propensity-matched samples

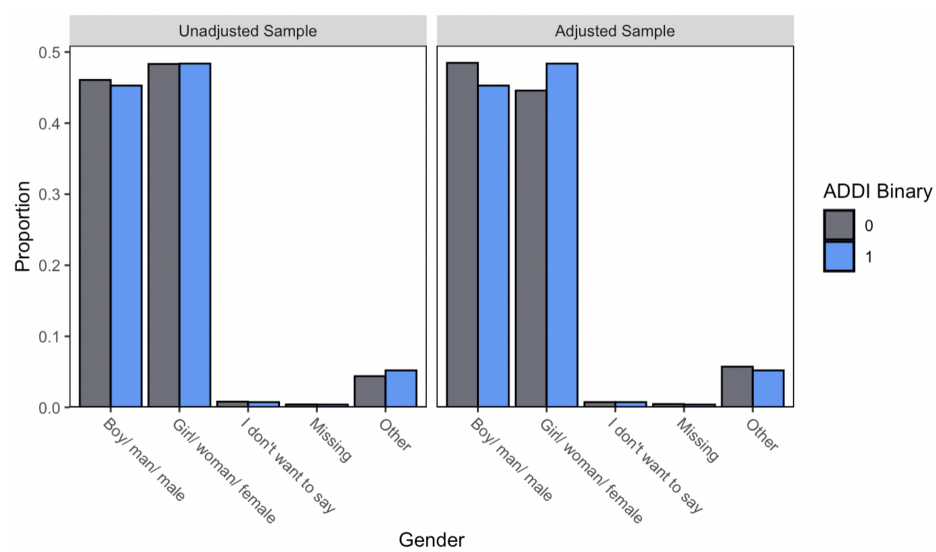


Figure 6.3.4: Gender distribution in unmatched vs. propensity-matched samples

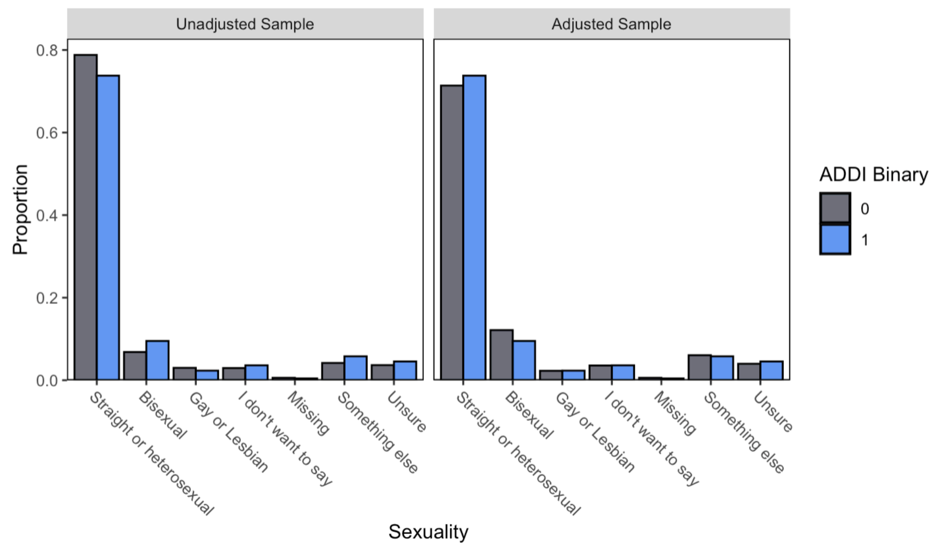


Figure 6.3.5: Sexuality distribution in unmatched vs. propensity-matched samples

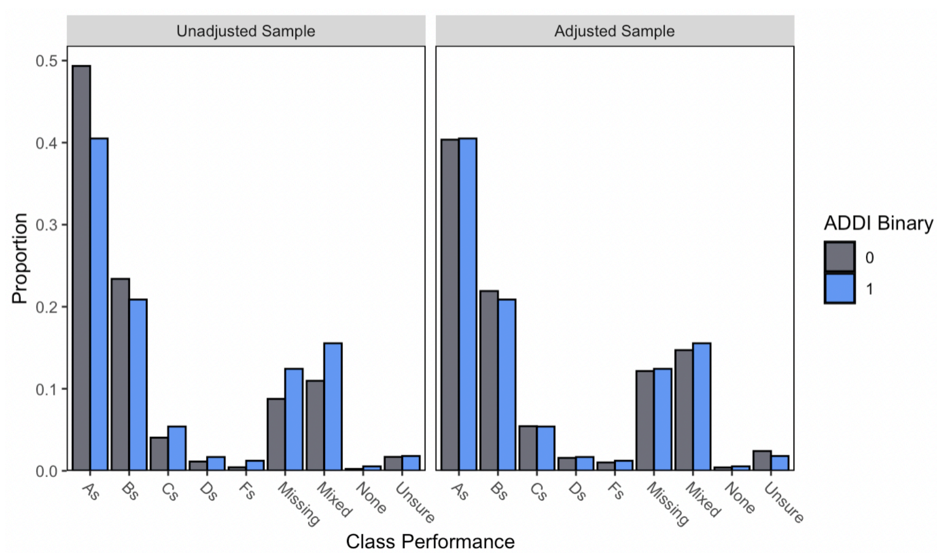


Figure 6.3.6: Class performance distribution in unmatched vs. propensity-matched samples

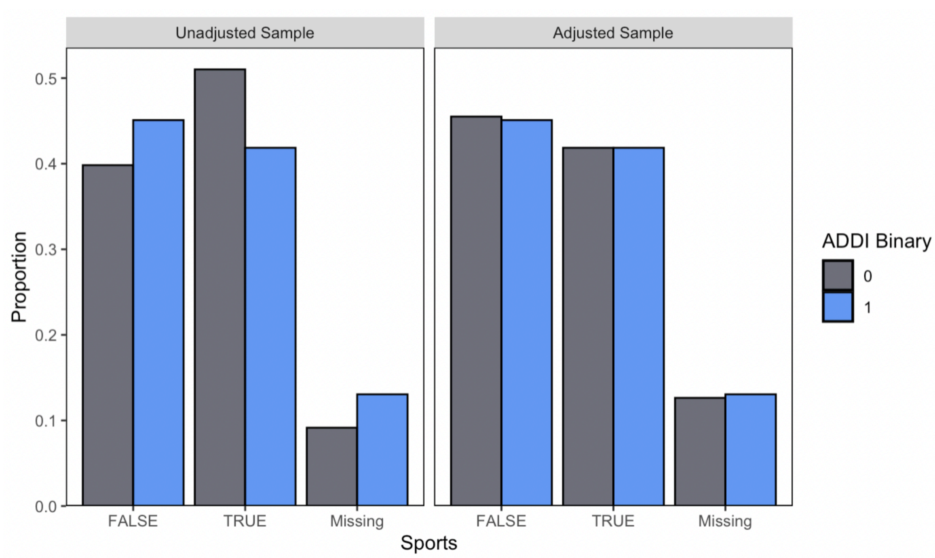


Figure 6.3.7: Sports participation in unmatched vs. propensity-matched samples

7

Appendix B: 2022 Additional Results

Model Type	AIC	ADDI Coefficient	Standard Error	95% CI
Linear	78940.13	0.3277	0.0243	(0.2801, 0.3753)
2nd Order Polynomial	78925.00	0.4465	0.0512	(0.3461, 0.547)
3rd Order Polynomial	78921.16	0.5679	0.0841	(0.4031, 0.7327)
4th Order Polynomial	78922.59	0.6259	0.1202	(0.3902, 0.8616)
5th Order Polynomial	78924.32	0.6849	0.2024	(0.2882, 1.0816)
Poisson	88586.43	0.0761	0.0041	(0.068, 0.0842)
Negative Binomial	69388.39	0.0824	0.0047	(0.0732, 0.0916)
Binomial	106526.18	0.1230	0.0085	(0.1062, 0.1397)

Table 7.0.1: Results for preliminary models using ADDI Total to predict PHQ-4 Total (2022 data). Standard errors adjusted for clustering by school.

	Negative Binomial Models Predicting PHQ4 Total			
	Demographic variables	*Full Interactions*	*Backward Stepwise*	*Mixed-Effects w/ demographics*
ADDI Total	0.080***	0.085***	0.080***	0.080***
RaceNative	0.046	−2.660	0.021	0.046
RaceAsian	−0.129***	0.342	−0.123***	−0.112***
RaceBlack	−0.219***	−0.157	−0.218***	−0.215***
RacePacific Islander	0.108	5.396	0.064	0.113
RaceMiddle Eastern	−0.076	−0.407	−0.050	−0.072
RaceMultiracial	−0.047	−0.366	−0.051	−0.053
RaceOther	−0.114**	0.014	−0.131***	−0.123**
GenderGirl/ woman/ female	0.554***	0.772***	0.679***	0.554***
GenderI don't want to say	0.342***	0.688	1.213***	0.340***
GenderOther	0.606***	1.350***	0.905***	0.601***
SexualityBisexual	0.531***	1.445***	1.340***	0.521***
SexualityGay or Lesbian	0.578***	1.314**	1.443***	0.576***
SexualityI don't want to say	0.166***	1.121*	0.397	0.172***
SexualitySomething else	0.540***	1.430***	1.219***	0.536***
SexualityUnsure	0.461***	1.607***	1.561***	0.452***
Grade	0.073***	0.119***	0.090***	0.07376***
BornUSA	0.037	0.627*	0.115**	0.033
ClassPerformanceBs	0.057***	−0.008	0.062***	0.071***
ClassPerformanceCs	0.186***	0.859*	0.195***	0.188***
ClassPerformanceDs	0.535***	−0.322	0.524***	0.567***
ClassPerformanceFs	0.561***	−0.731	0.564***	0.560***
ClassPerformanceMixed	0.248***	0.065	0.252***	0.247***
ClassPerformanceNone	0.101	2.947	0.092	0.085
ClassPerformanceUnsure	0.036	−1.231*	0.014	0.037
Sports	−0.151***	−0.288	−0.258***	−0.155***
GenderGirl * SexualityBisexual		−0.426***	−0.402***	
GenderI don't want to say * SexualityBisexual		−1.590***	−1.174***	
GenderOther * SexualityBisexual		−0.490**	−0.477**	
GenderGirl * SexualityGay or Lesbian		−0.351***	−0.328***	
GenderOther * SexualityGay or Lesbian		−0.413*	−0.399*	
GenderGirl * SexualityI don't want to say		−0.286**	−0.224*	
GenderI don't want to say * SexualityI don't want to say		−0.735*	−0.425	
GenderGirl * SexualitySomething else		−0.248**	−0.188*	
GenderOther * SexualitySomething else		−0.470**	−0.447**	
GenderGirl * SexualityUnsure		−0.324***	−0.339***	
GenderOther * SexualityUnsure		−0.445*	−0.455**	
GenderGirl * BornUSA		−0.207***	−0.190***	
GenderI don't want to say * BornUSA		−0.611	−0.818***	
GenderGirl * Sports		0.170***	0.204***	
SexualityBisexual * Grade		−0.052*	−0.050*	
SexualityUnsure * Grade		−0.081**	−0.084**	
SexualityI don't want to say * BornUSA		0.303	0.370**	
SexualitySomething else * BornUSA		0.054	0.286*	
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 7.0.2: Coefficients and significance of confounders in negative binomial models (2022 data). Interaction terms that were not significant in any models are not shown.

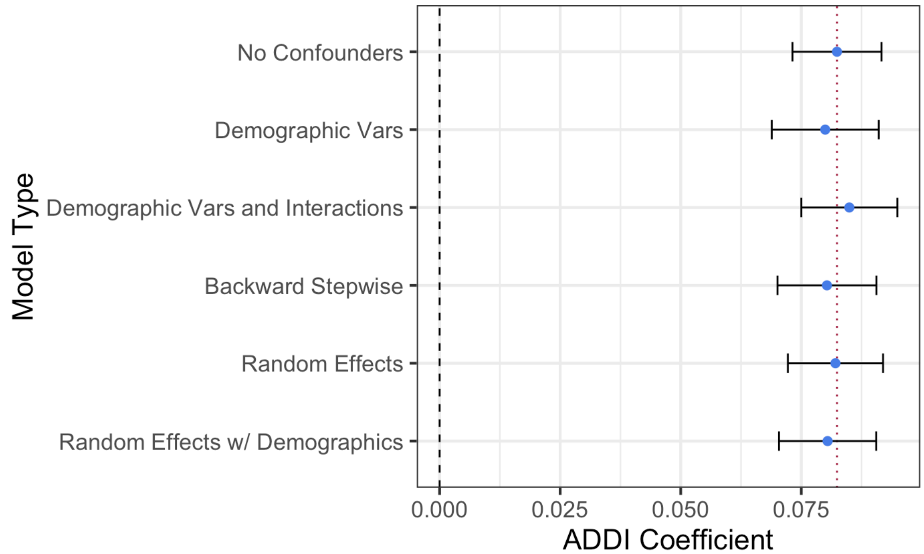
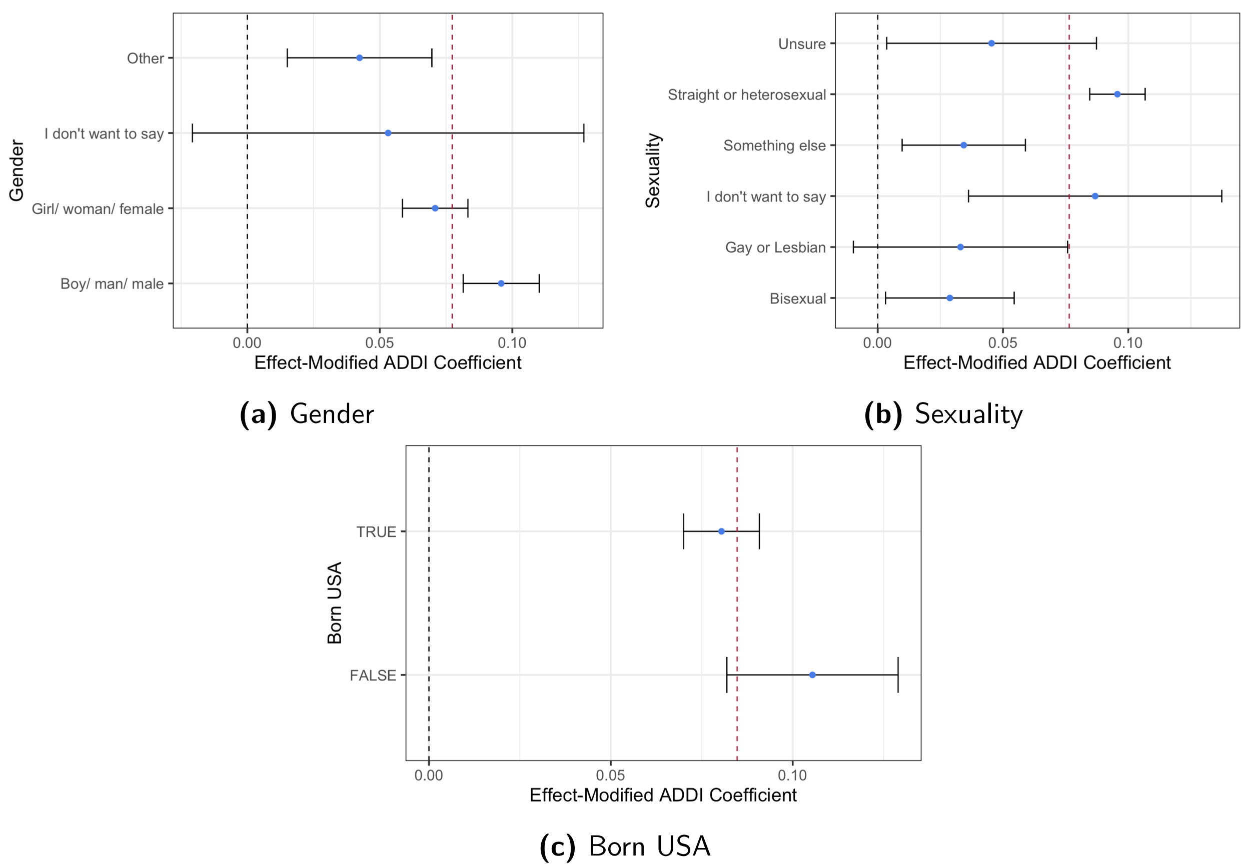


Figure 7.0.1: ADDI coefficients and 95% confidence intervals for negative binomial models with confounders (2022 data)



(a) Gender

(b) Sexuality

(c) Born USA

Figure 7.0.2: Effect modification forest plots for gender, sexuality, and USA birth status in negative binomial models (2022 data)

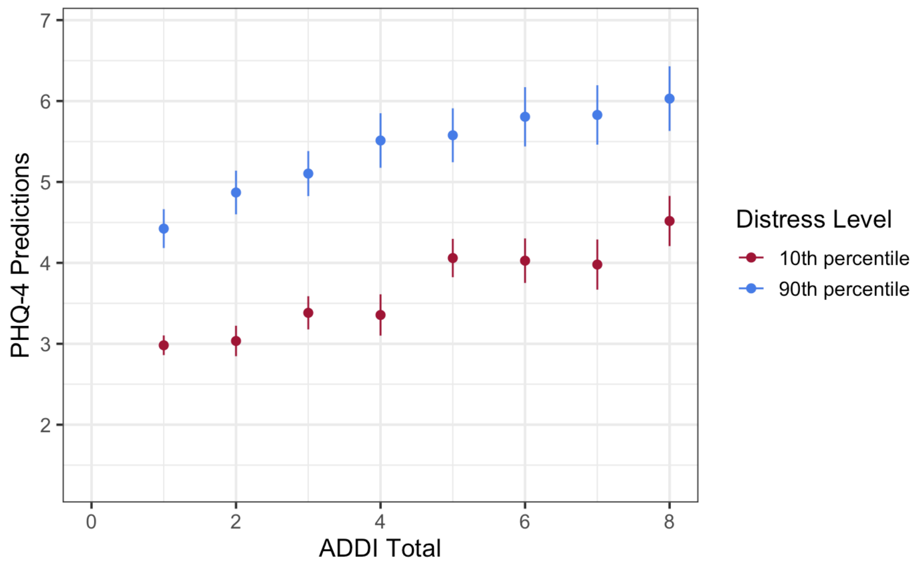


Figure 7.0.3: PHQ-4 predictions from a negative binomial model with ADDI predictors log-transformed at low and high distress levels for various discrimination exposure levels (2022 data)

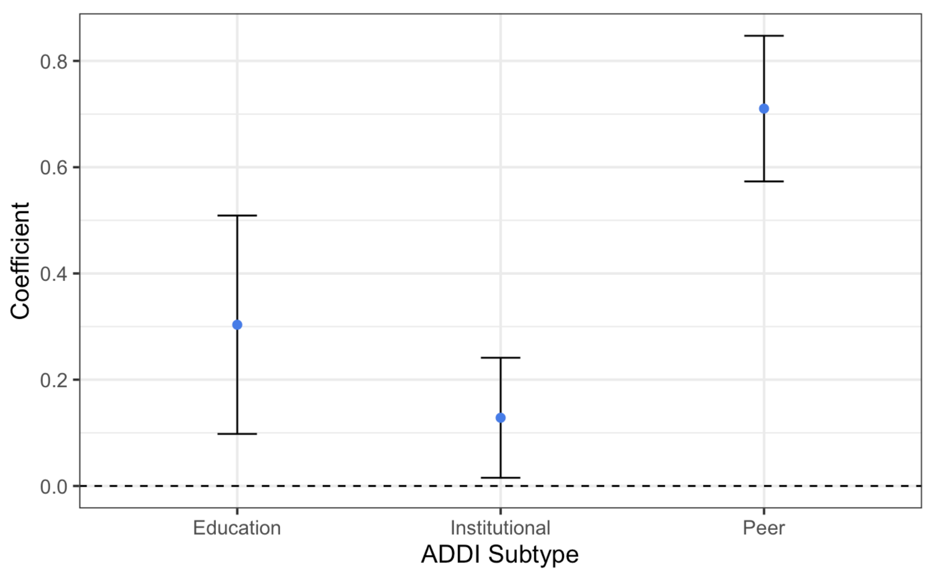


Figure 7.0.4: Coefficients of ADDI subtypes predicting PHQ-4 in a negative binomial with demographic covariates (2022 data)

	Exposure only	*With Distress*	*Log* Exposure	*Log* with distress
ADDI Distress		0.006*		
ADDI Total	0.080***	0.058***		
log(ADDI Total + 1)			0.298***	−0.121*
log(ADDI Distress + 1)				0.275***
RaceAmerican Indian/Alaska Native	0.046	0.050	0.005	0.001
RaceAsian	−0.129***	−0.124***	−0.196***	−0.206***
RaceHaitian, Black or African American	−0.219***	−0.220***	−0.266***	−0.290***
RaceHawaiian or Other Pacific Islander	0.108	0.111	0.098	0.079
RaceMiddle Eastern/North African	−0.076	−0.073	−0.122	−0.124
RaceMissing	−0.048	−0.046	−0.074	−0.077
RaceMultiracial	−0.047	−0.046	−0.082**	−0.096***
RaceOther	−0.114**	−0.112**	−0.141***	−0.146***
EthnicityMissing	0.089	0.088	0.109	0.114
EthnicityNot Hispanic/ Latino(a)	0.019	0.017	0.040	0.038
GenderGirl/ woman/ female	0.554***	0.551***	0.553***	0.542***
GenderI don't want to say	0.342***	0.341***	0.336***	0.321***
GenderMissing	−0.030	−0.029	−0.035	−0.044
GenderOther	0.606***	0.604***	0.611***	0.603***
SexualityBisexual	0.531***	0.531***	0.528***	0.523***
SexualityGay or Lesbian	0.578***	0.576***	0.576***	0.570***
SexualityI don't want to say	0.166***	0.165***	0.173***	0.174***
SexualityMissing	−0.017	−0.020	−0.007	−0.007
SexualitySomething else	0.540***	0.539***	0.543***	0.540***
SexualityUnsure	0.461***	0.461***	0.459***	0.455***
Grade	0.073***	0.073***	0.073***	0.069***
BornUSAMissing	0.191	0.192	0.193	0.206
BornUSA	0.037	0.037	0.053	0.053
ClassPerformanceBs	0.057***	0.058***	0.056***	0.060***
ClassPerformanceCs	0.186***	0.188***	0.178***	0.181***
ClassPerformanceDs	0.535***	0.539***	0.513***	0.517***
ClassPerformanceFs	0.561***	0.559***	0.596***	0.619***
ClassPerformanceMissing	0.083	0.085	0.078	0.077
ClassPerformanceMixed	0.248***	0.249***	0.244***	0.247***
ClassPerformanceNone	0.101	0.095	0.144	0.179
ClassPerformanceUnsure	0.036	0.038	0.043	0.056
Sports	−0.151***	−0.150***	−0.149***	−0.148***
SportsMissing	0.001	−0.001	0.008	0.007
Constant	−0.197**	−0.187*	−0.245***	−0.205**
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 7.0.3: Coefficients of negative binomial models with and without discrimination distress (2022 data)

	Model Type		
	Discrimination Variables Only	*With Interactions*	*With Interactions and Demographics*
ADDI.Binary	0.228***	0.264***	0.284***
DISC.Gender	0.309***	0.552***	0.235***
DISC.Sexuality	0.512***	0.709***	0.328***
DISC.Religion	0.128***	0.279***	0.295***
DISC.Disability	0.346***	0.622***	0.466***
DISC.Money	0.357***	0.615***	0.518***
DISC.Other	0.205***	0.373***	0.313***
ADDI.Binary * DISC.Gender		−0.067	−0.032
ADDI.Binary * DISC.Sexuality		−0.147*	−0.141**
ADDI.Binary * DISC.Religion		−0.091	−0.043
ADDI.Binary * DISC.Disability		0.020	0.078
ADDI.Binary * DISC.Money		−0.182**	−0.163**
ADDI.Binary * DISC.Other		−0.247*	−0.182
DISC.Gender * DISC.Sexuality		−0.311***	−0.142*
DISC.Gender * DISC.Religion		0.0002	−0.049
DISC.Gender * DISC.Disability		−0.167	−0.201*
DISC.Gender * DISC.Money		−0.150	−0.035
DISC.Gender * DISC.Other		0.180	0.224
DISC.Sexuality * DISC.Religion		−0.032	−0.027
DISC.Sexuality * DISC.Disability		−0.315***	−0.128
DISC.Sexuality * DISC.Money		−0.252**	−0.249***
DISC.Sexuality * DISC.Other		−0.253	−0.262
DISC.Religion * DISC.Disability		−0.141	−0.234*
DISC.Religion * DISC.Money		−0.149	−0.055
DISC.Religion * DISC.Other		0.227	0.218
DISC.Disability * DISC.Money		−0.160	−0.152
DISC.Disability * DISC.Other		−0.031	−0.064
DISC.Money * DISC.Other		0.003	−0.048
Akaike Inf. Crit.	68,491.370	68,400.760	66,763.230
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7.0.4: Coefficients and significance of negative binomial models predicting PHQ-4 using all discrimination variables (2022 data)

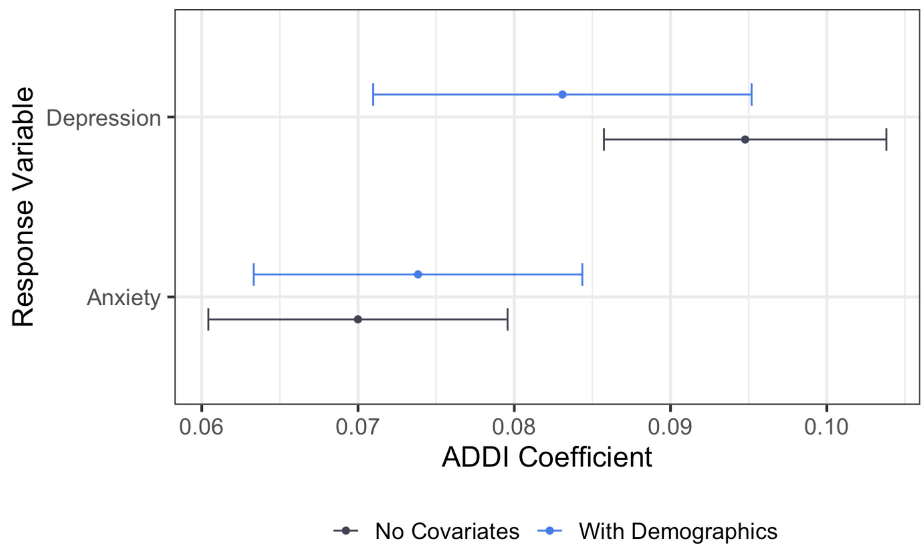


Figure 7.0.5: ADDI coefficients of predicting anxiety and depression subscales separately in a negative binomial model (2022 data)

	Negative Binomial	
Response	No Covariates	w/ Demographics
Anxiety	55431.93	52904.44
Depression	48950.84	47117.32

Table 7.0.5: AIC comparison of models using anxiety and depression as the response variable (2022 data)

Model	ADDI Coefficient	Cluster-adjusted Standard Error	Brant Test *p*-value
Without Covariates	0.1673***	0.0123	0.03
With Demographics	0.1707***	0.0138	0.11
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7.0.6: Ordinal regression results for predicting categorical PHQ-4 with ADDI Total (2022 data)

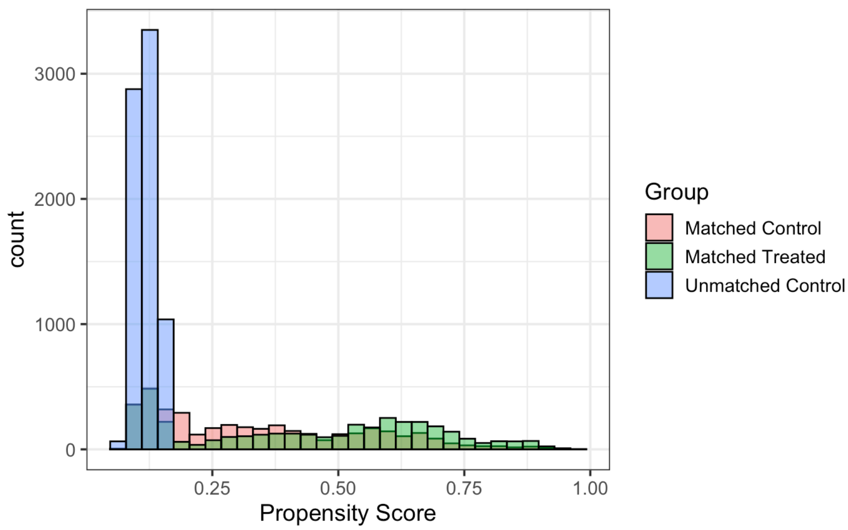
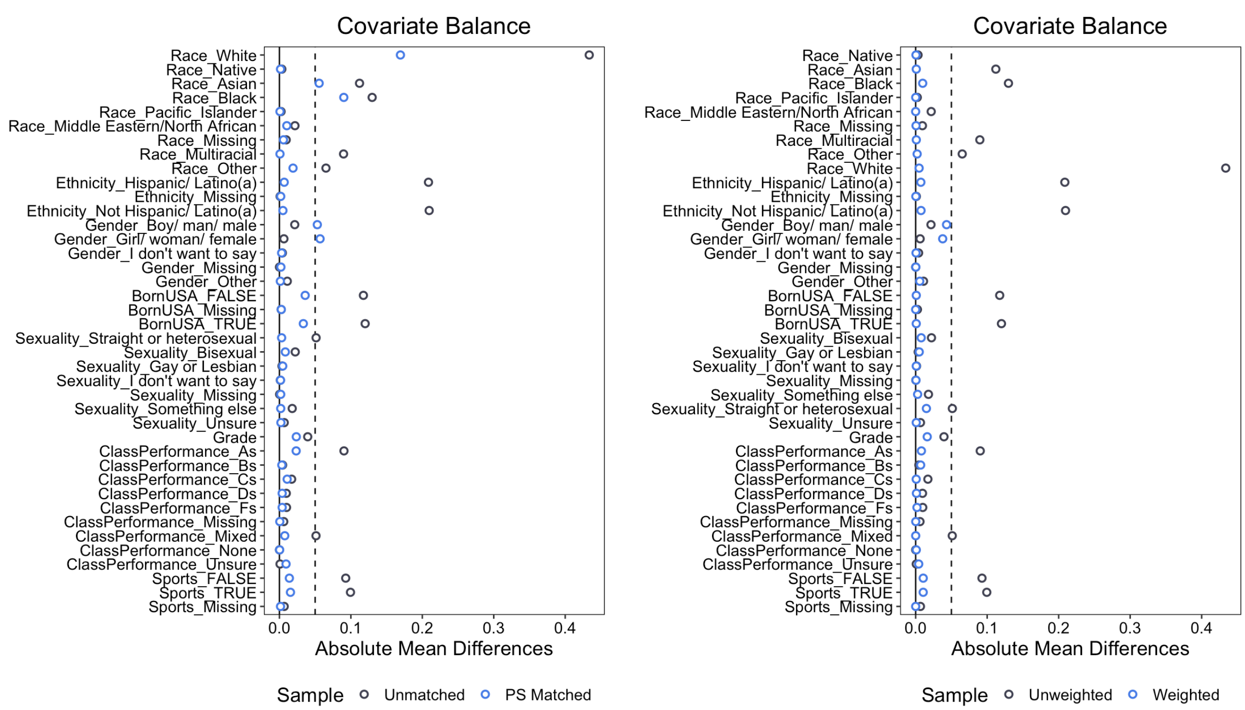


Figure 7.0.6: Distribution of propensity scores based on treatment status (ADDI Binary) and propensity matching status (2022 data)



(a) 1:1 Matching

(b) Inverse Probability Treatment Weighting

Figure 7.0.7: Standardized mean differences for unadjusted and propensity-score adjusted data (2022 data)

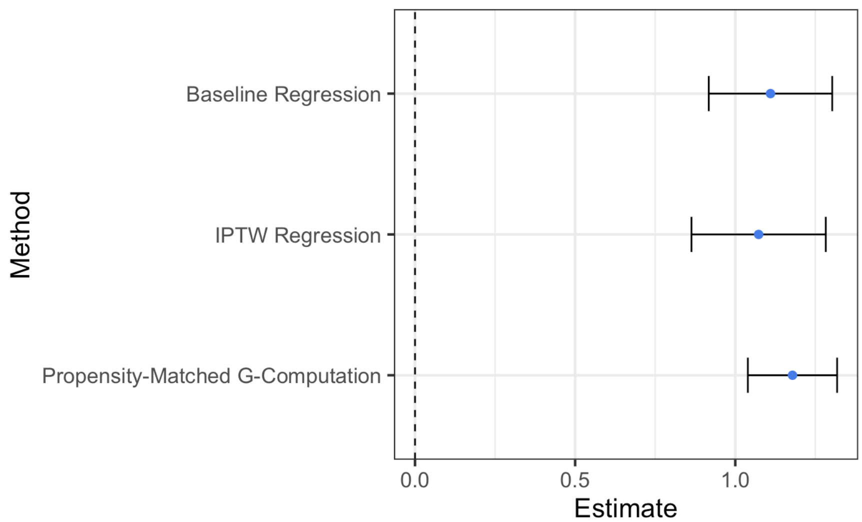


Figure 7.0.8: Propensity method estimates of the effect of ADDI Binary on PHQ-4 (2022)

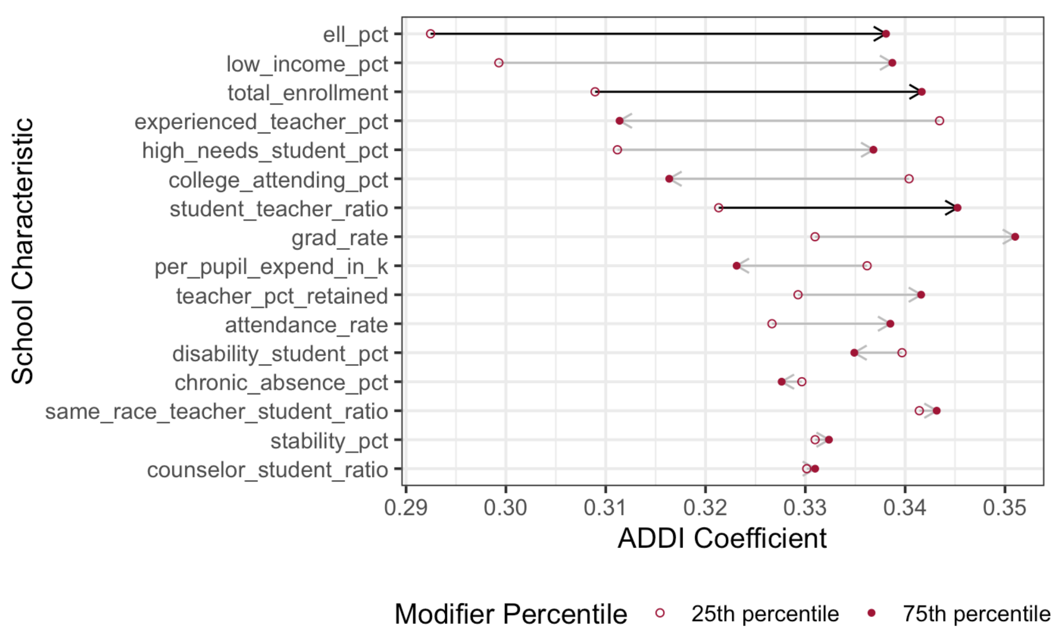


Figure 7.0.9: Differences in the estimated effect of ADDI on PHQ-4 between the 25th and 75th percentile of school characteristics (2022 data). Black arrows indicate variables that were significant effect modifiers in ANOVA testing.

	Dependent variable:	
	ADDI Binary	PHQ4 Total
	generalized linear mixed-effects	*linear mixed-effects*
ADDI.Total		0.294*** (0.022)
total_enrollment	0.0004 (0.0003)	−0.0001 (0.0004)
ell_pct	−0.032 (0.033)	−0.094* (0.054)
disability_student_pct	0.023 (0.045)	0.004 (0.074)
high_needs_student_pct	−0.066 (0.068)	0.063 (0.114)
low_income_pct	0.076 (0.063)	−0.008 (0.104)
grad_rate	−0.007 (0.023)	−0.061 (0.037)
college_attending_perc	−0.0001 (0.015)	0.040* (0.024)
attendance_rate	−0.062 (0.055)	0.119 (0.091)
chronic_absence_perc	−0.036** (0.016)	0.019 (0.028)
stability_pct	0.010 (0.032)	0.022 (0.051)
teacher_pct_retained	0.030* (0.016)	0.012 (0.025)
experienced_teacher_pct	−0.009 (0.012)	−0.016 (0.019)
per_pupil_expend_in_k	0.045 (0.039)	0.029 (0.064)
student_teacher_ratio	−0.008 (0.070)	0.035 (0.114)
counselor_student_ratio	25.891*** (7.767)	46.744 (84.846)
same_race_teacher_student_ratio	2.829*** (0.877)	−3.255*** (1.203)
Intraclass Correlation Coefficient	0.020	0.026
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 7.0.7: Coefficients for school-varying intercept models using school characteristics as predictors (2022 data)

	Stratum				
	(1)	(2)	(3)	(4)	(5)
total_enrollment	0.00001	−0.0001	0.0001*	0.00001	−0.00003
ell_pct	−0.018***	−0.002	−0.008	0.0004	0.003
disability_student_pct	−0.016**	−0.020**	−0.010	−0.021***	−0.018**
high_needs_student_pct	0.022**	0.016	−0.0002	0.017*	0.018*
low_income_pct	−0.008	−0.010	0.012	−0.009	−0.009
grad_rate	−0.002	0.003	0.007*	0.010**	0.007*
college_attending_pct	0.008***	0.004	0.004	0.001	0.003
attendance_rate	0.009	−0.013	−0.035**	−0.030***	−0.029**
chronic_absence_pct	0.002	0.001	−0.009**	−0.007**	−0.004
stability_pct	−0.010**	−0.016***	−0.001	−0.012**	−0.004
teacher_pct_retained	0.007***	0.010***	0.009***	0.009***	0.010***
experienced_teacher_pct	−0.009***	−0.005**	−0.007***	−0.002	−0.005***
per_pupil_expend_in_k	0.007	−0.003	−0.007	−0.007	−0.011*
student_teacher_ratio	0.005	−0.011	−0.025**	−0.023**	−0.019*
counselor_student_ratio	−7.170	−22.768**	13.581	−4.789	5.100
same_race_teacher_student_ratio	−3.484***	−2.769***	−2.807***	−2.639***	−2.831***
Constant	−0.138	2.477*	3.164**	3.357***	2.621**
Observations	3,163	2,386	2,789	2,712	2,793
Akaike Inf. Crit.	3,183.211	2,492.371	2,905.785	2,888.351	2,889.705
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 7.0.8: Model results for predicting racial discrimination (*ADDI Binary*) exposure using school characteristics by propensity score strata (2022 data)