

The Effect of Academic Rank Across Ethnicities and Races on Mental Health Outcomes
of Adolescents

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Abstract

Considering the United States is becoming increasingly diverse and mental disorders as well as academic achievement across these races and ethnicities are not evenly distributed, more research needs to be conducted with regards to both issues in order to understand the differences. In this paper, we will bring these two observations together by investigating whether overall academic rank or rank within one's race matters more for adolescent mental health outcomes. Using the data from the National Longitudinal Study of Adolescent to Adult Health, we will create a school-cohort fixed effect model to evaluate the overall relationship and the relationship within each racial and ethnic group, and will then compare the results.

Motivation and Introduction

According to an article in the journal *Health Affairs*, mental health disorders became the most expensive healthcare cost in the United States in 2013, totaling to \$201 billion (Roehrig, 2016). Taking a closer look, depression, as the most prevalent disability in people aged 15-44, was estimated to create an economic burden of \$210.5 billion in 2010 when including both direct and indirect cost. Approximately 45% of burden is due to direct medical expenditures, 5% to suicide-related expenses, and 50% to workplace costs, which combines costs from both

absenteeism and presenteeism (Greenberg et al., 2015). Despite such drastic economic costs, there is currently a lack of economists researching mental health.

Considering treatment for mental disorders like any other illness produces better outcomes when treated early, it becomes essential to gain a clearer understanding of mental health disorders in adolescents not only for the sake of their health but also to reduce economic costs across their lifetime. The World Health Organization regards adolescent years as a critical time to address mental health disorders. They estimate 50 percent of all mental health disorders appear before the age of 14 and 75 percent by mid-20s (“Adolescents and mental health”, n.d.).

Despite efforts of such organizations calling out for further mental health awareness and treatments, the prevalence of mental health disorders in adolescents has continued to increase in recent years. As reported in a study in the *Pediatrics* journal, the adolescent depression rate in the United States has increased from 8.7% in 2005 to 11.5% in 2014, creating a total increase of 32% (Mojtabai et al., 20).

One factor playing a role in the surge of adolescents with mental disorders is chronic stress. College admittance is becoming increasingly more competitive. In order to get into a renowned university, students are expected to have a high-class rank with near straight A's on top of an exceptional SAT scores and a plethora of extracurricular activities. While having more engaged and motivated students can be positive, it may also have negative effects on their mental health. In a survey by the American Psychology Association, millennials have repeatedly reported the highest level of stress compared to older generations. They had an average stress level of 5.7 out of 10, a slight increase from 5.6 in the previous year, while Generation X, Baby Boomers, and other older generations had a scores of 5.3, 3.9, and 3.3, respectively. Information on Generation Z, the generation after Millennials, was not recorded (“Stress in America: The

State of Our Nation,” 2017). Similarly, in another survey by the American Psychology Association, they found teens in 2014 had higher levels of stress than adults and 52% reported stress was impacting their mental health (Bethune, 2014). Another study analyzed the effects of stress on students’ mental health in top private secondary schools in the Northeast. Their study suggests that chronic stress is above average for this subset of the population, and the primary sources of stress were grades, homework, and preparation for college. In effect, about one in every four of the participants were classified as clinically depressed (Leonard et al., 2015). Thus, there is comprehensive evidence that increased academic pressure on the current generation is triggering poor mental health outcomes.

Within the context of different races and ethnicities in the United States, mental health disorders and academic achievement are not evenly distributed. The literature has well documented that minorities have higher rates of mental illness and are at a higher risk of obtaining such illnesses compared to their Caucasians. One study that also worked with the Add Health data compared CES-D scores across distinct races and ethnicities and their corresponding immigrant generation. They discovered third or greater generation blacks, first generation Asians, and all Hispanic generations were at greater-risk for depression than their White counterparts from any immigrant generation (Perreira et. al., 2005).

As for academic achievement, the gap between Blacks and Hispanics in comparison to Caucasians decreased substantially in the 1970s and 1980s, but these trends have not persisted. According to a study in 2015 by the Nation’s Report Card, the percentages of Asian, White, Hispanic, and Black students who had a proficient reading level were respectively 49, 46, 25, and 17. As for proficient math scores, the percentages were 47, 32, 12, and 7, respectively. The two results suggest Asian students performed the best academically in both reading and math,

followed by Whites, Hispanics, and Blacks (“NAEP - 2015 Mathematics & Reading Assessment”). These results can be further illustrated by the 2016 SAT scores, which range from 400 to 2400. Asian students performed best with a total score of 1665, followed by Caucasians with 1572, Hispanics with 1337, and African-Americans with 1270 (“Total Group Profile Report,” 2016). In addition, these trends are also mirrored by current high school completion, college enrollment, and college completion rates. There has been extensive research on some of the mechanisms that cause these groups to perform differently, which we will not examine in this paper.

In view of bringing together the increased academic pressure producing mental health issues and the variation in academic achievement and mental health status across races and ethnicities, we will explore the ramifications of academic rank on adolescent mental health across these subgroups in this paper.

Contribution

The main focus of this paper is to investigate the effect of academic rank within one’s race or ethnicity on these groups’ respective mental health outcomes. Most studies thus far have focused on the effects of poor mental health on academic achievement, but the reverse is seldom studied. These papers have found that poor mental health creates adverse effects on a student’s academic achievement (Shippee & Owens, 2011). This paper will contribute to the literature by exploring this reverse: the effect of academic achievement rank on adolescent mental health outcomes.

There have also been many studies on academic achievement differences and mental health outcomes across races and ethnicities. However, little research has been able to tie the two

results together. This paper contributes to the literature because no papers to our knowledge have explored if rank matters differently for students of different races and if within-race rank matters more than overall rank within the school on mental health outcomes.

The two papers will significantly contribute to this paper. First, the paper *What Are We Measuring? An Evaluation of the CES-D Across Race/Ethnicity and Immigration Generation* by Perreira et al. will serve as a model to measure CES-D across various races and ethnicities in this data. The other paper is *A Big Fish in a Small Pond: Ability Rank and Human Capital Investment* by Elsner and Isphording, which discusses the effect of cognitive ability rank within a school cohort on educational attainment. This paper will be used as guide for our measure of rank, fixed effects, and the statistical model.

Approach

We will measure academic rank by percentile GPA rank within an ethnicity in a school-cohort and mental health outcomes by the Center for Epidemiologic Studies Depression Scale, otherwise known as CES-D. We will also control for school-fixed effects. We hope to see whether or not rank within a race matters more than overall rank.

We predict that academic rank will have a non-linear effect on mental health. Precisely, we estimate that low-ranking and high-ranking individuals will have poor mental health outcomes in comparison to those in the middle. We anticipate that low-ability and high-ability students will have poor mental health outcomes due to feelings of incompetence, higher amount of stress, among other mechanisms. Therefore, if academic rank is on the x-axis and CES-D scores on the y-axis, the relationship will potentially resemble a U-shape, or equivalently a

quadratic equation. Due to these nonlinearities, we plan to use a polynomial regression to fit the data and will choose the degree of the polynomial that best fits the data.

Racial and Ethnicity Classifications

In this study, we will classify the adolescents into three racial groups and one ethnic group, creating a total of four groups, that are commonly used in the United States. The difference between race and ethnicity is that the first pertains to biology and the latter to culture. The racial groups are non-Hispanic White, non-Hispanic Black, non-Hispanic Asian; and the one ethnic group is Hispanic of any race. Hispanic is not a race because Hispanics can be part of any race since the term refers to those once under the Spanish Empire, including, Spain, most countries in Latin America, and the Philippines. Considering there is a large Filipino population in the data, we will not include the Philippines under Hispanic since the vast majority do not identify as Hispanic, and we will include them under the Asian population as Add Health does.

Data

For this study, we will be using the data from the National Longitudinal Study of Adolescent to Adult Health, otherwise known as Add Health, which is the largest and most comprehensive longitudinal survey of adolescents. The data was collected from a nationally representative sample of adolescents from grades 7 to 12, or equivalently ages 13 to 18, in 80 high schools and 52 middle schools across the United States and continued to track this cohort as they transitioned into adulthood. Add Health collected data on various topics, such as academic and education, physical and mental health, various types of relationships, sexual activity, substance abuse, among many other matters of interest.

The data was collected during the 1994-95 school year by first conducting an in-school questionnaire that was filled out by all students present during the time of the survey in the selected schools. To complement this, a nationally representative sample of these students was asked to partake in a series of in-home interview during the years 1995, 1996, 2001, 2002, and 2008. In spite of being representative, it should be noted certain groups of interest were oversampled. The first wave of in-home interviews was conducting during the same academic year as the in-school questionnaire and the second was held the year after. The last three were after each student had already transitioned into adulthood. Add Health selected the sample for the in-home interviews by randomly choosing approximately 17 males and 17 females in each grade from each school. To complement this, they also carried out in-home interviews for all enrolled students in 16 schools.

Altogether, Add Health collected data from approximately 90,000 students during the in-school questionnaire and 12,000 in the in-home interview. We will be using the data from the in-home interviews from Waves I and II. These two datasets roughly have the same sample except those who voluntarily chose not to participate and those who were in grade 12 during Wave I since these students had already graduated. In addition, Add Health still collected data on the students who were part of the genetic and adopted sample in grade 12 during Wave I.

The first wave had 6,504 participants. Demographically, the sample was distributed approximately 48% male, 52% female, 66% Caucasian, 25% African American, 4% Asian or Pacific Islander, 1% Native American, and 5% Other. In the second wave, 4,834 of the original parties continued to participate and the sample had the same sex ratio. As for racial composition, the sample was distributed 67% Caucasian, 23% African American, 4% Asian or Pacific Islander, 1% Native American, and 5% Other (Jacobson & Newman, 2016).

Problems with the Sample

Although the data is extremely comprehensive and well-planned, there are still aspects of the data that generate problems in this study, for instance, racial classification, under-sampling, and oversampling. There are also features of the sample that give rise to problems when measuring the explanatory variables, which we will touch upon in its respective section.

First, when asked to identify their race and ethnicity, the respondents were allowed to choose non-Hispanic “Other,” meaning the subject does not self-identify with Hispanic nor any of the races. Since no data is collected on their reasons for not identifying, the group becomes ambiguous and we will exclude from the sample. Additionally, Add Health accommodates those that are multiracial and allows students to choose more than one race, which may cause some unintended correlations. The last issue with regards to racial classification is the fact that Add Health categorizes Asians and Pacific Islanders into one group, and these two populations have significantly different educational outcomes and thus different depression scales. In context of this group, Add Health only asks if the respondents are Chinese, Filipino, Japanese, Asian India, Korean, Vietnamese, or other. Only 44 people responded with other, and we can therefore conclude the Pacific Islander population is relatively small and insignificant compared to their Asian counterparts.

As for sampling, the number of Native Americans interviewed is too low to be statistically significant, and we will therefore not include this group in our study. In contrast to the observation above, Add Health oversamples certain groups of interest, namely, Cubans (N = 450), Puerto Ricans (N = 437), Chinese (N = 338), Blacks with highly educated parents (N =

1,547), disabled students (N = 957), full siblings (N = 1,251), half siblings (N = 442), adopted adolescents (N = 560), and twins (N = 784).

The oversampling of students with Cuban, Puerto Rican, and Chinese heritage actually provides us with the necessary data to evaluate Hispanic and Asian students. However, when using the full population regression, the proportion of races in our sample will not be able to completely represent the United States racial composition, but we estimate this effect will be minimal on our results. Apart from the racial and ethnic groups oversampled, there is also a significant number of adolescents with Mexican, Nicaraguans, Japanese, South Koreans, Filipinos, and Vietnamese. The first two groups listed in addition to Cubans and Puerto Ricans will be the core sample for the Hispanic population and the last four along with Chinese will be the core sample for the Asian population.

Black adolescents with highly educated parents, specifically college educated parents, will create complications. There has been extensive research on the influence of family background on academic achievement, and there is a general consensus that parental educational achievement is the strongest factor for their offspring's academic success (Egalite, 2016). Consequently, the average GPA for black students in the sample is expected to be greater than the real values, which will cause both the overall regression across all groups as well as the regression specific to Black students to be skewed and our results to misrepresent the entire population and the subset. In order to counteract this, we may be required to decrease the amount of these students in our sample.

As for those with disabilities, students were asked if they had a physical condition with their limbs and if they have used a mechanical device for at least a year. Considering physical and mental health are closely related and affect one another, disabled students can potentially

create an issue within our study. However, Add Health has stated when their representatives followed up with the self-reported disabled students in the in-home interview, most of them were not actually disabled. We can therefore disregard the potential issues imposed by oversampling disabled students.

We do not expect any concerns with regards to the adopted sample. We do however expect there to be a small problem in the genetic sample. Data has shown that people with lower GPAs than their siblings are significantly more likely to inflate their self-reported grades, but will not take this into consideration for simplicity (Schwartz & Beaver, 2015).

Sample

We are still in the works of finalizing the complete sample. We will exclude the groups explicitly stated above in addition to those participants with missing responses for ethnicity or race and responses in their CES-D survey. We will also omit schools, school-cohorts, and racial or ethnic groups within school-cohorts that do not have a statistically significant amount of observations.

Outcome Variables

The outcome variables will be a measure of adolescents' mental wellbeing. This variable can be computed in this data through the Center for Epidemiologic Studies Depression Scale, otherwise known as CES-D, which is one of the most well-known tools to measure psychological distress.

In our data, the participants were provided with 19 questions from the CES-D under section ten called the "Feelings Scale" in the in-home interview. To each of statements,

respondents were asked to choose either 0 for never or rarely, 1 for sometimes, 2 for a lot of the time, 3 most of the time or all of the time, 6 if they refuse to answer, and 8 if they don't know for each question. We will exclude those from the sample that refused to answer (6) or didn't know (8) at least one of the questions.

Specifically, the 19 statements were: (1) "You were bothered by things that usually don't bother you.", (2) "You didn't feel like eating, your appetite was poor.", (3) "You felt that you could not shake off the blues, even with help from your family and your friends.", (4) "You felt that you were just as good as other people?", (5) "You had trouble keeping your mind on what you were doing.", (6) "You felt depressed.", (7) "You felt that you were too tired to do things.", (8) "You felt hopeful about the future.", (9) "You thought your life had been a failure.", (10) "You felt fearful.", (11) "You were happy.", (12) "You talked less than usual.", (13) "You felt lonely.", (14) "People were unfriendly to you.", (15) "You enjoyed life.", (16) "You felt sad.", (17) "You felt that people disliked you.", (18) "It was hard to get started doing things.", and (19) "You felt life was not worth living."

The CES-D statements are intended to gauge whether the subjects have experienced depressive symptoms in the past week, including, dysphoria or sadness, anhedonia or loss of interest, sleep, appetite, concentration, worthlessness or guilt, fatigue, movement and agitation, and suicidal ideation. In comparison with the original CES-D, two statements about restless sleep and crying spells were omitted and the last statement, "You felt life was not worth living.", was added to the list. There are questions in other sections of the in-home questionnaire that pertain to frequent crying and trouble falling asleep or staying asleep that we could utilize to make Add Health's version more similar to the original, but these questions have different response scales and time frames. More specifically, the questions have a range from 0 for never to 4 every day

and the time frame is within a year.

The CES-D depression scale can be calculated by summing the responses. Most questions are worded such that a response of 3, most of the time, is associated with a higher depression score. Only questions 8, 11, and 15 have been worded positively, and we will need to reverse the scale for these questions. In the normal test, respondents are asked 20 questions and the answers are then summed to determine a depression scale that ranges from 0 to 60. A score of 16 is the subthreshold for a person to be at risk for clinical depression, meaning a person with this score or under is not at risk. Considering Add Health asks 19 questions, our study will range from 0 to 57 and our threshold for depression will be 15.2, assuming proportionality. Scores are however recorded as whole numbers, and we should therefore round to the nearest whole number, 15.

Explanatory Variable

The explanatory variable for this paper will be a student's academic rank within their school's grade, or equivalently their cohort. GPA, grade point average, will be the determinant to calculate academic rank. In the public-use version of the Add Health data, we are not given information on the true GPA of the students for security reasons. The students are not asked to self-report their GPA and are instead asked four questions based on their most recent grading period. The time frame of these questions works for our study because we can estimate that relative rank in grades from the previous semester affect their current mental health.

Participants are asked their previous semester grades in English or language arts, mathematics, history or social studies, and science. The responses for these questions are 1 for A, 2 for B, 3 for C, 4 for D or low, 5 for "didn't take this subject", and 6 for "took the subject, but it

wasn't graded this way", 96 for refused, and 98 for "didn't know". We will exclude those from the dataset that do not fill out a response from one to four for all of four questions above.

Unfortunately, this style of self-reported GPAs creates many errors. According to a study on the differences between self-reported grades and official GPA that also uses the Add Health Data, students with higher GPAs and verbal IQ scores were significantly more likely to self-report correct or deflated grades, whereas students with lower GPAs and verbal IQ scores were more inclined to report higher grades. The mean score of self-reported GPA was 2.86 and the mean score of official transcript GPAs was 2.44, meaning the difference in self-reported scores is about one-letter grade greater than official transcript GPA (Schwartz & Beaver, 2015). Further, this form of self-reported GPA does not allow for differentiation in grades based on the rigor of the classes taken. Most high schools have Advanced Placement courses and honors courses count more towards GPA. For example, an A in a regular course is 4, in an honors course 5, and in an AP course 6. Although this does create a larger error term, many other studies have also used this self-reported GPA, for example, *Health and Behavior Risks of Adolescents with Mixed-Race Identity* by Udry et al. and the Family Structure Trajectory and Adolescent School Performance by Heard.

Transcripts that hold individuals' accurate GPAs are available through the restricted-use dataset from AHAA, Adolescent Health and Academic Achievement, which expands upon Add Health's data by collecting high school transcripts from Wave III sample members in order to have a more detailed measure of academic progress and school curriculum. Unfortunately, obtaining the restricted dataset is difficult, and not all transcripts were collected, making the sample size much smaller.

Moreover, many studies have used GPA as a proxy for cognitive skills, and we may be able to turn this around and measure relative academic rank by cognitive skills. Cognitive skills are measured in this data by using the Add Health Picture Vocabulary Test, which is an abridged version of the Peabody Picture Vocabulary Test. The test measures the participants receptive vocabulary. Although students can most likely broadly identify their relatively cognitive ability rank in comparison to their peers, most will not know their precise location, which may cause complications. As for now, we will continue to use the self-reported GPA as a measure.

In order to compute relative GPA rank, we will compute the self-reported GPA by averaging out the responses to the four questions. Next, we will organize student GPAs within the same school cohort in ascending order to compute ordinal academic rank. Lastly, in interest of comparing GPA rank across school cohorts that vary in size, we transform the ranks into percentiles, meaning the ranks will range from zero to one. The adolescent with the highest rank in a school cohort will have one as his or her percentile rank and the lowest-ranking student will have a score of zero. This process will satisfy the process for the overall regression, but we will need to repeat these steps after separating students into their racial or ethnic groups.

Unfortunately, there is another obstacle with the sample. Only about 22% of each school cohort is actually surveyed for the in-home interviews, meaning the sample rank will be different from the true value. According to Elsner and Isphording, we can assume this error averages to zero since some students receive a higher rank while others receive a lower one. Given that most students were randomly chosen for in-home interviews, we can assume the sample percentile ranks are still an appropriate proxy for the true value. Furthermore, they calculated the average deviation of sample rank from the true rank by using the data from the schools where all students received an in-home interview. They applied a bootstrap procedure to compare the difference in

rank and found that the standard deviation was 0.017, which they concluded was relatively small. This statistic means a student will on average will be misplaced 1.7 absolute positions away from their true rank. Although this standard deviation can provide some insight, it does not directly explain the variation in the academic rank used in this paper because they used cognitive abilities measured by the Add Health Picture Vocabulary Test instead of academic rank measured by GPA (Elsner & Isphording, 2016).

Control Variables

We will once again be using the paper “A Big Fish in a Small Pond” by Elsner and Isphording as a model but this time for school-by-cohort fixed effects. They identify a casual effect by using idiosyncratic variation in cohort composition. According to this paper, a model with school-by-cohort fixed effects “absorbs all mean differences between school cohorts, thus alleviating any of the endogeneity concerns.” We will therefore compare all students across all school cohorts as all mean differences between cohorts are eliminated.

Considering data was collected from grades 7 to 12, each school will have data on several cohorts. Ultimately, this enables us to control for school and cohort variation. Schools differ based on their affluence of the school’s location, urban vs. rural, gender makeup, teacher quality, among many other factors that will affect student’s mental health. Correspondingly, cohorts within the same school vary from year to year because of differences in cohort intelligence, size, etc. In context of our paper, this means students who have the same GPA and are the same race or ethnicity in a school will have different ranks depending on the distribution, particularly the mean and variance, of their cohort’s ability.

Empirical Model

$$Y_{isc} = \beta_0 + \beta_1 R_{isc}^E + \beta_2 (R_{isc}^C)^2 + g(a_{isc}) + \delta_s + \varepsilon_{it}$$

We will use this model for each racial or ethnic group as well as the sample as a whole. In this equation, Y is the outcome variable, mental health outcome for the student i in school s in cohort c that is part of ethnic or racial background E. β_1 is the explanatory variable and our coefficient of interest, which is the measure of the correlation between percentile rank within one's race in their school cohort and his or her mental health outcome. The fourth term on the right-hand side is a control for the student's ability. Finally, δ is school fixed-effects and ϵ is the error term that includes all other unobserved factors that affect mental health outcomes. We will later include a vector of dummy variables for age, gender, socioeconomic status, and other factors of interest in this model. We also assume all coefficients are strictly exogenous of the error term. This model is subject to change as we have not finalized it.

Potential Issues with the Model

As seen in the literature review, many studies have already researched the effects of mental health issues on GPA, which contradicts this paper. In order to affirm our model does not have an issue of reverse causality, we will utilize the longitudinal aspect of the data. We can do so by controlling for one's prior CES-D score and the prior effect of academic rank on the depression taken in 1994 and running the regression on the data from 1995.

References

- Adolescents and mental health. (n.d.). Retrieved November 13, 2017, from http://www.who.int/maternal_child_adolescent/topics/adolescence/mental_health/en/
- Bethune, S. (2014, April). Teen stress rivals that of adults. Retrieved November 13, 2017, from <http://www.apa.org/monitor/2014/04/teen-stress.aspx>
- Elsner, B., & Isphording, I. E. (2016). A Big Fish in a Small Pond: Ability Rank and Human Capital Investment. *Journal of Labor Economics, 35*(3), 787–828.
<https://doi.org/10.1086/690714>
- Galite, A. J. (2016). How Family Background Influences Student Achievement: Can Schools Narrow the Gap? *Education Next, 16*(2), 70.
- Greenberg, P. E., Greenberg, P., Fournier, A., Sisitsky, T., & Pike, C. (2015). The Economic Burden of Adults With Major Depressive Disorder in the United States (2005 and 2010). *The Journal of Clinical Psychiatry, 76*(2), 155–162.
<https://doi.org/10.4088/JCP.14m09298>
- Jacobson, N. C., & Newman, M. G. (2016). Perceptions of close and group relationships mediate the relationship between anxiety and depression over a decade later. *Depression and Anxiety, 33*(1), 66–74. <http://doi.org/10.1002/da.22402>
- Leonard, N. R., Gwadz, M. V., Ritchie, A., Linick, J. L., Cleland, C. M., Elliott, L., & Grethel, M. (2015). A multi-method exploratory study of stress, coping, and substance use among high school youth in private schools. *Frontiers in Psychology, 6*, 1028.
<https://doi.org/10.3389/fpsyg.2015.01028>

- Mau, W. (1997). *Parental Influences on the High School Students' Academic Achievement: A Comparison of Asian Immigrants, Asian Americans, and White Americans* (Vol. 34).
[https://doi.org/10.1002/\(SICI\)1520-6807\(199707\)34:3<267::AID-PITS9>3.0.CO;2-L](https://doi.org/10.1002/(SICI)1520-6807(199707)34:3<267::AID-PITS9>3.0.CO;2-L)
- McLeod, J. D., Uemura, R., & Rohrman, S. (2012). Adolescent Mental Health, Behavior Problems, and Academic Achievement. *Journal of Health and Social Behavior*, 53(4), 482–497. <https://doi.org/10.1177/0022146512462888>
- Mojtabai, R., Ramin Mojtabai, Mark Olfson, & Beth Han. (2016). National Trends in the Prevalence and Treatment of Depression in Adolescents and Young Adults. *Pediatrics (Evanston)*, 138(6), 1.
- NAEP - 2015 Mathematics & Reading Assessments (2015). Retrieved November 13, 2017, from https://www.nationsreportcard.gov/reading_math_g12_2015/
- Perreira, K., Deeb-Sossa, N., Harris, K., & Bollen, K. (2005). What Are We Measuring? An Evaluation of the CES-D across Race/Ethnicity and Immigrant Generation. *Social Forces*, 83(4), 1567-1601. Retrieved from <http://www.jstor.org/stable/3598404>
- Roehrig, C. (2016). Mental disorders top the list of the most costly conditions in the united states: \$201 billion. *Health Affairs*, 35(6), 1130-1135.
[doi:http://dx.doi.org.libproxy.lib.unc.edu/10.1377/hlthaff.2015.1659](http://dx.doi.org.libproxy.lib.unc.edu/10.1377/hlthaff.2015.1659)
- Schwartz, J. A., & Beaver, K. M. (2015). Making (Up) the Grade? Estimating the Genetic and Environmental Influences of Discrepancies Between Self-reported Grades and Official GPA Scores. *Journal of Youth and Adolescence*, 44(5), 1125–1138.
<https://doi.org/10.1007/s10964-014-0185-9>

Shippee, N. D., & Owens, T. J. (2011). GPA, Depression, and Drinking: A Longitudinal Comparison of High School Boys and Girls. *Sociological Perspectives*, 54(3), 351–376.

<https://doi.org/10.1525/sop.2011.54.3.351>

Stress in America: The State of Our Nation . (2017, November 1). Retrieved November 13, 2017, from <http://www.apa.org/news/press/releases/stress/index.aspx>

Total Group Profile Report. (n.d.). Retrieved November 11, 2017, from <https://reports.collegeboard.org/pdf/total-group-2016.pdf>