

# The Effect of Peers' Genetic Predisposition to Depression on Own Mental Health

Yeongmi Jeong  
University of Georgia

October 27, 2022

## Abstract

This paper studies how peers' genetic predisposition to depression affects own mental health during adolescence and early adulthood using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health). I exploit variation within schools and across grades in same-gender grademates' average polygenic score—a linear index of genetic variants—for major depressive disorder (the MDD score). An increase in peers' genetic risk for depression has immediate negative impacts on own mental health. A one standard deviation increase in same-gender grademates' average MDD score significantly increases the probability of being depressed by 2.3 and 3 percentage points for adolescent girls (an 8.7% increase) and boys (a 20% increase), respectively. The effects persist into adulthood for females, but not males. I explore several potential mechanisms underlying the effects and find that an increase in peers' genetic risk for depression in adolescence worsens friendship, increases substance use, and leads to lower socioeconomic status. These effects are stronger for females than males. Overall, the results suggest there are important social-genetic effects in the context of mental health.

# 1 Introduction

Depression is one of the most common mental disorders, affecting 17% of adolescents and 8% of adults in the U.S. (NIMH, 2022). Adolescents with depression are about three times more likely to be depressed in adulthood compared to non-depressed adolescents (Johnson et al. 2018). Understanding the determinants of adolescent depression and the role of the adolescent period in shaping later-life mental health is key for informing policy interventions and treatments and curbing the sharp rise in both adolescent and adult depression observed over the last several decades. Motivated by a large body of evidence that suggests peer influence peaks during adolescence, I explore how adolescent peers’ underlying risk for depression impacts own mental health.

Specifically, I examine whether peers’ genetic predisposition to depression affects one’s own mental health in the short- and long-run. Peers’ genetic endowments for depression may influence own mental health via peers’ depression as well as peers’ behaviors (e.g., substance use, interpersonal conflict). I use data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), which follows a nationally representative sample of US adolescents starting in the 1994-95 school year. The genetic data in Add Health include the polygenic risk score for major depressive disorder (hereafter, MDD score), a composite measure of genetic markers that are correlated with MDD. A higher MDD score means a higher genetic risk for depression. I define peers as same-gender grademates and exploit variation in peers’ average MDD score within schools and across grades while controlling for own genetic risk for depression.

There are three well-known challenges in identifying the causal effects of peers—the reflection problem, endogenous peer group formation, and common environments. The reflection problem arises when estimating own behavior as a function of average group behaviors because it is impossible to disentangle the effects of average group behaviors (e.g., average peer depression) and average group characteristics (e.g., peers’ average parental income) on individual behavior (e.g., own depression) since they move together in a linear-in-means model (Manski 1993). This is not a concern in my case since genes are not affected by others’ behaviors or characteristics. Concerns about endogenous peer group formation arise because individuals tend to befriend others who have similar observed and unobserved traits. To address this issue, I rely on cohort-to-cohort variation in the average MDD score within a school (Hoxby 2000, Hanushek et al. 2003, Angrist and Lang 2004, Lavy and Schlosser 2011). While parents might select a school for their children based on observed characteristics, the assignment into each grade within a school is determined by age, making the formation of grademates as good as random. Another challenge arises from the fact that peers share common environments, which may result in similar behaviors and outcomes. While school-grade correlated effects cannot be completely ruled out, I control for school and

grade fixed effects and include numerous school-grade level controls to alleviate these concerns.

I find that having same-gender grademates with higher genetic risk for depression during adolescence immediately deteriorates own mental health. A one standard deviation increase in peers' average MDD score significantly increases the likelihood of being depressed by 2.3 and 3 percentage points for adolescent girls and boys, respectively. These effects translate to 8.7% and 20% increases in depression relative to the sample means for female and males, respectively. The peer effects persist into adulthood, but only for females. A one standard deviation increase in peers' average MDD score during adolescence leads to a statistically significant 2.9 percentage point increase in the probability that a female is depressed in adulthood, a 14% increase. These findings suggest that depression in adolescence and adulthood is influenced not only by one's own genetic risk for depression, but also by the genes of those around us. In other words, there are important social-genetic effects in the context of mental health.

The results are robust to alternative measures of depression and specifications, and I provide various pieces of evidence in support of the main identifying assumption that within-school across-grade variation in peers' genetic predisposition to MDD is as good as random. I also explore non-linear effects of peers' genetic predisposition to depression. Both in the short- and long-run, having peer groups with relatively high average MDD scores increases the likelihood of experiencing depression for females, but not males.

Next, I explore mechanisms that could drive the link between peers' genes and own depression, including friendship, substance use, educational attainment, and labor market outcomes. Friendship is a natural mechanism to consider since peers with higher underlying risk for depression may reduce the quantity and quality of social ties. I find that having peers with high genetic risk for depression worsens friendship and social connectedness both in the short- and long-run. For both adolescent girls and boys, an increase in same-gender grademates' average MDD score decreases the probability of spending time with friends. The results also indicate that being exposed to peers with high genetic risk for depression during adolescence reduces the frequency of females hanging out or communicating with friends in adulthood, the number of high school friends females still have as adults, and the number of close friends for both genders in adulthood. Thus, weaker social ties may be an important channel that explains the baseline effects, especially for females.

Substance abuse is often associated with depression, and may be another channel linking peer genetic risk for depression and own depression. I find evidence that having peers with high genetic risk for depression increases substance use, particularly for females. An increase in same-gender grademates' average MDD score increases the frequency of female binge drinking both in adolescence and adulthood, and also generates a slight increase in marijuana use. There is little to no impact on male

substance use. Finally, I study effects on socioeconomic outcomes, including college attendance, employment, and labor income. Males who had same-gender grademates with higher genetic risk for depression during adolescence are less likely to attend college, while females are less likely to be employed. The findings indicate that substance abuse and lower socioeconomic status may be additional underlying channels that explain the persistence of the social-genetic effects into adulthood.

This paper contributes to the literature in several ways. First, I add to a growing literature studying peer effects on depression. While a significant correlation between peer and own mental health is well documented in the psychology and medical literatures, only a handful of studies explore causal peer effects on mental health (Eisenberg et al. 2013, Zhang 2019, Giulietti et al. 2022).<sup>1</sup> Eisenberg et al. (2013) and Zhang (2019) find no significant short-term effects of peers' mental health on own mental health using variation generated from random assignment of college roommates in the US and random assignment of junior secondary school students to classrooms in China, respectively. Different than Eisenberg et al. (2013) and Zhang (2019), I focus on the role of adolescent peers in the US context. Most similar to my work is Giulietti et al. (2022), which examines the long-term effects of peers' depression on own depression using Add Health. They find that an increase in the share of same-gender grademates in adolescence who are depressed significantly increases females' depression incidence in adulthood. My analysis differs from that of Giulietti et al. (2022) in several ways. First, because I focus on peers' genetic risk for depression, I can identify the contemporaneous effects of adolescent peers on own mental health, whereas Giulietti et al. (2022) cannot identify such effects due to the reflection problem. Second, I explore a wider range of potential mechanisms, including friendship and socialization and substance use. My results complement those of Giulietti et al. (2022) and suggest that social-genetic effects may be an important factor underlying their findings.

This work also contributes to a growing literature on social-genetic effects. The importance of genetics in mental health has been well-recognized (Abkevich et al. 2003, Greene and Vostanis 2007, NIMH 2020), but little is known about the indirect effects of the genetic makeup of those around us (i.e., social-genetic effects) (Baud et al. 2017, Domingue and Belsky 2017, Sotoudeh et al. 2019, Cawley et al. 2019). Most studies on social-genetic effects focus on genetically-related groups such as families and relatives.<sup>2</sup> Recently, researchers have examined indirect genetic effects using genetically-unrelated groups such as friends and classmates (Domingue and Belsky 2017). For instance, Sotoudeh et al. (2019) find a significant causal effect of peers' genetic risk for smoking

---

<sup>1</sup>See De Silva et al. (2005), McPherson et al. (2014), and Ehsan et al. (2019) for a systematic review of the relationship between social capital and mental health, and see Santini et al. (2015) for a literature review of the association between social relationships and depression. There is also a growing literature on social contagion of mental health (e.g., see Bearman and Moody 2004, Fowler and Christakis 2008, Rosenquist et al. 2011, Dishion and Tipsord 2011, and Schwartz-Mette and Smith 2018).

<sup>2</sup>For example, see Kong et al. (2018) and Cawley et al. (2019).

on own smoking behavior in adolescence. Brunello et al. (2020) explore the short- and long-term effects of peers’ genetic risk for body mass index (BMI) on own BMI. They find significant short-term peer effects on BMI for females, with no effects for males. My analysis contributes to this small but growing literature on genomic effects beyond the family. The results imply that there are significant social-genetic effects in the context of mental health, which are stronger among females, consistent with the findings in Brunello et al. (2020).

The remainder of this paper is organized as follows. Section 2 includes background information on polygenic scores. Section 3 describes the data, sample construction procedure, mental health outcomes, and descriptive statistics. In Section 4, I discuss the empirical strategy and identifying assumptions. Section 5 reports baseline results, and in Section 6, I explore and discuss possible mechanisms underlying the baseline effects. Section 7 discusses robustness of the baseline results. I offer some concluding thoughts in Section 8.

## 2 Background on Polygenic Scores

As a measure of genetic risk for depression, I use a polygenic score (PGS). A PGS is a linear index of genetic markers that are linked to a particular observable trait or outcome. The calculation of a PGS is based on the results from genome-wide association studies (GWAS), where geneticists run millions of separate linear regressions of the outcome or trait of interest on genetic variants, called single nucleotide polymorphisms (SNPs), conditioning on a set of controls. The PGS is calculated as a weighted sum of the estimated coefficients on each SNP:

$$PGS_i = \sum_{j=1}^K \beta_j SNP_{ij} \quad (1)$$

where  $SNP_{ij}$  is the genotype for individual  $i$  at SNP  $j$ , and  $\beta_j$  is the effect size for SNP  $j$  estimated in the GWAS.<sup>3,4</sup> A higher PGS means that an individual possesses more of the genetic variants associated with that trait or outcome. For example, a higher depression PGS indicates that the individual has a higher genetic risk for depression.

I focus on the PGS related to major depressive disorder (hereafter, the MDD score). Major depressive disorder (MDD), also known as clinical depression, is a common mental disorder characterized by negative feelings such as sadness, emptiness, and hopelessness that can interfere with one’s daily activities. The MDD score in the National Longitudinal Study of Adolescent

---

<sup>3</sup>More concretely,  $SNP_{ij}$  is the number of instances of the reference allele (zero, one, or two) at SNP  $j$ .

<sup>4</sup>See Benjamin et al. (2011) and Beauchamp et al. (2011) for a detailed discussion of the human genome and Barth et al. (2020) and Papageorge and Thom (2020) for a detailed discussion of PGSs. See Braudt and Harris (2020) for details on PGS construction in the Add Health.

to Adult Health (Add Health) is based on the GWAS by Howard et al. (2019), which identified 102 independent SNPs associated with MDD using a discovery sample of 807,553 individuals of European ancestry. Those 102 genetic markers accounted for 8.9% of the variation in MDD in the discovery sample.<sup>5</sup> In out-of-sample prediction exercises reported in Howard et al. (2019), the MDD score explained 1-3% of the variation in depression.<sup>6</sup> In Section 3.3, I report the association between the MDD score and depression in the analysis sample.

### 3 Data

The Add Health study follows a nationally representative sample of individuals in the U.S. who were in grades 7-12 during the 1994-95 academic year. Respondents were drawn from a sample of 80 high schools and 52 middle schools stratified according to region, urbanicity, school size, school type (public, private, parochial), ethnic composition, and size. Wave I data was collected in 1994-1995 when respondents were aged 12-20 and contains an in-school questionnaire completed by over 90,000 students who were present at school on the interview day and an in-home questionnaire completed by 20,745 adolescents. The in-home survey respondents from Wave I were followed for four subsequent waves in 1996 (Wave II) when they were aged 13-21, in 2001-02 (Wave III) when they were aged 18-27, in 2008-09 (Wave IV) when they were aged 24-33, and in 2016-18 (Wave V) when they were aged 33-44. The in-home survey includes detailed information on individual characteristics, physical and mental health, parents, family, and school. I use data from the in-home surveys primarily from Waves I and IVs.<sup>7</sup> Waves I is used to examine the short-term effects during the adolescent period, and Wave IV is used to explore the long-term effects in adulthood.

The Add Health collected genetic information from Wave IV in-home respondents who agreed to provide a saliva sample.<sup>8</sup> Among the consenting participants, approximately 12,200 respondents agreed to archive their genetic information for long-term use. After quality control procedures for genotyping, 9,974 individuals were eventually genotyped. The Add Health constructed and released a set of PGSs for various diseases and behavioral outcomes. I use the polygenic risk score for major depressive disorder (the MDD score), a composite measure of genetic markers that are correlated with MDD, from the second release of Add Health PGS data. The PGSs in the Add

---

<sup>5</sup>In Howard et al. (2019), MDD cases are defined as those who were ever diagnosed with MDD or those with “broad depression” based on self-reported help-seeking behaviors for problems related with nerves, anxiety, tension, or depression.

<sup>6</sup>Add Health data were not included in the GWAS discovery sample, and therefore not used in the estimation of the  $\beta_j$  coefficients.

<sup>7</sup>The in-school survey contains information on school context, peer networks, and school activities. It was conducted only in Wave I.

<sup>8</sup>Approximately 96% of Wave IV respondents agreed to provide their saliva sample (Braudt and Harris 2020).

Health are standardized to have a mean of zero and a standard deviation of one within ancestry groups to control for between-group population stratification (Braudt and Harris 2020).<sup>9,10</sup> A higher MDD score means that the individual has a higher genetic risk for MDD.

### 3.1 Sample Construction

I construct the analysis sample as follows. First, I select Wave I in-home respondents with non-missing information on school, grade, and race. Second, I restrict the sample to individuals with valid genetic data. Third, I exclude individuals who attended grades with fewer than 10 genotyped same-gender grademates to ensure that there is enough variation in peers’ average polygenic score. Then, I use this sample to construct the average PGS for same-gender grademates in a given school-grade. Finally, I consider Wave I in-home respondents with non-missing information on depression, demographics, family and parental characteristics, and sample weights.<sup>11,12</sup> After the above procedures, 2,335 females and 1,682 males from 91 schools are left for analysis. The average number of same-gender grademates in one’s peer group is 15.8 for females and 17.2 for males.

### 3.2 Mental Health Outcomes

The Add Health in-home survey includes rich information on individuals’ mental health. The main outcome I focus on is a binary depression variable based on the Center for Epidemiologic Studies Depression Scale (CES-D scale). The CES-D scale is based on self-reported symptoms of depression and psychological distress, and is widely used in the economics and medical literatures. Waves I, II, and IV of the Add Health include the 10-item version of the CES-D score (hereafter, the CES-D-10 score).<sup>13,14</sup> Several studies have found that the CES-D-10 score is a good screening tool for depression in the adolescent and adult populations (Radloff 1991, Andresen et al. 1994, Irwin et al. 1999, Bradley et al. 2010). The score ranges from 0 to 30, with higher scores representing more depressed

---

<sup>9</sup>Population stratification refers to differences in genetic variation arising from geographical separation. Geographic isolation leads to mating within the region which, in turn, results in high correlation between genetic variation and geography (Conley and Fletcher 2017, Hellwege et al. 2017, Braudt and Harris 2020).

<sup>10</sup>There are four genetic ancestry groups in the Add Health: (1) European ancestry, (2) African ancestry, (3) Hispanic ancestry, and (4) East Asian ancestry (Braudt and Harris 2020). There is concern about using GWAS results to calculate PGSs for individuals from different ancestry groups, as most discovery samples used in GWAS only include those of European ancestry (Martin et al. 2017, 2019, Ware et al. 2017). To address this concern, I normalize the PGSs within each ethnic group and conduct sensitivity analysis separately for each ethnic group following Brunello et al. (2020).

<sup>11</sup>To avoid losing information when constructing same-gender grademates’ average PGS, I drop individuals with missing values on depression, demographics, family and parental characteristics, and sample weights at the end of sample construction.

<sup>12</sup>Variables included as controls are listed in Section 4.

<sup>13</sup>Appendix Table A1 contains the 10 items used to construct CES-D-10 score.

<sup>14</sup>The Wave I in-home survey includes items that also allow me to construct the CES-D-19 score. I conduct a robustness check using the CES-D-19 score as an outcome in column (1) of Table A5.

mood. Andresen et al. (1994) recommends cutoffs of 8 and 10 for identifying individuals at risk of depression. Following Suglia et al. (2016) and Giulietti et al. (2022), I take a conservative approach and construct an indicator for experiencing depression that has a value of one if the respondent’s CES-D-10 score is greater than or equal to 11, and zero otherwise.<sup>15</sup> Appendix Figure A1 shows histograms of the CES-D-10 score in Waves I and IV by gender. The figures indicate that females’ CES-D-10 score distribution has more mass above the threshold of 11 in both Waves I and IV.

I also consider other mental health outcomes, including suicidal ideation and suicide attempts. Information on suicide risk is available in Waves I, II, IV, and V. I create an indicator for suicidal ideation that has a value of one if the respondent has ever seriously considered dying by suicide during the past 12 months, and zero otherwise. Similarly, I construct a suicide attempt indicator that takes on a value of one if the individual has ever actually attempted suicide during the past 12 months. The next two mental health measures are available only in Waves III, IV, and V. I create an indicator based on whether respondents reported ever having been diagnosed with depression by a doctor, nurse, or other health care provider. I also construct an indicator that takes on a value of one if the respondent has used any type of antidepressant in the past four weeks and zero otherwise.

### 3.3 Descriptives

Table 1 reports summary statistics separately for females and males. In the main analysis, I focus on Wave I for short-term effects and Wave IV for long-term effects.<sup>16</sup> Average ages in Waves I and IV are 16 and 28 regardless of gender, respectively. In both the female and male samples, over 60% of individuals are white. In both samples, over 70% of students’ mothers had at least a high school degree, and more than 30% of them had a blue-collar job in Wave I. The number of siblings and household income were also similar across gender. The proportion of individuals whose father was not present in the household was higher for the female than male sample, but overall, family and parental characteristics in Wave I are similar across the two samples. Generally, depression, suicidal ideation, suicide attempts, depression diagnosis, and antidepressant use are more prevalent among females than males in both waves. This is consistent with clinical findings.

The analysis sample only includes respondents who agreed to provide their genetic data. In Appendix Table A2, I present summary statistics for the non-genotyped sample for comparison.<sup>17</sup>

---

<sup>15</sup>In Section 7.1, I present results using different cutoffs.

<sup>16</sup>The attrition from Waves I to IV in my analysis sample is minimal since the genetic data is collected for the Wave IV respondents. To be included in the analysis sample (even for Wave I outcomes) one must appear in Wave IV. I discuss potential attrition bias from Waves I to IV in Section 7.4.

<sup>17</sup>There are four types of non-genotyped individuals: those who appeared in Wave IV and refused to provide a saliva sample; those who appeared in Wave IV and provided a saliva sample, but did not agree to archive it for long-term use; those who appeared in Wave IV, provided a saliva sample, and agreed to long-term archiving of the saliva sample, but did not pass quality control; and those who did not appear in Wave IV. Descriptive



In general, there are more white and fewer Hispanic individuals in my analysis sample. Moreover, females in the genotyped sample exhibit slightly worse mental health than females in the non-genotyped sample, but in most cases the differences are not statistically significant.<sup>18</sup>

The individual MDD score is normalized to have a mean of zero and a standard deviation of one by race and gender. Figure 1 displays the distribution of the MDD score in the analysis sample by gender. Both distributions look approximately normal. In the analysis sample, the MDD score explains approximately 0.5% and 0.1% of the total variation in the CES-D-10 score of adult females and males, respectively, and approximately 0.4% and 0.6% of the total variation in diagnosis of depression for adult females and males, respectively.<sup>19</sup>

Same-gender grademates' average MDD score is also normalized to have a mean of zero and a standard deviation of one for each gender. Figure 2 shows the distribution of same-gender grademates' average MDD score in the analysis sample by gender. Before the normalization, its standard deviation is one third of the standard deviation of the individual MDD score for both females and males. When interpreting the estimated coefficients, it is important to keep in mind that there is more variation in individual MDD scores than peers' average MDD score.

## 4 Empirical Strategy

I estimate the following baseline specification via ordinary least squares (OLS) regression:

$$Y_{isgw} = \beta_0 + \beta_1 \overline{PGS}_{-isgI} + \beta_2 PGS_{isg} + \alpha_0 X_{isgI} + \alpha_1 G_{sgI} + \rho_s + \delta_g + \varepsilon_{isgw}, \quad (2)$$

where  $Y_{isgw}$  is the measure of mental health of individual  $i$  at school  $s$  and grade  $g$  in wave  $w$ ,  $\overline{PGS}_{-isgI}$  is the average depression PGS of same-gender grademates, excluding individual  $i$ , attending the same grade  $g$  and school  $s$  of individual  $i$  in Wave I,  $PGS_{isg}$  is the depression PGS of individual  $i$ , and  $X_{isgI}$  is a set of individual and family characteristics measured in Wave I.  $G_{sgI}$  is a set of school-grade specific characteristics measured in Wave I.  $\rho_s$  and  $\delta_g$  are school and grade fixed effects, respectively. Standard errors are clustered at the school level.

Specifically,  $X_{isgI}$  includes a set of individual and family characteristics as well as the first 10 principal components of the full SNP matrix. The individual characteristics are age in months dummies, race dummies, a Hispanic origin dummy, and dummies for the number of siblings the respondent has.

---

statistics for the first three types are included in Appendix Table A2.

<sup>18</sup> $p$ -values from a test of equality of means across genotyped and non-genotyped individuals are presented in the last two columns of Appendix Table A2 separately for females and males.

<sup>19</sup>The prediction results are presented in Appendix Tables A3. The MDD score explains approximately 0.3% of the total variation in the binary depression variable (i.e., CES-D-10 score  $\geq 11$ ) of adult females, but is not predictive of males.

The family characteristics include household income, mother’s education dummies, mother’s occupation dummies, and an indicator for father’s presence in the household.<sup>20</sup> For mother’s education and occupation controls, I include dummies for missing values. Since a nontrivial amount of data on father’s education and occupation are missing, I do not include them in the model. Instead, I include an indicator for father’s presence in the household following Giulietti et al. (2022). Lastly, I control for the first 10 principal components of the genetic data to minimize the potential bias that arises from within-group population stratification (Price et al. 2006, Belsky et al. 2016, Barth et al. 2020).

$G_{sgI}$  is a set of school-grade specific characteristics measured using information from the wave I in-home survey, which contains average age in months, the proportion of females and proportion in each race category, the share in each category of mother’s education and occupation, the share of individuals whose father is present in household, average household income, and grade size. I estimate the baseline specification (equation 2) via OLS separately for males and females.<sup>21</sup>

## 4.1 Challenges in Identifying Peer Effects

There are three well-known challenges in identifying peer effects—the reflection problem, endogenous peer group formation, and common environments. First, by using peers’ genes, I avoid the reflection problem, which arises from the fact that we cannot separately identify the effects of average group behaviors (e.g., average peer depression) and average group characteristics (e.g., peers’ average parental income) on individual behavior (e.g., own depression) in a linear model since they are a function of one another (Manski 1993). That is, the reflection problem arises when we estimate own behavior as a function of average group behaviors. Since human DNA is determined at conception, does not change over time, and is not affected by others’ behavior, my identification strategy does not suffer from this concern.

Second, people tend to befriend others who have similar observed and unobserved traits, which leads to endogenous selection into a peer group. I rely on the widely used approach of defining grademates as one’s peer group (Hoxby 2000). Although parents might select a school for their children based on observed characteristics, the assignment into each grade within a school is primarily determined by age, which makes it reasonable to assume that the formation of grademates is as good as random.

---

<sup>20</sup>I impute household income with the average household income whenever it is missing and include a dummy variable to indicate that income was imputed.

<sup>21</sup>I do not use peers’ average MDD score as an instrument for peers’ actual depression (e.g., the share of same-gender grademates with CES-D-10 scores  $\geq 11$ ) because the exclusion restriction would not be satisfied due to pleiotropy. That is, genetic markers can associate with multiple traits. The MDD-associated SNPs identified in Howard et al. (2019) are also linked to schizophrenia, bipolar disorder, some cardio-metabolic traits, and earlier age of smoking initiation.

Third, another challenge arises from exposure to similar environments. Grademates share common environments, which may result in similar behaviors and outcomes and make it difficult to isolate true peer effects. While school-grade correlated effects cannot be completely ruled out, these concerns can be alleviated by controlling for school and grade fixed effects as well as school-grade observables.

## 4.2 Identifying Assumptions

The empirical strategy relies on two main identifying assumptions. I conduct several experiments to examine whether there is support for the assumptions following previous studies (Bifulco et al. 2011, Lavy and Schlosser 2011, Rodríguez-Planas et al. 2018, Brunello et al. 2020, Olivetti et al. 2020, Giulietti et al. 2022).

First, there needs to be sufficient variation in peers’ average depression PGS within school and across grades. Each row of Table 2 shows the residual standard deviation in same-gender grademates’ average PGS by gender after including various controls. After adding school and grade fixed effects as well as school-grade level controls, the residual standard deviation is about 70% of the raw standard deviation. Thus, there appears to be sufficient variation in the same-gender grademates’ average MDD score.

The second identifying assumption is that students were quasi-randomly assigned to a grade within a school (Hoxby 2000). To examine this assumption, I conduct balancing tests, Monte-Carlo simulations, and placebo tests.<sup>22</sup> I start by performing balancing tests. I regress each covariate (e.g., individual MDD score, individual and family characteristics, and 10 genetic principal components) on same-gender grademates’ average MDD score conditional on school and grade fixed effects as well as school-grade controls. Table 3 reports the estimated coefficients on same-gender grademates’ average MDD score, where each cell represents a separate regression. For both samples, the first row reports the estimated coefficients where the individual MDD is the outcome. I omit oneself when constructing same-gender grademates’ average MDD score, which may mechanically lead to a negative correlation between own MDD score and same-gender grademates’ average MDD score (Guryan et al. 2009, Giulietti et al. 2022).<sup>23,24</sup> In the female and male samples, only 2 and 3 out of 27

<sup>22</sup>The experiments are similar to those in Brunello et al. (2020) and Giulietti et al. (2022).

<sup>23</sup>For example, assume that there are four individuals with PGSs of 1, 2, 3, and 4 in a grade. For each of them, the grademates’s average PGS (calculated excluding oneself) is 3, 2.667, 2.333, and 2. This means that individual who has the lowest (highest) PGS has the highest (lowest) peer group average PGS.

<sup>24</sup>To verify whether the negative correlation I find is mechanical, I run the balancing tests again after additionally controlling for same-gender schoolmates’ average MDD score. Guryan et al. (2009) suggest controlling for the population mean, from where each individual is drawn, to correct this bias. These results are included in Appendix Table A4. The estimated coefficients in row (1) are smaller and no longer statistically significant for females and weakly significant for males after additionally controlling for same-gender schoolmates’ average MDD score, which

regression coefficients are significant at the 5% level or better, which may happen by chance, and the significant characteristics do not overlap across gender except the own MDD score. This suggests no systematic relationship between same-gender grademates' average MDD score and the covariates.

I also perform Monte-Carlo simulations following Lavy and Schlosser (2011), Rodríguez-Planas et al. (2018), and Brunello et al. (2020). The idea is that if students are quasi-randomly assigned into a grade within a school, the variation in average MDD score across grades within a school in the actual sample should be similar to the variation in the average MDD score calculated from randomly assigning peers within a school. For each female (male) in each school, I randomly draw an MDD score using a normal distribution with the school-specific MDD score mean and standard deviation.<sup>25</sup> Then, I compute school-grade specific averages of the simulated female (male) MDD score. For each school, I compute the standard deviation of these averages using residuals from a regression of the simulated female school-grade average MDD score on school and grade fixed effects as well as school-grade level controls. I repeat this procedure 1,000 times and construct a 90% empirical confidence interval for the simulated within-school standard deviations.<sup>26</sup> I find that approximately 88% and 89% of the schools' actual standard deviation falls within the 90% empirical confidence interval for both the female and male samples.<sup>27</sup> These results support the assumption of random assignment.

## 5 Main Results

In this section, I present estimates of the effects of peers' genetic predisposition to depression on own mental health in the short- and long-term. The results suggest that there is an immediate adverse effect of peers' genetic predisposition to depression on own mental health, which persists into adulthood for females, but not males.

### 5.1 Short-Term Effects

I first examine the short-term effects of same-gender grademates' average MDD score on mental health as measured by an indicator for being depressed (i.e., CES-D-10 score  $\geq 11$ ). Data from

---

implies that the negative significant correlation that I initially find is mechanical.

<sup>25</sup>The distributions of the actual individual MDD scores by school are approximately normal. I also perform a version of the simulation exercise where I randomly draw an MDD score from the empirical MDD score distribution, and the results are nearly identical.

<sup>26</sup>I calculate the actual standard deviation of school-grade specific averages similarly. That is, for each school, I compute the standard deviations of the actual school-grade specific averages of MDD score using residuals from a regression of the actual female (male) school-grade average MDD score on school and grade fixed effects as well as school-grade level controls.

<sup>27</sup>Appendix Figure A2 displays distributions of the actual and simulated school-specific MDD score standard deviations separately for the female and male samples.

Wave I is used to estimate these short-run effects.<sup>28,29</sup>

Each column of Table 4 contains separate regression results from various specifications. Columns (1)-(4) and (5)-(8) show point estimates for females and males, respectively. In columns (1) and (5), I control only for the genetic principal components. In columns (2) and (6), I add school and grade fixed effects and school-grade level controls. In columns (3) and (7), I additionally include individual-level controls. Columns (4) and (8) contain the results from the most exhaustive specification that additionally includes family and parental controls. This is my preferred specification going forward.

The estimate in column (4) indicates that a one standard deviation increase in peers' average MDD score significantly increases the likelihood of being depressed by 2.3 percentage points for adolescent girls, an 8.7% increase relative to the sample average. In column (8), I find a one standard deviation increase in same-gender grademates' average MDD score leads to a 3 percentage point increase in the probability of being depressed for adolescent boys, a 20% increase relative to the sample average.

Taken together, the estimates suggest there are immediate social-genetic effects on mental health. An increase in same-gender grademates' genetic risk for depression exerts short-run adverse impacts on own mental health for both females and males. The effect size is similar across gender in percentage point terms, though larger for males in percentage terms.<sup>30</sup> Notably, the effects of one's own MDD score on the probability of being depressed is positive for both genders but statistically significant only for girls.

The results are consistent with existing evidence on gender differences in peer effects on mental health. In particular, Giulietti et al. (2022) document significant peer effects on depression for females during adolescence, but no significant short-term effects for males.<sup>31</sup> They find that a one standard deviation increase in the share of same-gender grademates in adolescence who are depressed increases females' likelihood of being depressed the following 1-2 years (i.e., in Wave II) by 2.9 percentage points (an 11.8% increase). The social-genetic effects on females I find are about three-quarters the size of their estimated peer effects. The peer effects found in Giulietti et al. (2022) may, therefore, be partly explained by social-genetic effects.<sup>32</sup>

---

<sup>28</sup>In Waves I and II, most of the respondents are adolescents, and all of them are adults by Wave III.

<sup>29</sup>Most of the respondents who were in the 12<sup>th</sup> grade in Wave I were not included in the in-home survey sample in Wave II. Therefore, I focus on the short-term results using Wave I data.

<sup>30</sup>I fail to reject equality of the coefficients on same-gender grademates' average MDD score across genders.

<sup>31</sup>They fail to reject equality of the coefficients of interest across genders.

<sup>32</sup>While Giulietti et al. (2022) did not find evidence of short-run peer effects on male mental health, my results suggest substantial evidence of social-genetic effects for males. The difference in results is likely explained by the difference in our main explanatory variables. I rely on peers' genetic predisposition to depression, while Giulietti et al. (2022) rely on peers' self-reported depressive symptoms (i.e., the CES-D-10 score).

## 5.2 Long-Term Effects

Next, I explore whether the short-term peer effects found in the prior section persist into adulthood. I focus on mental health in Wave IV when respondents are aged 28-33 and consider the same indicator variable for depression (i.e., CES-D-10 score  $\geq 11$ ).<sup>33</sup>

In Table 5, I present estimated effects of same-gender grademates' average MDD score on the likelihood of experiencing depression in Wave IV. Columns (1)-(4) contain the results for females. Across most of the specifications, a one standard deviation increase in peers' average MDD score leads to a statistically significant 2.9 percentage points increase in the probability of being depressed, a 14% increase from the sample average. Columns (5)-(8) display the results for males. In the specifications with the most rigorous set of controls (column 8), I find a positive effect of same-gender grademates' average MDD score on the probability of being depressed, but it is not significant at conventional levels.

Earlier I found that peers' genetic risk for depression has an immediate negative impact on own mental health for both females and males. The findings in this section imply that the social-genetic effects on mental health in adolescence carry over into adulthood for females, but not males. My findings are in line with the evidence on gender differences in depression, which documents that females exhibit earlier onset of and a higher rate of depression, and that the gender gap continues throughout life (Mirowsky 1996, Piccinelli and Wilkinson 2000, Patten et al. 2001, Lewis et al. 2015, Breslau et al. 2017, Salk et al. 2017, Bogren et al. 2018). Giulietti et al. (2022) find that a one standard deviation increase in the share of same-gender grademates who are depressed during adolescence increases females' likelihood of being depressed by 2.6 percentage points (an 11.7% increase) in adulthood. My results suggest socio-genetic effects may explain, in part, their long-term effects.

One explanation for the more persistent peer effects on depression of females relates to different response styles to stress by gender. The response styles theory (RST) says females are more likely to repeatedly think about negative feelings and problems (i.e., ruminate and internalize) while males tend to deal with them by problem-solving (i.e., externalize) (Nolen-Hoeksema 1987, 1991, Hilt et al. 2010, Johnson and Whisman 2013). Giulietti et al. (2022) show that co-rumination, which means having excessive discussion about problems or concerns with others, is prevalent among adolescent girls, and may explain the gender difference in peer effects on depression. Evidence from the psychopathology field suggests that gender differences in reactivity to stress leads to gender differences in vulnerability to anxiety and depression, which becomes noticeable during

---

<sup>33</sup>I focus on Wave IV for the long-term results for two reasons. First, the CES-D-10 score is not available in Waves III or V. Second, it is the first wave where all of the respondents are over 20 years old. In Wave III, the respondents are aged 18-27.

adolescence and continues through adulthood (Rudolph 2002). If adolescent females with peers who are more genetically predisposed to depression tend to ruminate and co-ruminate, which in turn makes them more vulnerable to depression, this may partially explain the effects I find.

In addition, the scarring effects for females of exposure to peers during adolescence with a higher underlying risk for depression is consistent with the evidence in economics and social psychology that females are more vulnerable to peer influence (Eagly 1978, Minton and Schneider 1980, Han and Li 2009).<sup>34</sup> Moreover, the long-lasting importance of one’s adolescent experience throughout the life course is well-recognized since adolescence is a period in which individuals develop social and noncognitive skills (Alwin and Krosnick 1991, Gong et al. 2020). Thus, the effects of peer influence during this period may be especially salient and long-lasting.

## 6 Mechanisms

I find significant short-term social-genetic effects, which carry over into adulthood for females but not for males. I explore several possible mechanisms underlying these effects. Peers’ genes may influence own short- and long-term depression through peers’ depression as well as behavioral outcomes such as friendship, substance use, and socioeconomic status. I investigate the latter three in this section.

### 6.1 Friendship and Socialization

During adolescence, individuals seek social acceptance and show an increased sensitivity to peers’ reactions (Brown and Larson 2009, Andrews et al. 2020, Giulietti et al. 2022). Moreover, the importance of friendship (or peer support) for mental health during adolescence is widely studied and recognized (Reisman 1985, Ueno 2005, Sias and Bartoo 2007, King and Terrance 2008, King et al. 2016, Cleary et al. 2018, Narr et al. 2019). Peers with high genetic risk for depression may themselves have higher prevalence of depression, which may negatively influence their friendship. Worse friendships may, in turn, deteriorate own mental health. It could also be that individuals with high genetic risk for depression tend to emotionally and physically detach themselves from friends. Then, having peers with high genetic risk for depression may have a negative impact on the quality and/or quantity of friendships, which may lead to worse mental health. I investigate whether peers’ genetic risk for depression impacts friendship.

---

<sup>34</sup>Descriptive results using the Add Health also support the notion that females are more susceptible to peer influence. The Add Health asks Wave III respondents whether they agree or disagree that in social situations they tend not to follow the crowd. Approximately 10% of females disagreed or strongly disagreed whereas approximately 7% of males disagreed or strongly disagreed. I reject equality of the two at the 5% level.

### 6.1.1 Short-Term Effects on Friendship

In Wave I, the Add Health asks questions about interactions with friends, such as visiting friends' houses, hanging out with friends after school, and spending time with friends during the weekend.<sup>35</sup> Table 6 reports estimated results where the outcome variables take on a value of one if respondents did the corresponding activities (i.e., visit a friend's home, hang out after school, spend time together during the weekend) with one or more of their nominated friends during the past week. The coefficients on same-gender grademates' average MDD score are all negative. For females, there is a statistically significant decline in the probability of visiting friends' homes and hanging out after school. For males, there is a significant decrease in the likelihood of spending time with friends during the weekend. While the above-mentioned outcomes capture physical detachment from friends, I also explore emotional connectedness to friends and one's school in Appendix Tables A9 and A10, respectively. Although the estimates are not precisely estimated, the results imply a decrease in emotional attachment to friends and school.<sup>36,37</sup>

Taken together, the findings indicate that an increase in same-gender grademates' average MDD score has an immediate negative impact on friendship. Thus, weaker friendships due to less interaction with friends may be an important channel through which the short-term effects operate.

### 6.1.2 Long-Term Effects on Friendship

I consider friendship-related measures in Waves III and IV to explore the enduring effects of peers' depression genes. The Add Health asks respondents "In the past seven days, how many times did you just hang out with friends, or talk on the telephone for more than five minutes?" and "Thinking back to all your friends from high school, how many are you still friends with?" in Wave

---

<sup>35</sup>Specifically, respondents can nominate up to five best friends. They are then asked: "Did you go to [friend 1,...,5]'s house during the past seven days?", "Did you meet [friend 1,...,5] after school to hang out or go somewhere during the past seven days?", and "Did you spend time with [friend 1,...,5] during the past weekend?" Respondents answer yes or no.

<sup>36</sup>I consider sense of belonging at school since friendship plays an important role in developing adolescents' sense of belonging (Hamm and Faircloth 2005).

<sup>37</sup>I use the following items to measure emotional connectedness to friends: "Did you talk to [friend 1,...,5] about a problem during the past seven days?", "Did you talk to [friend 1,...,5] on the telephone during the past seven days?", and "How much do you feel that your friends care about you?" For the first two items, respondents answer yes or no. For the last item, respondents choose from five categories: not at all; very little; somewhat; quite a bit; and very much, and I create two indicator variables for whether respondents feel that their friends care about them quite a bit or more and very much, respectively. As measures of sense of belonging at school, I use questions asking how strongly one agrees or disagrees with the following: "I feel close to people at this school", "I feel like I am part of this school", and "I am happy to be at this school." Respondents choose from five categories: strongly agree; agree; neither agree nor disagree; disagree; and strongly disagree. I construct three indicators for whether individuals strongly disagree or disagree with 1 or more, 2 or more, and 3 of those statements.



III, and “How many close friends do you have?” in Wave IV.<sup>38,39</sup> For the number of high school friends one still has as an adult question, I create two dummies that have a value of one if the respondent answers that the corresponding number of friends is most or more, and all, respectively, and zero otherwise. For the number of close friends question, I create two indicator variables that take a value of one if the respondent answers that the number of close friends is three or more and six or more, respectively, and zero otherwise.

Table 7 includes estimated results for Waves III and IV. The results indicate that an increase in same-gender grademates’ average genetic risk score for depression negatively affects the frequency of hanging out or talking on the phone, decreases the probability of still being friends with all of one’s high school friends in adulthood, and decreases the probability of having many (i.e., 6 or more) close friends for adult females. For adult males, the point estimates are mostly negative, but not significant.

Overall, having peers with high genetic risk for depression during adolescence has negative impacts on friendship in the short- and long-term. The effects are more pronounced for females than males. Weaker social ties may be an important channel that explains the long-term baseline effects for females. Another possible pathway could be that being exposed to peers with high genetic risk for depression during adolescence reduces the likelihood of females joining new peer groups in adulthood, which possibly leads to isolation and worse mental health. However, due to lack of detailed data on adulthood friendships, I cannot directly explore this path.

## 6.2 Substance Use

There is growing evidence regarding peer effects on substance use (Lundborg 2006, Clark and Lohéac 2007, Cawley and Ruhm 2011, Eisenberg et al. 2014). Moreover, studies in epidemiology and economics suggest a negative correlation between substance use and mental health, although the causal link is unclear (Jane-Llopis and Matytsina 2006, Swendsen et al. 2010, Van Ours and Williams 2011, 2012, Lipari and Van Horn 2017, Conway et al. 2018, Friedman 2020). Some people may use substances such as alcohol, tobacco, and marijuana to relieve mental distress (Cornah 2006, Stapinski et al. 2016, Friedman 2020). On the other hand, substance use may lead to poor mental health by increasing anxiety and tension over time (Taylor et al. 2014, Plurphanswat et al. 2017, Taylor et al. 2021).

---

<sup>38</sup>When answering the number of high school friends the respondent still has as an adult question, they choose among none, one, a few, some, most, or all. This question was asked only to the Wave III respondents who were in 7<sup>th</sup> and 8<sup>th</sup> grades in Wave I.

<sup>39</sup>For the number of close friends question, respondents choose among none, one or two friends, three to five friends, six to nine friends, ten or more friends. According to the Add Health documentation, close friends include people whom we feel at ease with, can talk to about private matters, and can call on for help.

If peers with high genetic risk for depression are more likely to use substances, interacting with them during adolescence may increase own substance use, which may trigger or intensify a deterioration of own mental health. To test this hypothesis, I examine whether same-gender grademates’ average MDD score affects own use of alcohol, tobacco, and marijuana.<sup>40</sup>

### 6.2.1 Alcohol

The Add Health asks respondents “During the past 12 months, on how many days did you drink alcohol?”, “Over the past 12 months, on how many days did you drink five or more drinks in a row?”, and “Over the past 12 months, on how many days have you gotten drunk or very, very high on alcohol?”<sup>41</sup> For each question, I create indicator variables that have a value of one if the respondent answers that the corresponding number of days is once a month or more, 2 to 3 days a month or more, or 1 to 2 days a week or more, respectively, and zero otherwise.

Table 8 reports results from Wave I. The results in Panels A and B imply that the effects of same-gender grademates’ average MDD score on frequency of alcohol consumption, especially binge drinking, are positive for females. For males, there is some evidence of an increase in the frequency of binge drinking. In Table 9, I present results from Wave IV. The estimates generally indicate that having same-gender grademates’ with higher genetic risk for depression during adolescence causes more frequent alcohol use among adult females. For adult males, I find the opposite—an increase in same-gender grademates’ average MDD score during adolescence negatively affects alcohol use. Overall, the findings suggest that having peers with high genetic risk for depression during adolescence leads to increased use of alcohol for females both in adolescence and adulthood.

### 6.2.2 Tobacco

A strong correlation between smoking and mental illness is well-established although the causal link is unclear (Breslau et al. 1998, Prochaska 2011, Burki 2016, Lipari and Van Horn 2017, Friedman 2020, Choudhury 2021). If socializing with peers who have a higher genetic risk for depression increases own tobacco use, it may contribute to worsening mental health.

I consider three smoking-related measures in the Add Health—whether one ever smoked, the number of cigarettes smoked per day (CPD) in the past 30 days, and quit attempts during the past 6 months. Results are reported in Table 10. Panel A shows results in the short-term (Wave I) and Panel B shows the long-term effects (Wave IV). In general, I do not find significant impacts

<sup>40</sup>According to the Centers for Disease Control and Prevention (CDC), alcohol, marijuana, and tobacco are the most commonly used substances by adolescents and they are known to be closely related to mental health problems (Gart and Kelly 2015, Conway et al. 2018, Choudhury 2021).

<sup>41</sup>For these questions, individuals choose among none, one or two days in the past 12 months, once a month or less, two to three days a month, one to two days a week, three to five days a week, everyday or almost everyday.

of same-gender grademates' average MDD score on smoking in the short- or long-term. The one exception is a decline in the probability of attempting to quit among males in the short-run.

### 6.2.3 Marijuana

Although there is no consensus on the causal link between marijuana use and mental health (Richardson et al. 2010, Serafini et al. 2013, Keith et al. 2015, NIDA 2021), studies in economics and epidemiology have found causal evidence of marijuana use increasing the probability of mental illness, such as depression and suicidal ideation (Richardson et al. 2010, Van Ours and Williams 2011, 2012, 2015, Van Ours et al. 2013, Pieniazek 2022). If being around peers who have a higher genetic risk for depression during adolescence leads to an increase use of marijuana, it may result in a worse mental health outcomes. I investigate whether peers' genetic risk for depression affects the frequency of marijuana use.

In both Waves I and IV, the Add Health asks respondents "During the past 30 days, how many times did you use marijuana?" In Wave I, respondents report the frequency of marijuana use while in Wave IV they choose from categories representing different frequencies. Table 11 presents the short- and the long-term effects of peers' genetic predisposition to depression on marijuana use. In columns (1) and (2), I find that an increase in same-gender grademates' average MDD score weakly increases the frequency of marijuana use for females in the short-run (Wave I), with no effects for males. In columns (3)-(8), I explore the long-term (Wave IV) effects of same-gender grademates' average MDD score on days used marijuana. The outcome variable in columns (3)-(4) is an indicator variable that takes on a value of one if days used marijuana is once a month or more. The outcome variables in columns (5)-(6) and (7)-(8) are created similarly for two or three days a month and one or two days a week, respectively. The point estimates for females are all positive and insignificant, but the estimates for males are all negative and insignificant.

Taken together, I find that having peers with high genetic risk for depression increases alcohol and marijuana use for females. Thus, substance use may be a channel underlying the social-genetic effects.

## 6.3 Socioeconomic Status

Finally, I explore socioeconomic status (SES) as a mechanism that may explain the persistence of peer effects on mental health into adulthood. On the one hand, I show that having peers with higher genetic risk for depression increases adolescent depression, which may have a negative impact on SES in adulthood (Fletcher 2010, 2013, Lundborg et al. 2014, Cornaglia et al. 2015, Mousteri et al. 2019). Then, having worse SES may, in turn, result in worse mental health in the long-run (Chatterji et al. 2011, Layard 2013, Salokangas 2021). On the other hand, it could be that worse short-term

mental health causes both worse mental health and lower SES in adulthood. I explore the effects of peers' genetic risk for depression on college attendance, employment, and log labor income.

In Wave IV (when all respondents are aged 24 and older), the Add Health asked respondents about the highest level of education achieved. I create a variable that takes on value one if an individual attended any type of higher level of training or education after high school regardless of completion, and zero otherwise. The Add Health also collected information on the respondents' current employment and income in Wave IV by asking the following questions, respectively: "Are you currently working for pay at least 10 hours a week?", and "Now think about your personal earnings. In (2006/2007/2008), how much income did you receive from personal earnings before taxes, that is, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment?"

Table 12 presents the estimates. The results in column (2) indicate that a one standard deviation increase in same-gender grademates' average MDD score during adolescence significantly decreases the likelihood of pursuing higher education after high school by 4.5 percentage points, a 6.4% decrease, for males, but has no effect for females. The results in column (3) suggest that a one standard deviation increase in same-gender grademates' average MDD score during adolescence leads to a 2.7 percentage point decrease, a 3.6% decrease, in the probability of working for pay in adulthood for females, with no effects for adult males. I do not find any significant effects on the log labor income for either gender.

Overall, there is some evidence that having peers with high genetic risk for depression during adolescence adversely affects various socioeconomic outcomes.

## 7 Robustness

I conduct several exercises to assess robustness of the baseline depression results. I explore sensitivity of the results to different definitions of depression as well as additional measures of mental health, non-linearities in peer effects, attrition bias, and bias that may arise from the absence of valid genetic data. I also perform placebo tests that provide support for the identification strategy.

### 7.1 Sensitivity to Different Depression Outcomes

In Appendix Table A5, I estimate my preferred specification (i.e., the specification with the most exhaustive set of controls) using different definitions of depression as outcomes. Panels A and B include the estimates for Waves I and IV, respectively. In columns (1) and (8), I create an indicator variable for experiencing depression based on the CES-D-19 score (i.e.,  $\text{CES-D-19} \geq 16$ ).<sup>42</sup> The results in Panel A are qualitatively consistent with the short-term effects in that the

---

<sup>42</sup>The CES-D-19 score is available only in Wave I. A cutoff of 16 is recommended for the CES-D-20 score when screening for depression (Radloff 1977, Weissman et al. 1977). Instead of CES-D-20, the CES-D-19 score

estimates are positive for both genders, but they are not significant. In columns (2) and (9), I use the continuous CES-D-10 score as an outcome. In Wave I, the coefficients are positive although they are not precisely estimated (Panel A). In Wave IV, the point estimate for females is positive and significant at the 5% level, but negative and statistically insignificant for males (Panel B).

In columns (3)-(7) and (10)-(14), I explore robustness of the baseline results to using different CES-D-10 cutoffs to define depression (i.e.,  $\geq 8$ ,  $\geq 9$ ,  $\geq 10$ , and  $\geq 12$ ). For comparison, I present the baseline results in columns (6) for females and (13) for males. The short-term effects (Panel A) for both females and males are robust to using cutoffs of 8 to 10, and if anything are larger in magnitude for females.<sup>43</sup> However, the results decrease in magnitude and become less precisely estimated with cutoffs of 12. Thus, the adverse effects of peers' genetic predisposition to depression are larger among those very close to the clinically-defined threshold of depression (i.e., a cutoff of 11).<sup>44</sup> The long-term effects are presented in Panel B. I find that the increase in depression among females in the long-run due to peers' genetic risk is robust to perturbations of the cutoff, though the magnitude and statistical significance varies as the threshold changes.<sup>45</sup>

## 7.2 Nonlinear Effects of Peers' Average MDD Score

In the baseline model, I assume that the relationship between peers' genes for depression and own mental health is linear. But, the effect of peers' genetic risk for depression may differ across the distribution of peers' genetic risk. Moreover, evidence suggests that peer effects are often not linear (Betts and Shkolnik 2000, Hoxby and Weingarth 2005, Cooley 2010, Sacerdote 2011, Lavy et al. 2012, Imberman et al. 2012).

I re-estimate the baseline specification by replacing same-gender grademates' average MDD score with indicators for having same-gender grademates in different parts of the average MDD score distribution. Columns (1)-(4) and (5)-(8) in Appendix Table A6 contain results for the short- and long-term, respectively. In columns (1), (3), (5), and (7), I include an indicator for same-gender grademates' average MDD scores being above the median of the distribution. In columns (2), (4), (6), and (8), I use separate indicators for the first and third terciles of the same-gender grademates' average MDD score distribution.

I find nonlinear effects only for females. The results indicate that having same-gender peer

---

is available in Wave I. I use the CES-D-19 score with a cutoff of 16 following Giulietti et al. (2022).

<sup>43</sup>Andresen et al. (1994) identified CES-D-10 cutoffs of 8 and 10 as the optimal threshold for screening of depression.

<sup>44</sup>For females, I fail to reject the null hypothesis of equality of coefficients of same-gender grademates' average MDD score when using the CES-D-10 score cutoffs of 10 and 11. However, I reject equality of coefficients across the results with cutoffs of 11 and 12 at the 5% level. For males, I fail to reject equality of coefficients in both tests.

<sup>45</sup>I fail to reject the null hypothesis of equality of coefficients of same-gender grademates' average MDD score across the columns for both genders.

groups with average MDD scores in the third tercile of the distribution increases the likelihood of females' own depression by 7.6 percentage points both in adolescence and adulthood (relative to having peers with average scores in the middle of the distribution). This implies that the baseline linear effects for females are driven by the upper tercile of the distribution.

Peer groups' average MDD score could be high if a handful of peers have very high MDD scores or if most individuals in the peer group have high MDD scores. In future work, I will explore these two possibilities to better understand the main source of the nonlinear effects, which has implications for how to structure peer groups to improve mental health for females.

### 7.3 Additional Measures of Mental Health

I next consider more severe mental health outcomes such as suicidal ideation and suicide attempts as well as depression diagnosis and antidepressant use.<sup>46</sup> The latter two measures are not available in Wave I, and all four measures are available in Wave IV.

In columns (1)-(2) and (3)-(4) of Appendix Table A7, I present the short-term (Wave I) effects of same-gender grademates' average MDD score on the probability of self-reported suicidal ideation and suicide attempts, respectively. The results suggest that there is no statistically significant effect of same-gender grademates' average MDD score on these outcomes, and most of the point estimates are very close to zero.

In columns (5)-(12) of Appendix Table A7, I present the long-term (Wave IV) effects of same-gender grademates' average MDD score. Columns (5)-(6) and (7)-(8) report results for the likelihood of self-reported suicidal ideation and suicide attempts, respectively. For females, the estimate in column (5) indicates that a one standard deviation increase in same-gender grademates' average MDD score increases the probability of suicidal ideation by 2.2 percentage points (a 29.3% increase) and the probability of suicide attempts by 0.7 percentage points (a 53.8% increase). I find no statistically significant long-term peer effects on these outcomes among males.

Columns (9)-(10) and (11)-(12) show results for depression diagnosis and antidepressant use, respectively. For both genders, there is no evidence of peer effects on either outcome.

In sum, same-gender grademates' genetic risk for depression does not have immediate impacts on suicidal risk for either gender, but significantly affects suicidal ideation and weakly affects suicide attempts for females in the long-run.

---

<sup>46</sup>Information on suicidal ideation and suicide attempts are not available in Wave III, and the CES-D-10 score is not available in Wave V.

## 7.4 Attrition and Absence of Valid Genetic Data

I explore two potential sources of bias—one arises from attrition and the other from the absence of valid genetic data.

First, I examine attrition from Waves I to IV. If respondents who had same-gender grademates' with a higher genetic risk score in adolescence are more likely to attrite from Waves I to IV, this may lead to biased results. In columns (1) and (2) of Appendix Table A8, I present results from a regression of an indicator for whether an individual dropped out of the sample from Wave I to IV on same-gender grademates' average MDD score conditional on the usual sets of controls in the most preferred specification except for the genetic principal components and own MDD score.<sup>47</sup> In all cases, I do not find evidence that same-gender grademates' average MDD score systematically affects sample attrition.

Then, I assess whether peers' average MDD score significantly affects an individual's decision to be genotyped. If respondents who had same-gender grademates' with higher genetic risk for depression in adolescence are less likely to be genotyped, this may result in biased results. In columns (3)-(4) of Appendix Table A8, I present results where I regress an indicator for not being genotyped on same-gender grademates' average MDD score controlling for the usual sets of controls in the most preferred specification except for the genetic principal components and own MDD score and conditional on appearing in Wave IV. I do not find evidence that same-gender grademates' average MDD score significantly influences the decision to be genotyped. Thus, it seems concerns about bias arising from attrition or absence of genetic data are minimal.

## 7.5 Verifying the Identification Strategy

To further assess the validity of the identification strategy, I perform placebo tests where I estimate the baseline specification after randomly re-assigning individuals to a different grade within the same school. I replace the actual same-gender grademates' average MDD score with a placebo same-gender grademates' average MDD score.<sup>48</sup> I then estimate my preferred baseline specification using the binary depression measure in Waves I and IV as the outcome. I repeat this procedure 1,000 times. In Appendix Figures A3 and A4, I plot the histogram of the coefficients on the placebo same-gender grademates' average MDD score from each regression against the coefficient on actual same-gender grademates' average MDD score from the baseline results. The distributions of the placebo estimates are centered around zero. I calculate  $p$ -values for a one-tailed test of the likelihood

---

<sup>47</sup>In these analyses, the sample includes individuals who are not genotyped. Hence, their own genetic information is not available.

<sup>48</sup>Specifically, students are randomly re-assigned to a new grade (i.e., different grade) within the same school. They are then assigned their new grade's original same-gender grademates' average MDD score.

of observing a placebo coefficient being greater than or equal to the baseline estimate. For females, 1.3% and 0.1% of the placebo coefficients are greater than or equal to the actual coefficients in Waves I and IV, respectively. For males, 4.3% and 11% of the placebo coefficients are greater than the actual coefficients in Waves I and IV, respectively. With the exception of the effects for males in the long-run, these results provide strong support for the validity of the identification strategy.

## 8 Conclusion

I examine how peers' genetic risk for depression affects own mental health during adolescence and early adulthood using data from the Add Health. I find that a one standard deviation increase in peers' average MDD score significantly increases the probability of being depressed by 2.3 and 3 percentage points for adolescent girls (an 8.7% increase) and boys (a 20% increase), respectively. I also find that the short-term peer effects persist into adulthood for females. A one standard deviation increase in peers' average MDD score during adolescence leads to a statistically significant 2.9 percentage point increase in the probability of females being depressed in adulthood, a 14% increase. The findings suggest that depression in adolescence as well as adulthood is influenced not only by one's own genetic risk for depression but also by the genetic risk of one's peers. In other words, social-genetic effects are salient in the mental health context.

I explore several mechanisms underlying the effects, including friendship, substance use, educational attainment, and labor market outcomes. Interacting with peers with high genetic risk for depression worsens short- and long-term friendships. I find those with peers in adolescence with a higher genetic risk for depression interact less with friends during adolescence. Also, having same-gender grademates with higher genetic risk for depression decreases the frequency of hanging out with friends and the likelihood of having long-term and close friendships in adulthood. These effects are more pronounced for females than males. For females, being exposed to peers with high genetic risk for depression increases the frequency of binge drinking and marijuana use in both adolescence and adulthood. I also find that males and females who had peers with high genetic risk for depression in adolescence experience a lower SES in adulthood. Males who had same-gender grademates with higher genetic risk for depression during adolescence are less likely to attend college, and females who used to have same-gender grademates with higher genetic risk for depression while they were in middle or high school are less likely to work for pay.

Overall, my findings imply that genes are an important part of the social environment, and mental health is a function of the genes of those around us. Hence, efforts to prevent and treat depression would be more effective by taking peers' genetic risk into account. However, this study is limited in that, by construction, the estimates do not tell us whether the effects of peers'



genetic risk for depression operate mainly through peer depression. If the main mechanism is peer depression, my findings have implications for the design of interventions to curb adolescent depression (e.g., group-based vs. individual interventions) and suggest there are both short- and long-run social multiplier effects in schools in the context of mental health. In future work, I will explore whether there are circumstances or environments, such as childhood SES or relationships with parents, that mitigate the effects of peers' genetic risk for depression on mental health.

## References

- ABKEVICH, V., N. J. CAMP, C. H. HENSEL, C. D. NEFF, D. L. RUSSELL, D. C. HUGHES, A. M. PLENK, M. R. LOWRY, R. L. RICHARDS, C. CARTER, ET AL. (2003): “Predisposition locus for major depression at chromosome 12q22-12q23. 2,” *The American Journal of Human Genetics*, 73, 1271–1281.
- ALWIN, D. F. AND J. A. KROSNICK (1991): “Aging, cohorts, and the stability of sociopolitical orientations over the life span,” *American journal of sociology*, 97, 169–195.
- ANDRESEN, E. M., J. A. MALMGREN, W. B. CARTER, AND D. L. PATRICK (1994): “Screening for depression in well older adults: Evaluation of a short form of the CES-D,” *American journal of preventive medicine*, 10, 77–84.
- ANDREWS, J. L., L. FOULKES, AND S.-J. BLAKEMORE (2020): “Peer influence in adolescence: Public-health implications for COVID-19,” *Trends in Cognitive Sciences*, 24, 585–587.
- ANGRIST, J. D. AND K. LANG (2004): “Does school integration generate peer effects? Evidence from Boston’s Metco Program,” *American Economic Review*, 94, 1613–1634.
- BARTH, D., N. W. PAPAGEORGE, AND K. THOM (2020): “Genetic endowments and wealth inequality,” *Journal of Political Economy*, 128, 1474–1522.
- BAUD, A., M. K. MULLIGAN, F. P. CASALE, J. F. INGELS, C. J. BOHL, J. CALLEBERT, J.-M. LAUNAY, J. KROHN, A. LEGARRA, R. W. WILLIAMS, ET AL. (2017): “Genetic variation in the social environment contributes to health and disease,” *PLoS genetics*, 13, e1006498.
- BEARMAN, P. S. AND J. MOODY (2004): “Suicide and friendships among American adolescents,” *American journal of public health*, 94, 89–95.
- BEAUCHAMP, J. P., D. CESARINI, M. JOHANNESSEN, M. J. VAN DER LOOS, P. D. KOELLINGER, P. J. GROENEN, J. H. FOWLER, J. N. ROSENQUIST, A. R. THURIK, AND N. A. CHRISTAKIS (2011): “Molecular genetics and economics,” *Journal of Economic Perspectives*, 25, 57–82.
- BELSKY, D. W., T. E. MOFFITT, D. L. CORCORAN, B. DOMINGUE, H. HARRINGTON, S. HOGAN, R. HOUTS, S. RAMRAKHA, K. SUGDEN, B. S. WILLIAMS, ET AL. (2016): “The genetics of success: How single-nucleotide polymorphisms associated with educational attainment relate to life-course development,” *Psychological science*, 27, 957–972.

- BENJAMIN, D. J., D. CESARINI, C. F. CHABRIS, E. L. GLAESER, D. I. LAIBSON, V. GUDNASON, T. B. HARRIS, L. J. LAUNER, S. PURCELL, ET AL. (2011): “The promises and pitfalls of geno-economics,” 4, 627–662.
- BETTS, J. R. AND J. L. SHKOLNIK (2000): “The effects of ability grouping on student achievement and resource allocation in secondary schools,” *Economics of Education Review*, 19, 1–15.
- BIFULCO, R., J. M. FLETCHER, AND S. L. ROSS (2011): “The effect of classmate characteristics on post-secondary outcomes: Evidence from the Add Health,” *American Economic Journal: Economic Policy*, 3, 25–53.
- BOGREN, M., L. BRÅDVIK, C. HOLMSTRAND, L. NÖBBELIN, AND C. MATTISSON (2018): “Gender differences in subtypes of depression by first incidence and age of onset: a follow-up of the Lundby population,” *European archives of psychiatry and clinical neuroscience*, 268, 179–189.
- BRADLEY, K. L., A. L. BAGNELL, AND C. L. BRANNEN (2010): “Factorial validity of the Center for Epidemiological Studies Depression 10 in adolescents,” *Issues in mental health nursing*, 31, 408–412.
- BRAUDT, D. AND K. M. HARRIS (2020): “Polygenic scores (pgss) in the national longitudinal study of adolescent to adult health (add health)–release 2,” .
- BRESLAU, J., S. GILMAN, B. STEIN, T. RUDER, T. GMELIN, AND E. MILLER (2017): “Sex differences in recent first-onset depression in an epidemiological sample of adolescents,” *Translational psychiatry*, 7, e1139–e1139.
- BRESLAU, N., E. L. PETERSON, L. R. SCHULTZ, H. D. CHILCOAT, AND P. ANDRESKI (1998): “Major depression and stages of smoking: A longitudinal investigation,” *Archives of general psychiatry*, 55, 161–166.
- BROWN, B. B. AND J. LARSON (2009): “Peer relationships in adolescence.” .
- BRUNELLO, G., A. SANZ-DE GALDEANO, AND A. TERSKAYA (2020): “Not only in my genes: The effects of peers’ genotype on obesity,” *Journal of Health Economics*, 72, 102349.
- BURKI, T. K. (2016): “Smoking and mental health,” *The Lancet Respiratory Medicine*, 4, 437.
- CAWLEY, J., E. HAN, J. KIM, AND E. C. NORTON (2019): “Testing for family influences on obesity: The role of genetic nurture,” *Health economics*, 28, 937–952.

- CAWLEY, J. AND C. J. RUHM (2011): “The economics of risky health behaviors,” in *Handbook of health economics*, Elsevier, vol. 2, 95–199.
- CHATTERJI, P., M. ALEGRIA, AND D. TAKEUCHI (2011): “Psychiatric disorders and labor market outcomes: Evidence from the National Comorbidity Survey-Replication,” *Journal of health economics*, 30, 858–868.
- CHOUDHURY, R. S. (2021): “Essays on the Unintended Effects of Tobacco Control Policies on Adolescent Health Behaviors,” Ph.D. thesis, University of New Hampshire.
- CLARK, A. E. AND Y. LOHÉAC (2007): ““It wasn’t me, it was them!” Social influence in risky behavior by adolescents,” *Journal of health economics*, 26, 763–784.
- CLEARY, M., D. LEES, AND J. SAYERS (2018): “Friendship and mental health,” *Issues in Mental Health Nursing*, 39, 279–281.
- CONLEY, D. AND J. FLETCHER (2017): “The genome factor,” in *The Genome Factor*, Princeton University Press.
- CONWAY, K. P., V. R. GREEN, K. A. KASZA, M. L. SILVEIRA, N. BOREK, H. L. KIMMEL, J. D. SARGENT, C. A. STANTON, E. LAMBERT, N. HILMI, ET AL. (2018): “Co-occurrence of tobacco product use, substance use, and mental health problems among youth: Findings from wave 1 (2013–2014) of the population assessment of tobacco and health (PATH) study,” *Addictive behaviors*, 76, 208–217.
- COOLEY, J. (2010): “Desegregation and the Achievement Gap: Do Diverse Peers Help?” *Unpublished manuscript. Department of Economics, University of Wisconsin at Madison.*
- CORNAGLIA, F., E. CRIVELLARO, AND S. McNALLY (2015): “Mental health and education decisions,” *Labour Economics*, 33, 1–12.
- CORNAH, D. (2006): “Cheers? Understanding the relationship between alcohol and mental health,” *Mental Health Foundation.*
- DE SILVA, M. J., K. MCKENZIE, T. HARPHAM, AND S. R. HUTTLY (2005): “Social capital and mental illness: a systematic review,” *Journal of epidemiology & community health*, 59, 619–627.
- DISHION, T. J. AND J. M. TIPSORD (2011): “Peer contagion in child and adolescent social and emotional development,” *Annual review of psychology*, 62, 189.

- DOMINGUE, B. W. AND D. W. BELSKY (2017): “The social genome: Current findings and implications for the study of human genetics,” *PLoS genetics*, 13, e1006615.
- EAGLY, A. H. (1978): “Sex differences in influenceability,” *Psychological Bulletin*, 85, 86.
- EHSAN, A., H. S. KLAAS, A. BASTIANEN, AND D. SPINI (2019): “Social capital and health: A systematic review of systematic reviews,” *SSM-population health*, 8, 100425.
- EISENBERG, D., E. GOLBERSTEIN, AND J. L. WHITLOCK (2014): “Peer effects on risky behaviors: New evidence from college roommate assignments,” *Journal of health economics*, 33, 126–138.
- EISENBERG, D., E. GOLBERSTEIN, J. L. WHITLOCK, AND M. F. DOWNS (2013): “Social contagion of mental health: evidence from college roommates,” *Health Economics*, 22, 965–986.
- FLETCHER, J. (2013): “Adolescent depression and adult labor market outcomes,” *Southern Economic Journal*, 80, 26–49.
- FLETCHER, J. M. (2010): “Adolescent depression and educational attainment: results using sibling fixed effects,” *Health economics*, 19, 855–871.
- FOWLER, J. H. AND N. A. CHRISTAKIS (2008): “Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study,” *Bmj*, 337.
- FRIEDMAN, A. S. (2020): “Smoking to cope: Addictive behavior as a response to mental distress,” *Journal of Health Economics*, 72, 102323.
- GART, R. AND S. KELLY (2015): “How illegal drug use, alcohol use, tobacco use, and depressive symptoms affect adolescent suicidal ideation: A secondary analysis of the 2011 youth risk behavior survey,” *Issues in mental health nursing*, 36, 614–620.
- GIULIETTI, C., M. VLASSOPOULOS, AND Y. ZENOU (2022): “Peers, gender, and long-term depression,” *European Economic Review*, 144, 104084.
- GONG, J., Y. LU, AND H. XIE (2020): “The average and distributional effects of teenage adversity on long-term health,” *Journal of health economics*, 71, 102288.
- GREENE, S. AND P. VOSTANIS (2007): “Genes and Behaviour: Nature-nurture Interplay Explained,” *Journal of Children’s Services*.

- GURYAN, J., K. KROFT, AND M. J. NOTOWIDIGDO (2009): “Peer effects in the workplace: Evidence from random groupings in professional golf tournaments,” *American Economic Journal: Applied Economics*, 1, 34–68.
- HAMM, J. V. AND B. S. FAIRCLOTH (2005): “The role of friendship in adolescents’ sense of school belonging,” *New Directions for child and adolescent development*, 2005, 61–78.
- HAN, L. AND T. LI (2009): “The gender difference of peer influence in higher education,” *Economics of Education review*, 28, 129–134.
- HANUSHEK, E. A., J. F. KAIN, J. M. MARKMAN, AND S. G. RIVKIN (2003): “Does peer ability affect student achievement?” *Journal of applied econometrics*, 18, 527–544.
- HELLWEGE, J. N., J. M. KEATON, A. GIRI, X. GAO, D. R. VELEZ EDWARDS, AND T. L. EDWARDS (2017): “Population stratification in genetic association studies,” *Current protocols in human genetics*, 95, 1–22.
- HILT, L. M., K. A. McLAUGHLIN, AND S. NOLEN-HOEKSEMA (2010): “Examination of the response styles theory in a community sample of young adolescents,” *Journal of Abnormal Child Psychology*, 38, 545–556.
- HOWARD, D. M., M. J. ADAMS, T.-K. CLARKE, J. D. HAFFERTY, J. GIBSON, M. SHIRALI, J. R. COLEMAN, S. P. HAGENAARS, J. WARD, E. M. WIGMORE, ET AL. (2019): “Genome-wide meta-analysis of depression identifies 102 independent variants and highlights the importance of the prefrontal brain regions,” *Nature neuroscience*, 22, 343–352.
- HOXBY, C. M. (2000): “Peer effects in the classroom: Learning from gender and race variation,” .
- HOXBY, C. M. AND G. WEINGARTH (2005): “Taking race out of the equation: School reassignment and the structure of peer effects,” Tech. rep., Citeseer.
- IMBERMAN, S. A., A. D. KUGLER, AND B. I. SACERDOTE (2012): “Katrina’s children: Evidence on the structure of peer effects from hurricane evacuees,” *American Economic Review*, 102, 2048–82.
- IRWIN, M., K. H. ARTIN, AND M. N. OXMAN (1999): “Screening for depression in the older adult: criterion validity of the 10-item Center for Epidemiological Studies Depression Scale (CES-D),” *Archives of internal medicine*, 159, 1701–1704.

- JANE-LLOPIS, E. AND I. MATYTSINA (2006): “Mental health and alcohol, drugs and tobacco: a review of the comorbidity between mental disorders and the use of alcohol, tobacco and illicit drugs,” *Drug and alcohol review*, 25, 515–536.
- JOHNSON, D., G. DUPUIS, J. PICHE, Z. CLAYBORNE, AND I. COLMAN (2018): “Adult mental health outcomes of adolescent depression: A systematic review,” *Depression and anxiety*, 35, 700–716.
- JOHNSON, D. P. AND M. A. WHISMAN (2013): “Gender differences in rumination: A meta-analysis,” *Personality and individual differences*, 55, 367–374.
- KEITH, D. R., C. L. HART, M. P. MCNEIL, R. SILVER, AND R. D. GOODWIN (2015): “Frequent marijuana use, binge drinking and mental health problems among undergraduates,” *The American Journal on Addictions*, 24, 499–506.
- KING, A. R., T. D. RUSSELL, AND A. C. VEITH (2016): “Friendship and mental health functioning,” *The psychology of friendship*, 249.
- KING, A. R. AND C. TERRANCE (2008): “Best friendship qualities and mental health symptomatology among young adults,” *Journal of Adult Development*, 15, 25–34.
- KONG, A., G. THORLEIFSSON, M. L. FRIGGE, B. J. VILHJALMSSON, A. I. YOUNG, T. E. THORGEIRSSON, S. BENONISDOTTIR, A. ODDSSON, B. V. HALLDORSSON, G. MASSON, ET AL. (2018): “The nature of nurture: Effects of parental genotypes,” *Science*, 359, 424–428.
- LAVY, V., M. D. PASERMAN, AND A. SCHLOSSER (2012): “Inside the black box of ability peer effects: Evidence from variation in the proportion of low achievers in the classroom,” *The Economic Journal*, 122, 208–237.
- LAVY, V. AND A. SCHLOSSER (2011): “Mechanisms and impacts of gender peer effects at school,” *American Economic Journal: Applied Economics*, 3, 1–33.
- LAYARD, R. (2013): “Mental health: the new frontier for labour economics,” *IZA Journal of Labor Policy*, 2, 1–16.
- LEWIS, A. J., P. KREMER, K. DOUGLAS, J. W. TOUMBOROU, M. A. HAMEED, G. C. PATTON, AND J. WILLIAMS (2015): “Gender differences in adolescent depression: Differential female susceptibility to stressors affecting family functioning,” *Australian Journal of Psychology*, 67, 131–139.

- LIPARI, R. N. AND S. VAN HORN (2017): “Smoking and mental illness among adults in the United States,” *The CBHSQ report*.
- LUNDBORG, P. (2006): “Having the wrong friends? Peer effects in adolescent substance use,” *Journal of health economics*, 25, 214–233.
- LUNDBORG, P., A. NILSSON, AND D.-O. ROTH (2014): “Adolescent health and adult labor market outcomes,” *Journal of Health Economics*, 37, 25–40.
- MANSKI, C. F. (1993): “Identification of endogenous social effects: The reflection problem,” *The review of economic studies*, 60, 531–542.
- MARTIN, A. R., C. R. GIGNOUX, R. K. WALTERS, G. L. WOJCIK, B. M. NEALE, S. GRAVEL, M. J. DALY, C. D. BUSTAMANTE, AND E. E. KENNY (2017): “Human demographic history impacts genetic risk prediction across diverse populations,” *The American Journal of Human Genetics*, 100, 635–649.
- MARTIN, A. R., M. KANAI, Y. KAMATANI, Y. OKADA, B. M. NEALE, AND M. J. DALY (2019): “Clinical use of current polygenic risk scores may exacerbate health disparities,” *Nature genetics*, 51, 584–591.
- MCPHERSON, K. E., S. KERR, E. MCGEE, A. MORGAN, F. M. CHEATER, J. MCLEAN, AND J. EGAN (2014): “The association between social capital and mental health and behavioural problems in children and adolescents: an integrative systematic review,” *BMC psychology*, 2, 1–16.
- MINTON, H. AND F. SCHNEIDER (1980): “Differential Psychology Waveland Press,” *Prospect Heights*.
- MIROWSKY, J. (1996): “Age and the gender gap in depression,” *Journal of health and social behavior*, 362–380.
- MOUSTERI, V., M. DALY, L. DELANEY, P. TYNELIUS, AND F. RASMUSSEN (2019): “Adolescent mental health and unemployment over the lifespan: population evidence from Sweden,” *Social Science & Medicine*, 222, 305–314.
- NARR, R. K., J. P. ALLEN, J. S. TAN, AND E. L. LOEB (2019): “Close friendship strength and broader peer group desirability as differential predictors of adult mental health,” *Child development*, 90, 298–313.



- NIDA (2021): “Is there a link between marijuana use and psychiatric disorders?” <https://nida.nih.gov/publications/research-reports/marijuana/there-link-between-marijuana-use-psychiatric-disorders>.
- NIMH (2020): “Looking at My Genes: What can they tell me about my mental health?” Tech. rep., National Institute of Mental Health.
- NOLEN-HOEKSEMA, S. (1987): “Sex differences in unipolar depression: evidence and theory.” *Psychological bulletin*, 101, 259.
- (1991): “Responses to depression and their effects on the duration of depressive episodes.” *Journal of abnormal psychology*, 100, 569.
- OLIVETTI, C., E. PATACCHINI, AND Y. ZENOU (2020): “Mothers, peers, and gender-role identity,” *Journal of the European Economic Association*, 18, 266–301.
- PAPAGEORGE, N. W. AND K. THOM (2020): “Genes, education, and labor market outcomes: Evidence from the health and retirement study,” *Journal of the European Economic Association*, 18, 1351–1399.
- PATTEN, C. A., W. S. CHOI, K. S. VICKERS, AND J. P. PIERCE (2001): “Persistence of depressive symptoms in adolescents,” *Neuropsychopharmacology*, 25, S89–S91.
- PICCINELLI, M. AND G. WILKINSON (2000): “Gender differences in depression: Critical review,” *The British Journal of Psychiatry*, 177, 486–492.
- PIENIAZEK, J. R. (2022): “High, But Not Happy? The Impact of Cannabis Consumption on Mental Health,” Ph.D. thesis, Miami University.
- PLURPHANSWAT, N., R. KAESTNER, AND B. RODU (2017): “The effect of smoking on mental health,” *American journal of health behavior*, 41, 471–483.
- PRICE, A. L., N. J. PATTERSON, R. M. PLENGE, M. E. WEINBLATT, N. A. SHADICK, AND D. REICH (2006): “Principal components analysis corrects for stratification in genome-wide association studies,” *Nature genetics*, 38, 904–909.
- PROCHASKA, J. J. (2011): “Smoking and mental illness—breaking the link,” *New England Journal of Medicine*, 365, 196–198.

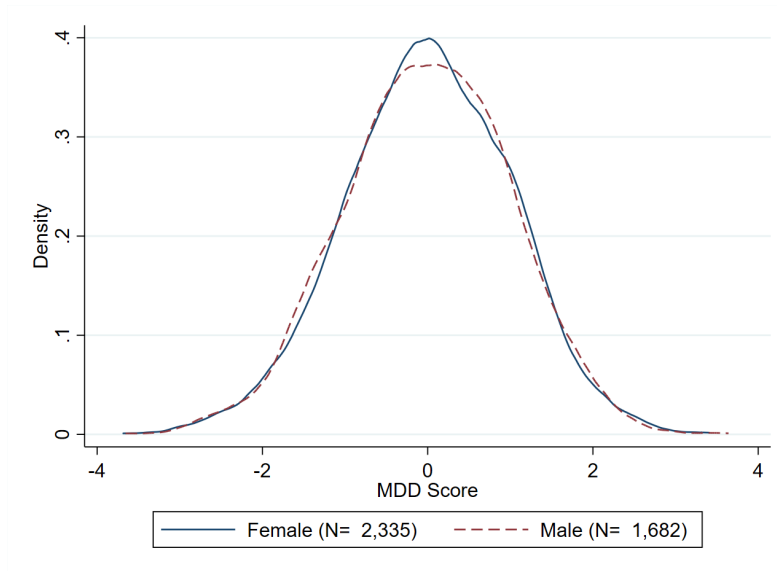
- RADLOFF, L. S. (1977): “The CES-D scale: A self-report depression scale for research in the general population,” *Applied psychological measurement*, 1, 385–401.
- (1991): “The use of the Center for Epidemiologic Studies Depression Scale in adolescents and young adults,” *Journal of youth and adolescence*, 20, 149–166.
- REISMAN, J. M. (1985): “Friendship and its implications for mental health or social competence,” *The Journal of Early Adolescence*, 5, 383–391.
- RICHARDSON, T. ET AL. (2010): “Cannabis use and mental health: a review of recent epidemiological research,” *International Journal of Pharmacology*, 6, 796–807.
- RODRÍGUEZ-PLANAS, N., A. SANZ-DE GALDEANO, AND A. TERSKAYA (2018): “Independent Thinking and Hard Working, or Caring and Well Behaved? Short-and Long-Term Impacts of Gender Identity Norms,” .
- ROSENQUIST, J. N., J. H. FOWLER, AND N. A. CHRISTAKIS (2011): “Social network determinants of depression,” *Molecular psychiatry*, 16, 273–281.
- RUDOLPH, K. D. (2002): “Gender differences in emotional responses to interpersonal stress during adolescence,” *Journal of adolescent health*, 30, 3–13.
- SACERDOTE, B. (2011): “Peer effects in education: How might they work, how big are they and how much do we know thus far?” in *Handbook of the Economics of Education*, Elsevier, vol. 3, 249–277.
- SALK, R. H., J. S. HYDE, AND L. Y. ABRAMSON (2017): “Gender differences in depression in representative national samples: Meta-analyses of diagnoses and symptoms.” *Psychological bulletin*, 143, 783.
- SALOKANGAS, H. (2021): “Exploring the labor market consequences of psychiatric disorders: An event study approach,” *Available at SSRN 3967949*.
- SANTINI, Z. I., A. KOYANAGI, S. TYROVOLAS, C. MASON, AND J. M. HARO (2015): “The association between social relationships and depression: a systematic review,” *Journal of affective disorders*, 175, 53–65.
- SCHWARTZ-METTE, R. A. AND R. L. SMITH (2018): “When does co-rumination facilitate depression contagion in adolescent friendships? Investigating intrapersonal and interpersonal factors,” *Journal of Clinical Child & Adolescent Psychology*, 47, 912–924.

- SERAFINI, G., M. POMPILI, M. INNAMORATI, E. C. TEMPLE, M. AMORE, S. BORGBARDT, AND P. GIRARDI (2013): “The association between cannabis use, mental illness, and suicidal behavior: what is the role of hopelessness?” *Frontiers in Psychiatry*, 4, 125.
- SIAS, P. M. AND H. BARTOO (2007): “Friendship, social support, and health,” in *Low-cost approaches to promote physical and mental health*, Springer, 455–472.
- SOTOUDEH, R., K. M. HARRIS, AND D. CONLEY (2019): “Effects of the peer metagenomic environment on smoking behavior,” *Proceedings of the National Academy of Sciences*, 116, 16302–16307.
- STAPINSKI, L. A., A. C. EDWARDS, M. HICKMAN, R. ARAYA, M. TEESON, N. C. NEWTON, K. S. KENDLER, AND J. HERON (2016): “Drinking to cope: A latent class analysis of coping motives for alcohol use in a large cohort of adolescents,” *Prevention science*, 17, 584–594.
- SUGLIA, S. F., R. T. DEMMER, R. WAHI, K. M. KEYES, AND K. C. KOENEN (2016): “Depressive symptoms during adolescence and young adulthood and the development of type 2 diabetes mellitus,” *American Journal of Epidemiology*, 183, 269–276.
- SWENDSEN, J., K. P. CONWAY, L. DEGENHARDT, M. GLANTZ, R. JIN, K. R. MERIKANGAS, N. SAMPSON, AND R. C. KESSLER (2010): “Mental disorders as risk factors for substance use, abuse and dependence: results from the 10-year follow-up of the National Comorbidity Survey,” *Addiction*, 105, 1117–1128.
- TAYLOR, G., A. MCNEILL, A. GIRLING, A. FARLEY, N. LINDSON-HAWLEY, AND P. AVEYARD (2014): “Change in mental health after smoking cessation: systematic review and meta-analysis,” *Bmj*, 348.
- TAYLOR, G. M., N. LINDSON, A. FARLEY, A. LEINBERGER-JABARI, K. SAWYER, R. TE WATER NAUDÉ, A. THEODOULOU, N. KING, C. BURKE, AND P. AVEYARD (2021): “Smoking cessation for improving mental health,” *Cochrane Database of Systematic Reviews*.
- UENO, K. (2005): “The effects of friendship networks on adolescent depressive symptoms,” *Social Science Research*, 34, 484–510.
- VAN OURS, J. C. AND J. WILLIAMS (2011): “Cannabis use and mental health problems,” *Journal of Applied Econometrics*, 26, 1137–1156.
- (2012): “The effects of cannabis use on physical and mental health,” *Journal of Health Economics*, 31, 564–577.

- (2015): “Cannabis use and its effects on health, education and labor market success,” *Journal of Economic Surveys*, 29, 993–1010.
- VAN OURS, J. C., J. WILLIAMS, D. FERGUSON, AND L. J. HORWOOD (2013): “Cannabis use and suicidal ideation,” *Journal of Health Economics*, 32, 524–537.
- WARE, E., L. SCHMITZ, J. FAUL, A. GARD, J. SMITH, C. MITCHELL, D. WEIR, AND S. KARDIA (2017): “Method of construction affects polygenic score prediction of common human traits,” *BiorXiv*, 1–13.
- WEISSMAN, M. M., D. SHOLOMSKAS, M. POTTINGER, B. A. PRUSOFF, AND B. Z. LOCKE (1977): “Assessing depressive symptoms in five psychiatric populations: a validation study,” *American journal of epidemiology*, 106, 203–214.
- ZHANG, A. (2019): “Peer effects on mental health: Evidence from random assignment into classrooms,” *Available at SSRN 3685374*.

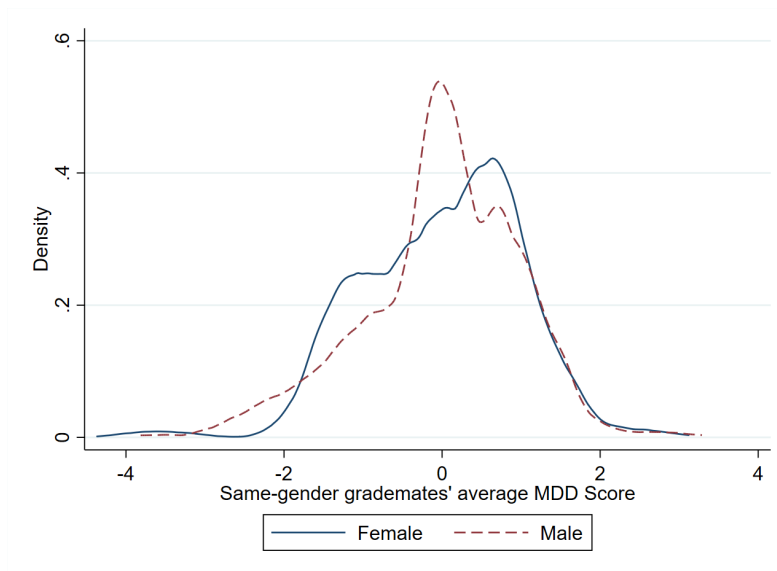
## Figures and Tables

Figure 1: Individual MDD Score Distribution



Note: This figure displays the distribution of the individual MDD score separately for males (dashed line) and females (solid line).

Figure 2: Same-Gender Grademates' Average MDD Score Distribution



Note: This figure displays the distribution of same-gender grademates' average MDD score separately for males (dashed line) and females (solid line).

Table 1: Summary Statistics

	Females		Males		<i>p</i> -value
	Mean	N	Mean	N	
<i>Demographics:</i>					
Age in Wave I	15.51 (1.66)	2,335	15.80 (1.59)	1,682	0.00
Age in Wave II	16.13 (1.54)	1,786	16.45 (1.52)	1,267	0.00
Age in Wave III	21.84 (1.68)	2,040	22.16 (1.60)	1,384	0.00
Age in Wave IV	28.39 (1.70)	2,331	28.71 (1.65)	1,680	0.00
Age in Wave V	37.36 (1.83)	1,791	37.71 (1.75)	1,058	0.00
Race: White	0.63	2,335	0.64	1,682	0.41
Race: Black or African-American	0.24	2,335	0.18	1,682	0.00
Race: Asian or Pacific Islander	0.05	2,335	0.09	1,682	0.00
Race: Other	0.07	2,335	0.09	1,682	0.03
Ethnicity: Hispanic	0.10	2,335	0.14	1,682	0.00
<i>Family and Parental Characteristics in Wave I:</i>					
Mother's edu: Missing	0.08	2,335	0.10	1,682	0.18
Mother's edu: High school/some college	0.53	2,335	0.52	1,682	0.84
Mother's edu: College degree or above	0.23	2,335	0.25	1,682	0.11
Mother's occ: Missing	0.05	2,335	0.05	1,682	0.85
Mother's occ: Managerial/professional	0.23	2,335	0.24	1,682	0.45
Mother's occ: Technical/office/sales	0.25	2,335	0.26	1,682	0.25
Mother's occ: Blue collar	0.33	2,335	0.32	1,682	0.20
Father not present	0.31	2,335	0.25	1,682	0.00
Number of siblings	1.47 (1.21)	2,335	1.46 (1.15)	1,682	0.86
Household income (imputed, thousands dollars)	44.47 (39.55)	2,335	44.53 (29.07)	1,682	0.96
<i>Depression Measures:</i>					
Depressed (CESD-10 $\geq$ 11) in Wave I	0.26	2,335	0.15	1,682	0.00
Depressed (CESD-10 $\geq$ 11) in Wave II	0.25	1,786	0.15	1,267	0.00
Depressed (CESD-10 $\geq$ 11) in Wave IV	0.21	2,331	0.12	1,680	0.00
Suicidal ideation in Wave I	0.16	2,327	0.11	1,671	0.00
Suicidal ideation in Wave II	0.13	1,783	0.08	1,261	0.00
Suicidal ideation in Wave IV	0.08	2,327	0.07	1,665	0.24
Suicidal ideation in Wave V	0.08	1,750	0.07	1,036	0.52
Suicidal attempt in Wave I	0.05	2,327	0.02	1,671	0.00
Suicidal attempt in Wave II	0.05	1,783	0.02	1,261	0.00
Suicidal attempt in Wave IV	0.01	2,328	0.02	1,665	0.19
Suicidal attempt in Wave V	0.02	1,751	0.01	1,035	0.46
Ever diagnosed with depression in Wave III	0.14	2,039	0.07	1,383	0.00
Ever diagnosed with depression in Wave IV	0.21	2,331	0.10	1,680	0.00
Ever diagnosed with depression in Wave V	0.30	1,786	0.17	1,054	0.00
Antidepressant use in Wave III	0.07	2,039	0.02	1,382	0.00
Antidepressant use in Wave IV	0.08	2,323	0.04	1,675	0.00
Antidepressant use in Wave V	0.14	1,783	0.07	1,054	0.00

Note: This table shows summary statistics separately for the female and male samples. Demographics and family and parental characteristics are measured in Wave I. The last column includes *p*-values from the test of equality of means across the female and male samples.

Table 2: Standard Deviation of Same-Gender Peers' Average MDD Score

	Females	Males
	SD	SD
Same-gender grademates' average MDD score	1.002	1.001
Same-gender grademates' average MDD score residualized after removing school FE and grade FE	0.740	0.765
Same-gender grademates' average MDD score residualized after removing school FE, grade FE, and school-grade	0.708	0.734
N	2,335	1,682

Note: The first row of this table reports the standard deviation of same-gender grademates' average MDD score by gender. The second row shows the standard deviation of residualized same-gender grademates' average MDD score after controlling for school and grade fixed effects. In row 3, I additionally control for school-grade level controls.



Table 3: Balancing Tests

	Females		Males	
MDD PGS	-0.381***	(0.109)	-0.557***	(0.128)
Age in months	-0.247	(0.265)	-0.254	(0.481)
Race: White	0.003	(0.017)	-0.025	(0.022)
Race: Black	0.006	(0.013)	0.015	(0.015)
Race: Asian	0.009	(0.007)	0.009	(0.010)
Hispanic	-0.010	(0.010)	-0.003	(0.009)
Number of siblings	0.036	(0.030)	-0.013	(0.045)
Father not in household	-0.012	(0.020)	-0.004	(0.029)
Household income (imputed)	2.066	(2.142)	-0.460	(1.186)
Household income (missing)	0.026**	(0.011)	-0.018	(0.013)
Mother's edu: Missing	-0.017	(0.012)	-0.017	(0.017)
Mother's edu: High school graduate/some college	0.009	(0.022)	0.030	(0.039)
Mother's edu: College graduate and above	0.007	(0.018)	-0.004	(0.037)
Mother's occ: Missing	-0.015	(0.010)	-0.031**	(0.012)
Mother's occ: Managerial/professional	0.012	(0.023)	0.018	(0.023)
Mother's occ: Technical/office/sales	-0.006	(0.018)	0.023	(0.025)
Mother's occ: Blue collar	0.019	(0.026)	0.020	(0.030)
PC1	-0.001	(0.000)	-0.000	(0.001)
PC2	-0.001	(0.001)	0.001	(0.000)
PC3	-0.000	(0.001)	0.000	(0.001)
PC4	-0.000	(0.001)	0.000	(0.001)
PC5	0.000	(0.001)	-0.001	(0.001)
PC6	0.000	(0.001)	-0.000	(0.001)
PC7	0.000	(0.001)	0.000	(0.001)
PC8	-0.001	(0.001)	-0.001	(0.001)
PC9	-0.000	(0.000)	-0.001	(0.001)
PC10	0.001	(0.001)	0.001***	(0.000)
N	2,335		1,682	

Note: Each row includes coefficients from a separate regression of a covariate on same-gender grademates' average MDD score conditional on school and grade fixed effects, and school-grade level controls. Standard errors are clustered at the school level and included in parenthesis. All individual and family level characteristics are measured in Wave I, and all genetic information (i.e., MDD PGS and PC1-10) is collected in Wave IV. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 4: Effect of Same-Gender Grademates' and Own MDD Score on Mental Health in Wave I

	Depressed (CES-D-10 $\geq$ 11)							
	Females				Males			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same-Gender Grademates' Average MDD Score	-0.004 (0.009)	0.017* (0.009)	0.025** (0.011)	0.023** (0.010)	0.001 (0.009)	0.024 (0.015)	0.031* (0.016)	0.030** (0.015)
Own MDD Score	0.019** (0.008)	0.023*** (0.008)	0.023** (0.009)	0.018** (0.009)	0.006 (0.010)	0.012 (0.010)	0.014 (0.010)	0.013 (0.010)
Principal Components	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School and Grade FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School-Grade Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Individual Controls	No	No	Yes	Yes	No	No	Yes	Yes
Family and Parental Controls	No	No	No	Yes	No	No	No	Yes
Mean	0.262	0.262	0.262	0.262	0.150	0.150	0.150	0.150
N	2,335	2,335	2,335	2,335	1,682	1,682	1,682	1,682
$R^2$	0.005	0.069	0.112	0.132	0.007	0.060	0.132	0.147

Note: The outcome is an indicator for being depressed (i.e., CES-D-10  $\geq$  11) or not in Wave I and each column includes separate regression results from various specifications. Columns (1)-(4) and (5)-(8) present the point estimates for females and males, respectively. In columns (1) and (5), I show results after controlling for the 10 genetic principal components. Then, I add school and grade fixed effects and school-grade level controls (columns 2, 6). Next, I include a set of individual controls in columns (3) and (7). Then, I add a set of family and parental controls (columns 4, 8). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 5: Effect of Same-Gender Grademates' and Own MDD Score on Mental Health in Wave IV

	Depressed (CES-D-10 $\geq$ 11)							
	Females				Males			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same-Gender Grademates' Average MDD Score	0.007 (0.009)	0.029** (0.013)	0.029** (0.013)	0.029** (0.013)	0.009 (0.007)	0.019** (0.009)	0.018* (0.010)	0.016 (0.010)
Own MDD Score	0.022*** (0.007)	0.027*** (0.007)	0.026*** (0.007)	0.024*** (0.007)	0.006 (0.007)	0.008 (0.007)	0.010* (0.006)	0.010 (0.006)
Principal Components	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School and Grade FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School-Grade Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Individual Controls	No	No	Yes	Yes	No	No	Yes	Yes
Family and Parental Controls	No	No	No	Yes	No	No	No	Yes
Mean	0.206	0.206	0.206	0.206	0.124	0.124	0.124	0.124
N	2,331	2,331	2,331	2,331	1,680	1,680	1,680	1,680
$R^2$	0.010	0.066	0.109	0.119	0.004	0.061	0.106	0.125

Note: The outcome is an indicator for being depressed (i.e., CES-D-10  $\geq$  11) or not in Wave IV, and each column includes separate regression results from various specifications. Columns (1)-(4) and (5)-(8) present the point estimates for females and males, respectively. In columns (1) and (5), I show results after controlling for the 10 genetic principal components. Then, I add school and grade fixed effects and school-grade level controls (columns 2,6). Next, I include a set of individual controls in columns (3) and (7). Then, I add a set of family and parental controls (columns 4, 8). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 6: Effect of Same-Gender Grademates' and Own MDD Score on Friendship in Wave I

	During the Past Week or Weekend					
	Visit		Hang out		Spend	
	Friends' Home		After School		Time Together	
	(1)	(2)	(3)	(4)	(5)	(6)
	Females	Males	Females	Males	Females	Males
Same-Gender Grademates' Average MDD Score	-0.022* (0.013)	-0.011 (0.017)	-0.032** (0.015)	-0.021 (0.013)	-0.004 (0.019)	-0.047*** (0.016)
Own MDD Score	-0.012 (0.011)	-0.008 (0.013)	0.004 (0.009)	0.002 (0.010)	0.001 (0.010)	-0.010 (0.011)
Mean	0.599	0.690	0.651	0.700	0.632	0.687
N	2,277	1,637	2,277	1,636	2,277	1,637
$R^2$	0.165	0.189	0.154	0.187	0.145	0.167

Note: The outcome variable in columns (1) and (2) is an indicator for whether respondents visit one or more of their nominated friends' houses during the past week. The outcome variable in columns (3) and (4) is an indicator for whether respondents hang out with one or more of their nominated friends during the past week. The outcome variable in columns (5) and (6) is an indicator variable for whether respondents spend time with one or more of their nominated friends during the past weekend. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 7: Effect of Same-Gender Grademates' and Own MDD Score on Friendship in Waves III or IV

	Wave III						Wave IV			
	Number of High School Friends Still Friends With						Number of Close Friends			
	Times Hang Out During Past Week		Most or More		All		3 to 5 Friends or More		6 to 9 Friends or More	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males
Same-Gender Grademates' Average MDD Score	-0.149** (0.068)	-0.205* (0.104)	-0.331 (0.512)	-0.658 (0.946)	-0.542** (0.258)	0.750** (0.332)	0.004 (0.017)	-0.009 (0.021)	-0.039** (0.016)	-0.028* (0.015)
Own MDD Score	-0.146*** (0.047)	0.035 (0.066)	-0.094 (0.154)	-0.256 (0.278)	-0.139* (0.074)	0.229** (0.098)	-0.010 (0.009)	-0.006 (0.010)	-0.027*** (0.010)	-0.004 (0.011)
Mean	4.322	4.214	0.283	0.474	0.046	0.052	0.714	0.745	0.235	0.316
N	2,034	1,380	389	232	389	232	2,298	1,651	2,298	1,651
R <sup>2</sup>	0.150	0.212	0.284	0.463	0.266	0.577	0.169	0.150	0.142	0.123

Note: Columns (1)-(6) and (7)-(10) contain results from Waves III and IV, respectively. The outcome variable in columns (1)-(2) is the frequency of hanging out with friends or talking on the phone during the past week. The outcome variables in columns (3)-(4) and (5)-(6) are indicator variables for whether the number of high school friends that respondents still have as adults is “most or more” and “all”, respectively. The outcomes in columns (7)-(8) and (9)-(10) are indicator variables for whether the number of close friends is 3 to 5 friends or more and 6 to 9 friends or more, respectively. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 8: Effect of Same-Gender Grademates' and Own MDD Score on Alcohol Use in Wave I

	During the Past 12 Months					
	Once a Month or More		2 or 3 Days a Month or More		1-2 Days a Week or More	
	Panel A: Days Drink Alcohol					
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.019 (0.018)	-0.002 (0.012)	0.025* (0.013)	0.012 (0.018)	0.012** (0.006)	0.001 (0.014)
Own MDD Score	0.014 (0.010)	0.020* (0.010)	0.010 (0.009)	0.010 (0.010)	0.006 (0.006)	0.009 (0.008)
Mean	0.272	0.322	0.148	0.199	0.067	0.117
N	2,324	1,672	2,324	1,672	2,324	1,672
R <sup>2</sup>	0.176	0.197	0.157	0.188	0.117	0.159
Panel B: Days Drink 5 or More Drinks in a Row						
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.028** (0.012)	0.014 (0.013)	0.024** (0.010)	0.026** (0.011)	0.011** (0.006)	0.006 (0.008)
Own MDD Score	0.005 (0.009)	0.005 (0.015)	0.004 (0.008)	0.004 (0.010)	0.002 (0.004)	-0.005 (0.006)
Mean	0.130	0.213	0.076	0.144	0.039	0.084
N	2,321	1,667	2,321	1,667	2,321	1,667
R <sup>2</sup>	0.150	0.193	0.129	0.179	0.110	0.149
Panel C: Days Get Drunk						
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.018 (0.013)	0.009 (0.013)	0.004 (0.008)	0.012 (0.011)	-0.005 (0.005)	-0.000 (0.009)
Own MDD Score	-0.000 (0.008)	0.010 (0.010)	-0.005 (0.007)	-0.005 (0.008)	-0.004 (0.004)	0.001 (0.006)
Mean	0.125	0.188	0.071	0.118	0.029	0.064
N	2,322	1,667	2,322	1,667	2,322	1,667
R <sup>2</sup>	0.177	0.174	0.124	0.174	0.092	0.153

Note: The outcome variable in columns (1) and (2) is an indicator variable for whether an individual used alcohol once a month or more during the past year in Wave I. The outcomes in columns (3)-(4) and (5)-(6) are created similarly for two or three days a month and one or two days a week, respectively. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 9: Effect of Same-Gender Grademates' and Own MDD Score on Alcohol Use Wave IV

	During the Past 12 Months					
	Once a Month or More	2 or 3 Days a Month or More	1-2 Days a Week or More			
	Panel A: Days Drink Alcohol					
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.045*** (0.015)	-0.041** (0.016)	0.029* (0.016)	-0.035* (0.019)	0.024* (0.015)	0.008 (0.015)
Own MDD Score	-0.011 (0.010)	-0.009 (0.011)	0.001 (0.011)	-0.017 (0.012)	0.009 (0.008)	-0.019 (0.012)
Mean	0.536	0.684	0.355	0.548	0.196	0.378
N	2,322	1,671	2,322	1,671	2,322	1,671
R <sup>2</sup>	0.188	0.203	0.168	0.170	0.146	0.165
Panel B: Days Drink 5 or More Drinks in a Row						
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.030** (0.013)	-0.042** (0.018)	0.003 (0.009)	-0.026 (0.022)	0.010 (0.008)	0.007 (0.013)
Own MDD Score	0.002 (0.009)	0.003 (0.013)	0.001 (0.008)	0.001 (0.015)	-0.002 (0.006)	0.012 (0.010)
Mean	0.225	0.373	0.135	0.254	0.061	0.157
N	2,319	1,667	2,319	1,667	2,319	1,667
R <sup>2</sup>	0.139	0.173	0.112	0.145	0.098	0.118
Panel C: Days Get Drunk						
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.029** (0.011)	-0.061*** (0.019)	0.013* (0.007)	-0.037** (0.018)	0.008 (0.006)	-0.007 (0.012)
Own MDD Score	0.004 (0.007)	-0.014 (0.014)	0.005 (0.005)	-0.011 (0.011)	0.005 (0.004)	-0.001 (0.008)
Mean	0.174	0.333	0.082	0.190	0.035	0.099
N	2,320	1,669	2,320	1,669	2,320	1,669
R <sup>2</sup>	0.156	0.187	0.123	0.158	0.091	0.132

Note: The outcome variable in columns (1) and (2) is an indicator variable for whether an individual used alcohol once a month or more during the past year in Wave IV. The outcomes in columns (3)-(4) and (5)-(6) are created similarly for two or three days a month and one or two days a week, respectively. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table 10: Effect of Same-Gender Grademates' and Own MDD Score on Tobacco Use in Waves I and IV

	Conditional on Smoking					
	Have Ever Smoked Regularly		CPD During Past 30 Days		Quit Attempt During Past 6 months	
	Panel A: Wave I					
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	-0.006 (0.013)	0.014 (0.012)	0.064 (0.536)	0.279 (1.287)	0.009 (0.036)	-0.195*** (0.054)
Own MDD Score	0.008 (0.008)	0.007 (0.009)	-0.128 (0.288)	0.540 (0.372)	0.004 (0.023)	-0.030 (0.024)
Mean	0.197	0.205	5.982	7.278	0.554	0.546
N	2,330	1,672	611	442	632	463
R <sup>2</sup>	0.206	0.177	0.373	0.361	0.359	0.426
Panel B: Wave IV						
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	0.002 (0.015)	0.006 (0.013)	0.170 (0.557)	0.797 (1.121)	0.028 (0.023)	-0.013 (0.046)
Own MDD Score	-0.002 (0.009)	0.017 (0.014)	-0.361 (0.437)	-0.347 (0.462)	0.040** (0.019)	-0.004 (0.021)
Mean	0.425	0.497	10.320	12.078	0.827	0.743
N	2,326	1,673	779	682	713	482
R <sup>2</sup>	0.202	0.168	0.334	0.378	0.308	0.380

Note: Panels A and B reports results from Waves I and IV, respectively. The outcome variable in columns (1) and (2) is an indicator variable for whether one has ever smoked. In columns (3) and (4), the outcome variable is the number of cigarettes smoked per day during the past month conditional on smoking. The outcome variable in columns (5) and (6) is an indicator variable for whether one attempts to quit smoking in the past 6 months conditional on smoking. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .



Table 11: Effect of Same-Gender Grademates' and Own MDD Score on Marijuana Use

	During the Past 30 Days							
	Wave I		Wave IV: Days Used Marijuana					
	Times ( $\geq 0$ ) Used Marijuana		Once a Month or More		Two or Three Days a Month or More		One or Two Days a Week or More	
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males	(7) Females	(8) Males
Same-gender Grademates' Average MDD Score	0.212* (0.118)	-0.797 (0.713)	0.008 (0.008)	-0.021 (0.015)	0.011 (0.007)	-0.011 (0.016)	0.011 (0.007)	-0.008 (0.015)
Own MDD Score	0.241** (0.093)	-0.004 (0.370)	0.008 (0.005)	-0.016 (0.010)	0.009* (0.005)	-0.006 (0.009)	0.007 (0.005)	-0.008 (0.008)
Mean	0.866	2.763	0.094	0.172	0.074	0.146	0.066	0.134
N	2,314	1,653	2,323	1,670	2,323	1,670	2,323	1,670
$R^2$	0.130	0.157	0.108	0.145	0.098	0.142	0.099	0.143

Note: The outcome variable in columns (1) and (2) is the number of times the respondent used marijuana during the past month in Wave I. In columns (3) and (4), the outcome variable is an indicator variable for whether an individual used marijuana once a month or more during the past 30 days in Wave IV. The outcomes in columns (5)-(6) and (7)-(8) are created similarly for two or three days a month and one or two days a week, respectively, in Wave IV. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

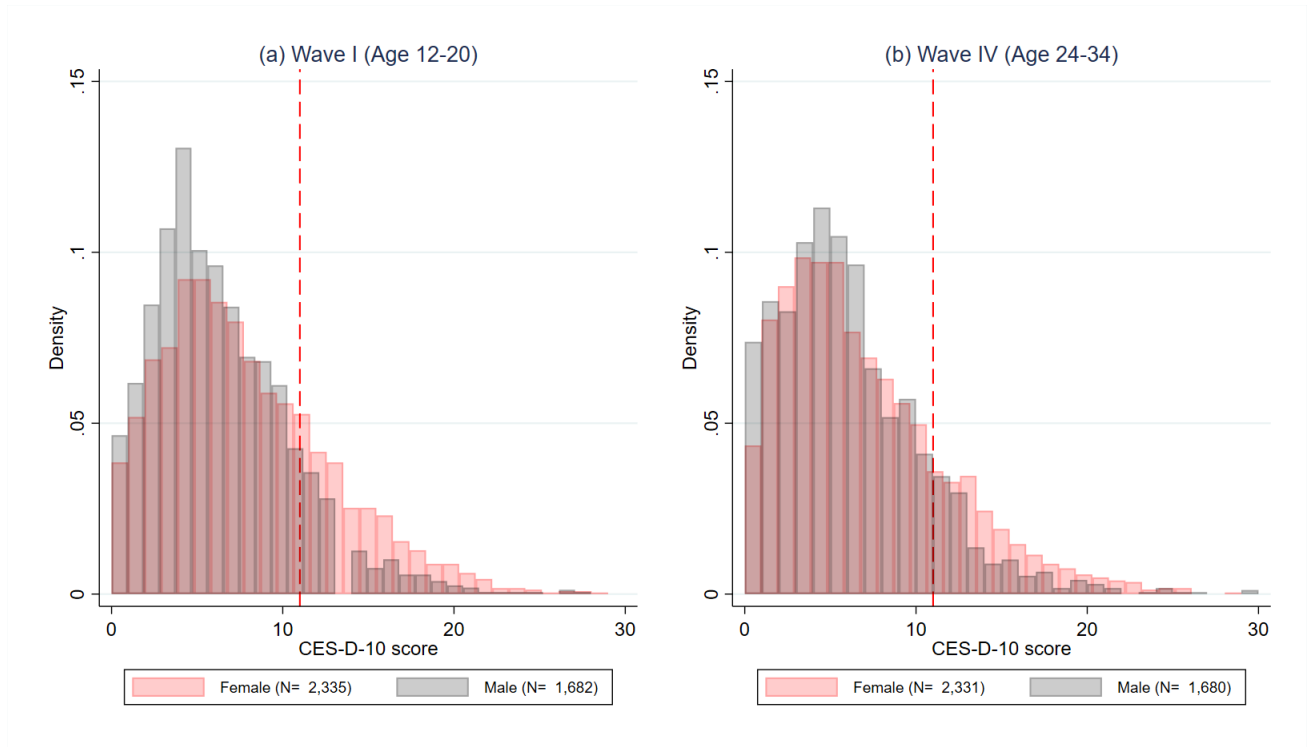
Table 12: Effect of Same-Gender Grademates' and Own MDD Score on Socioeconomic Status (SES)

	At Least Some College		Currently Work for Pay		Log Labor Income	
	(1) Females	(2) Males	(3) Females	(4) Males	(5) Females	(6) Males
Same-Gender Grademates' Average MDD Score	-0.005 (0.012)	-0.045*** (0.012)	-0.027** (0.011)	-0.013 (0.021)	-0.061 (0.072)	-0.013 (0.074)
Own MDD Score	-0.003 (0.009)	-0.029*** (0.007)	-0.018 (0.011)	0.018* (0.010)	-0.096 (0.081)	0.025 (0.063)
Mean	0.788	0.699	0.737	0.841	9.021	9.912
N	2,331	1,680	1,942	1,374	2,248	1,618
$R^2$	0.220	0.273	0.150	0.172	0.159	0.180

Note: The outcome variable in columns (1) and (2) is an indicator variable for whether individuals have attended any type of higher level of training or education after high school regardless of completion, and zero otherwise. The outcome in columns (3)-(4) is an indicator variable that has a value of one if respondents currently work for pay at least 10 hours a week, and zero otherwise. The outcome in columns (5)-(6) is log labor income. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

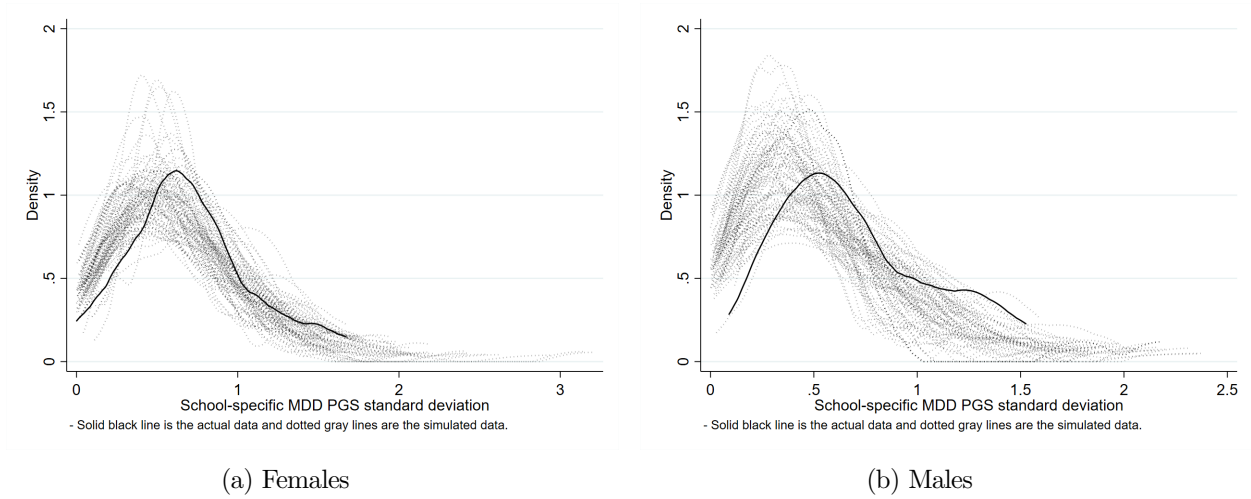
# Appendix

Figure A1: CES-D-10 Score Distribution



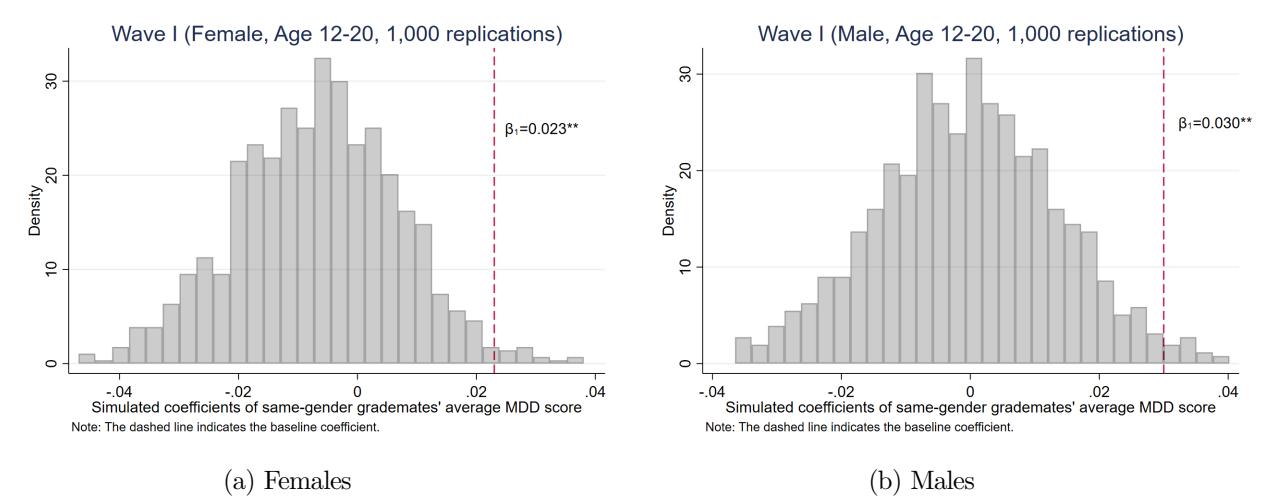
Note: Panels (a) and (b) show the histogram of the CES-D-10 score for the female (red) and male (gray) samples in Waves I and IV, respectively, along with the CES-D-10 score cutoff of 11 (red dotted line).

Figure A2: Distributions of Actual vs. Simulated School-Specific MDD Score Standard Deviations



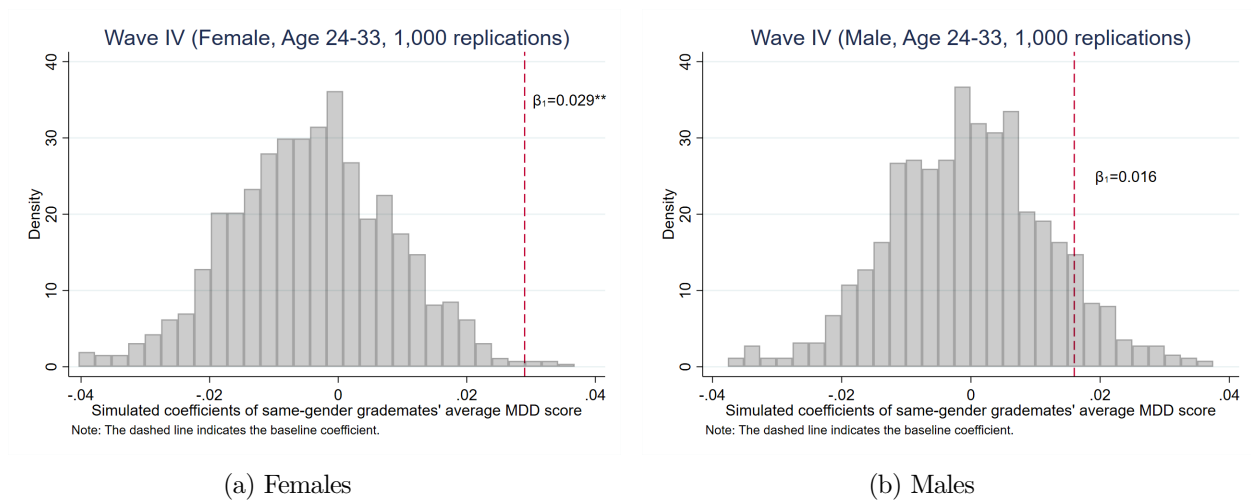
Note: The figures in Panels (a) and (b) display distributions of actual (solid line) and simulated (dotted line) school-specific MDD PGS standard deviations separately for the female and male samples, respectively. I show 100 randomly chosen simulated (dotted) school-specific MDD PGS standard deviations along with the actual (solid) standard deviation.

Figure A3: Placebo Coefficients on Same-Gender Grademates' Average MDD Score (Wave I)



Note: The dotted red line indicates the estimated coefficient from the baseline model. Panels (a) and (b) show the histograms of placebo coefficients for females and males, respectively. In the female and male samples, 1.3% and 4.3% of the placebo coefficients are larger than the actual coefficients, respectively. The number of replications is 1,000.

Figure A4: Placebo Coefficients on Same-Gender Grademates' Average MDD Score (Wave IV)



Note: The dotted red line indicates the estimated coefficient from the baseline model. Panels (a) and (b) show the histograms of placebo coefficients for females and males, respectively. In the female and male samples, 0.1% and 11% of the placebo coefficients are larger than the actual coefficients, respectively. The number of replications is 1,000.

Table A1: 10-Item Center for Epidemiologic Studies Depression Scale (CESD-10)

1.	You were bothered by things that don't usually bother you.
2.	You felt that you could not shake off the blues, even with help from your family and your friends.
3.	You felt you were just as good as other people.
4.	You had trouble keeping your mind on what you were doing.
5.	You felt depressed.
6.	You felt that you were too tired to do things.
7.	You were happy.
8.	You enjoyed life.
9.	You felt sad.
10.	You felt that people disliked you.

Note: Scores for each question range from 0 to 3 where 0 means never or rarely and 3 means most or all of the time. Scores for questions 3, 7, and 8 are reverse coded.

Table A2: Summary Statistics of Non-Genotyped Individuals

	Female		Male			Female	Male
	Mean	N	Mean	N	<i>p</i> -value	<i>p</i> -value	<i>p</i> -value
<i>Demographics:</i>							
Age in wave I	15.69 (1.75)	5,602	15.83 (1.74)	5,874	0.00	0.00	0.61
Age in wave II	16.20 (1.64)	3,854	16.32 (1.65)	3,842	0.00	0.10	0.02
Age in wave III	21.97 (1.78)	3,800	22.17 (1.79)	3,581	0.00	0.00	0.82
Age in wave IV	28.47 (1.77)	3,486	28.68 (1.81)	2,992	0.00	0.08	0.49
Age in wave V	37.57 (1.88)	3,215	37.79 (1.90)	2,510	0.00	0.00	0.22
Race: White	0.50	5,602	0.52	5,874	0.49	0.00	0.00
Race: Black or African-American	0.23	5,602	0.22	5,874	0.01	0.33	0.00
Race: Asian or Pacific Islander	0.10	5,602	0.09	5,874	0.05	0.00	0.44
Race: Other	0.17	5,602	0.16	5,874	0.44	0.00	0.00
Ethnicity: Hispanic	0.22	5,602	0.22	5,874	0.23	0.00	0.00
<i>Family and Parental Characteristics in Wave I:</i>							
Mother's edu: Missing	0.11	5,602	0.13	5,874	0.00	0.00	0.00
Mother's edu: High school/some college	0.47	5,602	0.47	5,874	0.13	0.00	0.00
Mother's edu: College degree or above	0.24	5,602	0.24	5,874	0.05	0.40	0.43
Mother's occ: Missing	0.06	5,602	0.07	5,874	0.02	0.00	0.00
Mother's occ: Managerial/professional	0.23	5,602	0.23	5,874	0.34	0.76	0.31
Mother's occ: Technical/office/sales	0.23	5,602	0.24	5,874	0.23	0.03	0.04
Mother's occ: Blue collar	0.33	5,602	0.30	5,874	0.00	0.84	0.31
Father not present	0.34	5,602	0.29	5,874	0.00	0.04	0.00
Number of siblings	1.47 (1.26)	5,602	1.48 (1.28)	5,874	0.91	0.90	0.74
Household income (imputed, thousands dollars)	45.18 (44.39)	5,602	45.43 (48.24)	5,874	0.93	0.52	0.49
<i>Depression Measures:</i>							
Depressed (CESD-10 $\geq$ 11) in wave I	0.26	5,602	0.16	5,874	0.00	0.97	0.33
Depressed (CESD-10 $\geq$ 11) in wave II	0.26	3,854	0.16	3,842	0.00	0.78	0.32
Depressed (CESD-10 $\geq$ 11) in wave IV	0.17	3,486	0.13	2,992	0.00	0.00	0.46
Suicidal ideation in wave I	0.16	5,557	0.10	5,796	0.00	0.95	0.13
Suicidal ideation in wave II	0.13	3,847	0.08	3,820	0.00	0.79	0.91
Suicidal ideation in wave IV	0.06	3,482	0.05	2,962	0.00	0.05	0.01
Suicidal ideation in wave V	0.06	3,147	0.06	2,471	0.23	0.03	0.11
Suicidal attempt in wave I	0.16	5,557	0.10	5,796	0.00	0.95	0.13
Suicidal attempt in wave II	0.13	3,847	0.08	3,820	0.00	0.79	0.91
Suicidal attempt in wave IV	0.06	3,482	0.05	2,962	0.00	0.05	0.01
Suicidal attempt in wave V	0.06	3,147	0.06	2,471	0.23	0.03	0.11
Ever diagnosed with depression in wave III	0.13	3,800	0.06	3,581	0.00	0.06	0.11
Ever diagnosed with depression in wave IV	0.18	3,492	0.08	2,999	0.00	0.01	0.01
Ever diagnosed with depression in wave V	0.28	3,216	0.15	2,511	0.00	0.05	0.18
Antidepressant use in wave III	0.06	3,796	0.02	3,585	0.00	0.28	0.99
Antidepressant use in wave IV	0.06	3,484	0.03	2,996	0.00	0.00	0.37
Antidepressant use in wave V	0.11	3,215	0.07	2,511	0.00	0.01	0.50

Note: This table shows summary statistics separately for females and males who have *not* been genotyped. Demographics and family and parental characteristics are measured in Wave I. The third from the last column includes *p*-values from a test of equality of means across the non-genotyped female and male samples. The last two columns include *p*-values from a test of equality of means across genotyped and non-genotyped individuals separately for females and males.

Table A3: Predictive Power of the MDD Score in the Analysis Sample

	Wave IV					
	CESD-10 Score		Depressed (CESD-10 $\geq$ 11)		Ever Diagnosed with Depression	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Female	Male
Own MDD Score	0.353*** (0.104)	0.152 (0.104)	0.023*** (0.008)	0.007 (0.008)	0.027*** (0.008)	0.023*** (0.007)
Mean	6.771	5.636	0.206	0.124	0.210	0.100
N	2,331	1,680	2,331	1,680	2,331	1,680
$R^2$	0.025	0.018	0.018	0.010	0.026	0.026
Incremental $R^2$	.005	.001	.003	0	.004	.006

Note: The outcome variables in columns (1)-(2), (3)-(4), and (5)-(6) are the continuous CES-D-10 score, a binary depression variable (i.e., CES-D-10 $\geq$ 11), and a dummy variable for whether respondents reported ever being diagnosed with depression, respectively. All regressions include age dummies, a female dummy, and race dummies.  
 \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$



Table A4: Balancing Tests Controlling for Same-Gender Schoolmates' Average MDD Score

	Females		Males	
MDD PGS	-0.022	(0.031)	-0.073*	(0.037)
Age in months	-0.115	(0.294)	-0.190	(0.570)
Race: White	-0.000	(0.019)	-0.028	(0.026)
Race: Black	0.007	(0.013)	0.017	(0.018)
Race: Asian	0.010	(0.008)	0.010	(0.012)
Hispanic	-0.013	(0.011)	-0.002	(0.008)
Number of siblings	0.034	(0.028)	0.050	(0.039)
Father not in household	-0.010	(0.021)	-0.012	(0.035)
Household income (Imputed)	2.371	(2.318)	-0.745	(1.345)
Household income (Missing)	0.027**	(0.011)	-0.014	(0.013)
Mother's edu: Missing	-0.013	(0.013)	-0.021	(0.018)
Mother's edu: High school graduate/some college	0.004	(0.024)	0.044	(0.045)
Mother's edu: College graduate and above	0.001	(0.018)	-0.021	(0.043)
Mother's occ: Missing	-0.015	(0.010)	-0.038***	(0.014)
Mother's occ: Managerial/professional	0.009	(0.024)	0.005	(0.026)
Mother's occ: Technical/office/sales	-0.017	(0.019)	0.038	(0.027)
Mother's occ: Blue collar	0.029	(0.028)	0.017	(0.034)
PC1	-0.001*	(0.001)	-0.000	(0.001)
PC2	-0.001	(0.001)	0.001**	(0.000)
PC3	-0.001*	(0.000)	-0.000	(0.001)
PC4	-0.000	(0.001)	0.000	(0.001)
PC5	-0.000	(0.001)	-0.000	(0.001)
PC6	0.000	(0.001)	-0.000	(0.001)
PC7	0.000	(0.001)	-0.000	(0.001)
PC8	-0.001*	(0.001)	-0.002	(0.001)
PC9	-0.000	(0.000)	-0.000	(0.001)
PC10	0.000	(0.000)	0.001***	(0.000)
N	2,335		1,682	

Note: Each row includes coefficients from a separate regression of a covariate on same-gender grademates' average MDD score conditional on school and grade fixed effects, school-grade level controls, and same-gender schoolmates' average MDD score. Standard errors are clustered at the school level and included in the parenthesis. All individual and family level characteristics are measured in Wave I, and all genetic information (i.e., MDD PGS and PC1-10) is collected in Wave IV. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A5: Robustness of the Effect of Same-Gender Grademates' and Own MDD Score Depression in Waves I and IV to Different Definitions of Depression

		Females						Males					
		CES-D-19			CES-D-10			CES-D-19			CES-D-10		
		$\geq 16$	CES-D-10		$\geq 8$	$\geq 9$	$\geq 10$	$\geq 16$	$\geq 8$	$\geq 9$	$\geq 10$	$\geq 11$	$\geq 12$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Wave I													
Same-Gender Grademates' Average MDD Score		0.015 (0.011)	0.125 (0.109)	0.037*** (0.012)	0.031*** (0.010)	0.029*** (0.009)	0.023** (0.010)	0.007 (0.010)	0.014 (0.015)	0.254 (0.196)	0.024 (0.026)	0.013 (0.020)	0.030** (0.015)
Own MDD Score		0.022** (0.010)	0.286** (0.116)	0.022** (0.011)	0.024** (0.010)	0.018* (0.009)	0.018** (0.009)	0.018** (0.008)	0.020 (0.015)	0.175 (0.138)	0.024 (0.018)	0.012 (0.018)	0.013 (0.010)
Mean		0.299	7.618	0.439	0.373	0.316	0.262	0.211	0.201	6.271	0.336	0.271	0.150
N		2,334	2,335	2,335	2,335	2,335	2,335	2,335	1,679	1,682	1,682	1,682	1,682
$R^2$		0.153	0.159	0.142	0.142	0.141	0.132	0.127	0.155	0.179	0.169	0.148	0.147
Panel B: Wave IV													
Same-Gender Grademates' Average MDD Score		0.377** (0.143)	0.029** (0.014)	0.026* (0.013)	0.030** (0.013)	0.029** (0.013)	0.024* (0.013)	-0.065 (0.141)	0.015 (0.014)	0.026** (0.012)	0.024** (0.011)	0.016 (0.010)	0.015* (0.008)
Own MDD Score		0.344*** (0.089)	0.027*** (0.010)	0.030*** (0.009)	0.022*** (0.008)	0.024*** (0.007)	0.021*** (0.007)	0.112 (0.095)	0.022* (0.012)	0.014 (0.010)	0.010 (0.008)	0.010 (0.006)	0.004 (0.007)
Mean		6.771	0.369	0.308	0.254	0.206	0.171	5.636	0.274	0.223	0.165	0.124	0.090
N		2,331	2,331	2,331	2,331	2,331	2,331	1,680	1,680	1,680	1,680	1,680	1,680
$R^2$		0.141	0.140	0.127	0.117	0.119	0.117	0.141	0.127	0.131	0.118	0.125	0.118

Note: In columns (1) and (8), the outcome is the continuous CES-D-19 score. The outcome in columns (2) and (9) is the continuous CES-D-10 score. In columns (3)-(7) and (10)-(14), the outcomes are indicator variables for being depressed based on CES-D-10 cutoffs of 8, 9, 10, 11, and 12. Each column includes a separate regression result. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A6: Nonlinear Effects of Same-Gender Grademates' and Own MDD Score on Mental Health in Waves I and IV

	Wave I				Wave IV			
	Females		Males		Females		Males	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Above Median Peer Avg MDD Score	0.025 (0.026)		-0.008 (0.026)		0.066** (0.028)		0.018 (0.021)	
Tercile 1 of Peer Avg MDD Score		0.029 (0.028)		-0.016 (0.031)		-0.017 (0.028)		-0.042 (0.030)
Tercile 3 of Peer Avg MDD Score		0.076*** (0.026)		0.011 (0.030)		0.076** (0.031)		0.002 (0.026)
Own MDD Score	0.016* (0.009)	0.018* (0.009)	0.008 (0.010)	0.010 (0.011)	0.023*** (0.007)	0.024*** (0.007)	0.009 (0.007)	0.011* (0.006)
Mean	0.262	0.262	0.150	0.150	0.206	0.206	0.124	0.124
N	2,335	2,335	1,682	1,682	2,331	2,331	1,680	1,680
$R^2$	0.131	0.134	0.146	0.146	0.120	0.121	0.125	0.126

Note: The outcome is an indicator for being depressed (i.e., CES-D-10  $\geq$  11) or not in Waves I and IV, and each column includes separate regression results. Columns (1)-(4) and (5)-(8) present the point estimates for Waves I and IV, respectively. The variable of interest in columns (1), (3), (5), and (7) is an indicator variable for whether same-gender grademates' average MDD score is above the median and zero otherwise. The variables of interest in columns (2), (4), (6), and (8) are indicator variables representing the first and the third terciles of same-gender grademates' average MDD score. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A7: Effect of Same-Gender Grademates' and Own MDD Score on Other Mental Health Outcomes in Waves I and IV

	Wave I				Wave IV							
	Suicidal Ideation		Suicide Attempts		Suicidal Ideation		Suicide Attempts		Depression Diagnosis		Antidepressant Use	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Same-Gender Grademates' Average MDD Score	0.005 (0.015)	-0.005 (0.013)	0.004 (0.009)	0.003 (0.007)	0.022*** (0.007)	-0.004 (0.007)	0.007* (0.004)	0.005 (0.005)	0.018 (0.012)	0.007 (0.009)	0.001 (0.008)	-0.004 (0.009)
Own MDD Score	0.014** (0.006)	-0.011 (0.007)	0.007 (0.005)	0.001 (0.005)	0.002 (0.005)	-0.001 (0.006)	0.003 (0.002)	-0.001 (0.002)	0.030*** (0.009)	0.026*** (0.007)	0.016*** (0.005)	0.009* (0.005)
Mean	0.161	0.111	0.053	0.023	0.075	0.065	0.013	0.018	0.210	0.100	0.081	0.035
N	2,327	1,671	2,327	1,671	2,327	1,665	2,328	1,665	2,331	1,680	2,323	1,675
R <sup>2</sup>	0.099	0.121	0.108	0.115	0.108	0.112	0.086	0.165	0.129	0.157	0.107	0.165

Note: The outcomes in columns (1)-(2) and (3)-(4) are indicators for suicidal ideation and suicide attempts, respectively, in Wave I. The outcomes in columns (5)-(6), (7)-(8), (9)-(10), and (11)-(12) are indicators for suicidal ideation, suicide attempts, depression diagnosis, and antidepressant use, respectively, in Wave IV. Each column includes a separate regression result. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A8: Effect of Same-Gender Grademates' MDD Score on Attrition

	Attrition from Wave I to IV		Absence of Valid Genetic Data	
	(1)	(2)	(3)	(4)
	Females	Males	Females	Males
Same-Gender Grademates' Average MDD Score	-0.023 (0.028)	0.053 (0.035)	-0.012 (0.074)	0.131 (0.098)
Mean	0.159	0.247	0.431	0.413
N	3,224	2,512	2,711	1,891
R <sup>2</sup>	0.083	0.106	0.164	0.186

Note: The outcome in columns (1) and (2) is an indicator for whether the respondent drops out of the survey from Waves I to IV. The outcome in columns (3) and (4) is an indicator for whether the respondent decided not to be genotyped conditional on being interviewed at Wave IV. Each column includes a separate regression result. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4) except for the 10 principal components and own MDD score. Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A9: Effect of Same-Gender Grademates' and Own MDD Score on Additional Friendship Measures in Wave I

	During the Past Week or Weekend				How Much Friends Care About You			
	Talk About Problems		Talk on Phone		Quite a Bit or More		Very Much	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Females	Males	Females	Males	Females	Males	Females	Males
Same-Gender Grademates' average MDD Score	-0.018 (0.013)	0.011 (0.023)	-0.015 (0.011)	-0.010 (0.013)	-0.020 (0.012)	0.001 (0.015)	-0.023 (0.014)	-0.003 (0.018)
Own MDD Score	-0.007 (0.009)	0.021 (0.014)	-0.008 (0.007)	0.015 (0.011)	-0.012* (0.007)	-0.006 (0.009)	-0.029*** (0.010)	0.002 (0.012)
Mean	0.766	0.497	0.863	0.795	0.881	0.802	0.507	0.343
N	2,277	1,637	2,277	1,637	2,331	1,678	2,331	1,678
R <sup>2</sup>	0.190	0.191	0.138	0.170	0.129	0.132	0.113	0.145

Note: The outcome variable in columns (1) and (2) is an indicator for whether respondents talk to one or more nominated friends on the phone during the past week. The outcome variable in columns (3) and (4) is an indicator variable for whether respondents talk to one or more nominated friends about a problem during the past week. The outcomes in columns (5)-(6) and (7)-(8) are indicator variables for whether respondents feel that their friends care about them quite a bit or more and very much, respectively. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .

Table A10: Effect of Same-Gender Grademates' and Own MDD Score on Sense of Belonging at School in Wave I

	Number of Sense of Belonging Statements Strongly Disagreed or Disagreed with					
	One or More		Two or More		All Three	
	(1)	(2)	(3)	(4)	(5)	(6)
	Females	Males	Females	Males	Females	Males
Same-Gender Grademates' Average MDD Score	0.015 (0.015)	-0.008 (0.020)	0.019* (0.011)	-0.011 (0.014)	0.001 (0.009)	-0.006 (0.008)
Own MDD Score	0.017* (0.009)	0.021** (0.009)	0.020** (0.008)	0.018** (0.007)	0.004 (0.005)	0.008 (0.007)
Mean	0.263	0.245	0.129	0.105	0.053	0.042
N	2,334	1,682	2,334	1,682	2,334	1,682
$R^2$	0.130	0.133	0.109	0.150	0.129	0.123

Note: As measures of sense of belonging at school, I use questions asking how strongly one disagrees or disagrees with the following: "I feel close to people at this school", "I feel like I am part of this school", and "I am happy to be at this school." The outcome variables in columns (1)-(2), (3)-(4), and (5)-(6) are indicator variables for whether individuals strongly disagree or disagree with 1 or more, 2 or more, and 3 of those statements, respectively. All regressions include the controls in my most preferred specification (columns 4 and 8 of Table 4). Standard errors are clustered at the school level. \* for  $p < 0.10$ , \*\* for  $p < 0.05$ , and \*\*\* for  $p < 0.01$ .