Discussion Paper Series

IZA DP No. 18623 May 2026

Peer Effects in Adolescent Mental Health

Hussain Hadah
Tulane University and IZA@LISER

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18623 May 2026

Peer Effects in Adolescent Mental Health*

Abstract

This paper examines peer mental health's influence on adolescents' wellbeing, academic performance, and behavior. Using friends-of-friends as an instrument, I find that a one standard deviation increase in friends' mental unwellness is associated with a 0.67 standard deviation increase in one's own. Peers' therapy participation significantly reduces individual mental unwellness while increasing therapy participation likelihood, highlighting positive spillover effects of interventions. The results reveal significant negative effects of peer mental unwellness on personal mental health, academic achievement, physical health, and risky behavior, confirming that adolescent mental health constitutes a social contagion.

JEL classification

D85, Z13, I12, I21, C36

Keywords

social network, peer effects, mental health, social contagion, instrumental variable, Add Health data set

Corresponding author

Hussain Hadah

hhadah@tulane.edu

* I thank Patrick Button, Willa Friedman, Chinhui Juhn, Vikram Maheshri, and Yona Rubinstein for their support and advice. I also thank Aimee Chin, Steven Craig, German Cubas, Elaine Liu, Emily Cook, Fan Wang, Augustine Denteh, Douglas Harris, Douglas Nelson, the participants of the Applied Microeconomics Workshop at the University of Houston, Stata Texas Empirical Microeconomics Conference, Tulane Economics Department, and Southern Economic Association for helpful feedback.

1 Introduction

Mental illness is prevalent among children and adolescents. Approximately one-third of school-aged children reported mental health challenges (United States Department of Health and Human Services 2021), compared to about one in five adults lived with mental illness in 2020 (Center for Behavioral Health Statistics and Quality 2022). Mental illness is also a major cause of disability. It is the number one cause of years lived with disability, affecting one in eleven people over the life course worldwide (Vos et al. 2012; World Health Organization 2010). Mental illness also carries a high economic cost. [1] Understanding how peer effects influence the mental health of adolescents is crucial.

The need for such understanding is becoming increasingly urgent. Suicide rates among teens are on the rise after years of decline (Charpignon et al. 2022). Among children and adolescents, mental health problems are more prevalent than physical health issues. These issues have significant long-term effects, not only on individuals but also on human capital accumulation, labor market outcomes, and overall public health (Biasi, Dahl, and Moser 2021a; Kessler et al. 1995). Understanding the mental health of adolescents is important for several reasons. Understanding how adolescents' mental health affects the mental health of their peers through social contagion could help clarify outcomes for high school students in a classroom setting. This could have important policy implications, such as targeted treatment of adolescents in schools to improve mental health overall. Addressing mental health problems early in life could lead to significant positive long-term effects on labor market outcomes and quality of life. Understanding how peers influence each other's mental health could help policymakers and parents mitigate the negative psychological effects of social media.

While the importance of understanding adolescent mental health is clear, researching this topic presents significant challenges. Identifying causal estimates of peer effects is challenging (Manski 1993). [2] One approach to estimate peer effects is random assignment (Sacerdote 2001; Zimmerman 2003); however, randomization is often not feasible in many situations. I leverage data from the Add Health network, the largest, most comprehensive

[1] The economic cost of depression alone was estimated to be \$83.1 billion in 2005, \$210.5 billion in 2010, and \$326.2 billion in 2018. These costs are incurred through missed days of work, lost productivity, suicide, and direct medical costs of depression like prescription medicine and office visits (Greenberg et al. 2015; Greenberg et al. 2021).

[2] Manski (1993) describes the difficulty in separating endogenous, contextual (exogenous), and correlated effects. Endogenous effects describe how an individual's behaviors are influenced by the average behavior of their peers within a reference group. Contextual effects describe how an individual's behaviors are influenced by the exogenous characteristics of peers. Correlated effects occur when individual health outcomes are influenced by peers sharing an environment, like having the same teacher, principal, or socioeconomic characteristics. These effects complicate the estimation of peer influences by creating a simultaneity problem, where individual and group behaviors are mutually determined.

longitudinal survey of adolescents ever undertaken, and apply an instrumental variable approach. [3] Specifically, I use the mental unwellness of friends' friends of a student, who are not direct friends (henceforth friends-of-friends), as an instrument for peers' mental health. [4] Despite their importance, peer influences on mental health—particularly among adolescents—remain understudied. This is especially troubling given the growing evidence of mental health crises among teens and the substantial impact these issues have on their development and future outcomes (Charpignon et al. 2022). Existing studies, such as the work of Eisenberg, Daniel et al. (2013), Zhang (2019), and Giulietti, Vlassopoulos, and Zenou (2022), provide useful insights but are largely focused on college-aged populations or long-term effects. Critical gaps remain in understanding how peer mental health directly affects adolescents during their formative years.

I aim to fill this gap in the literature by investigating the influence of social relationships on adolescent mental health and how it affects academic achievement, physical health, and behavioral issues. I estimate the peer effects on mental health among a representative sample of adolescents using a mental health measure based on 15 ques- tions from the Center for Epidemiologic Studies Depression Scale (CES-D). I focus on how the mental health of peers could affect an adolescent's' own mental health and consequently their academic performance, physical health, and behavior. To my knowledge, this is one of the first attempts in economics to use the friends- of-friends instrumental variable approach to causally estimate peer effects. This paper also provides evidence for social contagion as a mechanism in peer effects on mental health. I find that the presence of friends with poorer mental health has a negative effect on the mental health, academic achievements, behavior, and physical health of adolescents.

I use an adapted version of the Center for Epidemiologic Studies Depression Scale (CES-D) to measure mental health. The CES-D is a reliable, valid, and well-established tool used frequently in psychological studies. It uses a 20-item self-reported questionnaire to calculate a score of 0-60, with higher scores indicating more severe depression. I find that an increase of one standard deviation in peers' CES-D score causes a 0.67 standard deviation (SD) increase in adolescents' adverse mental health.[5] A one SD in peers' mental unwellness has deleterious effects on students: their GPA decreases by 0.35 SD, the monthly probability of missing school for health reasons increases by 20 percentage points, smoking cigarettes in the previous year by 37 percentage points, intoxication in the last year by 28 percentage points, and unexcused school absence in the previous year by 20 percentage points.

[3] Add Health contains network information—five female and five male friends—along with a plethora of other individual data.

[4] The instrumental variable approach follows the works of Bramoullé, Djebbari, and Fortin (2009) and Jackson and Rogers (2007) by using partially overlapping social network—friends-of-friends.

[5] A mental health index is scored based on the answers to 15 questions. A higher score indicates poorer mental health.

Additionally, I examine the spillover effects of peers' therapy participation on individual outcomes. Using an instrumental variable approach with school $\times$ grade fixed effects, I find that a one percentage point increase in friends' therapy participation leads to a 0.512 percentage point increase in an individual's likelihood of participating in therapy. This suggests a strong peer influence on seeking mental health support. Moreover, the same increase in friends' therapy participation results in a 0.291 standard deviation decrease in an individual's mental unwellness score. These findings indicate that peer therapy participation not only encourages individuals to seek help but also directly improves their mental health outcomes.

These results suggest that peer effects in mental health significantly influence an adolescent's own mental health, academic achievements, physical health, and behavioral issues in both the short and long term. Furthermore, they highlight the potential for positive spillover effects from mental health interventions, where encouraging therapy participation among some individuals can have broader benefits for their peer group.

Three papers have examined causal peer effects in mental health from an economics perspective. Eisenberg, Daniel et al. (2013) and Zhang (2019) found no peer effects in groups of randomly assigned college roommates and classmates. Giulietti, Vlassopoulos, and Zenou (2022) explore a causal estimate of peer effects in mental health on long-term outcomes using longitudinal Add Health data. By focusing on long-term outcomes, Giulietti, Vlassopoulos, and Zenou (2022) avoid the reflection problem that arises when estimating contemporaneous peer effects and find that exposure to higher numbers of depressed peers increases the probability of depression in adulthood.

In contrast, my paper represents a unique contribution to the literature by focusing on the immediate and short-term effects of peer mental health among high school adolescents rather than long- term outcomes or college students. Unlike previous studies, I use the friends-of-friends instrumental variable approach to leverage network information from the Add Health dataset, allowing for a more robust estimation of peer effects in a high school context. This method helps address endogeneity issues that have hampered prior research. My findings demonstrate that peer effects in mental health significantly influence an adolescent's own mental health, academic achievements, physical health, and behavioral issues in the short term. These results differ from Eisenberg, Daniel et al. (2013) and Zhang (2019) by providing evidence of substantial peer effects and expand on Giulietti, Vlassopoulos, and Zenou (2022) by showing significant short-term impacts. The paper not only fills a critical gap in understanding the short-term peer effects on adolescent mental health, but also introduces an innovative methodological approach to studying these effects.

The rest of this paper is structured as follows. Sections 2 and 3 comprise a review of the literature and current data. I introduce an empirical approach in section 4, then summarize and discuss the results in sections 5 and 6. The conclusions of the study are presented in section 7. The online appendix for this paper is available at this link.

2 Literature Review

2.1 Mental Health

Researchers are increasingly bringing an economics approach to the study of mental health, its effects on life and work, and the consequences of treating mental illnesses. Economists have studied the effects of access to services and treatment as they relate to several outcomes; for example, economic research has found that improving mental health lowers suicide rates (Cuellar and Markowitz 2006) and improves financial empowerment (Baranov et al. 2020).

Biasi, Dahl, and Moser (2021a) show that access to bipolar disorder treatment increases labor market participation and earnings by 30% and 26%, respectively, and Biasi, Dahl, and Moser (2021b) investigate the link between mental health and creativity. Kessler et al. (1995) find that people with early onset psychiatric problems were less likely to finish high school or go to college, while Goodman, Joyce, and Smith (2011) find that individuals with psychological problems in childhood earn 28% less than their peers as adult, but no causality was revealed. Others find that mental illness among adolescents in the United States and Canada has significant negative effects on the labor market, education, academic outcomes, and maternal education (Currie and Stabile 2007; Fletcher 2013). Cuellar, Markowitz, and Libby (2004) show that access to mental health treatment for adolescents reduces juvenile crime. The authors find that access to treatment for adolescents reduces crime. Peng, Meyerhoefer, and Zuvekas (2013) find that depression in adults reduces the likelihood of employment but has no causal effect on hourly wages or weekly hours worked. They also find that depression increases annual work loss by 1.4 days, representing a productivity loss of around $700 million to $1.4 billion. I contribute to this literature by introducing a new channel in which mental illness may affect the academic performance, physical health, and social behavior of adolescents, with additional consequences for the labor market, education, and social outcomes among adults.

2.2 Friends-of-Friends

The friends-of-friends instrumental variable approach is used to estimate causal peer effects. The method builds on the work of Jackson and Rogers (2007) and was first introduced by Bramoullé, Djebbari, and Fortin (2009), De Giorgi, Pellizzari, and Redaelli (2010), and Lin (2010). The method uses the average characteristics of friends-of-friends as an instrumental variable to estimate the effect of friends on an individual. Jackson and Rogers (2007) introduce the theoretical model that lays the groundwork for the friends-of-friends instrumental variable approach by exploring the formation of social networks and analyzing the relationship between random "meetings" and network-based "meetings" (i.e., through mutual friends). The authors find that a significant portion of social connections are formed through friends-of-friends, leading to structured, tightly knit communities rather than purely random networks. This research highlights the importance of indirect connections in social network formation, offering theoretical models that account for both types of meetings and providing insights into the dynamics and cohesion of social structures.

Bramoullé, Djebbari, and Fortin (2009) develop a method to identify and measure peer effects within social networks. The authors leverage the unique structure of social networks to address the reflection problem, which complicates the estimation of peer influences. By using information on friends-of-friends, they create a framework that allows for the isolation of peer effects from confounding factors. Their empirical approach provides robust estimates of how an individual's behavior is influenced by their peers, demonstrating significant peer effects in various contexts such as education and social behaviors. The study offers a novel contribution to the econometric analysis of social interactions, highlighting the importance of network structure in understanding peer influences.

De Giorgi, Pellizzari, and Redaelli (2010) employ a similar identification strategy using partially overlapping peer groups. They argue that by exploiting the presence of peers who do not directly interact with the individual but do interact with their peers, it is possible to construct valid instruments comprising exogenous characteristics of the excluded peers, which are correlated with the peers' behavior but not with the individual's group-specific shocks. This methodology was used to understand how peer effects influence students' choice of major at a university. This approach effectively addresses the reflection problem and allows for the identification of peer effects even in the presence of correlated group shocks. It revealed that a student is more likely to choose a certain major when their peers make the same choice. They also show that peers may lead students to choose a major that is a poor match for their skills or goals, meaning that peer effects can have negative consequences on academic and labor market outcomes.

Lin (2010) investigates peer effects on academic performance using the Add Health dataset, applying a spatial autoregressive model that includes both endogenous and contextual effects. The study leverages the friends-of-friends approach to identify peer influences by assuming that students' outcomes are influenced by their peers and indirectly by their peers' peers. Melo (2011) also uses the friends-of-friends method to identify peer effects in educational achievement using data from Uruguay and finds significant peer effects in standardized reading and math. To my knowledge, this is the first paper to use the friends-of-friends instrumental variable approach to estimate peer effects in mental health from an economics perspective.

3 Data

I use data from waves 1–5 of the restricted National Longitudinal Study of Adolescent Health (Add Health) In-Home Survey and In-School Survey. Add Health collected information from a sample of adolescents in the U.S (7^{th}–12^{th} grade). The In-Home survey began in the 1994–1995 school year and collected data on over 20,000 students for five waves. [6] The In-School survey was carried out during the 1994–1995 school year and collected data on more than 90,000 students (Harris et al. 2019). The data drew from a random sample of 80 high schools, paired with the largest middle schools that fed into them. Both the In-Home and In-School Surveys collected a plethora of unique data, including friendship networks. Summary statistics of the sample are shown in Table 4 and summary statistics of the mental health variables in Table 5. I also provide summary statistics broken down by different samples—full sample, sample of friends, and sample of friends-of-friends (6). The means are similar for each sample.

The In-Home and In-School Surveys collected data on friends in Wave 1. In both surveys, students were asked to list up to five female friends and five male friends. I use this information to match friends with each other, allowing me to construct a data set with information on the respondents and their friends. To construct a data set with information on non-mutual friendships (henceforth friends-of-friends), I match a person's friendships with the friendships of all the listed connections, and I drop those that were also listed by the target. These steps resulted in a sample of $n = 64,168$ students from the In-School Survey and a sample of $n = 12,088$ students from the In-Home Survey.

I construct a measure of adverse mental health (unwellness) from a battery of psychological questions collected by Add Health. The questions are based on the Center for Epidemiologic Studies Depression Scale (CES-D), a self-reported scale that measures depressive symptoms in the general population (Radloff 1977a). The CES-D scale is a 20-question test for which a person reports how frequently they have felt certain depression symptoms during the previous week. [7] Of the 20 questions that comprise the original scale, 15 were asked in the In-School survey and 19 in Waves 1 and 2 of the In-Home survey. Ten of the questions were asked in Waves 3, 4, and 5 of the In-Home Survey. The 19-, 15-, or 10-item CES-D allows me to construct a measure of mental health based on categories concerning depression, life, sadness, happiness, and "the blues" (Perreira et al. 2005). The In-School questions used for this analysis are provided in 7.

Using the CES-D questions, I calculate an average mental health variable. I use the 15-item CES-D questions from the In-School Survey to construct a measure of mental health. I follow the psychology literature by giving a higher (lower) value as the frequency of negative (positive) symptoms increases (Perreira et al. 2005; Radloff 1977b; Rosenquist, Fowler, and Christakis 2011). I sum the answers to all the questions and then normalize the mental health variable to have a mean 0 and a standard deviation of 1. I show the summary statistics for the mental health of students, their friends, and friends-of-friends

[6] Participants were followed through adolescence and into adulthood with five In-Home interviews in 1995 (Wave 1), 1996 (Wave 2), 2001–02 (Wave 3), 2008–09 (Wave 4) and 2016–18 (Wave 5).

[7] The frequency choices are: rarely or none of the time (less than 1 day), some or a little of the time (1-2 days), occasionally or a moderate amount of time (3-4 days), and most or all of the time (5-7 days).

in Table 5. I also use the 19-item CES-D questions in Wave 1 of the In-Home Survey as a robustness check.

4 Empirical Approach

4.1 Estimation

Let Y_{iag} be the outcome of interest for student i at school a in grade g. MU^{f}_{iag} is the average normalized mental unwellness among i's friends, $\mathbf{X}_{iag}$ is a vector of student-specific covariates, and ϕ_{ag} is school-by-grade specific fixed effects. The regression is:

$$Y_{iag} = \alpha_{0ag} + \lambda_1 MU^{f}_{iag} + \mathbf{X}'_{iag}\pi + \phi_{ag} + \mu_{iag} \tag{1}$$

Regression (1) estimates the peer effects of mental health on a student's own outcomes; however, this estimation will suffer from the endogenous and exogenous effects outlined in Manski (1993). Mental unwellness of friends could be endogenous, raising a concern that the OLS regression estimate of λ_1 will be inconsistent, so I use the following first stage of 2SLS estimation using the average depression score of friends-of-friends as an instrument:

$$\begin{aligned} 1^{\text{st}} \text{ stage: } MU^{f}_{iag} &= \delta_{0ag} + \theta_1 MU^{FoF}_{iag} \\ &+ \mathbf{X}'_{iag}\pi + \omega_{ag} + r_{iag} \end{aligned} \tag{2}$$

Where the dependent variable MU^{f}_{iag} is the average mental unwellness score among friends. The independent variable MU^{FoF}_{iag} is the average mental unwellness score among friends-of-friends. The average mental health variables among friends and friends-of-friends are calculated from the In-School survey and does not vary over time. The school-by-grade specific fixed effects variable ω_{ag} captures all characteristics of a school-grade cohort that do not vary over time, such as shared environment, cohort-specific factors, etc. Throughout my analysis, I cluster the standard errors at the school level to account for correlation in the error term, r_{iag}, within a school. [8]

[8]For the analysis that uses the In-School Survey, I control for sex, race, age, parental education, parental employment, parental occupation, and number of friends. For the the In-Home Survey Waves 1–3, I control for sex, race, age, parental education, parental employment, parental health, and number of friends. For the analysis that uses the In-Home survey Waves 4–5, I control for sex, race, age, educational attainment, parental education, parental employment, parental health, and number of friends. The different controls are due to the different dependent variables. For example, when estimating the effect of peer mental health on academic achievement, I control for the number of friends, while I control for educational attainment when estimating the effect of peer mental health on labor market outcomes in adulthood.

The parameter of interest in Equation (1) is λ_1, which indicates how peers within a school affect a student's own mental well-being and educational, health, behavioral, and labor market outcomes. For the estimate of λ_1 to represent the causal effect of peers' mental health on a student's own outcomes, MU^{FoF}_{ia} must be both sufficiently partially correlated with MU^{f}_{ia} (the relevancy requirement) and uncorrelated with the error term in the second stage (the exclusion restriction requirement). To be a valid instrumental variable (IV), it must be both relevant and satisfy the exclusion restriction. The mental health of friends-of-friends has a large negative effect on the mental health of friends, so the instrument is highly relevant. There is no established method in the instrumental variable literature to directly test the exclusion restriction; thus, I cannot determine whether MU^{FoF}_{ia} is uncorrelated with the error term. Instead, I perform robustness checks to show that the exclusion restriction is plausible. As discussed above, the IV likely satisfies the exclusion restriction because the mental health of friends-of-friends is unlikely to be correlated with the error term.

To further strengthen the validity of my instrumental variable approach, I argue that both the monotonicity and independence assumptions are likely to hold in this context. The monotonicity assumption requires that the mental health of friends-of-friends affects the mental health of friends in a uniformly positive or negative direction across all individuals. This is plausible, since the social transmission of mental health states is likely to operate in a consistent direction; if a friend-of-friend's poor mental health negatively affects a friend's mental health, it is unlikely to positively affect another friend's mental health under similar circumstances (see 3). The independence assumption posits that the instrument (friends-of-friends' mental health) performs as well as randomly assigned with respect to the outcome variables, conditional on the included covariates and fixed effects. [9] This assumption is supported by the network structure, as individuals typically have limited direct interaction with or influence over their friends-of-friends. The school $\times$ grade fixed effects and extensive set of individual-level covariates further bolster this assumption by controlling for potential confounders that might be correlated with both the instrument and the outcomes of interest.

Causally estimating λ_1 is challenging as it is difficult to differentiate between endogenous effects and the reflection problem (Manski 1993). The reflection problem occurs in research investigating how average group behavior influences the behavior of an individual in the same group (in other words: peer effects). The reflection problem leads to difficulties in identification due to the challenging nature of creating an empirical model that separates the influence of group behavior from other individual-specific factors that influence behavior. [10] To identify a causal estimate of λ_1 outside of a lab or an experi-

[9] The independence assumption is testable in case of discrete treatment but not in the case of continuous treatment as it is the case in this paper (Gunsilius 2021; Kédagni and Mourifié 2020).

[10] For instance, consider a study aiming to understand how the study habits of peers influence an individual student's academic performance. If all students are influencing each other's study

ment, an instrumental variable must be identified to provide exogenous variation in peer effects and avoid the reflection problem. Bramoullé, Djebbari, and Fortin (2009) show that endogenous and exogenous effects are identified when using partially overlapping networks, meaning that peer effects will be identified when using the characteristics of friends-of-friends are used as an instrumental variable to identify the impact of friends.

Characteristics of friends-of-friends, such as their average mental health score, are exogenous to the characteristics of the individual student. This stems from the endogenous formation of friendships: Individuals become friends, or choose not to become friends, based on a matching process involving various personal characteristics. This approach is validated by Bramoullé, Djebbari, and Fortin (2009), who demonstrated that such network structures allow for the separation of endogenous and exogenous effects, overcoming the reflection problem commonly encountered in peer effects studies. [11]

In other words, the friends-of-friends method helps identify peer effects by leveraging the structure of overlapping social groups. When groups partially overlap, some members, called "excluded peers," interact with each other only indirectly through mutual friends. [12] By using the characteristics of these excluded peers as instruments, researchers can separate true peer effects from shared group influences (Bramoullé, Djebbari, and Fortin 2009; De Giorgi, Pellizzari, and Redaelli 2010; Lin 2010). For example, in studying college students' choice of major, the method uses the characteristics of classmates who share some, but not all, classes to identify how peers influence each other's decisions. This approach ensures that the peer effects are not confounded by simultaneous interactions within the same group (De Giorgi, Pellizzari, and Redaelli 2010).

In the context of this study, I use the average mental health score of friends-of-friends as an instrument to estimate the unbiased causal effect of peer mental health on a student's own mental health. This approach allows me to examine not only the direct effects on

habits simultaneously, it becomes difficult to pinpoint the causal effect of the peer group's study habits on the individual student, as their individual behavior is also affecting the average behavior of the group.

[11]This approach effectively solves the reflection problem by breaking the simultaneity between an individual and their immediate peers. It also helps address correlated effects by using variation from outside the immediate peer group. The method relies on the network structure itself to generate instrumental variables, making it particularly powerful in settings with rich social network data. The use of friends-of-friends as instruments parallels the application of lagged variables in panel data to address serial correlation, as discussed by Chamberlain (1984). The peer effects literature frequently employs lagged peer outcomes as instruments for current outcomes, reinforcing the methodological soundness of this approach (Acton, Cook, and Luedtke 2022; Burke and Sass 2013; Carrell, Malmstrom, and West 2008).

[12]For example, a key insight of this method is the existence of intransitive triads in social networks: sets of three individuals where A is connected to B, B is connected to C, but A is not directly connected to C. In this case, C's characteristics can serve as valid instruments for B's outcomes when estimating their effect on A. The exclusion restriction is satisfied because C can only influence A indirectly through B.

mental health but also its subsequent impacts on academic achievement, physical health, and risky behavior.

4.2 Mechanisms

This paper establishes the existence of peer effects on mental health and the impact of these effects on other outcomes. To better understand these results, I propose a mechanism driven by the social contagion framework of mental health. While Glaeser and Scheinkman (2001) suggest that contagion in behavioral outcomes occurs through information exchange and preference modification, mental health contagion may operate differently. Eisenberg, Daniel et al. (2013) provide a useful framework, viewing mental health as an input in the production function.

Social interactions with peers experiencing worsening mental health could directly impact a person's own mental health. This mechanism is supported by psychological literature, which suggests several pathways, two of which I can be explored using the current data [13]:

1. Empathy: Deeply imagining oneself in the situation of someone experiencing mental health decline can potentially worsen one's own mental state.

2. Support dynamics: Offering support may either enhance or strain one's mental well-being, while receiving insufficient support in return can be detrimental.

These mechanisms suggest that peer mental health can significantly influence individual mental health outcomes. I test for these mechanisms by examining how peers socialize, support, and interact with each other. Therefore, I could offer some insights into the underlying mechanisms of peer effects, specifically in a school setting.

5 Results

5.1 Reduced Form, First Stage and 2SLS Estimation

Table 1 shows the results for the reduced form regression (Column 1), first stage (Column 2), and the two stage least squares (2SLS) results (Column 3). The results from the 2SLS regression described above are consistent with two findings: First, I find that the mental unwellness of peers significantly affects a person's own mental health; that is, if peers' mental health gets worse, a student's own mental health deteriorates. Second, the mental unwellness of peers also affects other outcomes, like education and behavior.

[13] For more detailed discussions on these pathways, see Hatfield, Cacioppo, and Rapson (1993), Joiner Jr. and Katz (1999), Hokanson et al. (1989), and Exline and Lobel (1997).

Table 1 shows the results of estimating the reduced form (Column 1). The results show a strong relationship between the friends-of-friends instrument and the mental unwellness of a student. An increase of one standard deviation in the average mental unwellness score among friends-of-friends is associated with a 0.191 standard deviation increase in the mental unwellness score of the students themselves.

Table 1 presents the outcomes of the first stage estimation (Column 2) and the 2SLS estimation (Column 3), showcasing a robust connection between the mental unwellness of an individual's friends-of-friends and their friends. Specifically, a one standard deviation increase in friends-of-friends' average mental unwellness correlates with a 0.124 standard deviation increase in friends' average mental health score. This lends credence to the validity of the instrument and its relevancy, which is crucial for the consistency of the 2SLS estimator for the parameter of interest. [14] The 2SLS regression also reveals a significant and substantial peer effect on mental health: a one standard deviation increase in the mental unwellness of friends is associated with a 0.606 standard deviation rise in an individual's own mental health score.

There are three reasons why the OLS estimates are smaller than the 2SLS estimates. *First*, the 2SLS estimates remove bias (i.e., 2SLS estimates are consistent, while the OLS estimates are not). In this setting, it is unclear in which direction the OLS estimates are biased. This is driven by correlated effects that could affect any two peers differently. On one hand, OLS estimates could be biased upward if individuals self-select into friendship networks based on similar unobserved traits that also influence their mental health outcomes. For example, more resilient individuals might be more likely to become friends and share positive mental health behaviors, leading to an upward bias in OLS estimates, as these unobserved factors are not accounted for. This selection could cause OLS to overestimate the true causal effect of friends' mental health on the reference individual's mental health due to shared characteristics that positively affect both outcomes. On the other hand, OLS estimates could be biased downward if there are negative spillover effects from non-peers that are correlated with both the mental health outcomes of individuals and their peers. For instance, if a non-peer negatively influences both the reference individual and their peer, this negative externality could attenuate the OLS estimates, as it would introduce noise that biases the estimates downward. In this case, the OLS estimates would understate the true effect of friends' mental health on the individual.

Second, the 2SLS and OLS are estimating different effects. 2SLS estimates a Local Average Treatment Effect (LATE) while OLS estimates an Average Treatment Effect (ATE). That

[14] The robustness of the instruments used is further supported by the Montiel-Pflueger Robust Weak Instrument Test, which reveals an Effective F statistic of 368.1,001 in my 2SLS model, confirming that my instrument is indeed strong (Olea and Pflueger 2013). The Montiel-Pflueger Robust Weak Instrument Test is presented in Table 8. In line with the findings of Staiger and Stock, the Effective F statistic for the first stage in our alternative specification, where the dependent variables are not own mental health, is substantially above the threshold of 10, indicating the strength of our instruments (Staiger and Stock 1997).

is, 2SLS uses a portion of the treatment variation that is exogenous: the portion of friends' mental health that is directly affected by their friends' mental health (i.e. the reference individual's friends-of-friends). To capture larger local average treatment effects, the instruments may induce changes in peer behavior for subgroups that are more susceptible to influence (Imbens and Angrist 1994).

Individuals who provide the treatment variation used by 2SLS could be different from the average population. These are individuals who have friends-of-friends (26.4% of sample individuals do not have friends-of-friends, and 17.8% do not have friends) or who have more friends-of-friends on average (due to having more friends and/or their friends having more friends). This sub-group with more friends-of-friends may have different treatment effects. For example, since their friendship networks (and their friends' friendship networks) are larger, there are more potential channels for friends-of-friends to influence their friend's mental health, and then for friends to influence the individual's own mental health. This sub-group with more friends-of-friends may be more socially driven and react more to a mental health "shock" from a given friend (and in this case, indirectly from a shock from friends-of-friends). In other words, the 2SLS estimates are capturing the effect of friends who are more susceptible to the influence of their friends' mental health (i.e., compliers). In contrast, the OLS estimates capture the average effect of friends' mental health on the whole population.

Third, a classical measurement error, which may be biasing the OLS estimates downward. Measurement error in the independent variable, mental health of friends, would bias the OLS estimates towards zero. This is because measurement error in the independent variable would be correlated with the error term, leading to attenuation bias. The 2SLS estimates are not affected by measurement error in the independent variable, as the instruments are assumed to be exogenous. This type of bias is particularly problematic when examining peer effects in mental health because mental health variables are often prone to substantial misreporting. For instance, self-reported mental health data may include both systematic errors (e.g., social desirability bias) and random errors (e.g., recall inaccuracies), further exacerbating the issue. These misreportings are likely to be correlated within social networks, as peers may share similar tendencies toward underreporting or overreporting their mental health status, compounding the attenuation bias in OLS estimates (Ammermueller and Pischke 2009).

Measurement errors in defining friendship networks or indirect peer relationships (i.e., friends-of-friends) can introduce additional biases. De Giorgi, Pellizzari, and Redaelli (2010) find that even small inaccuracies in identifying these relationships can lead to substantial distortions in the estimated peer effects. For example, if peers are misclassified due to measurement error in the network structure, the OLS estimates could understate the true effect of friends' mental health on the individual's mental health, as the spillovers from indirect peers may be either undercounted or misattributed to incorrect individuals. This would lead to a double downward bias, as the measurement error would obscure the actual relationships and attenuate the estimated coefficients towards zero.

Thus, while OLS remains susceptible to these multiple forms of bias, 2SLS provides a more robust approach by using instruments that are independent of these errors. This allows for more accurate identification of the causal peer effects on mental health, particularly in complex network settings where measurement error is likely to be correlated across individuals.

5.2 Contemporaneous Effects of Peers' Mental Health

I report in Figure 1 the results of the 2SLS estimates of Equation (1) on short-run outcomes. Every row in the figure is a separate regression with a different dependent variable. I find that a one standard deviation increase in the mental unwellness index of peers increases a student's own mental unwellness by 0.67 standard deviations. The magnitude of the effect is large: For comparison, the United Kingdom carried out a program to improve the mental health of students, which resulted in a 0.2 standard deviation improvement in mental health (Challen et al. 2011). [15] Having peers with worse mental health can negate the benefits of such a program.

The academic and attendance outcomes also respond sharply to peer mental health. A one standard deviation increase in the mental unwellness of peers decreases GPA by 0.35 standard deviations and raises the probability of unexcused absences by 20 percentage points. It also increases the probability of missing school for health reasons by 16 pp. These magnitudes imply that deteriorating peer mental health offsets the GPA gains from one-on-one tutoring (roughly 0.4 SD) (Nickow, Oreopoulos, and Quan 2020) and produces absenteeism effects comparable to other peer spillovers in schooling. [16]

Health and risky behaviors move in the same direction. A one standard deviation increase in peer mental unwellness raises the probability of intoxication in the previous year by 28 pp, increases the likelihood of feeling tired by 20 pp, feeling sick by 9 pp, and reporting poor health by 8 pp. It also raises cigarette smoking by 37 pp. These estimates align with peer effects in healthy behavior documented by Pruckner, Schober, and Zocher (2020) and with the magnitude of peer effects in smoking found in An (2015).

I also examine the spillover effects of peers' therapy participation on individual outcomes. Table 2 presents the results of a 2SLS estimation with peer' therapy participation as the independent variable. Column (1) shows that a 10 percentage point increase in friends' therapy participation leads to a 5.12 percentage point increase in an individual's likelihood of participating in therapy themselves. This suggests a strong peer influence on seeking mental health support. Moreover, as shown in Column (2), a 10 percentage point

[15] The program is called the UK Resilience Programme, which is a school-based mental health intervention that aims to improve the mental health of students.

[16] In a paper on peer effects in absenteeism at the workplace, (Godøy and Dale-Olsen 2018) find that peer effects in absenteeism at the workplace are small. The authors find that when a worker has a colleague who is absent, the worker is 41 p.p more likely to be absent.

increase in friends' therapy participation results in a 0.0291 standard deviation decrease in an individual's mental unwellness score. These findings indicate that peer therapy participation not only encourages individuals to seek help but also directly improves their mental health outcomes. These results highlight the potential for positive spillover effects from mental health interventions, where encouraging therapy participation among some individuals can have broader benefits for their peer group.

5.3 Heterogeneous Effects

Results of the 2SLS regression using different samples of the data to study heterogeneous effects are provided in 4. [17] I repeat my analysis on samples of men, women, students with above-median numbers of friends (popular students), and students with below-median numbers of friends (less popular students). I also report the p-value of the equality tests of the men-women, and popular-less popular heterogeneous analysis.

In 4, I find that female students are more affected by the mental health of their peers. A one standard deviation increase in peers' mental unwellness increases women's own mental unwellness by 0.84 standard deviations, versus 0.71 for men. The equality test between the two is statistically significant at the 10% level with a p-value of 0.06. I also find that more popular students' mental health is more affected by the mental health of their peers. A one standard deviation increase in peers' mental health increases popular students' mental health index by 0.89 standard deviations and 0.60 standard deviations for less popular students.

In 4, I find that female students' GPA is more affected by the mental unwellness of their peers. A one standard deviation increase in peers' mental unwellness decreases female students' GPA by 0.39 points, versus 0.22 for male students. That is equivalent to a 14% decrease in GPA for female students and a 7% decrease for male students. The equality test between the two is statistically significant at 10%. I also find that more popular students' GPA is more affected by the mental health of their peers. A one standard deviation increase in peers' mental unwellness decreases popular students' GPA by 0.55 points, versus a statistically insignificant 0.04 points for the less popular students, equivalent to a 19% decrease in the GPA for popular students.

In 4c, I show that female students' behavior is similarly affected by the mental health of their peers compared to men. A one standard deviation increase in peers' mental unwellness increases the probability of absenteeism for male and female students by 24 percentage points, equivalent to an 80% decrease in the probability of skipping school. More popular students' absenteeism is also more affected by the mental unwellness of their peers: A one standard deviation increase in peers' mental health increases absenteeism of popular students by 30 pp versus 15 pp for less popular students, equivalent to a 100%

[17] See the online appendix for more heterogenous effects.

decrease in the absenteeism probability for popular students and a 50% decrease for less popular students.

5.4 Robustness Checks

My empirical approach relies on the assumption that, after accounting for unobservable school characteristics and the observable characteristics of a student, the mental health of friends-of-friends is uncorrelated with the unobserved determinants of a student's own outcomes. In this section, I will discuss the result of a few robustness checks.

I present the results of the **horrace2014endogenous<empty citation>** (HLP) instrument as an additional robustness check. The estimates using this alternative instrument (Figure 9) closely mirror the baseline results: peers' mental unwellness significantly raises own mental unwellness, lowers GPA, and increases skipping school and health-related absences. This alignment with the main specification further supports the robustness of the findings. In fact, the HLP estimates are more significant than the friends-of-friends instrument estimates. Importantly, the **horrace2014endogenous<empty citation>** approach shares the same theoretical foundation as my primary identification strategy by leveraging network structure and accounting for endogenous network formation through a selectivity correction, reinforcing the validity and robustness of the peer effects identified throughout this analysis.

9 shows the results for a subset of students who did not choose the maximum number (5) of female friends or male friends. The outcomes in 9 closely resemble those in Table 1, suggesting that truncated data is not a significant concern. The results are similar to those in the main specification. 10 shows an alternate specification in which I include only reciprocated friendships. The results are unaffected throughout the different specifications, suggesting that the findings are robust regardless of the specification employed.

As another robustness check, I estimated the model using the average mental unwellness score of non-friends as an instrument. [18] A null result would be further evidence that the exclusion restriction holds. I present the results in Table 11. I find that non-friends have no significant direct effect on the mental health of a student (Table 11 Column 1). The instrumental variable estimation yields similarly insignificant results (Table 11 Column 2).

I also estimated the empirical model using predetermined outcomes and their effects on the mental health of a person as a falsification test. Since race, height, age, parental health, age, place of birth and religion are predetermined, a person's own mental health should not be affected by these characteristics of peers. I find that peers' mental health does not affect the height or the race of adolescents (Figure 2). Peer effects in mental health have no significant effect on these predetermined outcomes, providing further evidence that the results presented in this paper are not spurious.

[18] Non-friends are defined as individuals within a specific school who are not directly connected to a given student and are not friends-of-friends.

6 Discussion

In this paper, I use an instrumental variable approach to identify significant peer effects in mental health among adolescents. I also find that peer effects in mental health affect educational, health, and behavioral outcomes. I find that a one standard deviation increase in peers' mental unwellness causes a 0.67 percentage point increase in a student's own mental unwellness. I also find that a one standard deviation increase in the mental unwellness of peers causes an 11% decrease in GPA and a 20 percentage point increase in the probability of unexcused absence during the previous year. A one standard deviation increase in the mental health unwellness of peers causes percentage point increases of 8, 9, and 20 in the probability of reporting poor health, feeling sick, and feeling tired, respectively, in the previous month. Additionally, I discover significant spillover effects from peers' therapy participation. A 10 percentage point increase in friends' therapy participation leads to a 5.12 percentage point increase in an individual's likelihood of participating in therapy and a 0.0291 standard deviation decrease in their mental unwellness score. These findings underscore the potential for positive peer influences in mental health interventions.

This paper adds to the growing literature on peer effects and the results have multiple implications. First, the results suggest that programs that improve the mental health of students could have significant effects on the mental health of students' peers. Second, programs to improve the mental health of adolescents could have significant effects on their educational, health, and behavioral outcomes. Mental health programs could be more effective at improving grades, reducing absenteeism, and reducing risky behavior than programs that target these outcomes directly. They could also be more cost-effective, since targeting the improvement of student mental health could have multiple positive effects on other outcomes, like physical health and behavior.

Another implication is a possible relationship between peer effects on mental health and the persistence of smoking. A one standard deviation increase in the mental unwellness of peers causes a 0.37 percentage point increase in likelihood of smoking. Improving the mental health of adolescents could have significant effects on decreasing the probability of smoking and smoking-related diseases, which are significant and costly public health issues. These effects may be of higher magnitude than programs that target smoking directly or deterrent mechanisms like tobacco taxes.

Targeted programs that improve the mental health is another implication of this research. I find that where a student is located in a network of friends is really important. I find evidence of heterogeneity in peer effects, where female students and popular students are more affected by the mental health of their peers. Programs targeted toward improving the mental health of these specific populations in networks could have more significant effects on the mental health of the students in their networks than programs targeting all students. For example, a targeted program that improves the mental health of female students could have significant effects on the overall mental health of the school as a whole.

The spillover effects of peers' therapy participation provide further evidence of the importance of peer influence in mental health outcomes. These results suggest that encouraging therapy participation among adolescents could improve not only their own mental health but also that of their peers. This finding has important implications for the design and implementation of mental health interventions in schools and other adolescent settings. Programs that increase therapy participation rates could have broader impacts than previously thought, potentially improving mental health outcomes for entire peer networks.

The growing use and influence of social media increase the relevance of the results in this paper. Social media platforms could lead to the spread of mental health issues among adolescents since it expands their network of friends. This could be of importance to policymakers and represents a potential avenue for future studies.

6.1 Social Contagion

My analysis delves into how social contagion effects vary among individuals. Those who openly share their emotional struggles may influence the mental health of their peers differently compared to those who keep their distress to themselves. The psychological concept of "co-rumination", posits that regularly dwelling on and discussing negative thoughts and feelings can intensify distress within a peer group (Kennedy-Moore and Watson 2001); that is, whether and to what degree individuals communicate with peers about their emotional state can either mitigate or amplify the spread of distress

Evidence supporting the concept of social contagion and transmission and heterogeneity could explain why female students and popular students are more affected by peer mental health than male or less popular students. Using Add Health data, I constructed indicator variables that reflect socialization and show how these socialization variables differ by gender (Table 12) and by number of friends (Table 13). Female students and students with more friends are more likely to talk about problems when socializing with their friends compared to male students and students with fewer friends. This could facilitate the contagion and transmission of mental unwellness among peers and could explain why girls and more popular students are more likely to be affected by the mental health of their peers.

I also show the results of the 2SLS estimates of Equation 1, where the dependent variables are the socialization indicators in Table (3). These estimates could show how poor mental health is transmitted among friends. Having peers with worse mental health who talk openly about their problems may affect an individual's own mental health. These results indicate that social contagion is the mechanism most likely to explain peer effects in mental health. Future studies should examine whether social contagion may be a factor in other mental health outcomes.

7 Conclusion

This paper contributes to the literature by investigating peer effects on adolescent mental health and their subsequent impact on academic achievement, physical health, and behavioral issues. To circumvent the difficulties in estimating peer effects causally, I use an instrumental variable approach. I leverage the distinct network data supplied by Add Health and the mental health scores of a student's friends-of-friends—who are not directly connected to the student—as an instrument to measure the mental health of peers.

These findings demonstrate significant negative peer effects on mental health among adolescents. A one standard deviation increase in the mental unwellness of peers leads to a 0.67 standard deviation increase in the mental health of the individual. A 10 percentage point increase in friends' therapy participation leads to a 5.12 percentage point increase in an individual's likelihood of participating in therapy and a 0.0291 standard deviation decrease in their mental unwellness score. Peers' mental health significantly affects academic outcomes: A one standard deviation increase in peers' mental unwellness results in a 0.35 standard deviation decrease in GPA and a 16 percentage point increase in likelihood of having missed school for health reasons in the previous month. Peers' mental health influences behavioral issues, such as recent smoking and alcohol use: a one standard deviation increase in peers' mental unwellness is associated with a 40 and 30 percentage point increase in likelihood of recent smoking or alcohol use, respectively.

This study sheds light on the importance of addressing mental health issues among adolescents. Mental health problems have significant adverse consequences for academic achievement, health, and long-term labor market outcomes. Since peers play a crucial role in influencing mental health, targeting treatment and interventions to improve mental health in schools could have positive effects on reducing mental health prevalence and improving overall well-being among all students in the long run. These findings have important policy implications, emphasizing the significance of early interventions to improve mental health among adolescents and positively affect their future outcomes in multiple areas of life.

References

Acton, Riley K., Emily E. Cook, and Allison Luedtke. 2022. "The Influence of Peer Institutions on Colleges' Decisions: Evidence from Fall 2020 Reopening Plans." *Journal of Economic Behavior & Organization* 195 (March): 288–302. https://doi.org/10.1016/j.jebo.2022.01.016.

Ammermueller, Andreas, and Jörn-Steffen Pischke. 2009. "Peer effects in European primary schools: Evidence from the progress in international reading literacy study." *Journal of Labor Economics* 27 (3): 315–348.

An, Weihua. 2015. "Instrumental variables estimates of peer effects in social networks." *Social Science Research* 50:382–394.

Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko. 2020. "Maternal Depression, Women's Empowerment, and Parental Investment: Evidence from a Randomized Controlled Trial." *American Economic Review* 110, no. 3 (March): 824–859. https://doi.org/10.1257/aer.20180511.

Biasi, Barbara, Michael S Dahl, and Petra Moser. 2021a. *Career Effects of Mental Health.* Technical report. National Bureau of Economic Research.

———. 2021b. *Mental Health, Creativity, and Wealth.* Working Paper, 29422, October. https://doi.org/10.3386/w29422.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2009. "Identification of Peer Effects through Social Networks." *Journal of Econometrics* 150, no. 1 (May): 41–55. https://doi.org/10.1016/j.jeconom.2008.12.021.

Burke, Mary A., and Tim R. Sass. 2013. "Classroom Peer Effects and Student Achievement." *Journal of Labor Economics* 31, no. 1 (January): 51–82. https://doi.org/10.1086/666653.

Carrell, Scott E., Frederick V. Malmstrom, and James E. West. 2008. "Peer Effects in Academic Cheating." *Journal of Human Resources* 43, no. 1 (January): 173–207. https://doi.org/10.3368/jhr.43.1.173.

Center for Behavioral Health Statistics and Quality. 2022. *National Survey of Drug Use and Health [Dataset].* Technical report. Research Triangle Institute (RTI).

Challen, Amy, Philip Noden, Anne West, and Stephen Machin. 2011. *UK Resilience Programme Evaluation: Final Report.* Research Report DFE-RR097. Department for Education / Department for Education, London, UK, October.

Chamberlain, Gary. 1984. "Chapter 22 Panel Data." In *Handbook of Econometrics,* 2:1247–1318. Elsevier, January. https://doi.org/10.1016/S1573-4412(84)02014-6.

Charpignon, Marie-Laure, Johnattan Ontiveros, Saahil Sundaresan, Anika Puri, Jay Chandra, Kenneth D. Mandl, and Maimuna Shahnaz Majumder. 2022. "Evaluation of Suicides Among US Adolescents During the COVID-19 Pandemic." *JAMA Pediatrics* 176, no. 7 (July): 724–726. https://doi.org/10.1001/jamapediatrics.2022.0515.

Cuellar, Alison, and Sara Markowitz. 2006. *Medicaid Policy Changes in Mental Health Care and Their Effect on Mental Health Outcomes.* Working Paper 12232. National Bureau of Economic Research, May. https://doi.org/10.3386/w12232.

Cuellar, Alison Evans, Sara Markowitz, and Anne M Libby. 2004. "Mental Health and Substance Abuse Treatment and Juvenile Crime." *Journal of Mental Health Policy and Economics,* 59–68.

Currie, Janet, and Mark Stabile. 2007. *Mental Health in Childhood and Human Capital.* Working Paper 13217. National Bureau of Economic Research, July. https://doi.org/10.3386/w13217.

De Giorgi, Giacomo, Michele Pellizzari, and Silvia Redaelli. 2010. "Identification of Social Interactions through Partially Overlapping Peer Groups." *American Economic Journal: Applied Economics* 2, no. 2 (April): 241–275. https://doi.org/10.1257/app.2.2.241.

Eisenberg, Daniel, Ezra Golberstein, Janis L. Whitlock, and Marilyn F. Downs. 2013. "Social Contagion of Mental Health: Evidence from College Roommates." *Health economics* 22, no. 8 (August): 965–986. https://doi.org/10.1002/hec.2873.

Exline, Julie Juola, and Marci Lobel. 1997. "Views of the Self and Affiliation Choices: A Social Comparison Perspective." *Basic and Applied Social Psychology* (US) 19 (2): 243–259. https://doi.org/10.1207/s15324834basp1902_6.

Fletcher, Jason. 2013. "Adolescent Depression and Adult Labor Market Outcomes." *Southern Economic Journal* 80 (1): 26–49. https://doi.org/10.4284/0038-4038-2011.193.

Giulietti, Corrado, Michael Vlassopoulos, and Yves Zenou. 2022. "Peers, Gender, and Long-Term Depression." *European Economic Review* 144 (May): 104084. https://doi.org/10.1016/j.euroecorev.2022.104084.

Glaeser, Edward L., and José A. Scheinkman. 2001. "Measuring Social Interactions" (April). https://doi.org/10.7551/mitpress/6294.003.0006.

Godøy, Anna, and Harald Dale-Olsen. 2018. "Spillovers from Gatekeeping – Peer Effects in Absenteeism." *Journal of Public Economics* 167 (November): 190–204. https://doi.org/10.1016/j.jpubeco.2018.08.015.

Goodman, Alissa, Robert Joyce, and James P. Smith. 2011. "The Long Shadow Cast by Childhood Physical and Mental Problems on Adult Life." *Proceedings of the National Academy of Sciences* 108, no. 15 (April): 6032–6037. https://doi.org/10.1073/pnas.1016970108.

Greenberg, Paul E., Andree-Anne Fournier, Tammy Sisitsky, Crystal T. Pike, and Ronald C. Kessler. 2015. "The Economic Burden of Adults With Major Depressive Disorder in the United States (2005 and 2010)." *The Journal of Clinical Psychiatry* 76, no. 2 (February): 5356. https://doi.org/10.4088/JCP.14m09298.

Greenberg, Paul E., Andree-Anne Fournier, Tammy Sisitsky, Mark Simes, Richard Berman, Sarah H. Koenigsberg, and Ronald C. Kessler. 2021. "The Economic Burden of Adults with Major Depressive Disorder in the United States (2010 and 2018)." *PharmacoEconomics* 39, no. 6 (June): 653–665. https://doi.org/10.1007/s40273-021-01019-4.

Gunsilius, Florian F. 2021. "Nontestability of instrument validity under continuous treatments." *Biometrika* 108 (4): 989–995.

Harris, Kathleen Mullan, Carolyn Tucker Halpern, Eric A Whitsel, Jon M Hussey, Ley A Killeya-Jones, Joyce Tabor, and Sarah C Dean. 2019. "Cohort Profile: The National Longitudinal Study of Adolescent to Adult Health (Add Health)." *International Journal of Epidemiology* 48, no. 5 (October): 1415–1415k. https://doi.org/10.1093/ije/dyz115.

Hatfield, Elaine, John T. Cacioppo, and Richard L. Rapson. 1993. "Emotional Contagion." *Current Directions in Psychological Science* 2, no. 3 (June): 96–100. https://doi.org/10.1111/1467-8721.ep10770953.

Hokanson, J. E., M. P. Rubert, R. A. Welker, G. R. Hollander, and C. Hedeen. 1989. "Interpersonal Concomitants and Antecedents of Depression among College Students." *Journal of Abnormal Psychology* 98, no. 3 (August): 209–217. https://doi.org/10.1037//0021-843x.98.3.209.

Imbens, Guido W., and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62 (2): 467–475. https://doi.org/10.2307/2951620.

Jackson, Matthew O., and Brian W. Rogers. 2007. "Meeting Strangers and Friends of Friends: How Random Are Social Networks?" *American Economic Review* 97, no. 3 (June): 890–915. https://doi.org/10.1257/aer.97.3.890.

Joiner Jr., Thomas E., and Jennifer Katz. 1999. "Contagion of Depressive Symptoms and Mood: Meta-analytic Review and Explanations from Cognitive, Behavioral, and Interpersonal Viewpoints." *Clinical Psychology: Science and Practice* (United Kingdom) 6 (2): 149–164. https://doi.org/10.1093/clipsy.6.2.149.

Kédagni, Désiré, and Ismael Mourifié. 2020. "Generalized instrumental inequalities: testing the instrumental variable independence assumption." *Biometrika* 107 (3): 661–675.

Kennedy-Moore, Eileen, and Jeanne C. Watson. 2001. "How and When Does Emotional Expression Help?" *Review of General Psychology* (US) 5 (3): 187–212. https://doi.org/10.1037/1089-2680.5.3.187.

Kessler, R. C., C. L. Foster, W. B. Saunders, and P. E. Stang. 1995. "Social Consequences of Psychiatric Disorders, I: Educational Attainment." *The American Journal of Psychiatry* 152, no. 7 (July): 1026–1032. https://doi.org/10.1176/ajp.152.7.1026.

Lin, Xu. 2010. "Identifying Peer Effects in Student Academic Achievement by Spatial Autoregressive Models with Group Unobservables." *Journal of Labor Economics* 28, no. 4 (October): 825–860. https://doi.org/10.1086/653506.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60 (3): 531–542. https://doi.org/10.2307/2298123.

Melo, Gioia De. 2011. "Peer Effects Identified through Social Networks. Evidence from Uruguayan Schools." *Department of Economics University of Siena*, no. 627 (November).

Nickow, Andre, Philip Oreopoulos, and Vincent Quan. 2020. *The Impressive Effects of Tutoring on PreK-12 Learning: A Systematic Review and Meta-Analysis of the Experimental Evidence.* Working Paper, 27476, July. https://doi.org/10.3386/w27476.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics* 31, no. 3 (July): 358–369. https://doi.org/10.1080/00401706.2013.806694.

Peng, Lizhong, Chad D. Meyerhoefer, and Samuel H. Zuvekas. 2013. *The Effect of Depression on Labor Market Outcomes.* Working Paper 19451. National Bureau of Economic Research, September. https://doi.org/10.3386/w19451.

Perreira, Krista M., Natalia Deeb-Sossa, Kathleen Mullan Harris, and Kenneth Bollen. 2005. "What Are We Measuring? An Evaluation of the CES-D Across Race/Ethnicity and Immigrant Generation*." *Social Forces* 83, no. 4 (June): 1567–1601. https://doi.org/10.1353/sof.2005.0077.

Pruckner, Gerald J., Thomas Schober, and Katrin Zocher. 2020. "The Company You Keep: Health Behavior among Work Peers." *The European Journal of Health Economics* 21, no. 2 (March): 251–259. https://doi.org/10.1007/s10198-019-01124-4.

Radloff, Lenore Sawyer. 1977a. "The CES-D Scale: A Self-Report Depression Scale for Research in the General Population." *Applied Psychological Measurement* 1, no. 3 (June): 385–401. https://doi.org/10.1177/014662167700100306.

———. 1977b. "The CES-D Scale: A Self-Report Depression Scale for Research in the General Population." *Applied Psychological Measurement* 1, no. 3 (June): 385–401. https://doi.org/10.1177/014662167700100306.

Rosenquist, JN, JH Fowler, and NA Christakis. 2011. "Social Network Determinants of Depression." *Molecular psychiatry* 16, no. 3 (March): 10.1038/mp.2010.13. https://doi.org/10.1038/mp.2010.13.

Sacerdote, Bruce. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates*." *The Quarterly Journal of Economics* 116, no. 2 (May): 681–704. https://doi.org/10.1162/00335530151144131.

Staiger, Douglas, and James H. Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65 (3): 557–586. https://doi.org/10.2307/2171753.

United States Department of Health and Human Services. 2021. *Mental Health: A Report of the Surgeon General.* Technical report.

Vos, Theo, Abraham D Flaxman, Mohsen Naghavi, Rafael Lozano, Catherine Michaud, Majid Ezzati, Kenji Shibuya, et al. 2012. "Years Lived with Disability (YLDs) for 1160 Sequelae of 289 Diseases and Injuries 1990–2010: A Systematic Analysis for the Global Burden of Disease Study 2010." *The lancet* 380 (9859): 2163–2196.

World Health Organization. 2010. *2011 Global Status Report on Non-Communicable Diseases.* Technical report. Geneva: World Health Organization.

Zhang, Anwen. 2019. *Peer Effects on Mental Health: Evidence from Random Assignment into Classrooms.* SSRN Scholarly Paper, 3685374, Rochester, NY, November. https://doi.org/10.2139/ssrn.3685374.

Zimmerman, David J. 2003. "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment." *The Review of Economics and Statistics* 85, no. 1 (February): 9–23. https://doi.org/10.1162/003465303762687677.

Figure 1: Spillover Effects, in Standard Deviations, of Peers' Mental Unwellness on Own Mental Unwellness, Academic and Behavioral Outcomes

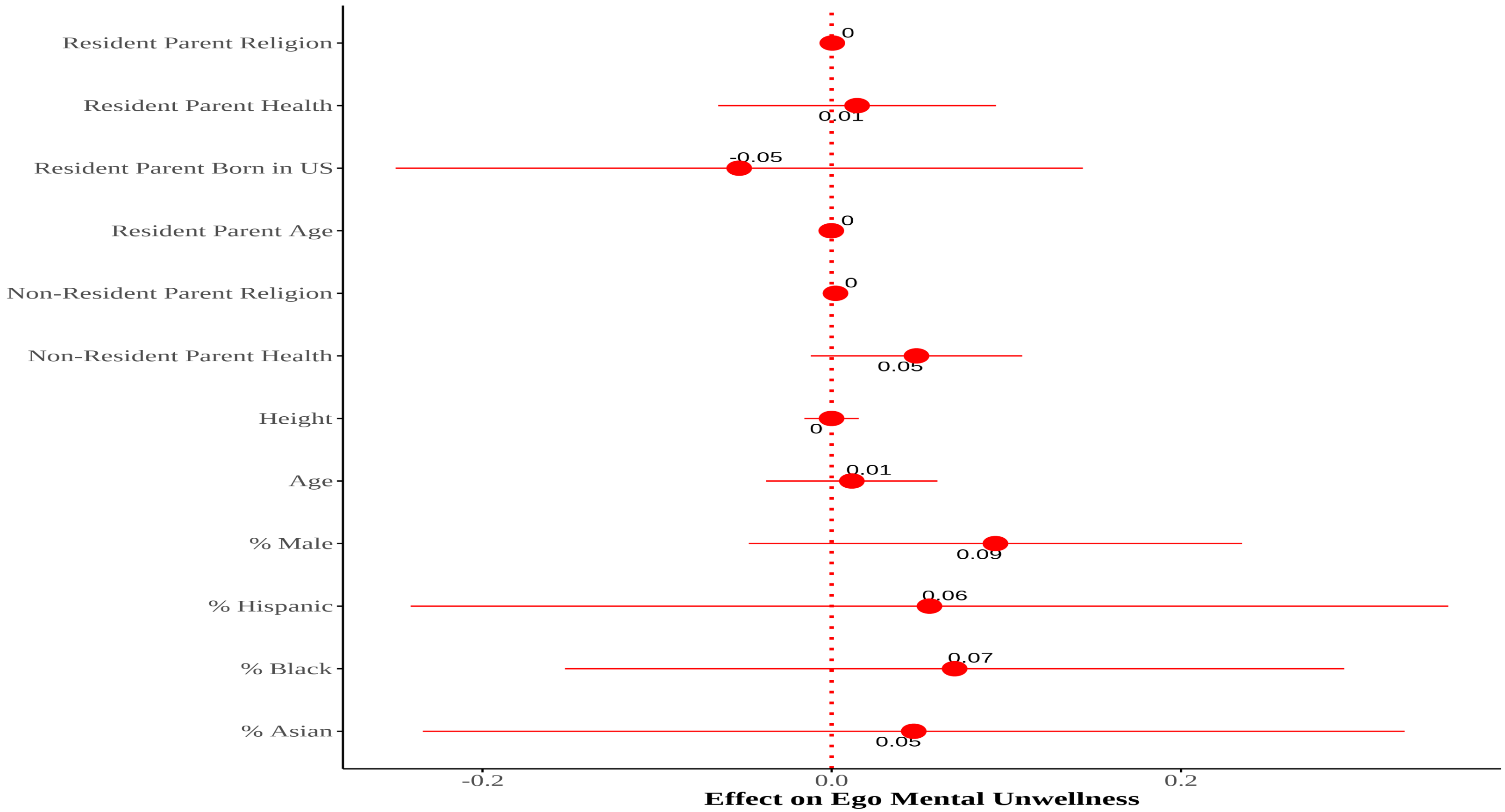
figure/all-in-one-gradexschoolFE-I.png

Note: This plot presents the 2SLS estimation of the regression (Equation 1) with school $\times$ grade fixed effects on mental unwellness, academic, and behavioral outcomes. The independent variable is the average mental unwellness of peers, standardized with a mean of zero and a standard deviation of one. This variable reflects mental unwellness, so higher values indicate more severe mental unwellness problems. For the analysis using In-Home survey waves 1–3, control variables include sex, race, age, parental education, parental employment, parental health, and number of friends. For the analysis using In-Home survey waves 4–5, control variables include sex, race, age, educational attainment, parental education, parental employment, parental health, and number of friends. Standard errors are clustered at the school level. For the analysis using In-Home survey waves 4–5, control variables include sex, race, age, educational attainment, parental education, parental employment, parental health, and number of friends. Standard errors are clustered at the school level. Each row on the y-axis is a separate regression with a different dependent variable. The x-axis is the coefficient of the mental unwellness of peers on the dependent variable. The dependent variables are (from bottom to the top): own mental unwellness index from the In-School survey (standardized), GPA from the In-School survey (standardized), the probability of skipping school for no reason in the last year from the In-School survey, the probability of getting intoxicated in the last year from the In-School, the probability of reporting general poor health from the In-School survey, the probability of missing school for health or mental reasons during the last month from the In-School survey, the probability of feeling sick in the last month from the In-School survey, the probability of feeling tired in the last month from the In-School survey, and probability of smoking cigarettes in the last year from the In-School survey.

The control variables used in the analysis using the In-School survey include sex, race, age, parental education, parental employment, parental occupation, and number of friends. Standard errors are clustered at the school level.

Source: The data source is the Add Health In-School and In-Home surveys.

Figure 2: Falsification: Spillover Effect of Mental Unwellness on Height and Race



This plot presents the 2SLS estimation of the regression (Equation 1) with school $\times$ grade fixed effects that estimates how some predetermined independent variables of friends-of-friends would affect the mental health of the student themselves. Each row on the y-axis is a separate regression with a different dependent variable. The x-axis is the coefficient of the predetermined independent variable of friends-of-friends on the dependent variable. The dependent variables are (from bottom to the top): percent Asian friends-of-friends, percent Black friends-of-friends, percent Hispanic friends-of-friends, percent Male friends-of-friends, friends-of-friends age, and Height of friends-of-friends in inches, friends-of-friends non-resident's parents health, friends-of-friends non-resident's religion, friends-of-friends resident's parental age, friends-of-friends resident's parent US born, friends-of-friends resident's parents health, and friends-of-friends resident's religion.

Table 1: Spillover Effect of Peers' Mental Unwellness on Own Mental Unwellness

	Mental Unwellness (1) OLS (Reduced Form)	Friends Mental Unwellness (2) First Stage	Mental Unwellness (3) 2SLS
Friends of Friends Mental Unwellness	0.191***	0.259***	
	(0.017)	(0.019)	
Friends Mental Unwellness			0.739***
			(0.053)
Observations	53,725	53,725	53,725
First Stage F-statistic			1,675.97

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation efeq:reduce-form) with school fixed effects. Column (1) displays the estimation of the reduced form equation using own mental unwellness as the dependent variable. In Column (2), I present the results of the first stage analysis using the average friends' depression as the dependent variable. Finally, column (4) includes the results of the instrumental variable (2SLS) estimation. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends.

[2] Standard errors are clustered on the school level.

[3] Data source is the Add Health in-school survey.

Table 2: Spillover Effect of Peers' Therapy Participation on Individual Outcomes

	Therapy (1) IV	Mental Unwellness (2) IV
Friends Therapy	0.512***	−0.291***
	(0.034)	(0.074)
Observations	36,861	38,022
First Stage F-statistic	5,927.98	6,178.09
Mean of Dependent Variable	0.63	21.17
		(11.00)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation 1) with school fixed effects. Column (1) includes the results of the instrumental variable (IV) estimation where the left hand side variable is own therapy participation and the right hand side variable is the average therapy participation of peers. Column (2) includes the results of the instrumental variable (IV) estimation where the left hand side variable is own mental unwellness and the right hand side variable is the average therapy participation of peers. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends. I also include contextual effects of friends' characteristics, such as the gender, race, age, and parental background of friends. This helps to control for the contextual effects of friends' characteristics on the mental unwellness of the respondent.

[2] Standard errors are clustered on the school level.

[3] Data source is the Add Health in-school survey.

Table 3: Peer Effects and Social Contagion in Mental Unwellness: Mechanism

	Talk to Frnds (1)	Call Frnds (2)	Visit Frnds (3)	Hang out Frnds (4)	Spend Weekend Frnds (5)
Panel A: Full Sample					
Friends Mental Unwellness	0.092***	0.058**	0.082***	0.091***	0.078**
	(0.025)	(0.024)	(0.029)	(0.028)	(0.030)
Observations	53,725	53,725	53,725	53,725	53,725
Panel B: Women					
Friends Mental Unwellness	0.046	0.032	0.073*	0.124***	0.092**
	(0.036)	(0.033)	(0.041)	(0.047)	(0.042)
Observations	28,609	28,609	28,609	28,609	28,609
Panel C: Men					
Friends Mental Unwellness	0.141***	0.084**	0.099***	0.068*	0.073*
	(0.042)	(0.035)	(0.037)	(0.037)	(0.039)
Observations	25,102	25,102	25,102	25,102	25,102
Panel D: Above median friends					
Friends Mental Unwellness	0.107***	0.079***	0.058	0.089**	0.059
	(0.030)	(0.026)	(0.037)	(0.036)	(0.038)
Observations	34,554	34,554	34,554	34,554	34,554
Panel E: Below median friends					
Friends Mental Unwellness	0.059	0.027	0.111***	0.088**	0.095**
	(0.046)	(0.040)	(0.041)	(0.041)	(0.045)
Observations	19,171	19,171	19,171	19,171	19,171

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation 1) with school fixed effects. Column (1) includes the results of the instrumental variable (IV) estimation where the dependent variables are indicators for confinding in female/male friends about mental unwellness problems. Column (2) includes the results of the instrumental variable (IV) estimation where the dependent variables are indicators for talking to female/male friends on the phone. Column (3) includes the results of the instrumental variable (IV) estimation where the dependent variables are indicators for visiting the houses of female/male friends. Column (4) includes the results of the instrumental variable (IV) estimation where the dependent variables are indicators for hanging out with female/male friends outside of school. Column (5) includes the results of the instrumental variable (IV) estimation where the dependent variables are indicators for spending the weekend at female/male house. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends.

[2] Standard errors are clustered on the school level.

[3] Data source is the Add Health in-school survey.

ONLINE APPENDIX

Peer Effects in Adolescent Mental Health

Hussain Hadah

Web.A Tables

Table 4: Summary Statistics of In-School Survey

	Mean	Std.Dev.	Range	Sample.Size
Demographic				
Age	15.00	1.71	[10, 19]	85,267
Female	0.50	0.50	[0, 1]	84,792
White	0.61	0.49	[0, 1]	85,267
Black	0.19	0.39	[0, 1]	85,267
Asian	0.07	0.25	[0, 1]	85,267
Native American	0.05	0.23	[0, 1]	85,267
Other	0.10	0.30	[0, 1]	85,267
Married (w5)	0.41	0.49	[0, 1]	20,854
Educational Outcomes				
GPA	2.86	0.79	[1, 4]	54,023
Number of Friends	6.53	3.64	[0, 10]	85,267
Health Outcomes				
Poor Health	0.07	0.26	[0, 1]	81,287
Feel Sick	0.30	0.46	[0, 1]	79,652
Feel Tired	0.55	0.50	[0, 1]	79,611
Miss School for Health Reasons	0.45	0.50	[0, 1]	78,110
Ever Saw a Therapist	0.63	0.48	[0, 1]	79,444
Behavioral Risk Outcomes				
During the last 12 months				
Skip School	0.30	0.46	[0, 1]	79,646
Smoke	0.36	0.48	[0, 1]	79,916
Get Intoxicated	0.31	0.46	[0, 1]	79,263
Freq. Drink Alcohol	1.69	1.84	[0, 6]	20,854
Freq. High on Drugs	0.04	0.35	[0, 4]	20,854
During the last 30 days				
Freq. marijuana (w1)	1.92	17.44	[0, 900]	20,854
Freq. marijuana (w3)	0.69	10.05	[0, 999]	20,854
Freq. marijuana (w4)	0.46	1.41	[0, 6]	20,854
Freq. Hang Out w/ Frnds	2.96	2.69	[0, 7]	20,854
Hurt Others b/c Drunk Including Unprotected Sex (w4)	0.61	0.49	[0, 1]	6,419

Table 4: Summary Statistics of In-School Survey *(continued)*

	Mean	Std.Dev.	Range	Sample.Size
Hurt Others b/c High Including Unprotected Sex (w4)	0.24	0.43	[0, 1]	4,241
Hurt Others b/c Drugs Including Unprotected Sex (w4)	0.43	0.50	[0, 1]	1,647
Paid for Sex (w4)	0.02	0.14	[0, 1]	13,504

Notes: Data source is the Add Health survey. Questions regarding skipping school without an excuse, frequency of smoking cigarettes, getting intoxicated, drinking alcohol, and getting high on drugs were asked over a 12 month period.
Source: Author's calculations from Add Health Survey (in-school survey and in-home surveys waves 1 through 5).

Table 5: Summary Statistics of the Mental Unwellness Variable

	Mean	Std.Dev.	Range	Sample.Size
Raw Mental Unwellness Score	21.17	11.00	[0, 67]	89,940
Raw Mental Unwellness Score: Friends	21.56	6.80	[0, 67]	67,993
Raw Mental Unwellness Score: Friends-of-friends	21.60	4.81	[0, 60]	64,168

[1] Data source is the Add Health survey. The mental unwellness score is the sum of the questions in table 7. The score for the friends and friends-of-friends is the average of the mental unwellness score of the friends and friends-of-friends.

Table 6: Summary Statistics of the Full Sample, Friends, and Friends of Friends

	Full Sample	Friends	Friends of Friends
Demographic			
Age	15.02	14.98	14.98
Female	0.50	0.51	0.51
White	0.61	0.62	0.62
Black	0.19	0.19	0.19
Asian	0.07	0.07	0.07
Native American	0.05	0.05	0.05
Other	0.10	0.09	0.09
Married (w5)	0.41	0.43	0.43
Educational Outcomes			
GPA	2.86	2.88	2.88
Number of Friends	6.20	6.52	6.57
Health Outcomes			
Poor Health	0.07	0.07	0.07
Feel Sick	0.30	0.30	0.30
Feel Tired	0.55	0.56	0.56
Miss School for Health Reasons	0.45	0.44	0.44
Ever Saw a Therapist	0.63	0.64	0.64
Miss School	0.45	0.44	0.44
Behavioral Risk Outcomes			
Skip School	0.30	0.29	0.29
During the last 12 months			
Smoke	0.36	0.36	0.36
Get Intoxicated	0.31	0.31	0.31
Freq. Drink Alcohol	1.69	1.74	1.75
Freq. High on Drugs	0.12	0.12	0.12
During the last month			
Freq. marijuana (w1)	1.92	1.76	1.74
Freq. marijuana (w3)	2.66	2.69	2.71
Freq. marijuana (w4)	0.46	0.46	0.46
Freq. Hang Out w/ Frnds	2.96	3.04	3.05
Hurt Others b/c Drunk Including Unprot. Sex (w4)	0.61	0.61	0.61
Hurt Others b/c High Including Unprot. Sex (w4)	0.24	0.24	0.24

Table 6: Summary Statistics of the Full Sample, Friends, and Friends of Friends *(continued)*

	Full Sample	Friends	Friends of Friends
Hurt Others b/c Drugs Including Unprot. Sex (w4)	0.43	0.42	0.43
Paid for Sex (w4)	0.02	0.02	0.02

[1] Data source is the Add Health survey. Questions regarding skipping school without an excuse, frequency of smoking cigarettes, getting intoxicated, drinking alcohol, and getting high on drugs were asked over a 12 month period. For example, the question on frequency of smoking was 'During the past 12 months, how often did you smoke cigarettes?'. Questions regarding missing school for health reasons and frequency of consuming marijuana, and frequency of hanging out with friends were asked over a 30 day period. For example, the question on frequency of consuming marijuana 'During the past 30 days, on how many days did you use marijuana?'

Table 7: Mental Health Question

Variable	Question
S60I	How often have you had a poor appetite?
S46B	Since school started this year, how often have you had trouble paying attention in school?
S60J	How often have you had trouble falling asleep or staying asleep?
S60L	How often have you had trouble relaxing?
S60K	How often was the following true during the past week [or month]? You felt depressed.
S60O	How often have you felt fearful?
S60N	How often have you cried frequently?
S60M	How often have you been moody?
S62A	Do you agree or disagree with the following statement? You have a lot of energy.
S62N	Do you agree or disagree with the following statement? You feel like you are doing everything just about right.
S62P	Do you agree or disagree with the following statement? You feel loved and wanted.
S62O	Do you agree or disagree with the following statement? You feel socially accepted.
S62H	Do you agree or disagree with the following statement? You have a lot of good qualities.
S62K	Do you agree or disagree with the following statement? You have a lot to be proud of.
S62M	Do you agree or disagree with the following statement? You like yourself just the way you are.

[1] These are the questions used to construct the depression index. The 15 items questions roughly translates to the 20 Center for Epidemiologic Studies Depression (CES-D) scale (Radloff 1977a). To construct my mental health measure, I summed the responses to the negative questions and subtracted the responses to the positive. The final mental health measure is a normalized score with a mean of 0 and a standard deviation of 1.

Table 8: Montiel-Pflueger Robust Weak Instrument Test

	TSLS	LIML
Effective F statistic: 368.734		
Confidence level alpha: 1%		
% of Worst Case Bias		
$\tau = 5\%$	46.219	46.219
$\tau = 10\%$	30.125	30.125
$\tau = 20\%$	20.816	20.816
$\tau = 30\%$	17.232	17.232

[1] The Montiel-Pflueger Robust Weak Instrument Test assesses the strength of the instruments used in the IV estimation. An Effective F statistic of 368.734, well above the threshold of 10 suggested by Staiger and Stock (1997), confirms the robustness of the instruments, ensuring the reliability of the 2SLS estimator. The values for different levels of worst-case bias (τ) further demonstrate the stability of the instrument's strength (Olea and Pflueger 2013).

Table 9: Spillover Effect of Peers' Mental Unwellness on Own Mental Unwellness: Trimmed

	Mental Unwellness (1) OLS (Reduced Form)	Friends Mental Unwellness (2) First Stage	Mental Unwellness (3) 2SLS
Friends of Friends Mental Unwellness	0.229***	0.272***	
	(0.022)	(0.018)	
Friends Mental Unwellness			0.839***
			(0.061)
Observations	41,868	41,868	41,868
First Stage F-statistic			1,422.54

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation 1) with school fixed effects. Column (1) displays the estimation of the reduced form equation using own mental unwellness as the dependent variable. Moving on to column (2), I present the results of the first stage analysis using the average friends' depression as the dependent variable. Column (3) includes the results of the instrumental variable (2SLS) estimation. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends.

[2] Students that used all of there friendship nominations were trimmed from the analysis.

[3] Standard errors are clustered on the school level.

[4] Data source is the Add Health in-school survey.

Table 10: Spillover Effect of Reciprocated-Friends Mental Unwellness on Own Mental Unwellness

	Mental Unwellness (1) OLS (Reduced Form)	Friends Mental Unwellness (2) First Stage	Mental Unwellness (3) 2SLS
Reciprocated Friends of Friends Mental Unwellness	0.105***	0.178***	
	(0.013)	(0.013)	
Reciprocated Friends Mental Unwellness			0.590***
			(0.078)
Observations	27,848	27,848	27,848
First Stage F-statistic			685.49

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation 1) with school fixed effects. Column (1) displays the estimation of the reduced form equation using own mental unwellness as the dependent variable. Moving on to column (2), I present the results of the first stage analysis using the average friends' depression as the dependent variable. Column (3) includes the results of the instrumental variable (2SLS) estimation. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends.

[2] Standard errors are clustered on the school level.

[3] Data source is the Add Health in-school survey.

Table 11: Spillover Effect of Non-Friends Mental Unwellness on Own Mental Unwellness

	Mental Unwellness (1) OLS (Reduced Form)	Mental Unwellness (2) IV
Friends Mental Unwellness		0.272
		(0.239)
Non-Friends Mental Unwellness	-0.525	
	(0.402)	
Observations	$48,418$	$39,451$

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table presents the 2SLS estimation of the regression (Equation 1) with school fixed effects. Column (1) displays the estimation of the reduced form equation using own mental unwellness as the dependent variable. Column (2) includes the results of the instrumental variable (IV) estimation. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends.
[2] Standard errors are clustered on the school level.
[3] Data source is the Add Health in-school survey.

Table 12: Descriptive Statistics About Social Interactions by Gender

	Men (N=42493)		Women (N=42494)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Talk about problems	0.581	0.493	0.823	0.382	0.241	0.003
Talk on the phone	0.700	0.458	0.848	0.359	0.148	0.003
Visit house	0.663	0.473	0.723	0.448	0.059	0.003
Hang out	0.683	0.465	0.739	0.439	0.056	0.003
Spend weekend	0.665	0.472	0.745	0.436	0.079	0.003

Source: Add Health in-school survey.

Table 13: Descriptive Statistics About Social Interactions by Number of Friends

	Above Median Friends (N=43664)		Below Median Friends (N=46276)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Talk about problems	0.867	0.340	0.478	0.500	-0.389	0.003
Talk on the phone	0.928	0.258	0.552	0.497	-0.376	0.003
Visit house	0.842	0.365	0.485	0.500	-0.356	0.003
Hang out	0.869	0.337	0.493	0.500	-0.376	0.003
Spend weekend	0.863	0.344	0.488	0.500	-0.375	0.003

Source: Add Health in-school survey.

Web.B Figures

Figure 3: Monotonicity Test

figure/monotonicity.png

Note: This plot demonstrates the test for the monotonicity assumption in our instrumental variable approach. The y-axis shows the estimated effect of the instrument (friends-of-friends' mental unwellness) on the treatment (friends' mental unwellness) across different quantiles of the data. Monotonicity holds if the effect is consistently positive or negative across all quantiles. The dashed red line at y=0 aids in assessing sign consistency. I also conduct a formal test of whether the slope of these quantile effects differs significantly from zero; a non-significant result ($p > 0.05$) supports the monotonicity assumption. Violations of monotonicity may indicate the presence of 'defiers' in the sample, potentially biasing IV estimates.

Figure 4: Spillover Effect of Peers' Mental Unwellness on Own Unwellness Health, Academic and Behavioral Outcomes

(a) Own Mental Unwellness

figure/own-depression.png

(b) GPA

figure/gpa.png

(c) Skipping School

figure/skip-school.png

Figure 5: Spillover Effect of Peers' Mental Unwellness on Health Outcomes

(a) Poor Health

figure/poor-health.png

(b) Feel Sick

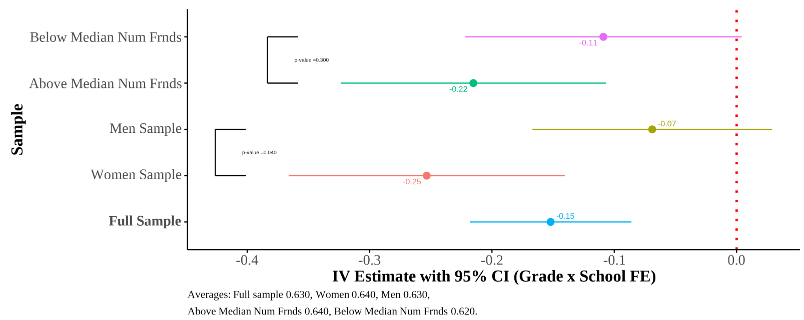
figure/feel-sick.png

(c) Feel Tired

figure/feel-tired.png

Figure 6: Spillover Effect of Peers' Mental Unwellness on Health Outcomes

(a) Never Seen a Therapist



(b) Miss School due to Health

figure/miss-schl-health.png

See the notes in Figure 4. Here we conduct separate 2SLS estimations for different samples. Panel (A) shows the 2SLS estimations

Figure 7: Spillover Effect of Peers' Mental Unwellness on Behavioral Outcomes

(a) Smoking Cigarettes

figure/smoking-cigs.png

(b) Intoxication

figure/intoxication.png

Figure 8: Spillover Effect of Peers' Mental Unwellness on Socialization

(a) Number of Close Friends

figure/close-friends.png

(b) Freq. Hang Out w/ Frnds

figure/frq-friends.png

Figure 9: HLP Instrument Robustness

figure/all-in-one-HLP-I.png

Note: This figure reports 2SLS estimates that instrument friends' mental unwellness using the higher-order network moments proposed by **horrace2014endogenous<empty citation>** (HLP instrument). Dependent variables are measured in the in-school survey. The control variables include sex, race, age, parental education, parental employment, parental occupation, and number of friends; standard errors are clustered at the school level. Point estimates with 95% confidence intervals are shown for own mental unwellness, GPA, skipping school, intoxication, poor health, missing school due to health, feeling sick or tired, and smoking. Results broadly align with the baseline specification, indicating that the main findings are robust to using the HLP