The Role of Friends in the Opioid Epidemic*†

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Abstract

The role of friends in the US opioid epidemic is examined. Using data from the National Longitudinal Survey of Adolescent Health (Add Health), adults aged 25-34 and their high school best friends are focused on. An instrumental variable technique is employed to estimate peer effects in opioid misuse. Severe injuries in the previous year are used as an instrument for opioid misuse in order to estimate the causal impact of a person's best friends' opioid misuse on their own misuse. The estimated peer effects are significant: Having a best friend who misuses opioids following a serious injury increases the probability of own opioid misuse by around 7 percentage points in a population where 17 percent ever misuses opioids. The effect is concentrated among non-college graduates and peers with strong ties who are central in their friendship networks. Peer opioid misuse eventually leads to deteriorating health and opioid addiction.

JEL: C26, D10, I12, J11.

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1 Introduction

Opioids have led to the worst drug overdose epidemic in US history–see Cutler and Glaeser [2021] and Maclean et al. [2022] for recent reviews–and have had a deleterious impact on public health and individual labor-market outcomes. What role have peers played in the spread of the opioid crisis? For those who misuse prescription opioids, friends are one of the most common sources for obtaining them. Table 1, panel A, shows the fraction of individuals between the ages of 26 and 34 who misuse opioids and get them from friends and relatives. Between 2010 and 2019, more than 50 percent of opioid misusers obtained opioids from friends or relatives.[1] In 2010, when the total opioid prescription shipments peaked in the United States, the role of friends and relatives was even stronger, possibly due to the wider availability of prescribed opioids. Hence, it is not surprising that peers have been highlighted as a potentially important factor in the fight against opioids [Compton et al., 2019, Blanco et al., 2020]. Yet, the empirical estimation of peer effects is challenging due to the unavailability of data and the difficulties in achieving identification.

Table 1: Individuals ages 26-34 who misuse prescription opioids: main method of acquiring and main reason for misuse

Year	All	Non-College	College
Panel A: Fraction that obtained opioids from friends			
2010	56.35%	56.16%	56.91%
2015	46.32%	46.15%	46.91%
2019	34.83%	33.26%	38.95%
Panel B: Physical pain as main reason for last misuse of opioids			
2015	59.14%	61.52%	58.42%

Note: Calculations based on NSDUH data.

This gap is filled here by exploiting rich information on opioid misuse by individuals between the ages 25-34 and opioid use by their high school best friends, utilizing a comprehensive set of controls that include information on demographics, health, and parental characteristics. The main analysis draws data from Wave IV of Add Health in 2009; i.e., at the first stage of the opioid epidemic, when knowledge regarding the risk of addiction and death due to opioid misuse was still limited and the prescriptions for opioids as painkillers were very common–see Guy [2017] and Figure A1.[2] For example, Muench et al. [2020] report that opioid

[1] The numbers in Table 1 come from the National Survey on Drug Use and Health (NSDUH), an annual nationwide survey that provides national and state-level data on the use of tobacco, alcohol, illicit drugs (including the non-medical use of prescription drugs), and mental health in the United States. The misuse of prescription drugs is defined as use in any way that is not directed by a doctor during the last 12 months–i.e., without a prescription, use in greater amounts than prescribed, more often than prescribed, longer than prescribed, or in any other non-directed way.

[2] Deaths due to opioid misuse increased sharply and steadily after 2014. The last part of this paper analyzes the welfare implications of peer opioid misuse on the probability of addiction and death.

prescriptions in U.S. community health centers serving low-income patients decreased by 73.7% from 2009 to 2018, highlighting the high prevalence of prescribing in 2009 and its decline over time. To estimate the causal impact of peer influence, an instrumental variable technique is employed while accounting for state- and/or school-specific factors. The identification strategy is the idea that individuals can develop misuse and addiction as a result of an opioid prescribed for a severe injury, an exogenous factor, which can then affect their peers. Previous research has shown that a one-time exposure to opioids, e.g., in an emergency room or during a C-section, increases the likelihood of opioid misuse six months and one month after, respectively [Barnett et al., 2017, Eichmeyer and Zhang, 2022, Carrico et al., 2020]. As Table 1, panel B, shows 59 percent of opioid misusers ages 26-34 report physical pain as the main reason for their behavior.

When using best friends' severe injuries as an instrument, there is a significant positive peer effect on opioid misuse. Having a best friend who misuses opioids following a serious injury increases the probability of own opioid misuse by around 7 percentage points (pp) in a population where 17 percent have misused opioids. A placebo analysis, which examines the probability of smoking as an alternative outcome, rules out the possibility that the findings are simply capturing a general tendency toward risky behavior among friends.

The effect is driven by individuals without a college degree, and by long-lasting, close friends who are of the same gender and live in the same county. Additionally, the effect intensifies within dense or large friendship networks and among individuals who have a central place in their friendship network. The effect is also stronger in areas with high opioid dispensing rates, low naloxone accessibility, higher prevalence of physical and mental health problems, lower accessibility of health care, and low social capital.

Last, the analysis reveals major health consequences and negative welfare implications of peer opioid misuse. Peer opioid misuse leads to a deterioration of self-reported health status, a higher likelihood of stimulant misuse, and an increased probability of opioid addiction. There is also some evidence suggesting a possible link between peer opioid misuse and an increased likelihood of death due to poisoning from toxic substances or suicide. However, as deaths are rare in this age group, these estimates are imprecise.

Related Literature. This study contributes to the recent literature on the determinants of the opioid epidemic in the United States (see, among others, Alpert et al. 2018; Ruhm 2019; Alpert et al. 2022;

Eichmeyer and Zhang 2022; Finkelstein et al. 2022; Dowd 2023; Eichmeyer and Zhang 2023; Janssen and Zhang 2023).[3] This appears to be the first paper that causally identifies at the micro level the role of friends in the spread of the opioid epidemic in the United States. Mäckle and Ruenzi [2022] and Cutler and Donahoe [2024] exploit friendship links (Facebook friends) between counties to study network effects on overdose deaths at the county level. The current investigation instead analyzes opioid misuse at the individual level and focuses on friendships formed many years before (during adolescence) without considering newly formed friendships, which are more likely to suffer from endogeneity concerns.

This appears to be the first paper that causally identifies, at the micro level, the role of friends in the spread of the opioid epidemic in the United States. Previous studies, such as Mäckle and Ruenzi [2022] and Cutler and Donahoe [2024], have examined network effects on overdose deaths using friendship links—such as Facebook connections—at the county level. In contrast, the current investigation offers a more granular analysis by focusing on opioid misuse and addiction at the individual level. It looks at long-established friendships formed during adolescence, intentionally excluding newly formed friendships that may be more prone to endogeneity concerns. The large effect found in this study aligns with Cutler and Donahoe [2024], who show that spillovers between geographically close counties or those linked through Facebook networks can account for 84 to 92 percent of opioid deaths from 1990 to 2018, highlighting the significant role of network effects in the opioid epidemic. The current study's individual-level approach provides a more detailed understanding of how peer relationships specifically contribute to the spread of opioid misuse and addiction.

Seamans et al. [2018] study opioid initiation among household members using a similar instrument (injury of a family member), distinguishing by injury type (ankle sprain or fracture, with the latter being treated more frequently with opioids). The estimated positive effect on other household members highlights the relevance of drug availability at home but is difficult to interpret as a peer effect due to homophily and correlated effects among family members.[4] The strategy here is to estimate peer effects among high school best friends including state and/or school fixed effects to account for correlated effects. Cappellari and Tatsiramos [2015] use the onset of best friends' health problems as an instrument of their employment status

[3] Finkelstein et al. [2022] find an important role for location-specific factors, which can potentially capture differences in peer effects across locations.

[4] See also [de Vaan and Stuart, 2019, Khan et al., 2019] for a similar approach, but with similar challenges in interpretation.

to examine peer effects on job finding. The proposed instrument here, that is, best friends' severe injuries, is conceptually similar but is used to study peer effects on opioid misuse. Finally, Thingholm [2023] documents spillovers in opioid prescriptions among practitioners in Denmark and the negative consequences on their patients' labor market outcomes, while Rose et al. [2024] examine the influence of peers on recovery from substance use disorders among patients in Norway.

The findings are also related to the literature that studies peer effects on the consumption of other substances such as tobacco or alcohol [Card and Giuliano, 2013, Cutler and Glaeser, 2005, Clark and Lohéac, 2007, Eisenberg et al., 2014, Kremer and Levy, 2008, Lundborg, 2006, Fletcher, 2012]. Some of these studies also adopt an instrumental variable technique, using substance availability at friends' parental homes or average characteristics of friends as instruments. Beyond substance abuse, the instrumental variables approach is widespread in the literature that causally estimates peer effects–see among others Dahl et al. [2014], De Giorgi et al. [2010] and Kim et al. [2024]. The current analysis contributes by focusing on opioid misuse 14 years after friendship formation (not contemporaneous) and by proposing an instrument whose exclusion restriction is more likely to hold.

2 Data

To analyze peer effects on opioid misuse, unique information is garnered from Add Health on best friends in high school and subsequent opioid misuse in adulthood (14 years after). Add Health is a longitudinal survey–see Figure A2 and Harris [2018]. Information is harnessed from four waves. Longitudinal survey weights are used to account for any possible attrition. More specifically, Wave I of the survey took place in 1994/1995 and entailed in-home interviews of a representative sample of high school students in the United States. Respondents were asked to nominate up to five male and five female friends. Nominations were made starting from the closest friend to the most distant friend. The focus is on the first male and female nominations; i.e., the best friends. This choice is motivated by the higher likelihood of the respondents staying in contact with best friends in adulthood and the low fraction of respondents, less than 1/3 of them, nominating more than two friends. Respondents were asked to nominate their friends again in Wave II, about a year after Wave I. This information is used to analyze heterogeneity in the effects among friendships of different duration. Given that, in most cases, individuals and their best friends were attending the same school, they were all part of the Add Health in-home interview, which allows the retrieval of a rich set of information for both the individuals and their best friends.[5]

Friends nominated in the Add Health study can be used to map out friendship networks within each high school, and Add Health also provides detailed information about these networks and each person's role within them. These measures include: i) Bonacich centrality, defined as the centrality of an individual weighted by the centrality of those they nominate as friends–see Bonacich [1987]; ii) a "reach" measure, representing the maximum number of connections a node (an individual) can connect within the entire friendship network; and iii) relative density, calculated as the ratio of actual ties to the maximum possible ties, computed under the assumption that each respondent could nominate up to 10 friends. These metrics help explore how different network characteristics affect outcomes.

Besides providing information on friendship formation, Wave I of Add Health also contains information on several socioeconomic, educational, and behavioral outcomes for teenagers and their families. In particular, it contains information on the availability of cigarettes and alcohol in respondents' homes. There is also information on the availability of drugs at home and on whether the respondent had consumed any illegal drug by Wave I. Last, for a subset of respondents whose parents participated in the parents' interview, there is information on whether the respondent lived with both parents and questions about maternal education and household gross income.

After Waves I and II, respondents (individuals and their friends) were followed to adulthood. Wave III took place in 2001 and Wave IV took place in 2008. A question that allows the *direct* measurement of opioid misuse was asked for the first time in Wave IV.[6] At that time, the respondents were between 25 and 34 years old. The question was:

"Which of the following types of prescription drugs have you ever taken that were not prescribed for you, taken in larger amounts than prescribed, more often than prescribed, for longer periods than prescribed, or that you took only for the feeling or experience they caused? Painkillers or opioids, such as Vicodin,

[5] Friendship networks are used to study peer effects on different socioeconomic outcomes, such as education, living arrangements, and teenage pregnancies (see, among others, Bifulco et al. 2011; Fernández-Villaverde et al. 2014; Patacchini et al. 2017; Adamopoulou and Kaya 2018; Agostinelli et al. 2022).

[6] In Wave I respondents were asked about illegal drug use and in Wave III about the use of painkillers (Darvon, Demerol, Percodan, or Tylenol with codeine) without doctor's permission. Respondents who reported illegal drug use in Wave I or unsubscribed painkiller use in Wave III are excluded in a battery of robustness checks.

OxyContin, Percocet, Demerol, Percodan, or Tylenol with codeine."[7]

Additionally, another question in Wave IV restricts the reference period to the last 12 months and assesses the intensity of the misuse: "During the past 12 months, on how many days did you use painkillers when they were not prescribed for you, in larger amounts than prescribed, more often than prescribed, or for longer periods than prescribed?: none, 1 or 2 days, once a month or less, 2 or 3 days a month, 1 or 2 days a week, 3 to 5 days a week, every day or almost every day."

Respondents in Wave IV were also asked to report their self-perceived health status, as well as stimulants, and other drug use. Additionally, there was a question to assess opioid addiction, which asked: "Have you ever continued to use painkillers after you realized using them was causing you any emotional problems (such as feeling depressed or empty, feeling irritable or aggressive, feeling paranoid or confused, feeling anxious or tense, being jumpy or easily startled) or causing you any health problems (such as heart pounding, headaches or dizziness, or sexual difficulties)?".

Importantly, respondents in Wave IV were asked whether they had suffered a serious injury in the previous year. This question is key for the construction of the instrument and asked: "In the past 12 months, have you suffered any serious injuries? For example, broken bones, cuts or lacerations, burns, torn muscles, tendons or ligaments, or other injuries that interfered with your ability to perform daily tasks."

Moreover, the Individual Vital Status and Underlying Cause of Death file provides the vital status of each Add Health sample member from Wave I through 2021 and the underlying International Classification of Diseases causes of death code for each decedent. Given that deaths in Add Health are rare events (respondents were between 37 and 46 years old in 2021), the causes of death are reported in aggregated categories. For the current analysis, deaths are then classified into two broad categories, namely, deaths due to medical factors (e.g., HIV, cancer, diabetes, CVD, parasitic, respiratory, or digestive diseases) and deaths due to poisoning from toxic substances or suicide. The latter include drug overdoses, which are likely to be due to opioid misuse.[8]

As Table 2, column 2, shows, almost 17 percent of individuals reported misusing opioids and 14 percent

[7] The definition of misuse of prescription drugs is very similar in the NSDUH and Add Health. A slightly different age bracket is used in Table 1 since age is reported in particular brackets in the NSDUH.

[8] The Add Heath category that contains deaths due to poisoning from toxic substances also includes deaths due to drowning, a number likely to be very small.

Table 2: Final sample statistics

	N (1)	mean (2)	sd (3)	min (4)	max (5)
Outcomes (Wave IV)					
Opioid misuse	2,826	0.169	0.375	0	1
Any best friend opioid misuse	2,826	0.192	0.394	0	1
Severely injured	2,826	0.138	0.345	0	1
Any best friend severely injured	2,826	0.161	0.368	0	1
Smoking	2,817	0.697	0.460	0	1
Prob(Opioid addiction)	2,521	0.035	0.184	0	1
Current self-perceived health status	2,826	2.731	0.918	0	4
Stimulants misuse	2,826	0.080	0.272	0	1
Additional outcomes (as of 2021)					
Death due to poisoning from toxic substances or suicide	2,826	0.007	0.081	0	1
Death due to medical factors	2,826	0.013	0.112	0	1
Characteristics (Wave IV)					
Female	2,826	0.523	0.500	0	1
College	2,826	0.370	0.483	0	1
African American	2,826	0.123	0.329	0	1
Hispanic	2,826	0.081	0.273	0	1
Age	2,826	28.63	1.771	25	34
Ever diagn. depressed	2,826	0.150	0.357	0	1
Ever diagn. post-traumatic stress	2,826	0.029	0.169	0	1
Ever diagn. anxiety	2,826	0.126	0.332	0	1
Characteristics (Wave I)					
Cigarettes avail. at parental home in WI	2,826	0.312	0.463	0	1
Alcohol avail. at parental home in WI	2,826	0.312	0.463	0	1

Note: Characteristics of individuals in the Add Health regression sample. Survey weights are used.

reported a serious injury during the last year.[9] The reference period for this question is 2008. This is a period when the opioid dispensing rate per 100 persons in the United States was high (above 75) and increasing.[10] Additionally, 3.5 percent of the respondents reported opioid addiction, while around 0.7 percent died due to poisoning from toxic substances or suicide by 2021.

Around 19 percent of the individuals have at least one best friend who reported misusing opioids and 16 percent have at least one best friend who suffered a serious injury in the previous year. Wave IV also contains information on additional socio-demographic characteristics for the respondents, such as race, occupation, and whether they completed college. There is also information on whether the respondents were ever diagnosed with depression, post-traumatic stress disorder, anxiety or panic disorder, and whether they

[9]Between 2005 and 2019, among individuals between the ages of 26 and 34, about 7 percent report misusing opioids during the last 12 months in the NSDUH. This percentage is lower than in Add Health as the reference period is "the last 12 months" in the NSDUH questionnaire as opposed to "ever taken" in the Add Health questionnaire.

[10]The opioid dispensing rate per 100 persons is defined as the ratio of the total number of prescriptions dispensed annually at the national level over the annual resident population. In the United States, it peaked in 2012 (reaching 81) and subsequently dropped (down to 43 in 2020). See https://www.cdc.gov/overdose-prevention/data-research/facts-stats/us-dispensing-rate-maps.html and https://www.cdc.gov/mmwr/volumes/66/wr/mm6626a4.htm.

were ever at risk under the influence of a drug. The survey in Wave IV also elicited information on the Big 5 personality traits (extraversion, agreeableness, openness, conscientiousness, and neuroticism) and a measure of risk aversion.[11]

Geographical information, such as respondents' state, county, or Census tract of residence, is anonymized in Add Health. Hence, beyond identifying whether two individuals are from the same location, it is impossible to merge it with local-level information from external sources. However, after the conclusion of the most recent wave, conducted from 2016 to 2018, Add Health created several local-level descriptors on outcomes that are likely to interact with the effect of peers on opioid misuse. As a result, while the respondents' county of residence is anonymous, it is possible to obtain the average characteristics of the state or county in which they live. In particular, Add Health provides state-level information on opioid dispensing rates (number of prescriptions per 100 persons) in 2016 and the number of months between the interview date and the implementation of naloxone access laws.[12] It also provides county-level measures on the average number of poor mental health days per month, the number of primary care physicians per 100,000 population at the county level, and information on the number of mental health facilities within 20 miles of the respondent's residence.[13] Finally, a county-level social capital index, based on the methodology of Rupasingha et al. [2006], is also provided for 2014.[14]

3 Empirical strategy

Estimating peer effects entails several empirical challenges related to homophily, the reflection problem, and correlated effects [Manski, 1993, 2000, Angrist, 2014]. To address these, a strategy based on a combination of data structure and instrumental variables is employed. The first challenge is the endogenous formation and termination of friendships, so-called "homophily." Individuals tend to choose friends who are similar

[11]The question on risk aversion was "How much do you agree with the statement about you as you generally are now, not as you wish to be in the future? 'I like to take risks'", and the respondents could answer on a five-point scale ranging from strongly agree to strongly disagree.

[12]State-level opioid dispensing rates provided by Add Health are from the Centers for Disease Control and Prevention (2020), https://www.cdc.gov/drugoverdose/rxrate-maps/county2016.html. The implementation of naloxone access laws are based on Lee et al. [2021]. These laws provided civil or criminal immunity to licensed health care clinicians or laypersons for administering opioid antagonists, such as naloxone hydrochloride, to reverse overdoses.

[13]County-level health outcomes provided by AddHealth are taken from the 2020 County Health Rankings & Roadmaps, https://www.countyhealthrankings.org/.

[14]The index is based on the following establishments in each county: (a) civic organizations; (b) bowling centers; (c) golf clubs; (d) fitness centers; (e) sports organizations; (f) religious organizations; (g) political organizations; (h) labor organizations; (i) business organizations; and (j) professional organizations.

to themselves, so any association in behavior can be driven from this endogenous choice of friends rather than direct peer influences. Homophily is mitigated by focusing on friendships formed during high school, in particular best friends, who are likely to maintain contact after high school graduation. This approach excludes new friendships formed in adulthood, which may involve individuals who misuse opioids or provide access to them after opioid misuse has begun. Additionally, by estimating an intention-to-treat effect without conditioning on current friendships, we avoid bias introduced by these later, endogenous relationships.[15]

The second challenge is the simultaneity of outcomes within a group, the so-called "reflection problem," which makes it difficult to differentiate between the effect of best friends on an individual and the impact of operating the other way. The reflection problem is tackled by studying opioid use at least 14 years after friendship formation and using a valid instrument: best friends' serious injuries. The idea is that best friends who were seriously injured were prescribed opioids, which in turn led to opioid misuse.

The identification is based on the presumption that a best friend's injury affects own opioid misuse only through its effect on the best friend's opioid misuse (and not directly). This exclusion restriction could be violated if the individual was injured together with their best friend (e.g., joint accident) or if the individual started misusing opioids due to the stress caused by the best friend's injury. Therefore, the benchmark specification controls for whether individuals suffered a serious injury themselves and for whether the individual has ever been diagnosed with depression, post-traumatic stress, or anxiety. Moreover, after controlling for a serious injury, people with and without a serious injury should have the same propensity to misuse opioids. Section 4.1 delves into the issue of conditional independence by excluding individuals who had previous experience with illegal drugs or non-prescribed painkillers as well as i) individuals (and their best friends) who are risk lovers, or ii) individuals (and their best friends) who report that they have ever put themselves or others at risk under the influence of a drug, or iii) individuals who suffered a severe injury themselves. A further test of the exclusion restriction, which regresses own injuries on best friends' injuries, is also conducted in this section. The null effect of this regression confirms that individuals and their best friends did not experience an injury simultaneously (e.g., as part of the same accident).

The third challenge is correlated effects; i.e., that both individuals and their friends are often subject to

[15] In Sections 4.1 and 4.2, the sample is restricted to individuals who reported never using drugs in Wave I, ensuring that any potential peer influence on opioid misuse during high school is excluded.

common factors/environment. Correlated effects are addressed by including different sets of fixed effects as described below.[16]

The benchmark empirical model consists of a second-stage equation, a first-stage regression, and an exclusion restriction:

$$\begin{aligned} \text{Opioid misuse}_{is} = \beta_1 (\widehat{\text{any best friend opioid misuse}})_{is} + \beta_2 (\text{serious injury})_{is} \\ + \beta_3 X_{is} + \eta_s + u_{is}, \end{aligned} \tag{1}$$

$$\begin{aligned} \text{Any best friend opioid misuse}_{is} = \gamma_1 (\text{any best friend serious injury})_{is} + \gamma_2 (\text{serious injury})_{is} \\ + \gamma_3 X_{is} + \mu_s + e_{is}, \end{aligned} \tag{2}$$

and

$$Cov(\text{any best friend serious injury}_{is}, u_{is} \mid X_{is}, \eta_s) = 0, \tag{3}$$

where i stands for the individual and s for the state of residence or school. The empirical specification instruments whether any best friend reports opioid misuse with whether any best friend suffered a severe injury in the previous year. The outcome variable in the benchmark specification is binary and refers to opioid misuse at any point in time prior to the Wave IV interview. Additional exercises restrict the reference period to the previous 12 months and also consider varying intensities of opioid misuse–see Section 4.2. The vector X_{is} includes socio-demographic characteristics, such as age, gender, education (with or without a college degree), and race; an indicator for having ever been diagnosed with depression, post-traumatic stress, or anxiety; and an indicator for the availability of cigarettes or alcohol in the parental home while in high school. Standard errors are clustered using the school identifier, as recommended by the Add Health guidelines, which specify that schools are the appropriate sampling units for clustering. Longitudinal survey weights are applied to address any possible attrition, ensuring that the analysis accounts for the study's sampling design and remains representative. The benchmark specification includes Wave III state fixed effects to control for policies that may affect the availability of opioids at the state level.[17] In a robustness

[16] Another way to address correlated effects is by examining the influence of non-best friends residing in the same county as the respondent–see Section 5.

[17] Wave III instead of Wave IV state fixed effects are used since the latter are endogenous (individuals in Wave IV may choose the state of residence based on the availability of opioids).

exercise, school fixed effects or a combination of school and state fixed effects are used and all results hold.

The robustness of the benchmark estimates is checked by including an extensive list of additional individual controls; i.e., the Big 5 personality traits (extraversion, neuroticism, agreeableness, openness, conscientiousness), risk aversion, occupational dummies, the availability of drugs in the parental home while in high school, and additional family-of-origin controls (maternal education, household gross parental income during high school, and living with both parents during high school). One robustness exercise includes (exogenous) peer characteristics, namely, the fraction of best friends who are college graduates, Hispanic, African American, and the fraction who had cigarettes/alcohol/drugs available in the parental home while in high school. Other robustness exercises consider different measures of peer influence (percentage, number or dyads of best friends who misuse opioids instead of any best friend misusing opioids).

4 Results

Table 3 reports the estimates of the second-stage regression equation (1). The first-stage results are reported in Table 4. Table 3, column 1 shows the estimated peer effect on opioid misuse without any controls. There is a positive and statistically significant effect. The estimated effect does not change much when own severe injury (column 2) is added and is reduced in size as soon as state fixed effects (column 3) are included. The estimated peer effect decreases slightly when controlling for demographic characteristics (column 4), and for having ever been diagnosed with depression, post-traumatic stress or anxiety (column 5). The availability of cigarettes or alcohol in the parental home while in high school does not seem to play any role (column 6).

In all specifications, the F-statistic of the first stage is above 10 (last row in Table 3), indicating that the instrument is not weak. To understand the economic significance of the results, consider both the first-stage and second-stage coefficients. As Table 4 shows, the coefficient of the first stage is 0.156, implying that if any best friend has a serious injury, the probability that they will misuse opioids increases by 15.6 pp.[18] The coefficient of the second stage is 0.472 (Table 3, column 6). Therefore, if any best friend has a serious injury, the probability of the respondent misusing opioids increases by $0.156 \times 0.472 = 7.36$ pp. An alternative way to compute the magnitudes is to consider that the estimated effect in the second stage is conditional on

[18] The baseline probability of any best friend misusing opioids is 19.2 percent (second row in Table 2). Recall that the period of reference is 2008, when the prescription of opioids was a common practice, especially in the case of a severe injury.

Table 3: Peer effects on opioid misuse-2SLS

	Dep. var.: Prob(Opioid misuse)					
	(1)	(2)	(3)	(4)	(5)	(6)
Any best friend opioid misuse	0.576**	0.613***	0.519**	0.495**	0.471**	0.472**
	(0.227)	(0.225)	(0.203)	(0.196)	(0.198)	(0.196)
Severely injured		0.132***	0.124***	0.115***	0.106***	0.106***
		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
College				-0.038*	-0.033	-0.032
				(0.023)	(0.022)	(0.023)
Female				-0.024	-0.040**	-0.040**
				(0.020)	(0.020)	(0.020)
Age				-0.009	-0.008	-0.009
				(0.007)	(0.007)	(0.007)
Hispanic				0.000	-0.002	-0.000
				(0.042)	(0.040)	(0.039)
African American				-0.002	0.002	0.005
				(0.037)	(0.036)	(0.036)
Ever diagn. depressed					0.071*	0.070*
					(0.042)	(0.042)
Ever diagn. post-traumatic stress					0.100	0.099
					(0.064)	(0.063)
Ever diagn. anxiety					0.041	0.042
					(0.044)	(0.045)
Cigarette avail. in parental home in WI						0.021
						(0.031)
Alcohol avail. in parental home in WI						0.023
						(0.028)
Observations	2,846	2,846	2,843	2,830	2,830	2,826
State FE	No	No	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald rk F statistic	17.43	17.21	16.90	18.58	18.27	18.44

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 with different sets of control variables and fixed effects (columns 1-6). The estimates in column 6 correspond to the benchmark specification. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01.

having a friend who experienced an injury. As Table 2 shows, 16.1% of individuals have at least one best friend who got injured. Hence, if any best friend misuses opioids following a serious injury, the probability of the respondent misusing opioids increases by $0.161 \times 0.472 = 7.60$ pp. This is substantial given that the average incidence of ever misusing opioids is 17 percent (Table 2).[19]

To place the magnitude of the estimated peer effect in perspective, consider the "reduced-form" regression that directly regresses own opioid misuse on best friends' serious injuries (instead of instrumenting best friends' opioid misuse with best friends' serious injuries):

$$\text{Opioid misuse}_{is} = \beta_1(\text{any best friend serious injury})_{is} + \beta_2(\text{serious injury})_{is} + \beta_3 X_{is} + \eta_s + u_{is}. \quad (4)$$

[19] Fletcher [2012] examines peer effects on alcohol use and finds that a 100 percent increase in classmates' alcohol use increases the likelihood of drinking by 50 percentage points in a population where 48 percent drink alcohol. The peer effects we find are stronger (a 47 percentage points increase in a population where 17 percent misuse opioids). This can be due to differences in IV strategies. During the peak of the opioid epidemic, individuals who experienced a severe injury were almost certain to be treated with opioids, which amplified the peer effect, as the probability of misusing opioids if you get prescribed opioids after an injury was 15.6% (Table 4). In contrast, Fletcher [2012] uses the availability of alcohol at classmates' parental homes as an instrument.

Table 4: First-stage regression

	Dep. var.: Prob(Any best friend opioid misuse)
Any best friend severely injured	0.156***
	(0.036)
Severely injured	-0.033
	(0.026)
College	0.029
	(0.029)
Female	-0.025
	(0.024)
Age	-0.018***
	(0.007)
Hispanic	-0.052
	(0.036)
African American	-0.113***
	(0.028)
Ever diagn. depressed	0.057*
	(0.034)
Ever diagn. post-traumatic stress	-0.056
	(0.055)
Ever diagn. anxiety	0.002
	(0.031)
Cigarette avail. in parental home in WI	0.001
	(0.022)
Alcohol avail. in parental home in WI	0.036
	(0.027)
Observations	2,826
State FE	Yes

Note: The estimated coefficients of equation 2 for the benchmark specification. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01.

As Table 5, column 1, shows, if any best friend has a serious injury, the probability that the respondent will misuse opioids increases by 7.3 pp. The reduced-form equation can also be used to exclude the possibility that the benchmark specification captures some general risky behavior among friends rather than a pure peer effect. To this end, equation 4 is estimated with the probability of smoking rather than the probability of opioid misuse as an outcome variable. As Table 5, column 2, shows, the estimated coefficient in the pla-

Table 5: Peer effects on opioid misuse: reduced-form estimates and placebo regression

Dep. var.:	Prob(Opioid misuse)	Prob(Smoking)
	(1)	(2)
Any best friend severely injured	0.073**	0.004
	(0.029)	(0.031)
Observations	2,826	2,817
Controls	Yes	Yes
State FE	Yes	Yes
Mean	0.169	0.697

Note: The estimated coefficients of equation 4 for the benchmark specification and for the placebo regression. The outcome variable in the placebo regression is the probability of smoking instead of the probability of opioid misuse. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.

cebo regression is essentially null, further supporting the interpretation of the estimated effect in the benchmark specification as a genuine peer effect.

4.1 Conditional independence

A key assumption in the instrumental variable analysis is the exclusion restriction or conditional independence– See [Angrist and Pischke, 2009]. In other words, the instrument should be independent of potential outcomes. To assure that severe injuries are not caused by risky behavior due to opioid misuse, this section re-estimates equations 1 and 2 excluding from the analysis individuals with previous experience with illegal drugs or non-prescribed painkillers. More specifically, the sample excludes individuals who reported in Wave I that they have ever tried illegal drugs or reported in Wave III that they have ever taken painkillers without a doctor's permission.

Table 6: Peer effects on opioid misuse-conditional independence

	Dep. var.: Prob(Opioid misuse)		
	(1)	(2)	(3)
Any best friend opioid misuse	0.468**	0.449**	0.420**
	(0.201)	(0.208)	(0.195)
Observations	2,633	2,598	2,476
Controls	Yes	Yes	Yes
FE	State	State	State
Description	Not at risk under drugs by WIV	No risk lovers	No own severe injury in WIV
Kleibergen-Paap Wald rk F statistic	17.18	16.60	19.67

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 for different sample restrictions. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. The sample is restricted to individuals who had not used any illegal drugs in Wave I or any painkillers in Wave III. See Table 3, column 6 for the list of controls.

Table 6 presents the results, with additional sample restrictions. Column 1 retains only individuals and best friends who either do not use drugs in Wave IV or they use drugs but report that they have never put themselves or others at risk under the influence of a drug.[20] In this way, serious injuries that may have occurred due to drug use are excluded. In a similar vein, column 2 excludes individuals and best friends who are risk lovers (answered strongly agree to the statement 'I like to take risks'). The results of both exercises are extremely similar to the benchmark estimates. Last, column 3 excludes individuals who suffered a severe injury themselves in Wave IV. Also in this case, the estimated peer effects are highly statistically significant

[20] More specifically, those who answered "never" to the following question in Wave IV are kept: "How often have you been under the influence of your favorite drug when you could have gotten yourself or others hurt, or put yourself or others at risk, including unprotected sex?" Within the context of the Add Health questions, drugs here exclude misuse of prescription opioids.

and of similar size as in the benchmark specification. Therefore, conditional independence is likely to be a valid assumption in this setting. A further test of the exclusion restriction is reported in Table 7. It regresses own injuries on best friends injuries and the effect is null, confirming that individuals and their best friends did not experience an injury simultaneously (e.g., as part of the same accident).

Table 7: Testing the exclusion restriction

	Dep. var.: Prob(Severely injured)	
	(1)	(2)
Any best friend severely injured	-0.023	-0.034
	(0.027)	(0.024)
Observations	2,131	2,118
Controls	No	Yes
State FE	Yes	Yes
Mean	0.117	0.116

Note: Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. The sample is restricted to individuals who had not used any illegal drugs in Wave I or any painkillers in Wave III. See Table 3, column 6 for the list of controls.

4.2 Timing and intensity of opioid misuse

The benchmark model uses as the outcome variable whether any opioid misuse ever occurred as reported in Wave IV. This may give rise to two potential issues. First, there is a potential time discrepancy between the outcome and the instrumental variable as severe injuries reported in Wave IV refer to the past 12 months. Second, the outcome variable does not distinguish between occasional and more intensive opioid misuse. This section addresses both issues by using a different question from Add Health that specifies the intensity of painkillers misuse in the past 12 months.[21] Individuals with previous experience with illegal drugs or non-prescribed painkillers are again excluded from the analysis as in Section 4.1.

Table 8 presents the results using this sample restriction for opioid misuse across different time frames (ever or past 12 months) and with progressively increasing levels of misuse intensity.[22] The coefficient for the peer effect remains statistically significant and comparable in magnitude to the benchmark specification when the sample is limited to individuals who had not used illegal drugs in Wave I or painkillers in Wave

[21]The question is: "During the past 12 months, on how many days did you use painkillers?: none, 1 or 2 days, once a month or less, 2 or 3 days a month, 1 or 2 days a week, 3 to 5 days a week, every day or almost every day."

[22]It is important to note that only the misuse intensity of the affected individual is adjusted, while the peers' misuse intensity remains unchanged. Peers are not excluded based on their level of misuse, ensuring that the peer group composition remains consistent with the benchmark analysis. Consequently, the first-stage relationship, which estimates the impact of a peer's injury on opioid misuse among peers, remains unaffected by the exclusion of individuals with lower-intensity misuse.

Table 8: Peer effects on opioid misuse-by timing and intensity of misuse

	Dep. var.: Prob(Opioid misuse)				
Intensity	Ever misused	Any misuse in the last 12 months	Once per month or more in the last 12 months	2-3 days per month or more in the last 12 months	1-2 days per week or more in the last 12 months
	(1)	(2)	(3)	(4)	(5)
Any best friend opioid misuse	0.505***	0.314**	0.291**	0.283**	0.258**
	(0.174)	(0.124)	(0.118)	(0.112)	(0.123)
Observations	2,118	2,010	1,985	1,967	1,950
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Mean	0.110	0.0584	0.0419	0.0311	0.0152
Kleibergen-Paap Wald rk F statistic	13.46	13.77	13.54	12.80	10.65

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 for different intensities of opioid misuse in the previous 12 months. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. The sample is restricted to individuals who had not used any illegal drugs in Wave I or any painkillers in Wave III. See Table 3, column 6 for the list of controls.

III (column 1). This holds true even when considering opioid misuse only within the past 12 months.[23] Peer effects remain significant as the intensity of opioid misuse increases (columns 3 and 4) and persist even at a relatively high level of misuse (1-2 days per week, as shown in column 5). The coefficients decrease in magnitude as misuse intensity rises, reflecting the lower prevalence of more intensive misuse within the population, as indicated by the mean.

4.3 Robustness checks

A battery of additional exercises are run to check the robustness of our benchmark estimates. Figure 1 and Table A1 report the results. The first exercise (E1 in Figure 1) introduces school instead of state fixed effects and the estimates continue to be statistically significant but of slightly smaller size. The second exercise (E2 in Figure 1) includes both state and school fixed effects. Although this specification is demanding (it includes 174 fixed effects), the coefficient continues to be statistically significant and of slightly smaller size than the benchmark estimate.

Exercises E3 and E4 control for whether drugs were available in the parental home in Wave I and for exogenous/pre-determined friend characteristics. The results are very similar to the benchmark estimate. The findings are also robust to the inclusion of the Big 5 personality traits and a risk aversion measure

[23] All specifications, robustness checks, and group heterogeneity analyses hold when the analysis is repeated using this variable and sample restriction as a benchmark. However, some estimates become less precise due to the smaller sample size.

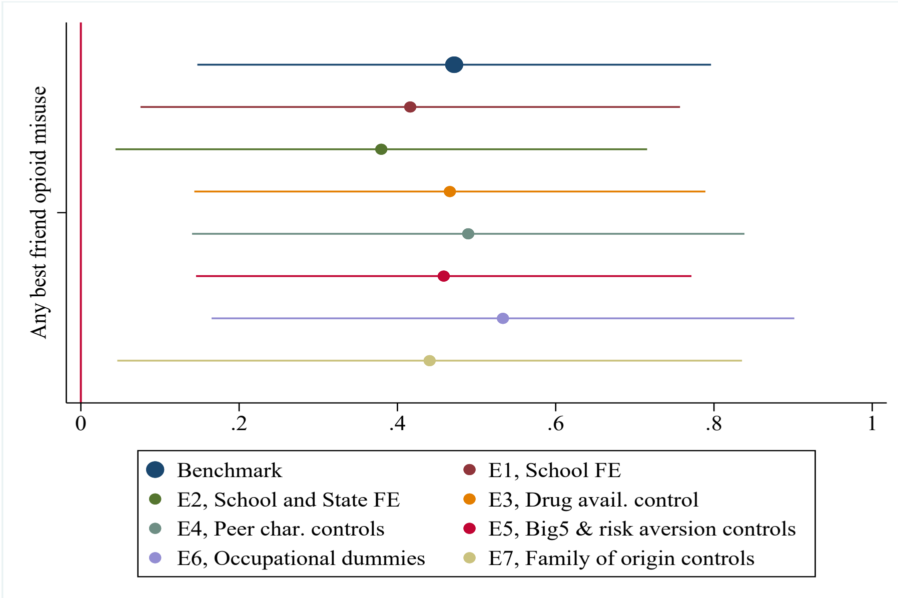

Figure 1: Peer effects on opioid misuse-2SLS robustness

Note: The estimated coefficients and 90% confidence intervals of equation 1 with different sets of fixed effects, control variables, and sample restrictions. See Table A1 for the full set of estimates.

(exercise E5) and to the inclusion of occupational dummies (exercise E6).[24] Last, exercise E7 controls for maternal education, household income, and household structure in Wave I. These variables are available for a smaller sample, but the peer effects remain significant.

Additionally, Table A2 reports estimates with different ways of measuring peer influence. In particular, while the benchmark regressor is whether any best friend misused opioids, column 2 shows the results with the percentage of best friends misusing opioids (0, 50% or 100%), column 3 with the number of best friends misusing opioids (0, 1 or 2) and columns 4 using dyads of best friends (i.e., considering the opioid misuse of each best friend of the respondent separately). All estimates are perfectly in line with the benchmark results.

5 Heterogeneous effects and mechanisms

There is substantial heterogeneity in opioid misuse by socioeconomic characteristics. In particular, opioid misuse is more common among less educated individuals and among non-Hispanic whites. As Table A3

[24]Previous research has shown that personality traits are an important determinant of other health-related outcomes such as bulimia. See Ham et al. [2021]. The current analysis shows that risk aversion and conscientiousness decrease the probability of opioid misuse while openness increases it.

shows, in Wave IV of Add Health, less than 15 percent of college graduates report ever using opioids, whereas the number for non-college graduates is 18.2 percent.[25] Moreover, 19.3 percent of non-Hispanic whites report ever using opioids in Wave IV, whereas the number is just 6.3 percent for other races.

Table 9: Peer effects on opioid misuse-2SLS by education and race

	Dep. var.: Prob(Opioid misuse)			
	By education		By race	
	College	Non-College	Non-Hispanic white	Others
	(1)	(2)	(3)	(4)
Any best friend opioid misuse	0.206	0.597**	0.395*	0.691
	(0.300)	(0.238)	(0.223)	(0.485)
Observations	1,072	1,747	1,726	1,095
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Mean	0.127	0.165	0.189	0.0728
Kleibergen-Paap Wald rk F statistic	9.829	12.42	12.31	9.177

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 for different educational groups (columns 1 and 2) and for different racial groups (columns 3 and 4). Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.

Some individuals are more prone to the influence of peers than others. This is examined by focusing on education and race and distinguishing between college and non-college graduates and between non-Hispanic whites and others. Table 9 presents the results. Peer effects in the second stage are significant and large for those without a college degree (column 2) but not among those with a college degree (column 1). There is no significant difference in the peer effect by race (columns 3 and 4).[26] The F-statistic of the first stage is close to or above 10 for all groups (last row of Table 9).

Peer effects could arise due to information sharing regarding the efficacy of opioids or through the direct provision of opioids. To shed light on the underlying mechanism, the type, duration and similarity of friendship is considered as well as the geographical proximity between the respondents and their best friends. Figure 2 and Table A4 report the results.

First, peer effects are statistically significant only among best friends (first female and male nomination). Other friends (second to fifth female and male nominations) do not exert any statistically significant effect on opioid misuse. Second, the duration of the friendship and the similarity of friends matters. The peer

[25] The educational gap in opioid misuse is higher in the NSDUH. Between 2005 and 2019, among individuals between ages 26 and 34, 4.7 percent of individuals with a college degree and 7.8 percent of those without a college degree reported misusing opioids during the last 12 months.

[26] Due to the small sample size, only two race categories, Non-Hispanic Whites and Others, are considered.

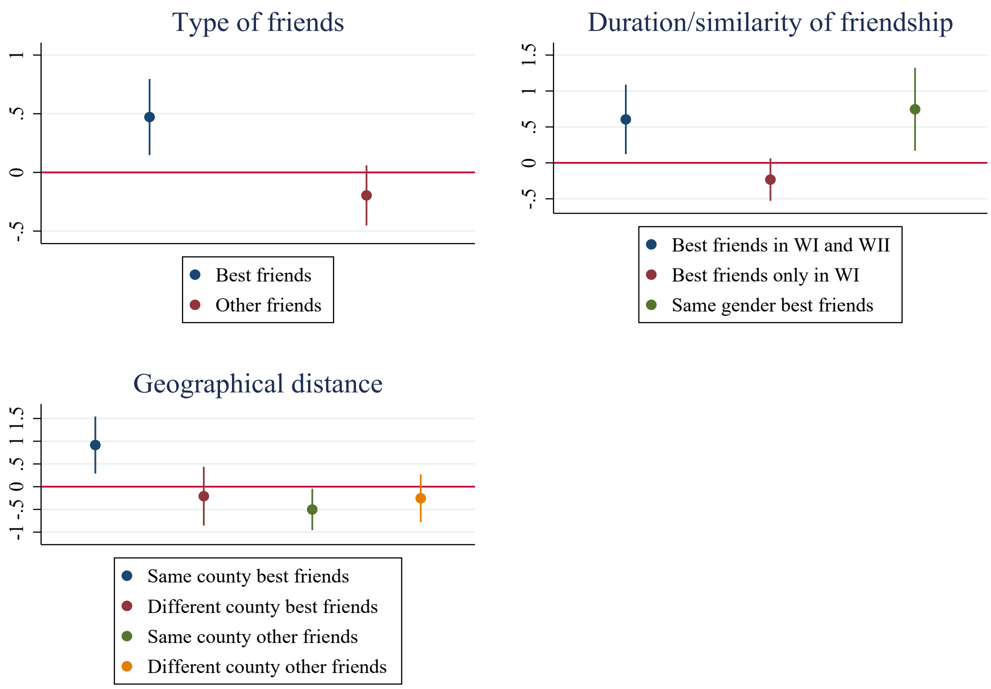

Figure 2: Peer effects on opioid misuse-by type of friends

Note: The estimated coefficients and 90% confidence intervals of equation 1 by type of friends. Estimates for best (first nominated) friends, other (second, third, fourth or fifth nominated) friends; for best friends nominated both in Wave I and Wave II, for best friends nominated only in Wave I, and for best friends of the same gender as the respondent; for best friends residing in the same or different county as the respondent, for other friends residing in the same or different county as the respondent. See Table A4 for the full set of estimates.

effect stems exclusively from best friends nominated both in Wave I and Wave II. Moreover, the peer effect becomes larger when same gender best friends are considered.

Geographical proximity is also crucial. For around half of the cases, the county of residence of the respondents and of their best friends in Wave III coincides. Therefore equation 1 is re-estimated considering best friends residing in the same county as the respondents and in a different county. The estimates show that peer effects arise exclusively from best friends in the same county, highlighting the key role of geographical proximity.[27,28] Note that the peer effect from non-best friends residing in the same county as the respondent is null. This is reassuring as it rules out the possibility that the estimated peer effects are subject to correlated effects (e.g., a common shock that affects everyone in the county). The results in Figure 2 and Table A4 can

[27]The results are very similar with the inclusion of county or school fixed effects instead of state fixed effects.

[28]The peer effects are stronger for non-college graduates, who are less likely to move. The fraction of college graduates is 37 percent in the overall sample and only 32 percent in the restricted sample with same county best friends. However, if we re-run the same county best friends regression for college and non-college separately, the peer effect is more substantial for both education groups.

be interpreted as supportive evidence both of the direct provision channel and information sharing among friends, who are more likely to stay in touch.

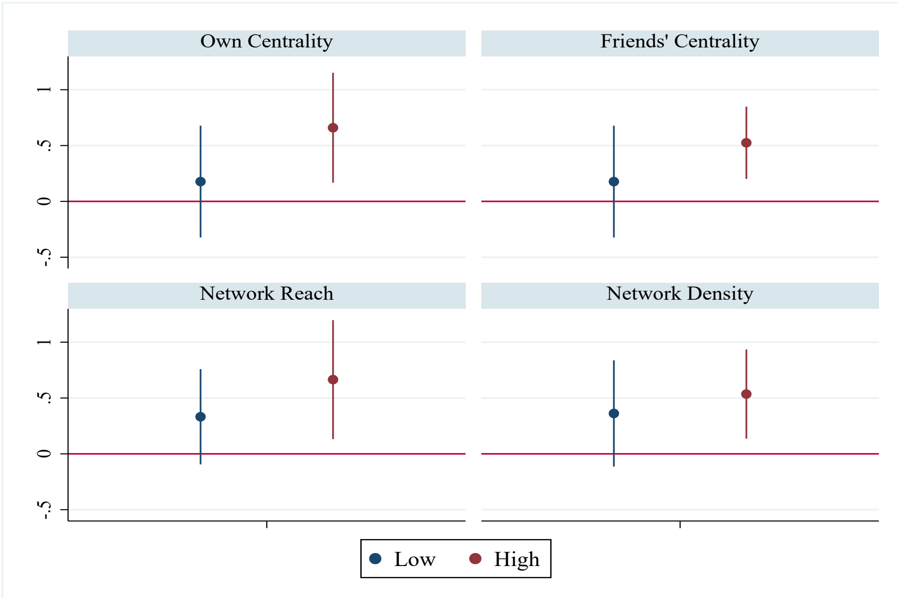

Figure 3: Peer effects on opioid misuse-by network characteristics

Note: The estimated coefficients and 90% confidence intervals of equation 1 by network characteristics. Estimates for individuals that are less or more central in the entire friendship network (Bonacich centrality below or above the mean); for individuals with a low or high reach (maximum number of individuals a node can connect within the entire friendship network is below or above the mean); and for individuals in relatively less or more dense friendship networks. See Table A5 for the full set of estimates.

The granularity and richness of information in Add Health allows for the exploration of heterogeneity based on the characteristics of the entire network of friendship nominations. In particular, own and friends' Bonacich centrality (the centrality of an individual weighted by the centrality of those they nominate as friends), network reach (the maximum number of individuals a node can connect within the entire network), and network density (the number of actual ties in the total friendship network divided by the maximum possible density given an out-degree of 10) are considered.[29] On the effectiveness of interventions that target individuals who are central in their networks, see, among others, Banerjee et al. [2013]. Figure 3 and Table A5 show the results. The peer effect is larger in dense networks and in networks with a high reach. Moreover, the analysis reveals that peer effects emanate from and influence individuals that are central or "key players" in their network.

Last, the impact of local-level factors and policies as mitigating factors on peer effects is investigated.

[29] Figures A3 and A4 illustrate examples of networks with low and high centrality; and low and high density.

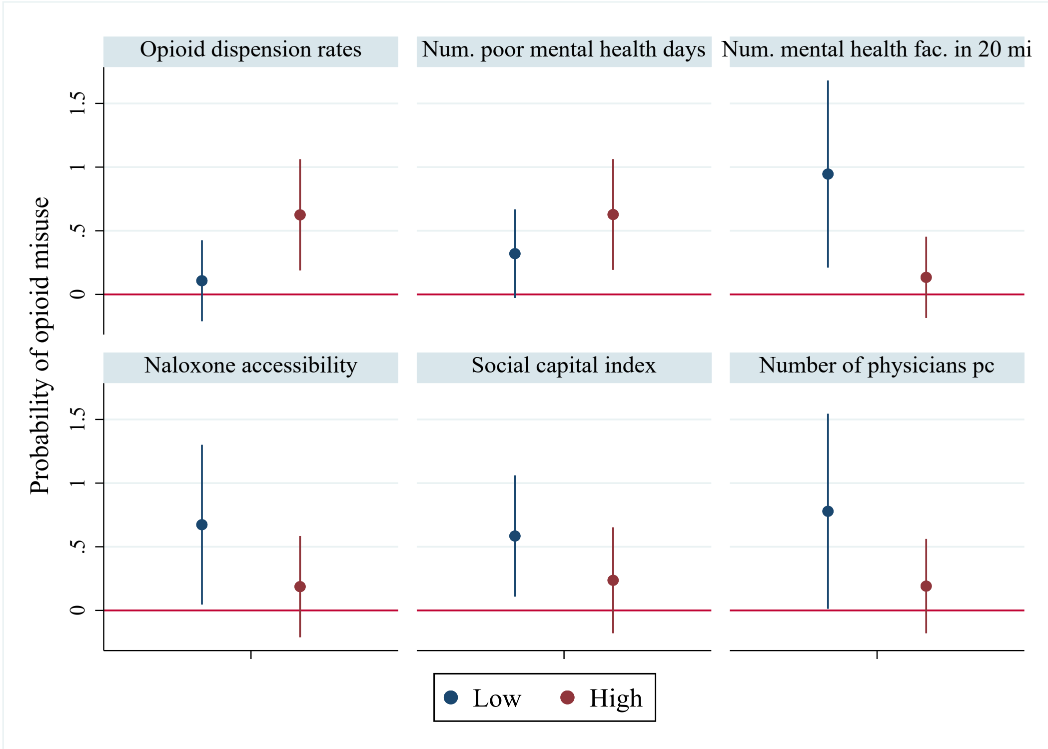

Figure 4: Peer effects on opioid misuse: by opioid and naloxone availability; prevalence of mental health problems; social capital index; mental health facilities and physicians availability
Note: The estimated coefficients and 90% confidence intervals of equation 1 by local-level factors. Low/high refers to values below/above the median in the sample. Estimates for individuals who reside in states with opioid dispense rates below or above the median; for individuals who reside in states that implemented naloxone laws earlier or later; for individuals who reside in counties with an average number of poor mental health days per month below or above the median; for individuals who reside in counties with a social capital index in 2014 below or above the median; for individuals who reside in locations with less or more than 13 mental health facilities within 20 miles; for individuals who reside in counties with less or more than 70 primary-care physicians per 100,000 population. The location of residence is as of the date of the Wave V interview (that took place in the period 2016-2018). See Table A6 for the full set of estimates.

Specifically, local variations in opioid availability, measured by opioid dispensing rates, and access to naloxone are considered. The health of the local population, assessed by the prevalence of mental health issues, and the quality of healthcare, measured by the availability of mental health facilities and primary care physicians, are also analyzed. Additionally, local differences in social capital are investigated as another potential mitigating factor.

The results (Figure 4, Table A6) show that peer effects on opioid misuse are stronger in states with high opioid dispensing rates and in states where naloxone access laws were implemented later. Delayed naloxone access may have limited harm-reduction measures, allowing stronger peer effects to develop, while high dispensing rates likely increased exposure to opioids and normalized misuse. Peer effects are also greater in counties with more poor mental health days and fewer primary-care physicians per capita, highlighting the role of unmet healthcare needs. These effects weaken when the availability of mental health facilities or primary-care physicians exceeds the sample median, underscoring the mitigating role of healthcare infrastructure. Finally, counties with low social capital exhibit stronger peer effects. This result aligns with prior evidence that links low social capital to higher rates of opioid overdose mortality (Zoorob and Salemi [2017]).

6 Welfare and broader implications of peer opioid misuse

A natural question is whether opioid misuse deteriorates welfare and has other broader consequences. To this end, this section analyzes the short-run and long-run implications of peer-initiated opioid misuse by considering different outcome variables. Table 10 reports the results. Column 1 shows that peer opioid misuse is detrimental for own self-perceived health. Self-perceived health status decreases by more than one point (-0.847×0.156 from the first-stage regression) in a 5-point scale if any best friend has a serious injury. Moreover, the probability of stimulants misuse increases by 3.9 pp (0.251×0.156) in a population in which 5 percent misuse stimulants (column 2). This is not surprising as stimulants are often combined with opioids [Ahmed et al., 2022].

Table 10: Welfare and broader implications

Dep. Var.:	Current self-perceived health status	Stimulants misuse	Opioid addiction	Death due to medical factors	Death due to poisoning from toxic substances or suicide
	(1)	(2)	(3)	(4)	(5)
Any best friend opioid misuse	-0.847*	0.251*	0.177*	-0.044	0.087*
	(0.453)	(0.137)	(0.097)	(0.044)	(0.080)
Observations	2,118	2,118	1,958	2,118	2,118
State FE	Yes	Yes	Yes	Yes	Yes
Mean	2.775	0.052	0.015	0.010	0.003
Kleibergen-Paap Wald rk F statistic	13.46	13.46	10.29	13.46	13.46

Note: The dependent variable is current self-perceived health status (5-point scale ranging from poor to excellent) in column 1; the probability of stimulants misuse in column 2; the probability of opioid addiction (continued opioid use despite mental and/or health problems due to it) in column 3; death due to poisoning from toxic substances or suicide in column 4; and death due to poisoning from toxic substances or suicide in column 5. Reference period of opioid addiction/stimulants misuse: ever in life. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. The sample is restricted to individuals who had not used any illegal drugs in Wave I or any painkillers in Wave III. See Table 3, column 6 for the list of controls.

To examine whether peer opioid misuse has severe consequences in the long run, information on opioid addiction and causes of death is utilized. Opioid addiction refers to the continued use of opioids despite the presence of mental and/or physical health problems caused by their use. The focus here is on deaths due to causes likely related to opioid misuse, namely, poisoning from toxic substances or suicide. These cover two of the causes that Case and Deaton [2020] label as the deaths of despair: drug overdose (including alcohol overdose), suicide, and alcoholic liver disease. Deaths due to alcoholic liver disease are left out since, in the Add Health classification, they are aggregated with digestive diseases. As column 3 in Table 10 shows, peer opioid misuse leads to an increase in the probability of opioid addiction. The effect is significant, as the probability of opioid addiction increases by 2.7 pp (0.177×0.156) if any best friend has a severe injury.[30] Columns 4 and 5 show the effects on the deaths due to medical factors and on deaths due to causes likely to be related to opioid misuse. There is a statistically significant effect on the probability of opioid addiction (column 3). There is no statistically significant effect of peer opioid misuse on the probability of death due to medical factors (column 4), and the estimated coefficient is negative. Furthermore, there is a positive effect of peer opioid misuse on the likelihood of death due to poisoning from toxic substances or suicide (column 5). Still, as deaths are rare in this age group, the estimates are imprecise. In summary, these results suggest that peer opioid misuse can deteriorate health, increase the likelihood of opioid addiction, and potentially contribute to eventual deaths from overdose or suicide, although the estimates for such rare outcomes are imprecise.

7 Conclusions

Using individual-level data from Add Health and a novel identification strategy, peer effects on opioid misuse between friends are causally identified. Concerns related to endogenous friendship formation and termination are mitigated by focusing on friendships formed during high school and subsequent drug use as an adult. The spotlight is on best friends, who are likely to maintain contact after high school graduation and the estimation of an intention-to-treat effect without conditioning on current friendships. By studying opioid use at least 14 years after friendship formation and using a credible instrument (best friends' serious injuries) the challenge of simultaneity (the reflection problem) in the estimation of peer effects is addressed. The analysis finds significant positive peer effects on opioid misuse, especially among individuals without a college degree and individuals with strong ties who are central in their network. Moreover, peer opioid misuse is likely to lead to deteriorating health and opioid addiction.

[30] This large effect aligns with the findings of Cutler and Donahoe [2024], who use county-level data to show that spillovers between counties that are geographically close or linked through Facebook friendship networks can account for 84 to 92 percent of opioid deaths from 1990 to 2018, and are a major factor in the sustained increase in opioid-related deaths over time.

By identifying the role of peer spillovers in opioid misuse, the current study provides a more comprehensive understanding of the mechanisms behind the epidemic, complementing the supplier-driven explanations and highlighting the importance of social networks in the spread of opioid misuse. The findings have implications for the design of policies that are meant to reduce opioid dependence [Currie and Schwandt, 2021]. The reformulation of OxyContin and the implementation of must-access prescription drug monitoring programs had unintended consequences, with opioid-dependent users resorting to illegal drugs including heroin [Alpert et al., 2018] and a subsequent increase in child abuse [Evans et al., 2022]. The large social multiplier that is identified suggests that policies targeted on selected individuals (e.g., those with a large social network) may be particularly effective. For example, educating juveniles about the perils of drug use via advertising campaigns on television and social media might be effective.

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Online Appendix

Figures and Tables

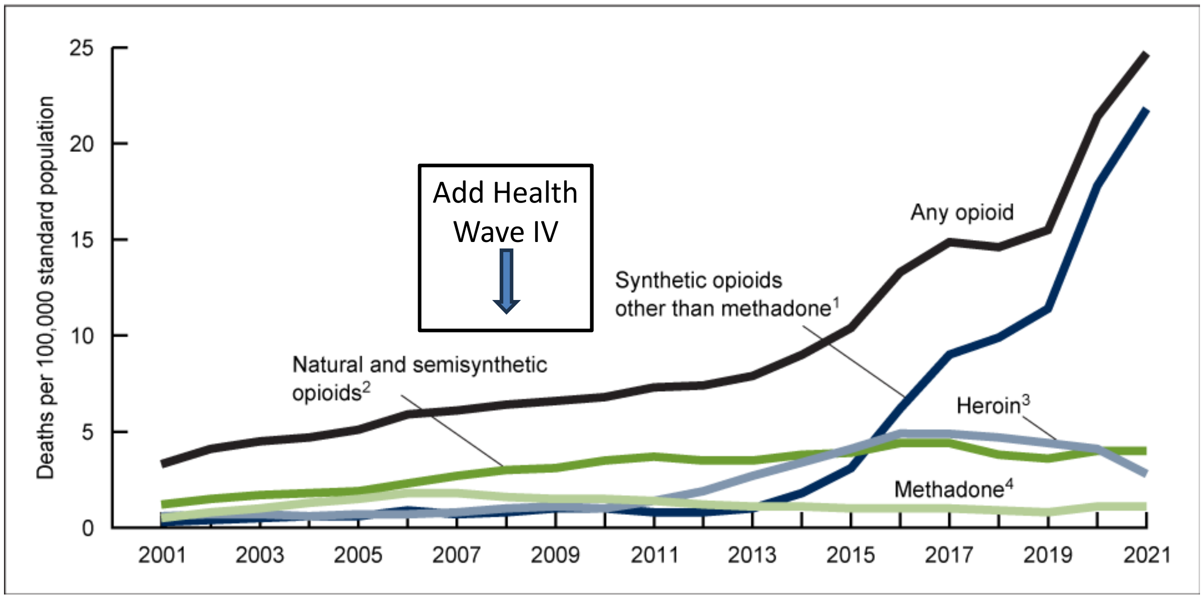
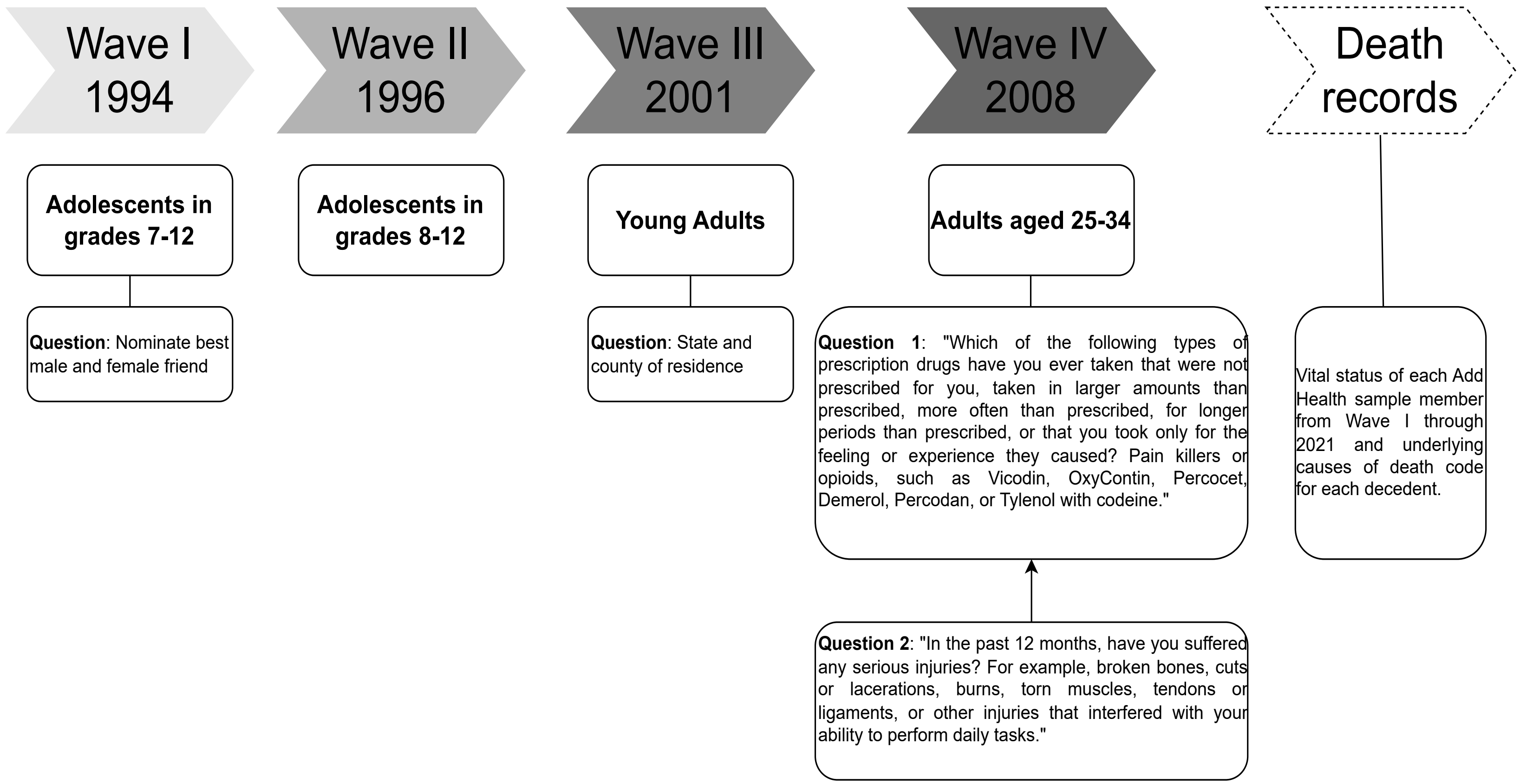


Figure A1: Trajectory of the opioid epidemic

Source: Spencer et al. [2022].



Wave I 1994
Wave II 1996
Wave III 2001
Wave IV 2008
Death records
Adolescents in grades 7-12
Adolescents in grades 8-12
Young Adults
Adults aged 25-34
Question: Nominate best male and female friend
Question: State and county of residence
Question 1: "Which of the following types of prescription drugs have you ever taken that were not prescribed for you, taken in larger amounts than prescribed, more often than prescribed, for longer periods than prescribed, or that you took only for the feeling or experience they caused? Pain killers or opioids, such as Vicodin, OxyContin, Percocet, Demerol, Percodan, or Tylenol with codeine."
Question 2: "In the past 12 months, have you suffered any serious injuries? For example, broken bones, cuts or lacerations, burns, torn muscles, tendons or ligaments, or other injuries that interfered with your ability to perform daily tasks."
Vital status of each Add Health sample member from Wave I through 2021 and underlying causes of death code for each decedent.

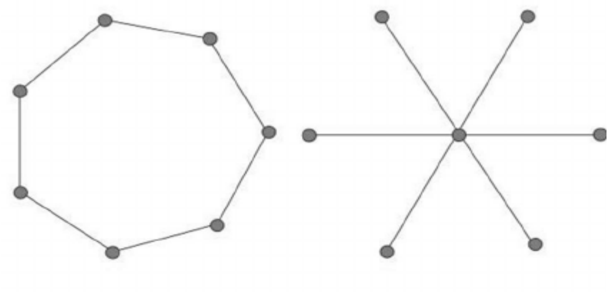


Figure A3: Examples of networks with low centrality (left) and high centrality (right)

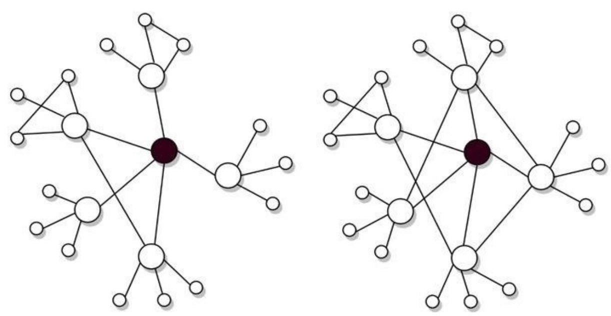


Figure A4: Examples of networks with low density (left) and high density (right)

Table A1: Peer effects on opioid misuse-2SLS robustness

	Dep. var.: Prob(Opioid misuse)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any best friend opioid misuse	0.416**	0.380*	0.466**	0.490**	0.459**	0.533**	0.441*
	(0.206)	(0.203)	(0.195)	(0.211)	(0.189)	(0.222)	(0.238)
Severely injured	0.122***	0.121***	0.105***	0.109***	0.097***	0.115***	0.103***
	(0.032)	(0.032)	(0.029)	(0.030)	(0.030)	(0.030)	(0.032)
College	-0.059**	-0.053**	-0.030	-0.043*	-0.033	-0.033	-0.028
	(0.023)	(0.024)	(0.023)	(0.025)	(0.026)	(0.026)	(0.031)
Female	-0.029	-0.036*	-0.039*	-0.038*	-0.014	-0.029	-0.041*
	(0.019)	(0.018)	(0.020)	(0.019)	(0.023)	(0.027)	(0.022)
Age	-0.012	-0.016*	-0.009	-0.010	-0.006	-0.007	-0.013
	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Hispanic	0.017	0.017	0.003	0.003	0.002	0.010	-0.030
	(0.047)	(0.048)	(0.040)	(0.049)	(0.040)	(0.040)	(0.055)
African American	-0.030	-0.025	0.004	0.009	0.006	0.015	0.025
	(0.046)	(0.046)	(0.036)	(0.080)	(0.035)	(0.039)	(0.050)
Ever diagn. depressed	0.090*	0.082*	0.070*	0.067	0.056	0.072*	0.054
	(0.046)	(0.043)	(0.041)	(0.041)	(0.041)	(0.042)	(0.048)
Ever diagn. post-traumatic stress	0.060	0.074	0.103	0.108*	0.089	0.129*	0.039
	(0.065)	(0.066)	(0.064)	(0.064)	(0.063)	(0.069)	(0.073)
Ever diagn. anxiety	0.021	0.035	0.036	0.041	0.031	0.037	0.053
	(0.047)	(0.043)	(0.043)	(0.044)	(0.043)	(0.046)	(0.047)
Cigarettes avail. at parental home in WI	0.020	0.023	0.013	0.016	0.018	0.011	0.049
	(0.030)	(0.031)	(0.031)	(0.033)	(0.032)	(0.029)	(0.035)
Alcohol avail. at parental home in WI	0.030	0.028	0.019	0.017	0.018	0.021	0.008
	(0.029)	(0.027)	(0.028)	(0.028)	(0.028)	(0.032)	(0.040)
Drugs avail. at parental home in WI			0.142*	0.145*			
			(0.076)	(0.077)			
% college educated best friends				0.036			
				(0.031)			
% Hispanic best friends				0.020			
				(0.051)			
% African American best friends				0.008			
				(0.077)			
% best friends with cigarettes avail. at parental home				-0.014			
				(0.029)			
% best friends with alcohol avail. at parental home				0.023			
				(0.029)			
% best friends with drugs avail. at parental home				-0.031			
				(0.070)			
Extraversion					-0.001		
					(0.004)		
Neuroticism					0.005		
					(0.004)		
Agreeableness					0.003		
					(0.005)		
Conscientiousness					-0.019***		
					(0.005)		
Openness					0.014***		
					(0.005)		
Risk aversion					-0.023**		
					(0.011)		
Maternal education in WI							0.008
							(0.021)
Gross Hhd income in thousand $ in WI							0.001**
							(0.000)
Live with both parents in WI							-0.053*
							(0.028)
Observations	2,826	2,823	2,824	2,804	2,807	2,767	2,151
FE	School	School and State	State	State	State	State	State
Description	Different FE	Different FE	Drug avail. control	Peer char. controls	Big5 & risk aversion controls	Occupational dummies	Family of origin controls
Kleibergen-Paap Wald rk F statistic	16.37	17.39	18.47	16.47	18.97	16.72	15.12

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 with different sets of fixed effects, control variables, and sample restrictions (columns 1-7). Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01.

Table A2: Peer effects on opioid misuse-different measures of peer behavior

	Dep. var.: Opioid misuse			
	(1)	(2)	(3)	(4)
Best friend opioid misuse	0.472**	0.544**	0.451**	0.530**
	(0.196)	(0.266)	(0.193)	(0.235)
Observations	2,826	2,826	2,826	3,257
Controls	Yes	Yes	Yes	Yes
FE	State	State	State	State
Description	Any best friend (Benchmark)	Percentage of best friends	Number of best friends	Dyads of best friends
Kleibergen-Paap Wald rk F statistic	18.44	12.72	16.98	12.10

Note: The estimated coefficients of equation 1 and the F-statistic of equation 2 with different measures of peer behavior. Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.

Table A3: Share of opioid misusers by education and race

By education		By race	
College	Non-College	Non-Hispanic white	Others
(1)	(2)	(3)	(4)
0.147	0.182	0.193	0.063

Note: Characteristics of individuals in the Add Health regression sample. Survey weights are used.

Table A4: Peer effects on opioid misuse-by type of friends

	Dep. var.: Prob(Opioid misuse)								
	Best friends	Other friends	Best friends in WI and WII	Best friends only in WI	Same gender friends	Same county best friends	Different county best friends	Same county other friends	Different county other friends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Any best friend opioid misuse	0.472**	-0.196	0.605**	-0.233	0.746**	0.916**	-0.209	-0.501*	-0.255
	(0.196)	(0.155)	(0.292)	(0.179)	(0.349)	(0.378)	(0.390)	(0.275)	(0.317)
Observations	2,826	1,873	935	1,034	2,127	1,330	1,304	1,130	1,033
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.169	0.190	0.181	0.162	0.164	0.160	0.169	0.167	0.203
Kleibergen-Paap Wald rk F statistic	18.44	35.76	12.27	13.19	10.97	8.407	10.13	11.94	11.55

Note: Estimated coefficients of equation 1 and F-statistic of equation 2 for best (first nominated) friends (column 1); other (second, third, fourth or fifth nominated) friends (column 2); for best friends nominated both in Wave I and Wave II (column 3); for best friends nominated only in Wave I (column 4); for best friends of the same gender as the respondent (column 5); for best friends residing in the same or different county as the respondent (columns 6 and 7); and for other friends residing in the same or different county as the respondent (columns 8 and 9). Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.

Table A5: Peer effects on opioid misuse-by network characteristics

	Own Bonacich Centrality		Best friends' Bonacich Centrality		Networks' reach		Networks' relative density	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any best friend opioid misuse	0.177	0.659**	0.379	0.525***	0.332	0.665**	0.362	0.535**
	(0.302)	(0.297)	(0.379)	(0.195)	(0.257)	(0.321)	(0.286)	(0.241)
Observations	1,078	1,743	1,141	1,677	1,103	1,715	1,406	1,414
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.161	0.173	0.157	0.176	0.161	0.175	0.177	0.164
Kleibergen-Paap Wald rk F statistic	9.667	11.16	4.794	17.75	8.917	13.10	8.270	11.49

Note: Estimates for individuals that are less or more central in the entire friendship network (own Bonacich centrality below or above the mean, columns 1 and 2); for individuals whose best friends are less or more central in the entire friendship network (best friends' Bonacich centrality below or above the mean, columns 3 and 4); for individuals with a low or high reach (maximum number of individuals a node can connect within the entire friendship network is below or above the mean, columns 5 and 6); and for individuals in relatively less or more dense friendship networks (columns 7 and 8). Relative density is measured as the number of actual ties in the total friendship network divided by the maximum possible density given an out-degree of 10 (each respondent could nominate at most 10 friends). Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.

Table A6: Peer effects on opioid misuse-by local level conditions

	Dep. var.: Prob(Opioid misuse)											
	Opioid dispense rate		Naloxone accessibility		Average number of poor mental health days per month		Social capital index		Number of mental health facilities within 20 miles		Number of physicians per 100k population	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Any best friend opioid misuse	0.108	0.625**	0.187	0.673*	0.320	0.628**	0.585**	0.237	0.134	0.946**	0.191	0.779*
	(0.192)	(0.263)	(0.240)	(0.378)	(0.210)	(0.262)	(0.287)	(0.251)	(0.192)	(0.443)	(0.224)	(0.462)
Observations	979	948	1,153	770	1,016	911	905	1,019	966	960	1,007	912
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald rk F statistic	21.16	9.701	17.38	9.527	18.72	9.502	10.95	11.92	12.57	6.415	19.44	5.264

Note: Estimates for individuals who reside in states with opioid dispense rates below or above the median (columns 1 and 2); for individuals who reside in states that implemented naloxone laws earlier or later (columns 3 and 4); for individuals who reside in counties with an average number of poor mental health days per month below or above the median (columns 5 and 6); for individuals who reside in counties with a social capital index in 2014 below or above the median (columns 7 and 8); for individuals who reside in locations with less or more than 13 mental health facilities within 20 miles (columns 9 and 10); for individuals who reside in counties with less or more than 70 primary-care physicians per 100,000 population (columns 11 and 12). The location of residence is as of the date of the Wave V interview (that took place in the period 2016-2018). Robust standard errors in parentheses are clustered at the school level. Survey weights are used. *p<0.10; **p<0.05; ***p<0.01. See Table 3, column 6 for the list of controls.