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The mechanism of social network spread of alcohol consumption

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An Abstract of

The Mechanism of Social Network Spread of Alcohol Consumption

by

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Previous literature has found the impact of peer drinking on adolescent drinking behavior. Most research has assumed that there are social reciprocations for not conforming to typical behaviors. In this paper I assess whether the two different mechanisms of peer influence, adherence to group norms (local-average model) and social multiplier effect (local-aggregate model), are present. I evaluate the presence of these mechanisms by using a modified spatial autoregressive model and by utilizing friendship nomination data from the National Longitudinal Survey of Adolescent to Adult Health (Add Health). I find the presence of adherence to group norms in the drinking behaviors of adolescents, and little evidence of the social multiplier effect. These findings indicate that anti-alcohol policies would have to target most adolescents in schools in order to effectively change alcohol consumption.

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Chapter One

Introduction

Over 4700 alcohol related deaths occur in youths under the age of 21 in the United States annually (USDHH, 2012). Despite attempts, such as the minimum age requirement, to control such occurrences, alcohol is the most commonly consumed substance by adolescents in the United States (USDHH, 2012). Adolescent alcohol consumption is associated with poor academic achievement, greater emotional distress and an increased risk for other adverse outcomes such as assault, motor vehicle accidents, and suicide (Crosnoe, Muller, & Frank, 2004). These outcomes have both implicit and explicit costs for involved parties, particularly concerning wage loss and heightened risk of incarceration (Bouchery, Harwood, Sacks, Simon, & Brewer, 2011). Between the years of 2002 and 2013, the National Survey of Drug and Health found a decline of 6.1 % in underage drinking (SAMHSA, 2014). Even so, the overall economic cost of adolescent drinking in 2006 was estimated to be $27 billion (Bouchery et al., 2011). It is important to determine the factors influencing underage drinking in order for the public policy to sustain this declining trend.

Both individual and family characteristics have been identified as significant factors affecting occurrences of adolescent drinking (Fletcher, 2012). Some studies assessed the variation in consumption trends by race noting white individuals were found to have greater propensity to consume alcohol than their minority counterparts (Windle, 2003; Gaviria & Raphael, 2001).The socially conservative values among African American communities in reinforce a consistently lower rate of drinking compared to white communities (Seffrin, 2012).From a comprehensive review of public health data, Windle (2003) further concludes adolescent males have a higher rate of drinking and heavily drinking compared to females. Using data from National Longitudinal Survey of Adolescent to Adult Health (Add health), Fletcher (2012) determined students in grades 9 and 10 typically consume less alcohol than those in grades 10 and 11. A study assessing the impact of religion on drinking habits found that adolescents who consider religion to be important had a lower probability to consume alcohol (Ali & Dwyer, 2010). Several studies have posited that the presence of at least one alcoholic parent greatly influences adolescent drinking patterns (Fletcher,2012; Clark & Loheac, 2007). Furthermore living in a single parent home was found to increase the probability of adolescent drinking as compared to living in a a two parent household(Norton, Lindrooth, & Ennett, 1998)Alcohol availability at home also acts an important influence on the likelihood of underage drinking. Having greater ease of access to alcohol will greatly increase the probability of adolescent alcohol consumption (Komro, Maldonado-Molina, Tobler, Bonds, & Muller, 2007)

Peer influence has been documented to affect a wide range of health behaviors among adolescents (Clark & Loheac, 2007; Nakajima 2007). An adolescent individual's social network has also been identified as an important factor of alcohol consumption (Fletcher,2012; Mundt,2011; Crosnoe et al. 2004; Rosenquist, Murabito, Fowler, & Christakis, 2010). Increased alcohol consumption by peers has been directly correlated with increased individual consumption (Fletcher, 2012; Clark & Loheac, 2007). This relationship, however, is very complex, and dependent upon composition of the peer networks. For example, the proportion of non-drinking individuals within a network diminishes the probability of consumption within the group (Rees & Wallace, 2014).On the other hand, the presence of only one non-drinker within a peer network does not affect the probability of drinking in a group. That is, a solo non-drinker will be more likely to drink underage within a network dominated by alcohol consumption (Rees & Wallace, 2014). Subsequently, network changes in alcohol consumption have been found to be reflected in individual drinking tendencies (Rosenquist et al., 2010).

Identifying peer effects solely from observational data is usually complicated by several empirical issues. Manski (1993) referred to these issues as "the reflection problem".A standard linear regression is usually unable to distinguish between the various competing explanations that are responsible for the correlation between individual's and peers' outcomes: the "correlated", the "endogenous" and the "contextual effects" (Manski 1993; 2000). Additionally, it is uncertain whether group behavior affects individual behavior or vice versa ("bi-directionality of peer influence"). The correlated effects arise as a result of some common unobserved characteristics faced by all individuals within the same peer group (Manski,1993). The endogenous effect measures how an individual's behavioral outcome is affected by the behavioral outcomes of his/her peers. Exogenous or contextual effects quantify the likelihood an individual's outcome responds to exogenous characteristics of the peer group. Most research has empirically identified the endogenous peer effect by utilizing two stage least squares and fixed effects (Ali & Dwyer, 2010; Fletcher, 2012). Introducing school fixed effects controls for shared unobservable characteristics of the peer group and the effect the school has on the behavior of individuals. Similarly, Clark and Lochec (2007) control for correlated effects by introducing school level fixed effects but utilizes lagged values of peer behavior to eliminate the problem of endogeneity. Lagged peer values avoid the reflection problem because past peer behavior is independent of current behavior. In comparison, Lundborg (2006) introduces school/grade fixed effects to identify the effect of peer behavior within schools and grades. Finally, Kremer and Levy (2008) identify peer effects in alcohol consumption by using data in which college roommates were randomly assigned in turn eliminating selection bias and being able to understand how peer behaviors affect individual actions.

Numerous pathways exist by which peer effects can influence individual behavior. Among the few studies that have examined the pathways of influence within a network, Bullers, Cooper, and Russell. (2001) found selection effects were more present than social influence effects. Individuals were found to associate themselves with social networks that displayed the same drinking patterns. This trend was found by examining pathways of influence between individuals and networks among adults from 21 to 87 years old based upon a survey from Erie County, New York. Other studies have controlled for selection and examined additional pathway mechanisms (Fletcher, 2012; Balsa, Homer, French, & Norton, 2011 Clark & Lochec, 2007 Kremer & Levy, 2008; Mundt, 2011). Using Add Health data, a national representative sample of adolescents and their health behaviors, Mundt (2011) examined the relationship between adolescent social network characteristics and alcohol initiation. This study finds a positive relationship between number of connections, both direct and indirect, within a social network and the spread of alcohol use. Balsa et al. (2011) finds similar results when exploring the relative use of alcohol among adolescents and popularity.Estimating this model with ordinary least squares indicated adolescents conformed to peer alcohol use (Balsa et al., 2011). In particular, conforming to peer alcohol usage was found to lead to higher levels of popularity defined as the number of friendship nominations (Balsa et al., 2011). In contrast, Kwaguchi (2004) used a perceived measure of peer behavior from the National Longitudinal Survey of Youth 1997 and found that current peer behaviors were more important than peer backgrounds. As such, she hypothesized that the social multiplier effect is an effective tool in reducing underage alcohol consumption. In order to identify social multipliers within a network, Yarnell, Brown, Pasch, Perry,and Komro (2013) chose to analyze the distribution of drinking behavior within schools.Using data from Project Northland Chicago, he identified adolescents with higher tendencies to consume alcohol as social multipliers. Kreager and Haynie (2011) employ data from Add Health to estimate Actor-Partner Interdependence models to suggest that romantic partnerships are important for understanding the spread of alcohol. Their findings show that an indirect connection, through a romantic partner, to an individual who consumes alcohol greatly increased the probability of future alcohol consumption (Kreager & Haynie, 2011). Direct connections with friends and/or romantic partners showed substantially smaller control on probability of alcohol consumption

Our analysis will focus on two mechanisms: the social norm and a social multiplier effect. We assess whether there is an adherence to group norms and whether a social multiplier effect is present in alcohol consumption. Specifically, we contrast occurrences of the social multiplier effect to adherence to group norms and identify the dominant force upon consumption trends. These two mechanisms dictate different policy implications. A strong adherence to group norms (average behavior in the reference group) necessitates a policy that targets most individuals within a network in order to change alcohol consumption behavior. In contrast, the presence of a social multiplier effect (behavior controlled by a few number of individuals) indicates the need to target only a few individuals in order to achieve effective policies. Understanding which mechanism(s) of social influence plays an important role in the spread of alcohol consumption will help schools develop effective intervention policies and will help to reduce the economic and medical burden of under-age drinking. This study builds upon existing literature by determining how alcohol consumption is transmitted within a social network (Fletcher, 2012; Clark & Loheac, 2007). Our analysis addresses the reflection problem and bi-directionality of peer influence within the framework of a spatial autoregressive model. The model is able to capture the observed and unobserved factors faced by the peer group because of the group fixed effects term in the model. We estimate the model using high order spatial lags as instrumental variables to address the bi directionality of peer influence. We use data from a nationally representative sample of adolescents in the U.S. (National Longitudinal Survey of Adolescent to Adult Health) and construct our peer measure based on nominations of close friends within the same school.

Chapter Two

Methods

Data

The data for my analysis come from the National Longitudinal Survey of Adolescent to Adult Health (henceforth "Add Health"). Add Health is a nationally-representative survey of adolescents in grades 7 to 12 who come from 132 schools. Add Health was started with an in-school survey in 1994 (Wave 1), which contains a cross-section of approximately 90,000 adolescents. A subset of the original sample (20,745 students) was also interviewed at home in 1994 with a follow-up survey in 1996 (14,739 respondents). A unique, invaluable feature of Add health for the current analysis of social networks is that it contains detailed data on friendships. Add Health asked the respondents to nominate up to 5 close male friends and up to 5 close female friends. Friendship nomination data was collected in two different settings: The survey attempted to survey every student from the in-school sample in the "saturated" setting (2 large and 10 small schools). In all other schools, the "unsaturated" setting was used, where each person was asked to nominate up to one male and one female friend. Because most of the nominated friends were also surveyed, I am able to create measures for most of the respondent's friends in his/her peer network. The average number of nominated friends per respondent is 1.55 in the survey and approximately 85% of friends are in the same school as the respondent. The sample used in my analysis includes all individuals under the age of 21 in 1996 who were interviewed in Wave II of the survey, who nominated at least one friend and had non-missing information on alcohol consumption measures and all other analysis variables (N = 3,229). Table A.1 reports summary statistics for the outcome measures and for all of the explanatory variables used in my analysis as well as the basic statistics describing the school networks.

Outcome variables. My outcome variables consist of five measures of alcohol consumption, which have previously been used in the literature on peer influence in alcohol consumption among adolescents (Fletcher 2012, Balsa et al. 2010). These variables were created based on the following four Add Health survey questions: 1) During the past 12 months, on how many days did you drink alcohol? (1-6, 1=every day or almost every day, 6=1 or 2 days in the past 12 months); 2) Think of all the times you have had a drink during the past 12 months. How many drinks did you usually have each time? (1-95); 3) Over the past 12 months, on how many days did you drink five or more drinks in a row? (1-6, 1=every day or almost every day, 6=1 or 2 days in the past 12 months); and 4) Over the past 12 months, on how many days have you gotten drunk or "very, very high" on alcohol? (1-6, 1=every day or almost every day, 6=1 or 2 days in the past 12 months). These survey questions were used to create the following five outcome variables: 1) dummy variable "drink12w2" (1=Drank alcohol in past year); 2) continuous variable "ndrink12w2" (count of the number of days drank alcohol in the past year); 3) dummy variable "heavydrinkmoliw2" (1=Binge drinking in past year (five or more drinks in a row); 4) dummy variable "drunk12w2" (1=Got drunk in past year); and 5) "ndrunk12w2" (count of the number of days got drunk in the past year).

Explanatory Variables. The main explanatory variables of interest are the peer-level measures of alcohol consumption based on the above five alcohol consumption variables. My control variables are based on the review of the literature on the determinants of alcohol consumption behavior of adolescents and include basic demographic characteristics such as gender, age, race and ethnicity and grade level. The in-home survey also allows me to control for the abridged version of the Peabody Picture-Vocabulary (PVT) test score, log pretax weekly family income, indicator of having both biological parents at home, indicator of alcohol being easily available at home, indicator for having a biological parent who is an alcoholic, indicator for the attendance of religious services at least once a month, indicator for having and an older sibling and location indicators (suburban, urban, rural).

Finally, I include a vector of school-level fixed-effects in order to account for any common environmental characteristics at the level of school that may be driving alcohol consumption among peers in the same school.

Estimation framework

There are several empirical problems that arise when trying to estimate peer effects using observational data. Manski (1993) referred to these problems collectively as the “reflection problem.” The identification problem arises because the coefficient on the average peer outcome in a standard linear regression may have different interpretations, which may not necessarily reflect response of an individual’s behavior to changes in his or her peers’ behavior. Manski (1993) pointed out three different potential interpretations for the coefficient on the average peer outcome in a linear model:

a. *Endogenous effect* – is the individual’s behavioral response to changes in the behavior of his or her peers. This effect is present, for example, if widespread drinking among peers creates a social norm and social acceptance of drinking and thus leads an individual to increase his or her drinking in an effort to adhere to the group norm. Peers’ behavior leads to a change in individual’s behavior, whose behavior, in turn, becomes part of the peer group behavior. The existence of such a behavioral effect implies that a policy targeting some individuals would spread to affect the behavior of other individuals in the group.

b. *Exogenous (contextual) effect* – is the effect of exogenous (background) characteristics of the peers on the behavior of an individual. For example, older siblings' drinking behavior can affect younger siblings' drinking because alcohol consumption increases with age. While exogenous effect is also a form of social influence, it has different implication for the policy: Targeting the behavior of peers will not lead to the same contagion effect as in the case of the endogenous effect and the behavior of other individuals in the peer group will not change.

c. *Correlated effect* – refers to similarities in behavior of individuals who share the same environment (e.g., geographical, institutional, cultural). For example, students in high-crime neighborhood with easy availability of alcohol will all have higher propensity to drink compared to students from low-crime neighborhood. Correlated effect also refers to similarities in behavior of individuals who sort themselves into groups based on similarities in their personal characteristics ("birds of feather flock together"). For example, students who have preference for risky activities may be more likely to become friends as well as consume more alcohol. However, if one of these students starts drinking less as a result of an intervention, this change in behavior fails to spill over to his or her friend.

Given these alternative interpretations of the correlation in the behavior of peers, a standard linear regression is unable to distinguish between the endogenous, the exogenous and the correlated effects. If the purpose is devising an effective policy to exploit the behavioral influences of peers, the econometric strategy needs to control for all other influences when identifying the endogenous peer effect (Norton et al. 1998).

There can be different mechanisms behind the endogenous peer effect (Manski 1993; An 2012). Two possible mechanisms of peer influence are social multiplier effect and social norm effect. When social multiplier effect is present, a change in behavior of any one individual in the peer group would spread to the other members of the group. When social norm effect is present, any individual in a group conforms to the average behavior in the peer group (group norm), and the deviation from this group norm is especially undesirable for individuals who are better connected to other individuals in the peer group (Liu et al 2014). The previous literature estimating peer effects in drinking behaviors focused almost exclusively on estimating the social norm effect by measuring the influence of average peer behavior on individual's outcomes (e.g., Clark and Loheac 2007, Balsa et al. 2010, Fletcher 2012). Yet another possibility is that an individual's drinking behavior can be influenced by the incremental changes in the sum of behaviors of the individuals in his/her peer group, giving rise to the social multiplier. It is important to discriminate between these two potential mechanisms because they have different policy implications. If the social norm influences behavior, the only way to affect any one individual's drinking habits is to change the social norm, i.e. average drinking behavior in the group - by targeting the behavior of most people the peer group. On the other hand, the presence of the social multiplier implies that a policy only needs to target some individuals, who, by changing their drinking behavior will influence drinking of their friends, who, in turn, will affect drinking of their friends, etc. The existence of the social multiplier also implies that individual's position in the network determines his/her effort in a given behavior; the more connected or "central" the individual is, as measured by the Bonacich centrality (Bonacich 1987), the more effort that individual will exert in changing his/her behavior (Liu et al. 2014).

In order to separate the endogenous peer effect from the contextual and correlated effects and to identify the mechanism(s) by which the endogenous peer effect in drinking operates (social multiplier effect, social norm effect), I will estimate spatial autoregressive model (Liu et al. 2014) for different types of drinking behaviors. Furthermore, unlike the standard approach of utilizing contextual variables as instruments for identifying the directionality of peer influence (see discussion in Halliday and Kwak 2009), the spatial autoregressive model allows to address the bi-directionality of peer group outcomes *in addition* to separately accounting for each of the mechanisms (correlated and the contextual effects) potentially responsible for the correlation between the individual and the peers' outcomes. I estimate the *hybrid model* introduced by Liu et al. (2014), which embeds different behavioral mechanisms of social interactions. In this model, the drinking behavior of an individual in peer group *r* is described by the equation:

$$Y_r = \delta_1 G_r Y_r + \delta_2 G_r^* Y_r + X_r \beta + G_r^* X_r \eta + \gamma_r l_{nr} + \epsilon_r \qquad \text{(Equation 1)}$$

where Y_r is the vector containing one of the five alcohol consumption outcomes containing values for the individuals who belong to the network *r*. Y_r is a function of his/her peers' drinking outcomes and other explanatory variables. G_r is the spatial weighting matrix (henceforce adjacency matrix), which describes the relationship between individuals connected to each other in the network. I define network as all students interviewed in the same school. The coefficients δ_1 and δ_2 measure the endogenous peer effects. The vector of coefficients β measures the effects of the individual characteristics on outcome, Y_r. The *contextual effects* (effects of the exogenous characteristics X_r of peers belonging to group *r*) are captured by the coefficient on the peer average characteristics, η. γ_r is the coefficient on the network fixed effect, l_{nr}, which controls for the *correlated effects* in the network.

The adjacency matrix $G_r = [g_{ij,r}]$ describes relationship among individuals in the network. Individuals *i* and *j* who are friends are indicated with one ($g_{ij,r} = 1$) and non-friends are indicated with zero ($g_{ij,r} = 0$). The sum of elements in each row of G_r is $g_{i,r} = \sum_{j=1}^{n_r} g_{ij,r}$ and equals to the total number of individuals nominated by respondent *i*. This specification of the adjacency matrix corresponds to the *local aggregate* model of peer effect. In this model, individual *i*'s outcome is affected by the aggregate effort of *i*'s peers, which is the social multiplier mechanism. When the adjacency matrix is row-normalized, $G_r^* = [g_{ij,r}^*]$, where $g_{ij,r}^* = g_{ij,r}/g_{i,r}$, then the adjacency matrix captures the *local average* model of peer effect. In this model, individual *i*'s outcome is affected by the average effort of *i*'s peer group, which is the social norm mechanism of peer influence. The hybrid model developed by Liu et al. (2014) and shown in Equation 1 incorporates both the local-aggregate and the local-average models as special cases. The two models have different implications: In the local-average model, where individual's effort does not depend on his/her position in the network, school-wide anti-alcohol policies would be effective; while in the local-aggregate network model, where individual's effort is proportional to his/her network centrality (Bonacich 1987), individual-based interventions would be effective because targeting an individual will have multiplier effects that reverberate throughout the entire network.

The “reflection problem” described in Manski (1993) can be interpreted as the inability to separately identify endogenous and contextual effects due to perfect collinearity: Everyone affects everyone else in linear-in-means model (Liu et al. 2013). In order to identify the endogenous peer effect, the hybrid model can be estimated using the instrumental variable strategy. The instruments have to satisfy two conditions: i) they have to be strongly correlated with the endogenous regressors ,$G_r Y_r$ and $G_r^* Y_r$, and ii) they should not be correlated with the error term of the model, ϵ_r (this condition is also called *the exclusion restriction*). Bramoulle, Djebbari, and Fortin (2009) noted that *intransitivity* in social connections can be used as an exclusion restriction to identify endogenous and contextual effects and derived identification conditions for the local-average model. The *intransitivity* in social connections amounts to a restriction on G_r that each peer group of nominated friends has some intransitive triads in G_r (i.e. some friends of my friends are not my friends). Liu et al. (2014) extend this result by giving the identification conditions of the local-aggregate model and the hybrid model and develop Two-Stage-Least-Squares (2SLS) and Generalized Method of Moments (GMM) estimators, which use instrumental variables (IV) based on higher-order spatial lags of X_r: $IV = [X_r, G_r X_r, G_r^* X_r, G_r^{*2} X_r]$. In order to improve asymptotic efficiency of the 2SLS and GMM estimators and to help achieve identification when these instruments are weak, I also estimate bias-corrected 2SLS estimator (BC2SLS) with additional instruments that are based on the information on different positions of group members measured by Bonacich (1987) centrality. The BC2SLS estimator also corrects the many-instrument bias that arises in the presence of many networks. In order to improve identification and estimation efficiency, the GMM estimator uses linear and additional quadratic moment conditions based on the covariance structure of the reduced form equation. The added quadratic moment help achieve identification when the instruments are weak. Similar to the corresponding BC2SLS estimator, a bias-corrected optimal GMM estimator (BCGMM) is used to correct the many-instrument bias when the additional instruments are used (Liu et al. 2014). I also present an over-identifying restrictions (OIR) test of the hypothesis that G_r is exogenous conditional on the explanatory variables and the network fixed effects (Lee 2007, as referenced in Liu et al. 2014). Failure to reject the null hypothesis means the adjacency matrix is exogenous.

In order to discriminate between the two models, I present an extended Kelejian's J test for non-nested spatial econometric models (Kelejian and Piras 2011, as referenced in Liu et al. 2014). The J test is based on the idea that, if the prediction based on an alternative model significantly increases the explanatory power of the null model, it is important to use all the available information in the alternative model. In particular the J-test is a model selection test to detect which behavioral mechanism better represents the data. In this case the null hypothesis could be local aggregate and the alternative could be the local average, or vice versa. Depending on which model is the null hypothesis, one must predict y of the alternative model and then substitute this prediction as an additional repressors into the null model. (Lee et. al 2010 as discussed in Liu et al. 2014). Failure to reject the null means that model better represents the data. Prior to estimation, the Equation 1 is transformed using within-transformation by means of subtracting peer group means from both sides of the equation This transformation effectively removes the model constant and the correlated effects (school fixed effects) in order to ease the estimation (Liu et al. 2014).

Chapter Three

Results

Table A.2 presents the estimates of the hybrid model for the outcome "Drank alcohol in past year (0/1)". The first two columns present the results for 2SLS and BC2SLS. Columns three and four present the results for GMM and BCGMM. All of the regressions are adjusted for school fixed effects and include peer average characteristics. The estimates of the local aggregate and local average peer effects are presented in the upper part of the table. The 2SLS and BC2SLS estimates of the peer effects are not statistically significant. This is likely a result of the weak instrument problem: The first stage F-statistic for the null hypothesis that the excluded instruments are statistically significant is only 1.67. In addition, the instruments likely suffer from being endogenous, as the p-value of overidentification test (0.055) is on the margin of rejecting the null hypothesis of exogeneity of the instruments. On the other hand, the GMM and BCGMM estimates demonstrate that the local average peer effect is highly statistically significant ($p < 0.01$) and the magnitudes of the coefficients suggests that a 10 percentage points increase in the proportion of drinkers among one's friends will increase his/her probability of drinking by approximately 1 percentage point. The estimate of the local aggregate effect in case of GMM is statistically significant at the 5% level and statistically significant only at the 10% level in case of BCGMM. The magnitude of the coefficient suggests that one additional friend who drinks alcohol increases one's probability of drinking by 3-4 percentage points. The identification test for the expanded list of instruments (p=0.078) indicates that the instruments are exogenous, which in turn indicates that the network structure of friendship connections is exogenous (i.e. is not correlated with the drinking behavior in the network). The Kelejian's J-test fails to reject the null hypothesis of local-average model ($p=0.118$)

I also find that several individual-level characteristics are correlated with alcohol consumption: The probability of drinking is higher with the increase in grade level, age, PVT score, availability of alcohol at home and is lower for males, for adolescents who have both biological parents at home, and for adolescents who attend religious services.

Tables A.3A and A.3B present estimates of the local aggregate and local average peer effects for the other measures of alcohol consumption. Because the estimates on the control variables do not change significantly across models, their coefficients are omitted from the tables in the interest of brevity. In the model for the number of days of drinking alcohol only the coefficient on the local average model in the BCGMM is statistically significant ($p < 0.01$) and it implies that an increase in the average number of days of alcohol consumption among friends by one day will add 0.1 days to an adolescent's days of drinking. The J-test again fails to reject the local-average model of peer effect. The estimates of peer effects in GMM and BCGMM models for the other three measures of alcohol consumption (Binge drinking in past year (0/1), Got drunk in past year (0/1), Days got drunk in past year) show that only local-average peer effect is statistically significant and the magnitudes of the estimates are comparable across all the models. In particular, increase in the incidence of binge drinking among friends by 10% will increase an adolescent's probability of binge drinking by about 1.5 percentage points; increase in the incidence of getting drunk among friends by 10% will increase an adolescent's probability of getting drunk by about 1.3 percentage points; and an increase in the average number of days of getting drunk among friends by one day will increase the days on which an adolescent gets drunk by about 0.15. In all of the models, the overidentification test supports exogeneity of the expanded set of instruments.

Chapter Four

Discussion

The majority of previous literature has focused on how peer effects influence individual behavior(Fletcher 2010; Clark & Loheac, 2007; Nakajima 2007). However the mechanism of peer effects within a social network spread have been neglected. In this paper I examine whether there is a social multiplier effect present and if there is adherence to group norms. I rely on the second wave of Add health to provide detailed network and background information as well as information drinking behaviors. I estimate the social network spread of alcohol consumption utilizing a modified spatial autoregressive model that allowed us to distinguish between the social norm and the social multiplier effect. This spatial model eliminates the econometric difficulties of estimating peer effects, particularly in regards to the reflection problem and simultaneity of peer influence.

I find that the average group behavior of an individual's reference group is more important than behavior of individual adolescents within their social network across several measures of drinking and heavy drinking. Specifically if the peer average increases from peers being non-drinkers to all of them being drinkers the individuals are 9 percent more likely to drink. Individuals also have a higher propensity to conform to the average number of days that their peer group drank alcohol or became drunk. Quantitative results such as these will greatly aid in formulating successful school intervention polices that focus on changing group behavior. In particular, classroom learning modules and a peer participation programs have been effective at reducing peer influence and norms. An example of such program is Project Northland in Minnesota, which successfully incorporated group discussions, class games, problem solving, and a peer group participation program of non-alcohol related activities. (Perry et al., 1996)

Although our results provide important insights, our analysis has limitations. The spatial matrix fails to account for relationships among neighborhoods and family. This can be identified through the information in the dataset. This study only considers directed networks, meaning friendship nominations may be non-reciprocal. Future studies might want to consider undirected networks, designating friendships nominations as reciprocal, in order to deal with potential under-reporting of friends. Also, future studies could check the robustness of our results with a larger social network. The present study could also be conducted using only friends nominated as best friends or by restricting the sample to saturated schools.

This work provides further support of the influence of peer effects and improves upon the accuracy of estimating such effects. Most of existing literature has utilized an average measure of peer behavior. Our analysis further confirms that these previous studies examined the correct mechanism of peer influence. An explicit understanding of how alcohol consumption spreads among U.S. adolescents will help to ensure continuation of the declining trend of underage drinking. This would eliminate some of the associated economic costs and decrease adverse outcomes such as motor vehicle accidents and assault. Our study has highlighted the mechanism by which peers can influence the behavior related to alcohol consumption.

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Appendix A

Tables

Table A.1: Descriptive statistics

Variable	Mean	SD	Min	Max
Dependent variables				
Drank alcohol in past year (0/1)	0.403	0.491	0	1
Days drank alcohol in past year	14.54	45.37	0	365
Binge drinking in past year (0/1)	0.243	0.429	0	1
Got drunk in past year (0/1)	0.252	0.434	0	1
Days got drunk in past year	8.451	36.94	0	365
Peer averages				
Drank alcohol in past year (0/1)	0.429	0.460	0	1
Days drank alcohol in past year	15.01	41.30	0	365
Binge drinking in past year (0/1)	0.257	0.411	0	1
Got drunk in past year (0/1)	0.266	0.416	0	1
Days got drunk in past year	8.781	33.65	0	365
Control variables				
Grade 7-8 (reference)	0.199	0.399	0	1
Grade 9	0.201	0.401	0	1
Grade 10	0.188	0.391	0	1
Grade 11	0.189	0.391	0	1
Grade 12	0.189	0.392	0	1
Age in 1996	15.87	1.570	12	20
Male	0.473	0.499	0	1
White race (reference)	0.693	0.461	0	1
Black race	0.223	0.416	0	1
Hispanic ethnicity	0.116	0.320	0	1
Other race/ethnicity dummy	0.0170	0.128	0	1
PVT score	101.0	14.60	12	136
Log pretax weekly income	3.585	0.924	-2.303	6.907
Both biological parents at home	0.559	0.497	0	1
Alcohol easily available at home	0.281	0.449	0	1
Biological parent alcoholic	0.123	0.329	0	1
Religious	0.631	0.483	0	1
Has older siblings	0.506	0.500	0	1
Suburban (reference)	0.452	0.498	0	1
Urban	0.300	0.459	0	1
Rural	0.244	0.430	0	1
School network measures				
Number of individuals in network	37.11	26.65	2	110

Number of nominated friends	1.55	1.20012	1	9
Number of networks		87		
Number of observations		3229		

Table A.2: 2SLS and GMM estimation of the hybrid model. Drank alcohol in past year (0/1).

	2SLS	BC2SLS	GMM	BCGMM
Peer effects				
Local-aggregate	0.0397	0.0283	0.0412**	0.0323*
	(0.0260)	(0.0243)	(0.0193)	(0.0187)
Local-average	0.1987	0.0914	0.0930***	0.1001***
	(0.1629)	(0.1076)	(0.0304)	(0.0299)
Individual controls				
Grade 9	0.0687**	0.0724**	0.0716**	0.0719**
	(0.0317)	(0.0314)	(0.0313)	(0.0313)
Grade 10	0.0570*	0.0620*	0.0607*	0.0611*
	(0.0342)	(0.0338)	(0.0335)	(0.0335)
Grade 11	0.0277	0.0316	0.0304	0.0307
	(0.0364)	(0.0361)	(0.0360)	(0.0360)
Grade 12	0.0730*	0.0805**	0.0787**	0.0793**
	(0.0395)	(0.0387)	(0.0382)	(0.0382)
Age in 1996	0.0415***	0.0416***	0.0418***	0.0417***
	(0.0085)	(0.0085)	(0.0085)	(0.0085)
Male	-0.0415***	-0.0420***	-0.0419***	-0.0422***
	(0.0178)	(0.0177)	(0.0177)	(0.0177)
Black race	-0.0548	-0.0587*	-0.0582*	-0.0583*
	(0.0337)	(0.0334)	(0.0332)	(0.0332)
Hispanic ethnicity	0.0839**	0.0798**	0.0802**	0.0802**
	(0.0364)	(0.0361)	(0.0359)	(0.0359)
Other race/ethnicity dummy	-0.0034	-0.0027	-0.0039	-0.0035
	(0.0690)	(0.0689)	(0.0688)	(0.0688)
PVT score	0.0032***	0.0031***	0.0031***	0.0031***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Log pretax weekly income	0.0074	0.0077	0.0076	0.0076
	(0.0101)	(0.0101)	(0.0101)	(0.0101)
Both biological parents at home	-0.0488***	-0.0510***	-0.0506***	-0.0511***
	(0.0187)	(0.0185)	(0.0184)	(0.0184)
Alcohol easily available at home	0.1184***	0.1219***	0.1211***	0.1217***
	(0.0196)	(0.0193)	(0.0191)	(0.0191)
Biological parent alcoholic	0.0237	0.0230	0.0232	0.0233
	(0.0259)	(0.0259)	(0.0259)	(0.0259)
Religious	-0.0467***	-0.0485***	-0.0484***	-0.0483***
	(0.0190)	(0.0188)	(0.0188)	(0.0188)
Has older siblings	0.0181	0.0208	0.0199	0.0207
	(0.0171)	(0.0169)	(0.0167)	(0.0167)
Urban	-0.1188	-0.1374	-0.1227	-0.1226
	(0.2347)	(0.2334)	(0.2328)	(0.2328)

Rural	0.1019	0.1548	0.1079	0.1082
	(0.3366)	(0.3313)	(0.3283)	(0.3284)
Contextual effects	included	included	included	included
Network fixed effects	included	included	included	included
First stage F statistic	1.67			
Overid test p-value	0.055		0.078	
J test p-value (H0: local aggregate model)	-			
J test p-value (H0: local average model)	0.118			

Note: Statistical significance: * p<0.1, ** p<0.05, *** p<0.01. The omitted categories are: grade 7 or 8, female, white race, non-Hispanic ethnicity, and suburban location.

Table A.3A: 2SLS and GMM estimation of the hybrid model. Other measures of alcohol consumption.

Days drank alcohol in past year

	2SLS	BC2SLS	GMM	BCGMM
Local-aggregate	-0.0393	-0.0988	-0.0171	-0.0410
	(0.0672)	(0.0602)	(0.0305)	(0.0305)
Local-average	0.0303	0.0577	0.0787*	0.1017***
	(0.2138)	(0.1528)	(0.0418)	(0.0418)
Individual controls	included	included	included	included
Contextual effects	included	included	included	included
Network fixed effects	included	included	included	included
First stage F statistic	1.202			
Overid test p-value	0.983		0.99	
J test p-value (H0: local aggregate model)	0.012			
J test p-value (H0: local average model)	0.227			

Binge drinking in past year (0/1)

	2SLS	BC2SLS	GMM	BCGMM
Local-aggregate	-0.0194	-0.0428	0.0121	-0.0002
	(0.0433)	(0.0396)	(0.0244)	(0.0240)
Local-average	0.2736*	0.1033	0.1460***	0.1520***
	(0.1505)	(0.1062)	(0.0352)	(0.0347)
Individual controls	included	included	included	included
Contextual effects	included	included	included	included
Network fixed effects	included	included	included	included
First stage F statistic	1.928			
Overid test p-value	0.565		0.563	
J test p-value (H0: local aggregate model)	-			
J test p-value (H0: local average model)	-			

Table A.3B: 2SLS and GMM estimation of the hybrid model. Other measures of alcohol consumption.

Got drunk in past year (0/1)

	2SLS	BC2SLS	GMM	BCGMM
Local-aggregate	0.0151	-0.0153	0.0232	0.0051
	(0.0384)	(0.0352)	(0.0233)	(0.0230)
Local-average	0.1757	0.0698	0.1196***	0.1345***
	(0.1438)	(0.1045)	(0.0342)	(0.0337)
Individual controls	included	included	included	included
Contextual effects	included	included	included	included
Network fixed effects	included	included	included	included
First stage F statistic	2.118			
Overid test p-value	0.127		0.174	
J test p-value (H0: local aggregate model)	-			
J test p-value (H0: local average model)	-			

Days got drunk in past year

	2SLS	BC2SLS	GMM	BCGMM
Local-aggregate	-0.0067	-0.1432*	-0.0492	-0.0692**
	(0.1019)	(0.0801)	(0.0334)	(0.0325)
Local-average	0.1108	0.1797	0.1447***	0.1647***
	(0.2308)	(0.1785)	(0.0449)	(0.0442)
Individual controls	included	included	included	included
Contextual effects	included	included	included	included
Network fixed effects	included	included	included	included
First stage F statistic	1.485			
Overid test p-value	0.736		0.801	
J test p-value (H0: local aggregate model)	0.000			
J test p-value (H0: local average model)	0.033			