Examining the Dynamic Spread of Marijuana Use in a Social Network with Community Structure

By

Albert Burgess-Hull

A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Human Ecology)

at the

University of Wisconsin – Madison

2018

Date of final oral examination: 8/8/2018

The dissertation is approved by the following members of the Final Oral Committee:
Kristin Litzelman, Assistant Professor, Human Development and Family Studies
Linda Roberts, Professor, Human Development and Family Studies
Robert Nix, Associate Professor, Human Development and Family Studies
Jason Fletcher, Professor, Public Affairs and Sociology

Abstract

Peers and peer relationships play an important role in the development of marijuana and other substance use in adolescence. Although social influence (peer influence, social contagion) is frequently cited as a primary determinant of non-illicit substance use in adolescence (e.g., alcohol and tobacco use), it is unclear to what extent social influence plays a role in the development of adolescent marijuana use, or what social-environmental factors may moderate the effect of social influence on adolescent marijuana use. The present study utilized a novel longitudinal community detection method (DLSMM; dynamic latent space mixture modeling) and the latent space estimator of Xu, 2018 to examine the association between the formation of longitudinal peer groups in a high school social network, social influence, and the development of marijuana use. Utilizing three waves of high school social network data collected from the PROSPER peers project, DLSMMs identified three longitudinal peer groups over the high school period (10^{th} – 12^{th} grade). The peer groups varied on important demographic, substance use, family, and school characteristics across the three waves, and exhibited differing levels of membership stability across time. Membership in the identified groups predicted later marijuana use, and the centrality of marijuana users compared to non-users differed within the overall network and the identified groups. Over time, marijuana users were more likely to move-to the periphery of the network compared to non-marijuana users. Latent space adjusted linear-in-means models identified time-varying social influence effects. In particular, the marijuana use of an adolescent's social connections in 11^{th} grade increases the probability of adolescent marijuana use in 12^{th} grade. Furthermore, the effect of social influence on marijuana use in 12^{th} grade was stronger for students who were members of peer group 1 in 11^{th} grade compared to students who were members of peer group 3 in 11^{th} grade, controlling for important demographic characteristics of the sample. The results of this dissertation collectively highlight the importance of adolescent peer groups to both the development of marijuana use, and the strength by which social influence processes have an effect on marijuana use behaviors.

To my friends, family, and mentors. Thank you all for the love, encouragement, and support along the way.

Table of Contents

Chapter 1

Introduction

Marijuana is the most commonly used illicit drug among adolescents in the U.S. and has recently surpassed cigarette smoking in popularity (Miech, Johnston, O'malley, Bachman, & Schulenberg, 2015). Although marijuana is commonly regarded as a harmless pleasure, an accumulating body of evidence indicates that exposure to marijuana and other cannabis products during adolescence can be especially harmful, and studies indicate that individuals who initiate regular marijuana use during adolescence are at higher risk for deleterious outcomes (e.g., cognitive/neurological impairments, psychiatric symptoms/disorders, poor educational/occupational outcomes) compared to infrequent/nonusers or individuals that initiate marijuana use after adolescence (Volkow et al., 2014). Considering that the initiation and regular use of marijuana typically begins in adolescence (Chen, Yu, Lasopa, & Cottler, 2017; SAMHSA, 2015), understanding the developmental correlates that lead to marijuana use in adolescence is exceptionally important.

One of the most consistent findings in the adolescent and substance use literature is the importance of peers and peer relationships to adolescent substance use development. During adolescence, the peer context becomes increasingly salient to an adolescent's life. Relationships during this period begin to increase in complexity, and the peer social system starts to extend beyond the *dyadic* friendships typically seen in childhood (Brown & Klute, 2008). Although adolescence is characterized by many different types of relationships, one commonly observed phenomena during this time is the tendency for individuals to self-organize into dense and closely connected social groups (Brown & Klute, 2008). These naturally occurring *peer groups* are exceptionally important to behavioral and social development during adolescence, and a large literature has examined the connection between an adolescent's peer group (e.g., the differentiating characteristics and structure of the peer group) and the development of many different types of behaviors, including marijuana use (e.g., Neighbors, Geisner, & Lee, 2008; Dishion & Owen, 2002; Dishion, Capaldi, Spracklen, & Li, 1995).

However, despite the strong link between an adolescent's peer group and marijuana use development, what actually constitutes a "group" has been the subject of great debate (Freeman, 1996). In particular, definitions of the peer group have varied widely across studies, with the majority of studies relying on informal/arbitrary definitions of a group (e.g., via self-reported perceptions of group membership; Neal & Neal, 2013). Furthermore, little is known about the specific processes which influence the development of marijuana use within and between groups. Although social influence is frequently cited as one of the most important predictors of adolescent substance use, it is still unclear to what extent social influence plays a role in the development of marijuana use in adolescence, or whether peer group membership may moderate the effect of social influence on marijuana use.

The primary purpose of this dissertation is to examine the formation and dynamic evolution of longitudinal adolescent peer groups within a high school social network utilizing a novel latent variable method for longitudinal social network data (dynamic latent space mixture modeling), and to determine whether the formation of the longitudinal peer groups influence marijuana use development in adolescence. In the next chapter (Chapter 2), I examine the longitudinal formation of adolescent peer groups within a single high school, and determine whether the location and number of marijuana users differs across the identified groups. I also examine the differentiating characteristics of the peer groups (e.g., demographic composition) and how these characteristics change over time. In Chapter 3, I exploit the novel theoretical and statistical properties of the dynamic latent space mixture model (DLSMM) to examine whether social influence plays a causal role in adolescent marijuana use while statistically controlling for confounds that have previously precluded the identification of social influence effects in observational social network data (e.g., homophily on observed and unobserved attributes, measurement error, missing data). Finally, in Chapter 4, I examine whether membership in the identified peer groups contributes to the later development of marijuana use, and whether membership in the identified peer groups moderates the link between social influence and the development of marijuana use within high school. In Chapter 5, I provide an overall discussion of the results of the three papers and discuss implications for policy, prevention research, and developmental science.

Chapter 2

Longitudinal Peer Groups in Adolescence: Prevalence, Location, and Movement of Marijuana users within and between Groups

Marijuana is the most commonly used illicit drug among adolescents in the U.S. and has recently surpassed cigarette smoking in popularity (Miech, Johnston, O'malley, Bachman, & Schulenberg, 2015). Regular marijuana-use has been linked to a number of negative health and lifestyle outcomes (e.g., cognitive/neurological impairments, psychiatric symptoms/disorders, poor educational/occupational outcomes), and evidence suggests that individuals who initiate regular marijuana use during adolescence are at higher risk for deleterious outcomes compared to infrequent/nonusers or individuals that initiate marijuana use after adolescence (Volkow et al., 2014). As of April 2018, nine states and the District of Columbia have legalized marijuana for adult recreational use. As more states move towards legalization, understanding the individual and environmental correlates of adolescent marijuana use is increasingly important.

Peers and peer relationships play a primary role in the development of adolescent marijuana use. During adolescence, the peer social system increases in complexity and relationships begin to extend beyond *dyadic* friendships that are typical in childhood (Brown & Klute, 2008). One commonly observed phenomenon during this time period is the tendency for adolescents to self-organize into dense and closely connected social groups (Brown & Klute, 2008). These naturally occurring *peer groups* are central to adolescent socialization and behavioral development, and the characteristics that differentiate these groups can have a marked impact on the development of marijuana use behaviors. For example, adolescents with a large number of marijuana users in their peer group are more likely to initiate marijuana use, report current use, or increase frequency of use (Ali, Amialchuk, & Dwyer, 2011; de la Haye et al., 2013; Moriarty, McVicar, & Higgens, 2016). Social group norms that are tolerant of alcohol and drug use are also predictive of early marijuana use (e.g., Neighbors, Geisner, & Lee, 2008). Furthermore, adolescents who affiliate with peer groups that promote or engage in rule breaking or norm violations are more likely to use marijuana (Dishion & Owen, 2002; Gatti, Tremblay, Vitaro, & McDuff, 2005) or escalate marijuana use in adolescence and young adulthood (Dishion, Capaldi, Spracklen, & Li, 1995).

Despite the strong link between the characteristics and behaviors of an adolescent's peer group and marijuana use development, what actually constitutes a "group" has been the subject of great debate (Freeman, 1996). Definitions of the peer group have varied widely across studies, and many studies have selectively focused on specific *types* of groups and how they relate to marijuana use (e.g., deviant peer groups; Dishion, Capaldi, Spracklen, & Li, 1995; Gatti et al., 2005; Lacourse, et al., 2006). Furthermore, the majority of research on peer groups has focused on static conceptualizations of the peer group, despite many studies documenting the dynamic nature of peer groups and relationships during this time (e.g., from new students entering or leaving a school, or friendship instability; Bukowski & Newcomb, 1984; Cairns, Leung, Buchanan, & Cairns, 1995). Overall, few studies have examined the stability and change of adolescent peer groups during the adolescent time period and how this dynamic change relates to the development of marijuana use behaviors.

The present study uses a novel latent variable method for longitudinal social network data to identify qualitatively distinct peer groups over the high school period, and determine whether the location and number of marijuana users differs across the identified groups. Because the network method used in this study models the evolution of peer groups over time, we also examine stability of membership within the identified peer groups, and how the differentiating characteristics of the groups (e.g., demographic composition) change over time. In the next section, we provide a brief overview of the importance of peer groups during adolescence, previous research on peer groups and adolescent substance use, limitations of previous peer group research, and recent research within the machine-learning and computer science fields that have informed the development of advanced computational methods to identify groups within the social network.

Background and Prior Work

As an individual transitions into adolescence, they begin to spend less time with family and more time at school, work, or in the community (Larson et al., 1996; Schulenberg & Maggs, 2002; Silverberg & Gondoli, 1996). As an adolescent's autonomy and independence grows, the peer context becomes increasingly salient to an adolescent's life. Although adolescence is characterized by many different types of relationships, the social groups that naturally form during this time have a profound effect on behavioral development. It is within these miniature social ecologies that an individual begins to experiment with and explore individual identities, group identities, ideas about what is approved or disapproved, and how to form and maintain relationships (Akers & Jennings, 2009; Brown, 2000; Brown & Klute, 2008). Peer groups also play a key role in the development and maintenance of a variety of substance use behaviors, including marijuana use.

Peer Groups and Substance Use

A large literature has examined the connection between an adolescent's peer group and the development of substance use behaviors. Although some studies have examined marijuana use and the peer group, the majority of work has focused on *identifying and describing* characteristics of the peer group (or individuals within the peer group) that are associated with the development of non-illicit substances such as alcohol or tobacco use. These studies have collectively found that the substance use behaviors (e.g., alcohol, tobacco, marijuana, or hard drug use; Alexander, Piazza, Mekos, & Valente, 2001; Ali, Amialchuk, & Dwyer, 2011; Fletcher & Ross, 2012; Moriarty, Mcvicar, & Higgins, 2016), deviant behaviors (Dishion, Capaldi, Spracklen, & Li, 1995; Gatti, Tremblay, Vitaro, & McDuff, 2005; Kreager, Rulison, & Moody, 2001), values and norms permissive of substance use and/or deviant behaviors (Blanton, Gibbons, Gerrard, Conger, & Smith, 1997; Dishion et al., 1995; Verkooijen, de Vries, & Nielsen, 2007), and the demographic make-up (e.g., racial composition; Seffrin, 2012) of the peer group all have a marked impact on the development of marijuana and other substance use.

Research has also linked an adolescent's position (i.e., structural location) within a peer group to substance use initiation and use. These studies have generally focused on three specific types of positions within the peer group: liaisons, who bridge multiple peer groups together; isolates, who are not part of any group; and peer group members, who occupy a more central position in a peer group. Findings across these studies have been mixed, with some studies finding that liaisons are more likely to smoke and use alcohol compared to other network positions (Henry & Kobus, 2007; Kobus & Henry, 2010), and other studies finding that isolates are more likely to smoke compared to other network members (Ennett & Bauman, 1993). A more recent study using the PROSPER sample examined in this paper, found that individuals who were isolates were most likely to smoke, liaisons were most likely to use marijuana, and peer group members were most likely to drink (Osgood, Feinberg, Wallace, & Moody, 2014).

Identifying Peer Groups within the Network

Despite the substantial amount of research devoted to examining the developmental role of peer groups in adolescence, there has been a remarkable lack of consistency across studies in what actually constitutes a peer "group." Within the peer group literature, adolescent groups have been defined in a variety of ways including informal conceptualizations based on the self-reported perceptions of network members (Neal & Neal, 2012); reputation-based crowds (e.g., "jocks," "burnouts," "geeks," etc.); or via "trial-and-error" rearrangements of interaction matrices or visual inspection of graphs (e.g., Homans, 1951). In contrast, research within fields such as mathematical sociology have taken a more formal approach, utilizing mathematical and statistical algorithms to identify formal criteria for identifying subgroups within the network (e.g., Moody, 2001).

Unfortunately, inconsistent or informal definitions of the peer group suffer from a number of limitations. First, informal definitions based on the self-reported perceptions of an adolescent can result in projection bias. For example, an adolescent's perception of their peer's behavior is typically much different than the actual self-reports of peers themselves (e.g., Bauman & Ennett, 1996; Haynie and Osgood, 2005). Second, replication across studies becomes particularly difficult when no formal criteria exist to determine what constitutes an optimal group solution. Third, the majority of formal attempts to identify groups within the network have generally failed to successfully capture the more intuitive or substantive notion of a naturally occurring group (Freeman, 1996),[1] have failed to represent many common features of the social network (e.g., transitivity, reciprocity), and run into computational hurdles when confronted with

[1] For example, early group models such as the well-known "clique" typically identify: (a) too many groups, (b) groups that overlap in ways that lack intuitive sense, and/or (c) groups that are too small to make intuitive sense (Freeman, 1996).

large networks (Moody, 2001). Finally, the majority of formal models of the peer group are designed for cross-sectional network data and are unable to represent dynamic data.

In recent years, to increase consistency across studies, social network researchers have become increasingly interested in the development and application of computational methods capable of identifying social groups within the network. This group of methods – called community detection methods – are a set of formal algorithms that aim to partition a network into a finite number of mutually exclusive sub-groups called network *communities* (see Figure 1; Porter, Onnela, & Mucha, 2009).[2] In contrast to methodological approaches that rely on self-reports or subjective identification of group membership, community detection methods recast the problem of identifying peer groups and the features that may define them as an empirical questions to be answered by the observed data (i.e., social ties derived by a peers report of their *own* relationships or behavior), and not via informal or sometimes arbitrary conventions. The mathematical and/or statistical framework underlying these methods also facilitates replication across studies and can facilitates model fitting, the selection of an optimal group solution, and complexity control. In addition, within the last few years, community detections methods for longitudinal social network data have been developed, allowing network researchers to examine changes in the size, composition, and characteristics of communities identified within the network over time. However, despite the numerous strengths of these computational approaches, few studies have applied these methods to examine the development of adolescent substance use behaviors.

Current Study

---

[2] Recent work in the community detection literature has also examined the identification of *overlapping* communities (e.g., Ding, Zhang, Sun, & Luo, 2016).

The present study uses a novel longitudinal community detection method (dynamic latent space mixture modeling) and data from a large high school network to address three inter-related aims: (a) to determine the number of longitudinal network communities that best summarize a school-based social network during the high school period, (b) to determine what characteristics differentiate the longitudinal network communities over time, and (c) to determine whether marijuana users are more prevalent in some communities than others, and where marijuana users are located within these communities.

Examining the connection between adolescent peer groups and the development of marijuana use utilizing *longitudinal* community detection methods has the potential to advance our understanding of both the natural evolution of adolescent peer groups, as well as the impact that these groups have on marijuana use. This innovative approach seems warranted considering the dynamic nature of adolescent social networks (Bukowski & Newcomb, 1984; Cairns, Leung, Buchanan, & Cairns, 1995), the lack of consistent methods across studies of the peer group, and recent evidence suggesting that the identification of qualitatively distinct groups of individuals within the network (and the characteristics that define them) may enhance the success of behavioral interventions (e.g., Valente, 2012). Although a small number of studies have begun to utilize community detection methods to examine peer groups and adolescent behavior (e.g., Kreager, Rulison, & Moody, 2011; Osgood, Feinberg, Wallace, & Moody, 2014), no study to date has utilized *longitudinal* community detection methods to examine the stability and change of peer groups in adolescence and how these groups relate to marijuana use.

Methods

Sample

The current study uses data from the PROmoting School-university-community Partnerships to Enhance Resilience (PROSPER) project. The PROSPER project is a multi-year test of a substance use prevention program (Spoth, Greenberg, Bierman, & Redmond, 2004; Spoth, Redmond, Shin, Greenberg, Clair, & Feinberg, 2007) which follows two cohorts (Cohort 1 year = 2002, Cohort 2 year = 2003) of 6^{th} grade students from 28 rural public school districts in Iowa (*n* = 14) and Pennsylvania (*n* = 14) from 6^{th} grade to 12^{th} grade. Within each state, seven communities were randomly assigned to a control condition (regular programming offered by the communities) and seven to a partnership intervention condition, yielding 14 intervention and 14 control communities across both states. Network and survey data was obtained from in-school questionnaires completed during the fall and spring of the 6^{th} grade, and every spring from 7^{th} – 12^{th} grade. Inclusion criteria included: (a) 1,300 to 5,200 enrolled students, and (b) ≥ 15% of the student population eligible for free or reduced-cost school lunches.

All analyses in the present study focus on 3 consecutive waves (10^{th} – 12^{th} grade) of network and survey data from a single high school. The high school and time-frame was selected to: (a) ensure a large amount of high school network data, (b) to ensure relative stability in participants across waves (i.e., a small number of students leaving or entering at different times), and (c) because marijuana use becomes more common over time in the age-range of the sample and in the population (Chen, Yu, Lasopa, & Cottler, 2017). The selected school started in 10^{th} grade and was part of the PROSPER control condition.

Measures: Social Network Data

At the end of each in-school questionnaire, students in the selected high school responded to questions asking for the names of up to two best friends and five additional friends in their current grade and school. These names were then matched to a class roster provided by the school. 58% of respondents named a friend, and 83% of the named friends were identified as fellow students. The percentage of complete network data is high relative to other studies examining high school social network (e.g., Add Health).

Measures: Marijuana and Substance use

Marijuana use. A self-report item measured students' *past month* marijuana use ("During the past month, how many times have you smoked marijuana (pot, reefer, weed, blunts)?"). The item was re-categorized to assess: non-use (not at all), social/moderate use (once a week or less), and chronic marijuana use (> once a week; Hall & Degenhardt, 2009),

Other substance use. Two questions assessed students' *past month* alcohol and cigarette use ("During the past month, how many times have you: (a) smoked any cigarettes? or, (b) had beer, wine, wine coolers, or other liquor?"). Both items were dichotomized to measure any use vs. non-use.

Substance use norms. A mean composite of three questions adapted from Elliott, Huizinga, and Menard (1989) and Spoth et al. (2007) measured students perceptions of how many adolescent's their age smoke cigarettes, drink alcohol, or smoke marijuana (e.g., "How many people your age do you think smoke cigarettes?"). Response options ranged from 1 = none to almost none to 5 = all or almost all.

Measures: Descriptive Variables

Demographics: (a) gender (0 = female, 1 = male*)*, (b) race/ethnicity (0 = non-white, 1 = white), and (c) received free/reduced-price lunch (0 = did not receive free/reduced-price lunch, 1 = received free/reduced-price lunch).

Mental health and deviant behavior. Depression and anxiety was measured by two self-report questions: "How true is each of these for you now or within the past 6 months: (a) I am unhappy, sad, or depressed?, or (b) I am too fearful or anxious?" Response options ranged from 0 = not true to 2 = very true or often true. A mean composite score of the two questions was created where higher scores indicated more self-reported anxiety and/or depression.

School characteristics: Grades were measured by a self-report question: "What grades do you generally get in school?" Response options ranged from 1 = mostly lower than D's to 5 = mostly A's (90 – 100).

Family characteristics: Family relations was measured by a mean composite of three self-report subscales adapted from the Iowa Youth and Families Project (Spoth, Redmond, & Shin, 1998) which assessed parent-child activities (6 items, e.g., "During the past month, how often did you work on homework or a school project together with your Mom or Dad?", 1 = everyday to 5 = not during the past month), child monitoring (5 items, e.g., "During the day my parents know where I am.", 1 = always to 5 = never), and parent's use of inductive reasoning (3 items, e.g., "My parent's give me reasons for their decisions.", 1 = always to 5 = never).
Two self-report questions measured whether the student lived with both biological parents (1 = yes, 0 = no), and religious attendance ("How often do you go to church or religious services?"). Response options for religious attendance were recoded as 1 = never; 2 = hardly ever, once or twice a year, about every other month…more than once a week.

Methodological Approach

Dynamic Latent Space Mixture Models. To identify longitudinal network communities, Dynamic Latent Space Mixture Models (DLSMM) were fit to the three waves of high school social network data. The DLSMM is a longitudinal network clustering (community detection) extension of the Latent Space model (LSM; Hoff et al., 2002). To describe how the DLSMM identifies subgroups of socially connected individuals within the network *over time,* the next section first describes the LSM, and then describes how the DLSMM extends the LSM to represent longitudinal network communities.

Latent space model. The LSM is a generative statistical model of the social network that posits that the *observed* network can be modeled as a function of each network members location within an unobserved social space. This latent space can be conceptualized as a multidimensional space of all characteristics/attributes that are relevant to the formation of a social tie within the network. To model the probability of a social-tie between two individuals in the network, the LSM assumes that individuals who are closer to each other in the social space (i.e., have a smaller distance between them) have a higher likelihood of having a social connection compared to individuals that are farther away in space. The strength of this modeling approach is that it is based on the well-known observation that most social network form via homophily (i.e., social selection) – that is, individuals form social connections with network members who are similar to each other on a variety of characteristics (e.g., on demographics, values, behaviors; McPherson, Smith-Lovin, & Cook, 2001).

The LSM (Hoff et al., 2002) was initially developed for cross-sectional network data and although extensions have been developed to identify communities utilizing cross sectional network data (Krivitsky, Handcock, Raftery, & Hoff, 2009), recent work has extended these models to identify communities within *longitudinal* network data.

Dynamic Latent Space Mixture Model. To identify longitudinal communities within the network, Sewell and Chen (2017) extended the LSM to incorporate clusters of actors (corresponding to network communities) at multiple time points. The DLSMM posits that at each time-point *t*, within an unobserved 3-dimensional hypersphere, the latent position of each network member is drawn from a G number of static probability distributions referred to as latent states (these states correspond to the number of communities).

The DLSMM models the latent position of the network members and the latent states via a Hidden Markov model (HMM) with multivariate normal distributions (see Figure 2).[3] To model the probability of a social tie, the DLSMM posits that social ties within the network depend on each dyad's *cosine* distance within the latent hypersphere – that is, the probability of a social tie between two individuals depends on the angle between them in the latent space. This formulation (hypersphere and cosine distance) has proven useful in a number of clustering problems involving complex high dimensional datatypes (e.g., Banerjee, Dhillon, Ghosh, & Sra, 2005; Cox & Cox, 1991).

One of the novel features of the DLSMM is that while it is assumed that the number of communities remain constant over time, the membership of individuals within the communities may change over time. To model changes in community membership, for every two points in time (t and $t + 1$) the DLSMM estimates the probability of initially belonging to a particular community g at time point t, and the probability of transitioning to another community at time $t + 1$. By estimating transition probabilities, we are able to examine the stability and change of the communities over time.

Model estimation procedure. DLSMMs with 1 – 10 communities were fit to the 3 waves of network data using the dnc package (Sewell & Chen, 2017) in R (R Development Core Team, 2018). The dnc package utilizes the Metropolis-Hastings algorithm within Gibbs sampling to obtain maximum *a posteriori* (MAP) estimators. Based on preliminary runs of the dnc

[3] The joint density function of the latent positions and community assignments can be found in Sewell and Chen (2016)

package, for each individual DLSMM model fit (i.e., 1-community, 2- community… 10-community) 140,000 iterations of the MCMC algorithm (post burn-in) were ran with 75,000 burn in-samples. The convergence criteria for the Gibbs sampler was set to 1 x 10^{-6} and the max number of iterations for the second stage of the Gibbs sampler was set to 250 iterations. All other algorithmic and model-fitting specifications (e.g., initialization values, prior distributions, etc.) were set to the *dnc* package defaults.

Model selection. To determine the best fitting model, primary consideration was given to the model with the lowest Bayesian Information Criteria (BIC) as calculated in Sewell and Chen (2017). Secondary consideration was given to substantive interpretability of the identified communities and community size (e.g., overly large/small communities). In addition, model convergence diagnostics (e.g., trace plots, autocorrelation plot) for each model was evaluated to remove models from further consideration.

Network community description. To assign network members to separate communities, participants were assigned to the community corresponding to their highest maximum a posteriori probability (MAPP) of membership. Next, the identified network communities were evaluated for differences on marijuana and substance use, demographics, mental health, and school and family characteristics. Differences across communities were compared with Omnibus Kruskall-Wallis (KWt) and post-hoc pairwise Mann-Whitney U tests (Mann & Whitney, 1947). To adjust for multiple tests of significance, all pairwise tests were adjusted for the false discovery rate (FDR; Benjamini & Hochberg, 1995).

Centrality and popularity of marijuana users. The popularity and centrality were computed for marijuana users: (a) in the *network,* and (b) within each community. Differences across communities were compared via Omnibus Kruskall-Wallis (KWt) and post-hoc pairwise Mann-Whitney U tests (Mann & Whitney, 1947) adjusting for the FDR.

Popularity. The popularity of marijuana users was assessed via the *average degree centrality* (ADC). The degree centrality is defined by the number of immediate social contacts an individual has in the network. Because the degree centrality depends on the size of the network, the degree centrality was normalized to create two ADC measures: (a) ADC within network (created by dividing by the number of *network members* minus 1; Freeman, 1978), and (b) ADC within community (created by dividing by the number of *community members* minus 1).

Centrality. The centrality of marijuana users within the network and within each community was assessed via the closeness centrality. The closeness centrality (Freeman, 1978) reflects the average distance between an individual and all other individuals in the network.

Closeness centrality for individual i was computed as

$$C_{close}(i) = \frac{N-1}{\sum_j d(i,j)}$$

where N is the number of nodes in the network, and $d(i,j)$ is the shortest path distance between individual i and individual j. Higher closeness centrality values (closer to 1) indicate that a node is closer to all other nodes in the network.

Results

Table 1 displays demographic, marijuana use, and other descriptive characteristics of the selected high school sample and full sample (cohort 1) at Wave 1 (10^{th} grade). At Wave 1 in the selected school, 52% of students were female, 41% were non-white, and 13% received free or reduced price lunch (Table 1). Few students reported using marijuana (13%) or smoking cigarettes (11%) over the past month. A little over $1/3^{rd}$ of students reported consuming alcohol over the past month (35%). Overall, student's perceptions of substance use at their high school was moderate (M = 3.23, SD = 0.88).

Compared to the overall sample, the selected high school contained a higher proportion of non-white students (41% vs. 15%) and a lower proportion of students who received free or reduced-price lunch (13% vs. 22%). Marijuana use (13% vs. 16%) and other substance use was generally lower in the selected school compared to the overall sample. The stability of the sample in the selected high school was relatively high. From Wave 1 to Wave 2, 92% of students from Wave 1 were present at Wave 2. From Wave 2 to Wave 3, 94% of Wave 2 students were present at Wave 3. For individuals who had missing data at Wave 2, 24% of students were missing data due to school absence, parental refusal, or student refusal. 12% of students were missing data at Wave 2 because their responses were not complete or were fully missing. At Wave 3, 12% of students were missing data due to school absence, parental refusal, or student refusal. 30% of missing data at Wave 3 was a result of ineligibility, incompleteness, or full missing data. Other descriptive characteristics of the school and overall sample at Wave 1 can be found in Table 1.

Identification of Adolescent Peer Groups

DLSMMs containing one through ten peer groups were fit to the three waves of the high school network data. Table 2 displays the model-fit indices for the 2 through 7-group DLSMMs identified by the dnc package. Examination of Table 2 reveals that the 3-group model minimized the BIC, indicating that the 3-group model fit the 3-waves of the network data the best. Substantive examination of the two closest fitting models – the 2 and 4-group models – revealed that the 2-group model combined two substantively meaningful peer groups, and the 4-group model was composed of extremely small (< 4% of the sample) groups. Based on these findings, the 3-group model was selected as the final model. The trace plot for the 3-group model is provided in the appendix.

Description of Longitudinal Peer Groups

Figure 3 displays the three identified peer groups for the three waves of high school network data. The three peer groups appear well separated, with the majority of students located in peer group 1 (colored in blue) across all three waves.

Demographic composition and size of longitudinal peer groups. Tables 3, 4, and 5 provide a description of the three peer groups on important demographic, substance use, personality, mental health, academic, and family characteristics from Waves 1 – 3 (10^{th} – 12^{th} grade). Peer group 1 was the largest of the three groups, and contained approximately 53% of the sample (n = 264) at Wave 1 and *90%* of the sample (n = 441) at Wave 3. Peer group 1 contained the largest proportion of non-white students, and the largest proportion of students who received free or reduced price lunch across the three waves. In contrast to the other three groups, the demographic characteristics of peer group 1 remained relatively stable over the three waves.

Peer group 2 was the second largest group at Wave 1 (25%, n = 125). However, over the course of the three waves, students transitioned out of this group and into other groups and by Wave 3, peer group 2 contained only 4% of the sample (n = 17). Peer group 2 was largely composed of male students across the three waves. In addition, students in this group were unlikely to receive free or reduced price lunch.

Peer group 3 was the smallest of the three groups at Wave 1 (21%, n = 103), and by Wave 3 a majority of students had transitioned out of this group and into other groups. In contrast to the other two groups, the demographic characteristics of peer group 3 changed significantly across the three waves. For example, at Wave 1, peer group 3 was composed of mainly female students (60%), roughly 30% non-white students, and only 9% of students who received free or reduced price lunch. However, by Wave 3, this group was composed of largely white (90%) male students (71%).

Substance use, mental health, academic, and family characteristics of longitudinal peer groups. The substance use and attitudes towards substance use varied across time and across groups. At Wave 1, peer group 3 was characterized by students who were the most likely to report past month substance use, and who scored highest on substance use norms, indicating that peer group 3 was more likely to believe that more peers their age used substances compared to the other two groups. In contrast, students in peer group 2 reported the lowest levels of past month cigarette use and perceptions of peer substance use at Waves 1 and 2. Interestingly, by Wave 3, cigarette use and substance use norms were similar for all three peer groups, suggesting that cigarette smokers and students with higher levels of substance use norms had sorted themselves equally across the three groups. However, alcohol use still differentiated the three groups at Wave 3, with almost 75% of students in peer group 3 reporting past month alcohol use. Peer group 1 reported low overall levels of alcohol use at Wave 1 and 3.

Despite their low cigarette and moderate alcohol use at Waves 1 and 2, students in peer group 2 reported the highest levels of risk/sensation seeking at Wave 1. In contrast, students in peer group 1 reported the lowest levels of risk/sensation seeking at Wave 1 and Wave 2. Interestingly, depression and anxiety did not differentiate the three groups except at Wave 2, when students in peer group 1 reported exceptionally high levels compared to students in the other two groups.

High grades differentiated students in peer group 2 at all three waves. In addition, peer group 2 reported the highest levels of school adjustment and bonding at Waves 1 and 2. At Wave

3, no differences were observed for school adjustment and bonding across the three groups. Although students in peer group 1 reported moderate levels of grades and school adjustment/bonding at Wave 1, at Wave 2 these students reported the lowest grades and lowest levels of school adjustment and bonding. At Wave 3, peer group 1 reported the lowest grades.

At Wave 1, peer group 3 was composed of students who reported the lowest levels of family relations. However, the composition of this group changed over the three waves and by Wave 3, students in this group reported significantly higher family relations than the other two groups. No group differences in family composition were exhibited at Wave 1; however, by Wave 2 and 3, peer group 2 contained students who were most likely to live with both biological parents, while peer group 1 contained students who were the least likely to live with both parents.

Membership stability across time. Transition matrices, which quantify stability (i.e., transitions) within and across groups are presented in Table 6. These matrices provide a description of how stable the identified groups are from Wave 1 to 2, and from Wave 2 to 3. Peer group 1 was the most stable of the three groups, and students who were initital members of peer group 1 at Wave 1 generally stayed in peer group 1 throughout the high school years. Only seven students from Wave 1 to 2, and fourteen students from Wave 2 to 3 transitioned out of peer group 1 and into other groups. In contrast, the other two peer groups were less stable with peer group 2 exhibiting the most instability over the three waves. Interestingly, differences in stability between peer groups 2 and 3 was largely a result of what groups students moved to over the years. In particular, students in peer groups 2 were somewhat indiscriminant in their movement – moving (or staying) across all three groups. In contrast, students in peer group 3 only moved to peer group 1 or stayed within peer group 3 over the three waves.

Marijuana Use within Longitudinal Peer Groups

Table 7 displays the past month marijuana use (use vs. non-use), and past month frequency of use for the three peer groups. The only differences in marijuana use within and across the peer groups were observed at Wave 1. At Wave 1, students in peer group 3 were the most likely to report past month marijuana use with almost 25% of students in this group reporting use. In contrast, students in peer group 2 were the least likely to report past month marijuana use at Wave 1 (7%).

When examining frequency of past month marijuana use, peer group 3 exhibited the largest amount of variation in different *types* of marijuana use: students in this group were most likely to report either social (17%) or chronic marijuana use (7%) compared to the other two groups. Similar to their low overall use, students in peer group 2 reported the lowest levels of social (4%) and heavy (3%) marijuana use over the past month.

Popularity and Centrality of Marijuana users: Network and Peer Group Locations

The popularity and centrality of marijuana users within the overall network, *and* the identified peer groups are displayed in Table 8. To provide a visualization of the location and movement of marijuana users within the groups at Wave 1, Wave 2, and Wave 3, a graphical representation of the network is displayed in Figure 4, with marijuana users enlarged. There were no popularity differences between marijuana users and non-marijuana users within the *overall high school network* across all three time points. However, when examining popularity levels within the three peer groups, a number of important differences emerged. The most obvious difference at Wave 1 and 2 was that marijuana users *and* non-marijuana users in peer group 2 displayed the highest popularity levels compared to the other two groups. At Wave 2, this difference was especially pronounced, with marijuana users in peer group 2 displaying three times the popularity level of marijuana users in peer group 1. These differences disappeared at Wave 3, when peer group 3 displayed the highest popularity levels of the three groups. In general, both marijuana users and non-marijuana user in peer group 1 displayed the lowest levels of popularity across all three waves. The only differences within the three groups were observed at Wave 3, when the popularity of non-marijuana users was significantly higher than the popularity of marijuana users within peer group 1. At Wave 1 and Wave 2, marijuana users were more popular than non-users in peer group 3 and peer group 2, respectively; however, these differences did not reach conventional significance.

At Wave 1, there was no difference in the centrality of marijuana users and non-marijuana users within the overall network. However, over time, marijuana users were slowly pushed to the periphery of the network (Figure 4), and by Wave 2 and 3 marijuana users were significantly less central compared to non-marijuana users. No differences in the centrality of marijuana users were observed across peer groups at Wave 1 and 2. However, at Wave 3, marijuana users in peer group 1 were less central compared to peer group 2 and 3. Similarly, across all three waves, non-marijuana users in peer group 1 were significantly less central compared to all other groups. The only differences in centrality between marijuana users and non-marijuana users within the three groups were observed at Wave 2 and 3. At both time-points marijuana users were significantly less central than non-marijuana users in peer groups 1 (Waves 1 and 2) and peer group 3 (Wave 3).

Discussion

This paper utilized longitudinal community detection methods to identify and characterize the longitudinal peer groups that naturally form within a high school network, and to examine the location and dynamics of marijuana use within the identified groups. Three peer groups were identified over the three waves of high school network data. The identified peer groups were differentiated by important demographic and individual/family characteristics across the three waves, and displayed differing levels of membership stability across time. In addition, the patterns of marijuana use, popularity of marijuana users, and the location of marijuana users within the peer groups *and* the network exhibited time-varying trends.

The size and membership stability of the three peer groups varied substantially over the high school period. In particular, the two smaller groups (peer group 2 and peer group 3) displayed substantial instability across time, with the majority of students moving to other groups over the course of the high school period. In contrast, the largest group – peer group 1 – remained relatively stable over time, with a surprisingly small number of students leaving this group over the three years. Interestingly, although students transitioned in and out of the three peer groups over the course of high school, the differentiating characteristics of some of the groups remained stable over time. In particular, the demographic characteristics of peer group 1 (diverse on gender, racial composition, and income) and peer group 2 (male and unlikely to receive free lunch) remained stable across the three waves, despite fluctuations in membership. This finding is consistent with other community detection studies of adolescent social networks which find that the social assortment of adolescent's into groups can be differentiated by demographic characteristics such as gender or ethnicity (e.g., González, Herrmann, Kertész, & Vicsek, 2007; Moody, 2001). What is particularly fascinating however, is that previous community detection studies have examined the social assortment of adolescent's within cross-sectional networks. Thus, it is intriguing that the identification of *longitudinal* communities revealed similar and *stable* patterns of demographic assortment within the adolescent groups over time. The stable patterns of high grades and high levels of school adjustment/bonding reported by peer group 2 across the three waves was also intriguing, and suggested that "academic achievement and cohesion" was an important norm/value of this group regardless of changes in student membership. Previous research has also found evidence for similarity among adolescents on academic achievement and motivation (Ryan, 2000; Wentzel & Caldwell, 2006); however, the processes that lead to this similarity among peers is less understood than other areas of network research (e.g., substance use clustering).

Similar to the normative trend of marijuana use development in adolescence (Chen, Yu, Lasopa, & Cottler, 2017), marijuana use increased over time in the selected high school. However, when examining peer group differences, marijuana use within the three groups only differed at Wave 1, when students in peer group 3 reported the highest levels of past-month marijuana use. In particular, the proportion of marijuana users in peer group 3 was more than two times greater than the proportion of marijuana users in peer group 1, and almost three and a half times greater than the proportion of marijuana users in peer group 2. Peer group 3 also exhibited the largest amount of variability in type of marijuana use at this time, with 7% of peer group 3 reporting chronic marijuana use. The high levels of non-illicit substance use and substance use norms, low levels of school adjustment and bonding, and low levels of family relations reported by peer group 3 at this time highlighted a wide-range of risk factors for poor developmental outcomes (Sameroff, 2006), suggesting that this group might benefit from early targeted interventions.

When examining the location and popularity of marijuana users within the network and the three groups, a number of interesting patterns emerged. Perhaps most interesting was the change in the centrality of marijuana users over the high school period. In particular, at the beginning of high school (Wave 1), there was no difference in the centrality of marijuana users and non-marijuana users within the overall network. However, over time, marijuana users were relegated to the periphery of the network. This pattern is consistent with research examining the location and movement of cigarette smokers within *adult* social networks, which find that smokers are more likely to move to the periphery of their networks compared to non-smokers (Christakis & Fowler, 2008). This finding suggest that much like cigarette smoking, marijuana smokers become less socially integrated within their high school networks over time. This possibly reflects social exclusion, the personal preference of marijuana users or “deviant” youth (e.g., Bowker & Raja, 2011; Nino, Ignatow, & Cai, 2016), or the possibly novelty or “coolness” associated with risk taking behaviors at a younger age. Marijuana users were also less likely to be central in some of the peer groups (peer group 1 and 3), but only at later waves. Although this pattern of network exclusion is concerning, the popularity (i.e., number of social contacts) did not differ between marijuana users and non-marijuana users over time. Therefore, although marijuana users appeared to be pushed towards that periphery of the network, the overall number of their social contacts did not change. We do not know, however, whether these connections were with other marijuana users (or deviant youth) or more protective social connections.

The use of community detection methods to identify longitudinal peer groups in adolescence is a novel *data-driven* approach that is based on a generative statistical model of the network. This formal model of the peer group potentially facilitates group comparisons across studies because the identified groups are not based on arbitrary or subjective definitions of the peer group. However, despite the strengths of this study, a number of limitations should be noted. First, this study only examined the formation of longitudinal peer groups within a single school. It is possible that the selected high school displays different social/behavioral assortment patterns than other schools in different regions or with different student characteristics.

Therefore, it would be useful to replicate these findings across other types of high schools. Second, although the selected high school was moderately large and missing network data was imputed via Gibbs sampling, it is well known that mixture models such as HMM are sensitive to sample size (e.g., Nylund, Asparouhov, & Muthén, 2007). Thus, the recovery of the identified peer groups (e.g., number of groups) may have been influenced by the size of the selected school. Third, the assumptions of a stable number of peer groups over time may be overly restrictive. It is well known that relationships during adolescence are dynamic and sometimes short-lived (Bukowski & Newcomb, 1984; Cairns, Leung, Buchanan, & Cairns, 1995). Thus, it may make sense to examine whether assuming a stable number of groups across time fits the peer group context in high school, or whether it relaxing this assumption reveals important variation within and between groups. Finally, the community detection method used in this study only utilized information on the social connections of network members within the sample. Recent work in the community detection field has explored the identification of social groups based on both social-tie *and* individual characteristics (e.g., demographic features) of the network members (e.g., Yang, McAuley, & Leskovec, 2013). In some contexts, these methods may perform better than community detection methods using only social-tie information. Although the current formulation of the DLSMM does not support clustering on social-tie and node-attribute information, we are exploring how our results compare to results derived from these new community detection methods.

Peer groups play an important role in adolescent behavioral and substance use development. These miniature social ecologies serve many roles including facilitating the diffusion of in-group values and norms, reinforcing valued in-group behaviors and punishing non-valued behaviors, and providing a reference for the development of individual or group identities (Breachwald & Prinstein, 2011). As a result, it is pertinent to better understand the formation of peer groups during the adolescent period and the dynamics within these groups as they relate to the development of substance use behaviors. Results from this study have important implications for substance use prevention programs aimed at adolescence and can be used to identify the groups and the time period in which members of this group are most vulnerable to risk.

Table 1.

Demographics, Marijuana use, and Descriptive Variables for Selected School and Full Sample at Wave 1 (10th Grade)

	Selected School*		Full Sample	
Demographics	n	%	n	%
Female	231	52	2463	52
Non-white	173	41	683	15
Free school lunch	47	13	992	22
Marijuana Use	*n*	%	*n*	%
Past month marijuana use	49	13	736	16
Descriptive Variables (categorical)	n	%	n	%
Past month alcohol use	130	35	2034	43
Past month cigarette use	41	11	1035	22
Lives with both biological parents	238	64	2750	59
Descriptive Variables (continuous)	Mean	SD	Mean	SD
Substance use norms	3.23	0.88	3.24	0.83
Risk/Sensation Seeking	2.26	1.01	2.40	1.02
Depression and Anxiety	0.31	0.52	0.40	0.46
Grades	4.07	0.87	3.91	0.95
School Adjustment/Bonding	3.59	0.70	3.56	0.72
Family Relations	-0.18	0.45	-0.22	0.47

Note. *N = 538. Full sample includes schools from cohort 1 only.

Table 2.

DLSMM Model Fit Statistics

Model	BIC
2-Group Model	40607.20
3-Group Model	40091.07
4-Group Model	40617.04
5-Group Model	40835.23
6-Group Model	41229.40
7-Group Model	42931.19

Note. Model-indices for the 8 through 10-group models available upon request

Table 3.

Demographic and Descriptive Variables by Peer Groups – Wave 1 (Means, Percentages, and Group Differences)

Variable	Peer Group 1 (n = 264, 53%)	Peer Group 2 (n = 125, 25%)	Peer Group 3 (n = 103, 21%)	*p*
Demographics				
Female (%)	59	31	60	0.000
Non-White (%)	54	23	29	0.000
Free School Lunch	17	10	9	0.100
Other Substance Use and Attitudes				
Past month alcohol use (%)	30	36	44	0.071
Past month cigarette use (%)	9	5	22	0.000
Substance use norms	3.25	3.06	3.40	0.003
Personality and Mental Health				
Risk/Sensation Seeking	2.13	2.45	2.32	0.042
Depression and Anxiety	0.37	0.30	0.39	0.109
School Characteristics				
Grades	3.96	4.41	3.95	0.000
School Adjustment/Bonding	3.59	3.74	3.42	0.002
Family Characteristics				
Lives with both biological parents (%)	60	72	61	0.106
Family relations	-0.16	-0.14	-0.27	0.050

Table 4.

Demographic and Descriptive Variables by Peer Groups – Wave 2 (Means, Percentages, and Group Differences)

Variable	Peer Group 1 (n = 416, 85%)	Peer Group 2 (n = 44, 9%)	Peer Group 3 (n = 32, 7%)	*p*
Demographics				
Female (%)	55	27	50	0.002
Non-White (%)	47	19	13	0.000
Free School Lunch	19	5	17	0.069
Other Substance Use and Attitudes				
Past month alcohol use (%)	34	33	37	0.945
Past month cigarette use (%)	17	2	13	0.047
Substance use norms	3.39	2.98	3.18	0.003
Personality and Mental Health				
Risk/Sensation Seeking	2.23	2.51	2.21	0.272
Depression and Anxiety	0.43	0.18	0.10	0.000
School Characteristics				
Grades	3.96	4.67	4.30	0.000
School Adjustment/Bonding	3.55	3.80	3.81	0.018
Family Characteristics				
Lives with both biological parents (%)	59	79	66	0.042
Family relations	-0.17	0.00	-0.19	0.105

Table 5.

Demographic and Descriptive Variables by Peer Groups – Wave 3 (Means, Percentages, and Group Differences)

Variable	Peer Group 1 (n = 441, 90%)	Peer Group 2 (n = 17, 4%)	Peer Group 3 (n = 35, 7%)	*p*
Demographics				
Female (%)	55	29	29	0.003
Non-White (%)	43	38	10	0.002
Free School Lunch	22	6	9	0.071
Other Substance Use and Attitudes				
Past month alcohol use (%)	48	65	74	0.011
Past month cigarette use (%)	24	18	12	0.258
Substance use norms	3.54	3.59	3.49	0.822
Personality and Mental Health				
Risk/Sensation Seeking	2.20	2.25	2.69	0.058
Depression and Anxiety	0.34	0.18	0.38	0.153
School Characteristics				
Grades	4.01	4.44	4.41	0.001
School Adjustment/Bonding	3.48	3.48	3.64	0.333
Family Characteristics				
Lives with both biological parents (%)	55	82	74	0.014
Family relations	-0.25	-0.20	0.04	0.006

Table 6.

Transition Matrices Quantifying Peer Group Membership Stability across Waves: Transitions from Wave 1 to Wave 2, and Wave 2 to Wave 3

		Wave 1 (10th grade)		
		Peer Group 1	*Peer Group 2*	*Peer Group 3*
	Peer Group 1	257	61	98
Wave 2 (11th Grade)	*Peer Group 2*	3	41	0
	Peer Group 3	4	23	5
		Wave 2 (11th Grade)		
		Peer Group 1	*Peer Group 2*	*Peer Group 3*
	Peer Group 1	402	20	18
Wave 3 (12th Grade)	*Peer Group 2*	7	10	0
	Peer Group 3	7	14	14

Note. The transition matrix shows how many participants from a given peer group of the estimated DLSMM at Wave X (columns), moved to each peer group at Wave Y (rows). For example, looking at the column corresponding to peer group 1 of Wave 1, we can see that 257 students remained in peer group 1 at Wave 2, 3 students moved to peer group 2 at Wave 2, and 4 students moved to peer group 3 at Wave 2.

Table 7.

Past Month Marijuana Use by Peer Groups (Percentages and Group Differences)

	Peer Group 1	Peer Group 2	Peer Group 3	*p*
Wave 1 (10th grade)				
Marijuana Use – Past Month (overall)				
Past Month Marijuana Use	11	7	24	0.001
Marijuana Use – Past Month (types)				
No use	89	93	76	0.008
Social use (≤ once a week)	9	4	17	
Chronic use (> once a week)	3	3	7	
Wave 2 (11th grade)				
Marijuana Use – Past Month (overall)				
Past Month Marijuana Use	18	24	13	0.488
Marijuana Use – Past Month (types)				
No use	82	76	87	0.122
Social use (≤ once a week)	12	24	10	
Chronic use (> once a week)	6	0	3	
Wave 3 (12th grade)				
Marijuana Use – Past Month (overall)				
Past Month Marijuana Use	28	24	29	0.904
Marijuana Use – Past Month (types)				
No use	72	76	71	0.514
Social use (≤ once a week)	18	24	24	
Chronic use (> once a week)	11	0	6	

Table 8.

Popularity and Centrality of Marijuana-users and Non-marijuana-users (Means and Between Group Differences)

	Sample	*p*	Peer Group 1	Peer Group 2	Peer Group 3	*p*
Wave 1 (10th grade)						
Popularity						
Marijuana-users	5.21	0.621	3.42	6.86	6.29°	0.048
Non-users	5.10		4.00	7.36	4.60	0.000
Centrality						
Marijuana-users	0.019	0.860	0.0180	0.0190	0.0190	0.198
Non-users	0.017		0.0161	0.0171	0.0175	0.000
Wave 2 (11th grade)						
Popularity						
Marijuana-users	4.81	0.701	3.64	11.00°	6.00	0.011
Non-users	4.95		4.02	8.42	6.92	0.000
Centrality						
Marijuana-users	0.015	0.053	0.0139*	0.0182	0.0181	0.418
Non-users	0.016		0.0157	0.0182	0.0175	0.008
Wave 3 (12th grade)						
Popularity						
Marijuana-users	3.22	0.095	2.04**	6.33	8.25	0.005
Non-users	4.05		3.38	4.85	8.23	0.000
Centrality						
Marijuana-users	0.009	0.002	0.0081***	0.013	0.0120*	0.059
Non-users	0.011		0.0104	0.0125	0.0126	0.002

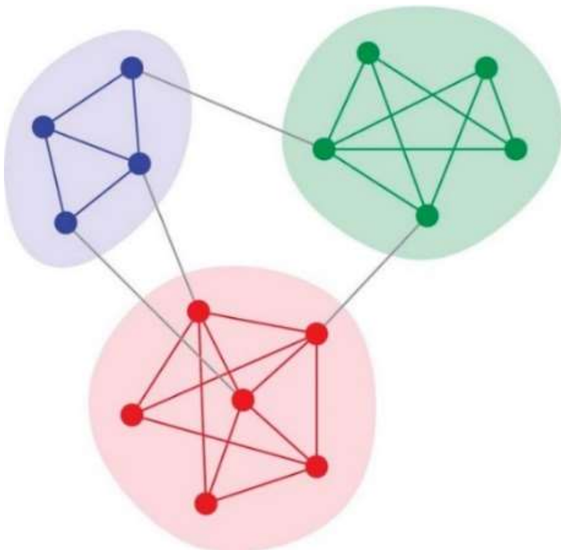

Figure 1. A small social network with three social communities. Communities are characterized by close dense within-group social ties, and few out-group ties.

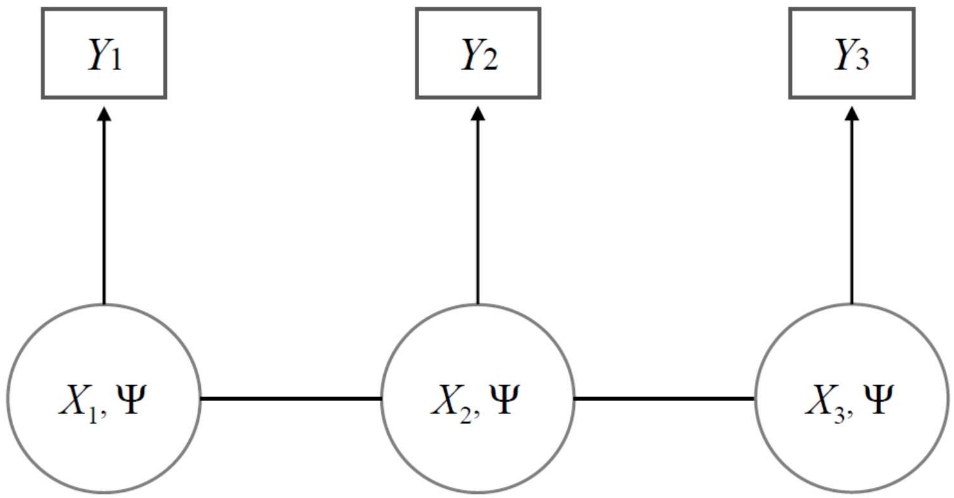

Figure 2. The dependence structure for the Dynamic Latent Space Mixture Model. Y_t represents the observed network, X_t represents the unobserved latent space positions for each network member, and Ψ is the vector of model parameters.

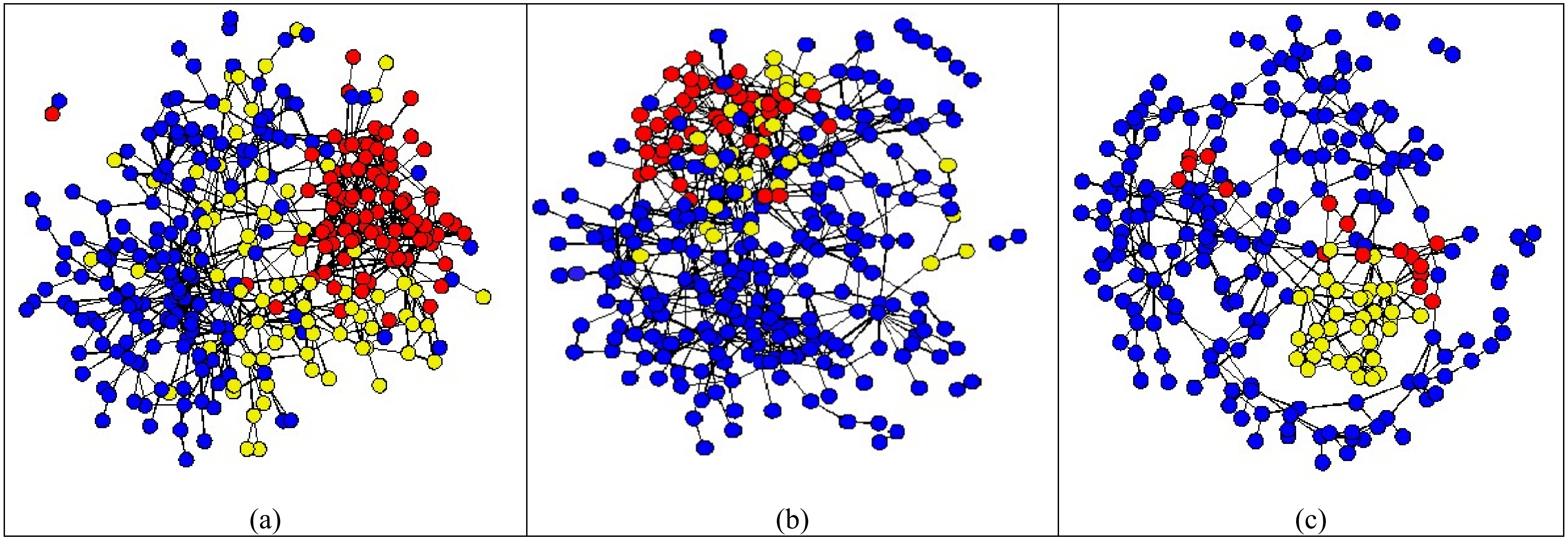

Figure 3. Visualization of the communities identified by the 3-group DLSMM at Wave 1 (pane a), Wave 2 (pane b), and Wave 3 (pane c). The three communities are colored as follows: Community 1 = blue, Community 2 = red, and Community 3 = yellow.

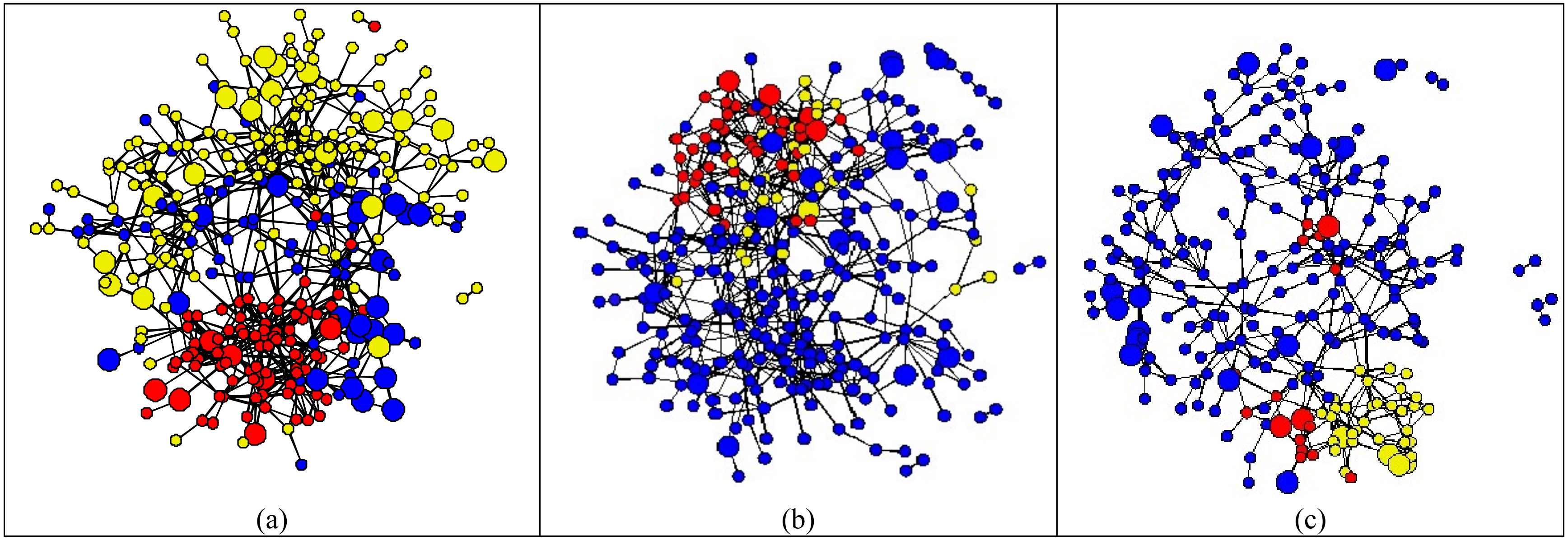

Figure 4. Visualization of marijuana users locations within the identified peer group at Wave 1 (pane a), Wave 2 (pane b), and Wave 3 (pane c). To differentiate marijuana users from non-users, marijuana user's nodes (circles) have been enlarged. The three communities are colored as follows: Community 1 = blue, Community 2 = red, and Community 3 = yellow.

Chapter 3

Social Influence and Adolescent Marijuana Use: A Latent Space Adjusted Approach

Marijuana is the most widely used illicit drug among adolescents in the United States (SAMHSA, 2015). Although the common perception is that marijuana is relatively harmless, accumulating evidence suggests that regular marijuana use – and especially regular marijuana use during adolescence – is associated with a range of negative outcomes including an increased risk of illicit substance use, legal problems, poor educational/occupational outcomes, and cognitive/neurological impairments (Volkow et al., 2014). Given that the initiation and regular use of marijuana typically begins in adolescence (Chen, Yu, Lasopa, & Cottler, 2017; SAMHSA, 2015), understanding the developmental correlates that lead to marijuana use in adolescence is exceptionally important.

Social relationships play an important role in the development of adolescent substance use behaviors. Many substance use behaviors, including marijuana use, are developed and reinforced within an adolescent's social network (e.g., Henry & Kobus, 2007; Urberg, Degirmencioglu, & Pilgrim, 1997). Although multiple features of an adolescent's network have been linked to the development of marijuana use, one of the most consistent findings in the adolescent substance use literature is the link between an adolescent's marijuana use and their network's (i.e., peers') marijuana use. Research examining this connection has found that peer marijuana use predicts marijuana use initiation in middle school (D'Amico & McCarthy, 2006), high school (Epstein et al., 2015), and early adulthood (Brook, Kessler, & Cohen, 1999). Furthermore, peer marijuana use during adolescence prospectively predicts frequency of use

(Bahr, Hoffmann, & Yang, 2005; Kandel & Chen, 2000) and longitudinal patterns of use (Epstein et al., 2015).

Social influence – also known as peer influence or social contagion – is one of the most frequently cited explanations for why the substance use behaviors of an adolescent tend to match the substance use behaviors of their peers. Research examining the impact of social influence on adolescent substance use behaviors has found strong evidence that social influence plays a primary role in the initiation of non-illicit drugs such as alcohol and tobacco use in adolescence (Andrews, Tildesly, Hops, & Li, 2002; Clark & Loheac, 2007; Duncan, Boisjoly, Kremer, Levy, & Eccles, 2005; Fletcher, 2010; Fletcher & Ross, 2012). A small number of studies have provided evidence that social influence contributes to marijuana use in adolescence, however, these findings have been mixed (Andrews et al., 2002; de la Haye, Green, Kennedy, Pollard, & Tucker, 2013; Duncan et al., 2005; Moriarty, Mcvicar, & Higgins, 2015). Some studies have found evidence of social influence effects on adolescent marijuana use in high school (e.g., Ali, Amialchuk, & Dwyer, 2011; Clark & Loheac, 2007; Moriarty et al., 2015), while other studies have found either context specific effects (e.g., gender specific; Andrews et al., 2002; de la Haye et al., 2013), or no effect at all (Duncan et al., 2005).

Some gaps in prior work may be due, in part, to the difficulty of accurately estimating social influence effects in observational social network data. In recent years, critiques of the social influence literature (e.g., Cohen-Cole & Fletcher, 2008; Lyons, 2011; Shalizi & Thomas, 2011) have highlighted that behavioral associations within the network (e.g., the clustering of substance use) may arise from a number of processes other than social influence/contagion. This literature has collectively identified four major threats to the identification of social influence effects. First, the association between network member’s substance use behaviors may arise from the tendency for adolescents to *select* friends who engage in similar substance use behaviors (i.e., homophily or social selection; Kandel, 1978). Second, shared environmental or contextual conditions (e.g., neighborhood drug availability; Crum, Lilli-Blanton, & Anthony, 1996) may lead to similar substance use patterns among network members. Third, in contrast to the behavioral choices of network members, an adolescent's network member's attributes/characteristics may be the driving factor influencing future substance use behaviors (e.g., religiosity of the peer group; Adamczyk & Palmer, 2008). Finally, adolescents within the same network often share similar unobservable characteristics – or third variables – that influence the uptake of substance use behaviors because they selected each other as friends, are members of the same local network, or are affected by similar environmental conditions (e.g., genetic similarly; Domingue et al., 2018). Because each of these processes may lead to behavioral associations among socially connected individuals, advanced methods capable of separating these associations apart are required.

Studies examining the role that social influence plays in marijuana use have attempted to separate social influence from other processes using a variety of methodological techniques. Most commonly, researchers have employed statistical models such as linear regression models that attempt to control for a number of *observed* confounds that a researcher may have measured during his or her study (e.g., Andrews et al., 2002; Coronges, Stacy, & Valente, 2011; Dishion & Loeber, 2009). Others have used advanced statistical methods such as Stochastic Actor Based models (Snijders, van de Bunt, & Steglich, 2010) to disentangle social influence from *observed* homophily while controlling for the influence of observed covariates related to marijuana use development (de la Haye et al., 2013). Others have used longitudinal network data and lagged peer group behavior to separate social influence from homophily while including school level fixed effects and/or an instrumental variable estimator in an attempt to address contextual/correlated effects and unobserved confounds (Ali, Amialchuk, & Dwyer, 2011; Clark & Loheac, 2007). However, while these studies have employed a variety of analytic techniques to disentangle social influence from confounding factors, all of these methods require either strong parametric or substantive assumptions (e.g., the standard instrumental variable assumption, that all the network dependencies or confounding mechanisms are captured by the observed variables). In addition, separating social influence from confounding factors require specific forms of network data (e.g., longitudinal network data, self-reports of marijuana use from all network members, or rich and numerous variable types) - all of which are rare in the social network field.

The purpose of the current paper is to exploit the novel theoretical and statistical properties of the latent space model (Hoff, Raftery, & Handcock, 2002) to examine whether an adolescent's marijuana use behavior is influenced by their network members marijuana use behaviors. We take advantage of recent evidence within the statistics and network science literature that indicates that controlling for the latent space parameters estimated from a latent space model can either completely, or substantially reduce bias in social influence estimates resulting from unobserved traits in the influence and selection process (Davin, Gupta, & Piskorski, 2014; Shalizi & McFowland III, 2016; Xu, 2018). This novel adjustment procedure allows us to more reliably remove bias associated with both observable *and* unobservable confounds than has previously been possible in prior research examining the effect of social influence on the development of adolescent marijuana use using observational network data. The present study also improves on previous studies by utilizing longitudinal information on an adolescent's social network ties, peer reports of their own marijuana use (as opposed to *perceptions* of peer use), and a rich dataset measuring a variety of behavioral/environmental correlates of adolescent marijuana use to estimate social influence effects in marijuana use.

Methods

Sample

This study uses data from the PROmoting School-university-community Partnerships to Enhance Resilience (PROSPER) project. PROSPER is a large multi-year longitudinal test of a substance use prevention program (Spoth, Greenberg, Bierman, & Redmond, 2004; Spoth, Redmond, Shin, Greenberg, Clair, & Feinberg, 2007) which follows two successive cohorts of 6th grade students from 28 rural public school districts in Iowa (n = 14) and Pennsylvania (n = 14) from 6th grade to 12th grade. To obtain network and survey data, students completed in-school questionnaires during the fall and spring of the 6th grade, and every spring from 7th – 12th grade starting in 2002 (cohort 1) and 2003 (cohort 2). Inclusion criteria for each selected school in the PROSPER study included: (a) 1,300 to 5,200 enrolled students, and (b) at least 15% of the student population eligible for free or reduced-cost school lunches. The overall study response rate for the PROSPER sample was high (87.2%).

The current study utilized data from a single high school in the PROSPER dataset. The high school was selected to ensure a *large* and *stable* (i.e., few students leaving or entering at different times) amount of high school network data. To ensure that the effect of the PROSPER substance use prevention program did not influence the natural development of marijuana use or social influence effects, the selected high school was also part of the PROSPER control condition. The study sample was limited to all students in 10th – 12th grade in the selected high school (10th grade = 583 students, 11th grade = 545 students, 12th grade = 525). This time-frame was chosen because marijuana use becomes more common over time in this age-range (Chen, Yu, Lasopa, & Cottler, 2017) and because the selected high school started in the 10th grade. The overall selection strategy for the school and age-range is consistent with a number of other social network studies examining the impact of social influence on substance use behaviors (e.g., de la Haye, 2013; Lakon, Hipp, Wang, Butts, & Jose, 2015).

Measures: Social Network Data

During the in-school questionnaire, students were asked for the names of up to two best friends and five additional friends in their current grade and school. These names were then matched to a class roster provided by administrators at the school to create an undirected adjacency matrix. Overall, 58% of respondents named a friend, and 83% of the named friends were identified as fellow students. This percentage of network data is high relative to other social network studies (e.g., Add Health).

Measures: Individual and Peer Marijuana use

Students reported on their *past month* marijuana use ("During the past month, how many times have you smoked marijuana (pot, reefer, weed, blunts)?"). The item was dichotomized to measure non-use ('not at all') or any use ('one time' to 'more than once a week').

Average peer marijuana use was measured by first adding together the self-reported past month marijuana use for each network member connected to an adolescent (from friendship nominations), and then dividing this value by the total number of peers connected to the adolescent. Thus, this variable measured the proportion of social connections (peers) who smoked marijuana during the past month (range 0 – 1). A value of 1 = all social connections were marijuana users, and 0 = no social connections were marijuana users.

Measures: Covariates

To control for *observed* developmental correlates of adolescent marijuana use, the following covariates drawn from the extant social influence and substance use literature were included in the social influence model:

Demographics: (a) gender (0 = female, 1 = male*)*, (b) race/ethnicity (1 = white, 0 = non-white), and (c) self-reported free/reduced-prices lunch (1 = receives free/reduced-price lunch, 0 = does not receive free/reduced-price lunch).

Sensation seeking, mental health, and coping skills: Students risk/sensation seeking was measured by an average of three items assessing self-oriented propensity for risky activities/behaviors (e.g., "How often do you do the following things: Do something dangerous because someone dared you to do it? Do crazy things just to see the effect on others?"). The items ranged from 1 – 5 (response options: 1 = "Never" to 5 = "Always") with higher scores indicated more sensation seeking. Student's depression and anxiety was measured by an average of two items ("How true is each of these for you now or within the past 6 months: (a) I am unhappy, sad, or depressed?, or (b) I am too fearful or anxious?") with response options ranging from 0 = "Not true" to 2 = "Very true or often true." Higher scores on the scale indicated more anxiety and/or depression.

Grades and critical thinking: Grades were measured by a continuous self-report question: "What grades do you generally get in school?" Response options ranged from 1 = "Mostly lower than D's" to 5 = "Mostly A's (90 – 100)." Critical thinking and problem solving skills were assessed with an average of five items measuring the student's ability to seek information ("When you have a problem, how often do you: Get information that is needed to deal with the problem'), evaluate alternative choices ("When you have a problem, how often do you: Think about which of the choices is best"), or think about potential consequences ("When you have a problem, how often do you: Think about the consequences of each choice") when faced with a problem. Higher scores on the scale indicated higher levels of critical thinking.

School engagement, bonding, and absence: School engagement and bonding was measured by a mean composite of ten questions adapted from Simons, Whitbeck, Conger, and Conger (1991) which assessed a student's connection with teachers or other students (e.g., "I like school a lot," "I try hard at school," or "I get along well with my teachers"). Response options ranged from 1 = "Never true" to 5 = "Always true." Days absent from school was measured by a single self-report item ("About how many days were you absent from school last year") that ranged from 1 = "None," 2 = "1 – 2 days," 3 = "3 – 6 days,"…5 = "16 or more days."

Family characteristics: Four characteristics of the family were measured: (a) lives with biological parents, (b) family relations/cohesion, (c) obtained alcohol from a sibling, and (d) religious attendance. A self-report question measured whether the student lived with both biological parents (1 = "Yes," 0 = "No"). Family relations/cohesion was measured by a mean composite of three subscales adapted from the Iowa Youth and Families Project (Spoth, Redmond, & Shing, 1998) that assessed parent-child activities (6 items, e.g., "During the past month, how often did you talk about what's going on at school with your Mom or Dad?", 1 = "Everyday" to 5 = "Not during the past month"), child monitoring (5 items, e.g., "During the day my parents know where I am.", 1 = "Always" to 5 = "Never"), and parent's use of inductive reasoning (3 items, e.g., "My parent's give me reasons for their decisions.", 1 = "Always" to 5 = "Never"). The average composite score weighed each subscale by 1/3. Two items measured whether the student had ever gotten alcohol from a sibling or an older person: "Have you ever gotten alcohol from an older sister or brother?" and "Have you ever gotten alcohol from some older person?" The two items were summed together and re-coded to create one item that measured either, 1 = Obtained alcohol from a sibling *or* older person, or 0 = Have never obtained alcohol from a sibling/older person. Finally, students reported on their religious attendance ("How often do you go to church or religious services?"). Responses were coded as 0 = "Hardly ever/never"; 1 = "Once or twice a year, about every other month…more than once a week."

Analytic Strategy and Empirical Model

The "latent space adjusted approach" (Xu, 2018) builds on the theoretical logic of the latent space model (LSM; Hoff et al., 2002) which models the *observed* network as a function of each individual network members location in a *d*-dimensional unobserved *social space of characteristics.* As the location of two individuals in this social space decreases, the probability of a social tie also increases. The strength of this methodological approach is that it builds on the well-known observation that most social network are *homophilous*: individuals who are socially-connected (i.e., close to each other in the network) are also likely to have similar characteristics (e.g., demographic, values, behaviors; McPherson, Smith-Lovin, & Cook, 2001). Thus, if two individuals are close to each other in this latent social space (and thus, are more likely to be socially connected), then they should also be close to each other on a number of other characteristics/attributes, including any unobserved characteristics that may influence social influence or selection (Hoff et al., 2002; Xu, 2018).

The latent space adjusted approach follows the conjecture of Shalizi and Thomas (2011) and recent proofs by Shalizi and McFowland III (2016) that frame the identification of social influence effects in observational network data as an omitted variable problem. In particular, Shalizi and McFowland III (2016) prove that if the network grows according to a continuous latent space model, then including the latent coordinates estimated from a LSM in an additive social influence model results in unbiased and consistent social influence effects in the presence of latent homophily. Multiple simulation studies support this proof, and in direct comparisons with other methodological approaches, the latent space adjusted approach has been found to outperform other state-of-the art methods for identifying social influence effects in observation network data including fixed effects, random effects, a variety of instrumental variable adjustments, and the structural equation modeling approach of Bollen and Brand (2010) (Davin, Gupta, & Piskorski, 2014; Xu, 2018).

Social influence model. Following Shalizi and McFowland III (2016) we fit the following OLS model with robust standard errors estimated from the sandwich package (Zeileis, 2006) in R (R Development Core Team, 2018):

$$Y_{it} = \beta_0 + \beta_1 Y_{i,t-1} + \beta X_{i,t-1} + \beta_3 Z_{i,t-1} + \beta_4 \frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}} + \in_{it}$$

With Y_{it} representing marijuana use (coded as monthly use vs. non-use) at time t, $Y_{i,t-1}$ representing the lagged marijuana use of the focal individual i, X_i representing a vector of time-varying (lagged) or time-invariant covariates predictive of the development of marijuana use, $Z_{i,t-1}$ representing the latent coordinates of the focal individual i at $t-1$, A_{ij} representing a dummy variable indicating if there is a link from individual i to j at time t-1, and $\frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}}$ representing the average lagged Y among focal individual i's direct social connections.

We are interested in identifying and estimating β_4 which is the social influence effect of the network on the marijuana use of the focal individual. Following Shalizi and McFowland III (2016), we make the following assumptions:

(i) The network grows according to a continuous latent space model

(ii) The latent space coordinates[4] of each individual capture *all* attributes of a node which are informative of their location in the network.

(iii) Individual and environmental covariates predictive of individual and *peer* marijuana use do not affect the structure/organization of the network.

(iv) Individual and environmental covariates predictive of *peer* marijuana use are independent of the focal individuals marijuana use at Time 1, conditioning on the latent space coordinates of the focal individual.

These assumptions are represented graphically in Figure 1. As Figure 1 displays, we are able to identify the causal effect of interest – past month *peer* marijuana use – by conditioning on the focal individuals past month marijuana use at Time 1 ($Y_{i,t-1}$), the vector of observed individual and environmental predictors of the focal individual's marijuana use (X_i), and the latent space coordinates of the focal individual at Time 1 ($Z_{i,\ t-1}$). For simplicity, we control for all individuals latent space coordinates at Time 1 which has no effect on the ability to identify the social influence effect of the network on the marijuana use of the focal individual.

Dynamic latent space model. The latent space coordinates for each network member are estimated with the dnc package (Sewell & Chen, 2017) in R. The DLSMM is a longitudinal network clustering (community detection) extension of the Latent Space model. In contrast to the basic LSM of Hoff et al. (2002), the DLSMM is a *dynamic* network model that assumes that the latent positions of the network members follow a Hidden Markov model, with the community assignments as hidden states.

[4] As a latent variable model, the LSM assumes that each network member's position in the latent space (i.e., their latent coordinates) is generated by an unobserved latent variable Z_i associated with each network member (Z_i ,..., Z_n).

The projection model of Sewell and Chen (2017) is fit to the three waves of network data. The projection model of Sewell and Chen (2017) models the joint density of the latent positions and community assignments as a hidden Markov model with multivariate normal distributions within the latent space.[5] This dynamic formulation of the LSM allows us to more accurately model the latent positions of each network member as it is able to account for the temporal dependence of the longitudinal network data.

Model estimation procedure. DLSMMs with 1 – 10 subgroups were fit to the 3 waves of network data. The Metropolis-Hastings algorithm within Gibbs sampling was used to obtain maximum *a posteriori* (MAP) estimators for each models parameters. For each DLSMM model fit (i.e., 1-subgroup, 2-subgroup … 10-subgroup) 140,000 iterations of the MCMC algorithm (post burn-in) were ran with 75,000 burn in-samples. We set the convergence criteria for the Gibbs sampler to 1 x 10^{-6} and the max number of iterations for the Gibbs sampler (2nd stage) was set to 250 iterations. All other algorithm and model-fitting values (e.g., initialization values, prior distributions, etc.) were set to the *dnc* package defaults.

Model selection. To determine the final DLSMM model, primary consideration was given to the DLSMM with the lowest Bayesian Information Criteria (BIC; Sewell & Chen, 2017). We also considered the substantive interpretability of the final models and convergence diagnostics (e.g., trace plots, autocorrelation plot) to remove models from final consideration.

Missing network data. We assume that all missing network data is ignorable (missing at random; Schafer & Graham, 2002). Thus, we are able to account for missing network data within the Gibbs sampler which treats ignorable (MAR, MCAR) network data as additional unknowns

---

[5] The projection model, as opposed to the distance model, estimates the probability of a social tie between to individuals as a function of each dyads *cosine* distance within the latent space. See Sewell and Chen (2016) for the specific form of the likelihood and joint density functions for the projection model.

and samples the missing data conditional on the latent positions and DLSMM model parameters at each iteration, then estimates the posterior distributions given these imputed values (Rochani & Linder, 2017).

Naïve social influence model. To compare social influence estimates derived from the latent space adjusted social influence model, we also estimate a naïve social influence model that only controls for lagged individual past-month marijuana use. Similar to the latent space adjusted social influence model, we also include the average lagged marijuana use of the focal individual's direct social connections which is the social influence effect of interest. The naïve OLS models are estimated with robust standard errors.

Peer marijuana use differences among marijuana users. Mann-Whitney U tests were conducted to examine differences in peer marijuana use among marijuana users and non-marijuana users across the three waves.

Results

Table 1 displays the demographic, marijuana use, and covariate summary statistics for Wave 1 of the high school sample. At Wave 1, 52% of students were female, 41% were non-white, and 13% received free or reduced price lunch. Marijuana use at Wave 1 was relatively rare, with only 13% of the sample reporting past month use. However, consistent with the normative trend of marijuana use development typically seen in adolescence, past month marijuana use increased across the three waves with 18% of students reporting marijuana use at Wave 2, and 28% of students reporting use at Wave 3.

The average marijuana use of marijuana user's and non-marijuana user's social connections is presented in Table 2. In general, the average marijuana use of marijuana user's social connections was higher than the marijuana use of non-marijuana user's social connections

(Wave 1 and Wave 3). However, at Wave 2 there was no difference in peer marijuana use between marijuana users and non-marijuana users.

To obtain latent space estimates for all social network members, DLSMMs with 1 – 10 communities were fit to the three waves of high school network data. Examination of the BIC, convergence diagnostics, and substantive characteristics of the estimated models revealed that the 3-community model fit the network data the best. Thus, we used latent space estimates from the 3-community DLSMM in the OLS regressions to estimate the effect of peer marijuana use on individual marijuana use. The BIC values of the estimated models, and the autoregression and trace plot of the final model are included in the appendix.

Tables 3 and 4 display the results of the OLS regressions estimating the effect of peer marijuana use on individual marijuana use at Wave 2 and 3. Column one of Table 3 displays the results of the naïve OLS model which only controls for an individual's past month marijuana use in 10th grade when estimating the effect of peer marijuana use on individual marijuana use. At Wave 1, there was no effect of peer marijuana use on an adolescents marijuana use in 11th grade. When including the latent space estimates and additional observed covariates, again no effect was observed for peer marijuana use on an adolescents marijuana use in 11th grade.

Next, we examined the effect of peer marijuana use on individual marijuana use in 12th grade. From column one of Table 4, we can see that peer marijuana use in 11th grade is associated with a large and significant increase in the probability for adolescent marijuana use in 12th grade. In particular, increasing the proportion of an adolescent's social connections who smoke marijuana from 0% to 25% increases an adolescent's likelihood of smoking marijuana by ~ 13.4 percentage points (0.534/4). Interestingly, when including the latent space coordinates and observable covariates in the model (column two), the social influence effect slightly increased in strength (0.56), with the standard error increasing as well. The latent space adjusted estimate indicates that increasing the proportion of an adolescent's social connections who smoke marijuana from 0% to 25% in 11^{th} grade, increases an adolescent's likelihood of smoking marijuana in 12^{th} grade by ~ 13.9 percentage points (0.555/4).

Discussion

In this study we examined whether an adolescent's marijuana use behaviors in high school are influenced by the marijuana use of their direct social connections. To address the many confounds that can bias the identification of social influence effects in observational social network data, we utilized a novel latent variable adjustment procedure (the latent space adjusted approach) which borrows information from the natural organization (i.e., the social assortment) of the social network to purge bias that may result from both observable and *unobservable* variables that affect the selection and influence process. Utilizing this novel adjustment procedure, we found evidence that the marijuana use of an adolescent's social connections in 11^{th} grade increases the probability of adolescent marijuana use in 12^{th} grade. No effects were found for 10^{th} grade peer marijuana use on 11^{th} grade individual marijuana use.

Although a small number of studies have examined the impact that social influence has on the development of marijuana use in adolescence, our study improves on this literature in a number of ways. First, we utilized survey and network data collected from the PROSPER study – a longitudinal substance use prevention trial conducted within the last decade (survey/network data during the 10^{th} – 12^{th} grade were collected from 2006 – 2009) which contains fine-grained dynamic social network data, information on important developmental determinants of marijuana use, and peer reports of their own marijuana use (in contrast to *perceived* reports). The availability of a rich variety of developmental determinants of adolescent marijuana use allowed us to control for a number of observed confounds not addressed in previous studies (e.g., Andrews et al., 2002; de la Haye, Green, Kennedy, Pollard, & Tucker, 2013; Moriarty, Mcvicar, & Higgins, 2015). Furthermore, we were able to exploit information on friendship nominations and peer reports of their own marijuana use to restrict our reference group to the *direct* social connections of an adolescent. We believe that this operationalization of the peer group is more credible than other operationalization's in the literature (e.g., best friend's marijuana use or grade-level marijuana use; Ali et al., 2011; Andrews et al., 2002), given that interactions with a single peer may not capture all the risky social interactions an adolescent is exposed to over the high school time-period, and the unlikely assumption that an adolescent interacts with all peers in their grade. In addition, in contrast to the majority of the social influence literature which has relied on network datasets that are decades old (e.g., Add Health), the use of a more contemporary social network dataset is more likely to reflect the rapidly changing values/norms towards marijuana in the U.S. (Pew Research Center, 2018), which recent evidence suggests can impact adolescent marijuana use (Rusby, Westling, Crowley, & Light, 2018).

A final strength of our study is the use of latent space controls to isolate social influence effects in the presence of unobserved variables that co-determine the social selection process (i.e., the formation of social-ties) and the social influence process. Although recent empirical and theoretical evidence suggests that the latent space adjusted approach outperforms methods traditionally used to deal with omitted variable bias (e.g., fixed-effects, random-effects, SEM, or IV based approaches; Davin, Gupta, & Piskorski, 2014; Shalizi & McFowland III, 2016; Xu, 2018), this study is the first to use this approach to quantify the effect that social influence has on marijuana use in adolescence. Considering the strengths of this novel analytic approach, this study provides strong evidence that social influence plays a primary role in the development of marijuana use during high school.

The time-varying social influence effects observed in this study suggest that there may be distinct periods of risk during adolescence when social influence has a marked impact on marijuana use behavior. In particular, these findings are consistent with explanations for the salience of the peer group on risky behaviors which posit that as adolescent's begin sort into more stable peer groups (i.e., "find" their group), pressure to conform (perceived or actual pressure) to a reference groups values or norms may intensify as individuals begin to adopt or maintain the values/norms of a valued in-group (Berger & Heath, 2008; Brown, 2004; Brown, Clasen, & Eicher, 1986; Newman, Lohman, & Newman, 2007). As students started their first year of high school (10^{th} grade) it is likely that individuals spent this first year exploring new relationships and "trying-on" different groups of friends. However, by 11^{th} and 12^{th} grade, students had likely found more stable relationships and/or a stable reference group which provided suitable expectations and modeling behaviors capable of conveying risk/protective norms/values such as marijuana use (Brown & Klute, 2008; Hallinan, 1979).

Although the methodological and substantive strengths of this study provide evidence that social influence plays an important role in an adolescent's decision to smoke marijuana, there are limitations that should be noted. First, we only examine the impact of social influence on adolescent marijuana use in a single school. While this decision was made to simplify the estimation of the DLSMM models which take an exceptional amount of computational power to fit, it is possible that the high school chosen for this study might not reflect marijuana use development or the impact of social influence on marijuana use within different geographical regions or schools with different demographic compositions. It would be beneficial to replicate these findings within other types of high schools. Second, the assumptions underlying the causal identification of social influence effects with the latent space adjusted approach may be overly restrictive. In particular, it is possible that the formation of social-ties within the high school network was also influenced by individual or environmental attributes of the network members. Non-dynamic formulations of the latent space model (e.g., Krivitsky, Handcock, Raftery, & Hoff, 2009) allow for the inclusion of covariates when estimating the probability of a social-tie between two individuals, which explicitly accounts for homophily on observed attributes within the selection process. Unfortunately, the dnc package used to fit the DLSMM models does not include the ability to include observed covariates in the DLSMM models; however, we plan to explore how the inclusion of covariates in the DLSMM and non-dynamic formulations of the LSM affect social influence effects on marijuana use in future work. Finally, similar to other studies examining whether social influence has an impact on health risk behaviors in adolescence, despite strong evidence of social influence effects on 12th grade marijuana use, we are unable to explain why these time-varying effects occurred. Future research should examine why social influence effects might vary across time, and through what social, individual, or environmental mechanisms these effects convey risk.

When estimating the social influence models, we found that the substantive results from both the naïve and the latent space adjusted models were similar. In particular, the inclusion of the latent space estimates did not impact the overall finding that the marijuana use of an adolescent's social connections in 11th grade increased the probability of adolescent marijuana use in 12th grade. What was particularly interesting however, was that the social influence effect estimated from the latent space adjusted model was slightly larger than the social influence effect estimated from the naïve model. Although this finding might seem counterintuitive, [6] studies examining the impact of social influence on marijuana use have generally found that the inclusion of statistical controls to purge bias in social influence estimates *increase* estimates of social influence effects (e.g., Ali et al., 2011; Moriarty et al., 2016). Thus, our findings corroborate previous findings in the marijuana use and social influence literature, and suggest that the removal of confounding influences results in larger social influence estimates.

Documenting the degree to which peers influence marijuana use behaviors in adolescence is a crucial first step towards the design of more efficacious and cost-effective intervention programs for youth. However, intervention designs or policy decisions that assume that social influence effects impact individual behavior require strong evidence to rule-out other causal factors. The novel analytic methods utilized in the present study provide strong evidence that the marijuana use behaviors of the peers surrounding an adolescent have a direct and strong impact on an adolescent's decision to smoke marijuana themselves, net of other causal influences. As behavioral intervention programs begin to implement more technologically advanced dissemination strategies (e.g., social networking sites, smartphone, wearable-sensor devices), the utility of these findings are likely to have an important impact on future public health initiatives and educational strategies.

---

[6] For example, studies examining the impact of social influence on alcohol and tobacco use have found that the inclusion of methodological controls when estimating social influence effects reduces estimates of social influence effects (e.g., Fletcher, 2010; Fletcher & Ross, 2012).

Table 1.

Sample Demographics, Marijuana use, and Covariates for Wave 1 (10th Grade)

Demographics	*n*	%
Female	231	52
Non-white	173	41
Free school lunch	47	13
Marijuana Use	*n*	%
Past month marijuana use	49	13
Covariates (continuous)	Mean	SD
Risk/Sensation Seeking	2.26	1.01
Depression and Anxiety	0.31	0.52
Grades	4.07	0.87
Critical Thinking	3.55	1.12
School Adjustment/Bonding	3.59	0.70
Days Absent from School	3.12	0.98
Family Relations	-0.18	0.45
Covariates (categorical)	*n*	%
Lives with both biological parents	238	64
Religious attendance	150	41
Obtained alcohol from sibling or older person	140	37

Note. N = 538

Table 2.

Peer Marijuana use of Marijuana Users and Non-Marijuana Users (Means and Standard Deviations)

	Marijuana Users	Non-Marijuana Users	*p*
Wave 1 (10^{th} grade)			
Peer marijuana use (proportion of social connections)	0.30 (0.31)	0.12 (0.22)	0.000
Wave 2 (11^{th} grade)			
Peer marijuana use (proportion of social connections)	0.08 (0.15)	0.10 (0.21)	0.503
Wave 3 (12^{th} grade)			
Peer marijuana use (proportion of social connections)	0.14 (0.23)	0.07 (0.19)	0.004

Table 3.

OLS Results for Social Influence Effects on Marijuana use at Wave 2 (11th grade)

	Naïve Model		Latent Space Adjusted Model	
	Estimate	*p*	Estimate	*p*
(Intercept)	0.136 (0.027)	0.000	2.80 (3.269)	0.394
Peer marijuana use (10th grade)	-0.027 (0.113)	0.814	-0.089 (0.130)	0.496
Marijuana use 10th grade (past month)	0.586 (0.107)	0.000	0.620 (0.121)	0.000
Female	-	-	-0.095 (0.058)	0.103
Non-white	-	-	-0.006 (0.066)	0.927
Free school lunch	-	-	-0.006 (0.072)	0.935
Risk/Sensation Seeking	-	-	0.024 (0.035)	0.485
Depression and Anxiety	-	-	-0.007 (0.061)	0.909
Grades	-	-	-0.036 (0.038)	0.352
Critical Thinking	-	-	0.055 (0.029)	0.059
School Adjustment/Bonding	-	-	-0.144 (0.049)	0.004
Days Absent from School	-	-	0.015 (0.033)	0.658
Family Relations	-	-	0.011 (0.075)	0.887
Lives with both biological parents	-	-	-0.037 (0.056)	0.517
Religious attendance	-	-	-0.007 (0.022)	0.766
Obtained alcohol from sibling or older person	-	-	0.069 (0.057)	0.226
Latent Coordinates (1st dimension)	-	-	0.001 (0.054)	0.992
Latent Coordinates (2nd dimension)	-	-	-0.006 (0.035)	0.862
Latent Coordinates (3rd dimension)	-	-	0.244 (0.358)	0.496

Table 4.

OLS Results for Social Influence Effects on Marijuana use at Wave 3 (12th grade)

	Naïve Model		Latent Space Adjusted Model	
	Estimate	*p*	Estimate	*p*
(Intercept)	0.133 (0.032)	0.000	0.313 (3.366)	0.926
Peer marijuana use (11th grade)	0.534 (0.182)	0.004	0.555 (0.225)	0.015
Marijuana use 11th grade (past month)	0.488 (0.090)	0.000	0.524 (0.109)	0.000
Female	-	-	0.037 (0.072)	0.605
Non-white	-	-	0.051 (0.076)	0.506
Free school lunch	-	-	-0.019 (0.123)	0.877
Risk/Sensation Seeking	-	-	0.029 (0.037)	0.427
Depression and Anxiety	-	-	-0.076 (0.062)	0.224
Grades	-	-	0.040 (0.051)	0.432
Critical Thinking	-	-	-0.039 (0.031)	0.205
School Adjustment/Bonding	-	-	-0.036 (0.059)	0.551
Days Absent from School	-	-	-0.021 (0.041)	0.620
Family Relations	-	-	-0.053 (0.079)	0.498
Lives with both biological parents	-	-	-0.044 (0.063)	0.487
Religious attendance	-	-	-0.003 (0.027)	0.899
Obtained alcohol from sibling or older person	-	-	0.142 (0.078)	0.069
Latent Coordinates (1st dimension)	-	-	-0.008 (0.059)	0.890
Latent Coordinates (2nd dimension)	-	-	-0.104 (0.051)	0.043
Latent Coordinates (3rd dimension)	-	-	0.013 (0.362)	0.972

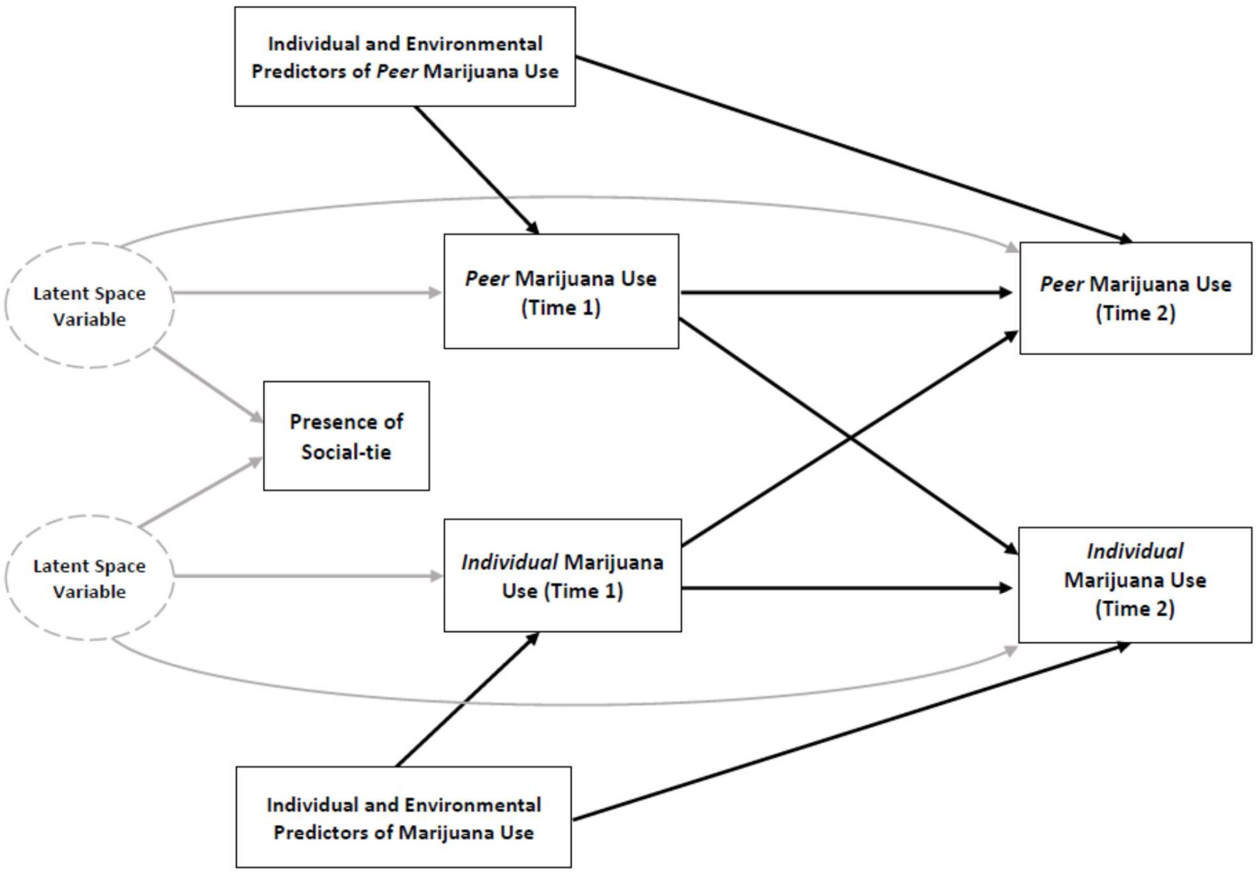

Figure 1. Directed acyclic graph (DAG) representing the causal model for the identification of social influence effects on marijuana use utilizing the latent space adjusted approach. The target of interest is the total causal effect of peer marijuana use at time 1 on individual marijuana use at time 2. We assume that: (a) unobserved latent variables (latent space variable) are causal determinants of the formation of all social ties within the network, and (b) individual and environmental predictors of marijuana use only influence marijuana use and not the network growth process.

Chapter 4

Longitudinal Communities in Adolescence: Moderation of Social Influence on Marijuana use

Marijuana is the most commonly used illicit drug among adolescents in the United States (SAMHSA, 2015). Although marijuana is commonly regarded as a harmless pleasure, accumulating evidence suggests that marijuana use – and especially marijuana use during adolescence – is associated with a range of negative outcomes including: increased risk of illicit substance use, cognitive/neurological impairments, psychiatric symptoms/disorders, and reduced earning potential (Volkow et al., 2014). As of June 2018, nine states and the District of Columbia have legalized marijuana for adult recreational use, and recent epidemiological surveys indicate that legalization efforts in some states have negatively impacted adolescent marijuana use (e.g., increased frequency of teen use: Rusby, Westling, Crowley, & Light, 2018). As more states move towards legalization, understanding the developmental correlates of adolescent marijuana use is exceptionally important.

Social influence is one of the most frequently cited predictors of adolescent marijuana and other substance use. Research examining the effect of social influence on adolescent substance use behaviors has found that social influence plays a primary role in the development of a variety of substance use behaviors including alcohol use (e.g., Clark & Loheac, 2007; Duncan, Doisjoly, Kremer, Levy, & Eccles, 2005; Fletcher & Ross, 2012), smoking (e.g., Clark & Loheac, 2007; Fletcher, 2010), marijuana use (e.g., de la Haye, Green, Kennedy, Pollard, & Tucker, 2013; Moriarty, Mcvicar, & Higgins, 2015), cocaine use (Bahr, Hoffman, & Yang, 2005; Iannotti & Bush, 1992), and I.V. drug use (Bahr et al., 2005; Eaves, 2004). However, despite the robust link between social influence and the development of substance use behaviors in adolescence, remarkably little is known about the individual or environmental factors that may increase an individual's susceptibility or vulnerability to social influence effects.

In recent years, a small number of studies have begun to examine potential moderators of social influence. The majority of this work has focused on individual attributes or relational-characteristics of the *influencer* and *influencee* (i.e., the adolescent being influenced), and moderators of *non-substance use behaviors* (e.g., aggressive/deviant/violent behaviors, or psychopathological symptoms). These studies have found that individual characteristics of the target adolescent (e.g., gender, age, psychological symptoms; Duncan et al., 2005; Gardner, Dishion, & Connell, 2008; Prinstein, 2007), individual characteristics of the *influencer* (e.g., status/popularity; Cohen & Prinstein, 2006; Prinstein, 2007), the nature of the relationship between the target and the influencing peer (e.g., high friendship quality, friendship reciprocity; Hall & Valente, 2007; Prinstein, 2007; Stevens & Prinstein, 2005), and the *type* of behavior (e.g., antisocial/unhealthy behaviors; Espelage, Holt, & Henkel, 2003; Maxwell, 2002) can all have a substantial impact on the potency of social influence effects.

Although individual and dyadic characteristics (e.g., relationship quality) play an important role in adolescent development, group-level characteristics/processes can impact development as well (Brown & Klute, 2008). Indeed, it is well known that the peer groups that naturally form during the adolescent period can have a profound impact on a variety of developmental outcomes including an adolescents identify formation, academic success, mental health, and the development of important health behaviors including substance use (Brown & Klute, 2008; Kreager, Rulison, & Moody, 2011; La Greca, Prinstein, & Fetter, 2001; Wentzel & Caldwell, 1997). Group contexts are important to adult development as well, and recent evidence within the epidemiology, statistical physics, and computer science fields indicates that the presence of dense and closely connected social groups, called network *communities*, can moderate the spread of infectious diseases, information, or behaviors within *adult* social networks. In particular, these studies have found that the social assortment (i.e., social structure) of community members, and the norms/values of specific communities can impact the transmission of disease, information, and behaviors within and between groups (Liu, Li, Chen, & Zhang, 2016; Salathe & Jones, 2010; Stegehuis, van der Hofstad, & van Leeuwaarden, 2016; Weng, Menczer, & Ahn, 2013).

However, while these studies collectively highlight that the natural formation of community structures can impact some types of contagious processes within adult social networks, none of these studies have explicitly tested whether network communities can impact the strength of social influence processes within an *adolescent's* social network. Adolescence is a critical time period for marijuana and other substance use development (Chambers, Taylor, & Potenza, 2003; Kandel & Logan, 1984). In addition, in contrast to older individuals, adolescents are particularly susceptible to peer pressure and other types of social information conveyed by their peer group (Steinberg & Monahan, 2007). Thus, it is pertinent to examine whether the presence of naturally occurring social groups (i.e., communities) within an adolescent's social network can impact the potency of social influence effects on adolescent marijuana use.

In this study, we examine how the presence of communities within a large high school network moderate the link between social influence and the development of adolescent marijuana use. To identify adolescent communities, we utilize a novel latent variable model for longitudinal social network data (Dynamic Latent Space Mixture Modeling) that allows us to identify longitudinal communities within the network, and characterize movement between groups over time. Results from this project will inform prevention efforts by determining whether members of some network communities are at an increased risk for marijuana use and the role that social influence plays in this risk. The focus on moderators of social influence in adolescence is especially pertinent considering recent evidence highlighting the impracticality and potential iatrogenic effects of discouraging harmful peer affiliations (Hall & Valente, 2007; Klein, 2006).

Methods

Sample

The present study uses data from the PROmoting School-university-community Partnerships to Enhance Resilience (PROSPER) project. The PROSPER project (Spoth, Greenberg, Bierman, & Redmond, 2004; Spoth, Redmond, Shin, Greenberg, Clair, & Feinberg, 2007) follows two cohorts of 6th grade students in 2002 (cohort 1) and 2003 (cohort 2) from 28 rural public school districts in Iowa (n = 14) and Pennsylvania (n = 14) to examine the impact of a large multi-year longitudinal test of a substance use prevention program from 6th grade to 12th grade. Starting in the fall and spring of the 6th grade, students completed in-school questionnaires assessing students demographic, substance use, personality, mental health, school, and family characteristics. In-school data collection continued every spring from 7th – 12th grade. Inclusion criteria for the selected schools included: (a) 1,300 to 5,200 enrolled students, and (b) at least 15% of the student population eligible for free or reduced-cost school lunches.

All analyses in the current study utilized data from a single high school in the PROSPER dataset. To ensure that the PROSPER prevention program did not influence marijuana use development or social influence effects, the selected high school was part of the PROSPER control condition. In addition, a large high school was selected to ensure a large and stable (i.e., few students leaving or entering at different time-points) amount of network data. All analyses are limited to all students in the 10^{th} – 12^{th} grade (high school began in the 10^{th} grade) of the selected high school because marijuana use becomes more common over time in this age-range of the population (Chen, Yu, Lasopa, & Cottler, 2017). The final sample size for each wave was: 10^{th} grade = 583 students, 11^{th} grade = 545 students, 12^{th} grade = 525 students.

Measures: Social Network Data

When completing the in-school questionnaires during the 10^{th} – 12^{th} grade, students were asked to name two best friends and up to five additional friends in their current grade and school. These friends were then matched to a class roster provided by school administrators. 58% of respondents nominated a friend, and 83% of the named friend were identified as fellow students. This percentage of matched network data is comparable to other social network studies (e.g., Add Health).

Measures: Individual and Peer Marijuana use

Student *past month* marijuana use was measured from a self-report question: "During the past month, how many times have you smoked marijuana (pot, reefer, weed, blunts)?" A dichotomous item was created that quantified non-use ('not at all') or any use ('one time' to 'more than once a week').

A measure of average peer marijuana use was created by summing the dichotomous self-report past month marijuana use for each student who was socially connected to an adolescent (from matched friendship nomination data) and dividing this value by the total number of social connections of the adolescent. This score ranged from 0 – 1, where 1 = all peers who were socially connected to an adolescent smoked marijuana, and 0 = no social connections smoked.

Measures: Covariates and Descriptive Variables

To control for *observed* correlates of adolescent marijuana use and to describe the identified communities, the following variables will be included in the social influence model and post-hoc descriptive analyses:

Gender (0 = female, 1 = male), race/ethnicity (1 = white, 0 = non-white), and self-reported free/reduced-prices lunch (1 = receives free/reduced-price lunch, 0 = does not receive free/reduced-price lunch).

Methodological Approach

Dynamic Latent Space Mixture Model. To identify longitudinal network communities within the selected high school, Dynamic Latent Space Mixture Models (DLSMM; Sewell & Chen, 2016) were fit to the three waves of social network data. The DLSMM is a longitudinal community detection (network clustering) extension of the Latent Space model (LSM; Hoff et al., 2002) which posits that the *observed* network can be modeled as a function of each network members location within an unobserved social space. This social space can be conceptualized as a multidimensional space of individual/environmental characteristics relevant to the formation of social-ties. To represent the presence or absence of an observed social-connection within the network, the DLSMM models the probability of a social tie as a function of the *distance* between two networks members in the unobserved social space: the closer two individuals are (i.e., the smaller the distance) in this space, the higher the probability of a social-tie.[7]

As a longitudinal community detection technique, the DLSMM models the position of each network member in the latent space and their community (subgroup) membership via a

[7] The DLSMM models the probability of a social-tie as a function of each dyads *cosine* distance within the latent space. In particular, the probability of a connection between two individuals depends on the angle between them in a latent hypersphere. This formulation (cosine distances and location in a hypersphere) has proven useful in clustering problems involving complex high dimensional datatypes (e.g., Banerjee, Dhillon, Ghosh, & Sra, 2005; Cox & Cox, 1991).

Hidden Markov model (HMM) with a mixture of multivariate normal distributions. Thus, at each time point *t,* the latent positions of each network members is generated from a mixture of *G* static probability distributions, with the number *G* corresponding to the number of communities in the network. Although the number of these communities are assumed to stay stable over time, as a HMM, the DLSMM also estimates transition probabilities between the estimated communities over time. Thus, the use of the DLSMM for community detection also allows for the examination of stability and change of community structures across time.

One of the many strengths of the latent space modeling approach underlying the DLSMM is that the conceptualization of an unobserved (latent) social space where neighboring individuals are more likely to be socially connected is based on the well-known observation that most social networks are homophilous: socially connected individuals are more likely to be similar on a number of characteristics (e.g., demographic, values, behaviors; McPherson, Smith-Lovin, & Cook, 2001). This theoretical foundation allows the DLSMM to represent common characteristics of the network that many computational models of the network have struggled to characterize (e.g., transitivity, reciprocity, and the tendency for individuals within the network to form social communities). In addition, in contrast to ad-hoc community detection methods, the DLSMM is a generative statistical model of the network which facilitates model-fitting and the selection of an optimal model.

Model estimation procedure. The dnc package (Sewell & Chen, 2016) in R (R Development Core Team, 2018) was used to fit DLSMMs with 1 – 10 communities to the three waves of high school network data. The dnc package finds maximum *a posteriori* (MAP) estimators via the Metropolis-Hastings algorithm within Gibbs sampling. Preliminary runs of the dnc package indicated that the DLSMM models converged around 75,000 MCMC iterations, thus, each individual DLSMM model (i.e., 1-community, 2- community… 10-community) was fit with 140,000 MCMC iterations (post burn-in) and 75,000 burn in-samples. Convergence for the Gibbs sampler was set to 1 x 10^{-6} and the max number of iterations for the second stage of the Gibbs sampler was set to 250. All other model-fitting and algorithmic specifications (e.g., prior distributions) were set to the dnc package defaults.

Model selection. To determine the final optimal model, models with the lowest Bayesian Information Criteria (BIC) as calculated in Sewell and Chen (2016) were given primary consideration. Substantive interpretability of the identified communities, community size (e.g., overly large/small communities), and model convergence diagnostics (e.g., trace plots, autocorrelation plot) were given secondary consideration to remove tentative models from consideration.

Community assignment and description. Students were assigned to the community corresponding to their highest maximum a posteriori probability (MAPP) of membership. To examine differences across communities on marijuana use and demographic characteristics, Omnibus Kruskall-Wallis (KWt) tests were conducted.

Community membership and moderation models. To examine the impact of community membership on next year marijuana use (past month) and to examine whether community membership moderated the impact of social influence on next year marijuana use, the following two models are estimated:

(a) Community membership model:

$$Y_{it} = \beta_0 + \beta_1 Y_{i,t-1} + \beta C_i + \in_{it}$$

Where *Ci* represents a vector of dummy variables corresponding to the community membership of the focal individual at *t – 1,* and $Y_{i,t-1}$ represents the lagged marijuana use of the focal individual *i* at *t – 1. C* separate regression models are estimated with one dummy variable left out of the regression to identify the reference category.

(b) Community x social influence (interaction) model:

$$Y_{it} = \beta_0 + \beta_1 Y_{i,t-1} + \beta X_i + \beta C_i + \beta_5 \frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}} + \beta_{c-1} C_i \frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}} + \epsilon_{it}$$

Where C_i represents a vector of dummy variables corresponding to the community membership of the focal individual at *t – 1,* $Y_{i,t-1}$ represents the lagged marijuana use of the focal individual *i* at *t – 1,* X_i represents a vector of time-invariant demographic characteristics of the focal individual, $\frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}}$ represents the average lagged *Y* (marijuana use) among the focal individual *i'*s direct social connections, and $C_i \frac{\sum_j A_{ij} Y_{j,t-1}}{\sum_j A_{ij}}$ represents the interaction between community membership and average peer marijuana use. β_{c-1} is the main coefficient of interest, as this represents the multiplicative effect of peer marijuana use on next year marijuana use when a student is a member of Community *C* at *t – 1. C* separate regression models are estimated with one dummy variable left out of the regression to identify the reference category.

The community membership and community x social influence interaction models are estimated with OLS regression with robust standard errors estimated from the sandwich package (Zeileis, 2006) in R.

Missing data. Missing network data was assumed to be missing at random (ignorable) and was imputed via the Gibbs sampler. The Gibbs sampler treats ignorable (MAR, MCAR) network data as additional unknowns and samples the missing data given the latent positions and model parameters at each iteration, then estimates the posterior distributions given these imputed values (Rochani & Linder, 2017). Missing data on the demographic characteristics included in the OLS models were imputed by replacing missing data within a single wave by non-missing data at a previous or future-time point within each participant (i.e., if Wave 1 was missing but Wave 2 was not missing, then the Wave 1 value was replaced by the Wave 2 value, etc.)

Results

Table 1 displays the demographic, marijuana use, and non-illicit substance use of the high school sample at Wave 1 (10^{th} grade). At the first wave, 52% of the sample was female, 41% was non-white, and 13% received free or reduced price lunch. Past month marijuana use at the first wave was relatively rare compared to alcohol use (13% vs. 35% respectively); however, past month marijuana use was slightly more common than past month cigarette use (11%). Over the three waves, past month marijuana increased, and by 11^{th} and 12^{th} grades 18% and 28% of the sample reported using marijuana during the past month, respectively.

Longitudinal Communities: Descriptive Characteristics and Membership Stability

Tables 2 and 3 display the demographic characteristics and membership stability of the communities across the three waves. Over the three waves, the three communities were differentiated by their gender and racial composition, but not by whether students received free or reduced price lunch. Of the three identified communities, the gender and ethnic composition of Community 1 was the most equally balanced across groups and time. In addition, the demographic characteristics of Community 1 stayed relatively stable across the three waves. In contrast, the demographic composition of Community 3 changed significantly over the three waves. At Wave 1, Community 3 contained mainly female students (60%) and 29% non-white students. However, by Wave 3, Community 3 members were largely male (71%) and only 10% of the members were non-white. The demographic composition of Community 2 remained relatively stable over the three waves, and at Wave 1 and 2, this community contained the fewest female student of the three groups.

There was substantial movement between the identified communities over the three waves of high school data (Table 3). In particular, students in Community 2 and Community 3 were the most likely to transition to other groups over the three years. Interestingly, although the majority of the students within these communities transitioned into Community 1 at Wave 1 and 2, students in Community 2 and Community 3 exhibited different transition patterns between the groups. In particular, members of Community 2 moved (or stayed) between all three groups, while members of Community 3 either stayed within Community 3 over the three waves, or transitioned into Community 1. No students in Community 3 transitioned into Community 2 over the three waves. Members of Community 1 exhibited substantial stability over the three waves. In total, only 21 students left this group over the three years.

Longitudinal Communities: Individual and Peer Marijuana use

Table 4 displays past month individual and peer marijuana use across communities and waves. At Wave 1, students in Community 3 were the most likely to report past month marijuana use while students in Community 2 were the least likely to report marijuana use. At Wave 2 and 3, no significant differences were observed across the three groups.

Similar to their high self-reported levels of marijuana use, at Wave 1 students in Community 3 were socially connected to the highest proportion of marijuana users (27%) compared to the other two communities. Students in Community 2 at Wave 1 were connected to the lowest number of marijuana users (8%). Over time, the differentiating pattern of peer marijuana use shifted across the three groups, and at Wave 2 and Wave 3, students in Community 2 were socially connected to the highest proportion of marijuana users. At Wave 3, only 7% of peers socially connected to students in Community 1 reported past month marijuana use.

Community Membership: Prediction and Moderation of Marijuana Use

The effect of community membership on next year marijuana use at Wave 2 and Wave 3 is presented in Tables 5 and 6. At Wave 1, membership in the identified social network communities did not significantly predict an adolescent's marijuana use at the next time-period (11^{th} grade). However, at Wave 2, membership in both Community 1 and Community 2 predicted an increase in risk for marijuana use during the next year (12^{th} grade) compared to students who were members of Community 3. In particular, students who were members of Community 1 in 11^{th} grade were 13% more likely to smoke marijuana during the 12^{th} grade compared to members of Community 3. Similarly, students who were members of Community 2 in 11^{th} grade were 23% more likely to smoke marijuana during the 12^{th} grade compared to members of Community 3. When demographic controls were included in the model, the effects still remained, with the estimate for membership in Community 1 increasing slightly (0.163) and the estimate for membership in Community 2 decreasing slightly (0.227).

When examining whether membership in the identified communities moderated the presence of social influence effects, no significant interaction effects were found between 10^{th} grade community membership and peer marijuana use on individual marijuana use in 11^{th} grade. Thus, in the 10^{th} grade, social influence appeared to play a similar role on 11^{th} grade marijuana use regardless of the community a student was a member of. At Wave 2 however, a significant positive interaction effect between membership in Community 1 and peer marijuana use in 11^{th} grade was identified, indicating that the impact of social influence on marijuana use in 12^{th} grade was stronger for students who were members of Community 1 in 11^{th} grade compared to students who were members of Community 3 in 11th grade. No interaction effects were observed for Community 2 at Wave 3 indicating that there was no difference in the impact that social influence had on marijuana use in 12th grade between students in Community 2 and Community 3, and students in Community 2 and Community 1.

Discussion

A large literature has demonstrated the impact of social influence on substance use behaviors in adolescence (e.g., alcohol, tobacco; Andrews, Tildesly, Hops, & Li, 2002; Clark & Loheac, 2007; Fletcher, 2010; Fletcher & Ross, 2012). However, remarkable little is known about what factors moderate social influence effects, and whether there may be critical time-periods when social influence may be of particular risk for adolescents. This research utilized a novel latent variable model for longitudinal social network data to identify longitudinal communities (subgroups) within a high school network, and to test whether membership in the network communities moderated the effect of social influence on the development of marijuana use. Three communities' were identified over the three waves of high school data. The three communities were differentiated by important demographic characteristics, the proportion of marijuana users (at Wave 1), and by the proportion of an adolescent's social connections (peers) who were marijuana smokers (at all waves). In addition, substantial movement was observed between the three communities over the three year high school period.

Community membership in the 10th grade did not predict an adolescent's past month marijuana use in the 11th grade, nor were there any significant interaction effects between community membership and peer marijuana use on individual marijuana use in 11th grade. However, students who were members of Community 1 and Community 2 in 11th grade had a higher likelihood of marijuana use in 12th grade compared to members of Community 3. In addition, the impact of peer marijuana use on an adolescents individual marijuana use was stronger for students in Community 1 compared to students in Community 3 controlling for important demographic characteristics of the sample. In particular, for members of Community 1, a 25% increase in the number of social connections who smoke marijuana increases an adolescent's likelihood of marijuana use in 12th grade by ~ 19.5% compared to members of Community 3.

The results presented here suggest that the communities that naturally form during the high school period play a *time-varying* role in the development of marijuana use behaviors and the extent to which peer marijuana use behaviors contribute to later marijuana use. These findings are consistent with prior substance use research that has found that the salience of the peer context *and* an adolescent's susceptibility to social influence (peer influence) can vary as a function of developmental maturation (Ary & Biglan, 1988; Brown & Klute, 2008; Steinberg & Monahan, 2007). In particular, previous explanations for the salience of the peer group during adolescence posit that as adolescent's naturally sort themselves into peer groups, perceived and actual pressure to conform to a groups values or norms may intensify over time as individuals attempt to adopt or maintain the values/norms (e.g., via identity signaling) of valued in-group and out-group members (Berger & Heath, 2008; Brown, 2004; Brown, Clasen, & Eicher, 1986; Newman, Lohman, & Newman, 2007). The moderate levels of "churn" observed within the three communities over the three waves seems to highlight the propensity for adolescent's within this high school to "try-on" different peer contexts, before finally settling on a community in-group. This instability may explain the lack of effects observed at the Wave 1, a time period when students in the selected high school were starting high school and establishing stable peer groups. The membership stability of Community 1 across the three waves may also explain why social influence effects were stronger for students who were members of Community 1 compared to students in other communities. In particular, the majority of students in Community 1 stayed in Community 1 over the three years. Furthermore, the students from other communities who transitioned into this community also were likely to stay within this community. Thus, this community likely served as a more stable reference group for which students could more easily evaluate the valued behaviors or norms of the group.

Although this research provides a first look at the moderating role that longitudinal network communities play on the effect of social influence and adolescent marijuana use development, there are limitation that should be noted. First, this study only examines the formation and influence of longitudinal communities on social influence and marijuana use in a single high school. It is possible that the selected high school may not reflect marijuana use development, community formation, or social influence processes in high schools located within other regions or with different demographic characteristics. It would be useful to replicate these findings in other high schools across different time-periods. Second, although the high school used in all analyses was selected based on the size of the available network data, it is well known that mixture models can be sensitive to sample size (e.g., Nylund, Asparouhov, & Muthén, 2007). Fortunately, although there were missing network data across waves, the DLSMM is able to account for missing network data via Gibbs sampling within a Bayesian framework, and thus it was possible to maximize sample size across waves. Nevertheless, it would still be helpful to replicate the findings within in a larger school. A third and closely related limitation is that community detection methods such as the DLSMM are exceptionally complex and novel analytic methods with few guiding principles for how to select a final optimal model. Fortunately, given that the DLSMM is a mixture model with solid statistical properties, it was possible to follow model selection techniques for mixture modeling to determine the optimal model (e.g., Nylund et al., 2007; Sewell & Chen, 2016). However, running additional model checks such as posterior predictive simulations (PPS; Hjort, Dahl, & Steinbakk, 2006) would be helpful in the current context, and we plan to examine this in future research. Finally, because the main objective of the study was to examine the impact of community membership on marijuana use and the multiplicative effect of community membership and social influence on marijuana use, it was not possible to directly test the mechanisms through which membership in the identified community's conferred risk.

This is the first study to examine whether the presence of longitudinal communities that form during the high school period impact the strength of social influence effects on adolescent marijuana use. Results from this study suggest that the effects of community contexts in adolescence have a time-varying effect on the development of marijuana use behaviors, and that some community contexts can magnify the effect of social influence on adolescent marijuana use. These results have important implications for both basic developmental science and the development of tailored interventions. In particular, these findings suggest that programs aimed at substance use prevention in adolescence should account for the self-assortment of adolescent's into unique communities as well as how these unique social milieus convey time-varying effects. Future research should examine the mechanisms through which communities in high school convey risk or protective effects against social influence effects.

Table 1.

Sample Demographics, Marijuana use, and Substance use for Wave 1 (10th Grade)

Demographics	*n*	%
Female	231	52
Non-white	173	41
Free school lunch	47	13
Marijuana Use	*n*	%
Past month marijuana use	49	13
Other Substance Use	n	%
Past month alcohol use	130	35
Past month cigarette use	41	11

Note. N = 538

Table 2.

Demographic Characteristics of Communities (Means, Percentages, and Group Differences)

	Community 1	Community 2	Community 3	*p*
Wave 1 (10th grade, n = 492)	(n = 264, 53%)	(n = 125, 25%)	(n = 103, 21%)	
Female (%)	59	31	60	0.000
Non-White (%)	54	23	29	0.000
Free School Lunch	17	10	9	0.100
Wave 2 (11th grade, n = 492)	(n = 416, 85%)	(n = 44, 9%)	(n = 32, 7%)	
Female (%)	55	27	50	0.002
Non-White (%)	47	19	13	0.000
Free School Lunch	19	5	17	0.069
Wave 3 (12th grade, n = 492)	(n = 441, 90%)	(n = 17, 4%)	(n = 35, 7%)	
Female (%)	55	29	29	0.003
Non-White (%)	43	38	10	0.002
Free School Lunch	22	6	9	0.071

Table 3.

Transition Matrix Quantifying Community Membership Stability across Waves: Transitions from Wave 1 to Wave 2, and Wave 2 to Wave 3

		Wave 1 (10th grade)		
		Community 1	*Community 2*	*Community 3*
Wave 2 (11th Grade)	*Community 1*	257	61	98
	Community 2	3	41	0
	Community 3	4	23	5
		Wave 2 (11th Grade)		
		Community 1	*Community 2*	*Community 3*
Wave 3 (12th Grade)	*Community 1*	402	20	18
	Community 2	7	10	0
	Community 3	7	14	14

Note. The transition matrix shows how many participants from a given community of the estimated DLSMM at Wave *X* (columns), moved to each community at Wave *Y* (rows). For example, looking at the column corresponding to Community 1 of Wave 1, we can see that 257 students remained in Community 1 at Wave 2, 3 students moved to Community 2 at Wave 2, and 4 students moved to Community 3 at Wave 2.

Table 4.

Past-month Individual and Peer Marijuana use by Communities (Means, Percentages, and Group Differences)

	Community 1	Community 2	Community 3	*p*
Wave 1 (10th grade)				
Individual marijuana use (%)	11	7	24	0.001
Peer marijuana use (proportion of social connections)	0.12	0.08	0.27	0.000
Wave 2 (11th grade)				
Individual marijuana use (%)	18	24	13	0.488
Peer marijuana use (proportion of social connections)	0.10	0.12	0.06	0.055
Wave 3 (12th grade)				
Individual marijuana use (%)	28	24	29	0.904
Peer marijuana use (proportion of social connections)	0.07	0.27	0.12	0.000

Table 5.

Community Membership in 10th grade (Wave 1) on 11th grade (Wave 2) Marijuana-use and Community by Social Influence Interaction Model– OLS Results (Community 3 Reference)

	Community Membership Model		Community Membership Model (*with controls*)		Community x Social Influence (Interaction) Model	
	Estimate	*p*	Estimate	*p*	Estimate	*p*
(Intercept)	0.131 (0.044)	0.003	0.132 (0.060)	0.027	0.151 (0.080)	0.058
Peer group 3 (reference)	-	-	-	-	-	-
Peer group 1	-0.005 (0.055)	0.924	-0.017 (0.055)	0.757	-0.031 (0.078)	0.688
Peer group 2	-0.005 (0.057)	0.926	-0.011 (0.057)	0.846	-0.046 (0.078)	0.554
Marijuana use 10th grade (past month)	0.568 (0.104)	0.000	0.566 (0.108)	0.000	0.584 (0.115)	0.000
Peer marijuana use (10th grade)	-	-	-	-	-0.098 (0.138)	0.480
Peer group 1 * Peer marijuana use (10th grade)	-	-	-	-	0.098 (0.273)	0.721
Peer group 2 * Peer marijuana use (10th grade)	-	-	-	-	0.146 (0.250)	0.560
Female	-	-	-0.025 (0.043)	0.562	-0.037 (0.049)	0.451
Non-white	-	-	0.004 (0.051)	0.932	0.026 (0.058)	0.658
Free school lunch	-	-	0.062 (0.076)	0.415	0.043 (0.081)	0.598

Table 6.

Community Membership in 11th grade (Wave 2) on 12th grade (Wave 3) Marijuana-use and Community by Social Influence Interaction Model– OLS Results (Community 3 Reference)

	Community Membership Model		Community Membership Model *(with controls)*		Community x Social Influence (Interaction) Model	
	Estimate	*p*	Estimate	*p*	Estimate	*p*
(Intercept)	0.040 (0.028)	0.159	-0.056 (0.063)	0.375	-0.068 (0.076)	0.371
Peer group 3 (reference)	-	-	-	-	-	-
Peer group 1	0.134 (0.042)	0.002	0.163 (0.048)	0.001	0.124 (0.063)	0.053
Peer group 2	0.233 (0.103)	0.025	0.227 (0.109)	0.039	0.172 (0.155)	0.269
Marijuana use 11th grade (past month)	0.545 (0.079)	0.000	0.606 (0.079)	0.000	0.549 (0.097)	0.000
Peer marijuana use (11th grade)	-	-	-	-	-0.279 (0.274)	0.309
Peer group 1 * Peer marijuana use (11th grade)	-	-	-	-	0.779 (0.348)	0.026
Peer group 2 * Peer marijuana use (11th grade)	-	-	-	-	0.622 (0.865)	0.473
Female	-	-	0.073 (0.055)	0.184	0.089 (0.066)	0.180
Non-white	-	-	0.067 (0.059)	0.261	0.098 (0.066)	0.142
Free school lunch	-	-	0.005 (0.076)	0.944	0.015 (0.085)	0.865

Chapter 5

Discussion

This dissertation utilized a novel longitudinal community detection method (DLSMM; Dynamic Latent Space Mixture Modeling) to examine the association between the formation of longitudinal peer groups in a high school network and the development of marijuana use. In Chapter 2, I utilized DLSMM to identify and characterize the longitudinal peer groups that naturally formed within an adolescent's high school network, and to examine the location and dynamics of marijuana use within the identified groups. Three peer groups were identified across the three waves of high school network data. The peer groups varied on important demographic, substance use, family, and school characteristics across the three waves, and exhibited differing levels of membership stability across time. Two of the identified peer groups displayed high levels of between-group transitions over the three years, with the majority of students within these groups transitioning into the largest of the three groups (peer group 1). Peer group 1 displayed almost no out-of-group movement. When examining the popularity and centrality of marijuana users within the network and the identified groups, there was a tendency for marijuana users to be pushed to the periphery of the network over the three years of high school. This "relegation" towards the periphery was observed within peer group 1 and peer group 3 as well.

In Chapter 3, I examined whether the marijuana use of an adolescent's social connections directly influenced adolescent marijuana use behaviors in 11th and 12th grade. To reduce bias in social influence estimates resulting from unobserved confounds in the influence and selection (homophily) process, I utilized a novel latent variable adjustment procedure (latent space adjustment) that controls for omitted variable bias with the inclusion of latent space estimates derived from the DLSMM. With the latent space adjustment to the standard linear-in-means model (Blume, Brock, Durlauf, & Ioannides, 2011), I found evidence for time-varying social influence effects in high school. In particular, I found evidence that the marijuana use of an adolescent's social connections in 11th grade increases the probability of adolescent marijuana use in 12th grade. No effects were found for 10th grade peer marijuana use on 11th grade individual marijuana use.

In Chapter 4, I extended the results of Chapter 2 to examine whether the identified longitudinal peer groups (referred to as communities in this chapter) predicated an adolescent's later marijuana use, and moderated the effect of social influence on marijuana use behavior. Similar to the time-varying effects observed in Chapter 3, I found time-varying effects for both the predictive influence of peer group membership on marijuana use and the moderating influence of the peer groups on marijuana use. In particular, I found that students who were members of peer group 1 and peer group 2 in 11th grade had a higher likelihood of marijuana use in 12th grade compared to students who were members of peer group 3. Furthermore, the effect of social influence on the likelihood of marijuana use in 12th grade was stronger for students who were members of peer group 1 in 11th grade compared to students who were members of peer group 3 in 11th grade, controlling for important demographic characteristics of the sample. Membership in the peer groups in 10th grade was not predictive of 11th grade marijuana use and peer group membership at this time-point nor did it moderate the effect of social influence on marijuana use.

Taken together, the results of the three chapters collectively highlight the importance of adolescent peer groups to the development of marijuana use. Not only does it appear that an adolescent's direct peer group (i.e., their direct social connections) play a role in individual marijuana use behaviors, it also appears that the meso-level structures that naturally form within the network – i.e., longitudinal peer groups – also have a profound effect on marijuana use behaviors, and the strength to which social influence processes have an effect on marijuana use behaviors. The results of the three chapters also emphasize the utility of longitudinal community detection methods for examining peer group dynamics *over time*. The unique ability of the DLSMM to model both the number of peer groups *and* transitions between groups over time allowed me to more fully characterize the dynamic composition of the peer groups and the time varying effects of peer group membership on marijuana use development. These findings suggest that the use of methods such as the DLSMM might illuminate other important social, behavioral, and/or physical processes in adolescents or other age groups.

In contrast to other studies of adolescent peer groups, the statistical method utilized in this dissertation identified longitudinal peer groups within an adolescent's social network solely from the patterns of *observed* social-ties within the network (i.e., the observed network structure over the three waves). This stands in direct contrast to the majority of the peer group literature which has relied on subjective or sometimes arbitrary conventions to operationalize the adolescent peer group. This data-driven approach, in conjunction with the statistical foundation underlying the DLSMM methodology, provides a more formal framework by which to examine peer groups in adolescence and facilitates replication across studies via a stable operationalization (the statistical model underlying the DLSMM) which can be tested in other samples/studies.

Despite the strengths of the present studies, a number of limitations exist. First, similar to other probabilistic clustering techniques (e.g., latent class analysis, Fuzzy C-means), the DLSMM assigns a community membership probability to each network member. Thus, community assignments are probabilistic as opposed to deterministic (0 or 1), and range from 0 to 1. While this facilitates the quantification of community assignment (and model) uncertainty, it may pose problems for practitioners, clinicians, or policy makers interested in explicitly enumerating “problem cases.” This is especially true for borderline cases (e.g., a membership probability of 0.55 or 0.60), or when a community (subgroup) solution is not well separated (i.e., groups overlap). Second, the assumptions of a stable number of peer groups over time may be overly restrictive. Relationships in adolescence can be tumultuous (Bukowski & Newcomb, 1984; Cairns, Leung, Buchanan, & Cairns, 1995) and it is possible that this dynamism may extend to the group context as well. Although this is the first study to examine the natural formation of longitudinal peer groups using community detection methods, previous studies of peer “crowds” have found that the assortment of crowds in adolescence appears to change with time. In particular, ethnographic evidence suggests that while early adolescent crowds are particularly distinct – with clear boundaries between groups – this distinction appears to fade over time with students more freely associating with multiple crowds in later adolescence (Brown et al., 1994). The results of Chapter 2 and Chapter 4 appear to support this finding and suggest that the importance of crowd/group affiliation diminishes towards the end of adolescence (Brown, Eicher, & Petrie, 1986). However, it would still be beneficial to examine whether relaxing the assumption of stable group numbers over time reveals any important dynamics or masks important variable within groups (e.g., the substantial number of students who migrated to peer group 1 over the high school period).

A third limitation is that because the DLSMM identifies groups based on longitudinal network connections, it is necessary to have longitudinal network data. At this time, longitudinal network data is rare; however, with increased access to longitudinal network datasets from social media platforms, public health databases, or wearable sensor data (e.g., fitbit, smartphones), these data may be more readily available in the near future. In addition, it may be possible to construct network datasets with a little researcher ingenuity (e.g., via the combination of classroom rosters and social media). Third, in many cases, community detection methods may identify groups within the network not readily observed by individuals themselves (Porter et al., 2009). Thus, in some contexts, the findings may be difficult to interpret or may not be practical for applied contexts (e.g., for school administrators) without a more formal collection and communication system in place. Fourth, longitudinal community detection methods such as the DLSMM are exceptionally complex and take a tremendous amount of computing power to fit to even a single high school. For example, one of the DLSMM models examined in this study (the 4-community model) took over five days to converge. Thus, unless more efficient algorithms are developed, the use of this method for time-sensitive problems seems impractical.[8] Finally, although the results of the three studies provide evidence for the presence of substantively meaningful longitudinal peer groups within a high school network, single studies can be subject to sample-specific variation which may lead to aberrant results. This is especially pertinent to exploratory analyses that are largely data-driven. Thus, in the present study, it would be beneficial to programmatically evaluate the validity of the identified peer groups via: (a) the replication of results in independent high school samples (Beauchaine & Marsh, 2006) or with alternative community detection methods, (b) advanced simulation methods such as posterior predictive simulations (PPS; Hjort, Dahl, & Steinbakk, 2006), and/or (c) different operationalization's of the social-ties (e.g., directed ties vs. undirected ties). Because of the complexity and computation power needed to fit the DLSMM to longitudinal network data, some

[8] Sewell and Chen (2016) did examine the fitting of the DLSMM within a Variational Bayes (VB) framework. However, the VB framework does not allow for missing network data which limits its flexibility.

of these validation techniques may not be feasible (e.g., PPS). However, I am currently examining the results of a cross-sectional community detection method (Latent Space Cluster Model, LSPCM; Handcock, Raftery, & Tantrum, 2007) fit to each wave of the PROSPER network data. The DLSMM is the longitudinal extension of the LSPCM, thus I will be able to indirectly test whether the assumption of a stable number of peer groups over the three waves of data is appropriate or whether this assumption should be relaxed.

Although results from these studies should be viewed as preliminary in light of the limitations listed above, the overall pattern of results from this dissertation nevertheless have important implications for developmental science, prevention research, and federal/state policies regarding marijuana legalization. In particular, results from the three studies suggest that the effects of peer group contexts in adolescence have a time-varying effect on the development of marijuana use behaviors, and that some peer groups can magnify the effect of social influence on adolescent marijuana use. Future research should examine whether these findings hold in other types of schools, and the mechanisms through which the identified peer groups convey risk (e.g., via the differentiating characteristics of the peer groups, instability/stability of some groups, etc). Researchers should also examine the processes that lead to the dynamic fluctuations observed in group membership over the high school period, and why group differentiation might become less important in the later years of high school (i.e., why many students appeared to transition into a single peer group).

These results also have implications for the design of next generation prevention programs. In particular, a growing body of evidence suggests that social networks can be utilized to augment behavior change, and that the identification of qualitatively distinct groups of individuals within the network may enhance the success of behavioral interventions (e.g., Valente, 2012). This is highlighted by the finding that certain peer groups exhibited heighted periods of risk over the three waves of high school data (e.g., peer group 3 in 10th grade). Thus, these findings may provide insight on critical periods for intervention and the groups that are at high risk. Future research into the norms/values of specific groups may provide key insights into why certain groups were less susceptible to social influence over the high school years. This is especially pertinent to the design of programs aimed at youth considering recent evidence highlighting the impracticality and potential iatrogenic effects of preventing harmful peer relationships (Hall & Valente, 2007; Klein, 2006).

Finally, the present findings have implications for federal/state/local policies regarding marijuana. For example, the findings that the marijuana use of the social connections of an adolescent in 11th grade have a strong effect on an individual's marijuana use in 12th grade suggest that policies and cost-effectiveness studies that do not take into account the spillover effect of untreated individuals will likely underestimate the benefits of a proposed or current program. In addition, although these results would benefit from addition validation, it appears that there are specific time periods and groups where social influence may not matter or may matter *more.* Finally, given that some studies have found that legalization initiatives in some states can have a negative impact on adolescent use (e.g., Rusby, Westling, Crowley, & Light, 2018), the finding that marijuana use can spread contagiously during the high school time period has important considerations for policy makers assessing the public health risks associated with legalization.

References

Adamczyk, A., & Palmer, I. (2008). Religion and Initiation into Marijuana Use: The Deterring Role of Religious Friends. *Journal of Drug Issues*, *38*(3), 717–741. https://doi.org/10.1177/002204260803800304

Alexander, C., Piazza, M., Mekos, D., & Valente, T. (2001). Peers, schools, and adolescent cigarette smoking. *The Journal of Adolescent Health : Official Publication of the Society for Adolescent Medicine*, *29*(1), 22–30. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11429302

Ali, M. M., Amialchuk, A., & Dwyer, D. S. (2011). The social contagion effect of marijuana use among adolescents. *PLoS ONE*, *6*(1). https://doi.org/10.1371/journal.pone.0016183

Andréasson, S., Engström, A., Allebeck, P., & Rydberg, U. (1987). Cannabis And Schizophrenia a Longitudinal Study of Swedish Conscripts. *The Lancet*, *330*(8574), 1483–1486. https://doi.org/10.1016/S0140-6736(87)92620-1

Andrews, J. A., Tildesley, E., Hops, H., & Li, F. (2002). The influence of peers on young adult substance use. *Health Psychology*, *21*(4), 349.

Anthony, J. C. (2006). The epidemiology of cannabis dependence. In R. Roffman & R. Stephens (Eds.), *Cannabis dependence: its nature, consequences and treatment* (pp. 58–105). Cambridge, MA: Cambridge University Press.

Ary, D. V, & Biglan, A. (1988). Longitudinal changes in adolescent cigarette smoking behavior: Onset and cessation. *Journal of Behavioral Medicine*, *11*(4), 361–382. https://doi.org/10.1007/BF00844936

Audrain-McGovern, J., Rodriguez, D., & Kassel, J. D. (2009). Adolescent smoking and depression: evidence for self-medication and peer smoking mediation. *Addiction*, *104*(10), 1743–1756. https://doi.org/10.1111/j.1360-0443.2009.02617.x

Baer, P. E., & Bray, J. H. (1999). Adolescent individuation and alcohol use. *Journal of Studies on Alcohol, Supplement*, (s13), 52–62. https://doi.org/10.15288/jsas.1999.s13.52

Bahr, S. J., Hoffmann, J. P., & Yang, X. (2005). Parental and Peer Influences on the Risk of Adolescent Drug Use. *The Journal of Primary Prevention*, *26*(6), 529–551. https://doi.org/10.1007/s10935-005-0014-8

Bambico, F. R., Nguyen, N.-T., Katz, N., & Gobbi, G. (2010). Chronic exposure to cannabinoids during adolescence but not during adulthood impairs emotional behaviour and monoaminergic neurotransmission. *Neurobiology of Disease*, *37*(3), 641–655. https://doi.org/10.1016/j.nbd.2009.11.020

Banerjee, A., Dhillon, I., Ghosh, J., & Sra, S. (2005). Clustering on the unit hypersphere using von Mises-Fisher distributions. *Journal of Machine Learning Research*, (6), 1345–1382. Retrieved from https://mathscinet.ams.org/mathscinet-getitem?mr=2249858

Beauchaine, T. P., & Marsh, P. (2006). Taxometric methods: Enhancing early detection and prevention of psychopathology by identifying latent vulnerability traits. In *Developmental psychopathology: Theory and method, Vol. 1, 2nd ed.* (pp. 931–967). John Wiley & Sons Inc.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society*. https://doi.org/10.2307/2346101

Berger, J., & Heath, C. (2008). Who drives divergence? Identity signaling, outgroup dissimilarity, and the abandonment of cultural tastes. *Journal of Personality and Social Psychology*, *95*(3), 593–607. https://doi.org/10.1037/0022-3514.95.3.593

Blanton, H., Gibbons, F. X., Gerrard, M., Conger, K. J., & Smith, G. E. (1997). Role of family and peers in the development of prototypes associated with substance use. *Journal of Family Psychology*, *11*(3), 271–288. https://doi.org/10.1037/0893-3200.11.3.271

Blume, L. E., Brock, W. A., Durlauf, S. N., & Ioannides, Y. M. (2011). Identification of social interactions. In *Handbook of social economics* (Vol. 1, pp. 853–964). Elsevier.

Bollen, K. A., & Brand, J. E. (2010). A General Panel Model with Random and Fixed Effects: A Structural Equations Approach. *Social Forces*, *89*(1), 1–34. Retrieved from http://dx.doi.org/10.1353/sof.2010.0072

Bowker, J. C., & Raja, R. (2011). Social withdrawal subtypes during early adolescence in India. *Journal of Abnormal Child Psychology*, *39*(2), 201–212.

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond Homophily: A Decade of Advances in Understanding Peer Influence Processes. *Journal of Research on Adolescence : The Official Journal of the Society for Research on Adolescence*, *21*(1), 166–179. https://doi.org/10.1111/j.1532-7795.2010.00721.x

Brook, J. S., Zhang, C., & Brook, D. W. (2011). Developmental trajectories of marijuana use from adolescence to adulthood: Personal predictors. *Archives of Pediatrics and Adolescent Medicine*, *165*(1), 55–60. https://doi.org/10.1001/archpediatrics.2010.248

Brook, J., Kessler, R. C., & Cohen, P. (1999). The onset of marijuana use from preadolescence and early adolescence to young adulthood. *Development and Psychopathology.*, *11*(4), 901–914. Retrieved from https://www.cambridge.org/core/journals/development-and-psychopathology/article/the-onset-of-marijuana-use-from-preadolescence-and-early-adolescence-to-young-adulthood/753B4C52B7A7F77BE6860597C27A3BB7

Brook, J. S., Lee, J. Y., Finch, S. J., Seltzer, N., & Brook, D. W. (2013). Adult Work Commitment, Financial Stability, and Social Environment as Related to Trajectories of Marijuana Use Beginning in Adolescence. *Substance Abuse*, *34*(3), 298–305. https://doi.org/10.1080/08897077.2013.775092

Brown, B. B. (2013, July 26). Adolescents' Relationships with Peers. *Handbook of Adolescent Psychology*. https://doi.org/doi:10.1002/9780471726746.ch12

Brown, B. B., Clasen, D. R., & Eicher, S. A. (1986). Perceptions of peer pressure, peer conformity dispositions, and self-reported behavior among adolescents. *Developmental Psychology*, *22*(4), 521.

Brown, B. B., Eicher, S. A., & Petrie, S. (1986). The importance of peer group ("crowd") affiliation in adolescence. *Journal of Adolescence*, *9*(1), 73–96.

Brown, B. B., & Klute, C. (n.d.). Friendships, Cliques, and Crowds. In *Blackwell Handbook of Adolescence* (pp. 330–348). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1002/9780470756607.ch16

Brown, R. (2000). *Group processes : dynamics within and between groups*. Blackwell Publishers. Retrieved from https://books.google.com/books/about/Group_Processes.html?id=e-9OtYRo45cC&source=kp_cover

Buchanan, C. M., Eccles, J. S., & Becker, J. B. (1992). Are adolescents the victims of raging hormones: evidence for activational effects of hormones on moods and behavior at adolescence. *Psychological Bulletin*, *111*(1), 62–107. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1539089

Buckner, J., Crosby, R., Silgado, J., Wonderlich, S., & Schmidt, N. (2012). Immediate Antecedents of Marijuana Use: An Analysis from Ecological Momentary Assessment. *Journal of Behavior Ther Exp Psychiatry*, *43*(1), 647–655. https://doi.org/10.1016/j.jbtep.2011.09.010.Immediate

Bukowski, W. M., & Newcomb, A. F. (1984). Stability and determinants of sociometric status and friendship choice: A longitudinal perspective. *Developmental Psychology*, *20*(5), 941–952. https://doi.org/10.1037/0012-1649.20.5.941

Cairns, R. B., Leung, M.-C., Buchanan, L., & Cairns, B. D. (1995). Friendships and Social Networks in Childhood and Adolescence: Fluidity, Reliability, and Interrelations. *Child Development*, *66*(5), 1330–1345. https://doi.org/10.1111/j.1467-8624.1995.tb00938.x

Cartwright, D. (1965). Influence, Leadership, Control. In *Handbook of Organizations* (pp. 1–47). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1497766

Chadwick, B., Miller, M. L., & Hurd, Y. L. (2013). Cannabis Use during Adolescent Development: Susceptibility to Psychiatric Illness. *Frontiers in Psychiatry*, *4*(October), 129. https://doi.org/10.3389/fpsyt.2013.00129

Chambers, R. A., Taylor, J. R., & Potenza, M. N. (2003). Developmental Neurocircuitry of Motivation in Adolescence: A Critical Period of Addiction Vulnerability. *American Journal of Psychiatry*, *160*(6), 1041–1052. https://doi.org/10.1176/appi.ajp.160.6.1041

Chen, X., Yu, B., Lasopa, S. O., & Cottler, L. B. (2017). Current patterns of marijuana use initiation by age among US adolescents and emerging adults: implications for intervention. *The American Journal of Drug and Alcohol Abuse*, *43*(3), 261–270. https://doi.org/10.3109/00952990.2016.1165239

Christakis, N. A., & Fowler, J. H. (2008). The collective dynamics of smoking in a large social network. *New England Journal of Medicine*, *358*(21), 2249–2258.

Christakis, N., & Fowler, J. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine*, *32*(4), 1–32. https://doi.org/10.1002/sim.5408.Social

Clark, A. E., & Lohéac, Y. (2007). “It wasn’t me, it was them!” Social influence in risky behavior by adolescents. *Journal of Health Economics*, *26*(4), 763–784. https://doi.org/10.1016/J.JHEALECO.2006.11.005

Clark, A. E., & Lohéac, Y. (2007). “It wasn’t me, it was them!” Social influence in risky behavior by adolescents. *Journal of Health Economics*, *26*(4), 763–784. https://doi.org/10.1016/j.jhealeco.2006.11.005

Cohen, G. L., & Prinstein, M. J. (2006). Peer Contagion of Aggression and Health Risk Behavior Among Adolescent Males: An Experimental Investigation of Effects on Public Conduct and Private Attitudes. *Child Development*, *77*(4), 967–983. https://doi.org/10.1111/j.1467-8624.2006.00913.x

Cohen-Cole, E., & Fletcher, J. M. (2008). Is obesity contagious? Social networks vs. environmental factors in the obesity epidemic. *Journal of Health Economics*, *27*(5), 1382–1387. https://doi.org/10.1016/j.jhealeco.2008.04.005

Coronges, K., Stacy, A. W., & Valente, T. W. (2011). Social network influences of alcohol and marijuana cognitive associations. *Addictive Behaviors*, *36*(12), 1305–8. https://doi.org/10.1016/j.addbeh.2011.07.008

Cox, T. F., & Cox, M. A. A. (1991). Multidimensional scaling on a sphere. *Communications in Statistics-Theory and Methods*, *20*(9), 2943–2953.

Crawford, A. M., Pentz, M. A., Chou, C.-P., Li, C., & Dwyer, J. H. (2003). Parallel developmental trajectories of sensation seeking and regular substance use in adolescents.

Psychology of Addictive Behaviors : Journal of the Society of Psychologists in Addictive Behaviors, *17*(3), 179–192. https://doi.org/10.1037/0893-164X.17.3.179

Crum, R. M., Lillie-Blanton, M., & Anthony, J. C. (1996). Neighborhood environment and opportunity to use cocaine and other drugs in late childhood and early adolescence. *Drug and Alcohol Dependence*, *43*(3), 155–161. https://doi.org/10.1016/S0376-8716(96)01298-7

D'Amico, E. J., & McCarthy, D. M. (2006). Escalation and Initiation of Younger Adolescents' Substance Use: The Impact of Perceived Peer Use. *Journal of Adolescent Health*, *39*(4), 481–487. https://doi.org/10.1016/j.jadohealth.2006.02.010

Davin, J. P., Gupta, S., & Piskorski, M. J. (2014). Separating homophily and peer influence with latent space. Retrieved from http://www.hbs.edu/faculty/Publication Files/14-053_f72cd431-8b9c-4991-8ea4-6ab5209f11a1.pdf

de la Haye, K., Green, H. D., Kennedy, D. P., Pollard, M. S., & Tucker, J. S. (2013). Selection and Influence Mechanisms Associated With Marijuana Initiation and Use in Adolescent Friendship Networks. *Journal of Research on Adolescence*, *23*(3), 474–486. https://doi.org/10.1111/jora.12018

Deng, H., & Runger, G. (2013). Gene selection with guided regularized random forest. *Pattern Recognition*, *46*(12), 3483–3489. https://doi.org/10.1016/j.patcog.2013.05.018

Ding, Z., Zhang, X., Sun, D., & Luo, B. (2016). Overlapping Community Detection based on Network Decomposition. *Scientific Reports*, *6*(1), 24115. https://doi.org/10.1038/srep24115

Dishion, T. J., Capaldi, D., Spracklen, K. M., & Li, F. (1995). Peer ecology of male adolescent drug use. *Development and Psychopathology*, *7*(04), 803. https://doi.org/10.1017/S0954579400006854

Dishion, T. J., & Owen, L. D. (2002). A longitudinal analysis of friendships and substance use: Bidirectional influence from adolescence to adulthood. *Developmental Psychology*, *38*(4), 480–491. https://doi.org/10.1037/0012-1649.38.4.480

Domingue, B. W., Belsky, D. W., Fletcher, J. M., Conley, D., Boardman, J. D., & Harris, K. M. (2018). The social genome of friends and schoolmates in the National Longitudinal Study of Adolescent to Adult Health. *Proceedings of the National Academy of Sciences*, 201711803.

Duncan, G. J., Boisjoly, J., Kremer, M., Levy, D. M., & Eccles, J. (2005). Peer effects in drug use and sex among college students. *Journal of Abnormal Child Psychology*, *33*(3), 375–385.

Eaves, C. S. (2004). Heroin Use Among Female Adolescents: The Role of Partner Influence in Path of Initiation and Route of Administration. *The American Journal of Drug and Alcohol Abuse*, *30*(1), 21–38. https://doi.org/10.1081/ADA-120029864

Ehrenreich, H., Nahapetyan, L., Orpinas, P., & Song, X. (2014). Marijuana Use from Middle to High School: Co-occurring Problem Behaviors, Teacher-Rated Academic Skills and Sixth-Grade Predictors. *Journal of Youth and Adolescence*, *44*(10), 1929–1940. https://doi.org/10.1007/s10964-014-0216-6

Ellgren, M., Spano, S. M., & Hurd, Y. L. (2006). Adolescent Cannabis Exposure Alters Opiate Intake and Opioid Limbic Neuronal Populations in Adult Rats. https://doi.org/10.1038/sj.npp.1301127

Elliott, D. S., Huizinga, D., & Menard, S. (1989). Research in criminology. Multiple problem youth: Delinquency, substance use, and mental health problems. New York, NY, US. Springer-Verlag Publishing. http://dx. doi. org/10.1007/978-1-4613-9637-6.

Ennett, S. T., & Bauman, K. E. (1993). Peer Group Structure and Adolescent Cigarette Smoking: A Social Network Analysis. *Journal of Health and Social Behavior*, *34*(3), 226. https://doi.org/10.2307/2137204

Ennett, S. T., Bauman, K. E., Hussong, A., Faris, R., Foshee, V. a., Cai, L., & DuRant, R. H. (2006). The peer context of adolescent substance use: Findings from social network analysis. *Journal of Research on Adolescence*, *16*(2), 159–186. https://doi.org/10.1111/j.1532-7795.2006.00127.x

Epstein, M., Hill, K. G., Nevell, A. M., Guttmannova, K., Bailey, J. A., Abbott, R. D., … Hawkins, D. J. (2015). Trajectories of Marijuana Use From Adolescence Into Adulthood: Environmental and Individual Correlates. *Developmental Psychology*, *51*(11), 1650–1663. https://doi.org/10.1037/dev0000054

Erikson, E. (1968). *Identity: Youth and crisis*. New York: W. W. Norton & Company.

Espelage, D. L., Holt, M. K., & Henkel, R. R. (n.d.). Examination of peer-group contextual effects on aggression during early adolescence. *Child Development*, *74*(1), 205–20. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12625446

Feld, J., & Zölitz, U. (2017). Understanding Peer Effects: On the Nature, Estimation, and Channels of Peer Effects. *Journal of Labor Economics*, *35*(2), 387–428. https://doi.org/10.1086/689472

Fergusson, D. M., Boden, J. M., & Horwood, L. J. (2006). Cannabis use and other illicit drug use: Testing the cannabis gateway hypothesis. *Addiction*, *101*(4), 556–569. https://doi.org/10.1111/j.1360-0443.2005.01322.x

Fletcher, J. M. (2010). Social interactions and smoking: Evidence using multiple student cohorts, instrumental variables, and school fixed effects. *Health Economics*, *19*(4), 466–484.

Fletcher, J., & Ross, S. (2012). *Estimating the Effects of Friendship Networks on Health Behaviors of Adolescents*. Cambridge, MA. https://doi.org/10.3386/w18253

Flory, K., Lynam, D., Milich, R., Leukefeld, C., & Clayton, R. (2004). Early adolescent through young adult alcohol and marijuana use trajectories: early predictors, young adult outcomes, and predictive utility. *Development and Psychopathology*, *16*(1), 193–213. https://doi.org/10.1017/S0954579404044475

Freeman, L. C. (1978). Centrality in Social Networks Conceptual Clarification. *Social Networks*, *179*, 215–239. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.320.5551&rep=rep1&type=pdf

Gardner, T. W., Dishion, T. J., & Connell, A. M. (2008). Adolescent Self-Regulation as Resilience: Resistance to Antisocial Behavior within the Deviant Peer Context. *Journal of Abnormal Child Psychology*, *36*(2), 273–284. https://doi.org/10.1007/s10802-007-9176-6

Gatti, U., Tremblay, R. E., Vitaro, F., & McDuff, P. (2005). Youth gangs, delinquency and drug use: a test of the selection, facilitation, and enhancement hypotheses. *Journal of Child Psychology and Psychiatry*, *46*(11), 1178–1190. https://doi.org/10.1111/j.1469-7610.2005.00423.x

Gaughan, M. (n.d.). Predisposition and Pressure: Mutual Influence and Adolescent Drunkenness. *CONNECTIONS*, *25*(2), 17–31. Retrieved from https://pdfs.semanticscholar.org/5742/c6c9498e10d11b8bb7b93dbe4c4328a6dfb4.pdf

Ghahramani, Z. (2002). Hidden Markov Models (pp. 9–42). River Edge, NJ, USA: World Scientific Publishing Co., Inc. Retrieved from http://dl.acm.org/citation.cfm?id=505741.505743

González, M. C., Herrmann, H. J., Kertész, J., & Vicsek, T. (2007). Community structure and ethnic preferences in school friendship networks. *Physica A: Statistical Mechanics and Its Applications*, *379*(1), 307–316.

Gorelick, D. A., Levin, K. H., Copersino, M. L., Heishman, S. J., Liu, F., Boggs, D. L., … Bucholz, K. K. (2012). Diagnostic criteria for cannabis withdrawal syndrome. *Drug and Alcohol Dependence*, *123*(1–3), 141–7. https://doi.org/10.1016/j.drugalcdep.2011.11.007

Hall, J. A., & Valente, T. W. (2007). Adolescent smoking networks: The effects of influence and selection on future smoking. *Addictive Behaviors*, *32*(12), 3054–3059. https://doi.org/10.1016/j.addbeh.2007.04.008

Hall, W., & Degenhardt, L. (2009). Adverse health effects of non-medical cannabis use. *Lancet*, *374*(9698), 1383–91. https://doi.org/10.1016/S0140-6736(09)61037-0

Hallinan, M. T. (1979). Structural effects on children's friendships and cliques. *Social Psychology Quarterly*, 43–54.

Hampson, S. E., Andrews, J. A., & Barckley, M. (2008). Childhood predictors of adolescent marijuana use: Early sensation-seeking, deviant peer affiliation, and social images. *Addictive Behaviors*, *33*(9), 1140–1147. https://doi.org/10.1016/j.addbeh.2008.04.010

Hampson, S. E., Andrews, J. A., & Barckley, M. (2008). Childhood predictors of adolescent marijuana use: Early sensation-seeking, deviant peer affiliation, and social images. *Addictive Behaviors*, *33*(9), 1140–1147. https://doi.org/10.1016/j.addbeh.2008.04.010

Handcock, M. S., Raftery, A. E., & Tantrum, J. M. (2007). Model-based clustering for social networks. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *170*(2), 301–354. https://doi.org/10.1111/j.1467-985X.2007.00471.x

Haynie, D. L., & Osgood, D. W. (n.d.). Reconsidering Peers and Delinquency: How do Peers Matter? *Social Forces*. Oxford University Press. https://doi.org/10.2307/3598492

Henry, D. B., & Kobus, K. (2007). Early Adolescent Social Networks and Substance Use. *The Journal of Early Adolescence*, *27*(3), 346–362. https://doi.org/10.1177/0272431607302005

Higuera-Matas, A., Botreau, F., Del Olmo, N., Miguéns, M., Olías, Ó., Montoya, G. L., … Ambrosio, E. (2010). Periadolescent exposure to cannabinoids alters the striatal and hippocampal dopaminergic system in the adult rat brain. *European Neuropsychopharmacology*, *20*(12), 895–906. https://doi.org/10.1016/j.euroneuro.2010.06.017

Hjort, N. L., Dahl, F. A., & Steinbakk, G. H. (2006). Post-Processing Posterior Predictive p Values. *Journal of the American Statistical Association*, *101*(475), 1157–1174. https://doi.org/10.1198/016214505000001393

Hoff, P. D., Raftery, A. E., & Handcock, M. S. (2002). Latent space approaches to social network analysis. *Journal of the American Statistical Association*, *97*(460), 1090–1098.

Hoffman, B. R., Sussman, S., Unger, J. B., & Valente, T. W. (2006). Peer influences on adolescent cigarette smoking: a theoretical review of the literature. *Substance Use & Misuse*, *41*(1), 103–155. https://doi.org/10.1080/10826080500368892

Hoffman, B. R., Sussman, S., Unger, J. B., & Valente, T. W. (2006). Peer influences on adolescent cigarette smoking: a theoretical review of the literature. *Substance Use & Misuse*, *41*(1), 103–155. https://doi.org/10.1080/10826080500368892

Homans, G. C. (1992). *The human group*. Transaction Publishers. Retrieved from https://books.google.com/books/about/The_Human_Group.html?id=7ZRKnwEACAAJ

Iannotti, R. J., & Bush, P. J. (1992). Perceived vs. actual friends' use of alcohol, cigarettes, marijuana, and cocaine: Which has the most influence? *Journal of Youth and Adolescence*, *21*(3), 375–389. https://doi.org/10.1007/BF01537024

Jessor, R. (1992). Risk behavior in adolescence: A psychosocial framework for understanding and action*1. *Developmental Review*, *12*(4), 374–390. https://doi.org/10.1016/0273-2297(92)90014-S

Johnston, L. D., O'Malley, P. M., Bachman, J. G., & Schulenberg, J. E. (2005). *Monitoring the Future national survey results on drug use, 1975-2004: Volume I, Secondary school students*. Bethesda, MD.

Kandel, D. (1975). Stages in adolescent involvement in drug use. *Science (New York, N.Y.)*, *190*(4217), 912–4. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/1188374

Kandel, D. B., & Chen, K. (2000). Types of marijuana users by longitudinal course. *Journal of Studies on Alcohol*, *61*(3), 367–378. https://doi.org/10.15288/jsa.2000.61.367

Kandel, D. B. (1978). Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology*, *84*(2), 427–436.

Kandel, D. B., & Logan, J. A. (1984). Patterns of drug use from adolescence to young adulthood: I. Periods of risk for initiation, continued use, and discontinuation. *American Journal of Public Health*, *74*(7), 660–666.

Kaplan, D. (2014). *Bayesian statistics for the social sciences*. Guilford Press. Retrieved from https://www.guilford.com/books/Bayesian-Statistics-for-the-Social-Sciences/David-Kaplan/9781462516513

Klein, M. (2006). Peer effects in naturally occurring groups: The case of street ganges. In K. A. Dodge & T. J. Dishion (Eds.), *Deviant peer influences in programs for youth: Problems and solutions* (pp. 234–250). New York: Guilford Press.

Kobus, K. (2003). Peers and adolescent smoking. *Addiction*, *98*(s1), 37–55. https://doi.org/10.1046/j.1360-0443.98.s1.4.x

Kobus, K., & Henry, D. B. (2010). Interplay of network position and peer substance use in early adolescent cigarette, alcohol, and marijuana use. *The Journal of Early Adolescence*, *30*(2), 225–245.

Kopstein, A. N., Crum, R. M., Celentano, D. D., & Martin, S. S. (2001). Sensation seeking needs among 8th and 11th graders: characteristics associated with cigarette and marijuana use. *Drug and Alcohol Dependence*, *62*(3), 195–203. https://doi.org/10.1016/S0376-8716(00)00170-8

Kossinets, G. (2006). Effects of missing data in social networks. *Social Networks*, *28*(3), 247–268. https://doi.org/10.1016/j.socnet.2005.07.002

Kreager, D. A., Rulison, K., & Moody, J. (2011). Delinquency and the Structure OF ADOLESCENT PEER GROUPS*. *Criminology*, *49*(1), 95–127. https://doi.org/10.1111/j.1745-9125.2010.00219.x

Krivitsky, P. N., Handcock, M. S., Raftery, A. E., & Hoff, P. D. (2009). Representing degree distributions, clustering, and homophily in social networks with latent cluster random effects models. *Social Networks*, *31*(3), 204–213. https://doi.org/10.1016/j.socnet.2009.04.001

La Greca, A. M., Prinstein, M. J., & Fetter, M. D. (2001). Adolescent Peer Crowd Affiliation: Linkages With Health-Risk Behaviors and Close Friendships. *Journal of Pediatric Psychology*, *26*(3), 131–143. https://doi.org/10.1093/jpepsy/26.3.131

Lacourse, E., Nagin, D. S., Vitaro, F., Côté, S., Arseneault, L., & Tremblay, R. E. (2006). Prediction of early-onset deviant peer group affiliation: A 12-year longitudinal study. *Archives of General Psychiatry*, *63*(5), 562–568.

Lakon, C. M., Hipp, J. R., & Timberlake, D. S. (2010). The social context of adolescent smoking: A systems perspective. *American Journal of Public Health*, *100*(7), 1218–1228. https://doi.org/10.2105/AJPH.2009.167973

Larson, R. W., Richards, M. H., Moneta, G., Holmbeck, G., & Duckett, E. (1996). Changes in adolescents' daily interactions with their families from ages 10 to 18: Disengagement and transformation. *Developmental Psychology*, *32*(4), 744–754. https://doi.org/10.1037/0012-1649.32.4.744

Lee, C. M., Neighbors, C., & Woods, B. A. (2007). Marijuana motives: Young adults' reasons for using marijuana. *Addictive Behaviors*, *32*(7), 1384–1394. https://doi.org/10.1016/j.addbeh.2006.09.010

Lessem, J. M., Hopfer, C. J., Haberstick, B. C., Timberlake, D., Ehringer, M. A., Smolen, A., & Hewitt, J. K. (2006). Relationship between Adolescent Marijuana Use and Young Adult Illicit Drug Use. *Behavior Genetics*, *36*(4), 498–506. https://doi.org/10.1007/s10519-006-9064-9

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(1), 68–72. https://doi.org/10.1073/pnas.1109739109

Liu, T., Li, P., Chen, Y., & Zhang, J. (2016). Community Size Effects on Epidemic Spreading in Multiplex Social Networks. *PLOS ONE*, *11*(3), e0152021. https://doi.org/10.1371/journal.pone.0152021

Lozano, S., Arenas, A., Sánchez, A., Moreno, Y., & Arenas, A. (2008). Mesoscopic Structure Conditions the Emergence of Cooperation on Social Networks. *PLoS ONE*, *3*(4), e1892. https://doi.org/10.1371/journal.pone.0001892

Lyons, R. (2011). The Spread of Evidence-Poor Medicine via Flawed Social-Network Analysis. *Statistics, Politics, and Policy*, *2*(1). https://doi.org/10.2202/2151-7509.1024

Lyons, R. (2011). The Spread of Evidence-Poor Medicine via Flawed Social-Network Analysis. *Statistics, Politics and Policy*, *2*(1), 1–26. https://doi.org/10.2202/2151-7509.1024

Mann, H. B., & Whitney, D. R. (1947). On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *The Annals of Mathematical Statistics*, *18*(1), 50–60. https://doi.org/10.1214/aoms/1177730491

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

Maxwell, K. A. (2002). Friends: The Role of Peer Influence Across Adolescent Risk Behaviors. *Journal of Youth and Adolescence*, *31*(4), 267–277. https://doi.org/10.1023/A:1015493316865

McLachlan, G. J., & Peel, D. (1998). Robust cluster analysis via mixtures of multivariate t-distributions. In A. Amin, D. Dori, P. Pudil, & H. Freeman (Eds.), *Advances in Pattern Recognition. SSPR /SPR 1998* (pp. 658–666). Berlin, Heidelberg: Springer. https://doi.org/10.1007/BFb0033290

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Meier, M. H., Caspi, A., Ambler, A., Harrington, H., Houts, R., Keefe, R. S. E., … Moffitt, T. E. (2012). Persistent cannabis users show neuropsychological decline from childhood to midlife. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(40), E2657-64. https://doi.org/10.1073/pnas.1206820109

Miech, R. A., Johnston, L. D., O'malley, P. M., Bachman, J. G., & Schulenberg, J. E. (n.d.). *Monitering The Future National Survey Results On Drug Use, 1975–2014*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.693.7381

Moffitt, T. E., Meier, M. H., Caspi, A., & Poulton, R. (2013). Reply to Rogeberg and Daly: No evidence that socioeconomic status or personality differences confound the association between cannabis use and IQ decline. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(11), E980-2. https://doi.org/10.1073/PNAS.1300618110

Moody, J. (2001). Race, School Integration, and Friendship Segregation in America. *American Journal of Sociology*, *107*(3), 679–716. https://doi.org/10.1086/338954

Moody, J. (2001). Peer influence groups: Identifying dense clusters in large networks. *Social Networks*, *23*(4), 261–283. https://doi.org/10.1016/S0378-8733(01)00042-9

Moore, T. H. M., Zammit, S., Lingford-Hughes, A., Barnes, T. R. E., Jones, P. B., Burke, M., & Lewis, G. (2007). Cannabis use and risk of psychotic or affective mental health outcomes: a systematic review. *Lancet (London, England)*, *370*(9584), 319–28. https://doi.org/10.1016/S0140-6736(07)61162-3

Moore, T. H., Zammit, S., Lingford-Hughes, A., Barnes, T. R., Jones, P. B., Burke, M., & Lewis, G. (2007). Cannabis use and risk of psychotic or affective mental health outcomes: a systematic review. *The Lancet*, *370*(9584), 319–328. https://doi.org/10.1016/S0140-6736(07)61162-3

Moriarty, J., Mcvicar, D., & Higgins, K. (2016). Social Science & Medicine Cross-section and panel estimates of peer effects in early adolescent cannabis use : With a little help from my ' friends once removed .' *Social Science & Medicine*, *163*, 37–44. https://doi.org/10.1016/j.socscimed.2016.06.032

Neaigus, Alan; Friedman, Samuel R.; Jose, Benny; Goldstein, Marjorie F.; Curtis, Richard; Ildefonso, Gilbert; Des Jarlais, D. C. (1996). High-Risk Personal Networks and Syringe Sharing as Risk Factors for HIV Infection Among New Drug Injectors. *Journal of Acquired Immune Deficiency Syndromes & Human Retrovirology*, *11*(5), 499–509. Retrieved from http://journals.lww.com/jaids/Abstract/1996/04150/High_Risk_Personal_Networks_and_Syringe_Sharing_as.11.aspx

Neal, J. W., & Neal, Z. P. (2013). The Multiple Meanings of Peer Groups in Social Cognitive Mapping. *Social Development*, *22*(3), 580–594. https://doi.org/10.1111/j.1467-9507.2012.00656.x

Neighbors, C., Geisner, I. M., & Lee, C. M. (2008). Perceived marijuana norms and social expectancies among entering college student marijuana users. *Psychology of Addictive Behaviors*, *22*(3), 433–438. https://doi.org/10.1037/0893-164X.22.3.433

Newcomb, M. D., Chou, C., Bentler, P. M., & Huba, G. J. (1988). Cognitive motivations for drug use among adolescents: Longitudinal tests of gender differences and predictors of change in drug use. *Journal of Counseling Psychology*, *35*(4), 426–438. https://doi.org/10.1037/0022-0167.35.4.426

Newman, B. M., Lohman, B. J., & Newman, P. R. (2007). Peer group membership and a sense of belonging: their relationship to adolescent behavior problems. *Adolescence*, *42*(166), 241–63. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/17849935

Newman, M. E. J. (2017). Measurement errors in network data. Retrieved from https://arxiv.org/abs/1703.07376

Newman, M. E. J. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences*, *98*(2), 404–409. https://doi.org/10.1073/pnas.98.2.404

Newman, M. E. J., & Park, J. (2003). Why social networks are different from other types of networks. https://doi.org/10.1103/PhysRevE.68.036122

Niño, M., Ignatow, G., & Cai, T. (2016). Social Isolation, Strain, and Youth Violence. *Youth Violence and Juvenile Justice*, *15*(3), 299–313. https://doi.org/10.1177/1541204016636435

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Osgood, D. W., Feinberg, M. E., Wallace, L. N., & Moody, J. (2014). Friendship Group Position and Substance Use. *Addictive Behaviors*, *39*(5), 923–933. https://doi.org/10.1016/j.addbeh.2013.12.009

Passarotti, A. M., Crane, N. A., Hedeker, D., & Mermelstein, R. J. (2015). Longitudinal trajectories of marijuana use from adolescence to young adulthood. *Addictive Behaviors*, *45*(FEBRUARY), 301–308. https://doi.org/10.1016/j.addbeh.2015.02.008

Petraitis, J., Flay, B. R., & Miller, T. Q. (1995). Reviewing theories of adolescent substance use: organizing pieces in the puzzle. *Psychological Bulletin*, *117*(1), 67–86. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/7870864

Phinney, J., & Kohatsu, E. (1997). Ethnic and racial identity development and mental health. In J. Schulenberg, J. L. Maggs, & K. Hurrelmann (Eds.), *Health risks and developmental transitions during adolescence* (pp. 420–443). New York: Cambridge University Press. Retrieved from http://doi.apa.org/psycinfo/1997-08245-016

Porter, M. A., Onnela, J.-P., & Mucha, P. J. (2009). Communities in networks. *Notices of the AMS*, *56*(9), 1082–1097.

Prinstein, M. J. (2007). Moderators of Peer Contagion: A Longitudinal Examination of Depression Socialization Between Adolescents and Their Best Friends. *Journal of Clinical Child & Adolescent Psychology*, *36*(2), 159–170. https://doi.org/10.1080/15374410701274934

Radhakrishnan, R., Wilkinson, S. T., & Dâ€™Souza, D. C. (2014). Gone to Pot â€“ A Review of the Association between Cannabis and Psychosis. *Frontiers in Psychiatry*, *5*, 54. https://doi.org/10.3389/fpsyt.2014.00054

Ramo, D. E., Delucchi, K. L., Hall, S. M., Liu, H., & Prochaska, J. J. (2013). Marijuana and tobacco co-use in young adults: patterns and thoughts about use. *Journal of Studies on Alcohol and Drugs*, *74*(2), 301–10. https://doi.org/10.15288/jsad.2013.74.301

Roberti, J. W. (2004). A review of behavioral and biological correlates of sensation seeking. *Journal of Research in Personality*, *38*(3), 256–279. https://doi.org/10.1016/S0092-6566(03)00067-9

Rochani, H., & Linder, D. F. (2017). Markov Chain Monte-Carlo Methods for Missing Data Under Ignorability Assumptions. In D. Chen & J. Chen (Eds.), *Monte-Carlo Simulation-Based Statistical Modeling* (pp. 129–142). Singapore: Springer, Singapore. https://doi.org/10.1007/978-981-10-3307-0_7

Roebuck, M. C., French, M. T., & Dennis, M. L. (2004). Adolescent marijuana use and school attendance. *Economics of Education Review*, *23*(2), 133–141. https://doi.org/10.1016/S0272-7757(03)00079-7

Rosenquist, J., Murabito, J., Fowler, J., & Christakis, N. (2010). The spread of alcohol consumption behavior in a large social network. *Annals of Internal …*, *152*(7). https://doi.org/10.1059/0003-4819-152-7-201004060-00007.THE

Rusby, J. C., Westling, E., Crowley, R., & Light, J. M. (2018). Legalization of recreational marijuana and community sales policy in Oregon: Impact on adolescent willingness and intent to use, parent use, and adolescent use. *Psychology of Addictive Behaviors*, *32*(1), 84–92. https://doi.org/10.1037/adb0000327

Ryan, A. M. (2000). Peer groups as a context for the socialization of adolescents' motivation, engagement, and achievement in school. *Educational Psychologist*, *35*(2), 101–111.

Salathé, M., & Jones, J. H. (2010). Dynamics and Control of Diseases in Networks with Community Structure. *PLoS Computational Biology*, *6*(4), e1000736. https://doi.org/10.1371/journal.pcbi.1000736

Sameroff, A. (2006). Identifying Risk and Protective Factors for Healthy Child Development.

Schafer, J. L., & Graham, J. W. (2002). Missing data: our view of the state of the art. *Psychological Methods*, *7*(2), 147.

Schneider, M. (2012). The impact of pubertal exposure to cannabis on the brain: a focus on animal studies. In D. Castle, R. Murray, & D. D'Souza (Eds.), *Marijuana and madness* (pp. 82–90). Cambridge, MA: Cambridge University Press.

Schulenberg, J. E., & Maggs, J. L. (2002). A developmental perspective on alcohol use and heavy drinking during adolescence and the transition to young adulthood. *Journal of Studies on Alcohol, Supplement*, (s14), 54–70. https://doi.org/10.15288/jsas.2002.s14.54

Schulenberg, J. E., Merline, A. C., Johnston, L. D., O'Malley, P. M., Bachman, J. G., & Laetz, V. B. (2005). Trajectories of Marijuana Use During the Transition to Adulthood: The Big Picture Based on National Panel Data. *Journal of Drug Issues*, *35*(2), 255–279. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/16534532

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Sewell, D. K., & Chen, Y. (2017). Latent Space Approaches to Community Detection in Dynamic Networks. *Bayesian Anal.*, *12*(2), 351–377. https://doi.org/10.1214/16-BA1000

Shalizi, C. R., & McFowland, E. (2016). Controlling for Latent Homophily in Social Networks through Inferring Latent Locations. Retrieved from http://arxiv.org/abs/1607.06565

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and Contagion Are Generically Confounded in Observational Social Network Studies. *Sociological Methods & Research*, *40*(2), 211–239. https://doi.org/10.1177/0049124111404820

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and Contagion Are Generically Confounded in Observational Social Network Studies. *Sociological Methods & Research*, *40*(2), 211–239. https://doi.org/10.1177/0049124111404820

Shrier, L. A., Walls, C., Rhoads, A., & Blood, E. A. (2013). Individual and contextual predictors of severity of marijuana use events among young frequent users. *Addictive Behaviors*, *38*(1), 1448–1456. https://doi.org/10.1016/j.addbeh.2012.05.026

Silverberg, S. B., & Gondoli, D. M. (1996). Autonomy in adolescence: A contextualized perspective. *Psychosocial Development during Adolescence*, *8*, 12–61.

Simons, R., B Whitbeck, L., Conger, R., & J Conger, K. (1991). Parenting Factors, Social Skills, and Value Commitments as Precursors to School Failure, Involvement with Deviant Peers, and Delinquent Behavior. *Journal of Youth and Adolescence*, *20*, 645–664.

Snijders, T., Bunt, G. G., & Steglich, C. (2010). *Introduction to Actor-Based Models for Network Dynamics*. *Social Networks* (Vol. 32). https://doi.org/10.1016/j.socnet.2009.02.004

Spear, L. P. (2000). The adolescent brain and age-related behavioral manifestations. *Neuroscience and Biobehavioral Reviews*, *24*(4), 417–63. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10817843

Spoth, R., Greenberg, M., Bierman, K., & Redmond, C. (2004). PROSPER Community–University Partnership Model for Public Education Systems: Capacity-Building for Evidence-Based, Competence-Building Prevention. *Prevention Science*, *5*(1), 31–39. https://doi.org/10.1023/B:PREV.0000013979.52796.8b

Spoth, R., Redmond, C., & Shin, C. (1998). Direct and indirect latent-variable parenting outcomes of two universal family-focused preventive interventions: Extending a public health-oriented research base. *Journal of Consulting and Clinical Psychology*. US: American Psychological Association. https://doi.org/10.1037/0022-006X.66.2.385

Spoth, R., Redmond, C., Shin, C., Greenberg, M., Clair, S., & Feinberg, M. (2007). Substance-use outcomes at 18 months past baseline: the PROSPER Community-University Partnership Trial. *American Journal of Preventive Medicine*, *32*(5), 395–402. https://doi.org/10.1016/j.amepre.2007.01.014

Spoth, R., Redmond, C., Shin, C., Greenberg, M., Clair, S., & Feinberg, M. (2007). Substance-Use Outcomes at 18 Months Past Baseline. *American Journal of Preventive Medicine*, *32*(5), 395–402. https://doi.org/10.1016/j.amepre.2007.01.014

Stegehuis, C., van der Hofstad, R., & van Leeuwaarden, J. S. H. (2016). Epidemic spreading on complex networks with community structures, *6*, 29748. Retrieved from http://dx.doi.org/10.1038/srep29748

Steinberg, L. (2008). A Social Neuroscience Perspective on Adolescent Risk-Taking. *Developmental Review : DR*, *28*(1), 78–106. https://doi.org/10.1016/j.dr.2007.08.002

Steinberg, L. (2007). Risk Taking in Adolescence. *Current Directions in Psychological Science*, *16*(2), 55–59. https://doi.org/10.1111/j.1467-8721.2007.00475.x

Steinberg, L., & Monahan, K. C. (2007). Age Differences in Resistance to Peer Influence. *Developmental Psychology*, *43*(6), 1531–1543. https://doi.org/10.1037/0012-1649.43.6.1531

Steinberg, L., & Silverberg, S. B. (1986). The Vicissitudes of Autonomy in Early Adolescence. *Child Development*, *57*(4), 841. https://doi.org/10.2307/1130361

Stevens, E. A., & Prinstein, M. J. (2005). Peer contagion of depressogenic attributional styles among adolescents: a longitudinal study. *Journal of Abnormal Child Psychology*, *33*(1), 25–37. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/15759589

Stone, A. L., Becker, L. G., Huber, A. M., & Catalano, R. F. (2012). Review of risk and protective factors of substance use and problem use in emerging adulthood. *Addictive Behaviors*, *37*(7), 747–775. https://doi.org/10.1016/j.addbeh.2012.02.014

Tarter, R. E., Blackson, T., Brigham, J., Moss, H., & Caprara, G. V. (1995). The association between childhood irritability and liability to substance use in early adolescence: a 2-year follow-up study of boys at risk for substance abuse. *Drug and Alcohol Dependence*, *39*(3), 253–61. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/8556975

Tarter, R. E. (2002). Etiology of adolescent substance abuse: a developmental perspective. *The American Journal on Addictions*, *11*, 171–191. https://doi.org/10.1080/10550490290087965

Team, R. (2018). R development core team. *RA Lang Environ Stat Comput*, *55*, 275–286.

Tschann, J. M., Adler, N. E., Irwin, C. E., Millstein, S. G., Turner, R. A., & Kegeles, S. M. (1994). Initiation of substance use in early adolescence: The roles of pubertal timing and emotional distress. *Health Psychology*, *13*(4), 326–333. https://doi.org/10.1037/0278-6133.13.4.326

Udry, J. (1990). Hormonal and social determinants of adolescent sexual initiation. In J. Bancroft & J. M. Reinisch (Eds.), *Adolescent and puberty* (pp. 70–87). New York: Oxford University Press.

United Nations Office on Drugs and Crime. (2016). *World Drug Report 2016*.

Urberg, K. a, Değirmencioğlu, S. M., & Pilgrim, C. (1997). Close friend and group influence on adolescent cigarette smoking and alcohol use. *Developmental Psychology*, *33*(5), 834–844. https://doi.org/10.1037/0012-1649.33.5.834

Valente, T. W. (2012). Network Interventions. *Science*, *337*(6090), 49–53. https://doi.org/10.1126/science.1217330

Valente, T. W., Gallaher, P., & Mouttapa, M. (2004). Using social networks to understand and prevent substance use: a transdisciplinary perspective. *Substance Use & Misuse*, *39*(10–12), 1685–1712. https://doi.org/10.1081/LSUM-200033210

van den Bree, M. B., & Pickworth, W. B. (2005). Risk factors predicting changes in marijuana involvement in teenagers. *Archives of General Psychiatry*, *62*(3), 311–319. https://doi.org/10.1016/S0084-3970(08)70082-3

Verkooijen, K. T., de Vries, N. K., & Nielsen, G. A. (2007). Youth crowds and substance use: The impact of perceived group norm and multiple group identification. *Psychology of Addictive Behaviors*, *21*(1), 55–61. https://doi.org/10.1037/0893-164X.21.1.55

Volkow, N. D., Baler, R. D., Compton, W. M., & Weiss, S. R. B. (2014). Adverse Health Effects of Marijuana Use. *New England Journal of Medicine*, *370*(23), 2219–2227. https://doi.org/10.1056/NEJMra1402309

Wells, J. E., Degenhardt, L., Bohnert, K. M., Anthony, J. C., Scott, K. M., & New Zealand Mental Health Survey Research Team. (2009). Geographical clustering of cannabis use: results from the New Zealand Mental Health Survey 2003-2004. *Drug and Alcohol Dependence*, *99*(1–3), 309–16. https://doi.org/10.1016/j.drugalcdep.2008.09.002

Wentzel, K. R., & Caldwell, K. (1997). Friendships, Peer Acceptance, and Group Membership: Realtions to Academic Achievement in Middle School. *Child Development*, *68*(6), 1198–1209. https://doi.org/10.1111/j.1467-8624.1997.tb01994.x

Windle, M., & Wiesner, M. (2004). Trajectories of marijuana use from adolescence to young adulthood: Predictors and outcomes. *Development and Psychopathology*, *16*, 1007–1027. https://doi.org/10.1017/S0954579404040118

Xu, R. (2018). Alternative estimation methods for identifying contagion effects in dynamic social networks: A latent-space adjusted approach. *Social Networks*, *54*, 101–117.

Yang, J., McAuley, J., & Leskovec, J. (2013). Community detection in networks with node attributes. In *Data Mining (ICDM), 2013 IEEE 13th international conference on* (pp. 1151–1156). IEEE.

Zammit, S., Allebeck, P., Andreasson, S., Lundberg, I., & Lewis, G. (2002). Self reported cannabis use as a risk factor for schizophrenia in Swedish conscripts of 1969: historical cohort study. *BMJ (Clinical Research Ed.)*, *325*(7374), 1199. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12446534

Zeileis, A. (2006). Object-oriented Computation of Sandwich Estimators. *Journal of Statistical Software; Vol 1, Issue 9 (2006)* . https://doi.org/10.18637/jss.v016.i09