Title: Exit, cohesion, and consensus: social psychological moderators of consensus among adolescent peer groups

Author: Jacob C. Fisher

Affiliation: Duke University

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Abstract

Virtually all social diffusion work relies on a common formal basis, which predicts that consensus will develop among a connected population as the result of diffusion. In spite of the popularity of social diffusion models that predict consensus, few empirical studies examine consensus, or a clustering of attitudes, directly. Those that do either focus on the coordinating role of strict hierarchies, or on the results of online experiments, and do not consider how consensus occurs among groups *in situ*. This study uses longitudinal data on adolescent social networks to show how meso-level social structures, such as informal peer groups, moderate the process of consensus formation. Using a novel method for controlling for selection into a group, I find that centralized peer groups, meaning groups with clear leaders, have very low levels of consensus, while cohesive peer groups, meaning groups where more ties hold the members of the group together, have very high levels of consensus. This finding is robust to two different measures of cohesion and consensus. This suggests that consensus occurs either through central leaders' enforcement or through diffusion of attitudes, but that central leaders have limited ability to enforce when people can leave the group easily.

Introduction

Virtually all social diffusion work – ranging from models of the spread of information or behaviors through a connected population (Christakis and Fowler 2007; Coleman, Katz, and Menzel 1966; Kreager and Haynie 2011) to theories of collective behavior (Baldassarri and Bearman 2007; Granovetter 1978; Moody 2001) – builds on a common formal basis: a model of interpersonal influence where people adjust their opinions or behaviors towards the weighted average of the opinions or behaviors of their peers (Friedkin 1998; Friedkin and Johnsen 2011). This formal basis is highly flexible. It has been adapted to incorporate different weighting among friends (cf. Valente 2010), networks that change in response to the diffusing opinion or behavior (Carley 1991), and complex contagions, where people need to be influenced by several people before they change their opinions or behaviors (Centola and Macy 2007). Despite surface-level differences, each model follows the same process: people in a connected population update their behaviors based on the weighted average of the people they are connected to.

A necessary, although typically unstudied, consequence of this model is that everyone connected by the network will converge to a single common value – a consensus – on the opinion or behavior that is diffusing (Berger 1981; Chatterjee and Seneta 1977; DeGroot 1974). The exceptional cases that have examined consensus focus on the coordinating role of strict hierarchies, rather than on the diffusion of beliefs through peers (Martin 2002), or the results of online experiments (Centola and Baronchelli 2015; Salganik, Dodds, and Watts 2006). Lacking from both branches of research is a consideration of how groups *in situ* develop consensus, and how that process is moderated by the presence of other groups.

This study uses unique, longitudinal data on social networks of adolescents to observe when adolescent peer groups develop a consensus on three different attitudinal topics: smoking attitudes, alcohol attitudes, and school attachment and bonding attitudes. By examining peer groups, meso-level social constructions that are ubiquitous in adolescence, this study focuses on two key differences induced by the lack of isolation of peer groups from one another. First, since peer groups are not isolated, members of the groups can leave one group to join another. Second, other peer groups in the school provide natural out-groups for comparison. Both of these differences suggest possible moderators for the effect of hierarchies or diffusion on consensus. For example, if a person can exit a group easily, he or she can avoid sanctions from the group's central leader, or if an out-group is more salient, the weighted averaging (diffusion) process that drives consensus may be strengthened.

The remainder of this article proceeds as follows. I begin by outlining the common, formal basis for consensus, meaning a convergence of beliefs measured at the peer group level. I then review the previous research on consensus, and develop hypotheses for how the interacting nature of peer groups might differ from the processes proposed elsewhere. I introduce a new measure of consensus, as well as a measure of peer group stability to control for selection into peer groups, and then show how the social network structures of peer groups relates to the groups' levels of consensus. These settings shed light on how the social psychological processes inherent to many peer groups moderate the process of consensus formation.

Background

Formal bases for consensus

Although formal mathematical or simulation models of diffusion have proliferated in the past decade, they all rely on a common core introduced by French (1956), and since elaborated by Noah Friedkin and colleagues (Friedkin 1998; Friedkin and Cook 1990; Friedkin and Johnsen 2011). In each model, people change their attitudes about a topic by considering the weighted average of the people that they are connected to in a friendship or social influence network. Formally, the attitudes of the n people in the population measured at time t are represented in an $n \times 1$ vector $\boldsymbol{A}^{(t)}$, and the pathways for influence are represented in a matrix $\boldsymbol{W}$, where the elements, $0 \leq w_{ij} \leq 1$, are the extent to which person i weights person j's attitudes. The model for attitudes at time $t+1$, then, is $\boldsymbol{A}^{(t+1)} = \boldsymbol{W}\boldsymbol{A}^{(t)}$, and if the interpersonal weights $\boldsymbol{W}$ do not change over time, then additional time periods can be simulated by taking powers of $\mathbf{W}$, i.e., $\boldsymbol{A}^{(t+k)} = \boldsymbol{W}^k\boldsymbol{A}^{(t)}$ for all $k = 1, 2, 3, \ldots$.

A necessary consequence of this model is that all of the people who are connected by the weight matrix $\boldsymbol{W}$ will converge to the same value for the diffusing attitude, meaning they will reach a consensus on that attitude (Berger 1981; Chatterjee and Seneta 1977; DeGroot 1974; Harary 1959).[1] This convergence happens after a very short number of iterations. Simulations using a typical attitude value, measured on a scale from 1 – 5, uniformly distributed in the population, and a typical social influence matrix constructed from social network data, show that the people converge to similar attitude values in fewer than 3 iterations (Fisher 2015), suggesting that the consensus-generating social influence process described by the model occurs very rapidly. Homophily, or the selection of friends based on attitude similarity commonly found in social networks (McPherson, Smith-Lovin, and Cook 2001), only speeds this tendency towards consensus because friends are already likely to have similar attitudes.

Given the frequency and consistency with which social diffusion models predicted consensus, modern diffusion models have explicitly focused on simulation strategies that produce polarization (Macy, Kitts, and Flache 2003). The strategies to produce polarization take one of three forms. First, models can produce polarization if they allow the social influence pathways to change concurrently with the attitudes (e.g., Carley 1991; Durrett et al. 2012; Holme and Newman 2006; Mark 1998). In those cases, polarization occurs when the social influence network becomes disconnected; at that point, each of the disconnected groups reaches a single consensus value, leading to apparent polarization in the network overall. Second, models can produce polarization if they allow negative influences (Macy et al. 2003). Negative influences

[1] The weight matrix must satisfy two regularity conditions, irreducibility and aperiodicity, for the model to converge to a consensus. Simply put, the weight matrix is irreducible if it is fully connected, meaning that any person can reach any other person in the network by moving along network ties, and it is aperiodic if it does not contain a cyclic pattern that would cause a bit moving along the ties to return to where it started at regular intervals. Most social networks satisfy the latter condition; the former condition is satisfied within each strongly connected component of the network. Practically, this means that each strongly connected component will converge to its own consensus value.

create polarization because they introduce a repulsive force, driving attitudes on either side of a negative social influence tie to opposite ends of the ideological spectrum. Third, and finally, models can produce polarization by considering multiple attitudes simultaneously (Baldassarri and Bearman 2007). If multiple attitudes are considered together, then the population can reach a consensus on one attitude while the other issues move independently.

In spite of the push to develop models for polarization, each of the approaches suggested in the literature operates on the same consensus mechanism, producing polarization by creating either disconnected or mutually repulsive groups that internally develop a consensus but are externally distinct from one another. Fundamentally, each of the diffusion models necessarily produces consensus when the population is closed, meaning there are no new ideas introduced into the population, and when there are no countervailing influences, like negative ties.

Social diffusion models, then, suggest that consensus should occur frequently in populations where diffusion occurs. Few studies have examined consensus empirically, however. This lacuna developed partially because consensus does not have a consistent definition. While consensus could be taken to mean general agreement, or some extent of shared understandings, specific definitions in the literature vary. Martin (1999, 2002) defines consensus as a concentration in a multidimensional belief space. Shwed and Bearman (2010) define consensus as a lack of internal divisions within a scientific community. Goldberg (2011) focuses on consensus about the axes, or the terms, of a debate, rather than the positions that actors take on a particular axis. Finally, several articles (e.g., Correll and Ridgeway 2006; Johnson, Boster, and Palinkas 2003) consider consensus about social roles or relative social positions, but do not consider consensus on attitudes not related to interpersonal status hierarchies.

The consensus induced by interpersonal diffusion resembles Martin (1999, 2002)'s definition most closely. Interpersonal diffusion generates consensus in the sense that people's positions on an attitudinal scale converge to a single value, meaning that, if the consensus process operates on several beliefs simultaneously, actors' positions in a multidimensional belief space will converge to a single common, consensus value over time. Few empirical studies of the effects of diffusion examine consensus as a group-level outcome, however. More often, studies focus on individual-level changes in attitudes and beliefs as the result of peer influence (e.g., Childress and Friedkin 2012). The few studies that do examine group-level consensus outcomes generally focus on centralized authority as a coordinating force producing consensus (Martin 2002), or examine the coordination that occurs as the result of online social influence experiments (Centola and Baronchelli 2015; Salganik et al. 2006).

However, this literature does not consider how consensus develops *in situ*, among groups that are not isolated or experimentally constructed. Peer groups embedded within a larger setting are a nearly ubiquitous feature of social life, but little research has examined how diffusion processes happen in the presence of other groups. To construct hypotheses for how consensus develops in peer groups that are embedded in a larger social organization, the following section describes how two features of the peer group environment – fluid boundaries and the presence of salient out-groups – distinguish the adolescent peer group context from previous studies of consensus.

Embedded peer groups

Informal peer groups represent the meso-level of social organization, an informal collection of people bonded by shared history, identity, and routine, face-to-face interaction[2], but embedded within a larger institutional structure (Fine 2012). Peer groups are a particularly important context for adolescents. As adolescents age, they begin to focus more on peers and less on parents and teachers (Erikson 1968; Newman and Newman 1976). The peer groups that develop as a result of this changing focus are the dominant feature of the social organization of schools (Corsaro and Eder 1990), and are also a primary site for peer influence related to health behaviors such as smoking (Hoffman et al. 2006; Simons-Morton and Farhat 2010).

Peer groups differ in two important ways from the contexts for previous studies of the development of consensus. First, unlike other settings (such as people in an urban commune, e.g. Martin 2002), informal peer groups are not isolated from one another. Instead, they exist in an environment where there are many peer groups occupying niches in the school's social environment (McPherson 1983). Since there are many peer groups with which students can choose to associate, membership in the peer groups is fluid (Cairns and Cairns 1994), meaning that students can exit a peer group relatively easily. Second, since peer groups in a school share a single social environment, the other peer groups in the school provide natural out-groups for comparison. As the defined out-groups become more salient, informal peer group members experience greater in-group attachment (Hogg 1992), manifested as higher in-group cohesion.

These two differences – the low cost of exit for members of the group, and the presence of salient out-groups for comparison – suggest that previous mechanisms associated with the development of consensus may occur differently in informal groups. Previous research on

[2] Increasingly, face-to-face interaction can be replaced by technologically mediated interactions, such as communicating by email or telephone. For informal peer groups to form, however, there must be a core of interpersonal interaction, whether it happens in person or through an electronic medium.

consensus and peer influence suggests that consensus may develop either as the result of a a diffusion process (Centola and Baronchelli 2015; Salganik et al. 2006) or coercive central authority (Martin 2002). I develop hypotheses for each of these in turn.

Focusing first on the diffusion process, previous research suggests that groups that are more connected, or more cohesive, will exhibit greater consensus. Following Moody and White (2003), I define social cohesion as the extent to which a group's ties hold it together. A cohesive peer group, then, is one that has many ties between the members. As the number of ties between the members increases, the amount of social influence that is possible in the group increases. As such, groups that are more cohesive should be expected to display greater consensus.

In a multi-group environment, like a school with multiple peer groups, the presence of salient out-groups could amplify the social influence process by strengthening in-group attachment (Hogg 1992; Tajfel 1982; Turner 1987). Greater in-group attachment leads to students weighting the opinions of others in the same group more heavily, creating a stronger association between cohesion and consensus at the peer group level. This suggests the following hypothesis:

H1: Peer groups that are more cohesive will display a higher degree of consensus.

By contrast, the previous empirical literature on consensus suggests that consensus is produced by the clarity of the power structure (Martin 2002). In an adolescent peer group, a group that is highly focused on a single person, or a highly centralized group, would represent a group with a clear power structure. The person who is at the center of the centralized group would represent a clear central authority who could enforce a particular set of beliefs among other students in the group. This prior literature suggests the following hypothesis:

H2: Peer groups that are more centralized will display a higher degree of consensus.

This relationship could be moderated by the peer group environment, however. Coercive pressures may be less important because members of peer groups can exit the group easily (cf. Hirschman 1970). Unlike in other studies on consensus (e.g., among members of an urban commune), leaving an informal peer group might mean that a student sits at a different lunch table or associates with different friends more often, a process that could happen quickly and with little difficulty. When group members can leave the group easily, they may be less susceptible to a coercive influence, since any sanctions that a central leader could impose could be avoided by leaving. Hypothesis 3 summarizes this expectation:

H3: Peer groups that are more centralized will not display a higher degree of consensus when students can exit the groups easily.

Hypothesis 3 is a special case of hypothesis 2. Finding evidence that supports hypothesis 3 would not refute hypothesis 2, but it would suggest that hypothesis 2 has important boundaries to its applicability. I focus on adolescent peer groups, a case where members of a group can exit the group easily. Therefore, in addition to testing hypothesis 1, I primarily focus on testing whether hypothesis 3 holds in this setting, versus hypothesis 2 being broadly applicable. The following section outlines the study setting in greater detail.

Data

I test these hypotheses using data from the longitudinal Promoting School-Community-University Partnerships to Enhance Resilience (PROSPER) study, a project designed to evaluate substance use interventions (Spoth et al. 2004, 2007). PROSPER followed two cohorts of sixthgrade students living in 28 rural communities in Iowa and Pennsylvania. Each community had a public school district with between 1,300 and 5,200 enrolled students where at least 15% of the families were eligible for free or reduced cost lunch, to include families of significant risk. Districts had at least a 95% English-speaking enrollment and were predominantly White (range: 61% -97%). Table 1 summarizes the characteristics of the sample.

[TABLE 1 ABOUT HERE]

The study followed the two cohorts of students for 7 years, interviewing them twice in 6th grade, and once annually in 7th, 8th, 9th, 10th, 11th, and 12th grades for a total of 8 in-school interviews. The first cohort began 6th grade in 2002, and the second cohort began 6th grade the following year. The frequency with which students were interviewed is unusual among network data, and presents the unique ability to understand changes in consensus over time. Network data were collected using an open name generator. Students named two "best friends" and five "other close friends" in response to the question "Who are your best and closest friends in your grade?" These nominations formed a network of students within each grade of each school. Each vertex, or point in the network, represents a student, and one student's nomination of another defines an edge connecting those two students. To address selection concerns, I create a stability variable, described below, which necessitated holding one wave out of the sample. The sample uses data from 161 school settings, meaning 161 unique combinations of school and cohort. Over the four waves of the survey considered, 527 networks were constructed, one representing each unique combination of cohort, school, and survey wave.

Informal peer groups

The unit of analysis for this study is the informal peer group. In a network sense, an informal peer group can be considered to be a community, or a subset of a larger population where ties within the subset occur more often than between subsets. A number of algorithms exist to identify communities in networks (Fortunato 2010; Porter, Onnela, and Mucha 2009). The most common class of algorithms identify the set of groups which maximizes modularity, or the comparison of the odds of within-community ties to those expected at random (Newman 2006). A high level of modularity, then, indicates that the groups identified have a higher ratio of ties within the group to ties between groups than would be expected. Such clustering methods have been used to identify communities in scholarly publications (Shwed and Bearman 2010), musical tastes (Goldberg 2011), and adolescent friendships (Kreager, Rulison, and Moody 2011).

The partitioning that maximizes modularity on each friendship network, therefore, defines informal peer groups. A variation of Moody's (2001) CROWDS algorithm was used to identify the appropriate partitioning. Among the 161 school settings, 6,443 mutually-exclusive peer groups were identified. An average of 12.2 groups per school (SD = 7.59), with roughly 7 to 12 students per group was observed, agreeing with past research on the size and number of adolescent peer groups (Brown 1990). Socially isolated students, meaning students who neither sent nor received friendship nominations (3,805 person-observations, of 5.15% of the total number of person-observations), students who could not satisfactorily be assigned to a single peer group (6,912 person-observations, 9.35% of the total)[3], and students in groups larger than 30 (85 groups, 1.14% of the groups, representing 3,231 person-observations, or 4.37% of the total person observations) were excluded from the analysis, because they do not conform to the theoretical definition of a group, namely a small group of people with shared history and identity

[3] Students who could not be assigned to a single group would not be expected to be similar to each other, so they could not be analyzed as a single peer group. Moreover, they often bridge several groups, making analyzing them individually difficulty, because it is not clear which groups should be influencing each person. The results hold when using community detection methods that do not create a "liaison" category. Results using different community detection methods available from the author on request.

who routinely interact face-to-face.[4] Prior research by Gest, Moody, and Rulison (2007) indicates that groups identified using network structure generally conform to those identified by asking students "who hangs around with whom?" As such, groups found by clustering a network of friendships would likely be observed by other methods as well.

Methods

Dependent variable

The dependent variable for this study is peer group consensus. Following Martin (1999, 2002), I measure consensus as the concentration of group members' attitudes in a multidimensional space of beliefs. This measure focuses on the structure, rather than the content, of the beliefs. For example, using attitudes about smoking, I consider the extent to which members of a group share the same opinions about smoking (i.e., their beliefs have a similar structure), rather than whether the group members think smoking is good or bad (i.e., the content of their beliefs has a particular valence). Figure 1 this the opinions of members of 2 groups plotted in a 2-dimensional hypothetical belief space.

[FIGURE 1 ABOUT HERE]

In Figure 1, the groups hold an opinion on 2 variables, X, and Y. In the group on the left, the points are clustered tightly in the space, indicating a high level of agreement among the group members on X and Y, and therefore indicating a high level of consensus among the group members. On the right, the group members' opinions are much less tightly clustered, implying a much lower level of consensus. Consensus among the group members relating to a particular

[4] The results presented here are robust to different community detection methods – specifically, a fast and greedy clustering (Blondel et al. 2008) and an edge betweenness clustering (Newman and Girvan 2004). These additional results are available from the author on request.

topic, then, can be defined as the average distance between all of the members' beliefs. I consider consensus on three different types of attitudes: attitudes about smoking, attitudes about alcohol use, and school attachment and bonding attitudes. Attitudes about smoking and alcohol use capture items like "How wrong do you think it is to smoke / drink?" and "Smoking / Drinking makes you look cool. (Agree/Disagree)," while school attachment and bonding captures attitudes like "I like school a lot" and "I try hard at school." An appendix gives the exact text of each of the survey questions used.

For a set of attitudes to converge to a consensus through a repeated social influence process, the attitudes must be salient for the people involved. Baldassarri and Bearman (2007) suggest that if people hold several attitudes simultaneously, where only some of the attitudes are important to those people, then the system may converge to consensus on the salient attitudes while failing to converge on the other attitudes. Other models differ; DellaPosta, Shi, and Macy (2015) suggest a model where groups of people come to share common opinions about a variety of unrelated activities through a repeated influence process, regardless of whether those activities are salient. For this study, I bracket the question of whether the attitudes must be important to the people involved to converge, and focus on subjects that are likely to be highly salient to middle and high school students: illicit substance use and beliefs about school.

Each set of attitudes is represented by several variables, which must be combined to obtain an average distance. To quantify the average distance between group members, I follow Cohen (1986) and use the mean Mahalanobis distance between the individual members of the group. The Mahalanobis distance for an individual x_i and the group's centroid, $\bar{x}$ is calculated as

$$D^2(x_i, \bar{x}) = (x_i - \bar{x})' \, \Sigma^{-1} \, (x_i - \bar{x})$$

Where each x_i is a vector of p attitude variables for person i, and Σ is the $p \times p$ covariance matrix of the population of the school. The Mahalanobis distance is similar to the Euclidean distance, but takes the covariance between the input variables into account; it can be considered to be roughly equivalent to a z-score on several dimensions. Since the Mahalanobis distance is commonly used to obtain solutions for cluster analysis, this measure follows studies of culture which use cluster analysis to map "shared understandings" as well (e.g., Martin 2000). The variables were standardized, and the Mahalanobis distance between each individual and the group's centroid was calculated using the standardized variables. The distances were averaged across the entire group to give a single, distance score for each group. For ease of understanding, the variable was multiplied by -1. Therefore, higher values of the inverse distance score indicate higher values of consensus among the members of the group, while lower values of the distance score indicate lower values of consensus.

Independent variables

I construct two measures of both peer group centralization and peer group cohesion to test my hypotheses. Using two different measures shows the robustness of these findings to different operationalizations of centralization and cohesion. For cohesion I use *node connectivity,* which I refer to as cohesion, following Moody and White (2003), and *density*, and for centralization, I use *closeness centralization* and *skewness of in-degree*. The following section explains these measures in detail.

Cohesion

Hypothesis 1 states that cohesive groups will show higher values of consensus, likely through a process of diffusion of ideas or through normative reinforcement. Following Moody and White (2003), a group can be considered to be cohesive to the extent that the relations of its members hold it together. In this sense, the cohesion of a group can be defined as the *node* *connectivity,* or the number of individuals who would have to be removed to disconnect the group. If, for example, to separate the group into two pieces, three individuals had to be removed, a group would be said to be 3-connected.

Using the node connectivity alone, however, does not take group size into account. A large group which could be disconnected by the removal of a single individual should be considered to be less cohesive than a small group with the same property. To account for group size, I follow the convention in the literature (e.g., Moody and Benton 2016) and divide the node connectivity by the total possible node connectivity, $n_k - 1$. Thus this measure of cohesion takes its maximum value, 1, if every member of the group could be removed without disconnecting the group. This maximum value occurs when the group is a completely connected clique. The measure takes its minimum value of 0 if the group is already disconnected.

Density

For robustness, I include a different measure of social cohesion, density. Density is the proportion of the possible ties in the group which were observed. The density of a group is given by the following formula:

$$\text{Density}_k = \frac{E_k}{\binom{n_k}{2}}$$

where E_k is the number of observed ties in the group. The value of density ranges from 0, where no ties were observed within a group, to 1, where all the possible ties within a group were observed. Groups with higher densities have a larger fraction of the total number of possible ties, and are therefore more cohesive.

Centralization

Hypothesis 1 states that highly centralized groups – that is, groups with clear power structures – should exhibit greater consensus. A group may be considered centralized by considering the degree to which the group's friendships focus on a single individual. To measure the extent to which friendships focus on a single individual, I use a network measure called *centralization*. Centralization measures the distribution of *centrality*, or the extent to which one person is involved in many ties. In particular, I use *closeness centrality*, which measures the number of times an individual falls on the path between two others.

Centralization measures the distribution of centrality – or, conceptualized as above, the distribution of popularity – within a group. A highly skewed distribution of centrality in the group suggests that one individual is much more popular than the others in the group. In that case, the group might be said to be focused on a very popular individual. Alternatively, a very even distribution of centrality within a group suggests that all individuals in the group are roughly even in popularity. A group with low centralization, then, would not be particularly focused on a single individual.

The closeness centralization of a group, k, is given by:

$$C_{C_k} = \frac{\sum_{i=1}^{n_k}[C'_C(n^*) - C'_C(n_i)]}{(n_k-2)(n_k-1)\Big/(2n_k-3)}$$

Where n_k is the number of individuals in group k, $C'_C(n_i)$ is the closeness for each actor i in the group, and $C'_C(n^*)$ is the largest standardized closeness among members of the group (Wasserman and Faust 1994). Centralization takes its maximum value of 1 in the case of a star graph, where all individuals in the group are connected via a single individual, and takes its minimum value of 0 in the case of a ring or circle graph, where all individuals are equally close to one another. Thus when centralization is 1, a group is perfectly focused on a single individual, and when centralization is 0, a group cannot be said to be focused on any individual.

Skewness of popularity

The measurement of centralization has a number of possible definitions. For robustness, I also include a measure of skewness of the popularity distribution of the group (cf. Wasserman and Faust 1994). Popularity is measured as the in-degree, which I will denote as d, meaning the number of times an individual was named as a friend. Using this measure, a distribution of popularities among the group can be said to exist. The skewness of that distribution, in turn, indicates whether a single individual is considerably more popular than the rest of the group, and is therefore able to unduly influence the members of the group. Skewness was calculated using the following formula:

$$(\text{skewness of indegree})_k = \left(\frac{n_k}{(n_k-1)(n_k-2)}\right)\sum_{i=1}^{n_k}\left(\frac{d_i-\bar{d}}{s}\right)^3$$

Where d_i represents the i^{th} person's in-degree, $\bar{d}$ represents the mean in-degree for all the members of the group, and $s = \sqrt{1/(n_k-1)\sum_{i=1}^{n_k}\left(d_i-\bar{d}\right)^2}$ represents the standard deviation of group members' in-degree values.

Controls

Group stability

In addition to the mechanisms described above, social diffusion and the presence of a clear leader, groups could develop a consensus through selection, meaning that people with similar attitudes could form a group together because they share those attitudes. To control for selection, I include a measure of group stability. To capture stability, I use pairwise measure indicating the fraction of the group members who were also grouped together at the previous wave of the survey (Moody, Fisher, and Osgood 2015). For a given group k, the stability measure is calculated as:

$$\text{stability}_k = \frac{\sum_{i<j} I\left(\text{group}_i^{(t-1)} = \text{group}_j^{(t-1)}\right)}{\binom{n_k}{2}}$$

Where $I(\cdot)$ represents the indicator function, $\text{group}_i^{(t-1)}$ represents the group that the i^{th} person belonged to at the previous wave of the survey, and n_k is the number of people in the k^{th} group.[5] This measure is a form of the Jaccard index, which is commonly used to compare clusters in cluster analysis (Bailey 1975), and ranges from 0 to 1. If the measure is 0, indicating a completely new group, none of the people in the group were in the same group in the previous wave. If the measure is 1, indicating a completely stable group, all of the members were members of the same group in the previous wave.

Demographic heterogeneity

To control for demographic heterogeneity, I include a measure of diversity for the gender, race, household composition, and socioeconomic status of the group. Household composition is measured by whether students lived in a two-parent household or not. Students were not asked about their families' household incomes directly, so whether the student receives free lunch was used as a proxy for socioeconomic status. The measure of diversity used is the index of qualitative variation, calculated as:

$$\text{IQV} = \left(\frac{K}{K-1}\right)\sum_{i=1}^{K}(1 - p_i)$$

where K is the number of categories, and p_i is the proportion of the group which falls into the i^{th} category. The index ranges from 0 to 1, where 0 represents a completely

[5] Because this measure uses groupings from waves t and $t-1$, it could not be calculated for the first wave of data. I therefore dropped the first wave from the analyses.

homogeneous group, and 1 represents a group with equal parts in each category. In addition, I include a control for group size, meaning the number of people in the group.

Missing data and network measures

A recent literature has considered how missing data influences the calculation of network measures (Borgatti, Carley, and Krackhardt 2006; Smith and Moody 2013; Smith, Moody, and Morgan 2017). This literature has generally found that some measures of centrality can be sensitive to missing data, and these measures are more sensitive when more central vertices are missing. The measurement of cohesion could also vary with missingness; a central person's absence could lead to fewer node-independent paths between several people in a peer group. This study addresses these concerns by using robust measures, and by using two measures for robustness. First, I measure centralization using closeness centralization, which is the centrality measure most robust to missingness (Smith and Moody 2013). Second, I use two measures for both central authority and cohesion. The skewness of the popularity distribution is not highly sensitive to missingness at random, nor is the density of group. While systematically missing highly central individuals could influence the measurement of the independent variables, there is no reason to believe that missingness is correlated with centrality in these data, nor is there reason to believe it would be correlated with consensus. As such, missingness of network data may add noise to the estimates, but is unlikely to change the direction of the results.

Analytic strategy

Since the dependent variable, consensus, is approximately normally distributed, I use ordinary least squares regression to model the association of group social structure and consensus. Groups are not isolated in the schools, however, suggesting that observations within schools may not be independent. To address this problem, I include random effects for each unique school and cohort combination. There are approximately 40.0 group-waves per unique school and cohort combination (std. dev. = 28.4, min = 2, max = 159). Models with random effects were fit using version 1.1-12 of the lme4 package (Bates et al. 2014) in R 3.3.1 (R Core Team 2016). I include fixed effects for each grade level, as well, to control for the age of the students.

Results

[TABLE 2 ABOUT HERE]

Table 2 tests hypotheses 1 – 3. The table shows regressions predicting the negative, average distance among the group members – that is, the consensus of the group – across each of the three sets of variables: attitudes about smoking, attitudes about drinking, and school attachment and bonding attitudes. The first models in each set, models 1, 6, and 11, predict consensus using only the control variables. The models include random effects for school setting, not shown in the table. Demographic heterogeneity is consistently associated with decreased consensus among the group members across each of the three consensus topics. The IQV measure for racial heterogeneity, gender heterogeneity, socioeconomic heterogeneity, and heterogeneity of household composition are all negatively associated with the consensus of the group. This suggests that as a group increasingly fills a particular socio-demographic niche, the group develops an increasing consensus on smoking attitudes as well. The only exception is gender heterogeneity, which is only significantly negative for the baseline models of smoking and school attachment and bonding consensus. In addition, group stability is positively associated with consensus, suggesting that when members have been in the same group for longer, they are more likely to share the same attitudes. This may indicate a selection process for remaining in the group; if members share similar attitudes about smoking, then they are more likely to remain in the same group as each other between waves.

The second model in each set – models 2, 7, and 12 – tests hypothesis 1, which states that consensus is associated with cohesion among the group members. The models provide strong support for hypothesis 1. Cohesion, measured as the average fraction of node-independent paths between each pair of people in the group, is significantly related to higher values of consensus on each topic among the group members. To test the robustness of this finding, the third set of models, numbers 3, 8, and 13, use a different measurement of the cohesiveness of the peer group, density. Density, or the fraction of possible ties that were observed in the group, is also highly correlated with greater consensus on each topic among the group members. Thus greater consensus is observed among the groups whose members are more closely connected, either because it would take removing more members to separate the group, or because there was a higher density of ties connecting the members of the group.

The fourth set of models in the table – models 4, 9, and 14 – include a term for closeness centralization, representing clarity of the power structure in the group. Hypothesis 2 and hypothesis 3 provide conflicting expectations for closeness centralization. Hypothesis 2 states that a group with a clearly defined central leader, or a clear power structure, should exhibit higher levels of consensus, because the central leader can enforce attitudinal consensus through sanctions or other means. Hypothesis 3, however, states that in situations where group members can leave, they need not endure the sanctions, and as a result, groups with central leaders will not show higher levels of attitudinal consensus. Models 4, 9, and 14 in table 2 provide support for hypothesis 3. Closeness centralization is negatively related to consensus, meaning that the clarity of the power structure does not predict greater similarity of attitudes among the group.

For robustness, a fifth set of models – models 5, 10, and 15 – include an alternative measure of centralization, skewness of the popularity distribution. In each case, the alternative measure is negatively associated with consensus among the group members. Groups which contain an individual who is substantially more popular than the other individuals in the group also do not display a higher level of consensus, as hypothesis 2 would have predicted. Instead, groups with a very popular individual relative to the rest of the group display a significantly lower level of consensus, providing additional support for hypothesis 3.

Coefficients for both measures of central authority are marginally significant in the negative direction. That is, more centralized groups display *less* consensus on each of the attitudes considered. This finding would suggest that not only do central authorities fail to enforce a common set of beliefs, but also their presence fosters a lack of consensus. The negative relationship is the opposite of what hypothesis 2 would have predicted, and cannot be fully explained by hypothesis 3, which only anticipates a lack of a relationship.

[FIGURE 2 ABOUT HERE]

Figure 2 illustrates the size of the effects in table 2 by showing standardized coefficients for each of the key independent variables on each of the forms of consensus. The first two panels of Figure 2 show standardized coefficients for the two measures of group cohesiveness, cohesion (meaning node connectivity) and density. Both have a relatively large effect. A one standard deviation in cohesion results in a roughly 0.15 standard deviation increase in consensus on each attitude value, while a one standard deviation increase in density results in a roughly 0.20 standard deviation increase in each consensus measure. The second two panels show the effects for the two measures of central authority, closeness centralization and skewness of the group's popularity distribution. Both measures of central authority have a small, but marginally significant, negative effect on consensus. A one standard deviation increase in either centralization or skewness of popularity results in a roughly 0.05 standard deviation *decrease* in any of the consensus measures.

Finally, Figure 2 shows a consistent pattern in which consensus values are most closely associated with network structure. School attachment and bonding consistently has the largest association with network structure. Cigarette smoking attitudes have the second-strongest association with network structure, although the effect is roughly comparable to that of school attachment and bonding for the centralization variables. Finally, alcohol use has the smallest association with each of the network structure variables. These associations may suggest differences in the importance of a given attitude value for middle and high school students.

Discussion

Although most social diffusion work predicts the formation of consensus, few studies examine consensus empirically. Using a novel measure of consensus, unique data, and a new measure of group stability, I tested how social network structures relate to observed consensus at the peer group level across three topics: smoking, alcohol use, and school attachment and bonding. Following the previous studies on consensus, I considered the cohesion of the peer group, or the extent to which the ties of the group hold it together, and the centralization of the peer group, indicating the extent to which the peer group is focused on a single, central leader. Cohesion would be associated with consensus if students influenced each others' beliefs, as in most social diffusion work, and centralization would be associated with consensus if a central leader in the peer group could enforce attitudinal consensus, likely through sanctions.

I tested three hypotheses about how cohesion and centralization of a peer group related to the formation of consensus, resulting in two key findings. First, highly cohesive groups showed higher rates of consensus, even net of group stability, measured as previous pairwise shared group membership. This provides some support for the common, formal basis that underlies most social diffusion work. Second, centralization was not associated with consensus, contrary to the findings from previous research. Indeed, more centralized groups displayed *lower* levels of consensus. This difference may occur because peer groups are not isolated. Students can exit a peer group rather than endure sanctions from a central leader in their group. These relationships are consistent across two different measures of both cohesion and centralization, and three different topics of attitudinal consensus.

The latter finding suggest an important boundary condition to previous work on power structures and consensus. The ability of a central authority to induce a set of attitudes among a group of people may be limited to the extent that people cannot escape the central authority's sanctioning power. This is particularly important for groups where members choose to join the group, as is the case for the peer groups considered in this study, or as is the case for other voluntary organizations not considered here. Although the findings in this study are consistent with the mechanism suggested, data on adolescent peer groups cannot directly compare groups where it is difficult to exit and groups where it is not. Future work may test this directly by considering a different setting, such as a set of work teams, where some projects are voluntary and some projects are not.

This study suffers from several additional limitations. First, while the sample is unusually complete in the network data it collects, it is limited to schools in rural areas in two states. The results presented here may not generalize to urban areas, other parts of the United States, or outside of the U.S.. Second, although this study controls for selection into the peer group, it does not control for level of consensus among the group members at the previous time. Since the groups were identified *de novo* at each wave of the survey, peer groups identified in one way are difficult to compare with peer groups identified at a second wave of the survey. New methods for identifying peer groups in networks, such as multislice community detection (Mucha et al. 2010), may allow future work on this topic to consider how changes in each group's membership influences both the social network structure of the group, as well as extent to which a consensus is observed among the group members. Finally, students range in age from approximately 12 – 18 years old. As such, there may be unobserved developmental effects that influence the results presented here. Future research should these mechanisms in other contexts, particularly among adults.

An important area not addressed by this study is the influence of global variation in the school environment between schools. Past research has found that schools have differing levels of hierarchy and cohesion (McFarland et al. 2014). These differing levels may influence the association between the cohesion or level of central authority in a group and the consensus of that group within a given school. For example, in more hierarchical environments, groups at the bottom of the hierarchy may view groups at the top of the hierarchy as a salient out-group, and may react by weighting in-group interactions more heavily. Or, as a second example, in schools that are more globally cohesive students may feel it is easier to move between groups, and centralization may have a lesser influence. The influence of global variation on the relationship between peer group social network characteristics and consensus is an interesting consideration, which future work may consider.

In spite of these limitations, this research has implications for future research on the relationship between social structure and attitudes, particularly for voluntary groups. Specifically, future research must take into account the nature of the inter-group environment in order to full understand how groups *in situ* develop a common set of attitudes. The presence of other groups may create a salient out-group, which causes group members to weight one anothers' opinions more heavily, or it may provide opportunities for group members to leave a group with a clear central authority. As an observational study on informal peer groups, this study cannot tease apart these mechanisms fully. However, the findings from this study suggest several possible directions for future work to explore. Understanding the influence of the inter-group environment will inform how social diffusion processes operate among interacting groups; this study takes a first step towards developing that understanding.

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Figure 1: Illustration of a high and low consensus group

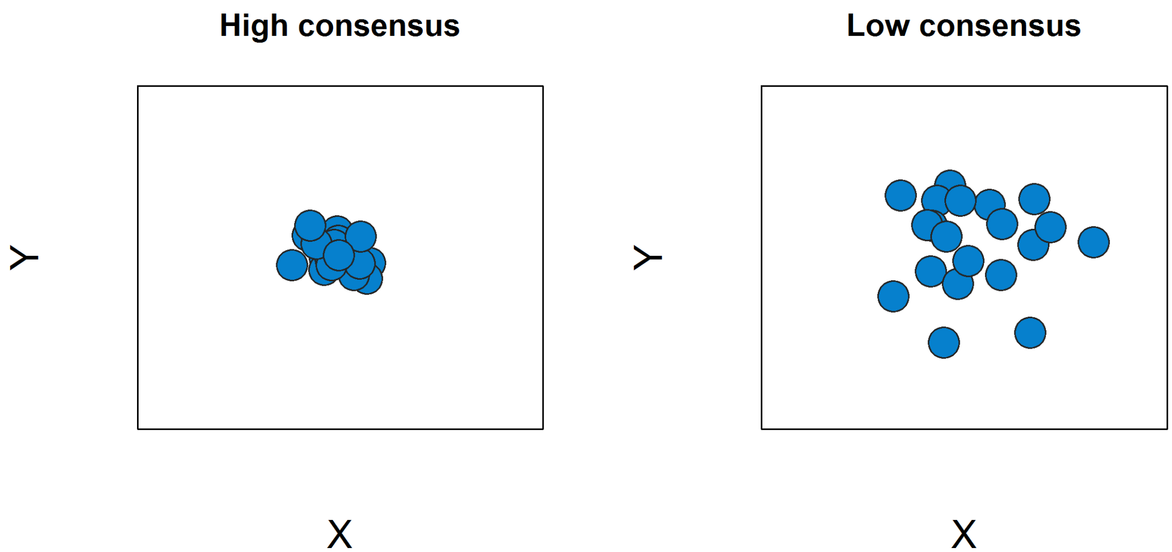

Figure 2: Standardized coefficients of cohesion and central authority predicting consensus

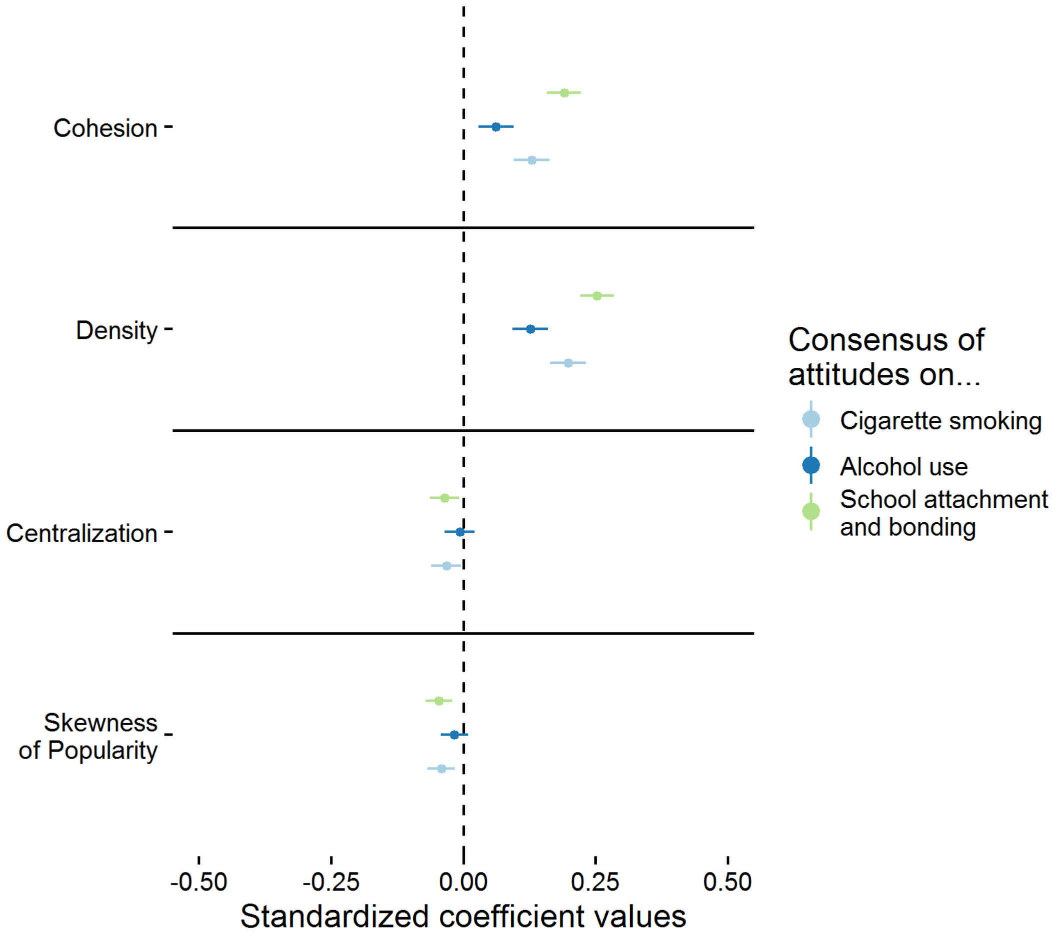

Table 1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Dependent variables					
Smoking attitude consensus	6,443	-1.820	0.492	-3.969	0.000
Alcohol attitude consensus	6,443	-2.177	0.556	-5.704	-0.000
School attachment and bonding attitude consensus	6,443	-2.468	0.433	-4.506	-0.827
Key Independent Variables					
Cohesion (node connectivity / (k - 1))	6,416	0.305	0.169	0.020	1.000
Density	6,443	0.307	0.147	0.053	1.000
Closeness centralization	6,443	0.433	0.174	0.000	1.000
Skewness of popularity	6,430	0.323	0.777	-2.828	2.869
Controls					
Group size	6,443	9.960	4.539	3.000	28.000
Stability (% of pairs grouped together at t - 1)	5,372	0.451	0.303	0.000	1.000
IQV: Race	6,443	0.233	0.243	-0.000	0.960
IQV: Gender	6,443	0.265	0.352	-0.000	1.000
IQV: Free lunch	6,443	0.567	0.355	-0.000	1.000
IQV: Household composition	6,443	0.598	0.324	-0.000	1.000

Table 2: Linear models of cohesion predicting mean group member similarity with school setting random effects

	Smoking attitude consensus					Alcohol attitude consensus					School attachment and bonding consensus				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	-1.547***	-1.748***	-1.887***	-1.495***	-1.546***	-1.815***	-1.923***	-2.056***	-1.802***	-1.816***	-2.117***	-2.374***	-2.498***	-2.066***	-2.116***
	(0.031)	(0.040)	(0.042)	(0.038)	(0.031)	(0.034)	(0.045)	(0.047)	(0.043)	(0.034)	(0.026)	(0.034)	(0.036)	(0.033)	(0.026)
Cohesion		0.375***					0.202***					0.488***			
		(0.049)					(0.056)					(0.042)			
Density			0.663***					0.477***					0.744***		
			(0.057)					(0.064)					(0.048)		
Centralization				-0.092*					-0.023					-0.089*	
				(0.041)					(0.046)					(0.035)	
Skewness of					-0.027**					-0.012					-0.026***
popularity					(0.008)					(0.010)					(0.007)
Size	0.001	0.007***	0.011***	-0.001	0.001	-0.007***	-0.004	0.0003	-0.008***	-0.007***	-0.006***	0.003*	0.007***	-0.007***	-0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Stability	0.087***	0.038	0.017	0.084***	0.081***	0.081**	0.052*	0.026	0.080**	0.078**	0.043*	-0.019	-0.037	0.040*	0.039*
	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)
IQV: Race	-0.196***	-0.181***	-0.174***	-0.194***	-0.192***	-0.174***	-0.157***	-0.149***	-0.173***	-0.170***	-0.174***	-0.149***	-0.143***	-0.171***	-0.168***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.027)	(0.030)	(0.031)	(0.031)	(0.031)	(0.030)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
IQV: Gender	-0.063***	-0.040*	-0.031	-0.062**	-0.063***	0.0003	0.015	0.024	0.001	0.0003	-0.056***	-0.026	-0.020	-0.055***	-0.056***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
IQV: Free lunch	-0.144***	-0.126***	-0.114***	-0.144***	-0.141***	-0.084***	-0.077***	-0.064**	-0.084***	-0.083***	-0.196***	-0.174***	-0.165***	-0.197***	-0.193***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
IQV: Household	-0.232***	-0.217***	-0.209***	-0.232***	-0.232***	-0.215***	-0.209***	-0.197***	-0.215***	-0.215***	-0.213***	-0.194***	-0.186***	-0.212***	-0.213***
composition	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)

Grade 7	-0.013	-0.018	-0.022	-0.012	-0.013	-0.036	-0.039	-0.041	-0.036	-0.036	-0.006	-0.013	-0.016	-0.005	-0.007
(ref.: 6 gr. spring)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)
Grade 8	-0.021	-0.026	-0.032	-0.021	-0.023	-0.070**	-0.074**	-0.077**	-0.070**	-0.070**	-0.010	-0.014	-0.022	-0.009	-0.011
(ref.: 6 gr. spring)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Grade 9	-0.057*	-0.044	-0.044	-0.054*	-0.058*	-0.174***	-0.170***	-0.165***	-0.174***	-0.174***	-0.027	-0.014	-0.012	-0.024	-0.027
(ref.: 6 gr. spring)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Grade 10	-0.052*	-0.035	-0.029	-0.050*	-0.053*	-0.174***	-0.166***	-0.158***	-0.174***	-0.175***	-0.041*	-0.020	-0.016	-0.040	-0.042*
(ref.: 6 gr. spring)	(0.024)	(0.025)	(0.025)	(0.024)	(0.024)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)
Grade 11	-0.065**	-0.039	-0.028	-0.064*	-0.063*	-0.198***	-0.185***	-0.172***	-0.198***	-0.197***	-0.030	0.004	0.011	-0.029	-0.026
(ref.: 6 gr. spring)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Grade 12	-0.063*	-0.035	-0.024	-0.062*	-0.065*	-0.197***	-0.184***	-0.170***	-0.197***	-0.199***	-0.050*	-0.014	-0.007	-0.049*	-0.051*
(ref.: 6 gr. spring)	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
N	5,372	5,357	5,372	5,372	5,363	5,372	5,357	5,372	5,372	5,363	5,372	5,357	5,372	5,372	5,363
Log Likelihood	-3,499.941	-3,462.037	-3,435.676	-3,499.690	-3,490.339	-4,153.231	-4,131.049	-4,127.799	-4,155.268	-4,147.803	-2,687.641	-2,607.832	-2,575.859	-2,686.787	-2,674.604
AIC	7,029.882	6,956.074	6,903.353	7,031.379	7,012.677	8,336.462	8,294.098	8,287.598	8,342.535	8,327.605	5,405.283	5,247.664	5,183.718	5,405.574	5,381.208
BIC	7,128.716	7,061.452	7,008.776	7,136.803	7,118.074	8,435.297	8,399.477	8,393.021	8,447.958	8,433.002	5,504.117	5,353.043	5,289.141	5,510.997	5,486.604

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$