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Simulation of Social Networks to Maximize the Prevention and Treatment of Alcohol Use Disorders

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by

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ABSTRACT

Introduction: Previous studies have found associations between alcohol use and having heavy-drinking social networks. This association is thought to be caused by (1) social influence, where one's social network influences his or her drinking, and (2) social selection, where an individual forms relationships with individuals who drink at similar levels. These processes are reciprocal and, when acting simultaneously, create a feedback loop with non-linear dynamics. Computer simulations have allowed complex systems to be modeled in many scientific fields; however, this method has not yet been used to study the dynamic associations between social networks and alcohol use. Method: The present study used computer simulations to model changes in drinking and social networks. Stochastic actor-based social networks were simulated using RSiena. Social ties between actors and drinking statuses evolved over time according to stochastic Markov processes. Social influence and social selection were each manipulated at three levels (none, medium, and high). Results: Correlations between actor drinking statuses and the percentage of heavy drinkers with whom actors shared social ties were approximately zero when neither social selection nor social influence were present, were positive but small when either social influence or social selection were medium or high, and were significantly higher when social selection and social influence were both present. Two individual-level manipulations, reducing the target actor's heavy drinking and reducing the target actor's susceptibility to social influence, reduced heavy drinking over time for the individual targeted for intervention. Reducing target actors' heavy drinking also reduced the heavy drinking of other actors not targeted for intervention. Discussion: Simulations of social networks offer a novel method for modeling dynamic associations between drinking and social relationships. These methods may be used to replicate findings from real-world populations and can help generate novel hypotheses involving nonlinear processes that can inform real-world prevention and treatment efforts.

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Introduction

Heavy drinking is a major public health concern associated with motor vehicle accidents, cirrhosis of the liver, liver cancer, epileptic seizures, fetal alcohol syndrome, sexual assault, homicide, and unintended injuries (World Health Organization, 2004). It is estimated that $275 billion per year is spent in the United States alone due to alcohol-related costs (McCarty, 2007). Several psychosocial treatments have been shown to be efficacious in reducing heavy drinking (Hallgren, Greenfield, Ladd, Glynn, & McCrady, 2012), but the mechanisms by which these treatments work is not well understood (DiClemente, 2007; Finney, 2007; Huebner & Tonigan, 2007; Longabaugh et al., 2005).

The social environment has been hypothesized to play an active role in maintaining and facilitating changes in individual drinking (Beattie & Longabaugh, 1999; Groh, Jason, & Keys, 2008; Hunter-Reel, McCrady, & Hildebrandt, 2009; McCrady, 2004; Orford, Hodgson, Copello, Wilton, & Slegg, 2009). However, most studies that evaluate the role of the social environment have not accounted for the social network dynamics that may influence drinking behavior.

Social Networks and Drinking are Dynamically Related

Across age groups and cultures, drinking levels tend to be positively correlated with the level of support for drinking and alcohol consumption one receives from friends and family members (Avery, Hallgren, Ladd, Greenfield, & McCrady, 2011; Beattie, 2001; Broome, Simpson, & Joe, 2002; Greenfield, Hallgren, Muñoz, O'Keefe, & Venner, 2011; Groh, Jason, Davis, Ferrari, & Olson, 2007; Litt, Kadden, Kabela-Cormier, & Petry, 2009; Longabaugh, Wirtz, Zywiak, & O'Malley, 2010; Manuel, McCrady, Epstein, Cook, & Tonigan, 2007; McAweeney, Zucker, Fitzgerald, Puttler, & Wong, 2005;

Project MATCH Research Group, 1997, 1998; Velleman, 2006; Warren, Stein, & Grella, 2007). This relationship is thought to be caused by two separate but interacting processes known as social influence and social selection (Kelman, 1958; Verbrugge, 1977). With social influence, the drinking behavior of others who are part of an individual's network predicts a higher likelihood that the individual will adopt drinking behaviors similar to the people in his or her network, while with social selection, individuals are more likely to form relationships with social network members whose drinking patterns are similar to their own. Time-lagged studies have suggested that both of these processes are important in explaining the correlation between network and individual drinking, and that factors such as developmental stage may be associated with different levels of relative influence of each process. For example, the correlation between substance use and social network substance use for children and young adolescents tends to be better accounted for by social influence, whereas this correlation in adult populations tends to be better accounted for by social selection, and this correlation in older adolescents and emerging adults tends to be accounted for by a combination of social influence and social selection (Ali & Dwyer, 2010; Bullers, Cooper, & Russel, 2001; Parra, Krull, Sher, & Jackson, 2007; Reifman, Watson, & McCourt, 2006; Schulenberg 1999; Sieving, Perry, & Williams, 2000).

The reciprocal relationship between the drinking of an individual and the individual's social network creates a feedback loop of bidirectional processes, as shown in Figure 1. Feedback loops, which are commonly encountered in many natural systems, can create nonlinear and dynamic effects on the variables of interest within the system, which are often either amplified or dampened by the feedback loop (Hellerstein, Diao,

Figure 1. Feedback loop of social influence and social selection.

Parekh, & Tilbury, 2004). For example, heavy drinking may be amplified when both social influence and social selection are present within a system, as an individual who is a heavy drinker is more likely to associate with heavy-drinking peers due to social selection, and these heavy drinking peers are likely to in turn reinforce the individual's heavy drinking due to social influence.

The presence of feedback loops indicates that the system behavior is likely to be nonlinear and dynamic, and cannot be understood by studying any component of the system in isolation (Bertalanffy, 1968; Valente, 2003). The dynamic effects that social environments can exert on drinking behavior have led to a call for the development of models of substance use that can account for nonlinear effects that are inherent due to social context (Galea, Hall, & Kaplan, 2009; Hunter-Reel et al., 2009).

Various aspects of the feedback loop – including the characteristics of social networks, individual drinking, and the processes of social influence and social selection – may be influenced by factors that are commonly discussed in the literature on the etiology and treatment of alcohol use disorders. For example, joining community non-drinking social groups may influence the amount of heavy drinking in an individual's social network and affect that individual's drinking status, e.g., by increasing the number of non-drinkers in one's social network and increasing the likelihood that participants maintain abstinence from alcohol (Hunt & Azrin, 1973; Smith, Meyers, & Delaney 1998). In other treatment approaches, the learning of drink-refusal skills (e.g., through cognitive-behavioral techniques) may decrease the effect of social influence on drinking behavior. Similarly, adhering to the recommendation to avoid "people, places, and things" associated with drinking (e.g., common in cognitive-behavioral therapy and

Alcoholics Anonymous) may decrease the number of non-drinkers in one's network or decrease the tendency for social selection of network members who are heavy drinkers (Huey, Henggeler, Brondino, & Pickrel, 2000; Litt et al., 2009). Factors that influence the feedback loop between social selection and social influence may be categorized broadly as exogenous variables that exist at the level of the system (i.e., are mostly constant across individuals within a particular social system but may vary from system to system) or that vary at the level of the individual (i.e., due to individual differences). Examples of real-world exogenous variables are provided in Table 1.

Computer Simulations Can Model Dynamic Relationships

In the ecological and physical sciences, computer simulations of complex system behavior have improved understanding of phenomena such as hurricane development, species population dynamics, the dispersion of pollutants, and other dynamic systems. This work has successfully modeled real-world observations that are typically unsuitable for simple linear modeling techniques, and often has provided additional hypotheses that may be tested using simulated data and real-world observation.

Applied to human social networks, much of the research utilizing network simulations has been focused on the dissemination of information and opinions across social networks. For example, using computer simulations of social networks, Nowak, Szamrej, and Latané (1990) showed that local groups tended to adopt similar opinions over time, and that the structure of the social network substantially influenced the clustering of opinions. Guided by these simulation results, Latané and L'Herrou (1996) conducted follow-up experiments with real human subjects that replicated the simulated findings, which Latané used to provide support for his theory of Dynamic Social Impact

(Latané, 1996). Extensions of this simulation research have modeled more complex social phenomena, such as creativity (Bhattacharyya & Ohlsonn, 2010), the maintenance of cultural attitudes (Shimura, Kobayashi, & Murakami, 2005), and consumer preferences (Vag, 2007).

In health research, simulations of social networks have been used to inform treatment and intervention practices to predict and control the spread of HIV and other infectious diseases (Kosiński & Grabowski, 2007; Kretzschmar & Weissing, 1998), cocaine use (Sánchez, Villanueva, & Santonja, 2011), and obesity (Bahr, Browning, Wyatt, & Hill, 2009). These simulations have produced results that replicate real-world observations, such as the clustering of obese individuals within networks of other obese individuals, and have provided additional testable hypotheses relevant to treatment and prevention. For example, the results from Bahr et al. suggest that the popular notion of dieting with a friend may less effectively reduce obesity rates within the general population compared to dieting with friends-of-friends, because the latter may spread dieting behavior across the network more quickly.

A review of the literature on social networks and alcohol consumption revealed one study that has used simulations to understand drinking within a social network context. Braun, Wilson, Pelesko, Buchanan, and Gleeson (2006) simulated drinking behavior in two types of social networks, comparing random social connections, which are not typically found in real-world social networks, and so-called caveman networks consisting of highly localized clusters of relationships (Watts, 1999), and found that alcohol dependence is likely to diffuse more slowly over time with more clustering of drinkers in caveman networks compared to random networks. Further, in their caveman network simulations, Braun et al. found that "treating" random selections of 4% and 6% of the alcohol-dependent individuals by fixing their drinking status as non-dependent had significant but small effects on reducing alcohol dependence in the rest of the network, but treating 8% substantially reduced the prevalence of alcohol dependence in the rest of the network, causing a cascading effect where alcohol dependence rates decreased exponentially until the entire network was no longer considered alcohol dependent. The results suggested that the manipulation of alcohol dependence had a nonlinear effect on drinking outcomes in the entire network, where changes in individuals' drinking produced small changes in the rest of the network until a threshold of individual change was met. Braun et al. provide a starting framework for simulating drinking in social networks, but several factors limit the applicability of their findings. First, their study only manipulated the drinking statuses of select individuals, but did not manipulate other functional relationships between individuals and their social networks that are commonly changed by treatment and prevention programs, such as an individual's susceptibility to social influence or social selection or the types of people they to whom they extend social ties. Second, and perhaps most important, all social relationships in this model were static over time, which is problematic because this assumption is unlikely to hold true in the real world and yields a model that does not account for social selection, which more strongly accounts for the correlation between individual and network drinking for adults (Bullers et al., 2001; Parra et al., 2007).

Present Study

The goal of the present study was to develop computer models that simulate drinking within social networks. These models accounted for individual- and system-level variables and both social selection and social influence were incorporated simultaneously in the evolution of the network models over time. One goal of this research is to provide a framework for understanding how feedback due to the dual processes of social influence and social selection (Figure 1) affect drinking, and how individual- and system-level variables affect the drinking of the larger network. A second goal of this research is to help inform treatment and prevention strategies that maximize effects of interventions and inform future hypotheses and research designs for studying drinking in simulated and real-world social networks. This research parallels recent work in the tobacco, heart disease, and obesity fields that has utilized the analysis of social network data to show that conceptualizing these health problems within a dynamic system may yield important implications for health policy and treatment targeting (Christakus & Howler, 2008; de la Haye, Robins, Mohr, & Wilson, 2010; Kobus & Henry, 2010; Mercken et al., 2010a, 2010b; Pollard, Tucker, Green, Kennedy, & Go, 2010).

Hypotheses

Clustering hypotheses. In accordance with previous work on tobacco and obesity (e.g., Bahr et al., 2009), it was hypothesized that (1) when social selection and/or social influence are present within a model, problematic drinkers and non-problematic drinkers will tend to cluster into groups, as indicated by a positive correlation between individual drinking status and the drinking status of the individuals to whom one extends social ties, as has been found in the empirical alcohol research literature (Beattie, 2001). It is also hypothesized that (2) when both social selection and social influence are present in the model, local clusters of problem and non-problem drinkers will become more isolated than when only one process is modeled, indicated by higher correlations between individual drinking status and the drinking status of individuals to whom one extends social ties when both of these effects are included in the model compared to when only one effect is included.

Individual-level manipulation hypotheses. A second set of exploratory analyses aimed to understand how various types of manipulations that occur at the individual level might impact drinking within the rest of the social network. Five manipulations that represent prevention and treatment strategies occurring at the level of the individual and one control condition were tested for the present study. These manipulations targeted one randomly-selected actor in the network (called the "target actor") and included:

(1) changing the target actor's drinking status from heavy drinker to non-drinker, as was tested by Braun et al. (2006), which represents intervention strategies that directly target the individual's drinking status without changing their relationship to their social network (e.g., through treatment programs that reduce drinking but do not directly target social relationships)

(2) decreasing the target actor's susceptibility to social influence, representing a prevention or intervention strategy that makes the individual's drinking behavior less dependent on the behavior of other individuals (e.g., through treatment or prevention programs that emphasize drink-refusal training)

(3) decreasing the target actor's susceptibility to social selection, representing a prevention or intervention strategy that makes an individual's choice of friends less dependent on similarities between his or her drinking status and the drinking statuses of others (not

explicitly emphasized in treatment programs, but used as a comparison to the companion effect of reducing susceptibility to social influence)

(4) adding one social tie from the focal actor to a non-drinking individual, representing a prevention or intervention strategy that aims to increase the number of non-drinking individuals in one's social network (e.g., through treatment programs that emphasize obtaining non-drinking sponsors or friends)

(5) removing one social tie from the focal actor to a heavy drinker, representing a prevention or intervention strategy that aims to decrease the number of heavy drinking actors in one's social network (e.g., through treatment programs that emphasize avoiding people, places, and things who are associated with drinking)

(6) making no change, representing the absence of prevention or treatment programs (e.g., control condition against which the previous five conditions may be compared).

The choice of proposed manipulations was based on empirical findings regarding social networks and alcohol use disorders that are used in treatment and prevention programs in the real world.

For example, manipulating a target actor's drinking status from heavy drinker to non-drinker, representing a treatment strategy that does not explicitly focus on changes in one's relationship to his or her social network, could have dynamic associations with one's social network. For example, relapse rates for actors receiving this intervention could be moderated by the number of heavy drinkers the target actor extends ties to at the time of the manipulation, mimicking real-world effects where support for abstinence and heavy drinking rates of network members predict subsequent abstinence (Groh et al., 2007; Gryczynski & Ward, 2012; Hunter-Reel, McCrady, Hildebrandt, & Epstein, 2010;

Litt et al., 2009; Longabaugh et al., 2010; Smock, 2011). In addition, it may be expected that individuals who receive this manipulation increase their ties to non-drinkers and reduce their ties to heavy drinkers (e.g., Kelly, Stout, Magill, & Tonigan, 2011; Litt et al., 2009). In addition, this manipulation could lead to significant changes in overall network drinking due to the influence of the target actor's reduced heavy drinking on other network members, although few or no studies have examined this hypothesis in real-world datasets.

Previous research has shown that two constructs related to reduced susceptibility to social influence, including drink refusal skills and abstinence self-efficacy (i.e., one's confidence in his or her ability to refuse drink in various situations) predict post-treatment abstinence rates. Participants in the COMBINE study who received drink-refusal training had significantly fewer drinking days during and after treatment compared to participants who did not receive drink-refusal training, and receiving drink-refusal training multiple times predicted greater abstinence than receiving drink-refusal training only once (Witkiewitz, Donovan, & Hartzler, 2012). Drink-refusal self-efficacy also has been shown to predict alcohol consumption among non-treatment-seeking community members (Oie, Hasking, & Philips, 2007). If manipulating an individual's susceptibility to social influence predicts a higher probability of abstinence for the target individual, the present study may help unveil how social network dynamics may contribute to the positive effects of drink-refusal training and abstinence self-efficacy (e.g., Oie et al; Witkiewitz et al.). Additionally, the findings of the present study also may provide practical implications for future research and real-world clinical treatment, for example, by suggesting specific instances in which reduced susceptibility to social influence may be most effective.

In contrast, little previous research has examined the effect of reduced susceptibility to social selection (i.e., reduced tendency to form friendships based on similarity in drinking statuses). Few treatment modalities typically focus on this type of intervention, but it was included in the present study for two reasons. First, the simultaneous presence of social influence and social selection was hypothesized to create the highest amount of clustering by drinking status, and it was therefore of interest to assess the effect of removing one aspect of the feedback loop by reducing target actors' susceptibility to social selection. Second, the effect of reducing the other aspect of the feedback loop (i.e., targeting reduced susceptibility to social influence) also was tested in a separate condition, and reduced susceptibility to social selection served as an interesting comparison to this condition.

Both reducing the number of ties to heavy drinkers and increasing the number of ties to abstinent people (or people supportive of abstinence or treatment) have been shown to correspond with greater abstinence rates in treatment- and non-treatment-seeking populations. For example, in the large-scale treatment study Project MATCH, individuals tended to decrease the number of drinkers in their social networks during treatments, and greater reductions in heavy drinking network members predicted higher abstinence rates after treatment (Mohr, Averna, Kenny, & Del Boca, 2001). In another large-scale treatment study, having at least one close friend who was supportive of treatment or having no close friends who encouraged alcohol use was associated concurrently with greater abstinence rates over a 9-year follow-up period (Satre, Chi, Martens, & Weisner, 2012). The degree of change within social networks was not assessed by Satre et al.; however, there have been mixed findings about whether individuals are more likely to increase their ties to non-drinkers (or individuals supportive of abstinence) or to decrease their ties to heavy drinkers (or individuals supportive of heavy drinking; Litt et al., 2009; Kelly, Stout, Magill, & Tonigan, 2011). One way in which AA involvement may increase network support for abstinence is through the acquisition of an AA sponsor. Having an AA sponsor predicts greater abstinence rates during the early stages of involvement with AA (Tonigan & Rice, 2010), and some evidence suggests that AA may be particularly effective for individuals who have pre-treatment social networks that are highly supportive of drinking (Wu & Witkiewitz, 2008). If the manipulation in the present study of extending ties to non-drinkers improves abstinence outcomes, then helping individuals make abstinent friends, which commonly occurs through mutual help groups such as Alcoholics Anonymous (AA) and other support communities, may be a beneficial recommendation. Similarly, if removing ties from heavy drinkers improves outcomes, then the common adage of avoiding "people, places, and things" associated with drinking may be a more helpful recommendation. These findings would also provide further theoretical support for the importance of the social environment on drinking outcomes within the context of dynamic social networks.

For all conditions, individual-level characteristics of the target actor, including the number of ties to heavy drinkers and non-drinkers at the time of the manipulation, were tested as potential moderators of changes in outcome variables. For example, such moderation analyses allowed for the assessment of whether intervening on individuals with more connections to heavy drinkers provided greater treatment efficacy compared to intervening on individuals with fewer connections to heavy drinkers. These analyses would complement the limited amount of previous research that has shown treatment effects to be moderated by pre-treatment heavy drinking (e.g., Wu & Witkiewitz, 2008; Zywiak, Longabaugh, & Wirtz, 2002) and would provide insight into new hypotheses that may be tested in real-world datasets.

Network-level manipulation hypotheses. The individual-level manipulations were examined across a variety of types of networks to examine the relative effectiveness of each treatment and prevention strategy in different social contexts. The four network-level variables that were manipulated included:

(1) the strength of social influence effects in the network

(2) the strength of social selection effects in the network

(3) the size of the network

(4) the heavy drinking rate (HDR) within the network.

The four network-level variables were chosen because they represent parameters that may naturally vary across real-world populations and can help establish whether the findings in the present study generalize across a variety of networks. For example, the magnitude of alcohol-related social influence and social selection effects varies by age, with social influence being stronger in youth populations compared to adult populations, and social selection being stronger in adult populations than youth populations (Parra et al., 2007; Reifman et al., 2006). Manipulating these variables at different levels provided results that are applicable to both populations. Drinking rates and social network sizes also may vary between various populations, and the manipulation of these parameters allowed for testing of whether the individual-level manipulations described below produced reliable changes across a variety of social network conditions.

The study focused on guiding future research with real-world populations aimed at improving prevention and treatment efficacy, as has been done in previous simulation studies (Bahr et al., 2009; Braun et al., 2006; Kosiński & Grabowski, 2007; Kretzschmar & Weissing, 1998). The results of the present study may suggest that, under conditions that are typical across networks, some parameters may have a greater effect on drinking across the network than others, which if targeted for prevention and treatment efforts, may be more effective in reducing problem drinking across the network. Future work will utilize the results of the proposed study to inform hypotheses about how specific parameters influence the system dynamics, therefore informing researchers about parameters that may provide the highest degree of change when addressed in treatment and prevention.

Method

Stochastic Actor-Based (SAB) Modeling Procedure

Several network modeling techniques were considered for the present study (de Nooy, 2011; see Lubbers et al., 2010). Among these, stochastic actor-based (SAB) network models (Snijders, 1996, 2001; Snijders, van de Bunt, & Steglich, 2010), a type of directed graph, were found to provide the most appropriate framework for the present study due to their focus on describing longitudinal changes in social networks, their ability to incorporate social ties (e.g., network relationships) and actor characteristics (e.g., drinking statuses) simultaneously into their models, and their relative wealth of theoretical and applied research available for reference in the network analysis literature (Steglich, Snijders, & West, 2006).

Assumptions of SAB models. Like all modeling techniques, SAB models have several assumptions about the nature of social networks and the individuals within them (called "actors"), which, if violated, will yield limitations to their accuracy. First, SAB models are stochastic, meaning that they assume changes within the network are probabilistic rather than purely deterministic, such that the probability of any possible change in the network is described by a probabilistic formula that can incorporate any number of individual- or network-level variables. Second, SAB models assume that longitudinal changes in social networks are Markov processes, where the state of the system at time $t + 1$ is predicted only by the state of the system at time t, or in other words, changes in the system are only influenced by the current state of the system and not by historical states. This assumption is unlikely to be true of real-world social networks, but is made out of necessity because including historical predictors in these models exponentially increases the number of effects that may be accounted for, adding a substantially larger level of computational complexity. Third, SAB models assume that relationships between network actors are not necessarily bidirectional; that is, an actor who receives a tie from another actor does not need to reciprocate this tie (i.e., actor i may consider actor j to be a friend, regardless of whether actor j reciprocates this friendship). This assumption holds commonly in many social networks: for example, a popular actor in a friendship-based social network may be listed as a friend by many actors but might only reciprocate a fraction of these ties.

SAB modeling foundations. Social ties within an SAB network with n actors are modeled using an $n \times n$ adjacency matrix, x, composed of 0's and 1's, where $x_{ij} = 1$ if actor i extends a tie to actor j (symbolically represented as $i \rightarrow j$, where actor i considers actor j to be a friend), and $x_{ij} = 0$ if actor i does not extend a friendship to actor j. The adjacency matrix need not be symmetrical, in accordance with the SAB model assumption that relationships are not always bidirectional. Social ties with oneself (i.e., the diagonal of the adjacency matrix where $i = j$), are not considered in any analyses. An example of a small social network adjacency matrix (with i-values represented as rows and j-values as columns) with $n = 5$ actors is provided below and the accompanying network graph is shown in Figure 2.

$$x_{ij} = \begin{bmatrix} - & 0 & 0 & 0 & 0 \\ 0 & - & 1 & 0 & 0 \\ 1 & 1 & - & 0 & 0 \\ 0 & 0 & 1 & - & 1 \\ 0 & 0 & 0 & 1 & - \end{bmatrix}$$

The probability of a change occurring among the ties between network members (i.e., that actor i will extend a friendship, retract an existing friendship, or make no change in his or her friendship status) is guided by the *objective function*, defined as

$$f_i(\beta, x) = \sum_k \beta_k s_{ki}(x) \tag{1}$$

where $f_i(\beta, x)$ is the value of the objective function for network changes for actor i, which is dependent on the configuration of the network x. The function $s_{ki}(x)$ represents the k number of effects entered into the model, and β_k is a vector of regression weights for each effect. In real-world observations, β_k are estimated parameters that can be subjected to significance tests, while in simulated networks, β_k may be manipulated by

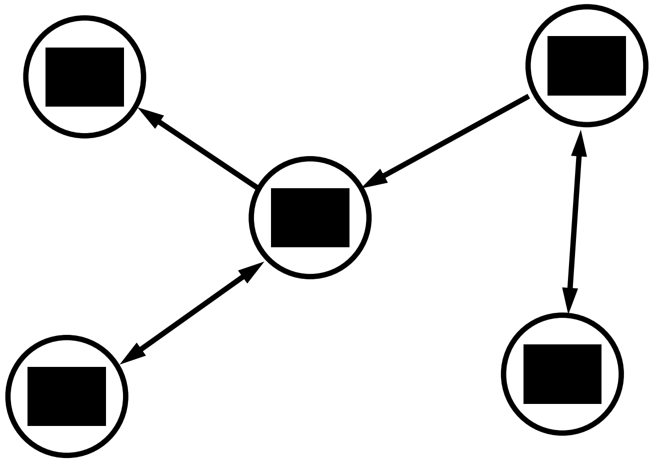


Figure 2. Example of a social network with five actors.

the researcher to test the impact of varying the magnitudes of different effects on social network behavior.

The $s_{ki}(x)$ effects in the model correspond with specific tendencies that guide the likelihood of actor i creating, eliminating, or making no change in their tie with an actor j. For example, most social networks tend to have a substantial negative *outdegree effect*, which describes the tendency not to form new ties with actors, indicating that people tend to extend a relatively small number of friendships relative to the network size. In other words, a negative outdegree effect indicates that the benefit of extending a large number of friendships typically does not exceed the cost of maintaining them. Another characteristic common in social networks is a positive *reciprocity effect*, which indicates the tendency for an actor i who is the recipient of a friendship from actor j (i.e., $j \rightarrow i$) to reciprocate friendship back to that actor ($i \rightarrow j$). The *transitive triplet effect*, also common in most networks, describes the tendency for actors to become friends with friends-of-friends ($i \rightarrow h$, given that $i \rightarrow j \rightarrow h$) more often than they become friends with far-removed actors. Many networks have a negative *three-cycle effect*, which describes the tendency for networks to avoid having cyclical tie patterns – e.g., if $i \rightarrow j$ and $j \rightarrow k$, then it is less likely that $k \rightarrow i$ (after other effects such as reciprocity and transitive triplets are accounted for). A negative three-cycle effect can be conceptualized as a form of hierarchy within a social network; when $i \rightarrow j$ and $j \rightarrow k$, actor k can be viewed as being at a higher end of the hierarchy than actor i, and it is common for higher-status actors to avoid extending ties to lower-status actors, and therefore in this case, actor k tends to avoid extending a tie to actor i.

The effects of individual-level variables (e.g., drinking status) on forming specific friendships (i.e., due to social selection) also may be modeled in many ways, for example with *similarity effects*, which indicate whether actors with certain values of a variable v are more likely to extend friendships to actors who have similar values of this variable. Similarity effects may be modeled with a categorical variable v, such as a binary indicator of drinking vs. non-drinking, or a continuous variable v, such as the typical number of drinks per day. Formulas for these effects are included below to aid with the conceptualization of their contribution to the objective function.

Outdegree effect	$s_{ki}(x) = \sum_j x_{ij}$	(2)
Reciprocity effect	$s_{ki}(x) = \sum_j x_{ij} x_{ji}$	(3)
Transitive Triplets	$s_{ki}(x) = \sum_{j,h} x_{ih} x_{ij} x_{jh}$	(4)
Three cycles	$s_{ki}(x) = \sum_{j,h} x_{ij} x_{jh} x_{hi}$	(5)
Similarity effect (for categorical variable v)	$s_{ki}(x) = \sum_j x_{ij}\ (if\ v_i = v_j)$	(6)

Snijders (2010) provides 20 additional examples of common social network effects that may be entered into a model that are not discussed here; however, any number of effects may conceivably be defined and tested, as may any number of interactions between these effects.

Quantifying SAB model dynamics. The process for simulating the evolution of social ties proceeds in several steps. First, a focal actor i in the network is chosen randomly and allowed the opportunity to make a single change in his or her social ties, creating a new tie, removing an existing tie, or making no changes. Next, the computation of relative probabilities for making each type of change is guided by the objective function in Equation 1 and the k effects in Equations 2-6. Specifically, the relative log-odds of each possible change actor i can make are computed based on the result of the objective function that would be obtained if each type of change were made to the network. The linear relative odds of each type of network change are then computed by exponentially transforming the log-odds values given by the objective function, then the proportional linear relative probabilities are computed based on the ratio of the linear relative probability divided by the sum of all linear relative probabilities. Finally, a random number determines which network change is to take place such that the likelihood of selecting each type of network change is equal to their respective proportional linear relative probabilities.

For example, for the network graph in Figure 2, we may select actor 5 as the focal actor and evaluate the objective function for all possible changes that actor 5 can make. These options include actor 5 making no change at all, removing the reciprocated tie to actor 4, or extending a tie to actors 1, 2, or 3. Suppose there are four effects modeled in the objection function, including outdegree (β_1 = -1.41), reciprocity (β_2 = 1.34), transitive triplets (β_3 = 0.97), and three cycles (β_4 = -0.32; values taken from Steglich et al., 2006), which provides the objective function

$$f_i(\beta, x') = -1.41 \sum_j x'_{ij} + 1.34 \sum_j x'_{ij} x'_{ji} + 0.97 \sum_{j,h} x'_{ih} x'_{ij} x'_{jh}$$

$$-0.32 \sum_{j,h} x'_{ij} x'_{jh} x'_{hi}$$

where x' is the network configuration that would result from any of the five networks that would result from a change (or no change) in actor 5's social ties. Consider the five options actor 5 can make and the resulting objective function values:

(a) Actor 5 could make no change in his or her personal ties, which would retain one outgoing tie, one reciprocated tie with actor 4 and provide no transitive ties or three-cycles. The objective function value for actor 5 for this resulting network would be

$$f_5(\beta, x') = -1.41(1) + 1.34(1) + 0.97(0) - 0.32(0) = -0.07.$$

(b) Actor 5 could drop the reciprocated tie with actor 4, which would lead to no outgoing ties, and thus no reciprocated ties, transitive ties, or three-cycles, giving an objective function value for actor 5 of

$$f_5(\beta, x') = -1.41(0) + 1.34(0) + 0.97(0) - 0.32(0) = 0.$$

(c) Actor 5 could extend a tie to actor 3, which would make two outgoing ties, one reciprocated tie with actor 4, one transitive triplet with actors 3 and 4, and no three-cycles, giving an objective function value of

$$f_5(\beta, x') = -1.41(2) + 1.34(1) + 0.97(1) - 0.32(0) = -0.51.$$

(d) Actor 5 could extend a tie to actor 2, which would give two outgoing ties, one reciprocated tie with actor 4, and no transitive triplets or three-cycles,

$$f_5(\beta, x') = -1.41(2) + 1.34(1) + 0.97(0) - 0.32(0) = -1.48.$$

(e) Actor 5 could extend a tie to actor 1, which would give two outgoing ties, one reciprocated tie with actor 4, and no transitive triplets or 3-cycles,

$$f_5(\beta, x') = -1.41(2) + 1.34(1) + 0.97(0) - 0.32(0) = -1.48.$$

Since the objective function values computed above provide the log odds of each possible network change, the linear relative odds may be obtained using the exponential transformation

$$e^{f(\beta, x\prime)}, \tag{7}$$

which yields the following linear relative odds for each of the five possible network configurations:

a) $e^{-0.07} = 0.932$

b) $e^{0} = 1.000$

c) $e^{-0.51} = 0.600$

d) $e^{-1.48} = 0.228$

e) $e^{-1.48} = 0.228$.

Finally, the linear relative probabilities of each type of network change may be computed as the ratio of the specific linear relative odds to the sum of all linear relative probabilities, or

$$p = \frac{e^{f(\beta,x\prime)}}{\sum_{x\prime} e^{f(\beta,x\prime)}}. \quad (8)$$

Thus, the probability of actor 5 making no change in social ties is

$$p = \frac{0.932}{0.932+1.000+0.600+0.228+0.228} = 0.312.$$

The proportional linear relative probabilities for each type of network change are shown in Table 2. The cumulative proportional linear probabilities are also shown in Table 2, which are used for selecting the specific change that actor 5 will make. For the purpose of simulating network changes as a stochastic process, the changes made to actor 5's network ties can be chosen by selecting a random number from a uniform distribution between 0 and 1 and making the network change based on the range in the cumulative distribution with which the random number falls. For example, if the random number was 0.513, then the option for actor 5 to remove a tie to actor 4 would be chosen because this falls within the cumulative probability range of 0.312 – 0.647 (see Table 2).

Quantifying SAB network dynamics with alcohol-related social selection. The previous example can be extended to incorporate alcohol-related social selection, where the probability of a focal actor extending a social tie to another actor is increased when the other actor has a similar trait level of drinking as the focal actor. Drinking levels for actor i may be coded in a vector v, where $v_i = 1$ if actor i is a heavy drinker and $v_i = 0$ if actor i is a non-drinker. For example, for the same social network graph x that is depicted in Figure 2, suppose

$$v = [1 \quad 0 \quad 1 \quad 0 \quad 1].$$

This would indicate that actors 1, 3, and 5 are heavy drinkers, and actors 2 and 4 are non-drinkers. The resulting network is shown in Figure 3 with actors who are heavy drinkers represented by bold circles.

Alcohol-related social selection may be incorporated into the network evolution process by specifying a *similarity effect* into the objective function used above in Equation 1. Suppose that the outdegree, reciprocity, transitive triplets, and three cycle effects remain in the objective function with the same coefficient values as used previously, and that the similarity effect in Equation 5 is added with a logistic regression coefficient $\beta_5 = 0.49$. The full objective function becomes

$$f_i(\beta, x') = -1.41 \sum_j x'_{ij} + 1.34 \sum_j x'_{ij} x'_{ji} + 0.97 \sum_{j,h} x'_{ih} x'_{ij} x'_{jh}$$

$$-0.32 \sum_{j,h} x'_{ij} x'_{jh} x'_{hi} + 0.49 \sum_j x'_{ij} \left(if \; v_i = v_j\right).$$

The probabilities of each possible network change are computed in the same manner as before. For example, the value of the objective function if actor 5 were to extend a social tie to actor 3, which would result in two outgoing ties, one reciprocated tie

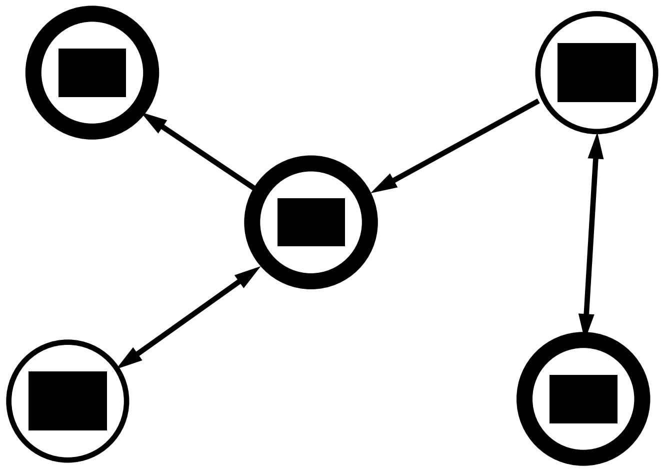


Figure 3. Example of a social network with five actors and one actor behavioral variable representing heavy drinking (bold circles) or non-drinking (normal circles).

with actor 2, one transitive triplet with actors 2 and 3, no three-cycles, and one tie with an actor with similar drinking levels, would be

$$f_5(\beta, x') = -1.41(2) + 1.34(1) + 0.97(1) - 0.32(0) + 0.49(1) = -0.02.$$

Computation of objective function values for all possible network configurations that actor 5 can change follow the same procedures as demonstrated above and are not shown here, but the resulting values, relative probabilities, and cumulative probabilities for these changes are presented in Table 3. As shown in comparing the proportional relative probabilities in Table 3 to those in Table 2, the addition of the similarity effect leads to a higher probability that actor 5 will extend a social tie to actors 1 or 3, who have similar drinking behavior as actor 5.

Quantifying behavior change due to social influence. Actor-level behavior changes may be incorporated into the network evolution in a similar manner to that by which social ties evolve. A focal actor i in the network is randomly chosen and allowed the opportunity to make a single change in his or her behavioral variable (i.e., variable v). For example, variable v may be a binary indicator indicating heavy drinking ($v_i = 1$) or non-drinking ($v_i = 0$). Next, the log odds of making each type of change are guided by the objective function for behavior change:

$$f_i^v(\beta, x, v) = \sum_k \beta_k^v \, s_{ki}^v(x, v)\,, \tag{9}$$

which states that the objective function for behavior change (with superscript v for all terms to distinguish it from the objective function for social network change) is a function of a set of s_{ki}^v effects that are determined by the modeler and the regression weights β_k^v that correspond with each effect.

Two s_{ki}^{v} effects will be considered here. First, the *linear shape* effect expresses the tendency for network members to have higher or lower values of v in general without regard to the behavior of their surrounding network members. Regression weights for this effect that are greater than zero indicate that any actor i has a higher probability of changing his or her behavior to $v_i = 1$, while values less than zero indicate that any actor has a higher probability of changing his or her behavior to $v_i = 0$. Second, the *average alter* effect expresses the tendencies for actors to adopt behaviors that are similar to the average behaviors of actors with which they have outgoing ties. These two effects are formulated as

Linear shape effect $\qquad s_{ki}^{v}(x, v) = v_i \qquad (10)$

Average alter effect $\qquad s_{ki}^{v}(x, v) = v_i\left(\sum_j x_{ij} v_j\right)/\left(\sum_j x_{ij}\right) \qquad (11)$

As with the objective function for social network changes, the objective function for behavior change can be computed for each possible behavior change that actor i could make (after v is centered about the mean), yielding the relative log-odds of each possible behavior change actor i can make. Then, the linear relative odds of each type of behavior change are computed by exponentially transforming the log-odds values, and the proportional linear relative probabilities are computed from these.

For example, actor 4 in Figure 3 could either maintain his or her status as a non-drinker ($v_4 = 0$) or change his or her status to a heavy drinker ($v_4 = 1$). Suppose the linear shape effect coefficient $\beta_1^{v} = 0$, indicating that actors have an equal probability of adopting non-drinking behavior as heavy drinking behavior (without accounting for the average alter effect), and the average alter effect $\beta_2^{v} = 3.0$, indicating that actors tend to adopt behaviors that are similar to the actors to which they extend ties. The full objective function for behavior change

$$f_i^v(\beta, x, v) = 0v_i + 3.0v_i\left(\sum_j x_{ij}v_j\right)/\left(\sum_j x_{ij}\right)$$

could be used to compute the log-scale relative probabilities of each type of change:

(a) If actor 4 retains his or her status as a non-drinker, then actor 4 maintains two ties with two actors who are also heavy drinkers. Mean-centering v produces a value for $v_i = 0.4$ if actor i is a heavy drinker and $v_i = -0.6$ if actor i is a non-drinker. The value of the objective function for actor 4 maintaining a non-drinking status ($v_4 = -0.6$) is computed as

$$f_4^v(\beta, x, v) = 0(-0.6) + 3.0(-0.6)(0.4 + 0.4)/(2) = -0.72.$$

(b) If actor 4 changes his or her status to a heavy drinker ($v_4 = 0.4$), then the value of the objective function would be

$$f_4^v(\beta, x, v) = 0(0.4) + 3.0(0.4)(0.4 + 0.4)/(2) = 0.48.$$

The relative linear odds of making either type of change can be computed using the exponential transformation

$$e^{-0.72} = 0.487 \qquad \text{(for maintaining a non-drinking status)}$$

$$e^{0.48} = 1.616 \qquad \text{(for changing to a heavy-drinking status)}$$

and the relative probabilities of making each type of change can be computed as

$$p = \frac{e^{f^v(\beta,x,v)}}{\sum_v e^{f^v(\beta,x,v)}}, \tag{12}$$

giving the relative probabilities of 0.23 for actor 4 maintaining a non-drinking status and 0.77 for actor 4 changing to a heavy-drinking status. However, note that the linear shape effect was zero in this example, and therefore the computed probability of actor 4 changing his or her status to heavy drinking would be if this value were less than zero.

For the purpose of simulating behavior change as a stochastic processes, the changes made to actor 4's network ties can be chosen by selecting a random number from a uniform distribution between 0 and 1 and making the network change based on the range in the cumulative distribution with which the random number falls. For example, if the random number was less than 0.23 then actor 4 would remain a non-drinker, and if the random number was greater than or equal to 0.23 then actor 4 would change his or her drinking status to heavy drinking.

Experimental Design

The procedures described above were used to simulate network evolution under a variety of conditions. For each combination of social influence, social selection, network size, and heavy drinking rate, 1000 networks were initialized and allowed to evolve according to the specified network effects until a steady state had been reached using the *RSiena* package in the R programming environment. Then, each network was copied and manipulated according to one or more of the individual-level manipulations described below, and again continued to evolve until a steady state was reached. Various outcome parameters were recorded at the conclusion of each simulation and retained for subsequent analysis.

Network-level parameters. The present study manipulated four network-level variables to represent different types of networks. These network-level parameters included the strength of social influence across the network (zero, medium, or high social influence), the strength of social selection across the network (zero, medium, or high social selection), the size of the networks (N = 25 or N = 100), and heavy drinking rate (HDR) of the networks (HDR = 50% or 25%). These effects are listed in Table 4 with a verbal description of the manipulated effect, the corresponding SAB network or behavior-change effect that contributes to the objective functions for network or behavior change, and the nominal values at which each effect was manipulated. The specific numeric values for some manipulated network effects were chosen based on pilot testing and were determined to create an adequate range of social influence and social selection levels based on clustering of actors by heavy drinking status.

The present study also included other network evolution parameters that were not of direct interest in relation to social influence and social selection but are typically found in real-world networks. The present simulations included constant values for reciprocity, transitivity, and three-cycle parameters, which were chosen to be similar to empirical values derived from real-world social network analyses (Steglich et al., 2006) and are shown in Table 4. The outdegree parameter, which influences the number of ties actors extend to other actors, was selected using an empirical Monte Carlo method to determine which outdegree parameter value reproduced a mean number of outgoing ties that was similar to the mean number of outgoing ties found in a large-scale real-world study of alcohol treatment-seeking adults (M = 5.53; Longabaugh et al., 2010). Specifically, 200 randomly-selected values for the outdegree parameter were chosen along a uniform distribution within each level of social influence, social selection, network size, and heavy drinking rate, and the networks were allowed to evolve freely according to the randomly-selected outdegree parameter value and the other parameters included in the network evolution objective functions. The mean number of ties was then computed for each of the resulting networks and outdegree parameter that was closest to providing 5.53 outgoing ties was retained for use in the subsequent simulations.

Individual-level manipulation. After networks were initialized (T1) and evolved until a steady state was reached (T2), several individual-level manipulations were performed on one randomly-selected heavy-drinking target actor. The networks then continued to evolve until a new steady-state was reached (T3), and outcome attributes of the target actor and the larger network were measured and analyzed.

Two classes of individual-level manipulations were performed at T2 to represent different strategies that intervention and prevention programs may use to reduce heavy drinking. The first class of these individual-level manipulations was a single *drinking status manipulation*, where a target actor's drinking status was manipulated from heavy-drinking to non-drinking without making any change in the actor's social network. The second class of these individual-level manipulations was a set of *social network manipulations*, where one attribute of the target actor's functioning within his or her social network was manipulated. The four social network manipulations are summarized in Table 5 and included (1) decreasing the target actor's susceptibility to social influence (i.e., making the target actor's drinking behavior less dependent on the behavior of other actors), (2) decreasing the target actor's susceptibility to social selection (i.e., making the target actor's friendship selection less dependent on his or her drinking status), (3) adding a social tie from the target actor to one randomly-selected non-drinking actor (i.e., increasing the number of non-drinking actors in the target actor's social network), and (4) removing an existing social tie from the target actor to one randomly-selected heavy drinker (i.e., decreasing the number of heavy drinking actors in the focal actor's social network).

Analytic Plan

Sensitivity analysis. Sensitivity analyses were conducted to test the stability of the obtained network properties (mean number of outgoing ties, heavy drinking rates) in the presence of small fluctuations in the parameters that were selected for guiding social network change. Specifically, after the values for the social influence, social selection, and outdegree parameters were chosen, a series of sensitivity simulations were conducted by adding a small amount of random variability to these parameter values by sampling from a uniform distribution with lower and upper limits of -0.01 and 0.01, respectively. Each network then evolved normally over time, and the obtained network properties were examined for systematic associations with the random fluctuations in the network parameters. If the obtained network parameters do not vary substantially when small random changes are made to the network effects, this would suggest that the network models are relatively stable to small fluctuations in the network-level effects. Alternatively, if the obtained parameters vary substantially when small random changes are made to the network-level effects (e.g., obtained parameters are vastly different when small changes are made), it would suggest that the network models are unstable to small fluctuations and are possibly chaotic. This type of unstable responding is undesirable because it suggests that small differences in parameter specifications used in the present study could produce vastly different results due to instability of the results, which would limit the degree to which the simulation results could be interpreted as being internally and externally valid.

Network-level properties. Network-level properties were examined across levels of social influence, social selection, network size, and HDR to understand the effects of these network-level manipulations on various outcomes. Network-level outcomes of interest included correlations between actor drinking and the drinking statuses of actors to whom they extend social ties, configurations of network graphs, and the distributions of outgoing ties. For each combination of social influence, social selection, network size, and heavy drinking rate, Pearson correlations were used to compute the mean correlation between the drinking statuses of actors and the mean drinking statuses of actors to whom they extended social ties as an index of clustering by drinking status. Network graphs from a representative sample of simulated networks were drawn using the R *igraph* package (Csardi & Nepusz, 2006) to show typical configurations of networks and clustering effects.

Individual-level manipulations. The effects of the individual-level manipulations across levels of social influence and social selection were tested in a series of analyses. The first set of analyses tested the effect of the drinking status manipulation vs. the control condition (manipulated at T2) on target actor heavy drinking outcomes (measured at T3). Significant differences between the status manipulation and control conditions were tested for each level of social influence, social selection, network size, and HDR using McNemar tests, which are suitable for dichotomous outcomes (e.g., heavy drinker vs. non-drinker) with paired-sample structures (due to the two conditions being copies of the same network). Subsequent logistic regression analyses were used to examine whether differences between the drinking status manipulation and control conditions were moderated by the number of ties to heavy drinkers or number of ties to non-drinkers at the time of the manipulation. To better understand the effect of the experimental condition on friendship formation, paired-sample *t*-test analyses examined whether the drinking status manipulation affected the number of outgoing ties from target actors to heavy drinkers and non-drinkers at the conclusion of the simulation (T3), relative to the control condition. Subsequent moderation analyses used linear regression to test whether these effects also were moderated by the number of ties that were present at the time of the manipulation. Last, to understand whether the drinking status manipulation affected the drinking rates of non-targeted actors, paired-sample *t*-tests were used to compare differences in heavy drinking rates at the end of the simulation (T3) among actors with social ties to the target actors (i.e., "peripheral" actors) at the time of the manipulation (T2). Peripheral actors were defined as non-targeted actors with social ties to the target actor at the time of the manipulation (T2) rather than at the conclusion of the simulation (T3) because target actors were expected to remove ties to heavy drinkers and add ties to non-drinkers after receiving the drinking status manipulation, therefore differences in ties to heavy drinking peripheral actors based on T3 ties would be expected due to social selection, rather than actual reductions in drinking of non-target actors.

This set of analyses was then repeated to examine the effects of each of the four social network manipulations compared against the control condition across levels of social influence, social selection, network size, and heavy drinking rate. Bonferroni correction (alpha level divided by four) was used to reduce type-I errors associated with having four tests of significance within each combination of network-level effects.

Due to the large volume of results, presentation of the findings in the present study is focused on describing the patterns of significance and non-significance rather than the specific findings for each comparison. Further, it was expected that the results would contain several type-I and type-II errors due to the high number of comparisons that were tested, and therefore patterns that failed to replicate across conditions were considered to be potential type-I or type-II errors, while patterns that did replicate across conditions were considered to be more robust.

Results are presented in graphical format to provide descriptive information to facilitate better understanding of the results through visualization. Significant effects are indicated in figures using asterisks to indicate levels of significance (* $p < .05$, ** $p < .01$, *** $p < .001$); significant effects also are described in corresponding sections of the text of this manuscript.

Results

Outdegree Selection

An empirical simulation method was used to select an outdegree parameter value that would result in an average of 5.53 outgoing ties for each of the three combinations of network size and drinking rates examined in the present study. Network evolution was simulated using constant reciprocity, transitivity, and three-cycle parameter values shown in Table 4, while values for the outdegree parameter varied randomly along a uniform distribution. After networks evolved according to these parameters and reached a steady state, the mean number of outgoing ties in the network was computed for each combination of network parameter values. These results are plotted in Figure 4.1 for networks of size $N = 25$ and HDR = 50%, Figure 4.2 for networks of size $N = 25$ and HDR = 25%, and Figure 4.3 for networks of size $N = 100$ and HDR = 50%.

The results in Figures 4.1 – 4.3 are presented in a 3 × 3 grid of plots such that the row and column positions within the grid indicate the level of social influence and social

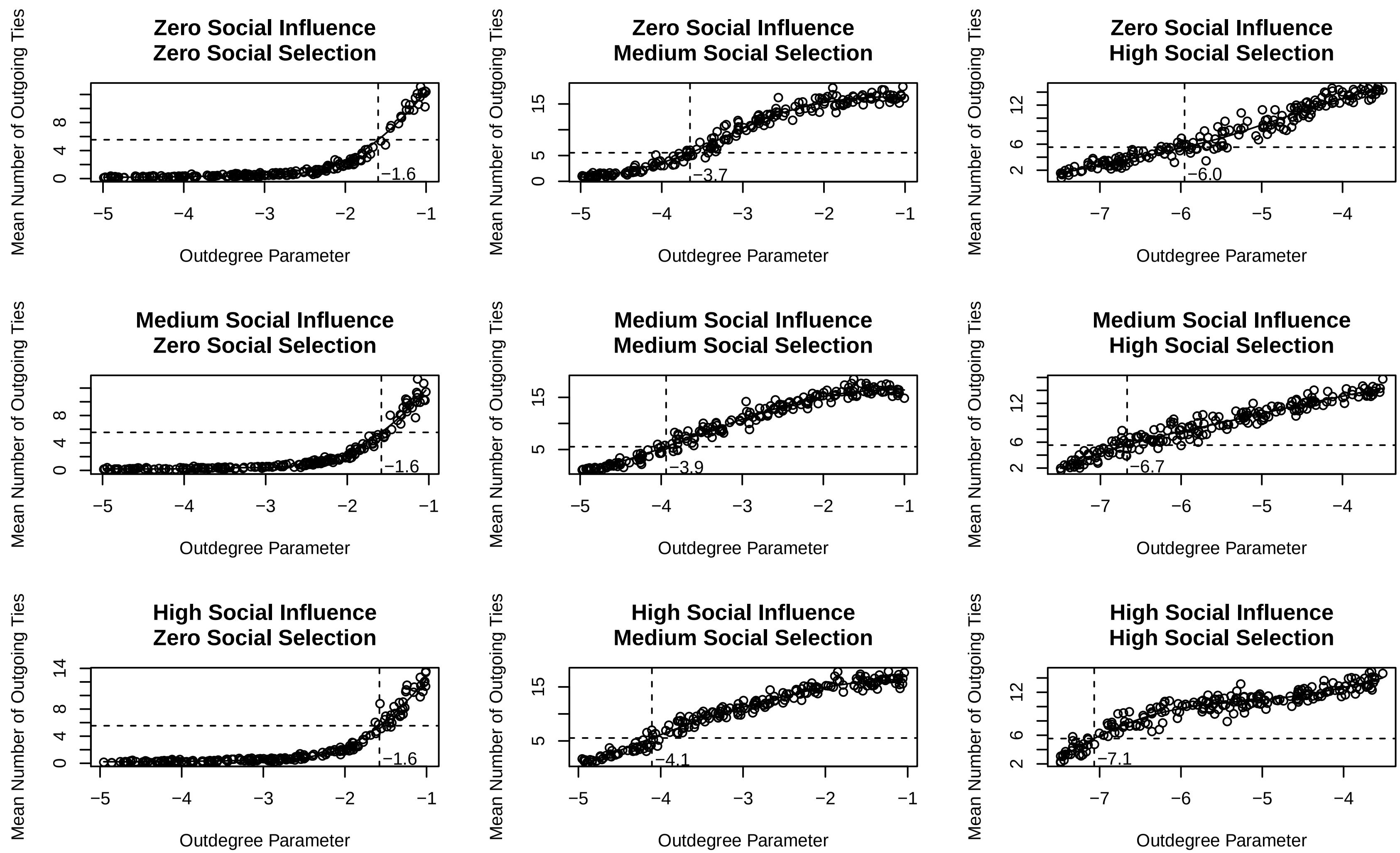


Figure 4.1: Outdegree Parameter Selection, N = 25, HDR = 50%

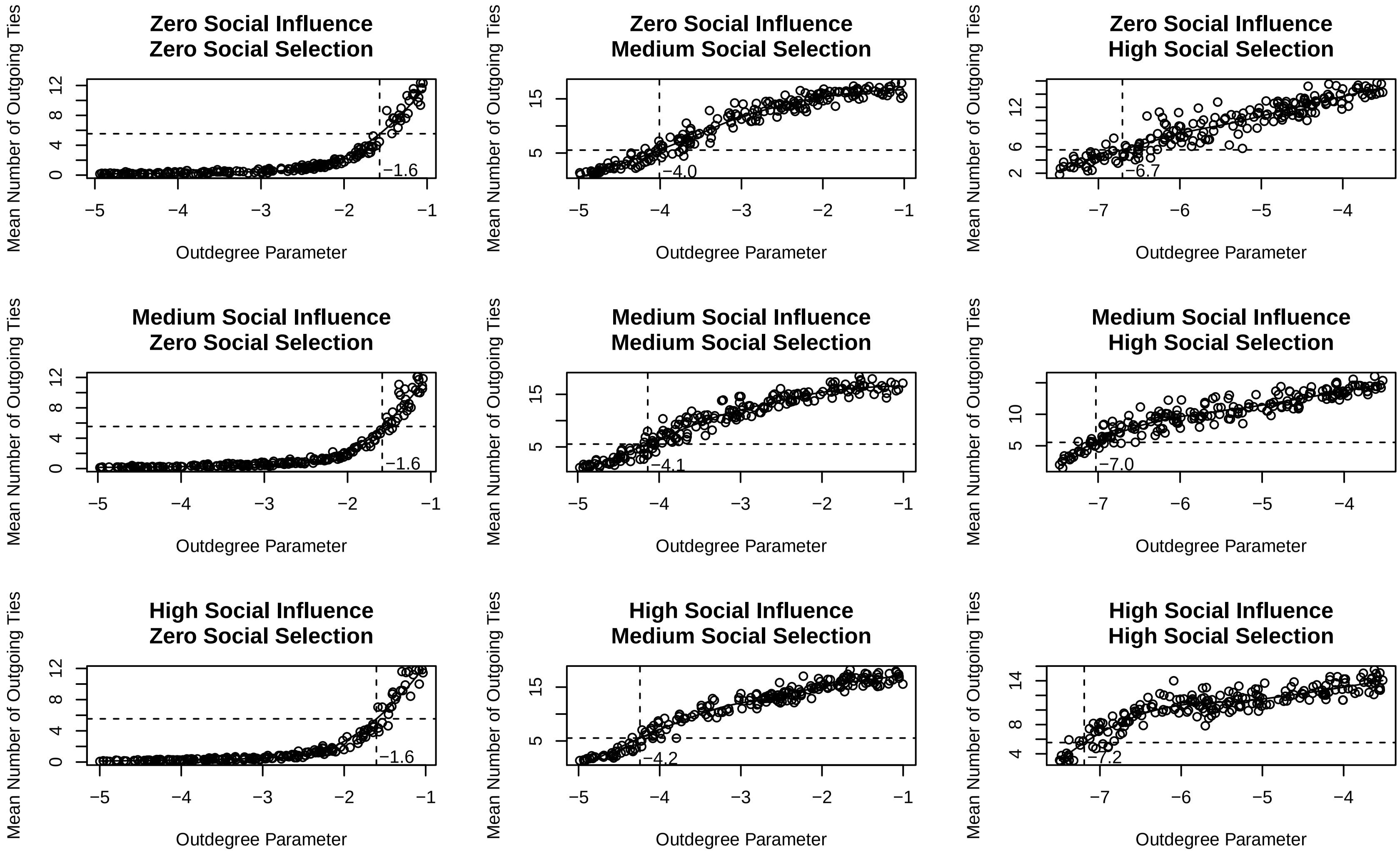


Figure 4.2: Outdegree Parameter Selection, N = 25, HDR = 25%

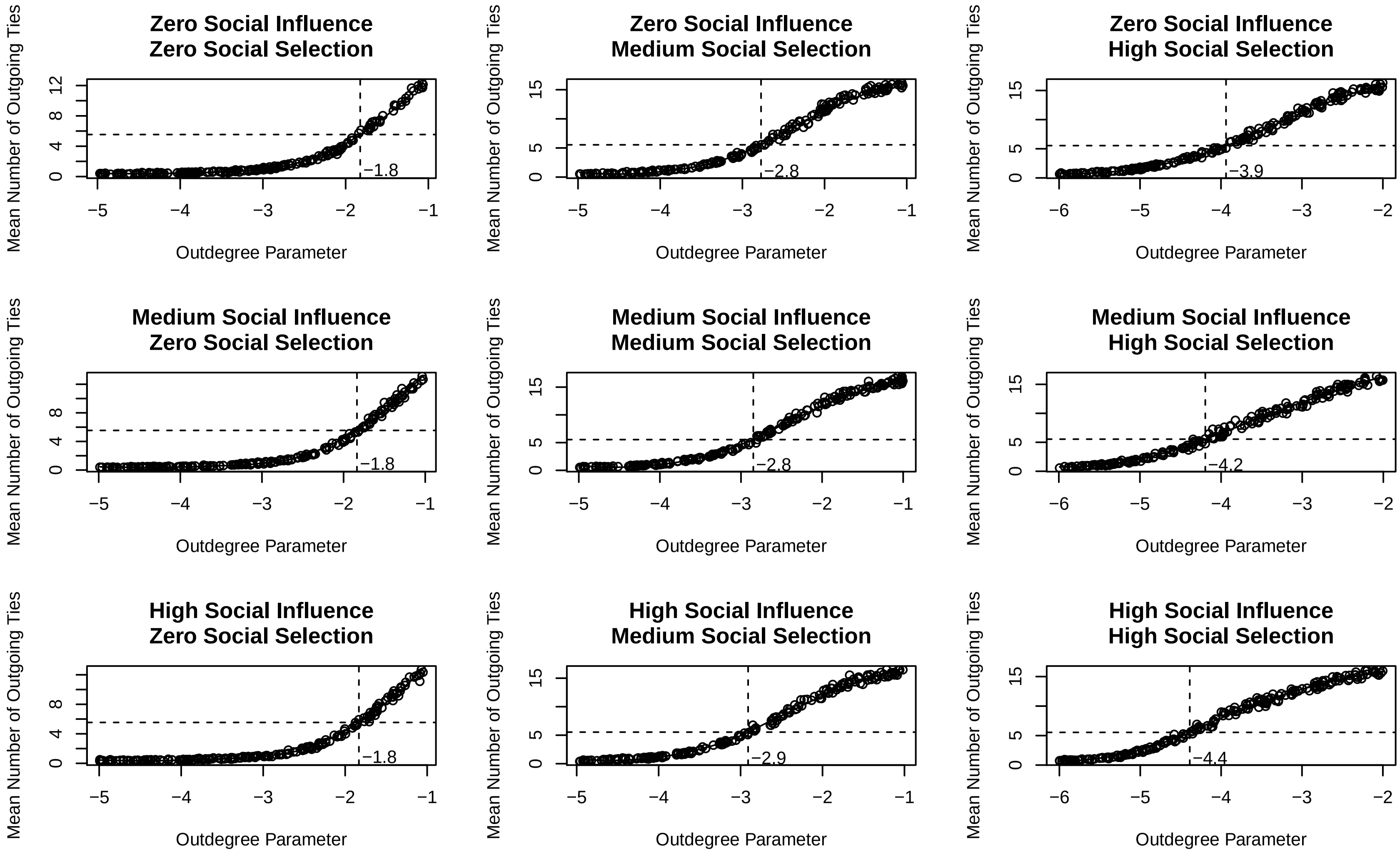


Figure 4.3: Outdegree Parameter Selection, N = 100, HDR = 50%

selection. Specifically, different values of social selection are presented based on the horizontal position of the plot, with the zero social selection conditions presented in the left columns, medium social selection presented in the center columns, and high social selection presented in the right columns. Likewise, different values of social influence are presented based on the vertical position of the plot, with the zero social influence conditions presented in the top rows, medium social influence conditions presented in the middle rows, and high social influence conditions presented in the bottom rows. Subsequent figures in this paper with 3 × 3 plot grids follow a similar convention.

Within each of the plots in Figures 4.1 – 4.3, the randomly-selected outdegree parameter values are plotted along the *x*-axis and the mean numbers of outgoing ties from the resulting networks are plotted along the *y*-axis. Polynomial regressions with local fitting were used to characterize the associations between outdegree parameter values and mean numbers of outgoing ties and are represented by the solid curves within each plot. In all cases, the mean number of outgoing ties increased monotonically as the outdegree parameter increased, as indicated by polynomial regression lines that always move up on the *y*-axis as they moves to the right on the *x*-axis. The monotonic nature of the outdegree effect allowed a single outdegree parameter to be selected that would result in a mean of 5.53 outgoing ties for a given network.

The outdegree parameter that provided a mean of 5.53 outgoing ties is shown using the crosshairs and the resulting value of the outdegree parameter that produced 5.53 outgoing ties is displayed on each plot. For example, in Figure 4.1, an outdegree parameter of -1.6 resulted in a mean of 5.53 outgoing ties in the network for all values of social influence when social selection was zero (left column). However, as similarity effects (social selection) increased (center and right columns), a stronger negative outdegree effect was required to maintain the same mean outgoing tie rate, e.g., an outdegree of -3.7 was required when the social influence was zero and the social selection was medium (top-middle plot of Figure 4.1), and an outdegree of -6.0 was required when social influence was zero and social selection was high (top-right plot of Figure 4.1). When similarity effects were greater than zero (center and right columns of plots), increasing social influence (middle and bottom rows) also required a stronger negative outdegree parameter to maintain the same number of outgoing ties. However, the effect of the outdegree parameter on outgoing ties was more strongly impacted by increases in social selection (moving horizontally across plots) than social influence effects (moving vertically across plots).

A similar pattern was found for the networks of size N = 25 and HDR = 25% (Figure 4.2) and for networks of size N = 100 and HDR = 25%. Relative to the N = 25 and HDR = 50% networks, outdegree parameters increased to a greater degree as social selection increased in the N =25 and HDR = 25% networks, but outdegree parameters increased to a smaller degree as social selection increased in the N = 25 and HDR = 50% networks.

For all three combinations of network size, HDR, and social selection, a constant value for the outdegree parameter was selected for simulating the networks in the present study (i.e., one outdegree parameter value for each column of Figures 4.1 – 4.3). Nine outdegree parameters were selected for each combination of network size, HDR, and social selection to control for the impact that these parameters had on the number of outgoing ties. Different outdegree parameters were not selected for different values of social influence (different rows in Figures 4.1-4.3) in order to retain similarity in parameter values across conditions, which reduces the likelihood of differences in outdegree parameter values being a confound in subsequent findings, and because the impact of outdegree parameter values across levels of social influence was relatively small compared to the effect of outdegree parameter values across levels of social selection. The final values for the outdegree effect values are presented in Table 4.

Sensitivity Analysis

Sensitivity analyses were conducted to assess the stability of the parameter values that were selected for subsequent simulations. The sensitivity analysis aimed to determine whether slight variations in parameter values resulted in networks with largely different properties. Problems related to sensitivity would be indicated by strong changes in the dependent variable due to small changes in the sensitivity parameter, such as sudden increases or decreases in a dependent variable or gaps in the plot when small changes in the sensitivity parameter are made. Adequate (i.e., non-problematic) sensitivity would be indicated by small or no increases in the dependent variables as the sensitivity parameters increase and random error (due to the semi-random nature of the network simulation) that does not follow a systematic pattern.

Results for the sensitivity analyses of average alter (social influence), similarity (social selection), and outdegree effects on the number of heavy drinkers are presented in Figures 5.1 – 5.3, respectively. For brevity, all three figures report the results only for a sample size of N = 25 and HDR = 50%; however, similar results were found for other network sizes and HDR values. The nine plots in each figure present the results for

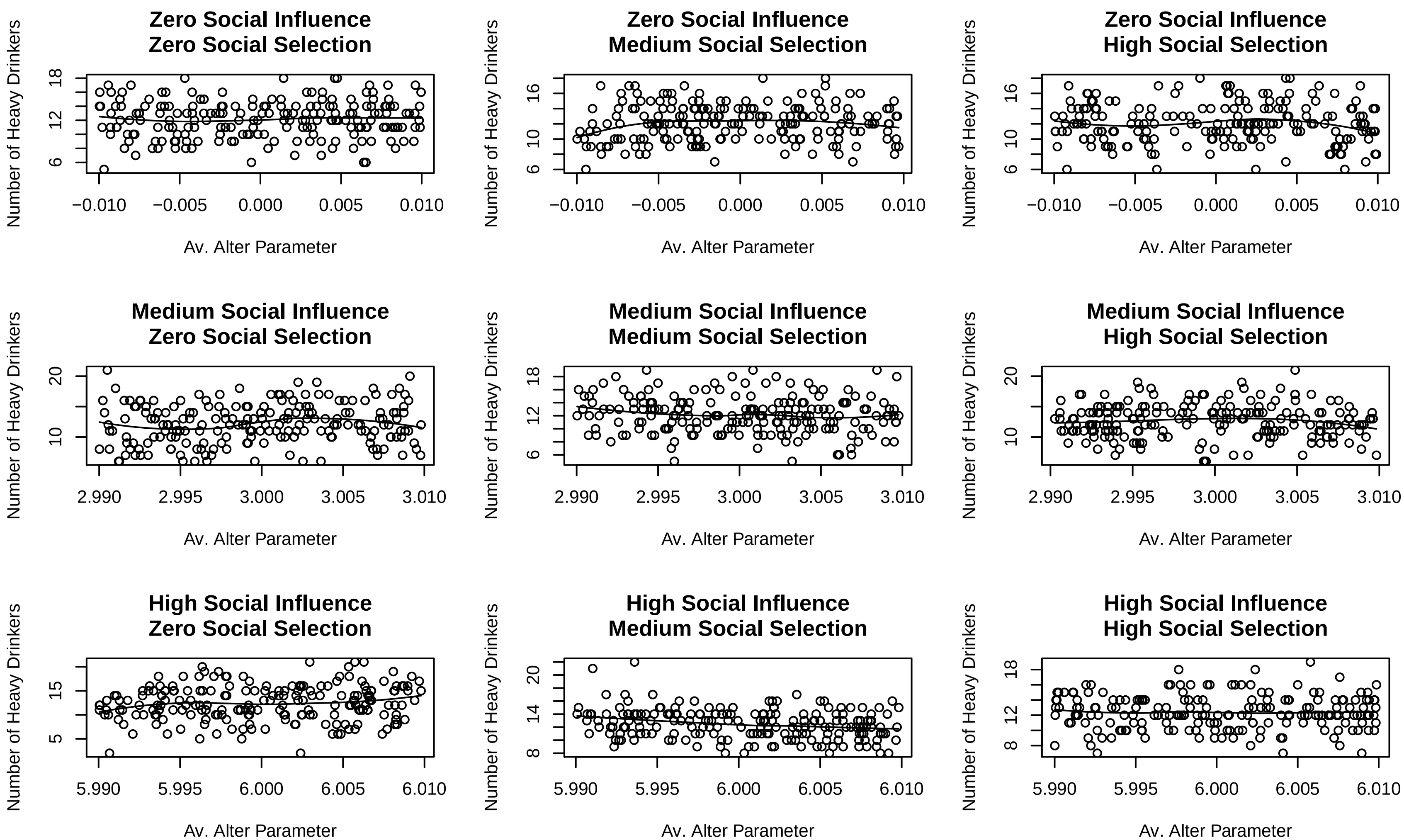


Figure 5.1: Sensitivity of Average Alter Effect on Drinking Rate, N = 25, HDR = 50%

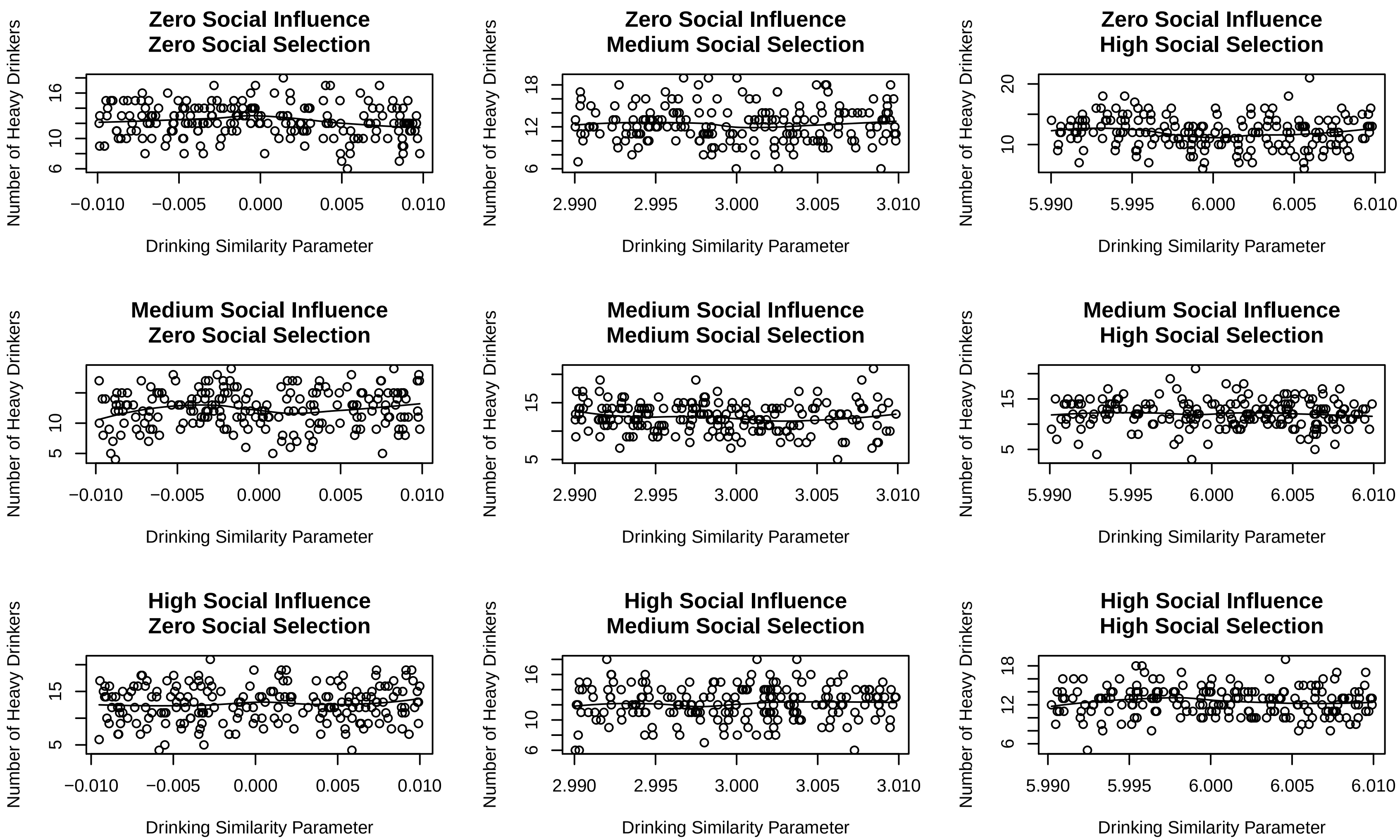


Figure 5.2: Sensitivity of Similarity Effect on Drinking Rate, N = 25, HDR = 50%

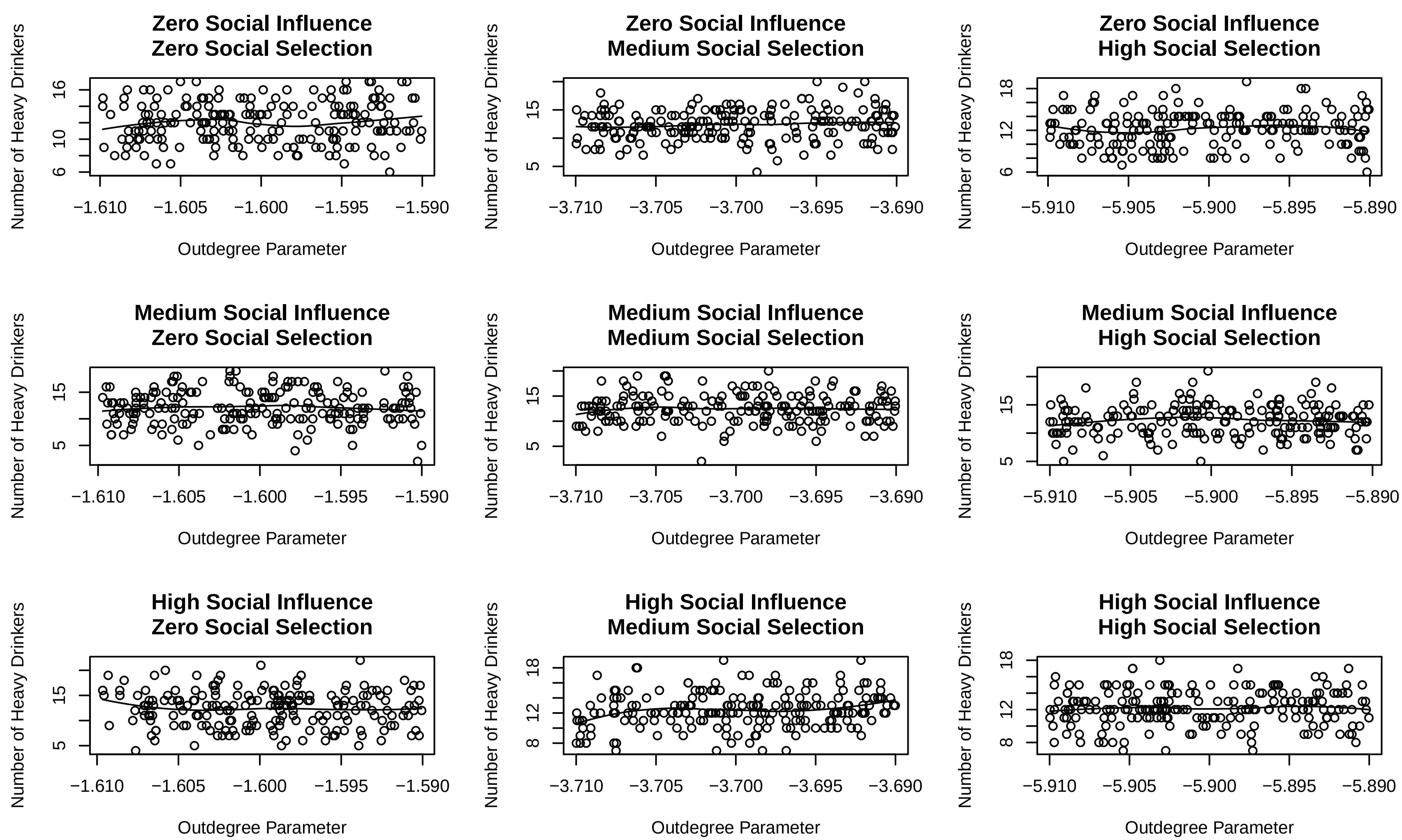


Figure 5.3: Sensitivity of Outdegree Effect on Drinking Rate, N = 25, HDR = 50%

different levels of the similarity and average alter effect conditions in the same manner as Figures 4.1 – 4.3; i.e., social selection levels vary by row and social influence levels vary by column. In all conditions, small changes in the average alter effect (Figure 5.1), similarity effect (Figure 5.2), and outdegree effect (Figure 5.3), presented on the *x*-axes, create little or no change in the number of heavy drinkers in the resulting networks, presented on the *y*-axes. Polynomial regression lines with local fitting are displayed in each plot and show that errors appear to be random and uniformly distributed about the regression lines. There are no sudden shifts or "breaking points" where small changes in a network effect produce large changes in the number of heavy drinkers, suggesting non-problematic sensitivity for these three effects on heavy drinking rates.

Similarly, results for the sensitivity analysis with the mean number of outgoing ties in the network as the dependent variable are presented in Figures 6.1 – 6.3. In all conditions, a small amount of change in the average alter effect, similarity effect, and outdegree effect create little or no change in the mean number of outgoing ties and errors are randomly and uniformly distributed, suggesting non-problematic sensitivity for these three effects on the number of heavy drinkers in the network.

Correlations between actor and network drinking.

Correlations between the drinking of actors and the mean drinking of the actors to which each actor extends a tie were examined for each combination of network parameters among the 1000 simulated control networks (i.e., networks with no individual-level manipulations). Correlations between each actor's drinking status and the mean drinking status of the actors connected to each actor were computed using bivariate Pearson correlation tests. The point estimates of the mean correlation value

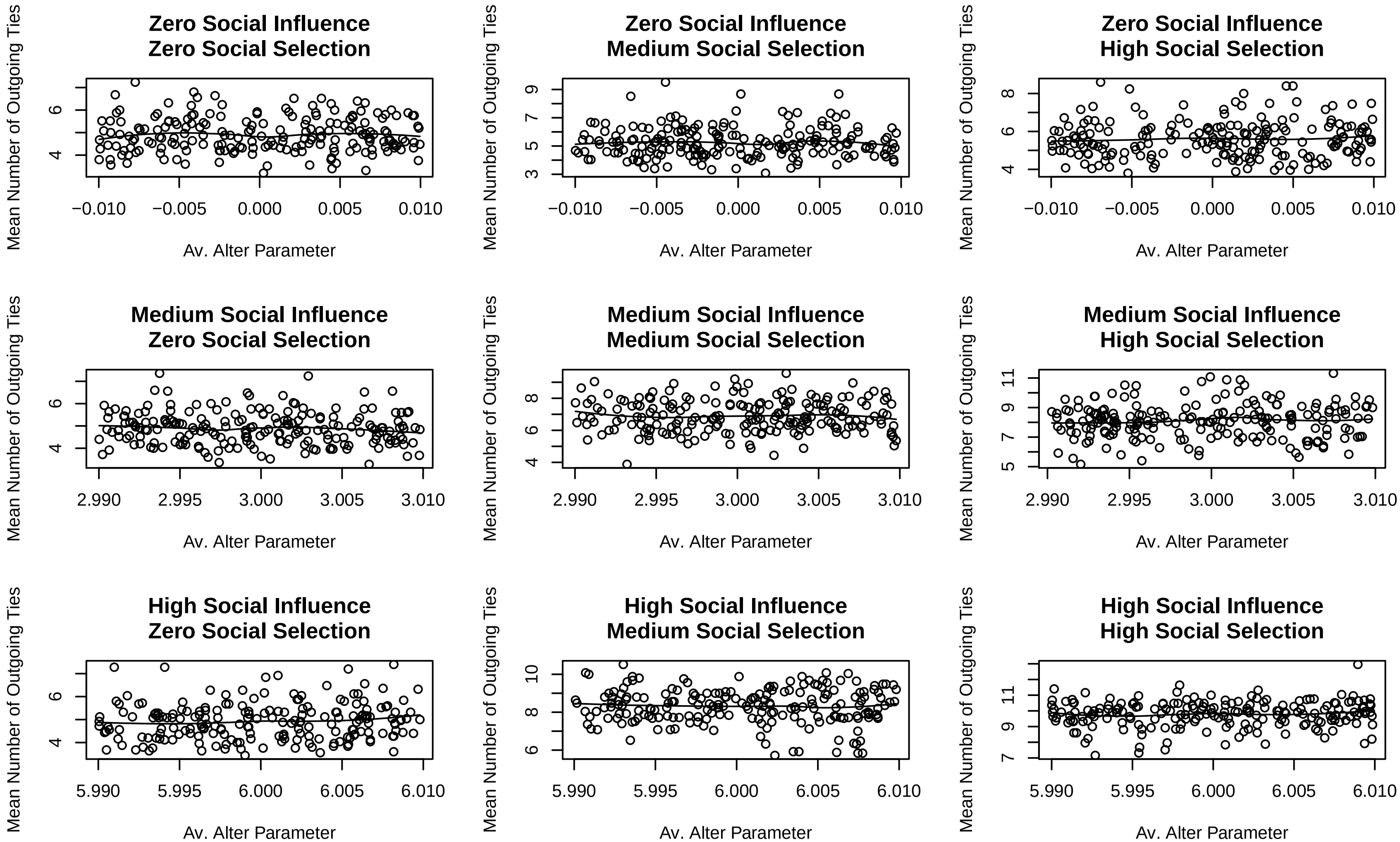


Figure 6.1: Sensitivity of Similarity Effect on Number of Ties, N = 25, HDR = 50%

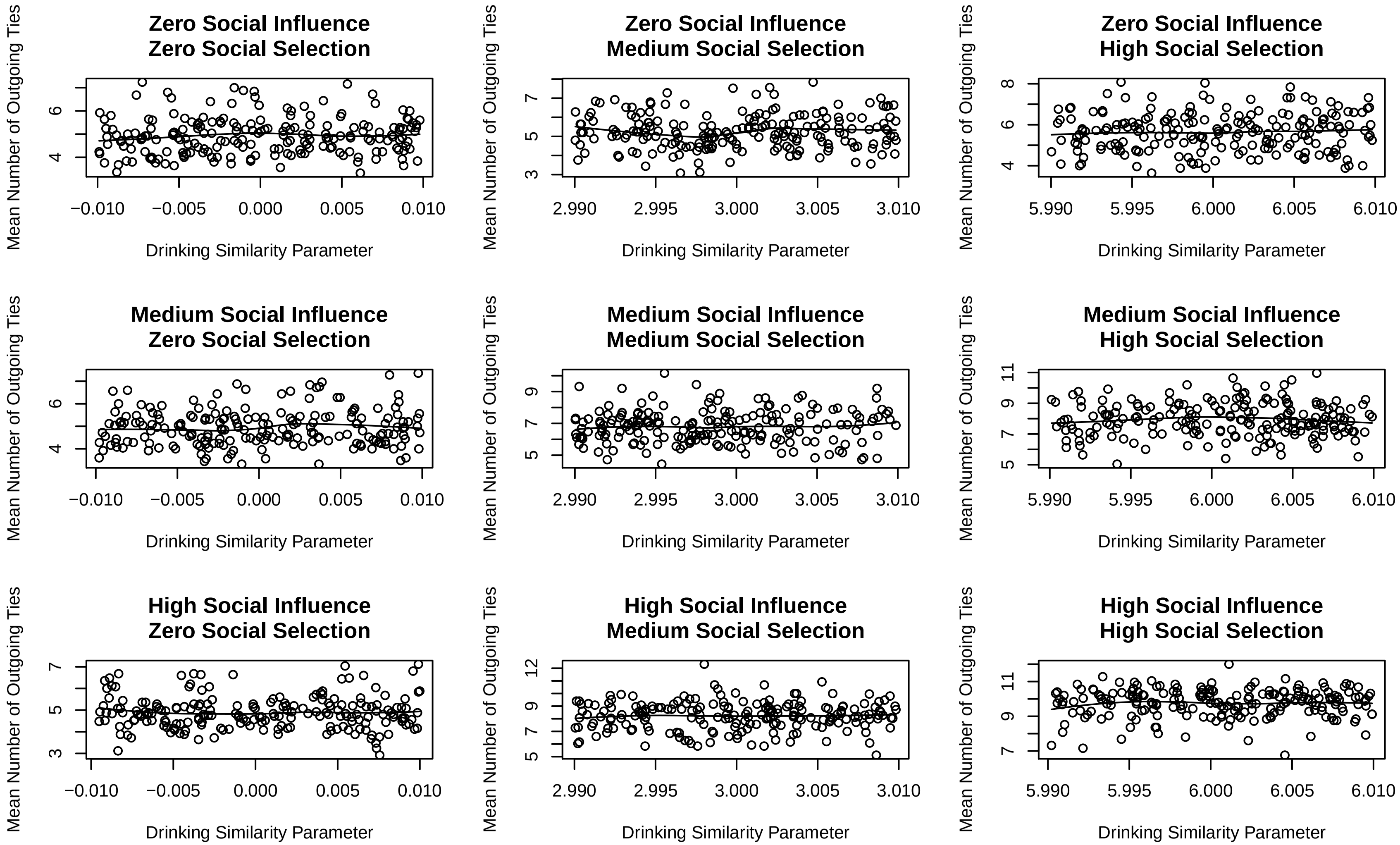


Figure 6.2: Sensitivity of Similarity Effect on Number of Ties, N = 25, HDR = 50%

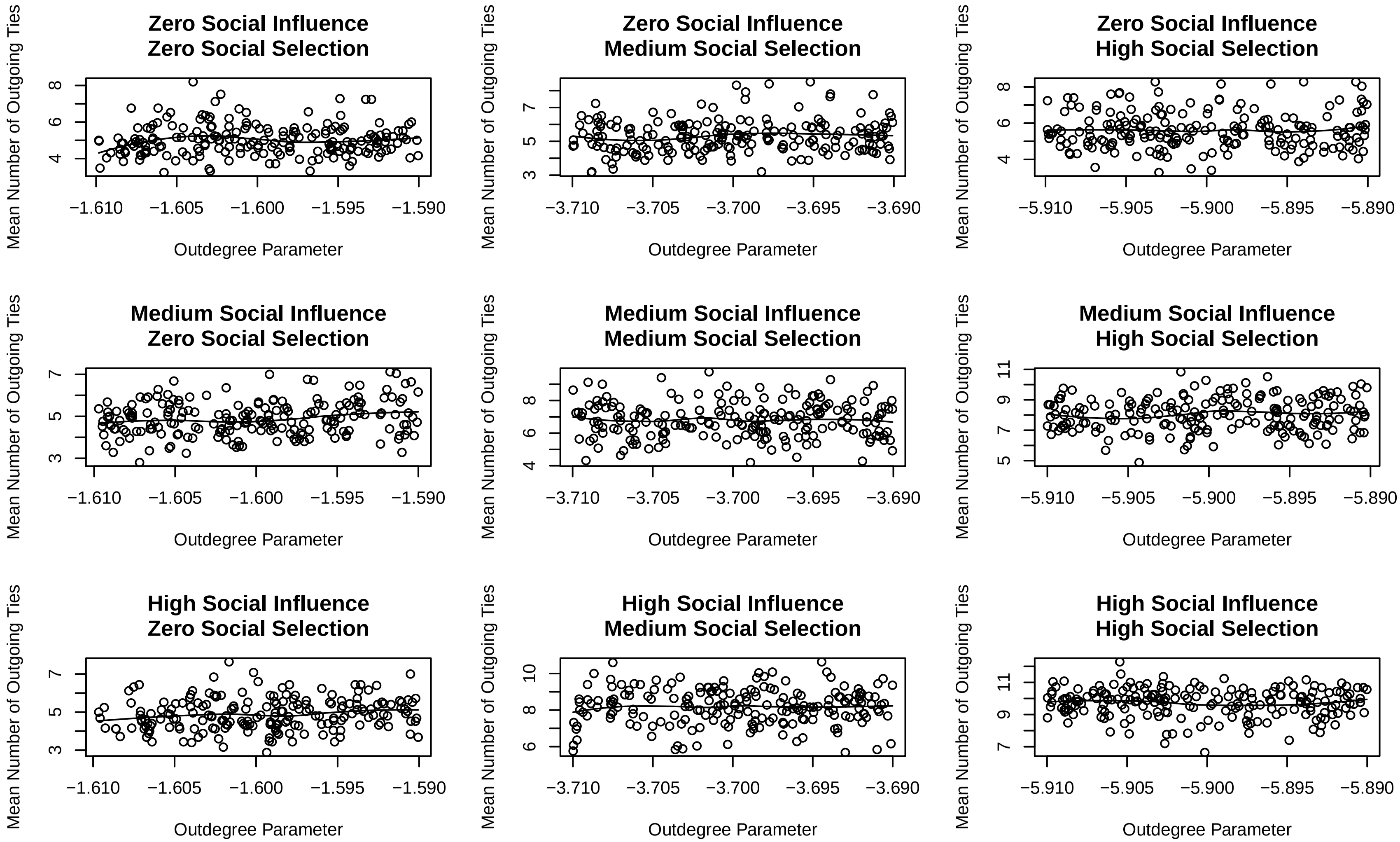


Figure 6.3: Sensitivity of Similarity Effect on Number of Ties, N = 25, HDR = 50%

within each condition are presented in Figure 7. Vertical lines represent standard deviations of the correlation point estimates based on the empirically-derived distribution of correlation values. As with previous figures, the various levels of social influence and social selection are plotted in different columns and rows of Figure 7, respectively. Within each plot, estimates for the mean correlations are presented for each combination of sample size and HDR.

As shown in Figure 7, the mean correlation between each actor's drinking status and the mean drinking status of the actors connected to each actor was slightly less than zero when no social selection and social influence were present (top-left plot of Figure 7; r = - 0.098 for the N = 25 and HDR = 50% and 25% conditions, r = - 0.02 for the N = 100 and HDR = 50% condition). Correlations increased slightly as social influence increased and social selection remained at zero (middle-left and bottom-left plots of Figure 7), e.g., producing correlations of r = 0.23, 0.25, and 0.28 for the highest level of social influence (bottom-left plot). Similarly, correlations increased slightly as social selection increased and average alter effects remained at zero (top-center and top-right plots of Figure 7), e.g., producing correlations of r = 0.12, 0.14, and 0.22 for the highest level of social selection (top-right plot). However, when both social influence and social selection were greater than zero (bottom-right, bottom-center, middle-right, and middle-center plots of Figure 7), correlations were substantially larger; e.g., r = 0.48, 0.57, and 0.52 when social influence and social selection were both medium (middle-center plot), and r = 0.81, 0.86, and 0.88 when social influence and social selection were both high (bottom-right plot).

Linear increases in social influence caused linear increases in correlation values, while linear increases in social selection caused non-linear increases in correlation values.

Figure 7: Correlations Between Individual and Peer Drinking

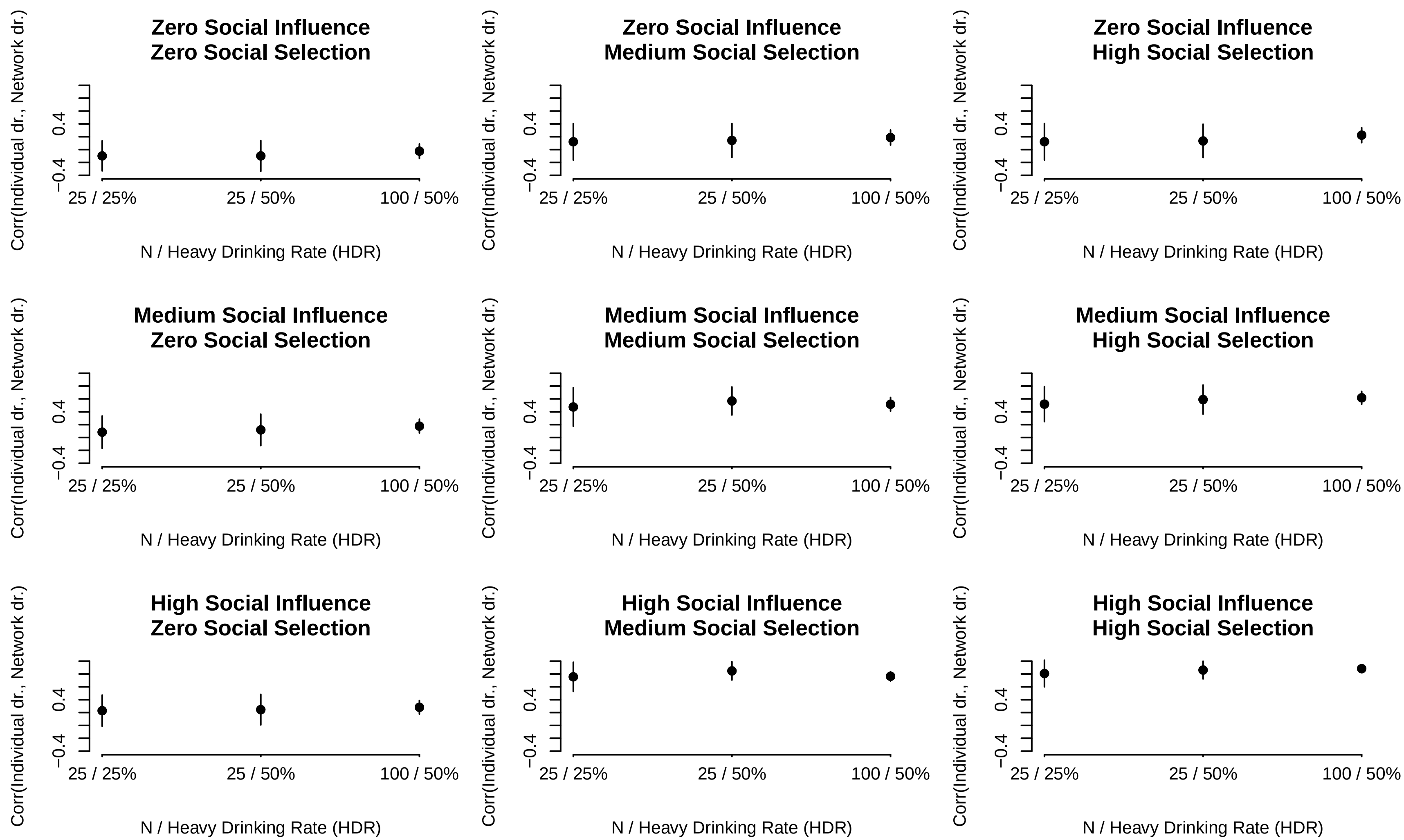


Figure 7: Correlations Between Individual and Peer Drinking

For example, increases in social influence from zero to medium (e.g., average alter parameter values of 0 and 3 when N = 25) corresponded with increases in correlation values when social selection was positive, and further increases in social influence from medium to high (e.g., average alter parameter values of 3 and 6 when N = 25) corresponded with increases in correlation values of a comparable magnitude. Alternatively, moving from zero to medium social selection (e.g., similarity parameter values of 0 and 3 when N = 25) created large increases correlation values when social influence was positive, but further increases from medium to high social selection (e.g., similarity parameter values of 3 and 6 when N = 25) did not cause a similar amount of increase. To assist with visualizing this non-linear effect, correlation values are presented using three-dimensional bar plots in Figures 8.1-8.3, which show the mean correlation values (*z*-axis, height of the vertical bars) based on the level of social influence and social selection (*x*- and *y*-axes). In Figures 8.1-8.3, it can be seen that increases in social influence correspond with linear increases in correlations, while increases in social selection from zero to medium correspond with an increase in correlations but increases in social selection from medium to high correspond with little or no increase in correlations.

Together, these results indicate that there was only a modest amount of clustering (i.e., drinking status correlating with the drinking status of actors one extends social ties to) when only social influence or social selection were present but both effects were not simultaneously present. Clustering increased substantially when both effects were present. Further, high social influence and medium or high social selection acting simultaneously produced the largest correlations, indicating the largest amount of

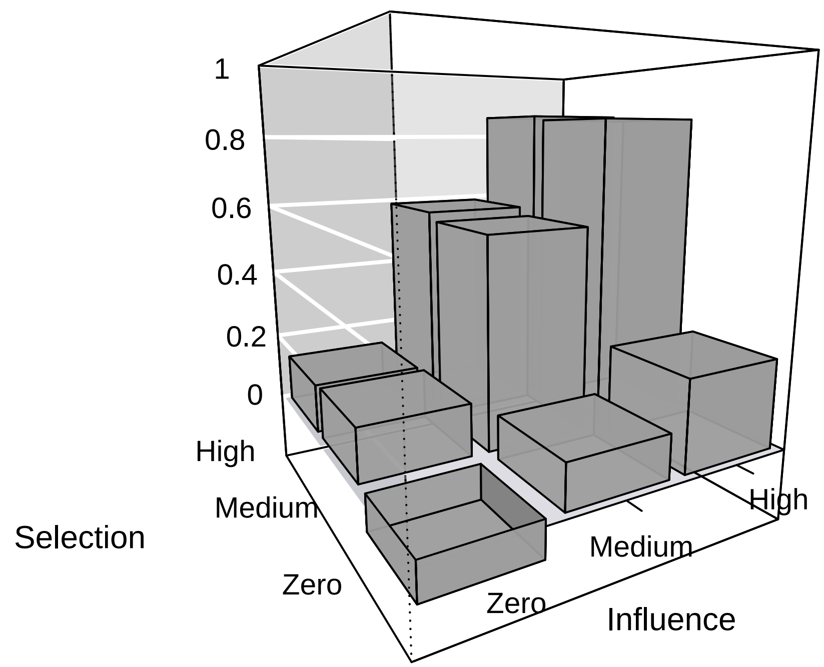


Figure 8.1: Correlations Between Individual and Peer Drinking, N = 25, HDR = 50%

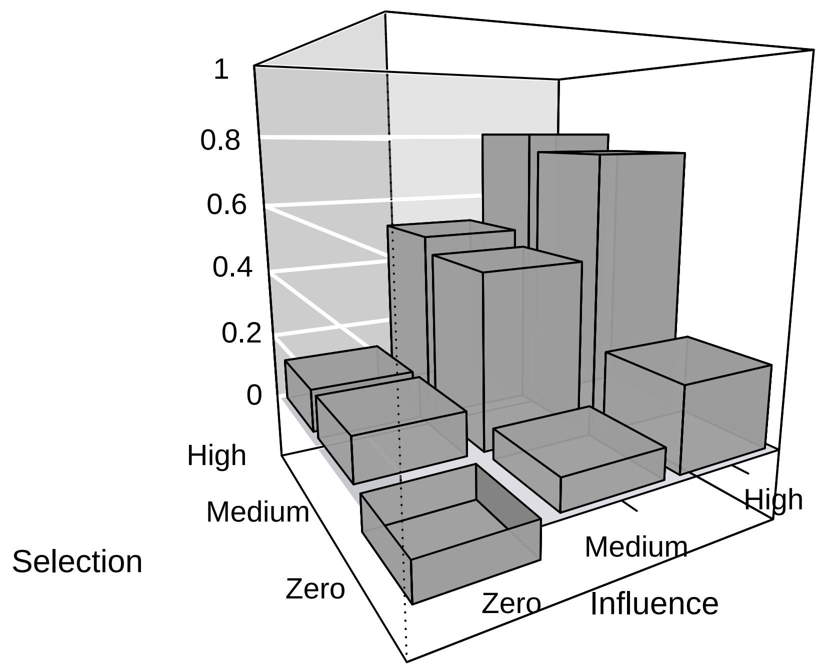


Figure 8.2: Correlations Between Individual and Peer Drinking, N = 25, HDR = 25%

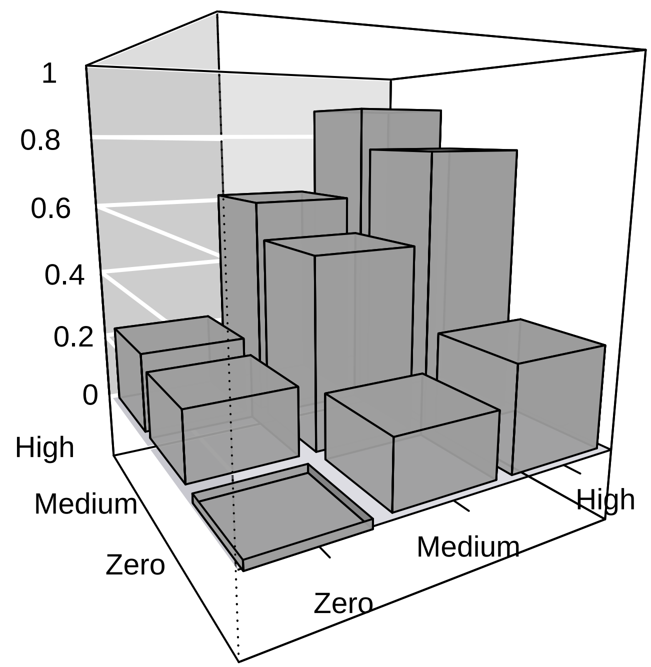


Figure 8.3: Correlations Between Individual and Peer Drinking, N = 100, HDR = 50%

clustering by drinking status. Although correlations as high as 0.88 are typically unlikely to occur in real-world networks, networks with high social influence and high social selection are useful within the present study to understand how networks may operate under exaggerated circumstances of very high clustering by drinking status.

Example network graphs with N = 25 and HDR = 50% are plotted in Figures 9.1-9.5. Figure 9.1 displays an example network graph with zero social influence and zero social selection, Figure 9.2 displays an example network graph with zero social influence and medium social selection, Figure 9.3 displays an example network graph with medium social influence and zero social selection, Figure 9.4 displays an example network graph with medium social influence and medium social selection, and Figure 9.5 displays an example network graph with high social influence and high social selection. Figures 9.6 – 9.10 display example networks with the same combinations of social influence and social selection with N = 100 to illustrate networks with a larger network size. Heavy drinking actors in Figures 9.1 – 9.10 are represented as black circles, non-drinking actors are presented as white circles, and ties between actors are presented as arrows. The correlation between each actor's drinking status and the mean drinking status of the actors connected to each actor for these example networks are displayed on each figure. Figures 9.1 – 9.10 represent typical networks from their respective conditions and demonstrate the varying degrees of clustering by drinking status, with higher Pearson correlations indicating higher clustering. For example, in Figures 9.1 and 9.6 (zero social influence and zero social selection), there appears to be minimal clustering by drinking status, in Figures 9.4 and 9.9 (medium social influence, medium social selection) there appears to be substantial clustering by drinking status, and in Figures 9.5 and 9.10 (high

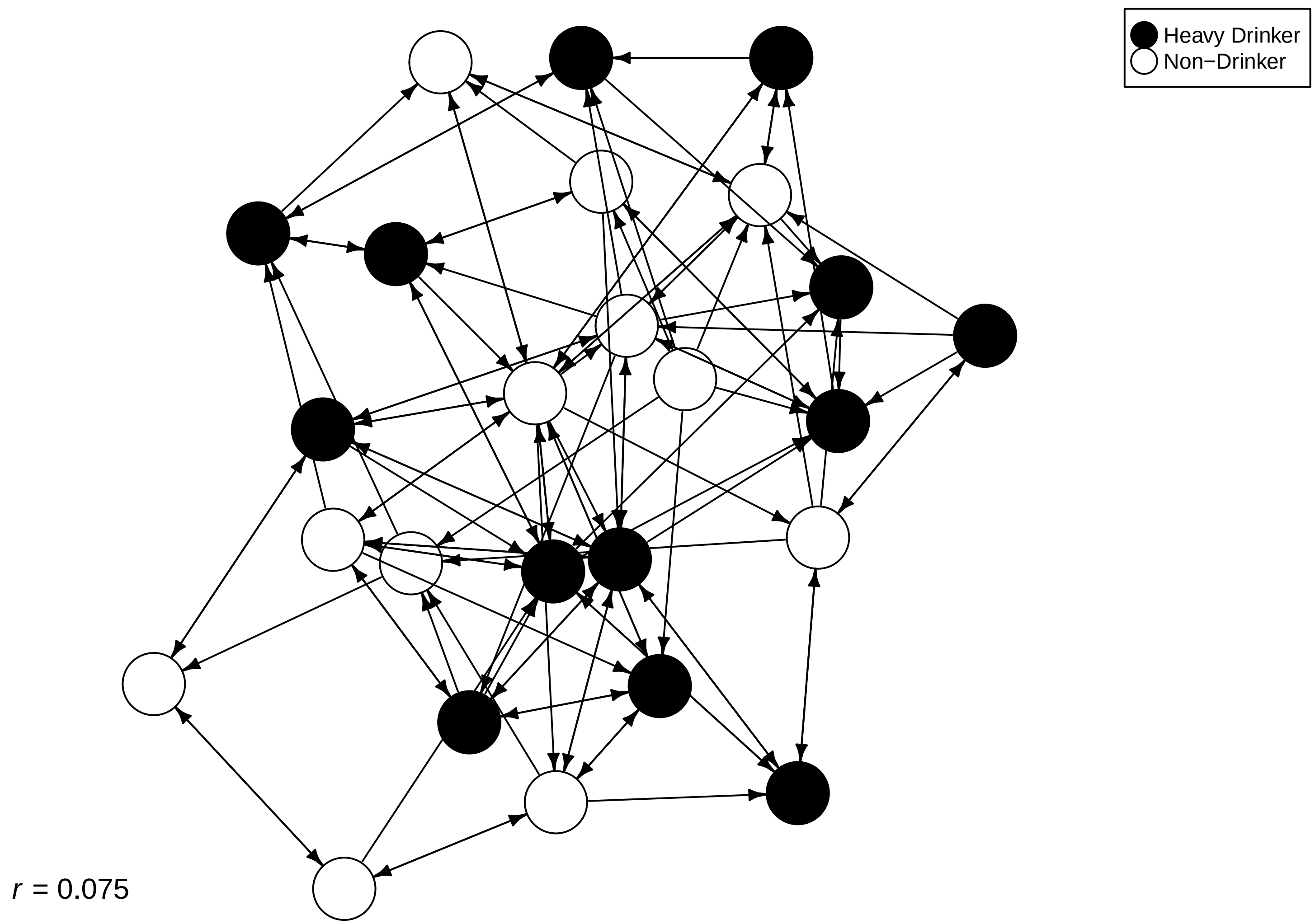


Figure 9.1: Example Network Zero Social Influence Zero Social Selection, N = 25, HDR = 50%

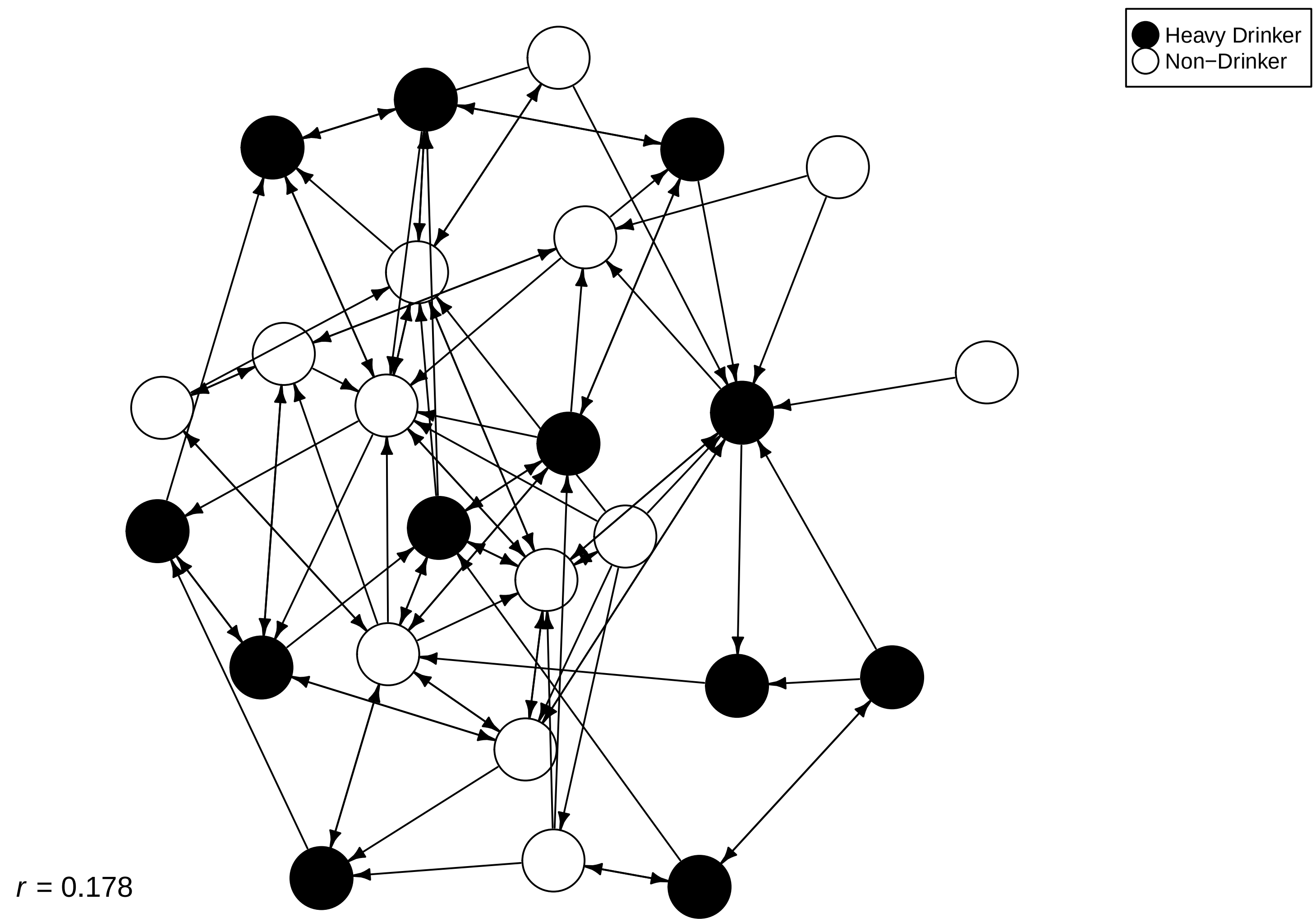
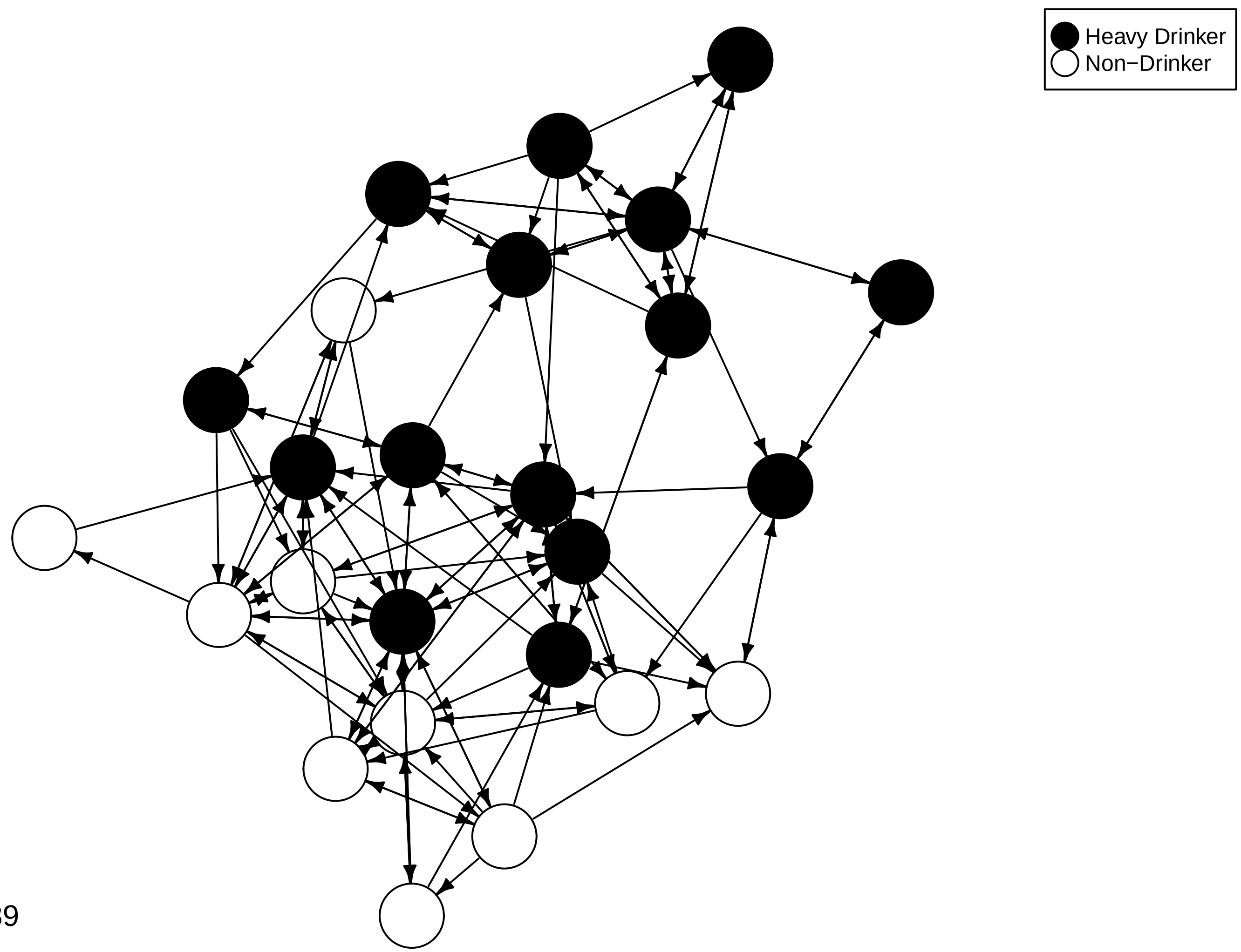


Figure 9.2: Example Network Medium Social Influence Zero Social Selection, N = 25, HDR = 50%



r = 0.189

Figure 9.3: Example Network Zero Social Influence Medium Social Selection, N = 25, HDR = 50%

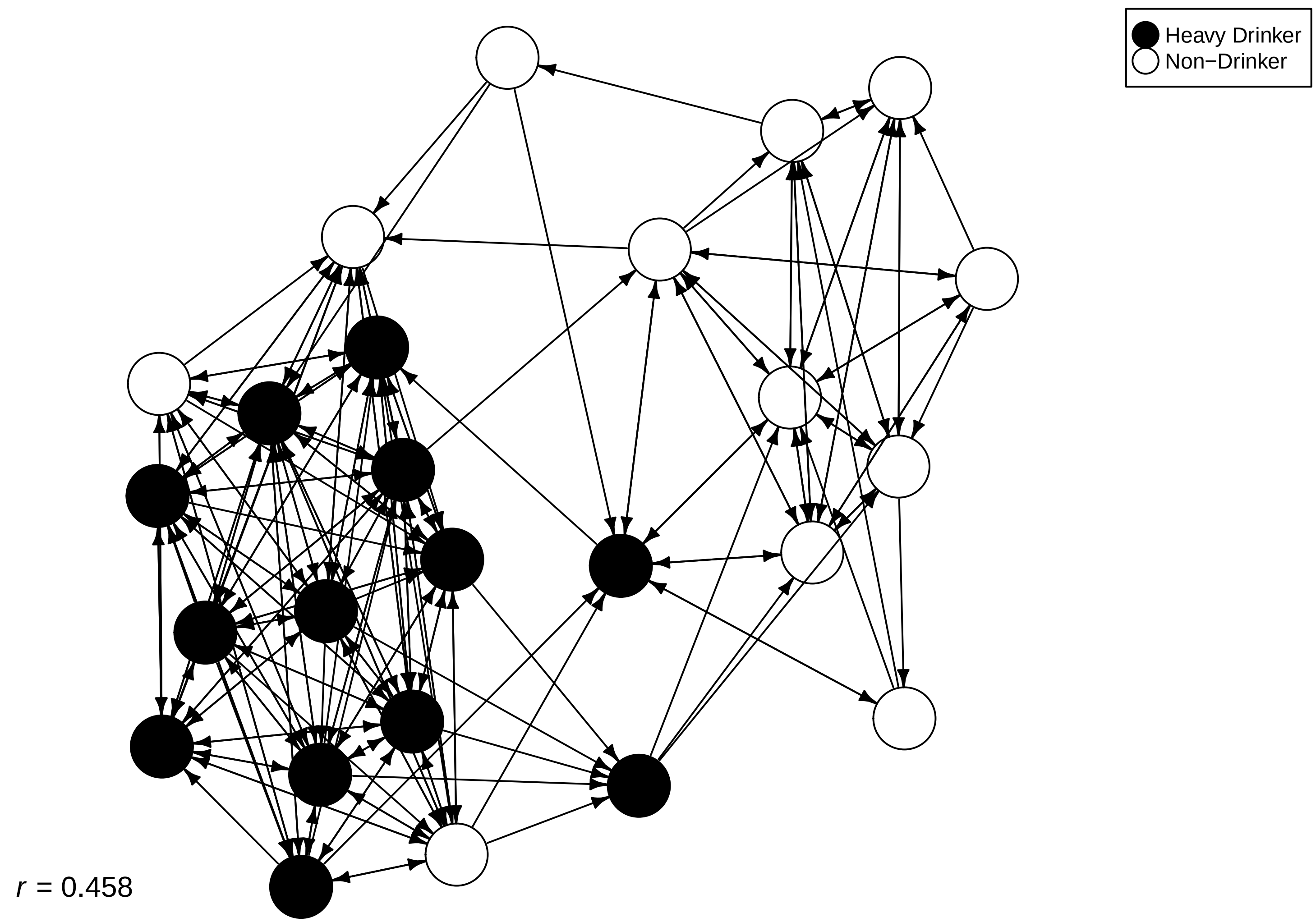


Figure 9.4: Example Network Medium Social Influence Medium Social Selection, N = 25, HDR = 50%

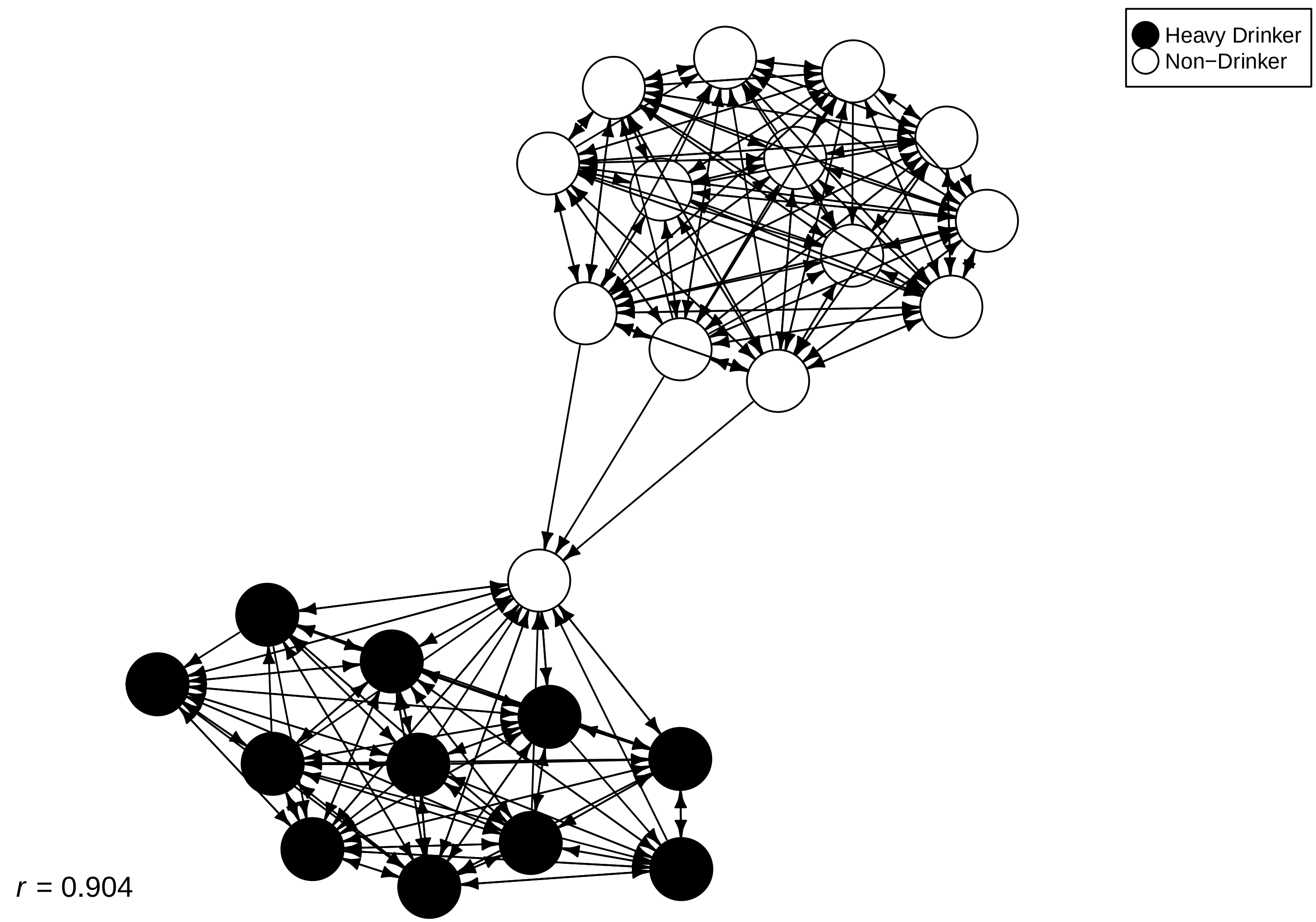


Figure 9.5: Example Network High Social Influence High Social Selection, N = 25, HDR = 50%

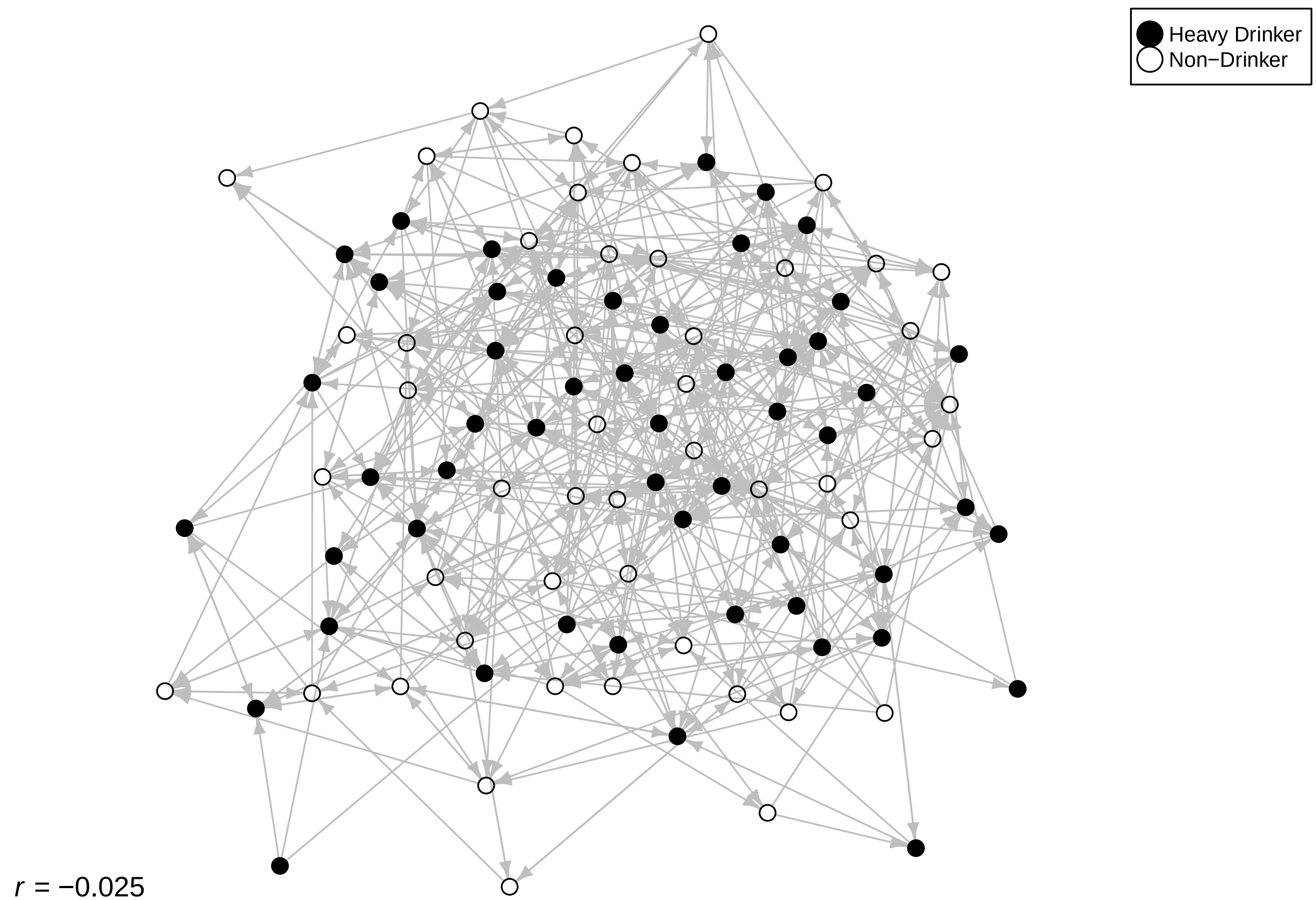


Figure 9.6: Example Network Zero Social Influence Zero Social Selection, N = 100, HDR = 50%

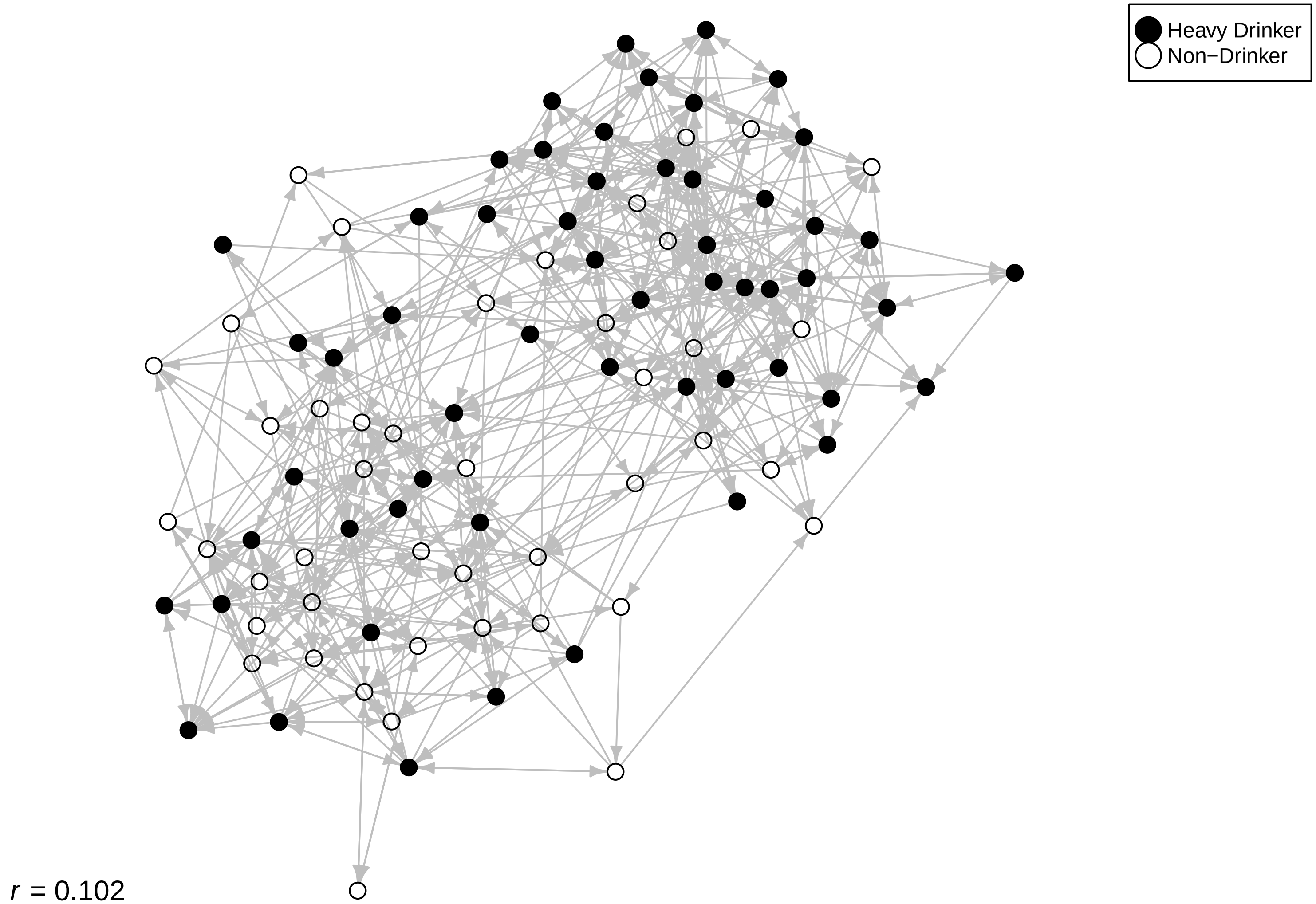


Figure 9.7: Example Network Medium Social Influence Zero Social Selection, N = 100, HDR = 50%

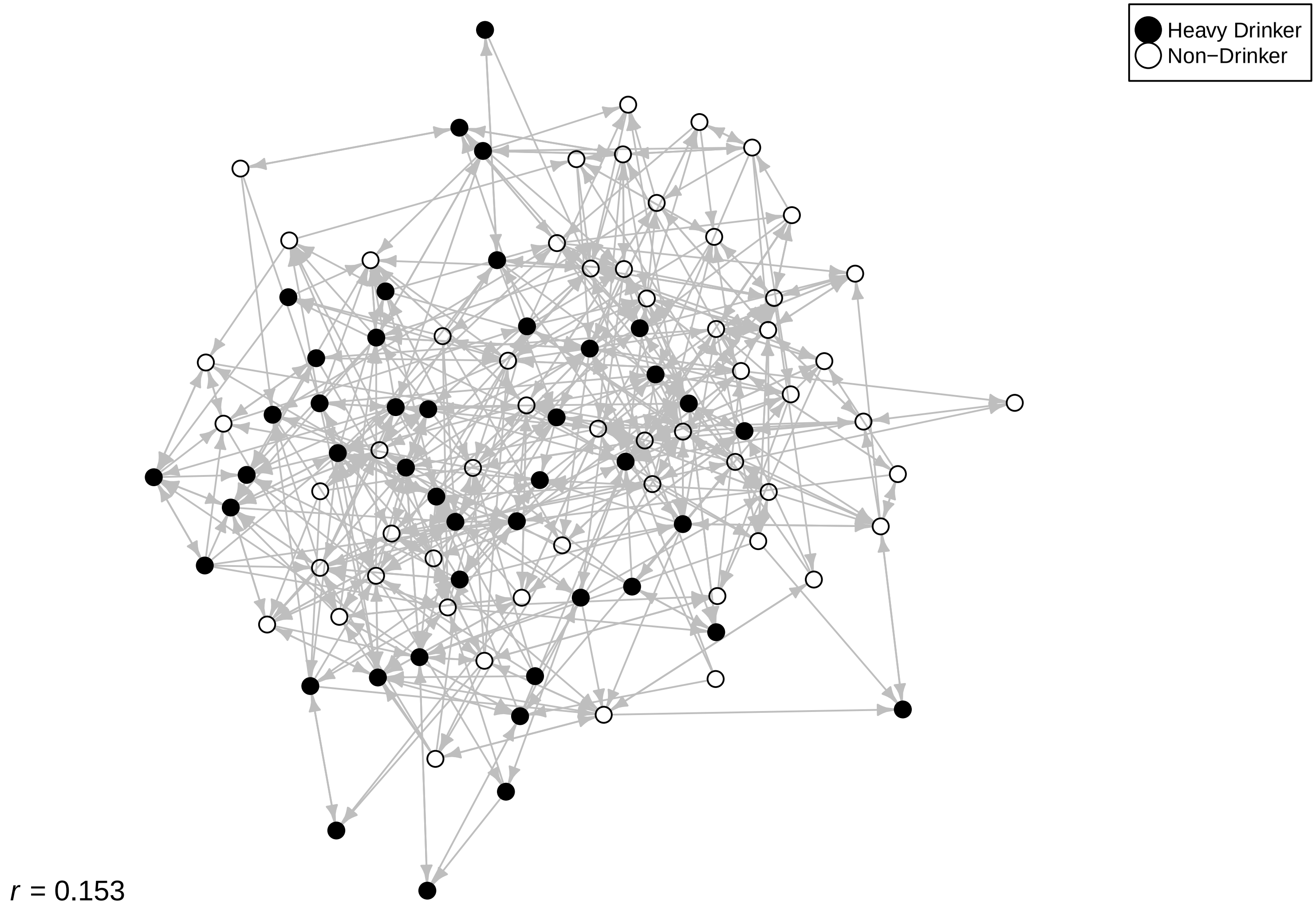
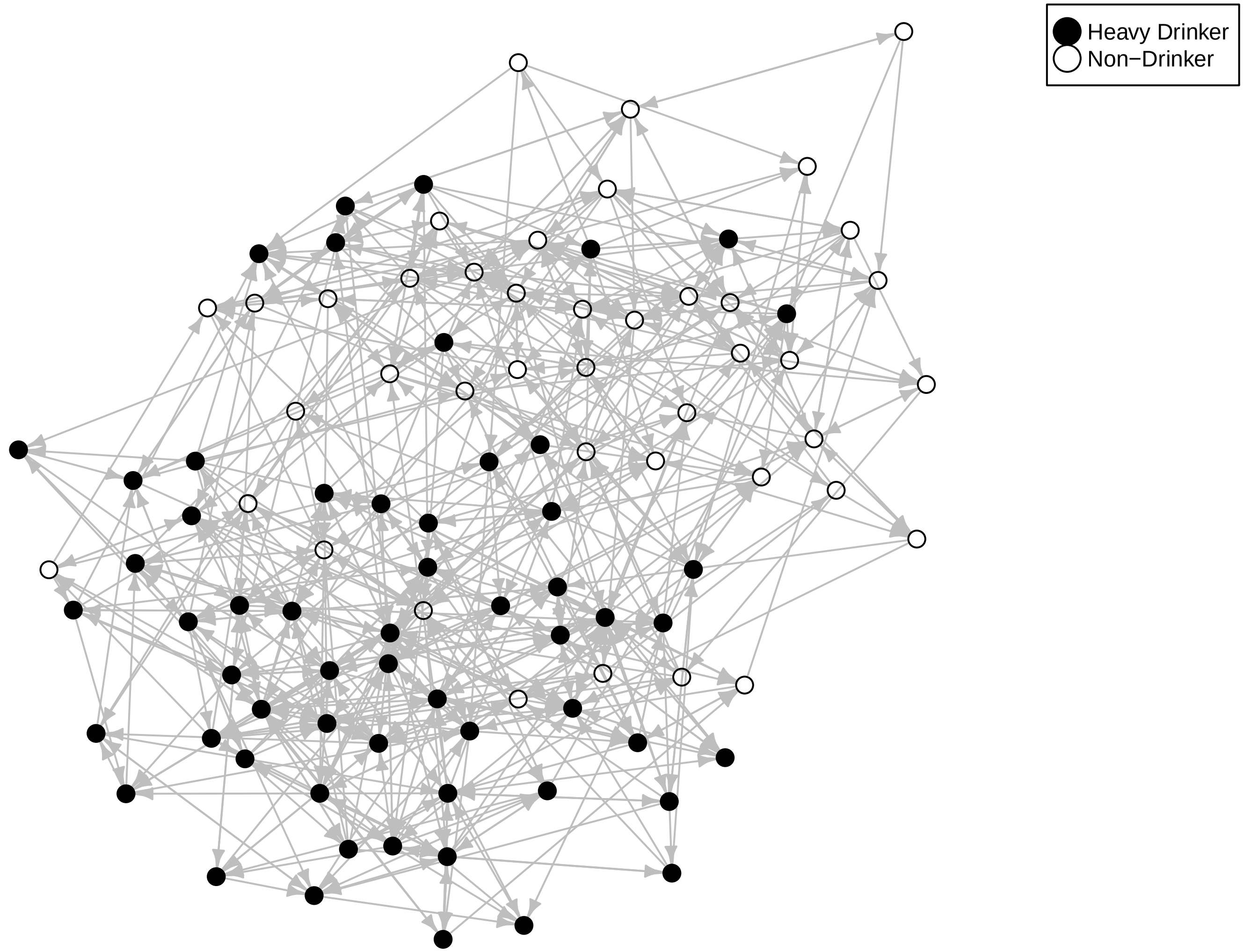


Figure 9.8: Example Network Zero Social Influence Medium Social Selection, N = 100, HDR = 50%



r = 0.546

Figure 9.9: Example Network Medium Social Influence Medium Social Selection, N = 100, HDR = 50%

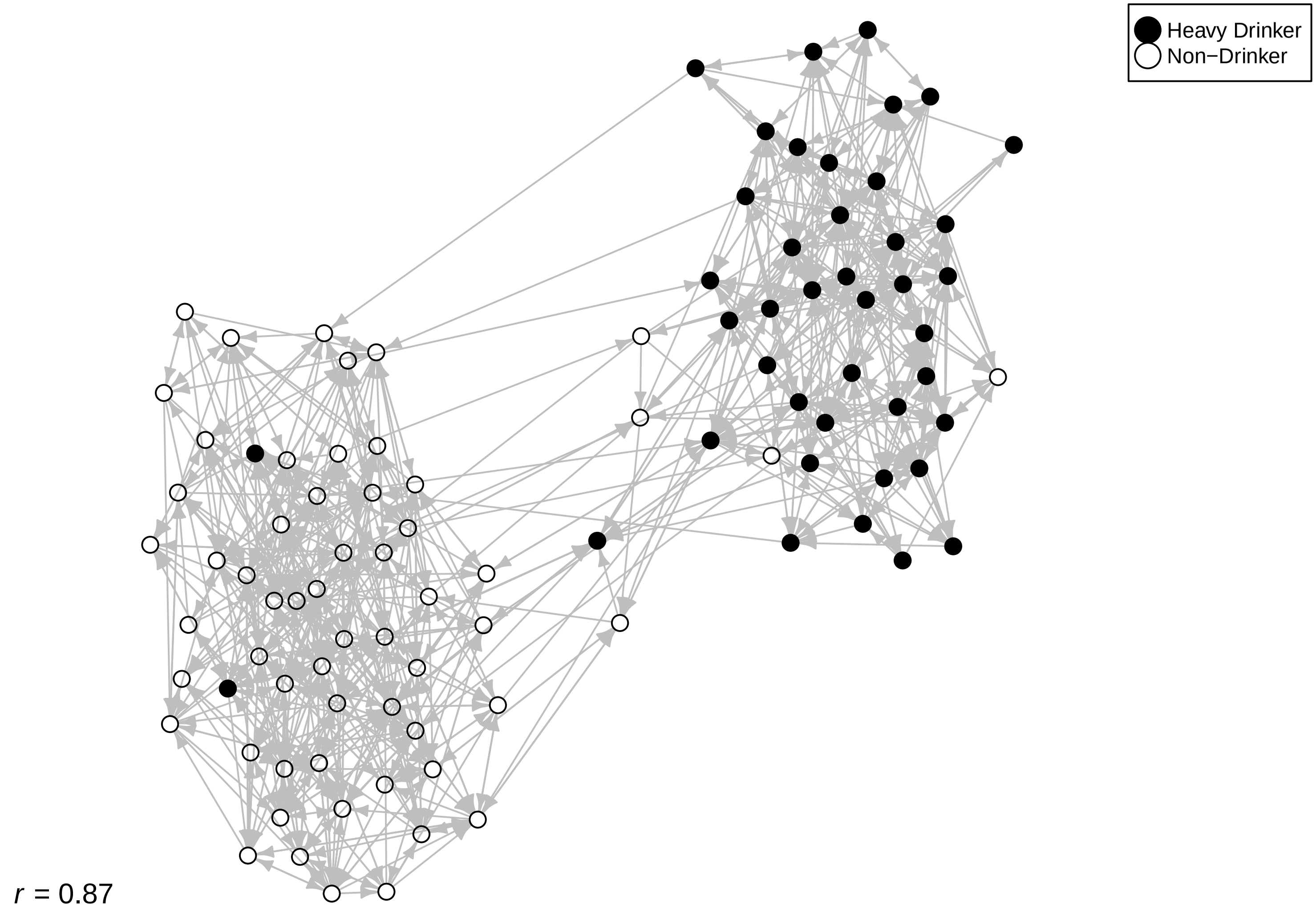


Figure 9.10: Example Network High Social Influence High Social Selection, N = 100, HDR = 50%

social influence, high social selection) clusters are almost entirely based on drinking status, for example, with one non-drinking actor serving as the sole bridge between dense heavy drinking and non-drinking clusters in Figure 9.5.

Drinking Status Manipulation

The manipulation of changing the drinking status of a randomly-selected heavy drinker was examined to understand how relapse rates may vary across levels of social influence and social selection and to understand how these effects may influence friendship ties and other actors' drinking behavior. Specifically, the results below examine (a) how the drinking status manipulation affected target actors' drinking over time relative to controls, (b) whether the effect of this manipulation of target actor drinking over time was moderated by the number of friendships to heavy drinking and non-drinking actors at the time of the intervention, (c) the effect of the drinking status manipulation on how target actors extend friendships to other heavy drinking and non-drinking actors, (d) whether this effect of the manipulation on ties to heavy drinkers and non-drinkers was moderated by the number of friendships to heavy drinkers and non-drinkers at the time of the intervention, and (e) whether the drinking status manipulation affected the drinking statuses of other actors who were not targeted for intervention.

Status manipulation and target actor drinking outcomes. The effects of the drinking status manipulation on target actor heavy drinking rates at T3 (i.e., at the conclusion of the simulation) are modeled in Figures 10.1-10.3. The values in the bar graphs for these figures represent the percentages of target actors who were heavy drinkers at T3 (*y*-axis) along with standard errors of these estimates (vertical lines), based on whether they were in the drinking status manipulation condition (drinking status of

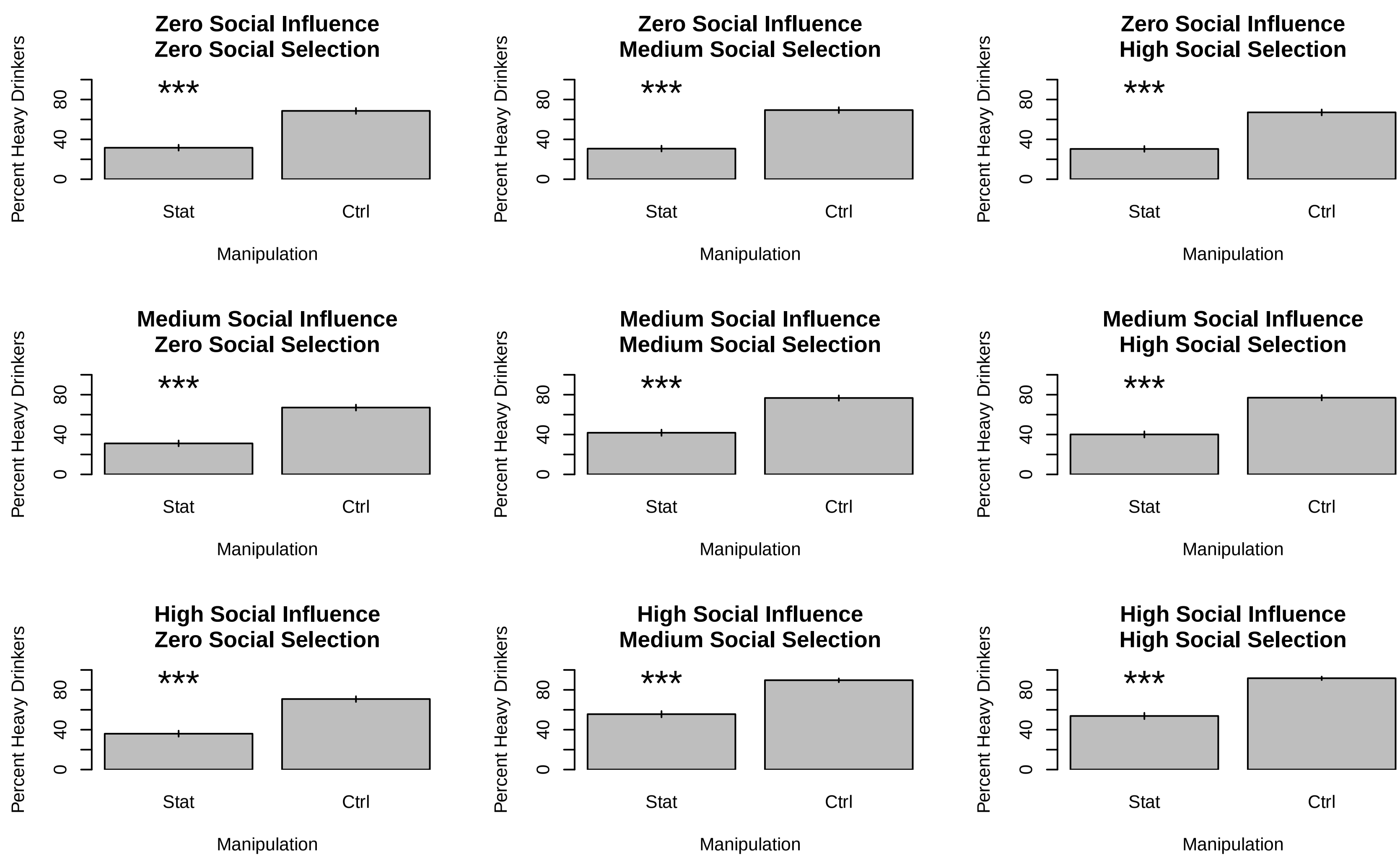


Figure 10.1: Drinking Status Manipulation and Target Actor Heavy Drinking, N = 25, HDR = 50%

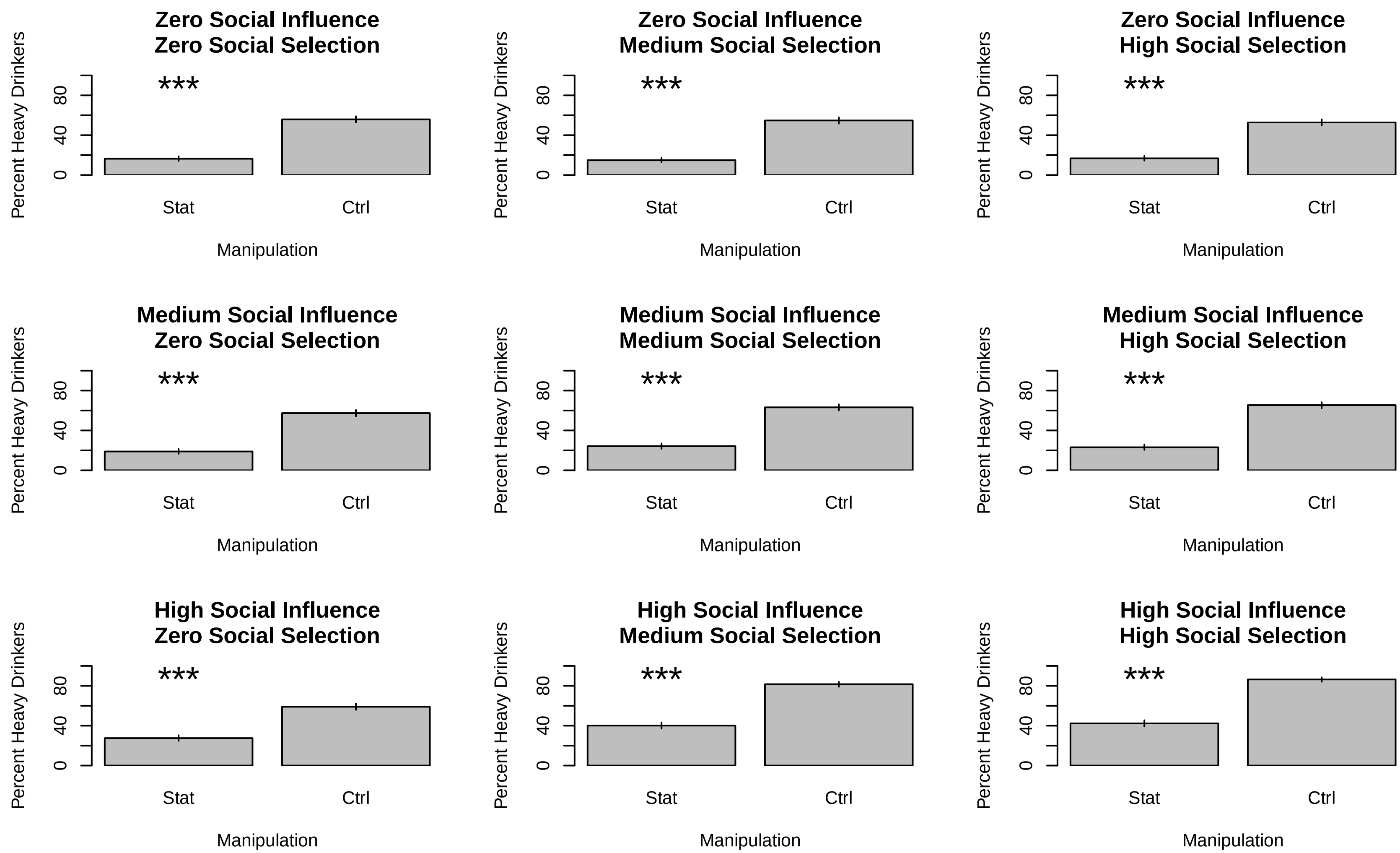


Figure 10.2: Drinking Status Manipulation and Target Actor Heavy Drinking, N = 25, HDR = 25%

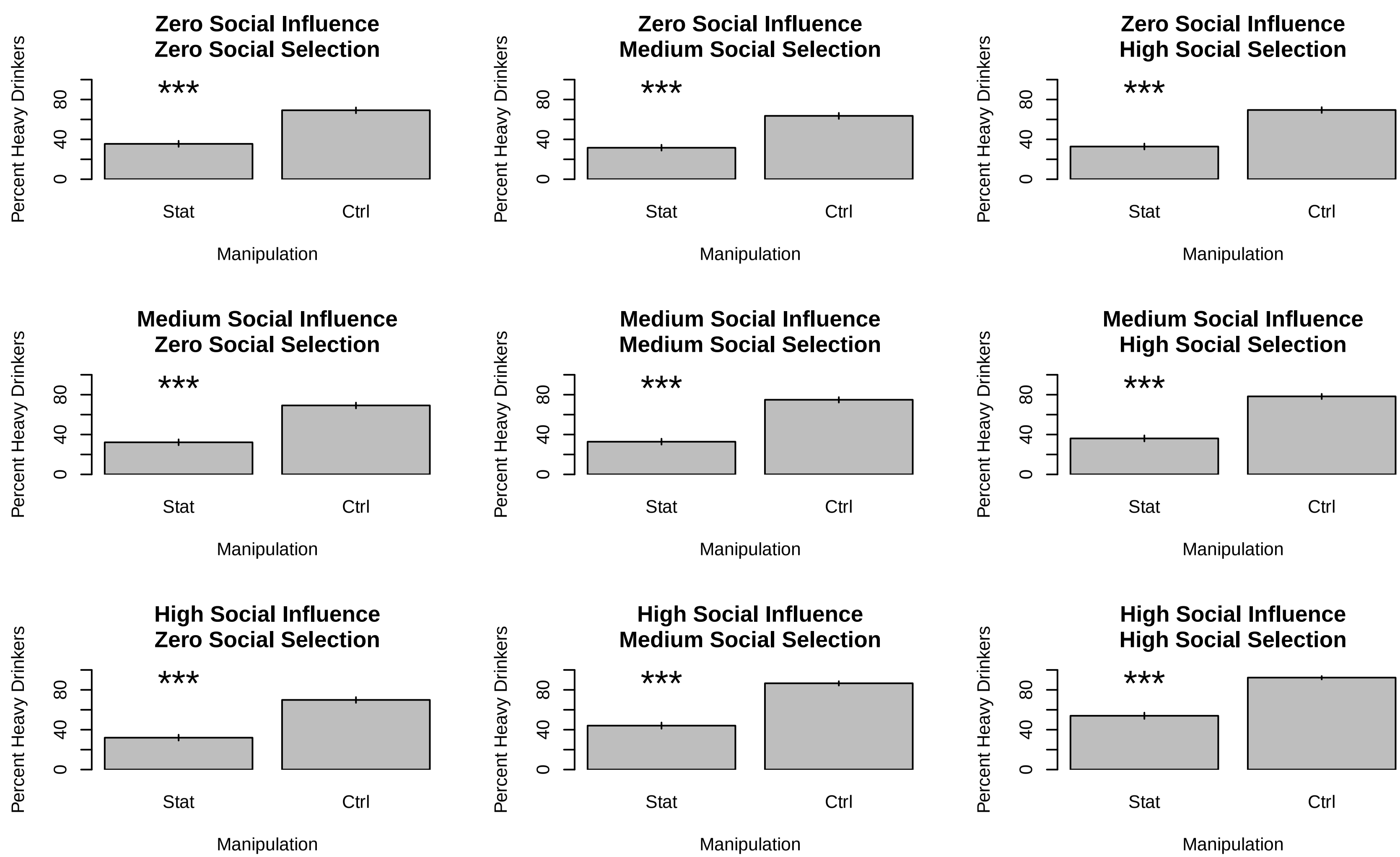


Figure 10.3: Drinking Status Manipulation and Target Actor Heavy Drinking, N = 100, HDR = 50%

target actor changed from heavy drinker to non-drinker at T2) or the control condition (drinking status of target actor not changed at T2) by the separate bars within each plot. Drinking statuses of target actors were free to change between T2 and T3 based on the objective functions for behavior change described above. For example, target actors who received the drinking status manipulation could maintain their non-drinking status or "relapse" back to heavy drinking, while target actors who did not receive the drinking status manipulation could maintain their heavy drinking status or change their status to non-drinking. As with previous figures, different levels of zero, medium, and high social influence are presented based on whether the plot is on the top, middle, or bottom row of the figure, and different levels of zero, medium, and high social selection are presented based on whether the plot is in the left, center, or right column of the figure. Figure 10.1 presents results for N = 25 and HDR = 50%, Figure 10.2 presents the results for N = 25 and HDR = 25%, Figure 10.3 presents the results for when N = 100 and HDR = 50%. Significance levels for paired-samples McNemar chi-square tests, which indicate a significant difference in heavy drinking rates for target actors in the drinking status manipulation vs. control conditions, are marked with asterisks within each plot.

As shown in Figures 10.1-10.3, changing the target actor's drinking status from heavy drinker to non-drinker resulted in reduced heavy drinking over time for target actors in all combinations of conditions. Heavy-drinking actors in the experimental condition typically maintained their non-drinking status but often relapsed back to heavy drinking, while actors in the control condition typically maintained their heavy drinking status but often naturally changed to have a non-drinking status. For example, when social influence and social selection were both zero in the N = 25 and HDR = 50%

condition (top-left plot of Figure 10.1), approximately 31.6% of the heavy-drinking actors in the drinking status manipulation condition who were manipulated to become non-drinkers at T2 relapsed back to heavy drinking by T3. Conversely, approximately 31.4% of heavy drinking actors in the control condition naturally changed their drinking status from heavy drinker to non-drinker by T3, or in other words, 68.6% maintained their heavy drinking status from T2 to T3.

As social selection increased and social influence remained at zero (top-center and top-right plots of Figures 10.1-10.3), the percentages of actors in the experimental condition who relapsed to heavy drinking did not change substantially. For example, when social influence was held constant at zero, 31.6%, 30.7%, and 30.4% of the target actors who received the drinking status intervention relapsed to heavy drinking when social selection was zero, medium, and high, respectively, when N = 25 and HDR = 50% (top row of Figure 10.1).

Likewise, as social influence increased and social selection remained at zero (middle-left and bottom-left plots of Figures 10.1-10.3), the percentages of actors in the experimental condition who relapsed to heavy drinking did not increase by a large amount. For example, when social selection was held constant at zero, 31.6%, 31.1%, and 36.0% of the actors targeted for intervention relapsed to heavy drinking when social influence was zero, medium, and high, respectively, when N = 25 and HDR = 50% (left column of Figure 10.1).

However, when social selection and social influence were both greater than zero (bottom-right, bottom-center, middle-right, and middle-center plots of Figures 10.1-10.3), the percentages of actors in the experimental condition who relapsed to heavy drinking increased by larger amounts. In particular, social influence produced the strongest effect on relapse rates for all conditions for any condition with social selection values greater than zero. For example, when average social influence was medium and social selection was medium, 41.8% and 40.1% of the actors in the experimental condition relapsed to heavy drinking when social selection was medium and high, respectively. But when social influence increased to a high level, relapse rates increased to 55.6% and 53.8% for medium and high social selection effects, respectively.

The results for the control conditions followed a similar pattern where actors were increasingly less likely to naturally change their drinking status from heavy drinker to non-drinker when social influence and social selection were both greater than zero in the model. As with the experimental condition, the magnitude of the social influence effect had a particularly strong effect on drinking outcomes of target actors in the control condition. These patterns suggest that the effect of social selection created a non-linear effect on heavy drinking rates, where moving from zero to medium social selection (e.g., similarity parameter values of 0 and 3 when N = 25) created large increases in heavy drinking rates of target actors, but increasing from medium to high social selection (e.g., similarity parameter values of 3 and 6 when N = 25) did not cause a similar amount of increase. The effect of social influence, however, did appear to have a stronger linear relationship with heavy drinking outcomes, where moving from zero to medium social influence and medium to high social influence both created fairly similar increases in heavy drinking rates in the control condition. The nonlinearity of these effects is presented using three-dimensional bar plots in Figures 11.1-11.3, which show the heavy drinking rates of target heavy drinking actors in control conditions (z-axis, height of the

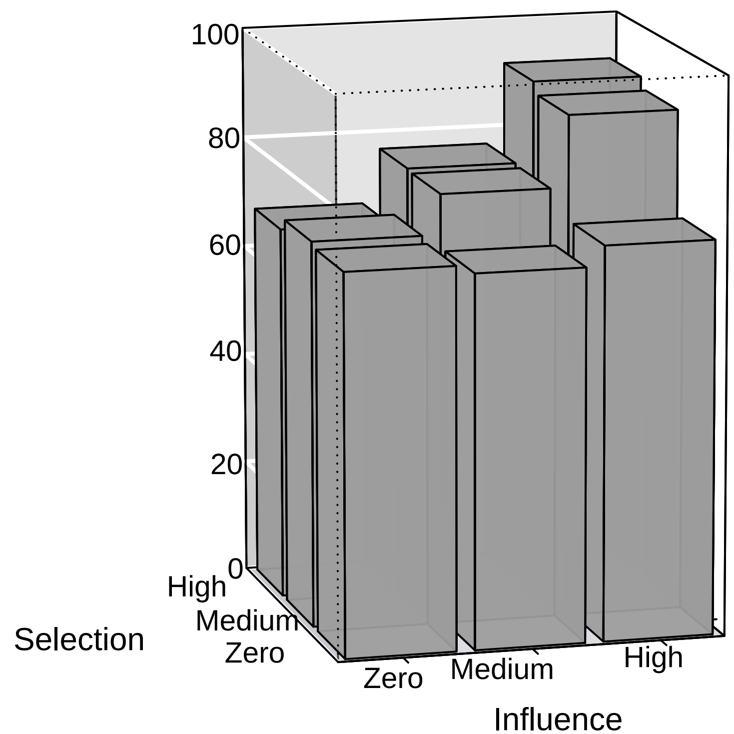


Figure 11.1: Target Actor Heavy Drinking Rate (Control Condition), N = 25, HDR = 50%

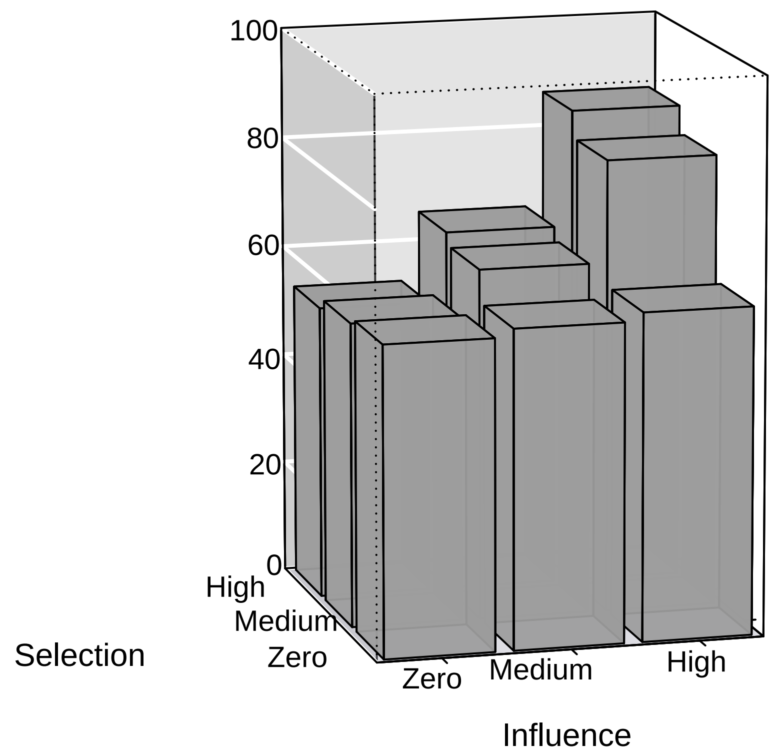


Figure 11.2: Target Actor Heavy Drinking Rate (Control Condition), N = 25, HDR = 25%

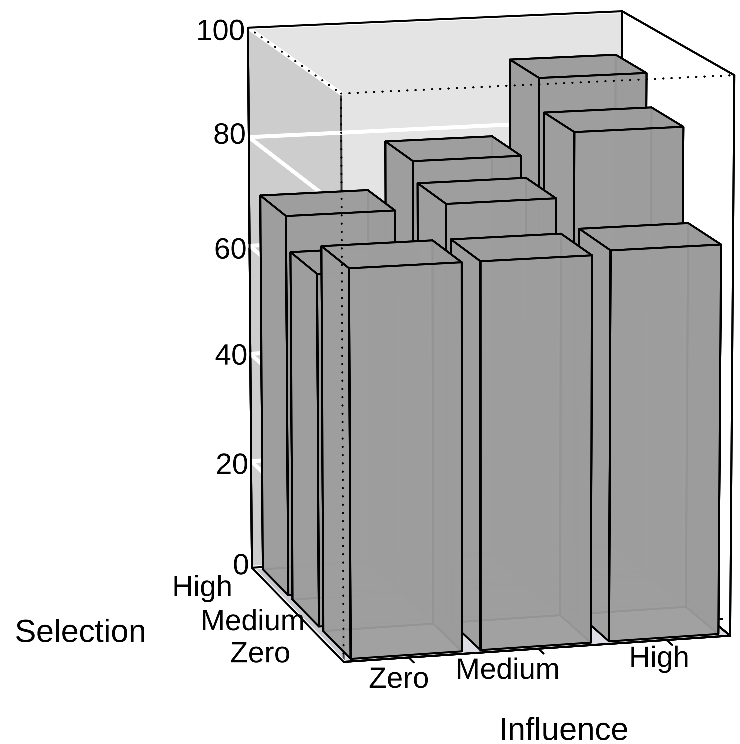


Figure 11.3: Target Actor Heavy Drinking Rate (Control Condition), N = 100, HDR = 50%

vertical bars) based on the level of social influence and social selection (*x*- and *y*-axes). In Figures 11.1-11.3, it can be seen that increases in social influence correspond with increases in heavy drinking rates of target actors, while increases in social selection from zero to medium correspond with an increase in heavy drinking but increases in social selection from medium to high corresponds with little or no increase in heavy drinking. This non-linearity is similar to the non-linearity found for the social influence on correlations of individual drinking statuses and the mean drinking statuses of actors with social ties to individuals.

In combination, the pattern of results suggest that neither social selection nor social influence by themselves strongly impacted heavy drinking rates after an actor was targeted for the drinking status intervention (experimental condition) or when the actor's drinking status is left unmanipulated (control condition). However, when both social selection and social influence are present in the model, the rates of relapse increase substantially, and rates of natural change decrease substantially by a comparable amount. None of the combinations of social selection and social influence effects substantially moderated the efficacy of the intervention; for example, for all nine combinations of social influence and social selection, the differences in heavy drinking rates between the experimental and control conditions were between 34.1 and 37.9 when N = 25 and HDR = 50%. However, the rates of social influence and social selection, and in particular the combination of both effects, increased the likelihood that a heavy drinking actor would remain a heavy drinking actor at T2 would be a heavy drinking actor at T3, regardless of whether the actor received the drinking status manipulation.

Status manipulation and target actor drinking outcomes: Moderating effect of network position. It is possible that target actors' likelihood of maintaining a non-drinking status in the experimental condition, relative to the control condition, may be moderated by the number of ties they have to heavy drinking and non-drinking peers at the time of the intervention. For example, when social influence is acting without social selection, some actors may have difficulty maintaining a non-drinking status due to having many ties to other heavy drinking actors, while other actors may have less difficulty maintaining a non-drinking status due to having many ties to other non-drinking actors. When both social influence and social selection both act simultaneously, network position may be even more important. For example, for actors with many ties to heavy drinkers, receiving the intervention may offer a rare opportunity to form new ties with non-drinkers due to social selection and the similarity of their drinking statuses. These new friends may in turn influence the target actor's drinking behavior due to social influence, and help the target actor maintain a non-drinking status. Conversely, actors who do not receive the intervention and have many ties to heavy drinkers and few ties to non-drinkers may be especially unlikely to form new ties with non-drinkers due to social selection and differences in drinking statuses. These heavy drinking friends may in turn continue to influence the target actor's drinking behavior due to social influence, and partly facilitate the target actor maintaining a heavy drinking status.

Number of heavy drinking peers at T2. The drinking outcomes for target actors at T3 are plotted based on the interaction of the number of outgoing ties to heavy drinkers at T2 (i.e., the time of the intervention) and experimental condition in Figures 12.1-12.3. The line graphs in these figures display the logit odds of an actor being a heavy drinker at

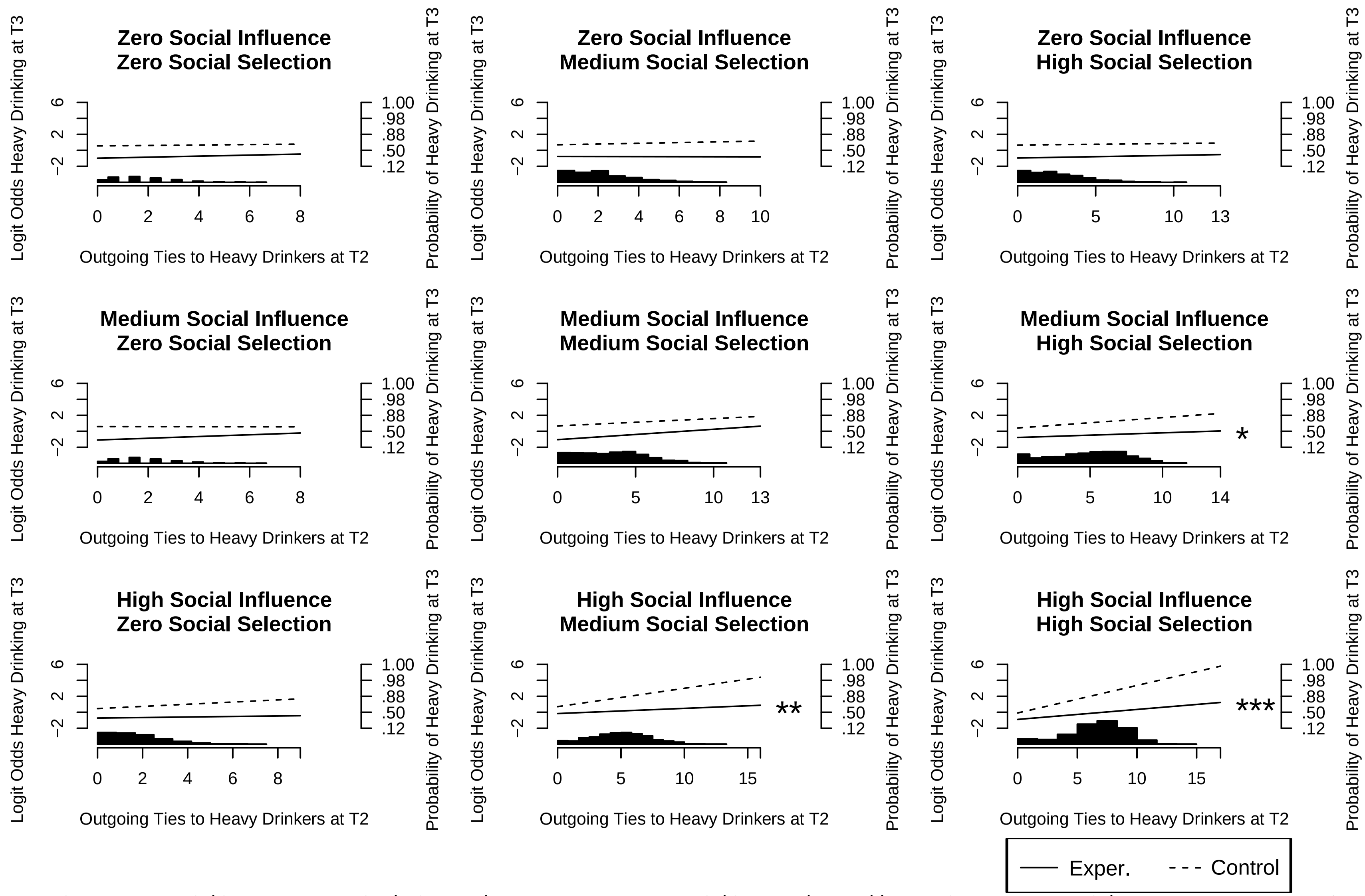


Figure 12.1: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 25, HDR = 50%

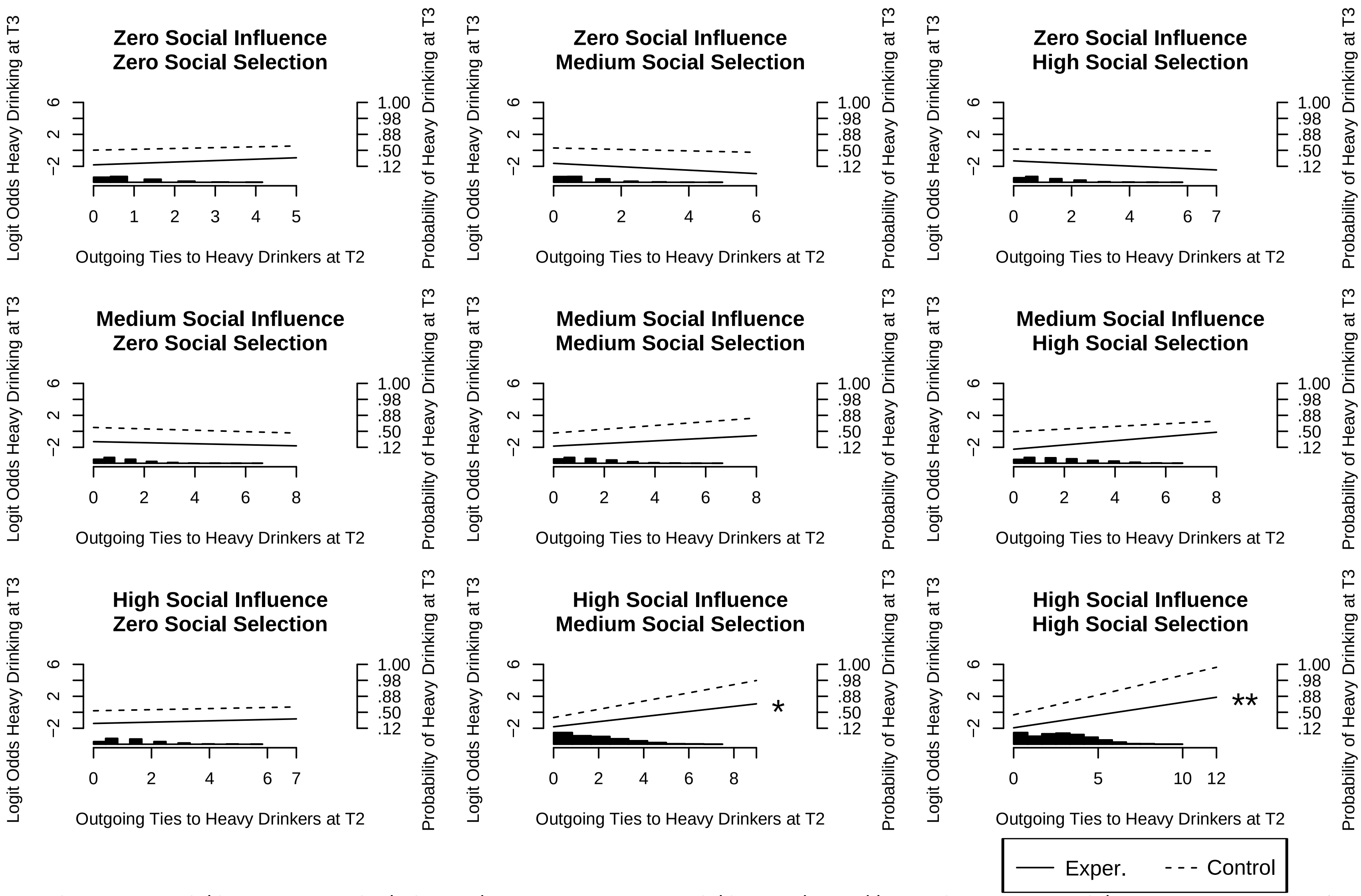


Figure 12.2: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 25, HDR = 25%

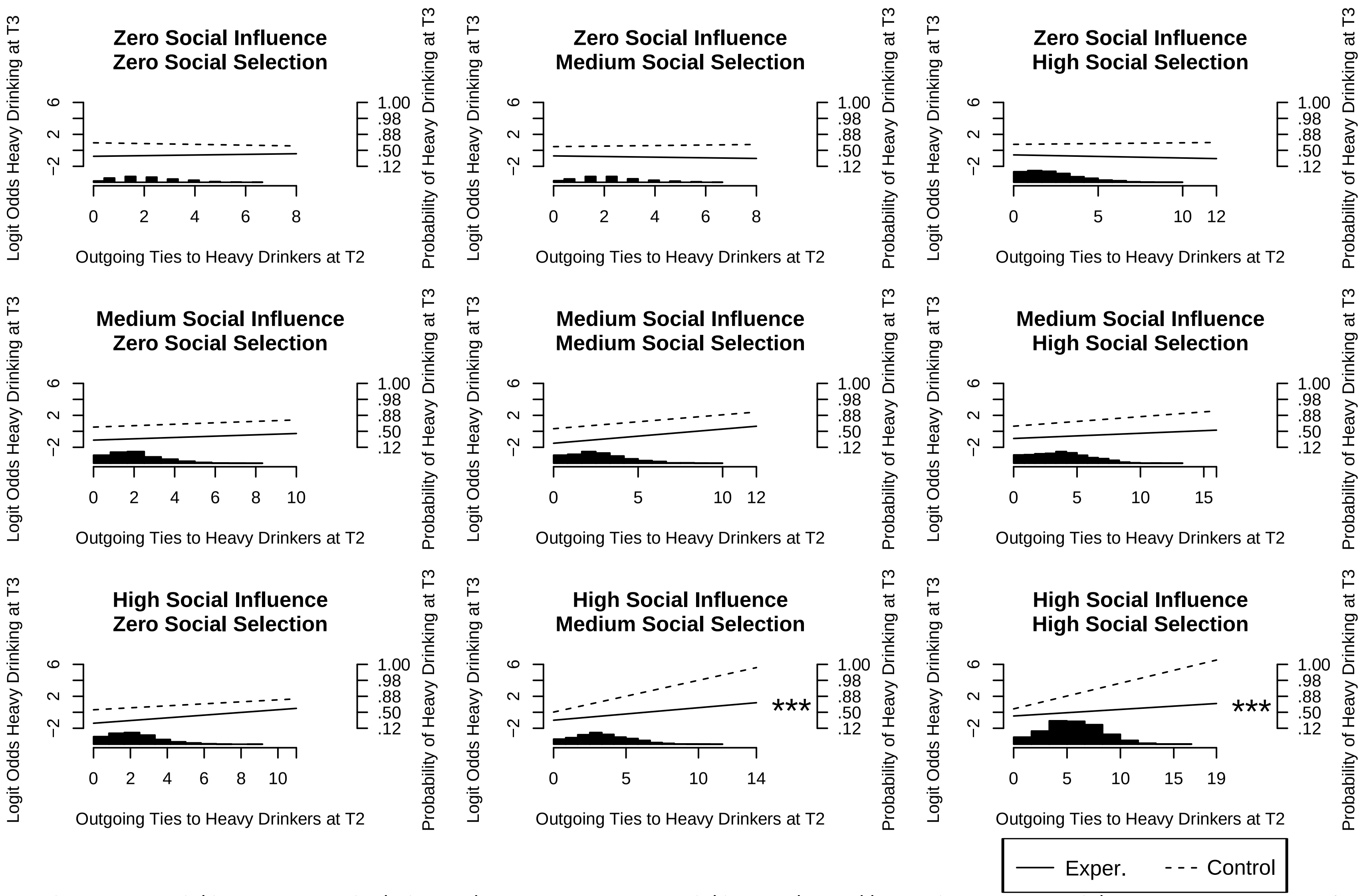


Figure 12.3: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 100, HDR = 50%

T3 (*y*-axis, left side of each plot) and the inverse-logit transformed simple probability of an actor being a heavy drinker at T3 (*y*-axis, right side of each plot), based on logistic regression models with the interaction of outgoing ties to heavy drinkers at T2 (*x*-axis) and treatment condition (separate lines; solid lines represent the experimental condition, dashed lines represent the control condition) as predictor variables. The efficacy of the experimental condition, relative to the control condition, on target actor drinking outcomes was moderated by the number of ties to heavy drinkers at T2 when the slopes of the lines for the experimental and control conditions are significantly different from each other. Significant interactions are indicated within each plot by asterisks.

The same figures present histograms of outdegree distributions to heavy drinkers at T2, with the heights of histograms corresponding with the relative number of ties to heavy drinkers that target actors had across the 1000 simulations in each condition. These histograms are displayed to provide additional information about the number of ties to heavy-drinking actors that were typically present at the time of the manipulation and help place the interactions into context. For example, in Figure 12.1 in the condition with zero social influence and high social selection (top-right plot), most target actors had ties to five or fewer heavy drinkers, whereas in the condition with high social influence and high social selection (bottom-right plot), most target actors had ties to six to twelve heavy drinkers, reflecting the tendency for heavy drinkers to have more ties to other heavy drinkers when social influence and social selection were positive and due to the tendency for outdegrees to be larger in conditions the same conditions.

In all three combinations of sample size and HDR, the efficacy of the intervention was not significantly moderated by the number of outgoing ties to heavy drinkers at the time of the intervention when social influence and social selection both absent (top-left plot of Figures 12.1-12.3), when social influence was present but social selection was absent (middle-left and bottom-left plots of Figures 12.1-12.3), or when social selection was present but social influence was absent (top-center and top-right plots of Figures 12.1-12.3).

In contrast, the efficacy of the intervention was significantly moderated by the number of outgoing ties to heavy drinkers only when social influence was high and social selection was medium or high for all combinations of sample size and HDR (bottom-center and bottom-right plots of Figures 12.1-12.3) and when social influence was medium and social selection was high when N = 25 and HDR = 50% (middle-right plot of Figure 12.1). In all cases with significant moderation, the slopes for target actors in the control conditions were greater than the slopes for target actors in the experimental conditions. That is, while target actors in the experimental conditions had somewhat greater chances of relapsing to heavy drinking if they had more ties to heavy drinkers at T2 (indicated by the positive slopes of the solid lines), target actors in the control conditions had even greater chances of remaining heavy drinkers, especially when they had more ties to heavy drinkers (indicated by the greater slopes of the dashed lines).

For example, a target actor in the high influence and high selection condition when N = 25 and HDR = 50% (bottom-right plot of Figure 12.1) who had ties to ten heavy drinking actors would have logit odds 0.36 (simple probability = 0.59) of relapsing to heavy drinking if they received the intervention, but had logit odds 3.37 (simple probability = 0.97) of remaining a heavy drinker if they did not receive the intervention. However, a target actor in the same high social influence and high social selection condition with only one heavy drinking friend would have logit odds -0.77 (simple probability = 0.32) of relapsing to heavy drinking if they received the intervention, and had a logit odds 0.25 (simple probability = 0.56) of remaining a heavy drinker if they did not receive the intervention. Thus, in the conditions with significant moderation, target actors with many ties to other heavy drinking actors were very unlikely to change their drinking status due to stochastic network influences alone without receiving the intervention.

Number of non-drinking peers at T2. The drinking outcomes for target actors are plotted based on the number of outgoing ties to *non*-drinkers at T2 and experimental condition in Figures 13.1-13.3 in a manner similar to the plots above. As with before, histograms of the distributions of ties to non-drinkers at T2 are displayed below each line graph. Similar to the results for the number of *heavy*-drinking peers at T2, the number of *non*-drinking peers at T2 did not significantly moderate the efficacy of the intervention in the cases when social influence and social selection were both zero (top-left plot of Figures 13.1-13.3), when social influence was positive but social selection was zero (middle-left and bottom-left plots of Figures 13.1-13.3), or when social selection was positive but social influence was zero (top-center and top-right plots of Figures 13.1-13.3). However, unlike the results for the number of heavy drinking peers at T2, the number of non-drinking peers at T2 also did not significantly moderate the efficacy of the intervention when social selection and social influence were both present for almost all conditions with the exception of the high influence and medium selection conditions when N = 25, HDR = 50% and N = 25, HDR = 25% (bottom-center plots of Figures 13.1 and 13.2).

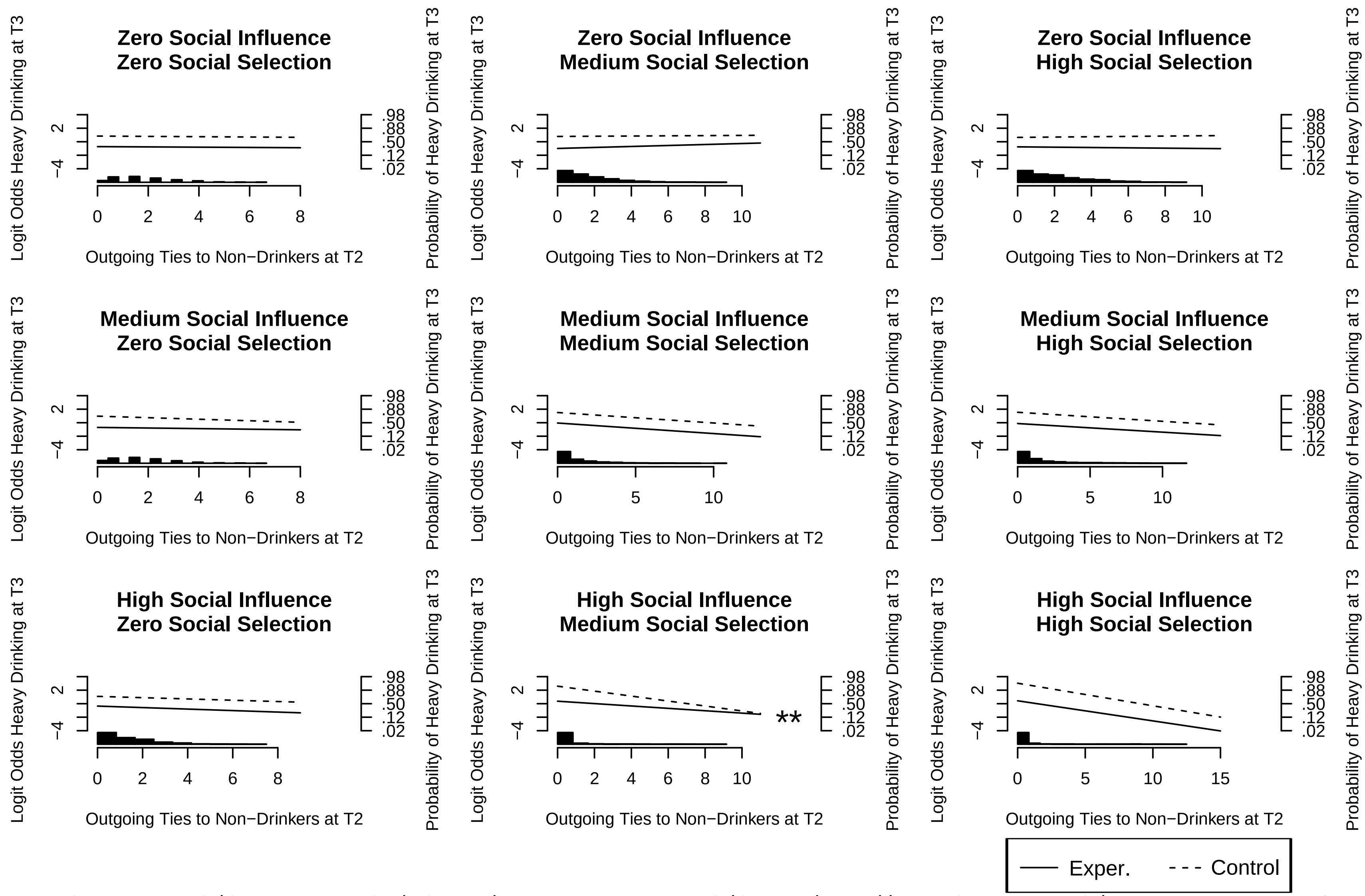


Figure 13.1: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 25, HDR = 50%

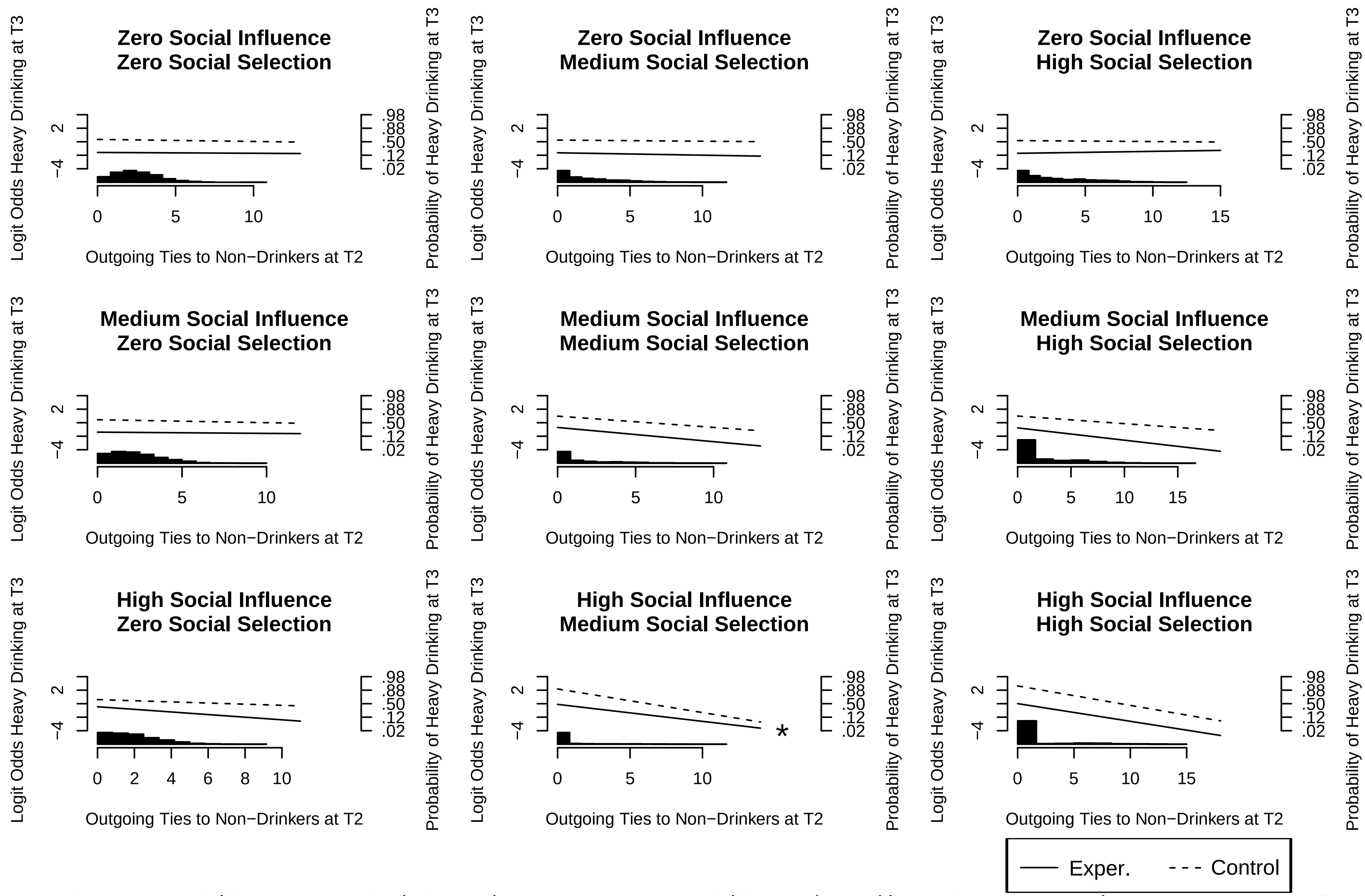


Figure 13.2: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 25, HDR = 25%

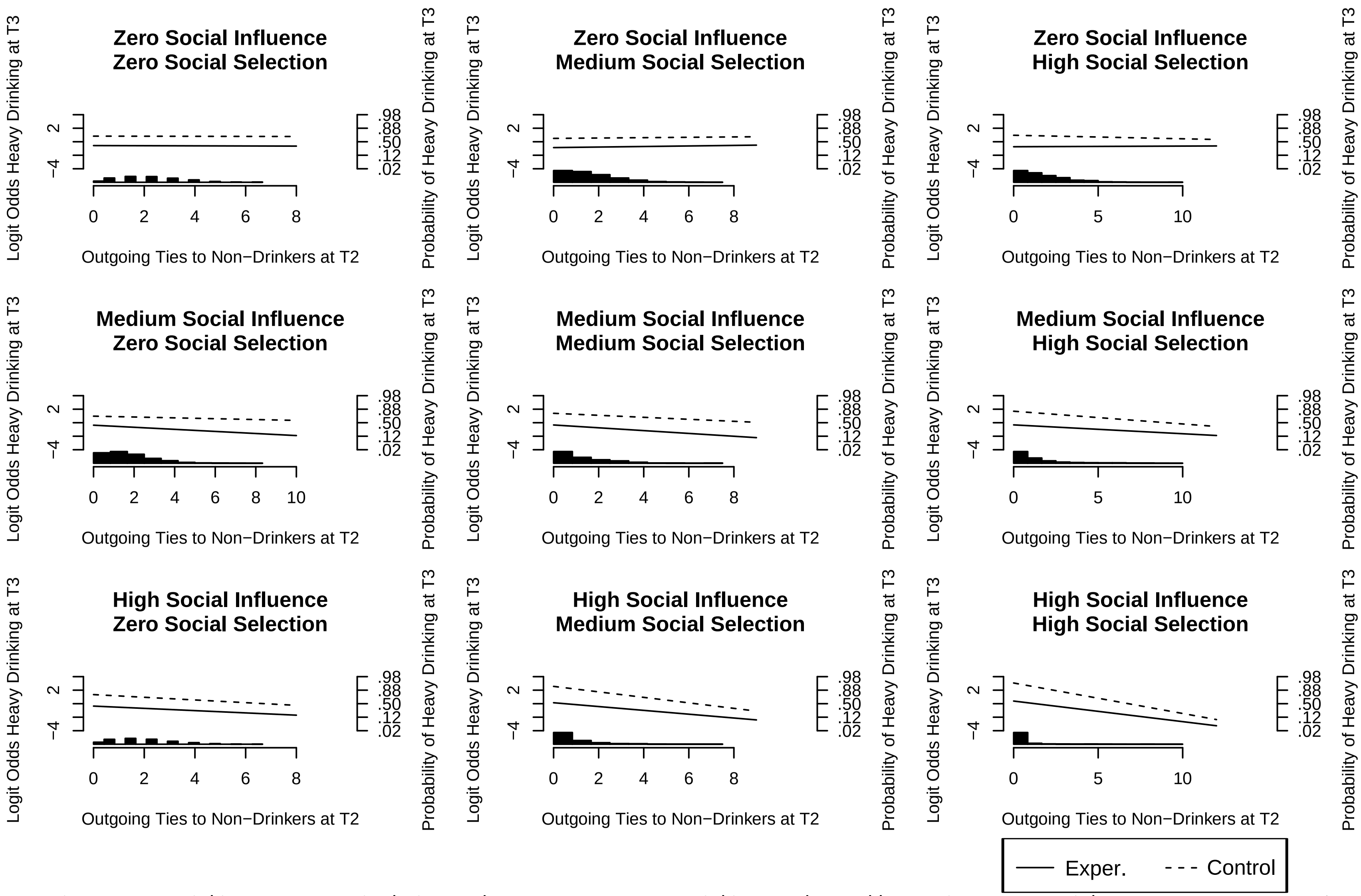


Figure 13.3: Drinking Status Manipulation and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 100, HDR = 50%

In the two cases with significant moderation, the slopes for target actors in the control conditions were lower (i.e., more negative) than the slopes for target actors in the experimental conditions. That is, while target actors in the experimental conditions had somewhat higher chances of relapsing to heavy drinking if they had fewer ties to non-drinkers (indicated by the negative slopes of the solid lines), target actors in the control conditions had even greater chances of remaining heavy drinkers, especially when they had fewer ties to heavy drinkers (indicated by the lower negative slopes of the dashed lines).

For example, a target actor in the high influence and medium selection condition when $N = 25$ and HDR = 50% (bottom-center plot of Figure 13.1) who had one non-drinking friend would have logit odds 0.19 (simple probability = 0.55) of relapsing to heavy drinking if they received the intervention, but would have a logit odds 2.26 (simple probability = 0.91) of remaining a heavy drinker if they did not receive the intervention. However, a target actor in the same condition with ten non-drinking friends would have logit odds -1.40 (simple probability = 0.20) of relapsing to heavy drinking if they received the intervention, but would have a logit odds -1.08 (simple probability = 0.25) of remaining a heavy drinker if they did not receive the intervention. Thus, in the conditions with significant moderation, target actors with few ties to other non-drinking actors were unlikely to change their drinking status due to stochastic network influences alone without receiving the intervention.

Status manipulation and actor friendship outcomes. To better understand how the experimental manipulations may have affected target actors' social environments, the effects of the experimental manipulations on the ties from target actors to heavy drinkers and non-drinkers were explored further. The following sections explore effect of the experimental conditions on the rates of ties from target actors to heavy drinkers and non-drinkers at the conclusion of each simulation (T3) and examine whether these effects were moderated by the target actor's social ties at the time of the manipulation (T2).

Ties to heavy drinkers. The effects of the drinking status manipulation on the number of ties from target actors to heavy drinkers at T3 are presented in Figures 14.1-14.3. The drinking status manipulation resulted in fewer ties to heavy drinkers at T3, relative to the control, in all conditions with positive social selection (center and right columns of Figures 14.1-14.3), suggesting that the drinking status manipulation caused actors to reduce their ties to heavy drinkers due to social selection. The drinking status manipulation also resulted in fewer ties to heavy drinkers at T3, relative to the control condition, in several conditions with positive social influence and zero social selection (middle-left and bottom-left plots of Figures 14.1-14.3). It is possible that the latter effect was due to the drinking status manipulation causing reduced drinking among the target actor's peers (i.e., the intervention having a "spreading" effect); however this is tested more thoroughly for all conditions in subsequent sections of this manuscript.

The effect of the drinking status manipulation on the number of outgoing ties to heavy drinkers at T3 also was moderated to a small degree by the number of ties to heavy drinkers at T2 (i.e., the time of the drinking status manipulation) in several conditions. These results are presented in Figures 15.1-15.3, which display the number of ties from target actors to heavy drinkers at T3 (*y*-axis) predicted by the interaction of experimental condition (separate lines; drinking status manipulation presented as solid lines, control conditions presented as dashed lines) and the number of ties to heavy drinkers at T2 (*x*-

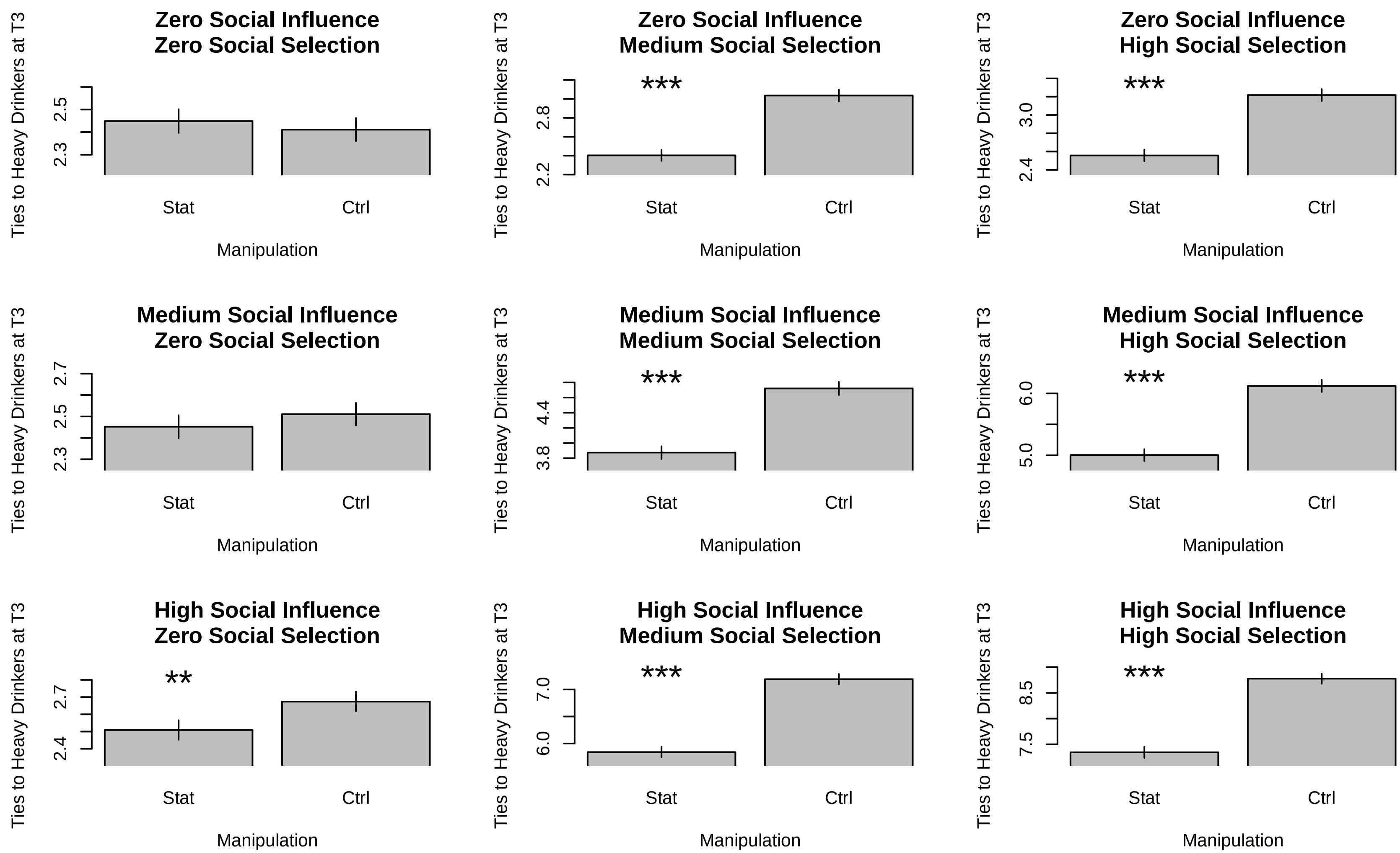


Figure 14.1: Drinking Status Manipulation and Ties to Heavy Drinkers, N = 25, HDR = 50%

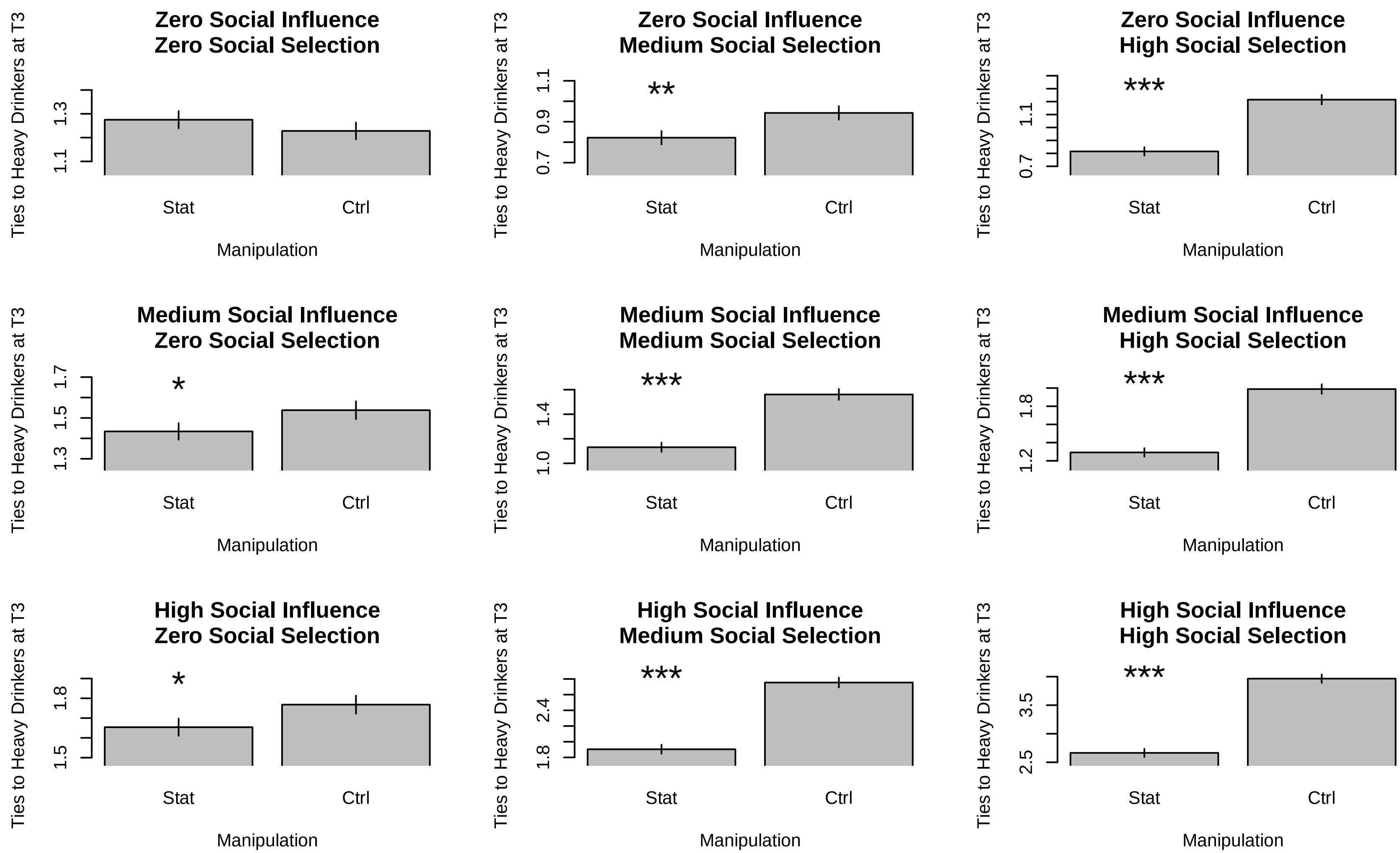


Figure 14.2: Drinking Status Manipulation and Ties to Heavy Drinkers, N = 25, HDR = 25%

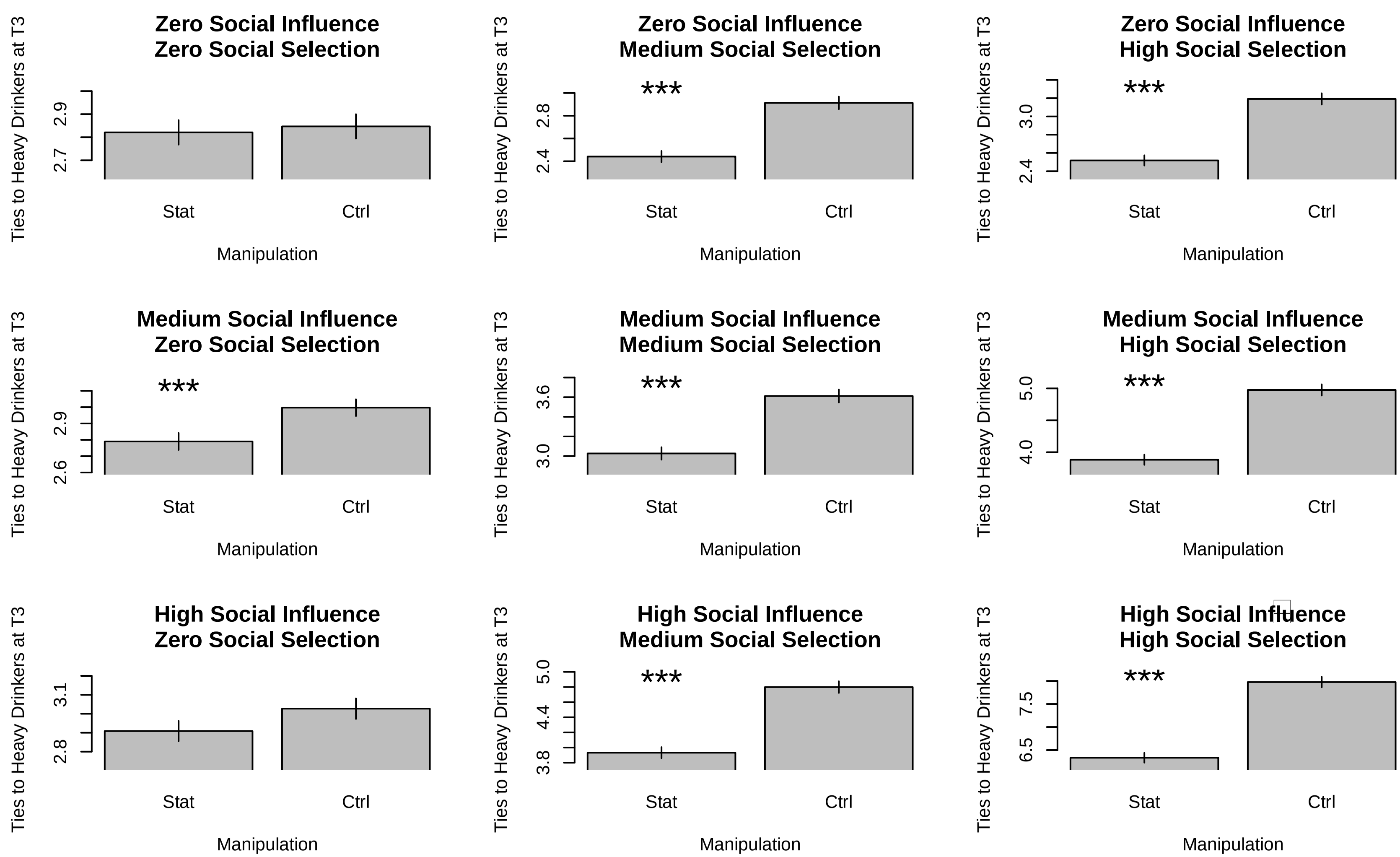


Figure 14.3: Drinking Status Manipulation and Ties to Heavy Drinkers, N = 100, HDR = 50%

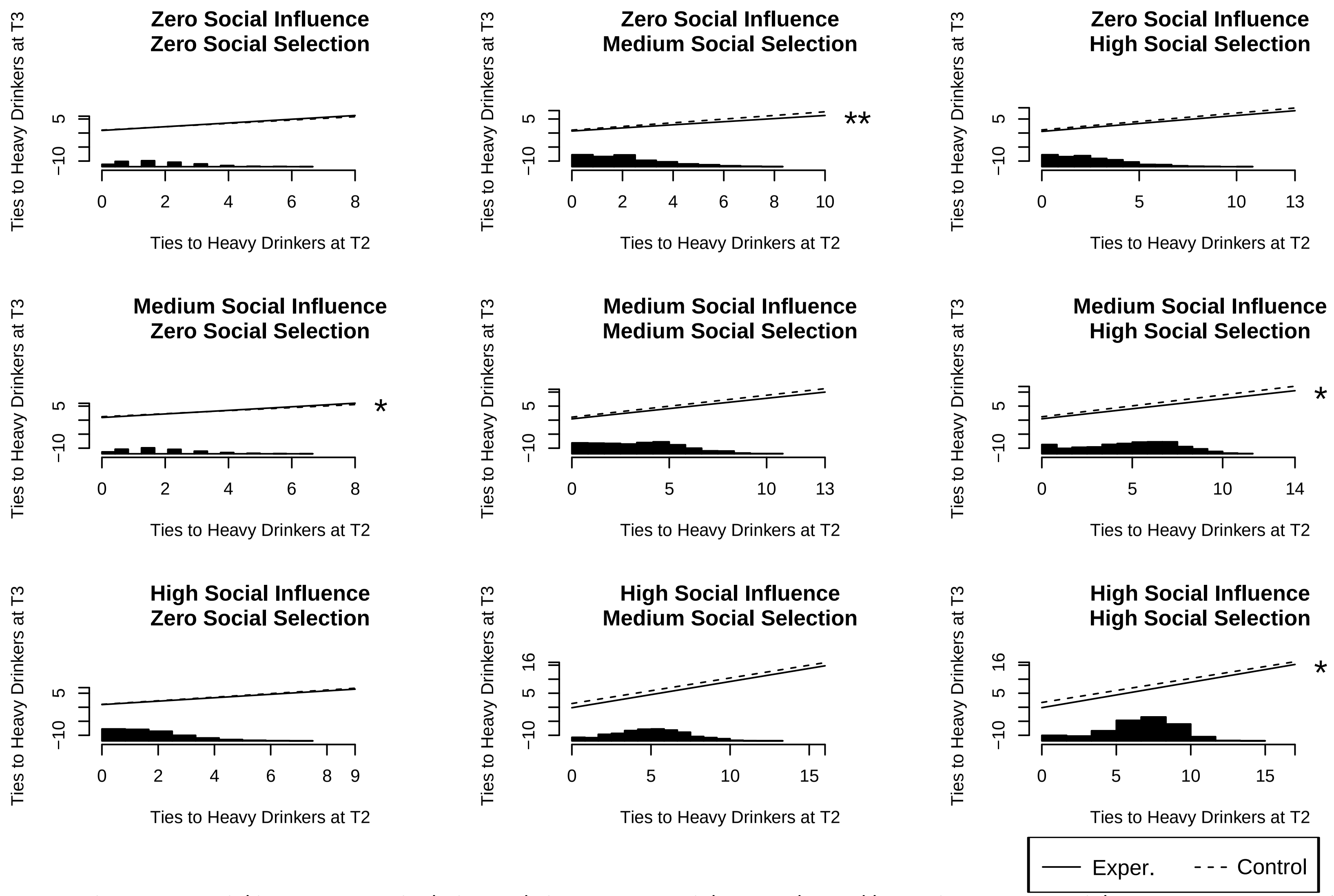


Figure 15.1: Drinking Status Manipulation and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 25, HDR = 50%

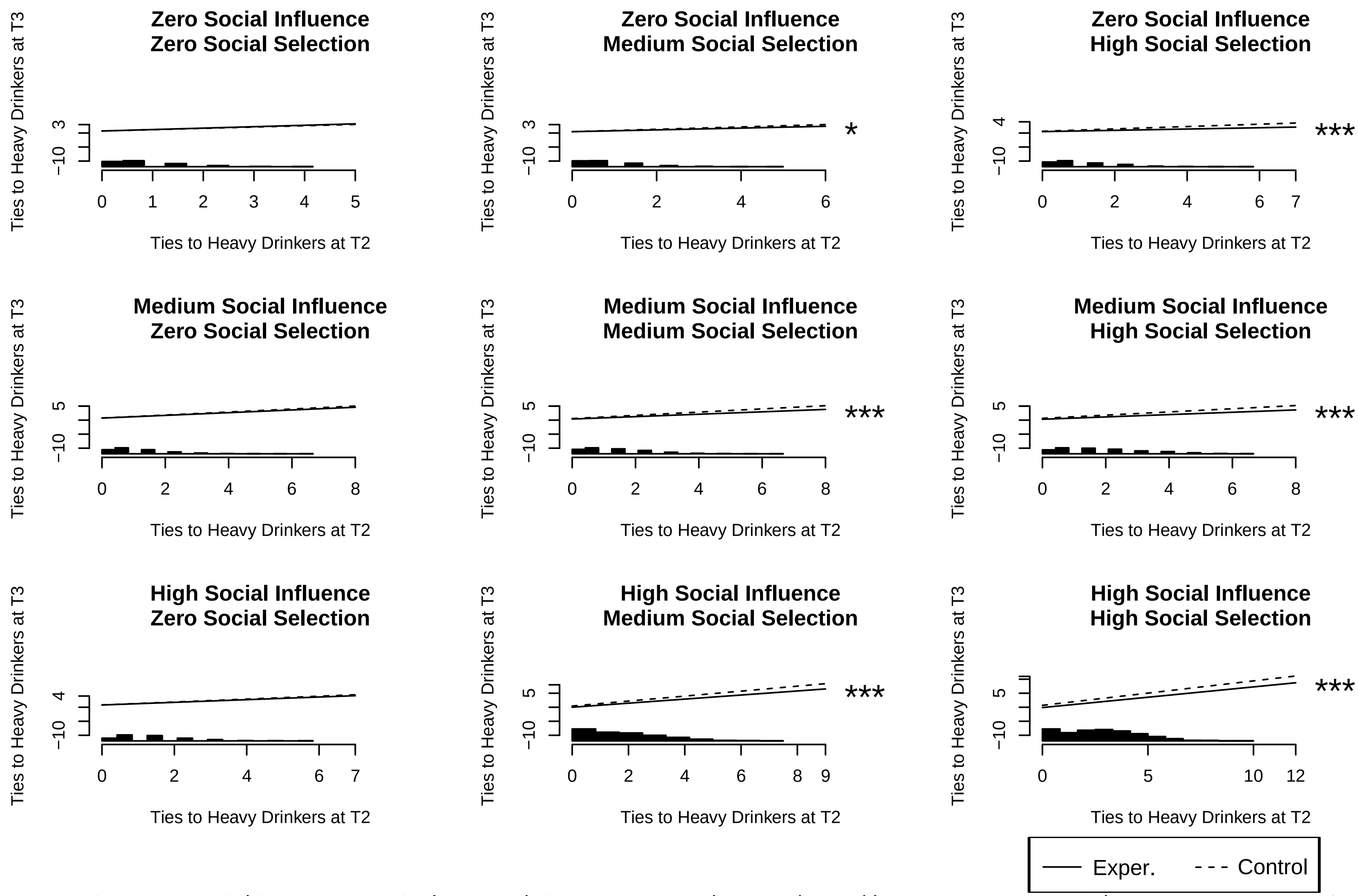


Figure 15.2: Drinking Status Manipulation and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 25, HDR = 25%

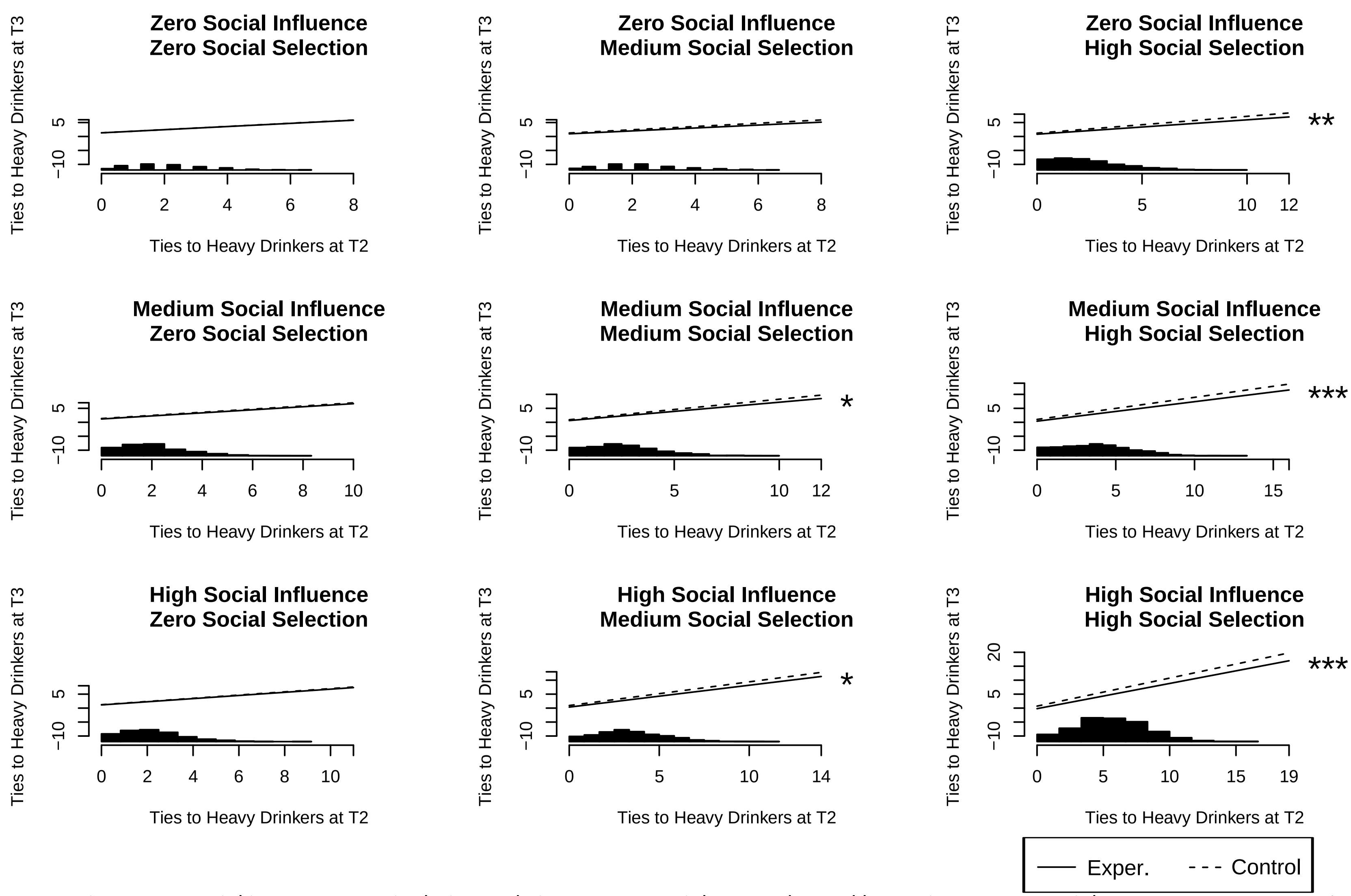


Figure 15.3: Drinking Status Manipulation and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 100, HDR = 50%

axis). For the *N* = 25 and HDR = 50% conditions, small but significant moderating effects were present in conditions with medium social influence and high social selection (middle-right plot of Figure 15.1), high social influence and high social selection (bottom-right plot of Figure 15.1), medium social selection and zero social influence (top-center plot of Figure 15.1), and medium social influence and zero social selection (middle-left plot of Figure 15.1). For the *N* = 25 and HDR = 25% networks, moderating effects were present in all conditions with positive social selection (center and right columns of Figure 15.2). In the *N* = 100 and HDR = 50% networks, moderating effects also were present in all conditions with positive social selection (center and right columns of Figure 15.3), with the exception of the medium social selection and zero social influence condition (top-center plot of Figure 15.3).

In all conditions, actors with a greater number of ties to heavy drinkers at T2 were more likely to have a greater number of ties to heavy drinkers at T3 (indicated by positive slopes for all lines). With two exceptions (medium social influence and zero social selection, high social influence and high social selection for *N* = 25 and HDR = 50%), the direction of all significant interactions indicated that actors in the control conditions were more likely to have a greater number of ties to heavy drinkers at T3 if they already had many ties to heavy drinkers at T2, while actors in the experimental conditions had slightly fewer numbers of ties to heavy drinkers at T3 (relative to control conditions) if they already had many ties to heavy drinkers at T2. In other words, the experimental condition produced the greatest reduction in ties to heavy drinkers at T3 for actors with a large number of ties to heavy drinkers at T2. One condition unexpectedly produced an interaction that followed an opposite direction; this occurred in the condition with zero social influence and medium social selection when N = 25 and HDR = 50% and was the only condition with zero social influence to produce a significant interaction.

Friendships to non-drinkers. The effect of the drinking status manipulation on the number of ties from target actors to non-drinkers at T3 are presented in Figures 16.1-16.3 in a similar manner to the results presented above for ties to heavy drinkers. The drinking status manipulation resulted in more ties to non-drinkers at T3, relative to the control, in all conditions with positive social selection (center and right columns of Figures 16.1-16.3), suggesting that the manipulation led to an increase in ties to non-drinkers. The drinking status manipulation also resulted in more ties to non-drinkers at T3, relative to the control condition, in several conditions with positive social influence and zero social selection (middle-left and bottom-left plots in Figures 16.1-16.3).

The effect of the drinking status manipulation on the number of outgoing ties to non-drinkers at T3 also was moderated by the number of ties to non-drinkers at T2 in several conditions. These results are presented in Figures 17.1-17.3 in a manner similar to the moderation analysis results for ties to heavy drinkers. Significant moderation was present for all conditions with positive social selection when N = 25 and HDR = 50% and when N = 25 and HDR = 25% (center and right columns of Figures 17.1-17.2). When N = 100 and HDR = 50%, significant moderation was present for four out of six conditions with positive social selection (center and right columns of Figure 17.3), and unexpectedly, in the conditions with medium social influence and zero selection (middle-left plot) and with zero social influence and zero selection (top-left plot). The direction of all significant interactions indicated that actors in the experimental conditions had more ties to non-drinkers at T3, relative to actors in control conditions, if they already

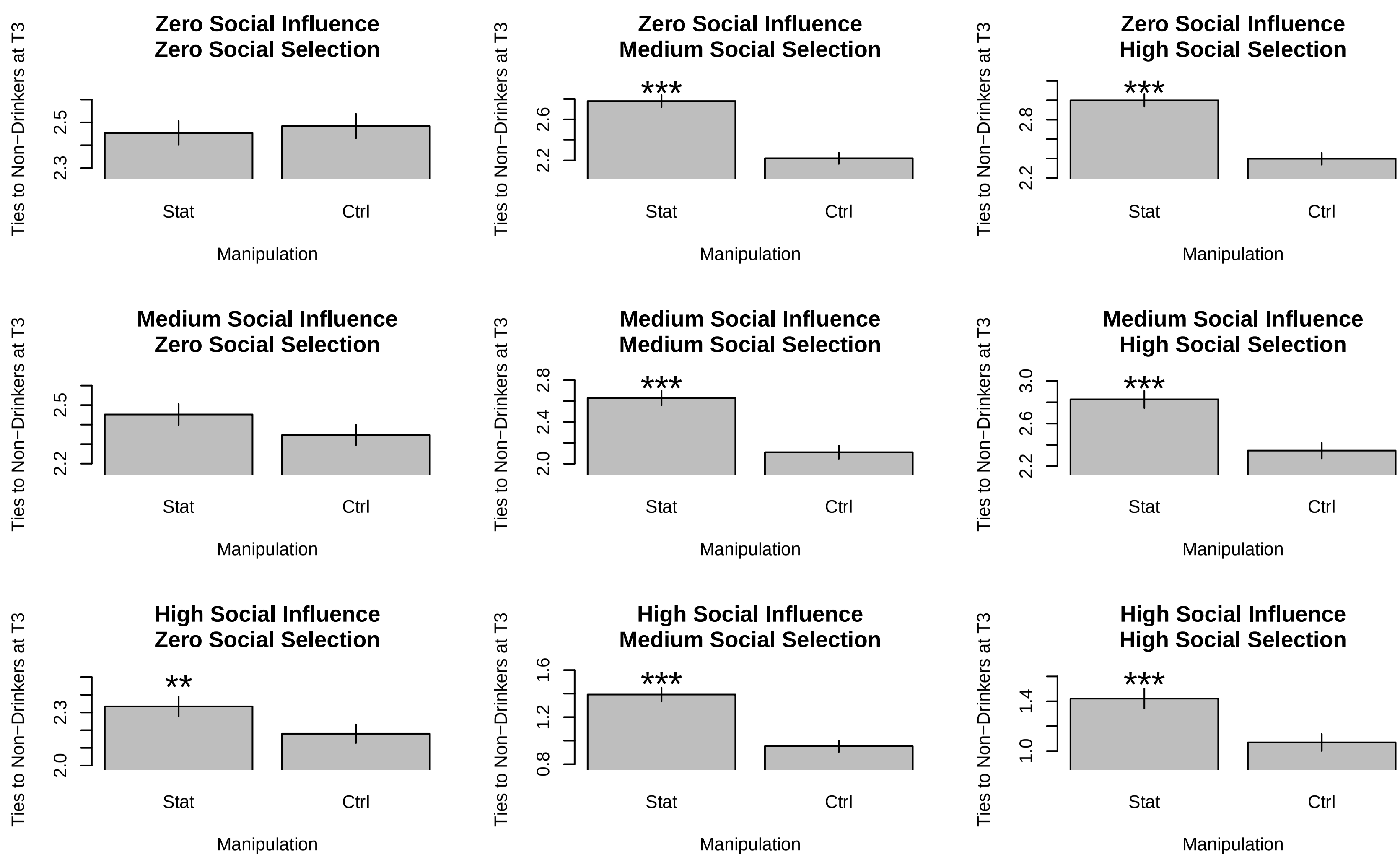


Figure 16.1: Drinking Status Manipulation and Ties to Non-Drinkers, N = 25, HDR = 50%

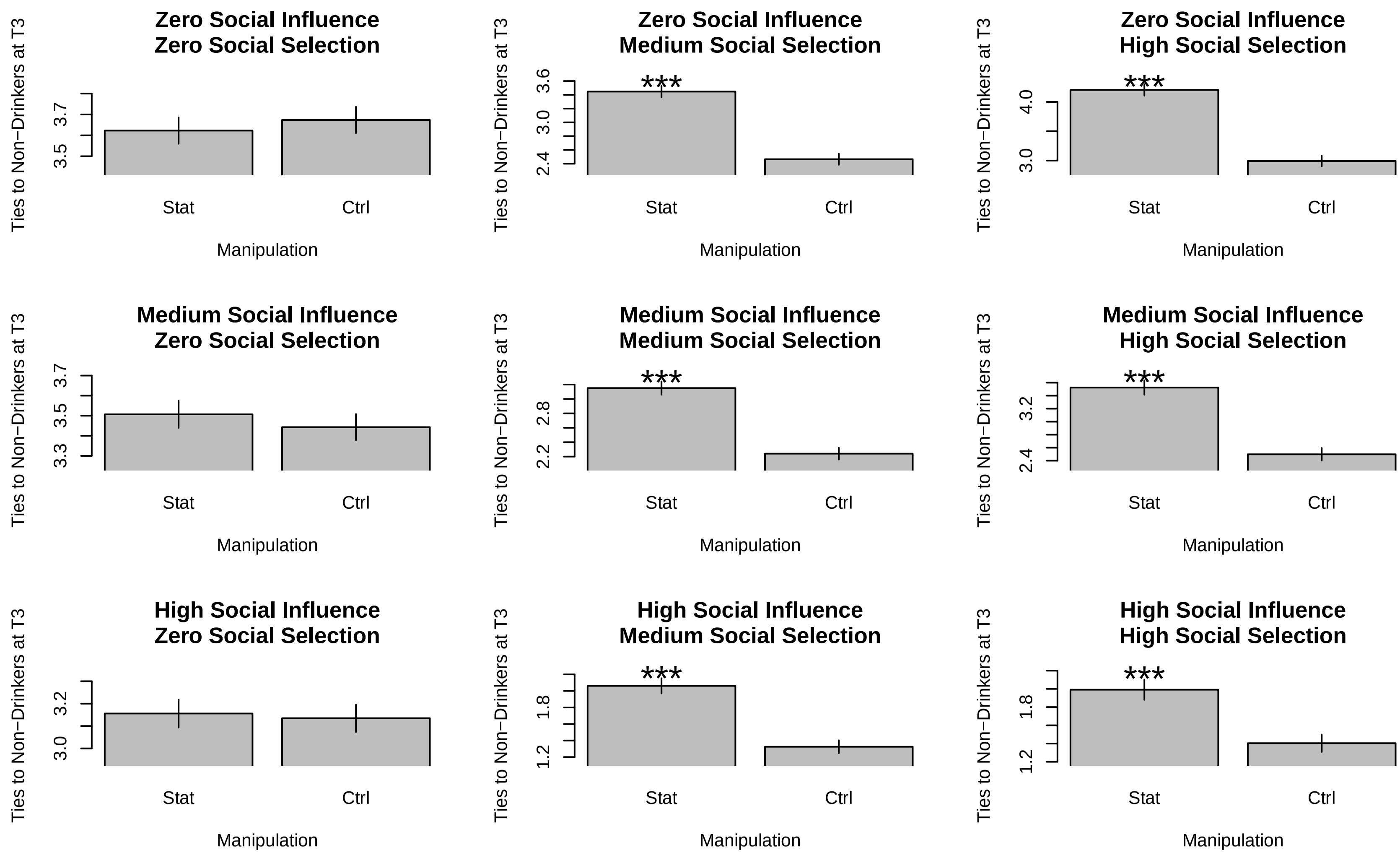


Figure 16.2: Drinking Status Manipulation and Ties to Non-Drinkers, N = 25, HDR = 25%

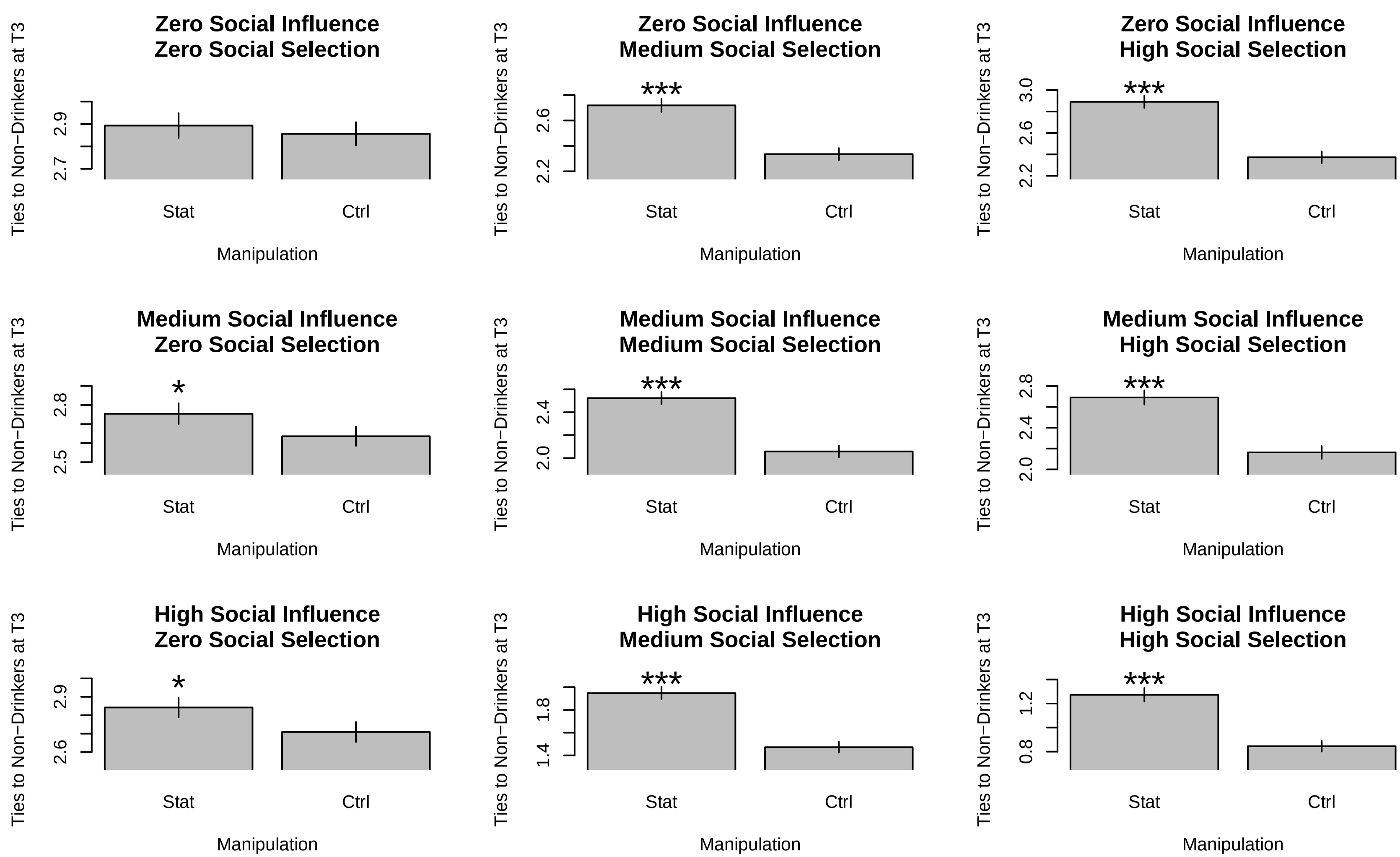


Figure 16.3: Drinking Status Manipulation and Ties to Non-Drinkers, N = 100, HDR = 50%

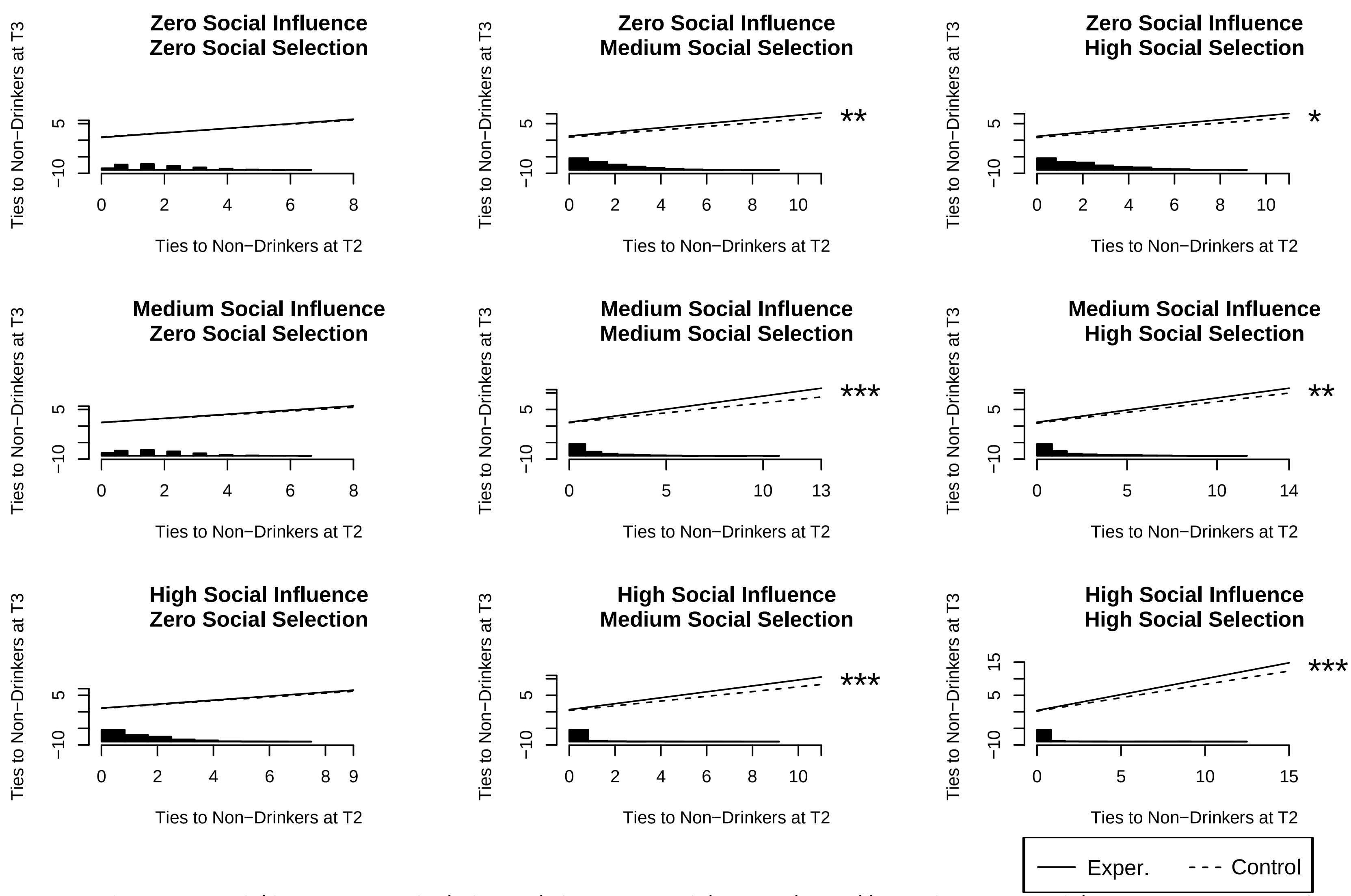


Figure 17.1: Drinking Status Manipulation and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 25, HDR = 50%

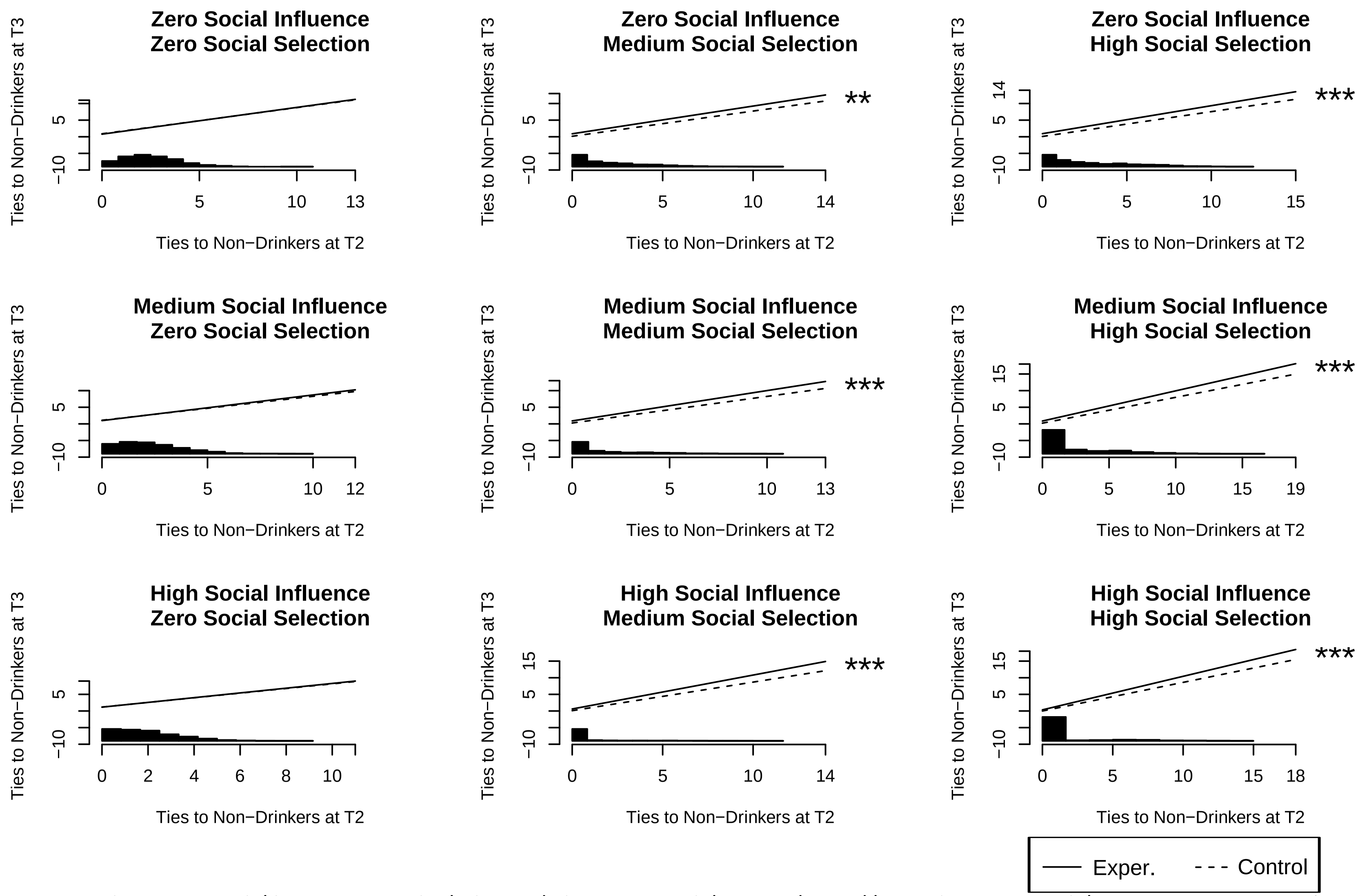


Figure 17.2: Drinking Status Manipulation and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 25, HDR = 25%

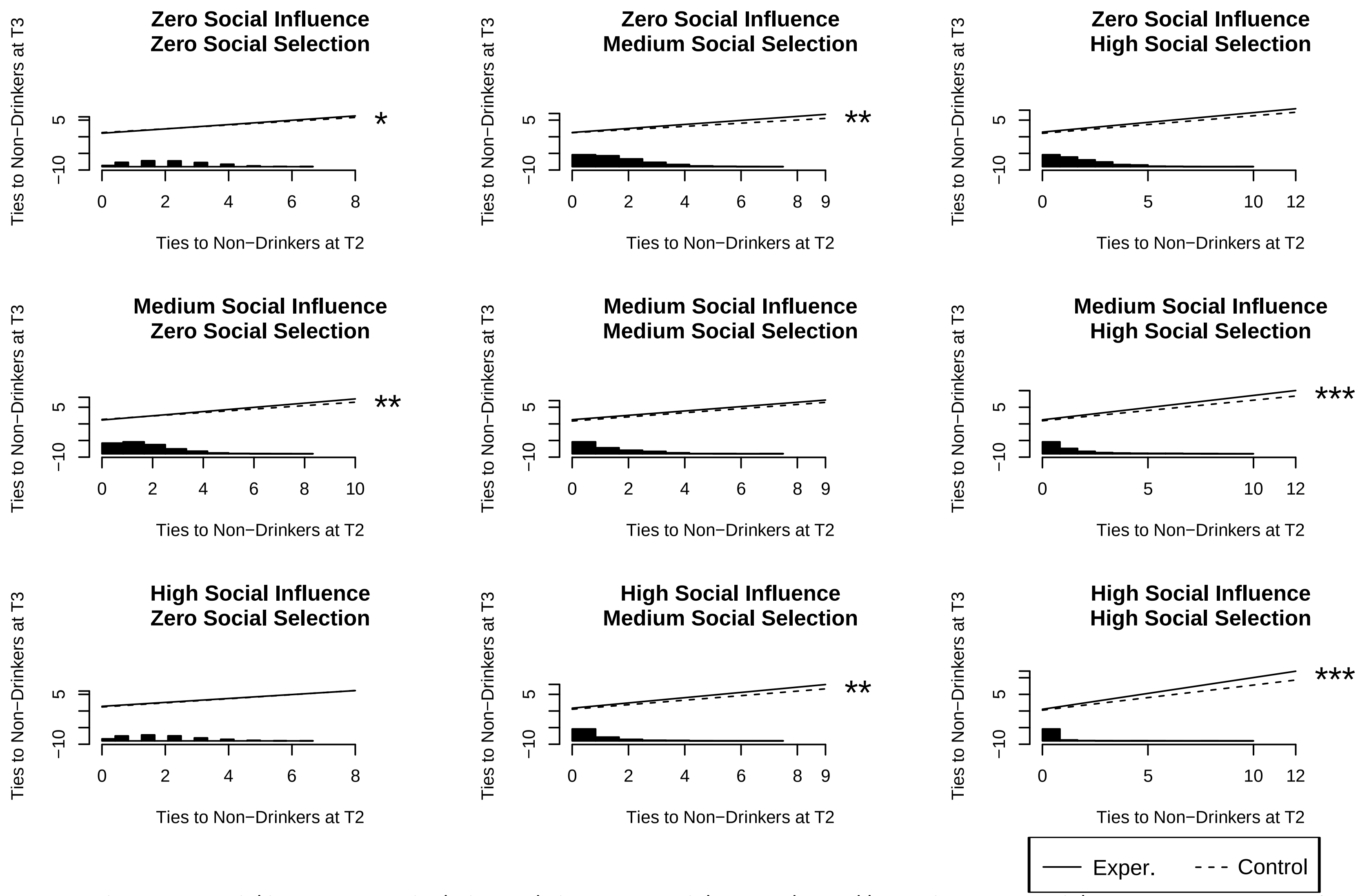


Figure 17.3: Drinking Status Manipulation and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 100, HDR = 50%

had many ties to non-drinkers at T2. Conversely, actors in the experimental conditions had smaller or no differences in ties to non-drinkers at T3, relative to actors in control conditions, if they only had a small number of ties to non-drinkers at T2.

Effect of status manipulation on non-target actors' drinking. It was hypothesized that the drinking status intervention might affect drinking outcomes for other non-targeted actors when social influence was present in the network models. Although the results presented above indicated that target actors receiving the drinking status manipulation often had fewer ties to heavy drinkers and more ties to non-drinkers at T3 when social selection and/or social influence were present, these outcomes could be explained by changes in ties extended by target actors at T3 rather than changes in the drinking statuses of non-target actors with pre-existing ties at the time of the manipulation. For example, it is possible that target actors removed existing ties to heavy drinkers and extended new ties to non-drinkers without affecting the drinking behavior of others in the network.

To test whether the drinking status manipulation affected the behavior of other actors in the network, the T3 drinking statuses of "peripheral" actors who extended ties to the target actor at T2 (the time of the manipulation) were compared between control and experimental conditions using paired-sample t-tests of peripheral actors' drinking statuses at T3.

The effects of the drinking status manipulation on the drinking statuses of peripheral actors are shown in Figures 18.1-18.3. The bar plots present the mean number of heavy drinking peripheral actors at T3 and vertical lines represent standard errors of the estimates for each condition. In all conditions where social influence was positive

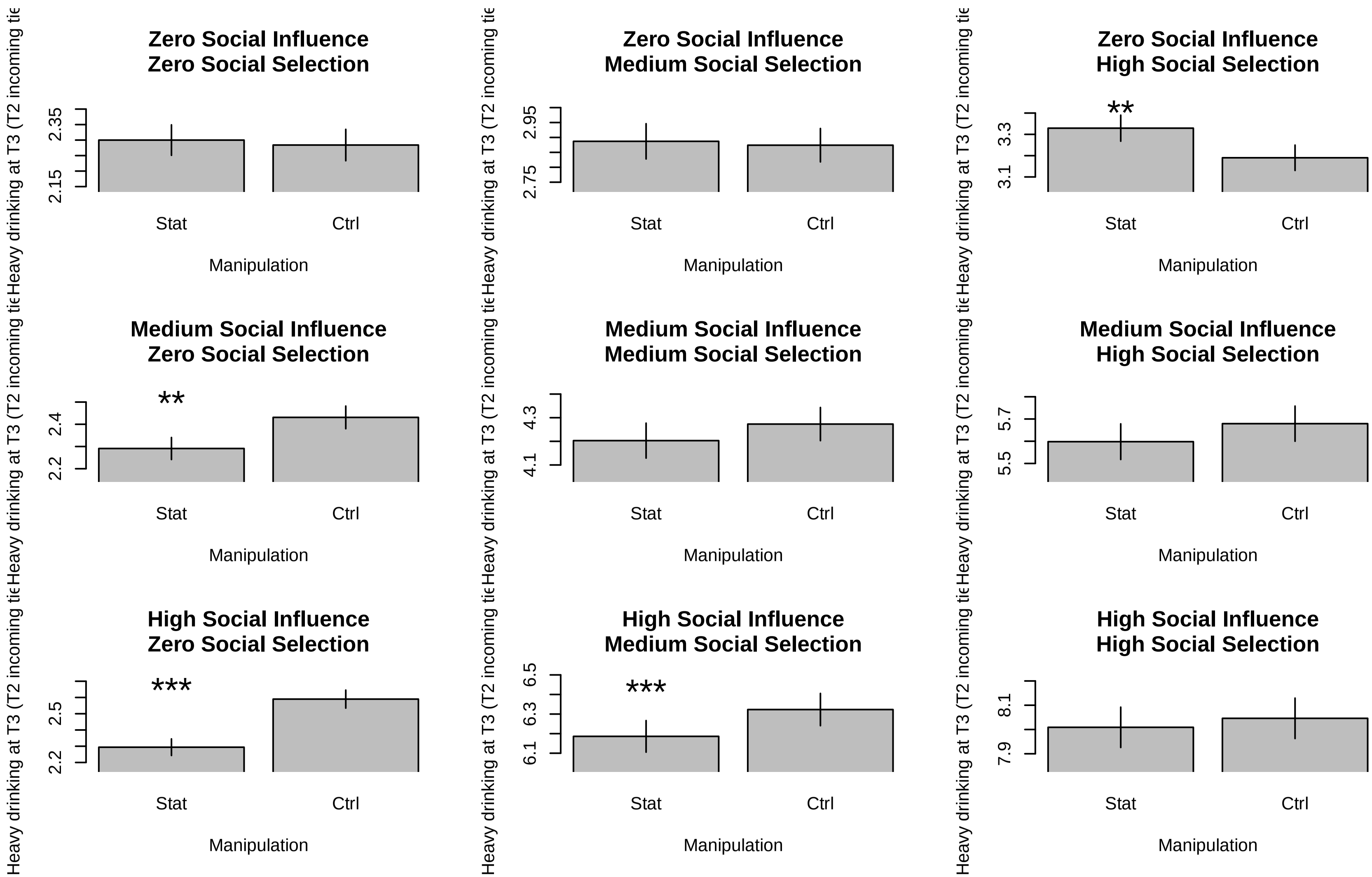


Figure 18.1: Drinking Status Manipulation and Peripheral Actor Heavy Drinking, N = 25, HDR = 50%

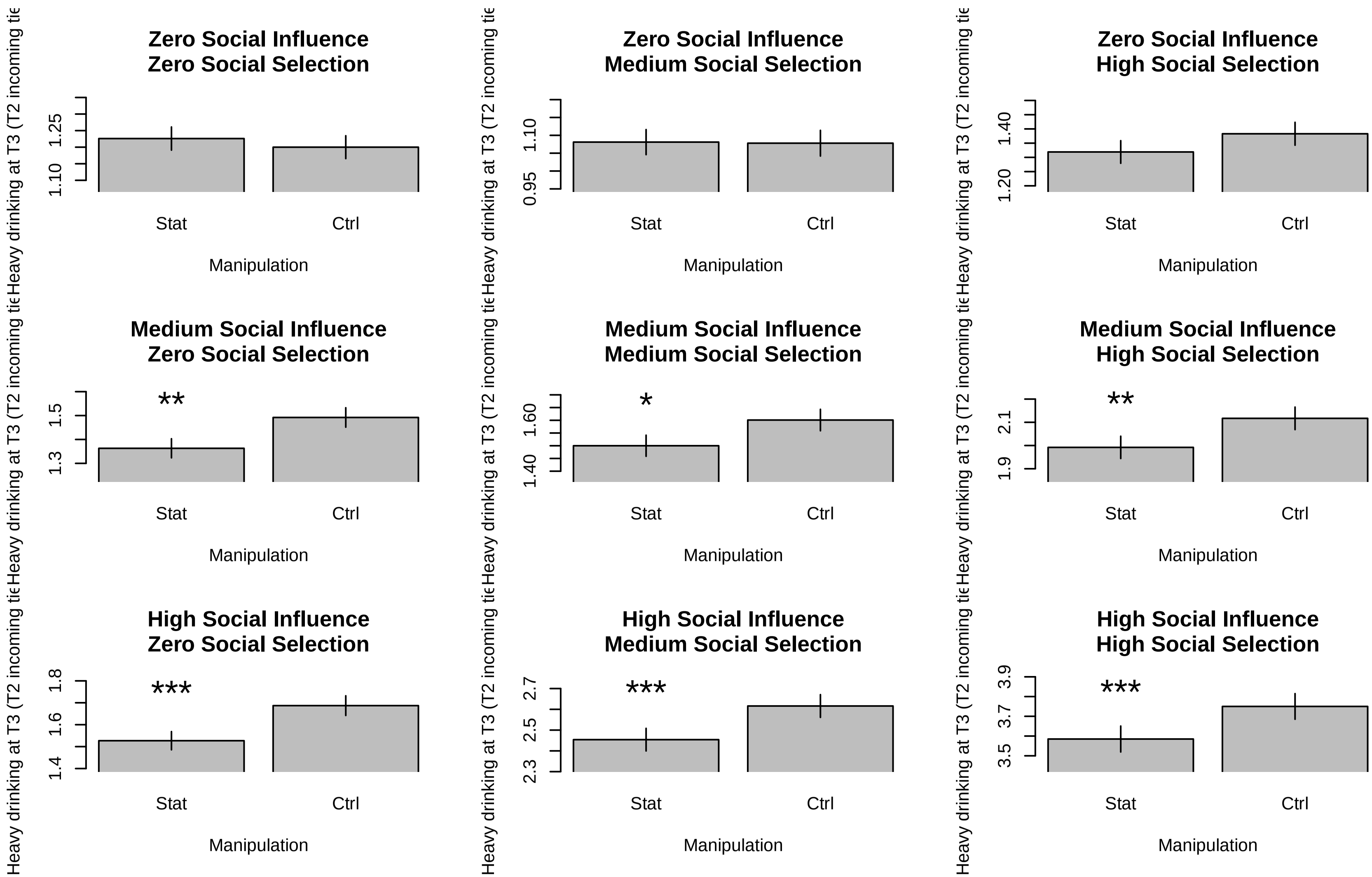


Figure 18.2: Drinking Status Manipulation and Peripheral Actor Heavy Drinking, N = 25, HDR = 25%

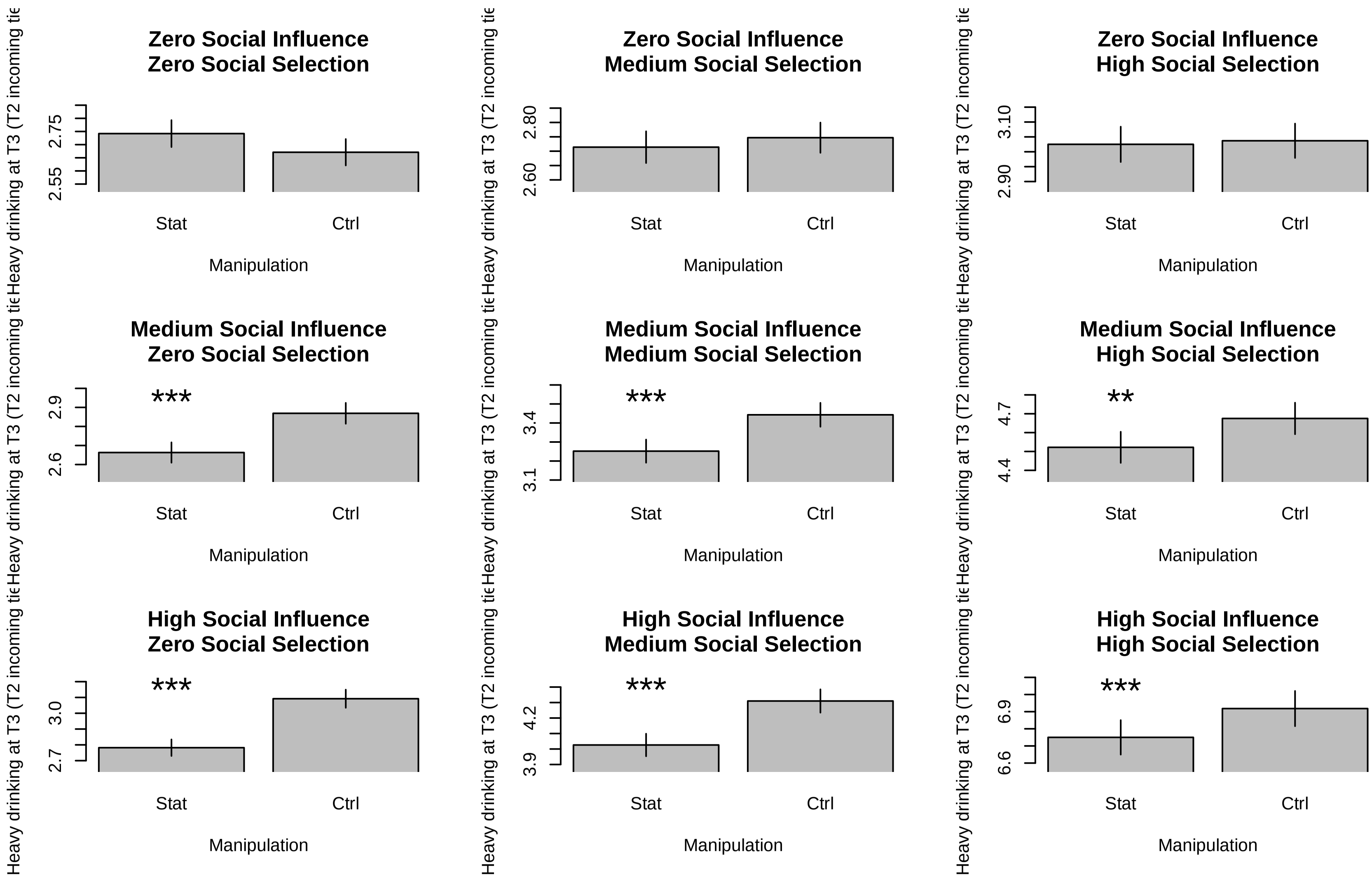


Figure 18.3: Drinking Status Manipulation and Peripheral Actor Heavy Drinking, N = 100, HDR = 50%

and social selection was equal to zero (middle-left and bottom-left plots of Figures 18.1-18.3), the drinking status intervention significantly reduced the heavy drinkers of peripheral actors. As expected, the magnitude of this reduction in heavy drinking was greater in the high social influence conditions than in the medium social influence conditions, indicating that greater social influence, in the absence of social selection, resulted in greater reductions in heavy drinking for peripheral actors, who were not targeted in the intervention.

In the N = 25 and HDR = 50% networks, the addition of social selection to social influence effects mitigated the differences between experimental and control-group peripheral actor heavy drinking. For example, on average, the manipulation reduced the heavy drinking of 0.40 peripheral actors when social influence was high and social selection was absent (M = 2.19 heavy drinking peripheral actors in the experimental condition vs. M = 2.59 in the control condition, bottom-left plot of Figure 18.1), whereas the manipulation only reduced the heavy drinking of 0.13 peripheral actors when social influence was high and social selection was medium (M = 6.19 vs. M = 6.32, bottom-center plot of Figure 18.1). Further, the drinking status manipulation did not significantly reduce the heavy drinking of peripheral actors when social influence and social selection were both medium (middle-center plot of Figure 18.1) or when social influence was medium and social selection was high (middle-right plot of Figure 18.1) in the N = 25 and HDR = 50% conditions. However, in the N = 25, HDR = 25% and N = 100, HDR = 50% conditions, the reduction in peripheral actor heavy drinking due to the drinking status manipulation was significant in all conditions with positive social influence, regardless of the level of social selection (middle and bottom rows of Figures

18.2-18.3), and each combination of influence and selection typically resulted in a similar level of reduction in heavy drinking for peripheral actors between the experimental and control conditions.

As anticipated, there were no significant differences between the experimental and control conditions when social influence was zero (top rows of Figures 18.1-18.3) except in the condition with high social selection in the $N = 25$ and HDR = 50% (top right plot of Figure 18.1), when the experimental condition unexpectedly resulted in a greater number of peers who were heavy drinkers ($M = 3.33$) compared to the control condition ($M = 3.19$).

Summary of findings for drinking status manipulation. The action of changing one randomly-targeted actor's drinking status from heavy drinker to non-drinker produced many changes in the targeted individual's drinking outcomes and friendships, as well as the drinking outcomes of the targeted actor's friends at the time of the intervention.

Across conditions, the drinking status manipulation was associated with a consistent reduction in target actor heavy drinking rates over time relative to the control condition. Post-manipulation relapse rates were highest when both social influence and social selection were present, but the efficacy of the intervention, relative to the control condition, was not substantially moderated by the level of social influence or social selection.

In several conditions with positive social influence and social selection, target actors embedded in clusters of heavy drinkers with few ties to non-drinkers experienced the most benefit from the drinking status intervention. Conversely, target actors embedded in clusters of non-drinkers with few ties to heavy drinkers experienced less benefit from the intervention, relative to the control condition, and often succeeded in reducing their heavy drinking without the assistance of the intervention.

The drinking status intervention typically reduced the number of ties from target actors to heavy drinkers and increased the number of ties from target actors to non-drinkers, relative to the control condition, when social selection was positive. This effect was most pronounced when target actors had a large number of heavy drinkers or non-drinkers, respectively, at the time of the intervention.

The drinking status intervention also typically reduced the drinking rates of peripheral actors, i.e., non-target actors who extended ties to the target actor at the time of the intervention. This effect increased proportionally as the level of social influence increased, and was mitigated in some, but not most, of the conditions with positive social selection.

Social Network Interventions

In addition to examining the effects of changing the target actor's drinking status, the present study also aimed to examine the effects of changing aspects of the targeted actor's social network, including (a) reducing the target actor's susceptibility to social influence, (b) reducing the target actor's susceptibility to social selection, (c) extending a tie from the target actor to a randomly-selected non-drinking actor, and (d) removing an existing tie from target actor to a randomly-selected heavy drinking actor. Similar analyses as those reported above examine the effects of each of these four interventions on target actor heavy drinking, target actor friendships, and peripheral actor heavy drinking.

Social network manipulations and target actor drinking outcomes. The effect of each of the four social network manipulations on target actor heavy drinking rates at T3 are modeled in Figures 19.1-19.3. The values in the bar graphs for these figures represent the percentages of target actors who were heavy drinkers at T2 (*y*-axis) with standard errors (vertical lines), based on experimental condition (separate bars). Significance levels for matched-samples McNemar chi-square tests with Bonferroni adjustment for four comparisons are marked with asterisks above each experimental condition and indicate significant differences in heavy drinking rates for target actors in the experimental conditions relative to the control condition.

As shown in Figures 19.1-19.3, reducing the target actor's susceptibility to social influence (conditions labeled "Infl" in Figures 19.1-19.3) was most commonly associated with reduction in target actor heavy drinking relative to the control condition (conditions labeled "Ctrl"). This reduction in susceptibility to social influence resulted in reduced heavy drinking rates for target actors in all conditions with positive social influence and positive social selection (bottom-right, bottom-center, middle-right, and middle-center plots of Figures 19.1-19.3), as well as in the condition with high social influence and zero social selection when N = 25 and HDR = 25% (bottom-left plot of Figure 19.2). As the amount of social selection and social influence increased, the magnitude of the decrease in the target actor's heavy drinking compared to the control group also decreased.

Regardless of the level of social influence and social selection in the overall network (all plots of Figures 19.1-19.3), drinking rates of target actors with reduced susceptibility to social influence were always similar to the heavy drinking rates of target actors in the control conditions with zero social influence and zero social selection

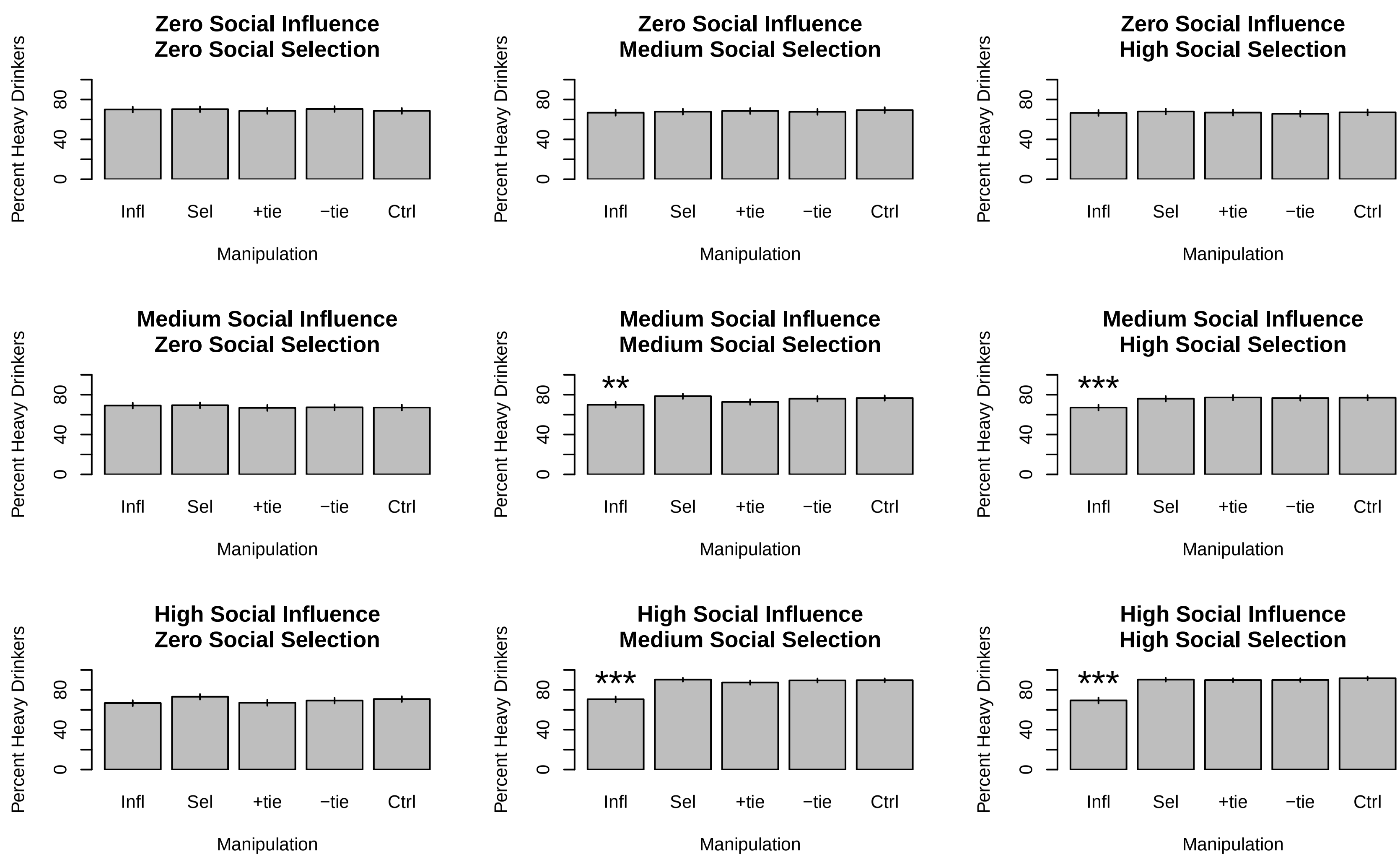


Figure 19.1: Network Manipulations and Target Actor Heavy Drinking, N = 25, HDR = 50%

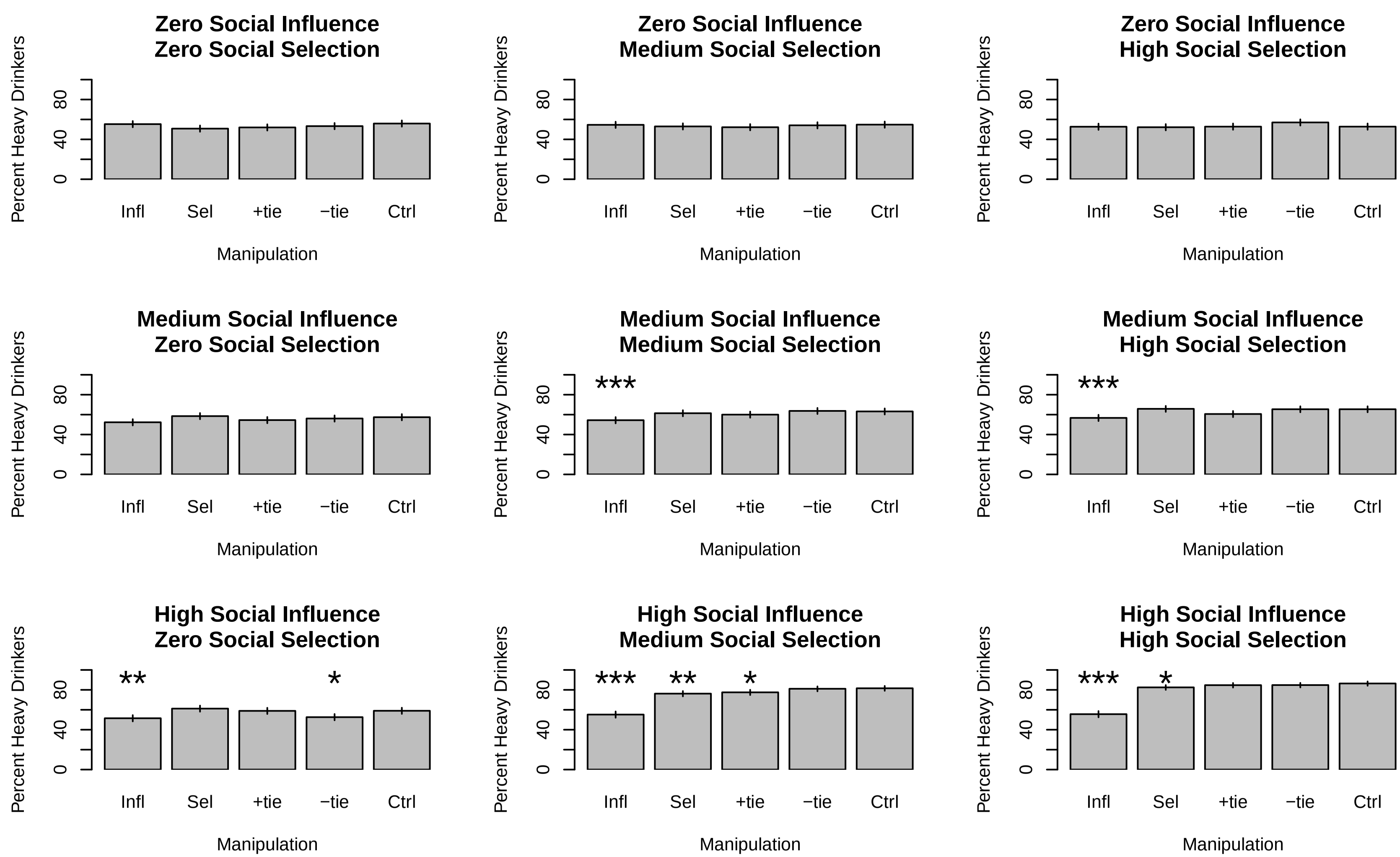


Figure 19.2: Network Manipulations and Target Actor Heavy Drinking, N = 25, HDR = 25%

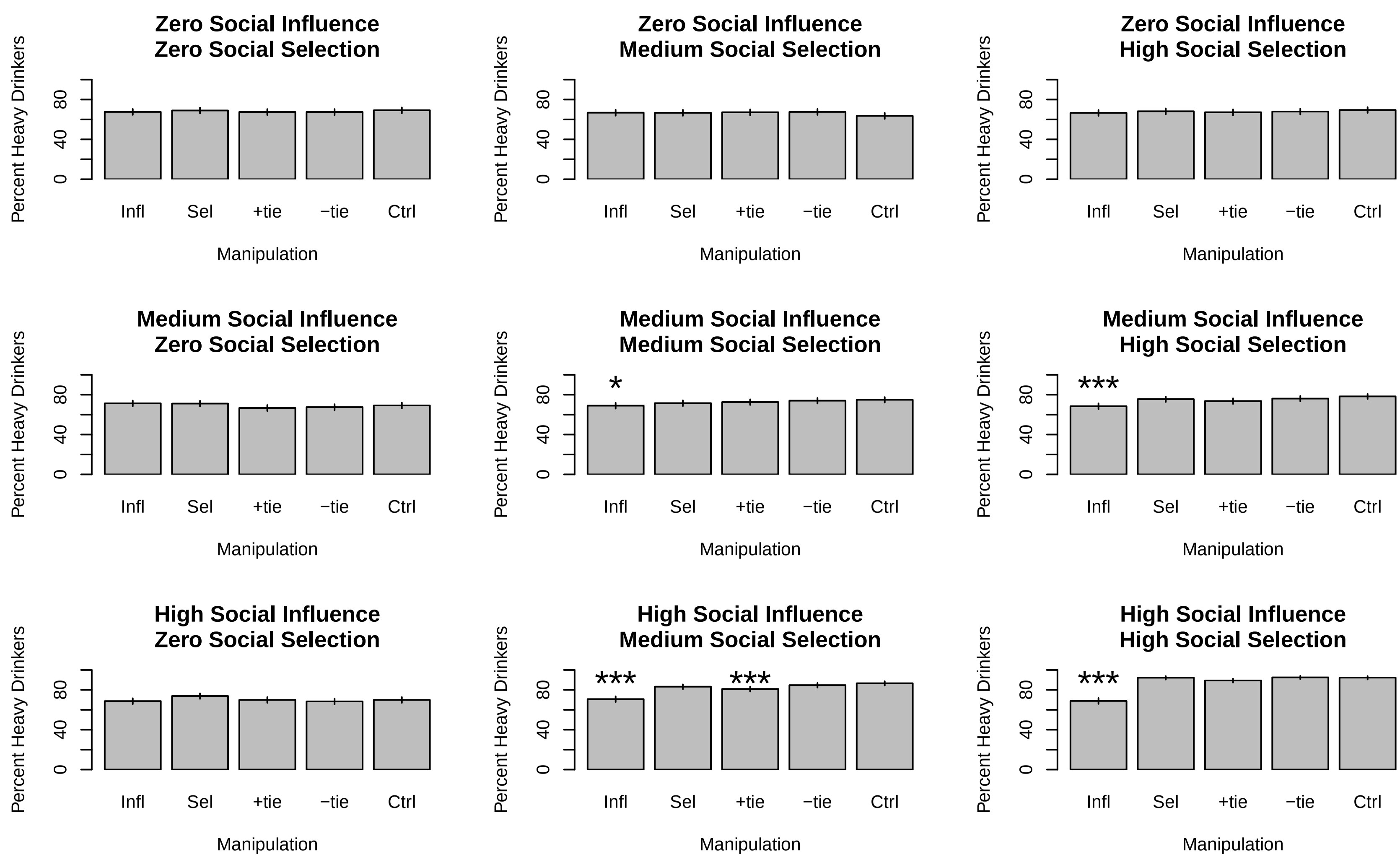


Figure 19.3: Network Manipulations and Target Actor Heavy Drinking, N = 100, HDR = 50%

(control conditions in top-left plots of Figures 19.1-19.3). For example, target actors with reduced susceptibility to social influence had heavy drinking rates between 66.1% and 70.6% for the N = 25 and HDR = 50% conditions, between 51.5% and 56.7% for the N = 25 and HDR = 25% conditions, and between 66.6% and 71.3% for the N = 100 and HDR = 50% conditions. In other words, reducing target actors' susceptibility to social influence placed target actors at a similar risk for heavy drinking as the participants who were in networks with no social influence or social selection at all.

Reduced target actor drinking was obtained occasionally from other manipulations, including removing a tie from the target actor to a heavy drinker was removed (condition labeled "-tie") when social influence was high and social selection was zero (bottom-left plot of Figure 19.2), adding a tie from the target actor to a non-drinker (condition labeled "+tie") in the high social influence and zero social selection condition (bottom-center plot of Figure 19.2), and reducing the target actor's susceptibility to social influence (condition labeled "Sel") in the conditions with high social influence and medium or high social selection (bottom-center and bottom-right plots of Figure 19.2). However, these effects did not appear to follow a consistent pattern and were not replicated in the N = 25, HDR = 50% and N = 100, HDR = 50% networks.

In combination, the pattern of results suggest that reducing a target actors' susceptibility to social influence consistently reduced heavy drinking rates for target actors that were in conditions with positive social influence and social selection. However, none of the other intervention methods provided consistent changes in target actors' heavy drinking.

Social network manipulations and target actor drinking outcomes: Moderating effect of network position.

Number of heavy drinking peers at T2. Moderation analyses were conducted to test whether the effects of the social network interventions on target actor heavy drinking outcomes were moderated by the target actor's ties to heavy drinkers and non-drinkers at the time of the manipulation. Figures 20.1-20.3 plot the drinking outcomes for target actors at T3 as logit odds (*y*-axis, left sides of plots) and in simple probabilities (*y*-axis, right sides of plots) based on the interaction of the number of outgoing ties to heavy drinkers at T2 (*x*-axis) and experimental condition (separate lines). Each experimental condition is represented by a solid line and only experimental conditions with significant interactions are labeled to facilitate easier interpretation. The control conditions are plotted as dashed lines. The efficacy of an experimental condition, relative to the control condition, on target actor drinking outcomes was moderated by the number of ties to heavy drinkers at T2 when the slopes of the lines for the experimental and control conditions are significantly different. As with the drinking status manipulation results, these figures also present histograms of outdegree distributions to heavy drinkers at T2, with the heights of histograms corresponding with the relative number of ties to heavy drinkers that target actors had across the 1000 simulations in each condition.

Reducing the target actor's susceptibility to social influence was the only experimental condition that was significantly moderated by the number of outgoing ties to heavy drinkers at T2 in more than one combination of conditions. For each combination of sample size and HDR, this moderation effect was present in three out of the four conditions with positive social influence and social selection (bottom-right,

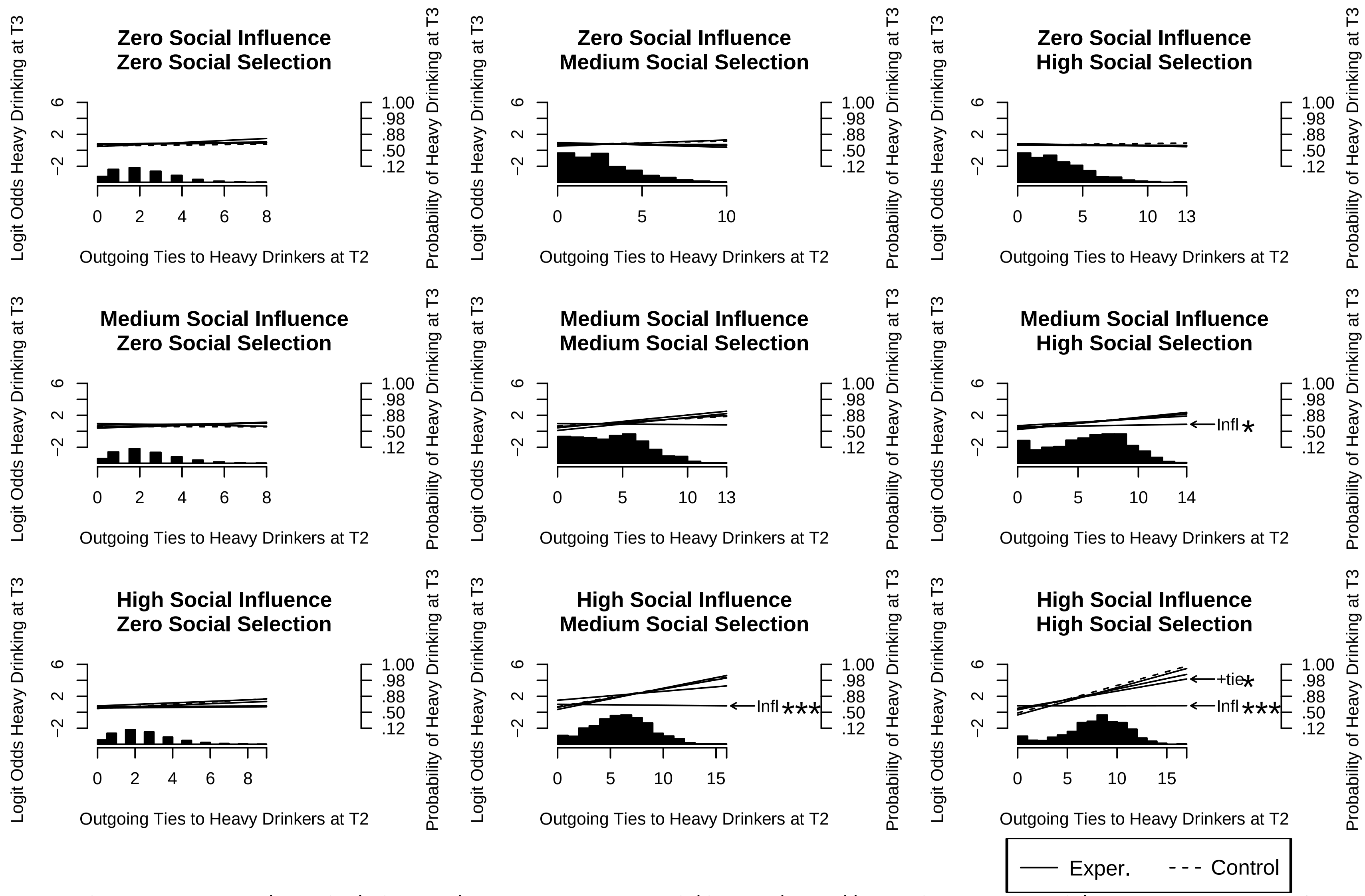


Figure 20.1: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 25, HDR = 50%

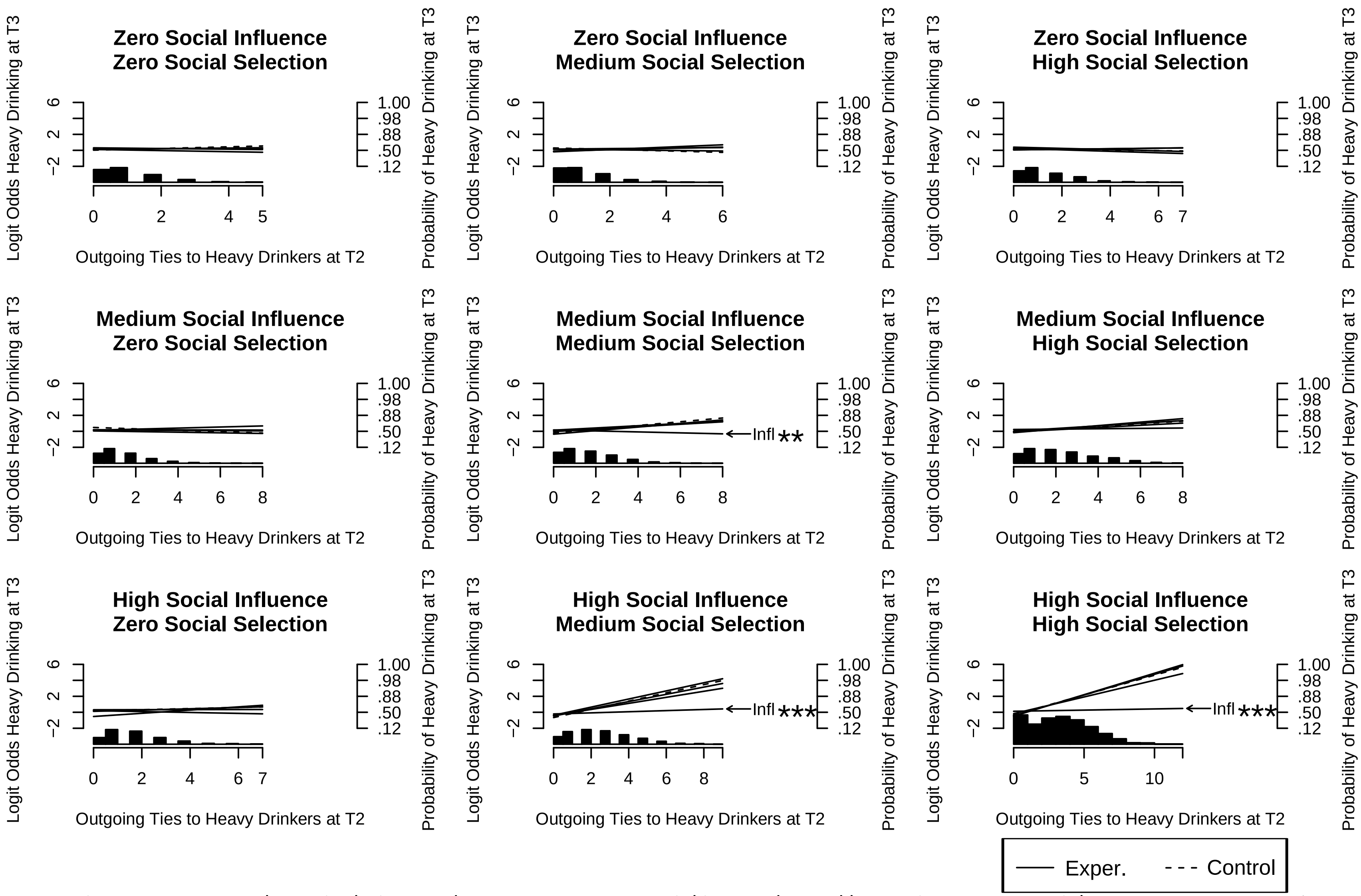


Figure 20.2: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 25, HDR = 25%

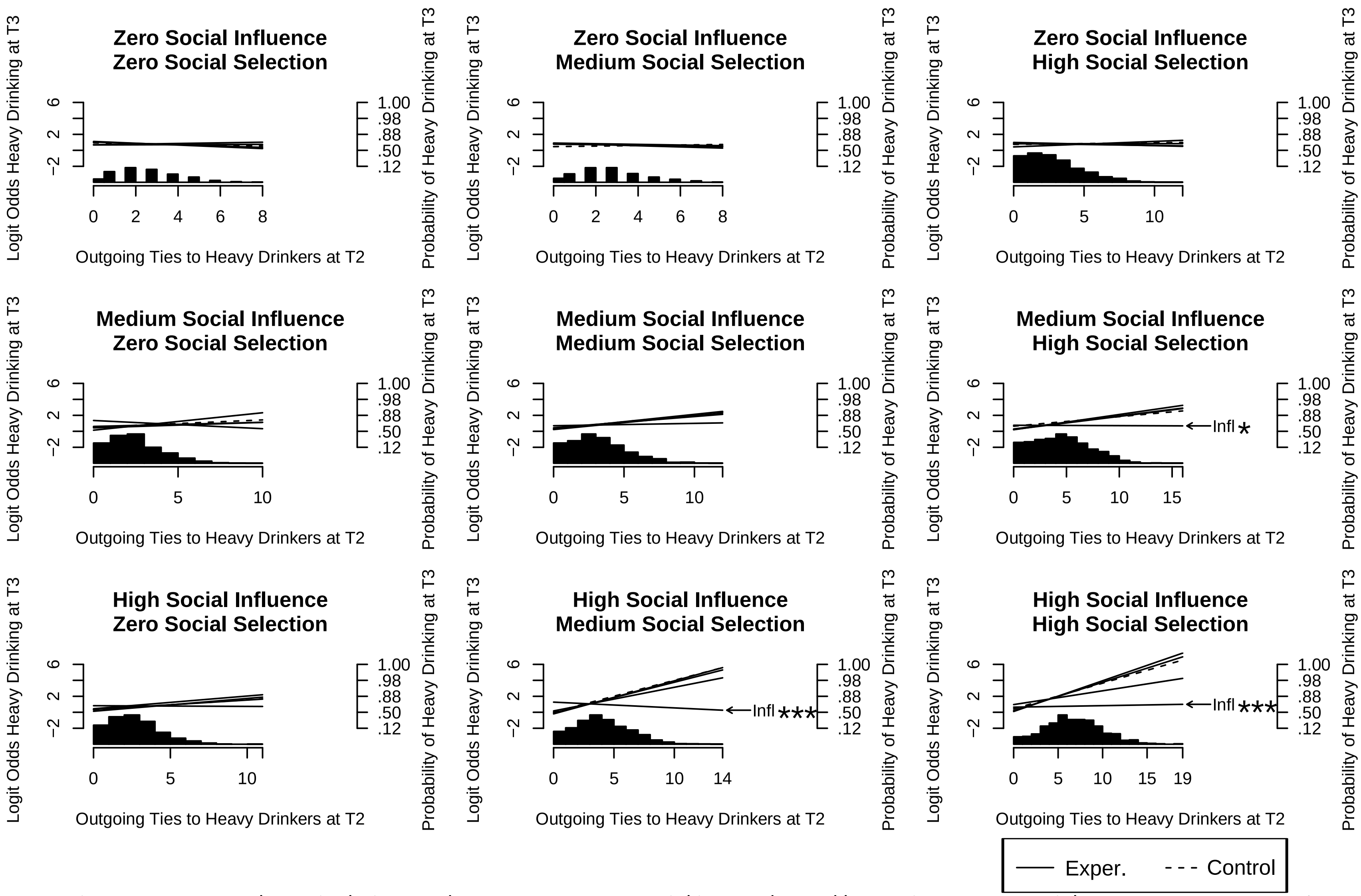


Figure 20.3: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Heavy Drinkers, N = 100, HDR = 50%

bottom-center, middle-right, middle-center plots of Figures 20.1-20.3), and the moderation effect was always absent when social influence and social selection were not both simultaneously present (left columns and top rows of Figures 20.1-20.3). The direction of the significant interactions indicated that slopes for the associations between ties to heavy drinking actors at T2 and target actor heavy drinking at T3 were close to zero in the reduced susceptibility to social influence manipulation, whereas slopes in the control condition were positive. This indicates that participants in the control condition experienced an increased likelihood of maintaining a heavy drinking status at T3 when they had a greater number of ties to heavy drinkers at T2, but participants in the reduced susceptibility to social influence manipulation experienced little or no increase in the likelihood of maintaining a heavy drinking status at T3 when they had a greater number of ties to heavy drinkers at T2.

Significant moderation was present in one other experimental condition when the target actor extended a tie to a non-drinker in the high influence and high selection condition of the N = 25 and HDR = 50% networks (bottom-right plot of Figure 20.1). The direction of this slope was similar to the direction of slopes for the moderation effects in the experimental conditions reported above for reducing target actors' susceptibility to social influence; however, the magnitude of the moderating effect was substantially smaller and was not replicated in any other combinations of conditions.

Number of non-drinking peers at T2. The moderation analysis results based on the number of ties to *non*-drinking peers at T2, presented in Figures 21.1-21.3, were similar to the moderation analysis results based on the number of *heavy*-drinking peers at T2. In most conditions with positive social selection and positive social influence, the

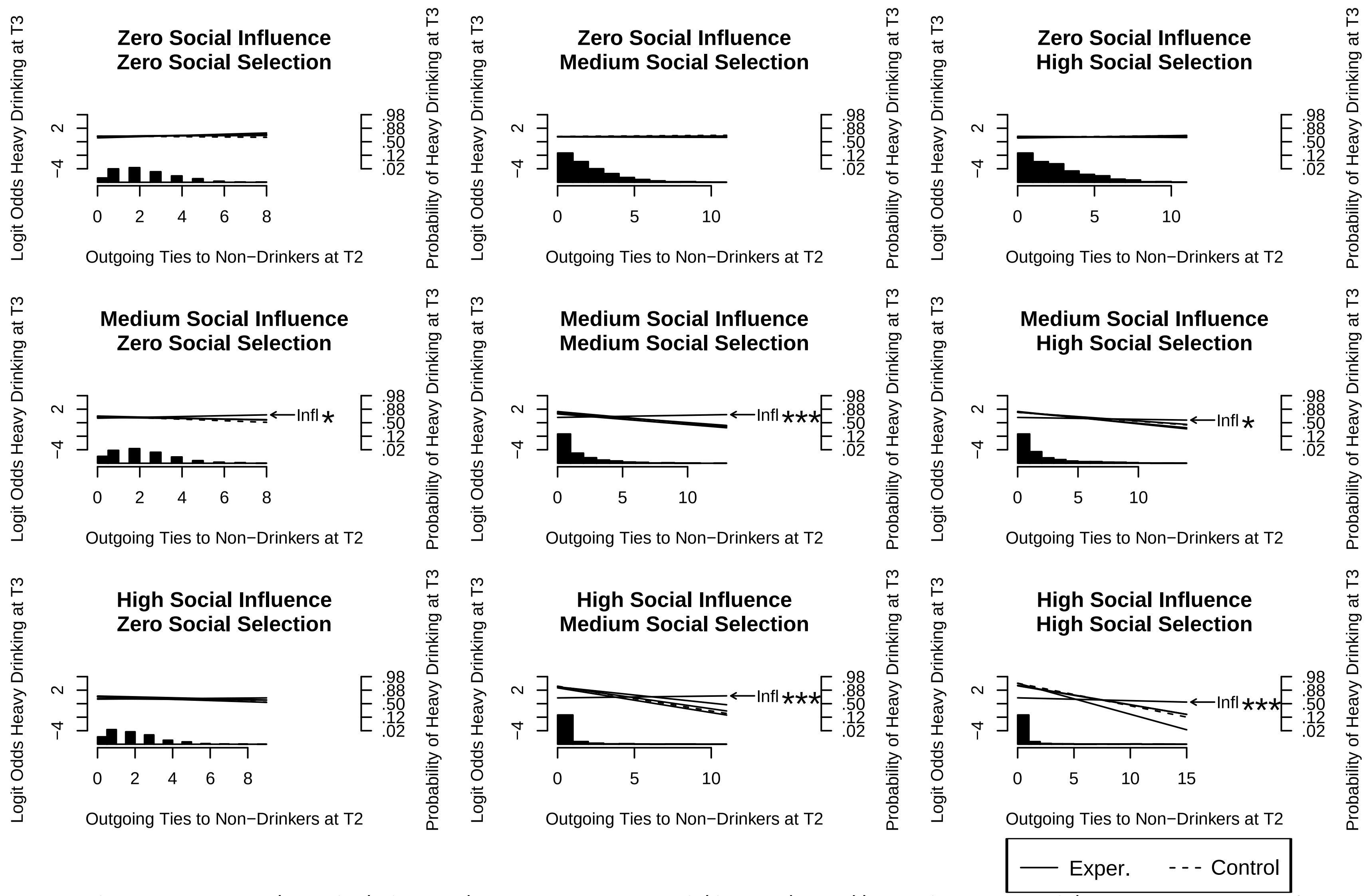


Figure 21.1: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 25, HDR = 50%

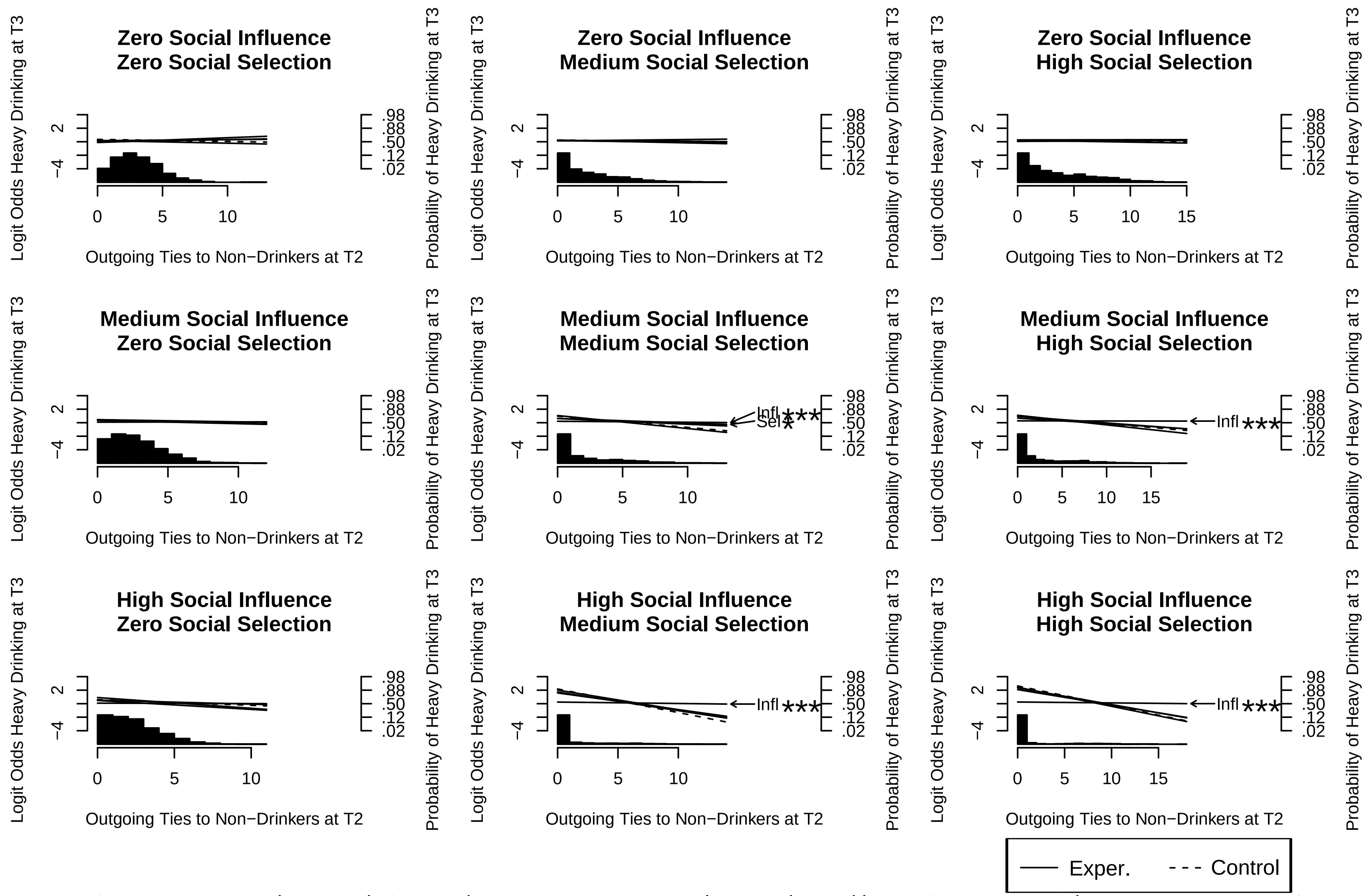


Figure 21.2: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 25, HDR = 25%

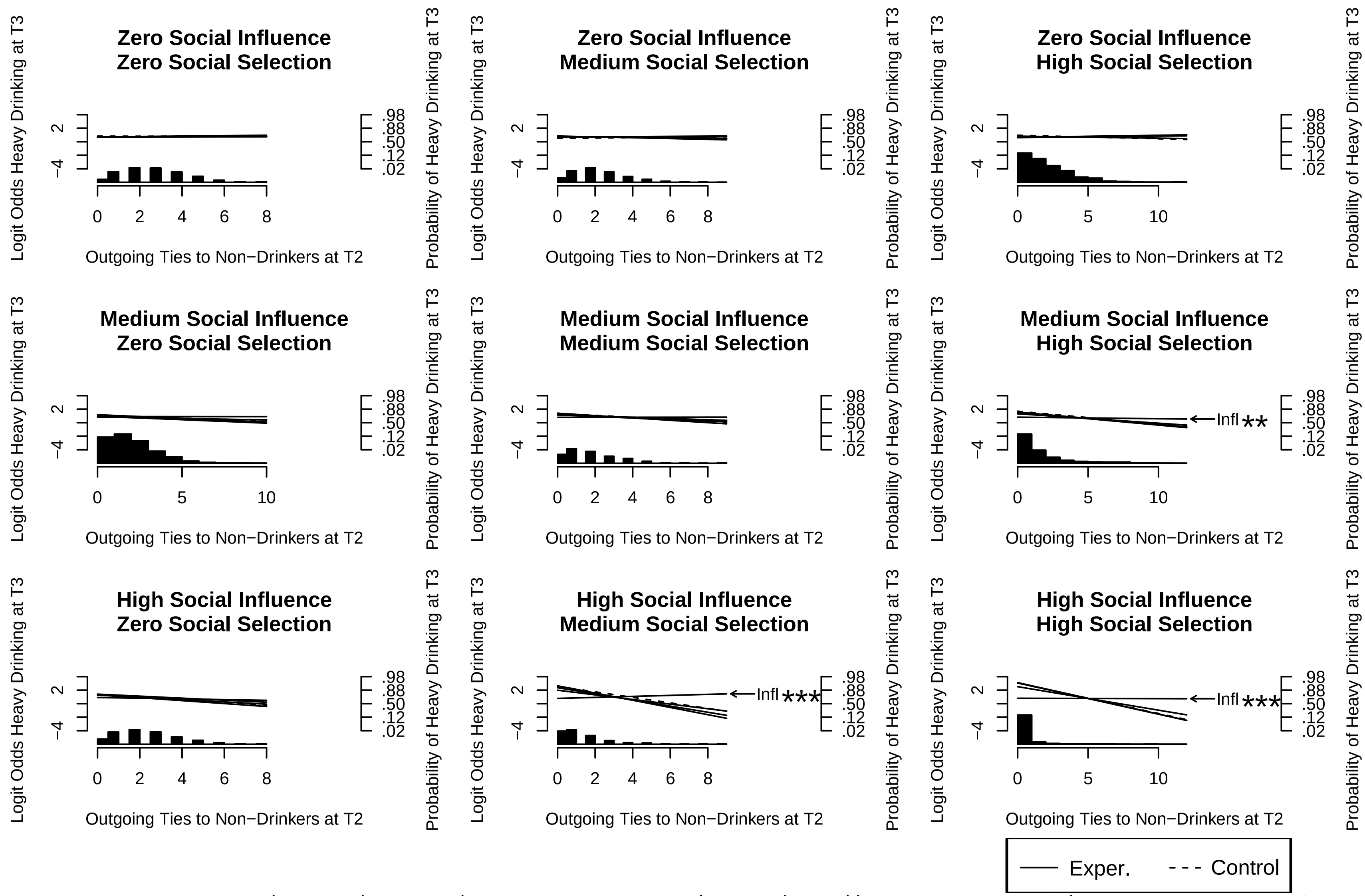


Figure 21.3: Network Manipulations and Target Actor Heavy Drinking Moderated by T2 Ties to Non-Drinkers, N = 100, HDR = 50%

effect of reducing the target actor's susceptibility to social influence on heavy drinking outcomes was moderated by the number of ties to non-drinking actors at T2. For each combination of sample size and HDR, this moderation effect was present in at least three out of the four conditions with positive social influence and social selection (bottom-right, bottom-center, middle-right, middle-center plots of Figures 21.1-21.3). The moderation effect also was present once in the condition with medium social influence and zero social selection when N = 25 and HDR = 50% (middle-left plot of Figure 21.1), but this effect did not replicate in other combination of sample sizes and HDR. In all other cases, the moderation effect was absent when social influence and social selection were not both simultaneously present (left columns, top rows of Figures 21.1-21.3).

Similar to the moderation effects for *heavy*-drinking peers, the direction of the moderation effects for *non*-drinking peers at T2 resulted in slopes that were closer to zero in the experimental condition compared to the non-zero negative slopes in the control condition. This indicates that participants in the experimental condition had little or no change in the likelihood of being a heavy drinker at T3 based on the number of ties to heavy drinkers at T2, whereas participants in the control condition experienced an increased likelihood of becoming a heavy drinker at T3 if they had few ties to non-drinkers at T2.

Significant moderation was present in one other experimental condition when the target actor's susceptibility to social selection was reduced in the medium social influence and medium social selection condition of the N = 25 and HDR = 25% networks (middle-center plot of Figure 21.2). However, the magnitude of the moderating effect was substantially smaller than the magnitude of the moderating effects for the experimental conditions that reduced susceptibility to social influence and was not replicated in any other combinations of conditions.

Social network manipulations and actor friendship outcomes. The following sections explore effect of the social network manipulations on the number of ties from target actors to heavy drinkers and non-drinkers at the conclusion of each simulation (T3) and examine whether these effects were moderated by the target actor's social ties at the time of the intervention (T2).

Ties to heavy drinkers. The effect of the social network manipulations on the number of ties from target actors to heavy drinkers at T3 are presented in Figures 22.1-22.3. These figures display the mean number of ties to heavy drinkers for each social network manipulation and the control condition, with significant differences for each experimental condition relative to the control condition based on paired-sample *t*-tests with Bonferroni correction indicated in the plots.

Reducing the target actor's susceptibility to social influence reduced the number of ties from target actors to heavy drinkers in several conditions with positive social influence and social selection (bottom-right, bottom-center, middle-right, and middle-center plots of Figures 22.1). This effect was significant in all conditions with high social influence and medium or high social selection (bottom-center and bottom-right plots of Figures 22.1-22.3), as one of two conditions with medium social influence and medium or high social selection in all three combinations of network size and HDR (middle-center and middle-right plots of Figures 22.1-22.3) Reducing the target actor's susceptibility to social influence did not reduce the number of ties to heavy drinkers in any of the conditions in which social influence and social selection were not acting

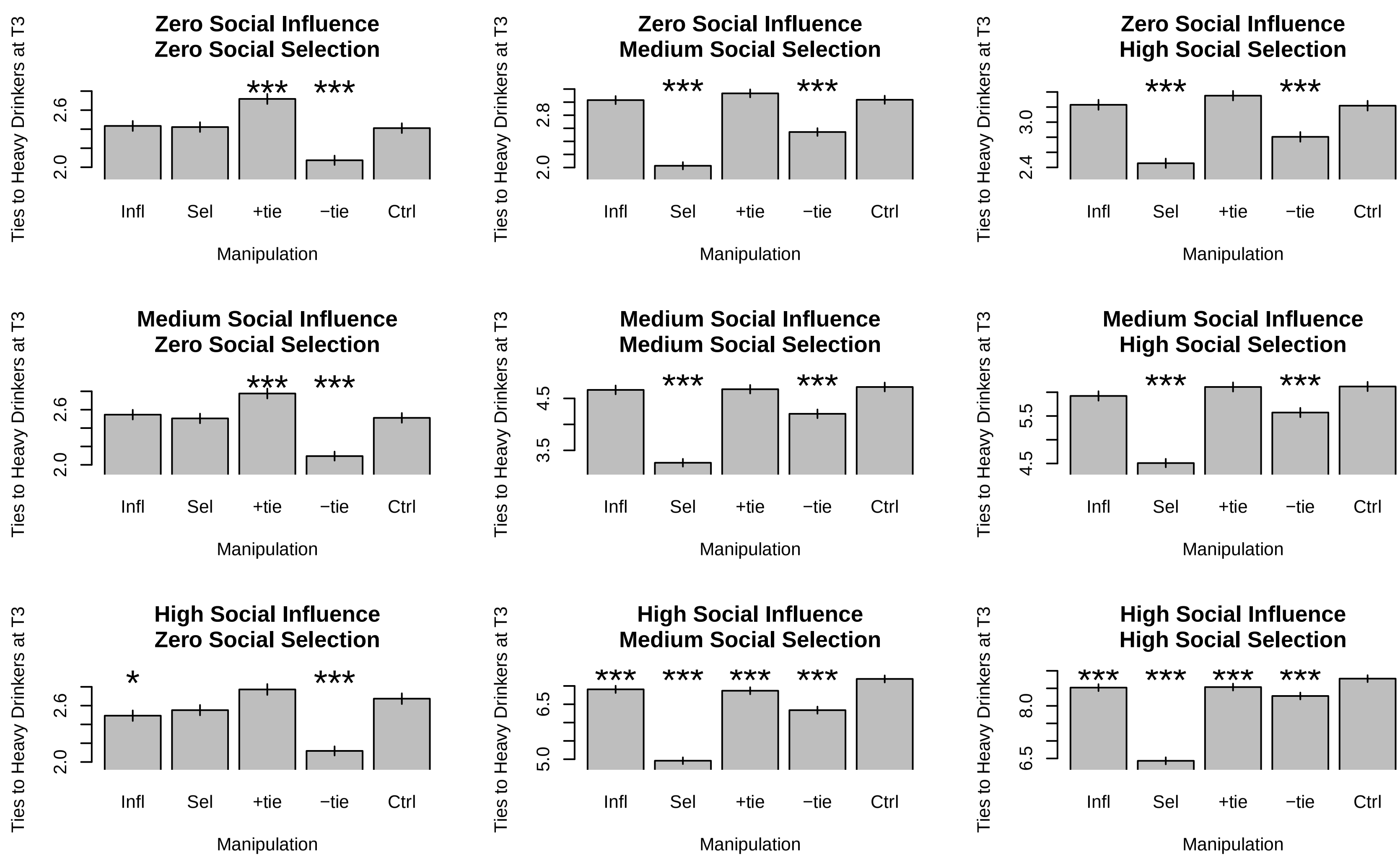


Figure 22.1: Network Manipulations and Ties to Heavy Drinkers, N = 25, HDR = 50%

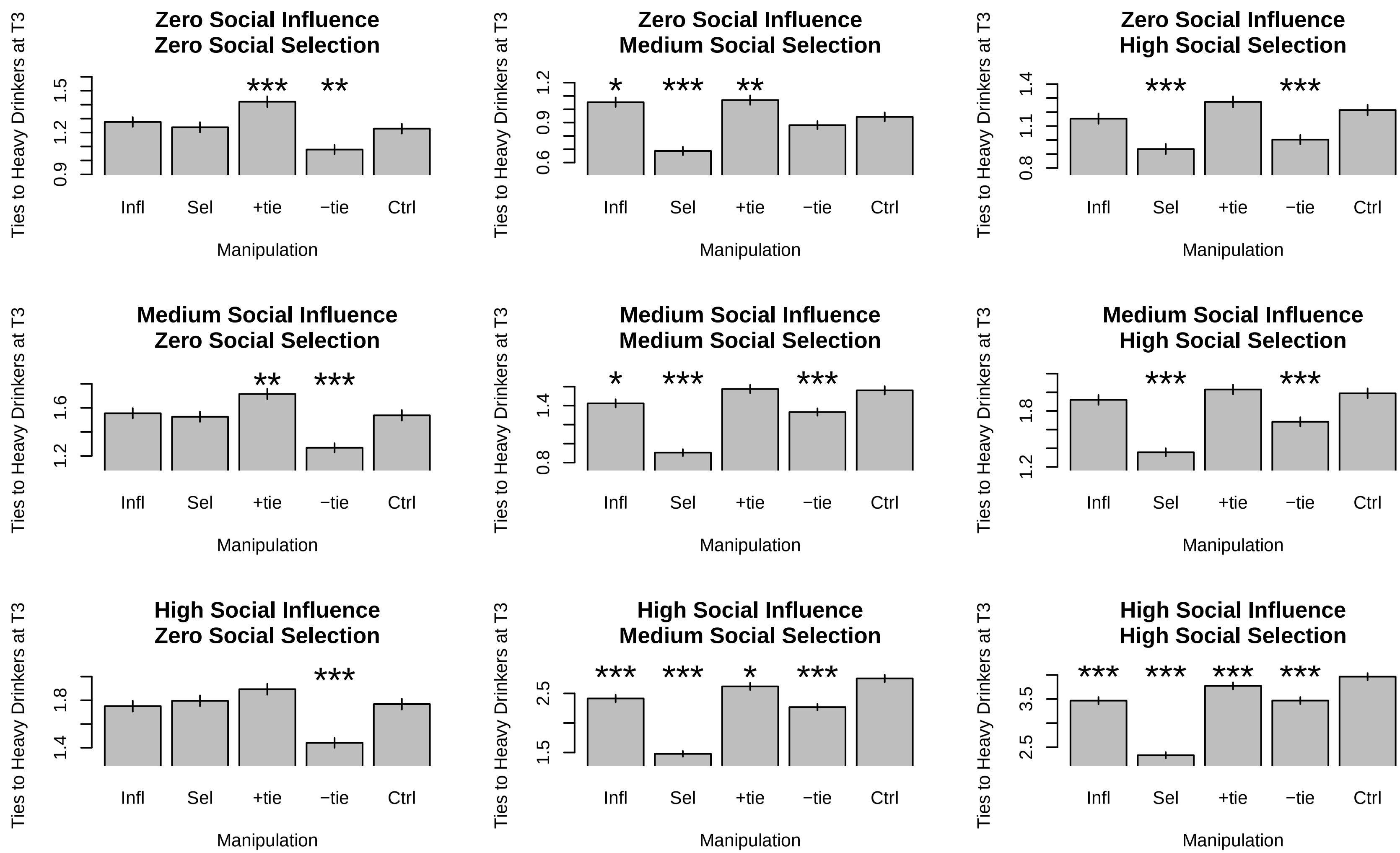


Figure 22.2: Network Manipulations and Ties to Heavy Drinkers, N = 25, HDR = 25%

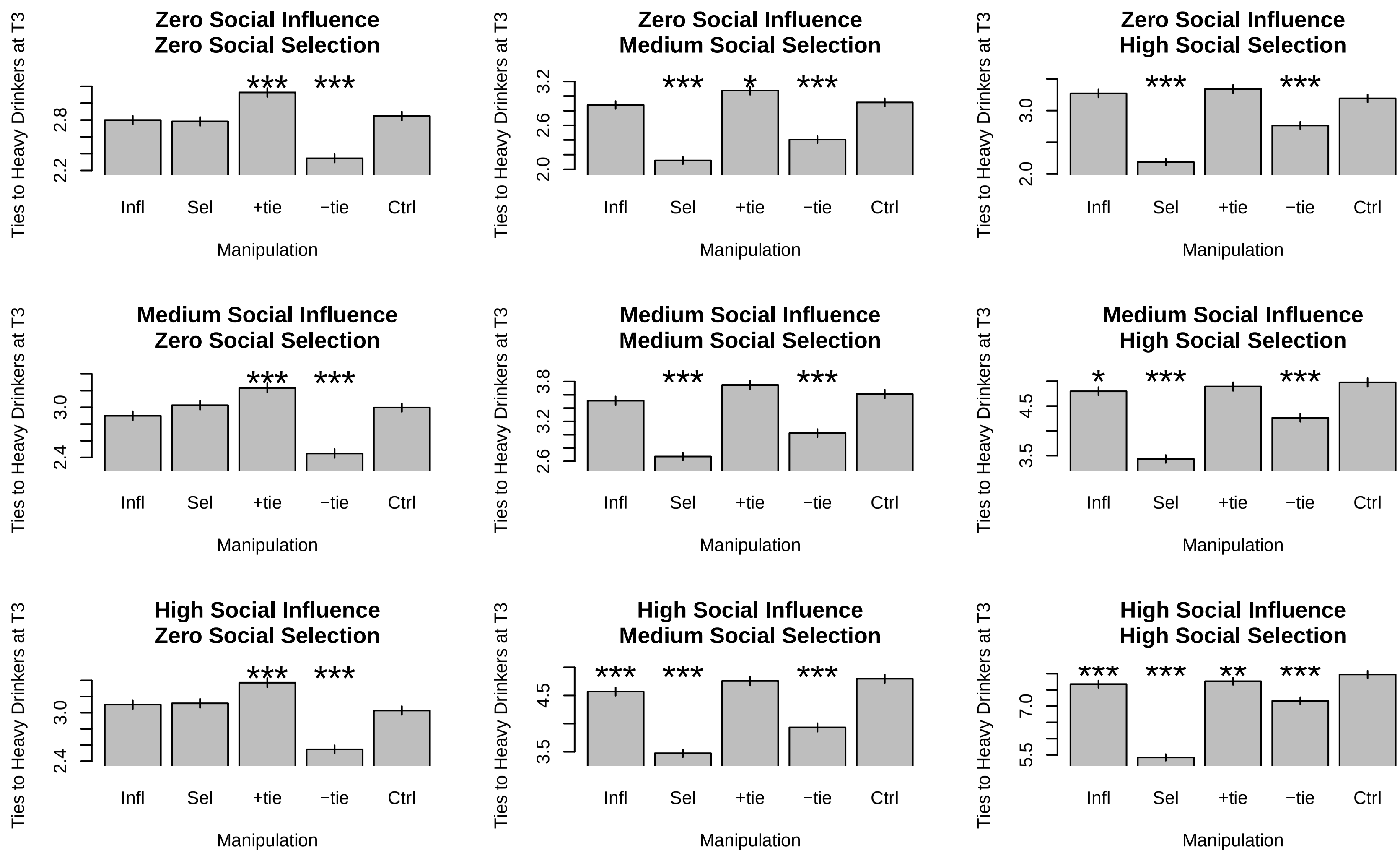


Figure 22.3: Network Manipulations and Ties to Heavy Drinkers, N = 100, HDR = 50%

simultaneously (left columns and top rows of Figures 22.1-223) except in the condition with high social influence and zero social selection when *N* = 25 and HDR = 50% (bottom-left plot of Figure 22.1). Reducing the target actor's susceptibility to social influence was never associated with an increase in ties to heavy drinkers.

Reducing the target actor's susceptibility to social selection significantly reduced the number of ties from target actors to heavy drinkers in all conditions with positive social selection (center and right columns of Figures 22.1-22.3). This manipulation did not affect the number of ties to heavy drinkers in any conditions with zero social selection, regardless of the level of social influence (left columns of Figures 22.1-22.3).

Adding a tie from the target actor to a non-drinker unexpectedly *increased* the number of ties to heavy drinkers at T3, relative to the control condition, in several cases. For example, adding a tie from the target actor to a non-drinker increased the number of ties from the target actor to heavy drinkers in all cases with zero or medium social influence and zero social selection (top-left and middle-left plots of Figures 22.1-223) and in the condition with high social influence and zero social selection when *N* = 100 and HDR = 50% (bottom-left plot of Figure 22.3). An increase in ties to heavy drinkers also was present in two of the three conditions with zero social influence and medium social selection when *N* = 25 and HDR = 25%, and when *N* = 100 and HDR = 100% (top-center plots of Figures 22.2-22.3). Conversely, adding a tie from the target actor to a non-drinker also *decreased* the number of ties to heavy drinkers at T3, relative to the control condition, in several cases with positive social selection and positive social influence acting simultaneously. For example, this manipulation reduced the number of ties to heavy drinkers in all cases when social influence and social selection were high (bottom-right plots of Figures 22.1-22.3) and in both of the $N = 25$ conditions when social influence was high and social selection was medium (bottom-center plots of Figures 22.1-22.2).

Removing an existing tie from the target actor to a heavy drinker significantly reduced the number of ties from target actors to heavy drinkers in almost all combinations of conditions, with the exception of one condition with zero social influence and medium social selection when $N = 25$ and HDR = 25% (top-center plot of Figure 22.2). However, this manipulation was associated with a reduction in heavy drinkers in the other combinations of sample sizes and HDRs for the same levels of social influence and social selection.

Moderation analyses tested whether the effects of each intervention on ties to heavy drinkers at T3 were moderated by ties to heavy drinkers at T2, and are presented in Figures 23.1-23.3. The only manipulations to produce significant moderation were the manipulations of reducing the target actor's susceptibility to social selection and removing a tie from the target actor to a heavy drinker. Reducing the target actor's susceptibility to social selection was a significant moderator only in conditions with both positive social influence and positive social selection (bottom-right, bottom-center, middle-right, and middle-center plots of Figures 23.1-23.3), but did not always have significant moderation in these conditions. Removing a tie from the target actor to a heavy drinker did not appear to follow any consistent pattern of significant moderation effects but was never a significant moderator in conditions with high social selection (right column of Figures 23.1-23.3). In all cases of significant moderation, the direction of the interactions indicated that actors in the control condition were especially likely to

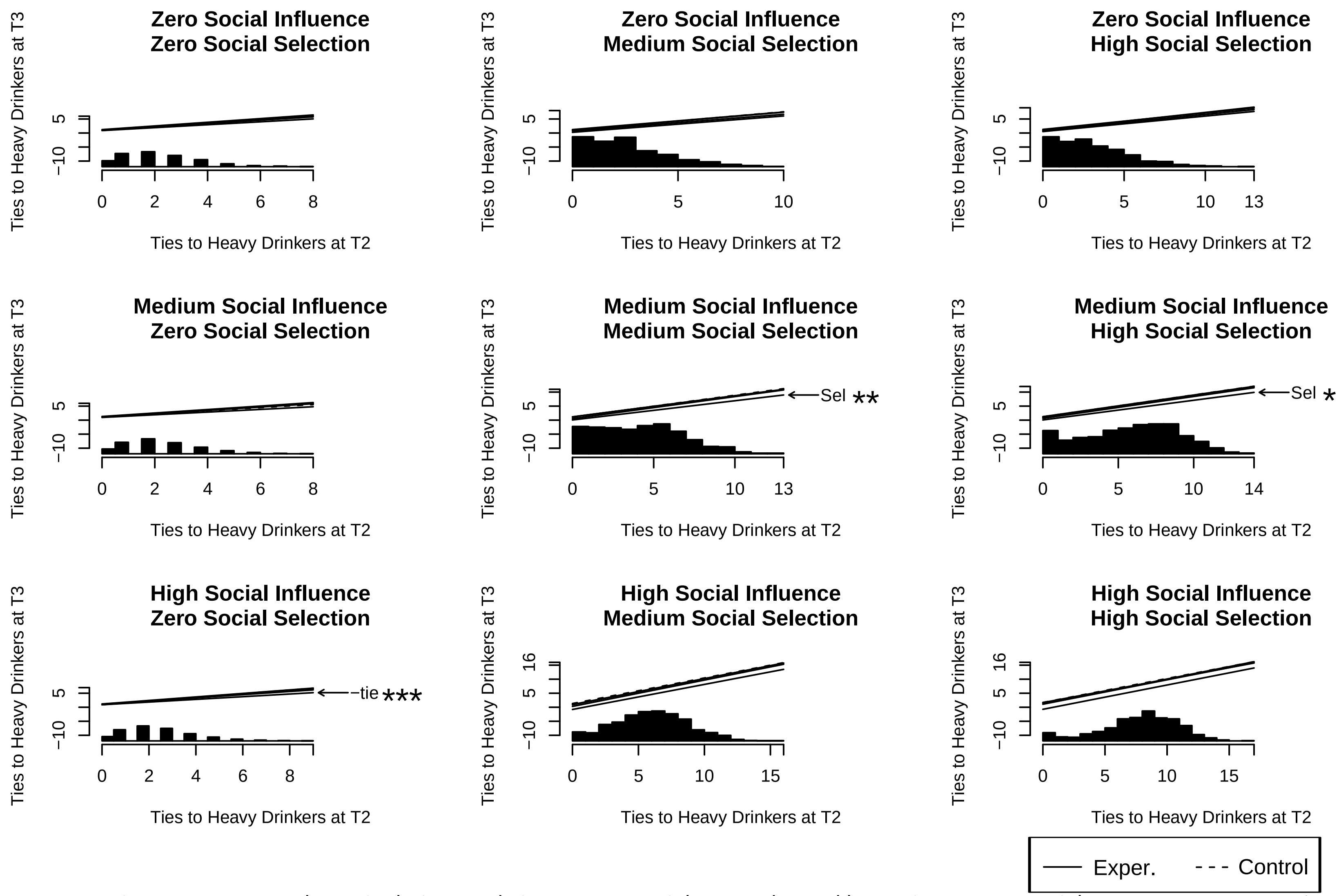


Figure 23.1: Network Manipulations and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 25, HDR = 50%

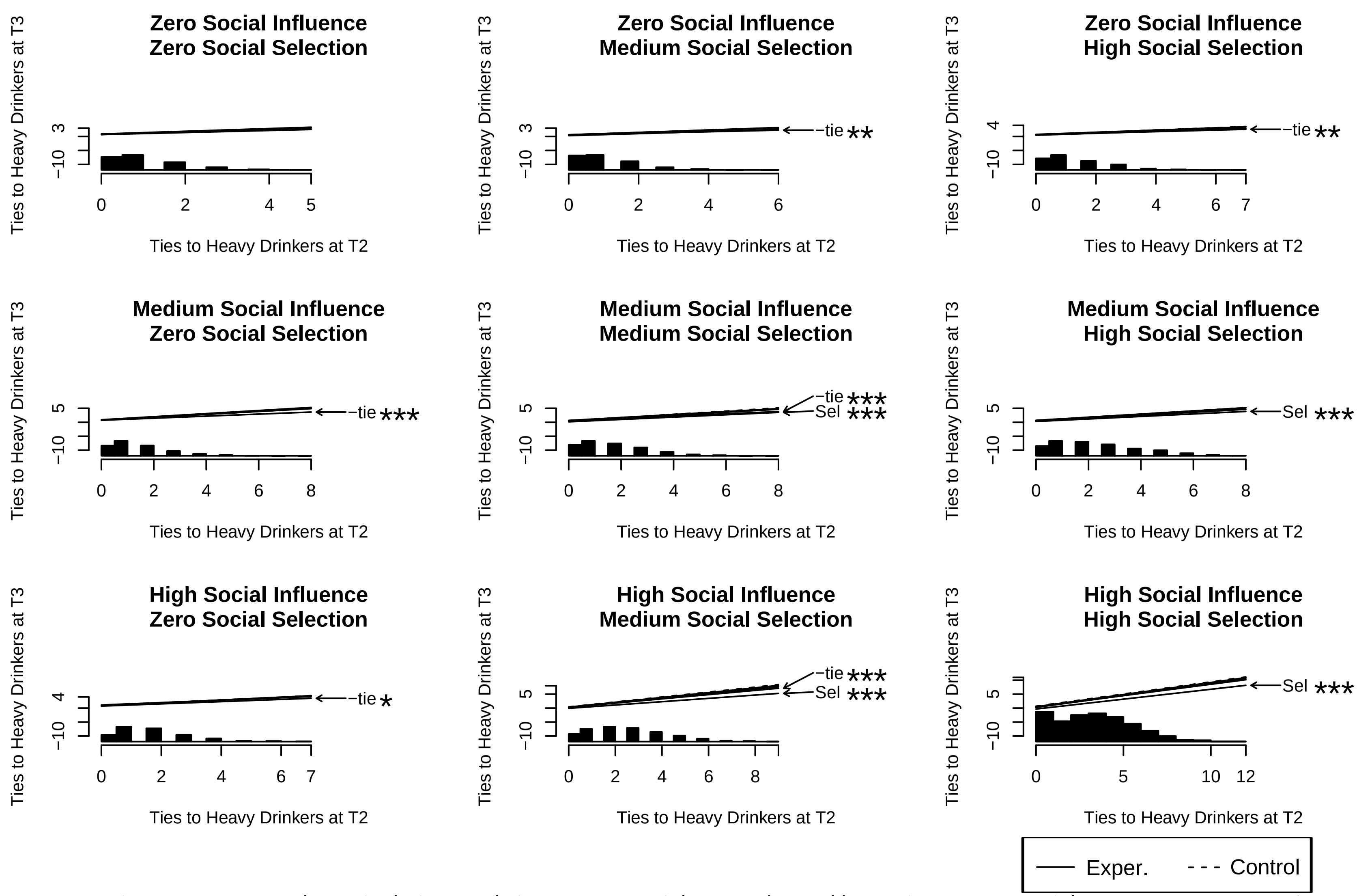


Figure 23.2: Network Manipulations and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 25, HDR = 25%

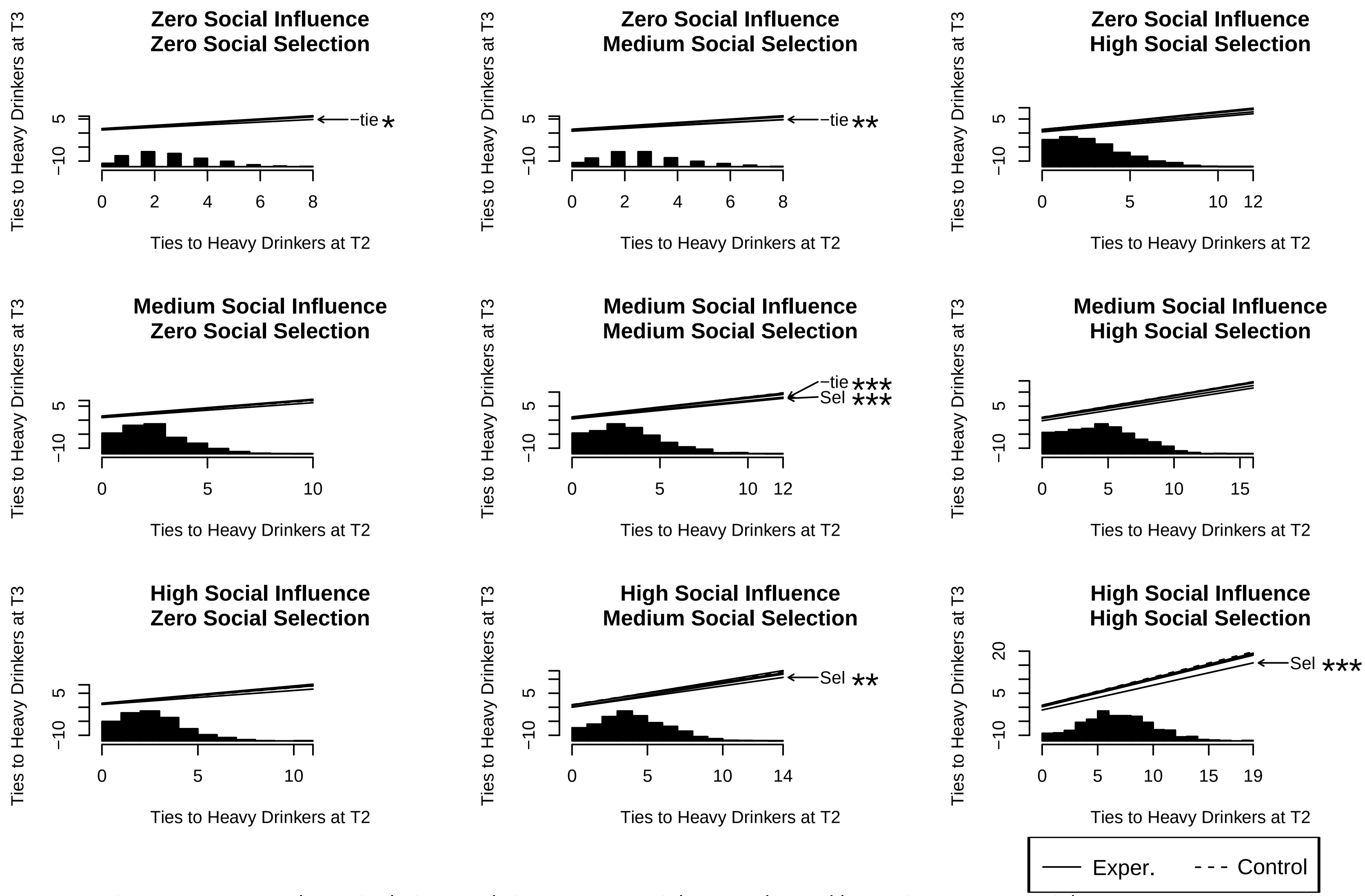


Figure 23.3: Network Manipulations and Ties to Heavy Drinkers Moderated by T2 ties to Heavy Drinkers, N = 100, HDR = 50%

have more ties to heavy drinkers at T3 if they already had many ties to heavy drinkers at T2, while actors in the experimental conditions had a somewhat lower number of ties to heavy drinkers at T3, relative to control conditions, if they already had many ties to heavy drinkers at T2. In other words, the experimental conditions with significant moderation produced the greatest reduction in ties to heavy drinkers at T3 for actors with a large number of ties to heavy drinkers at T2.

Friendships to non-drinkers. The effects of the social network manipulations on the number of ties from target actors to non-drinkers at T3 are presented in Figures 24.1-24.3.

Reducing the target actor's susceptibility to social influence increased the number of ties to non-drinkers, relative to the control condition, only in the conditions with high social influence and medium or high social selection when N = 25 and HDR = 25% (bottom-center and bottom-right plots of Figure 24.2) and in the condition with high social influence and high social selection when N = 100 and HDR = 50%. However, this effect was never replicated across all three combinations of sample size and HDR for any conditions with the same combinations of social influence and social selection levels.

Reducing the target actor's susceptibility to social selection significantly reduced the number of ties from target actors to non-drinkers in nearly all of the conditions with positive social selection (center and right columns of Figures 24.1-24.3), with one exception when social influence and social selection were both high in the N = 25 and HDR = 50% networks (bottom-right plot of Figure 24.1). This manipulation did not affect the number of ties to heavy drinkers in any conditions with zero social selection, regardless of the level of social influence (left columns of Figures 24.1-24.3).

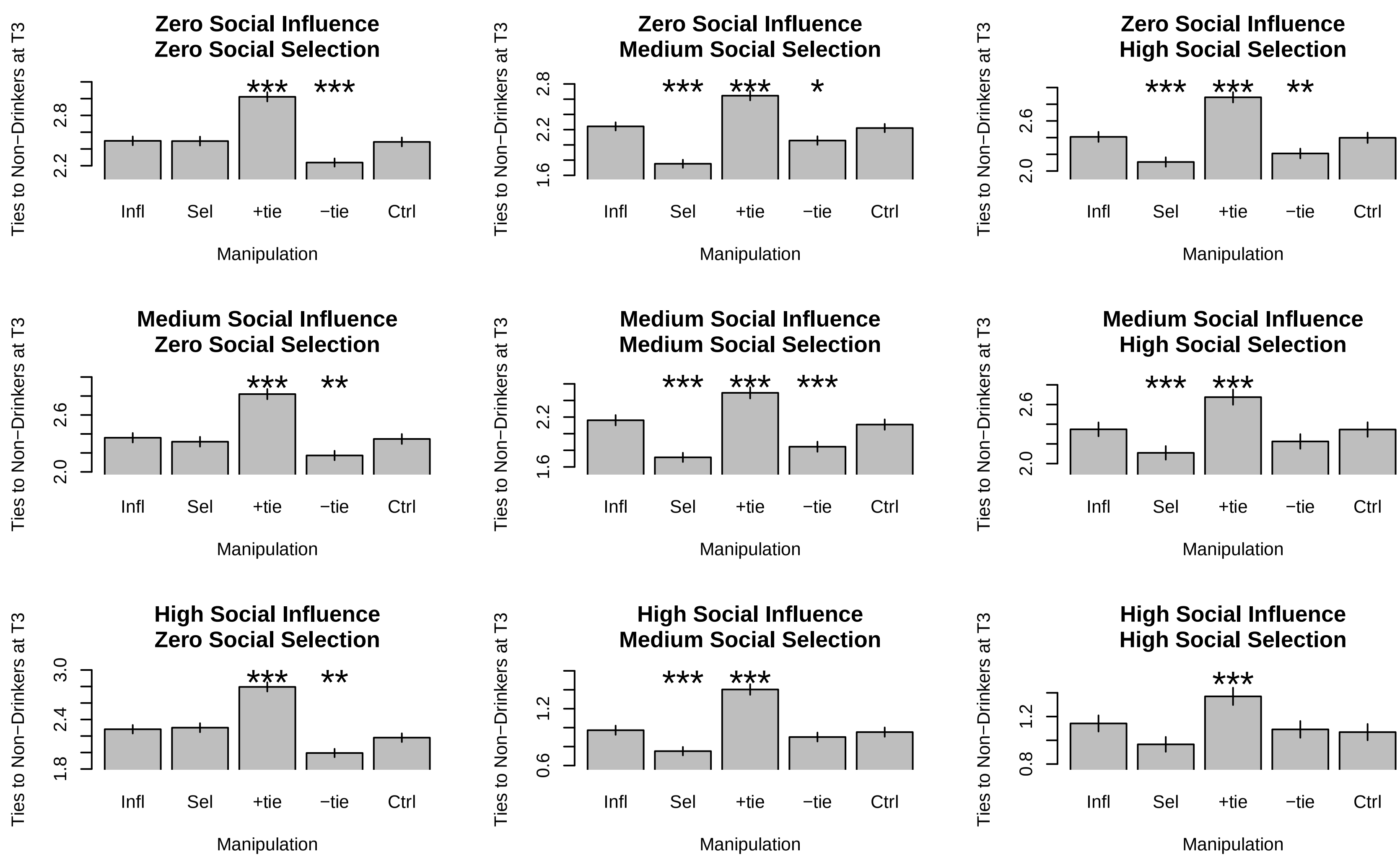


Figure 24.1: Network Manipulations and Ties to Non-Drinkers, N = 25, HDR = 50%

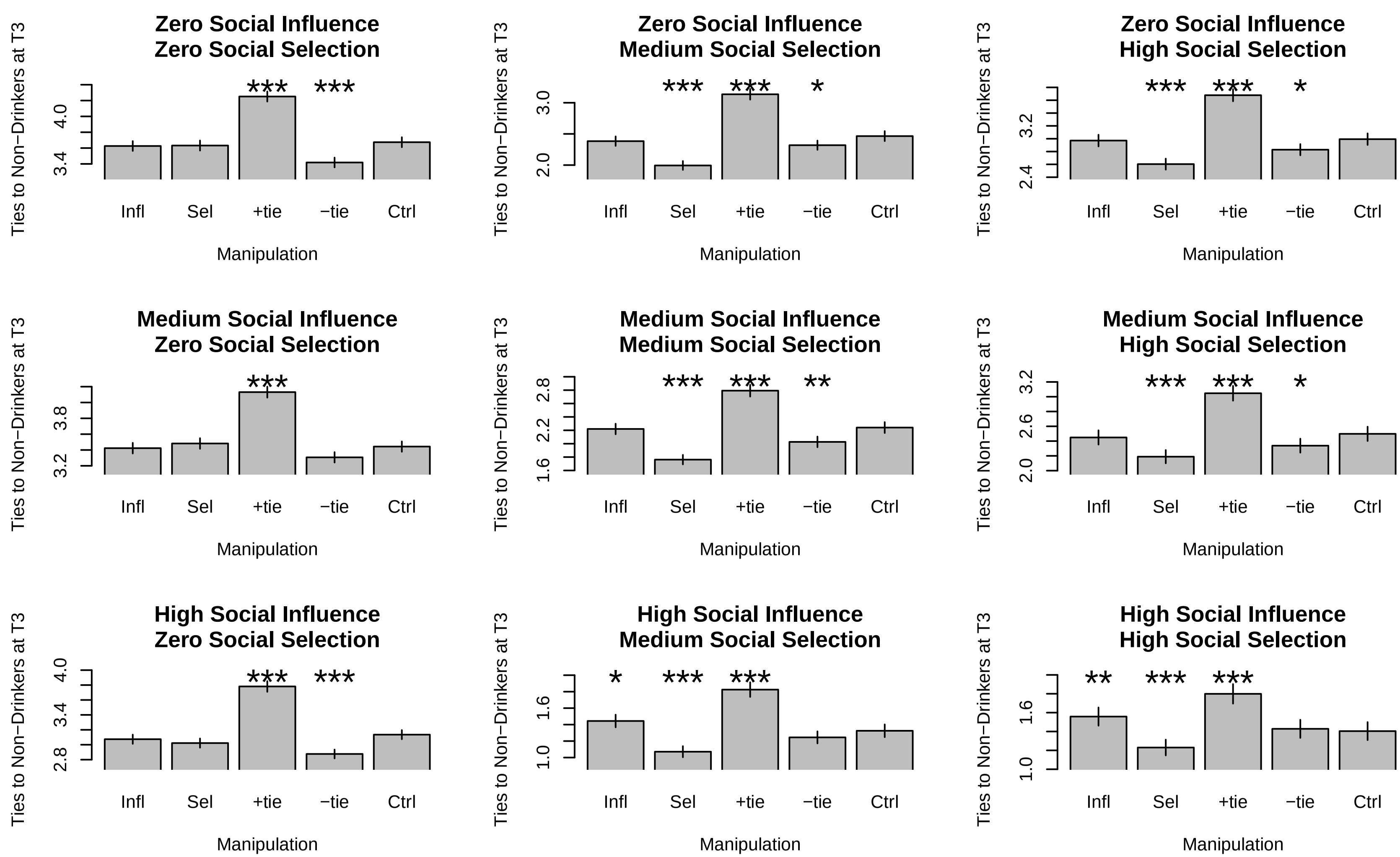


Figure 24.2: Network Manipulations and Ties to Non-Drinkers, N = 25, HDR = 25%

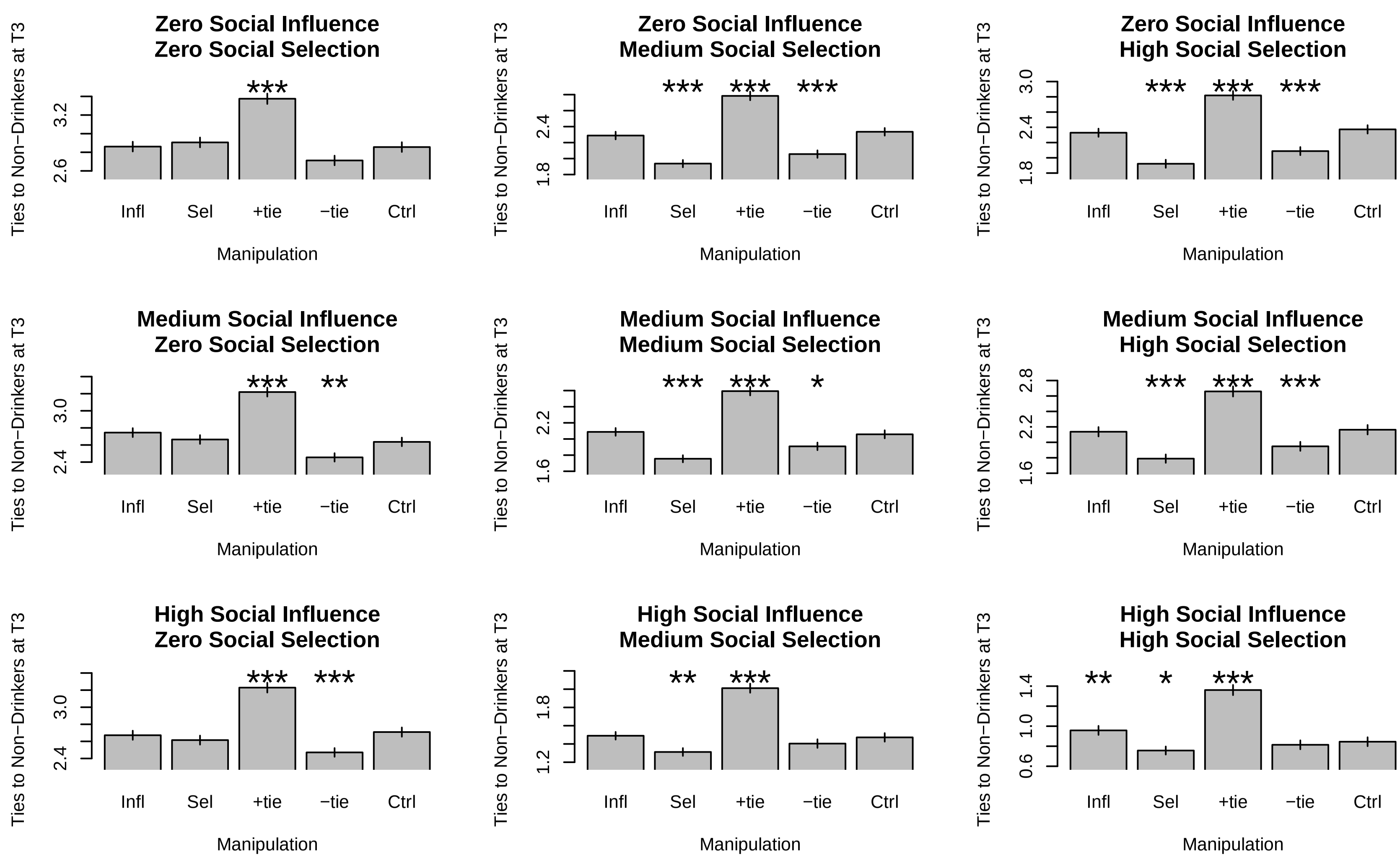


Figure 24.3: Network Manipulations and Ties to Non-Drinkers, N = 100, HDR = 50%

Adding a tie from the target actor to a non-drinker significantly increased the number of ties from target actors to non-drinkers all combinations of conditions, without exception.

Removing an existing tie from the target actor to a heavy drinker reduced the number of non-drinkers in the actor's network in several conditions, but the effect of this manipulation became smaller as social influence and social selection both became stronger. For example, removing an existing tie to a heavy reduced the number of ties to non-drinkers in at least four out of the five conditions where social influence and social selection were not acting simultaneously for all combinations of network size and HDR (left columns and top rows of Figures 24.1-24.3). In addition, the same manipulation produced significant reductions in ties to non-drinkers most of the times when social influence was medium and social selection was medium or high (middle-center and middle-right plots of Figures 24.1-24.3). In contrast, the manipulation of removing a tie from the target actor to a heavy drinker always produced no change in the target actor's ties to non-drinkers when social influence was high and social selection was medium or high (bottom-center and bottom-right plots of Figures 24.1-24.3).

Moderation analyses tested whether the effects of each intervention on ties to non-drinkers at T3 were moderated by ties to non-drinkers at T2, and are presented in Figures 25.1-25.3. Reducing the target actor's susceptibility to social influence was significantly moderated when social selection was medium and social influence was medium or high in the N = 100 and HDR = 50% conditions (middle-center and bottom-center plots of Figure 25.3), but this effect was not replicated in other combinations of sample sizes or HDR. Reducing the target actor's susceptibility to social selection was significantly

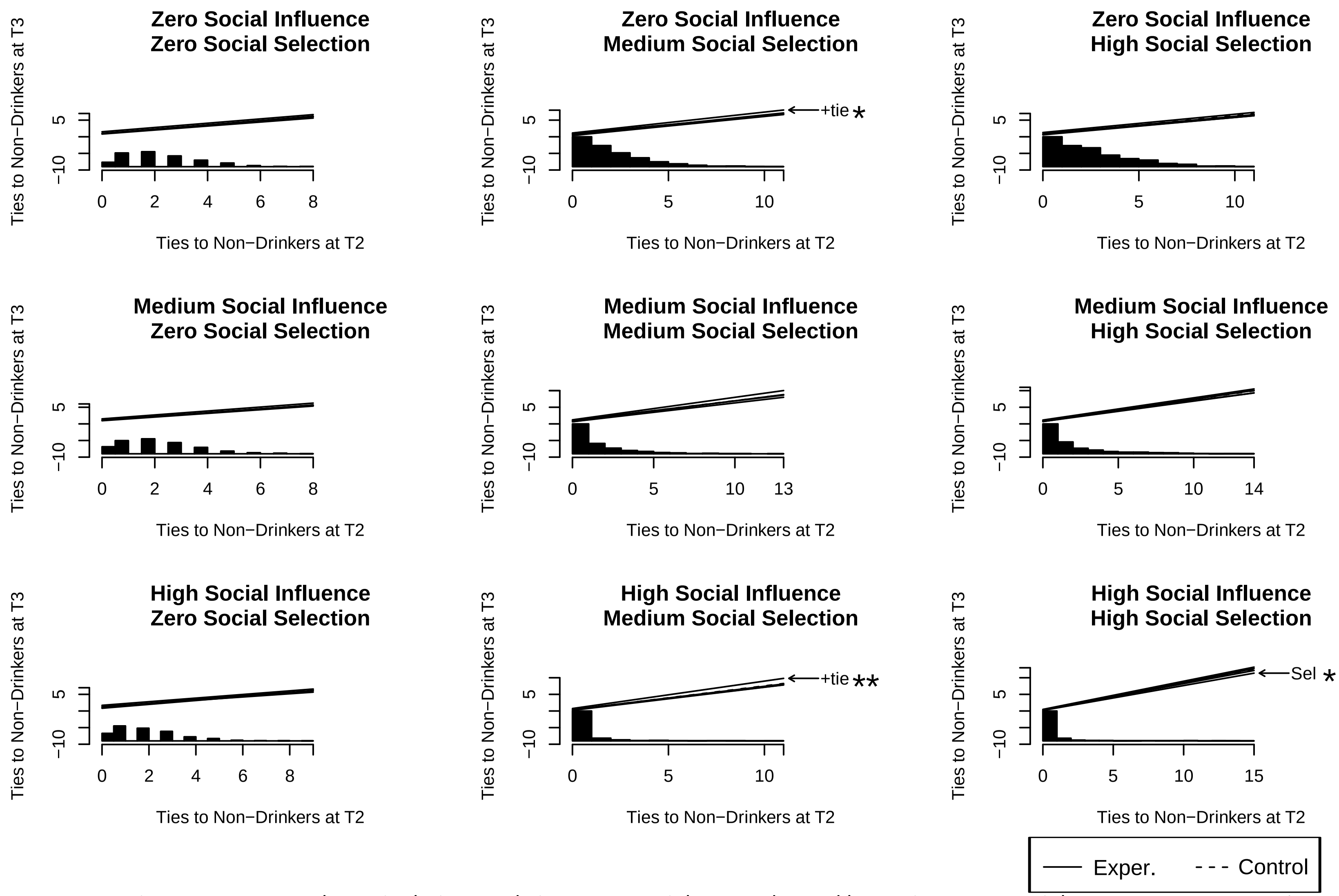


Figure 25.1: Network Manipulations and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 25, HDR = 50%

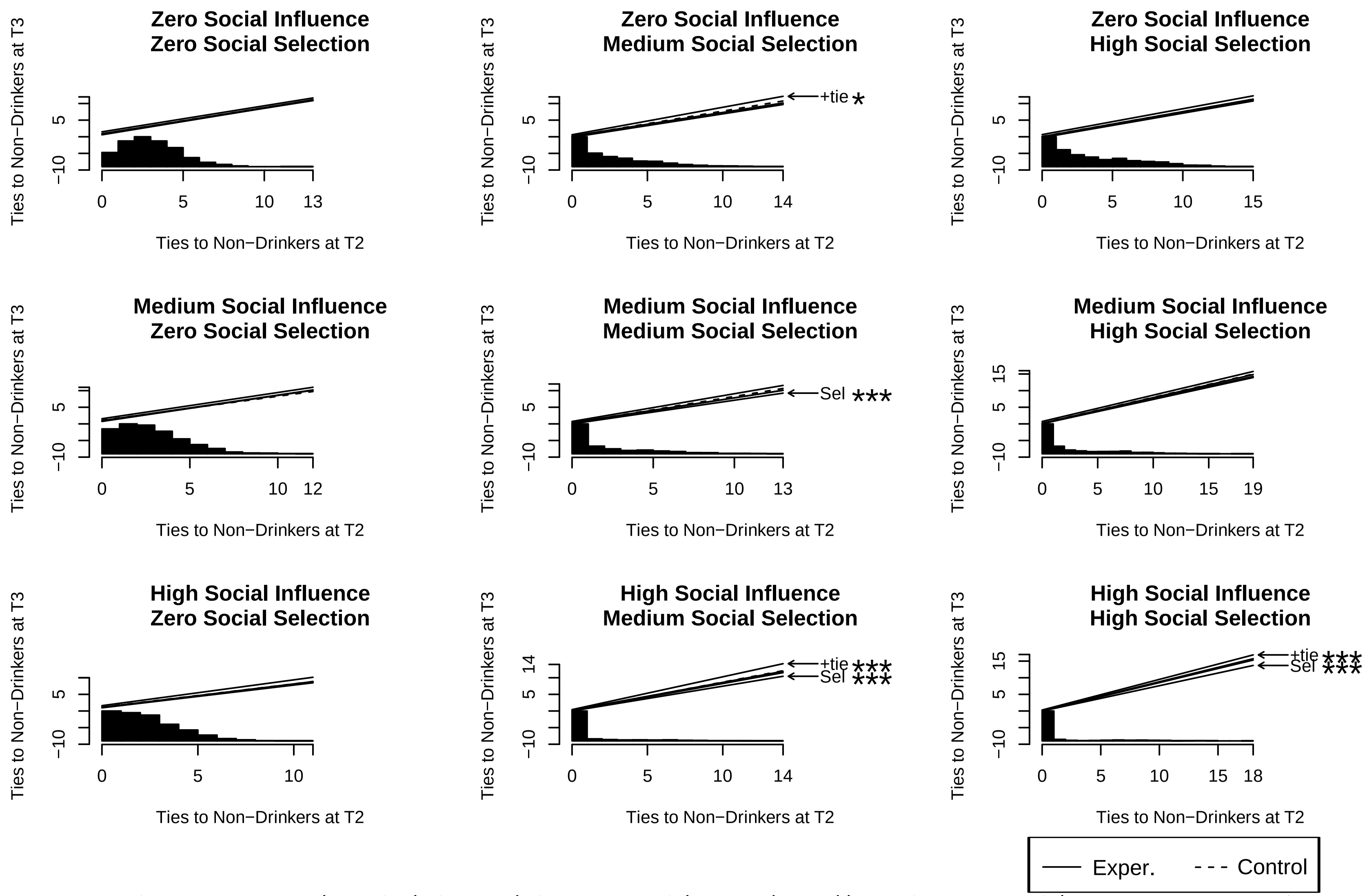


Figure 25.2: Network Manipulations and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 25, HDR = 25%

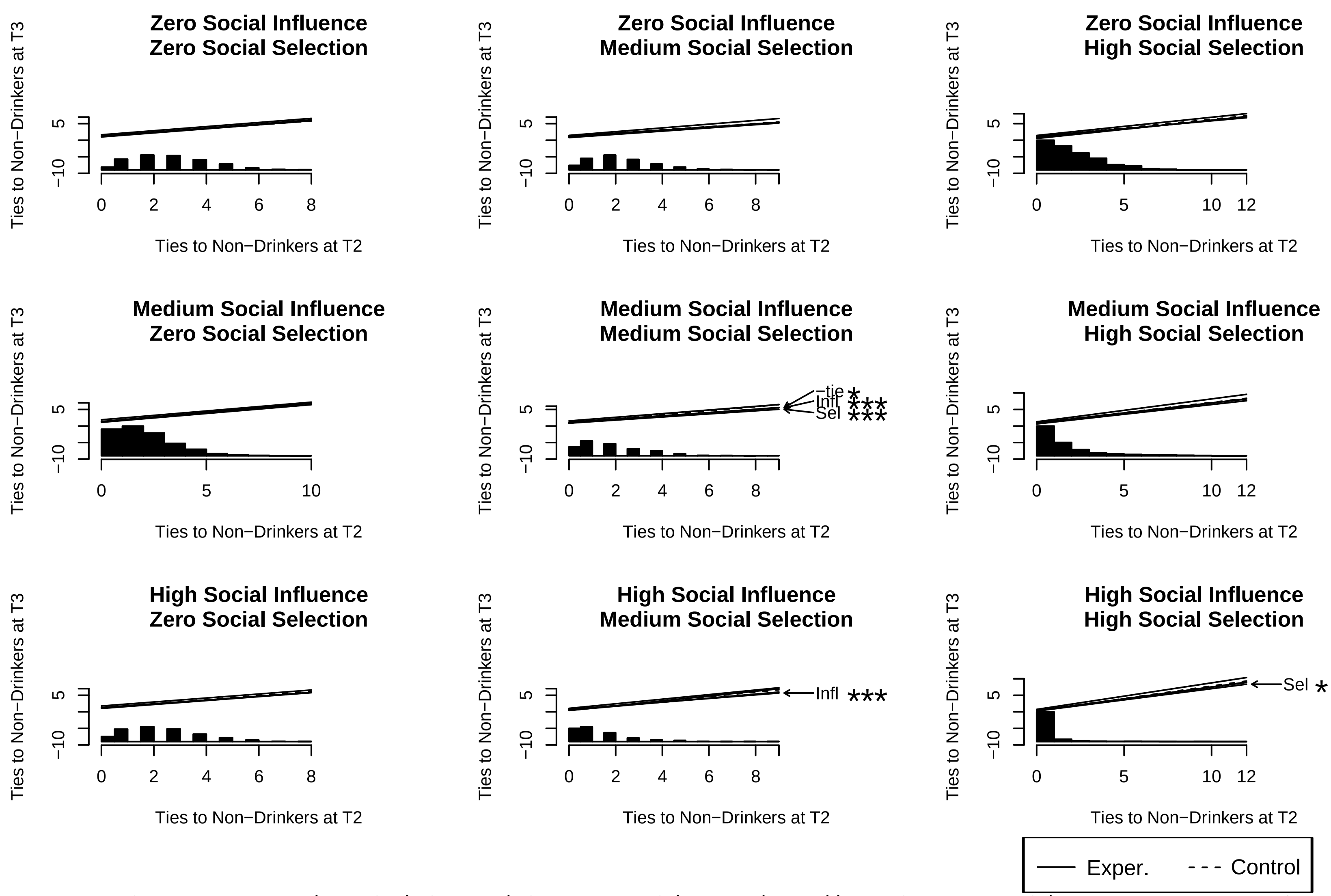


Figure 25.3: Network Manipulations and Ties to Non-Drinkers Moderated by T2 ties to Non-Drinkers, N = 100, HDR = 50%

moderated in several, but not all, conditions with both positive social influence and positive social selection, and was never significantly moderated in conditions without both social influence and social selection acting simultaneously. The direction of these interactions was such that target actors in the condition of reduced susceptibility to social influence were especially likely to have fewer ties to non-drinkers at T3, relative to the control condition, if they already had many ties to non-drinkers at T2.

Adding a tie to a non-drinker was significantly moderated four times: three times when N = 25 and HDR = 25%, one time when N = 25 and HDR = 50%, and never when N = 100 and HDR = 50%. This effect was only significant when social selection was positive (center and right columns of Figures 25.1-25.2). The direction of these interactions was such that target actors in the condition with an additional tie from the target actor to a non-drinker were especially likely to have more ties to non-drinkers at T3, relative to the control condition, if they already had many ties to non-drinkers at T2. Removing an existing tie from the target actor to a non-drinker was significantly moderated in one condition when social influence and social selection were both medium and N = 100 and HDR = 50%, but this effect was not replicated in any other conditions.

Effect of social network manipulations on non-target actors' drinking. No specific hypotheses were proposed about the effects of the social network manipulations on the drinking outcomes of other non-targeted ("peripheral") actors. However, the effects of each manipulation on peripheral actor drinking outcomes were explored to determine if any of the social network manipulations affected the drinking outcomes of other actors. The effects of the social network manipulations on the drinking statuses of peripheral actors who extended ties to the target actor at T2 are shown in Figures 26.1-

26.3. The bar plots present the mean number of heavy drinking peripheral actors at T3, vertical lines represent standard errors of the estimates for each condition, and asterisks are used to display the significance levels of paired-sample *t*-tests with Bonferroni correction based on differences between experimental conditions and the and control condition.

None of the social network manipulations consistently reduced the heavy drinking rates of peripheral actors. Reducing the target actor's susceptibility to social influence was associated with lower peripheral actor heavy drinking at T3 in the condition with high social influence and zero social selection when $N = 25$ and HDR = 50% (bottom-left plot of Figure 26.1) and in the high social influence and high social selection condition when $N = 25$ and HDR = 25% (bottom-right plot of Figure 26.2). Removing an existing tie from the target actor to a heavy drinker reduced the heavy drinking of peripheral actors in high social influence and high social selection condition when $N = 25$ and HDR = 25% (bottom-right plot of Figure 26.2), and adding a tie from the target actor to a non-drinker increased the heavy drinking of peripheral actors in the zero influence and zero selection condition when $N = 100$ and HDR = 100% (top-left plot of Figure 26.3). However, none of the significant effects were consistently replicated or followed stable patterns across combinations of social influence, social selection, sample size, or HDR.

Summary of findings for social network manipulations. The actions of reducing a target actor's susceptibility to social influence, reducing a target actor's susceptibility to social selection, adding a tie from the target actor to a non-drinker, and removing a tie from the target actor to a heavy drinker produced different changes in the targeted individual's drinking outcomes and friendships and were largely dependent on

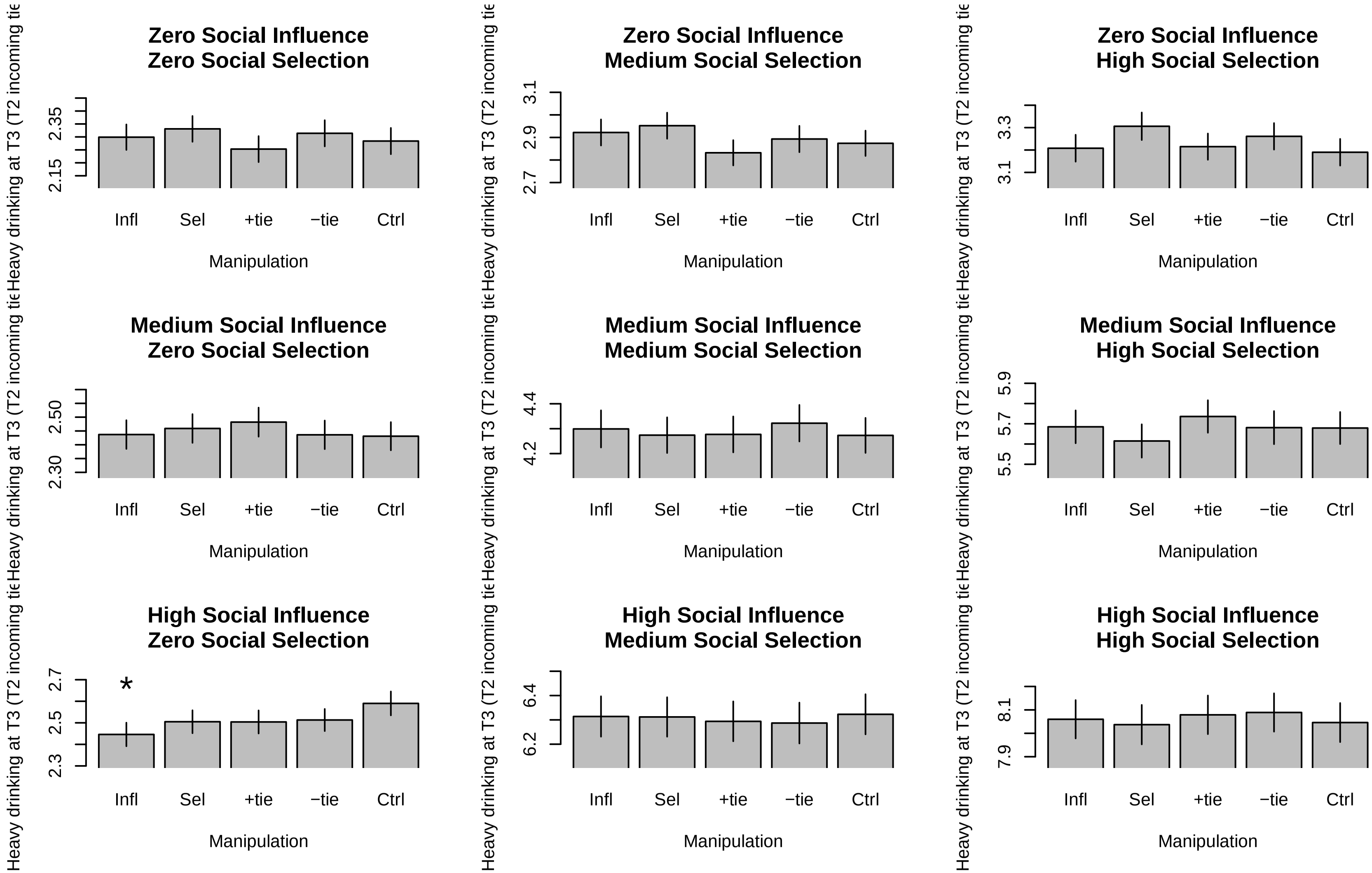


Figure 26.1: Network Manipulations and Peripheral Actor Heavy Drinking, N = 25, HDR = 50%

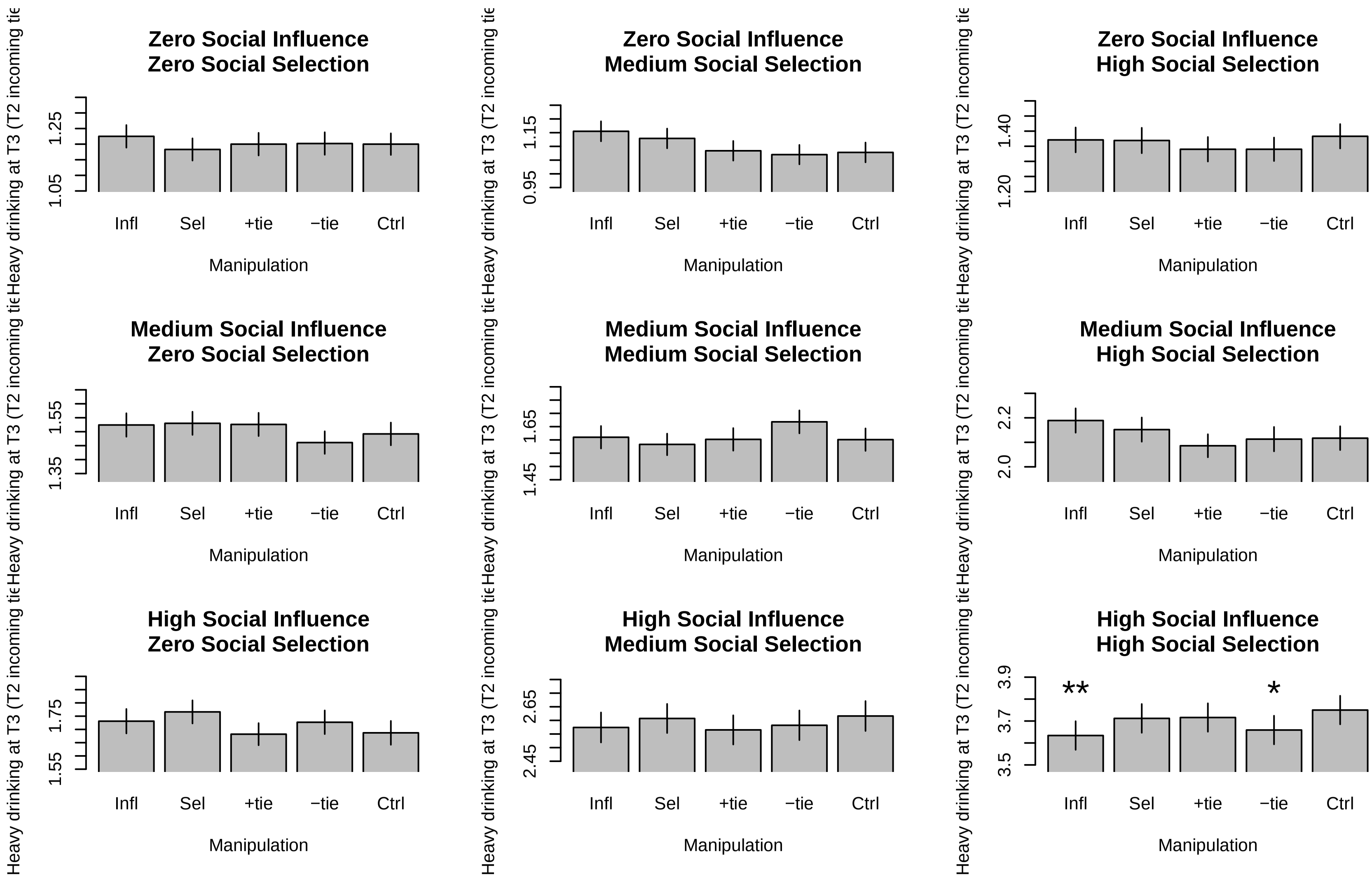


Figure 26.2: Network Manipulations and Peripheral Actor Heavy Drinking, N = 25, HDR = 25%

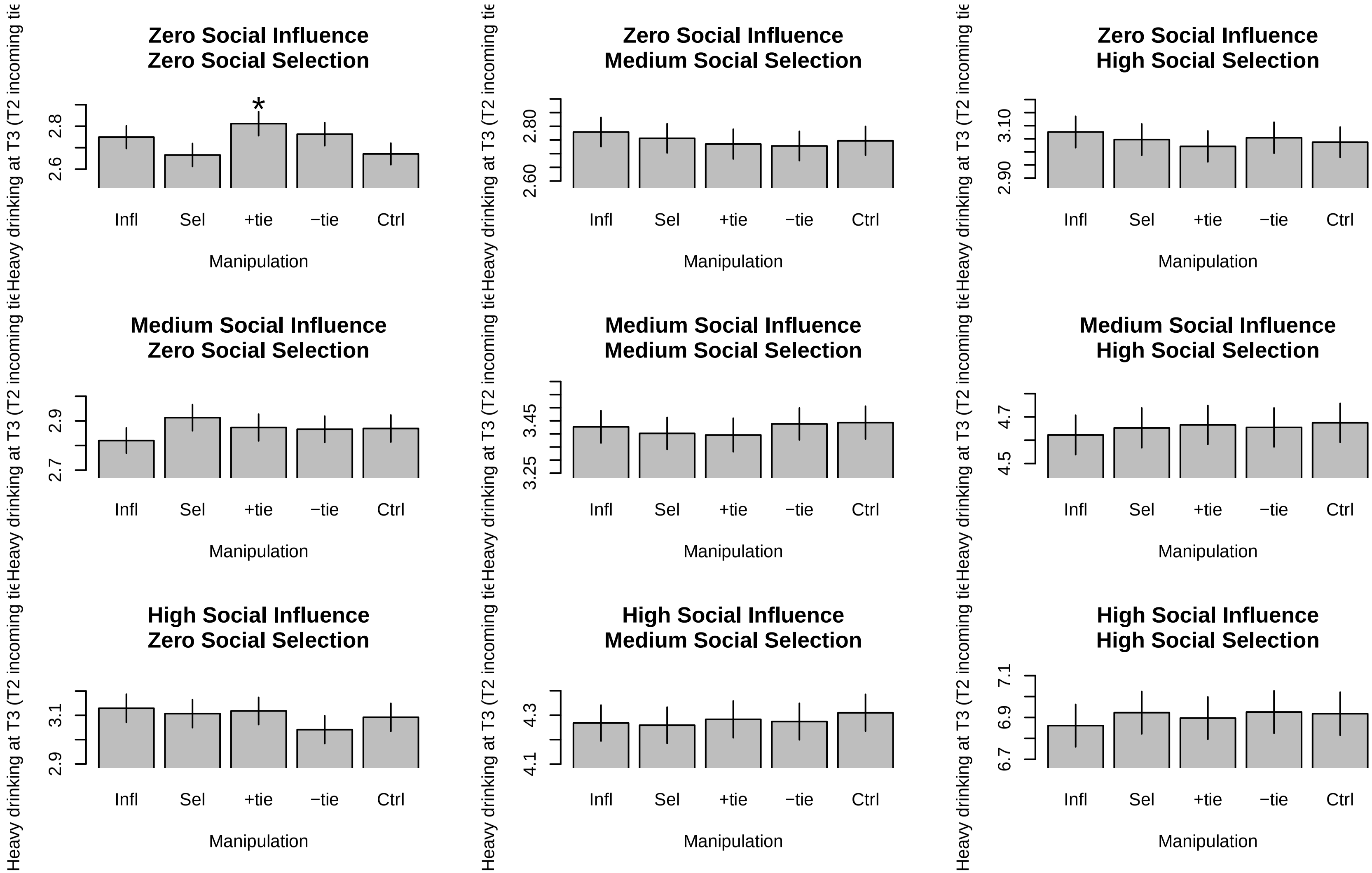


Figure 26.3: Network Manipulations and Peripheral Actor Heavy Drinking, N = 100, HDR = 50%

the properties of the social networks (e.g., social selection and social influence levels) and on actors' positions within the social networks (e.g, pre-manipulation ties to heavy-drinking and non-drinking actors).

Reducing target actors' susceptibility to social influence was consistently associated with reductions in target actor heavy drinking, relative to control conditions, when social influence and social selection were both present. This manipulation produced the strongest reductions in heavy drinking for actors with a greater number of ties to heavy drinkers at the time of the manipulation, and produced target actor heavy drinking rates that were similar to those found in the control conditions of networks with no social influence or social selection. Other social network manipulations, including reducing the target actor's susceptibility to social selection, adding a tie to a non-drinker, and removing a tie from a heavy drinker, failed to provide consistent reductions in target actor heavy drinking.

Although several network manipulations had little effect on target actor heavy drinking, all of the network manipulations affected target actor ties to heavy drinkers and non-drinkers. Reducing target actors' susceptibility to social influence reduced target actors' ties to heavy drinkers and increased their ties to non-drinkers in networks with positive social influence and social selection, and this effect was not moderated by the number of ties to heavy drinkers and non-drinkers at the time of the manipulation. Reducing target actors' susceptibility to social selection reduced their ties to both heavy drinkers and non-drinkers in networks with positive social selection, and this effect was often stronger for participants with a greater number of ties to heavy drinkers and non-drinkers at the time of the manipulation. Adding a tie to a non-drinker often increased the number of ties to heavy drinkers when social influence and social selection were low but decreased the number of ties to heavy drinkers when social influence and social selection were high; however, this manipulation always increased the number of ties to non-drinkers regardless of social influence and social selection levels. Likewise, removing a tie to a heavy drinker often reduced the number of ties to non-drinkers when social influence and social selection were low but resulted in little or no change in ties to non-drinkers when social influence and social selection were higher; however, this manipulation always reduced the number of ties to heavy drinkers.

The drinking status intervention provided no consistent changes in the drinking rates of peripheral actors, i.e., non-target actors who extended ties to the target actor at the time of the intervention.

Discussion

The goal of the present study was to model how various intervention strategies might affect drinking outcomes within dynamic social networks. Stochastic actor-based models (Snijders et al., 2010) provided the mathematical framework for generating social networks with several properties found in real-world networks, including outdegree, reciprocity, transitivity, three-cycle, social influence, and social selection effects. The simulated networks in the present study were non-chaotic to subtle changes in outdegree, social selection, and social influence and were stable over time. Social networks were simulated using three combinations of sample size and heavy drinking rates, and three levels of social influence and social selection were manipulated within each of these types of networks. For each combination of network-level effects, correlations between each actor's drinking and the average drinking status of individuals with ties to these actors were examined. The effects of different intervention strategies on target actor drinking outcomes, target actor friendships, and the drinking statuses of peripheral actors with ties extended to the target actor also were examined to understand how these types of interventions might affect change within social network contexts.

The following sections summarize the major findings of the present study and place them within the broader context of the literature on drinking and social networks. Specifically, the major findings of the paper are reviewed along with reasons for their existence within the simulation study from the framework of the stochastic actor-based modeling procedure and from the framework of real-world behavior. Similarities and discrepancies between these findings with real-world research on drinking and social networks also are discussed, along with recommendations for future simulation and real-world research.

Social Influence, Social Selection, and Clustering by Drinking Status

When either social influence or social selection was at a medium or high level but the other effect remained at zero, the resulting networks exhibited small amounts of clustering of heavy drinkers, as indicated by small positive correlations between individual drinking and peer drinking. However, when both social influence and social selection were simultaneously positive, the resulting networks exhibited large increases in the clustering of heavy drinkers.

This effect suggests that for the types of networks simulated in the present study, having only one direction of influence (e.g., behavior influencing friendships or friendships influencing behaviors) was not sufficient to create a substantial amount of clustering. However, having both directions of influence to create a feedback loop, such as shown in Figure 1, was sufficient for creating a substantial amount of clustering. Having the bidirectional processes of social influence and social selection acting simultaneously creates interdependence among drinking and friendships, which can result in dynamic systems with properties such as non-linearity and self-organization (Bertalanffy, 1968). Examples of self-organization are visible in the graphs of networks with positive social influence and social selection (e.g., see Figure 9.5). With positive social influence and social selection, networks that were initialized with randomly distributed ties and drinking statuses self-organized over time into a steady state attractor system (Hunt, 2007) where movement toward one end of the attractor system (e.g., movement toward a heavy drinking cluster or a non-drinking cluster) leads to increased probability of remaining at that end of the attractor system (e.g., remaining within a heavy-drinking or non-drinking cluster, and remaining a heavy drinker or non-drinker). In these cases, an actor's heavy drinking status is maintained by the social influence of his or her heavy drinking peers, and the actor's friendships with heavy drinking peers are maintained by his or her preference for making ties with other heavy drinking peers due to social selection.

The findings of the present study suggest that in real-world social networks, high correlations between individual and peer drinking may likely be the result of social influence and social selection acting simultaneously rather than either force acting without the other. This conclusion parallels real-world findings on differences in correlations between individual drinking and peer drinking across developmental stages. For example, longitudinal studies of adults have found social selection, but not social influence, to be the primary force guiding the association between individual and peer drinking, and correlations between individual and peer drinking from cross-sectional research with non-emerging adult populations typically have been positive but small, for example, $r = 0.21$ in a sample of 150 adults recently completing substance abuse treatment (Groh, Olson, Jason, Davis, & Ferrari, 2007), $r = 0.11$ for a sample of 1383 adults seeking alcohol treatment (Longabaugh et al., 2010), and $r = 0.19$ for a sample of 141 adults seeking treatment for cocaine dependence (this correlation is still related to individual and peer alcohol use; Zywiak et al., 2009). In contrast, research on children and young adolescents has found social influence, but not social selection, to be the primary force guiding the associations between individual and peer drinking, and correlations between individual and peer drinking from cross-sectional research with children and young adolescents likewise have been low but positive in most cases, for example, $r = 0.24$ in a sample of 1040 adolescents with a mean age of 14.4 years (Myers, 2012), $r = 0.27$-0.33 in a sample of 998 twelve-year-olds (Van Ryzin, Fosco, & Dishion, 2012), and $r = 0.20$ in a sample of 1050 third graders surveyed about their experiences sipping alcohol (Jackson, Ennett, Dickinson, & Bowling, 2013), but $r = 0.66$ for a sample of 454 adolescents aged 10.5 – 15.5 years (Curran, Stice, & Chassin, 1997). Whereas children and young adolescents are susceptible to greater social influence and adults are susceptible to social selection, longitudinal studies of older adolescents and emerging adults have found that social influence and social selection are both likely to be prominent in these age groups, and, as expected, the corresponding correlations between individual and family and peer drinking rates found in cross-sectional research also are typically high for this group, for example, $r = 0.66$ in a sample of 613 children with a mean age of 17.1 years (Samek, Keyes, Iacono, & McGue, 2013), $r = 0.54$ and $r = 0.47$

in two samples 489 and 119 adult college freshmen (Parra et al., 2007; Riefman et al., 2006), and $r = 0.34$ in a sample of 197 college students with a mean age of 21 (Hallgren, Ladd, & Greenfield, 2013). These real-world findings parallel the results of the present study, where populations that are susceptible to either social influence or social selection, but not both (e.g., children, young adolescents, adults), had small positive correlations between individual and peer drinking, but populations that are susceptible to both forces simultaneously (e.g., older adolescents, emerging adults) had the highest correlations between individual and peer drinking.

In light of the importance of both social influence and social selection in creating clustering by drinking status, future simulation and real-world research should use models that allow for both social selection and social influence effects to take place simultaneously. For example, simulations of social networks can allow both forces to act simultaneously at varying degrees to represent plausible levels of effects for the population to which the simulation is being applied. If real-world longitudinal data are collected, researchers can use cross-lagged panel models (e.g., Parra et al., 2007; Riefman et al., 2006) with path analysis or structural equation models to test whether individual and peer drinking influence changes in friendships and individual drinking respectively, rather than only testing for social networks as predictors of future drinking behavior. If real-world cross-sectional data are collected, researchers should refrain from assuming that a significant correlation is suggestive of a unidirectional causal effect, especially if the correlation is medium or large in size.

Changes in Target Actor Drinking Status

Heavy drinking actors experienced equal benefit from the drinking status manipulation relative to the control condition in their heavy drinking outcomes across levels of social influence and social selection – i.e., target actor heavy drinking rates dropped by about 35-40 percentage points in the drinking status manipulation condition relative to the control condition in most cases. However, overall drinking rates for target actors in both the status manipulation and control conditions were highest when social influence and social selection were simultaneously positive. In other words, target actors were more likely to relapse to heavy drinking if they were in the drinking status manipulation condition or remain heavy drinkers if in the control condition if social selection and social influence both were present in the models.

Although the relative efficacy of the drinking status manipulation was not moderated by level of social influence and social selection, the relative efficacy of the intervention was moderated by the number of ties from the target actor to heavy drinkers and non-drinkers at the time of the manipulation. With positive social influence and social selection, target actors embedded in clusters of heavy drinkers with few ties to non-drinkers often experienced the most benefit from the drinking status intervention. Conversely, target actors embedded in clusters of non-drinkers with few ties to heavy drinkers experienced less benefit from the intervention, relative to the control condition, and often succeeded in reducing their heavy drinking without the assistance of the intervention. As expected, the number of ties to heavy drinkers at the time of the manipulation did not moderate the efficacy of the drinking status manipulation when social influence or social selection was zero. In all cases, there was a positive main effect for a greater number of ties to non-drinkers and a smaller number of ties to non-drinkers predicting a greater probability of abstinence.

These finding suggests that an actor's position in the network (i.e., their ties to heavy drinkers and non-drinkers) is predictive of his or her future drinking status and moderates the efficacy of the drinking status intervention when both social influence and social selection are present simultaneously. With higher social influence and social selection, the networks created in attractor states where heavy drinking actors are likely to be embedded within heavy-drinking clusters and feedback where actors' drinking statuses are influenced by their peers' drinking the friendships are maintained by their similarity in drinking statuses. Changing a target actor's drinking status from heavy drinker to non-drinker likely provided the opportunity for some actors to extend friendships to other non-drinking actors and retract friendships to heavy-drinking actors due to social selection, and these ties to non-drinking actors may have in turn reinforced the target actor's non-drinking status due to social influence. Alternatively, not changing the target actor's drinking status (i.e., control condition) was likely to perpetuate the feedback loop where having a heavy drinking status and maintaining ties to heavy drinkers were mutually reinforcing.

This explanation is corroborated by the increases in ties to heavy-drinkers and decreases in ties to non-drinkers for actors in the drinking status manipulation condition, and partly corroborated by the interaction of the drinking status manipulation and the number of ties to heavy-drinking actors at the time of the manipulation. For example, target actors with many ties to heavy drinkers experienced the biggest amount of reduction in their ties to heavy drinkers when they received the drinking status manipulation and were in conditions with positive social selection, supporting the notion that the drinking status manipulation allowed target actors in heavy-drinking clusters to reduce their ties to heavy drinkers in addition to maintaining their new non-drinking status. Although actors receiving the drinking status manipulation significantly increased their ties to non-drinkers, the degree of increase in ties to non-drinkers was greatest for target actors with many pre-existing ties to non-drinkers rather than for target actors with few or no pre-existing ties to non-drinkers. One possible explanation for this finding is that changing the drinking status of target actors who already had many ties to non-drinkers allowed them to form ties with even more non-drinking actors, for example, due to a combination of social selection and transitivity effects (i.e., forming friendships with friends-of-friends, who are likely to be non-drinkers), whereas actors with few or no ties to non-drinking actors may have been less successful in migrating into a non-drinking cluster due to a lack of existing ties and friends-of-friends in non-drinking clusters.

The drinking status intervention also typically reduced the drinking rates of peripheral actors, i.e., non-target actors who extended ties to the target actor at the time of the intervention when social influence was positive. This effect increased proportionally as the level of social influence increased and sometimes but not always decreased as the level of social selection increased. One explanation for this finding is that, in conditions with positive social influence and zero social selection, target actors are likely to influence their peers while making few or no changes in ties based on the similarity or dissimilarity in drinking statuses, allowing the target actor to continuously exert an effect on reducing their peers' heavy drinking. However, when social influence and social selection are simultaneously positive, target actors receiving the drinking status manipulation may withdraw ties to heavy drinkers, and heavy-drinking peripheral actors may in turn withdraw their ties to target actors, reducing the degree of influence from the target actor to peripheral actors. This hypothesis is supported by results indicating that target actors in the drinking status manipulation reduced their ties to heavy drinkers and increased their ties to non-drinkers, relative to the control condition, when social selection was positive.

Several findings in the present study parallel effects found in real-world data, but many of the findings of the present study have not yet been tested directly in human populations. For example, several studies have shown that involvement in some treatments (analogous to the drinking status intervention) predicts subsequent reductions in ties to heavy drinking network members and increases in ties to non-drinking network members, and these changes in ties are in turn predict greater abstinence (e.g., Bond, Kaskutas, & Weisner, 2003; Humphreys, Mankowski, Moos, & Finney, 1999; Kaskutas, Bond, & Humphreys, 2002; Laudet, Cleland, Magura, Vogel, & Knight, 2004; Litt et al., 2009). Although previous alcohol and substance use treatment research has often examined the effect of peer behavior on substance use, there has been little focus on the effect of substance use on peer selection – that is, whether changes in individual drinking in turn predict further changes in ties to heavy- and non-drinking peers. Among the few studies that have examined this, one used retrospective recall of changes in social networks and substance use of 50 non-treatment-seeking incarcerated adult men, and found that greater individual drug use before incarceration was associated with a heavier drug-using social network after incarceration, which in turn was associated more individual drug use at a subsequent time point (Owens, McCrady, Moyers, & Tonigan, under review). In another study of 229 adults entering alcohol treatment, participants' pre-treatment abstinence did not predict post-treatment ties to heavy drinkers, and pre-treatment ties to heavy drinkers also did not directly predict post-treatment abstinence, failing to support both paths of the hypothesized feedback loop between individual and peer drinking statuses (Longabaugh, Beattie, Noel, & Stout, 1993). There are few studies, if any, that have examined whether pre-treatment social ties to heavy drinkers and non-drinkers moderate the efficacy of an active treatment relative to an inactive control condition to allow for comparison of the moderating effects in the drinking status manipulation condition analyzed in the present study. Instead, most studies have either examined main effects of treatment condition and pre-treatment social networks on drinking outcomes (e.g., Longabaugh et al., 2010), tested for moderating effects of pre-treatment social networks on the efficacy of two active forms of treatment (e.g., twelve-step facilitation vs. motivational enhancement therapy without a no-treatment control group; e.g., Longabaugh, Wirtz, Zweben, & Stout, 1998; Wu & Witkiewitz, 2008; Zywiak et al., 2002), or used mediation analysis to test causal chain hypotheses about treatment predicting changes in social ties, in turn predicting changes in drinking (Litt et al., 2009; Kelly et al., 2011).

Integration of the findings from the present study and from previous studies of real-world social networks points to gaps in the literature on the ways that social networks influence or support changes in drinking. For example, existing research on general adult populations typically has shown that social selection is more prominent for adults than social selection, yet many treatment studies in adult populations have found support for a model relying on social influence, for example, with pre- and post-treatment social networks predicting later substance use behavior. It is unlikely that social selection alone could account for these findings based on the results of the present study, which suggest that social influence effects may be more prominent for adult treatment-seeking populations than for the general population of adults.

Future studies with treatment-seeking adults may shed light on this gap in the literature by studying the longitudinal effects that changes in alcohol consumption have on ties to heavy drinkers and non-drinkers and vice versa. In addition, models of change in treatment-seeking adults may be strengthened by testing theoretical models of both social influence and social selection effects, of which the former has been tested many times but the latter hardly at all. Future research also may examine the effects of treatment interventions on the drinking outcomes of non-targeted peripheral individuals who are socially connected to individuals who receive alcohol treatment. For example, this research could target a subset of individuals for alcohol treatment or prevention and study the drinking outcomes of individuals who are socially connected to the targeted individuals within populations that have high social influence (e.g., children, adolescents, emerging adults).

Changes in Target Actor Social Networks

Four social network manipulations that emulate types of real-world changes in actors' relationships with their social network and often co-occur with reductions in heavy drinking were examined in the present study. These manipulations targeted one randomly-selected heavy drinking target actor and (a) reduced his or her susceptibility to social influence (e.g., representing improved skills for refusing drinks and reduced susceptibility to social pressure), (b) reduced his or her susceptibility to social selection (e.g., representing a reduction in tendencies to associate with others based on similarity in heavy drinking statuses), (c) extended a new social tie to a non-drinker (e.g., representing increases in support for abstinence and abstaining friends), (d) removed an existing to tie to a heavy drinker (e.g., representing attempts to reduce association with heavy drinkers), or (e) made no change (i.e., to serve as a control condition). Although reducing a target actor's susceptibility to social selection is perhaps the least likely of these interventions to be targeted directly in alcohol treatment programs, the effects of this manipulation were examined in the present study to test their disruption to the feedback loop caused by the presence of both social influence and social selection.

Reduced susceptibility to social influence. Reducing target actors' susceptibility to social influence was the only social network manipulation associated with consistent reductions in target actor heavy drinking. This manipulation was almost exclusively effective in networks with both positive social influence and social selection, which also were the conditions where target actor heavy drinking was highest in control conditions. For nearly all combinations of positive social influence and social selection, this manipulation produced target actor heavy drinking rates that were similar to the control condition with zero social influence and social selection. Unlike all other conditions, actors who received this manipulation had an equal probability of remaining a heavy drinker regardless of their ties to heavy drinkers and non-drinkers actors at the time of the manipulation.

A likely explanation for these findings is that target actors' drinking statuses were no longer reinforced by the drinking statuses of their peers, who were likely to be heavy drinkers in conditions with positive social influence and selection. Target actors receiving this manipulation could continue to maintain their social ties to heavy drinkers without consequence to their own drinking status. Reducing target actors' susceptibility to social influence may effectively disrupt the feedback loop created by simultaneous social influence and social selection, allowing actors, such as those in heavy-drinking clusters, to no longer be influenced by their peers and increasing their chances of naturally reducing their drinking. Drastic changes in social ties may be difficult to break in the present simulations due to social network forces such as reciprocity and transitivity and in the real world due to the support and reinforcement that come with maintaining social ties. Given the difficulty of making large changes in social ties, it is possible that reducing target actors' susceptibility to social influence may be a particularly effective strategy for reducing target actor heavy drinking.

There is evidence from several real-world studies that reduced susceptibility to social influence, operationalized in various forms, is associated with higher abstinence. For example, one operationalization of susceptibility to social influence may come in self-reported abstinence self-efficacy, i.e., one's confidence in his or her ability to avoid drinking in various situations. Abstinence self-efficacy often has predicted lower drinking outcomes, both in samples of non-problem drinking individuals (Baldwin, Oei, & Young, 1993; Oei et al., 2007; Young, Connor, Ricciardelli, & Saunders, 2006) and in samples of treatment-seeking individuals (Bogenschutz, Tonigan, & Miller, 2006; Forcehimes and Tonigan, 2008; Ilgen, McKellar, & Moos, 2007; Ilgen, McKellar, & Tiet, 2005). There is some evidence that social factors and abstinence self-efficacy may be interactive in predicting treatment outcomes; for example, higher abstinence self-efficacy may be particularly important in preventing heavy drinking among socially anxious individuals with expectancies that alcohol will facilitate positive social interactions (Gilles, Turk, & Fresco, 2005). Increases in abstinence self-efficacy and increases in ties to non-heavy drinkers may co-occur together in twelve-step facilitation therapy and may both mediate associations between treatment and abstinence outcomes (Kelly, Hoeppner, Stout, & Pagano, 2012; Litt et al., 2009). High therapeutic alliance with alcohol treatment providers, who offer another form of social support for abstinence, may reduce the association between higher abstinence self-efficacy and reduced drinking (Ilgen, Tiet, Finney, & Moos, 2006). However, little research has examined attributes of pre-treatment social networks that may also moderate the association between abstinence self-efficacy and drinking.

Increased skills for refusing drinks in social situations may serve as another operationalization of reduced susceptibility to social influence. Delivering skill training in drink refusal is associated with higher abstinence outcomes for adults (Chaney, O'Leary, & Marlatt, 1978) and young adolescents (Komro, Perry, Williams, Stigler, Farbakhsh, & Veblem-Mortenson, 2001; Schinke, Cole, & Fang, 2009). Further, the associations between drink-refusal training and better abstinence outcomes may be mediated by increases in abstinence self-efficacy (Witkiewitz et al., 2012).

Based on the results of the present study, future research with real-world populations may examine whether the reduced susceptibility to social influence, for example, operationalized as increases in drink-refusal skills or abstinence self-efficacy, creates a greater impact on drinking outcomes for individuals with many heavy-drinking peers and few non-drinking peers and in cases when social influence and selection are present. Based on social cognitive theories of self-efficacy (e.g., Bandura, 1977), greater abstinence self-efficacy would be particularly important in predicting better abstinence outcomes for individuals in heavy-drinking networks if being in these networks leads to greater exposure to situations requiring the use of drink-refusal skills; however, little previous research has tested this hypothesis.

Reduced susceptibility to social selection. Although both social influence and social selection were necessary for creating strong clustering by drinking status, reducing target actors' susceptibility to social selection alone did not reduce their heavy drinking. Reduced susceptibility to social selection was associated with a decrease in ties to both non-drinking and heavy-drinking actors in cases with positive social selection, and this effect was often slightly stronger for actors with many ties to non-drinking or heavy-drinking actors at the time of the manipulation.

One reason that reduced susceptibility to social *selection* was ineffective at reducing target actor heavy drinking even though reducing social *influence* was effective could be that by the time the manipulation occurred, heavy-drinking actors often already had many ties to heavy drinkers and few ties to non-drinkers, who continued to influence the target actors' drinking behavior. Even though similarities in drinking statuses may no longer drive target actors to remain friends with heavy drinkers, other network effects such as the tendency to keep reciprocated and transitive ties may cause target actors to keep their friendship ties with heavy-drinking actors that were present at the time of the manipulation, and these friendships in turn may have continued to influence the target actor's drinking. Although target actors receiving this manipulation would be expected to reduce their ties to heavy drinkers (i.e., because reduced social selection reduces the influence that similarities in drinking statuses have on maintaining social ties), the finding that target actors also decreased their ties to non-drinkers was unexpected. The reduced likelihood of maintaining ties with non-drinkers may be due to other network effects (e.g., reciprocity, transitivity) creating an overall higher probability of removing existing ties and a lower probability of adding ties when the similarity effect parameter (social selection) for the target actor becomes closer to zero based on Equations 1, 6, and 8.

Based on the results of the present study, targeting reduced susceptibility to social selection in treatment and prevention programs would be unlikely to produce significant reductions in heavy drinking. Instead, treatment programs may be more successful by targeting reduced susceptibility to social influence.

Adding a tie to a non-drinking actor. Adding a tie to a randomly-selected non-drinking actor did not produce consistent reductions in target actor heavy drinking but affected ties to heavy drinkers and non-drinkers in some cases. The manipulation significantly increased the number of ties to non-drinkers across all conditions, decreased the number of ties to heavy drinkers when social selection and social influence were high, and increased the number of ties to heavy drinkers when social selection and social influence were low.

Real-world studies of change during treatment have found that a greater number of ties to non-drinkers or individuals who are supportive of non-drinking often is associated with better abstinence outcomes (Groh et al., 2007; Longabaugh et al., 2010; Project MATCH Research Group, 1998; Spear, Crevecoeur-MacPhail, Denering, Dickerson, & Brecht, 2013). In addition, increases in ties to pro-abstinence network members partially mediate the relationship between twelve-step meeting attendance and abstinence outcomes (Chi, Kaskutas, Sterling, Campbell, & Weisner, 2009; Humphreys et al., 1999; Kelly et al., 2011; Stout, Kelly, Magill, & Pagano, 2012). However, typical increases in network members who are supportive of abstinence are small (e.g., 1.5% to 15% increase) and the amount of change in drinking explained by increases in pro-abstinent network members may be smaller than the amount of change in drinking explained by decreases in pro-drinking network members (Kelly et al., 2011).

There are several possible reasons that the present simulation study failed to find this effect that is often present in real-world data. For example, in the present study, the simultaneous presence of social influence and social selection created an attractor state where heavy drinkers were embedded in clusters of other heavy drinkers, and the action of adding a tie to one non-drinker may not have been strong enough to catapult the target actor from the heavy-drinking cluster into a non-drinking cluster. Instead, it is possible that target actors may need to have a greater increase in ties to non-drinkers to successfully change from the attractor state. Additionally, having target actors to form ties with a randomly-selected non-drinking actor may have decreased the chances of that tie being maintained over time because the tie may not have been reciprocated by the other actor or have had low transitivity (i.e., few friends-of-friends).

Alternatively, it is possible that individuals in real-world studies experience increased support for abstinence from network members due to their pre-existing network members changing their attitudes or behaviors, rather than individuals forming new ties to other individuals that previously did not exist. Another plausible explanation could be that in real-world data, new ties from target actors to non-drinkers may constitute special types of relationships that offer a degree or type of influence beyond what was modeled in the present study. For example, having an Alcoholics Anonymous sponsor may offer a special type of relationship where the sponsor has a greater degree of social influence on an individual's behavior than other network members (Bond et al., 2003), or the sponsor may offer a different type of support (e.g., assistance with engaging in a mutual help program, support during situations that pose a high risk for relapse) that was not modeled by simple network dynamics alone.

Future simulation studies may attempt to find ways to replicate the real-world finding of increased ties to non-drinking individuals predicting increased individual abstinence rates. For example, future simulation studies may use weighted ties to increase the degree of social influence from the randomly-selected non-drinker to the target actor, rather than equally-weighted ties as used in the present study. Simulation studies also could create ties to non-drinking actors that have a small social distance from the target actor or specify these ties to be reciprocated to increase the probability that the new social ties are kept over time and to increase the probability of forming ties with additional non-drinking actors. Simulation studies also may add ties to a greater number of network members and determine possible "breaking points" where the addition of a specific number of ties to non-drinking actors results in significant change in the target actor's drinking.

Future real-world studies may attempt to better understand why the addition of individuals who are non-drinkers or supportive of abstinence to a person's social network is associated with better abstinence outcomes. The results of the present study suggest that ties to a random non-drinking individual are not associated with reduced heavy drinking, even in conditions with high social influence. It is therefore unlikely that social influence alone, defined within the context of the present study, accounts for these real-world findings. Future research may find, for example, that the non-drinking individuals who receive new social ties are not randomly-selected or that they offer an additional degree of influence or a special type of support that is not typically provided by other network members.

Removing a tie to a heavy-drinking actor. Similar to the results for *adding* a tie to a non-drinking actor, *removing* an existing tie to a randomly-selected heavy-drinking actor did not lead to consistent decreases in target actor heavy drinking. Removing a tie to a heavy-drinking actor resulted in fewer ties to heavy drinkers for almost all levels of social influence and social selection and also typically resulted in fewer ties to non-drinkers when social influence and social selection were not simultaneously present.

Several real-world studies with treatment-seeking populations have found that having fewer friends and family who are heavy drinkers or supportive of drinking often is associated with higher abstinence outcomes (Groh et al., 2007; Longabaugh et al., 2010; Project MATCH Research Group, 1998; Spear et al., 2013), and that reductions in ties to heavy drinkers or individuals supportive of heavy drinking predicts better abstinence outcomes (Chi et al., 2009; Humphreys et al., 1999; Kelly et al., 2011; Stout et al., 2012). Unfortunately, in many of these studies, measurement issues conflated decreases in heavy drinking network members or network members who support heavy drinking with increases in non-drinking network members or network members who support abstinence.

There are several possible reasons that the present study failed to replicate real-world findings of reduced ties to heavy drinkers predicting higher abstinence levels. As discussed above, it is possible that the manipulation was not strong enough to allow actors to leave heavy-drinking clusters due to the simultaneous forces of social influence and social selection. In addition, it is possible that dissolved ties were often reestablished after the manipulation due to social selection, reciprocity, and transitivity effects.

An additional explanation could be that in real-world data, the effect of reduced ties to heavy drinkers (or individuals who support heavy drinking) on drinking outcomes is not accounted for by social selection and social influence effects alone. For example, it is possible that changes in ties to heavy drinkers and abstinence outcomes could both be affected by a third variable, such as motivation for change or beliefs about necessary actions for successful change (e.g., beliefs that successful change requires both abstinence and reduced affiliation with heavy drinkers). Alternatively, it is possible that the reduced affiliation with heavy-drinkers (and individuals who support heavy drinking) may reduce heavy drinking through some other means not modeled in the present study, for example, by reducing the likelihood of affiliating in places that may serve as cues for drinking or by reducing the role of alcohol in maintaining interpersonal relationships with other heavy drinkers (e.g., Rohrbaugh, Shoham, Butler, Hasler, & Berman, 2009; Shoham, Butler, Rohrbaugh, & Trost, 2007).

Future simulation studies may attempt to find ways to replicate the real-world effect of decreased ties to heavy drinkers increasing individual abstinence rates. For example, these studies could simulate the removal of varying numbers of ties to heavy-drinking actors to determine possible “breaking points” where removing a specific number of ties to heavy-drinking actors results in significant change in the target actor’s drinking. Future real-world studies may attempt to better understand why the removal of ties to heavy drinkers is associated with better abstinence outcomes. The results of the present study suggest that removing one pre-existing tie to a randomly-selected heavy drinker is not associated with reduced heavy drinking, even in conditions with high social influence. It is therefore unlikely that social influence alone, defined within the context of the present study, accounts for these real-world findings. Future research may, for example, find that removing ties to heavy drinkers offers some unique assistance with remaining abstinent aside from the network effects of social influence and social selection, or that they co-occur with a third variable, such as motivation for change or drink-refusal skills to predict better abstinence outcomes.

Limitations

Although the present study aimed to simulate alcohol consumption and social network evolution in a more realistic manner than has been done in previous research, the present study, as with all simulation studies, required several assumptions and over-simplifications that limit their ability to represent real-world behavior in an exact manner. For example, the present study used simplified models of social networks where social ties were equally weighted even though some real-world social ties may have higher or lower weightings and therefore provide stronger influence than others (e.g., Longabaugh et al., 1993). Changes in ties were memoryless (i.e., changes in ties were only influenced by present states in the system and not on previous states), even though real social ties are likely to be influenced by historical states. Drinking statuses were dichotomized and operationalized as being either heavy drinking or non-drinking, but real-world drinking is often better represented on a continuous scale and in multiple dimensions (e.g., alcohol consumption, alcohol-related negative consequences, and alcohol dependence symptoms). In addition, the networks in the present study only modeled the specific network effects described within the manuscript, and the network behavior therefore was not influenced by the many other outside parameters that could influence drinking and friendships in real life.

A few aspects of the mathematical model guiding friendship formation led to unequal numbers of outgoing ties between conditions. Different outdegree parameter values were required across levels of social influence and social selection in order to result in the same mean number of outgoing ties, set at 5.53 based on results from previous studies (Longabaugh et al., 2010), and a single outdegree parameter value was chosen for each combination of social selection, network size, and heavy drinking rate, but not for each level of social influence even though higher social influence increased the mean number of outgoing ties slightly. Although choosing three outdegree parameter values per combination of network size and heavy drinking rate instead of nine may have reduced the likelihood of different outdegree parameters confounding differences between conditions, it introduced the possibility for differences in distributions of outgoing ties to serve as an alternative confounding variable.

Finally, a major limitation of the present study is that some of the manipulations failed to replicate real-world findings. For example, the failure for target actor drinking to be reduced by increases in ties to non-drinkers or decreases in ties to heavy drinkers was unexpected based on previous findings in real-world treatment studies. Future simulation research may specify new simulation models that replicate these real-world findings, and future research with real-world populations may uncover the specific factors that contribute to the relationships between social networks and individual drinking.

Strengths

The present study also had several strengths. In addition to being a limitation, the failure of the present study to replicate some real-world findings about alcohol consumption and social networks is also a strength. For example, the failure to find that adding a tie to a non-drinker or removing a tie from a heavy drinker increased target actors' abstinence outcomes suggests that the effects of these social network changes on drinking outcomes are unlikely to be due solely to social influence and social selection alone, given the other assumptions made for the simulations in the present study. This failure to replicate real-world findings suggests that the assumptions and parameters that are thought to guide social network and behavioral change may need to be modified to successfully replicate this real-world finding, which can provide additional understanding of the processes that lead to these real-world findings. In addition, the failure to replicate these real-world findings suggests that real-world research may be improved by formulating and testing more specific hypotheses about the mechanisms by which changes in social network ties lead to subsequent changes in heavy drinking, as these changes do not appear to be explained by social influence and social selection effects alone in conjunction with the other assumptions made in the present study.

Several aspects of the results suggest that the network parameters and manipulations used in the present study affected the networks as intended, supporting the internal validity of the simulation design. For example, the number of ties to other actors increased when the outdegree parameter increased, and correlations between individual and peer heavy drinking increased when social influence (average alter) and social selection (similarity) effect parameters increased. Changing target actors' drinking statuses from heavy drinker to non-drinker was associated with lower target actor heavy drinking rates over time, adding a tie to a non-drinker was always associated with an increase in ties to non-drinkers and removing a tie to a heavy drinker was almost always associated with a reduction in ties to heavy drinkers. Reducing target actors' susceptibility to social influence was associated with reductions in heavy drinking when social influence and social selection were both positive. Reducing target actors' susceptibility to social selection was associated with reductions in ties to heavy drinkers when social selection was positive, but also was unexpectedly associated with reductions in ties to non-drinkers. Social ties were relatively stable over time, e.g., ties to non-drinkers and heavy drinkers at T2 were correlated with ties to non-drinkers and heavy drinkers at T3, respectively. Sensitivity analyses indicated network drinking rates and outgoing ties were stable at values close to those chosen for the present simulation.

The use of simulations provides many strengths by allowing researchers to know, control, and manipulate parameters that are not always accessible in the real world. For example, using simulations allowed for a strong level of control over all parameters that were included and excluded from the model, allowing the results to be interpreted as being caused by the parameters and manipulations in the present study rather than extraneous factors. Using simulations also allowed many networks to be generated according to the same set of parameters (i.e., 1000 networks in each combination of parameters) and allowed copies of the same networks to be subject to the same manipulation, reducing the chances that the results were obtained from networks that were atypical or outliers randomly sampled from the parameter set.

Although the present study operationalized the behavioral variable of network members as heavy drinking vs. non-drinking, another strength of the study is that the results may also be generalizable to other behaviors that are subject to social influence, social selection, and status and network manipulations. For example, these results could extend to represent individual and social network change related to any drinking vs. non-drinking, drug use vs. non-drug use, smoking vs. non-smoking, and other health behaviors.

Finally, the present study utilized a novel method for studying dynamic systems related to social networks and alcohol consumption. This research provides an alternative way to conceptualize alcohol use, social networks, and change over time within the context of dynamically-evolving social systems. This research highlights the importance of implementing new methods within psychological research (e.g., social network simulations) and allows for the modeling of complex real-world systems concepts, including nonlinearity, steady states, interdependence, and feedback. The use of this method can help improve the field's understanding of commonly studied problems by examining them in a new light.

Conclusion

The social environment is likely to play an active role in maintaining and facilitating changes in individual drinking, and few studies have accounted for the social network dynamics that may influence drinking behavior. The reciprocal effects of social influence and social selection create a feedback loop, which can in turn lead to non-linear dynamic effects in alcohol use and social tie changes. The present study aimed to help facilitate a better understanding of how changes in alcohol use may be influenced by social networks within the presence of social influence and social selection, as well as other common network properties such as reciprocity, transitivity, outdegree, and three-cycle effects. The present study also aimed to test several types of manipulations that mimic real-world interventions on the drinking statuses and friendships of actors targeted for various interventions and on the drinking statuses of peripheral actors who were not directly targeted for intervention.

The present study provides several clinical implications for understanding heavy drinking within dynamic social network contexts. Heavy-drinking individuals in social networks with both social influence and social selection present (e.g., adolescents, emerging adults) may be more strongly nested within groups of other heavy drinking individuals who may impact their behavior. The presence of both social influence and social selection can create an attractor state that makes it difficult to simultaneously change actors' drinking statuses and remove themselves from their heavy drinking network. However, successful change in one's drinking status may have a spreading effect in reducing the heavy drinking rates of other individuals in situations where social influence is present. This suggests that in some cases, alcohol treatment and prevention programs may provide an even larger benefit to public health by affecting individuals beyond those targeted for intervention.

The present study also provides several clinical implications for the efficacy of various intervention strategies within social network contexts. Of the manipulations tested, reducing heavy drinkers' susceptibility to social influence provided the greatest reductions in heavy drinking apart from directly manipulating a target actor's drinking status. This manipulation was particularly effective when both social influence and social selection effects were present and when target actors had many ties to heavy drinkers or few ties to non-drinkers. Reducing heavy drinkers' susceptibility to social selection, helping them form one new friendship with a non-drinker, or helping them dissolve one existing friendship with a heavy drinker may produce significant degrees of change in their friendships to heavy drinkers and non-drinkers, but may be insufficient to produce significant reductions in heavy drinking.

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Table 1. Examples of real-world variables that may impact social networks and drinking.

Variable Source	*Effect on Drinking/Network*	*Real-World Example*
Individual	Drinking level	Successful alcohol treatment
Individual	Social influence	Learning drink-refusal skills
Individual	Social selection	Avoiding people, places, and things, obtaining Alcoholics Anonymous sponsor; making sober friends
System	Drinking levels	Alcohol outlet density, alcohol taxes
System	Social influence	Social norm campaign
System	Social selection	Positive/negative cultural views of drinkers

Table 2. Proportional relative probabilities and cumulative probabilities for each possible network change for actor 5. Similarity effect is not included in the model.

Network change	Proportional relative probability	Cumulative relative probability	Corresponding random number range
No change	0.312	0.312	0.000 – 0.312
Remove tie with actor 4	0.335	0.647	0.312 – 0.647
Extend tie to actor 3	0.201	0.848	0.647 – 0.848
Extend tie to actor 2	0.076	0.924	0.848 – 0.924
Extend tie to actor 1	0.076	1.000	0.924 – 1.000

Table 3. Proportional relative probabilities and cumulative probabilities for each possible network change for actor 5. Similarity effect is included in the model.

Network change	Objective function value	Proportional relative probability	Cumulative relative probability
No change	-0.07	0.266	0.266
Remove tie with actor 4	0.00	0.285	0.550
Extend tie to actor 3	-0.02	0.279	0.829
Extend tie to actor 2	-1.48	0.065	0.894
Extend tie to actor 1	-0.99	0.106	1.000

Table 4. Network-level manipulations.

Manipulations	Verbal description	Network/Behavior Effect	Levels	Parameter Values
Social influence	Degree to which drinking statuses of network members influences drinking status of others	Average alter behavior effect	Zero, Medium, High	0, 3, 6
Social selection	Degree to which social ties in the network are established based on similarity of drinking	Similarity network effect *	Zero, Medium, High	N = 25: 0, 3, 6 N = 100: 0, 1.5, 3
Network size	Number of actors is the network	n/a	N = 25, N = 100	25, 100
Drinking rate	Proportion of network that is heavy drinkers	Linear shape behavior effect	50% and 25%	0, -1

Table 4. (cont.)

Constant Parameters	Verbal description	Network/Behavior Effect	Levels	Parameter Values
Outdegree	Degree to which number of outgoing ties is limited	Outdegree network effect	Varied based on Zero, Medium, or High social selection condition, respectively	*N* = 25, HDR = 50%: -1.6, -3.7, -6.0 *N* = 25, HDR = 25%: -1.6, -4.0, -6.7; *N* = 100, HDR = 50%: -1.8, -2.8, -3.9.
Reciprocity	Degree to which social ties are reciprocated	Reciprocity network effect	(constant)	2.0
Transitivity	Degree to which actors become friends with friends-of-friends	Transitive triplets network effect	(constant)	0.3
Three-cycle	Degree to which actors avoid having cyclical friendships	Three-cycles network effect	(constant)	-0.3

Table 4 (cont.)

Note: Parameter values for the similarity network effect (social selection) differed between the $N = 25$ and $N = 100$ networks. Pilot testing indicated that decreasing these parameter values by a factor of two when network sizes increased from 25 to 100 provided similar degrees of clustering, based on Pearson correlation tests and visual inspection of network graphs.

Table 5. Individual-level manipulations

Drinking status manipulation
Change focal actor’s drinking status from heavy drinker to non-drinker
Social network manipulations
Decrease focal actor’s susceptibility to social influence
Add one social tie from focal actor to a non-drinker
Remove one asocial tie from focal actor to a heavy drinker
Make no change (i.e., network continues to evolve normally)