Social Interactions and Social Preferences in Social Networks*

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Abstract

We extend the utility specification in Ballester et al. (2006) to study social interactions when individuals hold altruistic preferences in social networks. We show that rich network features can be captured in the best response function derived by maximizing the extended utility which incorporates altruism, thereby providing microfoundation for studies on how network features mediate peer effects or other important features in social interactions. We demonstrate that the often ignored altruism is another serious confounding factor of peer effects. Our results show that the estimates of peer affects are approximately 36% smaller under social preferences. Furthermore, we could separately identify two different types of effects caused by peers' outcomes: the (usually positive) spillover effects and the direct (negative or positive) externality effects, which is impossible in a conventional social interactions model based on the self-interest hypothesis.

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1 Introduction

An overwhelming amount of evidence from experimental and field works indicates that, instead of self-interest as assumed in classical economic theory, many people are altruistic and concerned about the welfare of others.[1] Many economists, including Arrow (1981), Becker (1974), Samuelson (1993), Smith (1759), and Sen (1995), pointed out that when making decisions in many situations, such as among family members and friends, and within organizations, altruism plays an important role in forming an individual's utility function. The literature on social preferences has been firmly established theoretically and empirically.

Recently, the literature on social preferences has started to uncover the connection between peer effects and social preferences. A few studies have shown that the extent to which people are willing to sacrifice their self-interest is sensitive to social influences; among these research are Falk et al. (2013), Fischbacher and Gachter (2010), Krupka and Weber (2009), and Mittone and Ploner (2011). Through a novel gift-exchange experiment, Thöni and Gächter (2015) provide strong evidence for peer effects in pro-social behaviors. Other studies on conditional cooperation, including Chen et al. (2010), Croson and Shang (2008), Frey and Meier (2004), and Rustagi et al. (2010), show that the observed results in their studies are consistent with peer influences and social preferences. These studies have indicated that situations in which social preferences matter are often suitable settings for peer effects.

Surprisingly, the literature on social interactions has mainly focused on the influences of peers on individual behaviors and decisions, rarely considering the possible formation of social preferences among peers. Many of these studies have applied the Spatial Autoregressive (SAR) model to study social interactions on various outcomes, such as academic performance, club participation, smoking, obesity, sports, and screen activities (see Boucher et al., 2014; Bramoullé et al., 2009; Calvó-Armengol et al., 2009; Christakis and Fowler, 2007; Hsieh and Lee, 2016; Lee et al., 2010; Lin, 2010; Liu et al., 2014).[2] Similar to most conventional economic models, the SAR model is based on the standard self-interest hypothesis, assuming that individuals act exclusively on their own self-interest. Ballester et al. (2006) and Calvó-Armengol et al. (2009) provide game-theoretical microfoundation for the SAR model

[1] See e.g., Andreoni, 1995; Andreoni and Miller, 2002; Anderson et al., 1998; Brandts and Schram, 2001; Croson, 2007; Fischbacher et al., 2001; Güth et al., 1982; Keser and Van Winden, 2000; Sonnemans et al., 1999; Sugden, 1984.

[2] The advantage of the SAR model over the conventional linear-in-means model in studying social interactions is that the SAR model on network data can solve the "reflection problem" inherited in the linear-in-means model (Manski, 1993). The spatial weights matrix of the SAR model can be used to represent the friendship (network) links of individuals in a group. As friendship links are specific to each individual and could be nontransitive, i.e., my friend's friend may not be my friend, the SAR model introduces necessary individual heterogeneity to distinguish between endogenous peer effects and contextual effects.

by considering a conventional non-cooperative game in which rational and self-interest individuals maximize their own utilities. The resulting SAR model captures the pure strategy played by individuals in a unique interior Nash equilibrium.

As social interactions occur on a regular basis and within small groups, altruism is expected to play an important role since people may intrinsically care about the well-being of their social contacts and take into account their preferences when making decisions. As shown in a number of studies, including those by Bourlès et al. (2017), Goeree et al. (2010), Jones and Rachlin (2006), Leider et al. (2009), and Yamagishi and Mifune (2008), frequent interactions with peers may have important impact on the formation of individuals' preferences. Hence, relaxing the assumption of individual selfishness under the social interaction framework becomes necessary. It would be interesting to see how an openness to the altruistic preferences leads to new perspectives on modeling social interactions.

In this paper, we provide the first analysis on social interactions and social preferences in social networks, building a bridge between the two strands of rapidly growing yet unrelated literature. We investigate the model specification issues that emerge after we extend the standard assumption of self-interest to a more evolutionary foundation in which individuals can be altruistic. In particular, we specify individual utility function by combining a general altruistic utility with the specific quadratic specification of Ballester et al. (2006) in order to capture the complementary effect from peers' behaviors.[3] We show that the extended utility framework has important implications for social interactions model specification.[4] Several papers on social interactions have extended the econometric model derived from the classical utility maximization of rational and selfish individuals to - arbitrarily, in a sense - include some additional terms for studying how network features mediate peer effects or other important features in social interactions. For instance, Ballester et al. (2006) examine how network centrality and individual position in the network affect social interactions and equilibrium outcomes. Battaglini et al. (2017) investigate the direct externality generated by peers in the self-control of students. Lin and Weinberg (2014) extend the standard SAR model to capture the peer effects generated by reciprocated, unreciprocated, and unchosen friends on adolescents' behaviors and outcomes. These studies have provided interesting and important insights into social interactions, but they do not have a clear microfoundation based on classical theory. We demonstrate that the interesting features investigated by these papers, such as the in-degree of the network, can be well captured in the best response function derived by maximizing

[3]We also extend the model to incorporate more structured forms of altruistic preferences, such as those specified in Leider et al. (2009) and Levine (1998).

[4]Blume et al. (2015) illustrate that different specifications of the utility function may give rise to different econometric models used for empirical studies.

the extended utility that incorporates altruism, thereby providing microfoundations for these studies.[5]

Another important contribution of this paper is that it shows that, although often ignored, altruism is another serious confounding factor of peer effects. Intuitively, peer effects imply that people respond to others' behaviors because they are - often unconsciously - influenced by others; while altruism means that people might adapt their behavior towards others - consciously - to either help or not hurt them. Therefore, the estimation of peer affects is even more challenging than previously thought because ignoring altruistic preferences in social networks will cause bias in peer effect estimation. In our analysis of the National Longitudinal Study of Adolescent to Adult Health (Add Health) data, we find that significant peer effects exist on students' academic achievement, smoking behavior, and extracurricular activities, even after controlling for altruistic preferences and endogenous network formation. We also find evidence of upward bias on the estimates of peer effects when omitting the effect of altruism. In particular, the estimates of peer affects are approximately 36% smaller under altruistic preferences as compared to the case with the conventional self-interest assumption. Furthermore, we can separately identify two distinct types of effects generated from peers' outcomes. Specifically, in addition to the positive spillover effects from peers, we find significant negative externality effects directly generated from peers' outcomes.[6] Note that the conventional SAR specification based on the self-interest hypothesis can only identify the mixture of these two effects from peers. We employ the procedure in Hsieh and Lee (2016) to address the potential endogeneity of network formation.

The remainder of this paper is organized as follows. Section 2 briefly reviews related literatures on altruistic preferences and social interactions. Section 3 describes the social interactions model with altruistic preferences and endogenous network formation. Section 4 explains the model estimation procedure and provides a simulation study to examine the performance of the proposed estimation method. The proposed approach is applied to the Add Health data in Section 5. Section 6 concludes the paper. Details of the estimation method used in this paper and some additional empirical results are relegated in Supplementary Appendixes

[5]In the conventional linear-in-means social interaction model (Manski, 1993), peer variables are specified as group means, therefore network links play no role in the model. In the standard SAR model, peer variables are captured by the means (or sums) of individuals' nominated friends, thus one particular network feature, i.e., the out-degree of the network, plays an important role in the model and helps resolve the "reflection problem." In our social interaction model which incorporates altruism, not only the out-degree of the network, but also the in-degree of the network, will play important roles in the model, providing another source for separately identifying various mechanisms underlying the observed correlated outcomes among network members.

[6]As shown in Equation (8) below, the spillover effect is represented by λ, whereas the externality effect is captured by η.

A and B.

2 Literature Review

Overwhelming evidence from experiments and field work that systematically violates the self-interest hypothesis has fostered several theoretical models in social preferences, which have clear departures from the standard self-interest hypothesis based model. The first type of model departs from classical utility theory by assuming that a player's utility function depends not only on personal payoff, but also on others' payoffs, including Becker (1976, 1981), Hori and Kanaya (1989), Hori (1992), Bergstrom (1999), Hori (2001), Andreoni and Miller (2002), Bolton (1991), Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Charness and Rabin (2002), Erlei et al. (2004), Cox et al. (2007), Benjamin (2004) and Bénabou and Tirole (2006). The second class of model focuses on intention-based reciprocity, which assumes that players care about their opponents' intentions; these include Rabin (1993), Dufwenberg and Kirchsteiger (2004), Falk and Fischbacher (2006), Charness and Rabin (2002) and Charness and Dufwenberg (2006). The third class of model assumes that people are concerned about the "type" of their opponents, which includes Levine (1998), Rotemberg (2008), and Gul et al. (2004). In particular, Levine (1998) formulates an altruism model in which a player interacts with different types (spiteful, selfish and altruistic) of opponents, and has a utility function which is linear in both her own and her opponents' payoffs, with the weight on the opponent's payoff depending on the opponents' types. Levine performs several experiments and shows that the results in the ultimatum game, centipede game, market competition, and public good game are all consistent with this theory. Through an online field experiment in large real-world social networks, Leider et al. (2009) demonstrate that agents show baseline altruism toward randomly selected strangers, whereas they show directed altruism toward their friends. Furthermore, directed altruism increases an agent's giving to their friends by a significant amount compared with giving to random strangers. Note that most models of social preferences predict either no peer effects or negatively correlated efforts in which agents' efforts are unrelated and strategic substitutes, respectively.[7]

Recently, a number of social preference studies have shown that agents' efforts in various experiment settings are positively correlated, contradicting standard theories of social preferences. For instance, Thöni and Gächter (2015) study a novel gift-exchange experiment and find that the positively correlated efforts among agents are strategic complements instead of

[7]Only two standard theories in social preferences are generally consistent with positively and negatively correlated efforts, such as, Charness and Rabin (2002) and Fehr and Schmidt (1999). Detailed discussions on these models can be found in Gächter et al. (2013).

substitutes. To provide explanation for the empirically observed positively correlated efforts, the recent generation of social preference theories introduces additional social motives beyond conventional distributional concerns as considered in standard social preferences theories. For instance, Sliwka (2007) considers conformism, López-Pérez (2008) incorporates social norm, whereas Bénabou and Tirole (2006), and Ellingsen and Johannesson (2008) introduce social esteem. In a recent study, Gächter et al. (2013) identify the behavioral mechanism underlying the peer effects observed in their three person gift exchange experiment. They find that both the standard model of social preferences in Fehr and Schmidt (1999) in which individuals are inequity aversion and the model of social norm compliance can explain the positive correlation in agents' efforts. Several other papers have examined and compared the relative importance of social norms and social preferences in explaining the observed correlated behaviors. Krupka and Weber (2013) show that the observed behavior differences in their Dictator game cannot be explained by most standard social preferences models, whereas social norm compliance can explain behavior changes in various contexts. Similarly, Krupka et al. (2016) find that elicited social norms have significant explanatory power for agents' behaviors in their Dictator and Bertrand games, whereas social preference models do not.

By contrast, altruistic preferences have seldom played a role in the literature on social interactions. The majority of studies on social interactions have focused on addressing well-known identification difficulties including the "reflection problem" and the endogeneity of network group formation, as well as selection and omitted variable biases. As demonstrated in numerous studies, such as Lin (2010), Bramoullé et al. (2009), Calvó-Armengol et al. (2009), and De Giorgi et al. (2010), the SAR model resolves the "reflection problem" by introducing nonlinearity through individual specific social network links.[8] To deal with the other potential confounding factors, different strategies have been proposed, including group fixed effect (Lin, 2010; Bramoullé et al., 2009), instrument variable (e.g., Evans et al., 1992; Rivkin, 2001), and experiment type strategies (e.g., Sacerdote, 2001; Zimmerman, 2003). Recently, some papers such as Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016) have proposed a comprehensive simultaneous equation system to model both network formation and peer effects to capture the influences of unobserved characteristics on friendship formation and/or social interactions.

At the same time, a number of studies, including Cosmides and Tooby (1989), Goeree et al. (2010), Jones and Rachlin (2006), Wang (1996), and Yamagishi and Mifune (2008) have confirmed that social interactions and/or group memberships are complementary determinants of altruistic behavior. Bell and Keeney (2009) analyze altruistic decisions among

[8] Lee (2007) and Boucher et al. (2014) use the size variation of groups to resolve the reflection problem when individual specific social network links are not available in data.

group members by using a group altruistic utility function that incorporates the preferences of each individual member. They study an additive utility function in which aggregated utility is the summation of all individual utilities in the group. In a recent paper, Bourlès et al. (2017) investigate altruism in social networks wherein individuals care about the welfare of their network neighbors. In their model, agents are altruistic, and an agent's social utility consists of several components, namely, personal private utility, as well as others' private and social utilities. They examine the Nash equilibrium of the resulting game of private transfers flow through altruism networks. On the other hand, several studies have extended the standard SAR model to capture some additional interesting network related effects (e.g., Ballester et al., 2006; Branas-Garza et al., 2010; Battaglini et al., 2017; and Lin and Weinberg, 2014), although they fail to realize that these additional effects will show up in the SAR model under altruistic preferences. The incorporation of altruism into social interactions models has important modeling consequences and can provide microfoundations for these studies.

3 Model

3.1 Conventional Social Interactions Model

We consider an environment in which individuals form network links in well-specified groups and their activities are subject to interaction (peer and spillover) effects. Examples of such groups include schools, workplaces, and villages. Suppose there are G groups in total, and in each Group $g \in (1, \cdots, G)$, $y_{i,g}$ denotes the activity outcome of individual i and $Y_g = (y_{1,g}, \cdots, y_{m_g,g})'$ represents a $m_g \times 1$ activity vector of individuals in Group g, where m_g is the group size. We let $x_{i,g}$ represent a k-dimensional individual's exogenous characteristics and X_g denote a $m_g \times k$ matrix of characteristics. Depending on the context, individuals are connected in a group due to friendship, supervisor and supervisee, and borrowing and lending, among others. The social links in Group g are observed by all members and represented by adjacency matrix (sociomatrix) W_g. The $(i, j)^{\text{th}}$ element of W_g, $w_{ij,g}$, equals one if individual i sends a social link to individual j. Otherwise, $w_{ij,g}$ equals zero. All links are directed, and thus they are not necessarily reciprocal. This asymmetric feature in the adjacency matrix plays a key role in identifying the proposed model, which we will explain in details later. Furthermore, the diagonal elements of W_g are set to zero by default.

Corresponding to the nature of interactions in groups, individual i's payoff $v_{i,g}$ is determined by his/her own activity and those of his/her friends. We adopt the quadratic specification from Ballester et al. (2006) and Calvó-Armengol et al. (2009) to capture the complementary effect from peers' activity levels:

$$v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) = \mu_{i,g} y_{i,g} - \frac{1}{2} y_{i,g}^2 + \lambda y_{i,g} \sum_{j=1}^{m_g} w_{ij,g} y_{j,g}, \tag{1}$$

where $Y_{-i,g}$ denotes the $(m_g - 1) \times 1$ activity vector excluding $y_{i,g}$. The first and second terms of Equation (1) capture the benefit (or cost) of performing the activity and $\mu_{i,g}$ denotes individual heterogeneity. The third term captures the complementary effect from nominated friends' activities, which provides the source of peer influences.

Rational and self-interest individuals determine their activity levels by maximizing the own payoff function in Equation (1). The implied pure strategy activity vector in a unique interior Nash equilibrium is given by[9]

$$Y_g = (I_{m_g} - \lambda W_g)^{-1} \mu_g, \quad g = 1, \cdots, G. \tag{2}$$

If we specify $\mu_g = X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g$ in Equation (2), where l_g is the m_g-dimensional vector of ones, then Equation (2) implies that we can model individual economic activity by the standard spatial autoregressive (SAR) model (and henceforth we call it conventional social interactions model),

$$Y_g = \lambda W_g Y_g + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \quad g = 1, \cdots, G. \tag{3}$$

In Equation (3), coefficient λ captures the endogenous (peer) effect. In this model, only the outward links of an individual, i.e., friends nominated by individual i as represented by the row i of the W, play a role in social interactions. By contrast, an individual's inward links, i.e., nominations received by individual i as captured in column i of the W, plays no role in social interactions of outcomes in the group. Therefore, the out-links feature of the social network provide valuable information for identifying the endogenous peer effect, while the role of the in-links feature of the social network is missing in this model.[10] Coefficients β_1 and β_2 capture the own and contextual effects from exogenous individual characteristics, respectively. Term τ_g represents the group fixed effect, which captures the correlated effects caused by the environmental variables shared by all individuals in the same group. The group fixed effect also controls group level unobserved factors which induce individuals to self-select into the group. Finally, $\epsilon_g = (\epsilon_{1,g}, \cdots, \epsilon_{m_g,g})'$ represents the vector of individual stochastic errors.

[9]Following Ballester et al. (2006), the existence and uniqueness of the equilibrium can be guaranteed as long as $|\lambda| < 1/\max_{g=1,\cdots,G} \kappa_{\max}(W_g)$, where $\kappa_{\max}(W_g)$ denotes the maximum eigenvalue of network matrix W_g.

[10]As will be shown in the following subsections, the in-links feature of the network contains valuable information for identifying other mechanisms underlying the correlated outcomes among group members such as altruism.

3.2 Altruistic Preference

Instead of assuming that individuals only care about their own payoff, we extend the model to allow altruism, such that individuals care about others' well-being when choosing an optimal activity level to maximize utility, $U_{i,g}$. The simplest form of the altruistic utility function is the linear function of individual's own and others' payoffs,[11]

$$U_{i,g} = v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) + \alpha_1 \sum_{j=1, j\neq i}^{m_g} v_{j,g}(y_{j,g}, Y_{-j,g}, W_g). \tag{4}$$

In this model, coefficient α_1 captures the altruism level, reflecting how much individuals care about others' payoffs. We follow Levine (1998) to assume α_1 to be bounded by [-1,1]. When α_1 is positive, individuals are altruistic and a higher value of α_1 represents a stronger level of altruism; when α_1 equals zero, individuals are selfish and Equation (4) will reduce to Equation (1); and when α_1 is negative, individuals are spiteful. In this model, individuals show altruism toward every other people in a group, which is the baseline altruism discussed in Leider et al. (2009).[12]

Under this altruistic utility function, the implied pure strategy played by individuals in a unique interior Nash equilibrium will change to[13]

$$Y_g = (I_{m_g} - \lambda W_g - \lambda^{\mathrm{I}} W_g^{\mathrm{T}})^{-1} \mu_g, \quad g = 1, \cdots, G, \tag{5}$$

where $\lambda^{\mathrm{I}} = \alpha_1 \lambda$, and W_g^{T} denotes the transpose of W_g. With the same specification of μ_g as above, we can obtain an extended SAR model as follows,

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \quad g = 1, \cdots, G. \tag{6}$$

This model can be called "altruistic social interactions model." The difference between Equations (6) and (3) is the new term, $\lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g$, which is related to the in-links feature of the network and reflects altruistic preference. We use superscript "I" on the coefficient to indicate

[11] This simple and intuitive utility function has been employed in several studies, including Bell and Keeney (2009) and Bourlès et al. (2017). Following Bourlès et al. (2017), except others' payoffs, one may also directly incorporate others' utilities into individual's utility function like $U_{i,g} = v_{i,g} + a\sum_j v_{j,g} + b\sum_j U_{j,g}$, which forms a system of equations. Utility U_i is implicitly defined as the solution of the above system of equations. By assuming that $|b| < 1/(m_g - 1)$, we can obtain a unique solution $U_{i,g} = \frac{1}{1-b} v_{i,g} + \frac{a}{1-b}\sum_j v_j$, which is consistent with our Equation (4). It implies that individuals care about others' payoffs when caring about others' utilities.

[12] We will consider directed altruism in an extended model in Section 3.4.1.

[13] From the first order condition of the utility maximization, $\frac{\partial U_{i,g}}{\partial y_{i,g}} = \frac{\partial v_{i,g}}{\partial y_{i,g}} + \alpha_1 \sum_{j=1, j\neq i}^{m_g} \frac{\partial v_{j,g}}{\partial y_{i,g}} = 0$, the best-response function of individual i is given by $y_{i,g} = \lambda \sum_{j=1}^{m_g} w_{ij,g} y_{j,g} + \alpha_1 \left(\lambda \sum_{j=1}^{m_g} w_{ji,g} y_{j,g}\right) + \mu_{i,g}$. Thus, as long as $|\lambda| + |\alpha_1 \lambda| \leq 1/\max_{g=1,\cdots,G} \kappa_{\max}(W_g)$, where $\kappa_{\max}(W_g)$ denotes the maximum eigenvalue of network matrix W_g, then the unique interior Nash equilibrium of Equation (5) exists.

that it is identified from "inward" friendship links. Therefore, under altruistic preference, individual outcomes are affected not only by the outcomes of their nominated friends which are related to the out-links of the network and captured by λ, but also by the outcomes of those who nominated them as a friend which are related to the in-links of the network, with the effect of the latter group being the endogenous peer effect, scaled by the altruism level, α_1.[14] Note that the in-links feature of the social network only plays a role when individuals are altruistic. As a matter of fact, if individuals are selfish, i.e., $\alpha_1 = 0$, then coefficient λ^{I} is zero and Equation (6) will be identical to Equation (3). The intuition is that an individual responds to her nominated friends' outcomes because of complementarity, i.e., keeping up with friends enhances her utility through her increased own payoff, and she also responds to the outcomes of the other individuals who nominated her as friend due to altruism, as their payoffs are a component in her utility function weighted by her altruism level towards them, i.e., α_1.[15] Therefore, different features of the network, such as out-degree and in-degree, contain unique information for identifying various mechanisms occurring inside the black-box of social interactions. Meanwhile, as can be seen from Equation (6), if the network matrix W_g is symmetric, then it is not possible to separately identify λ and λ^{I} as the out-links and in-links of the network will be identical. Therefore, having asymmetric network matrix is necessary for identification of altruism. This additional identification condition is usually satisfied as most social network links are asymmetric.[16,17]

3.3 Externality Effect

The social interactions effects considered in Sections 3.1 and 3.2 are the conventional complementary spillover effects generated by peers, as seen in the last term in Equation (1), where peers' outcomes, $\sum_{j=1}^{m_g} w_{ij,g} y_{j,g}$, are augmented by own outcome, $y_{i,g}$. However, another

[14] The latter group of friends include reciprocal and unchosen friends in the model specification in Lin and Weinberg (2014).

[15] These two components can be clearly seen from Equation (4).

[16] In our sample, only 44.10% links in the networks are reciprocal, therefore the resulting network matrix is certainly asymmetric.

[17] As the identification of our model hinges on the detailed structure of the network, the estimated parameters may be contaminated if some of the network links in data are missing. To check the sensitivity of our estimation to possible measurement errors in W, we perform some Monte Carlo simulations and find that for the endogenous peer effect λ, the bias caused by the missing link problem in the altruistic social interactions model is comparable to that in the standard SAR model, and the biases in the altruism effect as well as the externality effect in Equation (8) are slightly larger than the bias in λ, but the overall magnitudes are not significant under reasonable missing levels. These results are not reported to save space but are available from the authors upon request. Systematically address the measurement issues for social interaction models is of great importance, and will be investigated in a separate future research.

channel may exist for the direct effect of peers' activity on individual payoff, that is, the "direct externality" effects, wherein an individual may be directly affected by peers' activities, without being augmented by his/her own $y_{i,g}$, as captured by the last term in Equation (7) below.[18] For instance, an individual may enjoy smoking with his/her friends, but at the same time, his/her friends' smoking behaviors could directly have a negative externality effect on individual's own payoff due to health concerns.[19]

$$v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) = \mu_{i,g} y_{i,g} - \frac{1}{2} y_{i,g}^2 + \lambda y_{i,g} \sum_{j=1}^{m_g} w_{ij,g} y_{j,g} + \eta \sum_{j=1}^{m_g} w_{ij,g} y_{j,g}. \tag{7}$$

Combining this payoff function with the altruistic preference in Equation (4), we can derive the pure strategy played by individuals in a unique interior Nash equilibrium as follows

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \quad g = 1, \cdots, G. \tag{8}$$

Compared with Equation (6), $\eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g$ is a new term in Equation (8), where $\eta^{\mathrm{I}} = \alpha_1 \eta$ and $W_g^T l_g$ is the number of friendship nominations received by an individual, i.e., the in-degree centrality of an individual. We refer to Equation (8) as the "altruistic social interactions model with direct externality," in which we can identify the degree of altruism by coefficient λ^{I} from the term $W_g^{\mathrm{T}} Y_g$, i.e., the outcomes of the individuals who nominated individual i as friend and the direct externality effect from the in-degree of the network members, by coefficient η^{I}.[20] We can see a clear rationale behind Equation (8) using the indegree to capture the externality effect. Given that individuals are altruistic, they take into account the potential externality effect on their friends when choosing their activity levels. As a result, the more friendship nominations received by an individual from others, the stronger the externality effect that will manipulate individual activity outcome. In this stream of literature, researchers have explored various network effects on individual outcomes (Echenique and Fryer, 2007; Mihaly,

[18]Whether including this direct externality term or not in the model based on the self-interest assumption does not make any difference, as its derivative with respect to $y_{i,g}$ is zero, and therefore the coefficient η won't show up in the best response function.

[19]A few recent papers study externalities in social networks, but in settings different ours. For instance, Badev (2017) studies a social network model where payoff of an individual depends on own attributes, as well as two externality terms. The first term captures local externalities, i.e., a person may be influenced strongly by friends' behaviors as opposed to casual individuals. The second term captures aggregate externality, i.e., a person may be affected by the behavior of the surrounding population, regardless whether they are friends or not. Mele (2017) considers a network link formation process, where the value of the links formed by other players are captured as linking externalities.

[20]In particular, only the in-degree centrality, not the outcomes, is relevant for the identification of the externality effect. This is so because externality effect captures the direct effect of other individual's outcome Y_j on individual i, without being augmented through Y_i.

2009; Conti et al., 2013; Alatas et al., 2016). Although most studies have interpreted the effect of the indegree centrality as a popularity effect, our model provides an alternative justification that the in-degree centrality reflects the externality effect on individual outcome.

Clearly, Equation (8) reveals (at least) three different underlying channels operating in the social network system: the first is the (conventional) complementary peer effect, operating through the out-degrees of the network and outcome activities. The second is the complementary peer effect scaled by the altruism effect, occurring through the in-degrees of the network and outcome activities. The third is the externality effect, again, scaled by the altruism effect, operating solely through the in-degrees of the network. Therefore, the information contained in the in-degrees of the network is two-dimensional: one operates through the outcome activities and the other operates independently without being augmented by outcomes. However, under the conventional self-interest modeling hypothesis, it is not possible to capture the important role played by the in-degrees of the network in the interaction system.

Regarding the specification of weights matrix in social interactions models, one faces a choice between raw or row-normalized weights matrix (Liu et al., 2014). When using the raw weights matrix, the results can be interpreted as a local aggregated effect– the more peers an individual has, the stronger the effects the individual receives. When using the row-normalized weights matrix, the results are interpreted as a local average effect – individuals conform with the social norm reflected by the average peer behaviors and the number of peers does not matter. In this paper, we choose the local aggregate specification as the number of friendship nominations is important in identifying the effects of altruism and externality.

3.4 Two Extensions

3.4.1 Extension I: Directed Altruism

We can further extend the utility specification in Equation (4) to accommodate the concept of directed altruism (Leider et al., 2009),

$$U_{i,g} = v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) + \sum_{j=1, j\neq i}^{m_g} (\alpha_1 + \alpha_2 w_{ij,g}) v_{j,g}(y_{j,g}, Y_{-j,g}, W_g). \tag{9}$$

In this utility specification, coefficient α_1 denotes baseline altruism toward all group members, and α_2 represents directed altruism towards friends. Leider et al. (2009) find that altruism levels are stronger among friends than among randomly selected strangers. Combining the payoff function of Equation (7) with the utility function of Equation (9), we can obtain an outcome equation based on the vector of unique Nash equilibrium strategy as follows,[21]

$$\begin{aligned} Y_g = {} & \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \lambda^{\mathrm{R}} W_g^{\mathrm{R}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + \eta^{\mathrm{R}} W_g^{\mathrm{R}} l_g \\ & + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \quad g = 1, \cdots, G. \end{aligned} \tag{10}$$

Compared with Equation (6), we can see two new terms in Equation (10), $\lambda^{\mathrm{R}} W_g^{\mathrm{R}} Y_g$, and $\eta^{\mathrm{R}} W_g^{\mathrm{R}} l_g$, where W_g^{R} represents the network of reciprocal links, i.e., $w_{ij,g}^{\mathrm{R}} = 1$ if both $w_{ij,g}$ and $w_{ji,g}$ are 1 and 0 otherwise. Coefficients $\lambda^{\mathrm{R}} = \alpha_2 \lambda$ and $\eta^{\mathrm{R}} = \alpha_2 \eta$ capture the endogenous peer effect and the direct externality effect from reciprocal friendship links, which are the original spillover effect and externality effect scaled by the directed altruism coefficient α_2, respectively. We refer to Equation (10) as the "directed altruistic social interactions model." It provides microfoundation for the heterogeneous peer effects of chosen, unchosen, and mutual friends in Lin and Weinberg (2014).

3.4.2 Extension II: Heterogeneous Altruism

In Equations (4) and (9), the altruism level, captured by coefficient α_1 (and α_2), is assumed as homogeneous across individuals. It is possible to consider some alternative specifications which allow altruism levels to be heterogeneous among pairs of individuals. In this paper, we adopt the utility function proposed in Levine (1998) to extend the utility specification in Equation (4) to capture heterogeneous altruism based on fairness and reciprocality,[22] as specified below:

$$U_{i,g} = v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) + \sum_{j=1, j \neq i}^{m_g} \frac{\alpha_{i,g} + \rho \alpha_{j,g}}{1 + \rho} v_{j,g}(y_{j,g}, Y_{-j,g}, W_g), \tag{11}$$

where $\alpha_{i,g}$ reflects individual i's altruism level, which is again assumed to be bounded by [-1,1]. Similar to Equation (4), when $\alpha_{i,g} > 0$, individual i is altruistic; when $\alpha_{i,g} = 0$, individual i is selfish; and when $\alpha_{i,g} < 0$, individual i is spiteful. We use $A_g = (\alpha_{1,g}, \cdots, \alpha_{m_g,g})'$ to denote the $m_g \times 1$ vector of altruism levels in Group g. Coefficient $0 \leq \rho \leq 1$ reflects the reciprocity. A higher ρ implies that individuals respond more altruistically to someone

[21] We obtain the best response function from the first order condition similar to footnote 10. A sufficient condition for the unique Nash equilibrium based on the best response to exist is

$$|\lambda| + |\lambda^{\mathrm{I}}| + |\lambda^{\mathrm{R}}| \leq 1 / \max_{g=1,\cdots,G} (\kappa_{\max}(W_g), \kappa_{\max}(W_g^{\mathrm{R}})).$$

[22] Many other theoretical models can also explain heterogeneous altruistic behaviors, including Bolton et al. (1998), Charness and Rabin (2002), Cox et al. (2007), Fehr and Schmidt (1999), to name a few. Although these theories are comprehensive, they are too complex and cannot be applied in an empirical study in a straightforward way.

altruistic to them. The adjusted utility function in Equation (11) assigns different weights to others' payoffs based on how altruistic individuals are and how fairly they feel they are treated. Therefore, in this model, altruism is a fixed innate individual characteristic; however, the extent to which individual i cares about individual $j's$ payoff depends on the interactions between two individuals' altruism levels, which vary across individual pairs.

With the use of the utility specification in Equation (11), we can derive the best response function of individual i as,

$$\begin{aligned} y_{i,g} =& \lambda \left(\sum_{j=1}^{m_g} w_{ij,g} y_{j,g} + \sum_{j=1}^{m_g} \frac{\alpha_{i,g} + \rho\alpha_{j,g}}{1+\rho} w_{ji,g} y_{j,g} \right) + \eta \sum_{j=1}^{m_g} \frac{\alpha_{i,g} + \rho\alpha_{j,g}}{1+\rho} w_{ji,g} \\ &+ x_{i,g}\beta_1 + \sum_{j=1}^{m_g} w_{ij,g} x_{j,g} \beta_2 + \tau_g + \epsilon_{i,g}. \end{aligned} \tag{12}$$

Under this generalization, each individual j who nominates individual i as friend will generate effects on i, with the magnitude being the usual peer effect coefficient λ scaled by a factor of $\frac{\alpha_{i,g}+\rho\alpha_{j,g}}{1+\rho}$, which depends on both individuals' altruism types and the reciprocity coefficient ρ. Similarly, the effect of the indegree centrality is η scaled by the same factor. The vector of Nash equilibrium outcome can be written as

$$Y_g = \lambda(W_g + H_g(A_g, W_g, \rho))Y_g + \eta H_g(A_g, W_g, \rho) l_g + X_g\beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \tag{13}$$

where $H_g(A_g, W_g, \rho)$ represents a $m_g \times m_g$ matrix with each element $h_{ij,g}$ equals to $\frac{\alpha_{i,g}+\rho\alpha_{j,g}}{1+\rho} w_{ji,g}$. We refer to Equation (13) as "heterogeneous altruistic social interactions model."

3.5 Endogenous Network Formation

The endogenous formation of friendship networks is a serious identification concern for social interactions studies (Jackson, 2009; Durlauf and Ioannides, 2010; Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; Breza et al., 2017).[23] When unobserved factors that simultaneously affect friendship formation and outcomes exist but are uncontrolled for in the model, the estimated results will be biased. To address endogenous network formation, we follow Hsieh and Lee (2016) to include individual latent variables in the network formation

[23] As mentioned in Bramoullé et al. (2009) and Lee et al. (2010), if W_g, W_g^2, W_g^3, etc. are not perfectly collinear, one can use $(W_g^2 X_g, W_g^3 X_g, \cdots)$ as instruments to identify the conventional SAR model. However, if W_g itself is endogenous, then these instrumental variables are not valid.

and outcome SAR models. The network formation model is specified in a logistic form,

$$P(w_{ij,g}) = \left(\frac{\exp(\psi_{ij,g})}{1+\exp(\psi_{ij,g})}\right)^{I(w_{ij,g}=1)} \left(\frac{1}{1+\exp(\psi_{ij,g})}\right)^{1-I(w_{ij,g}=1)},$$
$$\psi_{ij,g} = \gamma_{0g} + c_{ij,g}\gamma_1 + \sum_{d=1}^{\bar{d}} \zeta_d |z_{id,g} - z_{jd,g}|, \tag{14}$$

where $I(\cdot)$ denotes an indicator function which equals to 1 if the corresponding condition holds and 0 otherwise. We use a $R \times 1$ vector of dyad-specific regressors $c_{ij,g}$ to capture the effect of homophily on observed characteristics, such as same gender, race, and age. The $\bar{d}$-dimensional individual latent variable $z_{i,g} = (z_{i1,g}, \cdots, z_{i\bar{d},g})$ is introduced through a distance form $|z_{id,g} - z_{jd,g}|$ to take into account the effect of homophily on unobserved characteristics. Intuitively, the larger the difference in two individuals' unobserved characteristics, the lower the chance that friendship will form between them. Therefore, we expect coefficients ζ_d's to be negative. Furthermore, we generalize the constant intercept γ_0 specified in Hsieh and Lee (2016) to group-specific constants γ_{0g} to reflect group heterogeneity. In the network formation model of Equation (14), each network link is assumed to be independent conditioning on the variables $C_g = \{c_{ij,g}\}$ and the latent variables $Z_g = (z'_{1,g}, \cdots, z'_{m_g,g})'$. Therefore, the probability function of the whole network W_g can be written as

$$P(W_g|C_g, Z_g, \gamma, \zeta) = \prod_{i}^{m_g} \prod_{j \neq i}^{m_g} P(w_{ij,g}|C_g, Z_g, \gamma, \zeta), \tag{15}$$

where $\gamma = (\{\gamma_{0g}\}, \gamma'_1)'$ and $\zeta = (\zeta_1, \cdots, \zeta_{\bar{d}})'$.

When considering heterogenous altruism levels (A_g) in outcome Equation (13), we further explore the role of A_g in network formation by extending the function $\psi_{ij,g}$ in Equation (14) to

$$\psi_{ij,g} = \gamma_{0g} + c_{ij,g}\gamma_1 + \gamma_2\alpha_{i,g} + \gamma_3\alpha_{j,g} + \sum_{d=1}^{\bar{d}} \zeta_d |z_{id,g} - z_{jd,g}|. \tag{16}$$

Coefficients γ_2 and γ_3 reflect the effects of sender's and receiver's altruism on the probability of forming a link, and we expect both to be positive. A higher γ_2 means more altruistic individuals tend to send more friendship links to others, whereas a higher γ_3 means more altruistic individuals tend to receive more friendship nominations. To some extent, $\alpha_{i,g}$ and $\alpha_{j,g}$ capture the feature of network degree heterogeneity in social networks discussed in Krivitsky et al. (2009), Graham (2017), and Breza et al. (2017). Note that altruism levels, $\alpha_{i,g}$ and $\alpha_{j,g}$, enter the network formation model in plain form instead of difference form in Equation (16). Otherwise, why two spiteful individuals (whose altruism levels are both -1) may be more likely to form friendship will be hard to explain. Furthermore, using different forms makes it possible to distinguish A_g from other unobserved latent variables Z_g.

To address the endogenous network issue, we assume that the error term ϵ_g in the activity outcome of Equations (8) and (10) is linearly correlated with unobserved latent variable Z_g, i.e., $\epsilon_g = Z_g\delta_1 + W_g Z_g \delta_2 + v_g$, and the error term in the activity outcome of Equation (13) is also correlated with altruism level A_g, i.e., $\epsilon_g = Z_g\delta_1 + W_g Z_g\delta_2 + \delta_3 A_g + \delta_4 W_g A_g + v_g$. The new error term v_g is assumed uncorrelated with any other regressors in the model. Following this assumption, we can rewrite the altruistic social interactions model with direct externality in Equation (8) into

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + X_g\beta_1 + W_g X_g \beta_2 + Z_g\delta_1 + W_g Z_g \delta_2 + l_g\tau_g + v_g; \tag{17}$$

the directed altruistic social interactions model in Equation (10) into

$$\begin{aligned} Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \lambda^{\mathrm{R}} W_g^{\mathrm{R}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + \eta^{\mathrm{R}} W_g^{\mathrm{R}} l_g \\ + X_g\beta_1 + W_g X_g\beta_2 + Z_g\delta_1 + W_g Z_g\delta_2 + l_g\tau_g + v_g; \end{aligned} \tag{18}$$

and the heterogeneous altruistic social interactions model in Equation (13) into

$$\begin{aligned} Y_g = \lambda(W_g + H_g(A_g, W_g, \rho))Y_g + \eta H_g(A_g, W_g, \rho)\ell_g \\ + X_g\beta_1 + W_g X_g\beta_2 + Z_g\delta_1 + W_g Z_g\delta_2 + \delta_3 A_g + \delta_4 W_g A_g + l_g\tau_g + v_g. \end{aligned} \tag{19}$$

We regard the activity outcome of Equation (17) or (18) (or [19]) and the network formation model of Equation (14) (or [16]) as a simultaneous-equations model and estimate the parameters in two equations jointly using the likelihood approach. We assume that error term v_g follows a normal distribution with mean zero and variance $\sigma_v^2 I_{m_g}$.

4 Model Estimation

To jointly model social interactions and network formation through unobserved latent variables, we follow Hsieh and Lee (2016), Hsieh and Lin (2017), and Hsieh and Van Kippersluis (2018) to list the necessary identification constraints:[24] First, we assume latent variables Z_g follow a known distribution, which in our case is the normal distribution with mean $\mu_{z,g}$ and

[24] When latent variables Z_g only appear in the network formation model through their distances, a serious identification problem exists because the likelihood value from the network formation model is invariant to the reflections, rotations, and translations of Z_g (Hoff et al., 2002). By further introducing Z_g and $W_g Z_g$ into the SAR outcome equation, we solve the invariant likelihood value problem with the joint likelihood of network and activity outcome. However, we still need other identification assumptions for model coefficients due to the multidimensioanlity and unobservability of Z_g. The online appendix of Hsieh and Van Kippersluis (2018) provides a heuristic argument on how we can use these assumptions to identify the coefficients in the network formation and outcome equations.

variance σ_z^2. Second, we cannot identify the variance of $z_{i,g}$, σ_z^2, and therefore we normalize it to one. Third, we assume that the different dimensions of $z_{i,g}$ are independent of each other. Lastly, to distinguish the different dimensions of $z_{i,g}$, we assume that the magnitude of coefficients ζ_d's in the network formation model of Equation (14) follows a descending order, i.e., $|\zeta_1| \geq |\zeta_2| \geq \cdots \geq |\zeta_{\bar{d}}|$. Note that the dyad-specific variables $c_{ij,g}$ only appear in the network formation model where observations are dyad-specific, but not in a SAR outcome equation in which observations are individual-specific. Therefore, we have natural exclusion restrictions to identify this simultaneous equations system. Furthermore, note that when another latent variables A_g are introduced in Equations (16) and (19), we should assume that $a_{i,g}$ follows a uniform $U[-1,1]$ distribution for identification purpose.

4.1 Bayesian Estimation

We use the Bayesian MCMC approach to estimate unknown parameters in our models. Taking Equations (14) and (17) for example,[25] the joint probability function of $\{Y_g, W_g\}_{g=1}^G$ can be written as follows,

$$
\begin{aligned}
&P(\{Y_g\}, \{W_g\} | \{X_g\}, \{C_g\}, \theta, \{\tau_g\}) \\
&= \prod_{g=1}^{G} \int_{Z_g} P(Y_g | W_g, X_g, Z_g, \theta, \tau_g) \cdot P(W_g | C_g, Z_g, \theta) \cdot f(Z_g) dZ_g,
\end{aligned} \tag{20}
$$

where $\theta = (\gamma', \zeta', \lambda, \lambda^{\mathrm{I}}, \eta^{\mathrm{I}}, \beta_1', \beta_2', \delta', \sigma_v^2)$. The Bayesian approach is used here instead of the classical approach for two reasons. First, the model involves multi-dimensional individual latent variables. The resulting high-dimensional integrations in Equation (20) is difficult to handle under the classical approach. By contrast, the Bayesian MCMC is more effective in estimating models with latent variables (Zeger and Karim, 1991; Hoff et al., 2002; Handcock et al., 2007). During the posterior MCMC simulation, latent variables $\{Z_g\}_{g=1}^G$ are drawn from the conditional posterior distributions along with other model parameters. Conditional on these latent variables, the probability function becomes simple to compute. Second, we have some constraints on the model parameters and latent variables, which generally significantly complicate the classical numerical optimization. By adopting a Bayesian MCMC rejection sampling method such as the Metropolis-Hastings algorithm, we can directly reject draws that violate constraints.

The prior distributions $\pi(\cdot)$ for θ, latent variables $\{Z_g\}$, and group effects $\{\tau_g\}$ are specified

[25] We illustrate the estimation algorithm using these two equations as example. The details of the estimation procedure for other extended equations can be found in Supplementary Appendix A.

as follows:

$$
\begin{aligned}
z_{i,g} &\sim \mathscr{N}_{\bar{d}}(\mu_{z,g}, I_{\bar{d}}), \quad i = 1, \cdots, m_g;\ g = 1, \cdots, G, \\
\mu_{z,g} &\sim \mathscr{N}_{\bar{d}}(0, \xi^2 I_{\bar{d}}), \quad g = 1, \cdots, G, \\
\omega = (\gamma', \zeta') &\sim \mathscr{N}_{G+R+\bar{d}}(\omega_0, \Omega_0) \text{ on the support } O_1, \\
\Lambda = (\lambda, \lambda^{\mathrm{I}}) &\sim U_2(O_2), \\
\beta = (\eta^{\mathrm{I}}, \beta_1', \beta_2') &\sim \mathscr{N}_{2k+1}(\beta_0, B_0), \\
\sigma_v^2 &\sim \mathscr{I}\mathscr{G}\left(\frac{\nu_0}{2}, \frac{\varsigma_0}{2}\right), \\
\delta = (\delta_1', \delta_2') &\sim \mathscr{N}_{2\bar{d}}(\delta_0, \Delta_0), \\
\tau_g &\sim \mathscr{N}(\tau_0, T_0), \quad g = 1, \cdots, G,
\end{aligned} \tag{21}
$$

where $\mathscr{N}$ represents a normal distribution, and $\mathscr{I}\mathscr{G}$ represents an inverse Gamma distribution. The coefficients γ and η in the function $\psi_{ij,g}$ of Equation (14) are grouped into ω with the support on O_1 wherein the identification constraint $|\zeta_1| \geq |\zeta_2| \geq \cdots \geq |\zeta_{\bar{d}}|$ is held. For the endogenous effects λ and λ^{I}, we employ a bivariate uniform distribution with a restricted parameter space O_2. The restricted parameter space O_2 reflects the stationary condition of the outcome Equation (17), which is $|\lambda| + |\lambda^{\mathrm{I}}| < 1/\max_{g=1,\cdots,G} \kappa_{\max}(W_g)$, where $\kappa_{\max}(W_g)$ denotes the maximum eigenvalue of network matrix W_g. The other priors are commonly used conjugate priors in the Bayesian literature. We choose hyperparameters $\xi^2 = 2$, $\omega_0 = 0$, $\Omega_0 = 100 I_{G+R+\bar{d}}$, $\eta_0 = 0$, $E_0 = 100$, $\beta_0 = 0$, $B_0 = 100 I_{2k+1}$, $\nu_0 = 2.2$, $\varsigma_0 = 0.1$, $\delta_0 = 0$, $\Delta_0 = 100 I_{2\bar{d}}$, $\tau_0 = 0$, $T_0 = 100$ to ensure that prior densities are relatively flat (uninformative) over the range of parameter spaces.

Given the probability function in Equation (20) and the prior distributions in Equation (21), the posterior distribution can be expressed as follows,

$$
P(\theta, \{Z_g\}, \{\tau_g\} | \{Y_g\}, \{W_g\}) \propto \pi(\theta) \cdot \pi(\{Z_g\}) \cdot \pi(\{\tau_g\}) \cdot P(\{Y_g\}, \{W_g\} | \{X_g\}, \{C_g\}, \theta, \{Z_g\}, \{\tau_g\}). \tag{22}
$$

The direct simulation of draws from Equation (22) is not straightforward. Therefore we employ the Gibbs sampling algorithm and work on the conditional posterior densities of parameters. With conjugate priors, $\mu_{z,g}$, η^{I}, β, σ_v^2, δ, and τ_g's can be sampled directly from their conditional posterior distributions, which are normal or inverse-gamma distributions. However, a Metropolis-Hasting (M-H) step within the Gibbs sampling is necessary to sample ω, Λ, and the latent variables $z_{i,g}$'s because their conditional posteriors are of unknown forms. We detail the conditional posterior distributions and MCMC sampling steps in Supplementary Appendix A.

4.2 Simulation Study

We conduct a Monte Carlo simulation study to evaluate the performance of our proposed estimation approach in finite sample and to investigate the potential bias inherited in misspecified models when altruistic preference, direct externality, and endogenous network formation are unaccounted for. We use the altruistic social interactions model of Equation (17) and the endogenous network formation of Equation (14), as the data generating process (DGP) to produce the artificial network and outcome data. The generated sample consists of 30 networks ($G = 30$) and each network has 50 individuals ($m = 50$). Specifically, we first generate the dyadic exogenous variable $\{c_{ij,g}\}_{i,j=1}^{m}$ for capturing homophily in Equation (14) by drawing two variables u_1 and u_2 from the uniform distribution $U(0,1)$ and then set $c_{ij,g} = 1$ if both u_1 and u_2 are greater than 0.7 or less than 0.3; and set $c_{ij,g} = 0$ otherwise. We generate the individual exogenous variable $\{x_{i,g}\}_{i=1}^{m}$ in Equation (17) from the normal distribution $\mathscr{N}(0, 2)$. The group effects $\{\tau_g\}_{g=1}^{G}$ are simulated from $\mathscr{N}(0, 1)$, whereas the stochastic error terms $\{v_{i,g}\}_{i=1}^{m}$ are simulated from $\mathscr{N}(0, \sigma_v^2)$. We specify latent variable $z_{i,g}$ in one dimension and simulate it from $\mathscr{N}(0, 1)$. The true parameters used in this DGP are shown in the first column of Table 1. The generated artificial networks have an average out-degrees of 4.82 for an individual and an average network density of 0.0983, which are quite comparable with the network samples considered in our empirical study in Section 5 (see Table 2).

The number of Monte Carlo repetitions is set to 100. We apply the estimation approach outlined in Section 4.1 to five alternative models and report the mean of estimation bias and the standard deviation across repetitions.[26] The simulation results are summarized in Table 1. Model (I) stands for the true DGP model, i.e., Equations (14) and (17). The results under Model (I) show that our proposed procedure works well: all the estimated parameters contain only insignificant sampling biases. Model (II) stands for a misspecified model in which we omit the direct externality effect, η^{I}, from Equation (17). The results in Model (II) display a significant downward bias (29%) on the estimate of inward endogenous effect (λ^{I}). Based on the standard omitted variable bias formula, the direction of bias can be inferred from $sign(\eta^{\mathrm{I}}) \times sign(corr(W_g' Y_g, W_g' l_g)) = (-) \times (+) = -$; therefore, the downward bias on λ^{I} is justified. Model (III) is another misspecified model where the inward endogenous effect in Equation (17) is excluded. The results in Model (III) show a significant upward bias (more than 150%) on η^{I}, and this can also be justified by the sign of omitted variable bias, $sign(\lambda^{\mathrm{I}}) \times sign(corr(W_g' Y_g, W_g' l_g)) = (+) \times (+) = +$. In addition, peer effect coefficient λ is biased upward by 37%. We next take away λ^{I} and η^{I} from Equation (17), which results in the standard SAR model. In particular, Model (IV) addresses endogenous network formation,

[26] For each repetition, the point estimate is obtained from 20,000 MCMC draws with the first 2,000 draws dropped for the burn-in.

whereas Model (V) simply takes networks as exogenously given. The results show significant upward biases (48% and 57%) on the estimated endogenous effect λ in Models (IV) and (V). These findings not only confirm that ignoring network endogeneity would lead to an upward bias on λ (Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016), but more importantly, they show that existing models in the literature may still contain significant upward bias in the estimated endogenous peer effect coefficient due to the omitted altruism and externality.

We also consider the DGP based on the heterogeneous altruistic social interactions model of Equation (19) and the network formation of Equation (16). We follow the previous setting to generate artificial network and outcome data with the true parameters reported in the first column of Supplementary Appendix Table A1. The simulation results are summarized in the other columns of Supplementary Appendix Table A1. Model (I) stands for the true DGP model, and the results show that our estimation approach can recover all true parameters, including the new reciprocality coefficient ρ, from the model. In Model (II) we omit the direct externality effect η from Equation (19) and see a downward bias (39%) on the estimate of endogenous effect λ and an upward bias (28%) on the estimate of reciprocality coefficient ρ. In Model (III), we exclude ρ and η from Equation (19) and in Model (IV), we further take the networks as exogenous. Again, we note that ignoring altruism and externality could lead to a significant upward bias in estimating λ, as well as in other parameters, even when the network endogeneity problem is properly controlled for.

5 Empirical Study

The aims of our empirical study are twofold. First, we aim to estimate the proposed altruistic social interactions model for different outcomes to examine the magnitudes of altruism and the direct externality effect. Although altruism has been investigated in some studies using experiments, such as Leider et al. (2009) and Ligon and Schechter (2012), direct externality effect has never been identified in the social interactions literature. Second, we would like to investigate the potential biases on the estimated endogenous peer effect inherited in the conventional social interactions model caused by the omitted altruism and direct externality.

5.1 Add Health Data

Our study is based on the Add Health data,[27] which is a longitudinal study on a nationally representative sample covering adolescents in grade 7 through 12 (average age from 12 to 17) from 132 schools. To understand how social environment and behaviors in adolescence are linked to health and achievement outcomes in young adulthood, the Add Health survey contains detailed information about respondents' demographic background, academic performance, and health related behaviors. A unique and desirable feature about Add Health is that each respondent nominates his/her male and female friends, which can be used to construct students' friendship networks. Furthermore, the data we use in this study are from the Wave I survey of Add Health, which was a census in the sampled schools. Therefore, most nominated friends are likely to be in the sample, making the missing links in the observed friendship networks less of a concern for our estimation.

We define groups at the school level. To reduce computational burden, we select a sample of 24 schools, each with size ranging from 15 to 245.[28] The sample consists of 2,926 students. We study four different activity outcomes: academic achievement (measured by GPA); smoking (measured by number of smoking days per month); extracurricular activities (measured by the number of school clubs attended); and misconducts (measured by frequency of doing dangerous activity, lying, and school skipping). These outcomes have been extensively studied in the literature, especially academic achievement and smoking.[29] In general, the literature has shown that there exist significant peer effects for these outcomes. In this paper, we offer a unique opportunity to examine the sustainability of these findings under a general model specification which considers altruistic preference, externality effect, and endogenous network formation.

In the empirical model, we control an array of explanatory variables, including gender, race, and family background, whose summary statistics are provided in Table 2. The average

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[28]The computation cost comes from estimating the network formation model in which the computational time increases exponentially with network size.

[29]See Calvó-Armengol et al. (2009), Fruehwirth (2013, 2014), Hanushek et al. (2003), Lin (2010), Zimmerman (2003), and Hsieh and Lee (2016) for academic achievement; see Clark and Lohéac (2007), Fletcher (2010), Nakajima (2007), Powell et al. (2005), Hsieh and Lin (2017), and Hsieh and Van Kippersluis (2018) for smoking behavior; see Bramoullé et al. (2009), Schaefer et al. (2011) for extracurricular and recreational activities. See Ballester et al. (2010) and Patacchini and Zenou (2012) for misconducts (delinquent behaviors).

student in our sample has a GPA of 2.902, smokes 4.414 days per month, and has 1.223 misconducts per month during the year. On average, the respondents attend 2.577 school clubs during the school year. The mean age is 15.553 years, and 48.36% of the sample are male. Approximately 61.41% of the sample are White, 24.09% are Black, 2.08% are Asian, 6.87% are Hispanic, and 5.54% are of other races. About 73.1% of the sample live with both parents. For mother's education, 40.7% of the respondents have a mother with more than high school education, 34.86% have a mother with high school education, and 10.63% have mothers who attained less than high school education level. For mother's occupation, 26.42% of the sample have a mother working on professional jobs such as teacher, doctor, and lawyer, 23.38% have a mother who is a Homemaker, 34.52% have a mother who works on other jobs, 1.09% have a mother who receives welfare assistance, and the information is missing for 7.38% of the sample. In our school network samples, the average number of friendship nominations is 3.5492 and the average network density is 0.0733.

5.2 Estimation Results

5.2.1 Conventional versus Altruistic Social Interactions Models

In this subsection, we compare the parameter estimates in the conventional social interactions model of Equation (3) with those in the altruistic social interactions models of Equation (6), and with direct externality from peers' outcome of Equation (8). For the four outcome variables, we only find a significant estimate of altruism for GPA and smoking, not for club participation or misconducts.[30] Therefore, we only focus on the cases of GPA and smoking in the following discussion. The results of club participation and misconducts are reported in Supplementary Appendix Table A2 for reference.

GPA The estimation results of GPA are presented in Table 3. In the left panel, the results under Model (I) show that the endogenous peer effect on GPA (0.0700) based on the conventional social interactions model of Equation (3) is significant. When we extend the model to the altruistic specification of Equation (6), the estimated endogenous effect under Model (II) decreases to 0.0610 (by 13%). We also observe a significant estimate of λ^{I}.[31] Model (III) is similar to the model specification in Mihaly (2009) which introduces an indegree centrality as a popularity measure. We can see that the estimated endogenous effect is nearly identical

[30]In Supplementary Appendix Table A2, we can see the estimates of λ^{I} and η^{I} for club participation and misconducts are insignificant, whereas the estimates of λ are significant. Thus, we can infer that the estimated altruism level α is insignificant.

[31]This misspecified model partially corresponds to those models in studies like Lin and Weinberg (2014), which introduce additional terms to the standard SAR model to capture the effects of different types of friends.

to the one under Model (I), and the coefficient on the indegree centrality is 0.021 and highly significant. Mihaly (2009) and other studies regard this as the positive effect of popularity on individual outcome. However, from our specification, we interpret this coefficient in this misspecified Model (III) as the mixed effects of altruism and externality. When additionally incorporating the altruism effect from peers' outcome, the results under Model (IV) show that the estimated endogenous effect is further reduced to 0.0450, lower than the conventional model by 36%. The estimates of λ^{I} and η^{I} are 0.0302 and -0.0701, respectively, and both are highly significant. Therefore, ignoring either altruism or direct outcome externality could cause serious upward bias in the estimated endogenous peer effect. To further address network endogeneity, we jointly estimate the altruistic social interactions model of Equation (17) and the endogenous network formation model of Equation (14). The estimation results are presented under Model (V) in Table 3.[32] We can see that the estimated endogenous effect λ further decreases from 0.045 to 0.0371 (by 18%), confirming the importance of controlling for endogenous network formation. The estimated effects of λ^{I} and η^{I} under Model (V) drop to 0.0251 and -0.0557, respectively, and both remain highly significant. Based on the estimates of λ and λ^{I}, we can derive the altruism level α, which equals to 0.6765. Furthermore, we can uncover the direct externality effect generated by peers' GPA as -0.0823 based on the derived altruism level and the estimate of η^{I}. Therefore, peers' academic achievement generates not only a positive complementary spillover effect on a student, but also a negative direct externality effect, which could be attributed to competition pressure. The estimated negative externality effect has revealed an unexplored pattern in existing social interactions studies and implies that the net effect generated by peers could be positive or negative, depending on the relative magnitudes of these two opposite mechanisms generated by peers: spillover and direct externality effects.

Based on our estimation results, an individual not only cares about his/her own payoff, but also cares about others' payoffs with a weight of 0.6765. In addition, an individual's payoff function consists of two distinct social components: one is the positive complementary effects generated by peers' outcomes, with the magnitude being the product of the estimated

[32] Note that the results under Model (V) in Table 3 are based on the model with unobserved latent variables in three dimensions chosen as the optimal dimension by the Akaike's information criterion - Monte Carlo (AICM) proposed by Raftery et al. (2007), an estimate of the conventional AIC. In particular, we estimate the models with different dimensions of latent variables and the dimension of three achieves the smallest AICM value compared with other latent dimensions. Detailed estimation results for the models with other dimensions of the latent variables are provided in Supplementary Appendix Table A3. Apart from using AICM as a criterion for dimension selection, we also compare the changes of estimated parameters when adjusting the dimension of the latent variables. From Table A3, we can see that as we continue to increase the dimension of the latent variables from three to four, the changes in the estimated peer effect parameters become relatively small.

coefficient 0.0371 and own outcome $y_{i,g}$.[33] As shown in Table 2, the mean of GPA in our sample is 2.902, therefore the average magnitude of the complementary effects generated by peers' outcomes is 0.108. The other social component is the negative externality effects generated by peers' outcomes, with the magnitude estimated to be -0.0823. Relating to the coefficients of the best response function of Equation (8), we can see that if the sum of person i's friends' GPA increases by 1, his/her GPA will increase by 0.0371, implying a standard deviation increase in the sum of person i's friends' GPA raises own GPA by 0.3228 points, or by 11.12% of its mean of 2.902.[34] Furthermore, if the sum of the GPA of the individuals who nominate person i as friends increases by 1, person i's GPA will increase by 0.0251, meaning that a standard deviation increase in the sum of the GPA of the individuals who nominate person i as friends raises own GPA by 0.2574 points, or by 8.87% of its mean.[35] Finally, if the in-degree centrality of person i increases by 1, his/her GPA will decrease by 0.0557, implying a standard deviation increase in an individual's in-degree centrality decreases own GPA by 0.1820 points, or by 6.27% of its mean.[36]

For the own effects of exogenous characteristics on GPA from Model (V), we find that students who are male, older, and whose mothers with lower than high school education tend to have lower GPA. Students who live with both parents and whose mothers with higher than high-school education tend to have higher GPA. For contextual effects, we find significant negative effects from friends who are older, whose mothers with lower than high-school education, and significant positive effects from living with both parents. For network formation, the results show significant homophily effects on individual characteristics for friendship formation. All three dummy variables – same age, same sex, and same race – which capture the similarity between individual pairs, show positive effects on the probability of forming friendship. In particular, the effect of same age is strongest, followed by the effects of same race and then of same sex. We also find supporting evidence of significant homophily effects on latent variables, that is, individuals who have more distant unobservables are less likely to become friends.

Smoking The estimation results for smoking are presented in Table 4. Similar to the case for GPA, as we move from Model (I) to Model (V), the estimated endogenous effect λ steadily declines. In particular, it significantly decreases from 0.0924 in Model (I) to 0.0592 in Model

[33] As can be seen from Equation (7), the effect of the third term on own payoff ($v_{i,g}$) is given by $\lambda y_{i,g}$.

[34] The mean and standard deviation for the sum of friends' GPA, i.e., $W_g Y_g$, are 10.7467 and 8.7004, respectively.

[35] The mean and standard deviation for the sum of the GPA of the individuals who nominate person i as friends, i.e., $W_g^{\mathrm{T}} Y_g$, are 10.6415 and 10.2541, respectively.

[36] The mean and standard deviation for the in-degree centrality are 3.5492 and 3.2680, respectively.

(IV), by 36%. In Models (IV) and (V), we can also see that λ^{I} is positive and η^{I} is negative, and both are highly significant. Although λ and λ^{I} are overall similar in Models (IV) and (V), η^{I} decreases by 7.8% after endogeneity in network formation is controlled for in Model (V).[37] In addition, although both λ^{I} and η^{I} are significant in the fully specified model, neither is significant in either Model (II) or (III), where either η^{I} or λ^{I} is omitted. Based on results from Model (V), we can derive the altruism level as 0.6376 and the direct externality effect as -0.2771. Therefore, for GPA and smoking behavior, we find that the estimated altruism levels are relatively stable, providing empirical evidence for social preference theories which assume altruism as a fixed innate personal attribute, including Levine (1998). By contrast, peers' smoking behaviors generate a much larger direct negative externality effect as compared with that of GPA, which could be attributed to the adverse impact of smoking on health and the environment, among others.

Specifically, the results indicate that an individual assigns a weight of 0.6376 to others' payoffs, similar to the case of GPA. The direct negative externality effect generated by peers' smoking behaviors is as high as -0.2771. The estimated coefficients of the best response function of Equation (8) show that the effects of the sum of person i's friends' smoking behaviors, the sum of the smoking behaviors of the individuals who nominate person i as friends, the in-degree centrality of person i, are 0.0574, 0.0366, and -0.1767, respectively. In other words, a standard deviation increase in the sum of person i's friends' smoking behaviors, or a standard deviation increase in the sum of the smoking behaviors of the individuals who nominate person i as friends, raises own smoking behavior by 1.4716 or 0.9421 times, or by 33.34%, or 21.34% of its mean of 4.4142. On the other hand, a standard deviation increase in an individual's in-degree centrality reduces own smoking behavior by 0.5775 times, or by 13.08% of its mean.[38]

For the own effects of exogenous characteristics on smoking, we can see that students who are Black, Hispanic or live with both parents tend to smoke less. By contrast, older students tend to smoke more. For contextual effects, having older friends tend to decrease an individual's smoking frequency. For network formation, the results of smoking behaviors confirm what we find for the GPA sample, that is, individuals who have similar observed characteristics such as age, race, and sex, in addition to unobservables are more likely to form friendship links.

[37]The dimension of the latent variables in this model is also three, which is chosen as the optimal model based on the AICM criterion. The estimation results with other dimensions of the latent variables are provided in Supplementary Appendix Table A4.

[38]The means and standard deviations for the sum of friends' smoking behaviors, for the sum of the smoking behaviors of the individuals who nominate person i as friends, and for the in-degree centrality based on the smoking sample, are 14.0132 and 25.6374, 13.0332 and 25.7416, 3.5492 and 3.2680, respectively.

5.2.2 Directed Altruistic Social Interactions Model

To empirically examine whether directed altruism is supported, i.e., stronger altruism toward friends, we apply the directed altruistic social interactions model of Equation (10) to our sample. The results are presented in Table 5. We consider cases with and without direct externality. However, in both cases we obtain insignificant estimates of λ^{R} and η^{R} for GPA and smoking. Therefore, we do not find evidence of directed altruism for these two outcomes in our sample.

5.2.3 Heterogeneous Altruistic Social Interactions Model

In this subsection, we estimate the heterogeneous altruistic social interactions model of Equation (19) and the extended network formation model of Equation (16). The GPA results are shown in the left panel of Table 6, and those for smoking are presented in the right panel of the same table. Based on the AICM values, we choose the model with three dimensions of latent variables, i.e., Model (D3) as the desired model for GPA and smoking.

The estimated endogenous effects are 0.0492 and 0.0747 for GPA and smoking, respectively, both are highly significant. Compared with the results of conventional social interactions models, i.e., Model (1), in Tables 3 and 4, the estimates drop by 30% and 19%, respectively. The reduction on estimate can be attributed to the control of altruism and the correction of network endogeneity bias. The coefficient ρ is estimated to be 0.6187 for GPA and 0.4120 for smoking, reflecting strong orientation toward fairness. The direct externality effects are still negative for GPA and smoking: -0.1303 and -0.4344, respectively. The direct externality effect is found to be stronger for smoking than for GPA.

From the endogenous network formation model, for GPA and smoking, we find that individuals with a higher level of altruism are more likely to send out friendship nominations, and they are also more likely to receive friendship nominations, with the effect on receiving friendship nominations being stronger. Specifically, for GPA (smoking), the effect of $\alpha_{i,g}$ is estimated to be 0.1412 (0.1357), whereas the estimated effect of $\alpha_{j,g}$ is 1.4109 (1.3834), all are highly significant. We find similar homophily pattern on observed variables including age, race, and sex, as well as unobservables for network formation. The age effect is still the strongest, followed by the effects of same race then same gender.

5.3 Multiplier Effects

In this section we compare the social multiplier effects implied by the altruistic social interactions model with the conventional social interactions model. In the conventional social interactions model as in Equation (3), the social multiplier effects in group g are calculated by

$(I_{m_g} - \lambda W_g)^{-1}\ell_g$, for $g = 1, \cdots, G$. The variation of the effects mainly relates to the number of out-links that each individual has. The more the number of out-links one has, the stronger the multiplier effect one receives. However, for the altruistic social interactions model as in Equation (8), in addition to the out-links, the multiplier effects further relate to the in-links of the networks, calculated by $(I_{m_g} - \lambda W_g - \lambda^{\mathrm{I}} W_g^{\mathrm{T}})^{-1}\ell_g$, for $g = 1, \cdots, G$. Therefore, the multiplier effects generated from the altruistic social interactions model would be different from those generated by the conventional SAR model due to two reasons. The first is the smaller endogenous peer effect (λ) in the altruistic social interactions model owing to the resolution of the confounding effects caused by altruism. The second is the heterogeneity of the in-degrees among the individuals. In general, the social multiplier effects under the altruistic social interactions model are expected to be more heterogeneous compared to those under the conventional social interactions model.

To provide a better visualization of the comparison, we plot in Figure 1 the distribution of multiplier effects (by pooling individuals across groups) based on the estimation results in Section 5.2.1. Panel (a) presents the multiplier effects with regard to GPA and Panel (b) shows the multiplier effects with regard to smoking. In both panels we can see that the distribution of multiplier effects is indeed more dispersed under the altruistic social interactions model. This pattern is consistent with the theoretical prediction made in Bourlès et al. (2017) that altruism could contribute to inequality in social networks.

It would also be interesting to see how the differences between the multiplier effects generated by the two models are related to the features of the social network. In Figure 2, we plot the distribution of the differences between the multiplier effects generated by the conventional SAR model and the altruistic social interactions model, as well as how these differences change with some network features including out-degrees and in-degrees.[39] Panel (a) shows the results for GPA, and panel (b) shows the results for smoking. We can see from both panels that the differences in the multiplier effects generated by these two models are positively related to the in-degrees of the network.

6 Conclusion

The classical self-interest hypothesis is essential in conventional economics models, including those which have been widely employed in social interactions studies. However, more and more experimental and field studies have provided evidence that people are altruistic. As social interactions occur regularly within small groups, altruism is expected to play an important

[39]The differences are calculated as the multiplier effects generated by the altruistic social interactions model subtract those generated by the conventional SAR model.

role in individual decision making. Therefore, relaxing the selfish assumption under the social interactions framework is necessary.

This paper provides the first analysis on social interactions and social preferences in social networks. We combine a general altruistic utility function with the specific quadratic specification of Ballester et al. (2006) to study social interactions when individuals hold altruistic preferences. We demonstrate that rich network features can be captured in the best response function derived by maximizing the extended utility, thereby providing microfoundation for studies which investigate how network features mediate peer effects or other important features in social interactions. We also show that ignoring altruistic preferences in social networks will cause serious upward bias in peer effect estimation. Our empirical study of Add Health data provides strong evidence for peer effects on students' academic achievement and smoking behavior, even after controlling for altruistic preferences and endogenous network formation. Strikingly, the estimate of peer affect coefficient is approximately 36% smaller under altruistic preferences compared with the case with conventional self-interest assumption, for GPA and smoking. We also find that the estimated altruism levels are similar for GPA and smoking, providing evidence for social preference theories which assume altruism as a fixed innate personal attribute.

In addition to the usual positive spillover effects generated from peers, we find significant negative externality effects directly generated from peers' outcomes. Interestingly, we find that peers' smoking behaviors generate a much larger direct negative externality effect compared with peers' academic achievement. The estimated negative externality effect reveals an unexplored pattern in existing social interactions studies and implies that the net effect generated by peers could be positive or negative, depending on the relative magnitudes of these two opposite mechanisms. The network formation model results show significant homophily effects not only on observed characteristics, such as same age, sex, and race, but also on latent variables, for friendship formation. We consider two possible model extensions. In the directed altruistic social interactions model, we do not find evidence for directed altruism (Leider et al., 2009). In the second extended model, that is, the heterogeneous altruistic social interactions model, we show evidence for heterogeneous altruism based on fairness and reciprocity (Levine, 1998). Individual altruism levels also play an important role in friendship network formation. Our approach can be potentially applied to identify the role of altruism in rural village social network data in countries like India and Indonesia, as studied in Banerjee et al. (2013) and Alatas et al. (2016), among others.

Table 1: Monte Carlo Simulation Result – Altruistic Social Interactions model with Endogenous networks

		Model (I)		Model (II)		Model (III)		Model (IV)		Model (V)	
Parameters	True	bias	s.d.	bias	s.d.	bias	s.d.	bias	s.d.	bias	s.d.
λ	0.0500	0.0000	0.0012	0.0009	0.0013	0.0187	0.0076	0.0239	0.0050	0.0287	0.0034
λ^{I}	0.0400	-0.0011	0.0019	-0.0116	0.0044						
η^{I}	-0.2000	0.0154	0.0217			0.3552	0.0587				
β_1	0.5000	0.0023	0.0200	0.0148	0.0211	0.0378	0.0323	0.0327	0.0324	0.0364	0.0371
β_2	0.2000	0.0013	0.0109	0.0080	0.0127	0.0091	0.0194	0.0007	0.0178	0.0034	0.0269
δ_1	0.5000	-0.0177	0.0518	-0.0678	0.1068	-0.1295	0.1507	-0.1126	0.1057		
δ_2	0.2000	-0.0022	0.0973	0.0387	0.0954	0.0483	0.1227	0.0480	0.0761		
γ_0	-1.2000	-0.0067	0.0254	-0.0161	0.0298	-0.0239	0.0314	-0.0353	0.0321		
γ_1	3.0000	-0.0185	0.0354	-0.0327	0.0411	-0.0395	0.0392	-0.0500	0.0390		
ζ	-3.0000	0.0200	0.0871	-0.0316	0.0924	-5.9567	0.0974	-0.0948	0.0982		
σ_v^2	1.0000	0.0429	0.1770	0.1834	0.2893	1.4291	2.4645	1.2029	1.2400	2.2971	1.1215

Note: Model (I): True DGP model, which is the altruistic social interactions model with endogenous networks, i.e., Equation (14) and Equation (17). Model (II): altruistic social interactions model WITHOUT direct externality effect, i.e., Equation (14) and Equation (17) without η^{I}. Model (III): Altruistic social interactions model WITHOUT inward endogenous effect, i.e., Equation (14) and Equation (17) without λ^{I}. Model (IV): conventional social interactions model, i.e., Equation (14) and Equation (17) without both λ^{I} and η^{I}. Model (V): conventional social interactions model with networks assumed exogenous, i.e., Equation (3). We conduct a Monte Carlo simulation study with 100 repetitions. For each repetition, the point estimate is obtained from 20,000 MCMC draws with the first 2,000 draws dropped for the burn-in. The mean bias and the standard deviation from the point estimates across repetitions are reported in the table.

Table 2: Descriptive Statistics

Variables	Min.	Max.	Mean	S.D.
GPA	1	4	2.9020	0.7379
Smoking	0	30	4.4142	9.8641
Club	0	6	2.5772	1.8540
Misconduct	0	6	1.2230	1.0267
Male	0	1	0.4836	0.4998
Age	11	19	15.5533	1.2383
White	0	1	0.6141	0.4869
Black	0	1	0.2409	0.4277
Asian	0	1	0.0208	0.1429
Hispanic	0	1	0.0687	0.2530
Other race	0	1	0.0554	0.2287
Both parents	0	1	0.7310	0.4435
Less HS	0	1	0.1063	0.3083
HS	0	1	0.3486	0.4766
More HS	0	1	0.4070	0.4914
Edu missing	0	1	0.0660	0.2483
Professional	0	1	0.2642	0.4410
Other job	0	1	0.3452	0.4755
Welfare	0	1	0.0109	0.1040
Job missing	0	1	0.0738	0.2615
Homemaker	0	1	0.2338	0.4233
Group size	15	245	171.9986	66.1802
Out-degree	0	10	3.5492	2.7327
In-degree	0	20	3.5492	3.2680
Network density	0.0036	0.2542	0.0733	0.0575
Number of groups (schools)		24		
Observations		2,926		

Note: Both parents means living with both parents. Less HS means student's mother has a lower than high-school degree. More HS means student's mother has a higher than high-school degree. The variables in italic are the reference categories in our estimation.

Table 3: Estimation Results of Conventional and Altruistic Social Interactions Models on GPA

	Model (I)		Model (II)		Model (III)		Model (IV)		Model (V)	
λ	0.0700***		0.0610***		0.0690***		0.0450***		0.0371***	
	(0.0069)		(0.0055)		(0.0069)		(0.0058)		(0.0064)	
λ^{I}			0.0074***				0.0302***		0.0251***	
			(0.0015)				(0.0062)		(0.0061)	
η^{I}					0.0210***		-0.0701***		-0.0557***	
					(0.0047)		(0.0194)		(0.0190)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.1280***	0.0078	−0.1155***	0.0052	−0.1189***	0.0058	−0.1109***	0.0038	−0.1073***	0.0026
	(0.0275)	(0.0167)	(0.0276)	(0.0168)	(0.0275)	(0.0166)	(0.0272)	(0.0168)	(0.0273)	(0.0162)
Age	−0.0076	−0.0126***	−0.0111	−0.0119***	−0.0057	−0.0133***	−0.0158	−0.0091***	−0.0205*	−0.0079***
	(0.0121)	(0.0017)	(0.0103)	(0.0015)	(0.0116)	(0.0017)	(0.0123)	(0.0016)	(0.0121)	(0.0017)
Black	−0.0383	0.0022	−0.0337	0.0055	−0.0351	0.0065	−0.0280	0.0038	−0.0498	0.0051
	(0.0526)	(0.0144)	(0.0512)	(0.0144)	(0.0526)	(0.0144)	(0.0528)	(0.0144)	(0.0519)	(0.0146)
Asian	0.1265	0.0346	0.1378	0.0407	0.1332	0.0410	0.1435	0.0365	0.1245	0.0416
	(0.0948)	(0.0435)	(0.0961)	(0.0430)	(0.0948)	(0.0436)	(0.0920)	(0.0436)	(0.0946)	(0.0424)
Hispanic	−0.0528	0.0065	−0.0493	0.0094	−0.0490	0.0092	−0.0444	0.0089	−0.0436	0.0176
	(0.0581)	(0.0285)	(0.0574)	(0.0279)	(0.0579)	(0.0284)	(0.0567)	(0.0283)	(0.0574)	(0.0285)
Other race	−0.0452	−0.0055	−0.0311	0.0038	−0.0314	0.0041	−0.0319	−0.0005	−0.0266	−0.0004
	(0.0585)	(0.0334)	(0.0575)	(0.0335)	(0.0583)	(0.0333)	(0.0573)	(0.0336)	(0.0573)	(0.0329)
Both parents	0.1023***	0.0288	0.0912***	0.0342**	0.0947***	0.0335**	0.0902***	0.0364**	0.0843***	0.0370**
	(0.0309)	(0.0173)	(0.0310)	(0.0169)	(0.0309)	(0.0172)	(0.0305)	(0.0172)	(0.0304)	(0.0167)
Less HS	−0.1046**	−0.0660***	−0.0955**	−0.0655***	−0.0983**	−0.0647***	−0.0939**	−0.0637***	−0.0926**	−0.0613***
	(0.0443)	(0.0247)	(0.0426)	(0.0243)	(0.0443)	(0.0245)	(0.0443)	(0.0249)	(0.0431)	(0.0243)
More HS	0.1471***	−0.0018	0.1451***	−0.0006	0.1469***	−0.0021	0.1439***	0.0030	0.1486***	0.0158
	(0.0318)	(0.0152)	(0.0316)	(0.0146)	(0.0316)	(0.0151)	(0.0314)	(0.0150)	(0.0314)	(0.0153)
Edu missing	0.0129	−0.0338	0.0198	−0.0279	0.0194	−0.0305	0.0201	−0.0255	0.0153	−0.0309
	(0.0534)	(0.0321)	(0.0527)	(0.0326)	(0.0538)	(0.0324)	(0.0527)	(0.0324)	(0.0526)	(0.0317)
Welfare	−0.0561	−0.1249	−0.0526	−0.1254	−0.0504	−0.1269	−0.0509	−0.1128	−0.0391	−0.0913
	(0.1244)	(0.0943)	(0.1243)	(0.0938)	(0.1235)	(0.0931)	(0.1215)	(0.0943)	(0.1227)	(0.0929)
Job missing	−0.0980	−0.0102	−0.1006*	−0.0083	−0.1001*	−0.0090	−0.0972*	−0.0089	−0.0997*	−0.0108
	(0.0524)	(0.0302)	(0.0509)	(0.0309)	(0.0530)	(0.0303)	(0.0516)	(0.0303)	(0.0523)	(0.0299)
Professional	0.0304	−0.0257	0.0273	−0.0283	0.0269	−0.0300	0.0331	−0.0278	0.0319	−0.0245
	(0.0371)	(0.0187)	(0.0364)	(0.0182)	(0.0368)	(0.0187)	(0.0363)	(0.0185)	(0.0359)	(0.0184)
Other job	−0.0188	0.0078	−0.0173	0.0085	−0.0177	0.0063	−0.0147	0.0113	−0.0190	0.0101
	(0.0327)	(0.0170)	(0.0319)	(0.0169)	(0.0326)	(0.0181)	(0.0324)	(0.0170)	(0.0316)	(0.0168)
Z_1									−0.0312	−0.0021
									(0.0303)	(0.0055)
Z_2									0.0904***	−0.0115**
									(0.0297)	(0.0058)

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Table – Continued

Z_3					-0.0742^{***} -0.0087
					(0.0280) (0.0064)
σ_ϵ^2	0.4607***	0.4561***	0.4579***	0.4522***	0.4389***
	(0.0122)	(0.0119)	(0.0122)	(0.0121)	(0.0127)
Network					
Age					0.6834***
					(0.0307)
Sex					0.3324***
					(0.0265)
Race					0.4700***
					(0.0390)
$\lvert z_{i1} - z_{j1}\rvert$					-2.7547***
					(0.0649)
$\lvert z_{i2} - z_{j2}\rvert$					-2.6319***
					(0.0443)
$\lvert z_{i3} - z_{j3}\rvert$					-2.5459***
					(0.0549)

Note: Model (I): conventional model. Model (II): altruistic Model. Model (III): conventional model with indegree effect. Model (IV): altruistic model with direct externality. Model (V): altruistic model with direct externality and endogenous network formation. The parameter estimates reported in this table are the posterior means and posterior standard deviations (in parentheses) computed on base of 50,000 MCMC draws. We draw the first 5,000 draws for the burn-in. The asterisks ***(**,*) indicates that its 99% (95%, 90%) highest posterior density range does not cover zero.

Table 4: Estimation Results of Conventional and Altruistic Social Interactions Models on smoking

	Model (I)		Model (II)		Model (III)		Model (IV)		Model (V)	
λ	0.0924***		0.0759***		0.0922***		0.0592***		0.0574***	
	(0.0047)		(0.0135)		(0.0048)		(0.0099)		(0.0093)	
λ^{I}			0.0184				0.0367***		0.0366***	
			(0.0127)				(0.0097)		(0.0090)	
η^{I}					-0.0602		-0.1915***		-0.1767***	
					(0.0620)		(0.0707)		(0.0692)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.3261	−0.2520	−0.3230	−0.2364	−0.3562	−0.2418	−0.3863	−0.2114	−0.3846	−0.2347
	(0.3602)	(0.2198)	(0.3595)	(0.2200)	(0.3631)	(0.2187)	(0.3601)	(0.2204)	(0.3543)	(0.2133)
Age	0.8532***	−0.0601***	0.8342***	−0.0577***	0.8806***	−0.0587***	0.8138***	−0.0484***	0.8088***	−0.0420**
	(0.1314)	(0.0166)	(0.1237)	(0.0167)	(0.1313)	(0.0167)	(0.1316)	(0.0170)	(0.1365)	(0.0165)
Black	−3.8458***	0.2138	−3.8009***	0.2002	−3.8424***	0.2011	−3.7804***	0.1463	−3.1854***	0.0142
	(0.6841)	(0.1867)	(0.7017)	(0.1891)	(0.6896)	(0.1886)	(0.6744)	(0.1863)	(0.6840)	(0.1980)
Asian	0.0034	−0.5869	0.0329	−0.5301	−0.0145	−0.6163	−0.0009	−0.5458	0.3822	−0.7343
	(1.2389)	(0.5694)	(1.2655)	(0.5751)	(1.2383)	(0.5723)	(1.2362)	(0.5652)	(1.2190)	(0.5811)
Hispanic	−1.7613**	0.6692*	−1.7800**	0.6425*	−1.7521**	0.6694	−1.8192**	0.5884	−1.6029**	0.3883
	(0.7605)	(0.3766)	(0.7556)	(0.3769)	(0.7626)	(0.3724)	(0.7517)	(0.3702)	(0.7622)	(0.3731)
Other race	0.6733	0.2931	0.7043	0.3660	0.6329	0.2687	0.6097	0.3180	0.6806	0.2382
	(0.7689)	(0.4376)	(0.7447)	(0.4360)	(0.7645)	(0.4377)	(0.7604)	(0.4276)	(0.7494)	(0.4367)
Both parents	−1.8285***	−0.2220	−1.8543***	−0.2335	−1.7922***	−0.2255	−1.7986***	−0.2806	−1.7092***	−0.2957
	(0.4058)	(0.2252)	(0.4050)	(0.2248)	(0.4053)	(0.2244)	(0.3994)	(0.2212)	(0.3977)	(0.2245)
Less HS	0.6337	0.2125	0.6024	0.2407	0.6167	0.2140	0.5255	0.2777	0.4986	0.2462
	(0.5819)	(0.3245)	(0.5783)	(0.3295)	(0.5825)	(0.3245)	(0.5917)	(0.3218)	(0.5697)	(0.3254)
More HS	−0.2130	0.3696*	−0.2180	0.3512	−0.2074	0.3755*	−0.2171	0.3542*	−0.2029	0.1879
	(0.4162)	(0.1987)	(0.4131)	(0.1951)	(0.4161)	(0.1975)	(0.4128)	(0.1996)	(0.4084)	(0.2020)
Edu missing	0.0660	0.7044*	0.0632	0.7475*	0.0460	0.6918	0.0087	0.7466*	0.0759	0.6576
	(0.7009)	(0.4217)	(0.7050)	(0.4269)	(0.7076)	(0.4276)	(0.7004)	(0.4338)	(0.7033)	(0.4161)
Welfare	2.1277	0.0474	2.1189	0.0793	2.1394	0.0731	2.1275	0.1835	2.0555	0.0777
	(1.6171)	(1.2267)	(1.5913)	(1.2113)	(1.6066)	(1.2205)	(1.6002)	(1.2080)	(1.5936)	(1.2061)
Job missing	0.7623	0.6897*	0.7092	0.6670*	0.7882	0.6904*	0.6656	0.6351*	0.7284	0.7239*
	(0.6893)	(0.3967)	(0.6883)	(0.3963)	(0.6982)	(0.3985)	(0.6980)	(0.3878)	(0.6836)	(0.3985)
Professional	0.6192	0.0995	0.5754	0.0964	0.6438	0.1156	0.5681	0.1250	0.6019	0.2308
	(0.4871)	(0.2423)	(0.4825)	(0.2373)	(0.4855)	(0.2425)	(0.4912)	(0.2367)	(0.4705)	(0.2389)
Other job	0.7322*	0.0253	0.6902	0.0370	0.7422*	0.0340	0.6333	0.0635	0.6323	0.1758
	(0.4292)	(0.2197)	(0.4280)	(0.2216)	(0.4302)	(0.2202)	(0.4243)	(0.2172)	(0.4204)	(0.2221)
Z_1									−0.0828	0.0825
									(0.3098)	(0.0744)
Z_2									0.2004	0.0581
									(0.4410)	(0.0923)

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Table – Continued

Z_3					-1.7947^{***} (0.4237) 0.3508^{***} (0.0812)
σ_ϵ^2	79.8120***	79.3284***	79.7811***	78.6922***	76.3781***
	(2.1105)	(2.0817)	(2.1157)	(2.0685)	(2.1719)
Network					
Age					0.6967***
					(0.0291)
Sex					0.3326***
					(0.027)
Race					0.4653***
					(0.041)
$\lvert z_{i1} - z_{j1} \rvert$					-2.7531***
					(0.0603)
$\lvert z_{i2} - z_{j2} \rvert$					-2.6681***
					(0.0544)
$\lvert z_{i3} - z_{j3} \rvert$					-2.4849***
					(0.0605)

Note: Model (I): conventional model. Model (II): altruistic Model. Model (III): conventional model with indegree effect. Model (IV): altruistic model with direct externality. Model (V): altruistic model with direct externality and endogenous network formation. The parameter estimates reported in this table are the posterior means and posterior standard deviations (in parentheses) computed on the basis of 50,000 MCMC draws. We draw the first 5,000 draws for the burn-in. The asterisks ***(**,*) indicates that its 99% (95%, 90%) highest posterior density range does not cover zero.

Table 5: Estimation Result: Directed Altruistic Social Interactions Models

	Directed Altruistic Model				Directed Altruistic Model w/ externality			
	GPA		Smoking		GPA		Smoking	
λ	0.0648^{***}		0.0765^{***}		0.0458^{***}		0.0564^{***}	
	(0.0071)		(0.0116)		(0.0075)		(0.0110)	
λ^{I}	0.0087^{***}		0.0025		0.0273^{***}		0.0306^{***}	
	(0.0021)		(0.0134)		(0.0093)		(0.0119)	
λ^{R}	-0.0044		0.0260^{*}		0.0012		0.0148	
	(0.0046)		(0.0144)		(0.0118)		(0.0138)	
η^{I}					-0.0563^{**}		-0.3007^{***}	
					(0.0287)		(0.0945)	
η^{R}					-0.0239		0.3792	
					(0.0388)		(0.2085)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	-0.1172^{***}	0.0036	-0.3119	-0.2366	-0.1150^{***}	0.0033	-0.3416	-0.1902
	(0.0278)	(0.0166)	(0.3563)	(0.2175)	(0.0270)	(0.0163)	(0.3586)	(0.2179)
Age	-0.0108	-0.0123^{***}	0.8603^{***}	-0.0591^{***}	-0.0146	-0.0089^{***}	0.8490^{***}	-0.0562^{***}
	(0.0113)	(0.0017)	(0.1317)	(0.0169)	(0.0109)	(0.0018)	(0.1338)	(0.0171)
Black	-0.0351	0.0059	-3.8138^{***}	0.2154	-0.0305	0.0024	-3.7602^{***}	0.1825
	(0.0523)	(0.0143)	(0.6701)	(0.1860)	(0.0525)	(0.0142)	(0.6794)	(0.1879)
Asian	0.1347	0.0404	-0.0134	-0.5625	0.1409	0.0389	0.0077	-0.5319
	(0.0936)	(0.0432)	(1.2483)	(0.5684)	(0.0930)	(0.0431)	(1.2416)	(0.5638)
Hispanic	-0.0487	0.0095	-1.7398^{**}	0.6309^{*}	-0.0452	0.0096	-1.7856^{**}	0.5564
	(0.0576)	(0.0275)	(0.7754)	(0.3718)	(0.0581)	(0.0280)	(0.7439)	(0.3657)
Other race	-0.0341	0.0020	0.6989	0.3409	-0.0341	-0.0015	0.6839	0.3454
	(0.0583)	(0.0331)	(0.7740)	(0.4323)	(0.0566)	(0.0330)	(0.7525)	(0.4382)
Both parents	0.0920^{***}	0.0343^{**}	-1.8452^{***}	-0.2218	0.0916^{***}	0.0366^{**}	-1.8053^{***}	-0.2794
	(0.0309)	(0.0170)	(0.4029)	(0.2231)	(0.0307)	(0.0174)	(0.3968)	(0.2199)
Less HS	-0.0964^{**}	-0.0647^{***}	0.5902	0.2203	-0.0937^{**}	-0.0641^{***}	0.4603	0.2624
	(0.0442)	(0.0250)	(0.5814)	(0.3210)	(0.0440)	(0.0240)	(0.5823)	(0.3188)
More HS	0.1459^{***}	-0.0012	-0.2242	0.3626	0.1443^{***}	0.0030	-0.2256	0.3496^{*}
	(0.0318)	(0.0151)	(0.4184)	(0.2010)	(0.0314)	(0.0150)	(0.4072)	(0.1994)
Edu missing	0.0218	-0.0295	0.0684	0.7035	0.0209	-0.0250	-0.0118	0.7032
	(0.0530)	(0.0326)	(0.7080)	(0.4369)	(0.0523)	(0.0314)	(0.6970)	(0.4300)
Welfare	-0.0522	-0.1244	2.1423	0.0432	-0.0518	-0.1143	2.1497	0.1281
	(0.1247)	(0.0942)	(1.6259)	(1.2217)	(0.1236)	(0.0931)	(1.5948)	(1.2103)
Job missing	-0.1021^{*}	-0.0098	0.7210	0.6641^{*}	-0.1000^{*}	-0.0085	0.6989	0.6676^{*}
	(0.0525)	(0.0301)	(0.7014)	(0.3997)	(0.0530)	(0.0305)	(0.6913)	(0.3973)
Professional	0.0268	-0.0305	0.6203	0.0916	0.0320	-0.0265	0.5920	0.1370
	(0.0373)	(0.0185)	(0.4811)	(0.2431)	(0.0366)	(0.0185)	(0.4818)	(0.2404)
Other job	-0.0189	0.0067	0.7144	0.0307	-0.0154	0.0123	0.6510	0.0717
	(0.0322)	(0.0170)	(0.4282)	(0.2190)	(0.0327)	(0.0166)	(0.4238)	(0.2164)
σ_ϵ^2	0.4558^{***}		79.2971^{***}		0.4525^{***}		78.5899^{***}	
	(0.0119)		(2.1347)		(0.0112)		(2.1244)	

Note: The parameter estimates reported in this table are the posterior means and posterior standard deviations (in parentheses) computed on the basis of 50,000 MCMC draws. We draw the first 5,000 draws for the burn-in. The asterisks ***(**,*) indicates that its 99% (95%, 90%) highest posterior density range does not cover zero.

Table 6: Estimation Results: Heterogeneous Altruism Model with Endogenous Friendship Formation

Activity	GPA				Smoking			
	D3		D4		D3		D4	
λ	0.0492***		0.0470***		0.0747***		0.0739***	
	(0.0055)		(0.0067)		(0.0045)		(0.0048)	
ρ	0.6187***		0.6369***		0.4120*		0.3387	
	(0.2338)		(0.2278)		(0.2751)		(0.2602)	
η	-0.1303***		-0.1085***		-0.4344**		-0.4208**	
	(0.0221)		(0.0253)		(0.1842)		(0.1704)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.1209***	0.0101	−0.1186***	0.0072	−0.1871	−0.1917	−0.0634	−0.2615
	(0.0271)	(0.0165)	(0.0266)	(0.0162)	(0.3551)	(0.2112)	(0.3448)	(0.2126)
Age	−0.0320***	−0.0097***	−0.0436***	−0.0084***	0.7580***	−0.0576**	0.7099***	−0.0492***
	(0.0118)	(0.0015)	(0.0136)	(0.0017)	(0.1319)	(0.0167)	(0.1359)	(0.0166)
Black	−0.0573	−0.0046	−0.0010	0.0060	−3.4775***	0.1567	−2.7953***	0.2163
	(0.0534)	(0.0146)	(0.0524)	(0.0144)	(0.6741)	(0.1833)	(0.6843)	(0.1834)
Asian	0.1030	−0.0008	0.0901	0.0051	−0.0532	−0.4186	0.0720	−0.5953
	(0.0949)	(0.0437)	(0.0927)	(0.0426)	(1.1285)	(0.5402)	(1.1479)	(0.5400)
Hispanic	−0.0604	0.0133	−0.0265	0.0257	−1.8048**	0.5007	−1.5848**	0.4833
	(0.0577)	(0.0283)	(0.0573)	(0.0285)	(0.7340)	(0.3602)	(0.7420)	(0.3647)
Other Race	−0.0399	−0.0106	−0.0227	0.0039	0.4595	0.3171	0.6785	0.4301
	(0.0586)	(0.0329)	(0.0567)	(0.0330)	(0.7206)	(0.4204)	(0.7158)	(0.4147)
Both parents	0.0944***	0.0388**	0.0842***	0.0359**	−1.8983***	−0.2393	−1.6849***	−0.2430
	(0.0313)	(0.0172)	(0.0301)	(0.0170)	(0.4043)	(0.2188)	(0.3928)	(0.2125)
Less HS	−0.0960**	−0.0534**	−0.0869**	−0.0459**	0.5740	0.1942	0.5574	0.2627
	(0.0441)	(0.0249)	(0.0433)	(0.0239)	(0.5690)	(0.3121)	(0.5659)	(0.3138)
More HS	0.1444***	0.0069	0.1352***	0.0151	−0.2244	0.3721*	−0.1183	0.3604*
	(0.0315)	(0.0149)	(0.0312)	(0.0147)	(0.4029)	(0.1929)	(0.3983)	(0.1926)
Edu missing	0.0282	−0.0165	0.0215	−0.0178	0.0724	0.6275	0.0274	0.6038
	(0.0525)	(0.0323)	(0.0522)	(0.0320)	(0.6706)	(0.4084)	(0.6608)	(0.4017)
Welfare	−0.0342	−0.1016	−0.0416	−0.0663	1.6425	0.0598	1.4548	0.3179
	(0.1234)	(0.0933)	(0.1221)	(0.0940)	(1.4234)	(1.1079)	(1.4249)	(1.1175)
Job missing	−0.0886	0.0076	−0.0902*	−0.0096	0.6909	0.7193*	0.7761	0.7044*
	(0.0521)	(0.0301)	(0.0508)	(0.0296)	(0.6727)	(0.3826)	(0.6769)	(0.3781)
Professional	0.0289	−0.0278	0.0303	−0.0377**	0.5876	0.1347	0.4279	0.0655
	(0.0360)	(0.0187)	(0.0362)	(0.0183)	(0.4675)	(0.2372)	(0.4569)	(0.2332)
Other job	−0.0169	0.0116	−0.0180	0.0137	0.7338	0.0745	0.6219	0.0029
	(0.0326)	(0.0167)	(0.0314)	(0.0167)	(0.4140)	(0.2109)	(0.4036)	(0.2133)
Z_1	−0.0987***	−0.0049	−0.1011***	0.0025	−2.5870***	0.4901***	−0.1807	0.0437
	(0.0309)	(0.0074)	(0.0224)	(0.0067)	(0.3474)	(0.0843)	(0.3145)	(0.0800)
Z_2	−0.0119	−0.0110	0.1032***	−0.0067	1.0381***	−0.2121**	0.7371	−0.1575
	(0.0245)	(0.0064)	(0.0244)	(0.0067)	(0.3493)	(0.0937)	(0.4570)	(0.1116)
Z_3	−0.0364	−0.0019	−0.0241	0.0001	0.1741	−0.0295	2.1789***	−0.2876**
	(0.0260)	(0.0068)	(0.0257)	(0.0070)	(0.3662)	(0.0888)	(0.3529)	(0.0931)
Z_4	–	–	−0.1451***	−0.0097	–	–	−2.6794***	0.4092***
			(0.0288)	(0.0081)			(0.3120)	(0.0914)
A	0.0155	−0.0144	0.0571	0.0029	2.4091***	0.0691	2.1153**	0.1226
	(0.0627)	(0.0188)	(0.0606)	(0.0187)	(0.9541)	(0.2273)	(0.9555)	(0.2324)
Network								
Age	0.6968***		0.7495***		0.6894***		0.7423***	
	(0.0321)		(0.0308)		(0.0355)		(0.0329)	
Sex	0.3561***		0.3616***		0.3646***		0.3549***	
	(0.0268)		(0.0291)		(0.0263)		(0.0329)	
Race	0.5344***		0.5449***		0.5011***		0.5203***	
	(0.0471)		(0.0479)		(0.0463)		(0.0576)	
$\lvert z_{i1} - z_{j1} \rvert$	-2.7467***		-2.6177***		-2.7889***		-2.6585***	
	(0.0421)		(0.0458)		(0.0496)		(0.0526)	

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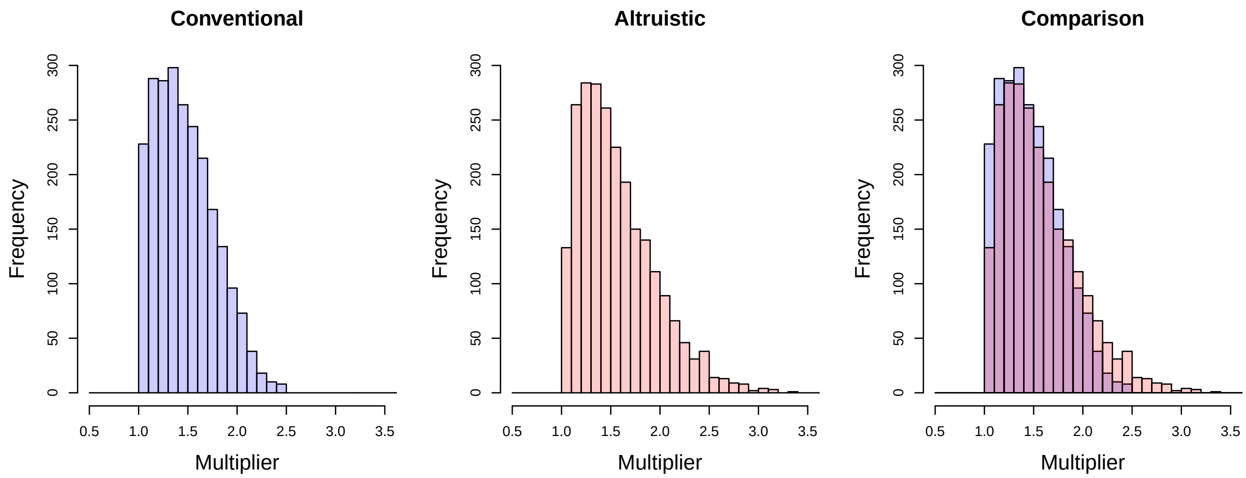
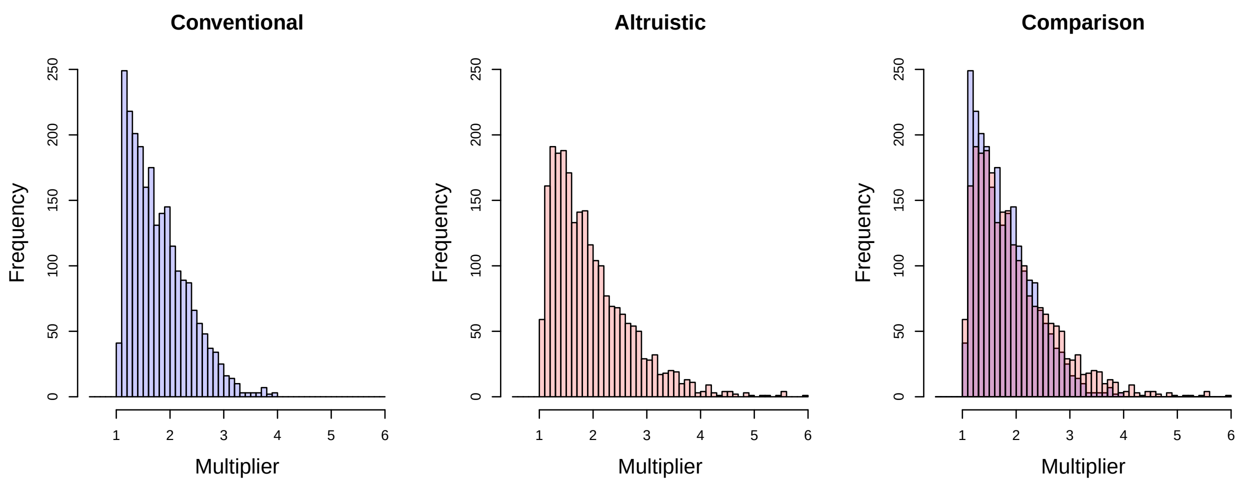
Table – Continued

$\lvert z_{i2} - z_{j2}\rvert$	-2.7122***	-2.5284***	-2.7241***	-2.5789***
	(0.0404)	(0.0428)	(0.0414)	(0.0532)
$\lvert z_{i3} - z_{j3}\rvert$	-2.6476***	-2.4735***	-2.6471***	-2.4929***
	(0.0446)	(0.0446)	(0.0494)	(0.0545)
$\lvert z_{i4} - z_{j4}\rvert$	-	-2.4260***	-	-2.3343***
		(0.0460)		(0.0675)
a_{ig}	0.1412***	0.1753***	0.1357***	0.1341***
	(0.0424)	(0.0494)	(0.0447)	(0.0532)
a_{jg}	1.4109***	1.4019***	1.3834***	1.4246***
	(0.0448)	(0.0498)	(0.0436)	(0.0541)
σ_v^2	0.4446***	0.4175***	72.6769***	69.7159***
	(0.0125)	(0.0121)	(2.2695)	(2.2621)
AICM	80,505	83,335	89,472	93,697

Note: D_i, $i = 3, 4$ refers to the dimensions of the latent variables Z used in the network formation and outcome equations. The parameter estimates reported in this table are the posterior means and posterior standard deviations (in parentheses) computed on basis of 50,000 MCMC draws. We draw the first 5,000 draws for the burn-in. The asterisks ***(**,*) indicates that its 99% (95%, 90%) highest posterior density range does not cover zero.

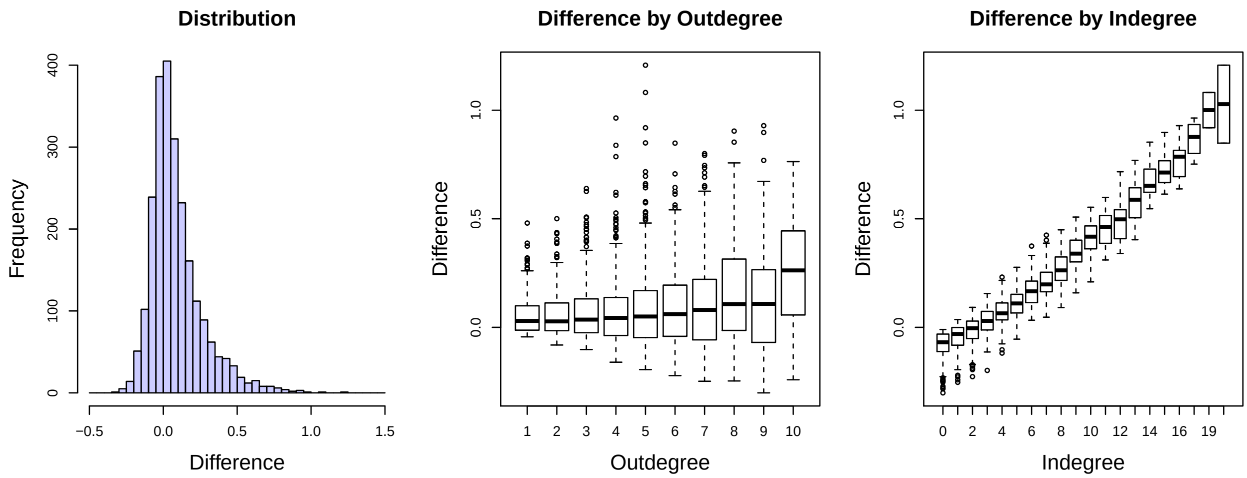


(a) Histogram of multiplier effects with regard to GPA

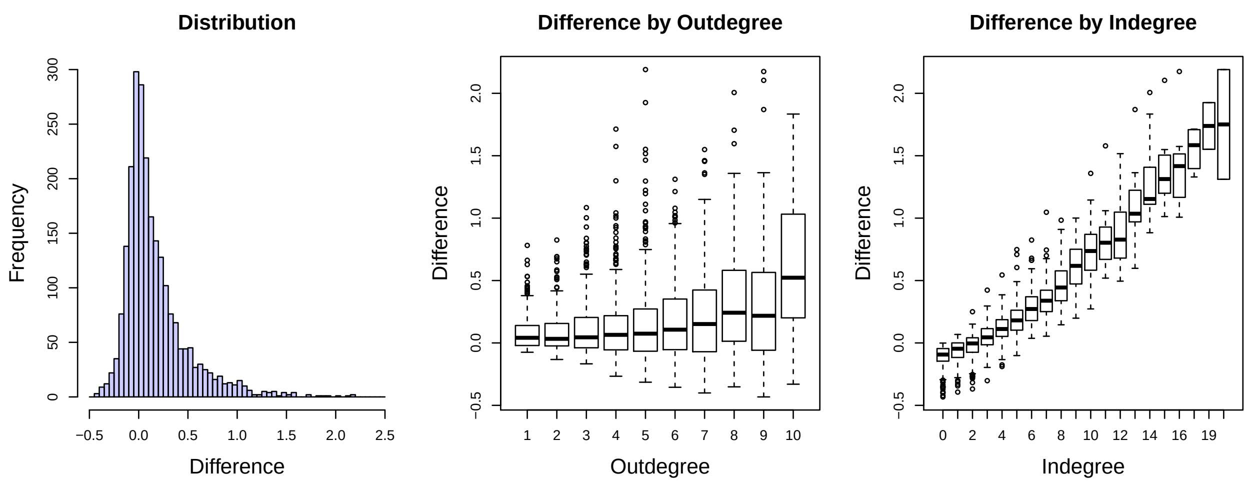


(b) Histogram of multiplier effects with regard to smoke

Figure 1: Histogram of Multipler Effects



(a) Difference of multiplier effects with regard to GPA



(b) Difference of multiplier effects with regard to smoke

Figure 2: Difference of Multipler Effects

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