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 more enriched network features can be captured in the best response function derived from the maximization of the extended utility which incorporates altruism, providing microfoundation for studies which investigate how network features mediate peer effects or other important features in social interactions. We demonstrate that often ignored altruism is another serious confounding factor of peer effects. Our results show that the estimates of peer affects are about 36% smaller under altruistic preferences. Furthermore, we are able to separate the two different types of effects generated by peers: the (usually positive) spillover effects from peers and the (negative or positive) externality effects directly generated from peers' outcomes, which is not possible in conventional social interactions model based on self-interest hypothesis.

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1 Introduction

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

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

Surprisingly, the literature on social interactions has mainly focused on the influences of peers on behaviors and decisions of an individual, rarely considering the possible formation of social preferences among the network links. Many of these studies apply the Spatial Autoregressive (SAR) model to study social interactions on various outcomes, such as academic performance, club participation, smoking, obesity, sport 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 individuals act in their own self-interest exclusively. 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 is free of 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 networks of individuals in a group. As friendship networks are individual specific, the SAR model introduces necessary nonlinearity to distinguish between endogenous peer effects and contextual effects.

by considering a conventional non-cooperative game where rational and self-interest individuals maximize 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 as people may intrinsically care about the well beings of their social contacts and take account of their preferences when making the decisions. As shown in a number of studies, including 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, there is a need for relaxing the assumption of individual selfishness under the social interaction framework. It would be of interest to see how an openness to the altruistic preferences leads to new perspective on social interactions modeling

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

[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 model used for empirical studies.

of the extended utility which incorporates altruism, thus providing microfoundation for these studies.

Another important contribution of this paper is that it shows the often ignored altruism is another serious confounding factor of peer effects. Intuitively, the idea of peer effects is 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 help them or not to hurt them. Therefore, the estimation of peer affects is even more challenging than previously thought, ignoring altruistic preferences in social networks will cause bias in peer effect estimation. In our analysis of the National Longitudinal Study of Adolescent Health (Add Health) data, we find that there exists significant peer effects on students' academic achievement, smoking behavior, extracurricular activities, even after controlling for altruistic preferences and endogenous network formation. And we find evidence of upward bias on estimates of peer effects when omitting the effect of altruism. In particular, the estimates of peer affects are about 35% smaller under altruistic preferences as compared to the case with conventional self-interest assumption. Furthermore, we are able to separately identify two distinct types of effects generated from peers. Specifically, in additional to the positive spillover effects from peers, we find significant negative externality effects directly generated from peers' outcomes.[5] It is worth noting the conventional SAR specifications based on 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 group 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. The proposed approach is applied to the Add Health data in Section 5. Concluding remarks are provided in Section 6.

2 Literature Review

The 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 the classical utility theory by assuming that a player's utility function depends not only on own payoff, but also on others' payoffs, including Becker (1976, 1981) ,

[5] As can be seen from Equation (6) below, the spillover effect is captured by λ, whereas the externality effect is captured by η.

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 is the intention based reciprocity model, assuming a player cares about his opponents intentions, for instance, 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), Gul et al. (2004), among others. In particular, Levine (1998) formulates an altruism model where a player interacts with different types(spiteful, selfish and altruistic) of opponents, and has a utility function which is linear in both own and their opponents' income, with the weight on the opponent's income depending on the opponents' types. Levine performs several experiments and shows that results in ultimatum game, centipede game, market competition and public good game are consistent with this theory. Through an online field experiments in large real-world social networks, Leider et al. (2009) demonstrates that agents show baseline altruism toward randomly selected strangers, and show directed altruism toward their friends. Furthermore, directed altruism increase an agent's giving to their friends by a significant amount as compared to giving to random strangers. It is worth noting that most models of social preferences predict either no peer effects, i.e. agents' efforts are unrelated, or negatively correlated efforts, i.e. agents' efforts are strategic substitutes.[6]

Recently, a number of social preferences studies show 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 substitutes. To provide explanation for the empirically observed positively correlated efforts, i.e., peer effects, recent generation of social preferences theories introduce additional social motives beyond the conventional distributional concerns as considered in standard social preferences theories. For instance, Sliwka (2007) considers conformism, Lpez-Prez (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) try to 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) where individuals are inequity aversion and the model of social norm compliance can

[6] In fact, only two standard theories in social preferences are generally consistent with both positively and negatively corrrelated efforts, i.e. Charness and Rabin (2002) and Fehr and Schmidt (1999). More detailed discussions on these models can be found in Gächter et al. (2013).

explain the positive correlation in agents' efforts. Several other papers also study and compare the relative importance of social norms and social preferences in explaining the observed peer effects. Krupka and Weber (2013) show that the observed differences in behaviors of their Dictator game cannot be explained by most standard social preferences models, while social norm compliance can provide explanation for the behavior changes in various contexts. Similarly, Krupka et al. (2016) find that elicited social norms have significant explanatory power in agents' behaviors for their Dictator and Bertrand games, while social preference models do not.

In contrast, altruistic preferences have seldom played a role in the literature of social interactions. As a matter of fact, the majority of the studies in social interactions have focused on addressing the well known identification difficulties, including the "reflection problem," endogeneity of network group formation, selection bias, omitted variable bias, and so on. As demonstrated in many papers, such as Lin (2010), Bramoullé et al., 2009; Calvó-Armengol et al., 2009, among others, the SAR model resolves the "reflection problem" by introducing nonlinearity into the individual specific social network. To deal with the other potential bias, different strategies have been proposed, including group fixed effect strategy (Lin, 2010; Bramoullé et al., 2009); instrument variable strategy (e.g., Evans et al., 1992; Rivkin, 2001); experiment type strategy (e.g., Sacerdote, 2001; Zimmerman, 2003). Recently, some papers such as Goldsmith-Pinkham and Imbens (2013), and Hsieh and Lee (2016) propose a comprehensive simultaneous equation system to model both network group 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) provide evidence that social interactions and/or group memberships are complementary determinants of altruistic behavior. Bell and Keeney (2009) analyze altruistic decisions among group members through the use of a group altruistic utility function which incorporates the preferences of each individual in the group. They study an additive utility function where the aggregated utility is the summation of all individual utilities in the group. In a recent paper, Bourlès et al. (2017) studies altruism in social networks where 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: her private utility, and others' private and social utilities. They study the Nash equilibrium of the resulting game of private transfers flow through networks of altruism. On the other hand, several studies have tried to extend 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. Incorporating altruism into social interaction models has important modeling consequences and can provide microfoundation 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, spillover) effects. Examples of such groups include schools, workplaces, villages and so on. 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 denotes the group size. We let $x_{i,g}$ denote 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, or borrowing and lending. The social links in group g are represented by an adjacency matrix (sociomatrix) W_g. The $(i, j)^{\text{th}}$ element of W_g, $w_{ij,g}$, equals to one if individual i sends a social link to individual j. Otherwise, $w_{ij,g}$ equals to zero. All links are directed, and there are no compulsory reciprocal links. 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 feature 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 $(m_g - 1)$ activity vector excluding $y_{i,g}$. The first and second terms of Equation (1) capture the benefit (or cost) from 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 from maximize the own payoff function in Equation (1). The implied pure strategy activity vector in a unique interior Nash equilibrium is given by[7]

$$Y_g = (I_g - \lambda)^{-1}\mu_g, \tag{2}$$

If we specify $\mu_g = X_g\beta_1 + W_gX_g\beta_2 + l_g\tau_g + \epsilon_g$, where l_g is the m_g-dimensional vector of ones, then we will obtain the standard spatial autoregressive (SAR) model,

$$Y_g = \lambda W_g Y_g + X_g\beta_1 + W_gX_g\beta_2 + l_g\tau_g + \epsilon_g, \tag{3}$$

Coefficient λ captures the endogenous (peer) effect. Coefficients β_1 and β_2, respectively, capture the own and contextual effects from exogenous individual characteristics. The term τ_g represents a group fixed effect, which captures effects from environmental unobservables (correlated effects) shared by all individuals in the same group. The group fixed effect also controls the 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.

3.2 Altruistic Preference

Instead of assuming individuals only care about own payoff, we extend the model to allow individuals to be altruistic, and thus care about others' well-being when choosing an optimal activity level to maximize utility. One simplest form of the altruistic utility function $U_{i,g}$ is a linear function of individual's own and others' payoffs,[8]

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

In this model, the 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 to zero, individuals are selfish and Equation (4) will reduce to Equation (1); and when α is negative, individuals are spiteful. In this model, individuals show altruism toward every other people in a group, which is the baseline altruism as discussed in Leider et al. (2009).[9]

[7] The existence and uniqueness of the equilibrium can be guaranteed as long as $|\lambda| < 1/\max_{g=1,\cdots,G}\{||W_g||_1, ||W_g||_\infty\}$, where $||W_g||_1$ and $||W_g||_\infty$ represent the maximum absolute values of the column sum and the row sum of W_g.

[8] This simple and intuitive utility function has been employed in several studies, including Bell and Keeney (2009) and Bourlès et al. (2017).

[9] We will consider directed altruism in an extension model in the next subsection.

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

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \tag{5}$$

This model can be called as "Altruistic social interactions model." Comparing with Equation (3), we see a new term of $\lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g$ in Equation (5), where $\lambda^{\mathrm{I}} = \alpha_1 \lambda$ and W_g^{T} denotes the transpose of W_g. We use the superscript 'I' to indicate that it is identified from "inward" friendship links, i.e., indegree. Therefore, under altruistic preference, an individual's outcome is affected not only by the outcomes of his/her nominated friends, but also by the outcomes of those who nominated him/her as a friend, with the effect of the latter group being the effect of the nominated friends (λ) scaled by the altruism level (α_1).[10] One can also note that if individuals are selfish, i.e., $\alpha_1 = 0$, then coefficient λ^{I} is zero and Equation (5) will be identical to Equation (3).

3.3 Externality Effect

The social interaction effects considered in sections 3.1 and 3.2 are the conventional complementary or spillover effects generated by peers, as can be seen from the last term in Equation (1), where peers' outcomes, $\sum_{j=1}^{m_g} w_{ij,g} y_{j,g}$, is augmented by own outcome, $y_{i,g}$. However, there could be another channel for the direct effect from peer's activity on individual's payoff, i.e. the "direct externality" effects, where an individual may be directly affected by peers' activities, without being augmented by her own $y_{i,g}$, as captured by the last term in Equation (6).[11] For instance, an individual may enjoy smoking together with his/her friends, but at the same time, his/her friends' smoking behaviors could directly cause a negative externality effect on individual's own payoff due to health concerns and so on.

$$v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) = \mu_{i,g} y_{i,g} - \frac{1}{2} y_{i,g}^2 + \lambda y_{i,g} \sum_{j=1}^{m_g} w_{ij,g} y_{j,g} + \eta \sum_{j=1}^{m_g} w_{ij,g} y_{j,g}. \tag{6}$$

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

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \tag{7}$$

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

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

Compared with Equation (5), we see a new term of $\eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g$ in Equation (7), where $\eta^{\mathrm{I}} = \alpha_1 \eta$. We refer to Equation (7) as the "Altruistic social interactions model with direct externality," in which we can identify both the degree of altruism by the coefficient λ^{I} and the direct externality effect from peers' activity outcome by the coefficient η^{I}. We can see a clear rationale behind Equation (7) using the number of inward network links to capture the externality effect. Since 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 influence individual's activity outcome. In this line of literature, researchers are interested in exploring various network effects on individuals' outcomes (Echenique and Fryer, 2007; Mihaly, 2009; Conti et al., 2013; Alatas et al., 2016). Although most of the studies interpret 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 an individual's outcome.

3.4 Extension: Directed Altruism

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

$$U_{i,g} = v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) + \sum_{j=1, j\neq i}^{m_g} (\alpha_1 + \alpha_2 w_{ij,g}) v_{j,g}(y_{j,g}, Y_{-j,g}, W_g). \tag{8}$$

In this model, the coefficient α_1 denotes baseline altruism towards all group members, and α_2 represents directed altruism towards friends. Leider et al. (2009) finds that altruism levels are stronger among friends than among randomly selected strangers. Combining the payoff function of Equation (6) with the utility function of Equation (8), we can solve the vector of Nash equilibrium strategy from the first order condition as follows,

$$\begin{aligned} Y_g = {} & \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \lambda^{\mathrm{R}} W_g^{\mathrm{R}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + \eta^{\mathrm{R}} W_g^{\mathrm{R}} l_g \\ & + X_g \beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \end{aligned} \tag{9}$$

We can see two new terms in Equation (9), $\lambda^{\mathrm{R}} W_g^{\mathrm{R}} Y_g$, and $\eta^{\mathrm{R}} W_g^{\mathrm{R}} l_g$, where W_g^{R} stands for the network of reciprocal links, i.e., $w_{ij,g}^{\mathrm{R}} = 1$ if both $w_{ij,g}$ and $w_{ji,g}$ are one. Coefficients $\lambda^{\mathrm{R}} = \alpha_2 \lambda$ and $\eta^{\mathrm{R}} = \alpha_2 \eta$ capture, respectively, the endogenous peer effect and 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 (9) as the "Directed altruistic social interactions model." It provides microfoundation to explain the results of heterogeneous peer effects between chosen, unchosen, and mutual friends in Lin and Weinberg (2014).

3.5 Extension: Heterogeneous Altruism

In both Equations (4) and (8), the altruism level, captured by the coefficient α_1 (and α_2), is assumed homogeneous among the individuals. In theory, there are a number of 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,[12] which is specified as follows,

$$U_{i,g} = v_{i,g}(y_{i,g}, Y_{-i,g}, W_g) + \sum_{j=1, j\neq i}^{m_g} \frac{\alpha_{i,g} + \rho\alpha_{j,g}}{1+\rho} v_{j,g}(y_{j,g}, Y_{-j,g}, W_g), \tag{10}$$

where $\alpha_{i,g}$ reflects individual i's altruism level, which is again assumed 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. The coefficient $0 \leq \rho \leq 1$ reflects the reciprocality. A higher ρ implies that individuals respond more altruistically to someone who are altruistic to them. This adjusted utility function assigns different weights to others' payoffs based on how altruistic individuals are and how fairly they feel being 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 individuals' altruism levels, varying across individual pairs.

Using Equation (10), we can derive the associated outcome equation implied by the pure individual strategy in a unique interior Nash equilibrium,

$$\begin{aligned} y_{i,g} =& \lambda \left(\sum_{j=1}^{m_g} w_{ij,g} y_{j,g} + \sum_{j=1}^{m_g} \frac{\alpha_{i,g} + \rho\alpha_{j,g}}{1+\rho} w_{ji,g} y_{j,g} \right) + \eta \sum_{j=1}^{m_g} \frac{\alpha_{i,g} + \rho\alpha_{j,g}}{1+\rho} w_{ji,g} \\ &+ x_{i,g}\beta_1 + \sum_{j=1}^{m_g} w_{ij,g} x_{j,g} \beta_2 + \tau_g + \epsilon_{i,g}. \end{aligned} \tag{11}$$

Under this generalization, each individual j who nominates individual i as friend will generate effects on i, with 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 reciprocal coefficient ρ. Similarly, the effect of the indegree centrality is η scaled by the same factor. The vector of equilibrium outcomes in Eq. (11) can be written as

$$Y_g = \lambda(W_g + h_g(A_g, W_g, \rho))Y_g + \eta h_g(A_g, W_g, \rho)\ell_g + X_g\beta_1 + W_g X_g \beta_2 + l_g \tau_g + \epsilon_g, \tag{12}$$

[12] There are many other theoretical models that 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 intuitive and comprehensive, they are too complex and cannot be applied to an empirical study in a straightforward way.

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 (12) as "Heterogeneous altruistic social interactions model."

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 are in favor of the local aggregate specification as the number of friendship nominations is important for identifying the effects of altruism and externality.

3.6 Endogenous Friendship Formation

The endogenous formation of friendship networks is a serious identification concern for social interaction studies.[13] (Durlauf and Ioannides, 2010; Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016). When there are unobserved factors which simultaneously affect both friendship formation and outcomes but are not controlled 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 both the network formation model and the outcome SAR model. The network formation model is specified in a logistic form,

$$P(w_{ij,g}) = \left(\frac{\exp(\psi_{ij,g})}{1+\exp(\psi_{ij,g})}\right)^{I(w_{ij,g}=1)} \left(\frac{1}{1+\exp(\psi_{ij,g})}\right)^{1-I(w_{ij,g}=1)}$$

$$\psi_{ij,g} = \gamma_{0g} + c_{ij,g}\gamma_1 + \sum_{d=1}^{\bar{d}} \zeta_d |z_{id,g} - z_{jd,g}|. \tag{13}$$

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, same race, same age, etc. The individual latent variable $z_{i,g} = (z_{i1,g}, \cdots, z_{i\bar{d},g})$ are introduced through a distance $|z_{id,g} - z_{jd,g}|$ form 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 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 heterogeneous γ_{0g} to capture group-specific constants. In the network formation model of Equation (13), each network link is assumed to be independent conditioning on the variables $C_g = \{c_{ij,g}\}$ and

[13] As mentioned in Bramoullé et al. (2009); 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 model in Eq. (3). However, if W_g itself is endogenous, then these instrumental variables are not valid.

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

$$P(W_g|C_g, Z_g, \gamma, \zeta) = \prod_{i}^{m_g} \prod_{j \neq i}^{m_g} P(w_{ij,g}|C_g, Z_g, \gamma, \zeta), \tag{14}$$

where $\gamma = (\{\gamma_{0g}\}, \gamma_1')'$ and $\zeta = (\zeta_1, \cdots, \zeta_{\bar{d}})'$.

When considering heterogenous altruism levels (A_g) in outcome Equation (12), we further explore the role of A_g in network formation by extending the function ψ in Equation (13) to

$$\psi_{ij,g} = \gamma_{0g} + c_{ij,g}\gamma_1 + \gamma_2\alpha_{i,g} + \gamma_3\alpha_{j,g} + \sum_{d=1}^{\bar{d}} \zeta_d |z_{id,g} - z_{jd,g}|. \tag{15}$$

The coefficients γ_2 (γ_3) reflects the effect of sender's (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 and a higher γ_3 means more altruistic individuals tend to receive more friendship nominations. Also note that altruism levels, $\alpha_{i,g}, \alpha_{j,g}$, enter the network formation model in a plain form instead of a difference form in Equation (15). Otherwise, it will be hard to explain, e.g. why two spiteful individuals (whose altruism levels are both -1) may be more likely to form friendship. Besides, 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 the error terms ϵ_g in the activity outcome of Equations (7) and (9) are linearly correlated with unobserved latent variables 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 (12) is additionally correlated with the 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 regressors in the model. Following this assumption, we can then rewrite the altruistic social interactions model with direct externality in Equation (7) into

$$Y_g = \lambda W_g Y_g + \lambda^{\mathrm{I}} W_g^{\mathrm{T}} Y_g + \eta^{\mathrm{I}} W_g^{\mathrm{T}} l_g + X_g\beta_1 + W_g X_g \beta_2 + Z_g\delta_1 + W_g Z_g \delta_2 + l_g \tau_g + v_g; \tag{16}$$

the directed altruistic social interactions model in Equation (9) into

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

and the heterogeneous altruistic social interactions model in Equation (12) into

$$\begin{aligned} Y_g = \lambda(W_g + h(A_g, W_g, \rho))Y_g + \eta h_g(A_g, W_g, \rho)\ell_g \\ + X_g\beta_1 + W_g X_g \beta_2 + Z_g\delta_1 + W_g Z_g \delta_2 + \delta_3 A_g + \delta_4 W_g A_g + l_g \tau_g + v_g. \end{aligned} \tag{18}$$

We regard the activity outcome of Equation (16) or (17) (or (18)) and the network formation model of Equation (13) (or (15)) as a simultaneous-equations model and estimate the parameters in two equations jointly using the likelihood approach. We assume the error term v_g follows a normal distribution with mean 0 and variance $\sigma_v^2 I_{m_g}$.

4 Model Estimation

The social interactions and network formation models proposed in this paper are extensions of Hsieh and Lee (2016), Hsieh and Lin (2017), and Hsieh and Van Kippersluis (2016). As discussed in these paper, we need some identification constraints to deal with unobserved latent variables Z_g and A_g in the simultaneous outcome and network equations.[14] First of all, we cannot identify the variance (σ_z^2) of latent variable Z_g and therefore we normalize σ_z^2 to one.

4.1 Bayesian Estimation

We use the Bayesian MCMC approach to estimate unknown parameters in our models. Taking Equations (16) and (13) as example, the joint probability function of $\{Y_g, W_g\}_{g=1}^G$ can be written into the one as follows,

$$P(\{Y_g\}, \{W_g\} | \{X_g\}, \{C_g\}, \theta, \{\tau_g\})$$
$$= \prod_{g=1}^{G} \int_{Z_g} P(Y_g | W_g, X_g, Z_g, \theta, \tau_g) \cdot P(W_g | C_g, Z_g, \theta) \cdot f(Z_g) dZ_g, \quad (19)$$

where $\theta = (\gamma', \zeta', \lambda, \lambda^{\mathrm{I}}, \eta^{\mathrm{I}}, \beta', \delta', \sigma_v^2)$. There are two reasons for using the Bayesian approach instead of the classical approach. First, the model involves multi-dimensional individual latent variables, and it is difficult to handle high-dimensional integrations in Eq. (27) under the classical approach. On the other hand, the Bayesian MCMC is more effective in handling estimation of 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 the other model parameters. Conditional on these latent variables, the evaluation of the probability function becomes much simpler. Second, we have some parameter constraints for the latent variables, which could complicates the classical numerical optimization. Using MCMC sampling such as the Metropolis-Hastings algorithm, the draws that violate the constraints will be directly rejected.

[14] The online appendix of Hsieh and Van Kippersluis (2016) provides heuristic arguments on how we can identify the coefficients in the network formation and outcome equations.

We specify the prior distributions for θ, latent variables $\{Z_g\}$, and group effects $\{\tau_g\}$ as follows:

$$z_{i,g} \sim \mathcal{N}_{\bar{d}}(\mu_{z,g}, I_{\bar{d}}), \quad i = 1, \cdots, m_g; \; g = 1, \cdots, G, \tag{20}$$

$$\omega = (\gamma', \zeta') \sim \mathcal{N}_{G+R+\bar{d}}(\omega_0, \Omega_0) \text{ on the support } O_1, \tag{21}$$

$$\Lambda = (\lambda, \lambda^{\mathrm{I}}) \sim U_2(O_2), \tag{22}$$

$$\xi = (\beta_1', \beta_2', \eta^{\mathrm{I}}) \sim \mathcal{N}_{2k+1}(\xi_0, Q_0), \tag{23}$$

$$\sigma_v^2 \sim \mathcal{IG}(\frac{\kappa_0}{2}, \frac{\nu_0}{2}), \tag{24}$$

$$\delta = (\delta_1', \delta_2') \sim \mathcal{N}_{2\bar{d}}(\delta_0, \Delta_0), \tag{25}$$

$$\tau_g \sim \mathcal{N}(\tau_0, T_0), \quad g = 1, \cdots, G, \tag{26}$$

where $\mathcal{IG}$ represents an inverse Gamma distribution. The coefficients γ and η in the function $\psi_{ij,g}$ of Equation (13) are grouped into ω with the support on O_1 where the identification constraint $|\eta_1| \geq |\eta_2| \geq \cdots \geq |\eta_{\bar{d}}|$ is held. For the endogenous effects λ and λ^{I}, we employ a bivariate uniform distribution with a restricted parameter space O_2.[15] The other priors are the commonly used conjugate (uninformative) priors in the Bayesian literature. We choose hyperparameters $\xi^2 = 2$, $\omega_0 = 0$, $\Omega_0 = 100$, $\beta_0 = 0$, $B_0 = 100$, $\kappa_0 = 2.2$, $\nu_0 = 0.1$, $\delta_0 = 0$, $\Delta_0 = 100$, $\tau_0 = 0$, $T_0 = 100$ to ensure that the prior densities are relatively flat over the range of the data. More details on the conditional posterior distributions can be found in Appendix A.

4.2 Simulation Study

We conduct a Monte Carlo simulation study to evaluate the performance of our proposed estimation approach. Also, through the simulation, we can investigate the potential bias inherited in the misspecified models when altruistic preference, direct externality, and endogenous network formation are not accounted for. We use the altruistic social interactions model of Equation (16) with endogenous network formation of Equation (13) as data generating process (DGP) to generate the artificial network and outcome data. The generated sample consists of 30 networks and each network has 50 individuals. The true parameters used in this DGP are shown in the first column of Table 1. The number of Monte Carlo repetitions is set

[15] The restricted parameter space O_2 reflects the stationary condition required by the outcome equation, which is the matrix $S_g = I_{m_g} - \lambda_{11} W_{11,g} - \cdots - \lambda_{22} W_{22,g}$, $g = 1, \cdots, G$, is invertible, i.e., $det(S_g) > 0$, $g = 1, \cdots, G$, where $det(\cdot)$ stands for the determinant. With an invertible S_g, the outcome vector Y_g is guaranteed not to explode. Due to the restriction imposed on the support of prior distributions, we reject Metropolis-Hastings candidate values of λ which violate this stationary condition during the posterior simulation.

to 100.[16]

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. The simulation results are summarized in Table 1. Model (I) stands for the true DGP model, i.e., Equation (13) and Equation (16). The results under Model (I) show that our proposed procedure works well: all estimated parameters only contain insignificant sampling biases. Model (II) stands for a misspecified model in which we omit the direct externality effect, i.e., η^{I}, from Equation (16). The results in Model (II) display a significant downward bias (29%) on the estimate of inward endogenous effect (λ^{I}). From the formula of omitted variable bias, the direction of bias can be inferred from $sign(\eta^{\mathrm{I}} \times Corr(W_g'Y_g, W_g'l_g)) = (-) \times (+) = -$, therefore the downward bias on λ^{I} is justified. Model (III) is another misspecified model where the inward endogenous effect in Equation (16) 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, $sign(\lambda^{\mathrm{I}} \times Corr(W_g'Y_g, W_g'l_g)) = (+) \times (+) = +$. In addition, the peer effect estimate λ is biased upward by 37%. We next take away both λ^{I} and η^{I} from Equation (16), which results in the standard SAR model. In particular, Model (IV) addresses endogenous network formation, while Model (V) simply takes networks as exogenously given. The results show significant upward biases (more than 48%) on the estimate of endogenous effect λ, in both Models (IV) and (V). These findings not only confirm that ignoring network endogeneity would result in an upward bias on λ (Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016), but more importantly, show that existing models in the literature still do not deliver the true endogenous effect due to the significant upward bias caused by the omitted altruism and externality.

We consider another DGP based on the heterogeneous altruistic social interactions model of Equation (18) and network formation of Equation (15). The true parameters are reported in the first column of 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 (18) and see a downward bias (39%) on the estimates of endogenous effect λ and an upward bias (28%) on the estimates of reciprocality coefficient ρ. In Model (III), we exclude both ρ and η from Equation (18) and in Model (IV), we further take the networks as exogenous. Again, we see that ignoring altruism and externality could cause significant upward bias on the estimate of λ, as well as other parameters, even when the the network endogeneity problem has been properly controlled for.

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

5 Empirical Study

The aims of our empirical study are twofold. First, we would like to estimate the proposed altruistic social interactions model for different outcomes so that we can examine the magnitudes of altruism and the direct externality effect which have never been identified in the social interaction 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 empirical study is based on the Add Health data,[17] which is a longitudinal study on a nationally representative sample covering adolescents in grade 7 through 12 (average age from 12 to 17) from a total of 142 schools. With the purpose of understanding 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 backgrounds, academic performance, health related behaviors and the like. A unique and desirable feature about Add Health is that each respondent was asked to nominate their male and female friends so that researchers can use the information to construct students' friendship networks.

We define groups at the school level. To reduce the computational burden, we pick a sample of 24 schools, each with size ranging from 15 to 245.[18] 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, etc). These outcomes have been extensively studied in the literature, especially academic achievement and smoking.[19] In general, the lit-

[17]This is a program project designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris, and funded by a grant P01-HD31921 from the National Institute of Child Health and Human Development, with cooperative funding from 17 other agencies. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Persons interested in obtaining data files from Add Health should contact Add Health, Carolina Population Center, 123 W. Franklin Street, Chapel Hill, NC 27516-2524 (addhealth@unc.edu). No direct support was received from grant P01-HD31921 for this analysis.

[18]The computation cost comes from estimating the network formation model where the computational time increases exponentially with the network size.

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

erature shows that there exists significant peer effects for these outcomes. In this paper we offer a unique opportunity to examine the sustainability of these findings under a more general model specification which takes into account 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. The summary statistics of variables are provided in Table 2.

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 model of Equation (5), and the altruistic social interactions model with direct externality from peers' outcome of Equation (7). For the four outcome variables, we only find significant altruism for GPA and smoking, but not for club participation or misconducts.[20] 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 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 effects 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 (5), the estimated endogenous effects in the second panel under Model (II) decrease to 0.0610 (by 13%). Meanwhile, we observe a significant estimate of λ^{I}.[21] Model (III) is similar to the model specification in Mihaly (2009) which introduces an indgree centrality as a measure of popularity. We can see that the estimated endogenous effect is almost identical to the one under Model (I), and the coefficient on indgree centrality is 0.021 and highly significant. Mihaly (2009) and other studies would regard this as the positive effect of popularity on an individual's outcome. However, from our specification, we see that what this coefficient captures in this mispecified Model (III) is the mixture effects of altruism and externality. When further incorporating the direct externality effect of peers' outcome, the results under Model (IV) show that the estimated endogenous effect further re-

See Ballester et al. (2010), Patacchini and Zenou (2012) for misconducts (delinquent behaviors).

[20] In Appendix Table A2, one can see the estimates of both λ^{I} and η^{I} for club participation and misconducts are insignificant, while the estimates of λ are significant. Thus, we can infer that the estimate of altruism level α is insignificant.

[21] 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.

duces to 0.0450, lower than the conventional model by 36%. And the estimates of λ^{I} and η^{I} are 0.0302 and -0.0701, 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 estimate jointly the altruistic social interactions model of Equation (16) and the endogenous network formation model of Equation (13). The estimation results are presented under Model (V) in Table 3.[22] We can see that the estimated endogenous effect λ further drops 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, both remain highly significant. Based on the estimate of λ^{I}, we can derive the altruism level α, which equals to 0.6765. Furthermore, based on the derived altruism level and the estimate of η^{I}, we can uncover the direct externality effects generated by peers' GPA to be -0.0823. Therefore, peers' academic achievement not only generates a positive complementary or spillover effect on a student, but also a negative direct externality effect, which could be due to the competition pressure. The estimated negative externality effect reveals an unexplored pattern in existing social interactions studies and implies that the net effects generate by peers could be positive or negative, depending on the relative magnitudes of these two opposite mechanisms generated by peers: spillover effects and direct externality effects.

For 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 on GPA, 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 result show significant homophily effects on individual characteristics for friendship formation. All three dummy variables – same age, same sex, and same race – which capture similarity between individual pairs, show positive effects on the probability of forming friendship nomination. In particular, the effect of same age is the strongest, followed by the effect

[22]Note that the results Under Model (V) in Table 3 are based on the model with unobserved latent variables in three dimensions, which is chosen as the optimal dimension by the AICM (Akaike's information criterion - Monte Carlo) proposed by Raftery et al. (2007), which is an estimate of the conventional AIC. We estimate the models with different dimensions of latent variables and the dimension of three achieves the smallest AICM value compared to other latent dimensions. The detailed estimation results for models with other dimensions are provided in Appendix Tables A3. Besides 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, 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.

of same race and then that of same sex. We also find significant homophily effects on latent variables, i.e., individuals who are similar in terms of unobservables are more 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 (IV), by 36%. Again, in both Models (IV) and (V), we can 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 the two models, η^{I} decreases by 7.8% after endogeneity in network formation is controlled for in Model (V). In addition, although both λ^{I} and η^{I} are significant in the correctly specified full model, neither is significant in Model (II) or Model (III), where the other effect is ignored. 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). On the other hand, peers' smoking behaviors generate a much larger direct negative externality effect, which could be due to the adverse impact of smoking on health and the environment, and so on.

For 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. On the other hand, students who are older tend to smoke more. For contextual effects, having older friends tend to decrease the an individual's smoking frequency. For network formation, the results on smoking behaviors confirms what we find for the GPA sample, i.e., individuals who are similar in terms of observed characteristics such as age, race, and sex, as well as in terms of unobservables are more likely to form friendship networks.

5.2.2 Directed Altruistic Social Interactions Model

To empirically examine whether there is evidence for directed altruism, i.e., stronger altruism toward friends, we apply the directed altruistic social interactions model of Equation (9) to our sample. The results are presented in Table 5. We consider both the cases: with or without the direct externality. However, in both case that we obtain insignificant estimates of λ^{R} and η^{R} for both GPA and smoking. Therefore, we do not find evidence for directed altruism in our sample.

5.2.3 Heterogeneous Altruistic Social Interactions Model

In this subsection, we estimate the heterogeneous altruistic social interactions model of Equation (18) and the extended network formation model of Equation (15). The results for GPA 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 dimension of latent variables as the desired model for both GPA and smoking.

The estimated endogenous effects are 0.0492 and 0.0747 for GPA and smoking, respectively, both are highly significant. Compared to the results of the conventional social interactions models 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 significant attitudes toward fairness. The direct externality effects are still negative for both GPA and smoking: -0.1303 and -0.4344, respectively. Again, the direct externality effect is found to be stronger for smoking than for GPA.

From the endogenous network formation model, for both 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. Again, 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.

6 Conclusion

The classic self-interest hypothesis plays an essential role in conventional economics models, including the SAR models, which have been widely employed in social interaction studies. However, more and more experimental and field studies provide evidence that people are are altruistic. As social interactions occur on a regular basis and within small groups, altruism is expected to play an important role is individuals' decision making. Therefore, there is a need for relaxing the selfish assumption under the social interaction framework.

This paper provides the first analysis of both social interactions and social preferences in social networks. We combine a general altruistic utility with the specific quadratic specification of Ballester et al. (2006) to study social interactions when individuals hold altruistic preferences. We demonstrate that more enriched network features can be captured in the best response function derived from the maximization of the extended utility, therefore provide 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 estimates of peer affects are about 36% smaller under altruistic preferences as compared to the case with conventional self-interest assumption, for both 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, we find significant negative externality effects directly generated from peers' outcomes, besides the positive spillover effects from peers. Interestingly, we find that peers' smoking behaviors generate a much larger direct negative externality effect compared to peers' academic achievement. The estimated negative externality effect reveals an unexplored pattern in existing social interactions studies and implies that the net effects generate by peers could be positive or negative, depending on the relative magnitudes of these two opposite mechanisms generated by peers. The results from the network formation model show significant homophily effects not only on observed characteristics, such as same age, same sex, and same 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). And in the second extended model, i.e. the heterogeneous altruistic social interactions model, we show evidence for heterogeneous altruism based on fairness and reciprocality (Levine, 1998). And individual altruism levels also play an important role in friendship network formation.

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 altruistic social interactions model with endogenous networks, i.e., Equation (13) and Equation (16). Model (II): altruistic social interactions model WITHOUT direct externality effect, i.e., Equation (13) and Equation (16) without η^{I}. Model (III): Altruistic social interactions model WITHOUT inward endogenous effect, i.e., Equation (13) and Equation (16) without λ^{I}. Model (IV): conventional social interactions model, i.e., Equation (13) and Equation (16) 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 values shown for each parameter are the mean bias and the standard deviation from the point estimates across repetitions.

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
Welfare	0	1	0.0109	0.1040
Job missing	0	1	0.0738	0.2615
Professional	0	1	0.2642	0.4410
Other job	0	1	0.3452	0.4755
Homemaker	0	1	0.2338	0.4233
group size	15	245	171.9986	66.1802
Number of groups (schools)			24	
Observations			2,926	

Note: Both parents means living with both parents. Less HS means student's mother only owned lower than high-school degree. More HS means student's mother owned higher than high-school degree. Variables in italic will be treated as omitting groups.

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^2_ϵ	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^{***} 0.3508^{***}
					(0.4237) (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)
$\|z_{i1} - z_{j1}\|$					-2.7531***
					(0.0603)
$\|z_{i2} - z_{j2}\|$					-2.6681***
					(0.0544)
$\|z_{i3} - z_{j3}\|$					-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 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 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^2_ϵ	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 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 6: Estimation Results: (Levine) 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)	
$\|z_{i1} - z_{j1}\|$	-2.7467***		-2.6177***		-2.7889***		-2.6585***	
	(0.0421)		(0.0458)		(0.0496)		(0.0526)	

Continued on Next Page

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 latent variables Z used in network formation and outcome equations. 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.

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Appendix

A Conditional posterior distributions

We use the Bayesian MCMC approach to estimate unknown parameters in our models. Taking Equations (15) and (??)) for example, the joint probability function of $\{Y_g, W_g\}_{g=1}^G$ can be written as follows,

$$\begin{aligned} &P(\{Y_g\}, \{W_g\}|\{X_g\}, \{C_g\}, \theta, \{\tau_g\}) \\ &= \prod_{g=1}^{G} \int_{Z_g} \int_{A_g} P(Y_g|W_g, X_g, A_g, Z_g, \theta, \tau_g) \cdot P(W_g|C_g, A_g, Z_g, \theta) \cdot f(A_g) \cdot f(Z_g) dA_g dZ_g, \end{aligned} \tag{27}$$

where $\theta = (\gamma', \zeta', \lambda, \rho, \eta, \beta', \delta', \sigma_v^2)$. There are two reasons why we adopt the Bayesian approach instead of the classical approach. First, the model involves multi-dimensional individual latent variables. As a result, it is difficult to handle high-dimensional integrations in Eq. (27) under the classical approach. Compared to the classical approach, the Bayesian MCMC is more effective in handling estimation of models with latent variables (Zeger and Karim, 1991; Hoff et al., 2002; Handcock et al., 2007). During the posterior MCMC simulation, latent variables $\{A_g\}_{g=1}^G$ and $\{Z_g\}_{g=1}^G$ are also drawn from the conditional posterior distributions along with the other model parameters. Conditional on these latent variables, evaluation of the probability function becomes much simpler. Second, we have some parameter constraints for the latent variables, which generally increases the difficulty of a classical numerical optimization. Using a Bayesian MCMC rejection sampling method such as the Metropolis-Hastings algorithm, the draws that violate the constraints will be directly rejected.

We specify the prior distributions for θ, latent variables $\{A_g\}$, $\{Z_g\}$, and group effects $\{\tau g\}$ as follows:

$$a_{i,g} \sim U[-1, 1], \quad i = 1, \cdots, m_g; \ g = 1, \cdots, G, \tag{28}$$

$$z_{i,g} \sim \mathcal{N}_{\bar{d}}(\mu_{z,g}, I_{\bar{d}}), \quad i = 1, \cdots, m_g; \ g = 1, \cdots, G, \tag{29}$$

$$\omega = (\gamma', \zeta') \sim \mathcal{N}_{\bar{q}+R+\bar{d}}(\omega_0, \Omega_0) \text{ on the support } O_1, \tag{30}$$

$$\Lambda = (\lambda, \rho, \eta) \sim U_3(O_2), \tag{31}$$

$$\beta = (\beta_1', \beta_2') \sim \mathcal{N}_{2k}(\beta_0, B_0), \tag{32}$$

$$\sigma_v^2 \sim \mathcal{IG}(\frac{\kappa_0}{2}, \frac{\nu_0}{2}), \tag{33}$$

$$\delta = (\delta_1', \delta_2') \sim \mathcal{N}_{2\bar{d}}(\delta_0, \Delta_0), \tag{34}$$

$$\tau_g \sim \mathcal{N}(\tau_0, A_0), \quad g = 1, \cdots, G, \tag{35}$$

where $\mathscr{IG}$ represents an inverse Gamma distribution. The coefficients γ and η in the function $\psi_{ij,g}$ of Eq. (4) are grouped into ω with the support on O_1 where the identification constraint $|\eta_1| \geq |\eta_2| \geq \cdots \geq |\eta_{\bar{d}}|$ is held. For the endogenous effect λ, we employ a multivariate uniform distribution with a restricted parameter space O_2.[23] The other priors are the commonly used conjugate (uninformative) priors in the Bayesian literature. We choose hyperparameters $\xi^2 = 2$, $\omega_0 = 0$, $\Omega_0 = 100$, $\beta_0 = 0$, $B_0 = 100$, $\kappa_0 = 2.2$, $\nu_0 = 0.1$, $\delta_0 = 0$, $\Delta_0 = 100$, $\alpha_0 = 0$, $A_0 = 100$ to ensure that the prior densities are relatively flat over the range of the data. We leave the detailed conditional posterior distributions in Appendix A.

Here we list the set of derived conditional posterior distributions that serve as input to the Gibbs sampler:

(i-1) $P(z_{i,g}|Y_g, W_g, \theta, \alpha_g, Z_{-i,g})$, $i = 1, \cdots, m_g$, $g = 1, \cdots, G$.
By applying Bayes' theorem,

$$P(z_{i,g}|Y_g, W_g, \theta, \alpha_g, Z_{-i,g}) \propto \phi_{\bar{d}}(z_{i,g}; \mu_{z,g}, I_{\bar{d}}) \cdot P(Y_g, W_g|\theta, \alpha_g, Z_g), \tag{36}$$

where $\phi_{\bar{d}}(.; \nu_{z,g}, I_{\bar{d}})$ is the multivariate normal density function. We simulate $z_{i,g}$ from $P(z_{i,g}|Y_g, W_g, \theta, \alpha_g, Z_{-i,g})$ using the Metropolis-Hastings (M-H) algorithm.

(i-2) $P(\mu_{z,g}|Y_g, W_g, \theta, \alpha_g, Z_g)$, $g = 1, \cdots, G$.
By applying Bayes' theorem,

$$P(\mu_{z,g}|Y_g, W_g, \theta, \alpha_g, Z_g) \propto \mathscr{N}_{\bar{d}}\left(\frac{m_g \bar{Z}_g}{m_g + 1/\xi^2}, \frac{1}{m_g + 1/\xi^2}\right), \tag{37}$$

where $\bar{Z}_g = \frac{1}{m_g}\sum_{i=1}^{m_g} z_{i,g}$.

(ii) $P(\omega|\{W_g\}, \{Z_g\})$.
By applying Bayes' theorem, we have

$$P(\omega|\{W_g\}, \{Z_g\}) \propto \phi_{\bar{q}+R+\bar{d}}(\omega; \omega_0, \Omega_0) \cdot \prod_{g=1}^{G} P(W_g|Z_g, \phi) \cdot I(\omega \in O_1), \tag{38}$$

where $I(A)$ is an indicator function with $I(A) = 1$ if A is true and zero otherwise. We simulate ω from $P(\omega|\{W_g\}, \{Z_g\})$ using the M-H algorithm.

[23] The restricted parameter space O_2 reflects the stationary condition required by the outcome equation of the SC-SAR model, which is the matrix $S_g = I_{m_g} - \lambda_{11}W_{11,g} - \cdots - \lambda_{22}W_{22,g}$, $g = 1, \cdots, G$, is invertible, i.e., $det(S_g) > 0$, $g = 1, \cdots, G$, where $det(\cdot)$ stands for the determinant. With an invertible S_g, the outcome vector Y_g is guaranteed not to explode. Due to the restriction imposed on the support of prior distributions, we reject Metropolis-Hastings candidate values of λ which violate this stationary condition during the posterior simulation.

(iii) $P(\lambda|\{Y_g\},\{W_g\},\beta,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\})$.

By applying Bayes' theorem, we have

$$P(\lambda|\{Y_g\},\{W_g\},\beta,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\}) \propto \prod_{g=1}^{G} P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g)\cdot I(\lambda\in O_2). \tag{39}$$

We simulate λ from $P(\lambda|\{Y_g\},\{W_g\},\beta,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\})$ using the M-H algorithm.

(iv) $P(\beta|\{Y_g\},\{W_g\},\lambda,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\})$.

By applying Bayes' theorem, we have

$$\begin{aligned} &P(\beta|\{Y_g\},\{W_g\},\lambda,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\}) \\ &\qquad \propto \phi_{2k}\left(\beta;\beta_0,B_0\right)\cdot\prod_{g=1}^{G} P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g). \end{aligned}$$

Since both $\phi_{2k}\left(\beta;\beta_0,B_0\right)$ and $P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g)$ are normal density functions, we simplify the expression to

$$\begin{aligned} &P(\beta|\{Y_g\},\{W_g\},\lambda,\sigma_u^2,\delta,\{\alpha_g\},\{Z_g\}) \propto \mathscr{N}_{2k}\left(\beta;\hat{\beta},\mathbf{B}\right) \\ &\hat{\beta} = \mathbf{B}\left(B_0^{-1}\beta_0 + \sum_{g=1}^{G}\mathbf{X}_g'(\sigma_u^2 I_{m_g})^{-1}(S_gY_g - \mathbf{Z}_g\delta - l_g\alpha_g)\right) \\ &\mathbf{B} = \left(B_0^{-1} + \sum_{g=1}^{G}\mathbf{X}_g'(\sigma_u^2 I_{m_g})^{-1}\mathbf{X}_g\right)^{-1}, \end{aligned} \tag{40}$$

where $\mathbf{X}_g = (X_g, W_gX_g)$, $\mathbf{Z}_g = (Z_g, W_gZ_g)$, and $S_g = (I_{m_g} - \lambda_{11}W_{11,g} - \cdots - \lambda_{22}W_{22,g})$.

(v) $P(\sigma_u^2|\{Y_g\},\{W_g\},\lambda,\beta,\delta,\{\alpha_g\},\{Z_g\})$.

By applying Bayes' theorem, we have

$$\begin{aligned} &P(\sigma_u^2|\{Y_g\},\{W_g\},\lambda,\beta,\delta,\{\alpha_g\},\{Z_g\}) \\ &\qquad \propto \mathscr{IG}\left(\sigma_u^2;\frac{\kappa_0}{2},\frac{\nu_0}{2}\right)\prod_{g=1}^{G} P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g) \\ &\qquad \propto \mathscr{IG}\left(\sigma_u^2;\frac{\kappa_0+\sum_{g=1}^{G} m_g}{2},\frac{\nu_0+\sum_{g=1}^{G} u_g'u_g}{2}\right), \end{aligned} \tag{41}$$

where $u_g = S_gY_g - \mathbf{X}_g\beta - \mathbf{Z}_g\delta - l_g\alpha_g$.

(vi) $P(\delta|\{Y_g\},\{W_g\},\lambda,\beta,\sigma_u^2,\{\alpha_g\},\{Z_g\})$.

By applying Bayes' theorem, we have

$$P(\delta|\{Y_g\},\{W_g\},\lambda,\beta,\sigma_u^2,\{\alpha_g\},\{Z_g\}) \\ \propto \mathscr{N}_{2\bar{d}}(\delta;\delta_0,\Delta_0)\prod_{g=1}^{G}P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g), \tag{42}$$

Similar to (v), we can further obtain

$$\begin{aligned} &P(\delta|\{Y_g\},\{W_g\},\lambda,\beta,\sigma_u^2,\{\alpha_g\},\{Z_g\}) \propto \phi_{2\bar{d}}(\delta;\hat{\delta},\mathbf{D}), \\ &\hat{\delta} = \mathbf{D}\left(\Delta_0^{-1}\delta_0 + \sum_{g=1}^{G}\mathbf{Z}_g'(\sigma_u^2 I_{m_g})^{-1}(S_gY_g - \mathbf{X}_g\beta - l_g\alpha_g)\right) \\ &\mathbf{D} = \left(\Delta_0^{-1} + \sum_{g=1}^{G}\mathbf{Z}_g'(\sigma_u^2 I_{m_g})^{-1}\mathbf{Z}_g\right)^{-1}, \end{aligned} \tag{43}$$

(vii) $P(\alpha_g|Y_g,W_g,\lambda,\beta,\sigma_u^2,\delta,Z_g)$, $g=1,\cdots,G$.

By applying Bayes' theorem, we have

$$P(\alpha_g|Y_g,W_g,\lambda,\beta,\sigma_u^2,\delta,Z_g) \propto \phi(\alpha_g;\alpha_0,A_0)\cdot P(Y_g|W_g,\lambda,\beta,\sigma_u^2,\delta,\alpha_g,Z_g). \tag{44}$$

Similar to (v), we can further obtain

$$\begin{aligned} &P(\alpha_g|Y_g,W_g,\lambda,\beta,\sigma_u^2,\delta,Z_g) \propto \mathscr{N}(\alpha_g;\hat{\alpha}_g,R_g), \\ &\hat{\alpha}_g = R_g\Big(A_0^{-1}\alpha_0 + l_g'(\sigma_u^2 I_{m_g})^{-1}(S_gY_g - \mathbf{X}_g\beta - \mathbf{Z}_g\delta)\Big), \\ &R_g = \Big(A_0^{-1} + l_g(\sigma_u^2 I_{m_g})^{-1}l_g'\Big)^{-1}. \end{aligned} \tag{45}$$

B Additional Tables and Figures

Table A1: Monte Carlo Simulation Result – (Levine) Heterogeneous Altruistic Social Interactions model with Endogenous networks

		Model (I)		Model (II)		Model (III)		Model (IV)	
Parameters	True	Bias	S.d.	Bias	S.d.	Bias	S.d.	Bias	S.d.
λ	0.0500	0.0060	0.0055	-0.0197	0.0130	0.0134	0.0069	0.0640	0.0076
ρ	0.5000	0.0249	0.1495	0.1219	0.0977	-	-	-	-
η	-0.3000	0.0108	0.0558	-	-	-	-	-	-
β_1	0.5000	0.0034	0.0165	0.0025	0.0160	0.0024	0.0174	0.0014	0.0172
β_2	0.2000	-0.0036	0.0130	0.0072	0.0137	-0.0073	0.0121	-0.0348	0.0140
δ_1	0.5000	0.1133	0.0229	0.0433	0.0284	0.0698	0.0232	-	-
δ_2	0.2000	-0.1239	0.0164	-0.0543	0.0265	-0.1116	0.0131	-	-
δ_3	0.5000	-0.0634	0.1449	0.3289	0.4159	-	-	-	-
δ_4	0.2000	0.0694	0.0693	0.0332	0.0871	-	-	-	-
γ_0	-2.2000	0.0112	0.0323	0.0251	0.0327	0.0869	0.0224	-	-
γ_1	0.3000	-0.0053	0.0206	-0.0030	0.0204	-0.0060	0.0226	-	-
γ_2	0.3000	0.0169	0.0458	0.0956	0.0635	-	-	-	-
γ_3	0.3000	0.0036	0.0453	-0.1634	0.1151	-	-	-	-
ζ	-1.0000	-0.0110	0.0422	-0.0393	0.0443	-0.0885	0.0327	-	-
σ^2	1.0000	-0.0380	0.0308	-0.1942	0.1125	0.1172	0.0250	0.5315	0.0308

Note: Model (I): Heterogeneous altruistic social interactions model, i.e., Equation (15) and Equation (18). Model (II): Heterogeneous altruistic social interactions model WITHOUT direct externality effect, i.e., i.e., Equation (15) and Equation (18) without ρ . Model (III): conventional social interactions model with endogenous networks. Model (IV): conventional social interactions model, i.e., Equation (3). We conduct a Monte Carlo simulation study with 100 repetitions. The values shown for each parameter are the mean bias and the standard deviation from the point estimates across 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.

Table A2: Estimation Result for Club participation and Misconducts

	SAR Model				SAR Model with Altruistic Preference			
	Club		Misconduct		Club		Misconduct	
λ	0.0500***		0.0489***		0.0471***		0.0497***	
	(0.0074)		(0.0075)		(0.0113)		(0.0179)	
λ^{I}					0.0049		0.0003	
					(0.0111)		(0.0171)	
η^{I}					0.0617		0.0047	
					(0.0454)		(0.0204)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.2811***	0.0163	0.4279***	−0.0095	−0.2448***	0.0070	0.4302***	−0.0117
	(0.0674)	(0.0411)	(0.0394)	(0.0243)	(0.0671)	(0.0413)	(0.0386)	(0.0240)
Age	−0.0432	0.0024	−0.0078	−0.0046	−0.0435	0.0010	−0.0133	−0.0047**
	(0.0276)	(0.0034)	(0.0163)	(0.0019)	(0.0303)	(0.0037)	(0.0170)	(0.0022)
Black	0.4265***	−0.1006***	−0.3249***	0.0194	0.4431***	−0.0866***	−0.3240***	0.0202
	(0.1288)	(0.0351)	(0.0755)	(0.0205)	(0.1265)	(0.0348)	(0.0754)	(0.0207)
Asian	0.3428	−0.0297	−0.0280	−0.0535	0.3739	−0.0020	−0.0273	−0.0504
	(0.2327)	(0.1067)	(0.1366)	(0.0626)	(0.2349)	(0.1092)	(0.1357)	(0.0609)
Hispanic	0.2212*	0.0171	−0.0456	0.0276	0.2280	0.0250	−0.0440	0.0279
	(0.1426)	(0.0702)	(0.0836)	(0.0410)	(0.1421)	(0.0683)	(0.0854)	(0.0419)
Other race	0.1089	−0.0415	−0.0022	−0.0552	0.1561	−0.0014	−0.0004	−0.0533
	(0.1441)	(0.0819)	(0.0844)	(0.0480)	(0.1449)	(0.0818)	(0.0848)	(0.0480)
Both parents	0.0616	−0.0524	−0.0510	−0.0211	0.0327	−0.0373	−0.0535	−0.0210
	(0.0757)	(0.0421)	(0.0445)	(0.0246)	(0.0752)	(0.0416)	(0.0449)	(0.0243)
Less HS	0.0033	−0.0811	0.0626	0.0551	0.0227	−0.0772	0.0639	0.0539
	(0.1088)	(0.0604)	(0.0638)	(0.0356)	(0.1097)	(0.0588)	(0.0638)	(0.0364)
More HS	0.3307***	−0.0177	−0.0662	0.003	0.3288***	−0.0160	−0.0661	0.0018
	(0.0777)	(0.0377)	(0.0457)	(0.0218)	(0.0766)	(0.0377)	(0.0463)	(0.0219)
Edu missing	0.0736	−0.0871	−0.1799**	0.1242***	0.0982	−0.0778	−0.1791**	0.1238***
	(0.1312)	(0.0789)	(0.0768)	(0.0463)	(0.1311)	(0.0775)	(0.0770)	(0.0464)
Welfare	0.1371	0.3659	−0.1532	0.0567	0.1540	0.3573	−0.1537	0.0540
	(0.3056)	(0.2316)	(0.1793)	(0.1354)	(0.2943)	(0.2289)	(0.1788)	(0.1365)
Job missing	−0.0120	0.0146	(0.0351)	0.0362	−0.0220	0.0207	−0.0353	0.0346
	(0.1289)	(0.0741)	(0.0755)	(0.0435)	(0.1289)	(0.0742)	(0.0775)	(0.0438)
Professional	0.1960**	0.1158***	0.0336	0.0099	0.1840**	0.1003**	0.0297	0.0080
	(0.0912)	(0.0454)	(0.0533)	(0.0265)	(0.0878)	(0.0454)	(0.0520)	(0.0266)
Other job	0.0011	−0.0274	0.0510	−0.0091	0.0072	−0.0325	0.0477	−0.0105
	(0.0802)	(0.0413)	(0.0472)	(0.0242)	(0.0797)	(0.0408)	(0.0467)	(0.0238)
σ_ϵ^2	2.7773***		0.9559***		2.7358***		0.9570***	
	(0.0732)		(0.0252)		(0.0728)		(0.0258)	

Note: 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 A3: Estimation Results for GPA: Altruistic Social Interactions Model with Endogenous Friendship Formation

	D1		D2		D3		D4	
λ	0.0449***		0.0432***		0.0371***		0.0381***	
	(0.0066)		(0.0069)		(0.0064)		(0.0082)	
λ^{I}	0.0299***		0.0289***		0.0251***		0.0270***	
	(0.0067)		(0.0065)		(0.0061)		(0.0075)	
η^{I}	-0.0696***		-0.0671***		-0.0557***		-0.0615***	
	(0.0207)		(0.0206)		(0.0190)		(0.0232)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.1106***	0.0023	−0.1090***	0.0039	−0.1073***	0.0026	−0.1182***	0.0066
	(0.0275)	(0.0166)	(0.0273)	(0.0167)	(0.0273)	(0.0162)	(0.0274)	(0.0167)
Age	−0.0169	−0.0090***	−0.0200**	−0.0089***	−0.0205*	−0.0079***	−0.0185*	−0.0088
	(0.0117)	(0.0017)	(0.0112)	(0.0017)	(0.0121)	(0.0017)	(0.0117)	(0.0019)
Black	−0.0277	0.0046	−0.0397	0.0027	−0.0498	0.0051	−0.0163	−0.0005
	(0.0514)	(0.0141)	(0.0518)	(0.0146)	(0.0519)	(0.0146)	(0.0537)	(0.0152)
Asian	0.1422	0.0374	0.1355	0.0408	0.1245	0.0416	0.1379	0.0437
	(0.0960)	(0.0432)	(0.0948)	(0.0436)	(0.0946)	(0.0424)	(0.0934)	(0.0433)
Hispanic	−0.0466	0.0083	−0.0473	0.0100	−0.0436	0.0176	−0.0392	0.0150
	(0.0577)	(0.0281)	(0.0579)	(0.0284)	(0.0574)	(0.0285)	(0.0576)	(0.0280)
Other Race	−0.0319	−0.0011	−0.0340	−0.0100	−0.0266	−0.0004	−0.0218	0.0037
	(0.0581)	(0.0329)	(0.0584)	(0.0338)	(0.0573)	(0.0329)	(0.0574)	(0.0330)
Both parents	0.0900***	0.0354**	0.0870***	0.0349**	0.0843***	0.0370**	0.0849***	0.0308*
	(0.0305)	(0.0168)	(0.0301)	(0.0175)	(0.0304)	(0.0167)	(0.0307)	(0.0168)
Less HS	−0.0950**	−0.0649***	−0.0913**	−0.0581**	−0.0926**	−0.0613***	−0.0914**	−0.0581**
	(0.0425)	(0.0244)	(0.0444)	(0.0248)	(0.0431)	(0.0243)	(0.0431)	(0.0247)
More HS	0.1435***	0.0014	0.1483***	0.0115	0.1486***	0.0158	0.1457***	0.0082
	(0.0311)	(0.0149)	(0.0316)	(0.0155)	(0.0314)	(0.0153)	(0.0311)	(0.0150)
Edu missing	0.0216	−0.0278	0.0258	−0.0256	0.0153	−0.0309	0.0243	−0.0216
	(0.0531)	(0.0324)	(0.0530)	(0.0318)	(0.0526)	(0.0317)	(0.0535)	(0.0321)
Welfare	−0.0503	−0.1146	−0.0701	−0.1362	−0.0391	−0.0913	−0.0567	−0.0883
	(0.1229)	(0.0927)	(0.1232)	(0.0931)	(0.1227)	(0.0929)	(0.1221)	(0.0944)
Job missing	−0.0984*	−0.0083	−0.0957*	−0.0112	−0.0997*	−0.0108	−0.0994	−0.0142
	(0.0526)	(0.0306)	(0.0525)	(0.0304)	(0.0523)	(0.0299)	(0.0513)	(0.0298)
Professional	0.0313	−0.0271	0.0315	−0.0259	0.0319	−0.0245	0.0379	−0.0259
	(0.0364)	(0.0184)	(0.0365)	(0.0184)	(0.0359)	(0.0184)	(0.0364)	(0.0187)
Other job	−0.0156	0.0120	−0.0148	0.0146	−0.0190	0.0101	−0.0179	0.0076
	(0.0323)	(0.0168)	(0.0325)	(0.0170)	(0.0316)	(0.0168)	(0.0324)	(0.0172)
Z_1	0.0084	−0.0058	−0.0531	0.0032	−0.0312	−0.0021	0.0261	−0.0080
	(0.0176)	(0.0056)	(0.0203)	(0.0052)	(0.0303)	(0.0055)	(0.0194)	(0.0047)
Z_2			0.0415***	−0.0116**	0.0904***	−0.0115**	0.0537**	−0.0083
			(0.0198)	(0.0055)	(0.0297)	(0.0058)	(0.0270)	(0.0058)
Z_3					−0.0742***	−0.0087	0.1238***	−0.0203***
					(0.0280)	(0.0064)	(0.0203)	(0.0054)
Z_4							0.0667*	0.0005
							(0.0362)	(0.0075)
Network								
Age	0.9413***		0.7867***		0.6834***		0.7205***	
	(0.0235)		(0.0283)		(0.0307)		(0.0336)	
Sex	0.3392***		0.3379***		0.3324***		0.3188***	
	(0.0218)		(0.0238)		(0.0265)		(0.0288)	
Race	0.5760***		0.4005***		0.4700***		0.5273***	
	(0.0303)		(0.0361)		(0.0390)		(0.0432)	
$\lvert z_{i1} - z_{j1} \rvert$	-3.6327***		-3.1488***		-2.7547***		-2.6008***	
	(0.0817)		(0.0652)		(0.0649)		(0.0436)	
$\lvert z_{i2} - z_{j2} \rvert$			-2.8433***		-2.6319***		-2.5583***	
			(0.0649)		(0.0443)		(0.0408)	
$\lvert z_{i3} - z_{j3} \rvert$					-2.5459***		-2.5013***	
					(0.0549)		(0.0481)	

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Table – Continued

$\lvert z_{i4} - z_{j4} \rvert$				-1.9911***
				(0.0591)
σ_v^2	0.4522***	0.4497***	0.4389***	0.4361***
	(0.0119)	(0.0118)	(0.0127)	(0.0120)
AICM	88,734	83,398	81,522	81,739

Note: D_i, $i = 1, 2, 3, 4$ refers to the dimensions of latent variables Z used in network formation and outcome equations. 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 A4: Estimation Results for smoking: Altruistic Social Interactions Model with Endogenous Friendship Formation

	D1		D2		D3		D4	
λ	0.0599***		0.0574***		0.0574***		0.0569***	
	(0.0102)		(0.0089)		(0.0093)		(0.0098)	
λ^{I}	0.0359***		0.0382***		0.0366***		0.0340***	
	(0.0100)		(0.0087)		(0.0090)		(0.0094)	
η^{I}	-0.2017***		-0.1904***		-0.1767***		-0.1764***	
	(0.0728)		(0.0668)		(0.0692)		(0.0682)	
	Own	Contextual	Own	Contextual	Own	Contextual	Own	Contextual
Male	−0.4138	−0.1841	−0.4419	−0.1947	−0.3846	−0.2347	−0.3425	−0.2013
	(0.3628)	(0.2157)	(0.3546)	(0.2151)	(0.3543)	(0.2133)	(0.3540)	(0.2129)
Age	0.8307***	−0.0498***	0.8626***	−0.0449**	0.8088***	−0.0420**	0.8482***	−0.0490***
	(0.1249)	(0.0165)	(0.1359)	(0.0170)	(0.1365)	(0.0165)	(0.1326)	(0.0163)
Black	−3.8043***	0.1848	−3.2300***	0.1349	−3.1854***	0.0142	−3.5953***	0.0141
	(0.6808)	(0.1900)	(0.6881)	(0.1949)	(0.6840)	(0.1980)	(0.6936)	(0.1933)
Asian	0.0359	−0.5421	0.2510	−0.4653	0.3822	−0.7343	0.0757	−0.5413
	(1.2321)	(0.5732)	(1.2403)	(0.5523)	(1.2190)	(0.5811)	(1.2300)	(0.5644)
Hispanic	−1.8004**	0.5954	−1.7115**	0.3352	−1.6029**	0.3883	−1.8562**	0.4037
	(0.7608)	(0.3656)	(0.7436)	(0.3720)	(0.7622)	(0.3731)	(0.7477)	(0.3646)
Other Race	0.5850	0.3255	0.7055	0.4043	0.6806	0.2382	0.6549	0.1979
	(0.7646)	(0.4366)	(0.7537)	(0.4313)	(0.7494)	(0.4367)	(0.7471)	(0.4377)
Both parents	−1.7755***	−0.2857	−1.7532***	−0.2406	−1.7092***	−0.2957	−1.7427***	−0.4110*
	(0.4089)	(0.2243)	(0.3982)	(0.2237)	(0.3977)	(0.2245)	(0.3989)	(0.2227)
Less HS	0.4994	0.2857	0.4632	0.2650	0.4986	0.2462	0.4222	0.3061
	(0.5794)	(0.3178)	(0.5696)	(0.3265)	(0.5697)	(0.3254)	(0.5736)	(0.3164)
More HS	−0.2177	0.3328*	−0.3001	0.1991	−0.2029	0.1879	−0.1949	0.3297
	(0.4138)	(0.1976)	(0.4088)	(0.1987)	(0.4084)	(0.2020)	(0.4089)	(0.2071)
Edu missing	0.1214	0.7360*	−0.0243	0.5811	0.0759	0.6576	−0.0569	0.8614**
	(0.6964)	(0.4261)	(0.6985)	(0.4223)	(0.7033)	(0.4161)	(0.6841)	(0.4293)
Welfare	2.0805	0.1576	1.9187	0.0146	2.0555	0.0777	1.6971	−0.0135
	(1.6329)	(1.2353)	(1.5921)	(1.2121)	(1.5936)	(1.2061)	(1.5979)	(1.1813)
Job missing	0.6286	0.6159	0.7265	0.6256	0.7284	0.7239*	0.7010	0.7161*
	(0.6898)	(0.4025)	(0.6883)	(0.4015)	(0.6836)	(0.3985)	(0.6775)	(0.3858)
Professional	0.5808	0.1414	0.5276	0.1570	0.6019	0.2308	0.5500	0.2352
	(0.4778)	(0.2369)	(0.4764)	(0.2377)	(0.4705)	(0.2389)	(0.4741)	(0.2376)
Other job	0.6403	0.0855	0.5905	0.0717	0.6323	0.1758	0.6401	0.2435
	(0.4244)	(0.2171)	(0.4163)	(0.2253)	(0.4204)	(0.2221)	(0.4086)	(0.2167)
Z_1	−0.6053***	0.0962	−1.4469***	0.1804***	−0.0828	0.0825	−2.4976***	0.2811***
	(0.2237)	(0.0671)	(0.2822)	(0.0709)	(0.3098)	(0.0744)	(0.2751)	(0.0670)
Z_2			0.7453***	−0.2760***	0.2004	0.0581	−1.0381***	0.2609***
			(0.2643)	(0.0717)	(0.4410)	(0.0923)	(0.2640)	(0.0689)
Z_3					−1.7947***	0.3508***	1.0764***	−0.1589**
					(0.4237)	(0.0812)	(0.3155)	(0.0739))
Z_4							−0.4839	0.0699
							(0.3422)	(0.0827)
Network								
Age	0.9150***		0.7449***		0.6967***		0.7520***	
	(0.0240)		(0.0286)		(0.0291)		(0.0364)	
Sex	0.3338***		0.3420***		0.3326***		0.3264***	
	(0.0220)		(0.0239)		(0.027)		(0.0285)	
Race	0.5484***		0.4290***		0.4653***		0.5325***	
	(0.0309)		(0.0340)		(0.041)		(0.0495)	
$\|z_{i1}-z_{j1}\|$	-3.6916***		-3.3265***		-2.7531***		-2.5928***	
	(0.0737)		(0.0820)		(0.0603)		(0.0534)	
$\|z_{i2}-z_{j2}\|$			-2.7755***		-2.6681***		-2.5166***	
			(0.0723)		(0.0544)		(0.0581)	
$\|z_{i3}-z_{j3}\|$					-2.4849***		-2.3229***	
					(0.0605)		(0.0454)	

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$\lvert z_{i4} - z_{j4} \rvert$				-2.0793***
				(0.0737)
σ_v^2	78.4844***	76.7708***	76.3781***	73.1263***
	(2.1137)	(2.1259)	(2.1719)	(2.0931)
AICM	103,310	96,393	93,830	95,164

Note: D_i, $i = 1, 2, 3, 4$ refers to the dimensions of latent variables Z used in network formation and outcome equations. 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.