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Beyond dyadic interdependence: Actor-oriented models for co-evolving social networks and individual behaviors

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Actor-oriented models are described as a longitudinal strategy for examining the co-evolution of social networks and individual behaviors. We argue that these models provide advantages over conventional approaches due to their ability to account for inherent dependencies between individuals embedded in a social network (i.e., reciprocity, transitivity) and model interdependencies between network and behavioral dynamics. We provide a brief explanation of actor-oriented processes, followed by a description of parameter estimates, model specification, and selection procedures used by the Simulation Investigation for Empirical Network Analyses (SIENA) software program (Snijders, Steglich, Schweinberger, & Huisman, 2006). To illustrate the applicability of these models, we provide an empirical example investigating the co-evolution of friendship networks and delinquent behaviors in a longitudinal sample of Swedish adolescents with the goal of simultaneously assessing selection and influence processes. Findings suggest both processes play a substantive role in the observed dynamics of delinquent behaviors, with influence having a relatively stronger role than selection (especially in reciprocated friendships).

Keywords: delinquency; friendship networks; interdependence; SIENA

To understand the importance of dyadic relations, and the effects of such relations on individual development, it can be helpful to regard them as being embedded within a larger social network that is comprised of a multitude of interconnected dyadic relationships, where the whole is equal to more than the sum of its parts (Carrington, Scott, & Wasserman, 2005; Hanneman & Riddle, 2005; Wasserman & Faust, 1994). This focuses attention on the mutual dependence between multiple dyadic relations. Some basic types of network dependence are *reciprocity* (Sahlins, 1972), "if you give to me, I will give to you," and *transitivity* (Davis, 1970), "friends of my friends are my friends." Individuals can occupy special positions in networks according to, for example, centrality (Freeman, 1979), degree of involvement in cohesive structures (Moody & White, 2003), or exclusivity of access to other individuals (Burt, 1992). Such positions are also aspects that will be overlooked if only dyadic relations are studied without the network perspective, and network positions can have important consequences for individual behavior.

A dynamic perspective is especially useful for understanding the importance of dyadic relations and networks for individual development and change. Friendships form and dissolve; relations between business partners typically last for a finite amount of time. These changes may result from network mechanisms like reciprocity, transitivity, and network position, or they may result from mechanisms depending on individual characteristics. Examples of the latter are patterns of homophily (i.e., preference for similarity; McPherson, Smith-Lovin, & Cook, 2001) in selection of relationship partners and various determinants of attractiveness. By contrast, characteristics of social actors can be influenced by their position in the social network. For instance, the behavior and attitudes of individuals may follow patterns of assimilation to others to whom they are tied. Changes in network structure are often referred to as *partner selection* (Lazarsfeld & Merton, 1954); changes in actor characteristics that depend on the characteristics of other actors to whom they are tied are called *influence* (Friedkin, 1998). This article proposes statistical models capable of delineating these two processes by simultaneously investigating changes in network structure and changes in individual behaviors.

One application of these models is to explain peer group homogeneity in friendship networks. Simply stated, friends tend to be more similar on various attitudes and behaviors than nonfriends (Cairns & Cairns, 1994; Ennett & Bauman, 1994; Hogue & Steinberg, 1995; Jaccard, Blanton, & Dodge, 2005; Kandel, 1978; Kirke, 2004; Urberg, Degirmencioglu, & Pilgrim, 1997). Researchers agree that this similarity, which is also called network autocorrelation, can be the result of selection, influence, or both simultaneously. Unfortunately, distinguishing the effects of these mechanisms has proven difficult because of the dynamic and interdependent nature of social network characteristics and individual behaviors. Separating the effects of selection and influence requires longitudinal data

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that capture relevant changes in both the social network and the behavior under study, and models for statistical analysis that incorporate both selection and influence effects. Such models have been recently developed, and are explained in this article. An illustrative example is presented in the field of adolescent friendship networks and delinquent behaviors.

Previously, researchers have used a variety of analytic strategies to delineate these two processes, most of which rely on variations of a two-step procedure: (1) network data (i.e., relationship ties) are collapsed or aggregated into either individual-level variables (e.g., sociometric position) or tie-level variables (e.g., dyadic similarity); and (2) these indices are then used in conventional longitudinal analyses (as outcome variables for assessing selection and as predictor variables for assessing influence). The limitations of this procedure are: (1) the individual- or tie-level variables do not fully account for aspects of network structure (e.g., reciprocity, transitivity, network position), so that only rough approximations of selection and influence processes are possible; (2) the observations between relationship partners are interdependent which violates assumptions that underlie conventional statistical methods and thus puts the results obtained into doubt; and (3) the network and behavior dynamics are a process in which feedback occurs between network and behavior in between the measurement points of the panel data, but such unobserved changes are not accounted for. These limitations and specific examples are elaborated in Steglich, Snijders, and Pearson (2007).

Longitudinal social network models

Due to the complicated dependence structures inherent in network data, analyzing social network dynamics is complex and requires sophisticated statistical techniques. Longitudinal network data are typically collected as panel data, where the relations between network actors are observed at two or more discrete time points. It is evident that changes in patterns of relations will have occurred between measurement points, and it has proven helpful to employ statistical models that explicitly postulate such a change process occurring continuously in time.

To model continuous changes between discrete time points, network analysts have utilized continuous-time Markov chains (Snijders, 2001; Wasserman, 1977, 1979). Markov chains are a general type of probabilistic (stochastic) process (Norris, 1997; Taylor & Karlin, 1998). Within a social network context, postulating a Markov process means that the conditional probability distribution of the changes in network ties at any moment depends only on the current network configuration, not on previous configurations.

Several continuous-time Markov chain models of social networks have been formulated. The reciprocity model, proposed by Wasserman (1977, 1979), accounts for interdependencies between dyadic partners. This reflects reciprocity of relations, but not more complicated types of dependence. This initial model was extended to also account for dependencies on individual attributes (Leenders, 1995, 1996), reflecting network similarity effects (i.e., homophilous selection processes). This was generalized by Snijders (2001, 2005) to stochastic actor-oriented models, which are dynamic network models that also account for transitivity and other three- or more-actor dependencies. Such models have been applied to the dynamics of networks for adolescents and young adults by Snijders and Baerveldt (2003), and Van Duijn, Zeggelink, Huisman, Stokman, and Wasseur (2003). Recently this model has been extended to include network–behavioral co-evolution (Snijders, Steglich, & Schweinberger, 2007; Steglich, Snijders, & Pearson, 2007). These are the models explained in this article.

Actor-oriented models for network–behavior co-evolution

It is assumed that at two or more observation moments, a directed network and one or more behavioral variables are observed for a finite set of social actors. The network is a dichotomous relational variable, indicating who directs ties to whom. The behavior is assumed to be a dichotomous or discrete ordinal variable. The actor-oriented network–behavioral models express that actors can change their behavior, and also their network ties, in response to the current network structure and the behavior of the other actors in the network. Formally, these models involve two types of myopic decisions made by actors regarding their outgoing network ties and their own behaviors. That is, each actor is thought to make decisions that optimize his or her position in the network according to short-term preferences and constraints as well as a residual unknown element, modeled as a random deviation. These decisions lead to changes in network ties (e.g., social selection) and changes in behavioral variables (e.g., social influence).

Several statistical assumptions are used in these models to simplify the modeling procedures. The evolution of social networks and individual behaviors are represented separately using transition probabilities between probable states in an overall state space. The state space is comprised of all possible configurations of the combination of network and individual behaviors. Because of the large number of possible transitions within the overall state space, three assumptions are made. First, changes between measurement points are modeled according to a continuous-time Markov process. This means that for obtaining parameter estimates, the model imputes likely developmental trajectories between observation moments (continuous-time property), and that the changes actors make are assumed to depend only on the current state of affairs, not on the past (Markov property). The latter also implies that the contingencies that led to the initial state of affairs at the first observation moment are not considered in the analysis and do not affect the results. Second, actors may change only one network tie (a so-called network micro-step) or one level of behavior (a behavior micro-step) at any moment in time. This eliminates simultaneous changes, for example, a nondelinquent adolescent at the next observation moment committing multiple property offenses and replacing many of his friends. Such big changes are modeled as the cumulative result from a series of smaller, nondeterministically related, changes over time. Third, actors react to each others' changes in network ties and behavior, but do not negotiate or otherwise make joint changes based on a prior agreement. An agreement like "I'll become your friend once you commit some property offense" again is modeled as resulting from two smaller changes, between which the causal link cannot be enforced: "you may commit the property offense, but whether that entails my friendship remains to be seen." These assumptions simplify the dynamic process, and reduce the modeling procedures to two smaller tasks: (1) modeling the preferences and other tendencies guiding the specific changes in network or behavioral micro-steps, referred to as objective functions; and (2) modeling the frequencies of network and behavioral micro-steps, referred to as a rate functions (see Snijders, 2005; and Snijders, Steglich, Schweinberger, & Huisman, 2006, for details). The total observed change between measurement points is decomposed into sequences of many small changes. The estimated model parameters indicate which of these sequences (unobserved trajectories) are most probable, given the observed data.

The separate network evolution and behavior evolution models are integrated because the current state of the continuously changing network is the dynamic constraint for the changes in behavior, and vice versa. The complexity of the resulting model does not allow for its properties to be explicitly calculated, but the model may be implemented as a computer simulation model and parameter estimates can be estimated from iterative simulations within a Markov chain Monte Carlo (MCMC) approach (Snijders, 2005; Snijders et al., 2007).

SIENA: Parameter estimates, model specification, and model selection procedures

Actor-oriented models for network evolution and co-evolving behavioral variables are implemented in the Simulation Investigation for Empirical Network Analyses (SIENA) software program (Snijders et al., 2006). SIENA is one of the statistical modules of StOCNET (Boer et al., 2006), a family of statistical programs for social network analysis. The software programs and respective manuals may be freely downloaded at: http://stat.gamma.rug.nl/stocnet/. Interested readers are also directed to the SIENA homepage (http://stat.gamma.rug.nl/snijders/siena.html), which provides links to many of the references cited here, as well as other manuscripts using or describing the models implemented in SIENA.

SIENA provides estimates of the network and behavioral rate and objective functions. The parameters of the network and behavioral rate functions represent the average number of changes in network and behavioral micro-steps between discrete points. Rates of change are often held constant from one discrete time point to the next, but they may be allowed to depend on actor characteristics. The parameters of the network and behavioral objective functions represent the direction of changes in network and behavioral micro-steps. The parameters described in the following paragraphs correspond to only some of the possible effects describing the network and behavioral objective functions (see Steglich, Snijders, & Pearson, 2007, for a longer list).

The network objective function consists of a combination of several parameters representing endogenous network effects, as well as selection effects associated with dyadic and individual attributes. Of the network effects, the *outdegree* parameter models the overall tendency of actors to have outgoing ties (i.e., the degree of dyadic connection in a network). The outdegree parameter is generally expected to be negative, indicating that actors tend not to have friendship ties with just anyone and ties are unlikely without some kind of network embeddedness. *Reciprocity* is the tendency for actors to reciprocate a relationship (i.e., directed ties that are shared between dyadic partners). The reciprocity parameter is generally expected to be positive, indicating that actors prefer to have reciprocated links. *Transitivity* is the tendency for actors to have transitive triadic patterns of relations (i.e., friends of my friends are friends). *Geodesic distance-2* is the tendency for actors to have indirect ties to others through one intermediate actor. The geodesic distance between two actors is the length of the shortest path between them, and this is equal to 2 if they are not directly connected, but connected through one intermediary. The transitivity and geodesic distance-2 parameters reflect different aspects of transitive closure (friendship groups where there is some tendency for friends-of-friends to become direct friends). The transitivity parameter is expected to be positive. Because the geodesic distance-2 parameter indicates the converse of transitive closure it is expected to be negative.

Various individual and dyadic attributes, or covariates, may also be included for modeling network dynamics. For individual-level covariates, three basic effects may be considered: the *attribute ego* effect (main effect of ego's attribute on partner selection), the *attribute alter* effect (main effect of alters' attribute on partner selection), and the *attribute similarity* effect (tendency for actors to select others with similar characteristics, homophily of choice). Using delinquent behavior as an example, a positive attribute ego effect indicates those with higher values on delinquency have a higher number of outgoing friendship nominations (i.e., a higher activity). A positive attribute alter effect indicates that those with higher values on delinquency have a higher number of incoming friendship nominations (i.e., a higher popularity). A positive attribute similarity effect indicates that individuals tend to nominate others with similar values of delinquency (i.e., homophilous selection). The effects of individual attributes that are constant (e.g., gender) are interpreted in a similar manner. Dyad-level covariates are covariates defined for pairs of actors. As examples, one could think of individuals who attend the same schools or classrooms, geographical distance of two pupils' homes, or a superior–subordinate relation in some formal or informal hierarchy. Each dyadic covariate thus constitutes a network of its own. The main *dyadic attribute* effect represents tendencies to choose partners in the outcome network (say, friendship) based on their connectedness in the covariate network matrix (say, attending the same school). Interactions between individual and dyadic attribute parameters and network-endogenous effects may also be considered.

The behavioral objective function also corresponds to a set of estimated parameters. The *behavioral tendency* parameter models the overall tendency toward high values on a behavioral variable. So, a negative parameter estimate represents a preference or trend for actors to demonstrate low levels of the behavioral attribute; a positive parameter estimate represents a tendency for actors to score high on the behavior. The *behavioral similarity* parameter models tendencies for actors to adopt the behaviors of others. A positive behavioral similarity effect represents an influence effect. Interactions between behavioral parameters and network-endogenous effects may also be considered.

A forward selection procedure of parameter estimates is used to specify a final model. This is preferred over a backward stepwise procedure because the algorithm used to estimate parameters may become unstable if too many effects are included and the standard errors of some parameters may become inflated due to the inclusion of several nonsignificant effects. This selection procedure, described by Snijders et al. (2007), is accomplished in three main steps using Neyman-Rao score tests developed by Schweinberger (2007). In the first step, a dyadic independence model is tested as a null hypothesis to determine if there is empirical evidence for network independence. A statistically significant score test of transitivity effects indicates network interdependence that goes beyond interdependence limited to dyadic relationships. That is, this initial step determines whether dyads are independent of each other in the network, or whether it is necessary to include the more complex network structuring (like transitive closure) that are expressed by the actor-oriented models. The second step tests whether network and behavioral evolution are independent of each other, by fitting a null model in which the dynamics of network and behavior are independent and running a score test for network effects on behavior, and behavior effects on network structure. A statistically significant score test indicates interdependence between network and behavior dynamics. In the third step, an interdependence model is fit to the data. This model includes all network and behavioral parameters of interest and serves to determine more precisely the strength of diverse components of the influence and selection processes.

Summary

To summarize, actor-oriented models provide parameter estimates based on actors' decisions regarding changes in social network ties and changes in individual behaviors. To model changes between discrete time points, network and behavioral micro-steps are estimated using continuous-time Markov chains, which means that the current state of the network, and of all actors' behaviors, determines the probabilities of changes in the network and changes in behavior. The number of changes is modeled with network and behavioral rate functions; the types of changes are modeled with network and behavioral objective functions. The objective functions may be specified by several parameters involving endogenous network effects and effects associated with individual and dyadic covariates. Selection and influence effects are represented, respectively, by changes in network ties depending on the behavior of self and others; and changes in behavioral variables depending on the network.

We illustrate the applicability of these models with an example examining the dynamics of adolescent friendship networks and delinquent behavior. Previous research suggests that adolescents are similar to their friends on delinquent behaviors and incorporate their friends' delinquent behaviors over time (Dishion & Dodge, 2005; Haynie, 2001; Ploeger, 1997; Snijders & Baerveldt, 2003; Vitaro, Trembley, Kerr, Pagani, & Bukowski, 1997). That is, changes in network ties (i.e., friendship selection) and changes in individual behaviors (i.e., peer influence) contribute to the development of adolescent delinquency. However, the extent of the contributions of selection and influence to the observed cross-sectional similarity, or network autocorrelation, has hardly been investigated. In addition to examining the relative contribution of selection and influence processes in explaining homogeneity in delinquency, we explore the possibility that these processes operate differently for unilateral and reciprocated nominations. So, three questions are addressed in this study:

1 Do adolescents select friends based on their levels of delinquent behaviors?
2 Are adolescents influenced by their friends' delinquent behaviors?
3 Does the relative strength of these processes differ for unilateral and reciprocated friendships?

Considering this is the first study to simultaneously investigate these questions, the relative contributions of both processes, as well as specific differences between these two types of relationships, cannot be anticipated.

Method

Participants

The sample included 260 students (132 males and 128 females) attending 52 classrooms in 9 schools in a small city (population 26,000) in central Sweden. Students ranged in age from 10 to 18 years (M = 12.33 years, SD = 1.36) at the outset of the study. Participants were drawn from the first four annual waves of the "10 to 18 Study," an ongoing community-based longitudinal study. The unemployment rate and proportion of single-parent households in the community were similar to other communities in Sweden; mean incomes were about 4% lower than that in the rest of the country. Descriptive statistics and previous results obtained with larger samples from this study are reported by Kerr, Stattin, and Kiesner (2007), Kiesner, Kerr, and Stattin (2004), and Persson, Kerr, and Stattin (2007).

Instruments

Questionnaires were completed in class during regular school hours and administered by trained research assistants. Teachers were not present. Identical questionnaires were completed at each wave of data collection.

Friendship nominations. Every year participants identified up to three important peers, defined as "someone you talk with, hang out with, and do things with;" as well as up to 10 peers with whom they spent time with in school, and up to 10 peers with whom they spent time with out of school. Participants were instructed that peers could be individuals that lived in different communities, be older or younger, boys or girls, but they could not be adults. While siblings and romantic partners could be nominated, only friendship nominations are included in the analyses. Thus, the friendship networks consisted of up to 23 nominations of friends each participant spent time with in school and in their free time.

Minor delinquency. Each year participants completed a 22-item instrument describing delinquent behaviors. This survey was developed and validated by Magnusson, Dunér, and Zetterbloom (1975) and updated by Kerr and Stattin (2000). The present study focuses on six items describing less serious property offenses, such as shoplifting, vandalism, and petty theft. Each item was rated on a 5-point scale: "no, it has never happened"; "1 time"; "2–3 times"; "4–10 times"; or "more than 10 times". Internal consistency measured with Cronbach's alpha was adequate for each of the four waves (.75 to .82).

Procedure

All students in the 13 schools of this community enrolled in grades 4–12 were invited to participate in the study each year. Students were recruited in classrooms during school hours.

Students were informed that participation was voluntary and confidential; they were assured that their answers would not be revealed to parents, teachers, the police, or anyone else. Parents were informed about the study in community meetings and through the mail, where they received a postage-paid card to return if they did not want their child to participate in the study. Parents and youth were informed that either was free to end participation in the study at any time. Youth were not paid for participation, but all students (participants and nonparticipants) were eligible for class parties and drawings provided by the project.

The 81 students in all three 6th grade classrooms from a single school were selected as the target sample (11–13 years old (M = 12.01, SD = 0.28) for this example. Of these, 76 adolescents participated in at least two consecutive waves of data collection, a precondition for inclusion in this investigation. All the friends nominated by this target group, who also participated in at least two consecutive measurement points, were also included. So, the network sample (n = 260) was identified using a modified "snowball" technique. Analyses contrasting the participants in the network sample and those in 6th grade classrooms from other schools revealed no statistically significant differences on demographic characteristics or delinquency.

Plan of analysis

A final model was specified using the three-step procedure outlined in the introduction. This model was designed to simultaneously assess selection and influence effects as they relate to friendship networks and delinquent activities while accounting for several endogenous network effects (e.g., reciprocity, transitivity) and selection effects based on school and classroom membership, adolescent age, and gender. To illustrate differences in selection and influence processes between unilateral and reciprocated nominations, interactions between reciprocity and the delinquency similarity (selection) effect and between reciprocity and the delinquency similarity (influence) effect were also included in the model.

Friendship network data are represented by directed adjacency matrices, which consist of dichotomous cells: the friendship tie directed from actor i to actor j is either present (x_{ij} = 1) or absent (x_{ij} = 0). The two dyadic-covariates (school and classroom) are represented by undirected adjacency matrices (0 = two actors in different schools or different classrooms, respectively; 1 = two actors in the same school or same classroom, respectively). Gender is entered as a constant individual covariate (1 = male and 2 = female). Age is entered as a changing individual covariate, ranging from 10 to 18 years. Delinquency is the dependent behavioral covariate. Because SIENA requires behavioral variables to be in integer form, averages of the six items were multiplied by 10 to give a delinquency score between 10 and 50. Finally, changes in network composition were also included in the model as exogenous events (see Huisman & Snijders, 2003 for details). To account for these changes, the algorithm used to simulate network evolution is extended so that the simulated networks consist of only the actors present in the network at a specific time. This is accomplished in SIENA with an additional data file that identifies when actors join the network and when actors leave the network. In this sample, 10 students joined the network between time 1 and time 2; 3 students joined and 16 students left between time 2 and time 3; and 34 students left between time 3 and time 4.

The three forward procedure steps outlined previously were used to specify the final model. The dyadic independence model included the outdegree and reciprocity parameters, two dyadic covariates (school and classroom), and two individual covariates (gender and age). Joint score tests examined if two triadic effects (transitive triplets and geodesic distance-2) added to the fit of the model. The joint score test statistic was statistically significant, $\chi^2(2)$ = 1886.54, p < .0001, indicating that a pure dyadic relational model (assuming independence between all dyadic relationships) is inadequate for these data. So, we proceed by fitting a model that includes the triadic effects mentioned above. The model with independence between networks and behavior included all of the parameters in the dyadic independence model, the two transitivity parameters, and the behavior tendency parameter. Joint score tests examined if network evolution associated with delinquency, and behavior evolution associated with delinquency of friends and potential friends, added to the fit of the model. The joint score test statistic was statistically significant, $\chi^2(2)$ = 10.87, p < .005, indicating interdependence between network and behavior evolution. This warranted expansion to the interdependence model, which included all parameters in the independence model, as well as a parameter for delinquency-based selection in the network model, and a parameter for friends' influence on delinquency. Also, interactions of these two effects with reciprocity were included to test whether the strength of influence differs between reciprocated and nonreciprocated friendships, and whether delinquency is a stronger determinant of unilateral friendship or of reciprocal friendship.

Results

Table 1 presents some descriptive statistics of the network structure and individual characteristics. Table 2 presents the parameter estimates of the final model. For network evolution, the rate function describes the average number of changes in network ties between measurement points. The endogenous

Table 1
Descriptive statistics of network structure and individual characteristics

	Measurement point			
	Time 1 (n = *247*)	*Time 2* (n = *257*)	*Time 3* (n = *244*)	*Time 4* (n = *210*)
Network structure				
Average outdegree	3.61	3.99	3.64	4.85
Number of ties	572	716	753	768
Reciprocity index	0.49	0.44	0.45	0.46
Individual characteristics				
Age	12.33	13.49	14.44	15.18
Delinquency	1.23	1.28	1.45	1.44

Notes. Average outdegree represents the average number of outgoing network ties. Number of ties represents the total number of network ties. The reciprocity index represents the proportion of reciprocated ties. Age represents the average age of individuals (in years). Delinquency represents the average delinquency score for individuals ranging from 1 (*has not happened*) to 5 (*happened more than 10 times*).

network effects (i.e., the reciprocity, transitivity, and geodesic distance-2 parameters) were all statistically significant. The significant reciprocity effect indicates a preference for reciprocating relationships; the significant transitivity and geodesic distance-2 effects indicate a tendency for transitive closure (i.e., actors prefer relationships with their friends' friends). Specifically, the transitivity effect indicates a preference for being friends with friends' friends and the negative value of the geodesic distance-2 parameter indicates a tendency to not prefer indirect relations to others. In terms of the dyadic attributes, the school effect was significant, whereas the classroom effect was not. This indicates that actors have a tendency to establish relationships with those in the same school, but do not necessary prefer relationships with others in the same class.

Regarding selection effects of individual attributes, gender similarity was a statistically significant predictor of ties, whereas age similarity was not. This indicates a preference for actors to nominate friends of the same gender, but not necessarily others of the same age. The delinquency similarity effect was significant; whereas the interaction between delinquency similarity and reciprocity was not. This indicates that actors tend to nominate others with similar levels of delinquent behaviors in unilateral relationships, but this effect is not significantly stronger in reciprocated relationships. Taken together, these results indicate that adolescents nominate friends who attend the same school, are of the same gender, and are similar in terms of delinquent behaviors.

For behavioral evolution, the rate function describes the average number of changes in behavior between measurement points. The behavioral tendency for delinquency was significant. The negative value of this parameter indicates a propensity for actors to report low levels of delinquent behaviors. Finally, both the delinquency influence effect and the interaction between delinquency influence and reciprocity were statistically significant and positive. This indicates that actors tend to adopt the delinquent behaviors of friends, and that this effect of peer influence is significantly stronger in reciprocated relationships than in unilateral relationships.

This study demonstrates the applicability of actor-oriented models while addressing several substantive research questions concerning the co-evolution of adolescent friendship networks and delinquent behaviors. The model included several endogenous network effects indicating tendencies for reciprocity and transitive closure. In terms of selection processes, adolescents tend to nominate friends who are the same gender and attend the same school, but do not tend to necessarily select friends of the same age or in the same classroom. Adolescents also tend to select friends with similar levels of minor delinquency, and this selection effect is not different between unilateral and reciprocated friendships. In terms of influence processes, adolescents have a tendency to adopt the delinquent behaviors of their friends in unilateral relationships and especially in reciprocated relationships. These findings suggest that both selection and influence processes play a role in the evolution of delinquent behaviors, with influence being particularly important in reciprocated friendships.

Table 2
Parameter estimates of the final model

Parameter	*Estimate*	*Standard error*	t-*value*
Network dynamics			
Rate period 1	3.226	0.302	
Rate period 2	2.881	0.287	
Rate period 3	2.913	0.256	
Outdegree	−2.252	0.427	−5.274***
Reciprocity	2.310	0.104	22.212***
Transitive triplets	0.278	0.018	15.444***
Geodesic distance 2	−0.446	0.041	−10.878***
School	0.243	0.086	2.826**
Classroom	−0.009	0.166	−0.054
Age similarity (selection)	0.118	0.473	0.249
Gender similarity (selection)	0.283	0.065	4.354***
Delinquent similarity (selection)	2.541	1.026	2.477*
Delinquent similarity (selection) × reciprocity	0.824	0.504	1.635
Behavior dynamics			
Rate period 1	−0.522	0.213	
Rate period 2	0.096	0.229	
Rate period 3	0.065	0.208	
Delinquency tendency	−0.724	0.097	−7.464***
Delinquent similarity (influence)	2.437	0.562	4.336***
Delinquent similarity (influence) × reciprocity	5.257	0.442	11.894***

Note. The t-values refer to tests based on the t-ratio defined as parameter estimate divided by standard error.
*$p < .05$; **$p < .01$; ***$p < .001$.

Discussion

Disentangling selection and influences processes presents an analytic challenge to researchers due to the dynamic and interdependent nature of social network ties and individual behaviors. We have provided a general overview of a new statistical method that is meant to overcome this obstacle: actor-oriented models of network and behavioral co-evolution. These models provide parameter estimates based on actors' decisions regarding changes in social network ties (which can represent selection) and changes in individual behaviors (which can represent influence). In addition, this method is capable of simultaneously accounting for various endogenous network effects as well as inherent dependencies between changes in network ties and changes in behaviors. To illustrate the applicability of these models, we presented an empirical investigation of the co-evolution of friendship networks and delinquent behaviors in a longitudinal sample of Swedish adolescents.

Actor-oriented models offer several advantages compared with previous analytic methods. First, actor-oriented models are capable of modeling a variety of endogenous network effects, including interdependencies related to dyads and triads (e.g., reciprocity, transitive network closure). Although recent advances in dyadic analyses (Kenny, Kashy, & Cook, 2005; Zijlstra, van Duijn, & Snijders, 2006) allow researchers to model interdependencies in dyadic relationships, the capability of modeling dependencies associated with triadic and indirect relationships are unique to these models. Since network closure is fundamental to affective networks, controlling adequately for triadic effects is important for the satisfactory modeling of network dynamics, and hence for plausible inference concerning influence and selection effects. Second, these methods are capable of simultaneously modeling dependencies involving network and behavioral evolution. Third, these models assume that changes between discrete time points occur in several micro-steps that follow Markov processes. This continuous-time modeling approach provides more precise estimates of selection and influence because it reduces the variation between assessments of individual behaviors and the onset of friendship nominations.

Not unlike most analytic techniques, the actor-oriented models implemented in SIENA also have limitations. First, the assumption of Markov chains implies that there are no systematic influences on the network and behavioral dynamics other than the influences implied by the effects in the model specification – in this example, those listed in Table 2. Although this is a much less restrictive assumption than the assumptions implied by traditional statistical techniques, it is still important to study the robustness of the conclusions obtained with respect to variations in the model specification. Second, these actor-oriented models do not provide a standard metric of effect sizes (e.g., R^2). Although the resulting t-statistics are standardized and may be used to assess the relative strength of various parameter estimates, it is not yet possible to compare results produced by SIENA with statistics calculated via other statistical techniques. Third, these models are currently limited to dichotomous network ties, so network data that consist of valued ties (e.g., a continuous measure of strength of relationship) must be dichotomized for use in these models. Fourth, because of the iterative process used to estimate parameters, SIENA analyses of large networks (i.e., more than 100 actors) is somewhat time consuming. Finally, the version of SIENA used for these analyses (2.4), is limited to 375 actors. All of these points are being addressed in current methodological work.

Although the empirical example was included for illustrative purposes, we were able to address several substantive research questions that extend our understanding of the underlying processes resulting in homogeneity in delinquent behaviors among adolescent friends. That is, we identified selection and influence effects related to minor delinquency in both unilateral and reciprocated friendships. Specifically, these results indicate that adolescents tend to select friends based on delinquent behaviors in both unilateral and reciprocated relationships and tend to be influenced by the delinquent behaviors of friends both in unilateral and (particularly) in reciprocated relationships. Unique to this study is the differentiation between unilateral and reciprocated nominations. There is some evidence that the type of friendship tie moderates the susceptibility to peer influence on delinquency (Kiesner, Cadinu, Poulin, & Bucci, 2002), but to our knowledge this is the first study to examine differences in selection and influence processes as a function of nomination ties. Although this study has strengths, such as the inclusion of 23 possible nominations of both in-school and free-time friends, it also has limitations. Two of these deserve comment. First, participants were drawn from a small community in central Sweden. Although they were representative of the population from which they were drawn, it will be up to future scholars to determine the extent to which the findings from this sample generalize to youth living in other countries and those living in more urban communities. Second, we examined selection and influence related to minor delinquency without considering other related behavioral covariates, such as substance use or more serious delinquent behaviors. Although we did include selection effects associated age, gender, school and classroom, it seems likely that the inclusion of other behaviors would impact these results.

In this article, we have focused on actor-oriented models implemented using the SIENA software. It should be noted, there are several other social network software packages within and aside from StOCNET that perform other techniques for social network analysis, such as Multinet (Richards & Seary, 2003), NetMiner II (Cyram, 2004), Statnet (Handcock, Hunter, Butts, Goodreau, & Morris, 2005), and UCINET (Borgatti, Everett, & Freeman, 2002). Huisman and Van Duijn (2005) provide an excellent review of the capabilities of these various analytic software programs.

Not unlike the empirical example presented here, most studies utilizing the methods illustrated in this article have focused on the evolution of friendship networks and co-evolving individual behaviors such as substance use, delinquency, or music listening habits (Steglich, Snijders, & Pearson, 2007; Steglich, Snijders, & West, 2007). However, these models may also be applied to a variety of other types of networks (support, leisure activities, trust, bully–victim, etc.) and behaviors or attitudes (performance in school, attitude towards learning, etc.). In fact, these models have been recently applied to delineate related social processes in the advice-giving networks of commercial court judges (Lazega, Lemercier, & Mounier, 2007; Lazega & Mounier, 2003) and to examine trust mechanisms in a network of factory managers (Van de Bunt, Wittek, & de Klepper, 2003). Furthermore, they also may be extended to investigate more complex network data, such as multiple parallel networks being studied in different locations, or in different cohorts. A multilevel approach to modeling such data in the present framework has been proposed by Snijders and Baerveldt (2003).

Taken together, the actor-oriented models presented here may be used in different applications to address a variety of interesting research questions. While longitudinal data of complete social networks and individual behaviors are required, these models provide a means of delineating selection and influence processes in numerous social network configurations, as well as exploring related research questions. In conclusion, actor-oriented models of network–behavioral co-evolution provide developmental researchers with a statistical technique for modeling dependencies beyond dyadic interdependence.

References

Boer, P., Huisman, M., Snijders, T.A.B., Steglich, C.E.G., Wichers, L.H.Y., & Zeggelink, E.P.H. (2006). *StOCNET: An open software system for the advanced statistical analysis of social networks*. Version 1.7. Groningen, The Netherlands: ICS/Science Plus.

Borgatti, S.P., Everett, M.G., & Freeman, L.C. (2002). *UCINET 6 for Windows: Software for social network analysis*. Cambridge, MA: Analytic Technologies.

Burt, R.S. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Cairns, R.B., & Cairns, B.D. (1994). *Lifelines and risks: Pathways of youth in our time*. New York: Cambridge University Press.

Carrington, P., Scott, J., & Wasserman S. (2005). *Models and methods in social network analysis*. New York: Cambridge University Press.

Cyram (2004). *Cyram Netminer II. Version 2.4.0*. Seoul, South Korea: Cyram.

Davis, J.A. (1970). Clustering and hierarchy in interpersonal relations: Testing two theoretical models on 742 sociograms. *American Sociological Review*, *35*, 843–852.

Dishion, T.J., & Dodge, K.A. (2005). A peer contagion in interventions for children and adolescents: Moving towards an understanding of the ecology and dynamics of change. *Journal of Abnormal Child Psychology*, *33*, 395–400.

Ennett, S.T., & Bauman, K.E. (1994). The contribution of influence and selection to adolescent peer group homogeneity: The case of adolescent cigarette smoking. *Journal of Personality and Social Psychology*, *67*, 653–663.

Freeman, L.C. (1979). Centrality in social networks I: Conceptual clarification. *Social Networks*, *1*, 215–239.

Friedkin, N. (1998). *A structural theory of social influence*. Cambridge: Cambridge University Press.

Handcock, M.S., Hunter, D.R., Butts, C.T., Goodreau, S.M., & Morris, M. (2005). *Statnet: An R package for the statistical analysis and simulation of social networks*. Center for Studies in Demography and Ecology, University of Washington.

Hanneman, R.A., & Riddle, M. (2005). *Introduction to social network methods*. Riverside: University of California, Riverside.

Haynie, D.L. (2001). Delinquent peers revisited: Does network structure matter? *American Journal of Sociology*, *106*, 1013–1057.

Hogue, A., & Steinberg, L. (1995). Homophily of internalized distress in adolescent peer groups. *Developmental Psychology*, *31*, 897–906.

Huisman, M., & Snijders, T.A.B. (2003). Statistical analysis of longitudinal network data with changing composition. *Sociological Methods & Research*, *32*, 253–287.

Huisman, M., & Van Duijn, M.A.J. (2005). Software for statistical analysis of social networks. In P. Carrington, J. Scott, & S. Wasserman (Eds.), *Models and methods in social network analysis* (pp. 270–316). New York: Cambridge University Press.

Jaccard, J., Blanton, H., & Dodge, T. (2005). Peer influences on risk behavior: An analysis of the effects of a close friend. *Developmental Psychology*, *41*, 135–147.

Kandel, D.B. (1978). Similarity in real-life adolescent friendship pairs. *Journal of Personality and Social Psychology*, *36*, 306–312.

Kenny, D.A., Kashy, D.A., & Cook, W.L. (2005). *Dyadic data analysis*. New York: Guilford Press.

Kerr, M., & Stattin, H. (2000). What parents know, how they know it, and several forms of adolescents adjustment: Further evidence for a reinterpretation of monitoring. *Developmental Psychology*, *36*, 366–380.

Kerr, M., Stattin, H., & Kiesner, J. (2007). Peers and problem behavior: Have we missed something? In R. Engels, M. Kerr, & H. Stattin (Eds.), *Friends, lovers, and groups: Who is important in adolescence and why?* (pp. 125–254). London: Wiley.

Kiesner, J., Cadinu, M., Poulin, F., & Bucci, M. (2002). Group identification in early adolescence: Its relation with peer adjustment and its moderator effect on peer influence. *Child Development*, *73*(1), 196–208.

Kiesner, J., Kerr, M., & Stattin, H. (2004). "Very important persons" in adolescence: Going beyond in-school, single friendships in the study of peer homophily. *Journal of Adolescence*, *27*, 545–560.

Kirke, D.M. (2004). Chain reactions in adolescents' cigarette, alcohol and drug use: Similarity through peer influence or the patterning of ties in peer networks? *Social Networks*, *26*, 3–28.

Lazarsfeld, P.F., & Merton, R.K. (1954). Friendship as social process. In M. Berger, T. Abel, & C. Page (Eds.), *Freedom and control in modern society* (pp. 18–66). New York: Octagon.

Lazega, E., Lemercier, C., & Mounier, L. (2006). A spinning top model of formal structure and informal behaviour: Dynamics of advice networks in a commercial court. *European Management Review*, *2*, 113–122.

Lazega, E., & Mounier, L. (2003). Interlocking judges: On joint (external and self-) governance of markets. *Research in the Sociology of Organizations*, *20*, 267–296.

Leenders, R.T.A.J. (1995). Models for network dynamics: A Markovian framework. *Journal of Mathematical Sociology*, *20*, 1–21.

Leenders, R.T.A.J. (1996). Evolution of friendship and best friendship choices. *Journal of Mathematical Sociology*, *21*, 133–148.

Magnusson, D., Dunér, A., & Zetterbloom, G. (1975). *Adjustment: A longitudinal study*. New York: Wiley.

McPherson, M., Smith-Lovin, L., & Cook, J.M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*, 415–444.

Moody, J., & White, D.R. (2003). Social cohesion and embeddedness. *American Sociological Review*, *68*, 103–127.

Persson, A., Kerr, M., & Stattin, H. (2007). Staying in or moving away from structured activities: Explanations involving parents and peers. *Developmental Psychology*, *43*, 197–207.

Norris, J.R. (1997). *Markov chains*. Cambridge: Cambridge University Press.

Ploeger, M. (1997). Youth employment and delinquency: Reconsidering a problematic relationship. *Criminology*, *35*, 659–675.

Richards, W.D., & Seary, A.J. (2003). *Multinet. Version 4.38 for Windows*. Burnaby: Simon Fraser University.

Sahlins, M. (1972). *Stone age economics*. New York: Aldine De Gruyter.

Schweinberger, M. (2007). Statistical modeling of digraph panel data: Goodness-of-fit. Manuscript submitted for publication.

Snijders, T.A.B. (2001). The statistical evaluation of social network dynamics. *Sociological methodology*, *31*, 361–395.

Snijders, T.A.B. (2005). Models for longitudinal network data. In P. Carrington, J. Scott, & S. Wasserman (Eds.), *Models and methods in social network analysis* (pp. 215–247). New York: Cambridge University Press.

Snijders, T.A.B., & Baerveldt, C. (2003). A multilevel network study of the effects of delinquent behavior on friendship evolution. *Journal of Mathematical Sociology*, *27*, 123–151.

Snijders, T.A.B., Steglich, C.E.G., & Schweinberger, M. (2007). Modeling the co-evolution of networks and behavior. In K. Van Montfort, H. Oud, & A. Satorra (Eds.), *Longitudinal models in the behavioral and related sciences* (pp. 41–71). Mahwah, NJ: Erlbaum.

Snijders, T.A.B., Steglich, C.E.G., Schweinberger, M., & Huisman, M. (2006). *Manual for SIENA, version 3*. Groningen, The Netherlands: University of Groningen.

Steglich, C.E.G., Snijders, T.A.B., & Pearson, M. (2007). Dynamic networks and behavior: Separating selection from influence. Manuscript submitted for publication.

Steglich, C.E.G., Snijders, T.A.B., & West, P. (submitted). Applying SIENA: An illustrative analysis of the co-evolution of adolescents' friendship networks, taste in music, and alcohol consumption. *Methodology*, *2*, 48–56.

Taylor, H.M., & Karlin, S. (1998). *An introduction to stochastic modeling* (3rd ed.). New York: Academic Press.

Urberg, K.A., Degirmencioglu, S.M., & Pilgrim, C. (1997). Close friend and group influence on adolescent cigarette smoking and alcohol use. *Developmental Psychology*, *33*, 834–844.

Van de Bunt, G.G., Wittek, R.P.M., & de Klepper, M.C. (2003). The evolution of intra-organizational trust networks: An empirical test of six trust mechanisms. *International Sociology*, *20*, 339–369.

Van Duijn, M.A.J., Zeggelink, E.P.H., Huisman, J.M., Stokman, F.N., & Wasseur, F.W. (2003). Evolution of sociology freshman into a friendship network. *Journal of Mathematical Sociology*, *27*, 153–191.

Vitaro, F., Trembley, R.E., Kerr, M., Pagani, L., & Bukowski, W.M. (1997). Disruptiveness, friends' characteristics, and delinquency in early adolescence: A test of two competing models of development. *Child Development*, *68*, 676–689.

Wasserman, S. (1977). *Stochastic models for directed graphs*. PhD thesis, Department of Statistics, University of Harvard, Cambridge, MA.

Wasserman, S. (1979). A stochastic model for directed graphs with transition rates determined by reciprocity. In K.F. Schuessler (Ed.), *Sociological methodology* (pp. 392–412). San Francisco: Jossey-Bass.

Wasserman, S., & Faust, K. (1994). *Social network analyses. Methods and applications*. Cambridge: Cambridge University Press.

Zijlstra, B.J.H., van Duijn, M.A.J., & Snijders, T.A.B. (2006). The multilevel p2 model: A random effect model for the analysis of multiple social networks. *Methodology*, *2*, 42–47.