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A MULTILEVEL NETWORK STUDY OF THE EFFECTS OF DELINQUENT BEHAVIOR ON FRIENDSHIP EVOLUTION

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A multilevel approach is proposed to the study of the evolution of multiple networks. In this approach, the basic evolution process is assumed to be the same, while parameter values may differ between different networks. For the network evolution process, stochastic actor-oriented models are used, of which the parameters are estimated by Markov chain Monte Carlo methods. This is applied to the study of effects of delinquent behavior on friendship formation, a question of long standing in criminology. The evolution of friendship is studied empirically in 19 school classes. It is concluded that there is evidence for an effect of similarity in delinquent behavior on friendship evolution. Similarity of the degree of delinquent behavior has a positive effect on tie formation but also on tie dissolution. The last result seems to contradict current criminological theories, and deserves further study.

Keywords: Actor-oriented model; Longitudinal data; Social networks; Criminology; Adolescents

1. INTRODUCTION

Network analysis has traditionally focused on the analysis of single networks, where the pattern of relationships in one group is being investigated. However, in the study of group phenomena such studies should be considered to be case studies, and for the generalizability of research results it is preferable to conduct parallel studies of each group in a collection of groups. This can be called a *multilevel social network*

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analysis, where the micro level is the study of the relational ties within each single network, and the macro level is the combination of these multiple network studies. Thus a combination of social network analysis (Wasserman and Faust, 1994) and multilevel analysis (Bryk and Raudenbush, 1992; Snijders and Bosker, 1999) is required.

This scheme is applied more concretely in this paper to a classical theoretical disagreement in criminology. It is generally accepted by criminologists that the friends of delinquents are also delinquent more often than others. However, criminologists disagree about the process leading to this situation. Social control theorists like Hirschi (1969) state that "birds of a feather flock together," i.e., delinquents select each others for friendship. On the other hand, differential association theory (Sutherland and Cressy, 1974) states that delinquent behavior is learned from delinquent friends; this process then generates delinquent groups. These theories are about relational behavior of individuals in groups in general. They have never been tested thoroughly, because appropriate research designs and analysis methods in criminology were not available. To test them, one should use observations not about a single group but about many groups. This paper tests the basic hypothesis of social control theory, that delinquents tend to select other delinquents as friends. We shall use data from 19 high schools. For each high school a micro-level within-school network analysis is carried out, and these network analyses are combined in a macro-level between-school analysis with 19 "cases." It would be better to have a larger sample size than 19, but the intensive data collection methods limited our study to this number.

The within-school network studies are about the development of the friendship networks. The actor-oriented network evolution model of Snijders (2001) and Snijders and van Duijn (1997) is used to represent the development of these networks, and to assess the role of delinquent behavior in the network development. This is elaborated below in Section 3. On the macro-level, it is assumed that the parameter values for the various effects that play a role in the network evolution, can differ between high schools. In the macro-level study, the parameter estimates obtained for each high school separately are combined in a way that takes into account the fact that the differences between the parameter estimates are composed of real variability together with unreliable (error) variability. The latter is reflected by the standard errors of the parameter estimates. Thus, the multilevel network analysis is done in a two-step approach, where the first step is the within-school network analysis, yielding parameter estimates and their standard errors, which are then combined in the second step to estimate and test the distribution of the parameters across schools.

2. DELINQUENCY AND FRIENDSHIP NETWORKS

Within the criminological debate it is generally accepted that delinquents have social relationships more with other delinquents than with non-delinquents. This has been reported by many researchers (Bender & Lösel, 1997; Elliot, Huizinga & Ageton, 1985; Jussim & Osgood, 1989; Reed & Rose, 1998; Thornberry et al., 1993; Thornberry et al., 1994; Vitaro et al., 1997). According to Ploeger (1997, p. 661), "The relationship between self-reported delinquency and the number of delinquent friends an adolescent has is one of the strongest and most consistent findings in the field of criminology." However, none of the quoted authors have used a social network design and analysis. In most studies the respondent is questioned simultaneously about his or her own delinquent behavior, the number of alters, and the delinquency of the alters. For instance, Reed and Rose (1998) report that they used the following question for the National Youth Survey: "Think of your friends. During the past year, how many of them performed a certain offence?" The answer categories ranged between 1 = none of them through 5 = all of them. This information is often severely biased, for example, people tend to overestimate their own popularity and the homogeneity of their networks. In criminology this point was stressed by Aseltine (1995), Kandel (1996), and Reed & Rose (1998). These authors suggest a network approach, where it is possible to check the information about relationships from the point of view of the alters. However, in criminology only a few social network studies (Baerveldt & Snijders, 1994; Baerveldt, Vermande and Van Rossem, 2000; Sarnecki, 1990) have been carried out.

A vehement theoretical debate in criminology has focused on the question, to which extent the association between own delinquent behavior and the delinquent behavior of one's friends is explained by a process of influence, and to which extent by a process of selection. One of the reasons for the importance of this question is that the answer is associated with how delinquents should be viewed theoretically: as people with a deficit or as normal people in abnormal circumstances. The lack of consensus can be traced back to traditional theories of delinquency. On the one hand, delinquents are believed to lack the social abilities that are necessary to develop close friendships with peers. Others have stated that juvenile delinquents have strong interpersonal bonds, showing that they are equally capable of the intimate, close friendships that are so evident during adolescence. Hansell and Wiatrowski (1981) described these competing conceptions of delinquent peer relations in terms of two models: the "social inability model" and the "social ability model."

The social inability model is expressed by Hirschi (1969), who states that all delinquent behavior is caused by a lack of social control. Adolescents who commit offenses do this because their bonds with parents and conventional institutions at school and work are weak. Therefore, it is not possible to have strong bonds and also to commit offenses. According to Hirschi, this holds for all types of delinquency and therefore also for petty crime. This is denied by cultural deviance theories such as differential association theory (Sutherland and Cressey, 1974). In this theory, delinquent behavior is believed to be learned through social interaction within a cohesive and intimate group of friends, where criminal norms, values, and knowledge are learned through normal socialization processes. In this view, delinquency is not to be regarded as a sign of individual social inaptitude, but as a result of normal social learning. This idea of the sociable delinquent is taken by Hirschi (1969, p. 159) for "a romantic myth." According to him, the similarity of friends' delinquent behavior shows that delinquents have no choice except to look for shallow ties with other delinquents, not that delinquent behavior is influenced by interpersonal ties. He concludes that the friendships of delinquent adolescents must be of poor quality.

As Marcus (1996) indicates, the research on this topic has not been conclusive. For instance, Aseltine (1995, p. 104) states that, in comparison with family influence, "For the most part, empirical tests of these competing theories have lent greater support to theories of peer influence," whereas according to Baron & Tindall (1993, p. 256), "Surveys of the literature suggest that there is little support for subcultural explanations of delinquency" and "Control explanations of delinquency have met with considerably more support." The possibility of combinations of selection and influence processes also has been acknowledged, and some criminologists have attempted to build theoretical bridges between them (Battin et al., 1998; Reed & Rose, 1998; Thornberry et al., 1993; Vitaro et al., 1997). In the social networks tradition, the question whether selection or influence is dominant is recognized as slightly ill-stated, because most researchers expect some combination of influence and selection (see Leenders, 1995, 1997, for a systematic introduction). However, until now criminologists did not try to solve this conflict by testing hypotheses using quantitative network research and analysis.

In this article, we concentrate on testing the selection hypothesis and, for the time being, ignore the influence hypothesis. Friendship selection effects on the basis of delinquent behavior were seldom tested empirically, and never before in an empirical multilevel network study. We use data from the Dutch Social Behavior Study (Baerveldt 2000), where pupils' networks are studied in 23 high schools. For 19 of these schools, two waves (one year apart) of network data are available; data from these schools are used here. The primary research question is, what are the effects of levels of delinquent behavior on the development of friendship relationships between pupils?

3. A MULTILEVEL APPROACH TO NETWORK EVOLUTION

The structure of this investigation is regarded as a multilevel structure (cf. Snijders and Bosker, 1999) in which the study of the relational ties within each separate school class is the *micro level* and the combination of these single-group studies is the *macro level*. At the micro level one can distinguish various units of analysis: the individual actor (student), the directed relation from one individual to another, and the dyad consisting of two actors. The fact that the micro level refers to ties in a network, implies that this investigation does not show the hierarchical nesting structure which is typical of the usual kinds of multilevel analysis. The network approach implies that these three units of analysis will not each receive a specific place in this multilevel scheme, but will be jointly subsumed in the network approach at the micro level. The multilevel analysis will be carried out by a rather simple and straightforward combination of the results of the micro-level analyses. Thus a two-step approach will be followed which could also be regarded as a meta-analysis of the micro-level network studies. A two-step approach was chosen because the statistical analysis of network evolution is quite complicated already, and an integration of the micro-level and the macro-level parts of the analysis is too complicated at this moment.

The basic approach is that a common model will be applied to all school classes separately. It is assumed that for each school class there exists a true parameter vector under this model, and for each of the coordinates of this parameter vector, the various school classes might have different true parameter values. Fitting the model yields, for each class separately, an estimated parameter vector. These parameter estimates are decomposed theoretically as the true parameter value plus a measurement error. The purpose of the macro-level analysis is to estimate and test the mean and variance across school classes of the true parameter values.

This section first presents the micro-level model, and then the macro-level model is treated for the case that a given micro-level model has been chosen. However, various micro-level models could be considered, differing in the set of effects included. In Section 3.3 the procedure of selecting the micro-level model will be discussed.

3.1 Micro Level: Network Analysis

Each network is analysed using the actor-oriented model for network evolution proposed by Snijders (2001). We refer to this publication for a more extensive description of this model and here only sketch an outline.

The basic idea of the model is that two observations are available of the network, made at times t_1 and t_2. Between the two observation moments time runs on continuously, and the actors in the network (here, the students in the class) may change their ties at stochastic moments during this period. The model is actor-oriented in the sense that each actor controls his or her outgoing ties, which are the ties that would be reported if this actor were questioned at the given moment about his or her relations to others in the group. The total network influences the tie changes made by the actors because the actors try to obtain a rewarding pattern of relationships and in doing so take into account the whole pattern of ties in the network. The changes in ties are also partially governed by chance, which is understood as the representation of changes which cannot be modeled explicitly by the researcher on the basis of observed variables. The model is constructed on the basis of single changes by one actor in his or her relation to one other actor. Such a single change is called a micro-step. Since the number of changes can be large, the total of all these micro-steps can add up to a large difference between the two observed networks.

The network is represented by its adjacency matrix $x = (x_{ij})_{1 \leq i,j \leq n}$, where n is the number of actors in this school class and the dependence on time is left implicit. As usual, the tie variable x_{ij} equals 1 if there is a tie from i to j and $x_{ij} = 0$ otherwise, while x_{ii} is conventionally defined as 0. We shall first describe the mechanism for the micro-steps and then the timing of these steps.

For the micro-step, it is assumed that one actor, denoted i, is "allowed" to make one change in the outgoing tie variables collected in the row vector $(x_{i1}, \ldots, x_{in})$. Making one change means that either one entry with the current value 0 is changed into 1 (creation of a new tie), or one entry with current value 1 is changed into 0 (deletion of an existing tie). The probabilities for choosing the entry to be changed are defined by two ingredients, the "objective function" and the "gratification function."

Basic Element of Micro-Step: Objective Function

The main aspect of the actors' preferences is represented by the so-called *objective function*, which for each actor is a function of the network structure together with the observed variables, and which is interpreted as the numerical summary of what the actor would like to maximize in his or her view of the network. The objective function is defined as a weighted sum of effects,

$$f_i(\beta, x) = \sum_{k=1}^{L} \beta_k s_{ik}(x), \tag{1}$$

where for each effect k the weight β_k is a statistical parameter expressing the importance of effect k, and $s_{ik}(x)$ is a function of the network from the point of view of actor i. The actor prefers higher values of $s_{ik}(x)$ more strongly to the extent that β_k is higher.

The following effects are included in the model. They are standard network effects reflecting well-known structural tendencies.

1. *Density effect*, defined by the out-degree
$$s_{i1}(x) = x_{i+} = \sum_j x_{ij};$$
2. *Reciprocity effect*, defined by the number of reciprocated relations
$$s_{i2}(x) = \sum_j x_{ij}\, x_{ji};$$
3. *Popularity effect*, defined by the sum of the in-degrees of the others to whom i is related,
$$s_{i3}(x) = \sum_j x_{ij}\ x_{+j} = \sum_j x_{ij} \sum_h x_{hj};$$
4. *Activity effect*, defined by the sum of the out-degrees of the others to whom i is related,
$$s_{i4}(x) = \sum_j x_{ij}\ x_{j+} = \sum_j x_{ij} \sum_h x_{jh};$$
5. *Transitive triplets effect*, defined by the number of transitive patterns in i's relations (ordered pairs of actors (j, h) to both of whom i is related, while also j is related to h),
$$s_{i5}(x) = \sum_{j,h} x_{ij}\ x_{ih}\ x_{jh};$$
6. *Indirect connections effect*, defined by the number of actors to whom i is indirectly related (through one intermediary, i.e., at sociometric distance 2),
$$s_{i6}(x) = \#\{j \,|\, x_{ij} = 0,\ \max_h (x_{ih}\, x_{hj}) > 0\};$$
7. *Balance*, defined by the likeness between the out-relations of actor i to the out-relations of the other actors j to whom i is related,
$$s_{i7}(x) = \sum_{j=1}^{n} x_{ij} \sum_{\substack{h=1 \\ h \neq i,j}}^{n} (b_0 - |x_{ih} - x_{jh}|),$$
where b_0 is a constant included to minimize correlation of this effect with the density effect. Given that the density effect also is included in the model, the inclusion of b_0 entails only a reparametrization of the model.

The parameters β_k used as weights in (1) can be qualitatively interpreted for these seven effects as follows. The parameter for the density effect reflects a tendency to a dense network (controlling for all other effects in the model). The reciprocity parameter reflects the preference for reciprocated ties. The popularity effect reflects the preference for being tied to popular others, where popularity is measured by the actors' in-degree. The activity effect reflects the preference for ties to others who themselves have many outgoing ties. The transitive triplets, indirect connections, and balance effects are three different mathematical specifications of the drive toward network closure, or transitivity. A more detailed discussion of the distinction between these three is given in Snijders (2003). Summarized briefly, the transitive triplets effects expresses that an actor i will be more attracted to another actor $j$if there are more indirect ties $i \rightarrow h \rightarrow j$; a negative indirect connections effect expresses that i will be more attracted to j if there is at least one such indirect connection, without the number of indirect connections playing a role; the balance effect expresses that i prefers to be friends with those others j who makes the same choices as i does him/herself. The effects of reciprocity and transitivity (expressed by any of these three implementations) are usually considered as the primary constituents of network structure.

Three actor-dependent covariates are included in the model: gender, because of its association with nature and extent of delinquent behavior as well as with friendship formation; the importance of school friends for the actor, as a control variable because it might have an effect on the friendship choices made by the actor; and the level of delinquent behavior, which is the main variable in the research question. The covariates refer to the values observed at time t_1. For each actor-dependent covariate V the following three basic potential effects are included.

8. *V-related popularity*, defined by the sum of v_j over all actors j to whom i has a tie,

$$s_{i8}(x) = \sum_j x_{ij}\, v_{ji};$$

9. *V-related activity*, defined by i's out-degree weighted by his value v_i, $s_{i9}(x) = v_i x_{i+}$;
10. *V-related dissimilarity*, defined by the sum of absolute differences $|v_i - v_j|$ between i and the other actors j to whom he is tied,

$$s_{i10}(x) = \sum_j x_{ij} |\, v_i - v_j|.$$

Positive V-related popularity or activity effects will appear in the form of correlations between V and the in-degrees and out-degrees, respectively. A negative V-related dissimilarity effect will appear in ties being formed especially between actors with similar values on V.

One pair-dependent covariate is included: a 0-1 dummy variable indicating by the value 1 that the two actors are from the same ethnic group. For this variable, denoted by W, the following effect is included:

11. *W-related preference*, defined by the number of actors in the same ethnic group to whom i is tied,

$$s_{i11}(x) = \sum_j x_{ij}\, w_{ij}.$$

The total number of these effects is 17 (note that effects 8–10 are included for each of the three actor-bound covariates).

Differences Between Creating and Breaking Ties: Gratification Function

The preferences expressed by the objective function treat the creation of new ties in a similar way (although, of course, in opposite direction) as breaking off existing ties. However, it is possible that some effects operate differently for these two types of change. For example, it is conceivable that actors like to start an as yet unreciprocated relation, but that they are quite reluctant to break off a reciprocated relation, because of the investments that were made in such a relation (as argued by van de Bunt, 1999; also see van de Bunt, van Duijn, and Snijders, 1999). Such as effect operating differentially for creation and breaking of ties cannot be represented by the objective function, but is represented by the so-called *gratification function*. The network evolution model assumes that actor i, by changing his or her relationship to actor j when the current network state (before the change) is x, experiences a gratification.

$$g_i(\gamma, x, j). \tag{2}$$

The gratification function is specified as a weighted sum,

$$g_i(\gamma, x, j) = \sum_{h=1}^{H} \gamma_h r_{ijh}(x). \tag{3}$$

The following effects with corresponding statistics r_{ijh} are used:

1. Reciprocity effect for breaking relations, where a negative parameter γ_1 reflects the costs associated with breaking off a reciprocated relation:

$$r_{ij1}(x) = x_{ij}\, x_{ji};$$

2. Indirect connections effect for initiating relations, where a positive parameter γ_2 reflects that it is easier to establish a new relation to

another actor j if i has many indirect connections to j via others who can serve as an introduction:

$$r_{ij2}(x) = (1 - x_{ij}) \sum_h x_{ih}\ x_{hj};$$

3. Association of breaking relations with a dyadic covariate W:

$$r_{ij3}(x) = x_{ij}\ w_{ij}.$$

Three dyadic covariates W are used in the gratification function: gender difference (0-1 dummy), ethnic group difference (0-1 dummy), and difference in the level of delinquent behavior (numerical, see below).

Model for Micro-step

The objective and gratification functions are combined in the model for the micro-step. It is assumed that when actor i makes a change in his or her relation pattern, the actor maximizes the sum of the objective function of the new state, the gratification inherent in the change, and a random term. Indicating the present network by x, and the network obtained when the single element x_{ij} is changed into its opposite $(1 - x_{ij})$ by $x(i \rightsquigarrow j)$, actor i changes the relation to that j for which the value

$$f_i(\beta, x(\rightsquigarrow j)) + g_i(\gamma, x, j) + U_i(t, x, j) \tag{4}$$

is maximal. For the random term $U_i(t, x, j)$ the assumption is made that it has a Gumbel distribution with mean 0 and scale parameter 1 (cf. Maddala, 1983), which implies that the probabilities of the various possible new states $x(i \rightsquigarrow j)$ are given by the multinomial logit form

$$p_{ij}(\theta, x) = \frac{\exp(r(\theta, i, j, x))}{\sum_{h=1, h\neq i}^{n} \exp(r(\theta, i, h, x))} \qquad (j \neq i) \tag{5}$$

where

$$r(\theta, i, j, x) = f_i(\beta, x(i \rightsquigarrow j)) + g_i(\gamma, x, j).$$

Timing of the Micro-steps

Second, it is described how these micro-steps are integrated into a model for network evolution. It is assumed that at stochastic times, a stochastically determined actor i makes a micro-step. In the simplest model specification, the actor is determined randomly, i.e., all actors have probabilities $1/n$, and the times between micro-steps are independently and identically distributed, with the exponential distribution with parameter λ. (Recall that the expected value of this distribution is $1/\lambda$; higher parameter values correspond to faster changes.) In a more complicated specification, each actor i has a rate function $\lambda_i(x)$ which determines how quickly the outgoing relations of this actor are changed. The times between micro-steps have exponential distributions with parameter.

$$\lambda_+(x) = \sum_{i=1}^{n} \lambda_i(x)$$

and the probability that, when a micro-step is made, this step is made by actor i, is given by $\lambda_i(x)/\lambda_+(x)$.

The rate function here was allowed to be a function of the actor's attributes (gender, level of delinquent behavior, and importance of school friends) and their degrees. Note that the rate function needs to be positive. If there is only a dependence on attributes V_h, the formula is

$$\lambda_i(x) = \rho \; exp\left(\sum_h \alpha_h v_{hi}\right) \tag{6}$$

where ρ is a base rate parameter. If there also is a dependence on, e.g., out-degrees x_{i+}, then this rate (6) is multiplied by

$$\frac{x_{i+}}{n-1}\exp(\alpha_1) + \left(1 - \frac{x_{i+}}{n-1}\right)\exp(-\alpha_1) \tag{7}$$

where α_1 is the parameter expressing the effect of out-degrees on the rate of change.

This completes the bird's eye view of the stochastic actor-oriented model for network evolution. The parameters of the statistical model are β_k for the objective function, γ_k for the gratification function, and ρ and α_k for the rate function. They are collected in the vector

$$\theta = (\rho, \alpha_1, \ldots, \alpha_4, \beta_1, \ldots, \beta_{17}, \gamma_1, \ldots, \gamma_5).$$

The parameters were estimated using the Markov Chain Monte Carlo method described in Snijders (2001) using the SIENA program, version 1.72 (see Snijders and Huisman, 2001).

3.2 Macro Level: Combination of Networks

In the macro-level analysis, each coordinate of the parameter vector θ is analysed separately. The parameters ρ are nuisance parameters reflecting the total amount of change between the two observations of the school class, and are not particularly interesting. For the procedure to analyse the other parameters, suppose that we focus on any of the α_k, β_k, or γ_k parameters, and denote this coordinate by θ. This could represent, e.g., the effect of similarity of delinquent behavior on the evolution of friendships, controlling for the other effects in the model under consideration.

The method for combining the micro-level analyses is along the lines of what was proposed already by Cochran (1954) for combining data from different experiments. These procedures were made more popular as methods for meta-analysis by Hedges and Olkin (1985).

Each of the N school classes $j = 1, \cdots, N$ has its own true parameter value θ_j. It is assumed that the true parameter values are a random sample from the parameter values in a population of schools. The distribution of the true parameters θ_j is the aim of the macro-level analysis. In particular, we are interested in estimating the mean and variance in the population of θ_j values,

$$\mu_\theta = \epsilon\theta_j, \quad \sigma_\theta^2 = \text{var } \theta_j, \tag{8}$$

and in testing whether these macro-level parameters are 0. Note that the effect under study is altogether absent when μ_θ and σ_θ^2 both are 0.

In the micro-level analysis, parameter θ_j is estimated with a statistical error:

$$\hat{\theta}_j = \theta_j + E_j,$$

and the standard error is the square root of $\text{var}(E_j)$. It is assumed here that the squared estimated standard error produced by the micro-level analysis is close enough to $\text{var}(E_j)$ to carry on as if these two quantities are equal. This standard error is denoted by s_j. Nothing is assumed about the possible dependence (or lack thereof) between θ_j and s_j^2.

What we observe in group j is not θ_j but the estimate $\hat{\theta}_j$. This is a random variable with mean μ_θ and variance $\sigma_\theta^2 + s_j^2$. In the following, an unbiased estimator for σ_θ^2 and a two-stage estimator for the mean μ_θ are given.

A preliminary unbiased estimator for μ_θ is given by

$$\hat{\mu}_\theta^{\text{OLS}} = \frac{1}{N} \sum_j \hat{\theta}_j. \tag{9}$$

This estimator does not take into account the fact that the standard errors s_j^2 may be different. This implies that, although it is unbiased, the estimator may be inefficient. Its standard error is

$$\text{s.e.}(\hat{\mu}_\theta^{\text{OLS}}) = \sqrt{\frac{1}{N}(\sigma_\theta^2 + \bar{s}^2)} \tag{10}$$

where

$$\bar{s}^2 = \frac{1}{N} \sum_j s_j^2. \tag{11}$$

An unbiased estimator for the variance σ_θ^2 is

$$\hat{\sigma}_\theta^2 = \frac{1}{N-1} \sum_j (\hat{\theta}_j - \hat{\mu}_\theta^{\text{OLS}})^2 - \bar{s}^2. \tag{12}$$

Given that the latter estimator has been calculated, it can be used for an improved estimation of μ_θ, viz., by the weighted least squares (WLS) estimator

$$\hat{\mu}_\theta^{\text{WLS}} = \frac{\sum_j (\hat{\theta}_j/(\hat{\sigma}_\theta^2 + s_j^2))}{\sum_j (1/(\hat{\sigma}_\theta^2 + s_j^2))}. \tag{13}$$

This is the "semi-weighted mean" of Cochran (1954) treated also in Hedges and Olkin (1985, Section 9.F). In the terminology of econometrics, the estimator for μ_θ could be called a 2SLS (two-stage least squares) estimator. If σ_θ^2 is estimated with a good precision, the standard error of the weighted least squares estimator can be calculated as

$$\text{s.e.}(\hat{\mu}_\theta^{\text{WLS}}) = \frac{1}{\sqrt{\sum_j 1/(\hat{\sigma}_\theta^2 + s_j^2)}}. \tag{14}$$

An assumption used in the derivation of this WLS estimator is that θ_j and s_j^2 are independent in the level-2 population. This type of assumption is commonly made in multilevel analysis, but it is not evident that it will always be satisfied. However, it is likely that in many cases when there is a bias due to failure of this assumption, the decrease in variance of (13) compared to (9) will be more important than the squared bias, so that the mean squared error of the WLS estimator will nevertheless be smaller than that of the OLS estimator. This independence assumption, however, does not play a role for the tests proposed next.

For testing μ_θ and σ_θ^2, it must be assumed that the parameter estimates $\hat{\theta}_j$ conditional on θ_j are approximately normally distributed with mean θ_j and variance s_j^2. This seems a reasonable assumption. The first null hypothesis to be tested is that the effects are 0 in all groups. This can be tested by the test statistic

$$T^2 = \sum_j \left(\frac{\hat{\theta}_j}{s_j}\right)^2 \tag{15}$$

which has an approximate chi-squared distribution with N degrees of freedom under the null hypothesis. The test that the mean effect μ_θ is zero can be tested on the basis of the t-ratio.

$$t_{\mu_\theta} = \frac{\hat{\mu}_\theta^{\text{WLS}}}{s.e.(\hat{\mu}_\theta^{\text{WLS}})} \tag{16}$$

which has approximately a standard normal distribution under the null hypothesis. Finally, the test that the variance of the effects σ_θ^2 is zero can be tested using the test statistic

$$Q = T^2 - \tilde{t}^2 \tag{17}$$

where

$$\tilde{t} = \frac{\sum_j \hat{\theta}_j / s_j^2}{\sqrt{\sum_j \mathrm{I}/s_j^2}} \tag{18}$$

which has under the null hypothesis approximately a chi-squared distribution with $N-1$ degrees of freedom. This test was given by Cochran (1954, p. 114) and Hedges and Olkin (1985, Section 9.E). Its optimality under the normality assumption is proved in Lehmann (1986, p. 377).

3.3 Stepwise Model Selection

The research question is about the effect of delinquent behavior on the development of friendships between students. It is desirable to control for various effects, viz., network effects and effects of important covariates. These network and covariate effects were mentioned in Section 3.1. For each school, the effect parameters are collected in the vector

$$\theta = (\rho, \alpha_1, \ldots, \alpha_4, \beta_1, \ldots, \beta_{17}, \gamma_1, \ldots, \gamma_5).$$

The first element, ρ, is a nuisance parameter, but the other 25 parameters all are potentially important. The estimation algorithm for the stochastic actor-oriented model becomes unstable, however, if the number of effects is too large (what is too large, will depend on the data set) and it is also possible that standard errors of effects will become rather large when too many unimportant effects are included. Therefore a theory-guided forward stepwise model selection procedure is used, with the aim of including only important parameters in the model. The remainder of this section describes this model selection procedure, in which theoretical arguments were used to group effects in seven ordered groups, which are sequentially entered into the model and tested, and retained in the next step only if they are supported by sufficient empirical evidence and do not lead to instability of the model.

This model selection is carried out at the macro level: in each step the fitted model is the same for all available schools, and effects are selected if their overall importance is large enough. Some pilot model fits showed that, with this large amount of data, seemingly small effects already can be significant. Therefore a strict testing approach, which would include all significant effects, would lead to unwieldy models. It would be preferable to base the model selection on a combination of testing and estimation of effect sizes. Unfortunately, effects sizes analogous to "variance explained," or goodness of fit measures analogous to the deviance, are not (or not yet) available for this model for network evolution. Therefore, given the lack of better measures, the T^2 statistic in (15) is used as an ad hoc measure for the importance of the effects.

A complication is caused by the stochastic nature of the estimation algorithm and the related instability of the algorithm for some model specifications and some data sets. In some combinations of model and data set, the estimation of one or some of the parameters is not satisfactory, either because the parameter vector found by the algorithm fails to satisfy the moment equation to a sufficient degree of precision for the corresponding statistic, or because the standard error of this parameter for this data set is overly large. In such cases, using this parameter estimate would spoil the results of the macro-level analysis as expressed by the macro-level standard error (14). Therefore such estimates are left out. The threshold for the standard error is determined, somewhat arbitrarily, as 5.0. In the tables with results, the number of schools on which the reported statistics are based is denoted by N. For comparing the importance of effects, it is better to use T^2/N than T^2.

Effects were selected in seven groups. The general order in the model selection procedure is that first come all effects that have the role of control variables, and then the tested effects (i.e., those related to level of delinquent behavior). The order within the set of control effects is as follows: first the structural effects, then the effects related to covariates. Among the structural effects, first come the effects in the objective function, then those in the gratification function, and then those in the rate function. The rationale for this order is that the objective function is considered to be more fundamental than the gratification and rate functions. The order between the latter two functions is arbitrary. In each of the following seven steps, the important effects of this step (as reflected by the size of (15)) are selected and included in the following steps, while the non-important effects are left out.

1. The density and reciprocity effects are included anyway because of their fundamental nature.
2. Next a selection is made from the effects related to network closure: transitive triplets, indirect connections, and balance. Incorporating all these three effects jointly may lead to instability in the algorithm. The one or two most important of these three effects are selected.
3. Following this, the popularity and activity effects are considered.
4. As a next step the two structural gratification function effects are tested: the reciprocity effect for breaking relations, and the indirect connections effect for initiating relations.
5. Next it is investigated whether rates of change depend on out-degrees, in-degrees, and/or reciprocated degrees (defined as the number of reciprocated relations in which an actor is involved).

6. For gender, the effects of gender-related popularity, activity, dissimilarity, and the gratification effect of dissimilarity were considered; for the importance of school friends, the effects of covariate-related popularity and activity; and the objective function and gratification function effects are considered of having the same ethnicity.
7. Finally the tested effects are introduced into the model: in the first place, the dissimilarity effect associated with the level of delinquent behavior; next, the dissimilarity in delinquent behavior as an effect in the gratification function; finally, the popularity, activity, and rate effects of delinquent behavior.

4. DATA

The main source of data is the Dutch Social Behavior study, a two-wave survey in classrooms (Baerveldt, 2000). In 1994/1995 the first wave took place in 22 Dutch urban high schools. All pupils in the third grade of the intermediate educational level (MAVO) of these schools were selected, resulting in a sample of 1,528 pupils aged between 13 and 18 years, excluding two pupils who did not seriously complete the questionnaire. One year later, 19 out of the 22 schools of the first wave participated again in the second wave, while also a new school participated. In this wave all fourth grade MAVO pupils participated, in total 1,317 respondents. Not included in these numbers are pupils absent during either day of data collection (due to illness or truancy). Excluded from the network analyses are those who left the school between the two waves, or for other reasons were not a member of the school class at both moments. Pupils who were in the sample for wave 1 but not for wave 2, mainly because they had to repeat third grade (due to poor results, usually 5—10% in the Dutch high school system), committed slightly more offenses than those who did participate in wave 2 (10.0 versus 8.2). A total of 990 pupils in 19 schools completed the survey in both waves. Only pupils who responded in both waves are included in the present study.

For each school all pupils in the same year of MAVO produced one network together. The number of pupils per network varied between 34 and 129. In both waves the number of girls (48%) who participated was almost the same as the number of boys (52%). The majority (90%) of the pupils were born in the Netherlands. One-third had one or two parents who were born outside the Netherlands, mainly in Surinam, Morocco, Turkey, or the Dutch Antilles.

The pupils completed the questionnaire during a lesson. Delinquency is measured by a self-report questionnaire, a widespread method in criminology. The respondents were asked how many times they had committed minor offenses from a list of 23 offenses such as shoplifting, petty theft, vandalism, and unarmed fights over the last twelve months. The total number of offenses is used as a scale with a sufficient internal cohesion (Cronbach's alpha = .87 for wave one and .91 for wave two) and which is sufficiently one-dimensional (first two eigenvalues factor analysis: for wave one 6.7 and 1.4, for wave two 8.6 and 1.5). As Table 1 shows, many pupils had committed at least one minor offense. It should be noted that most offenses are very light. Moreover, the delinquency rate of the population of MAVO pupils in urban schools is known to be relatively high.

TABLE 1 Petty Crime of Pupils in MAVO-3 (Wave One) and MAVO-4 (Wave Two). Percentages of Pupils who Commited an Offense at Least Once Within this Year

	Boys		Girls	
Offense	Wave one (N = 748)	Wave one (N = 663)	Wave one (N = 768)	Wave one (N = 651)
Shoplifting	46.7	48.6	35.0	31.5
Changing price tags in shops	30.2	37.2	32.9	29.4
Dodging fares	52.9	60.4	47.9	48.2
Buying stolen goods	37.2	48.4	18.1	22.5
Theft of (small) goods from school	40.0	43.1	31.4	25.9
Theft of money from home	22.5	21.9	23.8	23.0
Theft of money from fellow pupil	4.8	5.9	1.6	1.0
Theft of jacket/coat of another pupil	.9	2.4	.4	.0
Burglary/forbidden entry in a house or shop	12.3	18.7	1.8	2.9
Theft of a bike	21.8	28.0	5.7	6.7
Theft of a motor bike	8.0	9.3	.9	.2
Theft of something else	16.6	14.4	10.7	6.1
Graffiti	37.0	37.4	27.2	25.7
Vandalism in public transport	15.9	18.1	11.3	7.3
Vandalism on the street	29.9	35.4	12.4	8.6
Setting fire	48.8	46.3	20.1	14.6
Damaging a bike	35.2	38.6	15.2	11.5
Damaging a car	24.6	28.5	12.1	9.0
Vandalism at school	31.8	27.6	17.8	10.9
Smashing/throwing in a window	33.0	33.1	7.6	6.7
Miscellaneous vandalism	10.7	7.7	4.0	2.9
Unarmed fighting (kicking or hitting)	48.4	46.1	28.9	22.1
Threatening with knife/other weapon	16.8	14.4	4.3	4.4

The relationships were measured by various social network items in the questionnaire. All network items exclusively concern relationships with other pupils in the same year group. Only ties between pupils are investigated. Codes were used to ensure anonimity. For each network item, a maximum of twelve alters could be mentioned.

The dependent variable in the present study, which for convenience is labeled here as friendship, is defined by two network items:

1. Emotional support received: Which pupils help you when you are depressed, for example, after the end of a love affair or when you have a conflict with other people?
2. Emotional support given: Which pupils do you help when they are depressed, for example, after the end of a love affair or when they have a conflict with other people?

Friendship is operationalized this way because the term of "friendship" itself in a questionnaire item is ambiguous, and interpreted differently by boys and girls (see Houtzager and Baerveldt, 1999); the operationalization by emotional support refers to an intimate affective relation, in accordance with the use of "friendship" in criminological theories, and it leads to a good reliability of measurement (Baerveldt, 2000). Table 2 shows the distribution of the number of alters mentioned for these network items. The network was defined by ego mentioning alter in at least one of these two questions.

For most pupils their friends at school do matter. In wave two, the question was posed which friends were more important: friends outside school or at school. For 62% of the pupils both friends are equally important and for 10% friends at school are more important. However, for 28% of the pupils friends outside school are more important. These pupils have less positive social ties within the school networks and commit more offenses. Therefore, the analyses have to be controlled for the importance of school friends.

TABLE 2 Frequencies (in percent) of Emotional Support Relationships within the Pupil's Network (Wave two)

	Number of ties per respondent				
Type of relationship	0	1	2	3	4
Ego gives alter emotional support	30.4	17.7	15.4	13.1	23.4
Ego receives emotional supp. from alter	30.8	20.7	17.6	12.1	18.8

4.1 Descriptive statistics

The school averages of the variables are as follows. Gender is coded as 1 for girls and 2 for boys. The proportion of boys ranges between .37 and .67, with an average of .52. Most students are aged from 15 to 17 years. The average importance of school friends, on a scale ranging from 1 (friends outside school are more important) to 4 (no friends outside school), ranges from 1.79 to 2.29, with an average of 1.93. For ethnic background, the country of birth of the parents is taken. The fraction of pairs of students of the same ethnic background ranges between .15 and .80, with an average of .42.

The number of committed offenses has a very skewed distribution over the 990 students, ranging from 0 to 50, with a mean of 8.2 and a standard deviation of 8.8. Therefore this variable is logarithmically transformed using the variable $\ln(x+1)$. The resulting variable ranged from 0 to 4 with a mean of 1.78 and a standard deviation of .99. School averages of this variable range between 1.50 and 2.15 with a between-school standard deviation of .17.

The networks are quite sparse, reflecting that the definition of the relationship was given in rather strong emotional terms. Each school class is treated as one network. The number of pupils per school class ranges from 31 to 91. Average degrees per school range from .84 to 2.38 at the first, and from 1.00 to 3.42 at the second observation. The total number per school class of relations changed between the first and the second observation ranges from 37 to 280, with an average of 110. The average number per school class of newly formed ties is 69, of withdrawn ties it is 41, while the average number of ties reported at both observations is 45.

5. RESULTS

In the first estimation rounds with the stochastic actor-oriented model, it appeared that two of the schools often gave rise to convergence problems in the algorithm. These were the schools with the smallest amounts of change between the two waves: 37 and 49 differences, respectively, in the adjacency matrices. For the other schools, the numbers of differences ranged between 54 and 280. These two schools were deleted from the data set, so that there remained 17 schools. The two deleted schools were not unusual in other respects, except for having a relatively low number of pupils (31 and 33; there were four other school classes with less than 40 pupils, their sizes ranging from 31 to 38).

The results for steps 2–6 in the model selection procedure of Section 3.3 are summarized as follows. The number N of schools on which the reported results are based is explicitly mentioned only for the results based on less than all 17 schools.

2. Of the three effects related to network closure, by far the strongest was the indirect connections effect. In combination with transitive triplets, the effect sizes were $T^2 = 1027$ for indirect connections and $T^2 = 158$ for transitive triplets; when combined with balance, the effect sizes were $T^2 = 1786$ for indirect connections and $T^2 = 170$ for balance. Including balance as well as indirect connections led to instability in the algorithm. Therefore the next steps of the model search were done with the indirect connections effect but without the transitive triplets and balance effects.
3. The popularity and activity effects led to very unstable results. They were not used further.
4. The gratification effect of access through indirect connections led to $T^2 = 147$. The gratification effect of reciprocity was not significant ($T^2 = 13,\ N = 16$) and further was not considered.
5. The rate effect of out-degrees was quite strong $T^2 = 288$ ($N = 16$). Including the rate effects of in-degrees and reciprocated degrees led to instability of the algorithm for many schools, and small effects for the schools for which the model did converge; therefore these rate effects further were not considered further.
6. When this model was extended with the effects of the importance of friends at school on the activity and popularity of the actors, the results were $T^2 = 24$ for popularity and $T^2 = 23$ for activity. It was concluded that these effects are not important.

   For the four effects concerning gender, the results were:
   $T^2 = 87$ ($N = 16$) for the effect on popularity;
   $T^2 = 36$ ($N = 17$) for the effect on activity;
   $T^2 = 266$ ($N = 16$) for the dissimilarity effect;
   $T^2 = 49$ ($N = 15$) for the dissimilarity effect in the gratification function.

   It was concluded that there is an important similarity effect of gender, while the other three gender-related effects are statistically significant but have a smaller effect size.

   For testing the two effects of having the same ethnicity, next to the other effects found to be important in the preceding analysis, the transitive triplets effect also was included in the model. The effect of ethnicity in the objective function was $T^2 = 31$ while its effect in the gratification function was $T^2 = 33$ ($N = 16$).

Aggregating the results obtained in the steps reported until now, a model was obtained including all effects found to be important. This model was first fitted with the balance instead of the transitive triplets effect. However, including balance led to instability for rather many of the data sets and therefore balance was replaced by transitive triplets. The results

TABLE 3 Results for Model Without Effects of Delinquent Behavior

Effect	N	T^2	$\hat{\mu}_\theta^{WLS}$	(s.e.)	$\hat{\sigma}_\theta$	Q	(p)
Rate function							
Out-degrees effect on rate	14	218	2.51	(0.18)	0.0	19.5	(.11)
Objective function							
Density	15	496	−2.24	(0.16)	0.38	37.7	(.001)
Reciprocity	17	284	2.31	(0.14)	0.0	14.2	(.58)
Transitive triplets	16	109	1.19	(0.15)	0.0	41.7	($<$0.001)
Indirect connections	17	349	−0.66	(0.18)	0.61	50.6	($<$.001)
Same ethnicity	17	31	−0.29	(0.14)	0.0	26.5	(.048)
Gender popularity of alter	17	49	−0.61	(0.10)	0.0	9.6	(.89)
Gender activity of ego	16	34	0.43	(0.16)	0.36	22.4	(.10)
Gender dissimilarity	17	104	−0.91	(0.11)	0.0	33.2	(.007)
Gratification function: Effects on creating the tie							
Indirect connections	12	136	−1.06	(0.50)	1.16	135.3	($<$.001)
Gratification function: Effects on breaking the tie							
Same ethnicity	16	33	−0.62	(0.57)	1.24	28.3	(.020)
Gender dissimilarity	13	44	0.11	(0.81)	2.41	43.9	($<$.001)

N = number of schools on which statistics for this effect are based; T^2 = statistic for testing that total effect is nil, see (15); $\hat{\mu}_\theta^{WLS}$ = estimated average effect size (13), with its standard error, $\hat{\sigma}_\theta$ = estimated true between-schools standard deviation of the effect size, see (12); Q = statistic for testing that true effect variance is nil, see (17), with the p-value of the associated test.

for the other parameters were not substantially different between these two model specifications. The results are presented in Table 3. The conclusions from Table 3 are as follows.

- The density effect is substantially not very interesting, but must be included for fitting the observed density at the second observation.
- The reciprocity effect is quite strong ($T^2 = 284$), and there is no evidence that its effect size differs between schools, the estimated effect being 2.31.
- Network closure is represented by three effects: the indirect connections effects in the objective and in the gratification functions and the transitive triplets effect. The two indirect connections effects jointly show that for creating a tie the number of indirect connections has an average weight of $-.66\ -1.06 = -1.72$, while for breaking a tie ites weight is $-.66$. Thus the embeddedness of a potential tie in a web of common relations, as indicated by a relatively low number of indirect connections, has a strongly positive effect on tie creation, and also

protects an existing tie from being broken, but the former effect is more than twice as strong as the latter. Both effects vary strongly between schools ($p < .001$). In addition to the indirect connections effects there is a strong transitive triplets effect (i.e., a preference for closing intransitive triplets), which also has a variable effect size across schools ($p < .001$).

- The positive out-degree in the rate function ($T^2 = 218$, average effect size 2.51, no evidence for true parameter variance with $p = .11$) indicates that actors with higher out-degrees also change their relations more quickly. This could be, at least partially, be a matter of response tendency where some of the pupils have a lower threshold for reporting somebody as an emotional friend, and therefore also less stability in this type of reported relation.
- The main effect of gender is the similarity effect, which (changing the sign since the interpretation now is in terms of similarity instead of dissimilarity) has an average size of .91 for creating a tie and $.91 - .11 = .80$ as a protection against breaking a tie.

  In addition, boys have a higher tendency to create new ties (effect size .43, no significant true parameter variance with $p = .10$) and a lower tendency to receive new ties created by others (effect size $-.61$, no significant true parameter variance with $p = .89$).
- There is rather weak evidence about the effect of ethnicity on friendship evolution. There is a small preference in tie creation for those of a different ethnic background (effect size $-.29$). Additionally there seem to be effects of having the same ethnicity on breaking ties, which effects differ between schools (mean effect size -0.62, not significantly different from 0; estimated true between-school standard deviation 1.24 with $p = .02$).
- There is some inconsistency in the statistical results in that for some effects the estimated true parameter standard deviation is 0 but the test of the null hypothesis that this standard deviation is 0 has a significant result. This is due to the two-stage nature of the statistical procedures, which does not hang together quite as consistently as the more usual likelihood-based procedures. At this moment, this difficulty in interpretation is a price to be paid for the simplicity of the two-stage multilevel approach followed in this paper.

To obtain a base model including the effects for which the tests of the influence of delinquent behavior on friendship evolution are controlled, the least important effects were excluded from the model of Table 3. This was done in order to achieve a higher stability of the algorithm. The effects excluded were the two ethnicity effects and the gratification effect of gender dissimilarity. The other effects associated with gender were kept in the model, because it appeared that the parameter estimate for the gender activity effect was strongly correlated with the parameter estimate for the out-degree effect in the rate function, and excluding the gender activity effect led for some data sets to instability in estimating the out-degree effect in the rate function.

The first effect tested was that of dissimilarity of delinquent behavior. This effect yielded $T^2 = 12.39$, d.f. = 16, $p = .72$. The conclusion is that there is no evidence of a main effect of (dis)similarity of delinquent behavior on the evolution of the friendship network, given all control variables used. This conclusion was not altered when the less important control variables were dropped.

As the next step in the investigation of the effect of delinquent behavior, the gratification function effect of dissimilarity of delinquent behavior was included. The results are presented in Table 4.

For the effect of similarity of delinquent behavior on friendship evolution, this yielded for the objective function effect $T^2 = 38.1$, d.f. = 17, $p = .002$, and for the gratification function effect $T^2 = 47.03$, d.f. = 15, $p < .001$. Thus, the effect of dissimilarity of delinquent behavior on the

TABLE 4 Results for Model with Effects of Delinquent Behavior

Effect	N	T^2	$\hat{\mu}_\theta^{\text{WLS}}$	(s.e.)	$\hat{\sigma}_\theta$	Q	(p)
Rate function							
Out-degrees effect on rate	12	113	2.05	(0.20)	0.0	9.3	(.59)
Objective function							
Density	15	804	−2.07	(0.07)	0.0	35.5	(.001)
Reciprocity	14	318	2.39	(0.40)	1.33	12.0	(.53)
Transitive triplets	15	66	0.97	(0.15)	0.0	26.0	(.026)
Indirect connections	15	484	−0.63	(0.09)	0.28	58.7	(< .001)
Gender popularity of alter	16	71	−0.64	(0.09)	0.0	18.0	(.26)
Gender activity of ego	16	41	0.27	(0.10)	0.0	33.5	(.004)
Gender dissimilarity	16	111	−0.67	(0.07)	0.0	25.2	(.047)
Simil. delinquent behavior	17	38	−0.49	(0.12)	0.0	15.6	(.48)
Gratification function: Effects on creating the lie							
Indirect connections	13	48	−1.24	(0.31)	0.0	31.5	(.002)
Gratification function: Effects on breaking the lie							
Simil. delinquent behavior	15	47	−1.00	(0.36)	1.12	20.9	(.10)

N = number of schools on which statistics for this effect are based; T^2 = statistic for testing that total effect is nil, sec (15); $\hat{\mu}_\theta^{\text{WLS}}$ = estimated average affect size, see (13), with its standard error; $\hat{\sigma}_\theta$ = estimated true between-schools standard deviation of the effect size, see (12); Q = statistic for testing that true effect variance is nil, see (17), with the p-value of the associated test.

formation of friendship relations is different from its effect on dissolution of relations, and these effects appear only if the gratification effect also is included in the model. For both effects, the variances were non-significant ($p = .48$ and $.10$, respectively). The estimated effect sizes were $\hat{\mu}_{\theta}^{\mathrm{WLS}} = -0.49$ (s.e. $= .12$) for the objective function effect and $\hat{\mu}_{\theta}^{\mathrm{WLS}} = -1.00$ (s.e. $= .36$) for the gratification function effect. Combining these two estimates and transforming these to the more readily understood effects of similarity rather than dissimilarity, this yields for the formation of friendship an estimated effect size of .49 for similarity of delinquent behavior, and for the dissolution of friendship an estimated effect size of $1.00 - .49 = .51$. In other words, friendship relations between actors with a similar level of delinquent activity are *dissolved* more quickly, contrary to the expectation; and friendship relations between actors with a similar level of delinquent activity are also *formed* more quickly. The other effects reported in Table 4 differ from those reported in Table 3, but the differences are of a minor nature.

When also the effects of delinquent criminal activity on popularity and activity are included in the model, it turns out that these effects are not significant (for activity $T^2 = 13.5$, d.f. $= 17$, $p = .71$; for popularity $T^2 = 13.1$, d.f. $= 17$, $p = .73$). The effect of delinquent activity on the rate of change also is not significant ($T^2 = 19.1$, d.f. $= 14$, $p = .16$). The inclusion of these non-significant effect does not to an important extent affect the significances or estimated effect sizes of the other two effects of similar delinquent activity. When less control variables are used, the effects of delinquent activity on popularity and activity do gain significance; it can be concluded, however, that these effects can be explained away by the control variables.

6. CONCLUSION

The substantive conclusions from this multi-school network study of delinquency effects on friendship evolution can be summarized as follows.

In the evolution of the friendship networks, the level of delinquency does not have a main effect on the number of friendship choices made or received. However, similarity with respect to level of delinquency has a rather complicated effect on friendship evolution: similarity of the level of delinquency leads to friendship ties being formed more easily, but also being dissolved more easily. The rate of change of friendship choices does not depend directly on the level of delinquency.

What are the conclusions that may be drawn for the debate in criminology on the relation between delinquent behavior and friendship formation? As a preliminary, it should be noted that the conclusions cannot be generalized to all types of delinquents. Although the frequencies of delinquent acts as reported in Table 1 may seem high for this population, the fact remains that they still merely reflect petty crime, or as, Moffit (1993) would state, adolescence-limited delinquency. Friendship selection processes for life-time persistent delinquents may be quite different from those among these adolescents.

Following Hirschi (1969), and others who advocate the idea that delinquents are not able to maintain relationships, all relationships where delinquents are involved would be unstable. This means that the rate of change would be larger for the more delinquent pupils, which was not found in our data analysis. Our analysis does show that the selection of students' support relationships is associated with their levels of delinquency. However, the results do not in any way reflect that delinquents have more problems with relationships than non-delinquents. The level of delinquency is not associated significantly with the amount of change in relationships, nor with changes in the number of friendship choices received from, or given to others. This can be complemented by noting that Houtzager and Baerveldt (1999), using data from only the first wave of the Dutch Social Behavior Study, showed that the extent to which delinquents tend to have intimate relationships is not related to their delinquency level. Thus, the inability hypothesis is contradicted.

The finding that similarity of delinquency level promotes the formation of friendship ties is in line with the similarity effects that have generally been found for friendship formation; not only similarity in criminal behavior (Hirschi, 1969) but also in other relevant characteristics (e.g., Festinger, 1957; Kandel, 1978; Tuma and Hallinan, 1979; for mathematical models see Leenders, 1996 and Zeggelink, 1995). However, the finding that similarity in delinquency level also leads to a more rapid dissolution of friendship ties is new and unexpected. Further research is necessary to explain this finding.

We think that it may be illuminating to take into account also the duration and/or the intensity of friendships. Note that these friendship networks were in existence at the moment of our first wave of data collection. Most pupils had met each other at least several years earlier, e.g., in the first grade of secondary school, when they were 12 or 13 years old. Delinquent behavior usually starts later, at 15 or 16 years of age. Thus, many relationships were well established before the students became involved in this type of adolescence-related delinquent behavior. We hypothesize that the investments involved in these earlier existing, stable relationships implies that they are not quickly given up. Such well-established relationships can more easily withstand differences in delinquent behavior. On the other hand, in more recently formed relationships where less investments have been made, such differences may have more impact and be less tolerated. This hypothetical reasoning is in line with the finding that new relations are more easily formed between pupils of a similar level of delinquency.

Further investigations along these lines could be carried out in a longitudinal network study, starting in the first grade of secondary school, when stable relationships are formed, and lasting until the period where the delinquency level is highest. Some serious methodological problems are involved in such a study, e.g., the dropping out of respondents and the mixing of networks. However, for criminologists this is not the only problem to tackle. It will perhaps be an even greater effort to develop new theories which could generate hypotheses that sufficiently cover the richness of longitudinal network data.

7. DISCUSSION

The basic premise of this paper is that for testing and developing explanatory theories about social networks, it is desirable to use data about several networks. Such an approach leads automatically to an analysis involving several levels of analysis: the individual actor, the relational tie, and the network. Ideally, the networks studied empirically should be a collection that is representative for some population of networks— although in practice, there may be difficulties in defining precisely this population of groups and/or in drawing a sample from such a population.

For analyses involving multiple levels along the lines of regression analysis, an elaborate array of techniques has been elaborated based on the hierarchical linear model (e.g., Bryk and Raudenbush, 1992; Snijders and Bosker, 1999). This was extended to relational data by Snijders and Kenny (1999), but to a very limited extent because the only network effects considered in that paper were reciprocity and differential outgoingness and popularity, and continuous rather than dichotomous relational data were assumed. One of the elegant features of the hierarchical linear model is that the various levels of analysis are treated in an integrated fashion.

The present paper elaborates a multilevel analysis following the more modest approach along the lines of Cochran (1954) in which the two constituents of the model, the within-network and the between-network parts, are treated sequentially. The results of the within-network studies are used as input to the between-network study. The latter does take into account the imperfect precision of the within-network parameter estimates by separating 'error variance' from 'true variance', which is one of the basic requirements in a multilevel analysis. This more modest approach has the advantage that it is not required to make assumptions about normal (or other) distributional shapes for the distribution of true parameter values across the population of networks. A disadvantage is that this approach can lead to inconsistencies in the results obtained for estimates and tests (as was the case for some parameters in Tables 3 and 4).

The paper shows that such a two-stage multilevel approach is feasible for analysing network evolution in multiple "parallel" networks. The approach is quite computer-intensive and requires that all networks included in the analysis are sufficiently informative for estimating most of the parameters in the model.

The between-network analysis in this paper focused only on means and variances of the parameters. In view of the limited number of 17 networks included in this analysis, it would hardly have been appropriate to use network-level explanatory variables. If a larger number of networks is available, however, the method proposed can be directly extended to a two-stage regression approach which attempts to explain the network-level outcomes using network-level variables.

An interesting point is that the main substantive result, the positive similarity effect on creating as well as on breaking ties, here could be found only because the gratification function was taken into consideration. This function distinguishes between creating and breaking ties and is usually considered a second-order part of the model compared to the objective function. Neglecting it would have led to a much less substantively interesting paper.

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