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Actor-based analysis of peer influence in *A Stop Smoking In Schools Trial* (ASSIST)☆

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ABSTRACT

As shown by the success of network intervention studies that exploit the occurrence of peer influence in their target group, the reliable assessment of peer influence processes can be important for informing public health policy and practice. A recently developed tool for assessing peer influence in longitudinal social network data is stochastic actor-based modeling. The body of the literature in which this method is applied is growing, but how reliable are the results? In this paper, we identify two shortcomings in this literature: the questionable assumption of temporal homogeneity, and the potential dependence of results on the inclusion of nuisance parameters in the model specification. These issues are resolved by analyzing the data of three schools selected from ASSIST, a large UK-based trial of a school-based smoking prevention intervention. Results show that the co-evolution of friendship and smoking is a time heterogeneous process, and that results are sensitive to specification details. However, the peer influence parameter is not affected by either, but emerges as surprisingly stable over time and robust to model variation. This establishes confidence in the method and encourages detailed future investigations of peer influence in ASSIST.

1. Introduction

For interventions aimed at the reduction of smoking to be a success, it is pivotal to know in detail the processes by which smoking habits start and stabilize. An adolescent's school friends and their smoking habits can play a decisive role in these processes, enhancing or suppressing individual tendencies to take up smoking through processes of peer influence (Alexander et al., 2001; Valente et al., 2003). The notion of *peer influence* refers in general to any social process by which a behavior or attitude of a focal individual is affected by the behavior and attitudes that are present among the peers that act as reference points for the individual. In the literature on adolescent development, peer influence has been studied as a process of contagion, by which adolescents gradually adopt their friends' behavior, i.e., become more similar over time. Such similarity of friends is found on a host of behavioral and attitudinal dimensions that are salient in adolescence, for example, substance use patterns, delinquency, school performance, church attendance, participation in sports activities, or sexual behavior (Billy and Udry, 1985; Cohen, 1977; Kandel, 1978; McPherson et al., 2001). In the case of tobacco use, it has long been known that adolescent smokers tend to have more friends that smoke, while their non-smoking counterparts tend to have more non-smoking friends (e.g., Salber et al., 1963; Lanese et al., 1972). This alignment of similar smoking habits with friendship, however, is not an unequivocal indicator for the occurrence of peer influence. As discussed elsewhere (Cohen, 1977; Kandel, 1978; Ennett and Bauman, 1994; Mercken et al., 2009, 2010a,b; Steglich et al., 2010), similarity of friends can also result from other processes, in particular from *smoking homophily*, the selection of friends based on already similar smoking habits. In the methodological literature on peer effects, problems associated with confounding peer influence with peer selection is known as *endogeneity* (Manski, 2000; Moffitt, 2001). Any analytical method that claims to reliably assess peer influence must control for the endogeneity of peer selection. When studying the effects of peer influence on smoking behavior, this issue gains further importance, considering that success or failure of public health policy and practice might crucially depend on the quality of analytical research results.

Recent advances in the modeling of peer influence processes in a dynamic social network context (Snijders et al., 2007, 2010) enable the quantitative assessment of such peer effects on smoking, controlling for the endogeneity of partner choices (Moffitt, 2001). The literature making use of this method, called *stochastic actor-based modeling of network-behavior co-evolution* (henceforth abbreviated as SAB modeling), still is limited and, in general, focuses on diagnosing whether or not peer influence occurs at all (Burk et al., 2007;

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Knecht et al., forthcoming, 2010), and to what degree it can account for behavioral similarity of friends (Mercken et al., 2009, 2010a,b; Steglich et al., 2010).

In this paper, we identify and investigate two previously unaddressed methodological concerns about the reliability of results obtained by this method. The first issue of concern is the assumption of time homogeneity of the co-evolution process in the earlier studies. It is known that during adolescence, social networks as well as risk behavior, including substance use, are highly dynamic—which suggests that time homogeneity is questionable. A more adequate approach, which we take here, is to allow for time heterogeneity in SAB modeling, and assess to what degree analytical results are affected by time. The second issue is the seemingly *ad hoc* choice of model specifications. Notably, the way in which friendship dynamics are controlled for differs considerably across earlier studies, and the degree to which conclusions drawn from SAB modeling, in particular the conclusions about peer influence, are sensitive to such differences in these details remains unclear. We will address this by comparing results from two parallel analyses obtained with very different specifications of friendship dynamics: one is exclusively formulated on the dyad level, reflecting the psychological tradition of research on interpersonal relations; the other includes effects of higher order network structure (triads, classrooms), i.e., pays much more attention to the modeling of friendship selection.

The empirical data with which we will address these concerns were collected in *A Stop Smoking In Schools Trial* (ASSIST; Audrey et al., 2004; Campbell et al., 2008; Starkey et al., 2005). This was a cluster randomized controlled trial of the effectiveness of a school-based, peer-led smoking prevention intervention conducted between 2001 and 2004 in England and Wales. ASSIST collected social network data from over 10,000 students in 59 secondary schools on three annual occasions when the majority of students were aged 12–15. We confine the analyses in this paper to a subsample of 629 students in three schools. Considering the rather technical nature of questions addressed, a larger sample would not necessarily be of added value for our study. Future analyses of ASSIST have the potential to exploit the size of the dataset much better, and substantially deepen our insights into the workings of peer influence in adolescent smoking, provided the reliability issues identified above have been satisfactorily resolved.

The paper is organized as follows. In the following section, after a brief recall of the main methodological challenges encountered in peer influence research, a sketch of SAB modeling is given, followed by a brief summary of the adolescence literature making use of this methodology. Based on this we elaborate our two methodological research questions. As technical background, we sketch the use of goodness of fit criteria that allow testing our hypotheses, as well as the commonly applied meta-analytical procedures for aggregation of results from several independent studies. In the empirical section, we introduce our three schools subsample from ASSIST. We estimate SAB models for these three schools, and answer our research questions. In the discussion, we address implications of our results, and identify several issues on which future analyses of ASSIST will focus.

2. Stochastic actor-based modeling of peer influence

In early comprehensive reviews of the various theoretical accounts for homogeneity among friends, Billy and Udry (1985) and Fisher and Bauman (1988) broadly distinguish between theories of *influence processes*, according to which, for example, friendship begets similarity (*assimilation to friends* hypothesis), and theories of *selection processes*, according to which, for example, similarity facilitates friendship (*homophilic selection* hypothesis). A separation of both processes based on empirical data is indispensable if one is interested in drawing firm conclusions about the occurrence and strength of peer influence in these data. Accordingly, attempts to separate the two types of processes have been made at least since the late 1970s (Cohen, 1977; Kandel, 1978), and many different methods and datasets have been used over the years. A review and critique of these methods is given by Steglich et al. (2010), who derive criteria that an adequate methodological approach should meet. Some of these criteria relate to the design of data collection (longitudinal, complete networks), others to the analytical techniques by which these are to be analyzed, identifying SAB modeling as the preferable method. An introduction to these models is provided now, followed by a brief overview of research applying the method in adolescence research, and a derivation of our two research questions.

2.1. Stochastic actor-based models for network-behavior co-evolution

SAB modeling (Snijders, 2001, 2005; Snijders et al., 2007, 2010) assumes that friendship structure and the distribution of smoking in the school cohort change, in continuous time and in parallel, mutually dependent processes, propelled by individual decisions of the students. Assuming students come from the set $\{1, \ldots, n\}$, we abbreviate the process as $(X, Z)\,(t)$, where $X(t)$ is the friendship adjacency matrix (with x_{ij} being one or zero, indicating that student i calls or does not call student j a friend, respectively) and $Z(t)$ the vector of smoking variables (with z_i being student i's smoking level). While the processes occur in continuous time, the data need to be observed at a sequence of discrete moments only, for example, $t_1 < \ldots < t_m$. Observation $(X, Z)\,(t_1)$ serves as the starting value for the stochastic process, i.e., is not modeled but conditioned upon. Thus, all contingencies that may have led to the initial observation are taken for granted and only subsequent changes are studied. Each student i has control over his outgoing friendship nominations, expressed by the set of tie variables $\{x_{ij} \mid j = 1, \ldots, n\}$, and his own level of smoking z_i. Modeled using stochastic waiting times, students have opportunities to change these variables in between observations. In this paper, we do not elaborate on this model component, but assume that in each period, all students' waiting times are given by the same, constant rate of change—which seems reasonable in the rather egalitarian context of a school cohort. Once a student is identified as having an opportunity to change one of the variables under his control, this is modeled as resulting from comparisons of the alternative courses of action that are possible. Friendship change is modeled by adding or deleting students of the cohort from the current list of friends (i.e., 'swapping' a tie variable x_{ij} from zero to one, or vice versa). Change of smoking is modeled as increasing or decreasing the current level of smoking. The possible changes a student can make are compared on a common scale that reflects the student's satisfaction with the resulting situation. In this comparison, also the option of 'no change' (keeping the status quo) is considered. The scale scores under comparison then are transformed into choice probabilities by a multinomial logit link function, and the student chooses among the options according to this probability distribution. After this, waiting times for all the students are again sampled and the next student who has the opportunity to change something is identified. The total observed change between two observations $(X, Z)(t_r)$ and $(X, Z)(t_{r+1})$ is therefore modeled as resulting from a series of small changes that happen in continuous time between t_r and t_{r+1}, with each change being conditionally independent of the past, given the current state of the process (Markov assumption).

The scales that express a student's satisfaction with his immediate surroundings in the network (i.e., the set of friends, their interconnectedness, and their individual properties, including

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smoking) are the main elements of modeling, called objective functions. These are linear combinations $f_i(X,Z) = \sum_k \beta_k s_{ik}(X,Z)$ in which actor-specific effect statistics $s_i(X,Z)$ are weighted by model parameters β. All factors affecting the adolescents' decisions need to be specified as effect statistics, either in the network objective function f^{net} (when they affect friendship) or in the behavior objective function f^{beh} (when they affect the level of smoking). The model parameters β and their standard errors σ_β are estimated from the observed data. They indicate whether the corresponding effect statistics s measures a property of the process (X, Z) that students strive for (positive parameter) or avoid (negative parameter). In the empirical analysis below, we identify several such properties that operationalize our substantive research questions. The parameters follow an approximate normal distribution (Schweinberger, 2007) which allows the calculation of approximate p-values from the t-ratios β/σ_β according to the standard normal distribution. These are used for testing hypotheses about dynamic mechanisms. For more details on the statistical background of the method and the algorithm used to obtain the estimates, see Snijders et al. (2007, 2010). It is important to keep in mind that the model components do not directly relate to the observed data, but to objective functions governing a stochastic process that indirectly (by integration over unobserved changes that happen between the observations) explains the observed change in the data. As in logistic regression models, when interpreting single parameter estimates, one should consider the values of all other parameters included. Interpretation in terms of conditional probabilities is possible (estimates are 'log-odds'), but 'direct' interpretation in terms of observed outcomes (as possible for linear regression) is not.

2.2. Earlier studies applying SAB models to peer influence in adolescence

For several years now, SAB modeling has been used to study influence processes in a variety of domains, ranging from job satisfaction in organizations (Agneessens and Wittek, 2008), via military discipline at a Naval College (de Klepper et al., 2010) to various applications in adolescence research. Most relevant to the analysis of the ASSIST data are the five precedent studies investigating peer influence on adolescents' tobacco use (Mercken et al., 2009, 2010a,b; Steglich et al., 2010; Pearson et al., 2006). Other adolescence research focuses on delinquency (Baerveldt et al., 2008; Burk et al., 2007; de Cuyper et al., 2009; Knecht et al., 2010), antisocial behavior (Light and Dishion, 2007), weapon carrying (Dijkstra et al., 2010), alcohol consumption (Knecht et al., forthcoming), cannabis use (Pearson et al., 2006), or music taste (Steglich et al., 2006). As might be expected, findings on peer influence are domain and age group specific. Studies using younger samples, such as Light and Dishion (2007; age 11–13) or Knecht et al. (forthcoming, 2010; age 12–13) tend to find weaker peer influence effects than studies involving older adolescents, and peer influence is systematically stronger for some variables (such as alcohol consumption, where it reliably and strongly occurs) than for others (such as delinquency, where evidence is mixed).

For smoking behavior, evidence for peer influence is also mixed. In an international comparison of six countries, Mercken et al. (2009) found evidence for peer influence in only two countries (Finland and the Netherlands) while in the other four countries (Denmark, Poland, the UK and Spain), no such effects were found. The UK results are of particular interest here, as the ASSIST data we analyze in the empirical section are also from the UK. Mercken et al. report that the unavailability of classroom membership information for the four UK schools in which the data were collected may have biased the results in favor of smoking homophily. Because smoking homophily is a potential competitor effect for explaining similarity of smoking among friends, such a bias might also have affected the results on peer influence. In any case, their remark draws attention to the importance of considering the classroom as an important social context when analyzing the data. The other study assessing peer influence on smoking is Steglich et al. (2010) which also makes use of UK data, although these data were collected a decade earlier in Scotland. Here, a significant effect of peer influence on smoking was identified. Class membership information was available, but did not impact on friendship patterns, which the authors suggest was due to the fact that the variable in question referred to an administrative unit and did not reflect real interaction opportunities.

2.3. Two research questions

The present research addresses two methodological deficits of the earlier studies that need to be addressed before drawing conclusions about peer influence. The first is the issue of temporal heterogeneity of the co-evolution process. The role of friendship in adolescence changes with age. Friendships stabilize, develop from 'doing things together' to more intimate, confiding relationships (Berndt, 2004). Likewise, the role of tobacco use in adolescence changes with age, developing through stages (Mayhew et al., 2000). Given this, it is likely that also the degree to which adolescents' smoking is susceptible to peer influence changes with age. However, all previous studies making use of SAB modeling assume temporal homogeneity of the co-evolution process across observation periods. This assumption is a bold one. Moreover, it is made unnecessarily because the datasets analyzed in these studies typically include three or more observation moments, and as such allow for assessing (and testing) time heterogeneity. Here, we aim to address this issue and find out whether SAB models estimated separately for the two observation periods in our three schools' data indicate substantial time heterogeneity of peer influence. If so, this indicates a need to study different observation periods separately, thus casting doubt on the reliability of earlier results, and providing a useful guideline for future analyses. If no heterogeneity can be substantiated, a simpler, joint analysis is justified. As a consequence, the results reported in the extant literature would be strengthened.

As a second topic, we address the issue of robustness of SAB peer influence results, i.e., the question to what degree these depend on seemingly irrelevant details of the model specification. The main strength of SAB modeling lies in the controlling for peer selection effects that are notorious for being confounded with peer influence, as identified above. Therefore, special attention should be paid to the potential dependence of conclusions about peer influence on specification details in the model's peer selection component. Prior studies reporting SAB models differ here considerably. E.g., while many studies control for endogenous network evolution with just the two parameters *reciprocity* and *transitive triplets* (Burk et al., 2009; Dijkstra et al., 2010; Knecht et al., forthcoming, 2010; Mercken et al., 2009, 2010a,b), others include more and/or different parameters, such as the *popularity* (Agneessens and Wittek, 2008; Berardo and Scholz, 2010; Steglich et al., 2010), *activity* (Agneessens and Wittek, 2008), or *structural equivalence* of partners (Agneessens and Wittek, 2008; Steglich et al., 2010), or the *number of only indirectly connected actors* (Burk et al., 2007; Light and Dishion, 2007; Pearson et al., 2006; Steglich et al., 2006). When specifying an SAB model, it would be helpful to know how much care over model selection needs to be taken in this typically rather unimportant 'nuisance' part of the model. If estimates of effects of focal interest (in our case: the parameter assessing peer influence) do not differ much between alternative, reasonable model specifications, the whole body of research employing SAB modeling potentially benefits. On the one hand, such a result can strengthen the findings of prior studies by showing robustness of the method against specification of the nuisance/control part of the model. On the other hand, it can serve as justification for model selection in future studies: As long as a reasonably complex model of friendship dynamics is controlled for, the results of SAB modeling about peer influence are reliable—at least in comparable datasets and for comparable research focus as those used for the robustness check. The analyses we perform in the empirical section will therefore in particular be useful for future analyses of peer influence in ASSIST and similar datasets.

The one previous study reporting nested models (Steglich et al., 2010) suggests that even quite strong differences in the specification of friendship dynamics barely affect the conclusions about peer influence.[1] Estimates of the model parameters operationalizing peer influence on students' smoking, in this study, differed by less than one fifth of a standard error between model specifications; for alcohol consumption, the difference still was less than one-third of a standard error (Steglich et al., 2010: Table 6). The unfortunate aspect about these results is that the two models compared do not only differ in the way friendship selection is modeled, but also by a series of effects on the dependent behavioral variables (smoking and alcohol consumption). This means that the low sensitivity of peer influence that was found cannot strictly be established for specification differences in friendship selection, but could potentially be the result of opposite biases cancelling each other out. The present study will allow less equivocal conclusions to be drawn. We compare two strongly different strategies of modeling the selection component: based on dyads only, versus based on higher order context (triads or classrooms). Should conclusions about peer influence be affected by the specification of the selection part of the model, this would call for very detailed investigation of selection processes in future research. If, however, peer influence results are not so sensitive to specification details, this justifies the use of any reasonably complex specification in past and future research.

3. Goodness of fit and meta-analysis

A few technical hurdles need to be overcome before addressing the research questions in an empirical analysis of the three ASSIST schools. We need to know how results from different time periods can be compared, how models with differing specification can be compared, and how results for the three schools can be combined into one comprehensive set of results. To make a comparison of results obtained in different analyses – be it of different time periods, or according to different model specifications – confidence intervals are constructed and their overlap measured. This is a very conservative test of differences between two sets of results, which can be improved upon. In the case of time heterogeneity, this improvement consists of directly testing whether parameters differ significantly between periods. This is possible without making any additional assumptions because SAB models are Markov processes, which implies that subsequent periods are assumed to be conditionally independent. When comparing two models that are estimated on the same dataset, a direct test is not possible, however goodness of fit criteria can be used when the models are nested, which will be the case for comparing the two model specifications outlined above and detailed below. In the following two subsections, these goodness of fit tests will be described first, followed by the aggregation of results from different datasets into a joint set of results.

[1] The friendship selection models differed by three endogenous triadic effects, twelve effects of exogenous variables, and four more effects of the co-evolving behavioral dimensions (smoking and alcohol use) on friendship.

3.1. Goodness of fit for SAB models

When choosing between model specifications, goodness of fit criteria can provide statistical guidance. In SAB models, like in other non-linear models, there is no straightforward, omnibus goodness of fit measure like the variance accounted for (*r*-squared) in linear regression modeling. However, score-type tests (Schweinberger, 2007) may be used to assess the lack of fit of the smaller of two nested models compared to the larger one. In this case of nested models, the model parameters can be ordered such that vector (β_1, . . ., β_k) pertains to the effects included in the smaller model while vector (β_{k+1}, . . ., β_{k+r}) pertains to effects that are present in the larger model but absent in the smaller one. Formally, the smaller model can be written as a constraint on the larger one, requiring that the parameters in this second vector are all zero. The *score test* of this constraint is then calculated as an approximately chi-square distributed statistic with *r* degrees of freedom, where *r* is the number of parameters that are constrained to zero. It indicates the goodness of fit discrepancy between the two models. Some illustrations of how score tests can be used for forward model specification can be found in Snijders et al. (2007). Below, in the context of analyzing the sensitivity of peer influence to model specification details, we test whether a friendship model formulated on the dyad level sufficiently fits the data, or whether one should also include effects formulated on the level of triads or classrooms.

3.2. Combining results from multiple schools

The analytical procedures outlined thus far relate to single network datasets only, which in the ASSIST data would refer to a single school. In order to aggregate school-specific results across schools, and when assessing the moderating effects of school-level characteristics on the strength of peer influence and friendship selection (not done in this paper), it is necessary to consider the multilevel structure of the data. Because there currently is no way to simultaneously analyze data from multiple schools with a multilevel-variant of the actor-based network models, a meta-analysis can be performed on the results obtained for each school separately, i.e., treating those as independent studies. If the number of schools is high enough, explanatory variables at the school level can be included to model between-school heterogeneity of SAB effects like peer influence (Goldstein, 1995). Because in this paper we restrict the analyses to three schools only, such effects are extremely unlikely to be found. Therefore, we restrict the presentation here to methods of aggregating main effects across studies (Hedges and Olkin, 1985). Our discussion assumes that the same model was estimated for all schools, i.e., the same set of effects were included. For the model parameters estimated, *t*-tests of parameter significance obtained for the different schools can be combined with the help of meta-analytic procedures. For stochastic network models like those we use to analyze our data, this has so far largely been done by Cochran's (1954) method which essentially consists of a significance test for the average parameter value (Lubbers, 2003; Snijders and Baerveldt, 2003). A crucial assumption behind this method is that estimates and standard errors are uncorrelated across studies, i.e., that there are no severe scale differences between the studies that are aggregated and thus that the calculation of an average parameter is a meaningful operation. In network studies, such scale differences can arise, for example, from differences in network size or density. Because in the full ASSIST dataset, school year group size (and hence network size) varies between 70 and 404, there is reason to expect such scale differences when analyzing all schools. In this paper, there is little difference in school year group size (see Table 1). Nonetheless, we also explore Fisher's combination of *p*-values (cf. Hedges and Olkin, 1985, Chapter 3) as an alternative method of combining results from independent

Table 1
For all network measures, the structurally absent actors are not considered. The reciprocity index is $2M/(2M+A)$ where M and A are the number of mutual and asymmetric dyads, respectively. Transitivity and 3-cycle indices are calculated as the ratio of the numbers of actually by potentially transitive/cyclical triplets.

	Sweep	Sample		Friendship network					Smoking		Demographics			
		Number pupils	Pupils missing	Ties missing	Network density	Reciprocity index	Transitivity index	3-cycle index	Smoking missing	Average smoking	Sex (%girls)	Average age (years)	Parental smoking	Average FAS
School A	T2	158	7%	7%	0.029	0.64	0.47	0.40	11%	2.1	56%	12.5	43%	4.4
	T3	158	2%	3%	0.031	0.67	0.45	0.40	11%	2.5	55%		46%	4.2
	T4	156	3%	4%	0.031	0.61	0.39	0.32	10%	3.0	55%			
School B	T2	191	5%	6%	0.021	0.65	0.47	0.37	10%	1.7	46%	12.6	53%	3.6
	T3	189	6%	7%	0.023	0.64	0.45	0.38	9%	2.0	46%		51%	3.6
	T4	185	16%	18%	0.020	0.66	0.48	0.41	22%	2.4	48%			
School C	T2	247	0%	0%	0.019	0.57	0.32	0.26	5%	1.9	51%	12.7	38%	4.2
	T3	244	3%	3%	0.020	0.60	0.38	0.32	9%	2.4	52%		38%	4.3
	T4	244	5%	6%	0.018	0.61	0.37	0.31	10%	2.5	51%			

studies. This method is not sensitive to the scale on which the parameters are identified, and this is justification for its use as a replacement for Cochran's meta-analysis when the latter isn't applicable. In addition, Fisher's method is sensitive to strong results in single studies, which justifies its use in its own right. A comparison of both methods seems useful because, while they are known to differ in statistical power, there is no a priori reasoning for choosing between them in our case, i.e., it is not evident which of the two combined tests would yield highest power to detect effects of interest in the case of our three schools' data.

In Fisher's combined test, the product of k one-sided p-values is transformed into the χ^2 distributed test statistic $-2\ln\prod_{r=1}^{k}p_r$ with $2k$ degrees of freedom, indicating whether the null hypothesis that an effect is zero in all schools can be rejected against the one-sided alternative. Below, we apply the procedure to right-sided tests, where the null hypothesis is that the effect is nonpositive, and to left-sided tests, where the null hypothesis is that the effect is nonnegative. When both combination procedures are carried out at a significance level of $\alpha/2$, it follows that the total probability of a type-I error is α. An unusual feature of Fisher's method is that it can deliver departure from a null effect in both directions at the same time. If this happens, it indicates that there is a strong heterogeneity of the schools in terms of the sign of the effect, warranting further investigation. In the analyses reported in this paper, this case did not occur for any of the parameters estimated.

Cochran's method delivers a test for (and an estimate of) the true mean parameter in all schools, and captures heterogeneity across schools by providing a test for (and an estimate of) the true school-level variance of the parameter. The method comes at the cost of assuming that estimates are uncorrelated with their standard errors, which is not always the case in network studies like ours. More details on the calculations involved can be found in Snijders and Baerveldt (2003).

4. Empirical analysis

The two research topics identified above are (1) the potential occurrence of time heterogeneity in the co-evolution of friendship and smoking and (2) the sensitivity of SAB model results to potentially distracting details in the model specification. While the focal interest is on peer influence, the analyses offer the opportunity to study the heterogeneity and sensitivity issues also in relation to other dynamic processes. We accordingly follow an exploratory rather than a hypothesis-driven approach. We now give a description of the data to be analyzed, then the two alternative model specifications are introduced.

4.1. Data

The ASSIST data were obtained during an evaluation of a school-based, peer-led intervention, in which a subsample of the students were given (school-external) training on how to use their informal relationships at school to discourage their peers from smoking. By design, it should be peer influence processes that are responsible for the documented success of the intervention (Campbell et al., 2008). The focus on influence when designing the intervention is complemented by sociometric data collection that allows analysis of peer influence processes. As such, the ASSIST data are ideally suited not only to investigate the points of concern raised above, but also to set out a research agenda on social influence processes that goes considerably beyond the scope of this paper. Here, we analyze a subsample of three control schools from ASSIST (i.e., schools in which no intervention took place) to address our research questions; in the final discussion we describe more detailed plans to deepen our understanding of the workings of peer influence in ASSIST in particular, and adolescent smoking in general.

Students were aged 12–13 when entering ASSIST, and were in their second year of secondary school. Complete friendship networks among the whole cohort of students were obtained at three time points spaced at one-year intervals, making use of a name generator that allowed students to name up to six friends. While more details about these friendships are known, we here treat them as binary indicators. The smoking variable we analyze in this article is self-reported cigarette consumption, ranging from 1 (never smoked) to 6 (more than six cigarettes per week). The three schools that constitute our reduced sample are those on which process evaluation took place; in terms of our study, this primarily means that the data were available first, and were used for validating the network name generator. In terms of socio-demographic characteristics, the process evaluation schools were purposively selected to represent a range of schools from both urban (big city) and semi-urban (small town) communities, of varying size and level of deprivation, and from England and Wales. They are all state-funded co-educational schools. More precisely, School A is a small semi-urban school in England with a low level of social deprivation, as indicated by a low proportion of students entitled to free school meals (6.0%); School B is large urban school in England with high free school meal entitlement (23.9%), and School C is a large semi-urban school in Wales with low free school meal entitlement (8.3%).

The family context is captured in the two variables *parental smoking* and *family affluence*. Parental smoking is a dummy variable summarizing whether students indicated that one or more of the following individuals were smokers: mother (includes step and foster mother), father (includes step and foster father), parent's boyfriend, or parent's girlfriend. Family affluence is an index with range 0–6 derived from the following questions: "Does your family have a car or van?" (No, Yes, or Yes two or more), "Do you have your own bedroom for yourself?" (No or Yes), and "During the last 12 months, how many times did you travel away on holiday with your family?" (Not at all, Once, Twice, or More than twice). Where there were missing responses for the family affluence index, a value was imputed which comprised the sum of the responses provided over the maximum possible; this did not apply where all values were missing. Table 1 presents descriptive statistics of the three schools included in our analyses.

In terms of dynamic patterns the table illustrates that there is a strong increase in smoking in these three schools, while the structural features of the networks seem to be fairly stable. Overall, friendship networks are sparse, i.e., have low density. The values of the indices for reciprocity, transitive triplets, and 3 cycles are much higher than the network density, indicating strong evidence for mutuality and clustering of friendship.

4.2. Model specification

The data are analyzed by way of SAB modeling as introduced above. This involves the selection of effects into two objective functions. The behavior objective function consists of effects that model the changes in the adolescent's levels of smoking. It is here where the peer influence effect will be assessed. The network objective functions consist of effects that model changes in an adolescent's friendship choices. Here, smoking-based homophily is assessed. It also is the place where the two models used for the sensitivity analysis will differ, as detailed below. As previously discussed, all effects are formulated as statistics $s_i(X, Z)$ that express a property of an actual or potential (i.e., contemplated) state (X, Z) of the co-evolution process. The property, weighted by a parameter β, indicates whether the actor strives for or avoids this property of the state by own actions, i.e., friendship choices and decisions about own smoking.

The focal effect in this study is peer influence. The statistic used to operationalize it is given by the formula $s_i(X, Z) = \sum_j x_{ij}\left(1 - \left(\left(\left|z_i - z_j\right|\right) / (\text{range}_z)\right)\right)$. This statistic sums up the similarity of actor i to all his friends j on the smoking variable z. When including this statistic as an effect in the behavior objective function f^{beh}, it expresses actor i's tendencies to become more similar to his current friends, regarding smoking habits (hence peer influence). We refer to this effect as the *total similarity* effect on the dynamics of smoking. When including the same effect statistic in the network objective function f^{net}, it models homophilic selection, i.e., actor i's tendencies to select new friends that are similar to him in terms of smoking, or drop existing friends that are dissimilar in terms of smoking. Below, this homophily effect is reported as *smoking similarity* in the friendship part of the model. Other network effects related to smoking are modeling activity differences in friendship (*smoking ego* effect, formula: $s_i(X, Z) = \sum_j x_{ij} z_i$) or popularity differences (*smoking alter* effect, formula: $s_i(X, Z) = \sum_j x_{ij} z_j$, and a non-linear version of the same effect in which v_j is squared to more accurately identify which smoking levels make an actor popular as a friend).

When testing the sensitivity of SAB modeling results to specification details, a dyad-based 'interpersonal' specification of friendship selection is compared to a triad-based 'context' specification. In the interpersonal specification, effects of *sex*, *age*, *parental smoking* and *family affluence* are included as determinants of activity, popularity and homophily in partner selection (formulae as above), next to the endogenous dyadic effect of *reciprocity* (formula: $s_i(X, Z) = \sum_j x_{ij} x_{ji}$). In the context specification, an effect of being in the *same form* was added,[2] as well as several endogenous network effects: *transitive triplets* (formula: $s_i(X, Z) = \sum_{jk} x_{ij} x_{jk} x_{ik}$) and three more effects that operationalize triadic group interaction in the network: *transitive ties* (models, like transitive triplets, friendship groups with an intrinsic hierarchical structure), *3 cycles* (models non-hierarchical, egalitarian friendship group structure), and *number of actors at distance 2* (models tendencies to select a few well-connected middlemen instead of many direct friends). Finally, the *outdegree* effect (formula: $s_i(X, Z) = \sum_j x_{ij}$) is included in both model specifications with the role of intercept, i.e., modeling the average tendency to have friends expressed in the networks' density.

In the part of the model explaining smoking dynamics, peer influence was controlled for as were main effects of the variables: *sex*, *age*, *parental smoking* and *family affluence*, which were expressed by statistics $s_i(X, Z) = v_i z_i$, where v stands for the variable. These effects are included in the behavior objective function for both the interpersonal and the context specification—so these specifications differ exclusively by whether or not they account for the possibility to base friendship on larger-than-bilateral information (triads, classrooms). Two *shape effects* are included: the *linear shape* effect (formula: $s_i(X, Z) = z_i$) is an intercept expressing the average tendency to smoke, and the *quadratic shape* effect (formula: $s_i(X, Z) = (z_i - \bar{z})^2$) controls for underdispersion (regression to the mean) or overdispersion (polarization) of the smoking variable, which must be distinguished from genuine peer influence effects (Snijders et al., 2010). Together, they control for the distributional shape of the smoking variable. Based on the U-shaped empirical distribution depicted in Fig. 1, polarization is what can be expected, i.e., a positive quadratic shape parameter.

[2] The *same form* effect can formally be defined on the dyad level, by two students sharing the same classroom. We here nonetheless include it as 'context' because it refers to interaction opportunities that are not bilateral, but determined by larger social units. To check sensitivity of results to this decision, we estimated another dyad-based model (not reported in this paper) that also included the *same form* effect. Results were equivalent to those reported here.

Table 2
Determinants of smoking dynamics.

	Interpersonal model				Network context model			
	Average	(St. error)	Fisher	Cochran	Average	(St. error)	Fisher	Cochran
Effects period T2–T3								
1. Rate of change: smoking	1.724	(0.206)	–	–	1.728	(0.206)	–	–
2. Total similarity	0.691	(0.263)	0.011*	0.004**	0.619	(0.267)	0.027*	0.010*
3. Shape: linear	−0.029	(0.130)	0.336	0.403	−0.018	(0.130)	0.425	0.445
4. Shape: quadratic	0.302	(0.048)	<0.001***	<0.001***	0.293	(0.050)	<0.001***	<0.001***
5. Effect from sex	−0.142	(0.147)	0.190	0.147	−0.135	(0.147)	0.237	0.180
6. Effect from age	0.008	(0.008)	0.152	0.117	0.011	(0.008)	0.135	0.080+
7. Effect from parental smoking	0.645	(0.164)	<0.001***	<0.001***	0.665	(0.169)	<0.001***	<0.001***
8. Effect from family affluence	−0.038	(0.065)	0.153	0.294	−0.018	(0.065)	0.247	0.394
Effects period T3–T4								
1. Rate of change: smoking	1.660	(0.278)	–	–	1.677	(0.286)	–	–
2. Total similarity	0.641	(0.402)	0.003**	0.055+	0.569	(0.320)	0.005**	0.037*
3. Shape: linear	0.150	(0.171)	0.047*	0.191	0.169	(0.184)	0.018*	0.179
4. Shape: quadratic	0.186	(0.067)	<0.001***	0.003***	0.206	(0.098)	<0.001***	0.018*
5. Effect from sex	−0.334	(0.190)	0.014*	0.039*	−0.359	(0.195)	0.008**	0.032*
6. Effect from age	0.004	(0.007)	0.329	0.289	0.3	(0.007)	0.366	0.329
7. Effect from parental smoking	0.055	(0.154)	0.281	0.376	0.073	(0.154)	0.258	0.319
8. Effect from family affluence	−0.115	(0.055)	0.037*	0.018*	−0.113	(0.055)	0.037*	0.019*

+ $p < 0.1$ (one-sided).
* $p < 0.05$ (one-sided).
** $p < 0.01$ (one-sided).
*** $p < 0.001$ (one-sided).

5. Results

For each of the three schools, the two nested models, 'interpersonal' and 'context', are fitted separately to the data of the two observation periods, which gives a total of 12 sets of parameter estimates. In Tables 2 and 3, they are summarized per time period and per model specification. For each parameter we report its true mean over the three schools as calculated according to Cochran's procedure, its standard error, the results of Fisher's combined one-sided test in the direction of this average, and the one-sided test results for the true mean parameter according to Cochran's method. As a whole, there is little variation in the *p*-values obtained from the two meta-analytical procedures, which is reassuring. Results on parameter variance across studies, which the Cochran method also provides, are not reported. There is evidence for such variance between the three schools on almost all the significant parameters. What these school differences are due to cannot be investigated here in a statistically meaningful way because the number of schools is too small. It should be noted, though, that for the effects in question there were no qualitative (i.e., sign) differences between schools. We now first describe what the results mean in substantive terms. Then, time heterogeneity and sensitivity to specification details are addressed.

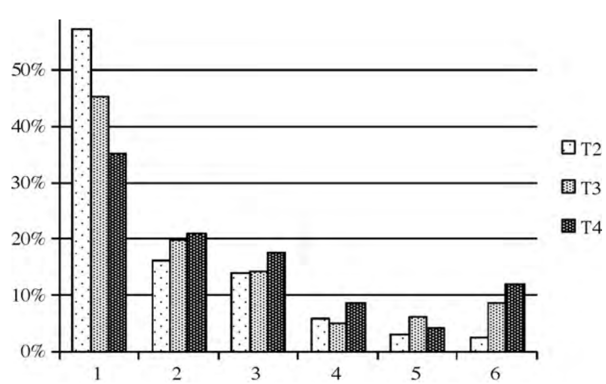

Fig. 1. Empirical distribution of smoking over the three sweeps.

5.1. Smoking dynamics

Peer influence is the focal mechanism in this analysis. It is measured by the *total similarity* parameter, which is significant positive in all the analyses. The positive sign means that whenever students change their smoking behavior over time, they strive to be similar to their friends. At face value, the estimates do not differ very much between observation periods and model specifications; this will be addressed in more detail below. There is a contagious (positive) effect of *parental smoking* in the earlier period which turns nonsignificant in the later period. The effects of *sex* and *family affluence* are also nonsignificant in the first period, but turn significant in the later period, when boys take up smoking less than girls do, and when students from more affluent families prove to be more resistant to smoking. Apparently, the mechanisms by which adolescents start smoking emancipate themselves from the influence of parents (Hu et al., 1995), by the third year of secondary school, and other individual and background variables become important in explaining smoking dynamics. The degree to which these period differences also are significant is addressed below. In addition, there seems to be a general developmental pattern towards smoking uptake that cannot be explained by our variables, but is captured in the sign change of the *linear shape parameter* from slightly negative (indicating an overall aversion to smoking) to marginally significant positive (indicating a shift of preference towards higher smoking levels). Finally, the significant positive *quadratic shape parameter* estimated in both models indicates that smoking has polarizing dynamics independent of the peer influence effect.

5.2. Friendship dynamics

In Table 3, the remaining part of model estimates are given—those pertaining to friendship dynamics that express peer selection processes. The main control parameter of interest here is *smoking similarity* (5th row in the table), which is significantly positive in all models and observation periods. It expresses tendencies of the students to increase the similarity to their friends not by adjusting their smoking, but by changing their friends, i.e., by dropping those whose smoking habits are dissimilar and selecting new ones whose habits are similar to their own. The parameter estimates are about the same for both time periods, but differ between

Table 3
Determinants of friendship dynamics.

	Interpersonal model				Network context model			
	Average	(St. error)	Fisher	Cochran	Average	(St. error)	Fisher	Cochra
Effects period T2–T3								
1. Rate of change: friendship	12.955	(0.461)	–	–	19.608	(1.674)	–	–
2. Smoking alter	0.087	(0.037)	0.023*	0.009**	0.069	(0.043)	0.117	0.055^{+}
3. Smoking squared alter	−0.006	(0.015)	0.471	0.355	−0.017	(0.017)	0.276	0.170
4. Smoking ego	0.028	(0.019)	0.082^{+}	0.069^{+}	0.022	(0.019)	0.224	0.126
5. Smoking similarity	0.695	(0.215)	<0.001***	<0.001***	0.459	(0.154)	<0.001***	0.001*
6. Outdegree (density)	−2.722	(0.072)	<0.001***	<0.001***	−2.438	(0.142)	<0.001***	<0.001*
7. Reciprocity	2.580	(0.051)	<0.001***	<0.001***	1.867	(0.075)	<0.001***	<0.001*
8. Transitive triplets	–	–	–	–	0.105	(0.024)	<0.001***	<0.001*
9. 3 Cycles	–	–	–	–	−0.189	(0.059)	<0.001***	<0.001*
10. Transitive ties	–	–	–	–	0.651	(0.147)	<0.001***	<0.001*
11. Number of actors at distance 2	–	–	–	–	−0.577	(0.038)	<0.001***	<0.001*
12. Sex alter	−0.018	(0.072)	0.127	0.443	−0.069	(0.072)	0.097^{+}	0.170
13. Sex ego	0.037	(0.063)	0.241	0.288	0.070	(0.063)	0.208	0.133
14. Sex similarity	1.099	(0.055)	<0.001***	<0.001***	0.526	(0.063)	<0.001***	<0.001*
15. Age alter	0.001	(0.002)	0.329	0.216	0.0005	(0.002)	0.490	0.391
16. Age ego	−0.002	(0.003)	0.028*	0.235	−0.002	(0.002)	0.203	0.140
17. Age similarity	0.082	(0.093)	0.242	0.168	0.059	(0.093)	0.426	0.263
18. Parental smoking alter	−0.054	(0.045)	0.097^{+}	0.115	−0.041	(0.045)	0.169	0.183
19. Parental smoking ego	0.030	(0.042)	0.353	0.249	0.059	(0.042)	0.153	0.078^{+}
20. Parental smoking similarity	0.091	(0.037)	0.015*	0.007**	0.057	(0.038)	0.133	0.068^{+}
21. Family affluence alter	−0.017	(0.015)	0.182	0.121	0.020	(0.016)	0.118	0.107
22. Family affluence ego	0.007	(0.016)	0.266	0.335	0.0003	(0.015)	0.419	0.493
23. Family affluence similarity	0.074	(0.099)	0.175	0.228	0.085	(0.185)	0.030*	0.323
24. Same form					0.322	(0.146)	<0.001***	0.014*
Effects period T3–T4								
1. Rate of change: friendship	9.384	(0.798)	–	–	13.567	(0.866)	–	–
2. Smoking alter	0.114	(0.062)	<0.001***	0.032*	0.090	(0.049)	0.002**	0.032*
3. Smoking squared alter	−0.045	(0.026)	0.003**	0.040*	−0.044	(0.019)	0.003**	0.010**
4. Smoking ego	−0.016	(0.021)	0.184	0.229	0.0	(0.021)	0.420	0.492
5. Smoking similarity	0.588	(0.264)	<0.001***	0.013*	0.398	(0.272)	<0.001***	0.072^{+}
6. Outdegree (density)	−2.692	(0.143)	<0.001***	<0.001***	−2.322	(0.174)	<0.001***	<0.001***
7. Reciprocity	2.592	(0.235)	<0.001***	<0.001***	1.951	(0.146)	<0.001***	<0.001***
8. Transitive triplets	–	–	–	–	0.148	(0.024)	<0.001***	<0.001***
9. 3 cycles	–	–	–	–	0.307	(0.057)	<0.001***	<0.001***
10. Transitive ties	–	–	–	–	0.438	(0.065)	<0.001***	<0.001***
11. Number of actors at distance 2	–	–	–	–	−0.534	(0.048)	<0.001***	<0.001***
12. Sex alter	0.081	(0.089)	0.087^{+}	0.182	−0.017	(0.059)	0.429	0.389
13. Sex ego	−0.047	(0.061)	0.360	0.234	70.491	(0.061)	0.547	0.491
14. Sex similarity	1.062	(0.082)	<0.001***	<0.001***	0.520	(0.056)	<0.001***	<0.001***
15. Age alter	0.009	(0.002)	<0.001***	<0.001***	0.009	(0.002)	<0.001***	<0.001***
16. Age ego	0.0001	(0.002)	0.412	0.489	−0.0002	(0.002)	0.444	0.468
17. Age similarity	0.043	(0.102)	0.465	0.338	0.056	(0.102)	0.434	0.289
18. Parental smoking alter	−0.114	(0.052)	0.020*	0.014*	−0.142	(0.100)	<0.001***	0.079^{+}
19. Parental smoking ego	−0.066	(0.051)	0.082^{+}	0.100^{+}	−0.031	(0.047)	0.255	0.255
20. Parental smoking similarity	0.013	(0.057)	0.336	0.404	0.009	(0.057)	0.356	0.436
21. Family affluence alter	−0.017	(0.018)	0.281	0.168	−0.031	(0.018)	0.088^{+}	0.042*
22. Family affluence ego	−0.014	(0.017)	0.246	0.204	−0.026	(0.016)	0.077^{+}	0.049*
23. Family affluence similarity	0.237	(0.107)	0.024*	0.014*	0.268	(0.121)	0.024*	0.014*
24. Same form	–	–	–	–	0.152	(0.047)	0.002**	<0.001***

$^{+}$ $p < 0.1$ (one-sided).
* $p < 0.05$ (one-sided).
** $p < 0.01$ (one-sided).
*** $p < 0.001$ (one-sided).

the two models, suggesting that in the interpersonal specification, tendencies towards clustering and within-classroom friendship choice are wrongly interpreted as tendencies towards choosing friends with similar smoking habits. According to all four analyses, friendship nominations are based on sex homophily (14th row) and on the nominated person's smoking level. Smoking makes a potential friend attractive (positive parameter *smoking alter*, 2nd row) but strong smoking is less attractive than average smoking (negative parameter *smoking squared alter*, 3rd row). Furthermore, typical properties of friendship networks are confirmed, such as overall low density (negative *outdegree effect*, 6th row), and a high degree of reciprocation in nominations (positive *reciprocity effect*, 7th row).

All other effects determining friendship dynamics are either nonsignificant according to all four analyses, or significant in only a subset of the analyses. Age differences and family affluence seem to play a role in the later period only, when older students become more attractive (positive *age alter effect*, 15th row) and students from more affluent families start selecting each other (23rd row) while avoiding other types of contact (21st and 22nd row). If included in the model specification, all five context parameters are strongly significant (8th–11th and 24th row), indicating strong effects of clustering based on triad and classroom level interaction opportunities. These effects identify tendencies that in the interpersonal model were falsely attributed to other mechanisms, as could already be seen for the *smoking similarity* parameter. For example, the parameter *sex similarity* (14th row) also shows a very strong reduction in effect size when moving from the interpersonal to the context model. One notable exception to this pattern of reduced effect sizes is the family affluence variable. Here, the pattern is

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inverted; selectivity on family affluence (parameter *family affluence similarity*, 23rd row) has a higher effect size in the network context model than in the interpersonal model. This suggests a role of family affluence that acts against network context effects. Apparently, friendship ties that would have formed due to sheer opportunity in the school context were deliberately avoided due to asymmetries in family affluence.

Two unexpected results, which we invited by including parental smoking as an explanatory variable for friendship formation, is the selection of friends based on similar parental smoking in the earlier observation period (20th rows) and the reduced attractiveness of adolescents whose parents smoke in the later observation period (18th rows). Presumably, these effects capture something about the family context that is different from (but correlated with) parental smoking. Considering the preliminary nature of our investigation, further speculations seem unwarranted at this stage.

5.3. Time homogeneity

The statistical testing of the time homogeneity assumption is carried out only for the more general context model. First, confidence intervals are constructed. A p-value is determined in the following way. For both periods, we take the estimates of the true mean parameter and its standard error according to Cochran's aggregation procedure into the interval construction. We then determine the highest confidence level at which such a construction would yield non-overlapping confidence intervals for the two period-specific true mean parameters. The p-value is taken as the corresponding significance threshold for one-sided testing. For example, should the procedure yield a confidence level of maximally 95% at which the two intervals do not overlap, this would correspond to a value of $p = 0.025$. According to this procedure, marginal time homogeneity can be diagnosed for the effect of *parental smoking* on student smoking ($p = 0.067$; the effect of parental smoking on student smoking wanes over time), while significant time homogeneity occurs for the effect of *age alter* in friendship formation ($p = 0.027$; maturity of friends becomes a stronger friendship selection criterion) and *rate of change: friendship* ($p = 0.017$; friendship stabilizes over time, i.e., friends are changed less frequently).

A second way to test time homogeneity is to base p-values on differences between the two periods' parameter estimates and their standard errors. The latter can be calculated from the periodwise results because the SAB model is a Markov process, enforcing zero correlations between parameters of different periods. The calculations are carried out at the school level, and then aggregated over schools according to the meta-analytical procedures outlined above. Because this makes more efficient use of the available information than the confidence interval method, the procedure delivers more positives. Time heterogeneity, i.e., a test for the parameter difference being nonzero, was consistently identified by the Cochran and the Fisher method for the three parameters already mentioned (*parental smoking* effect on student smoking: Fisher $p = 0.008$, Cochran $p = 0.003$; *age alter* effect on friendship: Fisher $p = 0.003$, Cochran $p = 0.001$; *rate of change: friendship*: Fisher $p < 0.001$, Cochran $p = 0.006$) and for the *transitive ties* effect in friendship formation (Fisher $p = 0.039$, Cochran $p = 0.039$), which suggests that triadic group dynamics differ between the two periods.[3]

According to both ways of testing, the *peer influence* effect shows no significant change over time (Fisher $p = 0.557$, Cochran $p = 0.473$, confidence interval $p = 0.933$); the same is true for the *smoking homophily* effect (Fisher $p = 0.383$, Cochran $p = 0.482$, confidence interval $p = 0.887$); both remain very stable over time. In the light of these results, it is useful to reflect on what *stability* of these parameters actually means. This requires a consideration of the models' rate functions. As indicated by the results for the *rate of change* parameters, friendship dynamics slow down from the first to the second period (row 1 of Table 3), while smoking dynamics do not (row 1 of Table 2). This implies that even though there is temporal stability of the parameters operationalizing smoking homophily (5th row of Table 3) and peer influence (2nd row of Table 2), there will be relatively less *opportunities* for smoking homophily than for peer influence to exert their effect in the later period. If our investigation were not primarily interested in the peer influence effect as such, but in explaining the similarity of smoking among friends (as, e.g., Mercken et al., 2009, 2010a,b; Steglich et al., 2010), then despite the temporal stability of the two parameters, we would conclude that the overall importance of the selection mechanism declines over time, relative to the influence mechanism—simply because the rate of friendship change drops.

Table 4
Lack of fit due to neglecting network context. Cells contain χ^2 statistics ($df = 5$) for the joint score test that five parameters are zero: transitive triplets, transitive ties, 3 cycles, actors at distance 2, and same form.

	School A	School B	School C
T2–T3	1035.1	1812.4	2027.5
T3–T4	665.1	848.6	773.0

5.4. Sensitivity to specification details

The comparison between the interpersonal model and the context model is done in two ways. First, we show that there is a significant improvement of model fit to the data. For this purpose, we conducted score-type tests, which are reported in Table 4 for the three schools and the two periods. Next, the confidence interval method introduced above is used, based on time-aggregated results for each model—i.e., we do not compare the models periodwise, but use Cochran's method to aggregate results not just across schools but also across periods. The implicit assumption that results of two periods from the same school are independent can again be justified with the Markov property of the SAB model.

The score tested block of effects by which the two models differ consists of all the triadic network effects plus the class membership information (*same form* effect). The results of the tests, given in Table 4, are that the relative lack of fit of the interpersonal model is highly significant for all schools and periods. The role which the tested effects play in the first period seems to be larger than their role in the second period—which is perhaps due to the overall more rapid network dynamics in the first period compared to the second, as indicated above. In line with the increased fit increase observed when the block of context effects were included, all of the effects included are highly significant. Other parameters reported in Table 3, also change between specifications. That the determinants of friendship (Table 3) are more sensitive to context inclusion than the determinants of smoking (Table 2) is not surprising because network context effects by definition are effects that explain friendship dynamics, and hence will naturally correlate with (and subtract effect size from) other determinants of friendship. The peer influence effect (2nd rows in Table 2) also shows a small decrease when moving from the interpersonal to the context model.

Whether these differences attain significance is investigated by assessing confidence interval overlap for the true mean parameters of both models, based on the Cochran method's aggregations over all schools and both time periods (i.e., after collapsing the two

[3] A more precise interpretation goes beyond the scope of this paper, but is in line with the general idea that friendship stabilizes over time and 'crystallizes' into change-resilient network structures.

subtables of Tables 2 and 3 into one). The *p*-values identify highly significant drops in parameter size for the effects *reciprocity* and *sex similarity* ($p < 0.001$; 7th and 14th rows of Table 3) resulting from the inclusion of the context effects. This suggests that group formation occurs between people of the same sex and follows norms of reciprocity, but is distinct from both and better explained by the block of context effects. Marginal upward changes were identified for the parameters *rate of change: friendship* ($p = 0.058$; 1st row of Table 3) and *outdegree* ($p = 0.065$; 6th row). Both the *peer influence* effect ($p = 0.835$) and the *smoking homophily* effect ($p = 0.441$) are not sensitive to the change in model specification. Whether conclusions would be different when based on more schools' datasets or on a more efficient testing procedure is unclear, considering that results do show a systematic negative effect of context inclusion on both parameters. However, we can be reasonably confident that specification details in the friendship part do not seriously affect conclusions about peer influence and smoking homophily.

6. Discussion

This study uses stochastic actor-based models for network-behavior co-evolution (SAB models, Snijders et al., 2010) to assess the strength of peer influence effects in three control schools of ASSIST, a school-based, peer-led intervention study to prevent adolescent smoking (Audrey et al., 2004; Campbell et al., 2008; Starkey et al., 2005). The analyses were conducted for the purpose of settling open methodological issues related to the application of SAB models, before applying them to the larger ASSIST dataset. A summary of the results and an overview of the plans are given below. The main conclusion from this paper, however, is that independent of the specifics of the illustrative analyses, the results demonstrate the suitability of SAB modeling for analyzing the ASSIST data, in particular for assessing peer influence effects, which encourages the planned systematic analysis of the full dataset.

6.1. Summary

There are two methodological issues that this paper addresses. The first is the assumption of time homogeneity of the co-evolution between friendship formation and behavior change that is made in previous applications of the SAB method. Ours is the first study to empirically address whether a co-evolution process indeed follows the same rules in different observation periods. It is shown that the co-evolution of friendship and smoking in our sample indeed is time heterogeneous. More precisely, over time, adolescent smoking tends to be less determined by parental smoking, their friendship changes tend to slow down, and older students become more popular as friends. The strength of peer influence on smoking remains stable over time, which is a post-hoc justification of the peer influence results reported in the earlier SAB studies that did not take time heterogeneity into account.

The second issue addressed concerns the leeway that researchers have when specifying a SAB model. Prior studies using the method to assess peer influence differ considerably in the way they specify the network evolution process. Prior to this study, the degree to which different specification choices would lead to different conclusions about peer influence has not been tested. We can show robustness of these conclusions in our study, which again strengthens the earlier results. Peer influence results in our study do not substantially differ between a specification that includes highly significant context effects on friendship formation (triangulation of friendship and intra-classroom friendship) and a specification that simply omits them. However, other results are affected by the omission. Neglecting context effects on friendship strongly inflates the parameters assessing reciprocity norms and sex segregation.

Substantively, all results show robust evidence of friends' influence on adolescents' smoking, even after controlling for various sources of friendship selection. This encourages the use of SAB modeling in more detailed further investigations of factors potentially affecting peer influence in the school context.

6.2. Plans for future analyses

As for all statistical methods, the amount of available data in SAB modeling is crucial for identifying more complex patterns. Encompassing data from over 10,000 students in 59 secondary schools, analysis of the full ASSIST dataset will allow more statistically powerful conclusions to be drawn about detailed aspects of peer influence. Also, it will be possible to generalize the results to the population of UK secondary schools, and hence serve as a comparatively solid basis for deriving policy recommendations aimed at the reduction of smoking. We finish by outlining four tasks that such future analyses shall address.

First, not only will the strength of peer influence be assessed while amply controlling for friendship selection mechanisms, but also how peer influence operates on the smoking dimension. Earlier studies using stochastic, actor-based models have used different operationalizations of peer influence, such as assimilation to the friends' average behavior (Steglich et al., 2010), an interaction of assimilation with the number of friends (Snijders et al., 2007; this study), or a main effect of friends' average behavior (Knecht et al., 2010; Mercken et al., 2009). By studying these concurrently, it will be possible to answer questions such as "Does one regular smoker wield the same influence as two occasional smokers?", "Does influence depend more on the *number of smokers* or more on the *percentage of smokers* among the friends?" or, "Do friends' smoking behaviors really become more similar to each other (does a group norm emerge), or do friends merely reinforce each other's smoking (without converging on a group norm)?"

Second, individual differences in terms of students' susceptibility to social influence will be identified, as well as individual differences in the strength of influence on others. Earlier research in this direction largely relied on correlation analyses of demographic or behavioral measures with self-reported reasons for own smoking, or reports on what students thought were their peers' reasons to smoke (Horn et al., 1959). With the SAB approach, it is possible to validate these studies with actual measures of peer influence. An example of such an analysis is provided by Mercken et al. (2010b), who show that in Finnish secondary schools girls are more susceptible to social influences in the school context than are boys.

A third set of analyses will study the effect of network-endogenous variables, such as friendship strength, clustering, isolation, or popularity, on the strength of peer influence. Earlier studies with less reliable methods gave mixed results, some indicating a positive association between popularity and smoking (Michell and Amos, 1997; Valente et al., 2005), others a negative association (Ennett and Bauman, 1994). Taking reciprocity of friendship nominations as an indicator of friendship strength, a first analysis employing SAB models was carried out by Burk et al. (2007) for delinquent behavior among Swedish adolescents. The authors show that while unilaterally nominated friends (who do not confirm the friendship nomination) exert an influence on a student's delinquent behavior, this influence is significantly stronger when friendship is reciprocated. For smoking behavior, Mercken et al. (2010a) did not find such an effect—maybe due to the relatively small size of networks and the total sample in their study.

Fourth, the ASSIST data make it possible to assess moderating effects of school-level characteristics such as rural versus urban location. For this purpose, a multilevel analysis of school-level results will be the appropriate approach (Goldstein, 1995). The meta-analytical techniques outlined in this paper are a first step in this direction. However, as we only analyze data from three schools here, it was not yet possible to include explanatory variables on the school level. As for the other three tasks identified above, also here the inclusion of more ASSIST schools' data in the SAB analyses will add sufficient statistical power to draw reliable conclusions.

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