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Postprint / Postprint
Zeitschriftenartikel / journal article

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Empfohlene Zitierung / Suggested Citation:
Kretschmer, D., & Roth, T. (2020). Why Do Friends Have Similar Educational Expectations? Separating Influence and Selection Effects. *European Sociological Review*, *37*(2), 201-217. https://doi.org/10.1093/esr/jcaa042

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European Sociological Review *following peer review.*
The version of record European Sociological Review, 2021, Vol. 37, No. 2, 201-217 is available online at:
url: https:// academic.oup/ esr/article/37/2/201/6000730
doi:10.1093/esr/jcaa042
page numbers have been adjusted, whereby this postprint is fully quotable

Why Do Friends Have Similar Educational Expectations? Separating Influence and Selection Effects

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Abstract

The influence of friends in shaping students' educational expectations has received considerable theoretical and empirical attention in past research. However, few studies have directly tackled the methodological problems associated with estimating such influence effects. In particular, the separation of selection effects—with students selecting friends with similar educational expectations—from influence effects has remained elusive. In this study, we therefore investigate whether friend influence persists once we account for selection effects and other confounding network-related processes. In addition, we quantify the contribution of selection and influence to the similarity of educational expectations among friends. We rely on two-wave longitudinal data on 1,821 German secondary school students in 77 classrooms and multilevel random-coefficients stochastic actor-oriented models for the coevolution of networks and behaviour. Our results demonstrate that both selection and influence contribute to expectation-based similarity and that selection effects are substantial. This shows that without explicitly accounting for selection, estimates of friend influence effects are likely to be biased.

Introduction

Interpersonal influence processes have been considered important for educational attainment ever since the pioneering work on the Wisconsin model of status attainment (Duncan, Haller, and Portes, 1968; Sewell, Haller, and Portes, 1969). The Wisconsin model explicitly set out to shed light on the factors that mediate the effect of parental status on children's educational attainment. Besides academic abilities, the model postulates a key impact of significant others in shaping students' educational aspirations and expectations. Educational expectations, which represent students' subjective expectations about future educational qualifications (Salikutluk, 2016; Roth, 2017),[1] have in turn been proven to be one of the most important predictors of educational success (cf. Bozick et al., 2010; Andrew and Hauser, 2011). The theoretical considerations of the Wisconsin model sparked a wealth of research on the interpersonal origins of educational expectations. In particular, the influence of friends has received substantial attention from the early days of the Wisconsin model (e.g. Sewell and Hauser, 1972; Alexander, Eckland, and Griffin, 1975; Picou and Carter, 1976; Alwin and Otto, 1977) until today (e.g. Buchmann and Dalton, 2002; Cheng and

Starks, 2002; Antonio, 2004; Salikutluk, 2016; Raabe and Wo¨lfer, 2019). Many of these studies documented substantial similarities in friends' educational expectations across various populations and contexts. This has frequently been considered evidence of strong friend influence.

However, as already noted in early research (e.g. Duncan, Haller, and Portes, 1968; Cohen, 1977, 1983), similarity of educational expectations among friends does not necessarily reflect friend influence. There is a plausible alternative source of similarity: selection—the tendency to choose friends with similar educational expectations. The necessity to disentangle selection from influence effects to provide convincing evidence on interpersonal influence has repeatedly been discussed (e.g. Cohen, 1977, 1983; Mouw, 2006). Nevertheless, few studies on educational expectations have employed appropriate analytical strategies. Though several recent studies address some of the shortcomings of past research, they are not able to fully account for selection. Furthermore, they suffer from other methodological limitations that complicate the estimation of influence effects, such as confounding by endogenous network processes or the problem of accounting for mutual influence in reciprocal social relations (e.g. Carbonaro and Workman, 2016; Kiuru et al., 2007; Mora and Oreopoulos, 2011; Roth, 2017).

Many of these methodological shortcomings originate from the fact that previous studies on interpersonal influence in educational expectations do not employ an explicit social network methodology. This is surprising given repeated calls for network studies in the domain of education-related friend influence (Morgan, 2005; Andrew and Hauser, 2011) and their successful application to the study of influence effects in educational achievement (e.g. Fortuin, Geel, and Vedder, 2016; Rambaran et al., 2017; Kretschmer, Leszczensky, and Pink, 2018). A network perspective is beneficial because interpersonal influence necessarily takes place within social networks and it allows to explicitly focus on the social processes that operate within networks and that are interconnected with influence—such as selection effects, endogenous structural processes, or correlated influence processes.

In this article, we respond to this shortage of network studies by applying stochastic actor-oriented models (SAOM) to study the evolution of friendship networks and educational expectations of secondary school students in Germany from a longitudinal perspective. The key advantage of these models is the fact that they are explicitly designed to differentiate between similarity of friends' educational expectations deriving from students selecting friends with similar expectations and similarity resulting from friends influencing each other's expectations. Therefore, SAOM enable us to answer two fundamental open questions in this research area: first, whether significant influence effects in the formation of educational expectations persist once selection—the key competing force in producing similarity—has been factored in and, second, to what extent selection and influence contribute to total similarity. This helps to conceptually assess whether past research is likely to have overestimated friend influence or not. Given the wealth of empirical research documenting similarity of educational expectations among friends, we believe that it is time to get a more complete picture of the role friend influence plays in producing this similarity.

Theoretical Considerations and Their Methodological Implications

We can distinguish three major factors that may be responsible for similarity in the educational expectations of friends: influence, selection, and endogenous processes of network evolution.

Friend Influence

According to the Wisconsin model, significant others are persons who communicate achievement expectations, define educational norms, or serve as role models. Besides parents, it is particularly students' friends who are likely to fulfil these criteria and influence students' educational expectations. This is because students tend to compare themselves to their friends and adjust their educational plans accordingly, and close friends may impose pressure towards conformity. Consequently, friends can be both role models and definers of norms (Sewell, Haller, and Portes, 1969; Buchmann and Dalton, 2002). The adjustment to friends' expectations is reinforced if friends explicitly communicate what educational degree they deem appropriate for someone like them and if students with different expectations have to expect sanctions, such as the loss of social standing. In addition to this norm-based effect, friend influence can arise through the exchange of information. For example, information about higher education might be more widespread in friendship networks with high educational expectations. This could result in better access to information and a higher awareness of educational opportunities for individuals in the network, leading to an adjustment of educational expectations (Fletcher, 2012; Rosenqvist, 2018). All of the aforementioned influence mechanisms can result in an assimilation of educational expectations among friends.

Selection

While most research on the similarity of friends' educational expectations has focused on influence, selection of friends with similar expectations is also likely to drive similarity. Usually, selection effects are thought to be the result of preferences or opportunities. Preferences for similarity—usually called homophily—can originate from the simplified communication and interaction that comes with sharing similar characteristics (McPherson, Smith-Lovin, and Cook, 2001). For example, similar educational expectations may be associated with similar interests, values, and priorities in life, which in turn facilitate interaction. Opportunity effects refer to the fact that students may be more frequently exposed to other students who have similar rather than dissimilar expectations. For example, students who share high educational expectations may attend specific extracurricular activities or meet to prepare for examinations, which facilitates friendship formation. The systematic selection of similar friends is empirically well documented for a wide variety of characteristics (for reviews, see McPherson, Smith-Lovin, and Cook, 2001; Brechwald and Prinstein, 2011), including the closely related domain of students' academic achievement (Flashman, 2012; Shin and Ryan, 2014; Gremmen et al., 2017; Rambaran et al., 2017). Given these findings and the considerations above, selection effects are likely to operate on the basis of educational expectations as well. From a methodological perspective, the insight that selection effects are likely to induce similar expectations among friends up and above the levels resulting from influence suggests that a correlational measure of friends' expectations cannot be used as an immediate indicator of friend influence, as it confounds influence and selection. This problem is both well-known and widespread in the general literature on interpersonal influence (e.g. Duncan, Haller, and Portes, 1968; Cohen, 1977; Mouw, 2006). Consequently, a convincing analysis of friend effects has to rely on an empirical strategy that allows to differentiate between similarity that originates from selection and similarity that originates from influence.

Endogenous Processes of Network Evolution

Besides selection and influence effects, similarity among friends is also exacerbated by endogenous processes of network formation, such as reciprocity and transitivity (Wimmer and Lewis, 2010). Reciprocity refers to the observation that incoming friendship nominations frequently are reciprocated by their recipients. If one student chooses another student as a friend on the basis of similar expectations while the latter student chooses the former on the basis of reciprocity, not accounting for reciprocation makes it seem like both relations originate from similar expectations, while only one of them in fact does. Now consider transitivity, the tendency to become friends with one's friends' friends: If some relationships emerge due to selection effects, tendencies towards transitive closure induce additional relationships, which are also characterized by the similarity of educational expectations. Consequently, we tend to overestimate selection effects if we do not account for endogenous processes of network formation. Finally, influence tends to be reciprocal. Therefore, the similarity of a focal actor and a friend does not only reflect the focal actor's influence on the friend but also the friend's influence on the focal actor (Manski, 1993; An, 2015). Given the standard conceptualization of an influence effect representing the impact of one actor on another, analytical approaches to estimate friend influence should ideally separate these multiple influence effects operating at the individual level.

Previous Analytical Strategies to Identify Friend Influence on Educational Expectations

How have these methodological issues been tackled in past research on interpersonal influence in educational expectations? Most early studies have relied on cross-sectional data and correlational approaches such as path analysis and regression models (e.g. Haller and Butterworth, 1960; Alexander and Campbell, 1964; Sewell and Hauser, 1972; Alexander and Eckland, 1975). Several recent studies are cross-sectional as well (Cheng and Starks, 2002; Kiuru et al., 2007; Mora and Oreopoulos, 2011). As already noted by Duncan, Haller, and Portes (1968) and Cohen (1977), cross-sectional approaches by design cannot distinguish whether similarity originates from selection or influence processes. Therefore, they could only provide unbiased estimates of friend influence if selection effects were completely absent. Consequently, subsequent studies mainly relied on longitudinal designs. Innovative early longitudinal studies by Cohen (1977) and Kandel (1978) used descriptive approaches to decompose selection and influence effects. However, given their descriptive nature, these studies could not account for correlated effects or endogenous processes of network evolution.

Afterwards, longitudinal multivariate models—in particular cross-lagged dynamic panel models—offered a promising approach to the estimation of interpersonal influence (Cohen, 1983; Antonio, 2004; Carbonaro and Workman, 2016). In cross-lagged dynamic panel models, the effect of friends' lagged expectations on a focal individual's expectations measured at a later point in time is investigated, controlling for the focal individual's own lagged expectations. While the inclusion of lagged expectations can account for selection effects on the basis of expectations, it can lead to severely biased estimates of friend effects if other sources of selection are not adequately controlled for (Halaby, 2004; Mouw, 2006). Furthermore, these models are not able to incorporate the structural processes driving network evolution (such as reciprocity and transitive closure).

As an alternative remedy to selection effects, longitudinal fixed-effects models have been suggested (Mouw, 2006). Because these models only investigate whether changes in friends' expectations affect a focal actor's expectations, the initial similarity that originates from selection effects is implicitly controlled for. However, fixed-effects models of friend influence on educational expectations are scarce and have largely been applied to study contextual effects (i.e. the influence exerted by the entire set of class- or schoolmates; Roth, 2017), which makes them vulnerable to bias due to simultaneous changes in the contexts themselves. Thus, an association of fellow students' educational expectations might simply reflect changes at the classroom or school level (e.g. new teachers, change in school climate) that affect both the focal student's and the fellow students' expectations. These problems are less pronounced when considering networks within broader contexts, such as friendship networks (Raabe and Wölfer, 2019). However, when it comes to the analysis of friendship networks, fixed-effects models face the problem that a correlation of changes in friends' expectations over time may again both reflect changes in the composition of friends (due to intertemporal selection) and influence processes. In addition, fixed-effects models, much like dynamic panel models, can hardly account for structural network processes and reciprocal influence among friends or quantify the relative contribution of selection and influence to similarity.

For other substantive research questions (but not influence effects on educational expectations), previous studies have also used experimental, quasi-experimental, and instrumental variable approaches to estimate influence net of selection effects (for a review see Sacerdote, 2014). These studies rely on exogenous variation or allocation of peers to rule out selection effects. For peer ffects in the domain of academic achievement, for example, studies have assessed the effect of randomly allocated roommates (e.g. Sacerdote, 2001; Zimmermann, 2003) or squadrons in the US air force (Carrell, Fullerton, and West, 2009), random variation in the gender composition of school classes across grades (e.g. Hoxby, 2000) or the effects of relocations due to natural disasters such as Hurricane Katrina (Imberman, Kugler, and Sacerdote, 2012). Given the focus on exogenous variation or allocation, however, these approaches cannot investigate the effects of those peers that individuals themselves identify as their close friends. This is different in Flashman's (2014) instrumental variable approach, which uses information on indirect friends to identify the influence of direct friends on academic achievement. However, given that all of these approaches aim at eliminating selection effects, they do not explicitly model friendship network structure and cannot quantify the relative contribution of selection and influence to similarity. Furthermore, none of these approaches has so far been applied to study friend influence in the domain of educational expectations.

In conclusion, concerning educational expectations, we believe that it is time to combine a convincing strategy to identify selection and influence effects with a social network approach focused on students' close friends to overcome the remaining methodological problems.

Stochastic Actor-Oriented Models

Following explicit calls for network studies to investigate education-related social influence processes (Morgan, 2005; Andrew and Hauser, 2011), our study relies on SAOM for network dynamics to address the methodological issues outlined above. SAOM combine a network perspective on the influence of friends with a longitudinal analytical strategy. They start with the empirical observation of social networks and distributions of expectations at (at least) two points in time. By means of agent-based simulation, the aggregate change in networks and behaviour observed over time is decomposed into single network tie and expectation changes conducted by individual actors. Changes in ties and expectations are guided by behavioural tendencies that are spelled out in the model specification—such as the tendency to initiate or maintain friendship with peers who have similar expectations or the tendency to assimilate friends' expectations. These behavioural tendencies are associated with coefficient values that reflect both the strength and the direction of the actual changes in the observed networks. Snijders, van de Bunt, and Steglich (2010), Steglich, Snijders, and Pearson (2010) and

Ripley et al. (2020) provide more detailed introductions to SAOM. SAOM allow to separate selection and influence processes by simultaneously modelling whether initial similarity in expectations shapes the formation and maintenance of friendship relations and considering whether initial friends' expectations shape a focal actor's expectations later on. Furthermore, a wide range of endogenous network processes, such as reciprocity and transitivity, can be included. Finally, because the simulation process disaggregates changes into individual-level behavioural processes, the coefficients reflect individual behavioural tendencies that are cleared of reciprocal influence.

In sum, SAOM are able to address the key methodological problem studies on interpersonal influence typically face by separating selection and influence effects while also controlling for endogenous network processes. In this way, SAOM offer a convincing test of friend influence and allow quantifying the contribution of selection and influence to the similarity of educational expectations among friends. Naturally, however, SAOM also have caveats. They do not implicitly adjust for time-constant covariates and the coefficient estimates cannot be rescaled in a way that allows for a direct comparison of effect sizes with more conventional estimation approaches. Finally, SAOM require high-quality longitudinal network data, which is why only few large-scale data sets allow such analyses and, frequently, only subsamples can be analysed due to attrition in the network data.

The German Educational Context

We apply our analyses to students at the end of lower secondary education in Germany. Germany's education system is highly stratified, with students typically being sorted into different educational tracks after grade 4. The most prestigious secondary education track is the Gymnasium, while the Hauptschule is the least prestigious track. Realschulen and comprehensive schools are positioned in between. Most of the students who attend a Gymnasium in lower secondary education attain a higher education entrance qualification, while those attending the other types of secondary school predominantly do not. This might suggest that students' educational expectations are largely predetermined by the school type they attend during lower secondary education. However, the German school system has become substantially more permeable in recent decades (Kurz and Böhner-Taute, 2016) and, nowadays, about one quarter of freshmen in higher education did not obtain their higher education entrance qualification at the Gymnasium (Autorengruppe Bildungsberichterstattung, 2018). Therefore, the link between the educational track attended in lower secondary education and the highest educational attainment is by no means deterministic (Müller, 2005; Roth, 2017). An early study by Buchmann and Dalton (2002) did not find evidence of friends' similarity in educational expectations in the German context, arguing the strong link between school type and educational attainment to be responsible for this result. By contrast, more recent studies do detect clustering of educational aspirations and expectations among friends even in the highly stratified German secondary educational level (Salikutluk, 2016; Roth, 2017; Raabe and Wölfer, 2019; Zimmermann, 2019). None of these studies, however, can fully separate selection and influence effects.

Data and Analytical Strategy

Our empirical analysis is based on German data from the first two waves of the Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU) (Kalter et al., 2016a, b). Data collection was based on a random sample of schools, oversampling schools with a high share of adolescents with a migration background. The first wave was collected in 2010 and 2011; the second wave was collected one year later. Within schools, all ninth graders (average age: 14–15) from two classrooms were targeted in the first wave. Parental characteristics were assessed in a separate questionnaire filled out by one of the student's parents. In addition, the student survey contained a sociometric questionnaire. Students could nominate up to five best friends from their classroom, and these friendship nominations represent the social network under analysis here. Given that entire classrooms were surveyed, individual-level information on expectations and relevant covariates is available for all network members. These data enable us to construct students' friendship networks in both waves and thus to assess friend effects longitudinally.

We restrict our sample to adolescents in general schooling and thus exclude special needs schools. Furthermore, we exclude classroom networks if there is no longitudinal sociometric information available. Because many Hauptschulen end after grade 9, they do not provide longitudinal network information and have to be excluded from the analysis. While we use techniques for longitudinal social network analysis that can to some degree accommodate missing information in the network data, high levels of non-response can cause instability in the estimation process and introduce biases (Huisman and Steglich, 2008; Ripley et al., 2020). Thus, we exclude classroom networks with a unit non-response of more than 30 per cent in one of the waves. Finally, SAOM require a minimal amount of variation in their dependent variables. Therefore, we exclude five classrooms in which educational expectations were either identical across all students within a given wave or did not change across waves. Applying these selection criteria, our analysis sample consists of N ¼ 77 classroom networks and N ¼ 1,821 students. In the Supplementary appendix, we provide a detailed assessment of differences between the gross CILS4EU sample and our analysis sample. As outlined above, Hauptschulen are underrepresented in our analysis sample. However, conditional on school type, the analysis sample does not differ substantially from the overall CILS4EU sample in demographics, academic achievement, and educational expectations.

Variables

Educational expectations are measured by asking students about the highest educational degree they expect to obtain, with five levels being differentiated.[2] Because expectations for 'no degree' or a 'degree from lower secondary school' were named very infrequently, these two categories are combined with 'degree from intermediate secondary school' to differentiate low expectations from medium expectations (degree from upper-secondary school) and high expectations (university degree). To assess parental expectations, we use the corresponding measure from the parental questionnaire.

In the analysis, we control for background factors that may be associated with selection and/or influence effects based on educational expectations. We account for parents' education (measured with an indicator of whether at least one parent has obtained tertiary education), their occupational status (measured by the average of father's and mother's occupational status according to the International Socio-Economic Index of Occupational Status (ISEI) scale), and the surveyed parent's educational expectations. Among adolescents themselves, we account for academic achievement, as measured by students' grade point average in the three main subjects German, mathematics, and English (ranging from 1 to 6, with higher values indicating worse grades), students' perceived educational performance, which is assessed on 5-point scales for the same subjects and then averaged, and students' gender and ethnic background (differentiating majority Germans from the largest minority subgroups in the data—adolescents of Turkish, Eastern European, and former Yugoslavian origin—and from a group of other Western and a group of other non-Western origin).

SAOM Set-Up and Model Specification

The agent-based simulation process underlying SAOM discussed above estimates two model components simultaneously, the first assessing change in the network and the second assessing change in educational expectations. Changes are modelled in so-called mini-steps. In a network mini-step, a (randomly selected) actor can form a friendship tie, remove a tie, or leave the network unchanged. In an expectation mini-step, an actor can increase or decrease their expectations by one unit or leave them unchanged. These changes represent a multinomial choice process, and choices are stochastically governed by so-called objective functions, the multinomial regression equations underlying the process. The resulting coefficients can be interpreted in terms of their sign and significance but not in terms of their absolute size. Though comparing coefficient sizes within a given model is possible, it is usually not useful to compare coefficients from the network and the expectations model component because the underlying dependent variables differ fundamentally. Since comparing the contribution of selection and influence to the similarity of educational expectations among friends is of key importance to our analysis, we use an indirect strategy to circumvent this problem, which we elaborate on in more detail in the Results section. Below, we discuss the exact specification of the model we use in this study.

Network evolution component

The network evolution component assesses processes relevant for the formation and maintenance of social networks. Selection processes are modelled with a set of three effects that jointly describe the dependence of friendship formation on individual characteristics. Concerning educational expectations, the ego expectations effect models whether high- or low-aspiring students tend to nominate more friends, i.e. are more or less active in the network. The alter expectations effect considers whether high- or low-aspiring students receive more friendship nominations, i.e. are more or less popular. Finally, the similar expectations effect provides information about selection on the basis of similar educational expectations net of the ego and alter effect and thus indicates whether the similarity of students' expectations affects friendship choices. Table 1 summarizes these effects.

Table 1. Key effects included in the SAOM network component

Effect	**Interpretation of positive coefficient**
Attribute effects on network evolution	
Ego effect	Actors with high attribute values tend to nominate more friends
Alter effect	Actors with high attribute values tend to be nominated more often
Similarity effect	Actors tend to nominate others with similar attribute values
Network effects on network evolution	
Reciprocity	Actors tend to reciprocate friendship relationships
Transitive closure (GWESP)	Actors tend to nominate friends of their friends as friends

Table 2. Key effects included in the SAOM expectations component

Effect	**Interpretation of positive coefficient**
Linear shape/quadratic shape	Actors tend to have high expectations/increasingly high expectations
Influence: average similarity effect	Actors assimilate their friends' expectations
Attribute effect	Actors with high attribute values tend to have high expectations

To avoid biased estimates of expectation-based selection due to confounding factors, we also model ego, alter, and similarity effects for the background factors described above.[3] To prevent biases due to general endogenous processes of network evolution, we furthermore model a reciprocity effect, account for transitive closure with the generalized weighted edge-wise shared partner (GWESP) effect, and account for a number of further effects related to network evolution, which we describe in more detail in the Supplementary appendix.

Expectations evolution component

In the second component of the model, we assess the evolution of students' educational expectations. To model friend influence, we consider whether friends' expectations assimilate over time, which we represent with the so-called average similarity effect. To ensure that we do not confound friend effects on expectations with the impact of other characteristics, we also control for the background factors we discussed above. These effects model variation in expectations according to different attribute values. Finally, a linear and a quadratic shape effect are used to model general trends in educational expectations over time. These effects are summarized in Table 2.

Multilevel Random-Coefficients SAOM Analysis

We rely on multilevel random-coefficients SAOM analysis, which jointly estimates coefficients across all networks but allows for variation in estimated effects at the network level through random effects (Ripley et al., 2020). This approach allows us to estimate complex SAOM, even though each single network we analyse is small and only two waves of data are available. Because the multilevel SAOM combine information from all of the networks, they can compensate for these limitations by leveraging the size of the CILS4EU sample. In the models we show below, we treat endogenous network effects (such as reciprocity and transitivity) as random effects and all covariate effects as fixed effects. For the expectation evolution component, we treat the rate and the shape parameters as random effects and the other parameters as fixed effects. This is akin to a random-intercept multilevel model, allowing the distribution and change in educational expectations to differ across networks but treating all other effects as constant across networks.

The multilevel random-effects SAOM are estimated with the RSienaTest package (Version 1-2.25) in R and rely on a Bayesian estimation technique. Therefore, priors have to be specified for all parameters, and we choose priors according to suggestions provided by the developers (Ripley et al., 2020). Item non-response is generally moderate to low in our data. Only for parental educational expectations, non-response is higher because only about 80 per cent of all parents participate in the parental questionnaire. In the SAOM analysis, missing information in the data is internally imputed by plausible values and treated in a way that minimizes the impact of missing information on parameter estimation

Ripley et al., 2020). All final models converge according to standard assessments of convergence for multilevel random-coefficients SAOM (Ripley et al., 2020). In the Supplementary appendix, we provide more information on the choice of priors in the SAOM models, item non-response, and convergence.

Results

The box plots in Figure 1 provide information on the sample of the 77 classrooms we rely on in the network analysis. Classrooms consist of 14–32 students, with an average of 24 students per class. Students nominate about 3.8 (of a maximum of 5) friends on average. The Jaccard index measures the extent of stability in friendship networks, indicating the share of friendships that persist across waves. The mean value of 0.41 is substantively higher than the proposed threshold of 0.3 for the minimal amount of stability necessary for a meaningful intertemporal analysis (Snijders, van de Bunt, and Steglich, 2010). The final box plot shows the extent of intertemporal change in expectations. On average, we observe 5.5 changes per network.

In Figure 2, we show the distribution of educational expectations in the first wave across our 77 networks. Expectations vary substantially across the networks, which is not surprising given that the classrooms are situated in different types of schools, which tend to lead to different educational degrees. Still, we find substantial heterogeneity in expectations within the networks as well.

Results from the SAOM are displayed in Table 3, which shows three models: a model that only includes selection effects, a model that only includes influence effects, and a model with both types of effects. Table 3 displays posterior means, their standard deviations, and 95 per cent credible intervals, which are Bayesian analogs to point estimates, standard errors, and confidence intervals.[4] As coefficients are estimated from nonlinear models, they can be interpreted in terms of their sign and significance, but not in terms of their absolute size. We start with a brief discussion of the models' network component. The endogenous network effects are similar across the different models: students tend to reciprocate incoming relationships and become and remain friends with the friends of their friends, inducing transitive closure.[5] This demonstrates the relevance of using an explicit social network methodology because both processes can be expected to exacerbate similar expectations up and above the levels induced by selection and influence effects. Concerning the selection effects that may confound selection based on educational expectations, we find selection on the basis of similar subjective school performance, and some indication for selection on similar grades, though the latter effect does not reach conventional levels of statistical significance (P ¼ 0.11 in the full model). As expected, we also find that same-gender and intra-ethnic friendships are more likely than cross-gender and inter-ethnic relationships. On the other hand, we find no clear evidence for the selection of friends with similar parental educational expectations or with similar socio-economic background. Overall, there

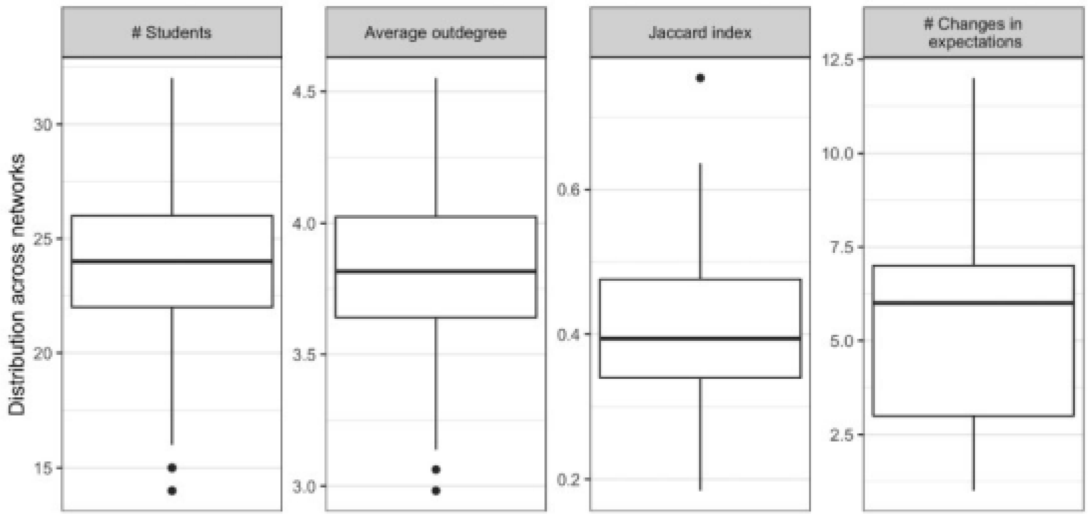

Figure 1. Description of networks for the SAOM analysis

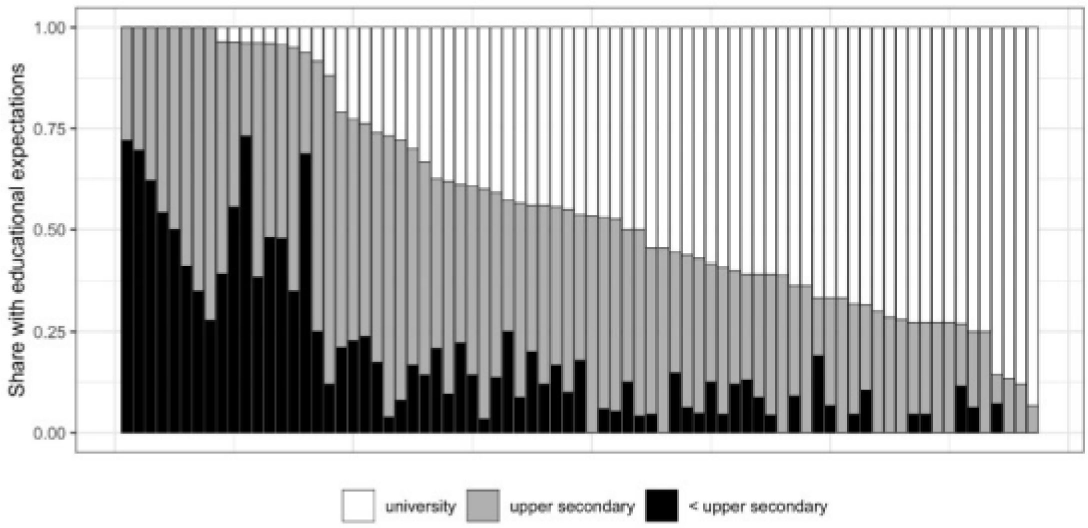

Figure 2. Distribution of educational expectations (wave 1)

is rather little variation in network activity (ego attribute effects) and popularity (alter attribute effects) according to our background characteristics.

Do students tend to select friends on the basis of similar educational expectations, even conditional on these other selection effects? The selection-only model, which does not account for influence on the basis of educational expectations, suggests so: the expectation similarity coefficient is statistically significant ($P < 0.05$), indicating that students are more likely to form and maintain friendships with classmates who have expectations similar to their own. The lower size of the expectation similarity coefficient in the full model provides a first hint of selection and influence effects being confounded. This observation, however, should not be considered conclusive proof given that the results come from nonlinear models and therefore coefficients can change across models even if there is no confounding (e.g. Mood, 2010). In any case, we see that a significant similarity effect on expectations persists even when influence is controlled for ($P < 0.05$). This demonstrates that selection indeed is a source of friends' similar educational expectations. To get an idea of the substantive size of selection on the basis of educational expectations, we can compare it to other selection effects from Table 3. In the full model, the effect of a classmate having identical rather than completely dissimilar educational expectations on friendship formation and maintenance (0.11 on a logit scale) is comparable to the effect of originating from the same rather than a different country of origin (0.09), and about half the size of the effect of belonging to the same gender (0.26) or having identical rather than completely different educational performance (0.21). Given that these covariates have proven to be of major importance for friendship selection, selection based on educational expectations appears to be not only of statistical but also of substantive significance.

In Figure 3, we visualize selection effects from the full model by plotting values on the objective function for student friendships according to a focal actor's educational expectations and a classmate's expectations. Higher values on the objective function indicate a higher likelihood of friendship formation and maintenance, measured on a logit scale. At each level of the focal actor's expectations, we see that they are most likely to become and/or stay friends with classmates who have identical expectations.

Having established the presence of selection effects, we now investigate influence effects. Concerning background factors, we find higher educational expectations among students with higher academic achievement, subjective performance, and parental educational expectations ($P < 0.05$), and, by tendency, among boys (P ¼ 0.08). In contrast, we observe little variation in expectations according to ethnic origin and parents' socio-economic background, given parental educational expectations.

Finally, friend influence is measured by the average similarity effect, which captures whether friends assimilate each other's educational expectations over time. In the model without selection effects, the average

Table 3. Effects from the SAOM

	Selection Only				Influence Only				Full Model			
	Posterior mean	SD of posterior mean	*P*	Credible interval	Posterior mean	SD of posterior mean	*P*	Credible interval	Posterior mean	SD of Posterior mean	P	Credible interval
Selection: effects of educational expectations on network evolution												
Educational expectations alter	0.01	(0.03)	0.79	[-0.05, 0.07]					0.00	(0.03)	0.87	[-0.05, 0.06]
Educational expectations ego	0.06+	(0.03)	0.08	[-0.01, 0.12]					0.05+	(0.03)	0.10	[-0.01, 0.12]
Educational expectations similarity	0.14**	(0.05)	0.01	[0.04, 0.25]					0.11*	(0.06)	0.05	[0.00, 0.22]
Influence: effect of friends' expectations on expectations evolution												
Friends' average similarity					0.86*	(0.33)	0.01	[0.20, 1.51]	0.71*	(0.35)	0.04	[0.02, 1.39]
Endogenous network effects on network evolution												
Outdegree (+)	0.21	(0.17)	0.23	[-0.13, 0.55]	0.19	(0.18)	0.30	[-0.15, 0.54]	0.20	(0.18)	0.24	[-0.14, 0.57]
Reciprocity (+)	2.25***	(0.09)	0.00	[2.09, 2.42]	2.24***	(0.09)	0.00	[2.07, 2.41]	2.25***	(0.08)	0.00	[2.08, 2.41]
Transitive closure (GWESP) (+)	1.66***	(0.05)	0.00	[1.57, 1.77]	1.66***	(0.05)	0.00	[1.55, 1.75]	1.66***	(0.05)	0.00	[1.56, 1.76]
Reciprocity x transitive closure (GWESP) (+)	-0.59***	(0.08)	0.00	[-0.74, -0.44]	-0.58***	(0.08)	0.00	[-0.73, -0.43]	-0.59***	(0.07)	0.00	[-0.73, -0.44]
Indegree popularity (square root) (+)	-0.21***	(0.05)	0.00	[-0.31, -0.11]	-0.21***	(0.05)	0.00	[-0.30, -0.11]	-0.21***	(0.05)	0.00	[-0.31, 0.11]
Indegree activity (square root) (+)	-0.35***	(0.05)	0.00	[-0.45, -0.25]	-0.35***	(0.05)	0.00	[-0.44, -0.26]	-0.35***	(0.05)	0.00	[-0.45, -0.25]
Outdegree activity (square root) (+)	-0.73***	(0.06)	0.00	[-0.84, -0.62]	-0.73***	(0.06)	0.00	[-0.84, -0.62]	-0.73***	(0.06)	0.00	[-0.84, -0.62]
Control effects on network evolution												
Average grade alter	-0.05	(0.03)	0.11	[-0.10, 0.01]	-0.05+	(0.03)	0.10	[-0.10, 0.01]	-0.05	(0.03)	0.11	[-0.10, 0.01]
Average grade ego	-0.05	(0.03)	0.11	[-0.11, 0.01]	-0.06*	(0.03)	0.04	[-0.12, -0.00]	-0.05+	(0.03)	0.10	[-0.12, 0.01]
Average grade similarity	0.20	(0.13)	0.12	[-0.06, 0.46]	0.24+	(0.13)	0.07	[-0.02, 0.50]	0.21	(0.13)	0.11	[-0.05, 0.48]
Subjective performance alter	-0.07+	(0.03)	0.05	[-0.13, 0.00]	-0.07+	(0.03)	0.05	[-0.13, -0.00]	-0.07+	(0.04)	0.06	[-0.14, 0.00]
Subjective performance ego	0.00	(0.04)	0.95	[-0.07, 0.08]	-0.00	(0.04)	0.92	[-0.08, 0.07]	0.00	(0.04)	0.93	[-0.07, 0.08]
Subjective performance similarity	0.23*	(0.10)	0.03	[0.03, 0.43]	0.25*	(0.10)	0.02	[0.04, 0.45]	0.24*	(0.11)	0.03	[0.03, 0.44]
Highest parental education alter	0.05	(0.04)	0.24	[-0.04, 0.14]	0.05	(0.04)	0.25	[-0.04, 0.14]	0.05	(0.04)	0.24	[-0.04, 0.14]
Highest parental education ego	0.01	(0.05)	0.90	[-0.09, 0.11]	0.01	(0.05)	0.82	[-0.09, 0.11]	0.01	(0.05)	0.82	[-0.09, 0.11]
Same highest parental education	-0.06	(0.04)	0.11	[-0.13, 0.01]	-0.06	(0.04)	0.12	[-0.13, 0.01]	-0.06	(0.04)	0.11	[-0.13, 0.01]
Parental mean ISEI alter	-0.00	(0.00)	0.57	[-0.00, 0.00]	-0.00	(0.00)	0.57	[-0.00, 0.00]	-0.00	(0.00)	0.57	[-0.00, 0.00]
Parental mean ISEI ego	-0.00***	(0.00)	0.00	[-0.01, -0.00]	-0.00***	(0.00)	0.00	[-0.01, -0.00]	-0.00***	(0.00)	0.00	[-0.01, -0.00]
Parental mean ISEI similarity	0.04	(0.09)	0.63	[-0.13, 0.22]	0.04	(0.08)	0.60	[-0.12, 0.21]	0.04	(0.09)	0.62	[-0.13, 0.21]
Parental expectations alter	0.06*	(0.03)	0.03	[0.01, 0.11]	0.06*	(0.02)	0.02	[0.01, 0.10]	0.06*	(0.03)	0.03	[0.01, 0.11]
Parental expectations ego	-0.04	(0.03)	0.15	[-0.10, 0.02]	-0.03	(0.03)	0.33	[-0.08, 0.03]	-0.04	(0.03)	0.15	[-0.10, 0.02]
Parental expectations similarity	0.00	(0.05)	0.93	[-0.09, 0.10]	0.03	(0.05)	0.58	[-0.07, 0.12]	0.01	(0.05)	0.84	[-0.09, 0.10]
Gender alter (ref.: boy)	0.04	(0.03)	0.22	[-0.02, 0.11]	0.04	(0.03)	0.22	[-0.02, 0.11]	0.04	(0.03)	0.23	[-0.03, 0.11]

(continued)

	Selection Only				Influence Only				Full Model			
	Posterior mean	SD of posterior mean	*P*	Credible interval	Posterior mean	SD of posterior mean	*P*	Credible interval	Posterior mean	SD of Posterior mean	P	Credible interval
Gender ego (ref.: boy)	-0.14***	(0.04)	0.00	[-0.21, -0.07]	-0.14***	(0.04)	0.00	[-0.21, -0.07]	-0.14***	(0.04)	0.00	[-0.21, -0.06]
Same gender	0.26***	(0.03)	0.00	[0.20, 0.32]	0.26***	(0.03)	0.00	[0.20, 0.32]	0.26***	(0.03)	0.00	[0.20, 0.32]
Same country of origin	0.09**	(0.03)	0.00	[0.03, 0.15]	0.09**	(0.03)	0.00	[0.03, 0.15]	0.09**	(0.03)	0.00	[0.04, 0.15]
Control effects on educational expectations evolution												
Linear shape (+)	-0.37***	(0.09)	0.00	[0.19, 0.55]	0.37***	(0.09)	0.00	[0.20, 0.54]	0.37***	(0.09)	0.00	[0.21, 0.55]
Quadratic shape (+)	-0.39***	(0.11)	0.00	[-0.60, -0.19]	-0.19	(0.13)	0.14	[-0.45, 0.06]	-0.22	(0.14)	0.10	[-0.50, 0.04]
Average grade	-0.54***	(0.13)	0.00	[-0.80, -0.27]	-0.50***	(0.13)	0.00	[-0.77, -0.25]	-0.51***	(0.13)	0.00	[-0.77, -0.25]
Subjective performance	-0.32*	(0.16)	0.04	[-0.63, -0.02]	-0.33*	(0.15)	0.03	[-0.63, -0.03]	-0.33*	(0.16)	0.03	[-0.64, -0.03]
Highest parental education	0.25	(0.20)	0.20	[-0.13, 0.64]	0.24	(0.20)	0.22	[-0.14, 0.64]	0.24	(0.20)	0.23	[-0.15, 0.63]
Parental mean ISEI	0.01	(0.01)	0.17	[-0.00, 0.02]	0.01	(0.00)	0.17	[-0.00, 0.02]	0.01	(0.01)	0.18	[-0.00, 0.02]
Parental expectations	0.67***	(0.12)	0.00	[0.44, 0.90]	0.66***	(0.12)	0.00	[0.43, 0.89]	0.66***	(0.12)	0.00	[0.43, 0.89]
Gender (ref.: boy)	-0.26+	(0.14)	0.05	[-0.53, 0.00]	-0.24+	(0.14)	0.08	[-0.52, 0.02]	-0.24+	(0.14)	0.08	[-0.52, 0.03]
Ethnic origin (ref.: German)												
Turkish origin	-0.12	(0.21)	0.55	[-0.53, 0.30]	-0.12	(0.21)	0.57	[-0.53, 0.30]	-0.12	(0.21)	0.56	[-0.54, 0.30]
Eastern European origin	0.02	(0.20)	0.90	[-0.36, 0.42]	0.03	(0.20)	0.87	[-0.35, 0.43]	0.04	(0.20)	0.84	[-0.35, 0.44]
Former Yugoslavian origin	-0.14	(0.38)	0.70	[-0.88, 0.60]	-0.14	(0.38)	0.71	[-0.88, 0.63]	-0.14	(0.39)	0.71	[-0.90, 0.65]
Other Western origin	-0.17	(0.24)	0.49	[-0.64, 0.31]	-0.18	(0.24)	0.45	[-0.66, 0.30]	-0.18	(0.25)	0.45	[-0.67, 0.31]
Other non-Western origin	0.25	(0.26)	0.34	[-0.24, 0.78]	0.25	(0.26)	0.34	[-0.26, 0.75]	0.26	(0.26)	0.33	[-0.25, 0.79]

Notes: *P <0.1, *P <0.05, **P <0.01, and ***P <0.001 from two-sided tests of the posterior distribution; posterior means, SDs (standard deviations) of the posterior means, and 95 per cent credible intervals are Bayesian ana- logs to point estimates, standard errors, and 95 per cent confidence intervals; (+) indicates random effects, other effects are fixed effect

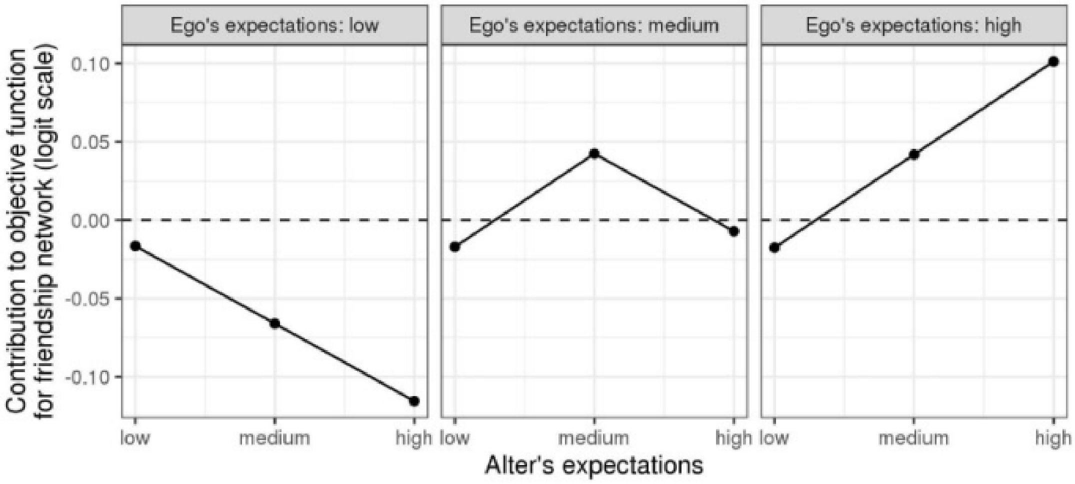

Figure 3. Ego-alter selection graph

similarity coefficient is positive and statistically significant ($P < 0.05$). In the full model, the coefficient decreases, which again hints at selection and influences effects being confounded. However, given that the effect is still significant in the full model ($P < 0.05$), influence effects induce similarity of friends' educational expectations even when selection is accounted for. Comparing the estimate for the influence effect (0.71), which measures the effect of all friends having identical rather than completely dissimilar educational expectations, to other determinants of educational expectations gives an intuition about the substantive impact of friend influence. The influence effect is stronger than the effect of a difference in average grades by one grade (-0.51) and comparable to the effect of a difference in parents' educational expectations by one unit (0.66).

Along the lines of Figure 3, Figure 4 visualizes these trends towards assimilation in an ego-alter influence graph. Higher values on the objective function indicate higher likelihoods of acquiring corresponding educational expectations; the scaling of Figures 3 and 4 differs because the different underlying dependent variables— students' friendships and their educational expectations—differ as well. In Figure 4, we see that students are most likely to assimilate their friends' expectations if friends' expectations are medium or high. If friends have low expectations, students are slightly more likely to have medium rather than low expectations themselves. This is because the influence effect is counterbalanced by the positive linear and negative quadratic shape effects included in the model. These reflect general tendencies of expectations to increase and become less extreme, meaning that low expectations become less frequent over time. In the absence of influence effects, however, these general tendencies towards increasing expectations would be even more pronounced among students with low expectations.

In sum, the results from our SAOM analysis suggest that both selection and influence effects produce the similarity of friends' educational expectations. This observation raises the question how much each of these processes contributes relative to the other. Because a direct comparison of coefficients from the network and the expectations part of the model is not useful given the different dependent variables, we exploit the simulationbased nature of the SAOM to address this question (see also Steglich, Snijders, and Pearson, 2010). Using the full model from Table 3, we simulate social networks for four different scenarios: a scenario that includes both selection and influence effects; a scenario that contains selection on expectations but no influence (by setting the coefficient for influence to zero); a scenario that contains influence, but not selection (by setting the selection coefficients to zero); and a scenario that contains neither selection nor influence effects. For these four scenarios, we each assess the extent of similarity in educational expectations in the simulated networks with a measure of network autocorrelation, Moran's I (Steglich, Snijders, and Pearson, 2010).6 The contribution of selection to similarity can then be estimated in two ways: first, as the difference in autocorrelation between the full model and the model containing influence only; and second, as the difference in autocorrelation between the model containing selection only and the model with neither selection nor influence effects. The ratio between this difference and the joint effect of selection and

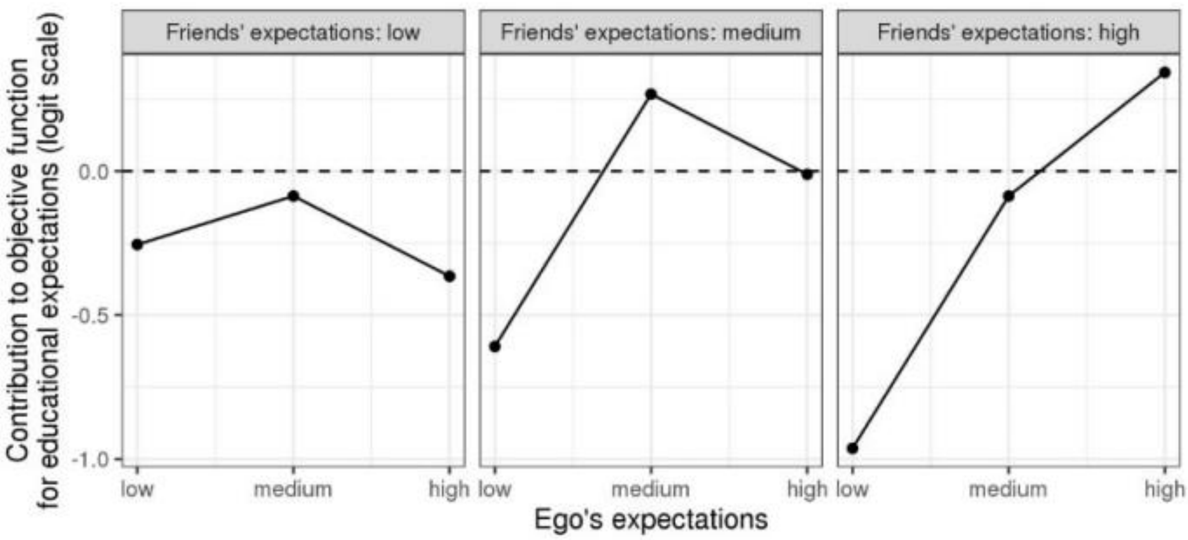

Figure 4. Ego-alter influence graph

influence indicates the relative contribution of selection effects. The remainder to 100 per cent, on the other hand, is the relative contribution of influence effects. Results from both estimates usually do not lead to exactly the same results (Steglich, Snijders, and Pearson, 2010) but differ only marginally in our application: across all networks, we find an average contribution of selection of 46–48 per cent and, correspondingly, a contribution of influence of 52–54 per cent, with 2 per cent indeterminate. Taken together, our findings suggest that selection based on similar educational expectations matters both statistically and substantively, meaning that assessments of friend effects that do not account for selection may indeed lead to biased results.

Discussion

Friend effects on educational expectations have been a topic of intensive empirical study since the 1960s. Early scholars quickly realized that the estimation of friend influence is plagued by methodological problems (Duncan, Haller, and Portes, 1968; Cohen, 1977; Kandel, 1978) and, until today, empirical applications have discussed these problems frequently. So far, however, few studies have tackled them empirically in a convincing way. In particular, previous studies were hardly able to separate influence from selection effects. Consequently, they were unable to quantify the contribution of selection and influence to the observed similarity of expectations among friends, and friend influence may have been overestimated because selection effects were insufficiently accounted for. In this study, we used multilevel random-coefficient SAOM to address these fundamental questions on friend influence in the domain of educational expectations by disentangling selection and influence effects, while at the same time tackling other methodological problems within a single analytical approach.

In line with previous reasoning, our empirical results suggest that similarity of friends' expectations results from both selection and influence processes. Even after controlling for general network processes and achievement-related and social background factors, similar expectations prove important for the formation and maintenance of friendships. At the same time, adolescents tend to adapt to their friends' expectations. We estimate the contribution of influence to be on average slightly higher than that of selection effects. This suggests that a key takeaway from previous research—that friend influence does matter in the domain of educational expectations—does not have to be called into question. However, our results also show that selection effects are clearly important in our sample. We therefore recommend that selection effects should be systematically accounted for in future research on influence effects in the domain of educational expectations.

While SAOM are well-suited to address the methodological problems associated with estimating friend effects, a drawback is that it is not possible to directly compare the (selection-adjusted) influence effects from the SAOM to influence effects estimated from other analytical approaches. Thus, we are not able to directly assess the extent of bias in more conventional empirical approaches. In this study, we have addressed this limitation by assessing the relative contribution of selection and influence effects to students' similarity in educational expectations. Given the substantive selection effects found, we conclude that analytical approaches that do not account for selection will tend to considerably overestimate peer influence. This should be particularly the case for cross-sectional analyses that cannot account for key dimensions of selection but are still widespread among recent empirical studies. While longitudinal approaches—in particular, cross-lagged models—may be more successful in detecting selection effects, they have other limitations, such as not accounting for the network structure of the data and being susceptible to biases if other selection effects (apart from those based on the dependent variable) are not appropriately modelled.[7]

A second drawback of the SAOM approach is high demands on data quality. As a consequence, we had to substantially reduce our sample and thus cannot claim that our analysis is representative of the total German student population. In particular, we cannot draw strong inferences for Hauptschulen. However, nowadays only about 13 per cent of pupils in lower secondary education attend this school type and several federal states have even abolished Hauptschulen as an independent school type. An analysis of sample selectivity shows that, apart from this dependence on school type, attrition in our sample is hardly related to any of the characteristics essential for this study.

At first sight, our conclusions may seem to be specific to the German context: In Germany, the type of secondary school attended strongly influences students' educational attainment and thus may more strongly affect their educational expectations compared to countries with less-differentiated secondary education systems. Consequently, classmates—and the friends selected among them—may generally have homogenous expectations, which may seem to artificially inflate selection effects. However, our descriptive results clearly show that there is substantial variation in educational expectations in most German secondary school classes. In addition, SAOM account for opportunity structures when estimating selection effects, thus considering the extent to which students make friends with classmates of similar and dissimilar expectations relative to the extent they can do so given the distribution of expectations. Consequently, we believe that our results are unlikely to be specific to the German context, such that a neglect of selection effects may also result in an overestimation of influence effects in contexts other than the one we study. We believe that our analyses are important because they demonstrate the relevance of selection and influence effects in educational expectations under stringent methodological conditions. We hope that our findings illustrate the potential of SAOM for the investigation of interpersonal influence based on educational expectations and stimulate future research on this issue using other data and populations. This could help us to gain a deeper understanding of the underlying processes and to further investigate conditions under which influence or selection plays a more important role for the similarity of friends' educational expectations.

Notes

1 While educational aspirations and expectations were not explicitly differentiated in the Wisconsin model, more recent studies are careful to distinguish the two. In contrast to (realistic) educational expectations, (idealistic) educational aspirations refer to desired future educational attainment (educational wishes). Like most recent studies, we will concentrate on expectations throughout our study.

2 This type of measure has emerged as a standard measure of educational expectations in the literature and has also been used in previous research in the German context (e.g. Salikutluk, 2016; Roth, 2017).

3 For ethnic background, gender, and parental education, we use a same attribute level rather than a similar attribute level effect, given the nominal nature of the underlying variables. We do not include ego and alter effects of different ethnic backgrounds in the network part of the model to keep the model specification parsimonious.

4 For all parameters, the Bayesian analysis provides a distribution of estimates that results from a sequence of simulations once the model has converged. We show the mean, the standard deviation, and the 2.5 and 97.5 percentiles of this distribution.

5 In contrast to other studies on friendship networks, we do not find a significant negative outdegree effect in our models. This is a consequence of the strong negative outdegree-activity effect we detect; when we remove this effect, the outdegree effect indeed becomes negative and significant. The strong negative outdegree-activity effect is likely to be a consequence of the CILS4EU friendship data. As students could only nominate a maximum of five best friends, students who nominated five friends in wave 1 could not nominate more but easily could nominate fewer friends over time. The fact that most students initially nominated a relatively large number of friends induces a strong negative outdegree-activity effect that partially captures the behavioral tendencies usually captured in the outdegree effect.

6 Because the simulations are stochastic, we simulate 4,000 networks for each of the classrooms in the analysis sample (for each model specification) and use the mean of Moran's I across these 4,000 networks as an indicator of similarity in friends' educational expectations.

7 In our application, cross-lagged models also detect substantial selection effects, which we investigated by comparing cross-sectional and cross-lagged regression results. To perform such a comparison, we used the model specification from the expectation component of our SAOM in a cross-sectional regression model on data from the second wave of the CILS4EU study, capturing friend influence with friends' average educational expectations. In the cross-lagged model, we additionally controlled for the focal actor's educational expectations in wave 1 to capture selection effects. Comparing these analyses, the point estimate for friends' expectations falls by 45% when the expectations in wave 1 are taken into account.

Supplementary Data

Supplementary data are available at ESR online.

Acknowledgements

CILS4EU research project funded in the NORFACE ERA NET Plus Migration in Europe-programme. The authors acknowledge support by the state of Baden-Württemberg through bwHPC. The authors thank the editor and three anonymous reviewers for their helpful comments on the manuscript.

References

Alexander, K. L. and Eckland, B. K. (1975). Contextual effects in the high school attainment process. American Sociological Review, 40, 402–416.

Alexander, K. L., Eckland, B. K. and Griffin, L. J. (1975). The Wisconsin Model of Socioeconomic Achievement: a replication. American Journal of Sociology, 81, 324–342.

Alexander, N. C. and Campbell, E. Q. (1964). Peer influences on adolescents educational aspirations and attainments. American Sociological Review, 29, 568–575.

Alwin, D. F. and Otto, L. B. (1977). High School context effects on aspirations. Sociology of Education, 50, 259–273.

An, W. (2015). Instrumental variables estimates of peer effects in social networks. Social Science Research, 50, 382–394.

Andrew, M. and Hauser, R. M. (2011). Adoption? Adaptation? Evaluating the formation of educational expectations. Social Forces, 90, 497–520.

Antonio, A. L. (2004). The influence of friendship groups on intellectual self-confidence and educational aspirations in college. The Journal of Higher Education, 75, 446–471.

Autorengruppe Bildungsberichterstattung, (2018). Bildung in Deutschland. Ein indikatorengestützter Bericht mit einer Analyse zu Wirkungen und Erträgen von Bildung. Bielefeld: wbv Publikation.

Bozick, R. et al. (2010). Framing the future: revisiting the place of educational expectations in status attainment. Social Forces, 88, 2027–2052.

Brechwald, W. A. and Prinstein, M. J. (2011). Beyond homophily: a decade of advances in understanding peer influence processes. Journal of Research on Adolescence, 21, 166–179.

Buchmann, C. and Dalton, B. (2002). Interpersonal influences and educational aspirations in 12 countries: the importance of institutional context. Sociology of Education, 75, 99–122.

Carbonaro, W. and Workman, J. (2016). Intermediate peer contexts and educational outcomes: do the friends of students' friends matter? Social Science Research, 58, 184–197.

Carrell, S., Fullerton, R. L. and West, J. (2009). Does your cohort matter? Measuring peer effects in college achievement. Journal of Labor Economics, 27, 439–464.

Cheng, S. and Starks, B. (2002). Racial differences in the effects of significant others on students' educational expectations. Sociology of Education, 75, 306–327.

Cohen, J. (1977). Sources of peer group homogeneity. Sociology of Education, 50, 227–241.

Cohen, J. (1983). Peer influence on college aspirations with initial aspirations controlled. American Sociological Review, 48, 728–734.

Duncan, O. D., Haller, A. O. and Portes, A. (1968). Peer influences on aspirations: a reinterpretation. American Journal of Sociology, 74, 119–137.

Flashman, J. (2012). Academic achievement and its impact on friend dynamics. Sociology of Education, 85, 61–80.

Flashman, J. (2014). Friend effects and racial disparities in academic achievement. Sociological Science, 1, 260–276.

Fletcher, J. M. (2012). Similarity in peer college preferences: new evidence from Texas. Social Science Research, 41, 321–330.

Fortuin, J., Geel, M. v. and Vedder, P. (2016). Peers and academic achievement: a longitudinal study on selection and socialization effects of in-class friends. The Journal of Educational Research, 109, 1–6.

Gremmen, M. C. et al. (2017). First selection, then influence: developmental differences in friendship dynamics regarding academic achievement. Developmental Psychology, 53, 1356–1370.

Halaby, C. N. (2004). Panel models in sociological research: theory into practice. Annual Review of Sociology, 30, 507–544.

Haller, A. O. and Butterworth, C. E. (1960). Peer influences on levels of occupational and educational aspiration. Social Forces, 38, 289–295.

Hoxby, C. (2000). The effects of class size on student achievement: new evidence from population variation. The Quarterly Journal of Economics, 115, 1239–1285.

Huisman, M. and Steglich, C. (2008). Treatment of non-response in longitudinal network studies. Social Networks, 30, 297–308.

Imberman, S. A., Kugler, A. D. and Sacerdote, B. I. (2012). Katrina's children: evidence on the structure of peer effects from hurricane evacuees. American Economic Review, 102, 2048–2082.

Kalter, F. et al. (2016a). Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU)—full version. Data file for on-site use. GESIS Data Archive, Cologne, ZA5353 Data file Version 1.2.0, doi:10.4232/cils4eu.5353.1.2.0.

*Kalte*r, F. et al. (2016b). Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU)—full version. Data file for on-site use. GESIS Data Archive, Cologne, ZA5353 Data file Version 2.3.0, doi: 10.4232/cils4eu.5353.2.3.0.

Kandel, D. B. (1978). Homophily, selection, and socialization in adolescent friendships. American Journal of Sociology, 84, 427–436.

Kiuru, N. et al. (2007). The role of peer groups in adolescents' educational expectations and adjustment. Journal of Youth and Adolescence, 36, 995–1009.

Kretschmer, D., Leszczensky, L. and Pink, S. (2018). Selection and influence processes in academic achievement—more pronounced for girls? Social Networks, 52, 251–260.

Kurz, K. and Böhner-Taute, E. (2016). Wer profitiert von den Korrekturmöglichkeiten in der Sekundarstufe? Zeitschrift für Soziologie, 45, 431–451.

*Mansk*i, C. (1993). Identification of endogenous social effects: the reflection problem. The Review of Economic Studies, 60, 531–542.

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

Mood, C. (2010). Logistic regression: why we cannot do what we think we can do, and what we can do about it. European Sociological Review, 26, 67–82.

Mora, T. and Oreopoulos, P. (2011). Peer effects on high school aspirations: evidence from a sample of close and not-so-close friends. Economics of Education Review, 30, 575–581.

Morgan, S. L. (2005). On the edge of commitment: educational attainment and race in the United States. Stanford: Stanford University Press.

Mouw, T. (2006). Estimating the causal effect of social capital: a review of recent research. Annual Review of Sociology, 32, 79–102.

*Müll*er, W. (2005). Education and youth integration into European labour markets. International Journal of Comparative Sociology, 46, 461–485.

Picou, J. S. and Carter, T. M. (1976). Significant-other influence and aspirations. Sociology of Education, 49, 12-22.

Raabe, I. J. and Wo¨lfer, R. (2019). What is going on around you: peer milieus and educational aspirations. European Sociological Review, 35, 1–14.

Rambaran, J. A. et al. (2017). Academic functioning and peer influences: a short-term longitudinal study of network–behavior dynamics in middle adolescence. Child Development, 88, 523–543.

Ripley, R. M. et al. (2020). Manual for RSiena. Oxford and Groningen: University of Oxford and University of Groningen.

Rosenqvist, E. (2018). Two functions of peer influence on upper-secondary education application behavior. Sociology of Education, 91, 72–89.

Roth, T. (2017). Interpersonal influences on educational expectations: new evidence for Germany. Research in Social Stratification and Mobility, 48, 68–84.

Sacerdote, B. (2001). Peer effects with random assignment: results for Dartmouth roommates. The Quarterly Journal of Economics, 116, 681–704.

Sacerdote, B. (2014). Experimental and quasi-experimental analysis of peer effects: two steps forward? Annual Review of Economics, 6, 253–272.

Salikutluk, Z. (2016). Why do immigrant students aim high? Explaining the aspiration–achievement paradox of immigrants in Germany. European Sociological Review, 32, 581–592.

Sewell, W. H., Haller, A. O. and Portes, A. (1969). The educational and early occupational attainment process. American Sociological Review, 34, 82–92.

Sewell, W. H. and Hauser, R. M. (1972). Causes and consequences of higher education: models of the status attainment process. American Journal of Agricultural Economics, 54, 851–861.

Shin, H. and Ryan, A. M. (2014). Early adolescent friendships and academic adjustment: examining selection and influence processes with longitudinal social network analysis.Developmental Psychology, 50, 2462–2472.

Snijders, T. A. B., van de Bunt, G. G. and Steglich, C. E. G.

(2010). Introduction to stochastic actor-based models for network dynamics. Social Networks, 32, 44–60.

Steglich, C. E. G., Snijders, T. A. B. and Pearson, M. (2010). Dynamic networks and behavior: separating selection from influence. Sociological Methodology, 40, 329–393.

Wimmer, A. and Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documentedon facebook. American Journal of Sociology, 116, 583–642.

Zimmermann, D. J. (2003). Peer effects in academic outcomes: evidence from a natural experiment. The Review of Economics and Statistics, 85, 9–23.

Zimmermann, T. (2019). Social influence or rational choice? Two models and their contribution to explaining class differentials in student educational aspirations. European Sociological Review.

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