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THE DIFFUSION OF ACADEMIC ACHIEVEMENTS: SOCIAL SELECTION AND INFLUENCE IN STUDENT NETWORKS

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THE DIFFUSION OF ACADEMIC ACHIEVEMENTS: SOCIAL SELECTION AND INFLUENCE IN STUDENT NETWORKS[4]

Peer group effects show the influence of student social environments on their individual achievements. Traditionally, a social environment is considered by researchers of peer effects as exogenously given. However, significant peers that affect performance are often those that are deliberately chosen. Students might choose their friends among peers with similar academic achievements. A dynamic analysis of student social networks and academic achievements is needed to disentangle social selection and social influence processes in network formation. Using data about the friendship and advice networks of first year undergraduate students, we show that friends tend to assimilate each others' achievements and choose advisers with similar grades. We explain these results by social segregation based on student performance. The article contributes to the dynamic analysis of student social networks and the understanding of the nature of peer group effects in education.

JEL Classification: D85, I21, I23

Keywords: social networks, academic achievements, peer group effects, higher education

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1. Introduction

Among various student achievements academic ones are the most analysed. Numerous papers show that the socioeconomic status of students (Sirin 2005, White 1980), the time spent on their studies (Gijselaers and Schmidt 1995, Van de Water 1996), part-time job (Pike et al. 2009, Perozzi et al. 2003) and their educational environment influence student academic achievements (Lamport 1993, Bank et al. 1990). Since the influential “Coleman Report” (Coleman et al., 1966), the influence of students’ peers on their individual achievements has also received a lot of attention in the sociological, educational, and economic literature. While many studies show the presence of peer group effects (Sacerdote 2000, Lyle 2007, Arcidiacono et al. 2012, Lin 2010), there is still little understanding about their formation and diffusion.

Peer group effect studies demonstrate that an increase in average peer achievement may lead to an increase of a student’s own achievements (Sacerdote, 2000). To prevent the potential endogeneity arising from the student’s choice of preferred peers, samples where peers were assigned in a random way are usually used. However, even in cases when students are divided into study groups or cohorts exogenously, the choice of significant peers is the result of a deliberate individual decision (Lomi et al., 2011). In randomly assigned groups students still tend to form smaller communities based on same race, gender, common interests, geographical proximity (McPherson et al., 2001). These individual network preferences can change the way students are influenced by their social environment.

Therefore, to estimate peer effects correctly we need an in-depth investigation of the individual position of a student and his or her peers in their social structure, a detailed analysis of this structure, and any behavioural changes. Two processes might participate in peer effects formation and transmission. On the one hand, we can observe social selection when students tend to select as friends other students with similar level of abilities and performance (McPherson et al., 2001). On the other hand, we can see social influence when friends over time tend to assimilate academic performance of each other (Friedkin, 2001).

We can conclude that the formation and transmission of peer group effects is a dynamic process that includes changes in both student achievements and their social connections. Such a focus on the micro-changes which could lead to a macro-change was, until recently, impossible due to the absence of appropriate statistical methods. Today, with the recently developed family of network models such as stochastically actor-oriented models (SAOM) (Snijders et al., 2010), we can distinguish the evolution of academic achievements and social ties and analyse peer effect formation and transmission in a more detailed way.

In this paper, we use questionnaire data about the friendship and advice networks of students studying at one Russian university. We observe the presence of peer group effects (peers influence each others achievements and tend to assimilate their grades) and demonstrate how the choice of significant peers is made (students choose advisers based on their achievements but for the choice of potential friends grades are not important). Thus, we disentangle the differences in the nature of peer effects for different social relationships.

The rest of the article is structured in a following way. Section 2 contains the literature review on peer group effects and on social network analysis of student behaviour and achievement. Section 3 describes the institutional characteristics of the Russian educational system and explains the essential characteristics of the educational process in the university under study. Section 4 describes our methodology and reports the descriptive statistics. Section 5 reports the network modelling results. Section 6 concludes the article by discussing possible explanations of the results and future directions in peer effect estimation studies.

2. Student Social Environment and Performance

2.1 Peer-effect identification

Numerous studies show that the social environment of university students affects their individual decisions, behaviour, and academic performance. For instance, Sacerdote (2000) demonstrates that student GPA increases if his or her dormmate is in the 25th percentile of the students with the highest GPA. In studies by Zimmerman (2003) and Carrell et al., (2008) peer effects are found to be non-linear: students with a low level of achievement are more influenced by their peers. Hallinan and Williams (1990) point out that peer influence depends on the peer's race and gender while Davies and Kandel (1981) find that peer influence is stronger among women than men.

However, results about the presence of peer group effects remain ambiguous. Some studies do not reveal any evidence for these effects or find only marginally significant ones (Arcidiacono and Nicholson 2005, Foste, 2006, Brunello et al. 2010, Epple et al. 2003). This disagreement in results might be because of the different groups that are perceived as a peer group. For instance, peers might be students of the same school (Angrist and Lang, 2015), or students of the same cohort (Carrell et al. 2008, Androushchak et al. 2013), classmates (Lavy and Sand 2012, Lyle 2007).

One of the most important conditions for the correct identification of peer group effects is the random assignment of peers made by the administration of an educational institution. At the same time, it is difficult to imagine that students' random social environment, in other words, people they might not even know personally, could influence their individual attainments. Peer group effects are probably stronger from close peers such as friends (Burke and Sass, 2013). Even if similarity in academic performance or abilities is not the most influential factor explaining ties between students, there is some evidence for this (Tuma and Hallinan 1979, Mayer and Puller 2008). Also, students might tend to form connections that are useful for their success in their educational environment. For instance, forming friendship or advice ties with high-achievers might help in gathering new information. Such structural characteristics as the tendency of ties to be mutual (Gouldner, 1960) or to be closed in triads (Davis and Leinhardt, 1972) might also explain the choice of peers in the classroom.

Therefore, as significant peers are selected based on visible and invisible student characteristics, according to the potential usefulness of the environment and hidden network tendencies, we need a detailed dynamic analysis of network changes and peer choices.

2.2 Social selection and social influence: the peer effect formation mechanism

It has been established in various network studies that individuals with similar characteristics tend to be closely related, in other words, they tend to be friends (Steglich et al., 2010). There are two possible explanations for this phenomenon, which is usually called *homophily* in network studies. On the one hand, we can observe selection mechanisms existing in the social environment (Lazarsfeld and Merton 1954, McPherson and Smith-Lovin 1987). From this point of view, individuals initially seek as friends those individuals who have similar characteristics (McPherson et al., 2001). In the case of academic performance, students initially tend to create ties with peers who have similar abilities. As a result, over time we observe social segregation based on academic performance.

On the other hand, the human tendency to be connected with those who are similar is explained by behavioural influence and contagion mechanisms (Friedkin 1998, 2001).

Individuals socialize in peer groups where certain behaviours and norms are created. Over time, individuals assimilate the behaviour of their peers and referent groups to be accepted in their social environment. In the case of achievement contagion, we hypothesize that over time students tend to influence each other and assimilate their peers' level of performance.

In sum, to understand peer group effect formation and evolution mechanisms, we need to distinguish the two processes which exist in dynamic social networks: *social selection* and *social influence* (Steglich et al., 2010). Social selection and influence do not contradict each other and can evolve in networks at the same time. With static data we cannot disentangle these processes whereas with dynamic data we can analyse their joint coevolution and separate selection from influence.

Social selection and influence in social networks are analysed in details in studies of deviant behaviours in secondary schools. These behaviours arouse special interest because they are transmitted through networks and cause behaviour contagion. Mercken et al. (2010) show that students with similar attitudes to smoking tend to form ties with each other, and friends tend to adopt this behaviour from each other. Baerveldt et al. (2010; Snijders and Baerveldt 2003) demonstrate that students tend to influence their friends and contaminate them with deviant behaviour such as bullying, vandalism, pickpocketing. Light et al. (2013) analyse the first alcohol use of early adolescents and reveal the presence of both social selection and influence in friendship networks. In other words, they show that students select friends based on the similar levels of alcohol use and over time adolescents influence alcohol intake of their friends. Kiuru et al. (2010) analyse Finnish adolescents and find that students select friends with a similar level of alcohol use. Burk et al. (2007) show that the delinquent behaviours of adolescents are important for both friendship selection and influence processes.

However, social selection and influence based on student performance have not been studied in detail yet. Flashman (2012) analyses secondary school students in U.S. and shows that they tend to form friendship ties with students who have similar grades. Together with the change in individual performance, students change their social environment and start to befriend peers with similar grades. Lomi et al. (2011) study MBA students in an Italian university and reveal that students with low levels of achievement tend over time to befriend other students with the same level of attainment. They show that students over time tend to assimilate the grades of their friends and advisers.

The small number of studies (to our knowledge, only the works by Flashman and Lomi et al.) on social selection and influence based on academic performance can be explained by the specific nature of the behaviourconnected with the performance demonstration. Patterns of student academic performance do not spread through social network as fast as smoking or other types of deviant behaviour, which are socially constructed. Also, the presence of social selection or influence based on academic performance might significantly depend on the sample of students. In some samples, a demonstration of high achievements might not be an important factor that determines student decisions about friendship ties or such behaviour might be even a negative signal for peers (Staff and Kreager 2008, Lusher 2011).

In this study we contribute to the studies of peer group effect formation and transmission through social networks. We analyse those effects which are produced by significant peers of students—their friends and academic advisers. As outlined by Lomi et al. (2011), in most social networks, we can distinguish two main types of relations: friendship and advice. The first is a more intimate relation, whereas the second one is more instrumental and status-oriented (Lazega et al., 2012). Both these social environments are closely intertwined and have an impact on student behaviour. However, the structure of these networks might differ and the strength of peer effects from these relations can vary.

To investigate the processes of social selection and social influence we tested the following hypotheses:

Hypothesis 1: There is a social selection process within the friendship network. Students tend to select friends with similar levels of academic achievements.

Hypothesis 2: There is a social influence process within the friendship network. Students tend to assimilate the level of academic achievement of their friends.

Hypothesis 3: There is a social selection process within the advice network. Students tend to select advisers with similar levels of academic achievements.

Hypothesis 4: There is a social influence process within the advice network. Students tend to assimilate the level of academic achievement of their advisers.

To analyse the joint evolution of student networks and performance, we use SAOM which allow social selection and social influence in networks to be distinguished.

3. Data

In this study we use the data about social networks and individual characteristics of first year Economics students in 2013–14 in a selective Russian university. We analyse their social connections and performance in their first year when they do not know each other well and their friendship ties are still under construction. The sample is special due to the selectivity of the university, a demonstration of high achievement is an important behaviour for these students. Additionally, this university has a public grading system which means that professors publicly announce student grades and all students know about the academic performance of each other. At the end of the semester students in the cohort are rated based on their GPA and top students receive additional financial aid. Therefore, university administration encourages high performance and grades may become signals for students to change their social connections or their performance.

In this university, students are randomly assigned by the administration to one study groups of up to 30 students. Lectures are usually delivered to several groups simultaneously, while seminar classes are delivered to each group separately. In the first year of study most of the courses are obligatory. Therefore, students have limited possibility to form networks with students from other programs or years of admission.

The academic year consists of four modules of three months. At the end of each module students take exams. The grading system is in 10-point scale where a higher number indicates a higher level of academic achievement. The course grade is the weighted average of midterm and final exams, homework, essays, and other academic activities during the course.

The grading system is publicly open. The information about student grades is publicly announced on the university website and in the university. It means that students can easily obtain all the information about the grades of their peers.The data for this research were gathered from two sources: from a student questionnaire and from the university administrative database. To study network and performance dynamics, we conducted three surveys (October 2013, February 2014, and June 2014). Information about network interactions was collected from the following questions:

1. *Please indicate the classmates with whom you spend most of your time;*
2. *Please indicate the classmates whom you ask for help with your studies.*

There were no limitations in the number of nominations. We established the fact that some students had known each other before university by an additional question. Both friendship and advice networks are directed.

Overall, number of students in the cohort is 131 and they are distributed in 5 groups. We gathered data about networks of 117 students (90% of the sample), who took part in at least two surveys. There were 89% participants in the first wave, 79% in the second, and 76% in the third. Missing data were treated by *composition change* technique (Huisman and Steglich, 2008) in *RSiena* package (Ripley et al., 2015) in *R* statistical environment (Team R, 2012). The sample is made up of 31% men and 69% women. Network visualizations are presented in Figures 1 and 2. Descriptive statistics for friendship and advice networks are presented in Tables 1 and 2.

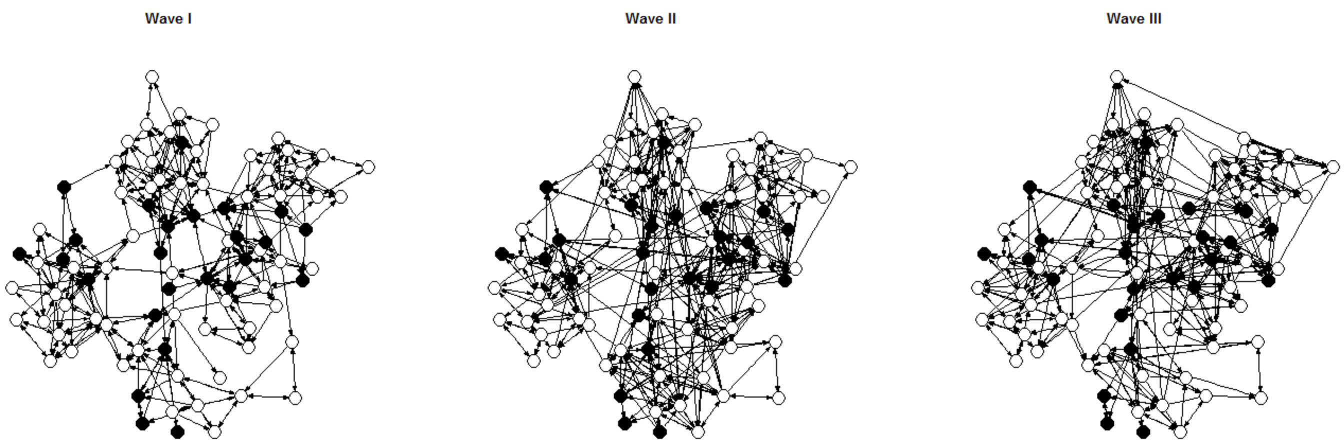


Figure 1. Friendship network at three waves of measurement (October 2013, February 2014, and June 2014). The nodes are students. The edges between nodes are student friendship relationships. Node colour represents gender (women—white, men—black).

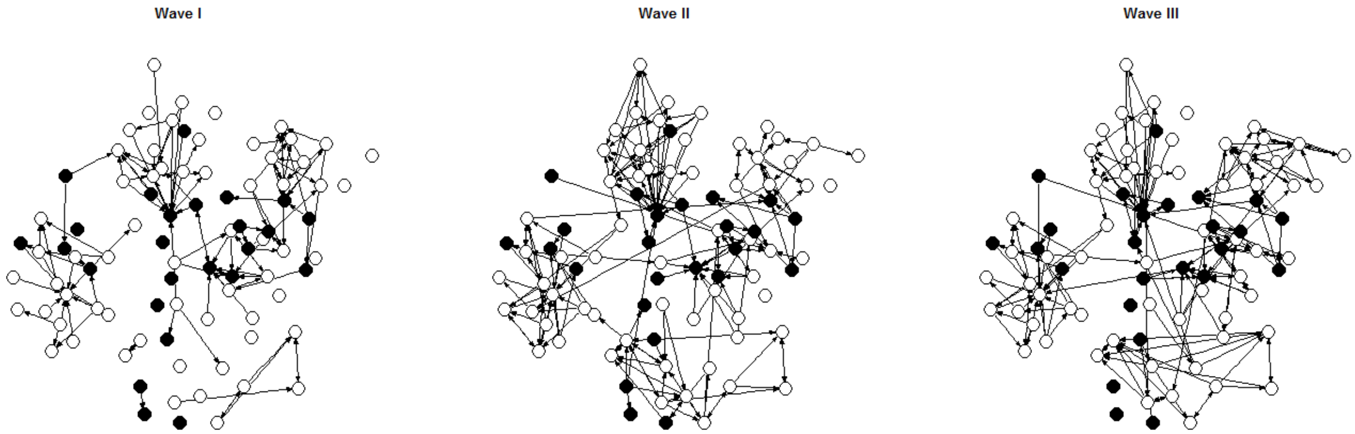


Figure 2. Advice network at three waves of measurement (October 2013, February 2014, and June 2014). The nodes are students. The edges between nodes are student advice relationships. Node colour represents gender (women—white, men—black).

Table 1. Friendship network descriptive statistics

Network parameter	First wave	Second wave	Third wave
Number of students	117	117	117
Number of links among students	715	662	557
Density	0.053	0.049	0.041
Reciprocity	0.63	0.60	0.51
Transitivity	0.42	0.37	0.35
Jaccard coefficient	-	0.35	0.32

Table 2. Advice network descriptive statistics

Network parameter	First wave	Second wave	Third wave
Number of students	117	117	117
Number of links among students	226	267	248
Density	0.017	0.020	0.018
Reciprocity	0.24	0.23	0.19
Transitivity	0.29	0.28	0.27
Jaccard coefficient	-	0.28	0.26

The data about students' grades were gathered from the university administrative database. To estimate the level of student academic achievement we used their *relative academic performance*. This was calculated by computing a student's grade point average as an arithmetical mean of all the subjects, taking into consideration the subject coefficient. On average, each student receives 6–10 grades per module. The number of subjects differs from module to module. The subject coefficient varies from 0 to 8 and is proportional to the difficulty and importance of the subject. The higher the coefficient, the more important is the subject. These average grades were divided by the maximum grade which can be obtained by the student if he or she receives maximum grades for all subjects. The relative performance is calculated as the ratio of grade point average to maximum grade:

$$\mathrm{RP}=\frac{\sum_i^N (k_i \times g_i)}{\sum_i^N (k_i \times 10)} \times 100\% , \tag{1}$$

where *RP i*s the relative performance, *N* is the number of subjects, k_i is the subject coefficient, and g_i is a student's performance in a particular subject.

We divide students into four groups, according to their academic performance. We distinguish "high-achievers" with relative performance from 80% to 100%, "above-average achievers" with relative performance from 60% to 79%, "below-average achievers" with relative performance from 40% to 59%, and, finally, "low achievers" with relative performance from 0% to 39%. Descriptive statistics for the student performance are in Table 3.

Table 3. Descriptive statistics for the relative performance

Parameter	First wave	Second wave	Third wave
Mean	2.47	2.39	2.79
St. deviation	0.67	0.78	0.73
Minimum	1	1	1
Maximum	4	4	4
"High-achievers"	7%	7%	14%
"Above-average achievers"	35%	36%	55%
"Below-average achievers"	55%	46%	26%
"Low-achievers"	3%	11%	4%

4. Methods

Standard statistical techniques such as regression models are not appropriate for the analysis of social networks due to the interdependence of network observations (Robins, 2013).

Therefore, we apply stochastic actor-oriented models (SAOM) (Snijders, 2010) which allows us to reveal the coevolution mechanisms of network and behaviour. This type of dynamic model is widely used for studying the joint evolution of social networks, actor attributes, and separating the processes of social selection and social influence.

For us, the following underlying principles of these models are important. Firstly, network and behaviour changes are modelled as Markov processes, which means that the network state at time *t* depends only on the (*t-1*) network state. Secondly, SAOM is grounded on the methodological approach of structural individualism. It is assumed that all actors are fully informed about the network structure and attributes of all other network participants. Thirdly, time moves continuously and all the macro-changes of the network structure are modelled as the result of the sequence of the corresponding micro-changes. This means that an actor, at each point in time, can either change one of the outgoing ties or modify its attribute. The last principle is crucial in the separation the social selection and social influence processes.

Snijders et al. (2010) distinguishes four sub-components of the coevolution of network and behaviour: *network rate function*, *network objective function*, *behaviour rate function* and *behaviour objective function*. The rate functions represent the expected frequencies per unit of time with which actors get an opportunity to make network or behavioural micro-changes (Lomi et al., 2011). The objective functions are the primary determinants of the probabilities of changes. The probabilities of the network and/or behaviour change are higher as the objective functions for network/behaviour are higher (Snijders et al., 2010).

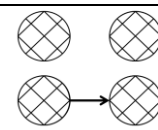
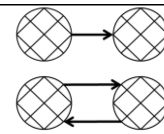
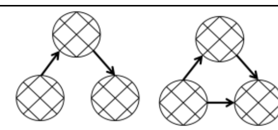
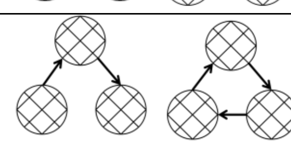
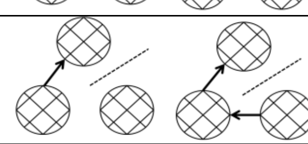
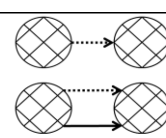
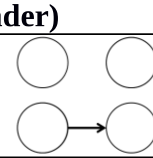
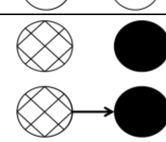
The objective functions for network (2) and behaviour change (3) are calculated as a linear combination of a set of components called *effects*.

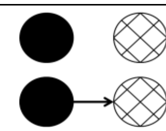
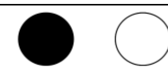
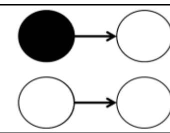
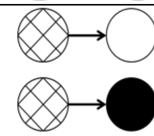
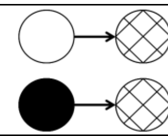
$$\mathbf{f_i(\beta, x)} = \sum_k \beta_k s_{ki}(x) \tag{2}$$

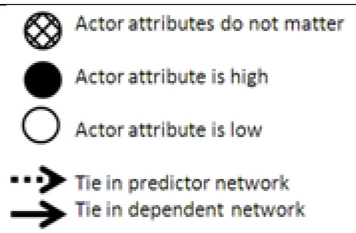
$$\mathbf{f_i^Z(\beta, x, z)} = \sum_k \beta_k^Z s_{ki}^Z(x,z), \tag{3}$$

where $s_{ki}(x)$ are the analytical functions (also called effects), which describe the network tendencies presented in Table 4; $s_{ki}^Z(x,z)$ are functions that depend on the behaviour of the focal actor *i*, but also on the behaviour of his or her network partners and his or her network position (Snijders et al., 2010). β_k and β_k^Z are statistical parameters which show the importance of the effects. SAOM coefficients are interpreted as logistic regression coefficients. Parameters are unstandardized, therefore, the estimates for different parameters are not directly comparable (Snijders et al., 2010). During the modelling, SAOM allows the inclusion of several groups of effects in the model, which are presented in Table 4.

Table 4. Network and behaviour dynamics effects

Effect	Description	Illustration
	Control network effects	
Density	Ego's tendency to create ties	
Reciprocity	Tendency of actors to reciprocate relations	
	Triadic effects	
Transitivity	Tendency of actors to befriend friends of their friends	
3-cycles	Tendency to create cycles	
Betweenness	Tendency of actors to seek for brokerage positions	
	Ties in exogenous networks	
Effect of exogenous network (e.g. advice network)	Tendency of actors to befriend with their advisers	
	Attributes effects (academic performance and gender)	
Social selection	Tendency of actors to create ties with similar others	
Attribute alter (e.g. performance)	Tendency of actors with high academic performance to be more popular	

Attribute ego (e.g. performance)	Tendency of actors with high academic performance to be more active	
Behaviour dynamics effects		
Linear and quadratic shape	Shape of the performance distribution	
Performance assimilation	Tendency of actors to assimilate individual performance to the average performance of friends	
Indegree (popularity)	Tendency of actors who receive many friendship nominations to show higher performance.	
Outdegree (activity)	Tendency of actors who send many friendship requests to show higher performance.	



First, we include endogenous network effects. One of the most important control endogenous effects in the dynamic network models is the *density*. It shows the tendency of actors to create ties that are not embedded in more complex structures. Usually it is negative and significant. *Reciprocity* is another basic network effect, which shows the tendency of actors to reciprocate ties over time. It is usually positive and significant. There are several important network triadic effects in the model. We controlled for the *transitivity*, which described the tendency of actors to become friends with friends of their friends. The *3-cycles* effect shows the tendency to create cyclic triangles. *Betweenness* shows the tendency of actor to seek for the brokerage position.

Second, we include several exogenous effects describing actor attributes. Exogenous effects such as acquaintance before enrolment to the university, belonging to the same study group, and the connection in the advice social network are included in the model. We also control gender homophily, the tendency of males be more popular and active than females, and the tendency of actors with high grades be popular and active. In addition, we include the gender-related effects in the model.

To test the hypothesis about social selection we include the selection effect based on academic achievement. It shows whether students with similar levels of academic achievement tend to form connections in the social network over time.

To test the hypothesis about social influence we estimate the effect of performance assimilation. It shows whether students, who are connected in the network, tend to assimilate the level of academic achievement of their friends.

In model construction we follow model specification of Lomi and colleagues (2011) and address the general network modelling requirements necessary for SAOM (Snijders et al., 2010).

5. Results

To test Hypotheses 1 and 2, we estimate the effect of performance similarity and performance assimilation during the coevolution of friendship and academic achievements.

We present the modelling results for the coevolution of friendship with performance, and advice with performance in Tables 5 and 6 respectively.

Table 5. Results on the coevolution of friendship and academic achievements.

Parameter	Estimate (st. deviation)	t-statistics
Rate parameter 1	16.92***(1.62)	-0.01
Rate parameter 2	15.83***(1.62)	0.02
Control network effects		
Density	-2.18***(0.10)	0.05
Reciprocity	1.74*** (0.11)	0.04
Triadic effects		
Transitivity	0.30***(0.02)	0.02
3-cycles	-0.28***(0.05)	0.03
Betweenness	-0.10***(0.02)	0.02
Ties in exogenous networks		
Acquaintance before enrollment	0.95***(0.16)	0.04
Studying in the same group	0.72***(0.07)	0.05
Tie in advice network	0.05***(0.01)	-0.01
Gender effects		
Gender of alter (1 - Male)	0.09(0.06)	-0.02
Gender of ego (1 - Male)	0.22*(0.06)	-0.04
Gender similarity	0.24***(0.06)	-0.00
Academic performance effects by		

Performance of alter	0.14**(0.05)	0.03
Performance of ego	0.18***(0.06)	0.03
Performance similarity (selection)	0.33(0.20)	-0.02
Behavior dynamics effects of		
Rate parameter 1	0.55*** (0.12)	-0.05
Rate parameter 2	1.13***(0.24)	-0.00
Linear shape effect	1.08(0.65)	0.06
Quadratic shape effect	0.39(0.38)	-0.02
Performance assimilation (influence)	7.32*(3.17)	0.03
Indegree (popularity)	0.05(0.10)	0.06
Outdegree (activity)	-0.13(0.15)	0.06
Overall maximum convergence ratio: 0.23		

*** p-value< 0.001, ** p-value<0.01, * p-value<0.05

The estimate of performance assimilation (influence) is positive and significant, which shows that the academic performance of an individual over time tends to become similar to the performance of his or her friends. At the same time, actors with high performance tend to be more active and popular in friendship networks. The performance selection effect for friendship networks is not significant, so we do not find the evidence of social selection. It means that the level of academic achievement does not play a key role in friendship formation. In sum, we could not find support for Hypothesis 1, while Hypothesis 2 was confirmed.

The significant and negative density effect shows that actors tend not to create friendship ties that are not embedded in more complex local configurations. The sum of positive transitivity and negative 3-cycles reveals the presence of a local hierarchy within the student friendship network. The negative betweenness effect and positive transitivity demonstrate that actors do not seek brokerage positions.

Being in the same study group, of the same gender, and acquainted before enrolment are strong predictors for friendship formation. We also reveal that men tend to be more active in friendship networks over time. Friendship and advice networks are closely intertwined.

The rate parameter describes the level of changes between observations. The network and behaviour evolution rate parameters are statistically significant and positive. The rate parameter for network dynamics is higher for the period between the first and second observations, which means that ties within the social network tend to become stable over time. Interestingly, the rate parameter for academic performance dynamics is higher for the period between the second and third observations.

The linear and quadratic shape parameters model the shape of the long-term performance distribution (Steglich et al., 2010). The linear shape parameter serves as an intercept. It shows the average performance to which student tend over time. The quadratic shape parameter shows the shape of the performance distribution.

We use the same model specification to estimate the coevolution of advice networks and academic performance and to test Hypotheses 3 and 4 (Table 6).

Table 6. Results on the coevolution of advice and academic achievements.

Parameter	**Estimate (st. deviation)**	**t-statistics**
Rate parameter 1	5.78***(0.61)	-0.02
Rate parameter 2	5.63***(0.60)	0.03
Control network effects		
Density	-2.94***(0.28)	0.05
Reciprocity	1.00***(0.23)	-0.01
Triadic effects		
Transitivity	0.52***(0.08)	0.03
3-cycles	-0.34(0.22)	-0.02
Betweenness	-0.39***(0.10)	0.00
Ties in exogenous networks		
Acquaintance before enrollment	1.06***(0.22)	-0.04
Studying in the same group	1.36***(0.12)	0.03
Tie in friendship network	0.14*(0.06)	-0.00
Gender effects		
Gender of alter (1 - Male)	0.21(0.12)	0.02
Gender of ego (1 - Male)	0.12 (0.15)	0.02
Gender similarity	0.37***(0.11)	0.03
Academic performance Effects		

Performance of alter	1.00***(0.26)	0.05
Performance of ego	0.20(0.34)	-0.01
Performance similarity (selection)	2.16*(0.85)	-0.00
Behaviour dynamics Effects		
Rate parameter 1	0.63***(0.15)	-0.01
Rate parameter 2	1.51***(0.35)	-0.00
Linear shape effect	-0.61(0.41)	0.06
Quadratic shape effect	-0.56*(0.22)	0.02
Performance assimilation (influence)	4.22(2.29)	-0.04
Indegree (popularity)	0.39*(0.17)	0.08
Outdegree (activity)	-0.13(0.16)	0.08
Overall maximum convergence ratio: 0.17		

*** p-value< 0.001, ** p-value<0.01, * p-value<0.05

In Table 6, for advice networks, the estimate for the performance similarity (selection) effect is positive and significant, which shows the presence of social selection in advice networks. Students with similar levels of academic achievement tend to ask each other for help. The social influence effect is not significant. This means that we do not observe a social influence process within this network. Students do not assimilate the performance of their advisers. The positive and significant effect of performance on popularity shows that students with high levels of academic achievement tend to increase their popularity over time, while the effect of performance shows that popular students tend to receive higher grades over time. Hypothesis 3 is confirmed, but not Hypothesis 4.

In the case of friendship networks, we show the presence of a negative density effect, positive estimates for transitivity, and negative estimates for betweenness. Students tend to ask peers from the same study group, those of the same gender, and students they knew before for help. Men tend to become more popular within the advice network.

In sum, we find the presence of a social influence process in the case of friendship networks and the coevolution of academic achievement. In advice networks we find the presence of a social selection process based on academic achievement.

In Tables 5 and 6 we presented the general estimates for social selection and social influence for an average performing student. Using the objective function notation (2) we can compute more precise estimates for the performance selection effect for the different achievement groups (Table 7). The higher the estimate, the higher the probability of advice tie formation between students from two groups (Ripley et al., 2015).

Table 7. Total performance effects on log-odds of advice selection.

		Alter, performance			
Ego, performance		Low-achievers	Below-average achievers	Above-average achievers	High-achievers
	Low-achievers	-1.22	-0.94	-0.66	-0.39
	Below-average achievers	-1.74	-0.02	0.26	0.54
	Above-average achievers	-2.26	-0.54	1.18	1.46
	High-achievers	-2.78	-1.06	0.66	2.38

Table 7 shows that the social selection process works only for above-average students and high-achievers. All groups of students tend to nominate high-achievers as advisers in this network. However, students with low academic achievements tend not to ask for any advice from their peers.

Similarly, using the formulation of the objective function for behaviour dynamics (3), we calculated more precise estimates for the social influence process for the four achievement groups. Table 8 presents the log-odds of performance to the objective function for friendship network dynamics. The estimates illustrate the influence of friends on individual academic achievement.

Table 8. The influence of friends on log-odds of an achievement increase compared to achievement decrease, if all the friends have the same achievements.

<table>
<tr><td></td><td colspan="5">Alter, performance</td></tr>
<tr><td rowspan="5">Ego, performance</td><td></td><td>Low-achievers</td><td>Below-average achievers</td><td>Above-average achievers</td><td>High-achievers</td></tr>
<tr><td>Low-achievers</td><td>1.09</td><td>-1.34</td><td>-3.78</td><td>-6.22</td></tr>
<tr><td>Below-average achievers</td><td>-1.02</td><td>1.41</td><td>-1.02</td><td>-3.46</td></tr>
<tr><td>Above-average achievers</td><td>-2.36</td><td>0.08</td><td>2.52</td><td>0.08</td></tr>
<tr><td>High-achievers</td><td>-2.91</td><td>-0.47</td><td>1.97</td><td>4.40</td></tr>
</table>

Table 8 shows that students with friends in the above-average and high-achievers groups tend to improve their grades over time. High and positive coefficients across the matrix diagonal shows that students tend to receive the same grades as their friends.

We also see the tendency of the negative social influence. High-achievers that name low-achievers as friends are more likely to decrease their performance in comparison with low-achievers that name high-achievers as friends.

6. Conclusion

This study analyses the mechanism of the formation and transmission of peer-effects through friendship and advice networks. We find the clear evidence for peer group effects within student friendship networks. Students do not pre-select friends with similar grades, but assimilate the academic performance of their friends. Students with high grades tend to become more popular and active over time.

A detailed investigation reveals the features of achievement assimilation among students with different levels of performance. Students with high achieving friends tend to increase their academic performance over time. Thus, establishing friendship relationships with high-achievers has a positive influence on an individual's academic performance. The only exception is students with low grades: they tend to decrease their academic performance over time within any social environment. Friendship with a low-achiever has a negative influence on his or her friends because they tend to decrease their grades over time. These results follow the line of existing peer-effects and social influence literature for friendship and academic achievements (Flashman 2012, Sacerdote 2000).

In the case of advice networks, we observe the opposite effects. Students choose advisers with similar levels of academic achievement but they do not assimilate their performance. Students also tend to ask peers with high grades for advice. However, advisers tend not to influence their counteragents' academic performance. At the same time, students with low grades tend not to ask for advice at all. This could be the result of the low motivation or they could anticipate that their requests would be denied. The obtained results contradict Lomi and et al. (2011), who fixed the presence of both social selection and social influence in the advice network of students. This difference in results can be explained by the characteristics of the sample. In this research, we investigate the relationships among first year university students with an average age of 18, while Lomi et al (2011) studied MBA students with an average age of 29. While both samples consist of students with high abilities, studying in selective programs, the age of students and their life experience could explain the differences.

Thus, different social relationships between university students serve for different peer-effects. The revealed combination of social selection and social influence processes demonstrate the presence of social segregation based on performance. Students with high levels of academic achievements tend to create a dense "core" (rich-club) within both networks and actively communicate with each other. At the same time, low-achievers tend not to form advice or friendship ties and constitute the sparse periphery in both networks. Similar empirical evidence is presented in Vaquero and Cebrian (2013) where from the very beginning first-year students with high performance actively communicate with each other and avoid low-achievers. As a result, students with high grades aggregate into a dense and stable network core. Students with lower grades try to establish advice relationships with the high-achievers but mostly did not receive any replies. Therefore, advice networks did not serve as a channel for performance diffusion.

We have shown different functions of friendship and advice networks in peer-effect formation and transmission. Friendship networks serve as channels for academic performance diffusion and play an important role in academic achievement formation. Advice relationships are more instrumental and pre-selective; they do not influence student grades.

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