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HOW SOCIAL TIES AFFECT PEER-GROUP EFFECTS: A CASE OF UNIVERSITY STUDENTS

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Among the key issues of peer effects estimation is the correct identification of relevant peers. In this study, we explore how the individual performance of university students is influenced by characteristics and achievements of peers from individual's social network. The analysis uses data from two directed networks: a network of friends and a network of study partners for third-year students at a top-tier Russian university. Data on network ties in randomly formed student groups enables us to address the endogeneity problem and disentangle the influence of peers' performance from the effect that a peer's background has on students. We show that both the GPA of peers and their ability measures are significant in the estimated regression model. A one-point increase in the average GPA of peers is associated with an increase in an individual student's own GPA of approximately one fourth. The regression on the data from the network of study partners has slightly greater explanatory power than the analysis based on data from the network of friends. No effect from a student's classmates is found in the model that assumes group interactions occur between group mates.

Keywords: peer effects, higher education, student achievement, social networks.
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1. Introduction

A wide range of factors affects individual learning. Some of these are in the sphere of traditional research interest because they are inputs of the educational production function, including a student's characteristics and personal ability, teacher quality, school resources, and peer characteristics. Peer characteristics and behavior can also play an important role in educational achievement. This influence is called the "peer effect". While there is much research devoted to estimating the effect of peers in secondary schools, studies of these effects in higher education are not so abundant.

One strand of empirical work on the effect of peers in institutes of higher education is based on the data analysis of students living in either one room or one section of a student dormitory. Sacerdote (2001), Zimmerman (2003), and Brunello et al (2010) consider randomly assigned roommates as peers. Sacerdote (2001) found that average grades were higher for those students whose roommate was in the top 25% of the class. In a study conducted by Zimmerman (2003), students in the middle of the distribution for SAT scores receive worse grades if their roommates are students with low grades. In Brunello et al (2010), positive and significant effects are found for students specializing in engineering and mathematics.

Another approach considers an entire study group as the peer group. However, having a free choice of subjects to study in most universities implies an endogenous formation of study groups, which impedes upon the correct estimation of peer effects. One exception of this practice is found in military institutions. In the specific environment of these institutions, students interact intensively within the groups that are formed administratively. Lyle (2007) finds a significant relationship between the achievement of individual first-year students and the average achievement of the entire group in the US Military Academy. It was also revealed that an increased dispersion of SAT math scores in a group correlated with improved overall student achievement, and that the observed effect was achieved due to the presence of more able students (Lyle 2009). Carrell, Fullerton, and West (2009) find significant peer effects among students at the US Air Force Academy: Students with low SAT verbal scores benefit from their communication with students who have high SAT results.

In some countries, institutions of higher education practice exogenous formation of student groups and have curricula dominated by compulsory courses. De Giorgi, Pellizzari, Redaelli (2010) find peer effects in the choice of college major among students of Bocconi University in Italy. During the first three semesters, all students took nine compulsory courses and attended lectures in randomly assigned classes for each course. De Paola and Scoppa (2010) use the exogenous assignment of students to different teaching classes in the compulsory courses in the University of Calabria in Italy. They find statistically significant positive peer group effects Androuschak et al (2012) estimate the influence of the ability of randomly assigned classmates on the achievement of first-year students at a top-tier research university in Russia. The presence of high-ability classmates has a significant positive effect on individual grades in key economic and mathematical courses, as well as on overall academic performance. Students at the top of the ability distribution derive the greatest benefit from high-ability classmates. Less-able students are not affected by peers and have no significant influence on the outcomes of peers.

Arcidiacono, Foster, Goodpaster, and Kinsler (2012) study University of Maryland data on groups formed endogenously but heterogeneous over time. They find statistically significant peer effects on course grades, particularly in courses that demand collaboration among students.

However, studying the effects of peers based on an entire entire group has certain drawbacks. Thus, we suppose that all members of a group have the same influence on a student. This assumption is quite possible in the first year of study, yet it fails later because students form their own specific social ties. Almost all previous work on peer effects in higher education focuses on the first year, so the study of how social interactions affect student achievement beyond the first year is of obvious interest.

Also, the group-interaction assumption complicates the differentiation between the effects of peer characteristics and the effect of peer outcomes. This differentiation is very important both for understanding the mechanisms of peer group effects and for educational policy. Some characteristics of peers – such as abilities and socio-demographic characteristics – are fixed and cannot be changed. Peer behavior (achievement) can be changed by the influence of educational policy. For example, if peer outcomes are a concern, then stimulating the achievement of a target group of students can affect the achievement of their peers, who will then in turn affect their peers (including target students), and so on, thereby creating a social-multiplier effect.

An analysis of each student’s individual connections allows researchers to overcome the above-mentioned limitations imposed by our assumption of group interaction. In fact, several studies recently addressed the effect of social ties on the achievement and behavior of students.

Lavy and Sand (2012) study the influence of different types of friendship relationships on the achievement and behavior of schoolchildren in Israel. Their results suggest that the presence of reciprocal friends (students who list each another as friends) and followers (those who listed fellow students as friends, but were not listed as friends by these same fellow students) in a class has a positive and significant effect. Empirical research by Calvó-Armengol et al (2009), Bramoullé et al (2009) and Lin (2010) is based on the extensive Add Health database on high school students in the USA, which contains information about friendship relations between respondents. Calvó-Armengol et al (2009) show that the number of friends has a positive significant influence on academic achievement. Bramoullé et al (2009) show that the mean level of recreational activities (participation in artistic, sports, and social organizations and clubs) and friends has a positive and significant influence on a student's recreational activity. Lin (2010) finds that both the achievements of friends and their social-economical characteristics significantly correlated with a student's own achievement.

The above papers on peer effects in social networks use data on students in secondary schools. Studies of the network impact on student achievement in a university environment are mostly limited to data from Internet activities (chats, on-line social networks) or e-mail exchanges. Mayer and Puller (2008) use data generated from the Facebook accounts of students from an American university. Among other results, they find that student performance is highly correlated with the average performance of friends: An increase of one point in the GPA of friends increased a student's own GPA by 0.46. However, web data should be used with caution, since they give rather raw estimates of real world friendship ties.

In this study, we use data on the social connections of third-year students from a Russian university. Data were gathered via questionnaire survey. In addition to friendship ties, data regarding ties with study helpers are also used. We find significant positive peer group effects from both academic achievement and peer abilities. The influence of group mates as a whole is insignificant. The results of this study help to better understand the actual mechanisms of peer effects in group interactions.

2. Empirical models of peer effects

We start with the following specification of the empirical peer effects model:

$$y_i = \alpha + \beta \overline{y}_{-i}^{peer} + \boldsymbol{\gamma}'\mathbf{x}_i + \boldsymbol{\delta}'\overline{\mathbf{x}}_{-i}^{peer} + \varepsilon_i,\ i = 1,2,...,n., \tag{1}$$

where y_i is an indicator of academic achievement of student *i*, $\mathbf{x}_i$ is k ×1 vector of individual characteristics of student *i*, $\overline{\mathbf{x}}_{-i}^{peer}$ is k ×1 vector of the mean exogenous characteristics of the peer group for student *i*, $\overline{y}_{-i}^{peer}$ is the mean academic achievement of the peer group of student *i*, ε_i are random disturbances, and *n* is the number of students in the sample.

Coefficient β in model (1) measures the degree to which individual achievement depends on the achievement of peers (endogenous effect). The components of vector δ measure the influence of exogenous characteristics of peers (exogenous or contextual effect). The important difference between these impacts is that only an endogenous effect ($\beta \neq 0$) has a social multiplier property. Indeed, suppose that the achievement of a certain student becomes higher as a result of some external influence (ε_i in equation (1)). This improvement influences the performance of his or her peers. In turn, a change in peer achievement also has a feedback influence on the student, etc. Pure exogenous peer effects ($\delta \neq 0$, $\beta = 0$) do not have a multiplier effect because external shocks do not influence the fixed characteristics of students.

The presence of endogenous effects is significant for educational policy. For example, additional training with certain students can lead to the better performance of not only those students that attend the additional classes, but also of their peers.

Since both the achievements of a student's peers have an effect on his or her academic outcomes and a student's own performance influences the outcomes of his or her peers, estimates of the coefficients of model (1) obtained by the least-squares regression method are biased. To avoid this bias, the reduced form model is frequently used:

$$y_i = \alpha + \boldsymbol{\gamma}'\mathbf{x}_i + \boldsymbol{\delta}'\overline{\mathbf{x}}_{-i}^{peer} + \varepsilon_i \, . \tag{2}$$

Estimates of reduced form can answer questions regarding the presence of peer effects, but they are of no help when differentiating endogenous and exogenous effects.

However, one may estimate endogenous and exogenous peer effects separately if data on student's personal social ties are available.

We assume that students that are connected to one another via social ties influence academic achievement. Each student has his or her own social network. We can then write the mean values of peers from (1) this way:

$$\overline{\mathbf{x}}_{-i}^{peer} = \frac{1}{n_i}\sum_{j=1}^{n_i}\mathbf{x}_j, \quad \overline{y}_{-i}^{peer} = \frac{1}{n_i}\sum_{j=1}^{n_i} y_j, \tag{3}$$

where we average over the set $P_{i,}$ which consists of n_i peers linked to a student i. When the means are calculated, the characteristics of student i are not included.

Model (1) for the sample of n students can then be written in matrix form:

$$\mathbf{y} = \alpha\mathbf{i} + \beta\mathbf{G}\mathbf{y} + \mathbf{X}\boldsymbol{\gamma} + \mathbf{G}\mathbf{X}\boldsymbol{\delta} + \boldsymbol{\varepsilon}, \;\; E\left[\boldsymbol{\varepsilon} \mid \mathbf{X}\right] \; = \; 0, \tag{4}$$

where **y** is n ×1 vector of the achievement for n students , **i** is n ×1 unit vector, **X** is n ×k matrix of student characteristics, **G** is n ×n matrix of interactions between elements

$$G_{ij} = \begin{cases} 1/n_i, & если \; j \in P_i, \\ 0, & если \; j \notin P_i. \end{cases}$$

G is the row-normalized matrix with zero diagonal elements. Row i of matrix **GX** consists of mean values for k characteristics of the peers of student i, and element i of vector **Gy** is the mean achievement of the peers of student i:

$$\mathbf{GX}=\begin{pmatrix}\bar{X}_{-1}^{peer}\\ \vdots\\ \bar{X}_{-n}^{peer}\end{pmatrix},\quad \mathbf{Gy}=\begin{pmatrix}\bar{Y}_{-1}^{peer}\\ \vdots\\ \bar{Y}_{-n}^{peer}\end{pmatrix}. \tag{5}$$

Structurally, model (4) looks like an autoregression model of spatial interaction (LeSage, Pace (2009) classifies this model as Spatial Durbin Model) that can be estimated by the maximum-likelihood method. In spatial statistics, matrix **G** is similar to the matrix of spatial weights that describes the geographical proximity between different objects in space and is therefore symmetrical. In the case of social ties, matrix **G** can be non-symmetrical if student *i* nominates student *j* as a friend, but not vice versa.

The problem of estimating vector parameters α, β, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$ in model (4) is related to the endogeneity of **GY** on the right side. As Bramoullé, Djebbari, and Fortin (2009) showed, the parameters can be identified if matrices **I**, **G**, and $\mathbf{G^2}$ are linearly independent. In network interactions, linear independence is assured by the presence of intransitive triads in a network structure. The triad of students A, B, and C is intransitive if A affects B and B affects C, but A does not affect C. This requirement usually holds in the case of social ties because not all friends of friends are normally also the friends of a student.

As mentioned above, a change in student characteristics affects both the student's own achievement (direct impact) and the achievement of other students (indirect impact). Estimations of the coefficients of spatial (network) regression take into account the interdependence between observations for a particular student. These characteristics advantageously differentiate this model from a simple regression model where observations are independent from each other.

Some quantitative measures that characterize connection between dependent and independent variables and reflect the specificity of network interactions are described in the Appendix. Average direct impact characterizes an impact of a student's characteristics on his or her own outcome averaged over the sample. Average total impact measures the influence on the achievement of one student from characteristics of all other students or, equivalently, measures the influence from a student's characteristics on all other students. Average indirect impact, by the definition, is the difference between average full impact and average direct impact. In Section 3 we present estimations of these parameters for the observed network.

3. Estimation of peer effects in a social network

Data

In this study, we use data on the academic achievement and characteristics of third-year students in the Economics Department at the Higher School of Economics during the 2011-2012 academic year. As a measure of academic achievement, we use student grades averaged over three years. At the Higher School of Economics, a 10-point grade system has been adopted. The higher the grade, the higher is the achievement in a certain subject.

The student cohort consists of 231 students divided into 8 student groups, which are formed prior to beginning of first academic year by the university administration and which remain in force for the first three years of study. Lectures are usually delivered to several groups simultaneously, while seminars and tutorials (classes) are delivered to each group separately. Therefore, HSE students spend one part of their study time together, while the other part of their study time is spent in groups.

In order to correctly determine each student's peer group, we used a questionnaire survey in the middle of the third year of study. Students were asked to indicate no more than five students with whom they usually spend their free time ("friends") and no more than five students to whom they approach for educational help ("study partners"). The data sample used is smaller than the number of all enrolled students. Some students missed the classes when the survey data were collected. Also, we exclude students who were nominated neither as friends nor study partners.

After processing the data from the questionnaire, we formed two types of matrices of social relations for each student: one matrix for friends and another for study partners. The proportion of friends among study partners is 60 %.

The most important predictor of a student's academic achievement in college is personal ability, which is measured by previous achievement (Burton and Ramist, 2001; Noble and Sawyer, 2002; Bauer and Liang, 2003; Shaw et al, 2012). In our study, as an exogenous measure of individual student ability, we used the grades on the Unified State Examination (USE) in Mathematics and Russian language. The USE in Mathematics and Russian language are national standardized tests that are compulsory for all secondary school graduates and used as the sole basis for university admission decisions. Besides test scores, we measure ability using dichotomous variables, which are indicators of awardees for the All-Russian Olympiad and regional Olympiads for secondary school students. Awardees of Olympiads have the right of priority in admission to higher-education institutions in Russia.

Although HSE students come from different regions of the country, ethnic composition is homogeneous, eliminating the need to introduce ethnic dummies. Descriptive statistics are presented in Table 1.

Table 2 presents some network characteristics. All the values are measured from 0 to 1. The help network is more centralized than the friendship network. We can explain this by the fact that students usually tend to approach the same high-achieving students for help. The friendship network is more reciprocal than help networks; almost half of all possible ties are mutual.

Estimation results

We estimate the model both in a reduced form without an endogenous term and in a full specification that differentiates between endogenous and contextual peer effects. In addition to the full set of the exogenous parameters characterizing abilities (USE scores on Math and Russian language and status of Olympiad winners and awardees), we also consider specifications with only USE scores as exogenous variables.

Table 3 reports the least squares estimates of the reduced form model for friendship ties:

$$\mathbf{y} = \alpha_r \mathbf{i} + \mathbf{X}\boldsymbol{\gamma}_r + \mathbf{G}\mathbf{X}\boldsymbol{\delta}_r + \boldsymbol{\varepsilon}_r. \tag{6}$$

A student's own characteristics are significant at the 1% level. The effect of USE scores in Russian language on GPA is weaker than the effect of USE scores in Math: An increase of 10 points in math USE scores leads to an increase in GPA of 0.41, while an increase in Russian-language USE scores leads to an increase in GPA of 0.23. The status of an awardee of the All-Russian Olympiad considerably increases GPA by 0.81 points, which is larger than status of an awardee of the Regional Olympiad of the HSE (0.43 points).

In this model, coefficient $\boldsymbol{\delta}_r$ "mixes" endogenous and exogenous effects, not allowing us to identify them separately. The mean USE Math scores of friends and the mean number of friends that are awardees of the All-Russian Olympiad are significant variables. Thus, there is an evidence of peer effects: A student's own achievement increases when the USE Math scores of his or her friends grow, as well as when this student has friends who are awardees of the All-Russian Olympiad.

The natural assumption is that strong friendship ties involve reciprocity. In Columns 3 and 4 of Table 3, we report the estimates for a case with reciprocal friendship ties: Two students are considered to be friends if their nominations are mutual. For reciprocal ties, the math USE scores of friends are significant at the 1% level.

Table 4a shows estimates of the model in a full specification spatial autoregression model (4) using the method of maximum likelihood. The values of the coefficients β are significantly positive. A one-point increase in the GPA of friends is associated with an increase in a student's own GPA of 0.25. The coefficients of exogenous variables are not significant for directed ties. In case of reciprocal ties, the mean value of the math USE scores of friends is significant at the 10% level. This result supports the assumption that the success of a student is influenced by the actual achievement of friends, rather than by their exogenous characteristics.

Table 4b presents estimates of average direct, average indirect, and average total impact of exogenous characteristics of friends.

Students that are connected by friendship ties usually study in the same student group. To compare peer effects generated by friends and by the entire study group, we estimated models (1) and

(2) for the situation where the peer group is supposed to include all students of a group. The results are presented in Table 5. The influence of exogenous characteristics of a student group is positive, but weaker than the influence caused by friends. Both exogenous and endogenous effects are statistically insignificant.

In the questionnaire, besides nominating friends, students nominated students whom they approach for help in studying. The lists of friends and study partners are partly overlapping, but generally, for an obvious reason, students tend to consult with the fellows that have higher achievement on educational questions.

In Table 6a, we present the results for networks of study partners. The results are nearly similar to the results from Tables 3 and 4 for friendship network. The coefficient of determination for the help network model is a little bit higher than for the friendship network model. The estimates show the presence of statistically significant peer effects. The higher the abilities and outcomes of a student's study partners, the higher the achievement of the student himself. The values of endogenous effects for the help network are similar to those of the friendship network. The exogenous effects of a study partner's USE score in Math and his or her status of being an awardee at the Olympiads are statistically insignificant.

Table 6b presents the estimates of average direct, average indirect, and average total impacts for study-assistance networks.

Table 7 summarizes the qualitative results.

The results of this study may be useful in identifying mechanisms in which peer group effects work. Our previous study (Androushchak, Poldin, Yudkevich, 2012), made on the same sample of students during their first year of study, reveals significant peer effects from those group mates that become non-significant by their third year. Highly able students in the group had the positive influence of students who also performed well. There were no effects from less-able group mates. However, in the second and the third year the influence of the group on the whole became insignificant. We can suppose that high-achievers can act as role models and study helpers for other students in the group. As time goes, students with close abilities form tighter friendship relationships. A good student may affect a friend's attitude toward learning, help them in doing homework, and assist in preparing for examinations. The influence on more distant group mates becomes weaker. This explains why the peer effect caused by the group in the second and the third year became insignificant, while the effect of friends and study partners is distinct.

4. Conclusion

Studying the influence of student social interactions on academic achievement is of significant interest because it helps to better understand the nature of the learning process and find a way to increase educational achievement. Correctly estimating peer effects is not an easy task. One of the difficulties is correctly identifying those students who interact during their study and therefore who can influence each other. Another issue is disentangling the influence of current outcomes – which are subject to change – from the effect of a peer's exogenous unchangeable characteristics, such as his or her capabilities.

In this work, we use data on social connections obtained from third-year students studying at a top-tier research university in Russia. Using questionnaire data, we construct a network of ties of two types: directed friendship ties and connections to study partners. Information about the individual social ties of each student allows us to apply a spatial regression model to analyzing individual outcomes. Using this model, we solve the problem of separating overall peer effect into the influence of the current achievements of peers (endogenous effect) and the influence of their abilities (exogenous effect).

We find significant positive peer effects both from academic achievement and from the abilities of students. A one-point increase in the GPA of study partners is associated with an increase of a student's own GPA of 0.25.

The presence of peer effects matters for educational policy. To exploit positive peer effects, a university may offer additional classes to help some students, or perhaps even provide financial aid to bright students in order to distract them from part-time working. Such help has a positive impact on the treated students and has a spillover effect on their peers. If there are endogenous peer effects, overall gain increases even further due to the multiplication effect. Another use of positive peer effects implies promoting a teaching practice that encourages intensive social interactions, such as group project assignments.

Appendix. Interpretation of coefficients of the spatial regression model

A change in the explanatory variable for one student influences his or her own achievement (direct impact) as well as indirectly influences the achievement of other students (indirect impact). The estimates of the coefficients of a spatial (network) regression take into account the interdependence between observations (students).

The quantitative relation between dependent and independent variables is described by a marginal effect. Following LeSage and Pace (2009), we can get values for marginal effects in a network regression.

Modifying equation (4), we receive

$$\begin{aligned}\mathbf{y} &= (\mathbf{I}-\beta\mathbf{G})^{-1}\mathbf{i}\alpha + (\mathbf{I}-\beta\mathbf{G})^{-1}\mathbf{X}\boldsymbol{\gamma} + (\mathbf{I}-\beta\mathbf{G})^{-1}\mathbf{G}\mathbf{X}\boldsymbol{\delta} + (\mathbf{I}-\beta\mathbf{G})^{-1}\boldsymbol{\varepsilon} = \\ &= \mathbf{V}\,\mathbf{i}\alpha + \mathbf{V}(\mathbf{X}\boldsymbol{\gamma} + \mathbf{G}\mathbf{X}\boldsymbol{\delta}) + \mathbf{V}\,\boldsymbol{\varepsilon} = \\ &= \mathbf{V}\,\mathbf{i}\alpha + \sum_{j=1}^{k}\mathbf{S}_j\mathbf{x}_j + \mathbf{V}\,\boldsymbol{\varepsilon},\end{aligned} \tag{П1}$$

where

$$\begin{aligned}\mathbf{V} &= (\mathbf{I}-\beta\mathbf{G})^{-1} = \mathbf{I} + \beta\mathbf{G} + \beta^2\mathbf{G}^2 + \beta^3\mathbf{G}^3 + \ldots, \\ \mathbf{S}_j &= (\mathbf{I}-\beta\mathbf{G})^{-1}(\mathbf{I}\gamma_j + \mathbf{G}\delta_j).\end{aligned} \tag{П2}$$

$\mathbf{x}_j$ is n ×1 vector equal column j of matrix **X**, and its elements are the values of exogenous variable j for n students.

From equation (П1), the achievement of student i is:

$$y_i = \alpha\sum_{l=1}^{n}V_{il} + \sum_{j=1}^{k}\sum_{l=1}^{n}(S_j)_{il}x_{lj} + \sum_{l=1}^{n}V_{il}\varepsilon_l .$$

The influence of exogenous variable j on y_i consists of the sum

$$\sum_{l=1}^{n}(S_j)_{il}x_{lj} = (S_j)_{i1}x_{1j} + (S_j)_{i2}x_{2j} + \ldots + (S_j)_{in}x_{nj}.$$

In this equation, we can clearly see the influence on a student's outcome that is caused by changing the characteristics of other students. The marginal effect from the change of a continuous variable is measured by the partial derivative

$$\frac{\partial y_i}{\partial x_{lj}} = (S_j)_{il}. \tag{П3}$$

The marginal effect for the discrete independent variable is defined by the difference:

$$\frac{\Delta y_i}{\Delta x_{lj}} = [y_i \mid x_{lj}=1] - [y_i \mid x_{lj}=0].$$

The diagonal elements of matrix $\mathbf{S}_j$ describe the direct impact on a student's achievement caused by changing his or her own characteristics. They are not equal to the parameters γ_j in equation (П2), because they take into account network interactions between students: Student A affects (when $\beta\neq 0$) the performance of other students connected to student A, and they, in turn, have a feedback effect on student A.

The non-diagonal elements of $\mathbf{S}_j$ represent the indirect impact of the characteristics of student l on the achievements of student i. This interdependence exists not only between friends; it is expanded further to the friends of the friends, etc.

Elements of $\mathbf{S}_j$ differ and this variation reflects the difference in the position of students in a network of social ties. LeSage and Pace (2009) proposed scalar aggregated measures that measure the averaged influence of exogenous variables.

Average direct impact is an average value of elements of the main diagonal of matrix $\mathbf{S}_j$:

$$ADI_j = \frac{1}{n}\sum_{l=1}^{n}(S_j)_{ll}.$$

The average total impact to an observation (student) is the average value of the sum of rows in matrix $\mathbf{S}_j$ and is interpreted as change in the achievement of a student associated with an increase of independent variable j of one unit for all students. The average total impact from an observation (student) measures the influence on all the students from changing a student's characteristic by one unit. These two impact measures differ by definition, but they are equal to each other:

$$ATI_j = \frac{1}{n}\sum_{l=1}^{n}\sum_{m=1}^{n}(S_j)_{lm} = \frac{1}{n}\sum_{m=1}^{n}\sum_{l=1}^{n}(S_j)_{lm}.$$

By definition, average indirect impact is the difference between average total impact and average direct impact:

$$AIM_j = ATI_j - ADI_j.$$

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Table 1. Descriptive statistics

Variable	Number of observations	Mean	Std. dev.	Min	Max
Friends					
USE in Russian language	167	80.0	9.6	50	100
USE in Math	167	76.4	8.0	48	100
Awardee of All-Russian Olympiad	167	0.16	0.37	0	1
Awardee of Regional Olympiad	167	0.24	0.43	0	1
GPA	167	7.35	0.88	5.57	9.21
Study assistants					
USE in Russian language	171	79.9	9.5	50	100
USE in Math	171	76.4	8.0	48	100
Awardee of All-Russian Olympiad	171	0.16	0.37	0	1
Awardee of Regional Olympiad	171	0.24	0.43	0	1
GPA	171	7.36	0.88	5.57	9.21

Table 2. Descriptive statistics of network characteristics

	Help network	Friendship network
Density	0.02	0.02
Centrality (indegree)	0.10	0.06
Reciprocity	0.19	0.42
Clasterization	0.24	0.27

Notes: The density of a network is the observed proportion of ties (both in and out) in a network in relation to all the possible ties in this network. Centrality (indegree) is the proportion of observed incoming ties in relation to all possible incoming ties in this network. Reciprocity is the observed proportion of mutual ties in relation to all the possible mutual ties in this network. Clasterization is a coefficient showing the probability of a tie between A and C in the event that they are both connected with B.

Table 3. Estimation of peer effects for friends (without differentiation of endogenous and exogenous effects).

	Nominated ties		Reciprocal ties	
	(1)	(2)	(3)	(4)
Dependent variable: GPA				
Constant	0.075 (0.063)	0.445 (0.338)	0.239 (0.258)	0.404 (0.384)
USE in Russian language	0.023*** (4.063)	0.021*** (3.445)	0.024*** (4.306)	0.022*** (3.437)
USE in Math	0.041*** (6.097)	0.047*** (6.331)	0.036*** (5.180)	0.044*** (5.789)
Status of awardee of All-Russian Olympiad	0.808*** (5.361)		0.843*** (5.399)	
Status of awardee of Regional Olympiad	0.429*** (3.465)		0.479*** (3.838)	
Mean USE in Russian language of friends	0.002 (0.181)	-0.011 (-0.905)	-0.004 (-0.491)	-0.008 (-0.959)
Mean USE in Math of friends	0.024* (1.817)	0.032** (2.346)	0.032*** (3.222)	0.032*** (3.062)
Mean number of awardees of All-Russian Olympiad among friends	0.545** (2.213)		0.302 (1.417)	
Mean number of awardees of Regional Olympiad among friends	0.303 (1.371)		-0.073 (-0.400)	
Number of observations	167	167	156	156
R^2	0.47	0.32	0.49	0.32

Notes: *t*-statistics are in parentheses.
* significant at the 10% level.
** significant at the 5% level.
*** significant at the 1% level.

Table 4a. Estimation of peer effects for friends (with differentiation of endogenous and exogenous effects)

	Nominated ties		Reciprocal ties	
	(1)	(2)	(3)	(4)
Dependent variable: GPA				
Constant	-0.066	0.140	-0.215	-0.119
	(-0.059)	(0.115)	(-0.249)	(-0.123)
USE in Russian language	0.024***	0.022***	0.025***	0.023***
	(4.497)	(3.865)	(4.812)	(4.000)
USE in Math	0.038***	0.043***	0.032***	0.040***
	(5.971)	(6.219)	(5.004)	(5.621)
Status of awardee of All-Russian Olympiad	0.772***		0.806***	
	(5.443)		(5.563)	
Status of awardee of Regional Olympiad	0.416***		0.448***	
	(3.572)		(3.876)	
Mean USE in Russian language of friends	-0.005	-0.015	-0.009	-0.011
	(-0.470)	(-1.428)	(-1.205)	(-1.462)
Mean USE in Math if friends	0.011	0.012	0.024**	0.018*
	(0.850)	(0.864)	(2.492)	(1.786)
Mean number of awardees of All-Russian Olympiad among friends	0.237		0.075	
	(0.961)		(0.363)	
Mean number of awardees of Regional Olympiad among friends	0.171		-0.203	
	(0.802)		(-1.183)	
β (endogenous effect)	0.253***	0.339***	0.232***	0.277***
	(2.612)	(3.662)	(3.172)	(3.860)
Number of observations	167	167	156	156
R^2	0.48	0.32	0.48	0.32

Notes: *t*-statistics are in parentheses.
* significant at the 10% level.
** significant at the 5% level.
*** significant at the 1% level.

Table 4b. Average direct, indirect, and total impact of exogenous characteristics for friendship network (for models (1) and (2) in Table 4a).

	(1)			(2)		
	Direct impact	Indirect impact	Total impact	Direct impact	Indirect impact	Total impact
USE in Russian language	0.024***	0.002	0.025*	0.021***	-0.011	0.010
USE in Math	0.039***	0.027	0.065***	0.044***	0.039**	0.083***
Status of awardee of All-Russian Olympiad	0.793***	0.560*	1.353***			
Status of awardee of Regional Olympiad	0.428***	0.369	0.797**			

Notes: ** significant at the 5% level, *** significant at the 1% level.

Table 5. Estimation of peer effects for group mates.

	Without endogenous variable		With endogenous variable	
	(1)	(2)	(3)	(4)
Dependent variable: GPA				
Constant	-0.842 (-0.233)	3.164 (0.946)	-0.895 (-0.254)	2.928 (0.870)
USE in Russian language	0.025*** (4.243)	0.020*** (3.235)	0.025*** (4.377)	0.021*** (3.295)
USE in Math	0.040*** (5.720)	0.048*** (6.281)	0.040*** (5.892)	0.048*** (6.377)
Status of awardee of All-Russian Olympiad	0.906*** (6.057)		0.912*** (6.244)	
Status of awardee of Regional Olympiad	0.478*** (3.680)		0.480*** (3.799)	
Mean USE in Russian language of group mates	0.024 (0.468)	-0.021 (-0.516)	0.029 (0.558)	-0.021 (-0.518)
Mean USE in Math of group mates	0.008 (0.258)	0.008 (0.297)	0.015 (0.430)	0.004 (0.134)
Mean number of awardees of All-Russian Olympiad among group mates	1.017 (1.250)		1.220 (1.306)	
Mean number of awardees of Regional Olympiad among group mates	0.520 (0.575)		0.616 (0.673)	
β (endogenous effect)			-0.119 (-0.441)	-0.073 (-0.322)
Number of observations	167	167	167	167
R^2	0.44	0.29	0.44	0.29

Notes: *t*-statistics are in parentheses.
*** significant at the 1% level.

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Table 6a. Estimation of peer effects for study partners.

	Without endogenous variable		With endogenous variable	
	(1)	(2)	(3)	(4)
Dependent variable: GPA				
Constant	-1.904 (-1.650)	-1.059 (-0.836)	-2.107* (-1.933)	-1.554 (-1.321)
USE in Russian language	0.024*** (4.547)	0.022*** (3.605)	0.024*** (4.756)	0.021*** (3.842)
USE in Math	0.034*** (5.210)	0.039*** (5.419)	0.032*** (5.160)	0.037*** (5.387)
Status of awardee of All-Russian Olympiad	0.857*** (6.100)		0.821*** (6.188)	
Status of awardee of Regional Olympiad	0.440*** (3.699)		0.427*** (3.801)	
Mean USE in Russian language of study partners	0.011 (1.026)	-0.004 (-0.302)	0.005 (0.464)	-0.010 (-0.919)
Mean USE in Math of study partners	0.043*** (3.969)	0.051*** (4.221)	0.031*** (2.668)	0.033*** (2.564)
Mean number of awardees of All-Russian Olympiad among study partners	0.625** (2.482)		0.380 (1.517)	
Mean number of awardees of Regional Olympiad among study partners	0.407** (1.983)		0.235 (1.156)	
β (endogenous effect)			0.250** (2.481)	0.337*** (3.520)
Number of observations	171	171	171	171
R^2	0.52	0.35	0.51	0.31

Notes: *t*-statistics are in parentheses.
** significant at the 5% level.
*** significant at the 1% level.

Table 6b. Average direct, indirect, and total impact of exogenous characteristics of network of study partners(for models (3) and (4) in Table 6a).

	(3)			(4)		
	Direct impact	Indirect impact	Total impact	Direct impact	Indirect impact	Total impact
USE in Russian language	0.026***	0.025	0.050	0.021***	-0.005	0.017
USE in Math	0.040***	0.008	0.047	0.038***	0.067***	0.106***
Status of awardee of All-Russian Olympiad	0.907***	0.947	1.854			
Status of awardee of Regional Olympiad	0.477***	0.514	0.991**			

Notes: ** significant at the 5% level, *** significant at the 1% level.

Table 7. Presence of peer-group effects in models with different specification of reference groups.

	Reference group		
	Student group	Friends	Study partners
Peer effect (without differentiation of endogenous and exogenous effects)	no	yes	yes
Endogenous effect	no	yes	yes
Exogenous effect	no	no	yes

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