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DISENTANGLING PEER INFLUENCE ON MULTIPLE LEVELS

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In this study we focus on the influence of peers on adolescents academic achievement. Specifically, how the learning motivation of peers is related to a student's school grades. We use multilevel regression to analyze the influence of peers on different levels of social circles: school, class, personal network, and compare the effects of "assigned friends" and "chosen friends". The methods of social network analysis are used to define the personal network of a student in different ways: cliques, complete ego networks, and mutual ego networks. We demonstrate that the model improves considerably when the level of personal networks is included between individual and class levels. The learning motivation of a student's friends (defined as a clique or ego network) has an important influence on the student's school performance, net of student's personal characteristics.

Keywords: social network analysis, schools, peer influence, ego networks, cliques

JEL Classification: Z

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Introduction

Since Coleman sociologists have known that peers in school are more important for educational outcome than other school characteristics. His book "The Adolescent Society" started a tradition of investigating peer effects in various aspects of children and teenager development – both for positive and negative outcomes. Researchers have investigated peer influence in the spread of delinquency, substance abuse, depression, obesity (Gaviria & Rafael, 2001; Trogdon et al., 2008; Starkey et al., 2009; Witvliet et al., 2010). In the sociology of education many studies focus on academic motivation and the influence of peers on academic achievement: school performance, test results, drop-out, and college choice (Bain & Anderson, 1974; Wentzel, 1998; Crosnoe, 2000; Chen et al., 2003).

Overview of the literature on peer influence demonstrates that "peer group" is a very loose concept. Peers have been defined as a whole school; a grade cohort; students in the same track or course; roommates in dorm; sports team or science club members; members of the same clique, crowd or a gang best friends, or just friends. All these definitions are valid because the social life of teenagers at school is complex and multi-level; each student belongs to many entities. The important distinction between different peer group definitions is whether a person chooses her peers (making friends or voluntarily joining a club), or whether peers are assigned to her (entering school, being put in a track). The influence of both types of peers has been studied extensively in the sociology of education and the sociology of childhood and youth.

In our work we use a social network approach for the operationalization of peers by choice. Two methods are employed to define peer relations based on personal interactions: ego networks, or student's friendship nominations, and cliques, identified as densely connected groups within a complete classroom network (Frank, 1995, 1996). We then investigate how the school-related attitudes of peers on different levels – grade cohort, class, cliques, and ego networks – affect an individual student's educational performance.

Previous research

Assigned peers, or peers as a whole school

In early studies of peer effects in the sociology of education peers were often understood as all school or grade cohort members. These "contextual" peer effects were often explained via school socio-demographic composition: race, ethnicity, socioeconomic status of peers (Bain & Anderson, 1974; Hallinan & Williams, 1990; Thrupp et al., 2002).

Researchers offered two different explanations for the mechanisms of peer effect: the influence of close friends (these effects will be described below) or conforming to common cultural norms of an organization. This type of influence is often referred to as "school culture", "classroom environment" or "larger peer group influence".

The school culture or academic culture refers to the system of norms, values and beliefs existing in the school as an organization (Hoy, 1990). In the field of school culture studies there is an assumption that the norms and values are shared by most, if not all of the students. Norms and values are rather stable over time and are passed from one generation of students to another; when new students join the school, they adopt its dominant rules and norms.

Peer influence at the level of school or grade cohort affects individual student behavior by setting norms and providing standards for comparison. A conformity paradigm developed in social psychology states that children at school try to modify their norms and behavior according to the norms prevailing in the school (Rutter et al., 1982).

School academic culture is usually evaluated through scores of individual student self-reported attitudes towards learning and education in general, aggregated to the school level. Van Houtte (2006) argues that the pro-school culture measured for a sample of students reflects the school's general level of academic culture because the culture of an institution – a school in this case – mostly remains constant over long periods of time and is passed from one generation to another.

The findings of peer influence on the school/grade level are controversial. The influence of school academic culture, over and above the effect of students' own academic attitudes, has been demonstrated in highly stratified educational systems, like Great Britain and Belgium (Opdenakker, Van Damme, 2001; van Houtte, 2006; van Houtte, Stevens, 2010), and also in some studies in USA (Brookover et al., 1979). Indeed, learning culture is expected to be higher in the schools preparing students for university than in vocational schools. Other authors, however, did not found any significant peer effect at a school level (Gray et al., 1990; Zimmer, Toma, 2000, Harker, Tymms, 2004). One explanation for this inconsistency is that aggregation on a school level conceals the within-school heterogeneity: even in one school there may be considerable difference in academic culture between grade cohorts (Galvan et al., 2011), tracks (Crosnoe, 2008) and classes (Lubbers, 2006). In our work we acknowledge the variance of the academic culture in groups of students by including additional levels between school and individual.

"Peers by choice", or peer groups in school

There is abundant evidence that schools are not homogenous and are often structured in different groups. Peer groups are often formed on the basis of similar social and cognitive attributes and common interests and activities. Within one school there are many groups that may have quite different norms and values. Conformity to group norms depends on the extent to which individual identifies herself with the group (Abrams et al., 1990). In US high schools, where most research in this area has been done, there are such crowds as popular kids, jocks, athletes, brains, geeks, nerds, burnouts, nonconformists, etc. Crowds are based on self-identification (or the identification perceived by others) and\or shared activity (sports, clubs etc.); members of a crowd may or may not have direct interaction with each other. Nevertheless, they usually take up the shared norms and values associated with the group.

The majority of studies in the area of crowd peer influences were focused on risk behavior and delinquency. An association with certain crowds (burnouts and non-conformists) has been shown to be related with the level of adolescence smoking, use of marijuana and other drugs, alcohol consumption, and risky sexual behavior. On the contrary, "brains" and their friends demonstrated the lowest levels of health-risk behavior across all the areas assessed (La Greca et al., 2001). Many studies confirm that some crowds (brains, intellectuals, academics, geeks) exert a positive influence on their members while association with other crowds (druggies, stoners, burnouts) may be detrimental for student health and school outcomes (Mosbach & Leventhal, 1988; Miller et al., 2006; Sussman et al., 2007)

Identification with a peer crowd has a fluid character: adolescence may shift their identification or report association with several crowds simultaneously. European researchers (Verkooijen et al., 2007) have shown that perceived group norms mediated the relation between group identity and substance use. Furthermore, identification with multiple groups with corresponding norms increased norm-consistent substance use, whereas identification with multiple groups with opposing norms reduced normative behavior.

As opposed to activity-based and/or identification-based crowds there are groups based on personal interactions – best friends and "just friends", classmates and schoolmates with whom a person hangs out a lot. In general, close friends of a student are associated with the same crowd (La Greca e a., 2001), but there are also exceptions.

There is a long tradition of looking for peer effects from immediate social contacts. One of the first articles on peer influence on the educational aspirations of teenagers was published in 1964 by Alexander and Campbell. They demonstrated that a teenager's college plans and aspirations are strongly related to those of the close friends (Alexander & Campbell, 1964). The remarkable feature of the study is that the data collected and analyzed by the researchers included sociometric information: the names of the best friend of every student. Therefore the conclusions were based on the actual data on friends' aspirations and college plans, as opposed to relying on student's opinion on his friend's plans.

Collecting and coding sociometric information is laborious and time-consuming. For large-scale surveys it is very expensive and difficult. That is why researchers studying the influence of friends often had to rely on self-reported information about friends' behavior or attitudes. For example, a large USA survey National Education Longitudinal Study, 1988-1994 (NELS) used self-reported measures to assess student's popularity and peer pressure. The item for constructing the popularity variable was formulated as follows: "Do you think that other students see you (a) as popular; (b) as socially active; (c) as part of the leading crowd?". The item for constructing peer pressure variable was "My friends make fun of people who try to do well in school".

These NELS data have been used for testing the key hypothesis of oppositional culture: that African American students are discouraged by their peers from doing well in school (Ainsworth-Darnell & Downey, 1998). The article ignited a heated discussion among sociologists of education; other researchers questioned its methodology and conclusions (Farkas et al., 2002; Downey & Ainsworth-Darnell, 2002; Downey et al., 2009). One of the reasons for the controversial results was the method of assessing peer pressure. Apparently self-reported feeling of "being put down by peers" is not an adequate measure for studying peer influence.

A network approach to understanding peer influences

Social network analysis is a useful tool for investigating peer effects. Firstly, it allows the precise identification of peers. There are interaction-based peer groups (friends); affiliation-based groups sharing common activity (sports, club); cognitive affiliation through shared identity (crowds); cohesive groups with denser interaction within than between groups (cliques, network communities). Special statistical techniques are developed for modeling each of these entities; these techniques take into account the inherent interdependency of network data (Frank, 1996; Field et al., 2006; Fujimoto et al., 2013). Secondly, certain data collection designs (namely, collecting information from every member of the network within defined boundaries) allow for the characteristics of most nominated friends to be measured directly from those friends. It is a valuable tool in peer influence research because alternative methods of collecting information about friends' characteristics has two important flaws: young people tend to overestimate the degree to which their peers are similar to them and they often have incomplete information about the lives of their peers (Crosnoe et al., 2008).

Thanks to the network paradigm, contemporary researchers of peer influence have new data sets containing information on interpersonal relations. The best known example is the data set from Add Health, the National Longitudinal Study of Adolescent Health, 1994 - 2002, a leading public-use survey on the social and health behavior of American adolescents (http://www.cpc.unc.edu/projects/addhealth). Studies of peer influence conducted on the Add Health data encompass a wide range of areas. To name just a few: the role of peers in adolescents being overweight (Trogdon et al., 2008; Ali et al., 2008); peer influence on the choice of recreational activities (Bramoulle, 2009); academic achievement and oppositional culture (Fryer & Torelli, 2010; Flashman, 2011); the effect of peers on alcohol consumption, smoking and spread of delinquency (Alexander et al., 2001; Schreck et al., 2004; Fletcher, 2012).

In our article we use our own data of high school students to further investigate peer influence using the network approach and taking into account the multiple levels of the peer system. We use standard notion of school and class as aggregated groups of peers and include an additional level of analysis: students' personal networks. On this level peers are elicited from complete classroom network data. We distinguish between two definitions of peers: cliques are defined as closely interacting groups of peers in the classroom, and ego networks are defined as friends nominated by a person.

Our research question is as follows: how does the motivation of peers at different levels affect student's academic achievement? To disentangle peer influence at different levels of the school social structure we examine the association between student's academic achievement and her/his peers school-related attitudes, controlling for student's own attitudes and socio-demographic characteristics.

We formulate two hypotheses. Hypothesis 1: the influence of *assigned peers* is drastically diminished when *peers by choice* are included in the model. Hypothesis 2: among *peers by choice*, the strongest influence comes from reciprocated ego networks, and the weakest influence is from cliques.

<u>Current Study</u>

In the Russian school system students from one class spend all class time together, often during their entire school career, from 1st to 11th grade. School class forms a natural network boundary since most in-school friendships are concentrated within one's class.

It is important that the students are not free to choose the classmates, but assigned to a certain class the same way as they are assigned to a school. Since they spend so much time together, a specific class culture may emerge, and it may be different for different classes in the same school. We expect that class influence is more important than school influence.

Between class and individual there is the intermediate level of student's personal network: those people with whom a student interacts most often. The influence of these people should be more important not only because of the frequency of interactions, but also because the interaction is with people who were chosen by the student, not assigned to her.

There is no doubt that different levels of peer context are important for child development. Close friends are an important source of persistent influence, and a wider circle of peers who are not immediate friends is also important, because it sets norms and provides the standards for comparison. The network approach makes possible to differentiate between levels of the peer system and assess them in the same model.

Using the network approach we separate the influence of assigned peers from the influence of chosen peers, modeling the relation of peer values and norms on student school performance. Furthermore, we use social network analysis techniques for distinguishing between groups of friends defined differently: ego networks, mutual ego networks, and cliques.

Operationalization of peers

To compare peer influence on different levels we use different definitions of peers. Students of the same school or same class can be defined as *assigned peers*. They did not choose each other; they were put in the same class or school by external circumstances (school capture system, parents, school administration). We compare two groups of assigned peers: school cohort (all students of the same grade in a given school) and classmates (all students from the same class). *Peers by choice* are those peers who are chosen by the individual. Social network analysis provides tools for their operationalization. Here we employ three definitions: ego network; symmetrized ego network; and clique. Ego network is simply all those classmates that were nominated by the student as friends. Symmetrized ego network is a subset of ego network where only reciprocated nominations were retained and asymmetric nominations were dropped.

Clique identification

Clique membership status was identified through social network analysis using the program Kliquefinder (Frank, 1995, 1996). Kliquefinder employs a clustering algorithm to detect cohesive subgroups. The algorithm identifies cliques by maximizing an objective function, which looks at the probability that an actor interacts with other actors in the clique. The program detects cohesive cliques by assessing the concentration of interactions within the cliques relative to the extent of interactions between the cliques. The original software was designed for single network analysis. Since our study deals with a multitude of networks, a special program modification has been written by Jonathan Morgan, PhD student at MSU, that enabled the Kliquefinder to work with multiple networks in a batch format.

Kliquefinder can be used when there is complete information on interactions in the group. Our study has been designed in such a way that every student in class was surveyed. The students were allowed to nominate up to 10 friends. Friendship choices were used as the input for the identification of cliques and for assessing the clique membership. Kliquefinder output includes several files: a file with clique membership, vna file for cliques visualization in NetDraw, and also a file with objective function values and statistical significance of modularity.

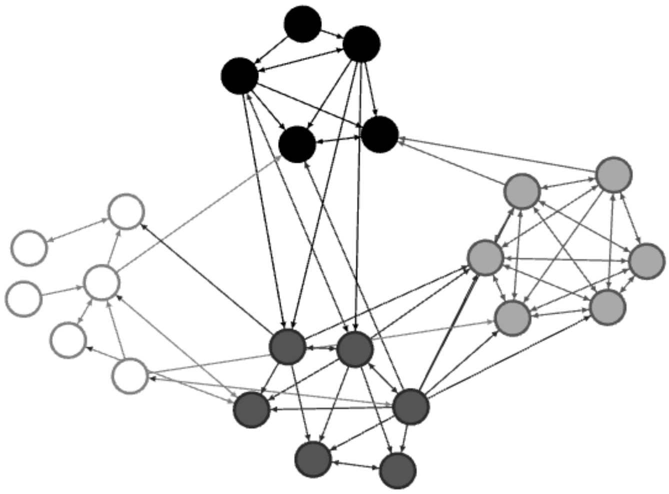

Figure 1. Four cliques in a class. Cliques are marked by different colors.

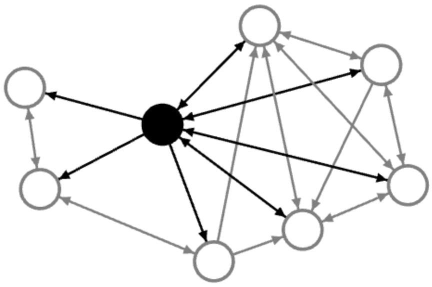

Figure 2. Complete ego networks (ego is colored black)

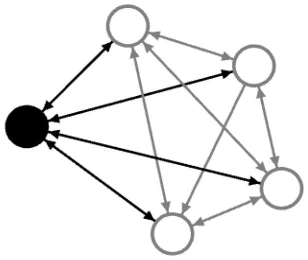

Figure 3. Reciprocated ego network (ego is colored black)

The reciprocated ego network is a subset of the complete ego network, though in a number of cases these two are coincide. Ego's friends also have ties between them, so that ego networks are usually quite dense. Cliques are defined on the basis of relative tie density within and between them; they are not "cliques" in strict sense of graph theory. It means that not every person of the clique have ties with every other; some of them may not have direct ties and have ties only through mutual friends.

For the purposes of applying multilevel regression the main difference between these entities is that cliques are non-overlapping while ego networks are overlapping. It means that the cliques can be included in standard hierarchical model as an extra level. As for the ego networks (complete and mutual), different models with cross-classified membership are needed.

Data and Method

Data

This study was a part of a larger school study conducted in 2010-2012. Randomized stratified samples of schools from the St. Petersburg and Moscow regions included 204 schools, 905 classes, and 15,700 students. All students of 9th and 10th (14-16 years old) grades who were present on the day of survey completed the questionnaires during one class hour. Survey data include extensive information on school life, academic performance, educational plans and aspirations, attitudes towards school and education, detailed socio-demographic information about student’s family, ethnic and migration stratus, languages spoken at home, living conditions, parents’ education and jobs. To collect network data, respondents were asked to nominate up to 10 friends in the class. For every nominated friend all the questionnaire information is available for analysis, which makes these data a valuable source for network analytic techniques. All the data were coded and anonymized.

The sample for the current study includes 5,252 students from 309 classes in 100 schools from St.Petersburg. We selected classes with complete network data (80% or more students were present at the day of the survey and answered the network questions). These data allow the reconstruction of the network of social interaction in the class precisely and without gaps. The more complete information on ties between actors we have, the more reliable our reconstructions of the networks and cliques are.

Method of analysis

Our data have multilevel hierarchical structure: students are nested within classes and classes within schools. Moreover, we introduce an additional level of analysis: network peer groups within a classroom. For this analysis we use multilevel regression; applying this method makes it possible to estimate separately effects on different levels: school, class, and network level (Bryk & Raudenbush, 1992).

At the network level peers are identified by different methods: as cliques and as ego networks. Cliques identified by Kliquefinder are non-overlapping entities. For the models that include clique levels we used hierarchical multilevel modeling for nested structures (schools→classes→cliques→students). The scheme is presented in Figure 4.

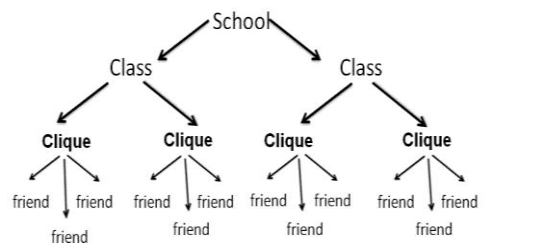

Figure 4 Nested hierarchical model (non-overlapping cliques)

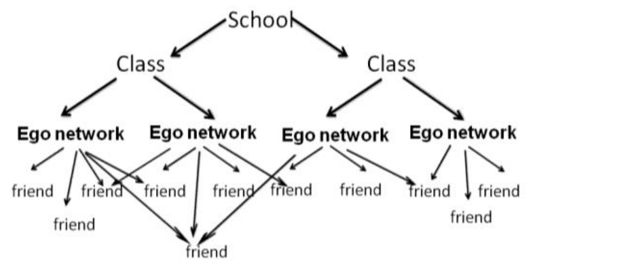

Figure 5. Overlapping cross-membership model (ego networks)

Ego networks, on the other hand, are overlapping structures; that is, the same student belongs to different ego networks if she is nominated as a friend by several persons (Figure 5). For the models that include the ego network level we used cross-classification multilevel model, also known as multiple membership model (Leckie, Owen, 2014).

The models were built in MLWIN software (version 2.27). For cross-classified models we employed Markov Chain Monte Carlo estimation (MCMC), because for this type of model only MCMC estimation is possible. Nested models were also run in MCMC mode, which allows the comparison of nested and cross-classified models with each other.

We use the student's school performance as a dependent variable and learning motivation as the main explanatory variable. According our hypothesis, friends' motivation is important for individual school performance, even controlling for the student's own motivation and socio-demographic characteristics, as well aggregated school and class characteristics.

The logic of the analysis is as follows. First we run a series of variance component models to investigate how the variance of the dependent variable is distributed between the levels. This operation allows us to determine the level structure of the model. Next we introduce control variables to set up a "base" full model. Then the main explanatory variables for every level of analysis are added.

Measures

To measure individual academic performance we used the grade point average (GPA) which is calculated as the mean grade for five academic subjects: Russian, Mathematics, Foreign Language, History, and Biology.

Our main explanatory variable is learning motivation; it is constructed as a measure of student pro-school attitudes. It was measured by means of a Likert-scale with 4 answer categories, from 1 "absolutely disagree" to 4 "completely agree". Motivation scale consists of 8 items; examples of items are ‘School is just a waste of time’ and ‘Only with a good education one can get a decent job’. Items were formulated in positive and negative directions in order to minimize “automatic replies”. For the analysis, all replies were re-coded unidirectionally, so that a higher place on the scale meant a higher level of pro-school values. The index of individual values was calculated as simple average of all questions; the index has a good level of reliability (Cronbach’s alpha = 0.65). This measurement has been used successfully in a number of studies in the past (e.g. Van Houtte, 2006; Van Houtte & Stevens 2010).

The motivation of peers on different levels has been calculated as the average motivation for a clique, ego network, class, or school. We constructed a series of models comparing peer influence (understood as peer motivation) on different levels on individual academic performance.

A number of demographic characteristics that are known to be related to student performance have been taken into account and included as control variables: gender; age; socio-economic status; ethnic minority status; migration status. For characterizing socio-economic status we used the approach employed in Programme for International Student Assessment. We run a principal component analysis of a number of relevant variables: the education of both parents and the international socio-economic index of both parents’ jobs. The first component has been used as a measure of family socio-economic status.

Minority status is a binary variable, where 0 is ethnic majority (Russian or Slavic). In our samples there were over 20 ethnicities, mostly by nations of South Caucasus (Azerbaijani and Armenians), North Caucasus (Lezgins, Ossetians,Chechens), and Central Asia (Uzbeks and Tajiks). All of them were coded as minority.

Migration status is a binary variable, where 0 means “born here or arrived before 7 years of age”. We also calculated an interaction term between the last two variables (migrant*minority) as we have shown previously (Alexandrov et al., 2011) that minority children who came to Russia quite more recently form a special category that often have academic trouble at school.

Results

Descriptive statistics

A description of the sample characteristics and descriptive statistics of variables is presented in Table 1. The sample was balanced for gender, consisting of 49% girls The average age of the students was 15. Students of non-Russian descent comprise 10% of the sample, students with migrant status who recently moved to St. Petersburg 13%. The average socio-economic status is 0 because the variable was constructed as a factor in principal component analysis. Dependent variable GPA ranged from 2.2 to 5.0 with an average grade 3.64. There was a very good response rate for every variable except socio-economic status: almost 23% of students did not answer the questions about their parents’ job and education. It diminishes the base for analysis considerably because SES is an important control variable that cannot be omitted. Nevertheless there are still over 4000 cases with complete data for modeling.

Table 1. Descriptive statistics of percentages or means with standard deviations, min, and max values (N=5252)

Variable	Percentage or Mean (SD; min - max) or %	N missing
% girls	48.9%	1
% minority	9.6%	57
% migrants	13.4%	59
% minority*migrants	2.5%	116
Age	15.0 (0.9; 13-17)	21
SES family	-0.01 (0.999; -2.60 – 2.18)	1247
GPA	3.64 (0.55; 2.2 – 5.0)	17
Individual motivation	2.88 (0.45; 1.13 – 4.0)	1
Peer motivation (ego network)	2.88 (0.28; 1.25 – 3.88)	0
Peer motivation (mutual ego network)	2.88 (0.32; 1.25 – 4.0)	2
Peer motivation (clique)	2.87 (0.25; 1.78 – 3.78)	0
Peer motivation (class)	2.87 (0.15; 2.32 – 3.27)	0
Peer motivation (school)	2.87 (0.11; 2.63 –3.09)	0

Table 2. Characteristics of units for multilevel modeling (on the 1st level N =5252)

Unit	Number of units	Unit size mean (SD; min-max)
School	100	457 (179.9; 116 – 852)
Class	309	20.5 (4.35; 8 – 29)
Clique	1050	6.2 (2.4; 1 – 16)
Ego network	5055	4.8 (2.4; 1 – 10)
Mutual ego network	4549	3.2 (1.7; 1 – 9)

Table 2 represents the level structure of the sample summarizing mean size, standard deviation and size range of the unit on every level. On average every class consists of 3.8 cliques (number of cliques ranged from 2 to 7) with the average clique size of 6.2. The average ego network size is just below 5. Even though the students were allowed to nominate up to 10 friends, only a small fraction of teenagers did. The size of mutual ego network is considerably smaller, because it consists only from the persons who returned the nomination; its size is 3.2.

Multilevel modeling

At the first stage of analysis we run a series of empty models to evaluate how the dispersion of the dependent variable is distributed between the levels (Table 3). Only a series of empty models for cliques is presented. Separate models were run also for ego network and mutual ego networks (not shown).

Empty models 1-4 represent 2-level models where first level (individual) is combined with one of higher levels: clique, ego network, class or school. Two-level models show that on the school level there is 5% variance, on the class level 10%, on the clique and ego networks level 22-25%. A comparison of the values of deviance information criterion[3] (DIC) shows that models with cliques or ego networks (model 1) have considerably better fit than the models without this intermediate level (models 2 and 3).

Table 3. Empty models for evaluating the distribution of the GPA variance between the levels

	Empty Model 1	**Empty Model 2**	**Empty Model 3**	**Empty Model 4**	**Empty Model 5**	**Empty Model 6**	**Empty Model 7**
school			0.018 (0.004) 5.8%		0.013 (0.003) 4.3%	0.014 (0.003) 4.5%	0.014 (0.003) 4.3%
class		0.030 (0.004) 9.6%		0.014 (0.004) 4.5%		0.015 (0.003) 4.8%	0.002 (0.002) 0%
clique	0.082 (0.005) 26.2%			0.069 (0.006) 22.0%	0.065 (0.005) 21%		0.066 (0.005) 21%
individual	0.230 (0.005) 73.8%	0.280 (0.006) 90.4%	0.290 (0.006) 95%	0.230 (0.005) 74.5%	0.234 (0.005) 75%	0.280 (0.005) 91%	0.230 (0.005) 75%
DIC	7629.2 (5116)	8186.5 (5116)	8256.9 (5116)	7617.79 (5116)	7600.75 (5116)	8169.2 (5116)	7600.58 (5116)

Then we run empty models with 3 or 4 levels (all possible combinations were run but not all are presented here for the sake of brevity). In sum, school and class are responsible for the 9% of the variance, which is divided between them almost equally. The intermediate level between individual and class accounts for 22-25% of the variance. 3-level models have better fit that 2-level models, as DIC shows.

[3] The deviance information criterion is a hierarchical modeling generalization of the AIC (Akaike information criterion) and BIC (Bayesian information criterion, also known as the Schwarz criterion). The idea is that models with *smaller DIC* should be preferred to models with larger DIC. Models are penalized by the value of deviance, which favors a good fit, and by the effective number of parameters (Leckie, Owen, 2014).

When combining school, class, and clique levels in one model (Empty model 7) the effect of the class disappears completely. An important conclusion can be drawn from this result: it shows that the class level effects are in fact reflections of clique level/ego network level effects.

The variety of empty models has been built for all possible combinations of school, class, ego network, and individual levels (not shown). The results were the same: for 3-level model, 75% of the variance on the individual level, 21% on the ego network level, 4% on school/class level.

Analyzing the distribution of the variance and deviance information criterion for the models we conclude that the best model structure is Model 5 that includes three levels: individual, clique, and school. Model 7, where one extra level – class – is added, does not change DIC, and there is no variance on the class level. Class level is important conceptually, so it was retained in the full models, but without random part.

The next step investigated how GPA variance is explained by the motivation of student's friends and peers, that is to fit the full models. A number of important controlled variables are included in models: the own student's motivation, gender, ethnic minority status, socio-economic status. On the higher levels control variables are % of minority, % of girls, average socio-economic status of the students.

A series of models with explanatory and control variables has been fitted in MLWIN (

Table 4). The main explanatory variable (motivation) has been centered to general mean. The results are briefly described below.

Table 4 Association between GPA and motivation: Effect of peer motivation on different levels. Results from multi-level analyses (MLWIN)

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Fixed Part									
const	3.617 (0.015)	4.252 (0.163)	3.429 (0.173)	3.276 (0.474)	2.907 (0.297)	2.860 (0.298)	2.636 (0.212)	2.638 (0.203)(	2.838 0.195)
boy		**-0.252*** (0.018)**	**-0.236 *** (0.017)**	**-0.237*** 0.017**	**-0.227*** (0.019)**	**-0.210 *** (0.019)**	**-0.212*** (0.018)**	**-0.213 *** (0.017)**	**-0.218*** (0.017)**
family SES		**0.099*** (0.009)**	**0.091*** (0.009)**	**0.091*** (0.009)**	**0.091*** (0.009)**	**0.091*** (0.009)**	**0.090*** (0.009)**	**0.097 *** (0.009)**	**0.098*** (0.009)**
minority		**0.068* (0.032)**	0.036 (0.032)	0.034 (0.032)	0.030 (0.030)	0.029 (0.030)	0.033 (0.025)	0.037 (0.032)	0.044 (0.031)
migrant		**0.058* (0.026)**	0.041 (0.026)	0.042 (0.026)	0.040 (0.026)	0.038 (0.026)	0.026 (0.028)	0.042 (0.026)	0.048 (0.026)
Minority*Migrant		**-0.131* (0.062)**	**-0.132* (0.063)**	**-0.125* (0.062)**	**-0.124* (0.063)**	**-0.124* (0.063)**	**-0.124* (0.062)**	**-0.136 * (0.065)**	**-0.140* (0.066)**
Age		**-0.033** (0.011)**	**-0.025* (0.011)**	**-0.025* (0.011)**	-0.021 (0.011)	-0.019 (0.011)	-0.019 (0.011)	-0.019 (0.011)	**-0.023* (0.010)**
Student's own motivation			**0.248 *** (0.019)**	**0.241*** (0.019)**	**0.231*** (0.019)**	**0.184 *** (0.021)**	**0.184*** (0.021)**	**0.228*** (0.019)**	**0.242*** (0.020)**
Peers motivation: School				0.053 (0.155)					
Peers motivation: Class					**0.171* (0.080)**	-0.098 (0.092)			
Peers motivation: Clique						**0.321 *** (0.051)**	**0.293 *** (0.047)**		
Peers motivation: Ego network								**0.250 *** (0.036)**	
Peers motivation: Mutual Ego network									**0.215*** (0.029)**
Level: school	0.015 (0.003)	0.011 (0.003)	0.012 (0.003)	0.012 (0.003)	0.012 (0.003)	0.012 (0.003)	0.012 (0.003)	0.011 (0.003)	0.011 0.004
Level: clique	0.067 (0.007)	0.049 (0.008)	0.039 (0.008)	0.039 (0.006)	0.039 (0.005)	0.036 (0.005)	0.036 (0.005)		
Level: egonetwork								0.034 (0.005)	
Level: mutual egonetwork									0.033 (0.007)
Level: individual	0.230 (0.006)	0.222 (0.007)	0.217 (0.007)	0.217 (0.007)	0.217 (0.006)	0.216 (0.006)	0.216 (0.006)	0.209 (0.007)	0.210 (0.008)
DIC: (clique)	7618.75	5363.09	5204.80	5206.11	5192.98	5154.06	**5151.07**		
DIC (ego network)								**5110.05**	
DIC (mutual ego network)									**5125.07**
N schools	98	98	98	98	98	98	98	98	98
N classes	282	282	282	282	282	282	282	282	282
N cliques	3597	2820	2820	2820	2820	2820	2820	2820	2820
N ego networks	5299	5055	5055	5055	5055	5055	5055	5055	5055

*** p<0.001; **p<0.01; *p<0.05;ˋ p<0.10. Numbers in parenthesis represent standard errors.

Variance component model (Model 0) shows that 24% of GPA variance is between school and individual level, that is on the level of student's friends. Model 0 serves as a baseline model.

In Model 1 individual controls are added. As expected, gender has considerable influence on school performance: boys have worse grades than girls (p<0.001). The socio-economic status of a student's family is also important: the SES coefficient is positive and highly significant ($p<0.001$). The age coefficient is significant ($p<0.01$) and has negative sign. It means that older students tend to have worse grades. The migration status and minority status are significant at the 0.05 level. It is interesting to note that both characteristics are positively related to school performance. It means that ethnic minority (non-Russian, non-Slavic) students have better grades at school than Russians; and all migrants (children whose families arrived after the students were 7) have better grades than those who were born in St.Petersburg. However the interaction term Migrant*Minority has a negative coefficient, and its statistical significance is just below 0.05. The interpretation is as follows: first generation non-Russian migrants experience learning difficulties, and a have lower GPA.

The next step is adding the main explanatory variable –learning motivation – on the individual level (Model 2). It considerably improves the model fit, as can be seen from DIC. Student learning motivation is positively related to GPA; the relation is highly statistically significant ($p<0.001$). The significance of almost all control covariates did not change. The only variable that lost significance was the minority status. It means that the improvement in grades attributed to the minority status in the previous model is can be explained by the fact that non-Russian students put more effort into their studies which is reflected in their learning motivation.

Having confirmed that students' own characteristics are important for their school performance, we proceed to the models with friends' motivation. Model 3 includes motivation at the school level, which is the aggregated motivation of all peers of the student. We can see that school motivation is completely non-significant. Moreover, the model fit worsens: DIC changed from 5504.80 to 5508.11. From this model we conclude that the overall school peer influence is not important since it adds nothing to personal characteristics.

In Model 4 motivation at the class level is added. We can see that DIC decreases from 5204 to 5192, meaning that class motivation explains some variance in GPA at the individual level.

Model 5 includes an additional variable: clique motivation. This model is much better as DIC drops to 5154. The clique motivation coefficient is positive and statistically significant ($p<0.001$). Introducing the clique motivation makes the class motivation coefficient non-significant. The interpretation is that a student's grades are strongly positively related to her own motivation and to her personal network motivation; but average class motivation is not related to her grades.

Next we proceed to compare the quality of the models with the network level, where personal networks are defined different ways: cliques, ego networks, mutual ego networks. In Models 6, 7, and 8 the motivation of immediate friends of the student is added as clique motivation (Model 6), ego network motivation (Model 7) and mutual ego network motivation (Model 8). We can see that all three full models have a considerably better fit compared to Model 2, which contains individual motivation of the student and all the controls, but does not contain friends motivation (DIC decreases significantly). It means that peers motivation when peers are defined as immediate friends (clique or ego network) has an important influence on school performance, net of student's personal characteristics.

Comparing the amount of the variance at the peer levels with the empty model we can see that it diminished significantly. The coefficients of the peer motivation variables are highly statistically significant ($p<0.001$). A student's motivation decreases a little but still remains highly significant, as well as the control covariates. It means that, holding student's socio-demographic characteristics constant and taking into account the students' own motivation, school-related attitudes of her immediate peers do still matter. Moreover, it does not matter how to define the peers: as friends nominated by the student; as reciprocated nominees; or as members of the cliques. The influence of chosen peers stands in striking contrast with the absence of the influence of assigned peers.

Discussion

This study contributes to the long-established tradition of studying peer influence by employing a social network approach for the definition of peer groups. We examine the influence of peers at different levels of student social circles focusing on the relation between student academic achievement and her/his peers' learning motivation. Particularly important is that we distinguish between assigned peers and chosen peers. By collecting network data on student in-school friendships we are able to construct and compare different interaction-based peer groups: (1) ego network: those classmates whom the student consider friends; (2) mutual ego network: those classmates whom the student consider friends and they also consider her a friend; (3) clique: a tight group of students within class who are not necessary friends with each other, but connected through other friends.

Our results demonstrate that the learning attitudes of chosen peers have considerable effect on a student's academic performance (controlling for the student's own motivation and background characteristics). The relation between a student's grades and her friends' motivation is very strong, no matter how the friends are defined: as complete ego network, reciprocated ego network or clique. One of the aims of our article was to find out what kind of personal network has stronger effect on students' academic achievement. Social network theory acknowledges the complex structure of human interaction and provides a number of approaches for the identification of peers. Having drawn a distinction between different definitions of personal networks, we hypothesized that the influence from mutual friends will be the strongest and the influence of clique members will be the weakest. A mutual ego network is connected with strong reciprocated ties. An ego network has additional weaker ties. Not all the clique members consider each other friends, but they are a part of a community formed by interactions.

Contrary to our hypothesis, the best model turned out to be the model with complete ego network, and the worst the model with cliques. There might be two explanations. The first explanation is statistical: ego networks, being overlapping entities, better represent the complex structure of social relations. The second explanation is more substantial and claims that social control and shared values and norms come not only from close friends but also from those whom a person perceives as friend even though the other does not reciprocate this perception. Similar finding by other authors confirm this rationalization. For instance, Alexander and Campbell (1964) found that friendship reciprocation is important for some effects (decision to attend college), but does not matter for others (attending the same college). In a recent article the influence on deviant behavior from reciprocal friends was not larger than the influence from non-reciprocal friends (Geven et al., 2013). It is known that adolescents are more influenced by a friend if they identify with that friend, and obviously this identification may be a strong factor of influence (Jaccard et al., 2005).

Our second contribution is to the debate on school academic culture. The concept of “school culture” is often used to explain the processes of peer influence when peers are understood as all students in a particular school. Differences between schools in term of academic culture are more pronounced in countries with stratified educational systems. In Russia the schools are stratified: there are academically bound gymnasiums and lyceums, and ordinary schools with standard curriculum. Nevertheless, our results demonstrate that the school effect does not exist beyond the composition effect, and the difference between schools disappears when student characteristics are taken into account. In other words, all the between-school difference is explained by the composition of the student body. The absence of pronounced differences in school academic culture between those two types of school may be explained by the fact that school differentiation in Russia began 20 years ago, and probably this is not a long enough period to produce a “culture of futility” in non-academic schools. An important policy implication from our findings is that school policy and environment, i.e. academic tracking, is neither necessary nor sufficient for creating “academically beneficial” or “academically detrimental” environments. What really matters for a student are the attitudes of her immediate friends.

The difference in peer effects between assigned and chosen peers demonstrated in our study is in line with the results of a recent article of Halliday and Kwak (2012). Using Add Health database for peer influence on drinking and smoking they demonstrated that peer effects largely depend on peer definition: influence from immediate friends (“inner ring”) is much stronger than influence from friends of friends (“outer ring”), and there was no influence from the grade cohort.

The third contribution of our paper is the demonstration that using network data for studying peers effects is highly beneficial. Multilevel modeling is a standard method in quantitative studies of the sociology of education because of the hierarchical nature of samples: students are nested in classes, classes are nested in schools. Using this approach and including a new analytic level between individual and class -- the level of personal networks -- we demonstrate that the model improves considerably. The rationale behind this is that the variance, or mix of attributes, within the group of immediate friends should affect individual student achievement. Hence this model is more correct than a model with the characteristics of average friends. For example, a group of friends with roughly the same level of a certain characteristic may generate a different peer effect than a group with the same mean score of the attitude but a wide range of individual attitude levels. By modeling ego networks and cliques as levels in a multi-level regression we are able to capture this variance. Our results demonstrate conclusively that peer effects on the class level observed in models without personal network level are only an approximation of the friend's peer influence. Introducing a network level in the classic multi-level models for schools gives more fine-grained picture. This benefit comes with the cost of the laborious process of collecting and coding personal network data.

The main limitation of the study lies in its cross-sectional nature. In our analysis we followed the well-established psychological paradigm of attitude-achievement model. However we cannot exclude the possibility of reverse causation, when achievement affects attitudes. Our research could be extended by a longitudinal study. First, it would be interesting to evaluate the validity of attitude-achievement model, which is not disputed in psychology but has hardly ever been experimentally proved. Second, a longitudinal design would allow disentangling the selection and influencing effects, and consequently the peer effects would be clearly outlined.

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