Is tracking beneficial? Study of tracking using peer effects.

Abstract

The aim of this article is identify the effects of tracking by ability levels using the peer effect linearity in students' social networks controlling by their math degree. First of all we divide the dataset in three parts (low, middle and high ability) according to the average scores of each network and estimate a spacial auto regressive model by maximum likelihood. In this first approach no significant results were found, which suggests that whether we group classrooms by math grades the peer effect does not have any linear importance in students' scores. Second, we used quantile regressions and the results suggest any significant differences among 10th, 25th, 50th and 75th peer effect quantiles coefficients, although all of them are positive and significant. In the 90th quantile, no significant results were found. Once more, the results suggests that the peer effect assumes a linear behavior and grouping students by academic achievement will not bring beneficial results.

Keywords: Peer effect, Linearity, Social Networks, Spartial Auto-Regressive model and Quantile Regressions;

Resumo

O objetivo desse artigo é identificar os efeitos de agrupar estudantes por desempenho utilizando a linearidade do efeito dos pares nas redes sociais dos estudantes controlando pelas suas notas de matemática. Primeiro nós dividimos os dados em três partes (baixo, médio e auto desempenho) de acordo com a nota média de cada rede e estimamos um modelo de econometria espacial auto regressivo por máxima verossimilhança. Nessa primeira estratégia não foram encontrados resultados significantes, isso sugere que independente de se agrupar as turmas pelas notas de matemática o efeito dos pares não tem nenhuma importância linear sobre as notas dos alunos. Em uma segunda estimação usamos regressões quantílicas e os resultando não mostram diferenças significantes entre os quantis 10, 25, 50 e 75 dos coeficientes do efeito dos pares, apesar de todos terem valor positivo e significante. No quantil 90 nenhum resultado significante foi encontrado. Mais uma vez, os resultados sugerem que o efeito dos pares assume um comportamento linear e agrupar alunos por desempenho acadêmico não trará resultados proveitosos.

Palavras-Chave: Linearidade, Efeito do Pares, Redes Sociais, Modelo auto regressivo espacial e Regressões Quantílicas;

Área ANPEC: Área 12 - Economia Social e Demografia Econômica

Classificação JEL: C13 e I21

1 Introduction

Studies in the area of economics of education like Langoni (1973), Barros and Rei (1990), Barros e Mendonça (1997), Hanushek and Wöbmann (2010), reinforce the importance of a good academic achievement to achieve good results in countries economy. The theoretical growth literature emphasizes at least three mechanisms through which education may affect economics growth. First, education can increase the human capital inherent in the labour force, which increases labour productivity. Second, education can increase the innovative capacity of the economy, and the new knowledge on new technologies, products and processes promotes growth. Third, education helps the diffusion and transmission of knowledge needed to understand and process new information and to successfully implement new technologies devised by others, which again promotes economics growth.

Langoni (1973), Barros e Rei (1990) and Barros e Mendonça (1997) focus in showing how higher educational standards can raise personal income and increase the quality of Brazilian labour. More specifically in Barros e Rei (1990) they found that there is a big education inequality between Brazilians and there is also a big difference in wages and this gap could be reduced in about 50% if the differential for educational level were ignored. This result suggests that investing in education could work as a wealth distribution mechanism.

In the economics of education literature, the concerns are about studying the education production and how to increase it. Some of the determinants of student achievement like individual inputs, parental counselling and education can not or is hardly influenced by public policies, however the use or allocation of school resources, especially public schools, can. The peer effect is a usual subject in this area and is concerned in evaluate the effects that peers, direct or indirect, can have over students scores. The idea is that normally a student is part of a social network of peers in his classroom and school and the way that those peers interact with each other (helping and discussing) and with the teacher (asking questions) can bring positive effects for each student. Following Hanushek (2006) linearity occurs when peer effect is equally identified through the different levels of students but not only on average.

Another topic that has being study is the efficiency of tracking policies in students scores. Tracking is a form of allocate students based on previous scores, grouping students with high grades in separated classes from average and lower grades students. These policies can cause a lot of conflicts and pedagogical issues. The central argument in favor of tracking is that more homogeneous classrooms permit a more specified curriculum and a more appropriate rhythm in lessons which maximizes the learning. Teachers won't have problems losing attention of faster learners or complicating the understand of slower learners. However, the arguments against tracking is that lower classrooms will always be in disadvantage by slower learning environments and it might create a gap between higher classrooms when technically they were supposed to finish school at the same level. When peer effects and tracking are considered the efficiency of tracking gets more unclear and that is why it is important to investigate peer effects linearity. When lower level students are allocated together they tend to interact less with the teacher and with each other which does not contribute to the peer effect.

The Educational Economics literature as Hoffer (1992), Argys et al (1996), Betts and Schkolnik (2000), Zimmer (2003), Hanushek(2006) and Raposo (2015) has explored well the peer effects and tracking but the linearity still have some space for innovation and proposals in it's methodology and could bring new results and discussions. Therefore, in this study, the effects of tracking are being investigated using students peer effects linearity. The link between tracking and the non-linearity of peer effect comes from the arguments in favor of tracking. These arguments focus in the relationship between teachers and the classroom, but by the peer effect literature mentioned before and Educational Economics literature (Hanushek (1979), Rivkin, Hanushek and Kain (2005), Menezes-Filho (2001) and Soares e Menezes(2010)) student achievement is explained by a complex set of factors and peers are included as an important influence over achievement, so, if peer effect does not persists in a grouped classroom tracking is cutting of the peer effect from the student achievement.

The paper is structured along the following lines. The next section look at the importance of peer effect in Educational Economics. Section 3 introduces the model for the empirical analysis, as well as the data availability and the units of analysis, while Section 4 present the empirical results and discussion. The conclusions and some policy implication are included in Section 5.

2 Peer Effect and Tracking

In the study of networks it is important to refer to Hoffer (1992) which compares the overall results of students in tracked and non-tracked classrooms and also students placed by their ability in specific high, middle and low classrooms. He also discuss that peer effect conflicts with tracking because if students are being allocated in more homogeneous classrooms the peers are going to be all from the same level and this could diminish the peer effect. However, is by evaluating the linearity of peer effect that is possible to show if even in a homogeneous classroom the effect is significant or not. Hoffer (1992) makes two covariance analysis, one to compare the average effect between tracked and non-tracked schools. The second analysis compares one high level student in a tracked school with a high level student in a non-tracked school and so on. From the first analysis it finds that the benefits from tracking are negligible and controlling for social background and initial student scores. In the second approach it finds that students in a high level classrooms have a positive effect of .26 and .18 standard deviation for seventh and eighth grades respectively. For students in the lower level classrooms they found a effect of -.36 and -.32 standard deviation for seventh and eighth grades respectively.

In the identification of social effects the work of Manski (1993) defines the Reflection Problem which means that when a researcher observing the distribution of a population's behaviour tries to infer if the average behaviour in a group or network influences the behaviour of the individuals part of this group. Manski (1993) defines three effects which are part of these social structures that may cause problems in the identification of peer effects. The three effects are:

1. Endogenous Effects - wherein the propensity of an individual to behave in some way varies with the behaviour of the group;
2. Exogenous Effects - wherein the propensity of an individual to behave in some way varies with the exogenous characteristics of the group, and;
3. Correlated Effects - wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments.

This problem is properly solved for the model used here (as mathematically demonstrated in Bramoullé et al (2009)) because the data utilized allowed to construct one big network by classroom composed by other smaller and heterogeneous networks. This composition of the networks will be properly explained later on.

Argys et al (1996) does an interesting analysis of the tracking with high school students in the USA and finds that removing the tracking would have a positive effect over lower level students. They estimate each student score if they were not in a tracked classroom and compares with their actual score and found an increase in scores from three up to seven points. They applied a simple production function of education, however if the students were placed in ability groups based on motivation and unobserved school quality and if these two variables were correlated with achievement the results will be biased. To avoid it, they use a multinomial logit model of track selection to estimate selectivity correction terms. For the model used in the Methodology and Data section this problem will not exist because there is no tracking or grouping and the classrooms are composed by age.

Another article which compares schools with tracking and those without tracking is Betts and Shkolnik (2000). Similarly to Hoffer (1992) they compare ability groups in tracked and non-tracked schools. In a first regression using all the controls and a dummy variable for tracking they found no effect in grouping students by ability. A second regression, where they use an interaction term between ability level of classrooms and the tracking dummy, for the three lower level classrooms they found a negative effect of 4,2 points for schools who track their students. For the highest level classrooms they found a positive effect of 3,2 for tracked students. This article also analyses the miss allocation of resources depending on classroom level and found tendency of allocate less experienced teachers and smaller classrooms for lower level students.

One of the articles that most influenced this study is Zimmer (2003), because he uses a very similar structure to the one used here, also the data and the main question is very similar. In Zimmer (2003) the peer effect linearity is analysed in schools that apply tracking and those that do not. In the article he uses a simple ordinary least squares model to estimate the peer effect and divides the data in four datasets based on the average scores of the class and the quantiles. The first 25% allocated as low level, from the 25% to the 75% quantile were classified as middle level and above the 75% quantile classified as high level classrooms. The fourth dataset includes all classes. Zimmer (2003) founds that the lower and middle level classrooms had a negative and significant coefficient of 0.3 and 0.7 standard deviation, respectively. For the highest quantile no significant effect was found showing that lower and middle levels students are worse of when allocated in a tracked classroom and the highest level students do not suffer any effect. One problem in this approach is that peer effect is measured by the average score of the classroom so the effect of one peer over other is treated as equal. When using the social network concept the reference group will be heterogeneous and protects your estimation from Manski's Reflection Problem. The model used in the methodology section applies this concept.

The second article that highly influenced this estimation and the proposed model is the PhD thesis of Raposo(2015). The thesis in a highly detailed approach of the peer effect and uses the same database used here, however, it only estimates the peer effect on average. In Raposo (2015) it manages to identify the social networks of each student by a relationship matrix which the lines and columns represents the students and it's respective friends. The construction of this matrix is possible because of FUNDAJ's (Fundação Joaquim Nabuco) data base which asks each student to list his five closest friends in the classroom. The measure of peer effect is the sum of the scores of each student network and it is found a positive and significant peer effect on students scores of 0.014 standard deviation.

In Schneeweis and Winter-Ebmer (2007) they study the peer effect and it's linearity for Austrian schools assessed by PISA 2000 and 2003. The Austrian school system has an interesting characteristic it has different types of schools depending on the goal of the student and it's parents. Each type of school has different curriculum's, allocation of resources and entry criteria based on previous academic scores. For this scenario they apply a production function including school fixed effects, individual and family characteristics and peers characteristics. As PISA has no information about peers and classrooms they assume that students from the same grade and school are peers which is a weakness compared to the database use for this article. Finally, they estimate the mean effect by an ordinary least squares estimation and found no significant effect when including fixed effects. The linearity is estimated by quantile regression and for the reading scores finds that a student with low socio-economic index moving to a new peer group with a quality of one standard deviation higher increase in achievement by 5.2 points. An student from the 75th percentile would benefit 3.3% from the same movement. For the math scores no increase was found.

Pinto (2010) utilizing data for Brazilian public schools does a semi parametric approach to estimate a production function with peer effect. It assumes that student achievement is function of students quality and peers quality and utilizes the allocation of students in class as a instrumental vector. It is found evidences that peer effect is positive independently of student quality and that middle quality students benefit more from their peers quality than does lower quality students.

A very interesting article is Hanushek (2006) which studies the effects or early tracking over education inequality and performance for the PISA database. He applies a differences in differences model and finds that early tracking increases inequality in most of the countries although the evidence on the level of performance is less certain. It is also discussed that the argument in favor of or against tracking gets more complicated when considering peer effect, because understand how the peer effect works through achievement becomes a key element in considering tracking.

3 Methodology and Data

3.1 Empiric Model

As already mentioned the methodology proposed here is very similar to Zimmer (2003) and Raposo (2015). The relationship matrix will be used as in Raposo (2015) to map each student friendship network and calculate the peer effect based on the sum of the friend's scores which compose each student reference group (network). The network matrix functions in this way: In a classroom with 20 students the questionnaires are applied for each student and from that it's taken the information of the individuals linked as part of his 5 closest friends. With this data the following matrix is constructed:

$$G = \begin{array}{cc} & \begin{array}{ccccccc} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} & \mathbf{5} & \mathbf{\dots} & \mathbf{20} \end{array} \\ \begin{array}{c} \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \\ \mathbf{4} \\ \mathbf{5} \\ \vdots \\ \mathbf{20} \end{array} & \begin{bmatrix} 0 & 1 & 1 & 1 & 0 & \dots & 0 \\ 1 & 0 & 1 & 0 & 0 & \dots & 1 \\ 1 & 1 & 0 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & 0 & 1 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & \dots & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & 0 & 1 & \dots & 0 \end{bmatrix} \end{array}$$

This way the G matrix displays that when the student i mention the student j as friend $g_{i,j} = 1$ and $g_{i,j} = 0$ when is not mentioned. By convention, when i=j, $g_{i,j} = 0$. In the networks is possible that $g_{i,j} = g_{j,i}$, meaning that both students mentioned each other as friends creating an indirect link. It is possible also to find $g_{i,j} \neq g_{j,i}$ meaning that only one student mentioned the other creating a direct link.

Following Zimmer (2003) and Raposo (2015) the model is represented below:

$$y_{t,h} = \mu y_{t-1,h} + \lambda G y_{t,h} + \theta(x) + \phi_\eta \eta + \phi_\zeta \zeta + \epsilon$$

$$And : \theta(x) = X\beta' + GX\gamma' \tag{1}$$

The equation above includes the scores of the first exam $y_{t,h}$, the scores of his direct peers $G_{y_{t,h}}$, the student individual characteristics and it's peers X and GX, two measures of fixed effect ζ and η representing the individual and the classroom's unobserved heterogeneities. However, as mentioned in Raposo (2015), even with the common characteristics of all network, it is possible to exist unobserved individuals differences ($\zeta_{i,k}$) that affect the formation of links (friendships) and the student achievement in fact, so, this kind of approach only stands valid if the inclusion of η_k also controls for the unobserved individuals characteristics.

It is important to notice the strength of using the first exam variable as control. By using this variable as control it is possible to capture a hole set of influences that could contaminate the coefficients. The observable and unobservable background of family, school and student community and also the student unobservable characteristics are controlled by this scores and it can be considered a student's fixed effect as argued by Ding and Lehrer (2007).

The estimation method used for the proposed model follows Raposo (2015) and Zimmer (2003) and two estimations are applied. The first is the quantile regression that analyses the peer effect by students ability level, so, in this approach, it is being considered the effect that peers have over a low, middle or high level student. Whereas, as described in Raposo (2015), this way of estimating the model is biased, because even if the network fixed effects and the individual fixed effects can control for any type of unobserved variable, the OLS estimation of the interested variable λ is biased, since the achievement simultaneously would generate a spatial dependency with the error term.

The second estimation uses a spatial auto regressive model estimated by maximum likelihood as proposed by Calvó-Armengol et al. (2009), Lee (2007) and also applied by Raposo

(2015). This model allows to control the spatial dependency in the error term induced by the simultaneity of the dependent variable y which the quantile regression does not.

The contribution in relation to Raposo (2015) proposed model and the one applied here is the division of the data by the average ability level of the networks (represented by the letter h) which allow to evaluate if the peer effect remains linear for different levels of networks. The division of the database follows Zimmer (2003) proposal to divide the data by the quantiles of the average scores of the network. In this case until the 25% quantile is classified as low level, between the 25% and 75% quantiles middle level and above the 75% quantile high level. As the schools from this dataset do not track their classrooms this article also contributes with a suggestion of analysing tracking policies even when it is not being applied in classrooms, different from Zimmer (2003), Hoffer (1992) and Argys et al (1996) which are able to use a tracking dummy in their models. This new way of analysing tracking helps to make more efficient decision when allocating students into classrooms especially for schools considering to track their students.

3.2 Database

An very important point of the realization of this research is the access to the database utilized. The data were provided by the Fundação Joaquim Nabuco (FUNDAJ) collected in the field research named *Acompanhamento Longitudinal do Desempenho Escolar de Alunos da Rede Pública de Ensino Fundamental do Recife*. The representative sample generated by the research focus on 6 years old middle school students and assess students skills in math by the application of two exams placed in the beginning of the year and in the end. Apart of the exams, there was applied also questionnaires for students, math teacher, school principal and the responsible for following the student academic life (tutor). The biggest innovation of this database is the possibility to map the student friendship network and with this information is possible to create an structure that allows to calculate more precisely the peer effect. Other informations were collected regarding a series of social characteristics that allows to construct a vast group of control variables allowing better model's specifications.

The database covers 4.191 students, 3670 parents or tutors, 120 school principals and 131 math teachers from 120 schools spatially distributed trough the eighteen micro regions of the city of Recife. The data has an average of .45 male students, initial score average of 41.92, final score average of 41.15, percentage of self declared white students of .19, average age of 11.19 and .73 of new students to that school. The rest of descriptive and control variables are displayed in the appendix section.

4 Results and Discussion

In this section will be displayed the results of the estimation and initiate a brief discussion. Table 1 shows the results for the quantile regression.

Table 1: Quantile Regressions

Quantile	**(10)**	**(25)**	**(50)**	**(75)**	**(90)**
Coefficient	0.021*	0.021**	0.019**	0.024**	0.022
Standard Deviation	0.011	0.009	0.009	0.011	0.014
Pseudo R^2	0.1162	0.1550	0.1785	0.2026	0.2482
F Test	F(4, 1807)=0.13 Prob>F=0.97				
*5% , **10%					*obs* = 1854

Source: Authors' elaboration.

These results show that the peer effect remains linear for most of the student ability level. Until the 75th quantile the effect is significant which may be a clue that the tracking would not be efficient for those students because, as mentioned before, in this first estimation the composition of the classroom is heterogeneous so the model here looks for a student in a pool of others different levels students. However, for the 90th quantile no significance were found. Even tough this estimation is biased, as explained before, the results are consistent comparing to the literature (Especially the results found in Raposo(2015)) and also consistent with the results from the maximum likelihood estimation.

Table 2 bellow display the estimation resulting after controlling of peer effect and using Maximum Likelihood:

Table 2: Maximum Likelihood Estimation

	Low	Middle	High
Peer Effect	-0.0056728	0.003785	-0.0033915
P-value	(0.74263)	(0.71911)	(0.8018)
Observations Number	458	950	446
Networks Number	37	69	33

Source: Authors' elaboration.

The coefficients displayed above did not show any significance at any acceptable level. It is not possible to confirm the behavior of the peer effect by network level (homogeneous classroom). If the significance levels were more acceptable and the linearity by network levels were confirmed the tracking would be a possibility to increase student achievement. On the other way around if non-linearity were identified the tracking would depend in which level the peer effect were significant. Comparing both results, one complements the other because when separated by network levels the peer effect was not significant and quantile regressions are showing that for this data the peer effect remains linear by student individual level, it might be an evidence that tracking classrooms may not have a positive effect.

It is important to confront the discussion of tracking versus peer effects and why these results are supporting the non-tracking policy. As mentioned through the literature, the peer effect emerges from the peer to peer learning and from the differences in this peers levels which are more likely to have different questions and doubts and bring up more diverse discussions.

So a tracked classroom will difficult gains from differences in peers because it will be composed by students with the same understanding level which are less likely to have different questions and doubts to be discussed in class, it is also less likely to students discuss with each other and the need of peer to peer helping is lower. So, technically, a tracked classroom works as if it was composed only by a single student and a teacher completely eliminating peer effects.

5 Conclusion

The proposal of this article to analyse tracking is properly achieved. Even though the quantile estimations are biased the results found make sense comparing to the Maximum Likelihood estimation and the literature. The persistence of the linearity of the effect found by Raposo (2015) indicates that students from different levels are affected similarly by it's peers if the student is from a certainty ability level in a heterogeneous classroom (the case which the quantiles are analysed).

From the results it is possible to say that tracking is not a efficient way to increase student achievement and this results must be taken into account when discussing classroom composition and allocation of students policies. Of course there is space for improvement and contribution in this study area. One of the regards that must be done concerns the small numbers of observations when the networks are divided in ability levels that might be causing the non-significance of the coefficients. For further studies would be interesting to examine the same strategy of dividing the networks but by the quantiles analysed here. Making three new ability levels, the results of the quantile regressions might indicates that it's possible to find better results for the maximum likelihood estimations.

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Appendix

Table 3: Summary statistics

Variable	Definition	Mean	Std. Dev.
Dependent Variable			
Second score(0-100) ($Y_{t,h}$)	Math exam realized in the end of the year	40.47	15.998
Individual Variables			
First score(0-100)($Y_{t-1,h}$)	Math exam realized in the beginning of the year	43.066	16.568
Study dedication	"How often do you study?": 1=everyday, 2=only in class days, 3=3 days a week, 4=less then 3 days, 5=only in exams week and 6= never/hardly ever	2,57	1,52
Age	Student age	11.191	0.866
Male	Dummy for Male=1	0.453	0.498
Ethnicity (White)	Self declared dummy for White =1 and others =0	0.191	0.393
Feels left out in classroom	1=always 2=sometimes,3=never	2.698	0.575
Personality	"Would you change something in your personality?" 1=Agreed, 2=Maybe, 3=Disagreed	2.413	0.875
Popularity	1=Yes, 2=Maybe, 3=No	1.344	0.671
Encouragement from teacher	1=Always, 2=Sometimes and 3=Never	1.49	0.664

New to School	Dummy for first year in this school=1	0.735	0.442
Religiousness	"How often you go to church?"1=always, 2=sometimes and 3=never	1.754	0.702
Your neighbourhood safety	Dummy=1 if he feels safe in his neighbourhood	0.793	0.405
Number of friends (indegree)	Number of citations as friend from others divided by the total possible	0.081	0.068
Goes to a club or gym	Dummy=1 if the student goes	0.23	0.421
Number of friends	Number of friends from school he normally visits	1.054	1.245
Tutor Characteristics			
Tutor Age		38.484	8.166
Male		0.135	0.342
Ethnicity (White)		0.175	0.38
Kinship to the student	Dummy=1 if Biological or Adoptive parents, 0 for others.	0.824	0.381
Conjugal	dummy=1 for married	0.546	0.498
Social programs	dummy=1 if receives government support	0.618	0.486
Educational level	1=first year,...,9=ninth year;10=high school first year,...,12=high school third year; 13=university first year,...,18=university sixth year	8.846	3.435

Checks student report card	1=always, 2=sometimes and 3=never/hardily ever	1.201	0.513
Classroom Characteristics			
Number of students		13.25	5.59
Disciplined Classroom	Teacher answers;1=agreed, 2=partially agreed and 3=don't agree	2.098	0.738
Aggressive Classroom	Teacher answers;1=agreed, 2=partially agreed and 3=don't agree	2.538	0.641
Exam cumulative subjects	dummy=1	0.654	0.476
Observations Number:1.855			
Networks/Classrooms Number:139			

Source: Authors' calculation from FUNDAJ dataset.

Table 4: Quantile Regression

Variable	**10**	**25**	**50**	**75**	**90**
Individual Characteristics					
Intercept	19.610* (11.584)	23.760* (10.084)	25.106** (9.246)	34.564** (11.423)	43.673** (14.473)
Peer Effect	0.021* (0.011)	0.021** (0.009)	0.019** (0.009)	0.024** (0.011)	0.022 (0.014)
First Score	0.348*** (0.031)	0.369*** (0.027)	0.438*** (0.024)	0.462*** (0.030)	0.438*** (0.038)
Male	-1.640 (1.682)	-0.522 (1.464)	0.973 (1.343)	1.540 (1.659)	-1.172 (2.102)
Ethnicity(white)	-0.779 (1.240)	−1.902* (1.079)	−1.945** (0.990)	-1.248 (1.223)	-1.170 (1.549)
Age	−1.111* (0.579)	-0.715 (0.504)	−1.137** (0.462)	−1.498*** (0.571)	−1.620** (0.724)
New to school	1.103 (1.376)	-0.416 (1.198)	0.415 (1.099)	-0.653 (1.357)	-0.731 (1.720)
Number of friends (indegree)	-0.277 (0.318)	-0.151 (0.277)	-0.118 (0.254)	-0.220 (0.314)	0.082 (0.398)
Encouragement from Teacher	-0.601 (0.726)	-0.447 (0.632)	-0.825 (0.580)	-0.998 (0.716)	-1.120 (0.908)
Personality	0.295 (0.544)	0.251 (0.474)	0.438 (0.434)	0.803 (0.537)	0.259 (0.680)
Feels left out in classroom	-0.673 (0.827)	0.441 (0.720)	-0.075 (0.660)	1.395* (0.816)	2.169** (1.034)
Popularity	0.697 (0.711)	1.424** (0.619)	1.117** (0.568)	0.986 (0.701)	-0.337 (0.889)
Number of friends	-0.222 (0.398)	-0.247 (0.346)	−0.565* (0.317)	−0.726* (0.392)	-0.329 (0.497)

	-1.934^{*}	-1.113	0.633	1.163	0.898
Goes to a club or gym	(1.140)	(0.992)	(0.910)	(1.124)	(1.424)
	-0.132	0.226	0.754	1.177	0.689
Your neighbourhood safety	(1.174)	(1.022)	(0.937)	(1.157)	(1.466)
	-0.004	-0.035	-0.822^{**}	-0.750^{*}	-0.862
Number of friends in classroom	(0.446)	(0.388)	(0.356)	(0.440)	(0.557)
	0.049	0.248^{*}	0.424^{***}	0.310^{**}	0.120
Educational level(tutor)	(0.146)	(0.127)	(0.117)	(0.144)	(0.183)
	-0.247	1.676	1.736	0.431	1.360
Male(tutor)	(1.443)	(1.256)	(1.152)	(1.423)	(1.803)
	0.771	1.287	0.974	1.018	0.479
Ethnicity(White-Tutor)	(1.274)	(1.109)	(1.017)	(1.256)	(1.592)
	0.119^{*}	0.023	0.063	0.103^{*}	0.118
Tutor Age	(0.063)	(0.055)	(0.051)	(0.062)	(0.079)
	1.334	1.665^{**}	1.577^{**}	0.042	-0.075
Conjugal	(0.958)	(0.834)	(0.764)	(0.944)	(1.197)
	-0.048	0.349	0.146	1.376	3.697^{**}
Kinship to the student	(1.350)	(1.175)	(1.077)	(1.331)	(1.686)
	-1.290	-1.736^{*}	-0.431	-0.545	-1.553
Social programs	(1.055)	(0.919)	(0.842)	(1.041)	(1.319)
	-1.318	-2.270^{***}	-1.560^{**}	-1.379	0.096
Checks student report card	(0.929)	(0.809)	(0.741)	(0.916)	(1.160)
Peers Characteristics$_1$					
	2.728	1.337	-0.076	0.753	1.194
Male	(1.895)	(1.650)	(1.513)	(1.869)	(2.368)
	-1.981	-2.849^{*}	-1.001	0.564	0.804
Ethnicity(White)	(1.766)	(1.537)	(1.409)	(1.741)	(2.206)
	-2.677^{***}	-0.982	-0.110	-0.153	0.491
Religiousness	(0.975)	(0.849)	(0.778)	(0.961)	(1.218)
	-0.721	1.315	0.928	1.306	0.652
New to school	(1.548)	(1.347)	(1.235)	(1.526)	(1.934)
	-0.360	-2.064	-0.034	0.949	0.418
Goes to a club or gym	(1.691)	(1.472)	(1.349)	(1.667)	(2.112)
	0.092	0.239	0.682^{*}	0.299	-0.157
Number of friends(indegree)	(0.448)	(0.390)	(0.357)	(0.442)	(0.559)
	1.070	-0.330	-0.650	-0.748	-0.780
Personality	(0.801)	(0.697)	(0.639)	(0.790)	(1.001)
	-0.844	-0.482	-0.698	-0.700	0.420
Feels left out in classroom	(1.258)	(1.095)	(1.004)	(1.240)	(1.571)
	0.996	-1.099	-1.056	-0.288	-1.303
Popularity	(1.049)	(0.913)	(0.837)	(1.034)	(1.311)
	-1.817	-3.057^{**}	-1.020	-1.423	-0.399
Your neighbourhood safety	(1.638)	(1.426)	(1.308)	(1.616)	(2.047)
	0.095	-2.402^{**}	-1.592^{*}	-0.954	0.348
Encouragement from teacher	(1.060)	(0.923)	(0.846)	(1.046)	(1.325)
	0.646^{***}	0.551^{***}	0.166	-0.034	0.128
Educational level(tutor)	(0.193)	(0.168)	(0.154)	(0.191)	(0.241)
	-4.109^{**}	-2.354	0.977	2.940	6.336^{**}
Male(tutor)	(2.027)	(1.764)	(1.618)	(1.999)	(2.532)
	1.920	1.419	0.705	0.477	-0.943
Ethnicity(White-Tutor)	(1.723)	(1.500)	(1.375)	(1.699)	(2.153)
	-0.011	0.090	0.179^{**}	0.155^{*}	0.087
Tutor age	(0.088)	(0.076)	(0.070)	(0.086)	(0.109)
	0.165	0.352	0.244	-0.766	-0.459
Conjugal	(1.335)	(1.162)	(1.066)	(1.317)	(1.668)
	2.344	0.453	1.586	1.506	-0.104
Kinship to the student	(1.855)	(1.615)	(1.481)	(1.829)	(2.318)
	-3.383^{**}	-2.003	-1.629	-1.782	-0.188
Social program	(1.450)	(1.262)	(1.158)	(1.430)	(1.812)

	-1.636	0.165	-0.812	-0.642	-1.363
Checks student report card	(1.283)	(1.117)	(1.024)	(1.265)	(1.603)
	-0.004	0.031	0.068**	0.086**	0.069
First score	(0.041)	(0.036)	(0.033)	(0.041)	(0.051)
Classroom Characteristics					
	-0.256	−1.631***	−1.510***	−1.370*	−1.610*
Disciplined Classroom	(0.720)	(0.627)	(0.575)	(0.710)	(0.899)
	-0.466	-0.006	0.421	-0.476	-0.261
Aggressive Classroom	(0.819)	(0.713	(0.654)	(0.808)	(1.024)
	2.656***	0.759	0.500	-0.110	1.346
Exam cumulative subjects	(1.021)	(0.889)	(0.815)	(1.007)	(1.275)

*10%,** 5%,*** 1% significance levels.

[1]Average value of direct friends.

Source: Authors' calculation from FUNDAJ dataset.

Table 5: Maximum Likelihood Estimation: High level networks

Variable	Coefficient	(Std. Err.)	$Pr(>\|z\|)$
Individual Characteristics			
Peer Effect	-0.0033915		0.8018
(Intercept)	40.320581	17.332548	0.0200029
First score	0.468895	0.039601	$2.2e-16$
Male	2.979830	2.078714	0.1517160
Ethnicity (White)	-1.260833	-0.7864	0.4316137
Age	-3.413563	0.936298	0.0002666
New to School	-1.940433	2.135724	0.3635827
Number of friends(indegree)	0.696479	0.424734	0.1010469
Encouragement from teacher	-0.365056	0.982875	0.7103270
Personality	-0.172616	0.712243	0.8085051
Feels left out in classroom	2.382426	1.093082	0.0292910
Popularity	0.187147	0.920524	0.8388965
Number of Friends	-1.376384	0.559258	0.0138516
Goes to a club or gym	0.420079	1.490949	0.7781330
Religiousness	-1.053235	0.867212	0.2245545
Your neighbourhood safety	2.686361	1.617561	0.0967641
Number of friends in classroom	-0.558696	0.589640	0.3433741
Educational level(tutor)	0.061591	0.193683	0.7504851
Male(tutor)	0.474418	1.788315	0.7907878
Ethnicity(White-tutor)	1.332670	1.759977	0.4489248
Tutor age	0.186102	0.083111	0.0251429
Conjugal	-1.003338	1.317721	0.4464069
Kinship to the student	3.296814	1.851944	0.0750447
Social Programs	0.658794	1.392049	0.6360311
Checks student report card	-0.627243	1.393875	0.6527108
Peers Characteristics[1]			
Male	-3.245887	2.333552	0.1642363
Ethnicity(White)	3.473887	1.3621	0.1731614
Religiousness	-1.591493	1.380059	0.2488257

New to school	5.237380	3.522118	0.1370155
Goes to a club or gym	-1.980084	2.297166	0.3887052
Number of friends(indegree)	0.189338	0.675233	0.7791678
Personality	1.559192	1.139105	0.1710660
Feels left out in classroom	-2.219928	1.951985	0.2554266
Popularity	-1.346084	1.548948	0.3848302
Your neighbourhood safety	-1.499150	2.311847	0.5166847
Encouragement from teacher	0.570429	1.595772	0.7207455
Educational level(tutor)	0.128122	0.304615	0.6740447
Male(tutor)	3.894396	2.558378	0.1279557
Ethnicity(White-tutor)	1.030546	2.455050	0.6746567
Tutor age	0.042816	0.127341	0.7366938
Conjugal	-0.164913	1.991916	0.9340175
Kinship to the student	-1.342400	2.812335	0.6331301
Social Program	-0.453835	2.081055	0.8273674
Checks student report card	-1.490868	1.978370	0.4510990
First score	0.019626	0.054472	0.7186278

[1] Average value of direct friends

Source: Authors' calculation from FUNDAJ dataset.

Table 6: Maximum Likelihood Estimation: Middle level networks

Variable	Coefficient	(Std. Err.)	$Pr(>\|z\|)$
Individual Characteristics			
Peer Effect	0.003785		0.71911
(Intercept)	32.7335527	11.7468732	0.0053268
First score	0.4014104	0.027682	2.2e-16
Male	0.9304878	1.5905723	0.5585464
Ethnicity (White)	-0.7674998	1.0900451	0.4813711
Age	-1.5998272	0.5850429	0.0062466
New to School	0.1611107	1.3417277	0.9044221
Number of friends(indegree)	-0.2975704	0.2870672	0.299928
Encouragement from teacher	-0.9833586	0.6619364	0.1373906
Personality	0.2158687	0.499848	0.6658369
Feels left out in classroom	0.4466892	0.7668726	0.5602423
Popularity	0.7231029	0.6348746	0.2547158
Number of Friends	-0.1290448	0.3591675	0.7193792
Goes to a club or gym	0.3780228	1.0178672	0.7103492
Religiousness	0.4253011	0.6136035	0.488234
Your neighbourhood safety	-0.7681494	1.0643127	0.4704588
Number of friends in classroom	-0.5742784	0.4135859	0.1649743
Educational level(tutor)	0.1650726	0.1340457	0.2181488
Male(tutor)	-0.8600787	1.3029759	0.5091974
Ethnicity(White-tutor)	0.7107775	1.1166723	0.5244415
Tutor age	0.0280198	0.0578147	0.627926
Conjugal	2.1652999	0.8583866	0.0116516
Kinship to the student	0.1712268	1.2074916	0.887235

Social Programs	-1.1091901	0.917108	0.2264926
Checks student report card	-1.3123455	0.8514039	0.1232219
Peers Characteristics[1]			
Male	-0.7447512	1.793482	0.6779557
Ethnicity(White)	-2.3068092	1.6778329	0.1691704
Religiousness	-0.6188262	0.9192988	0.5008517
New to school	-0.2264667	1.8626283	0.9032281
Goes to a club or gym	-0.8759231	1.5886384	0.581382
Number of friends(indegree)	0.4956827	0.4412018	0.2612324
Personality	-0.3390526	0.7654541	0.6578069
Feels left out in classroom	-0.663294	1.2041885	0.5817554
Popularity	-0.1159964	0.9944615	0.9071435
Your neighbourhood safety	-1.483799	1.6046503	0.3551288
Encouragement from teacher	-1.1445551	1.0873111	0.2925026
Educational level(tutor)	0.1970703	0.1933749	0.3081508
Male(tutor)	-0.1765275	1.8876112	0.9254913
Ethnicity(White-tutor)	-0.2133573	1.6353766	0.8961995
Tutor age	0.0421676	0.0834527	0.6133571
Conjugal	0.9393305	1.3245236	0.4782105
Kinship to the student	-0.2329234	1.7251388	0.8925983
Social Program	-0.2925507	1.3435194	0.8276243
Checks student report card	1.5304139	1.3344394	0.2514399
First score	0.0098097	0.0433677	0.8210467

[1] Average value of direct friends

Source: Authors' calculation from FUNDAJ dataset.

Table 7: Maximum Likelihood Estimation: Low level networks

Variable	Coefficient	(Std. Err.)	$Pr(>\|z\|)$
Individual Characteristics			
Peer Effect -0.0056728		0.74263	
(Intercept)	45.846288	15.266541	0.002673
First score	0.23673	0.046691	3.976e-07
Male	-2.215861	1.9749	0.261857
Ethnicity (White)	-3.149541	1.652754	0.056698
Age	-1.104055	0.682047	0.105504
New to School	1.927347	1.75319	0.271621
Number of friends(indegree)	-0.184147	0.423546	0.663726
Encouragement from teacher	0.050724	0.909409	0.95552
Personality	1.883547	0.681995	0.005748
Feels left out in classroom	-1.006938	1.022469	0.324717
Popularity	0.945104	0.919634	0.304093
Number of Friends	-0.547214	0.521693	0.294215
Goes to a club or gym	-1.23927	1.446048	0.391442
Religiousness	-0.248839	0.878435	0.776966
Your neighbourhood safety	1.40048	1.455904	0.336084
Number of friends in classroom	0.821174	0.575961	0.153942

Educational level(tutor)	0.167183	0.1878	0.373348
Male(tutor)	0.934665	1.939387	0.62985
Ethnicity(White-tutor)	2.244543	1.699755	0.186665
Tutor age	0.079619	0.082638	0.335313
Conjugal	-1.81768	1.23035	0.139577
Kinship to the student	-0.443059	1.688339	0.792995
Social Programs	0.511866	1.389614	0.712611
Checks student report card	-1.145778	1.053698	0.276866
Peers Characteristics[1]			
Male	6.571005	2.299755	0.004273
Ethnicity(White)	-0.266699	2.399141	0.911486
Religiousness	-0.719404	1.310343	0.582992
New to school	-1.647269	2.24229	0.462561
Goes to a club or gym	1.165412	2.45057	0.634383
Number of friends(indegree)	-0.479376	0.621137	0.44025
Personality	-0.414169	1.015413	0.68336
Feels left out in classroom	-0.717329	1.479888	0.627876
Popularity	-0.860136	1.295062	0.506584
Your neighbourhood safety	-2.956238	2.169589	0.173015
Encouragement from teacher	-0.790999	1.30724	0.545119
Educational level(tutor)	-0.148915	0.263888	0.572541
Male(tutor)	-5.548346	2.866766	0.052941
Ethnicity(White-tutor)	0.900826	2.376725	0.704673
Tutor age	0.191444	0.121404	0.114814
Conjugal	-1.962211	1.726327	0.255689
Kinship to the student	-0.560841	2.556624	0.826363
Social Program	-3.340075	2.039569	0.101497
Checks student report card	-1.869834	1.550727	0.227903
First score	0.064289	0.067736	0.342562

[1] Average value of direct friends

Source: Authors' calculation from FUNDAJ dataset.