**PEER NON-COGNITIVE SELF-PERCEPTION AND SCHOOL PERFORMANCE: ESTIMATES USING THE STUDENT FRIENDSHIP NETWORK AT CLASSROOM LEVEL**

Michela Barreto Camboim Gonçalves – Researcher at the Fundação Joaquim Nabuco – Ministry of Education, Brazil.

E-mail: [michelabcg@hotmail.com](mailto:michelabcg@hotmail.com)

Address: Rua Dois Irmãos, 92 - Ed. Anexo Anízio Teixeira - Apipucos – Recife/PE CEP: 52071-440

Phone: (81) 999170335

Isabel Pessoa de Arruda Raposo – Researcher at the Fundação Joaquim Nabuco – Ministry of Education, Brazil.

Email: [i\_raposo@hotmail.com](mailto:i_raposo@hotmail.com)

Address: Rua Dois Irmãos, 92 - Ed. Anexo Anízio Teixeira - Apipucos – Recife/PE CEP: 52071-440

Phone: (81) 996330181

**ABSTRACT:** This article investigates whether the individual academic performance is affected by peers’ self-perception about own personality and being valued in the classroom. The empirical estimations use a unique educational dataset that comes from a research institute of the Brazilian Ministry of Education (Fundação Joaquim Nabuco – FUNDAJ/ MEC, 2013), which provides crucial information for the proposed identification strategies. These strategies are based on: (i) the architecture of friendships network composed of heterogeneous reference groups within the classroom, (ii) the use of longitudinal evaluation of scholastic achievement, where all the students surveyed are submitted to a math test in the beginning and at the end of scholar year and (iii) the control of the network fixed effects. The results show students perform better when their friends demonstrate a positive self-perception of own personality and do not feel left behind in the classroom. Furthermore, when omitted variable bias is controlled for, the impact of peers’ socio emotional skills on individual achievement is even stronger.

**Keywords:** Self-perception, Peer Effects, School Performance, Friendship Networks.

**RESUMO:**Este artigo investiga se o desempenho acadêmico individual é afetado pelo autoconceito de seus pares quanto à personalidade e sentimento de pertencimento à turma. As estimações empíricas utilizam uma pesquisa da Fundação Joaquim Nabuco (FUNDAJ/ MEC, 2013) que traz informações cruciais para as estratégias de identificação propostas. Essas estratégias se baseiam: (i) na arquitetura de redes de amizades em sala de aula compostas por grupos de referência heterogêneos, (ii) na utilização de uma avaliação longitudinal do desempenho em duas provas de matemática e (iii) no controle do efeito fixo da rede. Os resultados mostraram que os alunos apresentam melhor desempenho acadêmico quando se relacionam com outros estudantes que têm autoconceito positivo de sua personalidade e que se sentem valorizados por seus colegas de turma e professores. E mais, quando se controla o viés de variáveis omitidas, o impacto das questões socioemocionais dos pares sobre o desempenho é ainda maior.

**Palavras chave**: Autoconceito, Efeito de Pares, Desempenho Escolar, Rede de Amizades.

**JEL: I21, I28, I39**

**Submeter à Área 12:** **Economia Social e Demografia Econômica**

**PEER NON-COGNITIVE SELF-PERCEPTION AND SCHOOL PERFORMANCE: ESTIMATES USING THE STUDENT FRIENDSHIP NETWORK AT CLASSROOM LEVEL**

**1 Introduction**

One of the prominent issues within the economics of education is devoted to understanding the role of peers in educational outcomes[[1]](#footnote-1). The behavioral influence received from friends in the social interaction process might affect educational results not only during the schooling period, but also latter in life, having an effect on standards of educational attainment to employment decisions. In the school environment, peer effects can be disseminated by externalities of knowledge or by imitation and contagion, in which case students have individual motivations for displaying a behavior/performance that is consistent with the group in which he or she is inserted.

Most studies evaluate the peers’ influence on the learning process for some measure of cognitive abilities such as grades, school attainment, grade repetition, etc. Less well investigated is the influence, on individual achievement, of peers’ non-cognitive or socio-emotional skills, which includes a range of personality features and social behavior, such as curiosity, perseverance, conscientiousness, self-control, positive self-perception, optimism, empathy and joy. Does the degree of joy or positive self-perception of a child’s friend have an impact on this child academic performance, independently of friend’s academic performance?

There is, indeed, a large emerging body of research showing the importance of the so-called non-cognitive skills on own individual success, inaugurated in the economics literature by Heckman *et al.* (2006). In Brazil, the Ayrton Senna Institute and the Organization for Economic Cooperation and Development (OECD) conducted a survey with 24,600 students of public schools in Rio de Janeiro State, and developed a tool to measure socio-emotional skills. Some of the conclusions are that stimulating the learning of skills such as planning and leadership among students improved their performance in mathematics and Portuguese language [SANTOS AND PRIMI (2014)].

Few evidence, whatsoever, were found for the effect of peers’ socio-emotional attributes on individual educational outcomes, even though there exists a wide documentation that sociability is strongly associated with non-cognitive skills and, as a consequence, non-cognitive peers effect may be disseminated in group interactions. In Brazil, the closest evidence we found was the work of Chikitani *et al.* (2015) that investigates how peers’ *locus of control* determines the individual’s *locus of control*. This paper contributes with this scarce literature and seeks to investigate the role of classmates’ self-perceptions about non-cognitive traits on individual academic performance.

Empirical identification of such peer effects, however, is an arduous exercise. As first noted by Manski (1993), and after by many other authors, the greatest difficulty is to properly separate the effect of peers’ non-cognitive self-perceptions in itself, from other contextual or non-observable correlated effects. In the present article, the contextual effect captures the effects of exogenous peers attributes, such as age, gender, race, etc, on individual outcome. The correlated or confounding effects correspond to non-observable characteristics shared by individuals in the same group that might be correlated with the peer variable of interest. These common traits occur either for being exposed to the same institutional environment, or for homophily, which is the propensity of people with similar attributes to associate with each other. In other words, the student group formation is susceptible to a self-selection bias that challenges the econometric estimations of peer effects.

We address these issues by proposing an identification strategy that uses the architecture of social networks - structures that keeps track of all the links among its members and builds information flow, social norms, and social behaviors (e.g. Patacchini and Venanzoni, 2014; Badev, 2014; Patacchini *et al.*, 2011; Mele, 2010; Calvó-Armengol *et al.,* 2009; Bramoullé *et al.,* 2009; and Ballester *et al.,* 2006). The main idea behind this strategy is that the students’ reference groups are not homogeneous; they might be different in sizes, and not necessarily completely overlap. For example, it is possible that within the same network student *i* and *j* are friends, student *j* and *k* also, but *i* and *k* are not friends, as a result an intransitive triad is formed and the only way *k* could influence *i’s* behavior is through *j*. Bramoullé e*t al.* (2009) argue this network structure based on intransitive triads provides natural exclusion restrictions, which in turn permits peer effects identification. Following these authors, we also assume that correlated unobservables are treated as network fixed effects.

For the empirical estimations, we use a unique educational dataset that comes from a research institute of the Brazilian Ministry of Education (Fundação Joaquim Nabuco/ FUNDAJ, 2013), which provides a large information set on the student’s school environment and family background. This dataset offers three crucial features for identifying the effect of peers’ non-cognitive self-perception: (i) raises the direct friendship network within the classroom; (ii) provides a rich set of control variables, including the students’ self-reported perceptions about their personality, behavior, and future aspirations; and (iii) provides a longitudinal evaluation of scholastic achievement, where all the students surveyed are submitted to a math test in the beginning and at the end of scholar year, which is especially appropriate to control for preexisting differences between students.

Besides this introduction, the work is divided in five sections. Section two reviews evidence published mainly on the fields of psychology and economics about the role of non-cognitive abilities on various outcomes (educational, professional, and social), establishing a link with the peer effects literature. The third section presents the database and variables used in the estimations. The fourth discusses the econometric model and its empirical implementation. The results are shown in the fifth section, and the concluding remarks are given at the end.

**2 Previous evidences**

There is a vast literature dedicated to understand the role of peers on individual behavior. Several studies demonstrate peers influence through the spread of some measure of cognitive skills (e.g.: Case and Katz, 1991; Evans *et al.,* 1992; Sacerdote, 2001; Zimmerman, 2003; Hanushek *et al*., 2003; Ballester *et al.,* 2006; Ding and Lehrer, 2007; Goux and Maurin, 2007; Vigdor and Nechyba, 2007; Duflo *et al.,* 2008; Bramoullé *et al.,* 2009*;* Calvó-Armengol *et al.,* 2009; Sund, 2009; Eisenkopf *et al.*, 2011; Patacchini *et al.*, 2011; Oosterbeek and Van Ewijk, 2014; Patacchini and Venanzoni, 2014 and Badev, 2014; Raposo, 2015).

Less studied is the impact of peers’ non-cognitive skills on individual behavior, even though group interaction, naturally, presents a potential to improve socio-emotional abilities. In fact many studies demonstrate that friends enhance individual satisfaction and the development of pro-social behavior. Robinson and Tayler (1986, 1991) argue a student's group of friends can play a key role in the reorganization of values through affiliation mechanisms that lead to a high level of identification with the group in question. Aboud and Mendelson (1996) show children with reciprocal friends[[2]](#footnote-2) are more independent, emotionally more mature, unselfish, exhibit pro-social behavior and are less aggressive than those who do not have that kind of relationship with friends. Wentzel *et al.* (2004), in turn, found that friendless students show lower levels of pro-social behavior, reduced school performance and increased problems with self-esteem and motivation compared to that of adolescents with reciprocal friends.

Recently the role of such socio-emotional abilities on individual outcomes has been a subject of a growing research agenda in the economics literature. Heckman *et al.* (2006) show non-cognitive skills strongly influence schooling decisions, and also affect wages given schooling decisions. In the US, the Perry Preschool Program targeted disadvantaged children that were randomly assigned to treatment and control groups and both were followed to age 40. The results show that the Program did not affect IQ tests (cognitive traits) in both groups, but improved significantly the schooling and social skills of the treatment group (Heckman *et al.,* 2006).

Two main points should be highlighted from the presented evidences: first, there exists a positive association between sociability and non-cognitive abilities and, second, such skills plays important role on personal success. Thus, it is natural to expect that friends’ endowments of socio-emotional skills might also play a role on individual cognitive outcomes. In this context, our goal is study the influence of peers’ non-cognitive self-perceptions on the student academic performance.

**3 The dataset and descriptive statistics of the variables**

This article uses a unique dataset from a survey conducted by the Joaquim Nabuco Foundation - FUNDAJ in 2013 with a sample of students in the 6th year of Public Schools in the city of Recife, Pernambuco State of Brazil. The research evaluated student performance on two math tests (developed by FUNDAJ and applied at the beginning and the end of the school year) and also collected a large set of information on internal and external aspects of school life through four types of questionnaires (one for students, one for the primary adult responsible for each child’s academic life, one for the math teacher, and another one for the school principal). The main highlight of the research was the identification of the student friendship networks inside the classrooms, an unprecedented type of data in Brazilian educational surveys and crucial to the identification of peer influence in the learning process. The main highlight of the survey was the identification of the student friendship networks inside the classrooms. This type of data is crucial for identifying the extent of peer influence on the learning process. In the student’s questionnaire, they listed up to five best friends and reported whether they were classmates, whether they studied together, whether they go to each other’s houses, and whether they talk about problems. The student’s caregivers also reported whether they knew those friends and/or their families and what kind of influence they believed these friends had on their child. Thus for every friend from the classroom, the data included not only the friend’s grade on the two math tests, but also, all of the additional information collected from the questionnaires. The survey also raised the perception of students about their self-esteem and their future aspirations, thus providing relevant information to investigate to which extent friends' socio-emotional skills may affect the academic performance of a student.

In total, 4,191 students, 3,670 parents or guardians, 120 principals, and 131 teachers from 120 schools were interviewed. The school units were spatially distributed among 18 micro-regions of Recife[[3]](#footnote-3). In some schools with higher enrollment in the 6th year, two groups were randomly selected, not just one. For this reason, the total number of classrooms selected for the sample was 146. After the exclusion of individuals with inadequate or missing information, the final sample consisted of 139 networks/classrooms and 1,855 students. This decrease of 56% compared to the original sample size (146 classes and 4,196 students) is due in large part to the very process of a friendship network construction: for 48% of interviewed students, the friendships that were cited could not be properly paired or the student did not name any friends in his/ her class. Other losses (about 15%) were due to the elimination of missing data. This large decrease in sample size is common when working with information from friendship networks. For instance, the various studies that use data from research called *Add Health*, which also considers student's friendship networks, face even greater losses in sample size. Some examples being, Patacchini and Venanzoni (2014) who work with only 19% of the saturated sample while using *Add Health*; Badev (2014) utilized 5.4% and Mele (2010) 5.5%. Only Cálvo-Armengol et al. (2009), with 55%, and Bramoullé et al. (2009), with 61%, worked with percentages of the original sample similar to this article.

Table 1 shows the definition and descriptive statistics of the variables used in the estimations of this paper. The performance in math was assessed at the beginning and at the end of school year and, on average, students in the sample had about 40% success, with no significant variation during the period of study. The initial average score was slightly higher than the final, 41.92 and 41.15, but also presented a higher dispersion. 45% of the students are male and 19% of all students declare themselves to be white. Students have an average age of 11 years, which is expected for students in 6th year of elementary school. There is a high percentage of newcomers, about 70% of the sample, which may be a result of the decentralization of basic education leading to the migration of students from the state-run schools to municipal schools.

Although most students feel satisfied with their personality and don't feel left out in the classroom, still about a quarter of the students strongly agree with the statement, "I would change something in my personality" or feel sometimes left out in the classroom. Most students (72%) stated that they study school material at least three days a week. More than half (60%) stated that the math teacher always praises them when they get a good grade or perform a task. The participation of sample students at masses or other church services is significant, 85% say they attend church sometimes or always.

The perception of safety in the neighborhood is very positive, 79% of the students say they feel secure, though less than a quarter of them have the habit of frequenting clubs or gyms in their neighborhood. 58% of the students visit the home of at least one classroom friend.

With regard to the adult that is responsible for the student's school studies, 82% of them are biological or adoptive parents, 87% are female, 17% declare they are white. The average age of the guardians or parents is 38 years. The average amount of schooling of those responsible is nearly nine years of study, corresponding to completing elementary school and the vast majority (85%) usually check the student's report card. 45% of those responsible are not married nor are in any stable relationship. In addition, 62% of them receive some kind of social benefit or aid from the government.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 1**  **Definition and descriptive statistics of the variables** | | | | |
|  | | Definition of Variables | Average | Standard Deviation |
| ***Dependent Variable (y)*** |  | |  |  |
| Math grade at the end of the year | Grade of the student *i* on math test conducted by FUNDAJ (2013) at the end of school year. Rating scale ranges from 0 to 100. | | 41.15 | 15.66 |
|  | | | | |
| ***Peers’ Self-Perception*** |  | |  |  |
| Personality | Student answers the question "I would change something in my personality": 1 = strongly agree, 2 = perhaps, 3 = strongly disagree | | 2.41 | 0.87 |
| Left out in classroom | Student answers the question "Do you feel left out in class": 1 = always or almost always, 2 = sometimes, 3 = never or almost never | | 2.70 | 0.57 |
| ***Individual Characteristic* *(X)*** |  | | | |
| Initial math grade *(y0)* | Grade of student *i* on math test conducted by FUNDAJ (2013) at the beginning of school year. Rating scale ranges from 0 to 100. | | 41.92 | 15.88 |
| Male | Dummy equals 1 if student is male | | 0.45 | 0.50 |
| Whites | Dummy equals 1 if students declare themselves as white and 0 if they describe themselves as black, mixed race, Asian, or indigenous | | 0.19 | 0.39 |
| Age | Age of the student in years | | 11.19 | 0.87 |
| Newcomer | Dummy equals 1 if student has been attending the school researched for less than one year | | 0.73 | 0.45 |
| Dedication to Studies | Student answers the question "How often do you study the school materials:" 1 = every day of the week, 2 = only on school days, 3 = 3 days per week, 4 = less than 3 days per week, 5 = only if there is a test, 6 = never or almost never | | 2.57 | 1.52 |
| Praise from Teacher | Student answers the question "the math teacher praises or congratulates you when you get a good grade or do the homework well": 1 = always or almost always, 2 = sometimes, 3 = never or almost never | | 1.49 | 0.66 |
| Visits to friends’ houses | Number of friends in the class who students regularly visit | | 1.06 | 1.25 |
| Religiousness | Student answers the question "Do you ever go to church/mass?": 1 = always or almost always, 2 = sometimes, 3 = never or almost never | | 1.75 | 0.70 |
| Sports clubs, gyms | Dummy equals 1 if student attends a sports club, sports center or fitness facility in their neighborhood | | 0.23 | 0.42 |
| Safety in the neighborhood | Dummy equals 1 if student says they feel safe in their neighborhood | | 0.79 | 0.40 |
| Male sex (parent or guardian) | Dummy equals 1 if a parent or person responsible for the student is male | | 0.13 | 0.34 |
| White (parent or guardian) | *Dummy* equals one for parents/guardians who declare *themselves* white and 0 if they declare themselves as black, mixed race, Asian, or indigenous | | 0.17 | 0.38 |
| Age (parent or guardian) | Age of student’s primary parent or guardian in years | | 38.48 | 8.16 |
| Educational level (parent or guardian) | Parents/guardians answer the question: "What is the highest grade finished successfully?": 1 = 1 year (literacy), ..., 9 = 9 years; 10 = 1 year of high school, ..., 12 = last year of high school; 13 = 1 year of university ..., 18 = final year of university | | 8.85 | 3.44 |
| Marital Status (parent or guardian) | Dummy equals 1 for parents/guardians married with a legally recognized union or common-law marriage | | 0.55 | 0.50 |
| Kinship (parent or guardian) with student | Dummy equals 1 for natural or adoptive parent and 0 for the other cases (grandparents, uncles, brothers, stepfather / stepmother, etc.) | | 0.82 | 0.38 |
| Beneficiary of social program (parent or guardian) | Dummy equals 1 if parents/guardian receives any government financial assistance | | 0.62 | 0.49 |
| Student grade report (parent or guardian) | Parents/guardians answered the question "Do you check the student’s grade report?”: 1 = always or almost always, 2 = sometimes, 3 = never or almost never | | 1.20 | 0.51 |
|  |  | |  |  |
| ***Peers’ characteristic (GX)*** | Average values of all students’ control variables among the group of direct friends of student *i* | | | |
|  |  | |  |  |
| *No. of observations: 1,855 students*  *No. networks/classrooms: 139 classrooms* | | | | |
| Source: Original compilation based on FUNDAJ (2013). | | | | |

**4 Econometric Model and Estimation Strategies**

Our empirical model departs from Manski’s (1993) *linear-in-means* model, in which the individual outcome is predicted by the mean characteristics of the group, all members are equally influent and have the same reference groups. In Manski’s approach the friends of student *i* are not directly identified, but assumed to be similar to an average of *i*. Thus, the dependent behaviour of intra-group members is treated homogenously; that is to say, each individual of the group is influenced by a set of average attributes which is exactly the same for all members of this group. The problem with this *linear-in-means* approach is that there is no empirical support to ensure the homogeneity of such intra-group externality. In fact, the way an individual influences another within the same group may vary according not only to their personal attributes, but also to their level of sociability within a given social network.

We extent Manski’s model to allow for intra-group diversity and use the architecture of social networks to identify each student reference group. The main idea behind this strategy is that the students’ reference groups are not homogeneous; they might be different in sizes, and not necessarily completely overlap. For example, it is possible that within the same network student *i* and *j* are friends, student *j* and *k* also, but *i* and *k* are not friends, as a result an intransitive triad is formed and the only way *k* could influence *i’s* behavior is through *j*. Bramoullé e*t al.* (2009) argue this network structure based on intransitive triads provides natural exclusion restrictions, which in turn permits peer effects identification.

Formally the model that describes the influence of peers’ non-cognitive self-perceptions on the individual performance can be represented by equation (1), where *yi* denotes the student’s *i* academic performance, including test grades, and *NC****j*** a vector of variables related to non-cognitive self-perceptions of student *j*.

|  |  |
| --- | --- |
| ; | (1) |

where:  ***λl***  is a vector of coefficients that captures the effect of peers’ non-cognitive self-perceptions on the student performance; represents the student's initial educational background and can be interpreted as an innate condition for learning and *gij* denotes the connections within the network. There is an active connection, or a friendship relation, within the network when *gij = 1* and not active when *gij = 0*, by convention*gii = 0*. The terms and represent individual and group unobservable heterogeneities, respectively. The component *θ(****x****)* introduces the exogenous observed heterogeneity that captures the differences between the individuals. Examples would be gender, race, age, family background, as well as some exogenous characteristics of direct friends, also called context variables, such as average parental education, the socio-demographic composition of the class, among others. The component *θ(****x****)* is expressed by equation (2) and the definition of its variables is presented in Table 1.

|  |  |
| --- | --- |
|  | (2) |

In matrix notation, equation (1) is denoted by:

|  |  |
| --- | --- |
| where: | (3) |

***G*** is constructed so as to form a block diagonal matrix, where the interaction matrix of each classroom *k = 1, 2, ..., K*, forms a specific block [[4]](#footnote-4). As a result, students who belong to a particular network or class, *gk*, do not connect to students in other networks and the total number of students corresponds, therefore, to the sum of them on each network: .

We hypothesize that there are several possible channels under which peers’ self-perception potentially affect academic performance. First, it may affect peers’ academic achievement which also determines student’s achievement. Second, there might exist endogenous peer effects amongst students’ non-cognitive skills which, in turn, influence educational outcome. Third, observed peers’ self-perception could be reflecting other latent skills, such as patience, generosity, motivation, making these peers more willing to help and share knowledge with their friends. Finally, peers’ socio-emotional characteristics may affect the way teachers treat the group, this in part shapes the learning environment the student encounters.

Ideally we would like to disentangle the effect of peers’ non-cognitive self-perception on academic performance (the structural parameter) from the effects which result from social interaction. However, since most of the non-cognitive skills are hardly measured, the resulting estimate is the combined (reduced form parameter) impact of peers’ non-cognitive self-perception on academic performance. This reduced form parameter is of policy interest especially if there exist some systematic patterns in the way the teachers, students and peers respond to certain conditions of group behaviors.

Now, it is worth noting a few remarks. First of all, least squares estimations of equation (1) require that the effect of peers’ non-cognitive self-perceptions on the student performance to be an exogenous interaction effect. There are indeed some evidences in the psychology literature suggesting a child personality is not subjected to contemporaneous peers’ personality influence. For instance, Berndt and Keef (1995) argue that group influence on individual behavior is not an immediate phenomenon and should be observed only after some time of members’ interaction. Wentzel *et al.* (2004) find that a student specific socio-emotional characteristic can predict group behavior after two years, in part because this same student has incentives to conform to the group behavior. In Section 5.1, we implement a robustness test that demonstrates there is not a statistically significant endogenous interaction effect for the non-cognitive self-perceptions variables. Also Chikitani *et al.* (2015) do not find evidence of endogenous peer effects in students’ locus of control. An additional remark is that least squares estimators also require the friendship matrix ***G*** to be uncorrelated with the error term, which is indeed a very strong assumption, since most probability unobservable students’ characteristics affect the friendship bonds.

We address these issues by proposing an identification strategy based on the assumptions that the exogeneity of ***GNC*** is met once equation (1) is conditioned to network fixed effects () and individual fixed effects (), such as . The strategy adopted to control for the network fixed effect is the inclusion of dummies per classroom/ network, which is the procedure usually adopted in the literature, as seen in Patacchini and Venanzoni, (2014); Calvó-Armengol *et al*, (2009); Bramoullé *et al*., (2009) and Lee, (2007). This strategy, however, cannot be adopted for the control of individual fixed effect, since we do not have panel data. However, since the outcome variable is observed at two times, the beginning and end of the school year, the strategy to control for the individual fixed effects will be based on two assumptions: (i) the student's initial grade and (ii) the assumption that when networks are sufficiently small, the inclusion of network fixed effects is a good approximation to also capture the individual attributes that are not observed.

With respect to the first assumption, Ding and Lehrer (2007) argue that the student's initial grade would be a sufficient statistic for capturing a variety of influences that may confound the analysis and include all observable and unobservable historical background information on family, school, and student’s community. The authors assume, hypothetically, that the student's initial grade follows a Markov process and, therefore, previous observable and unobservable factors in *t-1* conform to the same rate, so that none of these would cease to be represented by *yi, t-1.* The authors’ assumption therefore allows the student’s initial grade to work as a kind of individual fixed effect, since it brings with it unobservable components (such as effort, skill, etc.), which are invariable throughout the school year[[5]](#footnote-5). Thus, may act as a *proxy* for the student’s initial educational background.

In order to test the validity of the identification strategies proposed here, two robustness tests are applied in the Section 5.1 to check the exogeneity of ***GNC*** matrix given the control of network fixed effects (*dummies* per class) and individual fixed effects (initial grade).

**5 Results**

The estimation results of the empirical model (3) are presented in this section. A variety of models are tested using three variables that capture different aspects of friends’ non-cognitive self-perceptions: (i) "personality", in which the variable takes the value *1* when the student says that he/she fully agrees with the desire to change personality and *3* when he/she strongly disagrees; (ii) "left out in class," where the variable takes the value *1* when the student says he/she always or almost always feels left out in class and *3* when he/she says that never or hardly ever feels left out; (iii) " sum = personality + feeling left out", this derived variable is a simple sum of the first two and can be understood as an non-weighted index of two aspects of non-cognitive self-perceptions. Estimations use the indirect friendship network[[6]](#footnote-6), because only when the ***G*** matrix is symmetric it is possible to implement the robustness tests provided in the next section[[7]](#footnote-7).

The results of the model estimates (3) are reported in Table 2. For each model estimates are made in increasing order of covariates inclusion. The positive and significant coefficient λ shows that the individual academic result is directly correlated with his/ her friends’ non-cognitive self-perceptions. The strength of this correlation grows as additional regressors are inserted and when controlling for network fixed effects, as depicted in the second column of each model. This reveals how these regressors, somehow, help to capture the unobservable heterogeneity present in the analysis. The coefficients of the variables "personality" and "left out in class" have very similar magnitudes, but when it is estimated as the sum of the two, the impact is reduced, demonstrating that when some dimension of a friend's socio-emotional aspect is omitted, a negative bias of the omitted variable starts to act.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 2**  **Equation Estimations (3)**  **Dependent Variable: Math test grade at end of year** | | | | | | |
|  | **(i)**  **Personality** | | **(ii)**  **Left out of the classroom group** | | **(iii)**  **Sum**  **(personality + left out)** | |
| **1** | **2** | **3** | **4** | **5** | **6** |
| **Friend's self-perception (*λj*)**  *(Test statistics)* | 0.225  (2.90) | 0.283  (3.25) | 0.249  (3.47) | 0.279  (3.43) | 0.124  (3.27) | 0.147  (3.42) |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Peer Characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed network effect | No | Yes | No | Yes | No | Yes |
| Initial grade | Yes | Yes | Yes | Yes | Yes | Yes |
| *R2 ajusted* | 0.29 | 0.35 | 0.29 | 0.35 | 0.29 | 0.35 |
| Nº of observations | 1,855 | 1,855 | 1,855 | 1,855 | 1,855 | 1,855 |
| Nº of networks | 139 | 139 | 139 | 139 | 139 | 139 |
| Source: Original compilation based on FUNDAJ (2013).  Note: The complete results and statistics may be requested with the authors | | | | | | |

**5.1 Robustness Tests for Identification Strategies**

The identification strategy for spatial models presented in the previous section depends on the observance of . Patacchini and Venanzoni (2014) test this assumption based on the work of Goldsmith-Pinkham and Imbens (2013). Consider again the empirical model (1):

|  |  |
| --- | --- |
|  | (1’) |

Suppose now that there is a model of friendship network formation in which the variables that explain the connection between two students *i* and *j* belonging to a network *k* (*gij,k*) are the distances between the two in terms of the observable and unobservable characteristics, such as:

|  |  |
| --- | --- |
|  | (4) |

A test for the presence of unobservable heterogeneity at the student level consists in checking whether there is a significant correlation between the residuals of equation (1') and the probability of friendship formation. Therefore, it is possible to replace in (4) with from (1') and to estimate model (4). Evidence of exogeneity of the ***G*** matrix would be if . The results of this test are reported in Table 3 and, it turns out that, when there is no control of network fixed effect, we find a significant correlation between the probability of establishing friendship link and the non-observable similarities with peers. However, when dummies per class are entered into the model, this significant correlation disappears, as shown in the second row of Table 3. Therefore, by conditioning to a wide range of controls, to peers’ characteristics, to the initial condition for learning and to group fixed effects, there is no evidence of other unobserved individual attributes that may bias the results found herein.

|  |  |
| --- | --- |
| **Table 3**  **Robustness Tests – Estimations for Equation (4)** | |
|  | OLS |
| Difference between residuals () without control of fixed effect  *(p-value)* | 0.00001  (0.0529) |
| Difference between resíduals () with control of fixed effect  *(p-value)* | 0.00001  (0.504) |
| Source: Original compilation based on FUNDAJ (2013).  Note: Observations include all combinations *ij* between sample pairs used with n = 1,855, which generates a total number of observations for the estimation of (4) *[n\*(n-1)/2 = 1,719,585 observations]*. Control variables used are the same ones included in model (3). | |

A second robustness test seeks to identify the existence of endogenous interaction effects amongst students’ non-cognitive self-perceptions, once it is plausible to assume that students tend to cluster with others that have similar behavior. Accordingly, three separate spatial autoregressive models (SAR) were estimated for the target variables studied: *personality*, *left out of classroom group* and the *sum* *of the two.* The estimated models followed:

|  |  |
| --- | --- |
|  | (5) |

The results are reported in Table 4 and we observe there is no statistically significant spatial correlation between the student’s non-cognitive self-perception and those of direct friends.

|  |  |
| --- | --- |
| **Table 4**  **Robustness Test – Estimations for Equation (5)** | |
| **Estimations *ρ* for non-cognitive self-perception variables** | **SAR** |
| Personality  *(p-value)* | 0.0004  (0.94) |
| Left out of group  *(p-value)* | -0.001  (0.74) |
| Sum: Personality + left out  *(p-value)* | 0.0008  (0.81) |
| Source: Original compilation based on FUNDAJ (2013). | |

**6 Final Considerations**

This paper contributes to a recent debate about the role of non-cognitive or socio-emotional factors on educational performance, establishing a link with the peer effects literature. Specifically, we investigate how peers’ non-cognitive abilities affect student’s math achievement. Using a unique dataset (FUNDAJ, 2013), our identification strategy mainly relies on: (i) the architecture of friendships network composed of heterogeneous reference groups within the classroom; (ii) the use of longitudinal evaluation of scholastic achievement, where all the students surveyed are submitted to a math test in the beginning and at the end of scholar year, which is especially appropriate to control for preexisting differences between students and (iii) the inclusion of classroom dummies to control for the network fixed effects.

The results show that a friend's non-cognitive self-perception directly affects the student's grades. In other words, when a student relates to colleagues with positive self-concepts of their personalities and who feel valued in the classroom, this same student tends to show better academic performance. This positive association is further increased with the inclusion of network fixed effects and the initial math grade. Implemented robustness tests demonstrate that there is no contemporaneous correlation among students’ and friends’ self-perceptions and also that, once conditioning to network fixed effects and initial math grade, the ***G*** matrix might be considered as exogenous.

Educational policy recommendations add to these findings. The evidence presented here points the need for a broader discussion about the role of schools and teachers in promoting significant learning that focuses on the development of non-cognitive skills. It is important to point out that much can still be done in order to understand the restrictions of the learning process. Especially regarding the design of databases, with the inclusion of information, which take into account that the evolution of students is multidimensional and that learning also involves the domains of affective and behavioral skills.

**References**

ABOUD, F. E.; MENDELSON, M. J., 1996. Determinants of friendship selection and quality: Developmental perspectives. In: W. M. Bukowski, A. F. Newcomb, & W. W. Hartup (Eds.), The company they keep: Friendship during childhood and adolescence (pp. 87–112). New York: Cambridge University Press.

BADEV, A., 2014. Discrete games in endogenous networks: theory and policy. Disponível em: <<http://www.antonbadev.com/papers/discr_games_endog_networks.pdf>>. Acessed in: 4 jul. 2014.

BALLESTER, C., CALVÓ-ARMENGOL, A. AND ZENOU, Y., 2006. Who’s who in networks. wanted: the key player. Econometrica, v. 74(5), p. 1403–1417.

BERNDT, T. J.; KEEFE, K., 1995. Friends’ influence on adolescents’ adjustment to school. Child Development, 66, 1312–1329.

BRAMOULLÉ, Y., DJEBBARI, H. AND FORTIN, B., 2009. Identification of peer effects through social networks. Journal of Econometrics, v. 150, p. 41-55.

BUKOWSKI, W. M.; HOZA, B., 1986. Popularity and friendship: Issues in theory, measurement, and outcome. In T. J. Berndt & G. W. Ladd (Eds.), Peer relationships in child development (pp. 15–45). New York: Wiley.

CALVÓ-ARMENGOL, A., PATACCHINI, E. AND ZENOU, Y., 2009. Peer effects and social networks in education. The Review of Economic Studies, v. 76(4), p. 1239-1267.

CASE, A. C., AND KATZ, L. F., 1991. The company you keep: the effects of family and neighborhood on disadvantaged youths. NBER Working Paper 3705.

CHIKITANI, M.; PONCZEK, V.; PINTO, C., 2015. Peer Effects on Locus of Control. Anais do 37º Encontro Brasileiro de Econometria [Proceedings of the 37rd Brazilian Econometrics Meeting], SBE – Associação Brasileira de Econometria [Brazilian Association of Econometric].

DING, W AND LEHRER, S. F., 2007. Do peers affect student achievement in china's secondary schools? The Review of Economics and Statistics, v. 89(2), p. 300-312.

DUFLO, E.; DUPAS, P. AND KREMER, M., 2008. Peer effects, teacher incentives, and the impact of tracking: evidence from a randomized evaluation in Kenya. NBER Working Paper 14475.

EISENKOPF, G., HESSAMI, Z., FISCHBACHER, U., AND HEINRICH, U., 2011. Academic performance and single-sex schooling: evidence from a natural experiment in Switzerland. CESifo working paper: Economics of Education, 3592.

EVANS, W. N., OATES, W. E. AND SCHWAB, R. M., 1992. Measuring peer group effects: a study of teenage behavior. Journal of Political Economy, v. 100(5), p. 966-991.

FUNDAJ - FUNDAÇÃO JOAQUIM NABUCO, 2013. Coordenação de Estudos Econômicos e Populacionais. Acompanhamento longitudinal do desempenho escolar de alunos da rede pública de ensino fundamental do Recife.

GOLDSMITH-PINKHAM, P., AND IMBENS, G.W., 2013. Social networks and the identification of peer effects. Journal of Business and Economic Statistics, v. 31, p. 253–264.

GOUX, D., AND MAURIN, E., 2007. Close Neighbours Matters: Neighbourhood Effects on Early Performance at School. The Economic Journal, vol.117, No.523, pp.1193-1215.

HANUSHEK, E. A., KAIN, J. F., MARKMAN, J. M. AND RIVKIN, S. G., 2003. Does peer ability affect student achievement?*Journal of Applied Econometrics*, v. 18(5), pages 527-544.

HECKMAN, J. J.; STIXRUD, J.; URZUA, S., 2006. [The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior](http://ideas.repec.org/a/ucp/jlabec/v24y2006i3p411-482.html). [Journal of Labor Economics](http://ideas.repec.org/s/ucp/jlabec.html), University of Chicago Press, vol. 24(3), pages 411-482.

LEE, L., 2007. Identification and estimation of econometric models with group interactions, contextual factors and fixed effects. Journal of Econometrics, v. 140, p. 333–374.

MANSKI, C. F., 1993. Identification of endogenous social effects: the reflection problem. The Review of Economic Studies, v. 60(3), p. 531-542.

MELE, A., 2010. A structural model of segregation in social networks. *Working Papers 10-16*, NET Institute.

OOSTERBEEK, H. AND VAN EWIJK, R., 2014. Gender peer effects in university: evidence from a randomized experiment. *Economics of Education Review*, v. 38, p. 51-63.

PATACCHINI, E, RAINONE, E AND ZENOU, Y., 2011. Dynamic aspects of teenage friendships and educational attainment, *CEPR Discussion Paper* 8223.

PATACCHINI, E. AND VENANZONI, G., 2014. Peer effects in the demand for housing quality. *Journal of Urban Economics*, v. 83, p. 6–17.

PNUD *ET AL*. Metodologia de divisão do território do recife adotada no atlas municipal do desenvolvimento humano.In: *Desenvolvimento humano no recife – atlas municipal.* Recife, 2005.

RAPOSO, I. P. A., 2015. O papel da rede de amizades e da formação aleatória de turmas por faixa etária sobre o desempenho. Tese de Doutorado – Universidade Federal de Pernambuco.

ROBINSON, W. P.; TAYLER, C. A., 1986. Auto-estima, desinteresse e insucesso escolar em alunos da escola secundária. Análise Psicológica, 5, 105-113.

ROBINSON, W. P.; TAYLER, C. A., 1991. Correlates of low academic achievement in three countries: England France and Japan. Análise Psicológica, 9, 277-290.

SACERDOTE, B., 2001. Peer effects with random assignment: results for Dartmouth rommates. *The Quartely Journal of Economics*, v. 116(2), p. 681-704.

SANTOS, D.; PRIMI, R., 2014. Resultados Preliminares do Projeto de Medição de Competências Socioemocionais no Rio de Janeiro. Instituto Ayrton Senna, São Paulo.

SUND, K., 2009. Estimating peer effects in Swedish high school using school, teacher, and student fixed effects. *Economics of Education Review*, v. 28, p. 329–336.

VIGDOR, J. L. AND NECHYBA, T. J., 2007. Peer effects in North Carolina public schools.In: WOESSMANN, L; PETERSON, P. E (editors). *Schools and the equal opportunity problem*, p. 73-102, MIT Press.

WENTZEL, K. R.; CALDWELL, K. A.; MCNAMARA, C. B., 2004. Friendships in Middle School: Influences on Motivation and School Adjustment. Journal of Educational Psychology, vol.96, nº2, 195-203.

ZIMMERMAN, D. J., 2003. Peer effects in academic outcomes: evidence from a natural experiment. The Review of Economics and Statistics, v. 85(1), p. 9-23.

1. The sense of the term p*eers* in this article refers to all members belonging to a reference group, such as: same grade, classroom, school, neighborhood, etc. [↑](#footnote-ref-1)
2. Both in psychology and in literature about friendship networks, when identifying friendship relationships, there exist differences in direction of the consideration of friends. A child or adolescent may consider another child or adolescent as a friend, but not necessarily the other considers the same. A reciprocal friendship is when two friends mutually indicate the other as a friend. [↑](#footnote-ref-2)
3. Each political-administrative region of Recife is divided into three micro-regions "in order to define municipal interventions at the local level and in coordination with the population". Each region is composed of one or more of the 94 Districts established by Brazilian Law. The 18 micro regions correspond to the division of Political-Administrative Regions, which was conceived in 1995 by the Department of Social Policies to organize Participatory Budgeting meetings which had been limited to associations and their representatives (PNUD *et al*., 2005). [↑](#footnote-ref-3)
4. As an illustration consider two relational matrices for two hypothetical groups each with three students, g1 and g2. The diagonal joint matrix ***G***, is denoted by:

   [↑](#footnote-ref-4)
5. Consider two models with regression structure for the grades at the beginning and end of the year of student *i:*

   e

   where *ui* is an unobservable component invariant throughout the scholar year. According to Boardman and Murnane (1979), if and , the effects of variables ***X*** and ***u*** change at the same constant rate *θ* between *t-1* and *t*. Under such conditions, the inclusion of in the empirical model (3) allows to control for this fixed initial condition for each student. [↑](#footnote-ref-5)
6. In the case of indirect networks (***G*** is symmetrical) *gij = gji = 1*, but with a direct network *gij = 1* e *gji = 0*. [↑](#footnote-ref-6)
7. Some studies show that the results of peer effects do not change according to the symmetry of matrix ***G***. See, for instance, Patacchini and Venanzoni (2014), Liu *et al.*, (2014) and Calvó-Armengol *et al.* (2009). [↑](#footnote-ref-7)