Peer effects in After-school programs. Evidence from El Salvador.

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Abstract

This paper studies the impact of After-School Clubs on students' academic and violence-related outcomes, using an experimental design. Participants are enrolled in schools located in highly violent communities in a developing country. The premise is that clubs improve children's ability to handle conflicts, which also allows them to improve their protection factors and academic performance. Then, randomly assigning students in heterogeneous (non-tracking) or homogeneous (tracking) groups according to their predicted violence level, this paper directly measures peer effects on academic and non-cognitive outcomes. As results, there is a positive effect of the program on grades and behavior. Also a reduction in self- and external reports of students' violence and delinquency actions. Finally, we find a reduction in their perception of exposition to risky environments outside school. These results are driven by the homogeneous groups when they are compared with the control groups; but there is no impact differences due to the group composition. Finally, I find differences in terms of gender and the initial predicted level of violence. With these results, I will contribute to the design and implementation of public policies to prevent violence in children and adolescents involved in highly risky school environments.

Keywords: Peer effects, Tracking, After-school Programs, Violence, Education.

JEL Classification: I29, K42, Z13

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1. Introduction

After-School Programs (ASP) have been a policy traditionally used by developed countries[1], and more recently by developing countries[2], to achieve two main goals: first, reduce the exposure of vulnerable children to risky environments, and second, improve participants' cognitive and non-cognitive skills, so that they may be able to manage conflictive situations at their home, schools or neighborhoods. (Blau and Currie, 2006).

These programs are often set in highly vulnerable communities where there is a high risk of children to be engaged in or to be victims of criminal activities. Despite the increase in the number of programs being implemented in the last years, evidence of the impact of these ASP on social skills, crime and violence is mixed and inconclusive (Durlak, and Pachan Weissberg, 2010; Kremer et al, 2015). One possible explanation of these results is that these programs are often implemented assigning participants in heterogeneous groups in terms of social skills and vulnerability; without considering the possibility of targeting them according to a participants' specific characteristic, such as violence propensity.

This paper measures the impact of After-School Clubs (a version of ASP) on academic and violence-related outcomes using an experimental design. The study sample are 1056 students enrolled in 5 public schools, located in highly violent communities in El Salvador. It also presents evidence of whether the composition of clubs can modify the impact of the intervention on outcomes of interest, through an experimental design inspired by Lafortune, Tessada and Perticará (2014).

These After-School Clubs were implemented by a local NGO from April to mid-October 2016, during the full 2016 academic year within school facilities. Selected students were allowed to participate only in one type of Club[3], according to the random assignment and their preferences. They attend two sessions per week which last 1.5 hours each and take place just after school hours. Each session includes the implementation of the club's curricula according to each type of club and, at the end of the session, a discussion about a specific topic oriented to reduce violent behaviors. Clubs are organized by a school coordinator, and implemented by volunteers, who are also role

[1] For instance, in the US: The Quantum Opportunity Program, Higher Achievement Program, Citizen Schools, Pathways, Project NAFASI, After School Matters, Safe Haven, Challenging Horizons, and others. Kremer et al (2015) provide a more detailed review of ASP in the US

[2] Such as Boys and Girls Clubs in Mexico, VUELA in Colombia, Rainbow After-School Clubs in Uganda, the Amani Girls Clubs in Liberia, and Glasswing's Clubs in Central America, which is the intervention to be evaluated in this paper.

[3] The NGO offers a variety of clubs, such as Discovery, Art, Glee, Leadership, and others; with the objective to develop different children's skills.

models for students.

In order to measure the overall impact of these clubs, I randomly assigned students in two treatments and a control groups, stratifying by school and academic level. All students assigned to any treatment were allowed to attend clubs. Then, to provide evidence of whether the clubs' composition generates differential impacts on the outcomes, I define two categories of treatments: the first treatment was the exposure of the student to a club of heterogeneous peers according to a predicted propensity to commit a violent act or crime, and the second treatment was the assignment of the student to a Club of similar peers (homogeneous clubmates).

Within the second treatment, I divided students in two groups according to their percentile in the distribution function of the predicted propensity of violence. Students whose predicted propensity was higher than the median were assigned to a club constituted by peers with high predicted propensity to violence. And students with a propensity of violence lower that the median were assigned to a Club formed by peers of low predicted propensity to violence. As opposed to Duflo et al (2011), the instructors were not informed of what type of classrooms they were training. Therefore, the results may be less dependent on how mentors respond to group characteristics and more to the distribution of peers.

The predicted propensity of violence was estimated as a Violence and Vulnerability Index (IVV) following the procedure implemented by Chandler, Levitt and List (2011). First, during the registration process, the NGO collected information about youth's crime and violence propensity determinants, such as gender, age, area of residence, mother's education, time spend alone at home, travel time to school and household composition (Kim et al., 2015; Rodríguez-Planas, 2010; Springer et al., 2006; Gottfredson et al., 2004 and Gaviria and Raphael, 2001). At the registration phase, I have no information about individual levels of violence[4]. Therefore, I used an available database of violence and crime of a youth sample from El Salvador (FUSADES, 2015). With this database, I ran a regression of the likelihood of having committed a violent act and determinants listed before. Then, exploiting the availability of these determinants for the study sample, I predicted the IVV for each registered student using the coefficients estimated in the last regression and the explanatory variables for each child.

Violence-related and non-cognitive outcomes to be measure are protective and risk factors col-

[4]We decided not to ask questions about crimes and violence directly to the children because it was possible to identify the participants and this may put in danger both children and the NGO.

lected through a follow-up survey implemented at the end of October 2016. More specifically, I estimated Delinquency and Violence Indexes using items from the Self-Reported Delinquency Scale (SRD) originally developed for the National Youth Survey (NYS). Attitudes toward Antisocial Behavior, Friends' Delinquent Behavior and Self-perceived Academic Performance were estimated using items from the Communities That Care® Youth Survey[5]. Academic performance outcomes include math, reading, science and behavior scores, clubs and school attendance and drop-outs.

I present some empirical specifications in order to find evidence on outcomes of interest from this study. First, comparing results of aggregated treatment groups with the control group I get evidence of clubs' impact on academic performance and violence-related outcomes. Then, comparing results of each heterogeneous and homogeneous groups to the control group, and both treatments between them, I find evidence of improvement of the intervention caused by the assignment of participants, either by peer effects (if the results of the heterogeneous group are higher) or by tracking (if there is an improvement in the results of the homogeneous group).

I find evidence of positive effects of the intervention on GPA in math and science and a increase in the probability to pass reading course. These results appear to be driven by the homogeneous group. Also, I find no difference of impacts according to the group composition: comparing the results of the homogeneous and heterogeneous groups, I find no statistically difference between both treatments.

Then, in terms of non-cognitive outcomes, I find a increase in the positive attitudes toward school in the treated group, both in the self- or external reports. It seems that clubs participants have better attitudes to schools activities, they report higher time to do homework and put more attention during classes. These results are also supported with the administrative data: treated students reduced their absenteeism in 1.6 days on average. Finally, there is no impact on drop-out due to the intervention, which was expected: these youth usually drop school because they have to move to other areas, for many exogenous reasons out of the clubs scope. These results are very similar in both groups of treatment.

In terms of violence and delinquency, the intervention reduces the self reported criminal and violent actions and the attitudes toward antisocial behavior. According to the teachers reports, treated students have higher behavior grades compared to the control group. All these results are

[5]These questionaries has been already validated in a sample of youth living in highly risky communities in El Salvador by Olate et al (2015).

similar between homogeneous and heterogeneous groups.

Finally, these clubs keep students away from their risky environments for some hours during the week, which might reduce their perceived exposition to risk. I measured outcomes of exposition and find a reduction only in their self reported exposition to risky environments as witness, but no effect on exposition as victims. Also there is evidence of higher awareness index for the treated children.

Additionally, a novel aspect of this experimental design is that it also allow me to analyze separately the homogeneous and heterogeneous groups. Using the subsample of those randomly assigned to the heterogeneous composition of peers, I used the specification used in the literature of peer effects to measure how the outcomes of each student are determined by the baseline IVV of her peers. Results indicate that students randomly exposed to a higher average of peers' propensity to violence have higher academic grades in reading and math. They have also better attitudes toward school and a reduction of absences to school, report less criminal and violent actions and have higher behavior grades. But this exposition within the club does not explain students' self report of exposure in their risky environments.

Finally, using only the subsample of the homogeneous groups, I test whether being assigned to a highly violent set of peers has different impact than being in a group of low violent peers. Results provide evidence that being assigned to a set of more violent homogeneous peers increases the probability to fail any of the three courses (math, reading or science) and the exposure to risky environments, compared to students assigned to low violent homogeneous peers.

This paper contribute to three sets of literature. The first group consists on experimental impact evaluations of ASP studies on behavior, violence- and crime-related outcomes in developed countries, specially in the US. Evidence of these papers is less conclusive: Rodríguez-Planas (2010) evaluates the impact of Quantum Opportunity Program and find that overall the program was unsuccessful at reducing risky behaviors. On the other hand, Hirsch et al. (2011) evaluate the program After School Matters in Chicago and find positive impact on youth development and problem behaviors but no effects on job skills or academic outcomes. Additionally, Biggart et al. (2013) evaluates experimentally the program *Doodle Den* in Ireland and find improvements in violent behaviors in regular school classes, according to teachers' reports.

In developing countries there is evidence of interventions that end up impacting violence and crime; but they are very different to an ASP setting. For instance, Chioda, De Mello and Soares

(2015) find evidence of a reduction in crime due to the expansion of *Bolsa Família*, a Conditional Cash Transfers program in Brasil. Blattman, Jamison and Sheridan (2015) find reduction in crime and violence due to behavioral therapy and cash grants for recluses in Liberia.

The second set of papers relevant for this study is constituted by impact evaluations of ASP on academic and cognitive outcomes. Blau and Currie (2006) find that most of the ASP evaluations that measure cognitive outcomes are non-experimental[6], with difficulties to identify causal effects of the interventions. However, a more recent ASP evidence review by Kremer et al. (2015) find a significant increase of ASP impact evaluations on academic outcomes through experimental settings. Linden et al. (2011) experimentally evaluate the Higher Achievement program in the US, and find that this improves reading comprehension and problem solving in the mid-term. Biggart et al (2013) also find an increase of children's overall literacy due to the *Doodle Den* after-school literacy program in Ireland. Nonetheless, most of this evidence is for interventions implemented in developed countries too.

Hence, due to this lack of evidence of impact evaluation of ASP implemented in developing countries, this paper will contribute to both groups of literature, measuring the impact of a ASP on academic and non cognitive outcomes of students from a developing country, through an experimental design.

Additionally, this paper contributes to a complete strand of literature of peer effects on academic outcomes, violence and criminal behaviors. The evidence in this literature is wide and abundant. There is a large body of studies which measure peer effects on crime, violence and behavior in non-experimental settings for developed countries[7], most of them use panel data and school, class or family fixed effects to account for endogeneity in the peers composition. Other papers measure peer effects on violence or crime related outcomes exploiting random assignment of peers due to natural experiments, like hurricanes; or random assignments used to measure impacts in other interventions, such as Voucher Housing Programs, roommates at the university, lotteries of first-choice schools, and others[8]. Kremer and Levy (2008) exploit a random assignment of roommates

[6]Some papers with non-experimental settings are Posner and Vandell (1999); Marshall et al, (1997) and Huang et al (2000).

[7]Some examples are the papers of Case and Katz (1991); Payne and Cornwell (2007); Nakajima (2007); Bayer, Hjalmarsson, and Pozen (2009); Carrell and Hoekstra (2010); Chandler, Levitt and List (2011); Zimmerman and Messner (2011).

[8]For instance Kling, Ludwig and Katz (2005); Kremer and Levy (2008); Deming (2011); Imberman, Kugler and Sacerdote (2012); Ludwig, Drago and Galbiati (2012); Damm and Dustmann (2014). Most of these papers find evidence of reduction in crime, drugs and alcohol consumption and violent behavior when the individuals are reallocated in neighborhoods or schools with less violent or non criminal peers. These results support the relevance

at a university in the US. They find no evidence of peers' academic and family backgrounds on students' college GPA. But students assigned to peers who at baseline used to drank alcohol have a lower GPA than the assigned to non-drinking peers. Imberman et al (2012) exploit the exogenous reallocation of children in Houston and Louisiana due to hurricanes Katrina and Rita in 2005. They find improvement in student achievement of those assigned with high achieving peers and worse outcomes to those with low achieving peers and also the inflow of evacuees increased absenteeism and disciplinary problems of incumbents.

There are also plenty of studies which estimate peer effects on education and other outcomes, mainly concentrated in non experimental settings[9]. Nonetheless, there exist evidence of peer effects on academic outcomes through experimental settings to the assignment of peers: Duflo, Dupas and Kremer (2011) find evidence of a positive direct effect of high-achieving peers, but they also find that assigning students to more similar peers (tracking) benefits lower-achievers indirectly by allowing teachers to adjust the curricula to their level. In summary, the results in this literature are mixed: Some find evidence of peer effects with heterogeneous results by race, gender or initial academic achievement, and others find only modest or short lived peer effects. This paper contributes to this literature providing a measure of peer effects directly through a experimental setting.

Finally, this paper will contribute to the literature that analyzes the relation between highly violent environments and academic outcomes. Monteiro and Rocha (2016) find a negative effect of gunfights between drug gangs in Rio de Janeiro on students' math scores using variation in violence across time and space. Additionally, using a panel data from Mexico, Caudillo and Torche (2014) find a positive relation between children's exposure to local violence and grade failure. In school settings in the US, Burdick-Will (2013) finds that violent crime rates have a negative impact on academic outcomes. Olate et al (2015) use a protective and risk factors survey from El Salvador and find that school is a protective factor of aggression and delinquency, i.e. it could be a space to protect children from their outside violent environment.

The context of El Salvador is relevant for many reasons. First, El Salvador is a lower middle income country with high violence level and homicides rate: In 2015, El Salvador was the 3rd most dangerous country in Central America, ranks 7th in the Latin-American ranking and 53rd in

of assigning the participants to "good peers", providing evidence of the Boutique peer effects model. Additionally, some of these papers listed before find results of social multipliers of peer effects, but in a non linear relationship.

[9]Most of these papers measures peer effects on academic outcomes in developed countries: Lavy, Silva and Weinhardt (2012), Vardardottir (2013) and some for developing countries: McEwan (2003) in Chile; Lavy, Paserman and Schlosser (2012) in Israel and Balsa, Gandelman and González (2015) in Uruguay

the world ranking (Global Peace Index Report, 2016). Between 2009-2012 the country's average homicide rate was 69 homicides per 100,000 habitants (UNDP, 2013; IUDOP, 2015). Only in 2014, a total of 3,912 homicides were reported, 57% more than the previous year[10], most of them were gang related (PNC, 2015).

Second, the educational system has been highly affected by these violence and crime problems. Even when homicides are mainly concentrated in 18-25 years old men (PNC, 2016), in the last years these crimes have reached children and adolescents as victims: from 2005-2013 approximately 6,300 children and adolescents were victims of homicide (EPCD, 2014), especially because adolescents males are targeted more heavily for gang recruitment[11]. In 2014, 11.5% of students abandoned their school due to delinquency, which was reported as the third cause of drop out (National Education Census, 2014)[12]. Additionally, in the last years, El Salvador has faced a reduction in its education enrollment rate, specially at ages that makes students more likely to be recruited by a gang. In 2013 the primary and secondary net enrollment rates were 93.4% and 61.6% respectively, facing a relevant drop in 2015 when the primary and secondary net enrollment rates reached 86.2% and 37.9% respectively (MINED, 2015).

The rest of the paper is organized as follows: In Section 2, I describe the intervention and the experimental design and present details about the Vulnerability and Violence Index (IVV) estimation. In Section 3, I present descriptive statistics and results of balance tests between treatment and control groups. In section 4 I introduce specifications to estimate results that I present in the section 5. All appendix tables are at the end of this inform.

2. Intervention and Experimental Design

In this section, I provide a description of After-School Clubs to present the general framework of the intervention. Then I introduce the experimental design and some details of the IVV estimation. Finally I describe how registered students are assigned to the two treatments and control groups.

[10] As a reference, the worldwide homicide rate is 6.2 per 100,000 habitants (UNODC, 2013)

[11] Also in 2013, 458 adolescents were processed for extortion, 439 for aggravated robbery and 321 for aggravated homicide (CSJ, 2014), which according to the national security authorities, are crimes mainly related to gangs, which they implement to fund their activities (PNC, 2014)

[12] This may be a lower bound because 28.6% of students dropped school due to change of address, which from 2010 has been highly correlated with threats from gangs according to testimonies elicited by local newspapers (La Prensa Gráfica, 2014).

2.1 Intervention: Glasswing's After-School Clubs

Glasswing International is an NGO whose main intervention fields are education and health. Since 2013 it has operations throughout Central America. Their main activity is the provision of technical advice on social investment to corporations and private companies, formulating and executing strategic plans of social projects. In the education field, its principal program is "My school, my space" (MIEMIE). Since 2013, the MIEMIE has been implemented in 95 schools in Central America through 560 clubs, which are the main componente of the MIEMIE, benefiting approximately 20,000 children with ages between 8-15 years old.

The NGO offers a set of potential Clubs for each school by education level (*ciclos*), such as Discovery, Glee, Leadership and Art Clubs[13]; according to the availability of resources and potential demand. During the registration process, children fill out a form which collects personal information from participants, their households and families, and rank their three most preferred clubs from those listed by the NGO for the school. Then they are assigned to a club conditional on the number and type of clubs opened, their preferences and their parent's authorization[14].

Selected students attend two sessions[15] per week which last 1.5 hours each and take place just after school hours.[16]. Each session is divided in two sections: First, a tutor develops the club's curriculum and then they talk about a particular topic. For example, in a session of the Discovery Club, first the instructor introduces "Volcanoes" as the topic of the day, then implements and explains a experiment of a "volcano eruption" and summarizes this content. Then, at the end of the session, the instructor and children discuss how to manage conflicts with other kids (or any other topic) in school or at home.

Clubs are organized by a school coordinator, who verifies the participants' attendance and reasons for drop-out, and manages resources for the clubs implementation, including the distribution of volunteers as tutors. Glasswing has three categories of volunteers: Community volunteers, who

[13]Discovery curricula includes the implementation of scientific experiments for kids, Glee Clubs are designed for children which prefers to dance and sing, Leadership Clubs are for those who want to develop social and leadership skills and Art Clubs include activities to develop children's fine motor skills and creativity.

[14]The initial clubs offer is not definitive, it depends on the number of participants that prefer each club. For instance, if 20 students have defined Discovery Club as their first preference, the NGO opens two clubs of 10 participants each. Also, if only 2 students have ranked Glee as their most preferred club, this club will not be opened and these two students are assigned to their second or third alternative.

[15]This is a space which allow the students to interact with other children and a tutor, and learn "topics" such as conflict- and risk-management, school violence reduction, and soft skills related to improvement of academic outcomes, such as responsibility, self control, etc.

[16]According to Seppanen et al (1993), the minimal time of implementation of ASP sessions, in order to be cost-effective and generate impacts in violence and crime, should be between 2 to 8 hours per week.

live in the community and stand out for their leadership skills; Corporate volunteers, who are part of a particular firm that has a social project with Glasswing (which often includes funding and staff as volunteers); and Independent volunteers, who are usually college students doing their social work. All these volunteers implement clubs and are role models for students.

Qualitative assessments of the impact of the After-School Clubs have shown evidence of improvement in primary and advanced social skills: auto perception, self-esteem and social skills; but no impact on academic outcomes (Glasswing International, 2014). During 2016, the NGO implemented the MIEMIE in 5 additional schools in El Salvador, enrolling 1056 children, and was willing to evaluate the impact of the intervention through a randomized controlled trial and find evidence on alternatives to improve it.

2.2 Experimental Design

Following Lafortune, Perticará and Tessada (2014), I implemented an experimental design that take advantage of the heterogeneous or homogeneous clubs composition, but maintaining the traditional estructure of the intervention.

2.2.1 Violence and Vulnerability Index (IVV) estimation

The registration process was implemented in late March and early April 2016. At this phase, I had no information from enrolled children's violence propensity or likelihood to commit crimes to use as a proxy of the IVV, because we preferred the children safety than having access to this specific information[17]. Nonetheless, I follow Chandler, Levitt and List (2011) to estimate a crime and violence model from existing data[18]. First, I run a regression of the likelihood of having committed a violent act and determinants of violence and criminal behavior such as gender, age, area of residence, mother's education, time spend alone at home by the child, travel time to school and household composition[19], using a unique database of violence and crime of youths from El Salvador

[17]We decided not to ask any question about crime at the registration phase for two reasons. First, the enrollment form include questions that allow to fully identify the participants and we could not guarantee that this information will be absolutely classified during the study and after. Second, asking particular information about being an active gang member (which is highly correlated to crime and violence) in El Salvador may put in danger both children and the NGO.

[18]This procedure is similar to a Two Sample Least Square estimation

[19]Some relevant papers which find evidence that these variables are determinants of crime and violence are: Gender: Kim et al. (2015) and Rodríguez-Planas (2010); Age: Rodríguez-Planas (2010); Area of residence: Springer et al. (2006); Mother's education: Springer et al. (2006) and Gaviria and Raphael, (2001); Time spent alone at home by the child: Gottfredson et al. (2004); travel time to school: Springer et al. (2006); and Household

(FUSADES, 2015)[20]. Then, exploiting the availability of these variables in the registration forms for the students registered to participate in clubs, I predict the IVV for each registered student using the coefficients estimated in the last regression and the respective values for the explanatory variables of each child in this study sample.

Even when this Index is predicted using coefficients from another sample, in the appendix table A1 I present means and standard deviations of the determinants from the FUSADES (2015) database and descriptive statistics from the participants, to show that both samples are similar in some of the determinants. Also, Chandler, Levitt and List (2011) finds that this sort or crime and violence models estimated from existing data have a high predictive power. Finally, due to the lack of administrative data of youth violence in El Salvador, it was the only available alternative to predict the IVV and design the experiment.

2.2.2 Treatments

After estimating the IVV, 1056 registered children were randomly assign between three groups: control (C, 25%), heterogeneous IVV (HT, 25%) and homogeneous IVV (HM, 50%). Then, I use the predicted IVV to rank the students within the homogeneous group: All students with an IVV above the median were assigned to the High IVV group (HM-High, 25% of the full sample) and the rest of the homogeneous group were assigned to the Low IVV (HM-Low, 25%).

Treatments are described below:

1. *Control:* This group of students were not selected to participate in the clubs during 2016 academic year. However they faced school's infrastructure improvement as a base intervention. It is important to highlight this because the results can not be extended to schools without any intervention.

2. *Heterogeneous IVV (HT):* Registered and selected students are assigned to one of their preferred clubs with a heterogeneous composition of peers according to their IVV.

composition: Gaviria and Raphael (2001)

[20] This database is a sample of 8640 students of 6th and 9th grade, enrolled in public schools in El Salvador. This sample includes many variables of crime and violence and their determinants, and the sample is similar to the sample of this paper, except for some variables such as student's age and area of residence. Descriptive statistics and comparison of means (p-values) between the two samples can be found in Table A1 in the appendix. These p-values are similar to those obtained from a chi-square Two Samples Homogeneity Test

3. *Homogenous-Low IVV (HM-Low):* Registered and selected students are assigned to one of their preferred clubs formed by low violent peers, if their IVV is lower than the median.

4. *Homogenous-High IVV (HM-High):* Registered and selected students are assigned to one of their preferred clubs formed by highly violent peers, if their IVV is higher than the median.

The assignment was a single random draw at school and education level (*ciclos*[21]), because this is how the NGO implement the clubs, and I wanted to keep the experiment's settings as close as possible to their traditional implementation.

After the assignment was finished, each school coordinator informed children whether they have been selected to participate in the program and the club they were assigned. As opposed to Duflo et al (2011) neither instructors nor participants knew details of assignment.

3. Data and summary statistics

In following subsections I exhibit baseline data obtained during registration of students to clubs. I also present summary statistics of students characteristics and balance tests as evidence that prior to treatment, all groups were balanced in observables.

3.1 Data

Individual data of determinants to construct the IVV were obtained from forms filled out by students during the registration phase. To measure the academic outcomes, I have also access to administrative data provided from schools such as math, reading, science and behavior grades, and school absenteeism before and after the intervention. I have also data of drop outs at the end of the academic year.

Follow-up data on violence-related and non-cognitive outcomes were collected in school-based facilities at the end of October 2016, after all clubs have completely implemented their curricula. Most of surveys were self-administered in groups, with assistance from the staff trained in the survey methodology. The follow-up survey includes questions to measure the intervention impact in individual and peers domains outcomes. This questions were taken from different instruments

[21] *Ciclos* in El Salvador are levels or groups of three years of education. i.e., the first level is from 1st to 3rd year of education, second level is from 4th to 6th year of education and third level is form 7th to 9th year of education

previously validated in similar samples (Olate et al, 2015; Katz, 2010). I estimated indexes of Attitudes toward Antisocial Behavior, Friends' Delinquent Behavior and Self-perceived Academic Performance using items from the Communities That Care® Youth Survey[22]. Delinquency and Violence Indexes were estimated using items from the Self-Reported Delinquency Scale (SRD) originally developed for the National Youth Survey (NYS).

In Table A2 in the appendix, I present match rates with administrative data before and after the intervention. There is balance in all the fractions of matches with administrative data, except in the fraction of math scores data in Q1 2016 between HM and C group, significant at 10%, and in Absenteeism between both tracking groups, also significant at 10%. Table A2 shows the percentage of students present at follow-up survey, separated by treatments and control groups. The attrition rate of the complete sample and for the C and T groups was 8%. For the HM and HT groups, the attrition rate was 9% and 5% respectively. I found no statistical difference in attrition rates between treatments and control groups.

3.2 Summary Statistics

IVV descriptive statistics for the full sample are summarized in column 1 of Table 1. Panel A presents descriptive statistics of the available variables in the registration form for the full sample and for each treatment and control group. The sample is on average 12 years old, 49% are male and 73% live in urban area. Most of the students live with at least one parent (91%) and the rest live with a relative (8%) or with other non-related adults (1%). On average, 62% of students' mothers have intermediate education (between 7-12 years) and 31% have only basic education (less than 6 years of schooling).

In terms of exposure of participants to risky domains, only 5% of students reported to be alone at home after school, but they have to travel almost 18 minutes from their house to the school, on average. Additionally, 39% of students are enrolled on afternoon shift, increasing the probability to be without surveillance of an adult during the time their parents are at work.

Panel B shows academic scores and absenteeism during the first quarter 2016. If we consider a total of 20 school days per month, students have been absent 2.16 days, which accounts for

[22] The instrument was mainly based on the Communities That Care® Youth Survey. Therefore, it includes also questions related to Family and Community domains. This data may allow me to measure if the students are aware of their external risk and protective factors. I will not analyze these outcomes in this paper because Clubs are oriented to impact the Individual and Peers domains.

approximately 5.4% of the school time during this period. Columns 3-6 present descriptive statistics for control (C), All treated (T), and by treatment (HT and HM) respectively. In the last two columns, I estimate means by homogeneous subgroup.

As expected, the HM-High group has means of violence determinants that are higher that determinants of the HM-Low group. For instance, students in the HM-High group are mainly male (76% vs 22%) and older (12.4 vs 11.4 years old) than those in the HM-Low group. In terms of their household composition, most students at the HM-Low group live with both parents (59% vs 53%) and a higher percentage of them have mothers with either basic education or higher education[23].

[**Insert Table 1 here**]

Descriptive statistics of the IVV for each treatment and control groups are summarized in columns 2-7 in Table A3. The IVV mean for both Any Treatment (which includes both HT and HM treatments) and control groups is 0.038, with an standard deviation of 0.029[24]. As expected due to the experiment design, the IVV standard deviation of the HT group is higher than the IVV standard deviation of the HM group (0.035 and 0.026 respectively). Additionally, the IVV mean of the HT group (0.041) is between the IVV mean of the HM-High (0.05) and HM-Low (0.024) subgroups. Finally, the IVV median of both HM-High subgroup is 0.044, higher than IVV medians of HM-Low and HT subgroups (0.021 and 0.03 respectively).

Table A4 shows *p*-values of means balance tests of all variables in Table 1, after controlling by education level and school (cluster of random assignment). I find no statistically significant differences in any means in the Control-Treated groups comparison (column 1). In the C-HT groups comparison (column 2), I only find differences in the average student course at 10%. In the C-HM groups comparison (column 3), I find differences at the 10% in two categories of household composition (column 3).

When comparing HT and HM groups there is only difference at the 5% level in the predicted IVV (column 4). To account for this difference, in the final estimation I control for the predicted IVV. Finally, column 5 shows differences between the HM-High and HM-Low subgroups. As mentioned from Table 1, there are differences between both subgroups in many of the violence determinants.

[23]These results could be explained as follows: if their mother has basic education, it is posible that she will stay at home and take care of her child, reducing his exposure to risk. Or if the mother has higher education, she will probably have more financial means to pay surveillance for her child, reducing his exposure to risk too.

[24]This result is 0.012 higher than the mean probability of be victim of a shooting, estimated by Chandler et al (2015) for troubled students at Chicago Public Schools

There are also differences between some groups in grades at baseline. To account for this difference, I control for the grades at baseline in all estimations.

It was expected to have similar IVV distribution functions between HT, HM and C groups prior to treatment, due to the experimental design. As show in Figure 1, there is no difference between the distribution of the IVV by group at baseline. I use the two-sample Kolmogorov-Smirnov test for equality of distribution functions and can't reject the hypothesis of equality of distribution functions (p-values of 0.62 for the HT-HM comparison, 0.89 for the HT-C comparison and 0.68 for the HM-C comparison.).

[**Insert Figure 1 here**]

Figure 2 shows that IVV distribution functions between HM-High and HM-Low groups are different at baseline. In fact, using the two-sample Kolmogorov-Smirnov test, I reject the hypothesis of equality of both distribution functions at 1%. These two IVV distributions are also different from the IVV distribution function of the HT group. As showed in Table 1 and in Figure 2, there are difference in IVV means, standard deviations and median for each group. For instance, IVV mean and median of the HT group is between mean and median of the HM-High and HM-Low subgroups respectively; and the HT group has a higher standard deviation than any of the HM-High and HM-Low subgroups.

[**Insert Figure 2 here**]

An additional expected result of this design is that IVV distributions of HM-High and HM-Low subgroups should not be fully overlapped in the full sample, in order to have differences between distribution functions of both HM subgroups. If I had randomized without considering the education levels, there would not be a overlap between both groups; but, because the randomization was made within education levels and schools, there is overlap in 74,9% of the sample. Therefore, I still have variation between IVV distribution functions of HM subgroups at baseline.

Finally, I provide evidence that there is a sharp discontinuity at the fiftieth percentile for the whole HM subsample, consistent with the discontinuous assignment at the median IVV within each cluster. Figure 3 shows the median predicted IVV of student's clubmates as a function of the student's own baseline IVV in HM-Low and HM-High groups, and the expected jump at the fiftieth percentile. Estimating a RD-robust regression with this homogeneous subsample, and controlling with dummies for the stratification cells with local polynomial of third order, I found evidence that being assigned to the HM-High group generates an increase of 0.008 points to the peers mean predicted IVV, which is statistically significant at 5%[25].

[**Insert Figure 3 here**]

4. Empirical Framework

As discussed before, first I provide evidence of the After-School clubs impact on academic outcomes and non cognitive skills. Additionally, I analyze if there is evidence of greater impact on these outcomes when the participants are assigned in heterogeneous or homogeneous groups according to their predicted IVV. And finally, exploiting different variations generated by the experiment and using different specifications, I analyze results of within each treatment group.

Measuring the overall impact of Clubs

To measure the impact of the program, I estimate the following equation:

$$Y_{ij} = \theta_0 + \theta_1 T_{ij} + \theta_2 S_j + \theta_3 X_{ij} + \epsilon_{ij} \tag{1}$$

where Y_{ij} is the result of interest of the student i in school and education level (strata) j. T is a dummy that indicate whether the student has been assigned to treatment, S_j are fixed effects of school and education level (stratification cells) and X_{ij} is a vector of control variables, which includes the predicted IVV at baseline. In the estimations of impact on academic outcomes, I also include grades with imputed values and a dummy indicating whether that was a missing value at baseline. Standard errors will be clustered at the school and education level j. Because I have some level of attrition, θ_1 will be an ITT estimator of the intervention.

Measuring the differential impact of tracking and peer effects.

Exploiting the random variation in each treatment generated by the experimental design, I can directly estimate the intervention impact by treatment and test if this effect is higher, i.e. when

[25] I use a third order local polynomial in order following Duflo, Dupas and Kremer (2011) specification. For a first and second polynomial order, the coefficient is 0.009, statistically significant at 1%. This coefficient and its statistical significance are also stable using a conventional or bias-corrected RD Method.

students are assigned to similar or to more heterogeneous peers. Therefore, I run the following regression:

$$Y_{ij} = \alpha_0 + \alpha_1 HT_{ij} + \alpha_2 HM_{ij} + \alpha_3 S_j + \alpha_4 X_{ij} + \epsilon_{ij} \tag{2}$$

where Y_{ij}, S_j and X_{ij} are defined as before, but now HM and HT are dummies which indicate whether the treatment is an allocation into the homogeneous or heterogeneous group respectively. Here, the impact of clubs on different outcomes is measured by the ITT estimators α_1 and α_2. The impact of the HT treatment compared to the C group is captured by α_2. Similarly, α_1 captures the impact of being assigned to the HM treatment versus being assigned to C. And testing the differences between α_1 and α_2 will give evidence of clubs impact conditional on the peers assignation.

Another alternative to measure differential effects due to the random assignment on a particular group of peers, is estimating the following specification, but restricting the sample to treated individuals:

$$Y_{ij} = \alpha_0 + \alpha_1 HT_{ij} + \alpha_2 S_j + \alpha_3 X_{ij} + \epsilon_{ij} \tag{3}$$

where Y_{ij}, HT_{ij}, S_j and X_{ij} are defined as before. In this specification, α_1 is an ITT estimator of assigning child i to a more diverse group of peers compared to assigning him to a similar group of peers in terms of violence.

Measuring effects within Non tracking Clubs

Exploiting the random assignment of students within the heterogeneous group, I delimit the sample to those assigned to the heterogeneous treatment, and run the following specification:

$$Y_{ij} = \gamma_0 + \gamma_1 \bar{x}_{-ij} + \gamma_2 X_{ij} + \gamma_3 S_j + \epsilon_{ij} \tag{4}$$

where $\bar{x}_{-ij}$ is the average peer baseline IVV in the club to which a student i was assigned and the vector of control variables X_{ij} includes the student's baseline IVV. With this specification I can directly provide evidence of how student's i non-cognitives and/or his academic outcomes are affected by the average baseline violence of her peers.

However a student violent behavior may be affected not only by the average baseline violence of his peers, but also by its variability. To test this, I will run a regression of the following equation, restricting the sample to those students selected to participate in Clubs:

$$Y_{ij} = \beta_0 + \beta_2 var(x_{-ij}) + \beta_3 S_j + \beta_4 X_{ij} + \epsilon_{ij} \tag{5}$$

Measuring effects within Tracking Clubs

Finally, in order to measure the impact of assignment to a lower or upper IVV level group, I exploit the sharp discontinuity on the median of the IVV within each stratification cell, created by the experimental design. Controlling flexibly by the IVV percentile of the student and restricting the sample to the HM group, I will apply a RD-robust estimation to run the following equation

$$Y_{ij} = \lambda_0 + \lambda_1 HMH_{ij} + f(IVV_{ij}) + \lambda_2 S_j + \epsilon_{ij} \tag{6}$$

where $f(\mathrm{IVV}_{ij})$ is a flexible function defined by the percentile of the individual's IVV within each strata, and HM-$\mathrm{H}_{ij} = 1$ if the participant was in the HM-High IVV group. In this case, λ_1 will be a LATE estimator, that will indicate how being assigned to a homogeneous set of peers with high level of violence affects the cognitive and non cognitive outcomes of the Clubs participants.

5. Results.

In this section, I present the main results of the intervention. First, I show the overall impact of Clubs on cognitive outcomes. Then, I estimate heterogeneous treatment effects by level of predicted IVV, separating the participants whether they have a high or low level of violence within her distribution. Also, I present evidence of the impact on non-cognitive outcomes, which according to the intervention, might be plausible mechanisms for the academic results. Finally, I present preliminary results of the analysis within each treatment group.

Overall impact of Clubs on academic and non-cognitive outcomes

ITT results of the specification (1) are presented in Table 2. The intervention has a positive effect on math and science grades of students, with a magnitude of 0.11 and 0.13 standard deviation respectively. Using these grades, I also estimate the probability to pass each course[26] and find a

[26] In El Salvador, the minimum grade level to pass a course is 5. Using this threshold, I estimate a dummy for each course

reduction in the probability to fail any of the three courses, specifically a positive effect only in the probability to pass reading. This last result indicates that the impact of the intervention is higher for students in the middle of the reading scores distribution, but not for the rest of students, and the contrary might happen in the math and science score distributions.

[**Insert Table 2 here**]

In Table 3, I present the effects of the intervention on academic outcomes but separated by group composition, estimated using the specification (2). As shown, the results are driven by the homogeneous group compared to the control group. There is no statistically significant difference between the heterogeneously treated students and the control group. Also, when I test differences between the homogeneous and heterogeneous groups, I find no differential impact. This is evidence that the group composition is not relevant when all students are treated, it is only important when we compare treated with control students.

[**Insert Table 3 here**]

I find also heterogeneous effects of the intervention by level of predicted violence. Table 4 and 5 show that the impact of the intervention is higher when students have a predicted index of violence higher than their group average, compared to treated students with a lower than their group mean IVV. Results are similar in math grades for heterogeneous and homogeneous treated students with high level of predicted violence, but in the rest of outcomes, the effects are higher in the heterogeneous treatment.

[**Insert Table 4 here**]

[**Insert Table 5 here**]

In terms of non-cognitive outcomes, I provide evidence of three categories of results that according to existing evidence, might be driving the increase in grades and probability to pass the courses. First, these academic outcomes could be explained because treated students are more motivated to learn. Due to the clubs structure, treated students might be involved in a different and more interesting way of learning with experiments, different tutors, etc. This new environment may allow them to see school and learning as funnier and increase their attitudes toward school. In this sense, I compare self reported measures of actions to increase their motivation to learn and results are reported in Table 6 and 7. I find that Clubs participants report higher number of hours used to do homework and put more attention during classes, than students in the control group. This self report is also confirmed using administrative data: treated students have a lower absenteeism compared to control group. Results are driven mostly by the heterogeneous group when compared with control group, without differences between both treatments.

[**Insert Table 6 here**]

[**Insert Table 7 here**]

The second category of non-cognitive outcomes are changes in violence, crime-related and behavior. According to the clubs curricula, students also learn to manage conflict in their house, school and community. In this sense, if students are less conflictive and behave better, they may learn better (be more focused in classes) and have higher grades. They also may be less disruptive during their classes and improve the learning process. To measure these outcomes, I test changes in self reported and external assessment of behavior and violence, provided by students and their teachers respectively. I find a reduction in the index of criminality and violence of treated participants and in the index of attitudes toward antisocial behavior. In terms of external report, teachers' assessment of students behavior show that treated students have better behavior grades than the control group. These results are reported in Table 8. In Table 9 I present the estimations by treatment, finding that the effects are concentrated in the homogeneous group, but no differential impact is found in the comparison between both treatments.

[**Insert Table 8 here**]

[**Insert Table 9 here**]

Finally, these Clubs offer the opportunity to keep students away from their risky environments, such as their house or community, during some hours during the week, reducing their exposure to these domains. I measure children's report of their perceived exposure to risk, measure through indexes that separate if the children is exposed as victim or witness. I also include measures of awareness of risk within their communities and a index of exposure to risk in their home. All results are presented in Table 10 and 11. I only find a reduction in their exposition as witness, but no evidence of exposition as victim. I also find an increase in children's awareness of risk in their communities.

[**Insert Table 10 here**]

[**Insert Table 11 here**]

Effects within Non-tracking Clubs

Exploiting the random assignment of peers in the heterogeneous subsample, I can directly measure peer effects within the non-tracking group. Using the specifications (4) and (5), I estimate the mean and variance of IVV in each club, excluding the participant i for the academic outcomes. Table 12 presents the main results, which indicate that being exposed to a group of peers with higher mean of propensity to violence causes an increase in student's academic results. These results are concentrated in students with lower propensity to violence, indicating that they learn what kind of behavior should not follow.

[**Insert Table 12 here**]

In Table 13, I report results of exposure to peers propensity to violence on non-cognitives, particularly on behavioral (violence and crime-related) outcomes. I find that this is the main mechanism driving the results, because the estimations remains statistically significant especially for students with high probability to commit violent acts.

[**Insert Table 13 here**]

Effects within Tracking Clubs

Using the specification (4), I can measure directly the effects of being assigned to a group of homogeneous peers with higher violence within the tracking clubs. The results are summarized in Table 14. Controlling with a flexible polynomial of second order of the student' percentile in the IVV distribution of the homogeneous group, I find that being assigned to a group of similar peers with high violence has a negative effect on the probability to pass reading course and increases the probability to fail any of the three courses.

[**Insert Table 14 here**]

6. Concluding remarks.

This paper provides experimental evidence of impact of an ASP implemented in schools located in highly violent communities in a developing country and also estimation of peer effects within tracking and non-tracking groups, directly from the experimental design. The effects of the intervention are measured on academic outcomes, such as grades in math, reading and science; and probability to pass these courses. I also measure impact on non-cognitive outcomes; like self and external reported attitudes and actions oriented to improve their academic scores (time used to do their homework, positive attitudes toward school, absenteeism and drop out), behavior and violence-related outcomes (violence index, attitudes toward bad behaviors, and behavior grades) and exposure to risky domains outside school.

Despite the low intensity of the intervention (only 3 hours per week), I find positive ITT effects of the intervention on most of the academic outcomes, which are concentrated in those students exposed to more similar peers in terms of their predicted propensity to violence, compared to the control group. I also find that the group composition has no differential effect between the treated groups.

I also find effects on positive attitudes toward school, both in self and externally reported outcomes. Again, group composition has no differential effect in the treatment, and the results are more concentrated in the heterogeneous group. Finally, I find that the intervention reduces the violence index, increases the behavior grades reported by teachers at school and reduces the exposition of children to risky domains as a witness, with no effect on their exposition as victims. The results in these two groups of outcomes are no different within the treated participants, in terms of group composition.

Additional results are the measures of peer effects within each treatment. In the non-tracking group, I exploit the random assignment of clubmates to measure directly how being exposed to a more violent group (on average) could change the academic and non-cognitive outcomes. I find that a higher level of peers' IVV increases the grades and probability to pass some courses, which could be explained by the reduction of their violent behaviors. I also get evidence of heterogeneous effects: this results are driven by students with low level of propensity to violence.

This results may have implications for public policy discussions over policies to reduce violence and risky behaviors within schools. This is evidence that the group composition has no differential impact between the treated participants, conditional on being treated. But conditional on participate in a club or not, being exposed and treated with more similar peers may generate better academic and non-cognitive results. On the other hand, conditional on being treated with a heterogeneous set of peers in terms of propensity to violence, I find that less violent students have better results when they are exposed to a group of higher mean violence. That means, there is no contamination of bad behavior, but these good behaving students try to do their best to be far from being like their bad behaving peers. These results remain similar when we introduce the variance of the peers' propensity to violence instead of the mean, meaning that the variability of violence has a similar result on how children learn some behaviors.

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Table 1. SUMMARY STATISTICS: MEANS OF VARIABLES BY TREATMENT GROUP. PRIOR TO TREATMENT

	Full Sample	Control group (C	Any Treatment (T)	*Treatments* Heterogen. group (HT)	Homogen. group (HM)	*Tracking groups* Homog. High (HM-H)	Homog. Low (HM-L)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
PANEL A: IVV Determinants							
Student is male	0.49	0.51	0.49	0.48	0.49	0.76	0.22
Student's age	12.0	11.9	12.0	12.1	11.9	12.4	11.4
Student lives in urban area	0.73	0.72	0.74	0.73	0.74	0.78	0.70
Student's household composition							
Student living with both parents	0.53	0.47	0.55	0.53	0.56	0.53	0.59
Student living only with one parent	0.32	0.37	0.31	0.34	0.30	0.33	0.26
Student living with one parent and stepparent	0.06	0.07	0.06	0.06	0.07	0.06	0.07
Student living with other relative /adults	0.09	0.10	0.08	0.07	0.09	0.09	0.08
Student's mother level of education:							
Basic Education (1-6 years)	0.31	0.34	0.30	0.27	0.31	0.22	0.40
Intermediate education (7-12 years)	0.62	0.59	0.63	0.65	0.62	0.72	0.52
University or higher (13 and +)	0.07	0.07	0.07	0.08	0.07	0.06	0.08
Student's travel time from house to school (min.)	17.6	17.0	17.9	17.8	17.9	19.6	16.1
Student is alone at home after school	0.05	0.05	0.05	0.07	0.04	0.08	0.01
Student's course (schooling year)	5.75	5.67	5.77	5.81	5.76	6.02	5.49
Student enrolled on morning shift	0.71	0.71	0.71	0.68	0.73	0.73	0.74
Student's Violence Index	0.04	0.04	0.04	0.04	0.04	0.05	0.02
PANEL B: Academic outcomes							
Academic scores Q1 2016 (Baseline)							
Reading scores	6.67	6.46	6.73	6.76	6.71	6.54	6.88
Math scores	6.48	6.41	6.51	6.46	6.49	6.52	6.44
Science scores	6.62	6.46	6.67	6.62	6.54	6.63	6.55
Behaviour scores	7.38	7.25	7.43	7.37	7.33	7.39	7.34
Absenteeism Q1 2016	2.01	2.64	1.81	1.91	1.76	2.09	1.44

The table shows descriptive statistics of the available variables in the enrollment form for the full sample, from schools grades records for some of the students. These variables were also used as determinants for the VV Index prediction (except scores).

TABLE 2: OVERALL EFFECTS OF THE ASP ON ACADEMIC OUTCOMES.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Grades			Probability to pass			Fail at least one course
	Reading	Math	Science	Reading	Math	Science	
Any treatment	0.016	0.111**	0.133**	0.036***	0.018	0.029	-0.028**
	(0.050)	(0.050)	(0.058)	(0.013)	(0.018)	(0.018)	(0.011)
IVV	-0.018*	-0.010	-0.013	0.003	0.006	0.004	-0.001
	(0.010)	(0.012)	(0.012)	(0.004)	(0.005)	(0.003)	(0.003)
Observations	1,023	1,023	1,023	1,023	1,023	1,023	1,023
Mean control group	6.47	6.23	6.37	0.865	0.873	0.884	0.067
SD - control group	1.75	1.76	1.66	0.342	0.334	0.320	0.251
MDE T = C	0.149	0.100	0.110	0.030	0.044	0.046	0.044

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. Columns (1) - (3) are standarized grades from control groups at school-grade level. All regressions include the following controls: IVV, grades in the respective course before treatment, dummy indicating a missing value in the grade before treatment, and ciclo-school fixed effect (stratification level).

TABLE 3: EFFECTS OF GROUP COMPOSITION ON ACADEMIC OUTCOMES.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Grades			Probability to pass			Fail at least one course
	Reading	Math	Science	Reading	Math	Science	
Heterog. group	-0.010	0.058	0.116	0.023	0.014	0.025	-0.020
	(0.054)	(0.079)	(0.071)	(0.018)	(0.022)	(0.025)	(0.014)
Homog. group	0.029	0.136**	0.142**	0.043***	0.020	0.031*	-0.032**
	(0.059)	(0.051)	(0.060)	(0.013)	(0.018)	(0.016)	(0.012)
IVV	-0.018*	-0.009	-0.013	0.003	0.006	0.004	-0.001
	(0.010)	(0.013)	(0.012)	(0.004)	(0.005)	(0.003)	(0.003)
Observations	1,023	1,023	1,023	1,023	1,023	1,023	1,023
p-value joint test Het = Hom = 0	0.802	0.035	0.073	0.006	0.551	0.107	0.037
p-value Het < Hom	0.257	0.150	0.328	0.111	0.377	0.369	0.820
MDE Het = C	0.491	0.172	0.182	0.091	0.091	0.091	0.055
MDE Hom = C	0.159	0.139	0.157	0.079	0.079	0.079	0.047
MDE Het = Hom	0.160	0.201	0.187	0.067	0.072	0.068	0.027

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. Columns (1) - (3) are standarized grades from control groups at school-grade level. All regressions include the following controls: IVV, grades in the respective course before treatment, dummy indicating a missing value in the grade before treatment, and ciclo-school fixed effect (stratification level). Results are weighted according to the probability to be selected within each strata.

TABLE 4: HETEROGENEOUS TREATMENT EFFECTS BY IVV.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Grades			Probability to pass			Fail at least one course
	Reading	Math	Science	Reading	Math	Science	
Treated	-0.019	-0.018	0.029	0.020	-0.026	-0.000	-0.001
	(0.067)	(0.079)	(0.085)	(0.020)	(0.024)	(0.027)	(0.020)
Treated x High IVV	0.081	0.271**	0.223*	0.035	0.092**	0.062	-0.056
	(0.110)	(0.104)	(0.117)	(0.035)	(0.044)	(0.048)	(0.037)
High IVV	-0.208**	-0.325***	-0.311***	-0.035	-0.075*	-0.051	0.054
	(0.092)	(0.090)	(0.095)	(0.033)	(0.041)	(0.047)	(0.039)
Observations	1,023	1,023	1,023	1,023	1,023	1,023	1,023
Coeff. Treated + Treat x High IVV	0.062	0.253***	0.252***	0.055**	0.066**	0.062*	-0.057**

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses at course-school level. Columns (1) - (6) are standarized grades from control groups at escuela-ciclo level. All regressions include the following controls: grades in the respective course before treatment (imputed mean of the course), dummy indicating a missing value in the grade before treatment, dummy indicating if the student has dropped-out and course-school fixed effect. Results are weighted according to the probability to be selected within each strata. High IVV is a dummy equal to 1 if the student's IVV is higher than her strata mean.

TABLE 5: HETEROGENEOUS EFFECTS OF GROUP COMPOSITION BY IVV.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Grades			Probability to pass			Fail at least one course
	Reading	Math	Science	Reading	Math	Science	
Heterog. Group	-0.115	-0.138	-0.054	-0.013	-0.057*	0.003	0.005
	(0.092)	(0.130)	(0.104)	(0.026)	(0.028)	(0.028)	(0.022)
Homog. Group	0.026	0.039	0.068	0.035	-0.011	-0.002	-0.004
	(0.077)	(0.078)	(0.086)	(0.022)	(0.029)	(0.028)	(0.021)
Heterog. x High IVV	0.211	0.400**	0.347**	0.074*	0.147***	0.050	-0.054
	(0.142)	(0.168)	(0.134)	(0.043)	(0.044)	(0.046)	(0.040)
Homog. x High IVV	0.018	0.210**	0.164	0.017	0.065	0.068	-0.058
	(0.111)	(0.096)	(0.119)	(0.039)	(0.052)	(0.051)	(0.037)
High IVV	-0.208**	-0.326***	-0.312***	-0.035	-0.075*	-0.051	0.054
	(0.092)	(0.090)	(0.094)	(0.033)	(0.041)	(0.047)	(0.039)
Observations	1,023	1,023	1,023	1,023	1,023	1,023	1,023
Coeff. Het. + HighIVV x Het.	0.096	0.262***	0.293***	0.061**	0.09***	0.053	-0.049*
Coeff. Hom. + HighIVV x Hom.	0.044	0.249***	0.232***	0.052**	0.054	0.066**	-0.062**
p-val. Het. + HighIVV x Het. = Hom. + HighIVV x Hom.	0.397	0.872	0.412	0.700	0.224	0.547	0.492

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses at course-school level. Columns (1) - (6) are standarized grades from control groups at escuela-ciclo level. All regressions include the following controls: grades in the respective course before treatment (imputed mean of the course), dummy indicating a missing value in the grade before treatment, dummy indicating if the student has dropped-out and course-school fixed effect. Results are weighted according to the probability to be selected within each strata. High IVV is a dummy equal to 1 if the student's IVV is higher than her strata mean.

TABLE 6. POSITIVE ATTITUDES AND ACTIONS TOWARD SCHOOL AND LEARNING.

	(1)	(2)	(3)	(4)	(5)
	Self reported			Administrative data	
	Positive attitutes toward school	Time to do homework (hours)	Put attention during classes	Abseenteism (days)	Drop out
Any treatment	0.172**	0.331**	0.080**	-1.603***	-0.004
	(0.085)	(0.144)	(0.032)	(0.478)	(0.016)
IVV	-0.016	0.019	-0.011	0.080	0.005
	(0.019)	(0.029)	(0.008)	(0.138)	(0.005)
Observations	948	935	962	836	1056
Mean - Control group	-0.13	2.12	0.59	2.78	0.06
SD - Control group	1.49	1.89	0.49	5.04	0.23

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. Positive attitudes toward school is an Index constructed using 5 items with PCA with mean 0 and standard deviation 1.4. All items are dummy variables. All regressions include as controls: IVV and ciclo-school fixed effect (stratification level). Results are weighted according to the probability to be selected within each strata.

TABLE 7. POSITIVE ATTITUDES AND ACTIONS TOWARD SCHOOL AND LEARNING.

	(1)	(2)	(3)	(4)	(5)
	Self reported			Administrative data	
	Positive attitutes toward school	Time to do homework (hours)	Put attention during classes	Abseenteism (days)	Drop out
Heterog. group	0.278***	0.397**	0.101**	-1.819***	-0.010
	(0.097)	(0.195)	(0.048)	(0.618)	(0.020)
Homog. group	0.118	0.297*	0.070**	-1.496***	-0.002
	(0.101)	(0.158)	(0.030)	(0.519)	(0.016)
IVV	-0.018	0.018	-0.012	0.081	0.005
	(0.018)	(0.029)	(0.008)	(0.137)	(0.005)
Observations	948	935	962	836	1,056
Mean - Control group	-0.13	2.12	0.59	2.78	0.06
SD - Control group	1.49	1.89	0.49	5.04	0.23
p-value joint test Het = Hom = 0	0.023	0.075	0.053	0.007	0.832
p-value Het = Hom	0.146	0.613	0.434	0.589	0.568

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. Positive attitudes toward school is an Index constructed using 5 items with PCA with mean 0 and standard deviation 1.4. All items are dummy variables. All regressions include as controls: IVV and ciclo-school fixed effect (stratification level). Results are weighted according to the probability to be selected within each strata.

TABLE 8. DELINQUENCY, VIOLENCE AND SELF-CONTROL.

	(1)	(2)	(3)	(4)	(5)
	Self-reported			External reports	
	Criminal actions in the last 3 months (Index)	Number of violent actions (Index)	Attitudes toward antisocial behaviour	Behaviour grades	High Behaviour grade
Any treatment	-0.197**	-0.146**	-0.104***	0.178***	0.065**
	(0.093)	(0.062)	(0.029)	(0.062)	(0.025)
IVV	0.004	0.020	-0.004	-0.038**	-0.007
	(0.013)	(0.017)	(0.004)	(0.018)	(0.008)
Observations	956	956	962	1,010	1,010
Mean - control	0.509	0.314	0.174	7.18	0.72
SD - Control group	0.501	0.608	0.380	1.24	0.45

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. *Delinquency in the last 3 months* is an standarized sum of self reported delictive actions commited in the last 3 months such Been on suspension, skipped school, cheated on a test, sprayed walls (graffitis), taken something without paying for it). Column (2) is the standarized sm of other violent acts such as fight at school, hit someone to get money, and others. Self-control is an standarized index and Behaviour grades are administrative school reports, standarized using the control group at school-grade level.

TABLE 9. DELINQUENCY, VIOLENCE AND SELF-CONTROL. BY TREATMENT

	(1)	(2)	(3)	(4)	(5)
	Self-reported			External reports	
	Delictive actions in the last 3 months (Index)	Number of violent actions (Index)	Attitudes toward antisocial behaviour	Behaviour grades	High Behaviour grade
Heterog. group	-0.213*	-0.122	-0.103***	0.158*	0.101***
	(0.122)	(0.078)	(0.033)	(0.085)	(0.035)
Homog. group	-0.189**	-0.159**	-0.105***	0.187***	0.047*
	(0.088)	(0.064)	(0.029)	(0.062)	(0.024)
IVV	0.005	0.020	-0.004	-0.037*	-0.008
	(0.013)	(0.016)	(0.004)	(0.019)	(0.008)
Observations	916	956	956	1,010	1,010
Mean - Control group	0.509	0.314	0.059	7.18	0.72
SD - Control group	0.501	0.608	0.237	1.24	0.45
p-value joint test Het = Hom = 0	0.112	0.057	0.003	0.012	0.021
p-value Het = Hom	0.775	0.574	0.915	0.674	0.039

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. *Delinquency in the last 3 months* is an standarized sum of self reported delictive actions commited in the last 3 months such Been on suspension, skipped school, cheated on a test, sprayed walls (graffitis), taken something without paying for it). Column (2) is the standarized sm of other violent acts such as fight at school, hit someone to get money, and others. Self-control is an standarized index and Behaviour grades are administrative school reports, standarized using the control group at school-grade level.

TABLE 10. EXPOSURE TO RISKY ENVIRONMENTS OUTSIDE SCHOOLS.

	(1) Exposure as witness in the last 6 months (Index)	(2) Exposure as victim in the last 6 months (Index)	(3) Awareness of their community (Index)	(4) Exposure to risks at home (Index)
Any treatment	-0.198*	-0.112	0.219*	-0.084
	(0.105)	(0.084)	(0.121)	(0.161)
IVV	0.009	0.023	-0.007	-0.081**
	(0.021)	(0.020)	(0.036)	(0.032)
Observations	860	860	860	860
Mean - control	0.153	0.086	-0.163	0.029
SD - Control grou	1.403	1.185	1.239	2.070

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. *Column (1)* is an standarized Index of self report of being witness of robbery, fights in the community and at their home . Column (2) is the standarized index of the items mentioned before but as victim. And Column (3) is an standarized index of awareness of drugs selling, fights and gangs at their community.

TABLE 11. EXPOSURE TO RISKY ENVIRONMENTS OUTSIDE SCHOOLS. BY TREATMENT

	(1) Exposure as witness in the last 6 months	(2) Exposure as victim in the last 6 months (Index)	(3) Awareness of their community (Index)	(4) Exposure to risks at home (Index)
Heterog. group	-0.241*	-0.132	0.082	-0.282
	(0.134)	(0.114)	(0.136)	(0.214)
Homog. group	-0.175	-0.101	0.297**	0.014
	(0.107)	(0.079)	(0.127)	(0.171)
IVV	0.010	0.024	-0.004	-0.076**
	(0.021)	(0.020)	(0.035)	(0.030)
Observations	815	860	578	667
Mean - Control group	0.153	0.086	-0.163	0.029
SD - Control group	1.403	1.185	1.239	2.070
p-value joint test Het = Hom = 0	0.173	0.420	0.035	0.310
p-value Het = Hom	0.537	0.698	0.046	0.145

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. *Column (1)* is an standarized Index of self report of being witness of robbery, fights in the community and at their home . Column (2) is the standarized index of the items mentioned before but as victim. And Column (3) is an standarized index of awareness of drugs selling, fights and gangs at their community

TABLE 12: Direct Effects of Peers' IVV on Academic Outcomes (Heterogeneous Groups Only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Grades			Probability to pass			Fail at least one course
	Reading	Math	Science	Reading	Math	Science	
PANEL A: Clubmates' mean IVV							
Mean Clubmates' IVV	0.061**	0.117*	0.133***	-0.003	0.030*	0.054*	-0.004
	(0.027)	(0.060)	(0.042)	(0.012)	(0.017)	(0.032)	(0.010)
IVV	0.008	0.022*	0.015	0.010*	0.017***	-0.002	-0.003
	(0.015)	(0.012)	(0.014)	(0.006)	(0.005)	(0.006)	(0.003)
Observations	255	255	255	255	255	255	255
PANEL B: Clubmates' sd IVV							
Var Clubmates' IVV	0.008	0.022**	0.021***	0.001	0.004**	0.009***	-0.001
	(0.007)	(0.008)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
IVV	0.009	0.020*	0.016	0.010*	0.017***	-0.002	-0.003
	(0.014)	(0.012)	(0.014)	(0.006)	(0.005)	(0.006)	(0.003)
Observations	255	255	255	255	255	255	255
PANEL C: Clubmates' mean and sd IVV							
Mean Clubmates' IVV	0.062	-0.023	0.043	0.096	0.034	0.002	0.002
	(0.046)	(0.027)	(0.076)	(0.074)	(0.037)	(0.029)	(0.029)
Var Clubmates' IVV	-0.000	0.004	0.016	0.008	0.004	-0.001	-0.001
	(0.011)	(0.005)	(0.014)	(0.010)	(0.004)	(0.005)	(0.005)
IVV	0.008	0.010*	0.021*	0.014	-0.002	-0.003	-0.003
	(0.014)	(0.006)	(0.012)	(0.014)	(0.006)	(0.003)	(0.003)
Observations	255	255	255	255	255	255	255

TABLE 13: Direct Effects of Peers' IVV on Behaviour and violence (Heterogeneous Groups Only)

	(1)	(2)	(3)	(4)	(5)
	Self-reported			External reports	
	Criminal actions in the last 3 months (Index)	Number of violent actions (Index)	Attitudes toward antisocial behaviour	Behaviour grades	High Behaviour grade
PANEL A: Clubmates' mean IVV					
Mean Clubmates' IVV	-0.084	-0.038	-0.018*	0.120*	0.029
	(0.052)	(0.044)	(0.009)	(0.069)	(0.030)
IVV	0.019	0.031	-0.003	-0.025*	0.004
	(0.030)	(0.028)	(0.006)	(0.014)	(0.007)
Observations	236	246	246	251	251
PANEL B: Clubmates' var IVV					
Var Clubmates' IVV	-0.012	-0.011*	-0.004*	0.013	0.005
	(0.012)	(0.006)	(0.002)	(0.013)	(0.004)
IVV	0.019	0.033	-0.003	-0.025*	0.004
	(0.031)	(0.027)	(0.005)	(0.014)	(0.007)
Observations	236	246	246	251	251
PANEL C: Clubmates' mean and var IVV					
Mean Clubmates' IVV	-0.075	0.027	-0.003	0.154	0.014
	(0.102)	(0.096)	(0.022)	(0.094)	(0.059)
Var Clubmates' IVV	-0.002	-0.014	-0.003	-0.007	0.003
	(0.023)	(0.016)	(0.004)	(0.016)	(0.008)
IVV	0.019	0.033	-0.003	-0.024*	0.004
	(0.032)	(0.027)	(0.005)	(0.014)	(0.007)
Observations	236	246	246	251	251

TABLE 14: Effects of Assignment to High Violent Homogeneous Group.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Grades			Probability to pass		Fail at least
	Reading	Math	Science	Reading	Math	Science	one course
High-Homog group	0.012	-0.040	-0.174	-0.075*	-0.005	-0.034	0.048**
	(0.100)	(0.031)	(0.142)	(0.041)	(0.107)	(0.031)	(0.022)
IVV-percentile	-0.164	0.149	0.624	0.128	-0.179	-0.001	-0.122
	(0.464)	(0.122)	(0.483)	(0.148)	(0.501)	(0.136)	(0.097)
IVV-percentile2	-0.205	-0.088	-0.554	-0.029	-0.097	0.090	0.034
	(0.399)	(0.094)	(0.381)	(0.108)	(0.461)	(0.124)	(0.089)
Observations	516	516	516	516	516	516	516

***, **, * significant at 1%, 5% and 10% respectively. Robust standard errors in parentheses at course-school level. Columns (1) - (3) are standarized grades from control groups at school-grade level. All regressions include the following controls: IVV, grades in the respective course before treatment, dummy indicating a missing value in the grade before treatment, and ciclo-school fixed effect (stratification level). Results are weighted according to the probability to be selected within each strata.

Table A1. SUMMARY STATISTICS. COMPARISON OF THE STUDY AND FUSADES (2015) SAMPLES

	Study Sample		FUSADES (2015) Sample		*p*-value
	Mean	Std. Dev.	Mean	Std. Dev.	
	[1]	[2]	[3]	[4]	[5]
Student is male	0.49	0.50	0.47	0.50	0.227
Student lives in urban area	0.73	0.44	0.66	0.47	0.000
Household composition					
Student living with both parents	0.53	0.49	0.54	0.50	0.545
Student living only with one of his/her parents	0.32	0.47	0.30	0.46	0.191
Student living with one parent	0.06	0.25	0.08	0.27	0.024
Student living with other relative	0.08	0.27	0.07	0.26	0.248
Student's travel time from house to school (minutes)	17.64	14.37	17.25	12.98	0.371
Student's mother level of education	0.31	0.46	0.4	0.49	0.399
Student is alone at home after school	0.05	0.22	0.11	0.31	0.000
Student's age	11.95	2.95	13.87	1.67	-
Student's course	5.75	2.71	5.5	2.52	-
N	1056		6641		

The table provides means and standard deviations of the main variables from the Study Sample and FUSADES (2015) Sample. These variables were used to estimate the IVV for each student in the Study Sample. Column 5 shows the *p*-value of the comparison of means between both samples. ***, ** and * denotes difference significant at the 1%, 5% and 10% level respectively when comparing the means.

TABLE A2. MATCHING RATE WITH ADMINISTRATIVE DATA AND ATTRITION RATE.

	Full Sample	Control group (C)	Any Treatment (T)	*Treatments*		*Tracking groups*	
				Heterogen. group (HT)	Homogen. group (HM)	Homog. High (HM-H)	Homog. Low (HM-L)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Fraction of students with matched admin. data, Q1 2016							
Reading scores	0.98	0.97	0.98	0.98	0.98	0.98	0.98
Math scores	0.91	0.89	0.92*	0.90	0.92+	0.92	0.93
Science scores	0.95	0.94	0.96	0.96	0.96	0.96	0.96
Behaviour scores	0.93	0.91	0.94	0.94	0.94	0.94	0.94
Absenteeism	0.68	0.68	0.67	0.68	0.67	0.65	0.69
Fraction of students with matched admin. data, 2016							
Reading scores	0.97	0.98	0.97	0.97	0.96	0.96	0.97
Math scores	0.97	0.98	0.97	0.97	0.96	0.96	0.97
Science scores	0.97	0.98	0.97	0.97	0.96	0.96	0.97
Behaviour scores	0.96	0.96	0.97	0.95	0.95	0.95	0.96
Absenteeism	0.80	0.79	0.80	0.80	0.80	0.76	0.83¨
Number of students at baseline and follow up							
Number of students present at baseline	1056	258	798	263	535	267	268
Number of students present at follow-up	968	237	731	248	483	239	244
Retention rate (1-attrition)	0.92	0.92	0.92	0.94	0.91	0.90	0.91

The table provides match rate with administrative data, calculated as the fraction of students present at the survey at baseline whom could be matched with administrative data from schools. In comparing T and C, * denotes difference significant at the 10% level. Similar notation is used to indicate statistically significant differences between HM and C (+) and between HM_H and HM-L (¨).

TABLE A3: DESCRIPTIVE STATISTICS OF THE IVV BY TREATMENT GROUP.

	Full Sample	Control group (C)	Any Treatment (T)	*Treatments*		*Tracking groups*	
				Heterogen. group (HT)	Homogen. group (HM)	Homog. High (HM-H)	Homog. Low (HM-L)
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Mean	0.038	0.038	0.038	0.041	0.037	0.050	0.024
Std. Dev	0.029	0.029	0.029	0.035	0.026	0.028	0.014
Median	0.030	0.029	0.030	0.030	0.031	0.044	0.021
Min	0.001	0.003	0.001	0.001	0.002	0.009	0.002
Max	0.216	0.183	0.216	0.216	0.154	0.154	0.059
N	**1056**	**258**	**798**	**263**	**535**	**267**	**268**

The table provides summary statistics for the Vulnerability and Violence Index (IVV) predicted using FUSADES (2015) dataset and variables available at clubs enrollment phase.

TABLE A4.*p-values* OF DIFFERENCES BETWEEN TREATMENT AND CONTROL GROUPS.

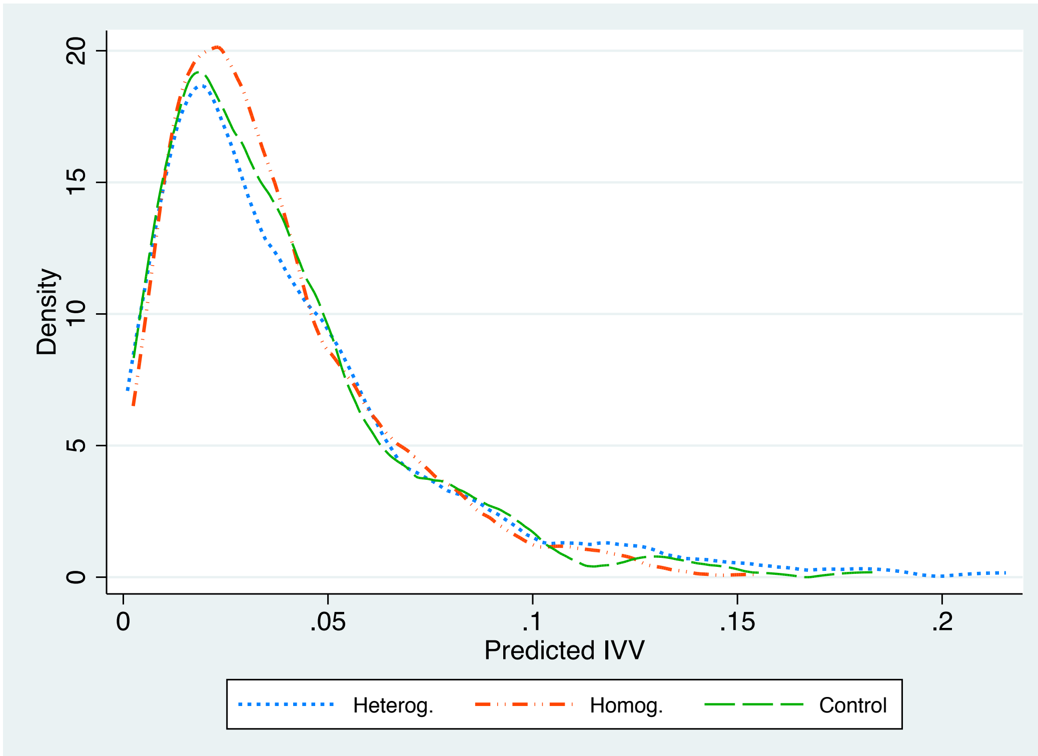
	Unadjusted p-values				
	Control = Heterog. = Homog.	Control = Heterog.	Control = Homog.	Heterog. = Homog.	Homog. High = Homog. Low
	[1]	[2]	[3]	[4]	[5]
PANEL A: IVV Determinants					
Student is male	0.785	0.521	0.729	0.635	0.000***
Student's age	0.308	0.149	0.371	0.178	0.000***
Student lives in urban area	0.790	0.903	0.520	0.557	0.102
Student's household composition					
Student living with both parents	0.118	0.230	0.105	0.298	0.137
Student living only with one parent	0.114	0.571	0.057*	0.247	0.340
Student living with a parent and stepparent	0.828	0.538	0.800	0.675	0.907
Student living with other relative /adults	0.799	0.542	0.619	0.786	0.844
Student's mother level of education:					
Basic Education (1-6 years)	0.751	0.543	0.517	0.977	0.002**
Intermediate education (7-12 years)	0.173	0.105	0.475	0.134	0.001***
University or higher (13 and +)	0.216	0.129	0.559	0.342	0.652
Student's travel time from house to school (min.)	0.726	0.441	0.994	0.637	0.034**
Student is alone at home after school	0.209	0.205	0.825	0.131	0.001***
Student's course (schooling year)	0.178	0.091	0.121	0.362	0.011**
Student enrolled on morning shift	0.122	0.268	0.354	0.053	0.471
Student's Violence Index	0.139	0.241	0.711	0.045**	0.000***
PANEL B: Academic outcomes					
Academic scores Q1 2016					
Reading scores	0.136	0.052*	0.038**	0.486	0.021**
Math scores	0.947	0.496	0.765	0.648	0.091*
Science scores	0.494	0.405	0.168	0.494	0.127
Behaviour scores	0.245	0.111	0.098*	0.798	0.056*
Absenteeism Q1 2016	0.101	0.080*	0.016**	0.586	0.046**
PANEL C: Sample composition and response rate					
Retention rate (1-attrition)	0.398	0.202	0.390	0.051*	0.383
Average club size at baseline	-	-	-	0.750	0.772

TABLE A5. DESCRIPTIVE STATISTICS OF PARTICIPANT SCHOOLS

School is located in urban area	60%	
Initial enrollment		
	Female enrollment	48%
	First level	18%
	Second level	20%
	Third level	26%
	Objective student population with the intervention	64%
Grade repetition		
	First level	10%
	Second level	28%
	Third level	22%
	Objective student population with the intervention	60%
Older students than their roster		
	First level	8%
	Second level	17%
	Third level	40%
	Objective student population with the intervention	65%
Facilities		
	Academic Support professor	60%
	Servicios psicológicos	20%
Additional income (average)		
	Cafeteria	$2879.6
	Voluntary contributions	$1500
	Celebrations	$579,87
	Donations	$1438,1
	Total	$4231,1
Subsidies and public programs		
	Paquete escolar	80%

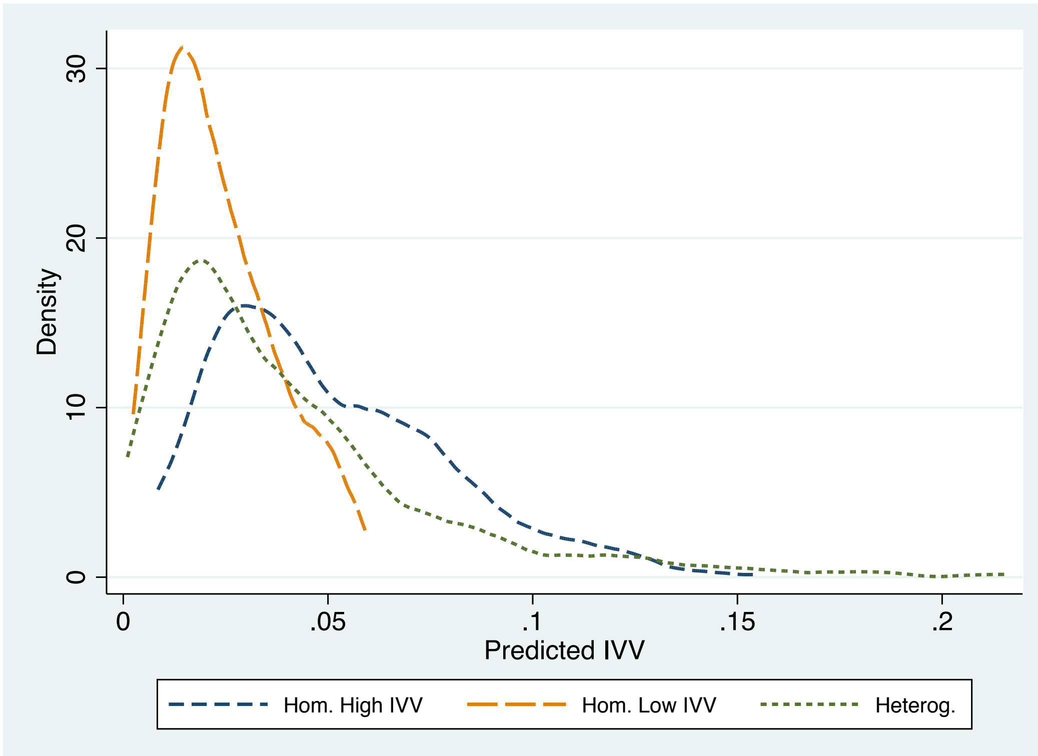
Source: MINED, El Salvador. Educational Census 2015

Figure 1. IVV distribution functions of Treatment and Control Groups.



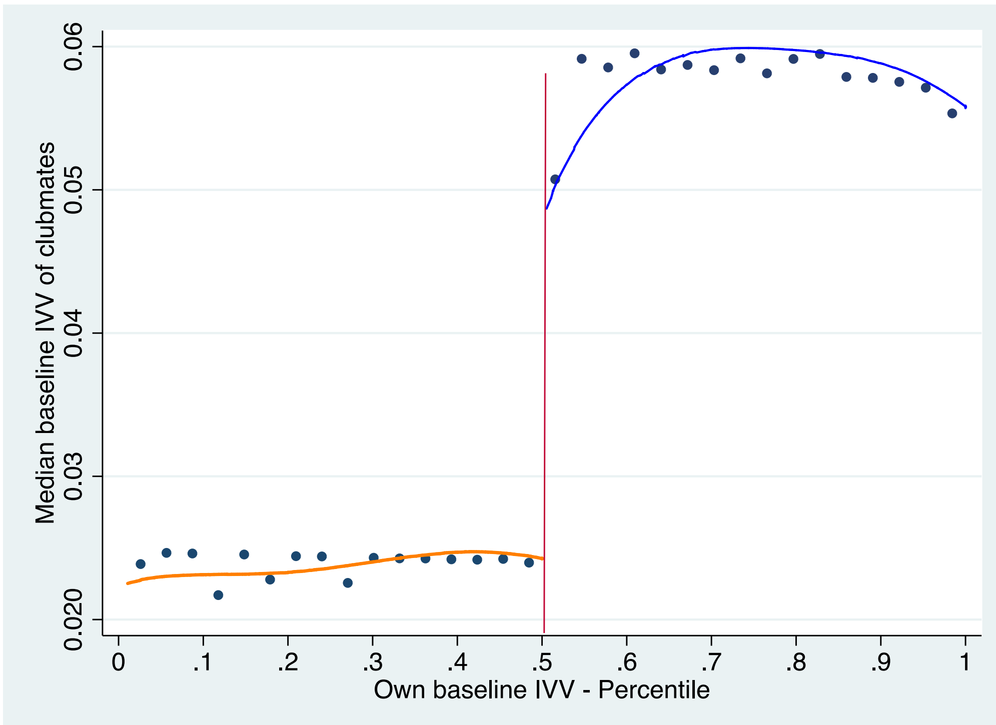
Predicted IVV distribution functions for the Control and Any Treatment (Homogeneous and Heterogeneous) Grupos, prior to treatment, for the whole study sample.

Figure 2. IVV distribution functions of Treated Groups.



Predicted IVV distribution functions generated by the experimental design, for the Heterogeneous Treatment group and each of the Homogeneous subgroups (High and Low IVV), in the whole study sample.

Figure 3. Experimental Variation in IVV Peer Composition, prior to treatment



Median predicted IVV of student's clubmates as a function of the student's own baseline IVV in homogeneous high and low groups. Consistent with the discontinuous assignment at the median IVV, there is a sharp discontinuity at the fiftieth percentile for the whole subsample.