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"TELL ME WHO YOU HANG OUT WITH": CLASSROOM PEER EFFECTS ON PSYCHOACTIVE SUBSTANCES CONSUMPTION

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RESUMEN

Usando datos Colombianos estimo efectos par para consumo de sustancias psicoactivas en estudiantes de bachillerato y canales para los mismos. Instrumentando el consumo de los estudiantes con el de los hogares obtengo que un incremento de 10% en el consumo de alcohol, cannabis, y cocaína incrementa la probabilidad individual de consumo en 3,14%, 4,29%, y 2,38% respectivamente. Los canales sugeridos por los datos son, que interactuar con consumidores hace más fácil acceder a drogas o reduce la percepción de riesgo de consumir las mismas.

Clasificación JEL: I12, I20.

Palabras claves: Efectos par, interacciones sociales, consumo de sustancias psicoactivas.

ABSTRACT

I use Colombian data to estimate peer effects for psychoactive substance consumption among high school students and identify channels for these effects. Instrumenting classroom consumption with that of the household yields that an increase of 10% in the proportion of classroom users of alcohol, cannabis, and cocaine increases the probability of students to use each substance in 3.14%, 4.29%, and 2.38% respectively. Data provides channels of these effects, specifically that the effect is explained by students who interact with consumers, leading to easier access to drugs or a decrease in the perceived risk of consuming these substances.

JEL Classification: I12, I20.

Keywords: peer effects, social interactions, psychoactive substance consumption.

"TELL ME WHO YOU HANG OUT WITH": CLASSROOM PEER EFFECTS ON PSYCHOACTIVE SUBSTANCES CONSUMPTION*

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I. Introduction

Understanding the dynamics of initiation and consumption of psychoactive substances for young people is important to establish more accurate public policies. Psychoactive substance consumption has negative effects on health and educational outcomes (Rice, 1999; Carpenter and Dobkin, 2011). Additionally Brook et al. (2002) finds that early initiation on psychoactive substance consumption leads to later psychiatric disorders and other substances dependence, Squeglia et al. (2014) finds that adolescent alcohol drinkers develop less brain volume than those who do not consume, Tapert et al. (2002) and Hanson et al. (2011) find visuospatial verbal learning and memory deficiencies by young psychoactive substances users later in life, and DuRant et al. (1999) finds a relation between being a young smoker and engaging in health related risky behaviors. Furthermore, Agrawal et al. (2006); King and Chassin (2007); Stueve (2005) provide evidence that individuals that initiate early on usage of such substances are more likely to develop an addiction in adulthood, worsening even more their health and educational outcomes.

Consumption of psychoactive substances in Colombia among young population is above world consumption level. According to United Nations Office on Drugs (2012) worldwide, the most widely used illicit drug is cannabis (global annual prevalence ranging from 2.6 to 5.0 per cent) while in Colombia according to *Ministerio de la Protección Social and Ministerio Del Interior y Justicia* (2011) 12.1% of Colombian high school students have used an illegal

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substance, namely cannabis, cocaine or other illegal substances. Specifically, 24%, 63.3%, 6.8%, and 2.6% of the students reported to have consumed cigarettes, alcohol, cannabis, and cocaine respectively.

In this paper I look for classroom-based peer effects on consumption of different substances among Colombian high school students. To do so I will use an instrumental variable (IV) approach to get causal effects of peers behavior on individual behavior. I instrument peers' behavior that individual *i* is exposed to, with the behavior of family members of individual *i*'s peers. Specifically, I construct the instrumental variable as the proportion of peers that have someone in their household that consumes psychoactive substances. This instrument is used for United States data in Fletcher (2010, 2012) with the difference that in his case family members is restricted to just parents. He compares this instrument to a set of instruments previously used in the literature –such as family income or religious attendance– and shows that it performs better in several tests. Additionally, I check for heterogeneous effects by grade, gender, and type (public or private) of school.

I use measures of consumption for four psychoactive substances: alcohol, cigarettes, cannabis, and cocaine. For each substance I define two dummy variables that indicate whether an individual has consumed during the last month and at any moment of life. Though it would be interesting to measure intensity of consumption of substances, in the dataset used I am able to identify intensity of consumption just for alcohol. Therefore, the scope of the article is effects of peers on the consumption of psychoactive substances measured through the discrete outcomes described above. Analyzing the decision whether a young individual consumes psychoactive substances or not is important, since early initiation is a good predictor of addictive behavior later in life. Additionally, it is important from a social perspective because of all the consequences that early initiation carries on educational and health outcomes later in life.

I use data from "*Estudio Nacional de Consumo de Sustancias Psicoactivas en Población Escolar*". This is a cross-section dataset for 2011 that gathers national representative information on psychoactive substances consumption of students from 6th to 11th grade in Colombia from 11 to 18 years old, as well as household characteristics that influence consumption.

Another research question I address is what are the mechanisms through which peers affect individual psychoactive substances consumption decisions.

To do so, I investigate two potential channels using the same IV approach. First, the effects of peers on the risk perception associated with psychoactive substances consumption. For instance, an individual that sees her peers smoking cigarettes can lower her risk perception associated with smoking cigarettes, which increases the likelihood of consumption. Second, the effects of peers on the easiness to access to these substances. For example, peers can directly sell or offer these substances or they can provide information on where to buy them. This analysis allows me to identify the relation between peer behavior and factors that directly affect propensity of consumption.

Despite the growth in the literature that evaluates peers' effect on risky and health related behaviors, to the best of my knowledge, this is the first study for Colombia analyzing peer effects on psychoactive substances consumption. Hence, this paper contributes to understand the role of peers on risky behaviors among Colombian students. Moreover, the channels through which peers affect the consumption of psychoactive substances is not well understood in the economic literature and there are few papers trying to identify them. This paper contributes to this literature analyzing two channels: the effects of peers' consumption on risk perception and easiness of access to psychoactive substances.

I find that for alcohol, cannabis, and cocaine there are positive and significant peer effects implying that if a student is transferred from a classroom where no students use any substance into a classroom where 10% has used at any moment of their life alcohol, cannabis, or cocaine, increases individual probability of using each substance in 3.14%, 4.29%, and 2.38% respectively. If I look for gender heterogeneous effects it is very similar except that the peer effects for cocaine disappears for women. Comparing with the results estimated by Fletcher (2012) my results are smaller, since he finds that a student moved from a classroom with no alcohol consumers to a classroom with 10% of alcohol consumers increases her likelihood of consumption in 5%.

Furthermore, I explore heterogeneous effects by grade and find that in all cases these are either null or positive (never negative). It is possible to identify grades for which the effect is large and grades for which the effect even disappears but for most substances the effect is stronger on lower grades (6th and 7th). Besides this, for cocaine and cannabis the effect is also positive and significant at 10th and 11th grade. Using this heterogeneity I find that positive peer effects on consumption of cigarettes and cannabis are associated with negative effects on risk perception towards frequent consumption of these substances, for cannabis specifically the channel works on every grade. I also find that positive peer effects on consumption of the four substances of study are associated with positive effects on easiness of access to illegal substances measured as direct offers to consume illegal substances, but if easiness to access is measured through seeing peers consume illegal substances the channel only works for smoking. This suggests that risk perception and easiness of access are channels for how peers' affect individual consumption.

Finally I conduct two robustness checks for these results: estimations using the sample of Bogotá only, and a Seemingly Unrelated Regression (SUR) and Three Stage Least Squares method (3SLS). On the first case, since school seats in Bogotá are assigned through a process that reduces the power of parents to determine to which school does their son goes to, doing this robustness check reduces the selection problem. On the second case, SUR and 3SLS are methods analogous to OLS and IV but that do not estimate each equation corresponding to each substance separately but as a system and accounts for correlation between errors of each equation corresponding to each substance. This makes errors more accurate and helps to identify correlation between consumption of different substances.

The paper is organized as follows: in section 2 I present a conceptual framework usually used by the literature regarding peer effects and its mechanisms. In section 3 I introduce the empirical strategy to be used and I discuss the conditions needed for validity of the methodology of estimation. In section 4 I present the dataset I use to estimate peer effects. In section 5 I present and discuss the main results of peer effects estimation and discuss the results on mechanisms of the peer effects. In section 6 I present robustness checks and further results. And in section 7 I provide some concluding remarks.

II. Concepts and Previous Research

Psychoactive substance consumption by young population is a subject that sparks spread concerns among the public policy and academic communities alike. Hence, it is a widely studied subject, to the extent that in Organization et al. (2015) the Global School-based Student Health Survey has a chapter dedicated to drug use and even further there is the project Warren et al. (2008) formulated by the WHO and collaborators that aims to fill a data gap regarding cigarette consumption among young population worldwide and provide inputs for policy makers to design adequate measures to fight this problem. The efforts have been well received and it is clear that there is still a wide array of important question regarding psychoactive substance consumption from young population left both in theoretical and empirical settings.

A comprehensive analysis of the research up to 1999 is provided in Chaloupka et al. (1999). This collection accurately portrays the difficulties both in terms of how to model and of data availability that research in this area endures. Moreover, the problem also encompasses a fast pace of change, for example as stated in Khanra et al. (2017) there is a recent rise in the use of new and chemical psychoactive substances leading to a regulation that fails to fully comprehend the phenomena occurring. Asides from the challenges imposed by new substances, the traditional substances also shift in importance and prevalence among young people. Vincenzi et al. (2017) provides evidence of a surge of consumption in cannabis by young population.

Peer effects are classified by Manski (1993) into three groups: endogenous effects, exogenous effects, and correlated effects. Endogenous effects refer to the behavior of peers that affect the propensity of an individual to engage in the same behavior. Exogenous effects indicate that exogenous characteristics of peers affect the propensity of an individual to do an activity. And correlated effects refer to the fact that being in a group exposes all of its members to variables that affect their propensity to engage in an activity. For example, in cigarette smoking, endogenous effects refer to peers smoking directly affecting smoking behavior of individuals; exogenous effects refer to characteristics from peers different from smoking, such as educational performance or participation in sports, affecting the probability of smoking, and correlated effects refer to the fact that all of the members of a classroom have the same teacher or access to the same facilities and this affects likelihood of smoking of students belonging to these reference groups.

Endogenous effects imply that a student that consumes psychoactive substances and interacts with peers increases their likelihood to engage in psychoactive substance consumption then, among these peers, the ones that actually end up consuming will also increase the probability of consuming from the peers they interact with and so on and so forth leading to a social multiplier effect. Thus, any policy aiming to refrain people from using illegal drugs or other substances, should take into account the spillover produced by endogenous peer effects. Given this, I look for endogenous peer effects on this paper.

Economists have devoted a great deal of interest to understand the role of peers, not only because of the importance the multiplier effect suggested by endogenous peer effects has on policy programs but also because of the empirical challenges to identify them. Previous studies, such as (Manski, 1993, 2000), have discussed these challenges, which can be summarized as follows:

- Reflection problem is not being able to distinguish between the effect of peers on an individual and that of the individuals on peers[1].
- Common factors refers to variables that affect everyone in the reference group, that could lead to correlations in the outcomes at the reference group level, but that do not reflect endogenous peer effect, hence if not controlled for, would bias the estimates of peer effects.
- Endogenous selection into reference groups which means that individuals similar in some variables, whether these are observables or unobservables, get together in the same reference group. This generates correlation between in the error term, leading to biased estimates.

If the estimation is carried out through OLS, all of these identification challenges generate endogeneity in the parameter associated to peers' effect, which leads to identification problems and biased estimates of the parameter of interest.

These identification problems have been addressed in the literature in different ways. Case and Katz (1991); Gaviria and Raphael (2001); Powell et al. (2005); Lundborg (2006); Fletcher (2012, 2010) use school and grade fixed effects, or a large set of reference group characteristics to identify common separately from endogenous peer effects, and instrumental variables to solve the reflection and self selection problems finding evidence of significant peer effects. Duncan et al. (2005); Eisenberg et al. (2014) use natural experiments in college rooms assignment to solve self selection problem, lags of the risky behavior to solve reflection problem, and a large set of roommate characteristics

[1] For instance, in the case of this paper, since the expected value of consumption average in a classroom is the same as the expected value of consumption for each of its members, there are not enough variables to estimate all of the parameters through OLS and it is only possible to get a combination of parameters for each variable instead of each parameter separately as one would wish to.

to rule out common factors, finding positive effects on alcohol binge drinking and suggestions of positive effects in smoking for men and negative for women.

On the other hand, the discussion of how do peers affect own behavior is addressed in Glaeser and Scheinkman (2004, 2000) where they suggest three types of mechanisms for peer effects: learning, stigma and taste. Learning is labeled as an information mechanism while stigma and taste are labeled as preference mechanisms.

Learning refers to the case in which by interacting with peers a person learns new information, for example, when a person sees or speaks with a peer that is a smoker, she acquires new information modifying her cost-benefit analysis and changing her likelihood of smoking. Furthermore, information obtained from peers can provide access to networks where it is possible to buy drugs, as well as this information can change a person's risk perception associated with drug consumption. In any case working as a channel to affect own decisions of engaging in consumption of psychoactive substances.

Stigma and taste are channels that operate through changes in preferences influenced by behavior of peers. Stigma refers to changes in valuation of an activity because of feelings or opinions towards a peer that does the activity, for instance, a person that hates smokers and then comes to her knowledge that a person she loves or admires is a smoker, and because of this she changes her perception towards smoking. And finally, taste-related mechanisms refers to peer effects operating as a herd behavior; a person that decides to do something solely because her peers decide to do it.

Recognizing these channels helps to understand how do peer effects operate, but do not indicate if the effect should be negative or positive. A person that faces peers consuming cocaine, according to stigma, can increase or decrease her likelihood to use it depending on whether she has a good or bad idea of the peers that consume cocaine. Taste effects depend on how does the classroom as a herd behave; students follow the group. Hence, if there is a wave of psychoactive consumption, peer effects increase the probability of consumption of each student. Finally, learning channel depends on the information provided by peers; a peer that uses cocaine but assures that it does not hurt him induces a peer to try it, while a peer that dies or gets hospitalized due to an overdose of cocaine provides information that discourages initiation or consumption of cocaine. Thus, it is an important empirical question to understand in which direction peers behavior affects own consumption of psychoactive substances.

As of today and to the best of my knowledge there are very few comparable studies to this for the Latin-America region, with Lucchese et al. (2014) being a prominent example. This study uses data from 2005 for Schools in Cordoba, Argentina to assess the state of consumption of psychoactive substances in school aged population.

III. Empirical Strategy

My identification strategy relies on an instrumental variables approach (IV). I instrument average consumption of peers using average consumption of peers' household members, both of the averaged measured at the classroom level. This methodology allows me to solve reflection and reversal causality problems, and enables me to disentangle the effect of peers on individuals from the reverse. To control for common factors I use school and grade fixed effects[2]. The IV specification involves a first and a second stage which are formally presented in equations 1 and 2 respectively:

$$y_{i,c,s} = \pi_0 + \pi_1 z_{i,c,s} + \pi_2 x_{i,c,s} + \rho_s + \rho_g + \varepsilon_{i,c,s}, \qquad (1)$$

$$y_{i,c,s} = \alpha_0 + \beta \hat{y}_{i,c,s} + \alpha_1 x_{i,c,s} + \rho_s + \rho_g + \mu_{i,c,s} \qquad (2)$$

where $y_{i,c,s}$ is a set of dummies that indicate if individual i attending classroom c at school s has consumed cigarettes, alcohol, cannabis, or cocaine. For each substance this equation is estimated separately, $y_{i,c,s}$ is the same variable averaged at the classroom level[3], z is the proportion of peers who have at least one household member that consumes each psychoactive substance and is the instrument for peers' average consumption, $x_{i,c,s}$ is a set of individual, family structure and school controls, ρ_s and ρ_g are school and grade fixed effects respectively, and $\varepsilon_{i,c,s}$ and $\mu_{i,c,s}$ are disturbance terms. The coefficient of interest is β associated to $\hat{y}_{i,c,s}$, which measures the approximate causal effect of peers on substance consumption.

[2] Classroom fixed effects are not recommended because given the size of the classrooms the average of peers consumption of a substance is highly correlated with a fixed effect inducing multicollinearity. Hence, the best approach is to combine school and grade fixed effects.

[3] All of the averages are calculated excluding individual i, this to provide more variation in the variable that measures peer effects in a classroom.

III.1 The instrument and potential estimation biases

I instrument the peer behavior that individual *i* is exposed to, with the behavior of household members of individual *i*'s peers. Specifically, I construct this variable as the proportion of peers that have someone in their household that consumes psychoactive substances. Peers' consumption variables and the instrument are specific to the substance of analysis, so in the regressions of alcohol I construct the instrument using household consumption of alcohol only, and the same procedure holds for each other substance of analysis[4].The validity of this instrument requires two conditions: that household members do affect individual behavior of students that belong to the household, and that family members in the household of the students only affect the behavior of the students' classroom peers through the effect they had on the students that belong to the household and not directly or by any other mean.

Validity of the instrument requires that a given student has limited contact with his classmates' household members, or that if there is contact, it does not influence the behavior of the student. This validates the instrument because there would be no other way in which household members of one student may affect his peers other than affecting the student. The data base does not provide a way to identify time spent between relatives and peers, still, psychology has studied this issue. During adolescence, parent-adolescent relationship deteriorates with age inherent conflict making harder for them to keep a good communication (Flannery et al., 1993; Renk et al., 2005). Hence, adolescents avoid their parents which makes it less likely for parents to interact with their kids' peers, and also harder for parents to affect the behavior of the classmates of their children.

This evidence accounts for parent-adolescent relations but the instrument I use is defined on household members. So, if the rejection of teenagers is only towards their parents there is a lot of room for other family members to affect both the teenager and its peers directly. On this there is also psychological

[4] To understand better the construction of the instrument let's consider a classroom *c* that has 6 students. Student *i* in classroom c does not consume alcohol but 3 of his peers does. This means that the peer measure of consumption of alcohol for student *i* in classroom *c* would be 3/5 since I exclude student *i* to calculate the average consumption she is exposed to. Now assume that of his five peers four have family members that consume alcohol, hence the instrument for alcohol consumption of student *i* in classroom *c* would be 4/5.

evidence that during adolescence authority figures in general (not only parents, but also any other family member that represents authority) are avoided by teenagers and that they tend to come into conflict with them (Levy, 2000; Zhang and Fuligni, 2006). In this case, younger siblings and cousins would represent the only problem for the instrument and for this problem there is little room for improvement, I do not have information on siblings and other age close relatives that might be affecting the instrument.

Another problem of the instrument is that adolescents rejection to their parents makes it unlikely for parents to affect adolescents behavior. This idea is refuted in two ways: on the one hand psychological literature finds that positive implicit attitudes towards smoking are intergenerationally transmitted and sons of persons with positive implicit attitudes towards smoking have early initiations in smoking (Sherman et al., 2009). On the other hand, my first stage regression offers a formal representation of the idea, therefore, a significant coefficient associated to the instrument suggests parents do affect their sons behavior. As discussed in the previous section, my estimations face three types of problems: reflection, endogenous selection into reference groups, and common factors. In order to solve them as exposed previously I use an IV approach. Reflection in this setting is solved since after the first stage, the expected value of the measure of peers' consumption is no longer the same as the expected value of the measure of individual consumption; using peers' household consumption to instrument peers's consumption makes that $E[\hat{y}_{i,c,s}] \neq E[y_{i,c,s}]$, hence making it possible to identify the parameter of interest.

In order to solve for common factors I use school and grade fixed effects which captures variables as facilities of the school location and other school fixed variables.

For endogenous selection problem is important to put upfront that in the case under analysis it may be present in different ways. There could be selection both at the school and at the classroom level. But it would be necessary to meet very specific conditions so that endogeneity invalidates my identification strategy. Endogenous school selection means that there are unobserved variables that determine the school a student attends to. But, unless the selection is correlated with the instrument, IV approach solves this problem. This means that if parents choose schools for their kids on the basis of psychoactive substance consumption at their sons peers' households (or characteristics that determine such consumption), then the endogenous school selection would be a possible source of bias for my IV estimations. I cannot test for this, and it is only possible to assume that if there is such endogeneity it may be more problematic in private education since parents usually take time to search and make an informed decision on which school to send their kids. On the contrary, public education has a fixed available number of seats and a regulated assignation process that even when it is not completely random reduces this selection. To check for this I will conduct a robustness check estimating the model for public and private schools separately and public schools in Bogotá, this will provide insights on the bias since seats in public schools of Bogotá are assigned with a clearer mechanisms that reduces the extent to which parents can affect the school that their sons attend to.

Endogenous classroom selection refers to the possibility that students are sorted into classrooms according to variables that determine their consumption of psychoactive substances. In Colombia, it is discretion of schools to assign their students into classrooms and information on how do they sort students into classrooms is not available. In any case, parents do not decide to which classroom does their son go to and this helps the validity of the instrument.

To sum up, if endogeneity is present, the IV approach estimation solves it under certain conditions but there is no test I can provide to support that these are met. It might be the case in which school or classroom endogenous selection is not fixed through the IV approach. There are other methodologies that could get unbiased estimates, for example Hoxby (2000) assumes that an exogenous source of variation for gender ratio comes from analyzing adjacent cohorts within a grade within a school and exploits this to find evidence for peer effects on academic achievement. Unfortunately I am not able to apply this method because the survey I use is a single year survey so I do not have two adjacent cohorts. In Lee (2007) variation of reference group sizes is exploited for identification of both endogenous and exogenous effects. An additional condition for identification in this method is that interaction between members of different reference groups be as low as possible. In order to use this method I could use classroom which have enough variation on their size, but since there are classrooms from the same school interaction between them is not likely to be small. On the other hand I could define school as the reference group, but for this case the variation of the size of schools is not high enough.

Other paper that gives an insight to identification of peer effects isBramoullé et al. (2009). He identifies peer effects through social networks but he also proposes some general conditions to achieve identification of endogenous peer effects. The first one is that the estimates of such effects should be smaller than one in absolute value ($\beta < 1$), this means that psychoactive substance consumption is inelastic with respect to consumption of peers. This makes sense since $\beta \geq 1$ would mean that with just one student in a classroom that consumes all of her peers with whom she interacts would end up consuming. As I will show in the results section my estimates meet this condition. The second one is that it is necessary, given that the social interactions are present through groups, that these reference groups have at least three different sizes. This condition is necessary because group sizes variation provide an exogenous source of variation to achieve identification of endogenous peer effects. This is not a problem since for my estimations classroom size goes from 2 to 60.

IV. Data and Summary Statistics

I use data from "*Estudio Nacional de Consumo de Sustancias Psicoactivas en Población Escolar*" (ECSP). This is a cross-section dataset for 2011 that collects information on psychoactive substances consumption of students from 6th to 11th grade in Colombia, as well as individual, family, and school characteristics, and factors that influence consumption.

ECSP has a multistage clustered random sampling. Municipalities are randomly selected with a probability proportional to the number of students between 6th and 11th grade they have, then schools are randomly selected and assigned into two groups where grades 6th, 8th and, 10th of the schools were selected from the first group and 7th, 9th, and, 11th from the schools of the second group. Finally in each grade a classroom was randomly selected and all of its students were surveyed. The final sample was 92,929 students in 3,212 classrooms from 1,134 schools at 161 municipalities. After dropping individuals with missing information in the variables of interest, my final sample is 90,668 students.

Table 1 presents descriptive statistics of variables that measure psychoactive substance use and risk perception towards it. I will analyze four substances: alcohol, tobacco cigarettes, cannabis, and cocaine. Consumption of these substances is assessed in the ECSP by asking students if they have consumed the substance at any moment of their lives[5]. It is interesting to note that only 2% of the sample is old enough to legally smoke or drink alcohol but 22.9% of the sample has ever smoked and 64.3% has ever drank alcohol. Still, the proportion of ever used illegal drugs is considerably lower (6.2% for cannabis and 2.5% for cocaine). Risk perception variables gather information on how the students perceive risk from consumption of psychoactive substances occasionally or frequently[6,7].Risk perception is measured in a scale from 1 to 4 where 1 is no risk at all and 4 is extreme danger.

In all of the variables that measure psychoactive substance consumption men have higher rates than women. Still, risk perception is very similar for both sex. The public and private schools comparison yields different results. While students in private schools have higher consumption rates than those in public schools in all of the substances, risk perception is higher in public schools.

In addition to consumption by students, Table 1 reports if at least one member of the household consumes the substance. I use this variable to construct the instrument averaging it at the classroom level[8].

Figures 1 and 2 show the proportion of students that report to have consumed each substance at any moment of life and in the last month respectively. There is a clear trend in all substances to increase as students attend a higher school grade, and it is also possible to see that alcohol is for any grade, the highest consumed substance followed by cigarettes, cannabis, and cocaine.

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5 The survey also asks about consumption during the last year and during last month, but for simplicity I only report results for measures of consumption at any moment of life, the full set of results are available upon request.
6 The exact question of risk perception states: What do you think is the risk a person takes when consumes the following? And the possible answers are: 1 (no risk at all), 2 (slight risk), 3 (moderate risk), 4 (great risk), 5 (I don't know).
7 The question for alcohol consumption is slightly different. It states: What do you think is the risk a person takes when binge drinks alcohol? And the options are the same.
8 The exact question asks: Does any of the persons with whom you live in your house or household consume any of these substances? And there is an item for each substance with the options yes or no.

Table 1.

Summary statistics of psychoactive substance use, risk perception about consumption

Variable	Full sample	Women	Men	Private	Public
Any moment in life:					
Smoked cigarettes	0.239	0.206	0.275	0.255	0.234
Drank alcohol	0.631	0.627	0.636	0.685	0.614
Smoked cannabis	0.068	0.054	0.083	0.073	0.066
Consumed cocaine	0.026	0.019	0.034	0.028	0.025
Someone in the household:					
Smoked cigarettes	0.282	0.285	0.278	0.272	0.286
Drank alcohol	0.613	0.63	0.593	0.661	0.589
Smoked cannabis	0.045	0.048	0.042	0.037	0.049
Consumed cocaine	0.017	0.017	0.016	0.014	0.018
Risk perception of occasionally:					
Smoking cigarettes	2.478	2.484	2.471	2.491	2.473
Drinking alcohol	3.519	3.582	3.448	3.571	3.500
Smoking cannabis	2.138	2.16	2.114	2.115	2.147
Consuming cocaine	3.265	3.321	3.202	3.317	3.246
Risk perception of frequently:					
Smoking cigarettes	2.986	3.03	2.935	3.009	2.978
Drinking alcohol	3.598	3.669	3.515	3.639	3.582
Smoking cannabis	3.224	3.248	3.197	3.286	3.202
Consuming cocaine	3.692	3.743	3.634	3.76	3.667
Easiness of access to illegal psychoactive substances:					
Has been offered to consume illegal drugs by schoolmates	0.214	0.177	0.253	0.252	0.201
Has seen schoolmates purchase or consume illegal drugs	0.311	0.286	0.339	0.283	0.321
Observations	90,668	47,599	43,069	29,383	61,285

Notes: the exact question of risk perception states: What do you think is the risk a person takes when consumes the following? And the possible answers are: 1 (no risk at all), 2 (slight risk), 3 (moderate risk), 4 (great risk), 5 (I don't know). The question for alcohol consumption is slightly different. It states: What do you think is the risk a person takes when binge drinks alcohol? And the options are the same.

Figure 1.
Percentage of consumers at any moment of life by grade and substance

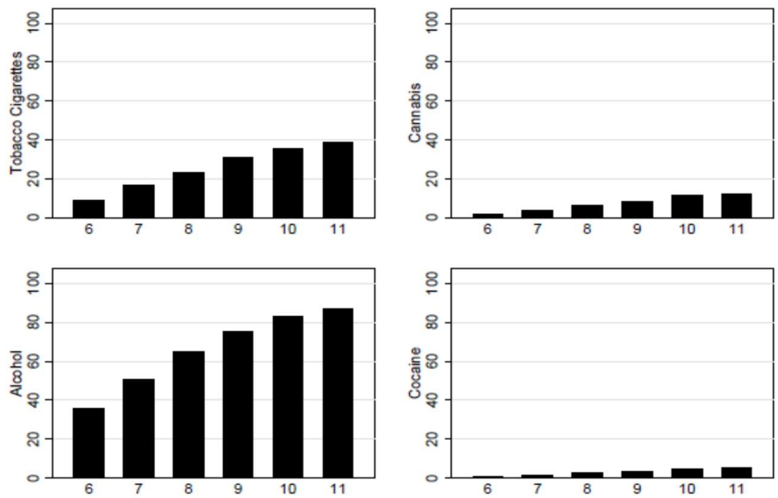
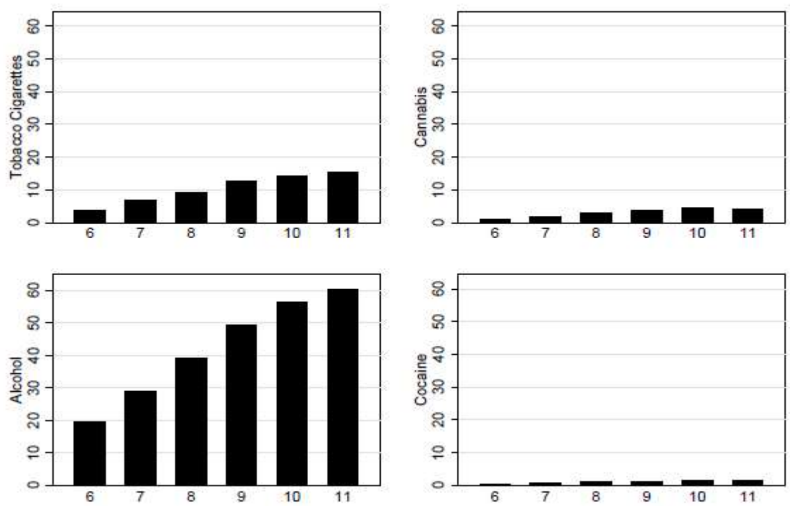


Figure 2.
Percentage of consumers at any moment of life by grade and substance



Tables 2 and 3 present descriptive statistics of school, individual and family characteristics. All of the models I report in the results section control for this set of variables. Table 2 presents the distribution of students among schools types. There are three dimensions in which schools are classified: Public, School day, and Single-sex or coeducational schools. Public schools are schools that are owned by national, or local government and most of them are also managed by the government, nonetheless some of them are managed by private schools. Some schools in Colombia do not provide the full eight hour a day studying scheme, this is what School day captures, some schools make students go part-time in one of these hours: 8:00 am to 4:00 pm, some from 6:00 am to 12:00 am, and some from 12:00 pm to 6:00 pm. Finally, some schools are coeducational and some are boys only or girls only schools. The proportion of students in each category is in line with national numbers, i.e. there is no under or over representation in any of the categories.

Table 2.
Distribution of students among school types

Variable	Mean
Public school	0.752
Morning Schedule	0.564
Afternoon Schedule	0.201
Complete Schedule	0.235
Single-sex schools (male)	0.015
Single-sex schools (female)	0.055
Coeducational schools	0.93
Observations	90,668
Number of Schools	1,134

Notes: school day means that schools have different study hours, morning schools study from 6 am to 12 pm, afternoon from 12 pm to 6 pm, and complete from 8 am to 4 pm.

In Table 3, I present variables that control for household and individual characteristics. For the students I have information on age, the grade they attend to, and if they have failed at least a year in any of elementary, middle, or high school. For the family structure I have information on whether they live with both of their parents or just one, and education of the mother classified in six categories from "No formal education" to "Graduate education". Finally, I have access to home environment, a variable that indicates whether the parents supervise leisure activities and places their sons go to, and days of a regular week the student has dinner with their parents[9]. It is important to mention that the proportion of students attending higher grades is lower that the proportion of students attending lower grades. This is a normal result of high school education as some of the students drop out of high school before finishing.

Table 3.
Summary statistics of individual and family characteristics

	Full sample	Women	Men	Private	Public
Age					
11 years old	0.112	0.119	0.105	0.128	0.107
12 years old	0.159	0.162	0.156	0.159	0.159
13 years old	0.181	0.178	0.185	0.178	0.182
14 years old	0.177	0.176	0.177	0.173	0.178
15 years old	0.166	0.169	0.164	0.169	0.166
16 years old	0.126	0.125	0.127	0.127	0.126
17 years old	0.06	0.056	0.065	0.052	0.062
18 years old	0.019	0.016	0.022	0.014	0.02
Have failed a year	0.295	0.244	0.351	0.226	0.318
Students attending:					
6th grade	0.201	0.191	0.213	0.189	0.205
7th grade	0.189	0.189	0.188	0.173	0.194
8th grade	0.192	0.185	0.199	0.2	0.189
9th grade	0.154	0.159	0.148	0.157	0.153
10th grade	0.153	0.152	0.154	0.156	0.152
11th grade	0.112	0.125	0.098	0.126	0.107
Highest education level reached by the mother:					
Elementary school	0.13	0.118	0.143	0.117	0.135
High school	0.245	0.265	0.223	0.123	0.285
Technician program	0.385	0.386	0.384	0.344	0.398
College	0.061	0.06	0.062	0.087	0.053
Graduate program	0.132	0.125	0.139	0.248	0.093
Does not have studies	0.034	0.031	0.037	0.074	0.021
Does not know	0.014	0.015	0.012	0.009	0.015
Parents supervise leisure activities	0.962	0.971	0.953	0.969	0.96
Days in a regular week that has dinner with family	5.856	5.821	5.894	5.739	5.895
Uniparental home	0.359	0.373	0.344	0.345	0.364
Observations	90,668	47,599	43,069	29,383	61,285

[9] All of the information on family structure is provided by the student.

The survey has a potential problem regarding the way it was collected. They pollsters visited the classrooms selected to participate and introduced the survey as compulsory activity. They also made it clear that the information provided would have no impact on their school performance, academic, or disciplinary standing given that the responses would be recorded in anonymity. Still, there is a chance that some students felt fear of plausible consequences for them or their families which would end in an under reporting of consumption both of the individual students as of their families.

This is a problem that I cannot solve but that its importance depend on whether the situation occurred in a particular setting. If it is assumed that the fear for consequences based on their answers was on average the same across the sample then it does not compromise the validity of the results. But, in the case that the problem occurs heterogeneously across students, assuming that those that consume or whose families consume had a larger fear of retaliation, then the estimates I report are downward biased since the variables that identify consumption would be larger than reported by the students.

V. Results

Table 4 reports the peer effects estimates on individual consumption (parameter β in equation (2)) by OLS (panel A) and IV (where panel B reports the first stage and panel C the second stage). Regressions are performed separately for the four substances (cigarette, alcohol, cannabis, and cocaine).

First stage regressions from the IV approach show positive and significant correlations between the instrument and the endogenous variable. This means that consumption of psychoactive substances at the household affects the consumption of psychoactive substances of each student. I present F-statistic from the first stage and they are above 10 which suggests that the instrument is not weak.

IV estimates show that peers affect the consumption of alcohol, cannabis, and cocaine. If a student is transferred from a classroom where no one uses any substance into a classroom where 10% has used at any moment of their life alcohol, cannabis, or cocaine, increases individual probability of using each substance in 3.14%, 4.29%, and 2.38% respectively (columns 3, 5 and 7)[10].

Table 4.
Estimation of peer effects on psychoactive substance consumption

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	Panel A: OLS Estimates			
Peer effect	0.142***	0.144***	0.212***	0.032
	(0.041)	(0.043)	(0.044)	(0.06)
	Panel B: First Stage			
Peer effect	0.21***	0.39***	0.42***	0.38***
	(0.04)	(0.033)	(0.05)	(0.052)
F-Statistic	27.952	136.996	70.87	52.735
	Panel C: IV Estimates			
Peer effect	0.032	0.314***	0.429***	0.238**
	(0.206)	(0.072)	(0.084)	(0.109)
Number of Obs.	90,668	90,668	90,668	90,668

Notes: This table reports β coefficient on equation 2 estimated through IV and OLS for each substance. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations school and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * p<0.1, ** p< 0.05, *** p<0.01.

In general, OLS estimates underestimate these effects for the IV estimations that present statistically significant effects. This happens because the β estimated through OLS is including other information besides the peer effect. This additional information could bias the results towards any direction. The instrument allows to identify the Local Average Treatment Effect (LATE) - an effect only on the students that the instrument has an effect on - i.e. the students

[10] These effects are calculated using the coefficients in Table 4. Since they reflect the effect of 100% increase in the classroom average of consumption a more readable number results from taking that 100% change and multiplying It for 1/10 to get the effect of a 10% increase e.g. for alcohol 0.314/10=0.0314.

who have been affected by peers only through the channel of household members also using substances. Although the LATE being larger than the OLS estimator could be a consequence of endogeneity and other biases being solved, it could be the case that the IV provides an inflated estimation that reflects only the effect on compliers while the actual effect for the entire population is smaller. It would be ideal to be able to discern between these two scenarios but given the dataset available it is only possible to estimate the two separately and being careful of making clear the external limitations of the methodology.

On the other hand, it is important to think about other possible drawbacks of the estimation. How accurate are the effects measured by the IV strategy? If the allocation into schools or classrooms is correlated with the likelihood to consume psychoactive substances, then although the strategy used controls for a wide variety of family and individual variables, the estimations would be biased. The coefficients would be capturing this correlation instead of the effect of peers on individual consumption decisions. The clearest way that this could happen is if either the schools assign students to classroom, or students are assigned to schools based on variables correlated with psychoactive substance consumption. For the classroom selection problem there is no guarantee that there is no selection, the regulation on classroom allocation is fuzzy and mostly left at the discretion of each school. On the other side, the Ministry of Education in Colombia has left the mechanism to assign students to schools on the discretion of regional education entities. Keeping aside private schools, to the best of my knowledge, the most organized mechanism for this process is in Bogotá where parents have to fill a form in which they declare their permanent address and some characteristics that can generate priority for some schools like if the student applying for a seat has siblings studying at the same institution. All in all, parents have small power to decide where their sons are going to be assigned for school aside from the choice of home location.

V.I Heterogeneous effects by grade

Grades' heterogeneous effects are estimated using the same IV and OLS approaches of equation (2) but separately for each grade. This is the same as if I would have interacted every variable of equation (2) with a set of dummies that identify if a student belongs to each grade. In both cases what I intent to do is incorporate to the analysis the fact that there are differences between grades in how consumption is affected by every variable. Following this methodology yields the results reported in Table 5.

Table 5.
Peer effects on psychoactive substance consumption: grade heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
Peer effect 6th	0.415 **	0.66 ***	0.47 ***	0.05
	(0.215)	(0.071)	(0.178)	(0.281)
F-Statistic	17.08	107.584	10.626	13.481
Peer effect 7th	0.174	0.612 ***	0.718 ***	0.429 ***
	(0.178)	(0.062)	(0.051)	(0.142)
F-Statistic	37.342	132.097	52.277	19.048
Peer effect 8th	0.222	0.301 **	0.138	0.441 ***
	(0.226)	(0.12)	(0.256)	(0.147)
F-Statistic	11.624	46.762	13.558	16.271
Peer effect 9th	0.504 ***	0.598 ***	0.570 ***	0.261
	(0.124)	(0.069)	(0.125)	(0.317)
F-Statistic	19.793	78.539	19.861	6.731
Peer effect 10th	0.181	0.077	0.491 ***	0.606 ***
	(0.239)	(0.206)	(0.128)	(0.117)
F-Statistic	13.744	36.347	18.904	35.361
Peer effect 11th	0.072	0.196	0.727 ***	0.359 *
	(0.294)	(0.154)	(0.079)	(0.207)
F-Statistic	9.982	30.006	16.294	17.309

Notes: This table reports β coefficient on equation (2) estimated through IV for each substance and each grade separately. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality fixed effects, and family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

Cigarette consumption starts at 6th grade with positive and significant peer effects for consumption at any moment of life; moving a 6th grade student from a classroom where no one smokes to another one where 10% smoked at any moment of life makes her likelihood of smoking increase in 4.15%. While the grade of analysis is larger the peer effect does not seem to have a trend, still there are heterogeneities on the effect that can be exploited to look for evidence of channels[11]. On the other hand, having mixed results across grades on terms of significance is an explanation to why I do not find effects when looking for them in the whole sample; significant effects of some grades cancel out with not significant effects of others.

Alcohol consumption effect does not follow a trend as cigarette consumption, it begins with positive and significant peer effects that seem to be stable across grades. Still it is possible to identify that by the time students reach 9th grade, moving a student from a classroom with no peers that consume alcohol to a classroom where 10% consumed during the last month increases the probability of engaging in alcohol consumption in 5.98%.

Cannabis peer consumption shows a similar behavior to the ones of alcohol and cigarette, except that it is least sable. At 6th grade peer cannabis consumption at any moment of life presents positive and significant effects on students consumption, the effects keep on being positive and significant with the exception of 8th grade and by 11th grade moving a student from a classroom with no cannabis consumption to a classroom with 10% of consumption at any moment of life increases the likelihood of the student in 7.27%.

Cocaine consumption starts at 6th grade with effects that are not significant but at 7th grade they become positive and significant peer effects and as the grade of the students is more advanced it does not seem to have a trend. Following the same structure of previous analysis the peer effect for consumption of cocaine at any moment of life is 3.59%.

V.2. Heterogeneous effects by gender

Table 6 reports gender heterogeneous effects. These effects are estimated as equation (2) but including an interaction between peers' consumption and gender. For women there are positive and significant peer effects on alcohol and

[11] A graphic exposition of these results is provided upon request.

cannabis while for males there are positive peer effects for alcohol, cannabis, and cocaine.

Peer effects are stronger for women than for men in alcohol consumption, but males have stronger peer effects for cannabis. Moving a female student from a classroom with zero peers that have consumed alcohol to a classroom with 10% peers who have consumed alcohol at any moment of life increases the likelihood of alcohol consumption in 1.21% more than the increase induced by the same transfer for a man. For the case of cannabis consumption, moving men from a classroom with no cannabis consumers to a classroom with 10% of peers that have consumed cannabis at any moment of life increases the likelihood of cannabis consumption to that man in 2.04% in addition to the increase experienced by a woman under the same transfer.

Table 6.

Estimation of peer effects on psychoactive substance consumption: gender heterogeneous

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
		Ever		
		IV Estimates		
Female peer effect	-0.006	0.375 ***	0.327***	0.087
	(0.202)	(0.071)	(0.178)	(0.281)
Male peer effect	0.174	0.612 ***	0.718 ***	0.429 ***
	(0.178)	(0.062)	(0.051)	(0.142)
Number of Obs.	90,668	90,668	90,668	90,668

Notes: This table reports estimations of β coefficient on equation (2) and coefficients associated to the interaction of peers' consumption and gender dummies estimated through IV and OLS for each substance. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation, still, I do not report the first stage because of its size. For all of the estimations school and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

V.3. Heterogeneous effects by type of school

Table 7 reports the results of peer effect estimation for private and public schools separately. Results for the IV approach are generally larger for public schools. As not conclusive as this is, given that the populations that attend public and private schools are completely different from each other and this makes it misleading to compare them, it is still worrying from a public policy perspective that peer effects on psychoactive substance consumption are stronger on public schools precisely because the kids that attend to such schools are more vulnerable and from poorer families than the ones attending private schools.

Cigarette consumption from peers is statistically significant only for public schools. A student transferred from a classroom with no cigarette consumption to a classroom with 10% both classrooms being in public schools increases the probability of engaging in cigarette consumption in 3.22% for last month peer consumption[12].

Alcohol consumption by peers have statistical effect for both public and private schools. Following the same stream of analysis used, the increase in the likelihood of consumption of alcohol is 3.29% for any moment of life in public schools and 2.70% for any moment of life in private schools.

Cannabis consumption by peers also has a positive and significant effect for both kinds of schools. The increase in probability of engaging in cannabis consumption is 4.49% and for consumption of peers at any moment of life in public schools and 3.34% for peers consumption in private schools.

Cocaine consumption by peer effect is only significant at public schools and it is of an increase of 2.4% in the likelihood of consumption related to peers consuming cocaine at any moment of life. It is not surprising that this substance is the least significant of the analyzed since it is also the hardest to get, the least consumed, and the more stigmatized of the substances included in the study.

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[12] Results available upon request.

Table 7.
Estimation of peer effects on psychoactive substance consumption: type of school heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
	Private schools			
Female peer effect	-0.26	0.27 *	0.334 *	0.228
	(0.923)	(0.138)	(0.172)	(0.205)
	Public schools			
Male peer effect	0.169	0.329 ***	0.449 ***	0.24 *
	(0.143)	(0.08)	(0.097)	(0.127)
Number of Obs.	90,668	90,668	90,668	90,668

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance but separately for public and private schools. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations school and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

VI. Mechanisms

In order to identify mechanisms through which peer effects operate I analyze the effect of peers' consumption behavior on two outcomes peers can affect: the perception that individual *i* has about the risk of consuming these substances and the easiness with which individual *i* reports to have access to psychoactive substances. To explore them I estimate equation (2) but changing the dependent variable for the measures of risk perception and easiness of access defined in the data section. Provided there are heterogeneous effects by grade, I estimate this equation with samples separated by grade to see if the sign of the effect on consumption and on the mechanism can provide suggestions on how these variables work as channels[13]. For instance, if risk perception is a channel for consumption I expect to find that as the proportion of classmates that consume increases in a given classroom, the perception of risk associated to consumption decreases making the students that belong to the classroom more likely to engage in consumption of psychoactive substances.

VI.1. Risk perception: grade heterogeneous effects

Table 8 presents the estimation of grade heterogeneous effects with risk perception of occasionally consuming each substance as the dependent variable. For most of the substances, the estimates of risk perception have either a negative sign (the opposite sign of the ones of consumption) or a positive but not significant effect. This is intuitive because, assuming that the students are risk averse, peers' consumption negative effect on risk perception would increase the probability of consuming as I found in the previous section. This suggests that interacting with classmates that consume the four substances makes students lower their perception of risk associated to consume, hence they end up having a larger probability of consuming.

Table 9 presents the estimation of grade heterogeneous effects with risk perception of frequent consumption of each substance.

For cigarette smoking, with exception of 6th grade, risk perception of frequent consumption seems to be a channel since positive effects in consumption are associated to negative effects on risk perception, but in 6th grade they have the same sign which implies that an increase of peers' consumption increases both risk perception and consumption of students, that under the assumption of risk aversion is counter intuitive.

In the case of alcohol, risk perception of frequent consumption does not seem to be a channel for the effect since for every positive effect on consumption there is a positive effect on risk perception.

On the other hand, cannabis has effects on consumption and risk perception with opposite signs; a positive effect on consumption matches with a negative effect on risk perception, therefore, risk perception of frequent consumption of cannabis seems to be a channel for the effect.

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[13] A graphic exposition of these results is available upon request.

Finally, in cocaine consumption it seems that risk perception works as a channel for the effect only for 11th grade, still the effect in consumption is present in other grades which makes it harder to state that risk perception is a channel for cocaine consumption.

Table 8.
Peer effects on risk perception of psychoactive substances' occasional consumption: grade heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
Peer effect 6th	-0.144	0385*	-2.109	-0.345
	(0.811)	(0.213)	(1.834)	(4.702)
F-Statistic	15.857	101.785	11.493	13.25
Peer effect 7th	-0.981*	-0.11	-1.051 **	-1.155
	(0.542)	(0.162)	(0.532)	(1.526)
F-Statistic	36.945	141.879	50.059	17.609
Peer effect 8th	0.341	0.382	-1.155	1.424
	(0.71)	(0.343)	(0.842)	(1.293)
F-Statistic	11.355	42.126	13.771	16.433
Peer effect 9th	-0.219	-0.219	-1.497 ***	-1.246
	(0.295)	(0.217)	(0.545)	(1.185)
F-Statistic	19.935	75.778	21.23	6.168
Peer effect 10th	0.075	0.414	-1.208 **	0.073
	(0.421)	(0.499)	(0.511)	(0.604)
F-Statistic	13.368	34.491	21.283	32.427
Peer effect 11th	0.375	-0.617	-1.562 ***	-0.987 *
	(0.494)	(0.479)	(0.45)	(0.525)
F-Statistic	9.903	27.866	16.679	16.009

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance and each grade separately, but using as a dependent variable perception of the risk of occasionally consuming each substance. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * p<0.1, ** p< 0.05, *** p<0.01.

Table 9.
Peer effects on risk perception of psychoactive substances' frequent consumption: grade heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
Peer effect 6th	2.466 **	0.693 ***	-3.621 *	0.844
	(1.021)	(0.23)	(1.952)	(5.417)
F-Statistic	15.184	97.278	11.467	13.236
Peer effect 7th	-0.512	-0.16	-1.25 **	-0.929
	(0.489)	(0.184)	(0.552)	(1.154)
F-Statistic	38.858	140.219	49.257	18.663
Peer effect 8th	-0.538	0.814 **	-0.541	0.362
	(0.689)	(0.39)	(0.83)	(1.104)
F-Statistic	10.801	40.101	13.921	16.206
Peer effect 9th	-0.428*	0.175	-0.746 *	-0.978
	(0.235)	(0.236)	(0.384)	(0.818)
F-Statistic	19.595	76.711	21.21	6.133
Peer effect 10th	-0.378	0.683	-0.507	-0.754
	(0.303)	(0.532)	(0.413)	(0.831)
F-Statistic	13.462	33.609	20.385	31.653
Peer effect 11th	0.196	-0.265	-0.655 *	-0.562 *
	(0.397)	(0.539)	(0.343)	(0.365)
F-Statistic	9.54	25.561	16.569	16.076

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance and each grade separately, but using as a dependent variable perception of the risk of frequently consuming each substance. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * p<0.1, ** p< 0.05, *** p<0.01.

VI.2. Offers to consume psychoactive substances: grade heterogeneous effects

Table 10 presents estimations of grade heterogeneous effects with offers to consume psychoactive substances. In most of the grades and most of the substances this channel seems to work, meaning that a positive effect of peers' consumption on students consumption is associated with positive effect on the probability of being offered to consume psychoactive substances. Hence, interaction between peers that consume makes it easier for students to access to psychoactive substances.

Table 10.

Peer effects on offers to consume psychoactive substance: grade heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
Peer effect 6th	0.196	-0.004	-0.091	-2.52 **
	(0.219)	(0.054)	(0.429)	(1.267)
F-Statistic	17.08	107.584	10.626	13.481
Peer effect 7th	0.233	0.083	0.664 ***	1.014 *
	(0.203)	(0.079)	(0.192)	(0.527)
F-Statistic	37.342	132.097	52.277	19.048
Peer effect 8th	0.982**	0.149	0.444	1.238 **
	(0.403)	(0.12)	(0.342)	(0.542)
F-Statistic	11.624	46.762	13.558	16.271
Peer effect 9th	0.377***	0.302 ***	0.234	1.074 *
	(0.142)	(0.114)	(0.197)	(0.577)
F-Statistic	19.793	78.539	19.861	6.731
Peer effect 10th	0.003	0.586 **	0.324	0.2
	(0.234)	(0.269)	(0.348)	(0.554)
F-Statistic	13.744	36.347	18.904	35.361
Peer effect 11th	0.202	0.018	0.112	0.414
	(0.336)	(0.304)	(0.226)	(0.286)
F-Statistic	9.982	30.006	16.294	17.309

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance and each grade separately, but using as a dependent variable if the student has been offered to consume illegal psychoactive substances. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * $p<0.1$, ** $p< 0.05$, *** $p<0.01$.

Cocaine estimations for 6th grade seems to be the only problem for this statement; for every other substance and grade, consumption and offers estimations behave alike, while on 6th grade cocaine estimations the effect of peers consumption on probability of being offered to consume is negative, still this is not a problem since the effect on consumption is null, so it is possible to think that this is a reflection of a negative stigma effect; students in 6th grade have strong beliefs that consuming cocaine is negative so avoid interacting with peers if they know that they consume, and this lowers their probability of being offered to consume.

VI.3. Seeing peers consume or purchase psychoactive substances: grade heterogeneous effects

Table 11 presents estimations of grade heterogeneous effects with seeing peers consume psychoactive substances. For this variable the evidence is less strong. Cigarette smoking, cannabis smoking, and cocaine have some grades for which seeing peers consume or purchase psychoactive substances seems to be a channel for the effect because the effect of the effect of peers consumption since the sign of consumption and seeing peers is the same, still it is more the exception rather than the rule and for alcohol it does not happen in any grade. Hence, I refrain from stating that this variable is a channel for the effect. In this line of thought it is possible to think that seeing peers consume or purchase is not strong enough always to induce students to use psychoactive substances, instead, direct offers to consume is strong enough and therefore works as a channel.

This is suggestive evidence for channels that rationalize the peer effects described earlier, still, they have to be carefully understood. Since I have only a cross section dataset the complete identification of these estimations as mechanisms is not clear. In an ideal setting I would have access to a panel and could use lags of the risk variables instead of contemporaneous observations. This would lead me to have more conclusive evidence about risk perception and easiness of access to psychoactive substances as channels for peers to affect individual outcomes of consumption.

I provide two robustness checks. On the one hand I estimate equation (2) for Bogotá. The idea of this robustness check is to use only the sample of Bogotá, which ex-ante would have a less endogenous selection of schools as discussed earlier, and would additionally provide an insight of the bias of the original estimations that is caused by endogenous school selection.

Table 11.

Peer effects on seeing psychoactive substance consumption or purchase: grade heterogeneous effects

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
		Ever		
		IV Estimates		
Peer effect 6th	-0.181	0.066	-1.049	-1.865
	(0.557)	(0.119)	(0.991)	(1.966)
F-Statistic	17.08	107.584	10.626	13.481
Peer effect 7th	0.425*	0.007	1.272 ***	1.912 *
	(0.244)	(0.106)	(0.379)	(1.112)
F-Statistic	37.342	132.097	52.277	19.048
Peer effect 8th	0.547	-0.291	-0.094	-0.206
	(0.524)	(0.206)	(0.587)	(0.849)
F-Statistic	11.624	46.762	13.558	16.271
Peer effect 9th	0.823***	0.074	0.633 **	1.072
	(0.211)	(0.163)	(0.318)	(0.794)
F-Statistic	19.793	78.539	19.861	6.731
Peer effect 10th	0.864***	0.957 ***	0.433	-0.113
	(0.284)	(0.343)	(0.333)	(0.408)
F-Statistic	13.744	36.347	18.904	35.361
Peer effect 11th	-0.197	-0.047	0.116	0.038
	(0.47)	(0.394)	(0.402)	(0.485)
F-Statistic	9.982	30.006	16.294	17.309

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance and each grade separately, but using as a dependent variable if the student has seen peers consuming illegal psychoactive substances. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

On the other hand I provide different estimation methods analogous to the OLS and IV that I presented but that does not take each equation for each substance as a separate regression and instead it estimates all of them as a system allowing the errors of each equation of the system to correlate. The alternative estimations methods are Seemingly Unrelated Regressions (SUR) and Three-Stage Least Squares (3SLS) presented in Zellner (1962) and Zellner and Theil (1962). This last robustness check also provides an opportunity to identify correlation between the unexplained part of consumption; after regressing consumption against all of the variables I presented earlier, I will see how the unexplained consumption represented by the errors correlate which might give an intuition on how consumption of different substances is related. This robustness checks work differently from the baseline strategy and do not follow the same underlying data generation process, still serve the purpose of enlightening the proper statistical functioning of the baseline estimations.

VI.4. Estimations for Bogotá

The estimations of equation (2) for Bogotá are presented in Table 12 and the estimations of equation (2) for each grade separately in Table 13. In terms of magnitude the estimates for the full sample and Bogotá do not differ considerably for cannabis and alcohol, but cigarette is lower and cocaine larger. The similarities are a good sign given that if it is true that Bogotá has less endogeneity than the full sample then the bias is not so big, but on the other hand for cigarettes and cocaine then the original estimates are biased.

Table 12.
Estimation of peer effects on psychoactive substance consumption: Bogotá

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	Panel C: IV Estimates			
Peer effect	-0.707	0.318	0.365 **	0.353 ***
	(1.252)	(0.199)	(0.155)	(0.117)
F-Statistic	1.633	20.236	21.784	23.878
Number of Obs.	9,209	9,209	9,209	9,209

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations school and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * p<0.1, ** p< 0.05, *** p<0.01.

Table 13.
Peer effects on psychoactive substance consumption: grade heterogeneous effects for Bogotá

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
	Ever			
	IV Estimates			
Peer effect 6th	0.608	0.805 ***	0.677 *	0.041
	(0.589)	(0.091)	(0.384)	(0.412)
F-Statistic	2.924	32.809	1.593	3.233
Peer effect 7th	0.224	0.459 ***	0.617 ***	0.481 **
	(0.278)	(0.178)	(0.125)	(0.229)
F-Statistic	13.56	22.457	15.482	5.476
Peer effect 8th	0.475 **	-2.06	-2.059	0.518 *
	(0.219)	(4.269)	(4.194)	(0.275)
F-Statistic	7.296	0.381	0.461	8.692
Peer effect 9th	0.664 ***	0.699 ***	0.727 ***	0.299
	(0.114)	(0.118)	(0.123)	(0.753)
F-Statistic	14.55	13.365	11.156	1.382
Peer effect 10th	0.011	0.555 ***	0.588 ***	0.731 ***
	(0.83)	(0.158)	(0.118)	(0.084)
F-Statistic	1.623	17.4	16.06	16.424
Peer effect 11th	3.197	0.354	0.703 ***	0.281
	(4.434)	(0.644)	(0.187)	(0.200)
F-Statistic	0.253	1.501	3.125	22.078

Notes: This table reports β coefficient on equation (2) estimated through IV and OLS for each substance and each grade separately. Each first stage uses the instrument defined as the average proportion of students that have someone in their household that consumes the substance of the respective estimation. For all of the estimations municipality and grade fixed effects, family and individual controls are used. Clustered at school level errors are used to calculate the standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

V.5 SUR and 3SLS estimates

This robustness check means to see if taking into account a system of equations with a structure for its residuals improves the estimates. Following Zellner (1962) the estimations methods can be represented by the next system of equations for each measure of consumption (at any moment in life and last month).

$$Y_{i,c} = \beta' Y_c + \delta' X_{i,c} + \varepsilon_{i,c}. \tag{3}$$

Where $Y_{i,c}$ is a $nx1$ block vector that stacks the vectors of consumption of the four substances for all of the sample, Y_c is a $nx1$ block vector that stacks the average consumption of the four substances at the classroom level for all of the sample, $X_{i,c}$ is a nxk block matrix that stacks the set of controls for every equation, and ε is a $nx1$ block vector that stacks the residuals for each of the four equations.

For this model the assumption is that $\varepsilon\varepsilon'$ is a block matrix of variances and covariances that allows different equations to have correlated their errors, hence, given the case of psychoactive substance consumption in which the consumption of one substance might be correlated with the consumption of other, this kind of error modeling is more appropriate. Besides, it will allow me to identify connections between consumption of different substances.

Since this estimation method identifies a structure for the errors it is estimated in as a 2SLS. In order to include the fact that there are endogenous regressors then it is necessary to rewrite equation (3) with the instruments for the endogenous regressors explicitly. Which following the terms in Zellner and Theil (1962) can be written in the following equation.

$$Y_{i,c} = \beta' Y_c + \pi' Z_c + \delta' X_{i,c} + \varepsilon_{i,c}. \tag{4}$$

Where Z_c is a $nx1$ block vector that stacks all of the instruments for each substance. And in this case the estimation uses another stage, one for the errors, one for the endogenous variables, and the third for the coefficients of interest.

Table 14 presents the estimates for the SUR and the 3SLS methods, once again in terms of magnitude they are not so different from the OLS and IV methods respectively, but the standard errors associated to the estimates decrease which means that the original variance covariance matrix is miss specified and needed to account for correlation between errors. With this structure on the errors, cigarette consumption also becomes significant for the three measures of consumption.

Table 14.
Estimation of peer effects on psychoactive substance consumption

	Cigarette Consumption	Alcohol Consumption	Cannabis Consumption	Cocaine Consumption
		Ever		
		SUR Estimates		
Peer effect	0.093***	0.173***	0.141***	-0.084***
	(0.015)	(0.015)	(0.013)	(0.016)
		3SLS		
Peer effect	0.338***	0.365***	0.385***	0.193***
	(0.054)	(0.039)	(0.053)	(0.072)
Number of Obs.	90,668	90,668	90,668	90,668

Notes: This table reports β coefficients on equations (3) and (4) estimated through SUR and 3SLS for each measure of consumption. Each system of equations uses the instrument defined as the average proportion of students that have someone in their household that consumes the substances. For all of the estimations school and grade fixed effects, family and individual controls are used. Standard errors reported in parentheses. *p<0.1, **p< 0.05, ***p<0.01.

Finally, Table 15 presents the correlation between the residuals associated to each equation, providing a relation between consumption of different substances after controlling for all the variables earlier explained. It is important to highlight the fact that there is a high correlation cigarette-cannabis and cigarette-cocaine, which means that there are things that make persons who engage in cigarette consumption more likely to engage in cannabis and cocaine consumption. Which in terms of public policy suggests that there should not only be a campaign to avoid that adolescents engage in illegal substance abuse, because probably the path to engage in them comes from more accepted or even legal (for persons older than 18) substances like cigarettes.

Table 15.
Estimation of correlations between errors of the SUR and 3SLS estimations

Ever		
SUR Estimates	3SLS	
Cigarette - Alcohol	0.225*** (0.004)	0.225*** (0.004)
Cigarette - Cannabis	0.527*** (0.006)	0.522*** (0.006)
Cigarette - Cocaine	0.492*** (0.008)	0.486*** (0.008)
Alcohol - Cannabis	0.155*** (0.004)	0.157*** (0.004)
Alcohol - Cocaine	0.147*** (0.005)	0.149*** (0.005)
Cannabis - Cocaine	0.633*** (0.01)	0.628*** (0.01)
Number of Obs.	90,668	90,668

Notes: This table reports correlations between the errors associated to each substance and each measure of consumption from the equations 3 and 4. Clustered at school level errors are used to calculate the standard errors reported in parentheses. * p<0.1, ** p< 0.05, *** p<0.01.

VII. Concluding Remarks

Social interactions as an explanation for different economic behaviors have provided evidence of sources for decision making besides market incentives. Specifically, for engaging in risky behavior it has been proved to explain obesity, psychoactive substance consumption, among others. In Colombia there are few works trying to identify social interaction effects and none specifically peer effects on psychoactive substance consumption.

In this paper I focused on Colombian high school students and used household consumption behavior to instrument peers consumption finding that alcohol, cannabis, and cocaine are the substances that exhibit strongest evidence of peer effects with effects of moving a student from a classroom with no consumption of psychoactive substances to one with 10% ranging from 2.28% to 4.53%. After finding evidence of peer effects I checked for heterogeneous effects finding that the grade at which the students attend does not determine the effect; even though the effect does differ between grades, it is positive in most cases.

Additionally, I explored for mechanisms and I found that direct offers to consume and risk perception towards consuming seem to be plausible channels for the effect to work in most substances. Finally through the use of a 3SLS estimator I identified a correlation between consuming partially legal drugs like cigarettes and illegal and stronger drugs like cannabis and cocaine. Pointing out an important policy issue.

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