

‘Me, my classmates and my buddies’: analysing peer group effects on student marijuana consumption

Rosa Duarte^a, José-Julián Escario^a and José-Alberto Molina^{a,b*}

^a*University of Zaragoza, Zaragoza, Spain;* ^b*IZA, Bonn, Germany*

The aim of this paper is to explore the influence of peer behaviour on student marijuana consumption. Our hypothesis is that, in contrast to the traditional measures of peer group effects carried out at class or school level, the use of a closer peer group, which we relate to the group of friends, is more relevant in the explanation of marijuana consumption. On the basis of the data provided by the 2004 Spanish Survey on Drug Use in the School Population, we estimate a probit model in which two alternative peer variables are introduced. The results show that, once the effect of the closer peer group is controlled for, the effect of classmates’ behaviour on the student is insignificant. Moreover, the closer peer group effects are asymmetric in their magnitude.

Keywords: students; peer effects; drug consumption

Introduction

Marijuana is the most commonly consumed illegal drug among students. Data provided by the European Monitoring Centre for Drugs and Drug Addiction (2005), based on school surveys for 2003, show worrying figures for the prevalence of marijuana use. For example, the average prevalence among students of 15 to 16 years old was 32% in Belgium, 44% in the Czech Republic, 38% in France, 39% in Ireland and 38% in the United Kingdom. Data collected by Johnston et al. (2005) for the United States in 2005 show that the average prevalence of use of marijuana for eighth, tenth and twelfth graders was 16.4%, 34.1% and 44.8%, respectively.

The concern of health and educational authorities over this increasing consumption, and its ever earlier onset, is clearly justified for several reasons. First, marijuana is an addictive drug, the habitual consumption of which can lead to dependence (Defonseca et al. 1997; Substance Abuse and Mental Health Services Administration 1998). Second, marijuana has been shown to be a gateway substance to harder drugs (Kandel 1975; Kandel, Yamaguchi, and Chen 1992; Chaloupka and Laixuthai 1997; Desimone 1998; Brook, Balka, and Whiteman 1999). Third, medical studies reveal clear negative effects on the present and future health of the student, such as the deterioration of cognitive and psychomotor functions, and an increase in respiratory and reproductive problems (Nahas and Latour 1992; Hall, Solowij, and Lemmon 1994; Pope, Gruber, and Yurgelum-Todd 1995). Finally, its consumption is often associated with other risky and anti-social behaviours, such as delinquency, unwanted

*Corresponding author. Email: jamolina@unizar.es

pregnancy and dropping out (Brook, Balka, and Whiteman 1999; Hawkins, Catalano, and Miller 1992; Bray et al. 2000; Duarte, Escario, and Molina 2006).

The study of the factors that lead students to consume drugs places an increasing emphasis on the need to investigate the personal and social environments in which such consumption originates. A growing number of papers refer to the importance of the family and, especially, of the peer group of the adolescent, as explanatory factors for this consumption (Dekovic, Wissink, and Meijer 2004; Eitle 2005; McArdle et al. 2000; Gecková et al. 2005). In particular, studies such as those of Dekovic, Wissink, and Meijer (2004) and of Mounts and Steimberg (1995) highlight the fact that, as children reach adolescence, they begin to spend more time with their friends, away from the supervision of their parents, and hence the peer group becomes their most important social reference.

The influence of the peer group on academic results has been frequently studied, with several authors concluding that belonging to a deviant group can lead to higher rates of truancy and school failure (Winkler 1975; Borjas 1994; Aaronson 1998; Sacerdote 2001; Hanushek et al. 2003). Moreover, other papers prove the influence of the peer group on the consumption of substances such as tobacco, alcohol and other drugs (Gaviria and Raphael 2001; Kawaguchi 2004; Powell, Tauras, and Ross 2005; Lundborg 2006).

From a theoretical point of view, the consideration of peer group influences further separates the explanation for the consumption of addictive substances from the traditional one, and from the theory of social relationships. The former is based on the fact that consumption depends only on the characteristics of the individual, whereas the latter considers the social network as an agent that modifies and directly affects this use (Manski 1993, 1995).

Similarly, DeCicca, Kenkel, and Mathios (2000) point out that the consumption of tobacco, alcohol and other drugs can be understood if we consider that adolescents need the recognition of their actions and behaviour from their group of friends, their family and their social environment. The consideration of these influences leads us to suppose the existence of 'social multipliers', meaning that a certain policy can not only have a direct effect on the individual, but can also have an indirect effect through the peer group. As Lundborg (2006) states, when the social multiplier is high, even small interventions can have a great effect on individual behaviour. Nevertheless, Manski (1995) establishes different levels of social interaction. First, the behaviour of the individual is influenced by the exogenous characteristics of the peer group; that is to say, the 'contextual effect'. Second, this behaviour is influenced by the behaviour of the peer group, which is identified as the 'endogenous effect'. Finally, Manski (1995) recognises the possibility of an unreliable relationship between the behaviour of the individual and that of the group, which can be wrongly identified as 'contextual' or 'endogenous' effects. These latter effects – the 'correlated effects' – are due to the existence of undetected characteristics shared by all members, which generally result from the previous sorting; that is to say, the non-random choice of group by individuals. Most of the literature highlights the importance of distinguishing among these three types of effects when deriving policy implications. Contextual and endogenous effects indicate that groups matter; that is to say, the individual is influenced by the group through its characteristics and its behaviour. However, 'social multipliers' are only yielded by the endogenous effects in so far as they can reflect feedback interactions. Contextual and correlated effects do not imply this multiplier effect.

Given that we focus on student behaviour, as Gaviria and Raphael (2001) pointed out, interaction between individuals will be less affected by contextual effects than in other social contexts. Given that, and following the common practice in the literature, the absence of contextual effects is assumed.

Therefore, the identification and measurement of the effect that a given group behaviour has on the individual's behaviour is not an easy task, since it is necessary to deal with at least two different questions. The first is the interpretation of the estimated correlation between the behaviour of the individual and that of the group, since it is reasonable to assume endogeneity between the variables that measure both types of behaviour. In other words, while it is true that the consumption of drugs within the group influences the behaviour of the individual, it is also true that the individual, as a member of the group, influences the behaviour of that group. Articles such as those of Gaviria and Raphael (2001), of Powell, Tauras, and Ross (2005) and of Lundborg (2006) are interesting examples of the development of econometric strategies dealing with the endogeneity underlying peer effects.

The second, and even more important question, is the identification of the actual relevant peer group for each individual. First, note that Gaviria and Raphael (2001), Powell, Tauras and Ross (2005) and Lundborg (2006) identify the peer group with either the school or the class, and find a significant influence of the peer group on the behaviours studied. Additionally, Kawaguchi (2004) confirms robust peer effects, after employing a strategy for identifying peer effects using teenagers' subjective perceptions of peer behaviours, and Lundborg (2006) points out that the broader the definition of the group, the less able it is to capture the real reference group for the individual, thus leading to biased estimations of these influences.

Based on this evidence, our paper takes a closer look at the groups of 'potential influence' on the student regarding the consumption of drugs. Our hypothesis is that the group of friends of the student, which we call the 'closer peer group', may be more significant for the study of influences on marijuana consumption. The latest Spanish Survey on Drug Use in the School Population (SDUSP 2004) puts the average prevalence of marijuana consumption among students of 15 to 16 years old at 41% (meaning that 41% of students have consumed marijuana at least once in their lives), and 25.6% of students acknowledge having consumed marijuana in the last month.

Using this Spanish Survey, collected by the Spanish Government Delegation for the National Plan on Drugs, we compare the influence of two peer group measures on the marijuana consumption of the student. Employing a probit model specification, we compare the influence obtained when a traditional measure of peer group, defined at the class level, is used, with that obtained when the group of friends constitutes the reference peer group. Moreover, both peer variables are studied together in order to analyse the existence of class-based peer influence, once the effect of the closer group is identified.

The results show that, while a class-based peer effect is significant if the closer peer group is not considered, which is consistent with previous studies (Gaviria and Raphael 2001; Powel, Tauras and Ross 2005), this significance disappears once the effect of the closer peer group has been defined, and the latter becomes clearly significant. Our results offer evidence in favour of a reconsideration of peer group measures and, in consequence, a re-interpretation of the references found in the literature.

Data

In order to examine the determinants of student marijuana consumption, data from the latest findings of the SDUSP (2004) have been used. This survey contains detailed information about drug consumption, as well as individual, family and school characteristics, directly obtained from responses to an anonymous questionnaire. Parents were not present during the survey and were not informed about the answers, thus reducing possible under-reporting on drug questions. The information was collected in different state/public and private centres of secondary education and vocational training throughout the country, and it constitutes a nationally representative sample of the student population of 12–18 years old. The final data-set contains 24,561 observations.

The dependent variable in the study is *MarijuanaConsumption*, a dichotomous variable that takes value one if the student has consumed marijuana in the past month and zero otherwise.

Given that the main objective of this paper is to evaluate the peer effect on student marijuana consumption, we must define appropriate measures for the peer group. As stated, two peer group measures have been considered. The first is a traditional measure of the peer effect computed at the class level, and the second is an attempt to capture the influence of the closer peer group.

For a student i belonging to class c in school k , peer group marijuana consumption at the class level (*ClassPeer*) is defined by taking the class average prevalence of marijuana consumption, after subtracting the student's contribution to this average:

$$P_{ick} = \frac{1}{N_C - 1} \sum_{\substack{j \in c \\ j \neq i}}^{N_c} Y_{jck},$$

where Y_{jck} is the dependent variable for student j who belongs to class c in school k , and N_C is the total of students in the class.

To deal with the closer peer group, we consider the response to the question ‘How many of your friends have consumed marijuana during the last month?’, taking values zero if none, one if only some, two if the majority, and three if all of them. This categorical variable (*CloserPeer*), representing the perceived peer behaviour, can be decomposed into four binary variables, one for each category, representing our measure of the closer peer group (*CloserPeer0*, *CloserPeer1*, *CloserPeer2*, *CloserPeer3*). This is the only information available about the use of marijuana among the group of friends.

Apart from these peer variables, other exogenous variables have been considered including individual, family and school characteristics, such as *Gender*, *Age* (coded as four dummy variables), living without the father at home (*WithoutFather*), the educational status of the parents (*SecondaryStudiesMother*, *UniversityStudiesMother*, *SecondaryStudiesFather*, *UniversityStudiesFather*), the labour situation of the parents (*UnemployedFather*, *Housewife*), unhealthy habits in the family (*SmokerFather*, *SmokerMother*), and the economic status of the student represented by the income variables and working situation (*Income*, *IncomeSquared*,¹ *Working*). Additionally, four variables have been introduced related to some aspects of the school environment, such as the educational programme followed by the student (*Program*),² whether the school is a state/public school or a private school (*StateSchool*), the size of the class (*Class15*) and whether the school has carried out informative campaigns

Table 1. Descriptive analysis.

Variable	Definition	Mean (standard deviation)
<i>MarijuanaConsumption</i>	This takes value 1 if the adolescent has consumed marijuana in the last month and 0 otherwise	0.256 (0.436)
<i>ClassPeer</i>	Marijuana consumption prevalence in the class after eliminating the individual's influence	0.413 (0.201)
<i>CloserPeer</i>	This takes value 0 if none of his/her friends consumed marijuana during the last month, 1 if some of them consume, 2 if the majority of them and 3 if nearly all of them	0.805 (0.875)
<i>CloserPeer0</i>	This takes value 1 if no friends consumed marijuana during the last month and 0 otherwise	0.447 (0.497)
<i>CloserPeer1</i>	This takes value 1 if some friends consumed marijuana during the last month and 0 otherwise	0.352 (0.478)
<i>CloserPeer2</i>	This takes value 1 if the majority of friends consumed marijuana during the last month and 0 otherwise	0.149 (0.356)
<i>CloserPeer3</i>	This takes value 1 if nearly all friends consumed marijuana during the last month and 0 otherwise	0.052 (0.221)
<i>Gender</i>	This takes the value 1 if the young person is male and 0 if female	0.492 (0.500)
<i>Age14</i>	This takes value 1 if the adolescent is 14 years old and 0 otherwise	0.142 (0.349)
<i>Age15</i>	This takes value 1 if the adolescent is 15 years old and 0 otherwise	0.276 (0.447)
<i>Age16</i>	This takes value 1 if the adolescent is 16 years old and 0 otherwise	0.349 (0.477)
<i>Age17</i>	This takes value 1 if the adolescent is 17-18 years old and 0 otherwise	0.233 (0.423)
<i>WithoutFather</i>	This takes value 1 if the adolescent lives without the father at home and 0 otherwise	0.122 (0.327)
<i>PrimaryStudiesMother</i>	This takes value 1 if the mother has a basic school certificate and 0 otherwise	0.202 (0.401)
<i>SecondaryStudiesMother</i>	This takes value 1 if the mother has a secondary school certificate or vocational training and 0 otherwise	0.298 (0.458)
<i>UniversityStudiesMother</i>	This takes value 1 if the mother has a university diploma or a university degree and 0 otherwise	0.203 (0.402)
<i>PrimaryStudiesFather</i>	This takes value 1 if the father has a basic school certificate and 0 otherwise	0.222 (0.415)
<i>SecondaryStudiesFather</i>	This takes value 1 if the father has a secondary school certificate or vocational training and 0 otherwise	0.264 (0.441)
<i>UniversityStudiesFather</i>	This takes value 1 if the father has a university diploma or a university degree and 0 otherwise	0.225 (0.417)
<i>UnemployedFather</i>	This takes value 1 if the father of the adolescent is unemployed and 0 otherwise	0.015 (0.123)
<i>HouseWife</i>	This takes value 1 if the mother is a housewife and 0 otherwise	0.324 (0.468)

Table 1. (Continued).

Variable	Definition	Mean (standard deviation)
<i>SmokerFather</i>	This takes value 1 if the father of the adolescent smokes and 0 otherwise	0.319 (0.466)
<i>SmokerMother</i>	This takes value 1 if the mother of the adolescent smokes and 0 otherwise	0.318 (0.465)
<i>Working</i>	This takes value 1 if the young person has a part-time job out of school hours and 0 otherwise	0.105 (0.306)
<i>Income</i>	Available income per week of the adolescent (in €)	16.249 (17.272)
<i>Program</i>	This takes value 1 if the young person is enrolled in the university-oriented branch 'Bachillerato' and 0 otherwise	0.371 (0.483)
<i>StateSchool</i>	This takes value 1 if the school is a state/public school and 0 otherwise	0.583 (0.493)
<i>Class15</i>	This takes value 1 if the adolescent attends a class with fewer than 15 students and 0 otherwise	0.139 (0.346)
<i>Information</i>	This takes value 1 if the adolescent studies at a school which has programmed information campaigns on the risks associated with tobacco, alcohol and drug consumption and 0 otherwise	0.754 (0.431)

about the risk of drug consumption (*Information*). Finally, dummy variables corresponding to the 19 Spanish autonomous regions have been included in the analysis.

Variable definitions and descriptive statistics are presented in Table 1. For the sake of brevity, the descriptive analysis of the regional variables does not appear in this table.

Model

In order to implement the empirical model, we can assume that the marijuana use decision is represented by the following empirical specification for an individual i attending a class c in school k :

$$Y_{ick}^* = \beta P_{ick} + \gamma X_{ick} + \varepsilon_{ick} \quad (1)$$

where Y_{ick}^* is a latent variable whose sign determines whether or not the student consumes marijuana, with an observable dummy variable Y_{ick} , which takes value one if $Y_{ick}^* > 0$ and zero otherwise. Moreover, P_{ick} is the peer group variable measuring the prevalence of marijuana consumption in the class, and X_{ick} is a set of covariates that can vary at the school, class or individual level. Given that the dependent variable is dichotomous, we use a probit model specification to estimate Equation (1).

This model can be easily modified to consider the influence of the student's closer peer group. Consider first that Y_2 represents the categorical variable (*CloserPeer*) that takes values zero to three depending on how many friends consume marijuana. Thus, we can write:³

$$Y_{ick}^* = \beta_1 P_{lick} + \beta_2 P_{2ick} + \beta_3 P_{3ick} + \gamma X_{ick} + \varepsilon_{ick} \quad (1')$$

where P_{0ick} , P_{lick} , P_{2ick} , P_{3ick} are dummy variables, indicating how many of the closer friends consume marijuana (the omitted category is none). This is to say: $P_{0ick} = 1$ if $Y_2 = 0$, $P_{0ick} = 0$ otherwise; $P_{lick} = 1$ if $Y_2 = 1$, $P_{lick} = 0$ otherwise; $P_{2ick} = 1$ if $Y_2 = 2$, $P_{2ick} = 0$ otherwise; and $P_{3ick} = 1$ if $Y_2 = 3$, $P_{3ick} = 0$ otherwise.

As the most important economic literature shows (Sacerdote 2001; Gaviria and Raphael 2001; Lundborg 2006), before implementing the estimation procedure we should deal with the potential endogeneity of the variables that measure peer effects. We will do so by substituting the peer effect variables by their instrumented counterparts. Gaviria and Raphael (2001) suggest using \bar{X}_{-ick} , which are the class averages of some selected exogenous variables, after excluding individual i in class c , as instruments. Under the assumption of absence of contextual effects, the class averages of exogenous variables are natural candidates for instruments.

The econometric strategy we follow for both models can be summarised in four steps. In the first, we instrument the peer variables, predict their instrumented counterparts, and test for the joint significance of the instruments.

Thus, we regress by ordinary least squares the class-level peer variable on the exogenous variables, plus several instruments (Z):

$$P_{ick} = \delta X_{ick} + \theta Z + v_{ick} \quad (2)$$

Similarly, and for the closer peer variable, we estimate an ordered probit model for the categorical variable of the perceived peer variable Y_2 , which takes values zero to three. To that end, we define a latent variable Y_2^* :

$$Y_2^* = \delta X_{ick} + \theta Z + v_{ick} \quad (2')$$

$$Y_2 = 3, \text{ if } Y_2^* > \mu_3; \quad Y_2 = 2, \text{ if } \mu_3 > Y_2^* > \mu_2; \\ Y_2 = 1, \text{ if } \mu_2 > Y_2^* > \mu_1; \quad Y_2 = 0, \text{ if } \mu_1 > Y_2^*;$$

Once we have estimates for $\hat{\delta}$ and $\hat{\theta}$, we can obtain the predicted variables \hat{P}_{ick} (for the peer variable level defined at the class level) and \hat{P}_{lick} , \hat{P}_{2ick} and \hat{P}_{3ick} for the binary variables of closer peer group. We now carry out a test of significance of the instruments ($H_0: \theta = 0$) in both models of Equations (2) and (2').

In the second step, we implement a test of exogeneity (Hausman 1978). For this purpose we estimate the following probit models:

$$Y_{ick}^* = \beta P_{ick} + \gamma X_{ick} + \xi(P_{ick} - \hat{P}_{ick}) + e_{ick} \quad (3)$$

$$Y_{ick}^* = \beta_1 P_{lick} + \beta_2 P_{2ick} + \beta_3 P_{3ick} + \gamma X_{ick} + \xi_1(P_{lick} - \hat{P}_{lick}) + \\ + \xi_2(P_{2ick} - \hat{P}_{2ick}) + \xi_3(P_{3ick} - \hat{P}_{3ick}) + e_{ick} \quad (3')$$

Under the null hypothesis of exogeneity of the class peer variable, the parameter ξ must be zero. Similarly, a test of the exogeneity of \hat{P}_{lick} , \hat{P}_{2ick} and \hat{P}_{3ick} in the second model consists of testing $H_0: \xi_1 = \xi_2 = \xi_3 = 0$. If the hypothesis is rejected, we must deal with the endogeneity of these variables.

Thirdly, we implement an over-identifying restriction test. To that end, we separate the instrumental variable vector into two parts: $Z = [Z_1, Z_2]$. We then use only Z_1 as instrumental variables to repeat the first step. Thus, we obtain new predictions of \hat{P}_{ick} (for the peer variable defined at the class level) and \hat{P}_{1ick} , \hat{P}_{2ick} and \hat{P}_{3ick} for the binary variables of closer peer group, but this time conditioned on X and Z_1 , but not on Z_2 . We then estimate by probit the following models:

$$Y_{ick}^* = \beta P_{ick} + \gamma X_{ick} + \xi(P_{ick} - \hat{P}_{ick}) + \pi Z_2 + e_{ick} \quad (4)$$

$$Y_{ick}^* = \beta_1 P_{1ick} + \beta_2 P_{2ick} + \beta_3 P_{3ick} + \gamma X_{ick} + \xi_1(P_{1ick} - \hat{P}_{1ick}) + \xi_2(P_{2ick} - \hat{P}_{2ick}) + \xi_3(P_{3ick} - \hat{P}_{3ick}) + \pi Z_2 + e_{ick} \quad (4')$$

A test of over-identifying restrictions consists of testing $H_0: \pi = 0$.

Finally, in the fourth step, if the exogeneity hypothesis is rejected, we will instrument the peer variables in estimating Equation (1) and Equation (1').

Empirical results

Using the traditional measure of peer effects

We first concentrate on estimating the peer effects using the traditional measure, at class level, in order to compare the results with previous work.

In order to deal with the endogeneity problem, we have selected the class means, computed after excluding the corresponding student, of the following variables as instruments: *Income*, *HouseSmoking*, *MotherDrinking*, *FatherDrinking*.⁴ In order to check the validity of the instruments, we have tested their joint significance, the exogeneity hypothesis, and we have run an over-identification test.

Given that, in most cases, we are going to use two-stage estimation procedures, we use bootstrap methods for statistical inference in the second stage. The bootstrap asymptotics rely on $N \rightarrow \infty$. Although the bootstrap can be asymptotically valid for a relatively low number of replications, it is clear that performance increases with the number of replications. We follow the recommendation of Efron and Tibsharani (1993), who stated that, for standard error estimation, 200 replications are almost always sufficient.

The instruments are clearly significant in explaining the peer effect variable after controlling for the exogenous variables in Equation (2) with a Likelihood Ratio statistic of 1919.41 ($p = 0.000$), which follows a chi-squared distribution with four degrees of freedom. The estimation of Equation (3) enables us to reject the hypothesis of exogeneity. Thus, the parameter ξ appears as significant with a Wald test statistic of 7.00 ($p = 0.0089$), which follows a chi-squared distribution with one degree of freedom.

In order to test the over-identifying restrictions, we obtain a new prediction of \hat{P}_{ick} after putting one instrument (*HouseSmoking*) in Z_2 and we estimate Equation (4). The Wald statistic for the hypothesis $\pi = 0$, which follows a chi-squared distribution with one degree of freedom, is equal to 0.467 ($p = 0.5509$) and, consequently, we cannot reject this hypothesis. Thus, we cannot reject the hypothesis of the validity of the instruments.

The results of the probit model, with the marijuana peer effect measured at class level, are presented in the three first columns of Table 2.

Table 2. Estimation results.

Variable	Class-based peer group		Closer peer group		Both peer group measures	
	Parameter	Standard deviation	Parameter	Standard deviation	Parameter	Standard deviation
<i>ClassPeer</i>	0.713	***	—	—	-0.322	0.257
<i>CloserPeer1</i>	—	—	0.688	***	0.680	***
<i>CloserPeer2</i>	—	—	1.521	***	1.515	***
<i>CloserPeer3</i>	—	—	1.717	***	1.714	***
<i>Gender</i>	0.117	***	-0.030	—	-0.033	0.021
<i>Age15</i>	0.345	***	0.193	***	0.214	***
<i>Age16</i>	0.586	***	0.294	***	0.329	***
<i>Age17</i>	0.712	***	0.342	***	0.387	***
<i>WithoutFather</i>	0.229	***	0.071	**	0.101	***
<i>SecondaryStudiesMother</i>	-0.012	—	-0.017	—	-0.016	0.025
<i>UniversityStudiesMother</i>	0.018	—	-0.038	—	-0.036	0.035
<i>SecondaryStudiesFather</i>	0.012	—	-0.009	—	-0.016	0.028
<i>UniversityStudiesFather</i>	0.034	—	-0.026	—	-0.029	0.033
<i>UnemployedFather</i>	0.053	—	0.131	*	0.121	0.081
<i>HouseWife</i>	-0.121	***	-0.051	**	-0.053	**
<i>SmokerFather</i>	0.055	**	0.014	—	0.010	0.024
<i>SmokerMother</i>	0.120	***	0.035	*	0.032	0.021
<i>Working</i>	0.165	***	0.092	***	0.088	**
<i>Income</i>	0.018	***	0.008	***	0.008	***
<i>IncomeSquared</i>	0.000	***	0.000	***	0.000	***
<i>Program</i>	-0.156	***	-0.118	***	-0.117	***
<i>State School</i>	0.065	***	0.024	—	0.033	0.022
<i>Class15</i>	-0.124	***	-0.088	***	-0.085	***

Table 2. (Continued).

Variable	Class-based peer group		Closer peer group		Both peer group measures	
	Parameter	Standard deviation	Parameter	Standard deviation	Parameter	Standard deviation
<i>Information</i>	-0.148	*** 0.021	-0.191	*** 0.024	-0.186	*** 0.025
<i>Intercept</i>	-1.717	*** 0.053	-1.441	*** 0.052	-1.398	*** 0.059
Number of observations	23,829		24,561		23,829	
Log likelihood	-		-		-	
	12,409.39		10,742.81		10,551.25	
	Probability change	Standard deviation				
Average changes in the probability class-based peer group						
<i>ClassPeer</i>	0.2084	*** 0.0588				
<i>Income</i>	0.0042	*** 0.0014				
Average changes in the probability closer peer group						
<i>Income</i>	0.0016	** 0.0007				
<i>CloserPeer</i> 0 to 1	0.1651	*** 0.0319				
<i>CloserPeer</i> 1 to 2	0.3119	*** 0.0138				
<i>CloserPeer</i> 2 to 3	0.0721	*** 0.0903				
<i>CloserPeer</i> 0 to 1, 1 to 2, and 2 to 3	0.2358	** 0.1838				

Note: Standard deviations are computed from standard error derived after bootstrapping with 200 replications. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

The peer effect estimates are listed at the top of the table, and provide evidence to support the idea that the higher the proportion of marijuana smokers in the class, the higher the probability a student has begun consuming marijuana. We will try to quantify this peer influence after highlighting some selected results concerning the other explanatory variables.

Regarding the physical variables, the results confirm that the probability of using marijuana increases with age and is higher among male students. If we focus on the characteristics of the family, we find that the probability of smoking marijuana is higher among those students who live without their father, is lower among those students whose mother is a housewife, and increases with the number of parents who smoke.

As regards the socio-economic situation, the estimates confirm that the probability of being a marijuana consumer increases as disposable income goes up. We will quantify this effect together with the peer effect. In addition, the proportion of marijuana smokers is higher among students with a part-time job. Finally, with respect to the school characteristics, the estimates reported show that the probability of taking marijuana is higher in state schools. On the contrary, the percentage of marijuana smokers is lower among students of 'Bachillerato', those who attend smaller classes (less than 15 students), and those who attend schools that have carried out informative campaigns about the risks of drug consumption. Although this last effect is highly significant ($p < 0.01$), the quantitative impact is not very important, since it cannot offset the probability of an increase in marijuana use due to the simple fact of becoming a year older. Similarly, the negative impact of informative campaigns on consuming marijuana is of a slightly lower magnitude than the positive impact of living without a father.

In order to shed more light on the interpretation of the results, in the second section of Table 2 we report the change in the probability of using marijuana, given a unit increment in both the peer effect variable and the available income variable.⁵ We can interpret the results in the following way: if students were in a class where the percentage of marijuana smokers was 10 points higher, their probability of becoming users would be 2.1 points higher. With reference to income, an increment of 10 would increase the probability of becoming users by 4.2 points.

Using our new measure of peer effects

As we have a better measure of the peer variable, we now present the estimates using our alternative measure, with three dummy variables in Table 2 (columns four to six). In addition, we have carried out the three tests explained earlier, using the same instruments as before. First, we have tested for the joint significance of the instrumental variables in Equation (2'). The Likelihood Ratio statistic follows a chi-squared distribution with four degrees of freedom and is equal to 48.15 ($p = 0.000$). Consequently, the instruments are clearly significant in explaining the peer effect variable after controlling for the exogenous variables in Equation (2'). Secondly, we must reject the exogeneity assumption for the closer peer variables in Equation (3'). In this case, the Wald statistic for the hypothesis that $\xi_1 = \xi_2 = \xi_3 = 0$ takes the value 32.213 ($p = 0.000$) and follows a chi-squared distribution with three degrees of freedom. In order to test the over-identifying restrictions, we must obtain new predictions of \hat{P}_{lick} , \hat{P}_{2ick} and \hat{P}_{3ick} after splitting Z into two parts. We have made the same partition as before when we dealt with the peer behaviour measured at the class level. The Wald statistic for the

hypothesis $\pi = 0$ is equal to 0.773 ($p = 0.7828$) and follows a chi-squared distribution with one degree of freedom. Thus, we cannot reject the validity of the instruments.

The results reported reveal that our ‘closer’ peer group variable has a positive and significant impact on the probability of adolescent marijuana use. Thus, the probability of using marijuana increases with the proportion of friends who smoke marijuana. This increase is especially high for the first two dummy variables, and more moderate for the third dummy variable. Comparing these estimates with those reported in the three first columns, there are two important results. First, the closer peer group variable is now the highest statistically significant regressor; and, second, some variables that first appeared to be significant are no longer so, once we control for the closer peer group variable. For example, having a father who smokes and whether the school is public or private are now not significant.

For further analysis, we have estimated the model introducing both peer group variables and the estimations appear in the last three columns of Table 2. The most important result is that, once we have controlled for the peer effect of closer friends, the peer effect of the class is insignificant. Except for this fact, the estimates of both models are very similar and, therefore, we concentrate on those estimates that only incorporate the closer peer variables.

As before, we calculate the change in the probability given a change in the closer peer group variable and in the income variable. The estimates appear at the bottom of Table 2. We interpret the effect of the income variable as in the previous model; that is to say, if the available income increases by €10, the probability of becoming a marijuana consumer will be 1.6 points higher.

The interpretation of the peer effect is slightly different now, since the peer measure is not a continuous variable but instead the measure includes three dummy variables. As a result, we estimate the change in the probability of consuming marijuana when the perceived closer peer behaviour increases by one unity; that is to say, it changes from none to only some, from some to the majority, or from the majority to all. The estimates reported reflect that the probability of being a marijuana user, for those without friends who use marijuana, would increment by 16.5 points if some of their friends became marijuana users. Similarly, for those with only some friends who consume marijuana, the probability of using marijuana would increase by 31.2 points if the majority of their friends became users. Finally, for those students, most of whose friends consume marijuana, the probability of being a consumer would increase by 7.2 points if all of their friends became consumers.

In order to compare the results for both peer variables, the traditional and the closer peer group, we compute the increase in the probability due to a unit increase in the closer peer variable for the sub-sample in which this variable does not take the maximum value (students whose categorical variable Y_2 takes values zero, one, and two), with this sample representing 90.4% of the total. The estimates imply that the probability of being a marijuana user would increase by 23.58 points. Moreover, given that the closer peer variable takes discrete values from zero to three, we can assume that each unit of this variable implies that the number of friends who smoke marijuana increases by 33.3%. In order to have a rough estimate of the change in the probability of becoming a marijuana smoker if the peer variable increases by 10 points, we should divide the change by 33.3 and multiply it by 10. The results can be interpreted in the following way. With respect to the peer effects, we can conclude that a 33.3% increase in the number of friends who smoke marijuana leads to a 23.58 point increase in the probability of becoming a marijuana user. This means that an increase of 10 points of

the closer peer variable will increase the probability of being a marijuana user by 7.1 points.

Clearly, and as expected, the effect of the closer peer group is quantitatively higher than the class peer group. In addition, the inclusion of the closer peer effect reduces the significance and the quantitative impact of the income variable. Moreover, the effects of closer peer group are asymmetric in their magnitude. Thus, the highest increment in the probability of consuming marijuana occurs when the closer peer variable changes from value one (only some of the friends use marijuana) to value two (the majority of the friends use marijuana). On the contrary, the lowest increment in the probability of being a marijuana consumer occurs when the closer peer variable changes from value two (the majority of the friends) to value three (all of them).

Finally, we want to test Steinberg's (1987) suggestion that peer group effects are probably greater in unstructured families, given that in this kind of family the affective links tend to be weaker. With this aim, we introduce interaction terms between the dummy variables that measure the peer effects, and the variable that indicates whether or not the student lives without his/her father. The results are summarised in Table 3, where only the peer variables appear. Similarly, we have introduced an interaction between the dummy peer effect variables and the variable that indicates whether or not the father is unemployed. In agreement with Lundborg (2006), we find that both interaction variables are not statistically significant at the 5% level. Consequently, we cannot reject the hypothesis that the peer effects are the same in the different kind of families considered.

Discussion

We have analysed the influence of the peer group and other socio-economic variables affecting the decision of a student to consume, or not, marijuana, using a closer measure of the peer group variable than used before. This narrower variable provides a more appropriate measure of peer groups and, therefore, more credible estimates. We have estimated a probit model using the most recent data provided by the SDUSP (2004).

Overall, the findings in this work are consistent with previous literature; namely, if no other measures of peer group effect are considered, the class-based measure of the peer group effect is statistically significant and positive. The estimates indicate that if the student attends a class where the proportion of marijuana smokers is 10 points higher, the probability of becoming a smoker would increase by 2.1 points.

However, one of the most important findings of our paper is that, when controlling for a closer peer group effect, the traditional peer variable measured at class level is non-significant. The estimates also show that the quantitative impact of the closer peer variable is higher than the effect of the peer variable measured at the class level.

Additionally, the use of this closer peer effect variable implies that some explanatory variables lose their importance as factors in the decision to consume marijuana. Moreover, some of the variables that continue to be significant show a decline in their *t*-ratio, with their marginal effects being lower. Nevertheless, income, and school campaigns that inform about the risks of using drugs, appear to be significant – the first as a risk factor, and the second as a protective factor.

Table 3. Estimation results with interaction variables.

Variable	Without father interaction		Unemployed father interaction		Standard deviation
	Parameter	Standard deviation	Variable	Parameter	
<i>CloserPeer1WithoutFather</i>	0.088	0.060	<i>CloserPeer1UnemployedF</i>	-0.086	0.169
<i>CloserPeer2 WithoutFather</i>	-0.070	0.087	<i>CloserPeer2UnemployedF</i>	0.063	0.301
<i>CloserPeer3 WithoutFather</i>	-0.328	0.197	<i>CloserPeer3UnemployedF</i>	0.438	13.06
<i>CloserPeer1</i>	0.681	0.023	<i>CloserPeer1</i>	0.689	0.022
<i>CloserPeer2</i>	1.532	0.039	<i>CloserPeer2</i>	1.520	0.032
<i>CloserPeer3</i>	1.778	0.117	<i>CloserPeer3</i>	1.717	0.101

Note: Standard deviations are computed from standard error derived after bootstrapping with 200 replications. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Acknowledgements

This paper was partially written while José Alberto Molina was Visiting Fellow at the Department of Economics of the University of Warwick (UK), to which he would like to express his thanks for the hospitality and facilities provided. Moreover, the authors would like to express their gratitude for the financial support provided by Fundación de Economía Aragonesa (FUNDEAR) in Project OTRI 2006/198. The usual disclaimers apply.

Notes

1. The *IncomeSquared* variable has been introduced into the analysis to capture a possible quadratic relationship between income and the probability of marijuana consumption.
2. The Spanish educational system for 14–18 year olds consists of two main levels: secondary education, which is a comprehensive programme, and a further level in which two branches are distinguished – vocational training and ‘Bachillerato’, the latter mainly oriented to preparing students for university. The *Program* variable captures this last branch.
3. Therefore, we will consider two basic models. In the first, we use the traditional measure of peer variable, and in the second we introduce our closer peer measure. Despite these two basic models, in the empirical application we will estimate a model with both peer effect measures simultaneously. In the second model the number of equations will be indicated ('). The estimates of the coefficient vector γ in both models are different. However, for ease of notation, we drop sub-indices. This simplification applies to the rest of the section.
4. *HouseSmoking* is a dichotomous variable that takes value one if someone who lives in the household, other than the student, smokes and zero otherwise. *MotherDrinking* and *FatherDrinking* are categorical variables that take the following values: one, if she/he never drinks alcohol; two, if she/he drinks occasionally; three, if she/he drinks only at weekends; four, if she/he drinks almost everyday in moderation; and five, if she/he drinks a lot every day.
5. To compute the change in the probability or marginal effect, we have averaged the following expression over all the individuals:

$$\frac{\partial \Phi(z)}{\partial x_j} = \phi(z) \frac{\partial z}{\partial x_j}.$$

The density function has been evaluated using the true explanatory variables; that is to say, we have used the true peer effect variables, instead of the instrumented peer effect variables.

References

- Aaronson, D. 1998. Using sibling data to estimate the impact of neighborhoods on children's educational outcomes. *Journal of Human Resources* 33: 915–46.
- Borjas, G. 1994. Ethnicity, neighborhoods and human capital externalities. *American Economic Review* 85: 365–90.
- Bray, J.W., G.A. Zarkin, C. Ringwalt, and J. Qi. 2000. The relationship between marijuana initiation and dropping out of high school. *Health Economics* 9: 9–18.
- Brook, J.S., E.B. Balka, and M. Whiteman M. 1999. The risks for late adolescence of early adolescent marijuana use. *American Journal of Public Health* 89: 1549–54.
- Chaloupka, F.J., and A. Laixuthai. 1997. Do youths substitute alcohol and marijuana? Some econometric evidence. *Eastern Economic Journal* 23: 253–76.
- DeCicca, P., D. Kenkel, and A. Mathios. 2000. Racial difference in the determinants of smoking onset. *Journal of Risk and Uncertainty* 21: 311–40.
- Defonseca, F.R., M. Rocio, A. Carrera, M. Navarro, G.F. Koob, and F. Weiss. 1997. Activation of corticotropin-releasing factor in limbic system during cannabinoid withdrawal. *Science* 276: 2050–4.
- Dekovic, M., I.B. Wissink, and A.M. Meijer. 2004. The role of family and peer relations in adolescent antisocial behaviour: comparison of four ethnic groups. *Journal of Adolescence* 27: 497–514.

- Desimone, J. 1998. Is marijuana a gateway drug? *Eastern Economic Journal* 24: 149–64.
- Duarte, R., J.J. Escario, and J.A. Molina. 2006. Marijuana consumption and school failure among Spanish students. *Economics of Education Review* 25: 472–81.
- Efron, B., and R.J. Tibshirani. 1993. *An introduction to the bootstrap*. London: Chapman and Hall.
- Eitle, D. 2005. The moderating effects of peer substance use on the family structure–adolescent substance use association: quantity versus quality of parenting. *Addictive Behaviors* 30: 963–80.
- European Monitoring Centre for Drugs and Drug Addiction. 2005. Studies of youth and the schools population. Statistical Bulletin. <http://stats05.emcdda.europa.eu/en/page009-en.html>.
- Gaviria, A., and S. Raphael. 2001. School-based peer effects and juvenile behaviour. *The Review of Economics and Statistics* 83: 257–68.
- Gecková A.M., R. Stewart, J.P. van Dijk, O. Orosová, J.W. Groothoff, and D. Post. 2005. Influence of socio-economic status, parents and peers on smoking behaviour of adolescents. *European Addiction Research* 11: 204–9.
- Hall, W., N. Solowij, and J. Lemmon. 1994. The health and psychological consequences of cannabis use. Monograph Series n° 25, Australian Government Printing Office, Canberra.
- Hanushek, E.A., J.F. Kain, J.M. Markman, and S.G. Rivkin. 2003. Does peer ability affect student achievement? *Journal of Applied Econometrics* 18: 527–44.
- Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica*, 46: 1251–71.
- Hawkins, J.D., R.F. Catalano, and J.Y. Miller. 1992. Risk and protective factors for alcohol and other drug problems in adolescence and early adulthood: Implications for substance abuse prevention. *Psychological Bulletin* 112: 64–105.
- Johnston, L.D., P.M. O'Malley, J.G. Bachman, and J.E. Schulenberg. 2005. Teen drug use down but progress halts among youngest teens. University of Michigan News and Information Services, Ann Arbor, MI. www.monitoringthefuture.org.
- Kandel, D.B. 1975. Stages in adolescent involvement in drug use. *Science* 190: 912–24.
- Kandel, D.B., K. Yamaguchi, and K. Chen. 1992. Stages of progression in drug involvement from adolescence to adulthood: further evidence for the gateway theory. *Journal of Studies on Alcohol* 53: 447–57.
- Kawaguchi, D. 2004. Peer effects on substance use among American teenagers. *Journal of Population Economics* 17: 351–67.
- Lundborg, P. 2006. Having the wrong friends? Peer effects in adolescent substance use. *Journal of Health Economics* 25: 214–33.
- Manski, C.F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60: 531–42.
- Manski, C.F. 1995. Economic analysis of social interactions. *Journal of Economic Perspectives* 1995; 14: 115–36.
- McArdle, P., A. Wiegiersma, E. Gilvarry, D. McCarthy, M. Fitzgerald, B. Kolte, A. Brinkley, et al. 2000. International variations in youth drug use: The effect of individual behaviours, peer and family influences, and geographical location. *European Addiction Research* 6: 163–9.
- Mounts, N.S., and L. Steimberg. 1995. An ecological analysis of peer influence on adolescent grade point average and drug use. *Developmental Psychology* 31: 915–22.
- Nahas, G., and C. Latour. 1992. The human toxicity of marijuana. *Medical Journal of Australia* 156: 495–7.
- Pope, H.G., A.J. Gruber, and D. Yurgelum-Todd. 1995. The residual neuropsychological effects of cannabis: The current status of research. *Drug Alcohol Dependence* 38: 25–34.
- Powell, L.M., J.A. Tauras, and H. Ross H. 2005. The importance of peer effects, cigarette prices and tobacco control policies for youth smoking behaviour. *Journal of Health Economics* 24: 950–68.
- Sacerdote, B. 2001. Peer effects with random assignment: Results from Dartmouth roommates. *Quarterly Journal of Economics* 116: 681–704.
- Spanish Survey on Drug Use in the School Population. 2004. Spanish Government's Delegation for the National Plan on Drugs.
- Steimberg, L. 1987. Single parents, step parents, and the susceptibility of adolescents to anti-social peer pressure. *Child Development* 58: 269–75.

- Substance Abuse and Mental Health Services Administration. 1998. Analyses of substance abuse and treatment need issues. Analytic Series A-7, US Department of Health and Human Services, Rockville, MD.
- Winkler, D.R. 1975. Educational achievement and school peer group composition. *Journal of Human Resources* 10: 189–204.

Copyright of Education Economics is the property of Routledge and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.