Does Illicit Drug Use Affect Labor Market Outcomes? Evidence from a Developing Country

BY

Carolina Calle Echeverri

Gabriel Jaime Suárez Obando

ADVISOR

Christian Manuel Posso Suárez

Universidad EAFIT

School of Economics and Finance

Department of Economics

Medellin

2017

Abstract

Illicit drug use is often related to several problems for individuals who participate on the labor market due to decreasing productivity, absenteeism, increasing crime and health consequences. This study analyzes the relationship between substance use and labor market outcomes using econometric methods to address the potential endogeneity problem. We use a large data set for Medellin, Colombia, to find the causal effect of drug use on labor supply and labor force participation. According to most existing research, we found that drug use affects negatively the probability of being employed and the probability of participate in the labor force.

1. Introduction

Drug use has been cataloged as a social problem due to the supposed harmful effects associated with health, criminal behavior and economic disadvantage, and it is often related to negative outcomes such as low educational attainment (Bray, 2000; Ellickson, 1998; Yamada, 1996); reduced cognitive ability (Pope, 1996; Solowij, 2006), and poor labor market outcomes (Kaestner, 1994; DeSimone, 2002). The labor market consequences of drug consumption have been of interest for the economic literature given the importance of the labor force for economic growth and welfare. However, most of the existing literature about the effects of drug use on labor market outcomes found evidence from developed countries, while there is little or none evidence from developing countries.

Developed countries have different politic and economic structure than developing countries, these countries have more problems associated with poverty, unemployment and crime. Given that, in the case of developing countries is necessary to take in account the differences on individuals' preferences and the specific characteristic in the drug market, in order to be consistent with the socio-economic policies needed to solve the problems associated with the drug use. For example, a recent study of drug use in Colombia shows that about 20% of males and 6.5% of females have ever consumed illicit drugs at least one time in their life. Similarly, 6% of males and 1.4% of females reported recent use or in the last year, which means about 839 thousand of people (Observatorio de drogas de Colombia, 2013). This numbers evidence the high incidence of substance use in the population of a developing country.

The effect of drug use may be negative for individuals who participate in the labor market due to decreasing productivity and limiting labor availability through health and social behavior (French, Roebuck, & Alexandre, 2001). In the same way, unemployment could lead to increased drug use due to higher leisure availability. But, on the other hand, the economic theory suggests that employment could lead to an increase in drug use because of increased disposable income, given that illicit drugs are normal goods (Van Ours & Williams, 2015). Then, the relationship between drug use and labor market outcomes may be positive or negative, and empirically remains inconclusive (Register & Williams, 1992; Gill & Michaels, 1992; Huang, Evans, Hara, Weiss, & Hser, 2011; Rivera, Casal, Currais, & Rungo, 2013; Van Ours, 2006; Kaestner, 1994; Zarkin, Mroz, Bray, & French, 1998).

The relationship between drug use and labor market outcomes seems to be of cause/effect, but it may be a spurious correlation due to unobserved factors that affect both, drug consumption and employment (Ringel, Ellickson, & Collins, 2006). Additionally, such apparently negative relationship is not completely clear in the existing literature and several authors argue that depends on cultural characteristics of the sample analyzed. This controversy leads to obstacles in the design of public policies since, if the effect is negative, then the implementation of treatment programs is crucial to prevent drug consumption among individuals.[1] Clearly, a negative relationship between drug use and labor market outcomes is an important dot to the policy makers given the economic costs of medical resources used for care, treatments, rehabilitation, crime enforcement and lost productivity caused by drug consumption (Rice, Kelman, & Miller, 1991).

Then, the questions of interest in this paper are: Does illicit drug use affect labor market outcomes? And, which are the main transmission mechanisms? The lack of evidence from developing countries with a historical background of drug traffic and consumption (e.g. Colombia), generates the necessity to study this relationship to guide policy makers in their efforts to solve the problems driven by drug use. This paper aims to test the effect of illicit drug use on employment and labor force participation using data from Medellin in 2008.

[1] Nonetheless, if such effect is not negative it would be necessary additional research to understand the key mechanism of such relationship.

This paper is organized as follows. Section 2 presents the theoretical background about the relationship between drug use and labor market outcomes. Literature review is provided in section 3. Section 4 presents the data and summary descriptive statistics. The methodology is presented in section 5 and section 6 presents the results. Finally, we conclude in section 7 with some policy recommendations.

2. Theoretical Framework

To guide the empirical work of the present study, we follow the theoretical framework developed by Mullahy & Sindelar (1996) and adapted by French et al. (2001). If markets are competitive and workers are price and wage takers, the functions for drug consumption and labor supply can be expressed as

$$D = D(\rho, \omega, X_{D,} \alpha_D) \quad (1)$$

$$L = L(\rho, \omega, X_{L,} \alpha_L) \quad (2)$$

Where ρ are prices, ω are wages, X_D and X_L are covariates (education, health status and demographics controls) that affects D, the demand for drug use, and L, the labor supply, and α_D and α_D are vectors of unobservable characteristics associated with both outcomes. A static utility maximization model of drug consumption and labor supply subject to a budget constraint can be used to derive equations (1) and (2). Here it is assumed that preferences for drug consumption and leisure are implicitly separable from other prices (Blundell & Meghir, 1986). That procedure lead to the followings reduced-form equations:

$$D = D(L, X, \alpha) \quad (3)$$

$$L = L(D, X, \alpha) \quad (4)$$

Where X is the union of X_D and X_L, and α includes all factors in X_D and X_L. The present analysis is focused on the effect of D on L. It is possible to address the problem by estimating the equation for L without considering the equation for D as conventional techniques do it, but solving the direct relationship would generate inconsistent estimators due to the correlation between D and α, that is, because of unobservable factors -such as cultural preferences- can be associated with drug use, it is not possible to find a ceteris paribus effect. Nonetheless, instrumental variables methods, such as bivariate probit regression model, allow us to obtain consistent and efficient estimators of the parameters of interest.

3. Literature Review

The existing literature about the effects of drug use on labor market participation is still without conclusion, there remains uncertainty about the apparently harmful impact of substance use.

Gills & Michaels (1992) with data of the NLSY for 1984 reported that drug use, measured as a binary variable indicating use in last year, decreased the probability of being employed. Register & Williams (1992), using the same data, reached the same conclusion for cannabis but found no significant effect for cocaine, defining substance use as the number of times it had been used in the previous 30 days. Both studies used instrumental variables to correct the endogeneity problem. Similarly, DeSimone (2002) investigates the relationship between employment and the use of marijuana and cocaine for males using the NLSY from 1984 and 1988, their results suggest that the use of both substances reduces the likelihood of employment.

Zarkin et al. (1998) made also an analysis for US with data from the NHSDA for 1991 and 1992, and found interesting relationships. Their results indicate that chronic drug use (60 or more joints at past month) has little negative effect on labor supply but young men who smoked 1 to 3 marijuana joints (moderate use) in the last month worked 42 more hours than nonusers. French et al. (2001) also, used the NHSDA, their analysis is for 1997. They found that chronic drug use is significantly related (negative) to employment, but nonchronic drug use is not.

Alexandre & French (2004) analyze the effects of chronic drug use on employment in low-income and high-crime neighborhoods in Miami. They found that regardless of gender, chronic drug use significantly reduced the probability of being employed. Van Ours (2006) study the employment effects of the use of cannabis and cocaine among the inhabitants of Amsterdam. His results show no significant effects for females while for males a negative relationship is found.

In the same line, Kandel & Davies (1990), using a longitudinal survey, analyze the effects of drugs use on labor market and conclude that drug consumption declines the employment transitions and increase the gap between employment and unemployment. Specifically, drug users have more probability of being unemployed than nonusers. According to Baldwin & Marcus (2014) the substance-use disorders (SUD) generates an increase in employment gaps, that is, the employment transitions rise when someone decide to consume drugs, but there is a difference between chronic use and light use. The authors argue that the negative effects of drug use depend on the frequency of consumption.

Buchmueller & Zuvekas (1998) examines the effect of drug use on wages and employment for young adults and prime-age (30-45 years old) using the ECA data. Their findings indicate a negative relationship between chronic use and employment among prime-age, but not younger, men. Burgess & Propper (1998) using NLSY from 1981 through 1992 found that soft drugs use had no harmful effects on labor market participation 10 years later. However, heavy substance use did have a negative effect on labor market participation. Huang et al. (2011) used the NLSY too, but their study covered 20 years (from 1979 to 2004) analyzing the impacts of drug use on employment trajectories. The authors concluded that early-initiation drug users, users of "hard" drugs, and frequent drug users were more likely to demonstrate consistently low levels of employment.

Rivera et al. (2013) study the evidence of simultaneity between illicit drug use and labor market participation in Spain. Using clinical data, the authors confirm that drug use is endogenously determined and the found evidence supports the negative relationship between drug use and employment. Ringel et al. (2006) examine the relationship between high school marijuana use and annual earnings at age 29 using a panel data set. The analysis finds that the negative relationship is explained by two ways. Early marijuana use affects human capital accumulation, which in turn affects earnings and the cumulative negative effect of marijuana use on cognitive ability and motivation.

4. Data

The data used in this study comes from the survey *Encuesta de Calidad de Vida de Medellin* (ECVM) for 2008 collected by the Municipality of Medellin, which has detailed information about socioeconomic conditions such as labor market experience, family background, personal characteristics, education, health and others, of more than 21600 households[2] per year in Medellin. The survey questionnaire has information about last twelve months of drug consumption (marijuana, cocaine, cocaine paste and ecstasy). Nonetheless, it has no information about frequency of use is provided. We use data for 2008 due to the availability of drug consumption information; more recent versions of the survey do not have this information anymore.

The outcomes considered are employment and labor force participation[3]. We consider individuals between 12 and 60 years old.[4] Because of the restricted occupational choices of youth, we analyze the incidence of drug consumption on labor force participation and employment in order to identify the effect for individuals aged 12-21, since youth between 12-16 years old are probably enrolled in secondary education and those aged 17-21 could be enrolled in higher education, nonetheless, the low enrollment rate in higher education in Colombia is relatively low compared with developed countries, then, people between 17-21 years old could participate in the labor market without occupational restrictions. For this purpose, we estimated a set of least squares and probit regressions starting with the age range 12-60 and consequently excluding one year per estimation.

As shown in Figure 1, for labor force participation the inclusion of individuals aged 12-19 years old produce a non-significant correlation. The same is true for individuals aged 12-

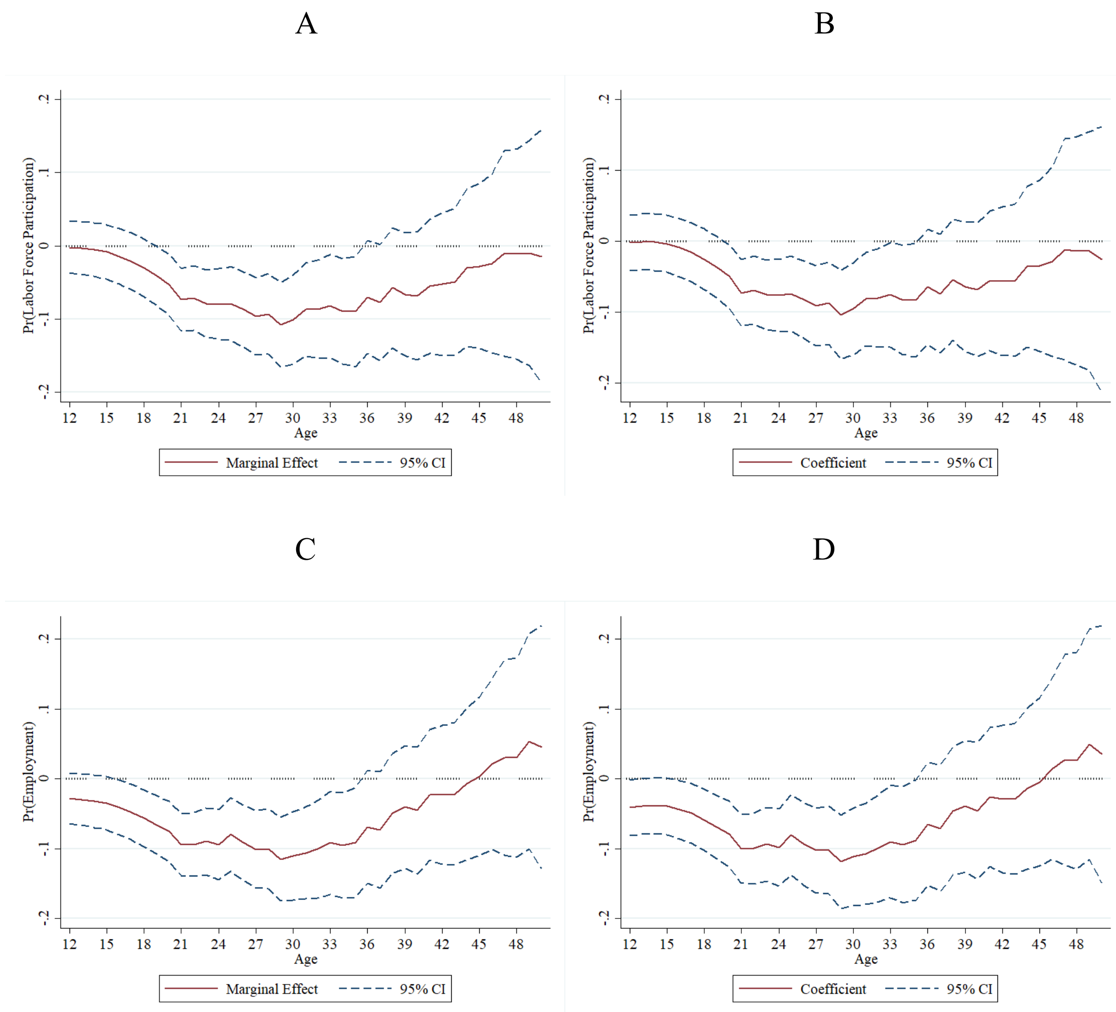
[2] The ECVM is collected at household level but each household member is interviewed, therefore, we have data available for almost 80000 individuals across all the neighborhoods in the city, which represents the 100% of the total population of Medellin.

[3] Employment is defined according to the definition of the Ministry of Health and Social Protection which established that employees are all persons, who, during the reference week, (1) had a pay work for at least one hour, (2) were not working but had jobs or businesses or, (3) had an unpaid work in a family business for at least one hour. Labor force participation include employers and unemployed people. Unemployment includes all persons, who, during the reference week, did not have a work but (1) were able to work, (2) looked for a job in the previous four weeks or, (3) did not look for a job in the previous four weeks but in the last year and had valid reasons to stop looking.

[4] 12 years old is the starting age of the working age population in Colombia and 60 years old was, approximately, the pension age in Colombia in 2007.

15 years old in the probability of being employed. These findings suggest that individuals between 12-20 years old have restricted occupational choices (full time high school or college students, occasional workers and new labor market participants), therefore, we estimate our main econometric models with different ranges of age (16-60, 16-45, 22-60, 22-45).

FIGURE 1. CORRELATION BETWEEN DRUG USE AND LABOR MARKET OUTCOMES BY AGE



Notes: Figure 1 reports the estimated coefficients of drug use on labor force participation (A and B) and employment (C and D) by age. Each point comes from a separate probit model (A and C) or linear probability model (B and D), starting with the age range 12-60 and consequently excluding one year per estimation. The regressions include the following controls: age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Ninety-five percent confidence intervals around the estimates also reported.

Table A1 in the Appendix shows the summary statistics of the outcomes and control variables. A mean difference test is provided. As shown in the table, most of variables statistics differs across users and nonusers. Furthermore, mean difference tests change for outcomes across the age ranges. This is probably because labor force participation and employment are choices that change over lifetime. This explanation is consistent with the results shown in Figure 1.

The percent of people that use drugs is about 1% in the sample. Among individuals between 22-60 years old, approximately 70% of users and non-users participate in the labor force, while 63% of non-users have employment compared with 57% of users. Non-users, on average, are older than users (39.5 versus 32.2 years old), have a lower proportion of males (0.44 versus 0.81), a greater proportion living in higher socio-economic stratums, more years of education (12.5 versus 10.6), a lower proportion of single people (0.4 versus 0.7), greater proportion of married people (0.32 versus 0.07) and greater percentage of heads of household (34% versus 21%). No statistical differences were found for homeownership, health status and race (see Table A1 for further summary statistics).

5. Methodology

First, we considered several econometric models that do not address the causal effect of drug use on labor market outcomes. We start with an OLS and probit regressions for equations (5) and (6), where the correlation between these two variables is analyzed in two directions: the impact of drug use on employment and the impact of employment on drug use. The results will say how large is the effect and the possible direction of the causality.

$$\Pr(L_i) = f(X_i\beta + \theta D_i + \mu_i) \quad (5)$$

$$\Pr(D_i) = f\left(\gamma X_i + \psi \mathrm{L_i} + \eta_i\right) \quad (6)$$

Second, multinomial logistic regression will be used to estimate equation (7), to identify in which employment categories the effect of drug use is concentrated. The employment categories considered are: employment transitions (Full time, Partial time, No work) and employment formality (Formal, Informal, No work). These results are important to recognize heterogeneous effects of drug consumption on labor market features.

$$\Pr(E_i = j|X_i, D_i) = \frac{e^{X_i\beta_j+\theta_j D_i}}{1+\sum_{k=1}^{2} e^{X_i\beta_k+\theta_k D_i}} \quad (7)$$

Third, since due to the endogeneity problem between labor participation and drug use, probit, logit or linear probability models produce inconsistent estimators, then we solve this problem using a bivariate probit model, where employment (or labor force participation) and drug use equations are related through the error terms. Han & Vytlacil (2017) shown that, in binary-response models with two equations and a binary endogenous covariate, having an exclusion restriction (i.e. instruments) is sufficient but not necessary for global identification in models with common exogenous covariates that are present in both equations, then, we estimate bivariate probit models with and without instruments. The following equations specify the model to estimate:

$$\Pr\begin{pmatrix} L_i \\ D_i \end{pmatrix} = \Phi\left(\begin{bmatrix} X_i\beta + \theta D_i \\ \gamma X_i + \delta Z_i \end{bmatrix} + \begin{bmatrix} \mu_i \\ \eta_i \end{bmatrix} > 0\right) \quad (8)$$

where X matrix includes control variables.[5] Z vector contains the instrument, victimization, for drug use equation that affect the probability of being employed through drug use. The error terms are independent of X and Z, are correlated ($\rho = Cov(\mu_i, \eta_i)$) and are jointly normally distributed as the next expression:

[5] The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects

$$\begin{bmatrix}\mu_i\\ \eta_i\end{bmatrix} \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_\mu^2 & \rho\\ \rho & \sigma_\eta^2\end{bmatrix}\right) \quad (9)$$

The maximum likelihood function can be derived finding the joint distribution of (L_i, D_i) given Z_i:

$$f(L_i, D_i|X_i, Z_i) = f(L_i|D_i, Z_i, X_i)f(D_i|Z_i, X_i) \quad (10)$$

and then, we can focus on the average treatment effect of drug use on employment with the following equation:

$$E(D_i|Z_i) = \Phi(X_i\beta + \theta) - \Phi(X_i\beta) \quad (11)$$

$$E(D_i|Z_i) = \frac{1}{\Phi(X_i\gamma + Z_i\delta)}\int_{-(X_i\gamma+Z_i\delta)}^{\infty} \Phi\left[\frac{X_i\beta + \theta D_i + \rho\eta_i}{(1-\rho^2)^{\frac{1}{2}}}\right]\phi(\eta_i)\, d\eta_i - \left(\frac{1}{1-\Phi(X_i\gamma + Z_i\delta)}\int_{-\infty}^{-(X_i\gamma+Z_i\delta)} \Phi\left[\frac{X_i\beta + \theta D_i + \rho\eta_i}{(1-\rho^2)^{\frac{1}{2}}}\right]\phi(\eta_i)\, d\eta_i\right) \quad (12)$$

The relationship between μ and η is tested with a Wald test (χ^2). If the null hypothesis of $\rho = 0$ is rejected, then a bivariate probit model is appropriate. The econometric method to be estimated in this work considers the potential endogeneity problem to generate consistent estimators[6].

6. Results

The theoretical effect of drug use on labor supply and labor force participation, could be positive or negative, like previously was stated. Nonetheless, according to previous studies, the relationship between illicit drug use and labor market outcomes is probably negative,

[6] The bivariate probit model with instruments is appropriate for global identification if the instruments are valid.

because drug consumption leads to lower productivity and more losses and accidents (Alexandre & French, 2004). Furthermore, due to correlation between unobserved characteristics that affect drug use and labor supply, there is a potential endogeneity problem that has been addressed in previous research with an instrumental variables approach. Even so, following the results of Han & Vytlacil (2017) we do not need an exclusion restriction for global identification because in our econoemtric specification there are common exogenous covariates that are present in both equations.

We present three econometric models using different specifications to try to identify the causal effect of drug consumption on labor supply measures. The results for equations (5) and (6) using OLS[7] are presented in Table 1 and Table 2, respectively. As can be seen in Table 1, the correlations between drug use and employment are statistically significant in both directions. Results suggest that the fact of using drugs is associated with a 5% reduction on the probability of being employed for individuals between 16-60 years old. The estimated effect increases to 10% when the range considered is 22-60 years old.

On the other hand, the estimates of employment on drug use, although statistically significant, are too small in magnitude. This provides some evidence that the cause-effect relationship is like the expressed in equation (5). Table 2 reports that the fact of using drugs is associated with a 7% reduction on the probability of participate in the labor force for individuals between 22-60 years old. Nonetheless, when people between 16-21 years old are included, the estimates are not statistically significant. The previous findings suggest that there is a significant correlation between drug use and labor outcomes.

[7] We also estimated probit regression provided in Table A2 in the Appendix. Results are similar to OLS regressions.

TABLE 1. OLS ESTIMATES OF DRUG USE AND EMPLOYMENT				
	(1)		(2)	
Response Variable	Employment		Drug use	
Age	Coefficient (SE)	N	Coefficient (SE)	N
16-60	-0.044 (0.021)**	52803	-0.002 (0.001)**	52803
16-45	-0.051 (0.022)**	38093	-0.004 (0.002)**	38093
22-60	-0.099 (0.026)***	43424	-0.005 (0.001)***	43424
22-45	-0.107 (0.027)***	28714	-0.006 (0.002)***	28714

Notes: Results are obtained from OLS estimations, robust standard errors in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Column (1) reports the estimated effects of drug use on the probability of being employed while column (2) presents the estimated effects of employment on the probability of use drugs. Significance levels: 1% ***, 5% **, 1% *.

The estimates of drug use on employment categories are presented in Tables 3 and 4 to identify heterogeneous effects. As shown in Table 3, the fact of using drugs is associated with less probability to being full time employed with respect to no work, but there is no statistically significant difference between partial time employment and no work for drug users and nonusers. These findings suggest that the effect of using drugs is concentrated on the employment transition “no work – full time job”.

Other important issue about employment categories is formality. As can be seen in Table 4, drug consumption is associated with less probability of being a formal employee with respect to no work. However, there is no statistically significant difference between informality and no work for drug users and nonusers. Therefore, these findings suggest that the effect of using drugs is concentrated on the employment category “no work – formality”.

TABLE 2. OLS ESTIMATES OF DRUG USE AND LABOR FORCE PARTICIPATION				
	(1)		(2)	
Response Variable	Drug		Labor Force	
Age	Coefficient (SE)	N	Coefficient (SE)	N
16-60	-0.009 (0.021)	52803	-0.001 (0.001)	52803
16-45	-0.009 (0.022)	38093	-0.001 (0.002)	38093
22-60	-0.069 (0.024)***	43424	-0.004 (0.001)***	43424
22-45	-0.064 (0.026)**	28714	-0.005 (0.002)**	28714

Notes: Results are obtained from OLS estimations, robust standard errors in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Column (1) reports the estimated effects of drug use on the probability of being employed while column (2) presents the estimated effects of employment on the probability of use drugs. Significance levels: 1% ***, 5% **, 1% *.

To address with the endogeneity problem, we use victimization of one member of the household in the previous twelve months as an instrument for drug use. We argue that the fact of a family member has been victim of offense induces to using drugs but does not affect directly the labor supply.[8] Victimization include: robbery, threats, extortion, homicide, traffic accidents, kidnapping, fights, shooting, drugs, rape and fraud. We computed victimization rates among neighborhoods to obtain a more exogenous instrument. We also considered a proxy of drug-related drugs capture rate at the neighborhood level but it turns out to be a weak instrument, and then we do not include those results in this study.

Table 5 presents results for employment from a bivariate probit regression with and without instrument following the results of Han & Vytlacil (2017). As can be seen, drug

[8] This instrument could affect directly employment and labor force participation because a psychological shock could affect productivity and willingness to work through declining the emotional state.

consumption is statistically significant at 5% and it is associated with less probability of being employed for individuals between 16-60, 22-60 and 22-45 years old. Other factors equal, the fact of using drugs reduces the probability of being employed by about 40% for people aged 16-60, more than 45% for people aged 22-60 and about 30% for people aged 22-45. The negative effect is lower for people between 22-45. This result holds with and without the use of instruments and supports the theory that the fact of using drugs generates lost in productivity and limit labor availability because of lack of concentration, absenteeism, accidents and other labor problems.

TABLE 3. ESTIMATES OF DRUG USE AND EMPLOYMENT TRANSITIONS

Age	Partial Time	Full Time	N
16-60	0.274	-0.344	51652
	(0.164)*	(0.117)***	
16-45	0.203	-0.371	37301
	(0.180)	(0.128)***	
22-60	0.110	-0.624	42412
	(0.182)	(0.130)***	
22-45	0.044	-0.630	28061
	(0.200)	(0.136)***	

Notes: Table reports coefficient estimates of drug use on employment transitions from multinomial logistic regressions; the base category is “No work”. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Robust standard errors in parenthesis. Significance levels: 1% ***, 5% **, 1% *.

Although employment is important to analyze the consequences of drug consumption, it is an outcome derived from a demand-supply process and, thus, it is out of total control for individuals. For that reason, we also analyze the impact of drug use on labor force participation, which is product of an individual’s making decision rational process.

Table 6 reports results for labor force participation. As shown in the table, drug consumption is statistically significant at 5% and it is associated with less probability of participate in the labor force for individuals between 16-60, 22-60 years old. Other factors equal, the fact of using drugs reduces the probability of participate in the labor force by more than 30% for people aged 16-60, more than 35% for people aged 22-60 and about 20% for people aged 22-45. With victimization at household level, drug consumption is not statistically significant in the range 22-45. These results suggest that the fact of use drugs generates a reduction of labor availability due to individuals' decision to not participate.

TABLE 4. ESTIMATES OF DRUG USE AND FORMALITY

Age	Informal	Formal	N
16-60	0.038	-0.576	45037
	(0.117)	(0.175)***	
16-45	-0.009	-0.605	32383
	(0.129)	(0.186)***	
22-60	-0.217	-0.777	36316
	(0.134)	(0.180)***	
22-45	-0.264	-0.778	23662
	(0.144)*	(0.189)***	

Notes: Table reports coefficient estimates of drug use on employment transitions from multinomial logistic regressions; the base category is "No work". The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Robust standard errors in parenthesis. Significance levels: 1% ***, 5% **, 1% *.

The appropriate use of the bivariate probit model is tested with a Wald test statistic, the inference indicates that there is evidence of simultaneity, that is, the econometric method is a better method than the naïve methods such as OLS and Probit models (See Table A3 in the Appendix). Moreover, the coefficients of victimization on drug use are provided in Table A4 in the Appendix, they indicate a high and significant correlation with victimization in household level but are less robust for victimization in neighborhood level (statistically significant at 10% for 16-60, 22-45 and at 5% for 22-60 years old). In general, there is a good fit of the econometrics model, that provides some evidence that the instruments are valid.

TABLE 5. BIVARIATE PROBIT ESTIMATES OF DRUG USE ON EMPLOYMENT

Instrument	Victimization Household level		Victimization Neighborhood level		No instrument	
Age	Marginal Effect (SE)	N	Marginal Effect (SE)	N	Marginal Effect (SE)	N
16-60	-0.377 (0.070)***	52803	-0.394 (0.066)***	52803	-0.400 (0.064)***	52803
16-45	-0.041 (0.102)	38093	-0.044 (0.108)	38093	-0.053 (0.107)	38093
22-60	-0.463 (0.063)***	43424	-0.477 (0.063)***	43424	-0.487 (0.061)***	43424
22-45	-0.293 (0.104)***	28714	-0.308 (0.107)***	28714	-0.322 (0.103)***	28714

Notes: Table reports marginal effects estimates of drug use on employment from bivariate probit regressions. Robust standard errors are in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Significance levels: 1% ***, 5% **, 1% *.

TABLE 6. BIVARIATE PROBIT ESTIMATES OF DRUG USE ON LABOR FORCE PARTICIPATION

Instrument	Victimization Household level		Victimization Neighborhood level		No instrument	
Age	Coefficient (SE)	N	Coefficient (SE)	N	Coefficient (SE)	N
16-60	-0.309 (0.080)***	52803	-0.347 (0.062)***	52803	-0.352 (0.060)***	52803
16-45	0.146 (0.105)	38093	0.071 (0.140)	38093	0.060 (0.145)	38093
22-60	-0.364 (0.068)***	43424	-0.391 (0.064)***	43424	-0.399 (0.063)***	43424
22-45	-0.173 (0.129)	28714	-0.232 (0.106)**	28714	-0.241 (0.103)**	28714

Notes: Table reports coefficient estimates of drug use on labor force participation from bivariate probit regressions. Robust standard errors are in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Significance levels: 1% ***, 5% **, 1% *.

7. Conclusion

We aimed to find the causal effect of drug consumption on labor market supply, considering the potential endogeneity problem. We use data from a representative survey to test this relationship for Medellin, the second most important city of Colombia, a developing country with historical background on drug traffic and consumption problems. We consider victimization as an instrument for drug consumption but there is important to realize that the validity of the instrument is not completely credible because victimization could impact labor supply. Nonetheless, Han & Vytlacil (2017) provide proofs that having an exclusion restriction (i.e. instruments) is sufficient but not necessary condition for global identification in models with common exogenous covariates that are present in both equations, as our econometric framework is specified. Then, we provided estimates without the use of instruments that have the same conclusions than estimates with instruments.

The validity of our instrument implies to make a strong assumption but due to lack of more powerful instruments in the survey used and the fact that the capture rate of drug related-crimes was not a valid instrument, we provide results as a first approximation to the evidence from a developing country. Additionally, we use cross-section data in our empirical analysis but longitudinal data allows to capture the long-term relationship between drug use and labor market outcomes. Finally, from our findings we highlight the large negative effect of drug consumption on employment and labor force participation, this fact shows that the effects are grater (more negative) compared with other findings in the existing literature, such as French et al. (2001) or Alexandre & French (2004) that a negative effect of, approximately, 10%. Then, it is important to differ between developed and developing countries and we make a call to find more evidence from these countries.

Our results are similar to those found in the existing literature and suggest that the use of drugs generates a negative effect on the probability of being employed and on the probability of participate in the labor force. Therefore, the implementation of treatment and prevention programs is justified because of reduced labor quality and availably which is a key productivity factor for economic growth. Finally, we suggest the necessity of create policies for workers to refrain from chronic drug abuse. Nevertheless, because we did not have frequency of use, the effect of nonchronic drug use was not analyze in this study. The literature suggests that nonchronic drug use does not have a significant effect on labor market outcomes.

References

Alexandre, P. K., & French, M. T. (2004). Further evidence on the labor market effects of addiction: chronic drug use and employment in metropolitan miami. *Contemporany Economic Policy*, 22(3):382:393.

Baldwin, M. L., & Marcus, S. C. (2014). The impact of mental and substance-use disorders on employment transitions. *Health economics, 23*(3), 332-344.

Blundell, R., & Meghir, C. (1986). Selection criteria for a microeconometric model of labour supply. *Journal of Applied Econometrics*, 1(1):55-80.

Bray, J. W. (2000). The relationship between marijuana initiation and dropping out high school. *Health Economics*, 9(1):9-18.

Buchmueller, T. C., & Zuvekas, S. H. (1998). Drug use, drug abuse, and labour market outcomes. *Health Economics, 7*(3), 229-245.

Burgess, S. M., & Propper, C. (1998). Early health-related behaviours and their impact on later life chances: evidence from the US. *Health Economics*, 7(5):381-399.

DeSimone, J. (2002). Illegal drug use and employment. *Journal of Labor Economics*, 20(4):952-977.

Ellickson, P. B. (1998). Does early drug use increase the risk of dropping out of high school? *Journal of Drug Issues*, 28(2):357-380.

French, M. T., Roebuck, M., & Alexandre, P. (2001). Illicit drug use, employment, and labor force participation. *Southern Economic Journal*, 68(2):349-368.

Gill, A. M., & Michaels, R. J. (1992). Does drug use lower wages? *Industrial and Labor Relations Review*, 45(3)419-434.

Han, S., & Vytlacil, E. J. (2017). Identification in a generalization of bivariate probit models with dummy endogenous regressors. *Journal of Econometrics, 199*(1), 63-73.

Huang, D. Y., Evans, E., Hara, M., Weiss, R. E., & Hser, Y. I. (2011). Employment trajectories: Exploring gender differences and impacts of drug use. *Journal of Vocational Behavior*, 79(1):277-289.

Kaestner, R. (1994). The effect of illicit drug use on the labor supply of young adults. *Journal of Human Resourses*, 29(1):126-155.

Kandel, D. B., & Davies, M. (1990). Labor Force Experiences of a National Sample of Young Adult Men. *Youth and Society, 21*(4), 411-445.

Mullahy, J., & Sindelar, J. (1996). Employment, unemployment, and problem drinking. *Journal of Health Economics*, 15(4):409-434.

Observatorio de drogas de Colombia. (2013). *Estudio nacional de consumo de sustancias psicoactivas en Colombia.* Ministerio de Justicia y del Derecho, Bogotá, DC, Bogotá, DC.

Pope, H. G.-T. (1996). The residual cognitive effects of heavy marijuana use in college students. *Jama*, 275(7):521-527.

Register, C. A., & Williams, D. R. (1992). Labor market effects of marijuana and cocaine use among young men. *Industrial and Labor Relations Review*, 45(3):435-448.

Rice, D., Kelman, S., & Miller, L. (1991). Economic costs of drug abuse. In W. Cartwright, J. Kaple, & R. M. Series (Ed.), *Economic costs, cost-effectiveness, financing, and community-based drug treatment* (pp. 10-32). Rockville, Maryland: National Institute on Drug Abuse.

Ringel, J. S., Ellickson, P., & Collins, R. L. (2006). The relationship between high school marijuana use and annual earnings among young adult males. *Contemporany Economic Policy*, 24(1):52-63.

Rivera, B., Casal, B., Currais, L., & Rungo, P. (2013). Illicit drug use and labour market participation: evidence of simultaneity. *Applied Economics Letters*, 20(15):1418-1422.

Solowij, N. (2006). Cannabis and cognitive functioning. *Cambridge University Press*.

Van Ours, J. C. (2006). Cannabis cocaine and jobs. *Journal of Applied Econometrics*, 21(7):897-917.

Van Ours, J. C., & Williams, J. (2015). Cannabis use and its effects on health, education and labor market success. *Journal of Economic Surveys, 29*(5), 993-1010.

Yamada, T. a. (1996). The impact of alcohol consumption and marijuana use on high school graduation. *Health Economics*, 5(1):77-92.

Zarkin, G. A., Mroz, T. A., Bray, J. W., & French, M. T. (1998). The relationship between drug use and labor supply for young men. *Labour Economics*, 5(4):385-409.

Appendix

TABLE A1. SUMMARY STATISTICS BY AGE

Variable	16 to 60			16 to 45			22 to 60			22 to 45		
	Non-users	Users	p-value	Non-users	Users	p-value	Non-users	Users	p-value	Non-users	Users	p-value
Labor Force	0.62	0.62	[0.91]	0.63	0.62	[0.57]	0.70	0.70	[0.91]	0.75	0.71	[0.12]
	(0.48)	(0.49)		(0.48)	(0.49)		(0.46)	(0.46)		(0.44)	(0.46)	
Employed	0.55	0.49	[0.00]*	0.55	0.48	[0.00]*	0.63	0.57	[0.01]*	0.66	0.56	[0.00]*
	(0.50)	(0.50)		(0.50)	(0.50)		(0.48)	(0.50)		(0.47)	(0.50)	
Age	35.80	28.32	[0.00]*	29.36	26.09	[0.00]*	39.49	32.17	[0.00]*	32.86	29.45	[0.00]*
	(12.93)	(10.04)		(8.78)	(7.36)		(11.18)	(9.53)		(7.15)	(6.61)	
Household size	4.53	4.99	[0.00]*	4.63	5.00	[0.00]*	4.45	4.96	[0.00]*	4.54	4.97	[0.00]*
	(1.86)	(2.08)		(1.87)	(2.10)		(1.85)	(2.05)		(1.86)	(2.09)	
Black	0.02	0.02	[0.59]	0.02	0.02	[0.78]	0.02	0.02	[0.63]	0.02	0.01	[0.19]
	(0.14)	(0.15)		(0.15)	(0.15)		(0.14)	(0.12)		(0.15)	(0.11)	
Mestizo	0.93	0.94	[0.64]	0.93	0.94	[0.44]	0.93	0.95	[0.29]	0.93	0.95	[0.15]
	(0.25)	(0.24)		(0.26)	(0.24)		(0.25)	(0.23)		(0.25)	(0.22)	
White	0.05	0.04	[0.36]	0.05	0.04	[0.46]	0.05	0.04	[0.35]	0.05	0.04	[0.43]
	(0.21)	(0.20)		(0.21)	(0.20)		(0.22)	(0.19)		(0.21)	(0.19)	
Male	0.44	0.81	[0.00]*	0.45	0.82	[0.00]*	0.44	0.81	[0.00]*	0.45	0.83	[0.00]*
	(0.50)	(0.39)		(0.50)	(0.39)		(0.50)	(0.39)		(0.50)	(0.38)	
Stratum 1	0.11	0.17	[0.00]*	0.12	0.19	[0.00]*	0.10	0.16	[0.00]*	0.11	0.17	[0.00]*
	(0.31)	(0.38)		(0.32)	(0.39)		(0.30)	(0.36)		(0.32)	(0.38)	
Stratum 2	0.37	0.48	[0.00]*	0.39	0.48	[0.00]*	0.36	0.48	[0.00]*	0.38	0.49	[0.00]*
	(0.48)	(0.50)		(0.49)	(0.50)		(0.48)	(0.50)		(0.49)	(0.50)	
Stratum 3	0.31	0.26	[0.01]*	0.30	0.25	[0.02]*	0.31	0.26	[0.04]*	0.30	0.25	[0.05]*

	(0.46)	(0.44)		(0.46)	(0.43)		(0.46)	(0.44)		(0.46)	(0.43)	
Stratum 4	0.10	0.06	[0.00]*	0.09	0.05	[0.00]*	0.10	0.06	[0.01]*	0.10	0.06	[0.01]*
	(0.30)	(0.23)		(0.29)	(0.22)		(0.31)	(0.24)		(0.30)	(0.23)	
Stratum 5	0.07	0.02	[0.00]*	0.07	0.01	[0.00]*	0.08	0.02	[0.00]*	0.07	0.01	[0.00]*
	(0.26)	(0.13)		(0.25)	(0.12)		(0.27)	(0.13)		(0.25)	(0.12)	
Stratum 6	0.04	0.02	[0.00]*	0.04	0.02	[0.01]*	0.04	0.02	[0.01]*	0.04	0.02	[0.05]
	(0.20)	(0.13)		(0.19)	(0.12)		(0.20)	(0.13)		(0.19)	(0.13)	
Single	0.50	0.77	[0.00]*	0.60	0.80	[0.00]*	0.40	0.70	[0.00]*	0.49	0.73	[0.00]*
	(0.50)	(0.42)		(0.49)	(0.40)		(0.49)	(0.46)		(0.50)	(0.44)	
Married	0.27	0.05	[0.00]*	0.19	0.03	[0.00]*	0.32	0.07	[0.00]*	0.25	0.05	[0.00]*
	(0.44)	(0.22)		(0.39)	(0.18)		(0.47)	(0.26)		(0.43)	(0.22)	
Widower	0.02	0.01	[0.07]	0.01	0.00	[0.09]	0.03	0.02	[0.17]	0.01	0.00	[0.13]
	(0.15)	(0.11)		(0.09)	(0.04)		(0.17)	(0.13)		(0.11)	(0.05)	
Divorced	0.06	0.04	[0.01]*	0.04	0.03	[0.19]	0.07	0.05	[0.08]	0.05	0.04	[0.39]
	(0.24)	(0.18)		(0.19)	(0.16)		(0.26)	(0.22)		(0.22)	(0.20)	
Free union	0.15	0.14	[0.32]	0.16	0.14	[0.14]	0.17	0.17	[0.80]	0.20	0.17	[0.29]
	(0.36)	(0.34)		(0.37)	(0.34)		(0.38)	(0.37)		(0.40)	(0.38)	
Education	12.49	10.64	[0.00]*	13.11	10.96	[0.00]*	12.48	10.58	[0.00]*	13.29	11.04	[0.00]*
	(5.39)	(4.71)		(4.95)	(4.59)		(5.73)	(5.04)		(5.35)	(4.93)	
Bad Health	0.01	0.01	[0.27]	0.00	0.01	[0.28]	0.01	0.01	[0.30]	0.01	0.01	[0.42]
	(0.08)	(0.10)		(0.07)	(0.09)		(0.09)	(0.11)		(0.07)	(0.09)	
Regular Health	0.08	0.09	[0.60]	0.06	0.08	[0.11]	0.09	0.10	[0.62]	0.06	0.08	[0.19]
	(0.27)	(0.28)		(0.24)	(0.26)		(0.28)	(0.29)		(0.24)	(0.27)	
Good Health	0.85	0.86	[0.63]	0.87	0.88	[0.95]	0.84	0.86	[0.58]	0.87	0.88	[0.68]
	(0.35)	(0.35)		(0.33)	(0.33)		(0.36)	(0.35)		(0.34)	(0.33)	
Excellent Health	0.06	0.04	[0.09]	0.06	0.04	[0.05]*	0.06	0.04	[0.07]	0.06	0.03	[0.03]*
	(0.24)	(0.20)		(0.24)	(0.20)		(0.24)	(0.19)		(0.24)	(0.18)	
Under 5	0.25	0.28	[0.08]	0.28	0.29	[0.84]	0.25	0.27	[0.27]	0.30	0.29	[0.59]
	(0.43)	(0.45)		(0.45)	(0.45)		(0.43)	(0.45)		(0.46)	(0.45)	
Over 65	0.21	0.22	[0.56]	0.20	0.19	[0.74]	0.22	0.26	[0.03]*	0.21	0.23	[0.37]
	(0.41)	(0.41)		(0.40)	(0.39)		(0.41)	(0.44)		(0.41)	(0.42)	
Homeownership	0.62	0.63	[0.45]	0.59	0.63	[0.06]	0.62	0.64	[0.35]	0.58	0.64	[0.04]*
	(0.49)	(0.48)		(0.49)	(0.48)		(0.49)	(0.48)		(0.49)	(0.48)	
Head	0.29	0.15	[0.00]*	0.21	0.14	[0.00]*	0.34	0.21	[0.00]*	0.27	0.19	[0.00]*
	(0.45)	(0.36)		(0.40)	(0.34)		(0.48)	(0.41)		(0.44)	(0.40)	
Observations	52714	567		37951	516		43415	401		28652	350	

TABLE A2. PROBIT ESTIMATES OF DRUG USE ON EMPLOYMENT AND LABOR FORCE PARTICIPATION								
	(1)		(2)		(3)		(4)	
Response Variable	Employment		Drug use		Labor Force		Drug use	
Age	Coefficient (SE)	N	Coefficient (SE)	N	Coefficient (SE)	N	Coefficient (SE)	N
16-60	-0.133 (0.065)**	52803	-0.068 (0.045)	52124	-0.049 (0.066)	52803	-0.004 (0.048)	52124
16-45	-0.155 (0.070)**	38093	-0.112 (0.049)**	37609	-0.050 (0.072)	38093	-0.031 (0.052)	37609
22-60	-0.297 (0.074)***	43424	-0.145 (0.050)***	42858	-0.249 (0.079)***	43424	-0.111 (0.054)**	42858
22-45	-0.320 (0.077)***	28714	-0.198 (0.053)***	28343	-0.244 (0.083)***	28714	-0.146 (0.059)**	28343

Notes: Results are obtained from probit estimations, robust standard errors in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Column (1) reports the estimated coefficient of drug use on the probability of being employed while column (2) presents the estimated coefficient of employment on the probability of use drugs. Column (3) reports the estimated coefficient of drug use on the probability of participate in the labor force while column (4) presents the estimated coefficient of labor force participation on the probability of use drugs. Significance levels: 1% ***, 5% **, 1% *.

TABLE A3. BIVARIATE PROBIT ESTIMATES OF RHO								
	EMPLOYMENT				LABOR FORCE PARTICIPATION			
Instrument	(1)	(2)	(3)		(4)	(5)	(6)	
Age	Coefficient [p-value]	Coefficient [p-value]	Coefficient [p-value]	N	Coefficient [p-value]	Coefficient [p-value]	Coefficient [p-value]	N
16-60	0.456 [0.000]	0.478 [0.000]	0.486 [0.000]	52803	0.413 [0.001]	0.465 [0.000]	0.471 [0.000]	52803
16-45	-0.007 [0.960]	-0.003 [0.982]	0.009 [0.950]	38093	-0.241 [0.125]	-0.127 [0.537]	-0.110 [0.603]	38093
22-60	0.483 [0.000]	0.500 [0.000]	0.512 [0.000]	43424	0.415 [0.000]	0.452 [0.000]	0.461 [0.000]	43424
22-45	0.258 [0.062]	0.276 [0.055]	0.295 [0.033]	28714	0.160 [0.394]	0.249 [0.110]	0.261 [0.084]	28714

Notes: Table reports rho (ρ) estimates of equation (9), the covariance coefficient between the error terms of both equations drug use and labor market outcomes. P-values are reported in brackets. Results comes from bivariate probit regressions, columns (1) and (4) include victimization at household level as instrument, columns (2) and (4) include victimization at neighborhood level as instrument and columns (3) and (6) does not include any instruments.

TABLE A4. BIVARIATE PROBIT ESTIMATES OF VICTIMIZATION ON DRUG USE								
	EMPLOYMENT				LABOR FORCE PARTICIPATION			
Variable	Victimization Household level		Victimization Neighborhood level		Victimization Household level		Victimization Neighborhood level	
Age	Coefficient (SE)	N	Coefficient (SE)	N	Coefficient (SE)	N	Coefficient (SE)	N
16-60	0.328 (0.061)***	52803	0.620 (0.376)*	52803	0.309 (0.063)***	52803	0.630 (0.378)*	52803
16-45	0.345 (0.066)***	38093	0.631 (0.407)	38093	0.360 (0.067)***	38093	0.646 (0.404)	38093
22-60	0.308 (0.072)***	43424	0.864 (0.435)**	43424	0.293 (0.074)***	43424	0.912 (0.437)**	43424
22-45	0.319 (0.082)***	28714	0.871 (0.484)*	28714	0.312 (0.087)***	28714	0.896 (0.482)*	28714

Notes: Table reports coefficient estimates of victimization on drug use from bivariate probit regressions. Robust standard errors are in parenthesis. The set of controls includes age and its square, gender, race, socioeconomic stratum, household size, marital status, years of education, health status, number of people under 5 and over 65 years old, homeownership, if the individuals is the head of the household and locality fixed effects. Significance levels: 1% ***, 5% **, 1% *.