The Effects of Marijuana Legalization on the Demand for Cocaine: A Simultaneous Three-part Model for Marijuana and Cocaine Demand

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Abstract

We propose a simultaneous three-part model to analyze the effects of the legalization of marijuana on cocaine demand in Colombia. We find that modeling simultaneous the demand for these drugs is relevant as there is an unobserved correlation. Our findings indicate that the probability of cocaine use is higher among men in their 20s, particularly those in higher socioeconomic strata with lower levels of education. On average, marijuana legalization is associated with a 2.6% increase in the probability of cocaine use. This increase is more pronounced among women than men, with rates of 3% and 2.5%, respectively.

JEL:

Keywords: Drug demand, Marijuana legalization, Three-part model.

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1 Introduction

We aim to analyze the effects of the legalization of recreational use of marijuana in the extensive and intensive margins of cocaine demand in Colombia. This is relevant as different countries have started legalizing nationwide commercial sale of marijuana, namely, Canada, Thailand, and Uruguay, and 23 states and 3 territories in the United States. In addition, recreational use of marijuana is legal in Georgia, Luxembourg, Malta, Mexico, and South Africa, plus Virginia and the District of Columbia in the United States, as well as the Australian Capital Territory. This trend is in part due to marijuana being the most commonly consumed illicit drug worldwide, with 219 million consumers in 2022 (UNODC, 2023).

Moreover, the Colombian case is particularly relevant as Colombia is one of the main producers of marijuana and cocaine in the world (UNODC, 2021), and recently, the Colombian national congress has been discussing the legalization of recreational use of marijuana. Therefore, having timely, rigorous evidence about the potential effects of legalization of marijuana on different spectra is relevant, particularly on cocaine demand, as this drug has remarkably bad consequences on society.

However, analyzing the potential effects of the legalization of marijuana on cocaine demand is not easy. On the one hand, the legalization of marijuana may imply that individuals decrease contact with drug dealers, who have in their portfolio cocaine in the Colombian case, and consequently, the legalization of marijuana may imply a reduction of cocaine consumption due to marijuana users decreasing contact with cocaine suppliers. On the other hand, legalization of marijuana may increase the consumption of marijuana and, consequently, the consumption of cocaine if these are complementary drugs. Thus, we have two contrasting effects, and the final outcome depends on what effect dominates.

The effects of drug use have been evaluated for decades in economics (Becker et al., 2006). Previous studies have provided evidence of these effects at different margins, such as education, crime, and the labor market, as well as the effects of decriminalization (Adda et al., 2014) and legalization scenarios (Jacobi and Sovinsky, 2016).

Skeptics of marijuana legalization are concerned that legalizing marijuana may make it a "gateway" drug for more hazardous drugs (DeSimone, 1998; Kandel, 1975; Bretteville-Jensen and Jacobi, 2011; Secades-Villa et al., 2015) and increase the risk of psychoactive substance use disorders (Mennis et al., 2021). Several studies correlate marijuana consumption with psychoactive substance usage using empirical methods (Fergusson et al., 2006; Odgers et al., 2008; Pudney, 2004).

Studies of the effects of marijuana legalization on "harder" drug usage are scarce. In particular, the US case shows mixed outcomes. Several studies show increased consumption of cocaine/crack and heroin (Wong and Lin, 2019), sedatives (Alley et al., 2020), and harsher drug usage (Sabia et al., 2021). However, Mennis et al. (2021) found no increase in youth consumption of opioid, cocaine, and methamphetamine treatments post-legalization, Chu (2015); Thies and Register (1993), and Wen et al. (2015) revealed legalization did not affect cocaine or heroin consumption overall, and Thompson and Koichi (2017) also noted that marijuana pricing adjustments do not affect heroin or cocaine usage, highlighting the complex link between marijuana legalization and hazardous drug use.

We try to disentangle the potential effects of the legalization of marijuana on cocaine demand using a novel nationwide representative dataset, where individuals are privately inquired about the consumption of legal and illegal psychoactive substances. The econometric framework has as a departure point a directed acyclic graph (DAG), where we use a structural equations model to simultaneously handle marijuana and cocaine demand, taking into account access restrictions and self-selection into the market for these drugs. We use the implied Bayesian network from the DAG to estimate the potential effects of the legalization of marijuana on cocaine demand using as transmission channels the probability of access to marijuana and the probability of being offered cocaine given marijuana consumption.

Our results show that the presence of drug dealers in the neighborhood increases access to marijuana and cocaine, as does having been offered either of these two drugs in the past. Regarding drug consumption, prior alcohol and cigarette use is associated with an increased likelihood of marijuana consumption, but has no significant effect on cocaine, on the other hand price increases are associated with a decrease in the likelihood of use. Both marijuana and cocaine are inelastic goods in the Colombian context; our estimates indicate that the elasticity of marijuana is -0.259, while cocaine is slightly more sensitive to price changes with an elasticity of -0.404.

Predictive analysis suggests that the probability of cocaine use is higher among men in their 20s, particularly those in higher socioeconomic strata with lower levels of education. On average, marijuana legalization is associated with a 2.6% increase in the probability of cocaine use. This increase is more pronounced among women than men, with rates of 3% and 2.5%, respectively.

After this introduction, Section 2 shows the dataset and some exploratory analysis. Section 3 shows the econometric framework, the DAG proposal, and the simultaneous three-part model for marijuana and cocaine demand. Section 4 shows the estimation results, the single world intervention graph (SWIG) used to perform the counterfactual exercises to evaluate the potential effects of marijuana legalization on cocaine demand. Section 5 shows some concluding remarks.

2 Data

We use the *National Survey of the Consumption of Psychoactive Substances* (*NSCPS*) done in 2019 by the National Statistical Department of Colombia. This survey is based on a probabilistic multistage, stratified cluster sample and aims to measure the consumption of legal and illegal psychoactive substances. It is representative at the national level, provinces, and four metropolitan areas. The method to collect data is based on direct private interviews to mitigate biases, where individuals between 12 and 65 years old were polled. The survey represents 23.6 million individuals, which is approximately 93% of the total Colombian urban population in this age range.

Table 1 shows the descriptive statistics of access and extensive and intensive margins of marijuana and cocaine demand. We exclude from our analysis under legal age individuals as well as individuals who declare to have addiction problems to these drugs. We exclude the former individuals due to not having a clear situation of access to marijuana under legalization, as this group would not have access to legal marijuana suppliers, and we exclude the latter individuals due to the potential endogeneity issues arising from their condition, for instance, socioeconomic condition and home location being potentially affected for their addict situation.

We see in Table 1 that 51.3% and 35.8% of individuals declare to have access to marijuana and cocaine. Regarding the extensive margin, 2% and 0.4% of the individuals declared to have consumed marijuana and cocaine in the last year. Marijuana users that declare not be addicts consume on average 37 joints per month, and no addict cocaine users consume on average 5 grams per month.

Figure 1 shows the distribution of individuals in the survey according to marijuana (green) and cocaine (red) use. We see that most of the individuals report not consuming marijuana or cocaine (97.85%). This means that 2.15% of the individuals report consuming marijuana (2.04%) and/or cocaine (0.38%). The largest group of users consume just marijuana (1.77%), followed by users of both drugs (0.27%) and users of just cocaine (0.11%).

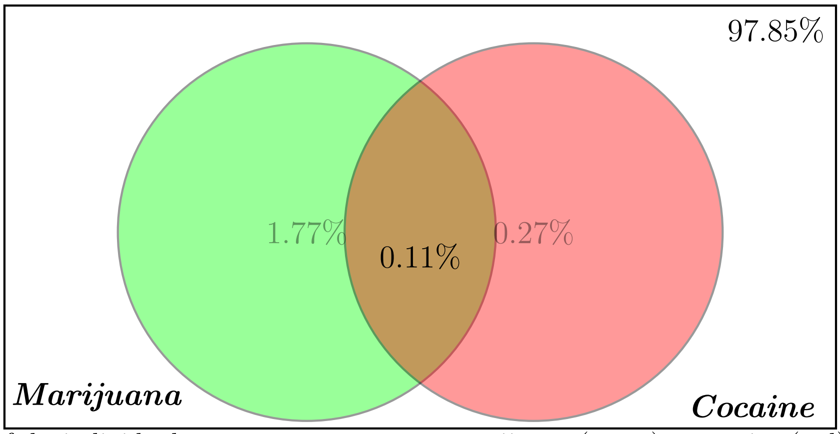
It is difficult to have an answer about the potential effects of the legalization of marijuana on the consumption of cocaine. On the one hand, the legalization of marijuana may imply that individuals decrease contact with drug dealers who have in their portfolio cocaine, and

Table 1: Summary statistics: access, extensive and intensive margins of marijuana and cocaine.

	All	Access (Yes)		User (Yes)	
		Marijuana	Cocaine	Marijuana	Cocaine
Variable	(1)	(2)	(3)	(4)	(5)
Dependent variables					
Access to marijuana (%)	51.334	100.000	98.955	100.000	97.143
	(49.983)	(0.000)	(10.169)	(0.000)	(16.708)
Marijuana consumer (%)	2.041	3.975	3.636	100.000	70.286
	(14.139)	(19.538)	(18.719)	(0.000)	(45.831)
Quantity consumed of marijuana	0.761	1.483	1.588	37.317	33.176
	(11.706)	(16.306)	(17.064)	(73.192)	(63.422)
Access to cocaine (%)	35.792	68.996	100.000	63.773	100.000
	(47.939)	(46.252)	(0.000)	(48.091)	(0.000)
Cocaine consumer (%)	0.383	0.724	1.069	13.183	100.000
	(6.175)	(8.480)	(10.286)	(33.849)	(0.000)
Quantity consumed of cocaine	0.019	0.037	0.054	0.736	5.019
	(0.551)	(0.768)	(0.920)	(3.487)	(7.389)
Observations	45,722	23,471	16,365	933	175

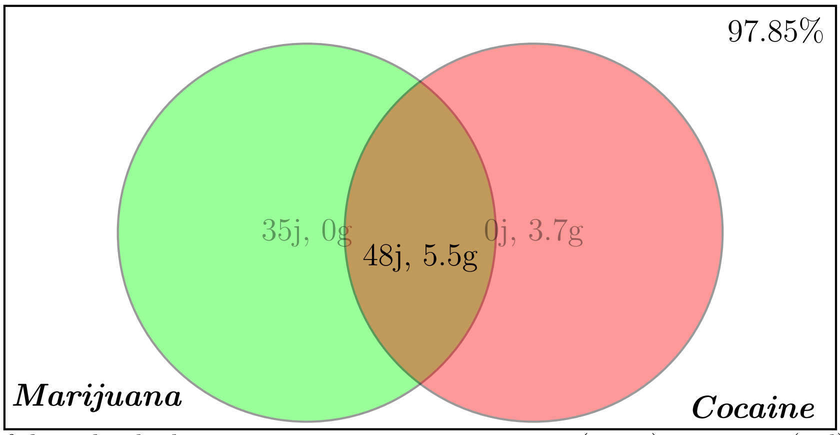
Notes: Standard deviations in parenthesis. This table presents descriptive statistics for *NSCPS* 2019 regarding access and consumption of marijuana and cocaine in Colombia, as well as control variables. Column 1 shows the information for the entire sample. Columns 2 and 3 show the information for individuals with access to marijuana and cocaine. Columns 4 and 5 show the information consumers of marijuana and cocaine, respectively. Prices are shown in 2019 USD and were converted using the average exchange rate in 2019 (3,274 USD/COP).
Source: Authors' construction using *NSCPS* data.

Figure 1: Distribution of individuals in the survey: no users, marijuana users, and cocaine users, 2019



Notes: Most of the individuals report not to consume marijuana (green) or cocaine (red). Individuals who consume marijuana represent the largest share.

Figure 2: Quantity consumed of each drugs by the individuals in the survey: no users, marijuana users, and cocaine users, 2019



Notes: Most of the individuals report not to consume marijuana (green) or cocaine (red). Individuals who consume marijuana represent the largest share. J represents the number of joints of marijuana consumed per month. Gr represents the number of grams of cocaine consumed per month.

consequently, the legalization of marijuana may imply a reduction in cocaine consumption due to marijuana users decreasing contact with cocaine suppliers. For instance, the probability of being offered cocaine given that the individual is a marijuana user is 54.13%, whereas this probability is 10.82% for non-marijuana users. In addition, the probability of having access to cocaine, given that this was offered in the past, is 66.32%, whereas this probability is 31.75% given no offering (see Table 2). Observe that we should take into account the timing of being offered drugs; this refers to any time in the past, whereas having access refers to the present. Thus, being offered drugs does not mean having access to them in the present. On the other hand, legalization of marijuana may increase the consumption of marijuana and, potentially, the consumption of cocaine. In particular, the probability of being a cocaine user given that the individual is a marijuana user is equal to 13.18%, whereas the probability of being a cocaine user given that the individual is not a marijuana user is just 0.11%.

We can use the rules of probability to perform an exploratory analysis of the potential effects of the legalization of marijuana on the probability of consumption of cocaine. In particular,

$$
\begin{aligned}
p(C_c = 1) = & p(C_c = 1|A_c = 1)p(A_c = 1) + \cancelto{0}{p(C_c = 1|A_c = 0)}p(A_c = 0) \\
= & p(C_c = 1|A_c = 1)\left[p(A_c = 1|O_c = 1)p(O_c = 1) + p(A_c = 1|O_c = 0)p(O_c = 0)\right] \\
= & p(C_c = 1|A_c = 1)\left[p(A_c = 1|O_c = 1)\left\{p(O_c = 1|C_m = 1)p(C_m = 1)\right.\right. \\
& \left. + p(O_c = 1|C_m = 0)p(C_m = 0)\right\} + p(A_c = 1|O_c = 0)\left\{p(O_c = 0|C_m = 1)p(C_m = 1)\right. \\
& \left.\left. + p(O_c = 0|C_m = 0)p(C_m = 0)\right\}\right] \\
= & p(C_c = 1|A_c = 1)\left[p(A_c = 1|O_c = 1)\left\{p(O_c = 1|C_m = 1)(p(C_m = 1|A_m = 1)\right.\right. \\
& p(A_M = 1) + \cancelto{0}{p(C_m = 1|A_m = 0)}p(A_M = 0)) + p(O_c = 1|C_m = 0)(p(C_m = 0|A_m = 1) \\
& \left. p(A_m = 1) + \cancelto{1}{p(C_m = 0|A_m = 0)}p(A_m = 0))\right\} + p(A_c = 1|O_c = 0)\left\{p(O_c = 0|C_m = 1)\right. \\
& (p(C_m = 1|A_m = 1)p(A_m = 1) + \cancelto{0}{p(C_m = 1|A_m = 0)}p(A_m = 0)) \\
& \left.\left. + p(O_c = 0|C_m = 0)(p(C_m = 0|A_m = 1)p(A_m = 1) + \cancelto{1}{p(C_m = 0|A_m = 0)}p(A_m = 0))\right\}\right]
\end{aligned}
\tag{1}
$$

where C_c and C_m refer to the binary events of being a cocaine and marijuana user, A_c and A_m are binary events of having access to cocaine and marijuana, and O_c is being offered cocaine. Any "yes" response is equal to 1, and any "no" response is equal to 0.

We should take into account some restrictions due to consistency. In particular, $p(C_c = 1|A_c = 0) = 0$, $p(C_m = 1|A_m = 0) = 0$, and $p(C_m = 0|A_m = 0) = 1$ are due to having access to drugs is a necessary condition to be a user.

Table 2 shows the decomposition in Equation 1. Green boxes in this table are calculated using sample information from *NSCPS* survey. We focus on the effects of legalization of marijuana on the probability of access to marijuana ($p(A_m = 1)$) and the probability of being offered cocaine given consumption of marijuana ($p(O_c = 1|C_m = 1)$) as potential mechanisms to affect the probability of consumption of cocaine ($p(C_c = 1)$). The first two probabilities are in red in Table 2. The probabilities of all other events are in white boxes, and their probabilities are calculated using the rules of probability based on simple sums and products.

Figure 3 shows the contour plot of the probability of being a cocaine user ($p(C_c = 1)$) based on the combination of the probability of having access to marijuana ($p(A_m = 1)$) and the probability of being offered cocaine given being a marijuana user ($p(O_c = 1|C_m = 1)$). The limits of $p(A_m = 1)$ are given by 50% and 100%. This is because legalization of marijuana would imply an increase of access to this drug, and the actual probability is 51.33%. $p(O_c = 1|C_m = 1)$ ranges between 10% and 70%, where the actual situation is given by 54.13%, whereas the actual probability of offering cocaine given no marijuana consumption is 10.82% ($p(O_c = 1|C_m = 0)$) (see Table 2). The contour curve given by 0.383% at the point (51.33%, 54.13%) is the actual situation of being a cocaine user.

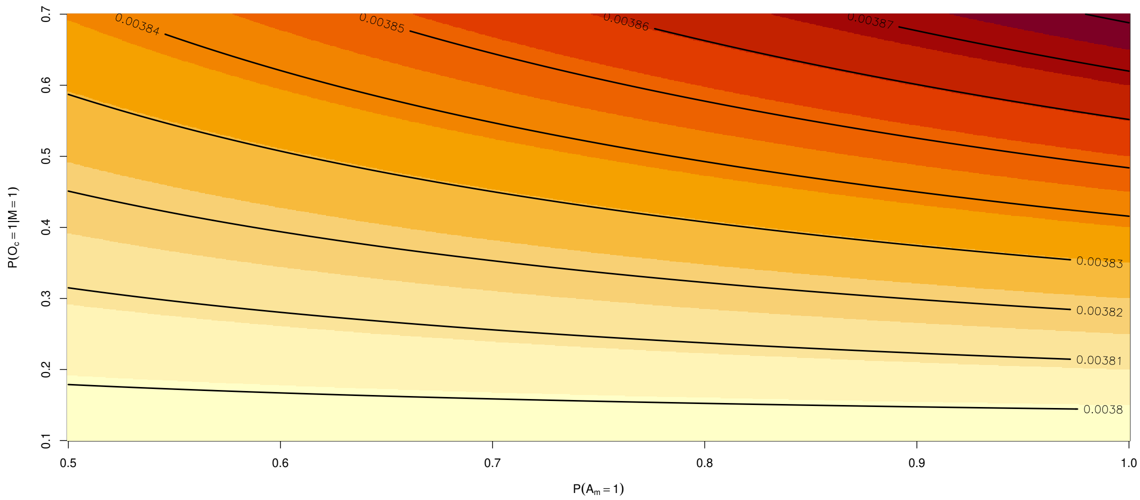
We see in Figure 3 that the probability of cocaine use does not change drastically due to variations in the probability of access to marijuana and the probability of being offered cocaine given marijuana consumption. This suggests that there should not be remarkable effects of the legalization of marijuana on cocaine demand in the short term. In addition, we see that the probability of cocaine use is more sensitive to the probability of being offered cocaine, given being a marijuana user, than the probability of access to marijuana. Given that under legalization, $P(A_m = 1)$ would be near 100%, we would expect that the probability of consumption of cocaine would be lower than the actual value (0.383%) if $p(O_c = 1|C_m = 1)$ is lower than 35%. This seems plausible as we would expect that under legalization of marijuana, $p(O_c = 1|C_m)$ would be close to $p(O_c = 1)$, which is 11.7% in our data set.

Table 2: Total probability analysis: status quo scenario (no legalization)

Status quo								
	Product	Sum	Product	Sum	Product	Sum	Product	Sum
$P(A_m=1)$ 51.33% $P(C_m=1\|A_m=1)$ 3.98% $P(A_m=0)$ 48.67% $P(C_m=1\|A_m=0)$ 0.00%	$P(C_m=1,A_m=1)$ 2.04%	$P(C_m=1)$ 2.04%	$P(O_c=1,C_m=1)$ 1.10%	$P(O_c=1)$ 11.70%	$P(A_c=1,O_c=1)$ 7.76%	$P(A_c=1)$ 35.79%	$P(C_c=1,A_c=1)$ 0.38%	$P(C_c=1)$ 0.38%
	$P(C_m=1,A_m=0)$ 0.00%							
		$P(O_c=1\|C_m=1)$ 54.13%						
$P(A_m=1)$ 51.33% $P(C_m=0\|A_m=1)$ 96.02% $P(A_m=0)$ 48.67% $P(C_m=0\|A_m=0)$ 100.00%	$P(C_m=0,A_m=1)$ 49.29%	$P(C_m=0)$ 97.96%	$P(C_c=1,C_m=0)$ 10.60%					
	$P(C_m=0,A_m=0)$ 48.67%							
		$P(O_c=1\|C_m=0)$ 10.82%						
				$P(A_c=1\|O_c=1)$ 66.32%				
$P(A_m=1)$ 51.33% $P(C_m=1\|A_m=1)$ 3.98% $P(A_m=0)$ 48.67% $P(C_m=1\|A_m=0)$ 0.00%	$P(C_m=1,A_m=1)$ 2.04%	$P(C_m=1)$ 2.04%	$P(O_c=0,C_m=1)$ 0.94%	$P(O_c=0)$ 88.30%	$P(A_c=1,O_c=0)$ 28.03%			
	$P(C_m=1,A_m=0)$ 0.00%							
		$P(O_c=0\|C_m=1)$ 45.87%						
$P(A_m=1)$ 51.33% $P(C_m=0\|A_m=1)$ 96.02% $P(A_m=0)$ 48.67% $P(C_m=0\|A_m=0)$ 100.00%	$P(C_m=0,A_m=1)$ 49.29%	$P(C_m=0)$ 97.96%	$P(C_c=0,C_m=0)$ 87.36%					
	$P(C_m=0,A_m=0)$ 48.67%							
		$P(O_c=0\|C_m=0)$ 89.18%						
				$P(A_c=1\|O_c=0)$ 31.75%				
						$P(C_c=1\|A_c=1)$ 1.07%		
						$P(C_c=1\|A_c=0)$ 0.00%		
				$P(A_c=0\|O_c=1)$ 33.68%				
$P(A_m=1)$ 51.33% $P(C_m=1\|A_m=1)$ 3.98% $P(A_m=0)$ 48.67% $P(C_m=1\|A_m=0)$ 0.00%	$P(C_m=1,A_m=1)$ 2.04%	$P(C_m=1)$ 2.04%	$P(O_c=1,C_m=1)$ 1.10%	$P(O_c=1)$ 11.70%	$P(A_c=0,O_c=1)$ 3.94%	$P(A_c=0)$ 64.21%	$P(C_c=1,A_c=0)$ 0.00%	
	$P(C_m=1,A_m=0)$ 0.00%							
		$P(O_c=1\|C_m=1)$ 54.13%						
$P(A_m=1)$ 51.33% $P(C_m=0\|A_m=1)$ 96.02% $P(A_m=0)$ 48.67% $P(C_m=0\|A_m=0)$ 100.00%	$P(C_m=0,A_m=1)$ 49.29%	$P(C_m=0)$ 97.96%	$P(C_c=1,C_m=0)$ 10.60%					
	$P(C_m=0,A_m=0)$ 48.67%							
		$P(O_c=1\|C_m=0)$ 10.82%						
				$P(A_c=0\|O_c=0)$ 68.25%				
$P(A_m=1)$ 51.33% $P(C_m=1\|A_m=1)$ 3.98% $P(A_m=0)$ 48.67% $P(C_m=1\|A_m=0)$ 0.00%	$P(C_m=1,A_m=1)$ 2.04%	$P(C_m=1)$ 2.04%	$P(O_c=0,C_m=1)$ 0.94%	$P(O_c=0)$ 88.30%	$P(A_c=0,O_c=0)$ 60.27%			
	$P(C_m=1,A_m=0)$ 0.00%							
		$P(O_c=0\|C_m=1)$ 45.87%						
$P(A_m=1)$ 51.33% $P(C_m=0\|A_m=1)$ 96.02% $P(A_m=0)$ 48.67% $P(C_m=0\|A_m=0)$ 100.00%	$P(C_m=0,A_m=1)$ 49.29%	$P(C_m=0)$ 97.96%	$P(C_c=0,C_m=0)$ 87.36%					
	$P(C_m=0,A_m=0)$ 48.67%							
		$P(O_c=0\|C_m=0)$ 89.18%						

Notes: Green boxes indicate data from the *NSCPS* survey, symbols in red signal probabilities that are affected under a legalization scenario, access to marijuana ($P(A_m = 1)$) and probability of being offered cocaine given that individual is marijuana user ($P(O_c = 1|M = 1)$), and boxes in write are calculated using probability rules based on column labels (sum or product).
Source:

Figure 3: Contour plot of the probability of cocaine consumption

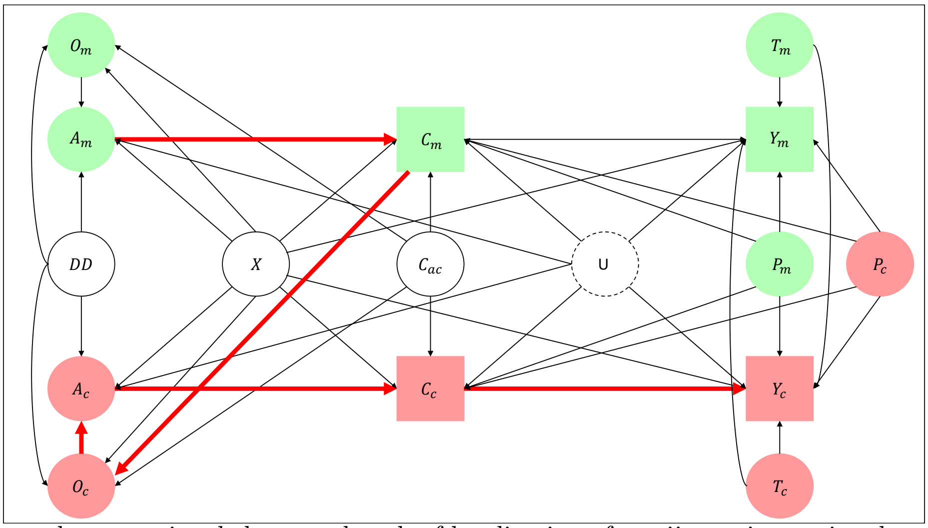


Notes: The probability of cocaine consumption increases with the probability of access to marijuana ($p(A_m = 1)$) and the probability of being offered cocaine given being a marijuana user ($p(O_c = 1|C_m = 1)$). The probability of cocaine use is more sensitive to the probability of being offered cocaine, given being a marijuana user.

However, these exploratory results do not consider confounding factors and potential endogeneity issues due to selection. Thus, we propose in the next section an econometric framework that would help to give a clearer answer to the effects of the legalization of marijuana on cocaine consumption, taking these aspects into account.

Table 3 shows the descriptive statistics of the "pre-treatment" variables that we use to control for, as well as some variables that would help as exclusion restrictions to identify the potential effects of marijuana legalization in cocaine demand. We see in Table 3 that most of the individuals are older than 50, belong to low socioeconomic strata, have high school, are females, have no children at home, and have no curiosity about trying drugs. These characteristics are very similar for individuals who declare to have access to marijuana and cocaine. Regarding users of these drugs, most of them are in their 20s, belong to low socioeconomic strata, have just primary education, are males, and have high curiosity

Figure 4: Directed acycle graph: Marijuana and cocaine demand



Notes: The red arrows signal the causal path of legalization of marijuana in cocaine demand. Marijuana access (A_m) is a necessary condition for its consumption (C_m), this is in turn affects being offered cocaine (O_c) that affects cocaine access (A_c), which is a necessary condition for cocaine consumption (C_c), and its intensive margin (Y_c).

about trying drugs. Therefore, there are different socioeconomic characteristics between the overall population and drug users.

Regarding the exclusion restrictions, we observe in Table 3 that the presence of drug dealers in the neighborhood is higher for individuals who have access to and use marijuana and cocaine than for the overall population. There is the same pattern regarding captures for drug dealing in the neighborhood. Moreover, there is an increasing pattern of being offered marijuana and cocaine, and previous consumption of alcohol and cigarettes, from the overall population to drug users. Drug prices are similar among these groups, and the marijuana and cocaine consumers have used these drugs for 11.6 and 12.3 years on average, respectively.

Table 3: Summary statistics: regressors of the simultaneous three-part model for access, extensive and intensive margins of marijuana and cocaine.

	All	Access (Yes)		User (Yes)	
		Marijuana	Cocaine	Marijuana	Cocaine
Variable	(1)	(2)	(3)	(4)	(5)
Exclusionary restrictions					
Drug dealer in neighborhood	0.382	0.49	0.528	0.475	0.594
	(0.486)	(0.500)	(0.499)	(0.500)	(0.492)
Offered marijuana	0.263	0.374	0.381	0.897	0.880
	(0.440)	(0.484)	(0.486)	(0.304)	(0.326)
Offered cocaine	0.117	0.179	0.217	0.541	0.886
	(0.321)	(0.383)	(0.412)	(0.499)	(0.319)
Alcohol and cigarette use	0.308	0.347	0.345	0.448	0.446
	(0.462)	(0.476)	(0.475)	(0.498)	(0.498)
Prices					
Marijuana	0.828	0.800	0.788	0.852	0.751
	(0.436)	(0.393)	(0.387)	(0.553)	(0.505)
Cocaine	2.841	2.880	2.871	3.095	2.842
	(1.448)	(1.478)	(1.503)	(1.611)	(2.015)
Years consuming marijuana	1.230	1.942	2.041	11.608	11.663
	(5.517)	(6.686)	(6.894)	(9.641)	(10.370)
Years consuming cocaine	0.359	0.582	0.751	3.356	12.303
	(3.075)	(3.830)	(4.333)	(7.696)	(10.235)
Controls					
Age					
20s	0.291	0.337	0.315	0.640	0.491
	(0.454)	(0.473)	(0.465)	(0.480)	(0.501)
30s	0.231	0.243	0.250	0.214	0.246
	(0.421)	(0.429)	(0.433)	(0.411)	(0.432)
40s	0.181	0.176	0.184	0.087	0.171
	(0.385)	(0.381)	(0.388)	(0.282)	(0.378)
50s and older	0.297	0.244	0.250	0.059	0.091
	(0.457)	(0.430)	(0.433)	(0.236)	(0.289)
Strata					
Low	0.638	0.645	0.666	0.534	0.606
	(0.481)	(0.478)	(0.472)	(0.499)	(0.490)
Medium	0.325	0.320	0.301	0.402	0.314
	(0.468)	(0.467)	(0.459)	(0.491)	(0.466)
High	0.037	0.034	0.033	0.064	0.080
	(0.189)	(0.182)	(0.179)	(0.245)	(0.272)
Education level before consumption					
No education	0.013	0.010	0.010	0.016	0.017
	(0.114)	(0.102)	(0.101)	(0.126)	(0.130)
Primary	0.172	0.179	0.187	0.572	0.623
	(0.377)	(0.383)	(0.390)	(0.495)	(0.486)
Secondary	0.426	0.438	0.442	0.339	0.303
	(0.494)	(0.496)	(0.497)	(0.474)	(0.461)
Undergraduate	0.346	0.336	0.325	0.066	0.034
	(0.476)	(0.472)	(0.468)	(0.249)	(0.182)
Gaduate	0.042	0.036	0.035	0.005	0.017
	(0.201)	(0.186)	(0.183)	(0.073)	(0.130)
Female	0.589	0.527	0.501	0.260	0.183
	(0.492)	(0.499)	(0.500)	(0.439)	(0.388)
Dummy = 1 if has children	0.402	0.373	0.380	0.029	0.051
	(0.490)	(0.484)	(0.485)	(0.168)	(0.222)
Curiosity towards drugs	0.162	0.243	0.243	0.940	0.954
	(0.368)	(0.429)	(0.429)	(0.238)	(0.209)
Observations	45,722	23,471	16,365	933	175

Notes: Standard deviations in parenthesis. This table presents descriptive statistics for *NSCPS* 2019 regarding access and consumption of Marijuana in Colombia, as well as control variables. Column 1 shows the information for the entire sample. Columns 2 and 3 show the information for individuals with access to marijuana and cocaine. Columns 4 and 5 show the information consumers of marijuana and cocaine, respectively. Prices are shown in 2019 USD and were converted using the average exchange rate in 2019 (3,274 USD/COP).
Source: Authors' construction using *NSCPS* data.

3 Econometric approach

The point of departure is the directed acycle graph in Figure 4. In particular, we see in this figure that access to marijuana and/or cocaine (A_m and A_c) affects their extensive margins (C_m and C_c), and these in turn affect the intensive margins (Y_m and Y_c). All these variables are affected by the "pre-treatment" variables in X,[1] which includes age group, socioeconomic strata,[2] education level, gender (female), presence of children in the household, and curiosity towards drugs. This vector also affects being offered marijuana (O_m) and cocaine (O_c). Therefore, variables in X are observable potential common causes of these variables. In addition, we should consider unobservable variables that affect access and extensive and intensive margins of these drugs. These unobservable variables may generate censoring in our dataset due to access restrictions and selection into consumption. We account for these effects using the latent variable U.[3] We do not observe these variables, but we consider this aspect in our inferential framework using a "Heckman-type" correction (see below). In addition, we use exclusion restrictions to improve the identification of the causal effects. In particular, we use the presence of drug dealers (DD) as variables that affect access to marijuana and cocaine. Moreover, we have offered marijuana and cocaine as exclusion restrictions in these equations. We use as exclusion restrictions in the extensive margins of previous consumption of alcohol and cigarettes (C_{ac}). This is because, according to the "gateway" hypothesis, previous consumption of these legal substances precedes the use of illegal drugs (Kandel, 1975). Finally, we have that the price of marijuana and cocaine (P_m and P_c) and the time-consuming these drugs (T_m and T_c) affect the extensive

[1]We calculate all these variables before first time consumption of marijuana and cocaine.

[2]Colombian households are classified by the government into socioeconomic strata to implement social programs. There are six categories: strata 1 and 2 signal low-socioeconomic (poor) households, strata 3 and 4 signal medium-socioeconomic households, and strata 5 and 6 signal high-socioeconomic (wealthy) households.

[3]In DAG tradition, latent (unobserved) variables are in dashed circles, and censored variables are in squares (see Hernán and Robins (2024) for a good introduction).

and intensive margins of these two drugs.

The DAG in Figure 4 defines a Bayesian network that can be used to write down the global (joint) probability distribution using local probability distributions due to the implied conditional independence structure. In particular, we require the joint probability distribution $p(Y_c, C_c, A_c, O_c, C_m, A_m|X, DD, C_{ac}, O_m, P_m, P_c, Y_m, Y_c, U)$ to analyze the effects of legalization of marijuana on cocaine demand (red arrows in the DAG), U is unobserved but we control for it in our inferential approach. Thus, the DAG implies

$$\begin{aligned} p(Y_c, C_c, A_c, O_c, C_m, A_m|Exo, U) =& p(Y_c|C_c, P_c, P_m, Y_m, Y_c, C_{ac}, X, U) \\ & p(C_c|A_c, P_c, P_m, C_{ac}, X, U)p(A_c|O_c, DD, X, U) \\ & p(O_c|C_m, DD, C_{ac}, X)p(C_m|A_m, P_m, P_c, C_{ac}, X, U) \\ & p(A_m|DD, O_m, X, U), \end{aligned} \tag{2}$$

where $Exo = \{X, DD, C_{ac}, O_m, P_m, P_c, Y_m, Y_c\}$.

Thus, we get the joint probability distribution function as the product of independent conditional distributions such that each local distribution is conditional on their parents (variables associated with arrows that get in each node of the DAG).

Observe that the structures of equations 1 and 2 are similar, except that the latter includes the intensive margin; there is conditioning on exogenous confounders and takes selection into account. Thus, we can get the probability of cocaine consumption (extensive margin) using the probabilities from lines 2 to 4 in Equation 2 and adding up the 32 (2^5) potential states. In addition, we can use access as a necessary condition for consumption to set 14 out of 32 probabilities equal to 0.

The DAG in Figure 4 implicitly defines a structural equation model. The complexity of this model is the presence of the latent effects associated with access restrictions and selection into consumption. Thus, our inferential strategy simultaneously takes access, as well as extensive and intensive margins, into account.

3.1 Drug access

We set the bi-variate vector of latent variables of individual i to define access to marijuana (M) and cocaine (C), $\boldsymbol{U}_i^a = [U_{iM}^a \ U_{iC}^a]^\top$, $i = 1, \dots, N$ where

$$A_{ij} = \begin{cases} 1, & U_{ij}^a = \boldsymbol{w}_i^\top \boldsymbol{\alpha}_{aj} + \boldsymbol{r}_{ij}^\top \boldsymbol{\delta}_{aj} + \omega_{aj} + d_i\beta_{aj} + c_i\theta_{aj} + o_i\tau_{aj} + V_{ij} > 0 \\ 0, & U_{ij}^a = \boldsymbol{w}_i^\top \boldsymbol{\alpha}_{aj} + \boldsymbol{r}_{ij}^\top \boldsymbol{\delta}_{aj} + \omega_{aj} + d_i\beta_{aj} + c_i\theta_{aj} + o_i\tau_{aj} + V_{ij} \leq 0 \end{cases}. \quad (3)$$

Equation 3 defines if individual i has access ($A_{ij} = 1$) to drug $j = \{\text{marijuana, cocaine}\}$, or not ($A_{ij} = 0$), as a function of demographic and socioeconomic characteristics ($\boldsymbol{w}_i$) such as gender, age group (teenager, 20's, 30's, 40's and 50's or older), years of education, socioeconomic strata (low, medium and high), mental and physical health status (good or bad), and dummy variables indicating if friends and/or family consumes, medical use of marijuana, living with parents, and work status. In addition, we control for risk perception ($\boldsymbol{r}_{ij}$) about using drug j (low, medium and high), previous consumption of alcohol and cigarettes (o_i), and characteristics of the market such as region-fixed effects (ω_{aj}), presence of drug dealers (d_i). We estimate the location parameters ($\boldsymbol{\alpha}_{aj}, \boldsymbol{\delta}_{aj}, \omega_{aj}, \beta_{aj}$, θ_{aj} and τ_{aj}), and the covariance matrix $\boldsymbol{\Sigma}_{VV}$ given our assumptions about the vector of stochastic errors $\boldsymbol{V}_i = [V_{iM} \ V_{iC}]^\top \stackrel{iid}{\sim} N_2(\boldsymbol{0}, \boldsymbol{\Sigma}_{VV})$, where $\boldsymbol{\Sigma}_{VV} = \begin{bmatrix} \sigma_{MM,a} & \sigma_{MC,a} \\ \sigma_{CM,a} & \sigma_{CC,a} \end{bmatrix}$.

3.2 Drug extensive margin

We set $\boldsymbol{U}_i^c = [U_{iM}^c \ U_{iC}^c]^\top$ be the bi-variate vector of net indirect utilities that define drug use (extensive margin), where

$$C_{ij} = \begin{Bmatrix} 1, & U_{ij}^c = \boldsymbol{w}_i^\top \boldsymbol{\alpha}_{cj} + \boldsymbol{r}_{ij}^\top \boldsymbol{\delta}_{cj} + \omega_{cj} + o_i \tau_{cj} + \boldsymbol{p}_{ij}^\top \gamma_{cj} + E_{ij} > 0 \text{ and } A_{ij} = 1 \\ 0, & U_{ij}^c = \boldsymbol{w}_i^\top \boldsymbol{\alpha}_{cj} + \boldsymbol{r}_{ij}^\top \boldsymbol{\delta}_{cj} + \omega_{cj} + o_i \tau_{cj} + \boldsymbol{p}_{ij}^\top \gamma_{cj} + E_{ij} \leq 0 \text{ and } A_{ij} = 1 \\ -, & A_{ij} = 0 \end{Bmatrix}. \quad (4)$$

Observe that in equation 4 we only have a record of the extensive margin if individual i reports to have access to marijuana and/or cocaine, that is, we take explicitly the incidental truncation issue as this is a valid concern in sensitive topics like drug use. Thus, we do not see C_{ij} if individual i does report not having access to drug j ($A_{ij} = 0$), as the latter is a necessary condition for use. On the other hand, we observe if individual i uses drug j ($C_{ij} = 1$), or not ($C_{ij} = 0$), conditional on having access ($A_{ij} = 1$). The net indirect utility variable defining drug use depends on socioeconomic characteristics ($\boldsymbol{w}_i$), risk perception about using drug j ($\boldsymbol{r}_{ij}$), city-fixed effects (ω_{cj}), a dummy indicating previous consumption of alcohol and cigarette (o_i), and the price of marijuana and cocaine ($\boldsymbol{p}_{ij}$). The location parameters related to drug use are $\boldsymbol{\alpha}_{cj}, \boldsymbol{\delta}_{cj}, \omega_{cj}$, τ_{cj}, and $\boldsymbol{\gamma}_{cj}$, and we assume that the stochastic errors $\boldsymbol{E}_i = [E_{iM} \ E_{iC}]^\top \overset{iid}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma}_{EE})$, where $\boldsymbol{\Sigma}_{EE} = \begin{bmatrix} \sigma_{MM,c} & \sigma_{MC,c} \\ \sigma_{CM,c} & \sigma_{CC,c} \end{bmatrix}$.

3.3 Drug intensive margin

We also take incidental truncation into account in the intensive margins of demand for drugs (see Equation 5). Thus, we consider that we do not observe consumption level for individuals who report not to have access, or given access, who report not to use drugs, this means that Y_{ij} is missing. On the other hand, we have individuals who report the quantity of drug consumption, and we model this intensive margin as a function of socioeconomic characteristics ($\boldsymbol{w}_i$), risk perception about use of drug j ($\boldsymbol{r}_{ij}$), city-fixed effects (ω_{yj}), dummy variables indicating addict condition ($\boldsymbol{a}_{ij}$), and price of drugs ($\boldsymbol{p}_{ij}$),

$$Y_{ij} = \begin{Bmatrix} \boldsymbol{w}_i^\top \boldsymbol{\alpha}_{yj} + \boldsymbol{r}_{ij}^\top \boldsymbol{\delta}_{yj} + \omega_{yj} + \boldsymbol{a}_{ij}^\top \boldsymbol{\psi}_{yj} + \boldsymbol{p}_{ij}^\top \boldsymbol{\gamma}_{yj} + W_{ij} > 0, & C_{ij} = 1 \\ -, & C_{ij} = 0 | A_{ij} = 1 \text{ or } A_{ij} = 0 \end{Bmatrix}. \quad (5)$$

The location parameters related to consumption level are $\boldsymbol{\alpha}_{yj}, \boldsymbol{\delta}_{yj}, \omega_{yj}$, $\boldsymbol{\psi}_{yj}$ and $\boldsymbol{\gamma}_{yj}$, and we assume that the stochastic error $\boldsymbol{W}_i = [W_{iM} \; W_{iC}]^\top \overset{iid}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma}_{WW})$, where $\boldsymbol{\Sigma}_{WW} = \begin{bmatrix} \sigma_{MM,y} & \sigma_{MC,y} \\ \sigma_{CM,y} & \sigma_{CC,y} \end{bmatrix}$.

3.4 Correlation on unobservables

We assume that the three stages regarding drug consumption (access, use, and quantity) are potentially correlated due to unobservables. Then, we have $\boldsymbol{\Xi}_i = \left[\boldsymbol{V}_i^\top \; \boldsymbol{E}_i^\top \; \boldsymbol{W}_i^\top\right]^\top \sim N_6(\mathbf{0}, \boldsymbol{\Sigma})$, where

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{VV} & \boldsymbol{\Sigma}_{VE} & \boldsymbol{\Sigma}_{VW} \\ \boldsymbol{\Sigma}_{EV} & \boldsymbol{\Sigma}_{EE} & \boldsymbol{\Sigma}_{EW} \\ \boldsymbol{\Sigma}_{WV} & \boldsymbol{\Sigma}_{WE} & \boldsymbol{\Sigma}_{WW} \end{bmatrix}. \quad (6)$$

Therefore, $\boldsymbol{\Sigma}_{VE}$ and $\boldsymbol{\Sigma}_{VW}$ take into account the association between the access decision and the extensive and intensive margins of drug consumption. If $\boldsymbol{\Sigma}_{VE} = \boldsymbol{\Sigma}_{VW} = \mathbf{0}$, there is no endogenous selection into access, and access would be exogenous. There may be the situation that $\boldsymbol{\Sigma}_{VE} \neq \mathbf{0}$ and $\boldsymbol{\Sigma}_{VW} = \mathbf{0}$, that is, access is not correlated to the intensive margin. This implies that more intensive users do not make a greater effort to gain access, for instance, when they arrive at a new market. There is also $\boldsymbol{\Sigma}_{EW}$, which is the association between extensive and intensive margins; if these margins are independent, then $\boldsymbol{\Sigma}_{EW} = \mathbf{0}$.

Observe that if $\boldsymbol{\Sigma}$ is a diagonal matrix, all decision stages are independent, this means that there is no endogenous selection neither unobserved dependence between access, use and consumption level of marijuana and cocaine. Consequently, the modeling strategy should be based on independent univariate equations. Another set would be $\mathbf{\Sigma}$ equal to a block diagonal matrix; then, there is dependence between stages, and the modeling strategy should be based on bi-variate models in each stage (access, extensive and intensive margins).[4]

3.5 Potential states of drug consumption

Table 4 shows the potential states (S_i) regarding the marijuana and cocaine situation of individual i in our econometric framework. We observe in this table that access equal to zero necessarily implies missing values for both drug margins, and use equal to zero implies missing values for the intensive margins. For instance, state 1 is given by reporting no access to marijuana and cocaine; as a consequence, we do not observe any realization regarding the extensive or intensive margins. State 5 is a situation where individual i reports having access to cocaine, but no access to marijuana, as a consequence, we do not observe any realization regarding marijuana margins, and given that this individual reports cocaine use, we have a realization of the extensive and intensive margins of this drug. State 9 is a situation where individual i reports having access and use of both drugs, thus, we have realizations of extensive and intensive margins associated with each drug.

Marijuana legalization implies that the access restriction is not binding. This implies that states 1, 4 and 5 are not available anymore, and we have that the decision about consumption is based just on preferences of individuals, that is, a positive net indirect utility means that individuals having this situation will use marijuana, and we will have

[4]We should take into account that the diagonal elements of $\mathbf{\Sigma}_{VV}$ and $\mathbf{\Sigma}_{EE}$ are equal to one due to just observing binary variables indicating access and use. Thus, there is an identification issue that implies just identification of the correlation matrices in these decisions. We take into account these restrictions in our estimation setting. See online Supplementary Material for details.

observations of the intensive margin of marijuana.

Table 4: Potential states: Marijuana and cocaine use.

State	**Access**		**Extensive margin**		**Intensive margin**	
	Marijuana	Cocaine	Marihuana	Cocaine	Marihuana	Cocaine
S_i	A_{iM}	A_{iC}	C_{iM}	C_{iC}	Y_{iM}	Y_{iC}
1	0	0	-	-	-	-
2	1	0	0	-	-	-
3	1	0	1	-	y_{iM}	-
4	0	1	-	0	-	-
5	0	1	-	1	-	y_{iC}
6	1	1	0	0	-	-
7	1	1	1	0	y_{iM}	-
8	1	1	0	1	-	y_{iC}
9	1	1	1	1	y_{iM}	y_{iC}

Notes: Potential states of access, extensive and intensive margins.
"-" is a missing value, and y_{ij} is a particular realization of Y_{ij}.
Source: Authors' construction.

Each of these states will have a contribution to the construction of the likelihood function to estimate the location parameters in equations 3, 4 and 5, and the covariance matrix in 6.

3.6 Estimation strategy

The likelihood function of our model is not standard due to individuals in different states contributing to estimating different sets of parameters. For instance, all individuals contribute to estimating parameters in the access equations ($\boldsymbol{\alpha}_{aj}, \boldsymbol{\delta}_{aj}, \omega_{aj}, \beta_{aj}, \theta_{aj}$, τ_{aj} and $\boldsymbol{\Sigma}_{VV}$, $j = \{$marijuana, cocaine$\}$). Individuals who report having access to marijuana (states 2, 3 and 6 to 9) contribute to estimating location parameters in equations 3, and equation 4 when $j =$ marijuana, $\sigma_{MM,c}$, and the first row of $\boldsymbol{\Sigma}_{EV}$, that is, $\sigma_{MM,ac}$ and $\sigma_{CM,ac}$. We continue in this way until we get to state 9 where individuals in this state contribute to estimate all parameters, that is, location parameters in equations 3, 4 and 5, and $\boldsymbol{\Sigma}$.

We follow a Bayesian approach to perform inference in our econometric framework due to the complexity of our model. In particular, modeling the joint distribution of access, extensive and intensive margins with two drugs would imply integration over a multivariate space to recover the likelihood function, and multivariate incidental truncation implies that different sets of individuals contribute to different sets of parameters. This also adds complexity to the likelihood function. We avoid this using data augmentation (Tanner and Wong, 1987); thus, we set the augmented full information model that explicitly takes the latent vectors into account,

$$\underbrace{\begin{bmatrix} \boldsymbol{U}_{iM}^{a} \\ \boldsymbol{U}_{iC}^{a} \\ \boldsymbol{U}_{iM}^{c} \\ \boldsymbol{U}_{iC}^{c} \\ \boldsymbol{Y}_{iM} \\ \boldsymbol{Y}_{iC} \end{bmatrix}}_{\boldsymbol{T}_i} = \underbrace{\begin{bmatrix} \boldsymbol{x}_{iM,a}^{\top} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{x}_{iC,a}^{\top} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{x}_{iM,c}^{\top} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{x}_{iC,c}^{\top} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{x}_{iM,y}^{\top} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{x}_{iC,y}^{\top} \end{bmatrix}}_{\boldsymbol{X}_i} \underbrace{\begin{bmatrix} \boldsymbol{\theta}_{Ma} \\ \boldsymbol{\theta}_{Ca} \\ \boldsymbol{\theta}_{Mc} \\ \boldsymbol{\theta}_{Cc} \\ \boldsymbol{\theta}_{My} \\ \boldsymbol{\theta}_{Cy} \end{bmatrix}}_{\boldsymbol{\theta}} + \underbrace{\begin{bmatrix} \boldsymbol{V}_{iM} \\ \boldsymbol{V}_{iC} \\ \boldsymbol{E}_{iM} \\ \boldsymbol{E}_{iC} \\ \boldsymbol{W}_{iM} \\ \boldsymbol{W}_{iC} \end{bmatrix}}_{\boldsymbol{\Xi}_i},$$

where $\boldsymbol{x}_{ij,s}$ is the vector of regressors associated with individual i and drug j in stage $s = \{\text{Access, use, quantity}\}$, and $\boldsymbol{\theta}_{js}$ is the vector of location parameters of drug j in stage s.

As individuals in different states contribute to different subsets of parameters, we define a *selector* function $f(S, \boldsymbol{M})$ that takes as arguments a state (S) and a matrix ($\boldsymbol{M}$), and returns as output the appropriate subset of rows and columns of $\boldsymbol{M}$. For instance, if we apply the selector function to an individual who is in state 5 in Table 4, then

$$\tilde{\boldsymbol{T}}_i \equiv f(S_i = 5, \boldsymbol{T}_i) = \begin{bmatrix} \boldsymbol{U}_{iM}^a \\ \boldsymbol{U}_{iC}^a \\ \boldsymbol{U}_{iC}^c \\ \boldsymbol{Y}_{iC} \end{bmatrix}, \ \tilde{\boldsymbol{X}}_i \equiv f(S_i = 5, \boldsymbol{X}_i) = \begin{bmatrix} \boldsymbol{x}_{iM,a}^\top & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{x}_{iC,a}^\top & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{x}_{iC,c}^\top & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{x}_{iC,y}^\top \end{bmatrix},$$

$$\tilde{\boldsymbol{\theta}}_5 \equiv f(S_i = 5, \boldsymbol{\theta}) = \begin{bmatrix} \boldsymbol{\theta}_{Ma} \\ \boldsymbol{\theta}_{Ca} \\ \boldsymbol{\theta}_{Cc} \\ \boldsymbol{\theta}_{Cy} \end{bmatrix} \text{and } \tilde{\boldsymbol{\Sigma}}_5 \equiv f(S_i = 5, \boldsymbol{\Sigma}) = \begin{bmatrix} \sigma_{MM,a} & \sigma_{MC,a} & \sigma_{MC,ac} & \sigma_{MC,ay} \\ \sigma_{CM,a} & \sigma_{CC,a} & \sigma_{CC,ac} & \sigma_{CC,ay} \\ \sigma_{CM,ca} & \sigma_{CC,ca} & \sigma_{CC,cc} & \sigma_{CC,cy} \\ \sigma_{CM,ya} & \sigma_{CC,ya} & \sigma_{CC,cy} & \sigma_{CC,yy} \end{bmatrix}.$$

We can formulate the likelihood function using this selector function,

$$\begin{aligned} p(\tilde{\boldsymbol{T}}_1, \ldots, \tilde{\boldsymbol{T}}_n | \tilde{\boldsymbol{X}}_1, \ldots, \tilde{\boldsymbol{X}}_n, \boldsymbol{\theta}, \boldsymbol{\Sigma}) = \prod_{S=1}^{9} \prod_{i \in S} \prod_{j=\{M,C\}} & \{\mathbb{1}(A_{ij} = 0)\mathbb{1}(U_{ij}^a \leq 0) + \mathbb{1}(A_{ij} = 1)\mathbb{1}(U_{ij}^a > 0) \\ & \times \left[\mathbb{1}(C_{ij} = 0)\mathbb{1}(U_{ij}^c \leq 0) + \mathbb{1}(C_{ij} = 1)\mathbb{1}(C_{ij}^c > 0)\right]\} \\ & \times \phi(\tilde{\boldsymbol{T}}_i | \tilde{\boldsymbol{X}}_i \tilde{\boldsymbol{\theta}}_S, \tilde{\boldsymbol{\Sigma}}_S), \end{aligned} \tag{7}$$

where $\phi(\cdot | \tilde{\boldsymbol{X}}_i \tilde{\boldsymbol{\theta}}_S, \tilde{\boldsymbol{\Sigma}}_S)$ is the density function of a multivariate normal distribution with mean $\tilde{\boldsymbol{X}}_i \tilde{\boldsymbol{\theta}}_S$ and variance $\tilde{\boldsymbol{\Sigma}}_S$.

We use the Bayes' rule to perform inference in our model; that is, the posterior distribution is proportional to the likelihood function (Equation 7) times the prior distribution $(\pi(\boldsymbol{\theta}, \boldsymbol{\Sigma}))$,

$$\pi(\boldsymbol{\theta}, \boldsymbol{\Sigma} | \tilde{\boldsymbol{T}}_1, \ldots, \tilde{\boldsymbol{T}}_n | \tilde{\boldsymbol{X}}_1, \ldots, \tilde{\boldsymbol{X}}_n) \propto p(\tilde{\boldsymbol{T}}_1, \ldots, \tilde{\boldsymbol{T}}_n | \tilde{\boldsymbol{X}}_1, \ldots, \tilde{\boldsymbol{X}}_n, \boldsymbol{\theta}, \boldsymbol{\Sigma}) \times \pi(\boldsymbol{\theta}, \boldsymbol{\Sigma}).$$

We follow similar ideas as Chib et al. (2009); Li (2011); Jacobi and Sovinsky (2016) in our estimation strategy and assume independent non-informative (vague) conjugate priors, particularly the prior distribution for the location parameters is normal, and the prior distribution for the covariance matrix is inverse Wishart. This allows us to get standard forms for the conditional posterior distributions, and consequently, we use a Gibbs sampling algorithm (Greenberg, 2012, p. 91) to get draws of the posterior distribution. Details are provided in the online Supplementary Material.

3.7 Exclusion restrictions

It is well known that we can identify causal effects in nonlinear models without exclusion restrictions (McManus, 1992). However, exclusion restrictions improve the precision of the estimates because of data variability (Munkin and Trivedi, 2003; Ramírez-Hassan and Guerra-Urzola, 2021). We use a dummy variable indicating the presence of drug dealers in the neighborhood in the access equations, as this variable should affect the local drug supply. Particularly, we would expect that this variable indicate more accessibility to drugs in the neighborhood, and consequently, it would positively affect the probability of an individual having access. We argue that the effect of this variable on the extensive and intensive margins should be just through the access equations.

However, if these supply-side variables directly affect the net utility of using drugs, then our exclusion restrictions would not be valid. We try to test these restrictions using the subset of individuals who were offered drugs; as a consequence, they do not have to search for drugs, which means that they are relatively free of the selection issue. We check the statistical significance of these supply-side variables running the model in this subsample.

We use previous consumption of alcohol and cigarettes as exclusion restrictions in the access and extensive margin equations. The *gateway drug hypothesis* would support this assumption as a pattern of legal substance use during adolescence would precede the progressive use of illicit substances (Kandel, 1975). This means that preference for consuming substances like alcohol and nicotine would increase the probability of using drugs. We assume that previous consumption of these substances does not directly affect the intensive margins. We also use the prices of marijuana and cocaine in the extensive and intensive margins, as these variables should not affect the access equations due to non-users not having information about drug prices.

Finally, we use dummy variables indicating addict condition as exclusion restrictions in the intensive margins due to these just affecting the intensive margin rather than the access and extensive equations, as this condition is directly linked to the intensive margins.

Our econometric framework differs from other literature regarding modeling drug consumption in a few fundamental ways. In particular, we follow a simultaneous three-part modeling approach that considers access a necessary condition for use, such that the latter is endogenously determined with extensive and intensive margins. We also incorporate that use is a necessary condition for the intensive margin and allow for unobserved correlation between these stages. In addition, we consider the incidental truncation issue due to missing reports when individuals report not having access to marijuana and cocaine or when reporting access; they report not consuming any drug. Omitting access restrictions, potential correlation on unobservables, and/or incidental truncation may generate inconsistent estimators. There is also a clear link between our modeling strategy and the policy that we want to analyze, as marijuana legalization implies basically free access for all potential users, such that the "breaking the law" hindrance will disappear; this is formally $P(A_{iM} = 1) = 1$ in our econometric framework and will be the basis for our counterfactual exercises. Finally, we model simultaneously marijuana and cocaine, this allows to identify potential effects of marijuana legalization on cocaine extensive and intensive margins. An issue that has not been considered previously and that is particularly relevant in the Colombian case due to the drug market conditions in this country.

3.8 Predictive effects of marijuana legalization on cocaine demand

The posterior predictive density of cocaine for individual 0 is

$$\begin{aligned}
p(A_{0c}, C_{0c}, Y_{0c}|\boldsymbol{T}, \boldsymbol{X}) = \int_{\boldsymbol{S}}\int_{\boldsymbol{\Theta}} & \{\mathbb{1}(A_{0c}=0)\mathbb{1}(U_{0c}^{a} \leq 0) + \mathbb{1}(A_{0c}=1)\mathbb{1}(U_{0c}^{a} > 0) \\
& \times [\mathbb{1}(C_{0c}=0)\mathbb{1}(U_{0c}^{c} \leq 0) + \mathbb{1}(C_{0c}=1)\mathbb{1}(U_{0c}^{c} > 0)]\} \\
& \times p(A_{0c}|\boldsymbol{T}, \boldsymbol{X}) \times p(C_{0c}|A_{0c}, \boldsymbol{T}, \boldsymbol{X}) \times p(Y_{0c}|C_{0c}, A_{0c}, \boldsymbol{T}, \boldsymbol{X})\pi(\boldsymbol{\theta}, \boldsymbol{\Sigma}|\boldsymbol{T}, \boldsymbol{X})d\boldsymbol{\theta}d\boldsymbol{\Sigma},
\end{aligned} \tag{8}$$

where $\boldsymbol{S}$ and $\boldsymbol{\Theta}$ are the support of integration of $\boldsymbol{\Sigma}$ and $\boldsymbol{\theta}$, respectively.

Observe that $p(A_{0c}, C_{0c}, Y_{0c}) = p(A_{0c}) \times p(C_{0c}|A_{0c}) \times p(Y_{0c}|C_{0c}, A_{0c})$, where $p(Y_{0c} = y_{0c}|C_{0c} = 1, A_{0c} = 1) = p(Y_{0c} = y_{0c}|C_{0c} = 1)$ for $y_{0c} \neq 0$ because $C_{0c} = 1$ is a sufficient condition for $Y_{0c} \neq 0$.

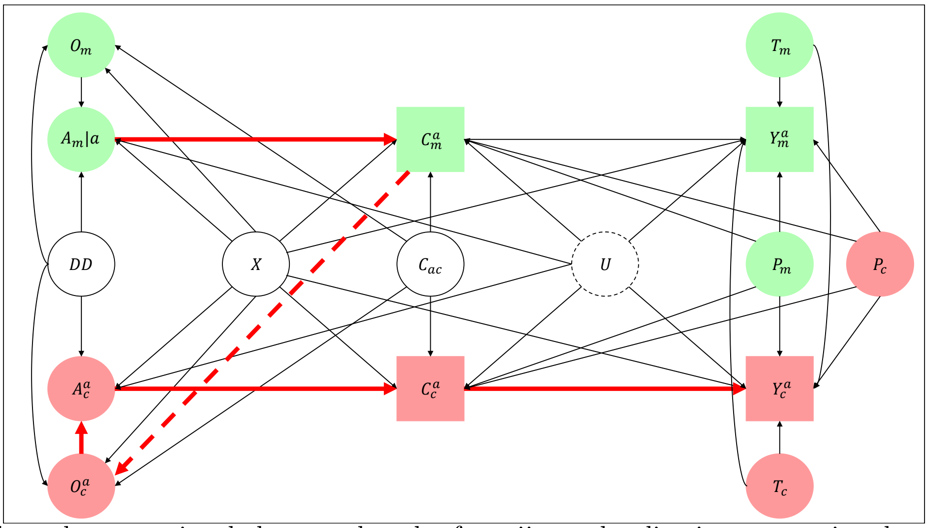
We can estimate the effects of legalization of marijuana on cocaine consumption using the law of total probability, that is,

$$
\begin{aligned}
p(C_{0c}=1)=&p(C_{0c}=1|A_{0c}=1)\times p(A_{0c}=1)+p(C_{0c}=1|A_{0c}=0)\times p(A_{0c}=0)\\
=&p(C_{0c}=1|A_{0c}=1,C_{0m}=1)\times p(A_{0c}=1|C_{0m}=1)\times p(C_{0m}=1)\\
&+p(C_{0c}=1|A_{0c}=1,C_{0m}=0)\times p(A_{0c}=1|C_{0m}=0)\times p(C_{0m}=0)\\
=&p(C_{0c}=1|A_{0c}=1,C_{0m}=1,A_{0m}=1)\times p(A_{0c}=1|C_{0m}=1,A_{0m}=1)\\
&\times p(C_{0m}=1|A_{0m}=1)\times p(A_{0m}=1)\\
&+p(C_{0c}=1|A_{0c}=1,C_{0m}=0,A_{0m}=1)\times p(A_{0c}=1|C_{0m}=0,A_{0m}=1)\\
&\times p(C_{0m}=0|A_{0m}=1)\times p(A_{0m}=1)\\
&+p(C_{0c}=1|A_{0c}=1,C_{0m}=1,A_{0m}=0)\times p(A_{0c}=1|C_{0m}=1,A_{0m}=0)\\
&\times p(C_{0m}=1|A_{0m}=0)\times p(A_{0m}=0)\\
&+p(C_{0c}=1|A_{0c}=1,C_{0m}=0,A_{0m}=0)\times p(A_{0c}=1|C_{0m}=0,A_{0m}=0)\\
&\times p(C_{0m}=0|A_{0m}=0)\times p(A_{0m}=0)\\
=&p(C_{0c}=1|A_{0c}=1,C_{0m}=1)\times p(A_{0c}=1|C_{0m}=1)\times p(C_{0m}=1|A_{0m}=1)\\
&\times p(A_{0m}=1)+p(C_{0c}=1|A_{0c}=1,C_{0m}=0,A_{0m}=1)\times p(A_{0c}=1|C_{0m}=0,A_{0m}=1)\\
&\times p(C_{0m}=0|A_{0m}=1)\times p(A_{0m}=1)\\
&+p(C_{0c}=1|A_{0c}=1,A_{0m}=0)\times p(A_{0c}=1|A_{0m}=0)\times p(A_{0m}=0).
\end{aligned}
\tag{9}
$$

The last equality considers that access is a necessary condition for consumption, and consequently, consumption is a sufficient condition for access. Then, $p(C_{0c}=1|A_{0c}=1,C_{0m}=1,A_{0m}=1)=p(C_{0c}=1|A_{0c}=1,C_{0m}=1)$, $p(C_{0c}=1|A_{0c}=1,C_{0m}=0,A_{0m}=0)=p(C_{0c}=1|A_{0c}=1,A_{0m}=0)$, $p(C_{0m}=1|A_{0m}=0)=0$, and $p(C_{0m}=0|A_{0m}=0)=1$.

We assume that under the legalization of marijuana, all individuals would have access to this drug, then $p(A_{0m}=1)=1$. This assumption implies an upper-bound situation as

Figure 5: Single world intervention graph: Effects of legalization of marijuana on cocaine demand.



Notes: The red arrows signal the causal path of marijuana legalization on cocaine demand. The new state of universal access to marijuana (a) affects marijuana consumption (C_m^a). The new state breaks down the causal path from marijuana use to being offered cocaine (dashed red arrow), O_c^a would be independent of C_m^a. The new state of O_c^a affects access to cocaine (A_c^a), which in turn affects cocaine consumption (C_c^a), and this is its intensive margin (Y_c).

teenagers and individuals in regions without legal suppliers would not have legal access, although they still would have access to the black market. We also assume that access to cocaine and consumption of marijuana are independent, that is, $p(A_{0c}|C_{0m}) = p(A_{0c})$, as legal marijuana providers would not supply cocaine, a situation that is different in the actual situation where marijuana providers also supply cocaine in most of the cases. However, we allow that $p(C_{0c}|C_{0m}) \neq p(C_{0c})$ due to the propensity of marijuana consumers to consume cocaine because of the gateway hypothesis. Then, Equation 9 becomes $p(C_{0c} = 1) = p(C_{0c} = 1|A_{0c} = 1, C_{0m} = 1) \times p(A_{0c} = 1) \times p(C_{0m} = 1) + p(C_{0c} = 1|A_{0c} = 1, C_{0m} = 0) \times p(A_{0c} = 1) \times p(C_{0m} = 0)$.

4 Results

We estimate the full model following the likelihood function of equation 7, i.e., jointly estimating access, intensive margin, and extensive margin for both marijuana and cocaine and using the selector function to calculate the subset of parameters to which each individual contributes. To do so, we executed 6,000 iterations with a burn-in of 1,000 and a thinning parameter of 5, resulting in 1,000 effective posterior samples. We performed several satisfactory diagnostics on the posterior chain's distribution (Raftery et al., 1992; Heidelberger and Welch, 1983).

Table 5 presents the posterior estimates. Columns 1 and 2 present the coefficients associated with marijuana and cocaine access, respectively; columns 3 and 4, the coefficients associated with the extensive margin; and finally, columns 5 and 6, the coefficients associated with the intensive margin. The exclusion restrictions are presented at the top of the table, followed by the control variables. We have excluded the categories of people in their 20s, low stratum, and primary level of education from the control variables to avoid multicollinearity problems.

The presence of drug dealers in the neighborhood increases the likelihood of access to both marijuana and cocaine (Table 5, columns 1 and 2). Similarly, having been offered marijuana at some point in life increases the likelihood of reporting current access to marijuana; the same pattern holds for cocaine. Additionally, prior use of alcohol and cigarettes raises the probability of access to marijuana but not to cocaine. Regarding control variables, access to both drugs shows similar patterns: women are less likely to have access, the probability of having access is lower for those living in medium or high socioeconomic strata, and it is lower for individuals with professional or graduate education, although in some cases these differences are not statistically significant at the 5% level. The probability of having access to marijuana decreases with age. However, it is not statistically different

Table 5: Posterior results of location parameters: Marijuana and cocaine demand in Colombia - Baseline model

	Access		Extensive margin		Intensive margin	
	Marijuana	Cocaine	Marijuana	Cocaine	Marijuana	Cocaine
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Exclusionary restrictions						
Drug dealer in neighborhood	**0.499**	**0.500**				
	(0.013)	(0.014)				
Offered Marijuana	**0.399**					
	(0.016)					
Offered Cocaine		**0.583**				
		(0.020)				
Alcohol and cigarette use	**0.060**	0.018	**0.087**	0.078		
	(0.014)	(0.014)	(0.042)	(0.082)		
Prices						
Marijuana			**-0.211**	**-0.322**	**-0.259**	0.094
			(0.049)	(0.087)	(0.103)	(0.153)
Cocaine			**-0.144**	**-0.677**	0.091	**-0.404**
			(0.063)	(0.104)	(0.152)	(0.161)
Years of consumption						
Marijuana					0.009	-0.004
					(0.012)	(0.013)
Cocaine					0.008	**0.041**
					(0.008)	(0.015)
Age						
30s	**-0.085**	0.026	**-0.284**	-0.078	**0.408**	-0.067
	(0.018)	(0.018)	(0.052)	(0.101)	(0.183)	(0.233)
40s	**-0.155**	-0.018	**-0.483**	0.011	0.364	**-0.732**
	(0.019)	(0.020)	(0.069)	(0.113)	(0.309)	(0.364)
50s and older	**-0.343**	**-0.160**	**-0.918**	**-0.486**	-0.022	**-1.036**
	(0.017)	(0.018)	(0.073)	(0.128)	(0.453)	(0.464)
Strata						
Medium	**-0.089**	**-0.116**	**0.312**	0.127	**-0.575**	-0.164
	(0.015)	(0.015)	(0.051)	(0.096)	(0.126)	(0.194)
High	**-0.250**	**-0.205**	**0.513**	**0.846**	**-1.085**	-0.406
	(0.035)	(0.035)	(0.103)	(0.169)	(0.257)	(0.365)
Education level						
No education	**-0.116**	**-0.150**	0.136	-0.016	0.280	-0.116
	(0.055)	(0.057)	(0.178)	(0.292)	(0.436)	(0.585)
Secondary	0.006	0.002	**-0.659**	**-0.513**	0.068	0.028
	(0.018)	(0.019)	(0.048)	(0.083)	(0.160)	(0.212)
Undergraduate	-0.036	**-0.043**	**-1.318**	**-1.196**	-0.067	0.481
	(0.020)	(0.020)	(0.071)	(0.166)	(0.335)	(0.478)
Graduate	**-0.100**	-0.069	**-1.499**	**-0.728**	1.300	-0.088
	(0.035)	(0.036)	(0.201)	(0.292)	(0.784)	(0.610)
Female	**-0.208**	**-0.248**	**-0.270**	**-0.297**	**-0.304**	-0.270
	(0.013)	(0.013)	(0.047)	(0.094)	(0.133)	(0.207)
Has children?	-0.004	0.012	**-0.832**	**-0.499**	0.322	-0.519
	(0.013)	(0.014)	(0.083)	(0.150)	(0.362)	(0.391)
Curiosity towards drugs	**0.432**	**0.285**	**1.365**	**1.226**	**-0.792**	0.078
	(0.020)	(0.018)	(0.059)	(0.119)	(0.346)	(0.429)
Regional fixed effects	✓	✓	✓	✓	✓	✓
Observations	45,722	45,722	45,722	45,722	45,722	45,722

Notes: Bold font indicates significant evidence against H_0. $\theta_{sk} = 0$ at 5%. Standard deviation in parenthesis. Columns (1), (3) and (5) show posterior results of simultaneous three-part model for marijuana. Columns (2), (4) and (6) show posterior results for cocaine. Columns (1) and (2) present the posterior results associated with access. Columns (3) and (4), the results associated with the extensive margin; and columns (5) and (6), the coefficients associated with the intensive margin. There are 38 regional fixed-effects in each equation. There are meaningful differences in the intensive margin equations due to significant evidence for an unobserved correlation between the extensive and intensive margin equations (see Table 6).
Source: Authors' construction using ENCSPA data.

between age groups for cocaine, except those aged 50 years and older.

Regarding drug use (extensive margin), previous alcohol and cigarette use increases the likelihood of marijuana use but does not affect the probability of cocaine use Table 5, columns 3 and 4). Conversely, the prices of both marijuana and cocaine are inversely related to the probability of using these drugs, both directly and crosswise. Women are less likely to use either drug compared to men, and this is also true for individuals with children in the household. For other control variables, marijuana use shows a clear pattern of decreasing likelihood with age, whereas this pattern is not observed for cocaine. Individuals from middle and high socioeconomic strata have a higher probability of using marijuana or cocaine. Additionally, those with more advanced education than elementary school are less likely to use both drugs.

Table 6: Posterior results of correlations: Marijuana and cocaine demand in Colombia

Equations correlation	A_m	A_c	C_m	C_c	Y_m	Y_c
A_m		**0.539**	**-0.041**	-0.025	**0.251**	**0.779**
		(0.004)	(0.016)	(0.017)	(0.112)	(0.152)
A_c			**-0.046**	-0.027	**0.229**	**0.671**
			(0.016)	(0.018)	(0.070)	(0.157)
C_m				0.020	**-0.553**	0.011
				(0.011)	(0.100)	(0.106)
C_c					-0.004	-0.028
					(0.031)	(0.123)
Y_m						0.165
						(0.100)
Y_c						

Notes: Notes: Bold font indicates significant evidence against H_0. $\rho = 0$ at 5%. The sample size is 45,722. Columns 1 to 6 correspond to the three margins for each of the two drugs, arranged in the same sequence as presented in the table 5.
There is a correlation between unobserved factors across various model margins for the two drugs.
Source: Authors' construction using ENCSPA data.

Finally, columns 5 and 6 indicate that both marijuana and cocaine are inelastic goods. Estimating the price elasticity of demand for drugs is complex. Previous studies in the US have shown that the price elasticity of marijuana ranges from -1.84 to -0.67 (Davis et al., 2016; Grossman, 2005; Kilmer et al., 2014; Mace et al., 2020; Nisbet and Vakil, 1972; Van Ours and Williams, 2007). In Australia, Thailand, and South Africa, researchers have similarly identified marijuana demand as inelastic (Jacobi and Sovinsky, 2016; Riley et al., 2020; Sukharomana and Chang, 2017). Conversely, the demand for cocaine has demonstrated greater elasticity in past studies. Jofre-Bonet and Petry (2008) highlighted an elastic demand for cocaine, Caulkins (1995) noted a cocaine price elasticity of -2.50, Chaloupka et al. (1998) found an average price elasticity of -1.28 among young people, and Grossman and Chaloupka (1998) reported a total cocaine use elasticity of -1.35 for young adults. Overall, marijuana demand exhibits less price sensitivity compared to other drugs such as cocaine (Gallet, 2014). This trend is also observed in Colombia, where the price elasticity of demand for marijuana is -0.259 and for cocaine is -0.404. Although both values are inelastic, cocaine demand is more responsive to price changes than marijuana. There is significant evidence to reject the hypothesis that own price is irrelevant at the 5% significance level for both drugs; however, the cross-elasticities are not significant at the same level.

Table 6 indicates significant evidence for a correlation between the unobserved factors of these equations. Specifically, access to marijuana is associated with access to cocaine, as well as the usage and quantities consumed of both marijuana and cocaine. Similarly, access to cocaine is linked to the quantities consumed of both drugs and the usage of marijuana. Additionally, there is a notable correlation between the unobserved factors related to both the extensive and intensive margins of marijuana use.

We performed a range of statistical tests to confirm the exclusionary restrictions and the robustness of our findings across multiple model definitions and specifications (see the online Supplementary Material). Overall, the exclusionary restrictions seem to be justified, and the results remain strong.

4.1 Predictive analysis

We conducted a counterfactual analysis to estimate changes in the probability of cocaine use for each individual and analyzed these changes on average across the entire population and by population groups. To do this, we estimate the posterior predictive probability described in equation 8 using the draws from the posterior distribution to obtain the probability of using cocaine in the status quo scenario.

We assume that under the legalization of marijuana, all individuals would have access to this drug, then $p(A_{0m} = 1) = 1$. We also assume that access to cocaine and consumption of marijuana are independent of each other, that is, $p(A_{0c}|C_{0m}) = p(A_{0c})$; however, we allow that $p(C_{0c}|C_{0m}) \neq p(C_{0c})$ due to the propensity of marijuana consumers to consume cocaine because of the gateway hypothesis. See section 3.8.

Table 7: Probability of consuming cocaine in status quo and legalization scenario

Population	Status quo (1)	Legalization (2)	Variation (%) (3)
Female	0.144%	0.148%	3.002%
Male	0.786%	0.806%	2.505%
All	0.457%	0.469%	2.629%

Notes: This table shows the probabilities of using cocaine under the status quo scenario and under a legalization scenario.

Table 7 presents the probability of cocaine use under the "status quo" and legalization scenarios, along with the percentage variation. These probabilities are computed by estimating the distribution function of the multivariate normal distribution, considering arbitrary limits and correlation matrices as per the scenario described in Equation 9. We calculate each probability for every individual (45,722) using 1000 posterior draws from the baseline estimation. Subsequently, we simulate, for each probability, 1000 binomial experiments using the probabilities derived from the multivariate normal distribution as parameters. Finally, we compute the average probability for each individual, followed by calculating the overall average or averages for specific groups (e.g., male vs. female, age categories, etc.).

On average, cocaine use increases by 2.6% in a legalization scenario, equating to a rise of just 0.012 percentage points. Women exhibit a higher percentage increase in the probability of cocaine use compared to men, at 3% versus 2.5%. However, since the baseline probability of cocaine use among women in the status quo is lower, the absolute increase in percentage points is greater for men (0.02 percentage points for men versus 0.004 percentage points for women).

We conducted a predictive analysis of the increase in cocaine use, stratified by control variables such as age, socioeconomic status, education level, and prior drug use. The results of this analysis are summarized in Figure 6, with detailed numbers broken down by gender provided in the appendix.

The probability of cocaine use decreases consistently with age. For example, a young adult in their 20s has an average probability of 0.729% of using cocaine, while this probability drops to just 0.126% for individuals aged 50 and above. Correspondingly, the percentage increase in the probability of cocaine use is greater for those in their 20s (3.069%) compared to those over 50 (1.464%).

In terms of socioeconomic status, individuals in higher socioeconomic strata exhibit the highest probability of cocaine use (1.029%), whereas those in lower strata have a probability of 0.412%. The greatest percentage increase in cocaine use probability is also observed among individuals in higher socioeconomic strata, with a 5.056% rise.

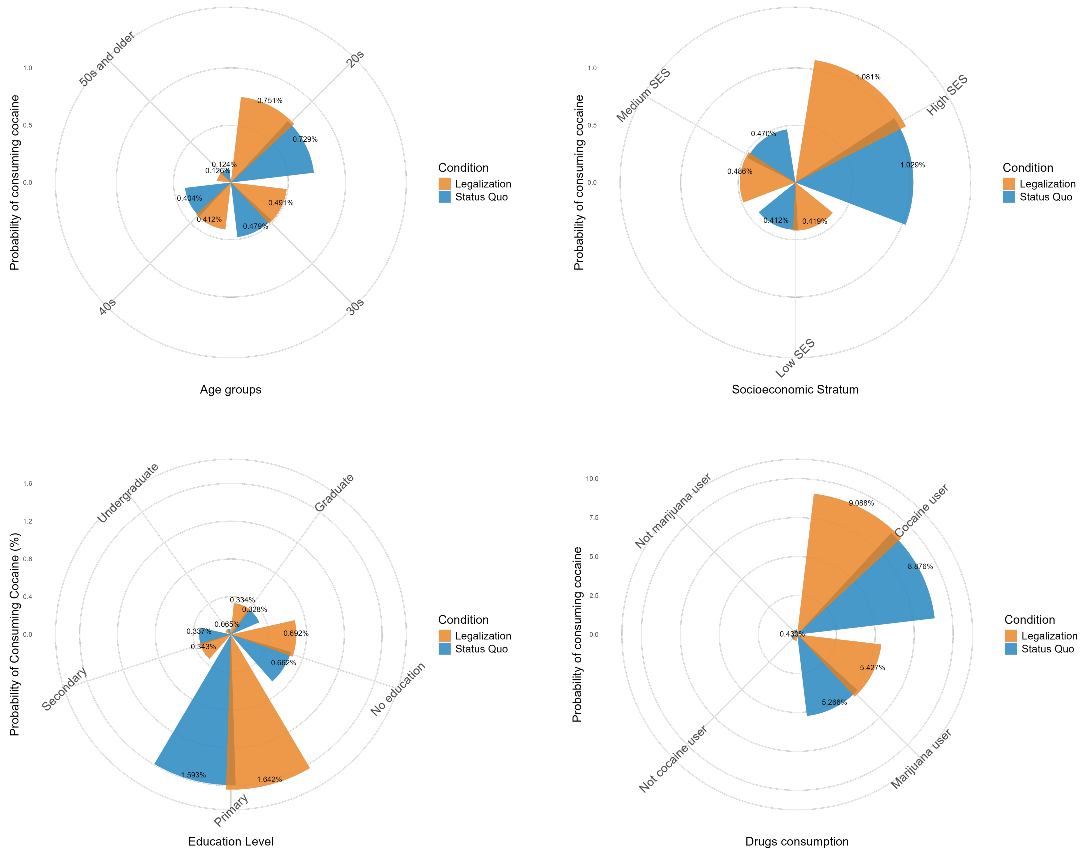


Figure 6: Probability of consuming cocaine in status quo and legalization scenario

Education level also plays a significant role. Individuals whose highest level of education is primary school have the highest probability of cocaine use (1.593%), followed by those with no formal education, postgraduate, secondary, and undergraduate education. The percentage increase in cocaine use probability varies across these groups, from 4.561% among those with no education to just 1.354% among those with undergraduate degrees.

Lastly, marijuana users have a 5.266% probability of using cocaine, with an increase of 3.069% under legalization, while current cocaine users have a probability of 9.088%, with a 2.385% increase. In contrast, non-users of marijuana or cocaine have a much lower probability of cocaine use, around 0.4%, although the percentage increase under legalization is still notable, ranging between 2.4% and 2.6%.

5 Concluding remarks

The analysis presented in this report underscores the complex dynamics between marijuana legalization and cocaine consumption in Colombia. By employing an econometric framework that accounts for both access and consumption margins, we find that the legalization of marijuana could lead to a nuanced increase in the probability of cocaine use, particularly among specific demographics such as younger adults and those in higher socioeconomic strata. The predictive models suggest that while marijuana legalization may decrease contact with cocaine dealers for some, it could also facilitate increased marijuana use, which is associated with higher likelihoods of cocaine consumption. This dual potential highlights the necessity for targeted policies that not only regulate marijuana but also consider its implications for cocaine use and the broader drug landscape in Colombia. Future research should continue to explore these relationships, especially as public health initiatives and drug policies evolve in response to changing societal attitudes towards psychoactive substances.

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