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Binge Drinking and Risk Preferences: an application to college students in Argentina

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Abstract

This study analyzes the decision of consuming alcohol in the modality of excessive episodic consumption (binge drinking) among college students. It uses primary data especially collected to this aim, which includes the design and implementation of the Consumption Habits in University Students' Survey (CHUS Survey). This survey took place in August 2019 in two Argentinian Universities: Universidad Nacional de Córdoba and Universidad Nacional de Cuyo, interviewing 1397 first year students of the Economic Sciences School in both Universities took part of this study, who represent the 73% of the enrolled students. The survey assesses principally knowledge about risky alcohol consumption, characteristics of consumption of alcohol and other substances, alcohol consumption in peer groups, preferences about alcoholic beverages, risk perception and vulnerability, propensity and accessibility to alcohol and other substances. Using the Latent Class Analysis 5 classes about risk preferences were defined, being the largest the one that groups students with the highest tolerance to risk (45% of the sample). On the contrary, the group most averse to risk represents only 3% of the sample. A probit model corrected by self-selection is estimated to analyze the decision of having a binge drinking episode. It is found that being man, participating in pre-gaming frequently and being a risk lover increase the probability of harmful alcohol consumption in a binge drinking pattern.

Key words: risk preferences, binge drinking, university students, latent class analysis
JEL Code: D12, D91, I12, C38

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Resumen

Este estudio analiza la decisión de consumir alcohol en la modalidad de consumo episódico excesivo (binge drinking) entre estudiantes universitarios. Utiliza datos primarios especialmente recopilados para este fin, que incluyen el diseño e implementación de la Encuesta de Hábitos de Consumo en Estudiantes Universitarios. Esta encuesta se realizó en agosto de 2019 en dos universidades argentinas: Universidad Nacional de Córdoba y Universidad Nacional de Cuyo, entrevistando a 1397 estudiantes de primer año de la Facultad de Ciencias Económicas de ambas Universidades, que representan el 73% de los estudiantes matriculados. La encuesta evalúa principalmente conocimientos sobre consumo nocivo de alcohol, características del consumo de alcohol y otras sustancias, consumo de alcohol en grupos de pares, preferencias sobre bebidas alcohólicas, percepción de riesgo y vulnerabilidad, propensión y accesibilidad al alcohol y otras sustancias. Mediante el Análisis de Clase Latente se definieron 5 clases de preferencias de riesgo, siendo la que agrupa a más individuos la con mayor tolerancia al riesgo (45% de la muestra). Por el contrario, el grupo más reacio al riesgo representa solo el 3% de la muestra. Se estima un modelo probit corregido por sesgo de selección para analizar la decisión de tener un patrón de CEE. Se encuentra que ser hombre, participar en previas con frecuencia y ser un amante del riesgo aumentan la probabilidad de consumo nocivo de alcohol en un patrón de CEE.

Palabras Claves: preferencias hacia el riesgo, consumo episódico excesivo, estudiantes universitarios, análisis de clases latentes
JEL Code: D12, D91, I12, C38

I. Introduction

Alcohol is a psychoactive substance that has an immediate effect on the mental state of people. Excessive drinking produces dependence, a behavior disorder with biological bases, characterized by a decrease in the control of consumption, a progressive increase in the tolerance of its effects, withdrawal symptoms, craving to consume and consuming it despite repeatedly having social and health problems (World Health Organization, 2014). In Latin America, more alcohol is consumed than in the rest of the world and it is expected that as the countries of the region develop, its consumption will increase and, consequently, the related damages (Pan American Health Organization, 2015).

Alcohol consumption can be harmful not only because of the volume of alcohol ingested, but also because of the pattern of consumption that people adopt. Binge drinking or heavy episodic drinking (HED) is the most prevalent harmful pattern among young people. HED refers to an intense consumption on a single occasion of at least 60 grams of pure alcohol, with special emphasis on the short duration of alcohol intake, which conduces to a high blood alcohol concentration (Gómez, 2017; World Health Organization, 2011; Acosta et al., 2011; Luque et al., 2014).

The binge drinking habit impacts on different dimensions; the most direct impact is on the health and productivity of the individual, both, in the short and long term; and indirectly produces negative externalities on the community. Health effects can occur immediately (nausea, vomiting, memory loss, strokes) and if repeated with some frequency, this habit is associated with risk of cancer, infertility, brain damage, heart and liver disease, among others. Furthermore, in the particular case of students, binge drinking can affect their academic performance. Negative externalities include the increase in the rate of road accidents and the greater probability of participating in violent acts such as sexual assaults and other criminal acts (Alcohol rehab guide, 2020; Olivieri, 2012).

According to data from the waves 2011, 2013 and 2018 of the National Survey of Risk Factors (NSRF) in Argentina, alcohol use prevalence among adult population does not show important changes along this period, while HED prevalence presents a sustained increase. Alcohol use prevalence during the month prior to the survey is around 54% for the total sample, whereas for the age group 18-24 years old it rises to 60%. Concerning HED prevalence, in 2008, 14% of the adult drinkers presented this pattern, while in 2013 and 2018 this proportion raised to 19% and 25% respectively. In the subsample of the population aged 18 to 24 years, HED prevalence rose from 27% in 2009 to 28.6% in 2013 and 34.6% in the last wave. Another notable phenomenon is that socioeconomic impact on the habit of harmful drinking has decreased. A more in-depth analysis with the NSRF data reveals that in 2009 harmful drinking presents higher prevalence in the first income quintiles, while in the last wave the prevalence were similar in all the quintiles. The findings about the youngest segment (18-24 years old) reveal that the household income level is not significantly associated with the harmful drinking in 2013 and 2018 (Carrazana and De Santis, 2019). These results suggest that this problem affects the whole of society and particularly young people, regardless of their household income level. Among the younger drinkers, those who study a higher education degree are of greater interest, since their academic performance and future productivity may be seriously compromised.

Alcohol is the most consumed substance among college students. Betancourth-Zambrano et al. (2017) report a lifetime prevalence of 96% for Colombia, 89% for Ecuador, 87% for Peru, and 77% for Bolivia. The National Institute on Alcohol Abuse and Alcoholism (NIAAA, 2020) of the United States reports that more than 55% of young people between 18 and 22 years have consumed alcohol and 1 in 3 have episodic excessive consumption. Briere et al. (2011) report a prevalence of 37% in 17-year-old students in Quebec, Canada.

In addition, the knowledge and information of individuals on the health consequences of harmful habits are indicated as relevant by different authors to explain the awareness of being exposed to risk and to stop the HED habit (Fernández, 2012; Olivieri, 2012; Shelton and Savell, 2011; Pashwan et al., 2015).

Traditionally, public policies aimed to prevent and discourage harmful alcohol consumption tend to restrict the availability and affordability of alcohol through price and tax modifications and prohibitions,

focusing on the amount of alcohol ingested by the population. In general, these policies consider the reduction of average consumption as an objective, assuming that the problems (social and health) are proportional (Jiang, Callinan and Room, 2014). However, studies in Australia have shown that alcohol-related problems have been increasing although levels of consumption remained stable, and that risky drinking patterns vary from one segment of the population to another, despite facing the same market and the same regulations (Livingston et al., 2010). Furthermore, little is known about the causal relationship between alcohol policies and changes in drinking patterns.

Another relevant aspect of the effectiveness of policies is that they do not have the same effect on all groups and sectors of the population. Among the factors that condition harmful behavior, can be mentioned the information of the individual on the effects of dangerous drinking, risk perception and risk preferences. Correct information may affect risky behavior. This aspect is taken into account in policies of AIDS prevention (Fernández, 2012) since the right knowledge about risky behavior on health not only may influence the demand and habits but also the perception that the individual has about the risk to which they are exposed. The attitude of individuals to take risks, that is, their harmful drinking utility function is implicit in their decision about consuming or not consuming and in the pattern of consumption. However, the lack of information about individuals´ preferences prevents it from being explicitly considered in empirical studies. In this sense, Dave and Saffer (2008) mention that alcohol price elasticity differs among individuals according to their attitude to expose one health´s to risk.

Knowing and analyzing the attitude towards risk in the analysis of the consumption patterns of alcoholic beverages among young people is crucial because it deals with contingent consumption decisions, in which the individual's decision depends on their attitude towards risk. One of approaches of health economics to analyze the behavior of drinkers poses consumption as a problem of maximizing utility under uncertainty, since individuals do not know exactly the result of their actions. In this research, the approach of contingent consumption of alcohol is used, considering the alternatives of moderate consumption and HED pattern. Data from 2019 Universidad Nacional de Córdoba and Universidad Nacional de Cuyo (Argentina) are used and students´ risk preferences about alcohol consumption are analyzed using the Latent Class Analysis. A probit regression with sample selection was applied to predict the probability of presenting HED pattern: male, single, engaged on pre-drinking, consuming alcohol mixed with energetic beverages and being risk tolerant are significant predictors. Finally, the decision of harmful drinking is analyzed controlling the individuals' preferences.

The remainder of this paper is organized as follows. Section II summarizes the economic literature background. Section III describes analytical framework. Data used in the empirical analysis is described in Section IV. The results are presented in Section V and Section VI concludes.

II. Prior studies

Traditionally, the economic literature on alcohol comprises different relationships among drinking patterns, current drinking, previous habits, health status and productivity and earnings (Cook and Moore, 2000). In addition, the availability of other psychoactive substances, taxes and government regulations and policies focused on specific groups have stimulated a wide range of studies in the field. Drinking by teenagers and young adults has conceited special attention for different reasons. In this regard, numerous authors acknowledge that most addictions begin in adolescence (Salazar et al., 2004; Borsari et al., 2007; Cicua et al., 2008; Cantillo et al., 2011; Briere et al., 2011; Chaloupka et al., 2012; Betancourth-Zambrano et al., 2017. In this stage of life individuals, in general, have limited knowledge of addiction and are strongly influenced by the desire for immediate gratification, and generally lack self-control. Orphanides and Zervos (1995) point out that they risk consuming addictive goods because they are unaware of the addictive potential, or, knowing it, tend to underestimate the risks they face and enjoy the immediate rewards of their consumption. In this sense, these authors emphasize that the incorporation of

individual subjective beliefs in rational addiction models contributes to explain the initiation of psychoactive substance use in adolescence and the importance of the peer effect.

The alcohol use in young people is particularly worrisome, since it sets the pattern for future consumption and it has repercussions on their health status, human capital, future earnings and family formation (Cook and Moore, 2000). In this line, numerous studies have identified students as a high-risk population (Lutsky et al., 1994; Arteta, 1995; Cáceres et al., 2006; Parada et al., 2012; ElAnsari et al., 2013; Cremonte and Pilatti, 2017; Betancourth-Zambrano et al., 2017). However not all adolescents who start drinking develop problems with alcohol and not those who do, exhibit the same drinking patterns. Pautassi (2013) points out that the results seem to indicate that those who exhibit an early onset of alcohol use consumption and who perceive the alcohol-induced state as more attractive and less aversive, would be especially at risk. Betancourth-Zambrano et al. (2017) have observed that the initiation of alcohol use at an early age is negatively related to the intensity and frequency of consumption.

The legal minimum age to consume alcohol varies between countries; it is usually in the range that goes from 16 to 21 years. However, the fact that it is an easily accessible substance has induced young people to start using it before the legal age. Cáceres et al. (2006), Castaño-Pérez et al. (2014), Betancourth-Zambrano et al. (2017) report ages of beginning to alcohol consumption that average 14 years old in the case of Colombia; Smyth et al. (2011) 15 years old for Ireland; Nair et al. (2016) aged 17 for India; Strunin et al. (2017) place it in 15 years old in Mexico; Lara et al. (2019) estimate an average age of onset of 17 years old for Argentina, Boubeta et al. (2018) report a starting age of 13 years old in the case of students from Galicia, Spain. Various studies show that recurrent drinking and heavy drinking episodes in adolescence, could affect negatively the cognitive development and the skills necessary for an adequate transition to adulthood (Parada et al., 2012; ElAnsari et al., 2013).

A phenomenon associated to alcohol consumption among young people is poly drug use or consumption of two or more substances on the same occasion. In relation to this, Ramirez et al. (2019) state that in adolescence the consumption of several psychoactive substances is relatively common. Comparing to the consumption of a single substance, poly drug use causes greater negative consequences at a personal and environmental level, attributable to cross-tolerance, additive effects and multiple biochemical processes: the mixture of two or more substances that alter mood to produce a third substance with essential properties. The most common substance involved in poly drug use is alcohol, most of the time associated with the use of marijuana (Lee et al., 2017; Subbaraman and Kerr, 2015; Terry-McElrath et al., 2014; Collins et al., 1998; Briere et al., 2011; Ramirez et al., 2019). Lara et al. (2019) find that a lower age of onset of alcohol consumption would be associated with a higher probability of using marijuana. The simultaneous consumption of alcohol with energy drinks is relatively new, however, it is not minor.[1] Berger et al. (2013), Marczinski (2011) and Schulenberg et al. (2019) report prevalences of simultaneous monthly consumption of alcohol and energy drinks by university students of 65%, 44% and 27% respectively. The simultaneous consumption of alcohol and energy drinks minimizes the perception of drunkenness, enhances stimulation and increases both the desire to continue drinking and the amount consumed, enhancing the harmful effects of alcohol (Ferreira et al., 2006; Marczinski and Fillmore, 2006; O'Brien et al., 2008; Marczinski and Fillmore, 2014; Malinauskas et al., 2007).

Regarding gender, evidence has been found that young men drink more than their female counterpart, which could be partially explained by biological differences (Borsari et al.; 2007, Wood et al., 2004; Wicki et al. 2010). In contrast, Betancourth-Zambrano et al. (2017) report similar levels of consumption by gender in young Colombian students, as did Wicki et al. (2010) in the United Kingdom and some Nordic countries. Yi et al. (2017) in a study in nine Asian countries found that excessive alcohol consumption in men is associated with age and living with family or legal tutors, while for women it is associated with social relationships with elder groups. Regarding the family and social

[1] Energy drinks typically contain high levels of caffeine and different combinations of lots of added stimulants like guarana, taurine, ginseng, synephrine, L-carnitine L-tartrate (LTLC) yerba mate, gingko, St. John's wort.

environment, Wicki et al. (2010) find that students who live alone or outside the family nucleus are more likely to consume alcohol. Cáceres et al. (2006) point out that having family and friends who consume alcohol and other psychoactive substances are important predictors of their consumption. In turn, it has found that the probability of consumption is associated with positive evaluations of it and that these could induce risky behaviors by underestimating the harmful effects, especially of legal psychoactive substances such as alcohol and tobacco. Wicki et al. (2010) affirm that students tend to overestimate alcohol consumption in quantity, frequency and pattern in their peers, being this bias more pronounced among heavier drinkers. Among the reasons why university students declare consuming alcohol two types can be mentioned: enhancement motives and social reasons. The former refers to positive experiences, where alcohol consumption is for pleasure, to relax and / or have fun (Wicki et al. 2010). Several authors agree that it has an important social component, related to leisure, fun and attendance at events in which the intake of alcoholic beverages is promoted (Kunsche et al., 2005; Cáceres et al., 2006).

In regards to econometric studies about demand alcohol price elasticities are estimated. Many empirical studies explain the current consumption with the former consumption, corroborating that past habit set the future ones (Waters and Sloan, 1995; Grossman et al., 1998; Bentzen et al., 1999; Baltagi and Griffin, 2002; Bask and Melkersson, 2004). These kind of studies employ data from longitudinal surveys that contain the "history" of individuals making it possible to analyze the reaction of consumption to variations in prices and regulations, in addition to controlling for unobserved heterogeneity. Many authors estimate the current consumption according to the rational addiction theory (Becker and Murphy,1988; Becker et al. 1991) which assumes that drinkers are rational in the sense that they anticipate the expected future consequences of their current actions. They are aware of their addiction but they may choose to drink because the gains from the immediate pleasure exceed the costs through future addiction. Baltagi and Geishecker (2006) estimate the current alcohol consumption in Russia using a nationally representative Russian survey spanning 1994-2003 and find that consumers are sensitive to price changes, since price elasticities are negative and statistically significant. These authors do not find concluding support for the rational addiction theory. In the same framework of rational addiction, Keng and Huffman (2006) estimate the impact of binge drinking on labor market earnings in the United States. The authors use data from a nationally representative sample of 12,686 young men and women who were 14 to 21 years old when they were first surveyed in 1979 and subsequent follow-ups and find that binge drinking behavior is quite alcohol-price responsive and is supports the rational addiction theory. An interesting result is that an individual's decision to binge drink has a statistically significant negative effect on his/her earnings, as opposed to previous studies that suggested a positive effect.

Binge drinking habit is a risky behavior that can be and modeled as a contingent consumption. In this sense, health economics can apply the approach of consumption under uncertainty conditions to analyze the decision of dangerous drinking. Dave and Saffer (2008) explicitly incorporate risk preferences in the empirical specification of an alcohol demand function. Traditionally, empirical studies about alcohol demand do not include individual preferences explicitly due to the lack of data and consider them part of unobserved heterogeneity. The mentioned authors introduce a measure of attitude towards risk based on the possibilities of increasing / decreasing labor income. These hypothetical questions are validated by psychologists and capture individual's willingness to gamble over lifetime income. The authors notice that accounting for risk preference in alcohol demand provides information on any differential effects of prices and policy across heterogeneous sub-populations. Risk preference may affect the price elasticity of alcohol and the response to other alcohol control policies. If, risk-tolerant individuals are not price-sensitive then increasing taxes may have a greater proportional effect on light or moderate drinkers and would not be effective in reducing alcohol-related harms. Dave and Saffer (2008) do not find significant differences in the price responses among risk - tolerant drinkers and the rest of them, suggesting that raising alcohol excise taxes is an adequate policy tool for discouraging alcohol overconsumption. Despite the contribution of the work, it should be noted that the variables used to captures the risk preferences are not specially designed to measure the risk of exposing health, since

hypothetical situations about labor incomes do not necessarily reflect individuals´ attitudes to the risk of exposing health.

Another aspect mentioned in the literature on the decision to consume alcohol is right information about the low risk consumption. Islam et al. (2019) analyze the knowledge of low-risk drinking among Australian population with data from six waves of the National Drug Strategy Household Survey in the period 2001-2016. The low-risk drinking was defined according to the Australian Guidelines to Reduce Health Risks from Drinking Alcohol in 2009. They conclude that public knowledge was better for long-term than short-term low-risk drinking, and women had better knowledge than men and notice that since 2010 there has been a small increase in knowledge of low-risk drinking. Correct information about risky behaviors influences not only the demand but also the perception that the individual has about the risk to which they are exposed, as Fernández (2012) and Prata et al. (2006) note in their studies about condom use and HIV risk perception in Ecuador and Mozambique, respectively. These authors conclude that right HIV risk perception is positively associated with condom use in spite high proportions of individuals who considered themselves to have no risk were actually at moderate or high risk. The relationship between low-risk drinking and correct self- perception of risk is also applicable to alcohol drinking although it has not been completely understood. This research makes a contribution in this sense to previous literature introducing explicitly the students´ risk attitudes combining self-perceptions with objective risky behavior measured by AUDIT questionnaire.

III. Analytical framework

The objective of this study is to analyze the decision of individuals to ingest high amounts of alcohol in a short period of time (binge drinking). For this, a model of consumption habits under uncertainty is proposed as an analytical framework. Following Dave and Saffer (2008) let consider the utility function of drinking alcohol as:

$$U = U(A, Y, e), \tag{1}$$

where U specifies an individual's utility as a function of alcohol consumption A; Y denotes income that can be used to consume other goods, with exogenous preference parameter (e). The function U presents the characteristics of regular preferences, that is, marginal utility of alcohol consumption is positive and diminishing.

In a model of contingent consumption, the utility is not known with certainty since there are different possible probabilistic outcomes. These outcomes can be associated to “gains” and “losses” in the sense that alcohol provides pleasure and negative consequences. The positive effects are associated with stimulation and pleasure as well as social enhancement while the negative ones include since vomits, nausea, gastrointestinal disorders, higher exposition to crime and traffic accidents in the short run to productivity and health status losses in the long run. The individual´s preferences about risk tolerance in the alcohol demand function are relevant due to the outcomes from consuming or not consuming are probabilistic rather than known with certainty. The consumer maximizes an expected utility function that takes into account the set of gains and losses and their subjective associated probabilities.

The consumer choice about alcohol consumption is the result of the expected utility maximization:

$$\max[(1-\pi_c)U_c(HD) + \pi_c U_c(LRD), (1-\pi_{nc})U_{nc}(HD) + \pi_{nc}U_{nc}(LRD)\,], \tag{2}$$

where: U_c and U_{nc} are respectively the utility from alcohol consumption and no consumption; HD (heavy drinker) and LRD (low risk drinker) are the two possible states of nature, which are mutually exclusive. π_c is the probability assigned to utility of consumption in NB and $(1-\pi_c)$ is the probability assigned to utility of consumption in B. π_{nc} is the probability assigned to utility of no consumption in NB and $(1-\pi_{nc})$ is the probability assigned to utility of no consumption in B.

These probabilities are subjective and perceived by every individual according to his risk preferences. It is reasonable to assume that risk-averse individual places a higher weight on the loss in income and health than on an equal sized gain. It follows that as the expected utility function becomes more convex, the individual becomes more tolerant to risk and finds more valuable the potential gains than the potential losses from consumption. Dave and Saffer (2008) notice that risk preferences can have non-concluding effects on the demand. They point out that price sensitivity depends inversely on the magnitude of the rate at which alcohol marginal utility diminishes. The faster this rate decreases, the less price-sensitive a risk-tolerant will be since he needs more and more alcohol and may be less responsive to price. On the other hand, if risk tolerants´ rate of diminishing marginal utility is lower they will react to changes in prices. In short, the reaction of risk-tolerant individuals is not conclusive but must be empirically tested.

Assuming rationality, the individual will choose to consume alcohol when it verifies:

$$(1-\pi_c)U_c(HD)+\pi_c U_c(LRD) > (1-\pi_{nc})U_{nc}(HD)+\pi_{nc}U_{nc}(LRD) \quad (3)$$

The individual´ choice reveals if equation (*3*) is satisfied: when he declares to have consumed alcohol implies that the expect utility of consuming is greater than the expected utility of not consuming. The equation of individual consumption is:

$$y_i = \beta_0 + X_{1,i}\beta_1 + R_{1,i}\beta_2 + \epsilon_i, \quad (4)$$

being y_i a binary variable that equals 1 when individual consumes alcohol and 0 otherwise; $X_{1,i}$ is a $1 \times k$ order vector containing socioeconomic and demographic variables and $R_{1,i}$ a vector of risk preferences which introduce explicitly the individual´ level of tolerance respect exposing his/her health.

Operationally, equation (*4*) will be estimated by maximum likelihood assuming a discrete election model.

IV. Data

This study uses primary data, which includes the design and implementation of the Consumption Habits in University Students' Survey (CHUS Survey). This survey took place in August 2019 in two Argentinian Universities: Universidad Nacional de Córdoba and Universidad Nacional de Cuyo. One thousand three hundred ninety-seven (1397) first year students of the Economics Faculty in both Universities took part of this study, who represent the 73% of the enrolled students.

The survey assess principally the alcohol consumption and consists in seven sections: 1) knowledge about risky alcohol consumption, 2) characteristics of consumption of alcohol and other substances, 3) alcohol consumption in peers groups, 4) preferences related to alcoholic beverages, 5) risk perception, 6) Vulnerability, propensity and accessibility to alcohol and other substances, 7) Socioeconomic and demographic individual characteristics.

Table 1 shows the principal characteristics of the population under study, by University and gender, considering two important aspects: men and women metabolize the molecule of alcohol differently (Cremonte and Pilatti, 2017; Borsari et al., 2007), and there is evidence that generally men consume more than women (Wood et al., 2004; Boland et al., 2006; Andersson et al., 2007, 2009; Dumitrescu, 2007; Wicki et al., 2010; Strunin et al., 2017; Raich, 2018, among others).

Table 1: Descriptive statistics

Variable	Total			Córdoba			Cuyo		
	Total	Male	Female	Total	Male	Female	Total	Male	Female
Male	41.86%			43.00%			40.65%		
Age	19.97	19.73	20.10	20.03	19.75	20.17	19.91	19.72	20.04
Age of alcohol use initiation	15.02	14.77	15.22	14.91	14.70	15.08	15.15	14.85	15.37
Lifetime prevalence of alcohol use	95.71%	96.92%	94.82%	96.68%	97.74%	95.86%	94.67%	95.99%	93.75%
Past month prevalence of alcohol use	76.81%	80.21%	74.25%	79.37%	84.16%	75.63%	74.02%	75.67%	72.80%
Age of tobacco use initiation	16.01	15.86	16.15	16.16	16.04	16.28	15.86	15.65	16.02
Lifetime prevalence of tobacco use	52.68%	54.45%	51.29%	50.97%	53.55%	48.91%	54.52%	55.47%	53.75%
Age of marijuana use initiation	17.28	16.96	17.69	17.41	17.19	17.77	17.14	16.68	17.63
Lifetime prevalence of marijuana use	37.65%	48.46%	29.72%	37.26%	50.00%	27.49%	38.07%	46.72%	32.00%

Source: own elaboration.

V. Methodology and results

A. Risk perception assessment

One of the main contributions of this work is the analysis of students' preferences regarding their tolerance to the risk of exposing their health to dangerous behaviors. In order to get measures of these preferences, the individuals in the sample were classified in different classes of risk tolerance taken into account their curiosity, predisposition and risk self-perception. The methodology used is the Latent Class Analysis (LCA), a technique that presents the advantage of determine the optimal number of classes instead of establish it discretionally. The main characteristics of this method are summarized below and then the classes obtained are presented.

1. Latent Class Analysis[2]

Latent Class Analysis (LCA) is a person-oriented approach that emphasizes on the individual as a hole. Its focus involves studying individuals on the basis of their patterns of individual characteristics that are relevant for the problem under consideration (Lanza and Rhodes, 2013; Collins and Lanza, 2009; Bergman and Magnusson, 1997; Goodman, 1974; Lazarsfeld and Henry, 1968). It is a kind of framework that typically conducted by researchers in social behavior, in medical and health sciences, in marketing, and many more.

LCA comprises a set of techniques used to model situation where there are distinct groups, types or categories of individuals in empirical data and group membership is not directly observed. The term *latent* means that an error-free latent variable which is measured indirectly by means of two or more observed variables. Following Collins and Lanza (2009), observed variables are refer as *indicators* of the latent variables, to emphasize their role in measurement or item. These authors also used the term *item* when the observed variables are obtained through questionnaires or interviews.

In LCA each latent class is categorical, comprised of a set of latent classes, and these latent classes are measured by observed indicators, which are categorical, too. The array of observed variables representing characteristics, behaviors, symptoms, or the like is used as the basis for organizing individuals into meaningful homogeneous groups.

A latent class model is made up of estimated latent class prevalences and item-response probabilities that can be used to obtain expected cell proportions for the contingency table formed by cross-tabulating all the observed variables involved in the analysis.

[2] This section is based on Collins and Lanza (2009).

Following Collins and Lanza (2009), assume that are $j = 1, \dots, J$ observed variables, and variable j has $r_j = 1, \dots, R_j$ response categories. The contingency table formed by cross-tabulating the J variables has $W = \prod_{j=1}^{J} R_j$ cells. Corresponding to each of the W cells is a complete response pattern, which is a vector of responses to the J variables, represented by $\boldsymbol{y} = (r_1, \dots, r_j)$. Let $\boldsymbol{Y}$ refer to the array of response patterns, which has W rows and J columns. Each response pattern $\boldsymbol{y}$ is associated with probability $P(\boldsymbol{Y} = \boldsymbol{y})$, and $\sum P(\boldsymbol{Y} = \boldsymbol{y}) = 1$.

Let L represent the categorical latent variable with $c = 1, \dots, C$ latent classes. γ_c represents the prevalence of latent class c, or in other words, the probability of membership in latent class c, or in other words, the probability of membership in latent class c of latent variable L. The latent classes are mutually exclusive and exhaustive, so each individual is a member of one and only one latent class. Therefore,

$$\sum_{c=1}^{C} \gamma_c = 1. \tag{5}$$

The item-response probability $\rho_{j,r_j|c}$ represents the probability of response r_j to observed variable j, conditional on membership in latent class c. The set of ρ parameters are measurement parameters and expresses the relation between each observed indicator variable and each latent class. These parameters express how closely individuals can be classified into latent classes given the set of observed variables. Each individual provides one and only one response alternative to variable j so,

$$\sum_{r_j=1}^{R_j} \rho_{j,r_j|c} = 1, \tag{6}$$

for all j. They provide the basis for interpretation and labelling of latent class.

The probability of observing a particular vector of response is function of the probabilities of membership in each latent class and the probabilities of observing each response conditional on latent class membership:

$$P(\boldsymbol{Y} = \boldsymbol{y}) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j}^{R_j} \rho_{j,r_j|c}^{I(y_j = r_j)}, \tag{7}$$

where $I(y_j = r_j)$ is an indicator function that equals 1 when the response to variable $j = r_j$, an equals 0 otherwise.

The factor $\prod_{j=1}^{J} \prod_{r_j}^{R_j} \rho_{j,r_j|c}^{I(y_j = r_j)}$ represents the probability of a particular observed response pattern y conditional on membership in latent class c:[3]

$$P(\boldsymbol{Y} = \boldsymbol{y}|L = c) = \prod_{j=1}^{J} \prod_{r_j}^{R_j} \rho_{j,r_j|c}^{I(y_j = r_j)}, \tag{8}$$

Equation *(8)* is used to evaluate the overall pattern of item-response probabilities. Because item-response probabilities are conditional probabilities, it is necessary to examine this pattern across all response alternatives for the variable and across all the latent classes. There are two criteria that define a

[3] The latent class model makes few assumptions. Due to the indicators are categorical, their joint distribution is multinomial. However, it makes the assumption of local independence, which states that conditional on latent class, observed variables are independent. It does not imply that the observed variables are independent in the full sample. Nevertheless, Huang and Bandeen-Roche (2004), Reboussin, Ip, and Wolfson (2008) lift the local independence assumption in latent class models (Collins and Lanza, 2009).

strong relation between an observed variable j and a latent variable L: homogeneity[4] and latent class separation[5]. The first is an array of item-response probabilities corresponding to variable j that are close to 1 and 0. The second criterion is a distribution of $\rho_{j,r_j|c}$ for variable j that varies across the latent classes. Each of these criteria is necessary for defining a strong relation, neither alone is sufficient. An observed variable is strongly related to the latent variable if the array of item-response probabilities across the latent classes for that variable clearly differentiates the latent classes.

After that, it is possible to turn things around and think in terms of the probability of membership in latent class c conditional on response pattern y, $P(L = c|\boldsymbol{Y} = \boldsymbol{y})$. The last expression is called the posterior probability or classification probability and is obtained using Bayes´s theorem. This reflects the person orientation inherent in LCA and enables to consider each individual´s likely latent membership given his or her observed response pattern.

Next equation can be used to obtain a vector of classification probabilities for each individual based on that individual´s observed response pattern and the latent class prevalences and item-response probabilities from any latent class solution fit to the data.

$$P(L = c|\boldsymbol{Y} = \boldsymbol{y}) = \frac{\left(\prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}\right)\gamma_c}{\sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}} \tag{9}$$

This vector will include the probability of membership in each of the C latent classes for that individual. In general, associated with each observed response pattern, there is a nonzero posterior probability of membership in each latent class.[6] Collins and Lanza (2009) assert that when there is both strong homogeneity and strong latent class separation, there is high degree of classification certainty, and individuals have large probability of membership in one and only one latent class and low probabilities in the remaining latent classes. That is, it is clear to which latent class the individual belongs based on his or her individual´s observed response pattern.

So, individuals with response pattern $\boldsymbol{y}$ are assigned to latent class c, using a modal assignment. In other words, individuals are assigned to the latent class for which their posterior probability, $P(L = c|\boldsymbol{Y} = \boldsymbol{y})$, is bigger.

2. Measures

Dichotomous variables are used for the LCA, which adopt the value "2" when the individual present the characteristic that each variable represent, otherwise the value is "1".

Among the collected, next student´s observed responses are chosen to conduct the LCA.

1. Use of psychoactive substances

Data from the CHUS Survey provides information about age of initiation and lifetime use of alcohol, tobacco and marihuana. Three variables for lifetime use of alcohol, tobacco and marijuana are created, the individuals that reported lifetime use of any of these substances are scored as "yes" in the

[4] Homogeneity of a latent class is the extent to which all members of the latent class are likely to provide the same observed responses. Item-response probabilities near 0 and 1 correspond to high homogeneity. This concept is analogous to factor´s saturation in factor analysis.

[5] Latent class separation is the extent to which the overall pattern of item-response probabilities across measured variables clearly differentiates among the latent classes. This concept is analogous to simple structure in factor analysis.

[6] Except for any latent class c for which $\rho_{j,r_j|c} = 0$ for at least one variable j.

variable concerned. Additionally, early psychoactive substance use is captured considering if the individual initiated alcohol, tobacco or marijuana use before 15 years old of age.

2. Risk perception coherence

The CHUS Survey includes the AUDIT questionnaire, which allows identifying risky drinking behaviors, according to the score obtained by each individual. They can be classified in low risk, risky and harmful drinkers, by their drinking characteristics. This measure of risky behavior regarding to alcohol consumption is called in this study, *objective risk*. The *subjective risk* is assessed by the individual risk perception of their own behavior related to alcohol. At individual level, when the objective risk matches with the subjective risk, it is scored as "yes" to the variable coherence. If the individual perceives a different risk exposure than the objective risk, it is scored as "no" to the variable *coherence*.

3. Propensity and accessibility to psychoactive substances

Regarding propensity to psychoactive substance use (alcohol, tobacco, marijuana, cocaine, ecstasy or tranquilizers), two variables are included in the analysis. If the respondent manifests that would try or have curiosity on any of the substances mentioned they are scored as "yes" in the variables *Would try psychoactive substances* and *Curiosity on psychoactive substances,* respectively.

Accessibility to substances is assessed by the behavior of their friends, when the individual declares that have friends that get drunk or consume marijuana frequently the variable "*Friends get drunk and/or consume marijuana"* are scored as "yes".

Table 2 resume the proportion of students presenting the characteristics describe above.

Table 2: Prevalence of behaviors, risk perception coherence, propensity and accessibility

	%
1. Behaviors	
Lifetime alcohol use	95.71
Lifetime tobacco use	52.68
Lifetime marijuana use	37.65
Early psicoactive substance use (<15 y.o.)	65.71
2. Risk perception vs AUDIT score	
Coherence	73.01
3. Propensity and accesibility	
Would try psicoactive substances	96.28
Curiosity on psicoactive substances	96.92
Friends get drunk and/or consume marijuana frequently	84.00

Source: own elaboration.

3. Results: Latent classes identified

Different LCAs are conducted to identify classes of students based on their risk preferences. Alternative solutions are studied, beginning with the most parsimonious (i.e., one class) and increasing the number of latent classes by one to determine the model that featured the best data fit. All LCA analyses are conducted with Stata 15 and LCA-Stata plugin, Version 1.2.1 (Lanza et al., 2018).

One of the advantages of LCA is the variety of tools available to assess the goodness-of-fit of the model and determine the appropriate number of latent classes. Table 3 represents goodness-of-fit indexes, entropy, likelihood-ratio statistic G^2 and LRT for different LCA models.[7]

Table 3: Fit statistics for different LCA solutions

LCA solutions	df	AIC	Adjusted AIC	BIC	Adjusted BIC	Entropy	G^2	LRT	LRT test (p)
1-Cluster	247	1570.72	1620.66	1612.66	1587.24	1.00	1554.72	-4874.44	0.00
2-Cluster	238	555.11	661.22	644.22	590.22	0.71	521.11	-4357.64	0.00
3-Cluster	229	214.21	376.50	350.50	267.91	0.80	162.21	-4178.19	0.00
4-Cluster	220	179.06	397.53	362.53	251.35	0.73	109.06	-4151.62	0.03
5-Cluster	**211**	**175.28**	**449.93**	**405.93**	**266.16**	**0.68**	**87.28**	**-4140.72**	**0.12**
6-Cluster	202	183.59	514.42	461.42	293.06	0.58	77.59	-4135.88	0.46
7-Cluster	193	192.11	579.12	517.12	320.16	0.63	68.11	-4131.14	0.66

Note: Bold indicates the selected class solution.

The parametric bootstrap likelihood ratio test for LCA is also used to choose the number of classes for latent class.[8] This test is described in McLachlan and Peel (2000); Nylund, Asparouhov, and Muthén (2007); and Collins et al. (1993). The bootstrap likelihood ratio test is performed using the LCA Bootstrap Stata function (Huang et al, 2016).

Furthermore, each model is assessed for its interpretability to determine whether the classes represent in effect different categories (Pilatti et al., 2020, Collins and Lanza, 2009).

The 5-class model provides the most parsimonious[9] model based on the LRT and Akaike Information Criteria (AIC). The LRT compares whether a c class solution fits better than $c-1$ class solution, where a significant value suggests that the model shows better fit than $c-1$ class model. AIC is a goodness-of-fit index and smaller values indicate a greater model fit. An entropy-measure is also reported. Entropy is used to determine the accurancy of assignments of individuals into classes. As entropy ranges between 0 to 1, a value of 0.68 is high, suggesting the model succeeds to find homogeneous groups of students with separate profiles (Pilatti et al, 2020; Clark and Muthén, 2009).

It is also the most readily interpretable model. Table 4 and Figures 1 and 2 present latent class prevalences and item-response probabilities across risk preferences.

Class 1 (labeled as "High risk tolerance") comprises 25.7% of the sample ($n = 294$). Students in this class report high probabilities of alcohol consumption ($> 99\%$) and low prevalences of tobacco and marijuana consumption; however, exhibit high propensity to substance use. They began to consume psychoactive substances before age 15 and has friends who get drunk and/or consume marijuana frequently.

Class 2 (labeled as "Risk aversion") represents 3.4% of the sample ($n = 45$). Students in this class endorses the lowest probability of alcohol, tobacco and marijuana consumption, and the lowest propensity

[7] The likelihood-ratio statistic G^2 is a measure of absolute fit and reflects the correspondence between observed and expected cell counts in the contingency table made up by crossing all indicators of the latent class variable. Absolute model fit refers to whether a specified latent class model provides an adequate representation of the data.

[8] The parametric bootstrap likelihood ratio test for LCA tests the null hypothesis that a c-class LCA model is adequate to describe the population a particular sample came from, versus the alternative hypothesis that a (c+1)-class model is required. If the observed LRT statistic is bigger than most (say 95%) of the simulated LRT statistic, then the hypothesis is rejected.

[9] Parsimony is a philosophical principle stating that all else being equal, simpler models are preferred to more complex models. According to this principle, statistical models should estimate no more parameters, than is absolutely necessary to represent the data adequately (Collins and Lanza, 2009, Box, Jenkins and Reinsel, 2011).

to psychoactive substances use. They began to consume after age 15 and have less friends who got drunk and/or consume marijuana frequently than the other four latent classes. This cluster exhibits high risk perception coherence.

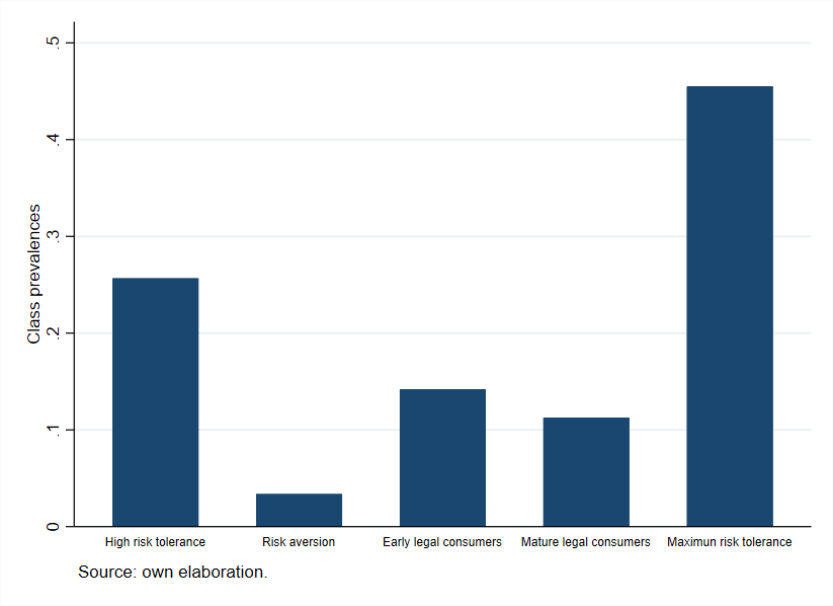
Table 4: Latent Class prevalences and Item-Response Probabilities

Class prevalences/Item-response probabilities	High risk tolerance	Risk aversion	Early legal consumers	Mature legal consumer	Maximun risk tolerance
	Class 1	Class 2	Class 3	Class 4	Class 5
Latent Class prevalences	25.67%	3.37%	14.19%	11.26%	45.50%
	(0.06)	(0.01)	(0.05)	(0.03)	(0.04)
1. Behaviors					
Lifetime alcohol use	99.90%	27.04%	99.87%	85.41%	99.87%
	(0.03)	(0.00)	(0.07)	(0.00)	(0.00)
Lifetime tobacco use	24.83%	4.28%	29.70%	6.90%	90.79%
	(0.04)	(0.05)	(0.03)	(0.02)	(0.00)
Lifetime marijuana use	2.39%	1.60%	1.97%	11.79%	78.02%
	(0.03)	(0.01)	(0.02)	(0.04)	(0.00)
Early psicoactive substance use (<15 y.o.)	76.58%	7.14%	41.59%	5.13%	86.76%
	(0.05)	(0.08)	(0.04)	(0.02)	(0.00)
2. Risk perception vs AUDIT score					
Coherence	74.62%	85.72%	97.08%	93.25%	58.52%
	(0.03)	(0.03)	(0.05)	(0.02)	(0.00)
3. Propensity and accesibility					
Would try psicoactive substances	98.69%	23.48%	97.89%	97.04%	99.81%
	(0.01)	(0.01)	(0.07)	(0.00)	(0.00)
Curiosity on psicoactive substances	99.98%	14.71%	99.93%	99.83%	99.83%
	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)
Friends get drunk and/or consume marijuana frequently	90.37%	45.37%	39.59%	89.89%	96.39%
	(0.04)	(0.03)	(0.07)	(0.01)	(0.00)
Observations	294	45	157	205	696

Note: standard errors in parentheses.

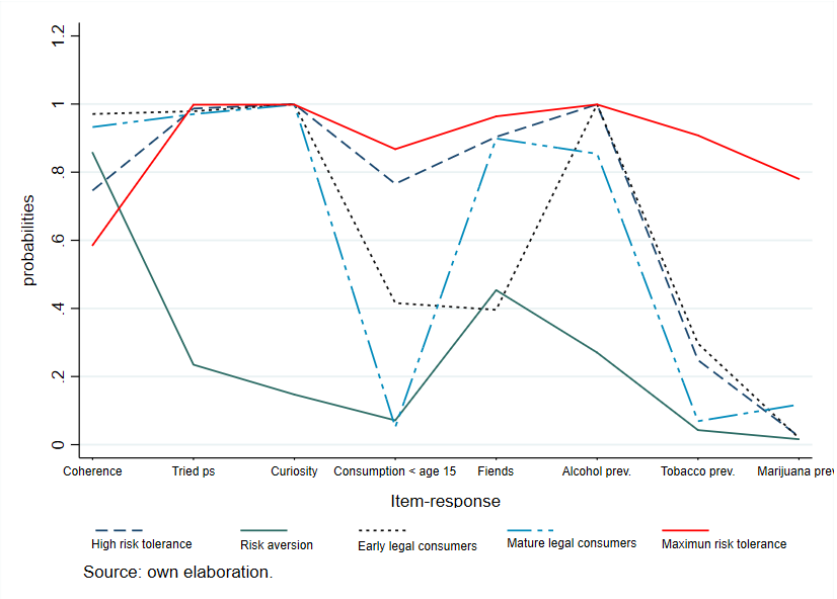
Latent classes 3 and 4 are relative homogeneous. Class 3 (labeled as "Early legal substances consumers") comprises of 14.2% of the sample ($n = 157$) and Class 4 (labeled as "Mature legal substances consumers") comprises 11.3% of the sample ($n = 205$). Students in both classes exhibit high probabilities of alcohol consumption, high propensity to psychoactive substances use and high risk perception coherence. The differences between both latent classes are lifetime tobacco and marijuana use, the onset age, and accessibility.

Figure 1: Prevalence of risk tolerance latent classes



Finally, Class 5 (labeled as "Maximun risk tolerance") comprises of 45.5% of the sample ($n = 696$). Students grouped in this class endorse the highest probabilities of lifetime alcohol, tobacco and marijuana use, the highest probability of begin consumption before age 15, and the highest propensity and accessibility to psychoactive substances use. This latent class exhibits the lowest risk perception coherence.

Figure 2: Item-response probabilities conditional on latent class membership.



The "Maximum risk tolerance" reports more risk behaviors and higher propensity and accessibility to psychoactive substances than the other four classes. But exhibits less risk perception coherence than the "High risk tolerance" class which, in turn reports less risk perception coherence than the "Risk Aversion"

class which also reports less risk perception coherence than "Mature legal consumers" and "Early legal consumers" classes do.

LCA posterior probabilities are used to assign students to classes. Then, a probit regression with sample selection was used to explore the contribution of a set of variables and the latent classes estimated on the adoption of HED pattern.

B. Heavy episodic drinking pattern analysis

1. Probit model with sample selection

For the estimation of the probability of incurring in the HED pattern we employ a probit model with sample selection (Van de Ven and Van Pragg, 1981). It assumes that there exists an underlying relationship:

$$y_j^* = x_j\beta + u_j \qquad \textit{latent equation,} \tag{10}$$

such that we observe only the binary outcome,

$$y_j^{probit} = (y_j^* > 0) \qquad \textit{probit equation.} \tag{11}$$

The dependent variable (HED) may not be always observed. The dependent variable for observation j is observed if the individual declares that consumes alcohol (selection equation),

$$y_j^{select} = (z_j\gamma + u_{2j} > 0) \qquad \textit{selection equation,} \tag{12}$$

where:

$$\begin{gathered} u_1 \sim N(0,1) \\ u_2 \sim N(0,1) \\ corr(u_1, u_2) = \rho \end{gathered} \tag{13}$$

When $\rho \neq 0$, means that both equations in the model are not independent and standard probit techniques applied to exploring HED pattern would yield biased results. We estimate the probabilities of HED using the heckprobit command of Stata, with robust standard errors (vce) robust.

2. Variables

Table 5 presents descriptive statistics for the variables used to estimate the probability of HED prevalence, divided according to whether respondents consume alcohol and presents HED pattern, consume alcohol and do not present HED pattern or do not consume alcohol nor present HED pattern. This set of variables include gender, marital status, living with parents or family, lived a traumatic family situation, drinking motives, consuming alcohol mixed with energetic beverages and participation on pre-drinking.

Table 5: Descriptive statistic of Heckprobit set of variables

	Consume alcohol and HED N=706	Consume alcohol and no HED N=631	Do not consume alcohol nor HED N=60
Variable			
Male	0.50	0.34	0.30
Single	0.97	0.93	0.95
Lives at home	0.73	0.77	0.90
Harmful drinking knowledge index (1 to 10 scale)	8.08	8.23	7.98
Lived traumatic family situation	0.40	0.40	0.33
Drinking motive: enhacement	0.85	0.71	0.00
Drinking motive: social	0.12	0.18	0.00
Drinks alcohol mixed with energetic beverages	0.73	0.52	0.00
Participates in pre-gaming or "previa"	0.98	0.88	0.57
Drinking before party or bar	0.53	0.38	0.17
Frequency of participation in pre-gaming			
1. more than once a week	0.07	0.03	0.00
2. once a week	0.21	0.10	0.11
3. 2 or 3 times a month	0.41	0.30	0.17
4. once a month	0.20	0.26	0.43
5. less than once a month	0.11	0.31	0.29
Class 1: High risk tolerance	0.19	0.26	0.00
Class 2: Risk aversion	0.00	0.01	0.58
Class 3: Legal substances early consumer	0.05	0.19	0.00
Class 4: Legal substances mature consumer	0.07	0.21	0.40
Class 5: Maximun risk tolerance	0.69	0.33	0.02

Source: own elaboration.

It may be interest also, analyze the variables used for a probit regression. Table 6 shows the percentages for the total and by classes of: gender, marital status, lives with parents or family, lives traumatic family situation, drinking motives, consuming alcohol mixed with energetic beverages and engaged on pre-drinking. Figures 3 and 4, shows frequency of participation in pre-gaming and harmful drinking knowledge index, for the total and by classes.

Table 6: Variables used for a probit regression, percentage by classes

	TOTAL	Class 1: Higth risk tolerance	Class 2: Risk averse	Class 3: Legal Substances early consumer	Class 4: Legal Substances mature consumer	Class 5: Maximum risk tolerance
Male	40%	43%	29%	28%	38%	47%
Single	95%	97%	93%	91%	98%	95%
Lives at home	76%	77%	78%	75%	84%	73%
Lived traumatic family situation	42%	36%	38%	42%	39%	41%
Drinking motive Enhacement	75%	79%	13%	70%	60%	83%
Drinking motive social	14%	14%	2%	16%	17%	14%
beverages	63%	65%	20%	46%	51%	70%
Participates in pre-gamin or "previas"	46%	47%	4%	25%	35%	53%

Figure 3 shows the frequency of participation in pre-gaming for the total sample and by classes.

Figure 3: Frequency of participation in pre-gaming by Latent Classes

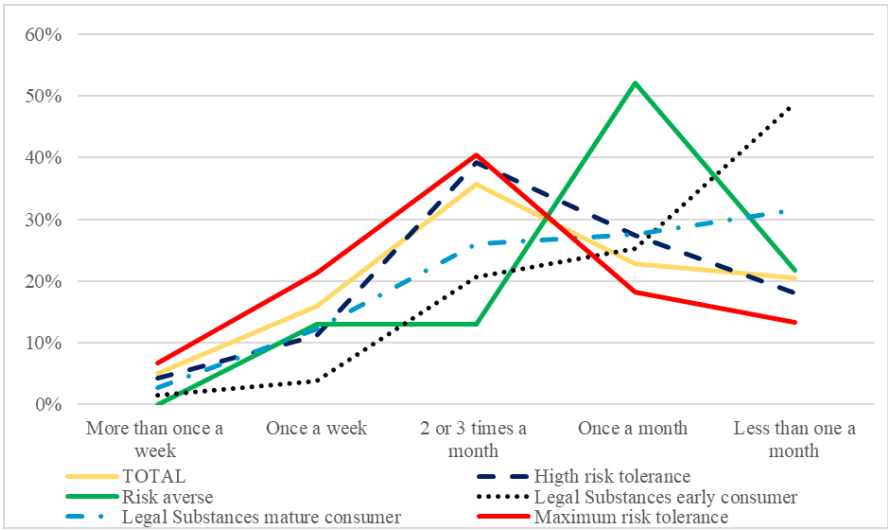
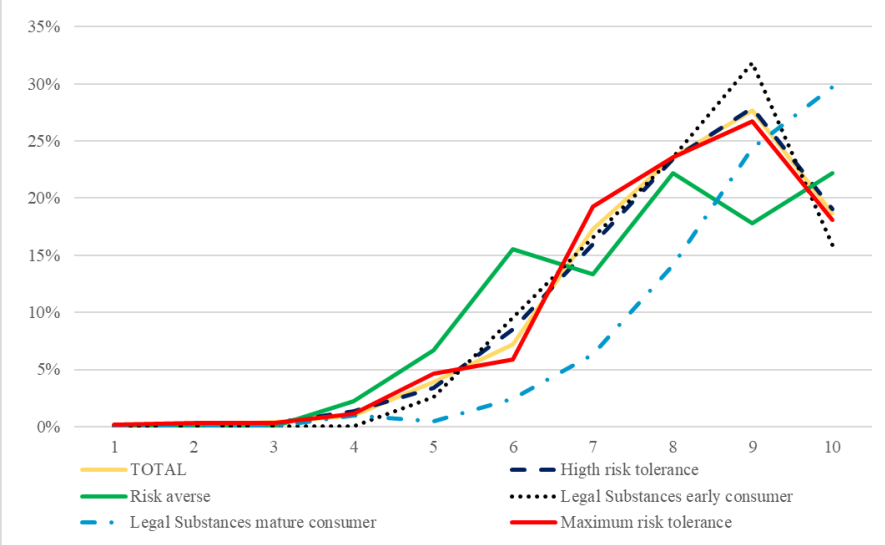


Figure 4 shows the knowledge index about harmful drinking for the total sample and by classes.

Figure 4: Harmful drinking knowledge index by latent classes



3. HED probabilities estimation results

The results of the probit regression with sample selection to estimate HED probability are presented in Table 7.

Table 7: Probit regression with sample selection results. Coefficients and marginal effects

	Consume alcohol	HED	HED Margins at means
	Selection ecuation		
Variable			
Male		0.333***	0.132***
		(0.078)	(0.031)
Single		0.575***	0.227***
		(0.198)	(0.078)
Lived traumatic family situation		0.097	0.038
		(0.079)	(0.031)
Drinks alcohol mixed with energetic beverages		0.333***	0.131***
		(0.083)	(0.033)
Drinking before party or bar (i)		0.586**	-0.086***
		(0.256)	(0.015)
Frequency of participation in pre-gaming (ii)		-0.159***	0.065**
		(0.046)	(0.032)
Interaction (i) (ii)		-0.125*	
		(0.073)	
High risk tolerance		0.884	0.349
		(0.611)	(0.241)
Legal substances early consumer		0.694	0.274
		(0.620)	(0.245)
Legal substances mature consumer		0.575	0.227
		(0.614)	(0.242)
Maximun risk tolerance		1.489**	0.588**
		(0.608)	(0.240)
Drinking motive: enhacement	12.339***		
	(0.957)		
Drinking motive: social	13.205***		
	(0.434)		
Lives at home	-0.735*		
	(0.420)		
Harmful drinking knowledge index (1 to 10 scale)	0.034		
	(0.084)		
Participates in pre-gaming or "previa"	7.150***		
	(0.376)		
Constant	-6.399***	-1.486**	
	(0.750)	(0.652)	
Observations	1317		
Censured observations	60		
Wald test of indep.	4.587		
p-value	0.0322		

Robust standard errors in parentheses; Latent class of reference: risk aversion
*** p<0.01, ** p<0.05, * p<0.1

The selection equation, for alcohol consumption, includes dummies variables about drinking motives (enhancement and social), living with family, knowledge index about harmful drinking effects and participation in pre-gaming. All these variables were statistically significant with exception of harmful drinking knowledge. The binary outcome of presenting HED is positively influenced by being male and single, having combined alcohol with energetic drinks, participation in pre-gaming before party

or bar and frequency of participation in pre-gaming. Maximum Risk Tolerance appears as the only latent class statistically significant predictor of HED, suggesting that individuals classified as highly tolerant about exposing their health are more likely to present HED pattern.

It also must be noted that the parameter rho is statistically different from zero (p-value<0.05), which means that equations in the model are not independent. This result suggests that there is a selection bias, since not all the student that drank alcohol have the same probability of presenting HED pattern.

Table 8 shows the predicted probabilities of HED by the latent classes previously identifies, for the total sample and by gender. The probability of HED is the lowest among the Risk Aversion Class, while the highest is among the Maximum Risk Tolerance Class. The other three intermediate risk classes present higher probability of HED as risk tolerance increases. When the predicted probabilities are analyzed by gender, it is notable that men are more likely to adopt the HED pattern.

Table 8: Predicted probabilities of HED by class evaluate at means

	High risk tolerance	Risk aversion	Legal substances early consumer	Legal substances mature consumer	Maximun risk tolerance
	Class 1	Class 2	Class 3	Class 4	Class 5
Total Sample	0.46	0.16	0.29	0.30	0.71
	(0.14)	(0.05)	(0.11)	(0.14)	(0.13)
Female students	0.39	0.14	0.26	0.24	0.66
	(0.12)	(0.09)	(0.10)	(0.10)	(0.13)
Male students	0.54	0.18	0.36	0.41	0.77
	(0.11)	(0.01)	(0.09)	(0.14)	(0.10)

Note: Standard deviation in parentheses.

VI. Discussion

In this study the patterns of alcohol consumption among college students is analyzed. With data raised through a validated instrument it was possible to characterize specific details about the motives, risk self-perception, information about the consequences of harmful drinking as well as habits such as pre-gaming, poly drug use, curiosity about psychoactive substances and availability of legal and illegal substances.

The results suggest that a vast majority of the students is correctly informed about the negative effects of heavy drinking. However, a high proportion fail to classify themselves correctly according to objective tests. In addition, it is confirmed that having consumed tobacco and alcohol at early age determines higher level of risk tolerance. In the same line, the habits of peers play a relevant role. As it was mentioned, who have friends that consume illegal substances have more chances of being maximum risk tolerant.

This research makes two main contributions to the literature of alcohol consumption. First, this study uses primary data, which includes the design and implementation of the Consumption Habits in University Students' Survey (CHUS Survey), in two Argentinian Universities: Universidad Nacional de Córdoba and Universidad Nacional de Cuyo. Second, another contribution of this research is the explicit incorporation of risk preferences in the analysis. In studies based on cross- section data these variables are in general ignored, while in data panel studies are treated as a fixed effect.

In this paper the individuals´ attitudes to risk are modelled with specific data about alcohol behavior, including a wide set of variables that reflect the utility function of the individuals. In addition, use of LCA to classify the individuals according to their risk is novel among economists and contribute rigorously to the analysis. Five classes of risk tolerance were defined to classify college students. These classes are heterogeneous regarding their lifetime prevalence of alcohol, tobacco and marijuana, their

propensity and accessibility to psychoactive substances use, and their risk perception coherence. The class including the most averse individuals only represents 4% of the sample, while the one with Maximum risk tolerant individuals represents 45% of the sample.

The analysis of harmful consumption with HED pattern reveals that a vast majority of students consumed alcohol in the last 30 days, 52% of them with a HED. The results of the model suggest that the probability of a harmful pattern is not uniformly distributed among all the students in the sample. On the contrary, those who participate in pre-gaming with high frequency and classified as maximum high risk tolerance have higher probabilities of HED. In fact, individuals in this class are 71% more likely to experience a HED respect the risk averse ones.

The habits of pre-gaming contribute to explain the higher probability of HED. Not only shows to be relevant participating in this kind of events, but also participating frequently.

The wide variety of degrees of risk tolerance suggests the relevance of targeted policies since the risk lovers have more chances of losing their future productivity and health. This cluster deserves special attention due not only their harmful drinking but also their simultaneous poly drug use.

It is necessary to highlight that there are some obvious limitations of this study. First, it is not based on data from the young population in general but from a group of university students; however, due to recent evidence that harmful consumption patterns in Argentina are no longer exclusive of lower income strata it is not considered a relevant limitation.

Second, although longitudinal data is not employed in this research, it contributes with specific variables to shed light about a current phenomenon that involves young college students in Argentina, who are exposed to harmful behaviors and social influences that can affect their future human capital and productivity. In further research it is necessary to make a deep analysis with longitudinal data to estimate the response of alcohol consumption to changes in prices and supply constraints.

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