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Modelling heterogeneity in young person's night-time choices – accounting for attitude towards alcohol consumption

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Abstract

This paper models behaviour of young people during leisure time, a context for which traditional rational choice models are of limited relevance. Young people are driven in their behaviour by hidden norms and group pressure that form their attitudes and which are not reflected in socioeconomic variables used normally in discrete choice analysis (income, professions, status etc.). We therefore construct psychological indicators of attitudes, normative beliefs and perception control following the Theory of Planned Behaviour and introduce them in our stated choice experiment.

Traditionally economists applying discrete choice analysis used to assume rational behaviour while the decision maker's preference formation remains unexplained. In contrast with this psychologists, and behavioural researchers in general, aimed at understanding how decisions come about and investigated (also) the nature of the decision-process itself. Over the last three decades, researchers moved by the desire to reduce the gap between behavioural theory and discrete choice models, have developed more complex and realistic models. Substantial efforts have already been devoted to incorporate preference heterogeneity on discrete choice models greatly enhancing the behavioural realism compared to the standard Multinomial Logit which assumes the same preference structure across individuals.

In this paper we investigate models capable to account for heterogeneity in individual's preferences and to incorporate indicators of psychological latent variables. Two kinds of models are estimated: Mixed Logit models which allow its preferences parameters to vary with a known continuous population distribution across individuals, and Latent Class models which assume that a small number of latent classes are sufficient to account for parameters heterogeneity.

Considering a leisure night-time activity choice context, we use survey data from high school and university students to test the significance of psychological variables – principally regarding on alcohol attitude and drinking behaviour – postulated to be relevant for night-time choices. Our results confirm the usefulness of the proposed extensions of the rational choice model.

Keywords

Stated Choice Models – Observable Preference Heterogeneity – Psychological Indicators – Theory of Planned Behaviour – Alcohol attitude

1. Introduction

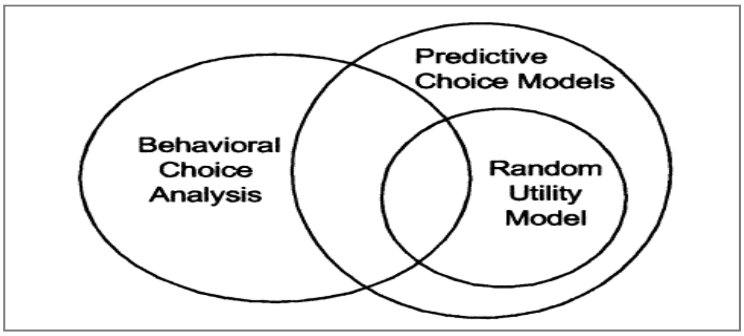
Over the past several decades there have been a variety of public initiatives aimed at curbing some undesired tendencies in young person's behaviours, such as the prevalence of abusive drinking, tobacco and drugs use, alcohol related fatalities as well as their related consequences. What is not very clear is why a lot of these policies tend to have unsatisfying results. From our point of view there is a lack of knowledge of young people's preferences and the transformation of their tastes into actual choices.

Since this subject deals with the complexity of human decision process, it is important to consider the potential contribution of different scientific disciplines (economists, engineers, psychologists, mathematicians, etc) to correctly identify the interacting variables in view of good policy advice.

From an economic perspective, Predictive Choice Models have been applied under a Random Utility Theory framework, assuming that individuals choose the preferred one from a set of available alternatives based on his own socio-economic characteristics and the attributes describing the available alternatives[1]. This approach has originated useful models enabling researchers to merge an explicit theory of behaviour with a micro representation (the neoclassical economics assumption of rational decision makers).

However, at the same time, it has been criticized, principally by psychologists, for its poor characterization of human behaviour.

Figure 1 Domain of Choice Research



Source: Ben-Akiva et al., 2002

[1] Throughout this work, we refer to Discrete Choice Analysis (DCA), which is when decisions are between mutually exclusive discrete alternatives.

In particular, recent literature in cognitive Psychology, Sociology and Behavioural Economics has shown that individuals very often violate the majority of the assumptions of the rationality postulate. Figure 1 (Ben-Akiva et al., 2002) shows the connection between Behavioural Choice Analysis and Predictive Choice Models.

On the one hand Behavioural Choice Analysis concentrates on deconstructing the decisional process and revealing potential irregularities. On the other hand, Predictive Choice Models highlight regularities in choice behaviour and introduce them in quantitative models with the objective of predicting individual decisions.

To reduce the existing gap, researchers in the field of discrete choice have recently made numerous efforts in order to introduce the preference formation process as well as psychological factors which determine human decisions in their models. Developing a general and more efficient approach, i.e. Hybrid Discrete Choice Models[2], Walker (2001) identifies three different methods that have been applied in order to model psychological latent variables in discrete choice analysis. One technique is to insert psychological indices directly into the utility function (see Greene, 1984 or Harris and Keane, 1998). A second approach is to insert the fitted variables obtained by performing a factor analysis on the indicators in the utility function (see Madanat et al. 1995). Another approach is to develop discrete choice models that infer latent attributes of the alternatives and individual preferences from choice data and, in a second step, use perceptual indicators to interpret latent variables. Following the methodological approach presented by Harris and Keane (1999) we add in our work psychological factors directly to the traditional discrete choice framework considering these indexes as a possible source of taste heterogeneity.

The paper examines the distribution of preferences in a sample of university and high school students who choose between hypothetical night-time leisure activities with different characteristics (see Hole, 2008 for an example on Health Economics). Choices about spare time are complex decisions involving several aspects such as destinations, activities, participants, etc. Furthermore they are also conditioned by several unobservable factors, such as beliefs about the likely outcomes, beliefs about the normative expectations of others, motivations to comply with expectations and beliefs about the presence of factors that may facilitate (or impede) performance of behaviour. In particular, our hypothesis is that alcohol related psychological variables are significant aspects in night-time leisure activities choice. We focus especially on the youth - an important segment of night-time leisure activity.

[2] HDCM can incorporate non-Random Utility Models and in particular they include: the addition of flexible disturbances, the explicit modelling of psychological factors and the inclusion of latent segmentation of the population (Ben-Akiva et al. 2002 and Raveau et al., 2010).

Attitude, social norms and perceived behavioural control with respect to alcohol consumption are chosen as relevant variables, and measured through ad-hoc instruments applied to a sample from university and high school students in Lugano. The survey, containing a stated choice experiment, allows to construct a stated preference (SP) database.

We estimated Mixed Logit Models and Latent Class Models which highlight significant preference heterogeneity almost for all the attributes. Moreover, the distribution of preferences implied by the preferred mixed and latent class models is similar for many attributes. Results show that preferences for different activities, such as spending some time in a pub or a disco, are positively related to positive alcohol attitudes. These results underline the additional insights that can be made from explaining preference heterogeneity trough psychological variables when analyzing data from discrete choice experiments.

The following Section 2 outlines the basic principles of the link between attitudes and behaviour. Section 3 give an introduction to the theoretical and methodological aspects of discrete choice models, in particular methodological specification refers to the mixed and latent class logit models. Section 4 describes the discrete choice experiment and how we have construct indicators for psychological variables. Section 5 presents our models and reports the results. The last one, Section 6 concludes.

2. Aspects linking attitudes and behaviour

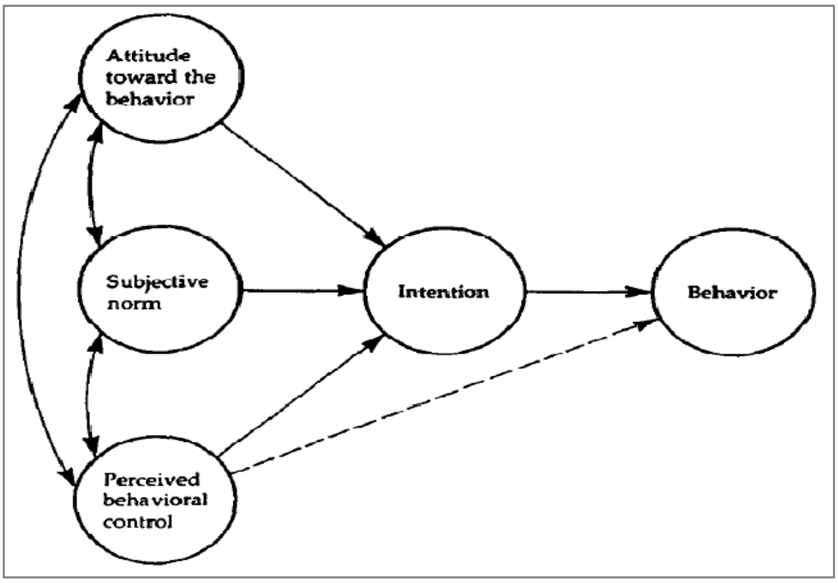
In the field of discrete choice analysis, attention has focused on the preferences for attributes related to the available options and individual constraints, but it is recognized that different interactions of psychological factors such as beliefs, emotions, attitudes, life styles and personality traits occur when individuals choose an alternative. Several researches in social psychology have shown that the relationship between attitude and behaviour can help to understand the decision making process underlying choices (Forward, 2004 and Domarci et al., 2008, for some applications in the transport field).

This research uses the Azjen's Theory of Planned Behaviours (TPB) as a base for the behavioural part[3]. Azjen proposes a hypothetical scheme illustrating how individual actions are guided. The scheme, depicted in Figure 2, explains the three psychological variables which TPB suggests will predict the intention to perform a behaviour.

[3] The TPB is one of the most successful predictive models of health behavior in Psychology.

In fact, it is assumed that, although there is not a perfect correspondence between behavioural intention and actual behavioural, intentions can be used as a proxi for behaviour.

Figure 2 Domain of Choice Research



Source: Ajzen, 1991

To predict whether a person intends to do something TPB considers three concepts: attitudes (whether the individual is in favour of doing something), subjective norm (how much the person feels social pressure to do it) and perceived behavioural control (whether the individual feels in control of the action in question). These three variables also influence each other.

Ajzen indicates, as a general rule, that the more favourable the attitude and the subjective norm, and the greater the perceived control, the stronger should be the person's intention to perform the behaviour in question.

3. Random Utility Models for Discrete Choice

Discrete choice models are useful when individual decisions involve making a choice between mutually exclusive discrete alternatives. Discrete Choice Analysis (DCA) is based on the integrated and tested Thurstone's (1927) Random Utility Theory (RUT) and it owes much to McFadden (1974) who extended Thurstone's pairs to multiple choices. The idea behind RUT is that there exists a latent construct, called "utility", in individual's heads which cannot be observed by researchers (and the decision maker might not even be conscious about it). It is assumed that decision makers are able to compare alternatives and choose the one that provides the greatest level of satisfaction or utility.

The unobservable utilities, one for each choice option, can be decomposed into two parts: one is systematic and observable (explainable) by the analyst and the other one is random and unobservable (unexplainable). Factors of the systematic component are the attributes of choice options, that can be identified, and individual characteristics that explain differences in choices. The random component includes all unidentified factors that impact choices and reflects the agent specific idiosyncrasies of tastes which are not observed. Different specifications of the random components lead to different multinomial models.

Manski (1977) identified the following distinct sources of randomness: unobserved attributes, unobserved taste variations, measurement errors and instrumental variables. Imposing different structure on the random component implies different assumptions on the sampled population distribution across the alternative in the choice set. All in all, the randomness arises because researchers do not have perfect information on the set of influencing factors and on the complete decision process, so they can only explain choices using a probability framework. It should be clear that the partition between deterministic and random components does not mean that decision makers maximize their utility index in a random manner (individuals could also be deterministic utility maximizers).

The common assumptions in Multinomial Logit models (MNL) are homogeneity of preferences - that is, the systematic component of utility is assumed not to vary across decision makers - and the variance of the random component is assumed to be independently identically distributed. The Mixed Multinomial Logit (MLM) and Latent Class Logit (LCM) models have the potential to overcome some of the limitations of the MNL model and, in particular, they offer two different ways of capturing heterogeneity[4]. More precisely, a characteristic of Mixed Multinomial Logit and Latent Class Logit models is the ability to extend the MNL model by allowing the parameters – which represent taste weights – to vary between respondents. This capacity to model preference heterogeneity has the potential to greatly enhance the behavioural realism of the model compared to the standard logit. In fact, incorrectly restricting preferences to be homogeneous, if in reality tastes do vary across decision makers, will lead to biased parameter estimates for any specific individual. For instance, in the present context, some students might have a strong preference for pub regardless of the other attributes or activities of the night, whereas others may strongly prefer cinemas.

[4] In the MNL model this variation in preferences may be captured by interacting alternatives attributes with the socio-demographic characteristics of the respondents, but it is likely that some of the preference heterogeneity is unrelated to observable personal characteristics.

An additional limitation of the MNL is that it assumes the observations to be independent, which is unlikely in data from discrete choice experiments where the respondents complete several hypothetical choices. Consider a sample of N decision makers choosing the alternative that provides the greatest utility from J alternatives on T choice occasions. The utility that individual n receives on choice occasion t from choosing alternative j is given by:

$$U_{njt} = V\left(z_{njt}, s_n\right) + \varepsilon_{njt}$$

The vector ε_{njt} is the random part of the utility function, also called disturbance (or random component). It captures the factors reflecting the individual specific idiosyncrasies of tastes which are not observed from the researcher and it is assumed to be distributed IID extreme value. On the other hand V_{njt} is the deterministic component of the utility, a sort of mean of U_{njt}, and describes the role of measured (observed from the researcher) attributes on choices. The vector z_{njt} contains attributes related to alternative j as viewed by the decision maker n and it is common to all the individuals facing the choice occasion t. Instead, s_n is a vector of characteristics of individual n, i.e. it is individual specific. Combining z_{njt} and s_n in a single vector x_{njt} of observed variables and assuming a linear form for V_{njt} we can rewrite U_{njt} as:

$$U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt}$$

where β_n is the vector of individual specific coefficients which represent the preference weights. The density of β is denoted as $f(\beta|\theta)$ where θ are the parameters of the distribution. Following Revelt and Train (1998), conditional on knowing β_n, the probability of respondent n choosing alternative i on choice occasion t is given by the Logit formula (Mc Fadden, 1974):

$$L_{nit}(\beta_n) = \frac{exp\left(\beta_n' x_{njt}\right)}{\sum_{j=1}^{J} exp\left(\beta_n' x_{njt}\right)}$$

The unconditional probability is a weighted average of a product of logit formulas evaluated at different values of β, with the weights given by the density f: The distribution of β can be either continuous, as in the specification of MLM model, or discrete, as specified by the LC model[5].

[5] A paper by Greene and Hensher (2003) compared the MLM with the LCM. They concluded that MLM and LCM give attractive specifications than the MNL, but it is not possible to decide that one approach is unambiguously preferred to the other.

Apart from these differences the two families of models differ in the estimation method6. The log-likelihood for both models is given by:

$$LL(\theta) = \sum_{n=1}^{N} ln\, P_n(\theta)$$

The challenge, for the MLM model, is that there is no closed-form solution for the integral (as mentioned the unconditional probability is a weighted average), whose dimension is given by the components of β_n that are random, with non zero variance, and it is therefore approximated using simulation methods (see Train, 2009). The simulated log-likelihood (SLL) is given by

$$SLL^{MLM}(\theta) = \sum_{n=1}^{N} \ln\left[\frac{1}{R}\sum_{r=1}^{R} S_n(\beta^r)\right]$$

where R represents the number of replications, and β^r, $r = 1, \dots, R$, are random draws from $f(\beta|\theta)$. Methods for speeding up computation include use of Halton sequences and alternative simulators. See Gourieroux, C. and A. Monfort (1996) and Train (2009) for discussion and extensive analysis of maximum simulated likelihood estimation.

In contrast, estimation of the LCM does not require simulation methods. The log-likelihood (LL) for the latent class logit model with C latent classes is given by

$$LL^{LC}(\theta) = \sum_{n=1}^{N} ln\left[\sum_{c=1}^{C} M_{nc} S_n(\beta_c)\right]$$

where M_{nc} is the probability that individual n belongs to class c and β_c is a vector of class-specific coefficients. The class formulation is unknown so various structures have been used for this probability (see Greene, 2001). Following Geene and Hensher (2003) a particularly convenient form is the multinomial logit:

$$M_{nc}(\gamma_c) = \frac{exp(\gamma'_c u_n)}{\sum_{c=1}^{C} exp(\gamma'_c u_n)}$$

where u_n is a vector of segmentation variables which could contain observable alternative's attributes and individuals' characteristics; γ_c is a vector of parameters for segment c ($c =$

[6] In the common practice the MLM and LCM differ in another respect: while both models can handle correlations between the coefficients the mixed logit is often estimated with uncorrelated coefficients while the latent class model implicitly allows the coefficients to be correlated. Allowing for correlations between the coefficients matters is an empirical question that in the mixed logit case can be tested using a likelihood ratio test by comparing two models with and without correlated coefficients.

$1, 2, \ldots, C$). For identification, segment membership coefficients for one of the segments are normalized to zero. Determination of the best number of segments, C, requires an evaluation of two indices: BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion). The BIC is often used because it imposes a harsher penalty on the number of parameters than the AIC and log-likelihood value (Walker and Li, 2007).

4. The Survey

Our questionnaire is composed by two parts: in the first one we collected data, based on the TPB, on alcohol consumption; in the second one, each student (they come from university and high schools) answered to a simple SP experiment choosing between two hypothetical alternatives describing night-time activities.

A total of 200 questionnaires were distributed (with a response rate of 62%) and, after a data screening phase, we identified 104 questionnaires valid for the study. Some descriptive statistics, regarding the valid response sample are summed up in Table1.

Table 1 Descriptive statistics

Age		
	Mean	19,8
	Min	16
	Max	30
Gender		
	Male	60
	Female	44

The final sample size represents a problem when attempting to extend our results, nevertheless the paper's objective is only to gain a better understanding of the choice phenomenon, by identifying observed heterogeneity in preference and measuring alcohol attitude and behaviour associated with it[7].

Even though in Switzerland it is forbidden to sell alcohol to under age (18 years old), we decided to extend the analysis also to 16 years old students. In fact, there is more and more evidence that also in this age range the alcohol consumption level is significant.

[7] Azjen indicates that a sample size of 80 is acceptable for TPB studies.

4.1 The Psychological Indicators of Attitude toward Alcohol Consumption

This research focuses on modelling observed heterogeneity in young persons' night-time choices accounting for habit, attitude and behaviour using conventional methods and adapting them into an ad hoc survey. The premise is that alcohol consumption intention has an important effect on night time choices. The ad-hoc part of the survey, measuring psychological indicators, was based on the TPB scheme. The psychological indicators are hypothetical or latent variables, i.e. they cannot be directly observed but instead they should be inferred from observable responses. We have constructed and scored a questionnaire which measures these variables involving the use of both qualitative and quantitative methods. These internal constructs can be measured directly, asking individuals about their overall attitude, or indirectly, asking respondents about specific behavioural beliefs and outcome evaluations. In this case, we considered only direct measures of attitude, social norm and perceived behavioural control.

Questions were developed from pilot interviews with 13 undergraduates and 10 university students (not included n the later analysis). All items were scored on a seven point response scale following the procedure outlined by Ajzen (1988) and, in particular, we followed step by step the useful and detailed manual by J.J Francis et al. (2004) to construct our questionnaire based on TPB.

Respondents' direct measurement involves the use of pairs of opposite adjectives (e.g. bad-good) being evaluated. Students' direct attitude towards alcohol consumption was measured through the use of seven point Likert scales. We use five items following the same open ended statement: <<*In a typical session with my friends, to increase my alcohol consumption would be…*>>. We included two instrumental items (whether the behaviour achieves something, e.g. *useful-worthless*) and two experimental items (how it feels to perform the behaviour, e.g. *unpleasant-pleasant*) and the last was the *good-bad* scale, as it captures overall evaluation of the behaviour. To minimize the risk of "response set" we arranged the items so that the ends of the scales were a mix of positive and negative endpoints. The synthetic index for an overall attitude indicator was calculated as a simple mean of correlated items (see APPENDIX A).

Direct measurement of individuals' subjective norm involves the use of questions referring to the opinions of important people in general. In this research, subjective norms are respondent's own estimate of the social pressure to increase their alcohol consumption. We used three items: <<*In a typical session with my friends, It is expected of me that I increase my alcohol consumption*>>, << *Most people who are important to me think that I should/I should not to increase my alcohol consumption*>> and <<*People who are important to me think that to increase alcohol consumption is …*>>. Where items are a complete sentence students' responses range from '*Strongly disagree*' to '*Strongly agree*'. The synthetic index for an overall subjective norm indicator was calculated as a simple mean of correlated items.

Items developed for a direct measurement of perceived behavioural control should reflect respondents' confidence that they are capable of implementing the target behaviour. More precisely, we assessed the student's self efficacy and his beliefs about the controllability of the behaviour using the following statement: <<*I am confident that I could increase my alcohol consumption during a session with my friends*>>. Controllability was assessed by asking students to answer two questions: <<*The decision to increase my alcohol consumption during a session with my friends is beyond my control*>> and <<*Whether increase or not my alcohol consumption during a session with my friends is entirely up to me*>>. By calculating the mean of these item scores we obtained an overall perceived behavioural control indicator.

4.2 The Stated Preference Experiment

The data used in micro-econometric studies about discrete choices often arise from individual consumer choice. The analyst may collect this kind of data according to two different approaches: Revealed Preference (RP) survey and Stated Preference (SP) survey. RP data represent data collected on actual choices and they represent datasets on real life. Stated preference (SP) data refers to choices made given hypothetical situations. SP data are generated by some planned design process in which attributes and their levels are defined and varied to create choice alternatives.

In this work, we decided to use SP data because of its flexibility and because these data are more useful for forecasting changes in behaviour. As a consequence, an SP experiment was developed at the University of Lugano and at the Liceo2, a high school in Lugano, with the aim of quantifying the relative strength of young people's preferences for different activities at night-time. In order to refine our understanding of the problem we conducted an interviewer briefing. The objective was twofold: to summarize aspects and activities of night-time decisions that could act as repulsion or attraction factors and to identify relevant attributes and attribute levels characterizing these kinds of decisions. The attributes' levels are shown in the Table 2.

We used the NGENE software to develop an unlabeled experiment - with the classical assumption of orthogonality between attributes' levels - and the result was an experiment composed by two blocks with 12 choice tasks for each block.

Students are asked to choose between two hypothetical night plans (for a typical session during the week-end) and the "*no choice*" option is given by "*I will stay at home*".

Table 2 Attributes and levels in the discrete choice experiment

Attribute / Activity	**N°Levels**	**Levels**
N° of participants	2	≤ 3 8 ≤ x ≤ 10
Dinner	3	At home Restaurant 25CHF Restaurant 50CHF
After dinner	2	Pub Cinema
Discotheque	2	Discotheque Come back to home
Cost (dinner not included)	2	20CHF 60CHF

Each student was asked to complete a pencil and paper questionnaire were the front page gave them a brief description of alternatives and levels (except for price levels) of their attributes.

Figure 3 Example of a choice task presented to respondents during the DCE

Scenario #	**Alternative A**	**Alternative B**	**I will stay at home**
N° of participants	≤ 3	8 ≤ X ≤ 10	
Dinner	Restaurant 25CHF	At home	
After dinner	Cinema	pub	
Discotheque	No, come back to home	Yes, discotheque	
Cost *(dinner not included)*	20 CHF	60 CHF	
Please show your preferred alternative by ticking one box	☐	☐	☐

In each choice task the students could select between two unlabeled alternatives described by different characteristics (see Fig. 3 for an example).

5. Results

Data from our survey were analyzed in two steps. First, psychological data were analyzed using a multiple regression procedure, entering intention as the dependent variable and the direct measures of attitude, subjective norms and perceived behavioural control as the predictor variables[8]. Then, instrumental variables were taken into account in MLML and LCM models in order to explain preferences' heterogeneity using methodology described in the Section 5.2.

5.1 The Reliability of Psychological Indicators

The survey results about psychological latent variables were analysed in two steps. First, psychological elements were studied in the context of each instrument, in terms of internal consistency in order to verify the reliability of the instruments. Then, we examined the ability of the TPB to explain intention to use alcohol regressing attitudes, subjective norms and perceived behavioural control on intention to drink.

For the direct measure of attitude we checked the internal consistency between the attitude items, i.e. that scores on these items correlate (>0.6) with each other and we decided to include all these items. Consistency of direct attitude items is confirmed, reporting Cronbach's alpha index equal to 0.927[9]. Direct indices of social norm were measured by several items and we decided to exclude the non correlated item <<*It is expected of me that I increase my alcohol consumption*>>. The Cronbach's alpha index, based on correlated items, equals to 0.740.

Because of the correlation between the three items about perceived behavioural control is always below 0.6, we decided to consider item separately. The first item refers to self efficacy (PBC1*eff*), the second (PBC2*contr*) and the third (PBC3*contr*) are both about the controllability of the behaviour.

The results about the ability of TPB to predict intention to use alcohol are shown in Table.2. The intention to use alcohol variable is the mean of two items <<*I intent to increase my alcohol consumption*>> and <<*I intend to decrease my alcohol consumption*>>, where the

[8] We also take into account for socioeconomics variables.

[9] Cronbach's alpha measures the closeness between the responses and the target construct to be measured. This relationship is more reliable when the test is closer to 1.

second item was opportunely recoded. The hypothesis of this model is that attitude, subjective norms and perceived behavioural control account for intention to use alcohol.

The resulting R^2 value for this regression equation was 0.61. Because of the nature of this analysis, which looks for psychological indicators that can be used in order to study intention to use alcohol, this level of R^2 can be accepted. In fact, the estimated model shows that there is still an amount of variance that cannot be explained by covariates, as the constant is statistically significant and very high.

The results of this analysis showed that attitude, social norm and one of the perceived behavioural control variable indicators (PBC2*cont* contains the answers to the item <<*The decision to increase my alcohol consumption during a session with my friends is beyond my control*>>) reached significance.

Table 2 The TPB of intention to use alcohol

	Coefficients	***Standard error***
Intercept	-5,85966***	0,99721
Attitude	0,46560***	0,10935
Social Norms	0,41124***	0,08610
PBC1*eff*	0,07009	0,05717
PBC2*contr*	0,14972*	0,07039
PBC3*contr*	-0,00116	0,00114
Age	0,19769***	0,05089
Gender	0,14568	0,23047
x18	0,31548	0,31372
R^2 = 0,607		

Note: ***, **, * = Significance at 1%, 5%, 10% level.

The age has a positive and significant impact on the stated intention to increment alcohol consumption, while it seems that there are no gender differences. The “x18” coefficient, not significant different from zero, is related to a dummy variable taking value one for people who are of age and zero for the others. It can be seen from the table that the TPB coefficients have the expected signs: on average students with high value for attitude, social norms and perceived behavioural control show stronger intention to use alcohol. More in general, it appears that the TPB constructs can effectively be utilized in order to understand and predict the intention to use alcohol.

5.2 Results from MLM and LCM

The modelling results using the MLM and LCM are presented in this section. NLOGIT[10] was used for these analyses. The advantage of the LCM relative to the MLM is that it allows to identify distinct groups of students with differences in preference for night time activities.

In particular, Table 3 shows the results for MLM obtained using 1000 Halton draws (Bhat, 2001 and Train, 2003). The model converged after 34 iterations and it is statistically significant presenting a *Chi-square* value of 861.58269 with 17 degree of freedom.

The overall model fit for our model obtained from the *pseudo*-R^2 is 0.3142, which is acceptable for this class of model[11]. The constant term is not statistically different from zero as expected in any unlabeled experiments. Its significance would indicate a preference for "Alternative A" over "Alternative B" net of the influence of the attributes. The set of socio-economic and socio-demographic characteristics in the data is limited to the students' gender, age, parents' schooling level and employment.

Due to some problems of multicollinearity within attributes and some socio-economic variables (in particular dummy variables for parents' schooling level and employment) and because the gender and age parameters were not significant, these variables were not included in our models. Thus, it appears that preferences for night time activities were unrelated to demographic variables.

All the explanatory variables related to attribute of alternatives, are treated as generic variables that have the same coefficients for "Alternative A" and "Alternative B". The parameter "no choice" refers to a dummy variable for the no option alternative.

The interpretation of the output, associated with the mean of a random parameter estimate, is the same as with non-random parameters of a standard MNL. For example, the model predicts a higher probability of selecting the alternative with the higher number of participants. We note also that the mean of the "Cost" parameter is, as expected, negative.

The output related to the amount of dispersion that exists around the sample population is the last set of coefficients. The two letters preceding the name of the parameters show that random parameters are drawn from a normal distribution. If dispersion is statistically significant this suggests the presence of heterogeneity. The spread of the "25CHF Restaurant"

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[10] NLOGIT Version 4.0 (Econometric Software, Inc., 2003)

[11] Hensher et al. (2005) indicate that *pseudo*-R^2 values between the range of 0.3 and 0.4 can be translated as an R^2 of between 0.6 and 0.8 for the linear model equivalent.

is not statistically significant so, in this case, all individuals within the sample may be represented by a single point coefficient.

Table 3 Estimation results of the MLM

	Coefficient	Standard Error
Random parameters in utility functions		
Participants	0.04882**	0.02195
50chf-Restaurant	-0.86006***	0.11169
Pub	-0.63937**	0.28167
Disco	-0.87753**	0.39668
Cost	-0.04860***	0.00985
No choice	-3.02405***	0.41918
Non-random parameters in utility functions		
Constant	- 0.12545	0.09063
25chf-Restaurant	0.33746***	0.09673
Heterogeneity in mean, Parameter:Variable		
PUB : Att	0.26828***	0.07777
DISC : Att	0.28037***	0.10514
COST : Att	0.00690***	0.00255
Distns. of RPs. - Std.Devs		
NsPART	0.15150***	0.02910
Ns50RIST	0.57407***	0.11506
NsPUB	0.73141***	0.11389
NsDISC	1.18665***	0.13819
NsCOST	0.01461**	0.00703
NsNOCHI	2.96816***	0.38859

Log likelihood function	- 940.27679
McFadden *Pseudo* - R^2	0.4142013
Number of observations	1248
Number of respondent	104

Note: ***, **, * = Significance at 1%, 5%, 10% level.

In order to account for alcohol attitudes in our night-time activities context, we use a refinement of the standard version of the ML model (Revelt and Train, 1998). Usually marginal utilities are specified as

$$\beta_{kn} = \beta_k + \sigma_k v_{nk}$$

where β_k is the mean, v_{nk} is the individual specific heterogeneity (with mean zero and standard deviation one) and σ_k is the standard deviation of the distribution of β_{kn}s around β_k.

In particular, it is possible (see Hensher et al, 2005 for more details) to introduce a set of invariant characteristics, u_n, that produces individual heterogeneity in the mean of the randomly distributed coefficients so that:

$$\beta_{kn} = \beta_k + \delta' u_n + \sigma_k v_{nk}$$

More precisely, this specification introduces an interaction between the mean estimate of the random parameter and a chosen variable. We are interested in measuring the possible influences of different alcohol attitude on night-time activities choices. As a consequence, we have tested the three psychological indicators related to alcohol consumption as a possible explanation for preferences' heterogeneity. If the interaction is not statistically significant then we can conclude that there is homogeneity of preferences around the mean on the basis of the psychological indicator, but this does not imply preference homogeneity. We tested several specifications for our model and the results shown that only alcohol attitude index is statistically significant offering a possible explanation why that spread exists.

In our model, there are "non random parameters", "random parameters" and random parameters which heterogeneity can be explained by interaction with covariates.

The general formulations for these taste weights are respectively given by:

$$\beta = \beta_{attribute\ mean}$$

$$\beta = \beta_{attribute\ mean} + \sigma_{attribute\ standard\ deviation} \times N$$

$$\beta = \beta_{attribute\ mean} + \delta_{heterogeneity\ in\ mean} \times u + \sigma_{attribute\ standard\ deviation} \times N$$

where N has a standard normal distribution and u is the covariate interacting with the random parameter. In formatting our data, we used effect coding so we are able to infer also the parameter for the base level as the difference between the coefficient of the constant term and the sum of the other levels' coefficients.

The taste weights for our model are:

$\beta_{Participants} = 0.04882 + 0.15150 \times N$

$\beta_{Dinner-Home} = \beta_{Constant} - (\beta_{25chf-Restaurant} + \beta_{50chf-Restaurant})$

$\beta_{25chf-Restaurant} = 0.33746$

$\beta_{50chf-Restaurant} = -0.86006 + 0.57407 \times \mathrm{N}$

$\beta_{Cinema} = \beta_{Constant} - \beta_{Pub}$

$\beta_{Pub} = -0.63937 \;+\; 0.26828 \times \mathrm{Att} + 0.73141 \times \mathrm{N}$

$\beta_{Disco} = -0.87753 \;+ 0.28037 \times \mathrm{Att} + 1.18665 \times \mathrm{N}$

$\beta_{Cost} = -\, 0.04860 + 0.00690 \times \mathrm{Att} + 0.01461 \times \mathrm{N}$

$\beta_{No\ choice} = -3.02405 \;+ 2.96816 \times \mathrm{N}$

On average, in our sample, the number of participant has a positive impact on the students' utility function – young people care about company - but it is interesting to note that there is an important heterogeneity revealing that for some individuals less company is better. A similar interpretation is given to the "No choice" parameter which is negative, but with a high spread. So we can conclude that there are also people who prefer to stay at home.

The preferred activity for the dinner is to have it at home with friends and, as expected, more expensive restaurants are less preferred. We obtain significant heterogeneity around the mean parameter of activity during the after dinner period, i.e. going to a pub instead of cinema or going to a discotheque instead coming back to home, that can be explained by different attitude to alcohol consumption. In particular, our results show that young people who have a higher attitude towards alcohol use tend to choose pubs and discos. The sign of the cost coefficient is negative, and also in this case it is possible to conclude that some of the heterogeneity in the distribution of this parameter is due to different alcohol attitude.

The estimation results of LCM are reported in Table 4. Determination of the optimal numbers of segments requires a balance assessment of some statistics: the log-likelihood, the McFadden *Pseudo* - R^2, the AIC and the BIC. However, in our case, as the number of segments increases to three, the parameter estimates became unstable. Therefore, we adopted a "two classes solution" for our model.

The first panel of Table.4 shows the utility coefficients associated with the alternative attributes, while the second panel gives the coefficients for the segments.

Table 4 Estimation results of the LCM

	Segment 1		Segment 2	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Parameters in utility functions				
Constant	- 0.14966	0.09275	-0.09176	0.13914
Participants	0.06465***	0.01697	-0.00739	0.02264
25chf-Restaurant	0.32526***	0.10428	0.21695*	0.12470
50chf-Restaurant	- 0.64377***	0.08659	- 0.63028***	0.12953
Pub	0.44061***	0.06469	- 0.21802**	0.09087
Disco	0.41703***	0.06385	- 0.74621***	0.09382
Cost	- 0.01778***	0.00374	- 0.01959***	0.00463
No choice	- 11.7755***	1.21386	6.33213***	1.17781
Age	0.48593***	0.05842	- 0.38461***	0.06398
Gender	- 0.63008*	0.36419	0.28870	0.26988
Segment membership function				
Constant	-1.88663**	0.87937	(Fixed Parameter)	
Att	0.73454***	0.25494	(Fixed Parameter)	
Log likelihood function		-949.37059		
McFadden *Pseudo* - R^2		0.2498660		
Number of observations		1152		
Number of respondent		96		

Note: ***, **, * = Significance at 1%, 5%, 10% level.

The coefficients for the second segment are normalized to zero, permitting us to identify the remaining coefficients of the model. Our proposed LCM consists of segment membership functions that include constant terms and alcohol attitude indicator. The demographic variables “Age” and “Gender” were included in the utility function of the no option alternative.

The model converged in 40 iterations and it is statistically significant presenting a *Chi-square* value of 632.46154 with 22 degree of freedom.

The membership coefficient for segment one, indicates that these consumers are more likely to have a higher index of attitude on alcohol consumption. The utility coefficients show that almost all of the tested attributes and demographic variables are significant determinants of young persons' night time activities choice for both segments. In line with the economic theory, members of the two segments prefer night time session with lower costs. However, as expected, some of the other coefficients differ among the two segments.

Respondents in segment one (they have a stronger alcohol attitude) prefer night time sessions with a larger number of participants. They prefers to have a dinner with their friends in a cheap restaurant ($\beta_{25CHF-Rest} = 0.3526$), or at least at home ($\beta_{Dinner-Home} = \beta_{Cons} - \beta_{25CHF-Rest} - \beta_{50CHF-Rest} = 0 - 0.3526 + 0.64377 = 0.31851$), in comparison with the same dinner in a restaurant spending 50 CHF ($\beta_{50CHF-Rest} = -0.64377$).

For segment two, the coefficient related to the number of participants is statistically not different from zero, and we observe a different preferences' ranking of dinner destination, that is: "home" ($\beta_{Dinner-Home} = 0.4133$), "25CHF restaurant" ($\beta_{25CHF-Rest} = 0.21695$) and "50CHF restaurant" ($\beta_{50CHF-Rest} = -\ 0.63028$).

Also the impact (positive or negative effect) of after dinner activities on the individual utility differs for the two segments. The respondents' s utility for the first segment increases spending some time in a pub ($\beta_{Pub} = 0.44061$). They also strongly prefer "Disco" to "Come back to home". Students' in the second segment, in contrast, highlight negative coefficients for "Pub" and "Disco" ($\beta_{Pub} = -\ 0.21802$ and $\beta_{Disco} = -\ 0.74621$).

Overall both the estimated Mixed Logit Models and Latent Class Models highlight significant preference heterogeneity almost for all the attributes. Moreover, the distribution of preferences implied by the preferred mixed and latent class models is similar for many attributes. These results show that preferences for different activities, such as spending some time in a pub or in a disco, are positively related to positive alcohol attitudes.

6. Conclusions

This work studies the distribution of preferences in a sample of students who responded to a stated choice experiment where they were asked to choose between different hypothetical activities at night time.

Traditionally, in DCA, preference heterogeneity has been accounted for by interacting attributes with socio-demographic characteristics, but this approach only partially accounts for the taste differences embodied in the data (Iraguen and Ortuzar, 2004). MLM and LCM offer an alternative which is applicable even when sources of heterogeneity are unknown.

Our hypothesis is that "*soft information*", such as psychological characteristics, have more influence than "*hard information*", such as socio-economic characteristics, on leisure night-time activity choices. As a consequence we have constructed psychological indicators of attitudes, normative beliefs and perception control following the Theory of Planned Behaviour. Introducing them in our stated choice experiment we improved our understanding of the decision making process.

It is found that there is preference heterogeneity and that the distribution of these preferences implied by MLM and LCM is similar for many attributes. Moreover, our results show that the preference heterogeneity for different night-time activities can be explained by alcohol consumption attitudes.

In particular, this capacity to model preference heterogeneity accounting for alcohol attitude has the potential to greatly enhance the behavioural realism of the model. This can be very important if the objective is to implement public initiatives in order to curb some undesired tendencies in young peoples' behaviour, because their success will ultimately be decided by the knowledge of how young people make decisions.

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APPENDIX A: DEVELOPING A DIRECT MEASURE OF ALCOHOL ATTITUDE (EXAMPLE)

This section describes the items that we develop in order to construct the direct attitude towards alcohol consumption indicator (Francis, J., 2004).

- We used of bipolar adjectives (i.e. pairs of opposites) which are evaluative (e.g. *good – bad*)
- We included instrumental items (whether the behaviour achieves something e.g. *useful–worthless*) and experiential items (how it feels to perform the behaviour e.g. *pleasant – unpleasant*)
- We arranged the items so that the ends of the scales are a mix of positive and negative endpoints

In a typical session with my friends, to increase my alcohol consumption would be…

Funny	O	O	O	O	O	O	O	**Boring**
Harmful	O	O	O	O	O	O	O	**Beneficial**
Good	O	O	O	O	O	O	O	**Bad**
Pleasant (for me)	O	O	O	O	O	O	O	**Unpleasant (for me)**
Worthless	O	O	O	O	O	O	O	**Useful**