# CONSUMERS' PREFERENCES FOR COFFEE CONSUMPTION: A CHOICE EXPERIMENT INCLUDING ORGANOLEPTIC CHARACTERISTICS AND CHEMICAL ANALYSES

Preferenze del consumatore e consumo di caffè: un esperimento di scelta comprendente caratteristiche organolettiche e analisi chimiche

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**Abstract** In this work we propose an innovative approach for the analysis of consumers' preferences for coffee consumption by integrating a choice experiment with a consumer sensory test and chemical analyses (caffeine and antioxidants by HPLC). The same choice experiment has been administered in two consecutive time occasions, e.g. before and after the sensory test (including a descriptive illustration by an expert), in order to analyze the role of tasting in guiding the consumers' preferences. All these elements, e.g. the attributes involved in the choice experiment, the scores obtained for each coffee through the sensory tests and the HPLC analyses, are analyzed through Random Utility Models.

Abstract Nel presente lavoro si propone un approccio innovativo per l'analisi delle preferenze del consumatore relativo al consumo del caffè. Tale approccio permette di integrare un esperimento di scelta con i risultati derivanti dal test d'assaggio e analisi chimiche (caffeina e composti antiossidanti valutati tramite il metodo HPLC). Lo stesso esperimento di scelta viene somministrato sia prima che dopo il test d'assaggio con l'obiettivo di capire se l'assaggio, unito alla descrizione operata da un esperto, può costituire una "guida" nella definizione delle preferenze del consumatore. Gli attributi dell'esperimento di scelta, i punteggi ottenuti dal test d'assaggio e i risultati HPLC sono stati analizzati con Modelli di Utilità Casuale.

**Key words:** choice experiment, consumer sensory test, Random Utility Models-RUM, HPLC analysis

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# **1** Introduction

In this work, consumers' preferences for the coffee consumption are analyzed with an innovative approach, which integrates a choice experiment with consumer sensory tests and chemical analyses of two different types of coffee ground for moka (e.g. 100% Arabica, and a blending of Arabica and Robusta). More specifically, at the beginning a choice experiment based on optimal design theory is planned. In addition, a coffee tasting is planned in order to better analyze the consumers' preferences. To this end, a scoring card is developed, where tasters have to give a score for each organoleptic descriptor of coffee; this scoring card is administered jointly with the choice experiment. Moreover data relating to the coffee, e.g. quali-quantitative composition (caffeine, antioxidants), were acquired by using a High Performance Liquid Chromatography (HPLC) method and specific calibration curves, and then involved in the modeling step. More precisely, the same choice experiment is administered in two consecutive time occasions (Lombardi et al., 2017), e.g. before and after the sensory test, in order to analyze the role of tasting in the determination of consumers' preferences. All these elements, e.g. the attributes involved in the choice experiment, the scores obtained for each coffee from the sensory test and the HPLC analyses, are jointly analyzed in the modeling step to better evaluate the consumers behavior relating to the coffee consumption and to verify if the tasting session produced a modification in consumer's attitude.

## 2 Choice experiment and Random Utility Models

In the following Subsection we briefly describe the choice experiment and the collection of the data. Following, the theory of Random Utility Models (RUM) is briefly explained.

#### 2.1 Choice experiment and data collection

At the beginning, a choice experiment based on optimal design theory is planned for building the choice-sets with the following aims: i) an efficient estimation of the attributes for the choice experiment, and ii) the detection of the effect of the sensory assessment's scores obtained through the sensory test. To this end, a compound design criterion (Atkinson et al., 2007) is applied in order to address the issues described above.

In order to collect the data, a background questionnaire about the respondent (age, gender, education) was administered at the beginning. Furthermore the choice experiment was supplied before and after the coffee tasting. For the tasting, a scorecard was developed, in which the consumer/taster is asked to assign a vote (ranging from 1 to 7, evaluated as discrete votes) to each organoleptic characteristic (smell,

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taste and tactile sensations). Moreover, the two types of coffee ground for moka (100% Arabica, and a blending of Arabica and Robusta varieties) were previously analyzed for their content in polyphenolic antioxidants (chlorogenic acid and other caffeoyl-quinic derivatives) and caffeine by a HPLC/DAD method.

#### 2.2 Choice Modeling

Once data were collected, the preferences expressed by the consumers are analyzed through Random Utility Models. Therefore, as an initial step, the class of Random Utility Models (RUM) is defined. In general, every alternative is indicated by j, so that the choice-set is formed by J alternatives (1, ..., j, ..., J), while i denotes the respondent (i = 1, ..., I). The respondent is asked to give his/her preference within each choice-set, formed by two or more alternatives. In the Random Utility class of models, the individual i who chooses the alternative j has a random utility  $U_{ij}$  that may be generally expressed as in formula (1). Furthermore, it is assumed that the respondent i maximises his/her utility by choosing the alternative j, belonging to the choice-set  $C_i$  so that  $U_{ij}$  is the highest of all the utilities  $U_{ik}$ , k = 1, ..., J.

Thus, the following expression is characterized by a stochastic utility index  $U_{ij}$ , which may be expressed, for each unit *i*, as a linear function of the attributes for the alternative *j*, as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$
$$V_{ij} = x'_{ij}\beta$$

where  $V_{ij}$  is the deterministic part of the utility and is defined here in relation to a vector  $x_{ij}$ , containing the characteristics of respondent *i* and alternative *j*,  $\beta$  is the vector of unknown coefficients and  $\varepsilon_{ij}$ , j = 1, ..., J is the random component. The random component is generally supposed to be independent and also Gumbel or type I extreme value distributed.

It must be noted that each alternative will be characterized by a vector of characteristics (attributes), while the response (dependent) variable is the binary variable related to the expressed preference for each choice-set.

In this study, we start by applying the Multinomial (conditional) Logit model, after we apply the Heteroscedastic Extreme Value-HEV model, described in the following Subsection.

#### 2.2.1 The Heteroscedastic extreme value model

The Heteroscedastic Extreme Value (HEV) model (Bhat, 1995; Hensher, 1999) also belongs to the RUM class. The main feature of this model concerns the modified assumptions on the random component, which is supposedly distributed as a type I extreme value distribution, independently but not identically distributed. It must

be noted that this different hypothesis on the random component makes it possible to treat the relaxation on the Independence of the Irrelevant Alternatives (IIA) property differently with respect to the Multinomial Logit model. This relaxation is fundamental and strengthens the improvement with respect to the basic logit model. Furthermore, in the HEV model, different scale parameters between alternatives are estimated. Moreover, the presence of large variances for the error terms influences the effects of changing the systematic utility for the generic alternative *j*. The main evident advantage is that the scale parameters may be defined as the weights in order to measure the uncertainty relating to the alternatives and the attributes involved. Therefore, the probability that a respondent *i* chooses the alternative *j* from a choice-set  $C_i$  is:

$$P_{ij} = \int_{\varepsilon} \prod_{k \in C_i; k \neq j} \Lambda\left(\frac{x'_{ij}\beta - x'_{ik}\beta + \varepsilon_{ij}}{\theta_k}\right) \frac{1}{\theta_j} \lambda\left(\frac{\varepsilon_{ij}}{\theta_j}\right) d\varepsilon_{ij}$$
(2)

with the error term distributed as follows:

$$f(\boldsymbol{\varepsilon}_{ij};\boldsymbol{\theta}_j) = \lambda\left(\frac{\boldsymbol{\varepsilon}_{ij}}{\boldsymbol{\theta}_j}\right) = \exp\left(-\frac{\boldsymbol{\varepsilon}_{ij}}{\boldsymbol{\theta}_j}\right) \exp\left\{-\left[\exp\left(-\frac{\boldsymbol{\varepsilon}_{ij}}{\boldsymbol{\theta}_j}\right)\right]\right\}$$
(3)

In formula (2),  $\theta_j$  is the scale parameter for the *j* alternative and  $\lambda(.)$  is the probability density function of the Gumbel distribution, as detailed in formula (3), while  $\Lambda(.)$  in formula (2) is the corresponding cumulative distribution function evaluated by considering two distinct choices for the *i* respondent. In fact, the term  $x'_{ij}\beta$  denotes the deterministic part of utility of formula (1) related to alternative *j* and alternative *k*, respectively. Note that the integral function is defined on the domain  $[-\infty, +\infty]$  of the random component  $\varepsilon$ , related to the unit *i* and the alternative *j*. In this case, preferences of respondent *i* are evaluated by considering a scaling term (scale parameter)  $\theta_j$  for the alternative *j* in the choice-set  $C_i$  i.e., the heteroscedasticity of the error term. In the case-study, two alternatives are included in each choice-set and therefore only one scale-parameter is estimated.

# **3** Results and Discussion

In what follows, we describe the results we have obtained for the HEV model by considering i) Choice1, that is the choice experiment administered before the tasting (Table 1), and ii) Choice2, that is the same choice experiment administered after the tasting (Table 2). More precisely, the following attributes of the choice experiment has been analyzed through the HEV model: price for a quantity of 250 grams at 3 levels:  $\in$ 4.50 considered as a reference level,  $\in$ 6.00 (labeled as "Price 2") and  $\in$ 7.50 (labeled as "Price 3"); coffee type with two levels: "-1" for blending Arabica and Robusta, and "+1" for 100% Arabica; packaging with two levels: "-1" for soft bag with modified atmosphere, and "+1" for jar with modified atmosphere; Label

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Indication with two levels: "-1" for the presence of an indication of origin, and "+1" for a certification about the product sustainability; soft and velvety taste with two levels: "-1" for fairly present and "1" for highly present (labeled as Soft Velvety Taste), and typical of a 100% Arabica coffee; intense and aromatic taste with two levels: "-1" for fairly present and "1" for highly present (labeled as Intense Aromatic Taste) typical of a blending Arabica and Robusta. It must be noted that in both estimated models we also included the constant ("Constant") term settled with all the attributes at lower level.

Table 1 HEV model results before tasting (Choice1)

Variable	Estimate	Std.Error	t-value	p-value
Constant	0.6086	0.5546	1.10	0.2725
Price 2	-0.0251	0.0268	-0.94	0.3486
Price 3	-0.0914	0.0268	-3.41	0.0006
Coffee Type	-0.2855	0.1034	-2.76	0.0058
Packaging	0.0995	0.0718	1.39	0.1659
Soft Velvety Taste	-0.2002	0.2197	-0.91	0.3620
Intense Aromatic Taste	0.2304	0.1128	2.04	0.0411
Label Indication	0.1795	0.0693	2.59	0.0097
Caffeine	-0.5326	0.5572	-0.96	0.3392
Soft Velvety Taste*Caffeine	1.3756	0.8725	1.58	0.1149
Scale	1.3546	0.4660	2.91	0.0037

Table 2 HEV model results after tasting (Choice2)

Variable	Estimate	Std.Error	t-value	p-value
Constant	-0.1240	0.4963	-0.25	0.8027
Price 2	0.0272	0.0227	1.20	0.2308
Price 3	-0.0224	0.0201	-1.11	0.2650
Coffee Type	0.0866	0.0744	1.16	0.2448
Packaging	-0.1176	0.0649	-1.81	0.0700
Soft Velvety Taste	0.1871	0.0823	2.27	0.0230
Intense Aromatic Taste	-0.0583	0.0711	-0.82	0.4126
Label Indication	0.1570	0.0822	1.91	0.0560
Caffeine	0.4443	0.2395	1.85	0.0636
Taste Score	0.5643	0.3527	1.60	0.1097
Taste Score*Soft Velvety Taste	-0.6174	0.3882	-1.59	0.1118
Taste Score*Label Indication	-0.4264	0.3967	-1.07	0.2824
Scale	1.4265	0.5049	2.83	0.0047

When observing the results for Choice1 (1) and Choice2 (Table 2), we can note that the tasting session, together with the information provided on each type of coffee, have a relevant role in unequivocally guiding the consumers' preferences. More precisely, in Choice1 the negative signs of the estimated coefficients related to the

type of coffee and caffeine indicate a preference toward the blending 100% Arabica. This result is also confirmed when considering the estimated coefficients related to the attributes of soft velvety and intense aromatic taste. In fact, the consumers' preferences go towards a highly present level of soft and velvety taste that is typical for the blend 100% Arabica, and towards a fairly present level of the intense aromatic taste. However, when considering the interaction between caffeine and soft velvety taste, when the level of caffeine increases the presence of soft and velvety taste also increases; therefore we note that this result is not in line with the preference expressed towards the blend 100% Arabica. In fact, the blend 100% Arabica is characterized by a lower level of caffeine should decrease when the soft and velvety taste increases. Therefore, the result related to the interaction term is probably due to the fact that during the session "Choice1" the respondents do not have enough knowledge about the two types of coffee, and consequently their preferences are not perfectly defined.

Instead, when considering the session "Choice2" (results shown in Table 2), we can see a notable change in consumers' preferences with respect to Choice1, e.g., apart from the constant term that is negligible, a clear preference towards the blend Arabica and Robusta is outlined. Moreover, the positive signs of the estimated coefficients related to the type of coffee and caffeine indicates a preference towards the blend Arabica and Robusta. In line with this result, the respondents choose a highly present intense and aromatic taste (typical for the blend Arabica and Robusta) and fairly present soft and velvety taste. The estimated coefficient of the tasting scores (labeled "Taste Score" in Table 2) obtained through the sensory tests, is positive and slightly significant, by indicating a preference towards the blend Arabica and Robusta. Furthermore, the interaction term between "Taste Score" and "Soft Velvety Taste" confirms that, after the intermediate session with the sensory test and information step, the consumers are more capable of differentiating between the two types of coffee. In fact, this interaction indicates that when the "Taste Score" goes towards the blend 100% Arabica, then the "Soft Velvety Taste" increases. This result confirms the role of guiding performed by the intermediate session, which helps the respondents for giving a coherent evaluation during the  $2^{nd}$  choice session.

A change in the consumer preferences also concerns the packaging: in Choice1 the estimated coefficients related to the packaging goes towards the soft bag with modified atmosphere, even though this coefficient is not significant. In Choice2 instead the packaging coefficients becomes almost statistically significant with a clear preference towards the jar in a modified atmosphere. When considering the label indication, there is no change in the consumers' preferences between Choice1 and Choice2: in both occasions the respondents choose the indication of geographical origin with respect to the certification of product sustainability. The interaction between the taste score and the label indication, even though not significant, indicates that more the consumers' preferences go towards the blend 100% Arabica, more the importance of the certification of product sustainability decreases. This result could be in accordance with a more perceived quality of 100% Arabica coffees by the consumers, hence, less concerned in this case to sustainability issues.

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In Choice1 (Table 1) we can observe that both price coefficients ("Price 2" and "Price 3") are negative; this means that the willingness-to-pay decreases when price increases, as expected. Nevertheless, after the tasting session (Choice2) a light increment of a willingness-to-pay is highlighted (the intermediate level of price shows a positive coefficient), even though in Choice2 both price coefficients are always not significant.

Moreover, a highly significant scale coefficient relating to the measurement of the heteroscedasticity effect is obtained for both Choice1 and Choice2 HEV models, e.g. the alternatives are not so irrelevant for the respondents, when doing their choices. In this direction, and with respect to the conditional logit model, the HEV model and the Mixed MNL logit model could be considered as competitive models for identifying and measuring the presence of an over-dispersion when modelling the respondent preferences. Nevertheless, the results for the Mixed MNL logit model are not presented in this paper because they require further investigations.

### References

- 1. Atkinson, A.C., Donev, A.N., Tobias, R.D.: Optimal experimental designs, with SAS. Oxford University Press, Oxford (2007)
- Bhat, C.R.: A heteroscedastic extreme value model of intercity travel mode choice. Transportation Research Part B-Methodological. 29, 471–483 (1995)
- 3. Hensher, D.A: HEV choice models as a search engine for the specification of nested logit tree structures. Marketing Letters. **10**, 339–349 (1999)
- Lombardi, G.V., Berni R., Rocchi B.: Environmental friendly food. Choice Experiment to assess consumers attitude toward climate neutral milk: the role of communication. Journal of Cleaner Production. 142, 257–262 (2017)