Individual preferences for food items within couples: validating choice experiments predictions with real purchases data

Cristiano Franceschinis[1], Riccardo Scarpa[2,3,4], Mara Thiene[1], Roselinde Kessels[5,6]

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1 Department Land, Environment, Agriculture and Forestry, University of Padova, Italy

2 Department of Economics, Durham University Business School, U.K.

3 Department of Management, University of Verona, Italy

4 Department of Economics, University of Waikato, New Zealand

5 Department of Data Analytics and Digitalization, Maastricht University, The Netherlands

6 Department of Economics, City Campus, University of Antwerp, Belgium

Corresponding author: Cristiano Franceschinis, cristiano.franceschinis@unipd.it

Abstract

Despite the popularity of choice experiments (CEs) for the valuation of environmental goods and services, some of its shortcomings have been only partially addressed by the literature. Among these, of particular saliency, are the hypothetical nature of CEs and the lack of information on joint choices (e.g. choices made by couples) in traditional CEs. In this study, we contribute to the filling of these gaps by investigating joint choices concerning cheeses produced via different processes, involving environmental and social sustainability features. We use a two-stage preference elicitation approach, using first stated and then real consumption choices collected from a sample of 90 couples. In the first stage, each member of the couple took part separately in a web survey with a hypothetical CE. In the second, these couples jointly engaged in a field experiment with monetary incentives in which they jointly chose the cheeses to purchase. This approach allows us to evaluate the role of individual preferences in shaping joint choices and to investigate whether predictions from stated-choice data are congruent with, and validated by, real purchase data. We use CE data to estimate individual preferences with discrete choice models and use joint purchase data via the Multiple Discrete-Continuous Nested Extreme Value model. Results suggest that joint real choices follow a substantively different decision process from that of individual stated choice.

1. Introduction

Choice experiments (CEs) have gained increasing popularity over the last two decades, and the range of food economics applications has broadened. Many focus on the valuation of non-market goods and services and on the analysis of food choice. In spite of their popularity and advantages, the use of CEs has important drawbacks. To list but a few, stated choice CEs are subject to hypothetical bias (Fifer et al., 2014; Gschwandtner and Burton, 2020); they do not allow for multiple item selection (i.e. only one alternative can be chosen in a given choice task); and it impossible for respondents to choose quantities for the chosen option (Corsi, 2007). Furthermore, to date, little attention has been paid to the analysis of joint choices (e.g. choices made jointly by members of a couple or groups). Most examples are outside the food choice context. A seminal study that used CEs data is that by Dosman and Adamowicz (2006) who explored the concept of intrabargaining household between couples using both stated and revealed preference data on vacation site choice. Beharry-Borg et al. (2009) studied choice of beach destination by couples extending the framework to deal with unobserved heterogeneity; Rungie et al. (2014) analysed joint choices concerning tap water services via a Structural Equation Modelling approach; Mariel et al. (2018) studied preference for higher school education for children by their parents; and Boto-Garcia et al. (2023) also examined partners' influence in couple's vacation choice.

The artificial food choice contexts proposed in standard hypothetical CEs are subject to hypothetical bias as they substantially differ from real food purchase choices. A further difference is the food basket composition that prevails in real food purchases where people often simultaneously select multiple products/services in varying quantities. Finally, the mode of choice varies as such choices are often made jointly by people sharing the purchase decision. So hypothetical bias, food basket composition and jointness of choice are all features that may affect the predictive power of structural choice models obtained from stated CEs when these are used in predicting food purchase decisions. Over the last decades, different streams of literature have emerged to address such shortcomings. Hypothetical bias has been addressed by CE studies (Moser and Raffaelli, 2012; Gracia, 2014; Bazzani al., 2017; Brent et al., 2021) that used incentives for participants who were asked to purchase the selected products. The food basket composition has been addressed by studies dealing respectively with multiple discrete choices (MDC) (Russel and Petersen, 2000; Caputo and Lusk, 2019) and multiple discrete-continuous choices (MDCC). In MDC experiments, respondents are allowed to choose multiple food items in each choice occasion, while in MDCC they can also choose the quantity of each selected food type. However, jointness of food choice is still relatively unexplored, and the main focus of this study.

In this paper, we seek to contribute to the above literature by analysing joint choices concerning different cheeses via an approach involving both hypothetical CE data and real purchase data obtained via a field experiment. In the field experiment participants were given real cash endowments before performing cheese purchases to be consumed at home. The cheeses included in the two experiments were described in terms of several features, including one related to environmental sustainability, namely the production by using milk from mountain pastures, which has also a social sustainability component, given the effort recently deployed to maintain economically viable mountain communities. By this approach, we seek to firstly analyse the role of individual choices in shaping joint choices and secondly to investigate whether CE predictions are aligned with those obtained from the data on real purchases. To this end, we present here an exploratory analysis based on the estimation of discrete choice models to analyse cheese choice and of the Multiple Discrete-Continuous Nested Extreme Value (MDCEV, Bhat 2008) to analyze the choice of cheese and quantity purchased.

The remainder of the paper is structured as follows: section 2 reviews the literature regarding the type of choices we examine. Section 3 describes the data collection framework and the econometric model we used to analyse the collected data; section 4 reports the preliminary results, and section 5 reports the conclusions of the study.

2. Literature review

This section firstly reviews the state of the art on joint choices (section 2.1), then it focuses on reviewing previous studies comparing results from online and field CEs (2.2). Finally, we outline previous applications of studies investigating multiple discrete-continuous choices.

2.1 Joint choices

An increasing body of empirical evidence has shown that the standard practice of selecting only one member as a household to represent joint household preferences when conducting CEs may be inappropriate because household decisions are often the result of a bargaining process among their members. As such, given the important economic implications of the balance of power between household members, increasing attention has been paid to the intra-household allocation of bargaining power, which can be in part justified by the allocation of resources across household members'. In the context of CEs, joint choices are typically investigated by having each member fill in the survey individually, followed by all members filling in the survey jointly. The analysis of data collected in this fashion varies from comparing utilities across members to tailored econometric models, such as the weighted utility across members of the couple used by Dosman and Admowicz (2007) and Beharry et al. (2009) or the Structural Choice Model adopted by Rungie et al. (2014).

Overall, the literature provides mixed results, with some studies finding preferences to be similar and neither member of a household having a predominant role on joint choices (e.g. Mariel et al., 2018) and others finding preferences to be substantially different across members, with one of them having a predominant role on joint choices (e.g. Beharry-Borg et al, 2009). Alternatively, yet other studies reported that when preferences differ, a bargaining process occurs which leads to joint choices lying somewhere in between the individual ones (e.g. Hensher et al., 2017).

Among the first studies on this topic, Arora and Allenby (1999) provide individual and attribute-specific estimates of husbands' and wives' influence in the couple's choice of two types of household appliances, showing that wives exert more influence on self-cleaning features while males are dominant in choosing lawnmower attributes. Beharry-Borg et al. (2009) analysed joint choice concerning recreational visits to coastal sites. They found the preferences of women and men to be substantially different and those of women to be dominant in the joint CE. O'Neill and Hess (2014) focused on joint choices affecting commuting time and salary of both members of a couple. They found that men place more weight on their partner's travel time, while women place more weight on their partner's salary. Menon et al. (2014) investigated joint recreational demand by using revealed preference data. Their findings highlight substantial differences between spouses in terms of willingness to pay to access recreational sites. Rungie et al. (2015) focused on tap water quality, by using a Structural Choice Model on stated CE data. They found women to have greater influence than men on joint choice. Hensher et al. (2017) analysed stated choices concerning automobile fuels. They observed that the power contribution of the household members to joint choices varies across alternatives. Mariel et al. (2018) investigated joint choices of husbands and wives concerning school choice, by combining revealed and stated preferences data. Their results show that the husband's and wife's preferences do not differ substantially, and that neither preferences systematically prevail in the actual joint school choice decision. Boto-Gracia et al. (2023) examined partners' influence on vacation choice. They found that, overall, men have a more influential role on joint choice, but at the same time they highlight a gender specialization process similar to that found in Arora and Allenby, in that women dominate on the type of accommodation and men on trip cost.

2.2 Hypothetical vs real CEs

Over the last two decades, several studies compared results from hypothetical CEs (typically embedded in surveys) and real experiments with monetary incentives. Most of the studies focused on discrete choices in both the survey and the field experiment. The field experiment typically entails making respondents pay with real money for one or more of the products they choose in the choice sets. The comparison between hypothetical and real settings has mostly relied on identifying differences in the estimated WTP values, which were mostly found to be larger in hypothetical experiments. For example, among the first studies on this subject, Cameron et al. (2002) found that the proportion of respondents choosing to partake in a green energy program was higher in the hypothetical CE compared to the real payment one. The authors also observed WTP values obtained from the hypothetical CE to be higher, but the differences were not statistically significant. Lusk and Schroeder (2004) compared hypothetical and non-hypothetical CEs in an application involving beef ribeye steaks with differing quality attributes. The authors found an overestimation of total willingness-to-pay (WTP) for beef steaks, but the marginal WTP values for a change in steak quality was statistically insignificant across settings. In a CE focusing on wildlife rehabilitation programs, Ready et al. (2010) reported WTP values estimated from hypothetical choices to be three times larger than those obtained from choices requiring actual payments. Moser et al. (2013) carried out a CE in a supermarket employing a hypothetical and a real treatment. Their results confirmed the presence of hypothetical bias. Grebitus et al. (2013) carried out a hypothetical and a real CE on preferences for apples and wines. Their results also support the existence of hypothetical bias, which is found to be affected by participants' personality. In Japan, Aoki and Akai (2021) combined hypothetical and non-hypothetical treatments in a CE focusing on the carbon footprint of mandarin oranges. The authors observed that differences in WTP values were statistically insignificant across treatments. Differently from the above studies, Liebe et al. (2019) compared hypothetical and real CE in an online survey on ethical food consumption. The results highlighted how WTP values were substantially lower in the real CE for several attributes.

2.3 Multiple discrete-continuous choices

Since its introduction by Bhat (2008), the MDCEV has become the state-of-the-art model to analyse multiple discrete-continuous choices. It has been applied mainly in three fields: transport, energy and time allocation across activities.

In transport research, the MDCEV model has been used to investigate the choice of transport mode. For example, Jian et al. (2017) investigated vehicle choices in the context of car sharing in Australia. Khan and Machemehl (2017) analysed time of day choice behaviour of commercial vehicles in the US. Tapia et al. (2020) modelled destination port and transport mode choice for freight. Augustin et al. (2015) implemented the MDCEV model in conjunction with a Stochastic Frontier (SF) regression to accommodate household ownership and utilization of vehicles (see also Pellegrini et al., 2020).

In the field of energy choices, Jeong et al. (2011) used survey data collected from households in Seoul, South Korea, to investigate residential energy consumption patterns. Yu and Zhang (2015) also used household survey data to model domestic energy use in China. Frontuto (2019) used survey expenditure data from Italian households to estimate residential energy demand. Acharya and Marhold (2019) investigated the determinants of households' energy choices.

In time use research the focus has been on time allocation across activities, Chikaraishi et al. (2010) used data from the German travel survey Mobidrive to investigate how different days of the week affect the likelihood of allocating time to different activities. Calastri et al. (2020) selected a subset of the same data to investigate the correlation between time allocations to various activities within and between days. Castro et al. (2012) modelled survey data collected in the US to investigate how time, money, and capacity constraints affect time use. In Japan, Kuriyama et al. (2020) analysed survey data concerning trips to national parks to estimate leisure time value in weekends and that in long holidays. Lloyd-Smith et al. (2020) used data from a survey of recreational anglers in the Gulf of Mexico to estimate how value of time varies seasonally. Watanabe et al. (2021) explored variations of time use in leisure activities during non-working days by using GPS-based data collected in two Japanese cities (Matsuyama and Yokoyama). More recently, Pellegrini et al. (2021) integrated monetary and time constraints into a single economic constraint coupled with a non-additively separable utility form to capture complementarity and substitution patterns in recreational activities in the Netherlands.

Few studies adopted the MDCEV model in other fields. For example, as previously mentioned, Richards et al. (2012) analysed demand for different apple varieties by using panel survey data from households in New York State. Han et al. (2016) investigated how preferences and consumption patterns related to mobile apps vary across demographic groups. Dekker et al. (2019) investigated data collected via an online survey in which respondents selected a portfolio of public sector projects given a governmental budget constraint. Pellegrini et al. (2021) proposed a MDCEV model to assess herbicide use decisions in the context of weed control strategies in Australia. Finally, Franceschinis et al. (2022) investigated preferences toward local and organic products via a field experiment entailing real purchase of different food items.

3. Methodology

3.1 Data collection

In this food choice exploratory study, a total of 90 couples took part in both experiments. Couples were recruited by a market research firm, which secured a sample with a good stratification in terms of the main socio-demographics. We adopted a two-stage sequential approach in our data collection, since results from the first stage were deemed informative for the second stage. At first, each member of the couples, separately from their partner, filled in a web-based questionnaire, which included a hypothetical CE. Then, couples engaged in a field experiment with monetary incentives in which they jointly chose the cheeses to purchase from an experimentally arranged market stand setting where all combinations of cheeses used in the CE were made available. This approach is somewhat different from previous studies, in that we have two elements changing across the two experiments (individuals vs joint choices and hypothetical vs real ones). We opted for this approach as the available budget for the research did not allow us to replicate individual and joint choices in both the hypothetical and the real experiments. While we recognize that this may lead to possible confounding of the two effects, we believe our study can nonetheless provide some preliminary insights on the possible presence and size of hypothetical bias and on the bargaining processes in joint choices concerning multiple-discrete continuous food items selection.

3.1.1 The online CE

Five attributes were included in the CE: i) presence of Grana Padano logo on the packaging (levels: yes and no); ii) seasoning (levels: 10 - 16 months; 17 - 20 months; more than 20 months); iii) presence of lysozyme (levels: yes and no); iv) mountain milk (levels: yes and no); v) price (six levels ranging from €1.90/200g to €3.30/200g, reflective of real market prices). The attributes were selected in a focus group with members of the consortium Agriform (which funded the study), one of the leading companies in the production and marketing of Grana Padano. The main criterion for the selection was to ensure the possibility of having combinations of attributes and levels that correspond to the cheese types available for the field experiment.

Before the choice task, respondents were asked to imagine a scenario in which they had to purchase cheese for home consumption and asked to act as if only those cheeses presented in each choice set were available for choice. They were then asked to indicate the cheese they would purchase among those presented to them, with the possibility to choose an opt out option (i.e. no purchase). Respondents could not choose the quantity (i.e. number of 200g units) of the selected cheese. For this reason, the CE did not entail an explicit budget constraint.

The design of the CE, shown in Table 1, involves 20 choice sets each with two cheese alternatives, which were presented in a randomized order to the respondents. It is a partial profile design meaning that the levels of only a subset of the attributes are varying in the choice sets to reduce the cognitive burden on the respondents (Green, 1974; Kessels et al., 2011a, 2015). More specifically, four attributes have variations in levels between alternatives (indicated in yellow) while one attribute has the same levels between alternatives. The constant attributes are shown to the respondents to present actual alternatives of cheese types. In the design, each attribute is held constant in four choice sets and varied in sixteen choice sets. The design has been generated using the Choice Design platform in the statistical software package JMP Pro 16 (SAS Institute Inc, Cary, NC, USA).

Table 1. Bayesian D-optimal partial profile design

Choice set	Logo	Seasoning	Lysozyme	Mountain milk	Cost
1	present	more than 20 months	no	no	3.30 €/piece
1	not present	16-20 months	no	yes	2.50 €/piece
2	present	more than 20 months	yes	no	3.00 €/piece
2	not present	more than 20 months	no	yes	2.80 €/piece
3	not present	up to 16 months	no	yes	3.00 €/piece
3	present	more than 20 months	yes	no	3.00 €/piece
4	present	16-20 months	yes	no	2.50 €/piece
4	present	up to 16 months	no	yes	3.00 €/piece
5	present	up to 16 months	yes	yes	2.20 €/piece

5	not present	16-20 months	no	yes	1.90 €/piece
6	not present	up to 16 months	yes	yes	3.30 €/piece
6	not present	more than 20 months	no	no	3.00 €/piece
7	present	up to 16 months	yes	no	2.20 €/piece
7	not present	more than 20 months	yes	yes	3.30 €/piece
8	present	up to 16 months	no	no	2.80 €/piece
8	not present	more than 20 months	yes	no	1.90 €/piece
9	not present	16-20 months	yes	no	2.80 €/piece
9	present	up to 16 months	no	yes	2.80 €/piece
10	not present	16-20 months	yes	yes	1.90 €/piece
10	present	16-20 months	no	no	2.50 €/piece
11	present	up to 16 months	yes	yes	3.00 €/piece
11	not present	more than 20 months	no	yes	2.20 €/piece
12	not present	up to 16 months	no	yes	1.90 €/piece
12	present	up to 16 months	yes	no	3.30 €/piece
13	present	16-20 months	yes	no	2.80 €/piece
13	not present	more than 20 months	yes	yes	2.50 €/piece
14	not present	more than 20 months	no	no	1.90 €/piece
14	present	16-20 months	yes	yes	1.90 €/piece
15	not present	up to 16 months	no	no	2.20 €/piece
15	not present	more than 20 months	yes	yes	2.80 €/piece
16	not present	more than 20 months	yes	no	2.80 €/piece
16	present	16-20 months	no	no	3.30 €/piece
17	not present	16-20 months	yes	yes	2.20 €/piece
17	present	16-20 months	no	no	1.90 €/piece
18	not present	16-20 months	no	yes	2.20 €/piece
18	present	up to 16 months	no	no	2.50 €/piece
19	present	up to 16 months	yes	no	1.90 €/piece

19	present	16-20 months	no	yes	3.00 €/piece
20	not present	16-20 months	yes	no	3.30 €/piece
20	present	more than 20 months	no	yes	3.30 €/piece

The partial profile design is Bayesian D-optimal in the sense that a Bayesian perspective is taken by incorporating a multivariate normal prior distribution of parameter estimates from a pilot study in the design construction (Kessels et al., 2011b). D-optimal stands for determinant optimal and is used because the alternatives or profiles appearing in the choice sets are selected so that, roughly speaking, the statistical model and quantities such as WTP can be estimated with maximum precision. One major benefit of Bayesian D-optimal designs for CEs is that, using a proper prior distribution, they do not involve choice sets in which one profile dominates the other profile(s) on every attribute (Crabbe and Vandebroek, 2012).

3.1.2 The field experiment

The field experiment involved the real purchase of cheeses with different characteristics, reported in Table 2, along with their prices. The latter were defined over a range that contained the average market price of each product. Each cheese was sold in 200g pieces, a relatively common quantity in real markets. To ensure that the field experiment could serve as validation of the online CE predictions, all cheeses presented combinations of the features described by the CE attributes. The experiment was designed to mirror as closely as possible consumers' experience in a real shopping scenario when purchasing food to consume at home. To make the experimental market more realistic, the cheeses were placed in two refrigerated displays identical to those used in supermarkets (Figure 1).

We provided each couple with a budget of €15 to make their joint purchases. This amount was selected *ad hoc*, based on the funds available for the research. Crucially, it was large enough to enable respondents to purchase multiple cheese units. This is necessary to have enough variation in purchased quantities to enable the investigation of saturation effects with the MDCEV model.

At the entrance of the room in which the cheeses were displayed, all participants received instructions in written form. In essence, these were as follows: i) a budget of €15 was provided to participants to purchase any cheese available in the refrigerator aisles; ii) participants could choose to spend all budget or part of it; iii) at the end of the experiment participants took home all purchased products and the cash change left over; iv) choices were to be made jointly. After reading the instructions, the couples accessed the room with the products and made their choices jointly. Once they made their choice, participants left the products to the experimenter who registered the choices and calculated the remaining budget to be cashed out. Afterward, they were given the purchased food items and the cash left over, if any.

Table 2. Cheeses included in the field experiment

Cheese	Price (€/200g)
Italian hard cheese 10 – 16 months seasoning, lysozyme and no mountain milk	1.90
Italian hard cheese 17 – 20 months seasoning, lysozyme and no mountain milk	2.40
Italian hard cheese 20+ months seasoning, lysozyme and no mountain milk	2.80
Grana Padano 10 – 16 months seasoning, lysozyme and no mountain milk	2.70
Grana Padano 17 – 20 months seasoning, lysozyme and no mountain milk	2.90
Grana Padano 20+ months seasoning, lysozyme and no mountain milk	3.30
Grana Padano 10 – 16 months seasoning, no lysozyme and no mountain milk	2.90
Grana Padano 20 +months seasoning, lysozyme and mountain milk	3.10

Figure 1. Cheeses sold in the field experiment

3.2 Econometric modelling

Data collected via the hypothetical CE were used to estimate structural preferences by means of two Multinomial Logit (MNL) models, one for men and one for women. We also estimated a Mixed Logit model which incorporates socio-demographic covariates (including gender), which is reported in Appendix 1. Given our focus on differences between members of the couples, in the paper we decided to refer to the results from the MNL models. The data on purchases made by the couples in the field experiment were specified using the MDCEV model, since the observed choices included not only the type of cheese selected, but also a combination of cheeses in differing quantities. The outcomes of the two experiments were compared in terms of differences between utility estimates across cheese types for men and women via the MNL model and for the joint choices via the MDCEV model. Since the CE entailed only discrete choices, no comparison was possible in terms of purchased quantities.

The two models are formally described in what follows.

3.2.1 The MNL model

The MNL is based on Random Utility Theory (McFadden, 1973), according to which individual *n* facing a set of *J* mutually exclusive alternatives has utility U_i for alternative *i* as a function of attributes X_k, so that:

$$U_{ni} = \beta x_{ni} + \varepsilon_{ni} \quad \text{(Eq. 1)}$$

where ε_{ni} is the unobserved error assumed to be i.i.d. extreme value type I. The probability of respondent *n* choosing alternative *i* in choice occasion *t* is expressed as:

$$P_{nit} = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_{nit})}{\sum_{j=1}^{j} \exp(\boldsymbol{\beta}'\mathbf{x}_{njt})} \quad \text{(Eq. 2)}$$

With utility linear in the parameter, the WTP value for a given attribute can be calculated as the opposite of the ratio between the coefficient associated with the attribute (β_x) and the cost coefficient (β_{cost}):

$$WTP = -\frac{\beta_x}{\beta_{cost}} \quad \text{(Eq. 3)}$$

3.2.2 The MDCEV model

Since its introduction by Bhat (2005), the MDCEV model has become the state-of-the-art approach for analysing multiple-discrete continuous choices, and it is commonly adopted in fields such as transportation, energy and allocation of time across different activities (including recreational ones in environmental economics studies). Its main advantage, compared to discrete choice models, is that it allows the identification of saturation effects. That is, it does not only provide information on marginal utilities of goods (which is also retrieved with discrete choice models), but also on how quickly such utilities decrease when consumption levels increase. Marginal utilities estimated with discrete choice and MDCEV models are not directly comparable, but the order of utilities across different goods is. This is the approach we used in our study to compare results from the online and the field experiments.

The MDCEV model is based on a direct utility function $U(\mathbf{x})$ that individuals maximise by consuming a vector $\mathbf{x}$ of quantities of each of the *K* products, $\mathbf{x} = (x_1, \dots, x_k)$**.** The total consumption level is subject to a budget constraint $\mathbf{p}'\mathbf{x} = E$, where E is the budget and $\mathbf{p}$ is the vector of prices. In our case, the $\mathbf{x}$ vector includes a unit-priced outside good (Lu et al., 2017), representing the expenditure on goods other than the food products included in the experiment. We note that, differently from the opt out option of a CE, the outside good is not explicitly chosen by participants. Rather, it implicitly represents the unspent budget by participants on cheeses. The utility formulation is expressed as:

$$U(\mathbf{x}) = \frac{1}{\alpha_1}\psi_1 x_1^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha_k} - 1\right) \quad \text{(Eq. 4)}$$

In the above equation, $U(\mathbf{x})$ is quasi-concave, increasing and continuously differentiable with respect to $\mathbf{x}$ and ψ, and ψ_k, γ_k and α_k are parameters associated with the *k* product. ψ_k corresponds to the baseline utility of product k, i.e. the marginal utility of the first consumed unit. It is assumed that ψ_k is composed by a deterministic part V_k and by a stochastic one ε_k:

$$\psi_k = \exp(V_k + \varepsilon_k) \qquad \text{(Eq. 5)}$$

Given that utilities can be interpreted only in a relative sense, V_k is fixed to zero for the baseline good, so that $\psi_1 = \varepsilon_1$. The γ_k parameter in Equation 1 is a shift parameter that allows for corner solutions and also measures satiation effects. Specifically, the lower the value of γ_k, the higher the satiation effect associated with consumption of the product k, i.e. the higher is the rate at which marginal utility of consumption decreases. The α_k parameter measures satiation effects as well. In this case, the higher is the value of α_k, the lower is such effect. Specifically, a value of $\alpha_k = 1$ implies no satiation effect, whilst as $\alpha_k \rightarrow -\infty$ immediate satiation is implied with respect to consuming an additional unit.

The model, as described in equation 1, is unidentified because both and γ_k and α_k reflect satiation effect. For this reason, it is necessary to normalise one to identify the other. We opt for the hybrid profile, which estimates a generic α parameter and product-specific γ_k[1]. The utility function expressed in Equation 1 thereby takes the following form:

$$U(\mathbf{x}) = \frac{1}{\alpha}\psi_1 x_1^{\alpha} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha} - 1\right) \qquad \text{(Eq. 6)}$$

The probability that a consumer chooses a specific vector of consumption quantities $x_1^*, x_2^*, \dots, x_M^*, 0, \dots, 0$ where M of the K goods are consumed, is given by:

$$P(x_1^*, x_2^*, \dots, x_M^*, 0, \dots, 0) = \frac{1}{p_1}\frac{1}{\sigma^{M-1}}\left(\prod_{m=1}^{M} f_m\right)\left(\sum_{m=1}^{M}\frac{p_m}{f_m}\right)\left(\frac{\prod_{m=1}^{M}\exp\left(V_i/\sigma\right)}{\left(\sum_{k=1}^{K}\exp\left(V_k/\sigma\right)\right)^M}\right) \qquad \text{(Eq. 7)}$$

where *p*$_1$, *…*, *p*$_m$ are the unit prices of the *M* chosen goods, σ is a scale parameter and $f_m = \frac{1-\alpha}{x_m^* + \gamma_m}$. The above probability formulation is obtained assuming an i.i.d. extreme value distribution for the stochastic part of utility (ε_k in Equation 5).

4. Results

The results from the two MNL models (section 4.1) based on the hypothetical CE data are reported first, followed by those from the MDCEV model based on the field experiment on joint cheese purchases (section 4.2). In section 4.3, we report a comparison of estimated utilities for the 8 field experiment cheeses across the three models.

4.1 MNL model estimates

Table 3 reports the results of the two MNL models, while Table 4 shows the WTP values. First, note that all estimated coefficients are statistically significant at least at the 95% level. In terms of the relative importance of cheese attributes, the same ordering is found across sexes: the most important attribute is the presence of the Grana Padano logo on the packaging, followed by mountain milk, seasoning over 20 months, 17-20 month seasoning, and last in importance is the absence of lysozyme. As expected, the price has a negative coefficient. The same was found for the opt-out option constant, thus indicating that - on average - both men and women prefer one of the proposed cheeses to the no-purchase option. At the start of the CE survey, respondents knew they would partake in the experiment entailing real purchase

[1] We also estimated gamma profile models and found results to be similar both in terms of data fit and predictions

of cheeses, which may have influenced their decision to choose the cheese types over the opt-out option. Moving to the WTP estimates, it can be seen that the estimated values for the model estimated on women's choices are consistently higher than those of men (estimated differences are all statistically significant according to the test proposed by Poe et al., 2005). The highest values estimates are observed for presence of the logo (€3.34/200g for women and €2.13/200g for men), followed by mountain milk (€2.68/200g for women and €1.29/200g for men), seasoning over 20 months (€2.11/200g for women and €1.10/200g for men), seasoning 10-16 months (€1.45/200g for women and €0.41/200g for men) and, finally, absence of lysozyme (€0.36/200g for women and €0.66/200g for men).

Table 3. MNL model estimates for men and women (hypothetical CE data)

	Men		Women	
Variable	**Estimate**	**|t|**	**Estimate**	**|t|**
Grana Padano logo on packaging	0.77	10.29	0.76	9.99
Seasoning 16-20 months (baseline 10-16 months)	0.15	1.82	0.33	3.99
Seasoning more than 20 months (baseline 10-16 months)	0.40	4.79	0.48	5.66
No Lysozyme	0.13	2.35	0.15	2.63
Mountain milk	0.47	7.22	0.61	9.20
Price	-0.37	4.55	-0.23	2.82
Opt out option	-1.27	5.97	-0.69	3.18
Sample size; Number of observed choices	90; 1800		90; 1800	
Log-likelihood at maximum	-1816.275		-1824.593	
AIC	3646.55		3663.18	

Table 4. WTP values based on the MNL models (hypothetical CE data)

	Men	Women	Poe test
Attribute	**WTP (€/200g)**	**WTP (€/200g)**	**p value**
Grana Padano logo on packaging	2.13	3.34	<0.001
Seasoning 16-20 months	0.41	1.45	<0.001
Seasoning more than 20 months	1.10	2.11	<0.001
No Lysozyme	0.36	0.66	0.003
Mountain milk	1.29	2.68	<0.001

4.2 MDCEV model estimates

We start the description of the MDCEV estimates from the baseline utility parameters ϑ (Table 5), noting that the outside good was the reference alternative so as to identify the parameters for the other products. All coefficient estimates are statistically significant at least at 95% level and positive, thus suggesting that – at zero consumption level – consumers benefit more from purchasing cheeses than from the outside good. We note that the highest value estimate is obtained for the cheese Grana Padano with more than 20 months of seasoning and mountain milk; this suggests that consumers - on average - prefer this cheese most and confirms the interest in cheese made from mountain milk as identified from the results of the MNL estimates described in the previous section. Then, the second and third highest baseline utility values were estimated for the Grana Padano and the Italian hard cheese with the longest seasoning. This suggests that participants are strongly interested in this long-seasoned cheese, again consistent with the results of the MNL models. The following cheeses, in terms of associated utility, are Grana Padano without lysozyme, Grana Padano with 17 – 20 months seasoning, Grana Padano 10 - 16 months seasoning and Italian Cheese with 17 - 20 months seasoning. Finally, the cheese associated with the lowest baseline utility is the Italian hard cheese seasoned for 10 - 16 months. When comparing Grana Padano and Italian hard cheese with the same characteristics (in terms of seasoning, use of lysozyme and milk production area) the results suggest that consumers consistently prefer the former. This is consistent with the estimates of the MNL models, which showed a strong preference for cheeses with the Grana Padano logo. With regards to the effects of the satiation parameters, we first note that the α coefficient is statistically insignificant, as found in other studies (Calastri et al., 2017). The γ parameters, instead, are all different from zero in a statistically significant manner (at least 95% level). We remind the reader that the higher the estimated value for γ, the lower is the satiation effect. As such, the lowest satiation effect estimate is for Italian hard cheese with 10 - 16 months of seasoning. Interestingly, this cheese has both the lowest baseline utility and the lowest rate of its decrease as quantities purchased increase. Similarly, the highest satiation effect was found for the cheese with the highest baseline utility, i.e. the Grana Padano cheese with mountain milk. The other two kinds of cheese with the longest seasoning (Grana Padano and Italian Hard cheese 20+ months of seasoning) have the second and third highest satiation effect. A low satiation effect, instead, was also estimated for the Grana Padano 10-16 months of seasoning and for the Italian hard cheese with 17-20 months of seasoning.

Finally, Table 6 reports the predictions of the average purchased quantities. These are reasonably close to the observed values, with a slight overestimate for all products.

4.3 Comparison of utilities across models

In this section, we report a comparison of the utilities for the 8 cheeses estimated with the three models illustrated in the previous sections. For the MDCEV model, the utility values are represented by the ϑ coefficients, while in the case of the two MNL models, the utility values were obtained from the coefficients reported in Table 2. The first interesting result (Table 7) is that the Grana Padano with mountain milk is consistently associated with the highest utility across the three models, thus corroborating how strong consumers preferences are for cheese produced from mountain milk, no matter whether choices are jointly performed for real purchases or stated individually. The order of preferences towards other cheeses, instead, is substantially different across the three models. For example, according to the MDCEV model and the MNL on women data, the cheese associated with the lowest utility is the Italian hard cheese with 10-16 months of seasoning, but not so in the MNL model for men. Some differences also emerge when comparing utilities for cheeses between men and women. For men, Grana Padano with over 20 months of seasoning is associated with a higher utility than that with 17-20 months of seasoning, while the opposite was found for women. Then, looking at the Italian hard cheese, it can be seen as the order of preferences for men is to favour most the cheese with 20 months of seasoning, followed by that with 10-16 months and ending with that with 17 - 20 months. For women, instead, the order is 17-20 months, over 20 months and 10-16 months. We do not have, however, any additional information that could help explain these apparent gender differences with respect to savoury preferences of cheeses with different lengths of seasoning.

Table 5. MDCEV model estimates (field experiment data)

	ϑ baseline utilities		γ satiation parameters	
	value	**|t|**	**value**	**|t|**
Italian hard cheese 10 – 16 months seasoning, lysozyme and no mountain milk	0.34	1.98	1.32	6.18
Italian hard cheese 17 – 20 months seasoning, lysozyme and no mountain milk	0.41	1.99	1.12	8.38
Italian hard cheese 20+ months seasoning, lysozyme and no mountain milk	1.24	5.28	0.90	7.17
Grana Padano 10 – 16 months seasoning, lysozyme and no mountain milk	0.64	3.30	1.23	7.12
Grana Padano 17 – 20 months seasoning, lysozyme and no mountain milk	0.67	3.16	1.05	9.43
Grana Padano 20+ months seasoning, lysozyme and no mountain milk	1.53	6.24	0.88	6.32
Grana Padano 10 – 16 months seasoning, no lysozyme and no mountain milk	0.95	5.20	1.00	8.02
Grana Padano 20+ months seasoning, lysozyme and mountain milk	2.75	3.55	0.21	2.50
α satiation parameter	0.85	0.87		
σ scale parameter	0.69	3.40		
Log-likelihood: -793.208				

Table 6. MDCEV model predictions of average consumption levels (field experiment data)

Cheese	**Observed consumption**	**Model predictions**
Italian hard cheese 10 – 16 months seasoning, lysozyme and no mountain milk	0.44	0.47
Italian hard cheese 17 – 20 months seasoning, lysozyme and no mountain milk	0.26	0.30
Italian hard cheese 20+ months seasoning, lysozyme and no mountain milk	0.59	0.65
Grana Padano 10 – 16 months seasoning, lysozyme and no mountain milk	0.33	0.35
Grana Padano 17 – 20 months seasoning, lysozyme and no mountain milk	0.26	0.30
Grana Padano 20+ months seasoning, lysozyme and no mountain milk	0.68	0.71
Grana Padano 10 – 16 months seasoning, no lysozyme and no mountain milk	0.42	0.47
Grana Padano 20+ months seasoning, lysozyme and mountain milk	1.37	1.54

Table 7. Comparison of cheeses' utilities across models

Cheese	MDCEV	MNL men	MNL women
Italian hard cheese 10 – 16 months seasoning, lysozyme and no mountain milk	0.34	-0.56	-0.28
Italian hard cheese 17 – 20 months seasoning, lysozyme and no mountain milk	0.41	-0.59	-0.07
Italian hard cheese 20+ months seasoning, lysozyme and no mountain milk	1.23	-0.48	-0.08
Grana Padano 10 – 16 months seasoning, lysozyme and no mountain milk	0.63	-0.07	0.30
Grana Padano 17 – 20 months seasoning, lysozyme and no mountain milk	0.67	0.04	0.58
Grana Padano 20+ months seasoning, lysozyme and no mountain milk	1.53	0.11	0.56
Grana Padano 10 – 16 months seasoning, no lysozyme and no mountain milk	0.95	-0.28	0.10
Grana Padano 20+ months seasoning, lysozyme and mountain milk	2.75	0.39	1.12

5. Conclusions

We presented the results of a preference study aimed at investigating joint choices by couples concerning purchases of Italian cheese types in hypothetical and real choice settings. To this end, we adopted a two-stage approach using choices from a sample of 90 couples of cheese consumers. At first, each member of the couple filled in a web-survey including a hypothetical CE investigating preferences towards cheese features. Then, the couples partake in a field experiment with monetary incentives in which they jointly choose which cheeses to purchase, as well as the consumption quantity. We modelled CE data via MNL models and the real purchases data via the MDCEV model. The results highlighted a strong preference of consumers towards cheese with the Grana Padano logo, long seasoning and mountain milk. These results were consistent across both men and women and real and hypothetical choices. When comparing the preferences of men and women for cheese attributes, we found them to be similar, a result that is consistent with previous studies on joint choice (e.g. Mariel et., 2018). However, we found differences in terms of WTP values for cheese attributes (similarly to Menon et al., 2024), with women wanting to pay substantially higher values than men.

When comparing utilities obtained from the hypothetical CE and the real purchase experiment, however, several differences were found in terms of the ordering of preference toward different cheeses. This provides some preliminary evidence that there may be some differences in the decision process when choices are made individually, compared to when choices are made jointly, although these differences can also be underscored, and hence confounded, by the real choice setting that framed the collection of joint choices. This result is consistent with several studies in the joint choice literature (e.g. Beharry-Borg et al., 2009; Rungie et al., 2014; Hensher et al, 2017). In our case, utility values estimated from joint choices were closer to those of men, who seem to have more bargaining power in the joint cheese choices in the real purchase context. This result differs from previous studies, in which women were found to have more bargaining power in the context of choices over tap water quality (Rungie et al., 2015) and beach site visitation (Beharry-Borg et al, 2009). This seems to suggest that bargaining power across members of a household may vary depending on the good/services being chosen, or the hypothetical versus real choice context. The results also suggest the possible existence of a form of hypothetical bias still relatively unexplored in the literature, that is the order of preference for different cheeses changes when comparing hypothetical and real choices. The presence of possible hypothetical bias is consistent with the large body of literature highlighting such an effect when comparing real and hypothetical choices (e.g. Moser et al., 2013; Ready et al., 2010; Grebitus et al.; 2013).

There are clear implications of our results for the food supply, as they seem to support investments in production, marketing and logistics for cheese produced from mountain milks.

We acknowledge three main limitations of our study. The first lies in the relatively small sample size that could affect the accuracy of the estimates, as well as limiting the possibility of estimating dedicated models to explore the influence of individuals on joint choices (as the Structural Equation Model estimated in Rungie et al., 2014). This is important as it would allow one to uncover more nuanced individual effects on joint choices, compared to the sole comparison of utilities across individuals and joint choices. The second limitation of our study lies in the framework we adopted for investigating joint choice and hypothetical bias, which may have led to confounding of the two effects. It would be of interest for future research to carry out both the hypothetical and the real experiment with the same framework (i.e. individual first and joint choices later in both experiments) to avoid this possible confounding, an approach that we could not implement in our study given the available budget. Finally, the attributes in our field experiment were not balanced in the same way they were in the choice experiment, which might have an influence on the comparison between the real and hypothetical data.

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