Nudging consumers' choices for niche milk: a real purchase experiment

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Cristiano Franceschinis
University of Padua

Riccardo Scarpa
Durham University, University of Verona, University of Waikato

Mara Thiene
University of Padua

Abstract

Policies based on nudging have become increasingly popular internationally, but the literature provides mixed evidence of their effectiveness and it has hosted an intense academic debate. This study contributes to the debate by investigating the effect of different nudging techniques (availability enhancement, visibility enhancement, and healthy eating call) via a framed field experiment involving purchases of milk types. Participants were endowed with a cash amount to purchase any desired quantity of the different products and then were split into groups receiving different nudging treatments. Treatment effects on observed real choices are analysed with a multiple discrete–continuous nested extreme value model based on random utility maximization, and with differences in correlations between purchases of milk types. Nudges based on healthy eating call are found to affect participants' milk choices in a statistically significant manner. We derive simulated demand curves conditional on nudging treatments, which measure the effect of the latter on consumers' consumption levels of the different milk types available. Changes on correlations provide implications for complement and substitution patterns of the significantly effective nudge.

1. Introduction

Policies based on nudging have become increasingly popular internationally in the context of consumers' food choices. They seek to change for the better the way people make choices, including those associated with food items, by systematically affecting the subjects' responses to available options (Matjasko et al., 2016). The "nudge theory" was introduced as a type of policy intervention (Thaler and Sunstein, 2008) with the following requirements: i) to be liberty preserving; ii) to not rely on economic incentives; iii) to not involve overt methods of persuasion; and iv) to redesign the choice context in line with the principles of behavioural economics (Oliver and Ubel, 2014). A growing body of research has since developed to assess the effectiveness of different nudging interventions. To date it still provides limited guidance on how and in what conditions nudges can be effectively used (Codagnone et al., 2014, Candario and Chandon, 2019). Unquestionably, directing choice by means of techniques based on nudging is theoretically appealing. But the conclusions from the evidence reported in the existing literature have been criticised as pointing to inconsistent and weak findings regarding its effectiveness (Libotte et al., 2014, Nørnberg et al., 2016, Laiou et al., 2021). For example, Hummel and Maedche (2019) reviewed 100 papers using different types of nudging and found that only 62% of them report statistically significant effects. Importantly, the evidence is inconsistent even when looking at the effect of specific nudges. For example, in availability nudges some studies found substantial positive effects in terms of guiding consumers toward the "desired" choice (e.g. Velema et al., 2018; Van Kleef et al., 2012), others only modest (e.g. Rozin et al., 2011) and others (e.g. Goto et al., 2013) report little to no effect. To provide further detail, Goto et al. (2013) carried out an intervention in a school cafeteria aimed at inducing students to choose white milk over chocolate milk. Specifically, the availability nudge consisted in a visual cue whereby white milk quantity was three times as much as that of chocolate milk. The authors found no significant effect of this intervention on students' choice patterns. In a similar school setting van

Kleef (2020) gradually increased, over a period of 10 months, the availability of healthy foods and found a positive, albeit small, effect on the quantity of healthy food purchased by students. Weingarten et al. (2024) designed a virtual supermarket to investigate the effect of a combined availability and visibility nudging approach on choices of products with high animal welfare (AW) standards. They found this combined approach to almost double the percentage of AW products purchased by participants.

Concerning positioning nudging, the recent review by Laiou et al. (2021) highlights how only half of the twelve existing studies using randomized controlled trials found significant and positive effects. For example, Kroese et al. (2016) investigated – in an experiment at a train station snack shop - the effect of placing healthy foods at the cash register desk, while keeping unhealthy products available elsewhere in the shop. They found a positive effect of this approach on healthy choices. Romero and Biswas (2016) found that displaying healthy items to the left of unhealthy items enhances preference and increases the volume of purchased healthy products. Kongsbak et al. (2016) altered the order of placement of healthy food items in a buffet setting and found that the consumption of self-served fruit and vegetables increased while that of unhealthy meal components decreased. Foster et al. (2014) designed a product visibility intervention in supermarkets. The intervention involved different categories of products, and it consisted in placing healthy products on shelves at eye level and on the middle level along the category aisle. Their findings suggest that the nudge was effective for some categories of products but not for others.

Finally, there is also inconsistency in the results of studies focusing on nudges based on conveying messages to consumers to guide their choices (such as healthy eating call). The literature is divided among positive (e.g. Ensaff et al., 2015; Coffino et al., 2020), insignificant (e.g. Chapman et al., 2019) and even negative effects (e.g. Avitsland et al., 2017; Moran et al., 2019). Furthermore, the effect of this nudging may even vary across different consumers. For example, Goncalves et al.

(2021) carried out a nudging intervention in a supermarket, where customers received social norms messages about fruit and vegetables. The authors reported contrasting findings, depending on consumers' purchasing habits. Customers with less healthy habits were positively affected while those with healthy habits were slightly negatively affected.

This paper contributes to the nudging literature by investigating the effect of different nudge-based stimuli in a framed field experiment regarding milk types. The experiment is based on real choices across multiple products and their respective quantities. This gives rise to real data suitable to estimate a discrete-continuous choice model. The milk options are as follows: *i*) whole milk, *ii*) semi-skimmed milk, *iii*) organic milk, *iv*) milk from hay-fed cows, and *v*) milk enriched with beta-casein A2. We chose Beta-Casein A2 milk as the target of our nudging treatments due to its emerging role as a "niche" product in the market, primarily aimed at the growing number of lactose intolerant consumers. Recent global trends indicate a growing interest in the production and marketization of A2 milk types (Dantas et al., 2023) and as such investigating the demand of this product and how this can be influenced by nudging interventions can be relevant for industries looking to differentiate their products, and to make this new product known and assessed by consumers.

The focus on milk is motivated by its large consumption among the Italian population. According to ISTAT (Italian National Institute of Statistics) data (collected in 2020)[1], 48.1% of Italians aged 3 or older drink milk at least once per day, 28.7% does so occasionally and only 22.2% does not consume this product at all. We choose to include organic and hay milk in our “milk basket” due to the increasing demand in Italy for sustainably produced milk. According to a recent report[2] published by SINAB (National Information System on Organic Agriculture), in 2022 there was an

[1] C_17_pubblicazioni_3167_allegato.pdf (salute.gov.it)
[2] 151123_Bio in cifre 2023.pdf (sinab.it)

increase of 5.2% of the demand for organic milk compared to the previous year. Overall, organic dairy products account for 21.1% of the total expenditure for organic products of Italian consumers.

Our experiment involved 355 participants who could use real cash endowments to purchase milk bottles in any desired quantity to take home after the experiment, along with the cash left over. We note that this experimental design is similar to a large extent to the so-called “Basket-Based Choice Experiment” (Caputo and Lusk, 2022), in which participants can freely choose among different products to create their own combination (or basket) of consumed goods.

Three different nudging treatments were used within our experiment, namely: i) availability enhancement, ii) visibility enhancement, iii) healthy eating call.

Choices of milk products selected by subjects and their purchased quantities were analysed via the multiple discrete continuous extreme value (MDCEV) model proposed by Bhat (2005; 2008), which is an evolution of the Khun-Tucker model discussed by von Haefen and Phaneuf (2005) in the context of outdoor recreation (see also Phaneuf 1999, Phaneuf et al. 2000). Despite the popularity of such model in other fields (e.g. transportation and energy), where it has become the state-of-the-art approach for analysing multiple-discrete continuous choices, there is still a paucity of empirical applications for the analysis of food choices. The only exceptions we found are Richards et. al. (2012), which investigated brand effect of apple varieties, Richards and Mancino (2014) focusing on demand for food-away-from-home and Franceschinis et al. (2022) who analysed preferences for organic and locally produced foods. None of these studies focused on the effects of experimental nudging treatments on real purchases. This study contributes to the existing literature of nudging effects by exploring the potential of the MDCEV model for their investigation. Finally, we use the estimates of our model to simulate demand curves for the different milk types, conditional on nudging treatments.

The remainder of the papers is structured as follows: section 2 describes our experimental setting; section 3 formally describes our econometric approach; section 4 presents our results while section 5 draws the conclusions of our study and points to further research questions.

2. Experimental approach

The field experiment involved the real purchase of five different milk types, as reported in the previous section. All types were purchased from the same company, to ensure that brand effects could confound our results. Price levels were defined per bottle (1 liter) according to the price values prevailing in the market of the Veneto region, where the experiment took place. The three different sets of prices used within the experiments are reported in Table 1. To maintain our experiment as close as possible to the real market conditions, we decided to change the price of all products by the same amount (0.20€) across the three sets. As the relative change of the prices across the products vary (as reported in Table 1) our design allows to capture price effects on the demand of milk types and the potential substitution effects across bundles of milk types purchased.

Table 1. Prices of different milk products

Milk type	Baseline	Set 2	Set 3
Whole	€1.30	€1.50 (+15.38%)	€1.70 (+30.77%)
Semi-skimmed	€1.30	€1.50 (+15.38%)	€1.70 (+30.77%)
Organic	€1.70	€1.90 (+11.76%)	€2.10 (+23.53%)
Hay milk	€1.70	€1.90 (+11.76%)	€2.10 (+23.53%)
Beta-casein A2	€1.60	€1.80 (+12.50%)	€2.00 (25.00%)

Note: Percentage increase from the baseline price in brackets

The experiment was designed to mirror as closely as possible consumers' experience in a real shopping scenario when purchasing milk to be consumed at home, typically during breakfast. For this purpose, we carried out the experiment at a dairy shop located in Lancenigo (Veneto region, North-east Italy, coordinates 45.702539, 12.248085). To make the experimental market more natural and realistic to subjects, we placed the food items in two refrigerators of the type commonly used in dairy shops. Upon entering the shop, all participants received instructions for the experiment in written form (reported in Appendix 1). The instructions included information about the purpose of the study and outlined the rules of the experiment, as follows: *a*) a budget of €10 was provided to participants to purchase any milk available in the shop refrigerators; *b*) participants could choose to either spend all their budget or part of it; *c*) at the end of the experiment participants took home all purchased products and, if any, the cash change left over. After reading the instructions, participants proceeded to choose the milk to purchase. Next, the member of the research team in attendance registered the milk choices and quantities purchased by each subject, and then calculated if any cash change was due back to the participant. At the end, subjects were given the milk types they purchased, and the change left over in cash. A total of 355 subjects partook in the field experiment. Participants in the experiment were recruited by a market research firm, who ensured the final sample had the desired stratification in terms of the leading socio-demographic variables.

2.1 Nudging treatments

The nudging approaches used during the experiment were as follows: *i*) availability enhancement, *ii*) visibility enhancement, *iii*) the healthy eating call (Figure 1). The nudging treatments focused on the Beta-Casein A2 milk, as already reported in the introduction section. Subjects were evenly and randomly allocated to four subsamples: one acting as control (e.g. with no nudging treatment) and the other three receiving a different nudging treatment each.

In the availability enhancement nudge the proportion of displayed products was manipulated. The number of bottles of the target product (milk with Beta-casein A2) displayed on the refrigerator shelves was more abundant than those of the other non-targeted milk types.

In the visibility enhancement approach, instead, the position of displayed products was manipulated. The bottles with Beta-casein A2 milk were placed in the most visible shelf (eye-levelled), e.g. the one at the level of the head for most respondents not too high and not too low. This positioning ensured that the target product fell in the immediate field of vision of the subjects.

Finally, for the healthy eating call, a message concerning the health benefits of the Beta-casein A2 milk was shown to participants. This consisted in a poster that was placed adjacent to the shelves with the milk bottles. The poster illustrated the advantages of the milk type targeted by the nudge. Specifically, the poster reported the following sentence: “Beta Casein A2 milk is more easily digestible and makes you feel lighter compared to other milk types”. Note that in Italian common parlance a food that is "making one feel lighter" is intended as a food requiring less digestive effort, and it does not mean--as it may appear from a literal translation--to make someone lose weight.

Figure 1. Position of the products in the four treatments.

Control group	Proportion	Position	Healthy eating call
			

3. Econometric approach

The observed choices of purchase were milk baskets, composed of bundles of quantities across five types of milk bottles. Econometric modelling of these baskets need to account for counts of each type of milk bottle purchased, including corner solutions (zero bottles of some or all types). A suitable econometric model is represented by the multiple discrete continuous model with an error structure that makes it compatible with random utility, which is explained below (see also Franceschinis et al., 2022). The main advantage of this model for the analysis of nudging effects is the possibility of measuring both choice effects (i.e. understanding if nudges increase the likelihood of choosing targeted products) and satiation effects (i.e. identifying if nudges affect the quantity consumed conditional on having chosen a given product). In terms of policy implications, this allows one to tailor strategies to either increase the probability of initial choice or to encourage higher consumption by lowering the rate of satiation. Furthermore, the estimation of these two effects allows analysts to simulate how nudging approaches change demand curves for targeted products. Finally, the model explicitly handles zero purchases (i.e. corner solutions), which is crucial in scenarios where many baskets are generated with zero purchase of certain food types.

3.1 The multiple discrete continuous extreme value model

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 product types available, $\mathbf{x} = (x_1, \dots, x_k)$. The total consumption level is subject to a budget constraint $\mathbf{x}'\mathbf{p} = E$, where E is the expenditure budget and $\mathbf{p}$ is the K dimensional vector of prices, one element of the vector for each product type. In our case, the vector $\mathbf{x}$ includes a unit-priced outside good (Lu et al., 2017), which represents the expenditure on goods other than the food products included in the experiment, i.e. a standard numeraire outside good. The utility formulation is expressed using the notation from Bhat (2008):

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

In the above equation, $U(\mathbf{x})$ has the standard properties of a utility function, i.e. it 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 one unit of the good at zero consumption. One of the goods (denoted with the subscript "1" in equation 1) is chosen as numeraire and acts as baseline, and utility levels for alternative products are defined relative to this baseline good. In our model, we used the outside good as the baseline.

The model assumes that the baseline utility ψ_k is composed by a deterministic component V_k and by a stochastic one ε_k, so that it can be expressed as an additive argument in the exponential function, which ensures a non-negative value:

$$\psi_k = \exp(V_k + \varepsilon_k) \quad \text{(Eq. 2)}$$

Given that only differences in utilities matter, V_k is fixed to zero for the first (baseline) good, so that $\psi_1 = \exp(\varepsilon_1)$.

The γ_k parameter in equation 1 is a translation parameter that allows for corner solutions, i.e. it accounts for the possibility of a participant choosing a quantity equal to zero for one (or more) of the milk products included in the experiment. γ_k also reflects satiation effects; specifically, the higher the value of γ_k, the lower is the satiation effect with the consumption of the product k, i.e. the lower is the rate at which marginal utility of consumption decreases. This is because a higher γ_k implies that more consumption of the corresponding x_k is needed to reach satiation (i.e. the point in which marginal utility equals zero).

The α_k parameter solely reflects satiation effect. In this case, the higher is the value of α_k, the lower is the satiation effect. More specifically, a value of $\alpha_k = 1$ implies no satiation effect, whilst as $\alpha_k \rightarrow -\infty$ the model implies immediate satiation with respect to consuming an additional unit of product k.

The model, as described in equation 1, is unidentified because both and γ_k and α_k reflect separate satiation effects. For this reason, it is necessary to normalise one of the two to identify the other. This leads to different MDCEV specifications (or profiles), according to the type of normalization used. In our case, we adopted a hybrid profile, which estimates a generic α parameter and product-specific γ_k. As such, the γ_k coefficients allow us to measure satiation effects for the different milk types, an information which is not obtainable with traditional discrete choice models. In this profile, the utility function expressed in equation 1 becomes:

$$U(\mathbf{x}) = \frac{1}{\alpha}\psi_1 x_1^{\alpha} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1\right)^{\alpha} - 1\right) \qquad \text{(Eq. 3)}$$

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

$$P(\mathbf{x}^*) = \frac{1}{p_1}\frac{1}{\sigma^{M-1}}\left(\prod_{m=1}^{M} f_m\right)\left(\sum_{m=1}^{M}\frac{p_m}{f_m}\right)\left(\frac{\prod_{m=1}^{M}\exp\left(\frac{V_i}{\sigma}\right)}{\left(\sum_{\mathrm{k}=1}^{\mathrm{K}}\exp\left(\frac{\mathrm{V_k}}{\sigma}\right)\right)^{M}}\right)(M-1)! \qquad \text{(Eq. 4)}$$

where $\mathbf{p} = \{p_1, p_2, \dots, p_m\}$ 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 2).

The MDCEV structural model does not identify substitution and complementarity effects in consumption. However, the effect of nudging on such relationships can be identified via the changes in correlation of milk bundles purchased across treatments and control groups. This analysis is conducted separately and as a complement to the structural model results.

3.2 Nudging treatments analysis

The effect of different nudging techniques is included in the utility function by parameterizing ψ_k γ_k to be function of dummy variables identifying the nudging treatments.

Specifically, the baseline utility expressed in equation 2 can be further parametrized as:

$$\psi_k = \exp(V_k + \varepsilon_k) = \exp(\vartheta_k + \boldsymbol{\beta}'_k \mathbf{z}_k + \varepsilon_k) \qquad \text{(Eq. 5)}$$

where ϑ_k is a constant, z_k is a vector of the dummy variables for the nudging treatments with an associated vector of parameters $\boldsymbol{\beta}'_k$ and ε_k captures unobserved factors that affect baseline utility of good k.

A similar parametrization can be used to investigate the effect of nudge treatments on satiation. In the case of the hybrid profile (the one we estimated), this is done by expressing the satiation parameter γ_k as:

$$\gamma_k = \exp(\omega_k + \boldsymbol{\lambda}'_k \mathbf{z}_k) \qquad \text{(Eq.6)}$$

where ω_k is a constant and the vector of parameters $\boldsymbol{\lambda}'_k$ measures the effect of the nudging treatments on satiation.

Given the parameterizations reported in equations 5 and 6, a positive element of $\boldsymbol{\beta}'_k$ would imply that the associated nudging treatment increases the perceived baseline utility for product k, thus increasing its choice probability. A positive element of $\boldsymbol{\lambda}'_k$, instead, would imply a lower satiation effect (given that satiation decreases when γ_k increases). In turn, this would imply that a given nudging treatment increases the chosen consumption level of product k.

3.3 Demand curves simulation

To generate the simulated demand curves for each milk type, we used the estimated coefficients from the above model to predict consumption levels for 50 price levels ranging from €0.30 to €3.00. The predictions were obtained by using the forecasting algorithm proposed by Pinjari and Bhat (2010). The algorithm consists in the following steps:

1. Assume that only the outside good is chosen and let the number of chosen goods $M = 1$;
2. Given the input data, the estimated model parameters and the simulated error term draws, compute the price-normalized baseline utility values for each product k. Then, arrange all the products in descending order according to their price-normalized baseline utility values (with the outside good in the first place).
3. Compute the Lagrange multiplier λ as:

$$\lambda = \left(\frac{E + \sum_{k=2}^{M} p_k \gamma_k}{p_1 \left(\frac{\psi_1}{p_1}\right)^{\frac{1}{1-\alpha}} + \sum_{k=2}^{M} p_k \gamma_k \left(\frac{\psi_k}{p_k}\right)^{\frac{1}{1-\alpha}}} \right)^{\alpha - 1} \quad \text{(Eq. 7)}$$

4. If λ is greater than the price-normalized baseline utility of product in position $M + 1$, compute the optional consumption level for the first M products in the step 2 order, by using the following formulae:

$$\frac{e_1^*}{p_1} = \frac{\left(\frac{\psi_1}{p_1}\right)^{\frac{1}{1-\alpha}} \left(E + \sum_{k=2}^{M} p_k \gamma_k\right)}{p1 \left(\frac{\psi_1}{p_1}\right)^{\frac{1}{1-\alpha}} + \sum_{k=2}^{M} p_k \gamma_k \left(\frac{\psi_k}{p_k}\right)^{\frac{1}{1-\alpha}}} \quad \text{(Eq. 8)}$$

$$\frac{e_k^*}{p_k} = \left(\frac{\left(\frac{\psi_k}{p_k}\right)^{\frac{1}{1-\alpha}} \left(E + \sum_{k=2}^{M} p_k \gamma_k\right)}{p1 \left(\frac{\psi_1}{p_1}\right)^{\frac{1}{1-\alpha}} + \sum_{k=2}^{M} p_k \gamma_k \left(\frac{\psi_k}{p_k}\right)^{\frac{1}{1-\alpha}}} - 1 \right) \gamma_k;\ \forall k = (2,3, \dots, M) \quad \text{(Eq. 9)}$$

where e_k is the expenditure for product k. Then, set the consumption level for the other products to zero and stop the algorithm. If, instead, λ is not greater than the price-normalized baseline utility of product in position $M + 1$, proceed to step 4.

5. Update $M = M + 1$. If $M = K$, then compute the optional consumption levels by using Equations 7 and 8. Else, go to step 2.

4. Results

4.1 Descriptive statistics of the sample

This section reports at first the descriptive statistics of our sample (Table 2), then those of the observed choices (Figures 2 to 5).

Table 2. Descriptive statistics of the sample

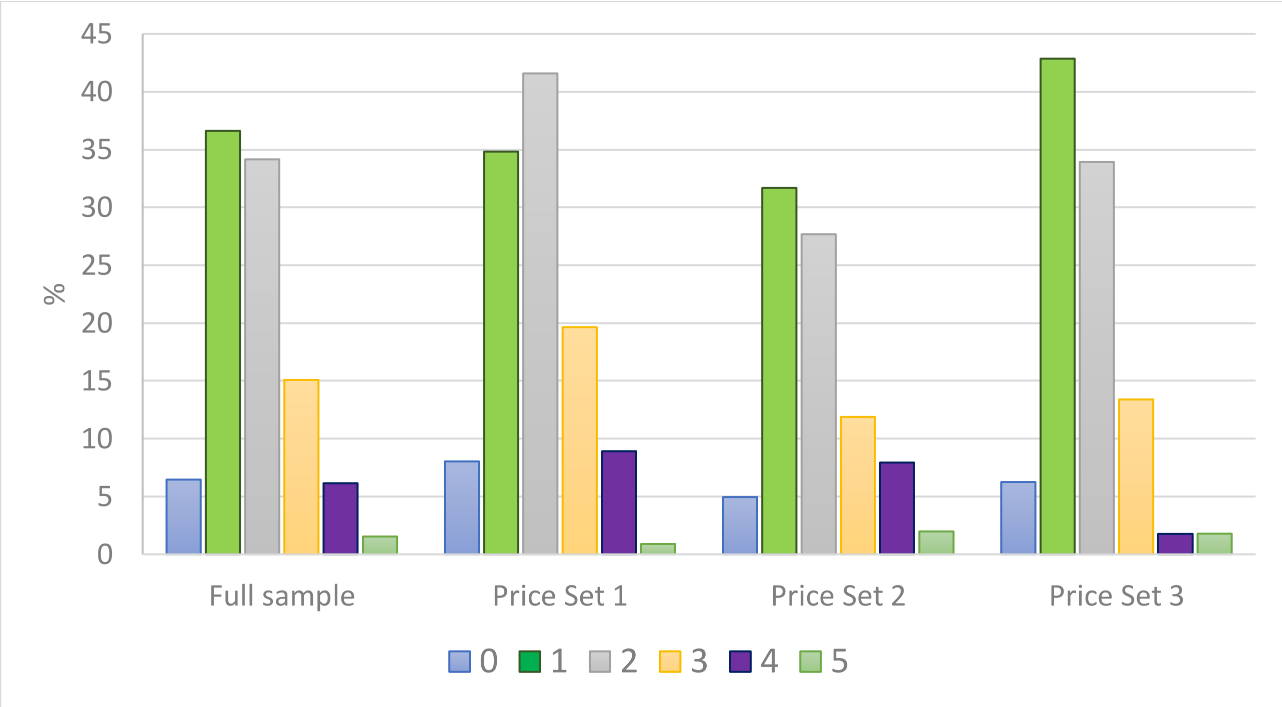
Treatment	**Control**	**Proportion**	**Position**	**Healthy eating**	**Full sample**
Sample size	88	86	93	88	355
Gender					
Woman	0.56	0.61	0.62	0.58	0.59
Man	0.44	0.39	0.38	0.42	0.41
Age					
18 - 30	0.19	0.25	0.24	0.27	0.24
31 - 40	0.31	0.35	0.28	0.28	0.30
41 - 50	0.27	0.22	0.27	0.25	0.25
51 - 60	0.17	0.14	0.18	0.17	0.16
61 - 70	0.06	0.04	0.04	0.03	0.04
Education					
Middle school or lower	0.08	0.07	0.06	0.09	0.08
High school	0.57	0.58	0.62	0.54	0.58
Bachelor’s degree	0.09	0.15	0.13	0.16	0.14
Master’s degree	0.12	0.16	0.16	0.13	0.14
PhD/Master	0.13	0.04	0.03	0.08	0.07
Household income (€/month)					
0 - 1,000	0.07	0.09	0.08	0.06	0.07
1,001 - 1,500	0.08	0.12	0.15	0.18	0.13
1.501 - 2,000	0.09	0.16	0.19	0.08	0.13
2,001 - 2,500	0.25	0.24	0.21	0.29	0.25
2,501 - 3,000	0.25	0.21	0.22	0.21	0.22
3,001 - 3,500	0.05	0.02	0.01	0.04	0.03
More than 3,500	0.04	0.05	0.03	0.07	0.05
No answer	0.16	0.11	0.11	0.07	0.11

The sample is fairly balanced in terms of gender, with a slight prevalence of women (61%) but this reflects the fact that more women than men are in charge of this category of purchases. It is also well distributed in terms of age, with the highest frequency (31%) class being aged between 31 and 40. With regards to education attainments, most of the sample achieved a high school diploma (58%) or a university degree (21%), which are percentages in line with the official national statistics[3]. Around half of the sample declared a monthly household income between €2,001 and €3,000, while the lowest income class (less than €1,000/month) includes around 7% of respondents and the highest (more than €3,500) represented by only the 4%. We note, however, that 16% of participants preferred not to disclose this information. Regarding the sample allocation across nudging treatments, the subsamples present similar distributions for all the main socio-demographics.

Figure 2 reports the distribution of the number of milk types participants chose. Looking at first at the full sample (first set of bars), it can be noticed how the most common choice is the purchase of only one milk type, closely followed by two types (37% and 35%, respectively). Around 6% of participants decided not to purchase milk, while only a little less than 2% chose all available milk types.

[3] Italy | Education at a Glance 2022: OECD Indicators | OECD iLibrary (oecd-ilibrary.org)

Figure 2. Number of chosen milk types



With reference to the aforementioned study of Caputo and Lusk (2022), we note that within their experiment, participants also tended to choose a small subset of the available products as well (the most frequent choices being three or four out of the 21 available products).

Moving to the price subsamples, we note that for the baseline price levels (i.e. the lowest) the most common choice is to purchase two milk types (42%). A substantial number of participants (almost 20%) opted for the choice of three milk types. This subsample also has the highest share of participants choosing four milk types (almost 10%). For the second and third set of prices, instead, one milk type is the most frequent choice. In the set with highest prices (the third), the difference between the shares of those who bought one type and those who bought two milk types is substantial (43% vs 34%). We also note that – compared to the baseline prices – the percentage of participants choosing three different types also decreases considerably in the higher price sets. It is hence clear that lower prices positively correlate with an increase of the frequency of purchase of a more diverse milk bundle. Finally, it can be seen how price does not seem to affect the decision of not making any purchase at all, as complete corner solutions remain stable. We note that during debriefing, participants who chose to buy no milk often declared at the end of the experiment to either be lactose intolerant or not to be equipped to transport the fresh product(s) back home given the long distance from their place of residence. So, price levels did not seem to affect this choice.

Figure 3 reports the choice frequencies for milk types. Starting from the full sample data, the histogram highlights how the most frequently chosen product is hay milk (46%), followed by organic and Beta-Casein A2 (both at 38%). The price subsamples exhibit a similar distribution, with the only notable difference being the semi-skimmed milk being chosen more frequently than the organic one in the third set (i.e. the highest price one). We remind the reader that the semi ski-skimmed is the cheapest milk type, while the organic one is the most expensive, which may explain such results and even the large number of respondents choosing two milk types. We report the pairings of milk types which were most chosen together in Figure 4. The most common pairing is hay milk and Beta-casein A2 (25% of participants), that is a milk type with environmental benefits and one with health ones. The second most common pairing is organic and hay milk, the two products associated with environmental benefits, in a good part of a public nature. Finally, it is of interest to notice how semi-skimmed milk, despite being only the fourth most commonly chosen product, was also frequently paired with other milk types. This might be due to intra-household preference diversity. There is often one household member preferring lower fat milk for various reasons. It can also be due to the particular suitability of types of milk for specific recipes.

Figure 3. Choice frequencies of milk types

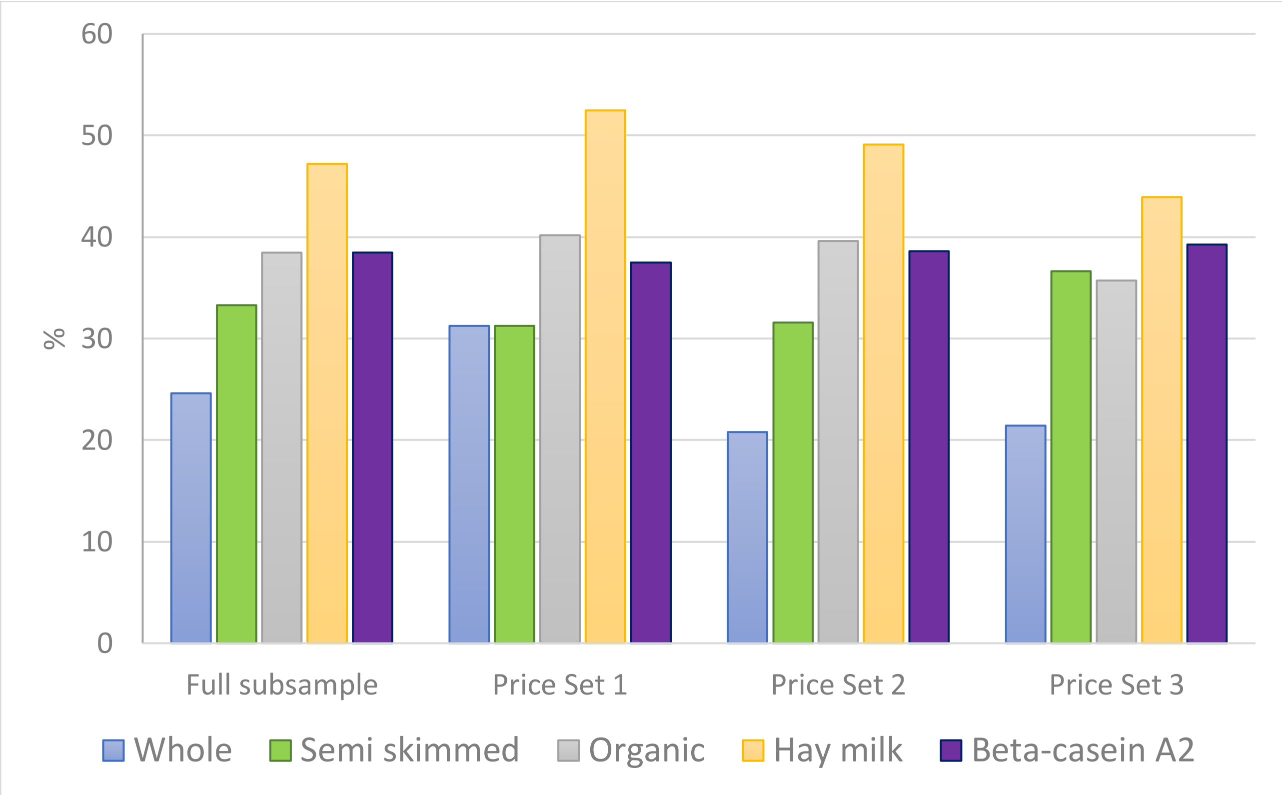


Figure 4. Pairings of milk types

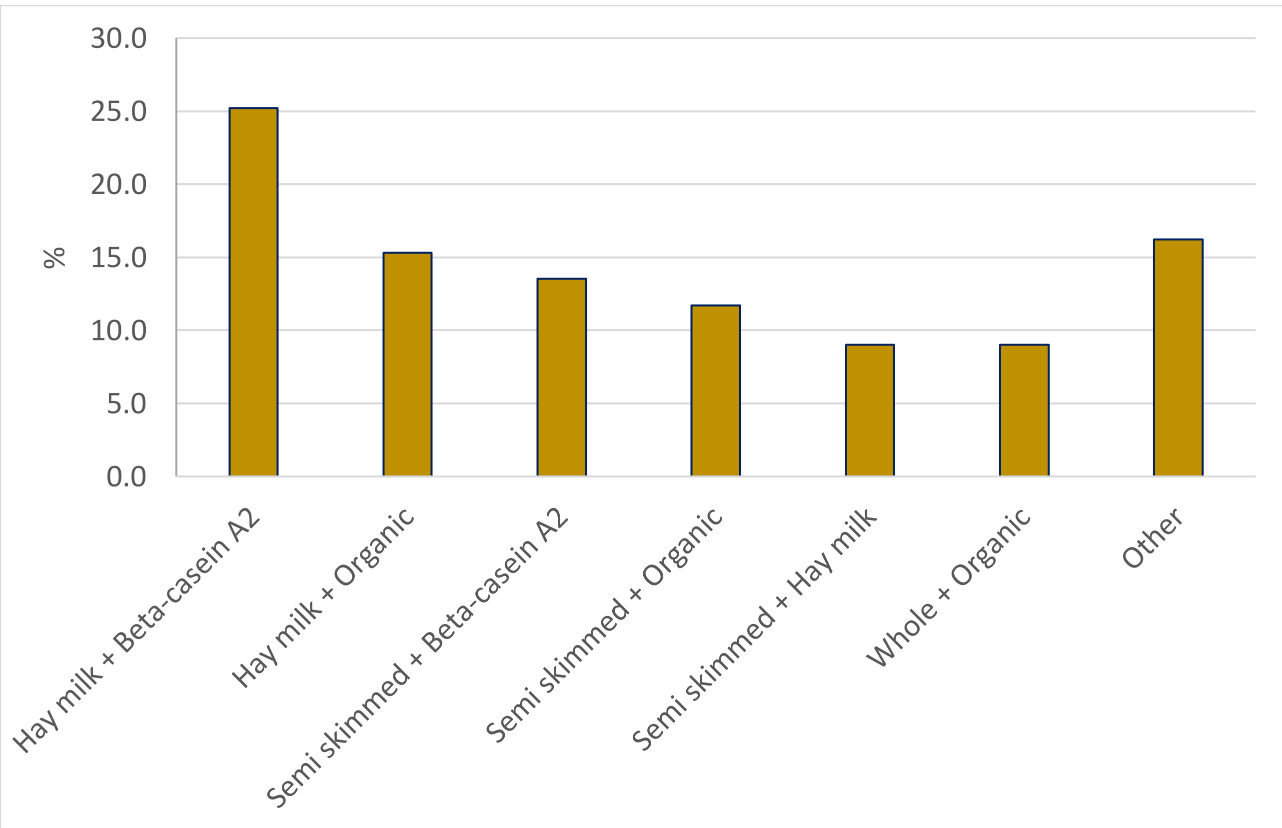
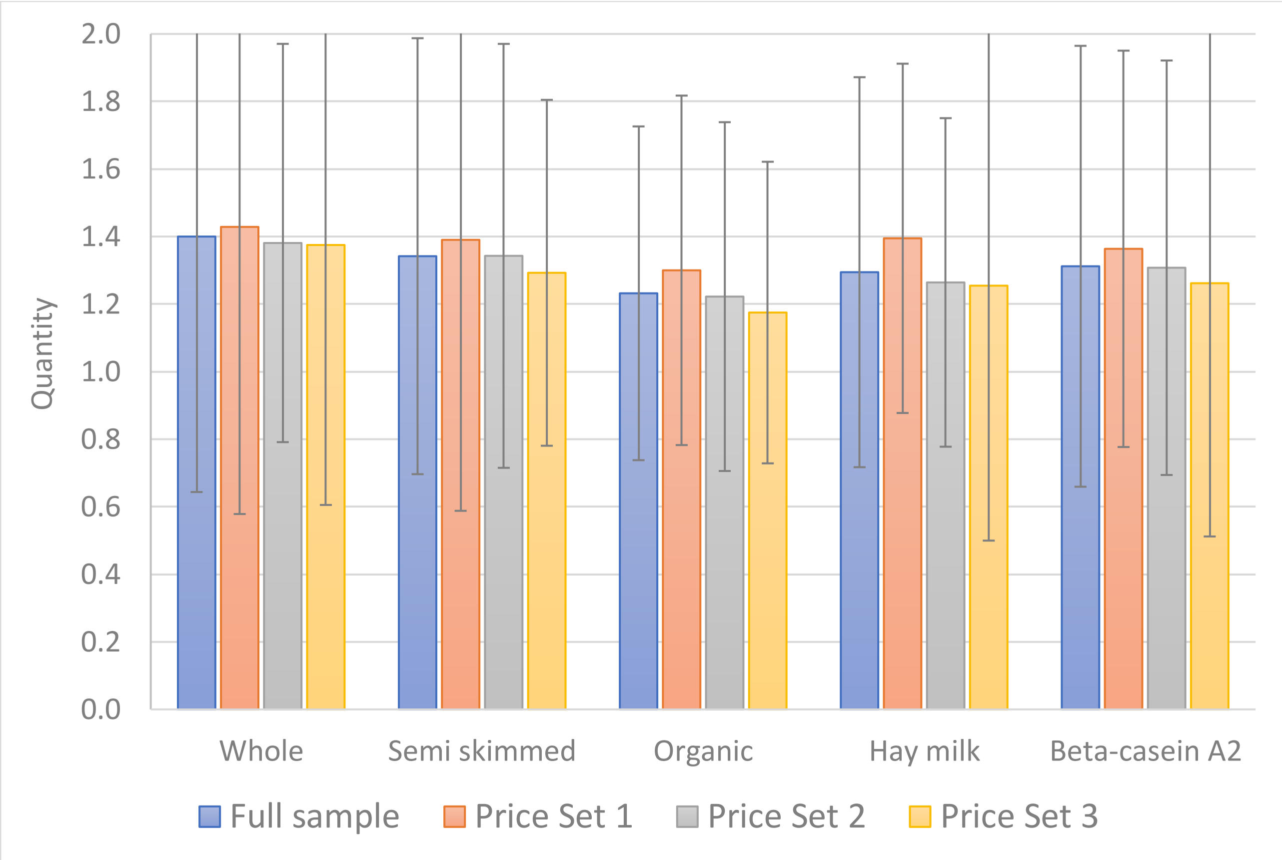


Figure 5. Average purchased quantity of milk types when chosen



We finally move to the statistics related to the purchased quantities. Specifically, Figure 5 shows the average purchased quantities for the different milk types (when chosen). Overall, we note how there are no substantial differences in purchased quantities, across products or across prices for the same product. The semi-skimmed milk is associated with the highest purchased quantity across all prices, followed by the whole milk one. These milk types are typically the cheapest, which may explain the – albeit marginally – highest average purchased quantities. When comparing quantities for the same product across prices, it can be noticed how - as expected - there is a monotonic decreasing relationship between quantity and price. The highest difference was found for hay milk (the most expensive product, along with organic milk), whose average purchase quantity moves from 1.4 bottles at €1.70 to 1.1 bottles at €2.10.

4.2 Multiple discrete-continuous extreme value model estimates

This section reports the discussion of our estimates of the coefficients of the proposed MDCEV model. Table 3 reports the estimated values for the constants of baseline utility vector $\boldsymbol{\vartheta}$ and those for the satiation parameter vector $\boldsymbol{\omega}$, while Table 3 reports the estimates capturing each of the nudging treatments' effect on the baseline utility (the vector $\boldsymbol{\beta}$) and the attendant satiation parameter vector $\boldsymbol{\lambda}$.

Starting from the baseline utility parameters $\boldsymbol{\vartheta}$, we remind the reader that we set the outside good as the reference alternative to identify the parameters for our core products, which is a standard approach in these models. All the estimated values in the vector $\boldsymbol{\vartheta}$ are statistically different from zero at 95% level and negative, thus suggesting that – at zero consumption level – consumers benefit more from consuming the outside good compared to the milk products included in our experiment. Such a result is common in MDCEV applications using the outside good as the baseline alternative (e.g. Calastri et al., 2017). Looking at the estimated values, we note how the value for the hay milk coefficient is higher (i.e. less negative/closer to zero) than that of the estimated coefficients for other products; this suggests consumers prefer such milk type. We then have the following order of preferences over milk types: organic $\succcurlyeq$ Beta-casein A2 $\succcurlyeq$ semi-skimmed $\succcurlyeq$ whole. Overall, such result suggests that consumers prefer environmentally sustainable milk types.

Regarding the effects of the satiation parameters, all the elements in the parameter vector $\boldsymbol{\omega}$ are statistically different from zero and positive at least 95% level. We remind the reader that the higher the estimated values in this parameter vector, the lower the satiation effect of the marginal quantity purchase. We note how utility for whole and semi-skimmed milk decreases as the quantity purchased increases, but compared to the other milk types, it does so at a lower rate. The satiation effect for Beta-casein A2 milk is intermediate (as in the case of baseline utility), while organic and hay milks are associated with the highest satiation effect. Interestingly, such results are the opposite of those retrieved for baseline utility: the milk types providing highest utility have also highest satiation effects.

Taken together, the results suggest that consumers are more likely to choose milk types with environmental benefits (hay milk and organic milk), but they are also likely to purchase such products in smaller quantities, compared to the alternatives. On the contrary, whole and semi-skimmed milk are the least likely to be chosen because of their comparatively low utility, but when they are chosen, they do tend to be purchased in higher quantities than other products.

Table 3. MCDEV estimates - Baseline utility and satiation parameters

ϑ baseline utility	**Value**	**|t|**	**ω satiation**	**Value**	**|t|**
Whole	-0.79	14.26	Whole	1.76	5.36
Semi-skimmed	-0.63	13.39	Semi-skimmed	1.63	6.39
Organic	-0.34	7.48	Organic	1.48	6.46
Hay milk	-0.21	4.96	Hay milk	1.40	6.80
Beta-casein A2	-0.41	8.88	Beta-casein A2	1.59	6.36
σ scale parameter	0.41	21.07			
Number of observations: 355 Log-likelihood: -2011.14					

4.3 Nudging effects on baseline utilities and satiation

We now focus on describing the effects of nudging treatments on baseline utility and our estimates of satiation parameters for Beta-Casein A2 milk (the milk type on which our nudging treatments were focused). As seen in Table 4, the baseline utility of such products was significantly affected only by the healthy eating call treatment. The coefficient of the interaction term is positive, thus suggesting that the treatment increased the preference for such milk type compared to the baseline of no nudge treatment. In turn, this implies an increase in the probability that this product is chosen by consumers under this nudge type only.

When focusing on satiation effects, instead, none of the treatments was found to have a statistically significant effect. This seems to suggest that nudges only affect baseline utility. So, they only influence the probability of purchasing a given product in a single purchasing event. But they do not affect satiation and hence have no effect on the quantity purchased during a single event. That is, nudging treatments have the same effect on utility across all quantities purchased. This result may be related to the low shelf life of our products, which could make consumers less prone to increase the chosen quantity of the target milk, regardless of the type of nudges employed.

Table 4. MCDEV estimates - Effect of nudging treatments on baseline utility and satiation parameters of Beta-Casein A2 milk

β **baseline utility**	**Value**	**|t|**	λ **satiation**	**Value**	**|t|**
Healthy eating	0.13	2.36	Healthy eating	0.14	0.36
Positioning	-0.03	0.39	Positioning	0.36	0.59
Proportion	0.06	0.46	Proportion	0.48	0.16

4.4 Control group – healthy eating call treatment comparison

In this section we compare the choices made by participants in the control group and in the healthy eating call treatment, the only one found to affect purchases significantly. We also report the simulations of demand curves obtained using predictions of purchased quantities based on the model parameters presented in the previous sections.

Table 5 and Figure 6 report the choice frequencies for milk types in the two groups. Starting from the full control group data, the most frequently chosen product is hay milk (51%), followed by semi-skimmed (38%) and organic and Beta-Casein A2 in similar percentages (between 30% and 35%). When looking at the healthy eating call treatment, instead, it can be noticed how the choice frequency for the Beta-casein A2 milk raises substantially, aligning to that of the hay milk (above 50%). When comparing the two groups, it can be seen as the choice frequency for the Beta-casein A2 milk increased by 15% in the healthy eating call treatment, an effect statistically significant at 95% level, and of substantive economic significance. Consistently with the outcomes of the MDCEV model, this highlights a strong effect of the healthy eating call treatment in nudging consumers towards the choice of the milk with Beta-casein A2. We note that the choice frequencies within price sets and treatments should be analyzed with caution, given the small subsamples for each combination (around 30 participants). Nonetheless, it is of interest to note how the choice frequency of the Beta-casein A2 milk in the nudge treatment is particularly high in the second price set, where it substantially higher than that of the hay milk.

Table 5. Percent of respondents purchasing milk types by treatment

Milk type	**Control**	**Healthy eating call**	
Whole	23.68	32.89	$\chi^2 = 0.53$, p-value = 0.461
Semi skimmed	36.84	42.11	$\chi^2 = 0.11$, p-value = 0.742
Organic	31.58	48.68	$\chi^2 = 1.81$, p-value = 0.181
Hay milk	50.00	57.89	$\chi^2 = 0.03$, p-value = 0.869
Beta-casein A2	32.89	57.89	$\chi^2 = 6.09$, p-value = 0.013

Note: the significance of differences across the two groups was tested by using a Pearson's Chi-squared test

Table 6 reports the average quantity of milk types when chosen in the control and the healthy call treatment subsamples. In this case, no differences are statistically significant at 95% across groups, which is consistent with results from the MDCEV model. Overall, we observe an increase in the purchases of all frequencies of milk, with a statistically significant increase in that with Beta-casein A2.

We now move to examine the complement-substitute effects focusing on changes in correlations of milk bundles purchased under different treatments. The top part of Table 7 reports the matrix of correlations of purchases across milk types within individual milk bundles for control (lower triangular) and those treated by the healthy eating call (upper triangular). It is noteworthy that five out of ten correlations change sign between treatment, from positive (complements) to negative (substitutes). The lower part of table 7 shows that the magnitudes of these changes are substantive and statistically significant under the null of no difference for two of the correlations involving beta-casein A2 milk purchases. The first is the correlation with whole milk, with a 50% change in correlations between the control and the treated subsample (from a positive 26.5 % to a negative 23.5%). The second is the correlation with organic milk, with a 37% change in correlations (from a positive 18.2% to a negative 12.8%). This is consistent with a causal effect of the treatment on the complement-substitute pattern of real purchases. Specifically, organic and whole milk move from a complement relationship to a substitute one with beta-casein A2 milk.

Table 6. Average purchased quantity of milk types by treatment

	Control	**Healthy eating call**	
Whole	1.22	1.64	|t| = 1.94, p-value = 0.061
Semi skimmed	1.43	1.56	|t| = 0.67, p-value = 0.504
Organic	1.17	1.32	|t| = 1.28, p-value = 0.205
Hay milk	1.18	1.31	|t| = 1.21, p-value = 0.230
Beta-casein A2	1.16	1.36	|t| = 1.45, p-value = 0.151

Note: the significance of differences across the two groups was tested by using a t-test

Table 7. Correlation of purchased quantity of milk types by treatment

Control group (lower triangular) healthy eating (upper triangular)					
	Whole	**Semi skimmed**	**Organic**	**Hay milk**	**Beta-casein A2**
Whole	1.000	-0.095	0.038	-0.128	-0.235
Semi skimmed	0.147	1.000	-0.123	-0.109	-0.059
Organic	0.083	0.061	1.000	-0.042	-0.189
Hay milk	0.055	-0.065	0.162	1.000	0.215
Beta-casein A2	0.265	-0.019	0.182	0.189	1.000
Correlation differences control-treatment (p-values H0 differences = 0)					
Semi skimmed	0.243 (0.134)	na	na	na	na
Organic	0.045 (0.783)	0.184 (0.257)	na	na	na
Hay milk	0.183 (0.259)	0.043 (0.789)	0.204 (0.207)	na	na
Beta-casein A2	0.499 (0.002)	0.039 (0.810)	0.371 (0.021)	-0.027 (0.864)	na

Figure 7 reports the demand curve simulated for the two groups. In the control group, hay milk has the highest demand curve, followed by organic milk and then by milk with Beta-casein A2. Semi-skimmed and whole milk, instead, have the lowest demand curves. Overall, the demand curves follow the order of preferences described by the baseline utility parameters described in the previous section. When looking at the rates at which quantities demanded decrease as prices increase, we note that such rates are lower for the semi-skimmed and the whole milk, as a consequence of the lower satiation effect. The order of the curves is consistent across the two groups, but in the healthy eating call treatment, the demand for milk with Beta-casein A2 is higher and much closer to those of the two milk types with environmental benefits. This corroborates how the healthy eating call treatment effectively increased the demand for the target milk.

Figure 6. Choice frequencies of milk types in the control and the healthy eating call treatment subsamples

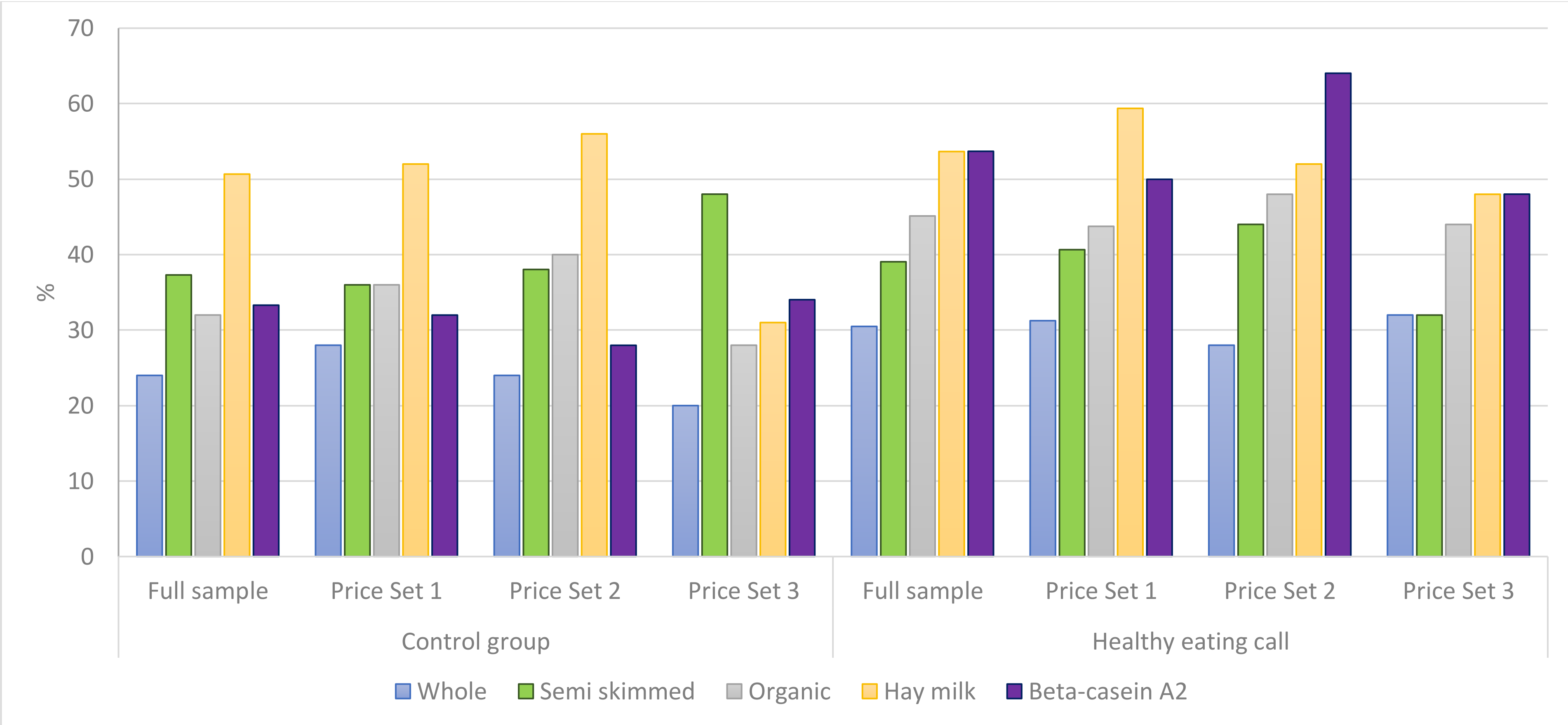
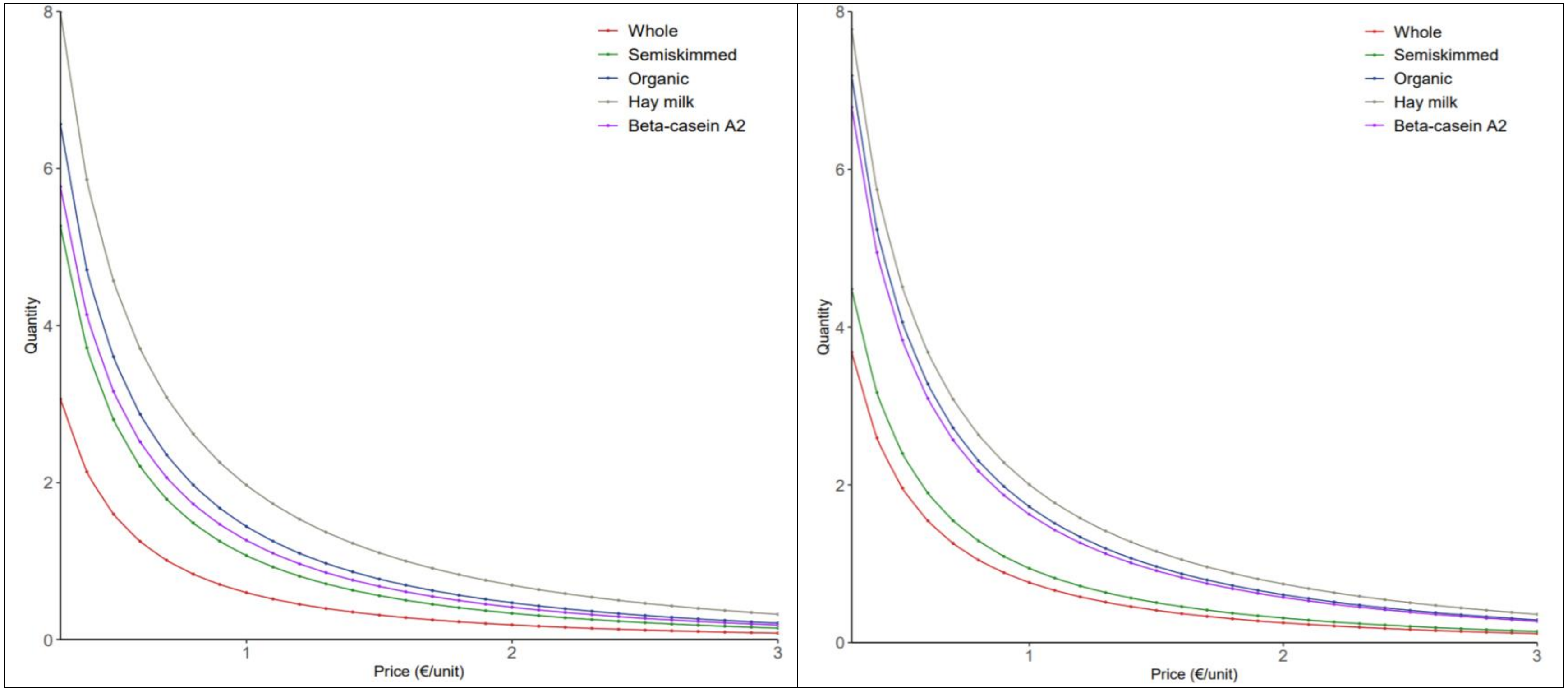


Figure 7. Demand curves in the control group (left) and in the healthy eating call treatment (right)



5. Conclusions and policy implications

In this paper we investigated the efficacy of different nudging stimuli using a framed field experiment involving multiple discrete-continuous choices of different milk types. The experiment simulated a real grocery market situation in which participants were provided with a cash endowment to spend on their desired quantities of different milk types. Observed combinations of milk choices and quantities (the milk basket) were used to estimate a MDCEV random utility model which, to date, has yet to receive in-depth attention in food economics and has been never – to the best of our knowledge – used for investigating the effect of nudges on food choices for a common product, such as milk. Our results highlighted a preference (and higher demand) for milk types with environmental benefits, expressed by a higher baseline utility. Milk types with no specific benefits in terms of either environment of health, instead, where associated with the lowest utility but also with the lowest satiation effect. The milk with Beta-Casein A2, our target niche product, was found to be intermediate in utility and satiation. The MDCEV model allowed us to analyse the effect of three nudging techniques on both preference and satiation towards the target milk. The model results highlighted how only the healthy eating call treatment had a significant effect on choices, and only on baseline utility. The simulated demand curves showed how such treatment increased the demand for milk with Beta-Casein A2, making it much closer to the curves for the two milk types with environmental benefits. The other two treatments (availability and visibility enhancement) had no significant effect on the two parameters.

Further results can be obtained from the treatment effect of healthy eating call from the raw data on frequencies of purchases of milk types and on correlations of purchases across milk types. The raw data analyses show that this type of nudge increases significantly the frequency of purchase of milk with Beta-Casein A2, and modifies the relationship from complement to substitutes of this milk type with whole and organic milks.

The main policy implication of our study is to provide evidence in support of the use of healthy eating call nudges to increase the consumption of easy-to-digest milk types, which are healthier for the increasing group of otherwise healthy people who find other milks hard to digest, or are interested in improving their digestive microbiome (Tagliamonte et al. 2023). Our results fail to support the effectiveness of both availability and visibility nudges. This result can be of policy relevance is several contexts, such as school canteens, university cafeterias, retirement homes, and other collective meals environments, in which there has been a strong interest in effective interventions aimed at increasing milk consumption as a substitute for unhealthy sugar-rich drinks (Goto et al., 2013; Samek, 2019; Metcalfe, 2020).

Our study, however, stops short of investigating the reasons behind the different efficacy of alternative nudging techniques. Exploring these underlying mechanisms can provide a better perspective for utilizing healthy eating call to motivate people toward healthier dietary habits. Another limitation is the non-randomization of products and prices, which was not feasible during our experiment for practical reasons. This may have led to bias, such as primacy effects (i.e. participants being more likely to choose the first milk type they saw) or anchoring bias (i.e. participants anchoring their judgment of all products and prices to the first they saw). Finally, from a modelling perspective, another limitation lies in the lack of analysis of complementarity and substitution patterns between different milk types and how this can be potentially affected by nudges. The analysis of the substitution effect would be of particular interest, as it would enable us to better understand how the increase in the purchase of the target milk affects the chosen quantities of the other milk types. To enable such an investigation, it would have been necessary to obtain substantially more observations within each subgroup, a task that was beyond the available budget for the study. Future research should focus on the analysis of such effects, to shed further light on the effect of nudging treatments. It would also be of interest to explore the role of taste, knowledge and experience in shaping the effect of different nudging treatments.

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Appendix 1 – Experiment instructions

Thank you for your participation. This study is carried out by the University of Padua and concerns the analysis of consumers' preferences towards different food products. Through your choices, you will be able to represent all consumers who do not participate in the experiment and have preferences similar to yours. All information collected will be used confidentially and for research purposes only. At any time, you can decide to withdraw from the experiment.

For your participation, you will be given €10. During the experiment, you can use this amount to make real purchases, if you wish. The products that can be purchased are different types of milk, namely: i) whole, ii) semi-skimmed, iii) organic, iv) hay milk, v) beta-casein A2.

At the end of the experiment, we will record your choices and afterwards you will be given the products you have chosen and the cash left over. You can also decide not to make any purchases, if you are not interested in the products available. In this case, you will be given the €10 entirely in cash.