Time Preferences and Food Choices: Evidence from a Choice Experiment

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Time Preferences and Food Choices: Evidence from a Choice Experiment

1. Introduction[1]

Food consumption trends have changed rapidly in the last decade due to consumers' increased interest in what they eat. For example, consumers are becoming more aware that their food choices can potentially affect their health (Chrysochou, 2010; Sirò, Ka´polna, E., Ka´polna B., & Lugasi, 2008; Verbeke, 2005) and are showing growing interest in the health-related attributes of food. Besides this increased attention on the health dimension of food consumption, a number of studies have shown that consumers are becoming more sensitive to sustainability issues, and are more aware about the effects that their diets may have on the environment in the long run (Banterle, Cereda & Fritz, 2013; Vermeier & Verbeke, 2006).

These emerging trends can be viewed as remarkable changes in consumers' food consumption habits. Indeed, on the one hand, healthier food choices might contribute to tackling the problem of food-related chronic diseases (i.e., obesity, hypertension, diabetes, etc.) that still represent a major public health concern in many countries (Banterle & Cavaliere, 2014; Courtemanche, Heutel, & McAlvanah, 2014; Roberto, Pomeranz & Fischer, 2014). On the other hand, the increased demand for environmentally friendly foods is related to more interest in sustainable use of resources and consequently, future wellbeing (Reisch et al., 2013). However, the extent to which consumers value and respond to environmentally friendly food products

[1] Abbreviations used in this paper: BMI = Body Mass Index, CE= choice experiment, MPL= Multiple Price List, CFC= Consideration of Future Consequences, CFC-I= Consideration of Future Consequences-Immediate subscale, CFC-F= Consideration of Future Consequences-Future subscale, MNL= Multinomial Logit Model, PCA=Principal Component Analysis, RPL= Random Parameter Logit, RPL + EC= Random Parameter Logit with error component.

through value-consistent behavior still remains a questionable point (Haws, Winterich & Walker Naylor, 2014).

In reality, various factors can discourage consumers from choosing food with healthy and sustainable characteristics. For instance, the higher price of these products is often perceived as a limiting factor in the purchase of these products (Bhattacharya & Sen, 2004; Marian, Chrysochou, Krystallis, & Thogersen, 2014; Verhoef, 2005). Another important limiting factor is peoples' tendency to pursue immediate gratification, which leads them to underestimate the value of future benefits that can be derived from the consumption of such products.

In this paper, we focused specifically on this latter aspect and explore the possible role of time preferences in food choices. This topic has been studied extensively by economists and psychologists, especially on its effects on intertemporal decisions. Additionally, much of the previous research on time preferences demonstrated that it is able to affect a number of human behaviors, including health and environment-related ones (Adams & Nettle, 2009; Blaylock, Smallwood, Kassel, Variyam, & Aldrich, 1999; Franzen & Vogl, 2013; Frederick et al., 2002; Joireman, Lasane, Bennett, Richards,& Solaimani, 2001; Takanori & Goto, 2009).

Scant literature, however, exists on the effect of time preferences on food choice behavior. The aim of this paper is twofold. First, we analyze if healthy and environmentally friendly attributes are relevant in driving food choices; second, we investigate if people with different time preferences will have different choice behavior using a choice experiment (CE) approach. The CE allows us to specifically analyze consumers' behavior in a decision-making context. To the best of our knowledge, this is the first study that examines the role of time preferences in consumers' valuation for environmentally friendly and healthy attributes. While a few recent CE studies have explored the effects of some psychological traits on consumers' preferences (Grebitus, Steiner & Veeman, 2015; Grebitus, Steiner & Veeman, 2013; Grebitus, Lusk, & Nayga, 2013a), none have specifically considered time preferences. If we find that there is heterogeneity in choice behavior and preferences based on time preferences, then this in itself is an important finding since it would imply that future CE studies (which currently represent one of the most popular methods being used for valuation of food products/attributes) should also elicit time preferences and check if there is choice/preference heterogeneity based on these measures.

This paper is organized as follows: the next section contains an overview on time preferences and their role in affecting intertemporal decisions. In the following sections, we describe the experimental procedures used for the time-preference estimation and CE. We then explain the data collection, describe the sample characteristics, discuss the empirical analysis of the data, and, finally, present the results and the conclusions of our study.

2. Time Preferences: Background and Research Hypothesis

Human behaviors can differ significantly among individuals according to their time preferences; that is, how they discount future events (Adams, 2012; Bishai, 2001; Blaylock et al., 1999). Time-discounting behavior generally refers to any motive that leads individuals to care less about future outcomes. As such, it is of great importance to intertemporal decisions; namely all choices in which individuals have to decide whether to favor a present utility or delayed benefit (Frederick et al., 2002). Individuals with high time preferences heavily discount future events and typically show a tendency to value present gratification more than future rewards. On the other hand, individuals characterized by low time preferences value future events to a greater extent, and are more willing to forgo immediate needs to give priority to future utility (Frederick et al., 2002).

There is a robust literature that examined the effects of time preferences on intertemporal decisions and explored how time preferences influences health-related behaviors. Their results suggest that individuals with low time preferences tend to be less likely to smoke (Adams & Nettle, 2009; Harrison, Lau, & Rutstrom, 2010; Robb, Huston, & Finke, 2008; Scharff & Viscusi, 2011; Takanori & Goto, 2009), more likely to exercise (Adams & Nettle, 2009; Ouellette, Hessling, Gibbons, Reis-Bergan, & Gerrard, 2005; Wardle & Steptoe, 2003), less likely to drink alcohol (Bishai, 2001; Takanori & Goto, 2009), and more willing to undergo medical examinations (Bradford, 2010; Chapman, Brewer, Coups, Brownlee, & Leventhal, 2001). Other studies also showed that high future-discounting is associated with higher BMI (Body Mass Index) levels (Adams & White, 2009; Borghans & Golsteyn, 2006; Ikeda, Kang, & Ohtake, 2010; Komlos, Smith, & Bogin, 2004; Smith, Bogin & Bishai., 2005).

Time preference has also been analyzed in the context of environmentally friendly behaviors, although the literature in this field is less extensive. The general evidence is that higher time preferences are related to lower environmental concern (Carmi & Arnon, 2014; Franzen & Vogl, 2013; McCollough, 2010). Franzen and Vogl (2013) and Carmi and Arnon (2014) found that individual discount rates influence environmental concern and provide evidence that low time preferences are associated with increased pro-environmental attitudes. Joreiman et al., (2001) reported the same result. Moreover, Ebreo & Vining (2001) and McCollough (2010) found that more future oriented individuals are more likely to engage in recycling behaviors and less likely to waste.

The specific relationship between time preferences and food choices has been analyzed only in a few studies (e.g., Cavaliere, De Marchi & Banterle, 2014; Piko & Brassai, 2009; Houston & Finke, 2003). For example, Houston and Finke (2003) examined the effects of time preferences on diet choices and found that individuals showing high future discount rates have a lower diet quality (measured using the Healthy Eating Index), and are less likely to use nutritional labels. No other known study, however, has investigated how time preferences could affect consumers' valuation for healthy and environmentally friendly attributes in food.

In this study, we hypothesize that (i) individuals would value both healthy and environmentally friendly attributes when choosing food products and that (ii) the extent to which individuals would give importance to such attributes is associated with their time preferences. In particular, individuals with high time preferences (present orientation) are expected to attach a lower value to both healthy and environmentally friendly attributes. On the other hand, since future-oriented individuals (low time preference) are supposed to be more sensitive to the long-term consequences of their food choices, they are expected to attach more importance to such attributes. Actually, both healthy and environmentally friendly quality features might be perceived as tools to achieve future personal and/or social benefits. For instance, healthy foods might contribute to the maximization of personal utility by improving health, which would then lead to health benefits in the long run. On the other hand, environment-related attributes are more strongly linked to a social dimension (Aprile, Caputo & Nayga 2012); individuals that are interested in such attributes are generally driven by a social concern and give higher importance to the social utility that can be derived from sustainable consumption (Haws et al., 2014).

3. Experimental Procedures and Data

To assess if time preferences are associated with food-related decision-making, we used the Consideration of Future Consequences 14-item scale (CFC), and implemented a CE on yogurt consumption. The following subsections explain in detail how we estimated time preference and set-up the CE study. The last subsection discusses the survey procedure and data collection.

3.1 Time Preference Elicitation

Previous literature on intertemporal choices used a variety of different methods to elicit time preferences (for an extensive review, see Frederick et al., 2002), among which Multiple Price Lists (MPLs) and psychometric scales represent two of the most commonly used.

MPLs consist of multiple-choice tasks in which individuals are asked to choose between smaller amounts of money to be received closer to the present time, or larger amounts to be claimed further in the future. These methods have been the norm in experimental studies analyzing intertemporal decisions and the effect of time preferences on a variety of individuals' behaviors (e.g. smoking, drinking, gambling, etc.) and health outcomes (e.g., obesity) (Andreoni & Sprenger, 2012; Borghans & Golsteyn, 2006: Chapman, 1996; Courtemanche et al., 2014; Ikeda, Kang & Ohtake, 2010; Takanori & Goto, 2009; Van der Pool, 2011).

The psychometric scales, on the other hand, are generally based on different statements aimed at measuring some of the psychological traits of individuals. One of the most popular of these scales is the Consideration of Future Consequences (CFC) scale which has been used in several studies analyzing individual time preference and health-related behaviors (Adams & Nettle, 2009; Adams & White, 2009; Borghans & Golsteyn, 2006; Piko & Brassai, 2009; Strathman, Gleicher, Boninger, & Edwards, 1994). This scale is meant to detect the extent to which individuals value the future outcomes of present actions, and the extent to which they are affected by these possible outcomes (Joireman, Shaffer, Balliet & Strathman, 2012) (Table 1).

(INSERT TABLE 1 HERE)

The scale is composed by 14 items. Seven of them typically characterize present-concerned individuals and constitute the CFC-Immediate (CFC-I) subscale; the other seven items, are mainly characteristics of those who highly value the possible effects of present actions on future events and constitute the CFC-Future (CFC-F) subscale.

This is the first study implementing the CFC scale in CEs. We decided to use this method for a number of reasons. First, the CFC construct is very easy for the respondents to understand and, therefore, is suitable to be used in our study given that we conducted an online survey of a random sample of yogurt consumers. Second, the use of the CFC does not require providing individuals with incentives in order to obtain reliable results. Indeed, when using time-preference elicitation methods (such as the above mentioned MPL), money incentives are typically used to motivate people to truly reveal their preferences. The use of monetary incentives, however, has been criticized by a number of authors[2]. The use of CFC has a third advantage, namely that it is not affected by domain dependence. Indeed, time preferences across health and money domains have been found to be not strongly correlated (Cairns, 1994; Chapman, 2003; Chapman & Elstein, 1995; Lawless, Drichoutis, & Nayga, 2013). Specifically, discount rates in the health domain have been found to be higher than those in the monetary domain (Chapman et al., 2001; Chapman & Elstein, 1995; Lazaro, Barberan, & Encarnacion, 2001). This might be due to the fact that future health-related outcomes are subject to uncertainty, which might lead individuals

[2] O'Donoghue and Rabin (2015) highlighted that if monetary incentives are not relevant then they might not be effective and respondents might not behave in accordance with a utility maximization strategy. Additionally, some studies have argued that real money experiments present considerable tactical problems related to payment reliability issues (e.g., Andreoni & Sprenger, 2012). Sprenger (2015) argued that the inconsistent findings in past studies could be due to payment uncertainty and transaction cost issues.

to highly depreciate them. Finally, the validity of the CFC scale for measuring time preferences has already been established in a number of previous studies investigating both healthy and pro-environmental behaviors (Adams & Nettle, 2009; Adams & White, 2009; Carmi & Arnon, 2014; Joireman, Van Lange & Van Vugt, 2004; Joireman et al., 2001; Joireman et al., 2012; Lindsay & Strathman, 1997; Piko & Brassai, 2009; Strathman et al., 1994).

3.2 Choice Experiment

In CEs, respondents are generally asked to choose one product among a set of product profiles, within a number of choice sets that differ in terms of their attribute levels. In this study, we conducted an online CE survey on a sample of US consumers using a four-count packed yogurt product as the product of interest. Yogurt is largely consumed among both men and women, and is a common component of everyday diets (Miklavec, Pravst, Grunert, Klopcic, & Pohar, 2015; Wang, Livingston, Fox, Meigs, & Jacques, 2013). The fact that individuals are familiar with this product makes yogurt a suitable food item to be used in a CE study. This simplifies the evaluation of the different attributes and facilitates individuals in making choices in accordance with their personal preferences. Moreover, yogurt can easily be associated with different healthy and environmentally friendly food attributes.

The yogurt attributes we used in our CE design are price, calories per serving, health claim, organic label, and carbon trust label. For each of these attributes, different levels were selected. Four levels were selected for the price attribute to mirror the market prices of yogurt in the US. The second attribute is the number of calories per serving. To define the different calorie levels, we started from the observed highest and lowest calorie content for an average serving (70 grams) of low-fat yogurt. Within these values, we then chose three calorie levels, from 80 to

140 calories per serving. Calories represent an important attribute of food products about which many individuals care. For example, according to the International Food Information Council Foundation (2006), two-thirds of Americans say they look at the calorie content on the Nutrition Facts Panel. The third attribute is represented by a health claim, i.e. a concise message concerning the healthy properties of a food and typically placed in the front of pack (Cavaliere, Ricci & Banterle, 2015) . To describe our yoghurt product a disease-risk reduction claim was chosen. Indeed, due to its nutritional values, and in line with the FDA guidelines for health claims, a low-fat yogurt could be associated with the claim that diets low in saturated fat and cholesterol may reduce the risk of heart disease.

The last two attributes are environment-related; we took into consideration the USDA-organic and carbon trust labels. It should also be mentioned that there are various reasons why certain individuals would show a positive attitude toward organic food. Indeed, organic consumption could be perceived as carrying both environment and health benefits. On the one side, it is related to a number of environmental and social concerns such as sustainable food production, support of local economies, animal welfare, etc. (Hughner, McDonagh, Clifford, Shultz, & Stanton, 2007; Loureiro, McCluskey, & Mittelhammer, 2001; Van Loo, Caputo, Nayga, & Verbeke, 2014). On the other hand, organic consumption might be driven by health-related motives (Hjelmar, 2011) as organic products are often considered safer due to the absence of common chemicals used in conventional food production (Van Loo, Caputo, Nayga, Meullenet, Crandall, & Ricke, 2010). Finally, the carbon trust label identifies environmentally friendly foods, whose production process minimizes the environmental impact. The issue of ‘food miles’ and carbon emissions is becoming of increasing interest to consumers as shown in several studies (Teisl, 2011; Caputo, Nayga & Scarpa 2013; Caputo, Vassilopoulos, Nayga &

Canavari, 2013). Grebitus, Lusk and Nayga (2013b) for example, found that consumers' utility decreases with an increase in food miles and Grebitus et al. (2015) found a similar result in their analysis on food labelled with environmental footprint. Individuals' interest in both organic- and carbon-labeled food may be linked to socially conscious consumption that could be of main interest to individuals with low time preferences. Table 2 shows an overview of the attributes and attribute levels used in this application.

(INSERT TABLE 2 HERE)

The allocation of the attribute levels was designed using a sequential experimental design with a Bayesian information structure, geared to the minimization of the expected D_b-error (Sándor & Wedel, 2001; Scarpa, Campbell, & Hutchinson, 2007). Accordingly, it was performed in three stages. In the first stage, an orthogonal fractional factorial design was generated. It consisted of 36 choice tasks, which were then randomly divided into three different blocks of 12 choice sets each. This design was then used to carry out a pilot survey (second stage) that was used to obtain the Bayesian priors for the main design (third stage). The Bayesian priors used to generate the final design were obtained through the estimation of an MNL.

The final CE online survey consisted of a set of 12 choice questions (choice tasks), each comprising two experimentally designed yogurt alternatives and a no-purchase option[3]. An example of choice task is reported in Figure 1.

(INSERT FIGURE 1 HERE)

Finally, due to the hypothetical nature of our CE, the online survey also included a cheap talk script (see Appendix A) before the CE task. This method consists of a script that explains the

[3] It is important to mention that in real buying situations, there may be other attributes that could have an influence on the purchasing behavior of the consumer that are not included in the CE experimental design (e.g., brand names, package, among others). In this study, it is assumed that all other attributes not included in the design are the same in the yogurt alternatives.

potential issue of hypothetical bias to the respondents before the start of the experiment (Cummings and Taylor,1999). The objective of the cheap talk is to lead respondents to reveal their real preferences making them aware of the existence of hypothetical bias. Previous studies showed that informing respondents about the issue of hypothetical bias could be effective in reducing its effect (Lusk, 2003; Murphy, Stevens, & Weatherhead, 2005; Silva, Nayga, Campbell, & Park, 2007).

3.3 Survey

We created an online survey that was sent to a random sample of US consumers in 2015. The data collection was carried out by Qualtrics, an industry-leading provider of online survey software. Consumers were invited to participate in the survey via email, and informed about the questionnaire length and type. The average time necessary to complete the survey was about 14 minutes. To guarantee the quality of the data, a time cutoff was fixed at one-third the median time, to exclude all of the respondents that did not take enough, or took too much, time to complete the survey. Moreover, respondents were excluded *a priori* if they did not buy yogurt products in the month preceding the survey and if they were younger than 18 years old. This age threshold was used as a screener in order to exclude the younger population that, generally, is not yet in charge of grocery shopping. To monitor the quality of the final data and be able to exclude respondents that were only clicking through the questions, we also included an attention filter and reverse-wording questions at different points in the survey[4]. In addition to the questions related to the CE and time-preference measurement scale, the survey also included socio-demographic characteristics, and other health- and environment- related questions.

[4] The attention filter is a trick question, which uses a large block of text and asks respondents to answer in a certain way. The reverse-wording questions change the direction of the scale by asking the same question two times, in a positive (or negative) voice.

4. Empirical Analysis

To determine how time preferences are associated with food choice behavior, the data were analyzed following two different steps.

In the first step, the CFC 14 items were analyzed using a principal component analysis (PCA)[5], which is a variable-reduction technique that maximizes the amount of variance accounted for in the observed variables, by a smaller group of variables called *components*. The number of components to be retained is generally determined as the number of eigenvalues higher than one. Previous studies (Adams, 2012; Joireman, Balliet, Sprott, Spangenberg, & Schultz, 2008; Joireman et al., 2012) showed that performing a PCA on the CFC 14-item scale leads to the identification of two factors (CFC-I and CFC-F). The two-factor PCA has a number of advantages compared to the common one-dimensional approach initially used by Strathman et al. (1994). For instance, the one-factor analysis considers the sum of the scores related to future items and reverse-coded immediate items. This implies that CFC-I and CFC-F are perfect opposites. However, if one completely agrees with a CFC-I item, he/she would not necessarily disagree with the converse CFC-F item. As such, the adoption of a two-factor PCA allows us to separately analyze the CFC-I and CFC-F components, which then facilitates the interpretation of the results. In addition, these two subscales allow us to specifically understand if a behavior is determined by an individual's high consideration of future consequences (low time preference),

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[5] 5 In this study, the CFC scale was analyzed using a PCA rather that a Factor Analysis (FA) for a number of reasons. Firstly, since our objective is not to find the underlying factors that can explain the observed responses, the PCA allowed us to simply reduce the 14 items of the CFC scale to a smaller set of independent variables. Indeed, the CFC construct is specifically meant to capture two main components, namely CFC-I and CFC-F (respectively corresponding to the two CFC subscales). Second, we decided to use the PCA to validate the CFC scale, similar to what Joireman et al., (2012) did in their study.

or if an action is mainly due to the consideration of immediate consequences (high time preference) (Adams, 2012; Joireman et al., 2008; Joireman et al., 2012).

When performing a PCA, researchers should predetermine which factor rotation should be used. Two methods are generally used: oblique or orthogonal. Orthogonal rotation methods assume that the factors are uncorrelated, while oblique rotation methods assume correlation. In the exploratory phase, an oblimin rotation approach was first applied because the CFC-F and CFC-I factors are generally assumed to be (negatively) correlated (e.g., Joireman et al., 2008). The results of this exploratory phase revealed that the two factors are negatively, but not strongly, correlated (0.26). As such, an orthogonal rotation method was successively applied for a more intuitive interpretation of the results.

In the second step, the identified time-preference factors (CFC-I and CFC-F) were included in the analysis of the CE data. As mentioned previously, in our survey, respondents made choices among a set of choice questions (choice tasks), each comprising two experimentally designed yogurt alternatives (buying options) and a no-purchase option (status quo). Assuming that our CE data can be analyzed in a random utility framework, the utility of individual *n* of choosing alternative *j* in choice situation *t* can be described as:

$$U_{njt} = \beta' X_{nit} + \varepsilon_{njt},$$

where x_{njt} is a vector of observed variables relating to alternative *j* and individual *n*; β is a vector of structural taste parameters, which characterize choices; and ε_{njt} is the random and unobserved part of the utility. Depending on the assumption underlying the structure of consumer preferences, different choice models can be used.

In this study, we estimated a random parameter logit with an error component (RPL+EC) model with panel structure, as proposed by Scarpa, Ferrini, and Willis (2005), and Scarpa, Campbell, and Hutchinson (2007). We used this model because it allows us to jointly account for (1) random taste variations, (2) correlation across taste parameters, and (3) correlation across utilities of the two buying options. Indeed, the literature suggests that all of these issues should be considered when modeling food-choice behavior. Specifically, as the standard RPL model, the RPL+EC accounts for random taste variation, by allowing the coefficients of the different attributes to vary randomly across individuals and deviate from the population mean, and, for correlation across taste parameters, by estimating the elements of the Cholesky matrix. Moreover, unlike the RPL, the RPL+EC accounts for correlation structure across utilities, by capturing the extra variance of the utility shared by the two buying options, which is different from the no-purchase option (status quo) (for computational details, see: Scarpa et al., 2005; Scarpa et al., 2007; Train, 2003). Previous studies on food choices (Caputo et al., 2013; Scarpa, Thiene, & Marangon, 2008; Scarpa, Zanoli, Bruschi, & Naspetti, 2013; Van Loo et al., 2014; Van Wezemael, Caputo, Nayga, Chryssochoidis, & Verbeke, 2014) found that the RPL+EC model outperforms other model specifications such as the RPL model. Given the main hypotheses of this study, two RPL-EC models were specified. Model 1 is the basic specification, accounting for the main effects only. The utility that respondent *n* gets from choosing one of the product alternatives *j*, within each choice task, can be expressed as follows:

$$U_{nj\,t} = \beta_0 * NoBuy_{nj} + \beta_1 * PRICE_{nj} + \beta_2 * CAL_{nj} + \beta_3 * HC_{nj} + \beta_4 * ORG_{nj} + \beta_5 * CT_{nj} + \eta_{it} + \varepsilon_{njt} \quad (1)$$

where $n = 1, ..., n$ is the number the respondents, t is the number of choice occasions, j is option A, B, or C (where A and B represent the two buying alternatives and C refers to the no-buy alternative); NoBuy is an alternative-specific dummy variable taking the value equal to 1 for the no-buy alternative, and 0 for all other alternatives in the choice set. β_0 is therefore an alternative-specific constant representing the no-buy option. PRICE$_{njt}$ is a continuous variable referring to the price of a package (4-count) of yogurt. CAL$_{nj}$ is a continuous variable indicating the amount of calories per servings (e.g. 80, 110, and 140). The rest of the variables refer to the other experimental design attributes, namely claim (HC), USDA organic (ORG), and carbon trust (CT) labels; these entered the model as effect coded variables. Effect coding has been preferred to dummy coding since it makes the coefficients of the attributes not correlated with the constants and avoids confounding effects (Bech and Gyrd-Hansen, 2005); ε_{ijt} is the unobserved random error term and η_{it} is the error component.

Model 2 determines how consumer choice behavior varies with time preferences. Accordingly, this model adds the interaction terms between each non-monetary attribute (e.g., calories, USDA organic label, health claim, and carbon trust label) and respondents' observed CFC-factor scores from the PCA, namely the CFC-I and CFC-F, to Model 1. We used interaction terms since discrete choice models are defined on utility differences across attribute values. Thus, including an individual's time preference as a variable in the model would produce no effects, since it is constant across choice alternatives (Grebitus et al., 2013). We estimated the interaction terms between the CFC-factor scores and all non-monetary attributes (e.g., 80 calories per serving, 110 calories per serving, USDA organic label, carbon trust label, and health claim). In Model 2, the utility function can be expressed as follows:

$$U_{njt} = \beta_0 * NoBuy_{nj} + \beta_1 * PRICE_{nj} + \beta_2 * CAL_{nj} + \beta_3 * HC_{nj} + \beta_4 * ORG_{nj} + \beta_5 * CT_{nj} + \eta_{it} + \varepsilon_{njt}$$

$$+ \gamma^{CFC\text{-}I\_CAL}\, 1(CFC\text{-}I)^{*}CAL_{nj} + \gamma^{CFC\text{-}F\_CAL}\, 1(CFC\text{-}F)^{*}CAL_{nj} + \gamma^{CFC\text{-}I\_HC}\, 1(CFC\text{-}I)^{*}HC_{nj} + \gamma^{CFC\text{-}F\_HC}\, 1(CFC\text{-}F)^{*}HC_{nj} + \gamma CFC^{-I\_ORG}\, 1(CFC\text{-}I)^{*}ORG_{nj} + \gamma^{CFC\text{-}F\_ORG}\, 1(CFC\text{-}F)^{*}ORG_{nj} + \gamma CFC^{-I\_CT}\, 1(CFC\text{-}I)^{*}CT_{nj} + \gamma^{CFC\text{-}F\_CT}\, 1(CFC\text{-}F)^{*}CT_{nj} + \eta_{it} + \varepsilon_{njt} \qquad (2)$$

where $\gamma^{CFC\text{-}I\_CAL,}$ $\gamma^{CFC\text{-}I\_HC,}$ $\gamma^{CFC\text{-}I\_ORG}$, and $\gamma^{CFC\text{-}I\_CT}$ are the coefficients of the interaction terms between the non-monetary attributes and the individual CFC-I observed factor. Similarly, $\gamma^{CFC\text{-}F\_CAL,}$ $\gamma^{CFC\text{-}F\_ORG,}$ $\gamma^{CFC\text{-}F\_HC,}$ and $\gamma^{CFC\text{-}F\_CT}$ represent the coefficients of the interactions with the CFC-F factor. The other variables in the utility function are specified as in Model 1.

5. Results

5.1 Sample Characteristics

The final sample consisted of 173 respondents. Table 3 reports the socio-demographic and economic characteristics of the sample.

(INSERT TABLE 3 HERE)

The most represented age categories are those between 50 and 69 years old, with a lower percentage of respondents aged between 30 and 39 years old. The number of female respondents is almost double that of men. This result, in fact, reflects a real buying context in which women are mostly in charge of the grocery shopping. The majority of respondents are non-Hispanic White/Caucasian. The income distribution is heterogeneous, and only a small percentage of respondents (4.6%) have very low annual income, while the percentage of individuals ranking in the highest income level is considerably higher (10.4%). The level of education is quite high, with 23.1% of the respondents having a 4-year college degree. Finally, almost 65% of the respondents have one child younger than 18 in the household.

5.2 Results of Principal Component Analysis

To test the suitability of the data for the PCA, we considered three measures commonly used in the literature. Particularly, we examined: (1) the Kaiser-Meyer-Olkin measure, which was acceptably high (0.832) (Field, 2009; Joireman et al., 2012); (2) the determinant of the correlation matrix (0.002), which rules out multicollinearity; and (3) the Bartlett's test of sphericity ($\chi^2 = 91$, $p < 0.000$), which suggests that the correlations are acceptably large for the PCA (Joireman et al., 2012).

As in Joireman et al. (2012), in an exploratory analysis, we found that three eigenvalues exceeded one suggesting the possibility of the existence of three factors. However, the scree plot (Figure 2) clearly indicates the presence of only two factors.

(INSERT FIGURE 2 HERE)

Following Joireman et al. (2012), we also based our PCA on two factors, which explained 50.4% of the variance. The rotated factor loadings of the rotated component matrix are displayed in Table 4.

(INSERT TABLE 4 HERE)

As can be noted, all items loaded on their expected factors. Specifically, the CFC-I subscale items had the largest loadings on the CFC-I factor, while the CFC-F subscale items had the largest loadings on the CFC-F factor. Moreover, according to the results of Cronbach's statistics, the seven items of the CFC-I and CFC-F subscales are highly reliable (Cronbach's alpha = 0.85 and 0.80, respectively), strengthening the reliability of our PCA (descriptive statistics of the factor loadings are provided in Appendix B).

5.3 Results of Choice Experiment

As previously discussed, the CE data were analyzed using two RPL+EC models: Models 1 and 2. All specifications allowed for correlation across random taste, using a full Cholesky matrix and correlation across utilities (results are available upon request). The aim here is to identify the additional information that can be gleaned upon when moving from Model 1 (baseline model), which allowed us to verify if the presence of the main health and environmental attributes affected yogurt selection (main effects) and if individuals exhibited heterogeneous preferences, to Model 2, which in addition to Model 1 also explores the interactions between each non-monetary product attribute with the two CFC factors (CFC-I and CFC-F) observed for each individual. In other words, the specification of Model 2 not only provides insight into the general preferences for the different attributes that characterize the yogurt products considered in the CE (main effects), but it also allows us to analyze how these preferences vary according to individual present or future orientation (interaction effects).

All of the model estimations were based on 2,076 observations (173 respondents performing 12 choice tasks each), with three options per choice task, for a total of 6,228 alternatives evaluated. All coefficients, except for that of price, are allowed to be random, following a normal distribution. Results are displayed in Table 5.

(INSERT TABLE 5 HERE)

When looking at the main effects, results are consistent across Model1 and Model2. Thus, we now focus our discussion of the results on Model 2 since it provided the best fit for our data among the two models that we estimated. In Model 2, price and no-buy coefficients are negative and significant. Individuals' utility increases for yogurt with lower amount of calories per serving, having the USDA label, health claim, and carbon footprint label. This evidence confirms our first hypothesis that both healthy and environmentally friendly attributes affect yogurt selection. Specifically, the negative and significant coefficients of CAL (CAL = -0192) generally suggests that low calorie amounts increase individuals' utility when selecting yogurt, compared to higher calories amounts. Individuals may perceive low calories as a proxy of healthier products. This might be because calorie-labeling has often been used as a tool to help consumers make healthier food choices. As for the USDA organic label, our finding reflects previous evidence concerning consumers' evaluation of the organic label. For instance, Van Loo et al. (2011) found that Americans have a higher willingness to pay for organic chicken breast, especially when labeled as USDA organic. This positive attitude toward organic products is also observed in Europe. For example, Van Loo, Caputo, Nayga, Muellenet & Ricke (2014) and Aprile et al. (2012) found that consumers positively value the European Union organic label. The fact that our results indicate that the USDA organic logo is the attribute that is most responsible for increasing consumers' utility (ORG = 0.535) might be due to its link with both the environment and health sphere. As such, this attribute might capture the interest of both environment- and health-concerned individuals. The positive and significant coefficient related to the health claim (HC) shows that individuals value health claims when choosing among different kinds of yogurts. However, the effect of HC is relatively small, which might be due to the fact that yogurt is perceived as a healthy product (Miklavec et al., 2015). Finally, consistent with other studies analyzing carbon footprint labels on other food-product selections (Van Loo, Caputo, Nayga, Seo, Zhang & Verbeke, 2015; Van Loo et al., 2014), the coefficient of the carbon trust label is positive and significant, meaning that this label also affects yogurt selection, although the statistical significance of the coefficient is lower.

Standard deviations of all attributes are significant as the diagonal values of the Cholesky matrix (Cholesky matrix of Model 2 available upon request), except for the carbon trust label (CT). The significant standard deviations indicate variation across taste parameters, implying the heterogeneity of individuals' preferences across both healthy and environmental attributes.

Moreover, the presence of extra variance shared by the two buying alternatives is confirmed by the significance of η_{nj}. This evidence is in line with the results of previous studies, using the RPL-EC model to analyze food-choice behavior (Caputo et al., 2013; Lee, Han, Caputo, & Nayga, 2015; Scarpa et al., 2008; Scarpa et al., 2013; Van Loo et al., 2014; Van Wezemael et al., 2014).

Turning to the interaction effects between the CFC-I and CFC-F factors and yogurt attributes, our results suggest that time preferences affect the choices of yogurt products associated with USDA organic label, health claims, and characterized by low calorie amounts. Specifically, the interaction term between CFC-I (high time preference) and ORG is negative and significant ($\gamma^{\text{CFC-I\_ORG}}$ = -0.173). In contrast, when ORG interacts with CFC-F (low time preference), the (significant) coefficient becomes positive ($\gamma^{\text{CFC-F\_ORG}}$ = 0.163). As for the HC, the interaction with CFC-I is significant and negative ($\gamma^{\text{CFC-I\_HC}}$ = -0.109) suggesting that the presence of this health-related attribute does not positively contribute to consumers' utility.

With regard to calories, we observe that the interaction term between CAL and CFC-I is positive and significant ($\gamma^{\text{CFC-I\_CAL}}$ = 0.161), whilst when calories are interacted with CFC-F the coefficient becomes negative ($\gamma^{\text{CFC-F\_ CAL}}$ = -0.007). These results suggest that the more consumers are future-oriented, the more they derive utility from low calorie products.

6. Discussion

In line with recent studies demonstrating an increased interest of consumers in healthy and sustainable features of food products (Chrysochou, 2010; Sirò et al., 2008; Verbeke, 2005), our results generally confirm that both health- and environment-related attributes are relevant in consumers' choice of yoghurt products.

Particularly, consumers derive the higher utility from the presence of the USDA organic logo, followed by the presence of the disease risk reduction claim, the carbon trust label and last, from low calorie contents. The high interest in organic is in line with previous evidence. For instance, Van Loo et al. (2011) found that Americans have a higher willingness to pay for organic chicken breast, especially when labeled as USDA organic. This positive attitude toward organic products is also observed in Europe. For example, Van Loo et al. (2014) and Aprile, et al. (2012) found that consumers positively value the European Union organic label. As mentioned previously, this effect could be due to the link of organic with both the environment and health spheres. As such, this attribute seems to capture the interest of both environment- and health-concerned individuals. The presence of the disease risk reduction claim, contributes to increase consumers' utility to a lower extent, and this could be attributable to the fact that yogurt is already perceived as a healthy product (Miklavec et al., 2015). As for the carbon trust label, our results are in accordance with recent literature analyzing the topic of environmental footprint labelling (Grebitus et al. 2013b) and confirm that the issue of sustainable food consumption is becoming of increasing interest among consumers. Food calories represent the less preferred attribute, compared to the others included in the CE. In general results show that consumers favor lower calorie contents.

Results of Model 2 provide evidence that consumer preferences for healthy and sustainable features of food products vary according to their present or future orientation. Indeed, the significance of some of the interaction terms between time preferences and certain yogurt attributes indicates that accounting for time preferences when analyzing food choices better explains the heterogeneity around the mean of some random parameters and individuals' decision-making.

Specifically, the coefficient estimates suggest that individuals with low time preferences are more careful about organic logo and low calorie contents. These consumers, due to their higher orientation towards the future, may be more interested in health-related and sustainability issues. They may perceive organic foods as healthier compared to ordinary ones due to the absence of common chemicals used in the production process (Magnusson, Arvola, Koivisto Hursti, Aberg, & Sjoden 2003). Meanwhile, they may see organic consumption as a means to enhance environmental protection. Consumers with low time preference could also perceive the low calorie attribute as a cue for healthier products. Indeed, calorie-labeling is often used as a tool to help consumers make healthier food choices, both on food product packaging and on restaurants menus.

High time preference individuals, typically characterized by a high orientation towards the present and less willingness to delay gratifications, do not derive utility from organic food, and show scarce interest in health claims and low calories content. Being mainly present concerned, they may fail to recognize the long-term future benefits of healthier and more sustainable food consumption favoring taste and other food characteristics that are able to give immediate gratification.

7. Conclusions and caveats

The study contributes to the literature by providing novel evidence from attribute-based CE concerning the relevance of healthy and environmentally-friendly product attributes in food choices, and the role of time preferences in consumers' choices of such foods. We specifically focused on healthy and environment-related attributes to better understand if time preferences can be associated with more healthful and sustainable food choices.

We can conclude from our results that healthy attributes and environment-related characteristics are important in consumers' choice of food products and that, as hypothesized, people with different time preferences could also have different food preferences. We would like to reiterate that our goal was not to determine if time preference causes choice behavior to change. Rather, we were only interested to know if people with different time preferences have different choice behavior and valuations in relation to our specific CE context, given all the possible confounding factors that could come into play when attempting to conduct a "causal" analysis on the effect of time preferences (see for example discussions about this issue by O'Donoghue & Rabin, 2015).

Research on time preferences and health outcomes has conventionally had applications in shaping public policy by uncovering motivations behind seemingly irrational health behaviors (Lawless et al. 2013). However, the specific effect of time preferences in food choices has not been explored much by researchers.

Overall, our results support the importance of time preferences in explaining heterogeneity in consumers' preference for food attributes. To some extent, while this finding may not be surprising or earth-shaking, it is still useful information for policy makers since it implies that they should account for time preferences when developing public policies geared toward making people purchase and consume, among others, healthier and more environmentally friendly food products. Although the possibility to influence time preferences is still an open question in the literature, we believe that policies or programs that could lead consumers to attach more importance to future events might be an effective approach to helping them make healthier and environmentally sustainable food choices. For example, policies and programs that can educate people about the long-term benefits that could be derived from healthier and more sustainable food consumption could be helpful in this regard. This may also contribute to reducing the feeling of uncertainty that consumers experience when evaluating future consequences of present actions, which often acts as deterrent in undertaking virtuous behaviors. In turn, this increased awareness may result in a greater attention towards healthy and sustainability aspects of food products. This issue is very important in the food policy and health arena given high and increasing obesity and medical expenditure rates not just in the US but also in many other countries. Time preference-based evidence could also be relevant for marketing purposes since differences in time preferences could be used to design targeted labels that could be more effective in communicating healthy and environmentally-friendly attributes to consumers.

While we have shown, at least in our CE study, that people with low vs high time preferences can have different food choices, this paper has some caveats that needs to be discussed. First of all, the analysis is based on a relatively small sample and, even though the results are powerful enough to derive conclusions, it would be valuable to repeat the study with a larger number of respondents in order to confirm the robustness of our results. Larger sample sizes could also better allow testing of whether there are relationships between time preferences and other socio-demographic variables. Another limitation of our study, as mentioned above, is that we cannot definitively determine if time preferences can *cause* changes in food choice behavior, given the host of possible confounding variables that could potentially affect both time preferences and food choice behavior (e.g., habits, projection bias, anticipatory utility). Moreover, on-line choice experiments are conducted in a hypothetical context where product images and attributes are specifically designed according to the aims of the research. Therefore, the experimental design could contribute to increase/decrease the salience of certain product characteristics.

Given that experimental findings are generally context dependent, future research should test the robustness of our findings in other contexts including other types of food and food attributes, other time preference measures, and other countries. Since it is conceivable that individuals may not value their health and money in the same way, then it would be interesting as well to check the relationship between time preferences in the health domain and food choice behavior.

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Table 1.

Consideration of Future Consequences (CFC) 14-Item Scale.

	CFC 14-item scale	Sub-scale*
1	I consider how things might be in the future, and try to influence those things with my day-to-day behavior.	F
2	Often I engage in a particular behavior in order to achieve outcomes that may not result for many years.	F
3	I only act to satisfy immediate concerns, figuring the future will take care of itself.	I
4	My behavior is only influenced by the immediate (i.e., a matter of days or weeks) outcomes of my actions.	I
5	My convenience is a big factor in the decisions I make or the actions I take.	I
6	I am willing to sacrifice my immediate happiness or well-being in order to achieve future outcomes.	F
7	I think it is important to take warnings about negative outcomes seriously, even if the negative outcome will not occur for many years.	F
8	I think it is more important to perform a behavior with important distant consequences than a behavior with less important immediate consequences.	F
9	I generally ignore warnings about possible future problems because I think the problems will be resolved before they reach crisis-level.	I
10	I think that sacrificing now is usually unnecessary since future outcomes can be dealt with at a later time.	I
11	I only act to satisfy immediate concerns, figuring that I will take care of future problems that may occur at a later date.	I
12	Since my day-to-day work has specific outcomes, it is more important to me than behavior that has distant outcomes.	I
13	When I make a decision, I think about how it might affect me in the future.	F
14	My behavior is generally influenced by future consequences.	F

Source: Joreiman et al. (2012)

*Subscale: F = CFC-Future subscale item, I = CFC-Immediate subscale item; CFC 14-item scale instructions: For each of the statements shown, please indicate whether or not the statement is characteristic of you. If the statement is extremely uncharacteristic of you (not at all like you) please write a “1” in the space provided to the right of the statement. If the statement is extremely characteristic of you (very much like you), please write a “7” in the space provided. Of course, use the numbers in the middle if you fall between the extremes.

Table 2.

Product Attributes and Levels for the Choice Experiment.

Product: Yogurt (1 pack, 4-counts)

Attributes	Description	Levels
Price	Price for a 4-count pack	\$1.89 \$2.59 \$3.29 \$3.99
Calories	Calories per portion (70g on average)	80 110 140
Organic	USDA organic logo	Present Absent
Carbon Trust	Carbon trust label	Present Absent
Health Claim	Diets low in saturated fat and cholesterol may reduce the risk of heart disease	Present Absent

Table 3.

Socio-Demographic and Economic Characteristics of the Sample.

Socio-demographic and economic characteristics		*% of total (n =173)*
Age	18-29 years	6.5
	30-39 years	19.2
	40-49 years	20.4
	50-59 years	24.1
	60-69 years	24.4
	>70 years	6.0
Gender	Male	32.9
	Female	67.1
Race	White/Caucasian	90.8
	African American	3.5
	Asian	4.6
	Native American	0.6
	Pacific Islander	0.6
Ethnicity	Hispanic	4.6
	Not Hispanic	95.4
Annual Household Income	<$15,000	4.6
	$15,000-$24,999	12.7
	$25,000-$34,999	12.7
	$35,000-$49,999	15.0
	$50,000-$74,999	22.0
	$75,000-$99,999	15.0
	$100,000-$149,999	5.8
	$150,000-$199,999	1.7
	≥$200,000	10.4
Education	Less than High School	1.7
	High School/GED	16.2
	Some College	21.4
	2-Year College Degree	17.9
	4-Year College Degree	23.1
	Master Degree	16.2
	Doctoral Degree	2.3
	Professional Degree	1.2
Children Younger than 18 in the Household	1	64.7
	2	13.9
	3	12.7
	4	6.4
	5	1.2
	>6	1.2

Table 4.

Rotated Component Matrix.

Items	CFC-I factor	CFC-F factor
CFC 3 (I)	0.784	-0.239
CFC 4 (I)	0.747	-0.150
CFC 5 (I)	0.419	0.090
CFC 9 (I)	0.640	-0.389
CFC 10 (I)	0.809	-0.200
CFC 11 (I)	0.824	-0.278
CFC 12 (I)	0.617	0.053
CFC 1 (F)	-0.109	0.766
CFC 2 (F)	-0.089	0.691
CFC 6 (F)	-0.056	0.591
CFC 7 (F)	-0.269	0.669
CFC 8 (F)	0.043	0.460
CFC 13 (F)	-0.179	0.696
CFC 14 (F)	-0.140	0.729

Table 5.

Results of RPL-EC Models 1 and 2.

Main Effects			
		Model 1	Model 2
CAL	Mean	-0.013***	-0.192***
		(0.003)[1]	*(0.003)*
	St. Dev.	0.031***	0.040***
		(0.002)	*(0.003)*
HC	Mean	0.121**	0.223***
		(0.054)	*(0.052)*
	St. Dev.	0.527***	0.475***
		(0.058)	*(0.054)*
ORG	Mean	0.178***	0.535***
		(0.068)	*(0.066)*
	St. Dev.	1.068***	0.856***
		(0.075)	*(0.067)*
CT	Mean	0.120*	0.194***
		(0.061)	*(0.056)*
	St. Dev.	0.445***	0.384***
		(0.073)	*(0.074)*
Price		-2.319***	-2.361***
No Buy		-14.283***	-12.781***
Interaction Effects			
CAL*CFC- I	Mean		0.161***
			(0.002)
CAL*CFC- F	Mean		-0.007***
			(0.002)
HC*CFC- I	Mean		-0.109**
			(0.050)

HC*CFC- F	Mean		0.028
			(0.057)
ORG*CFC- I	Mean		-0.173***
			(0.063)
ORG*CFC- F	Mean		0.163***
			(0.060)
CT*CFC- I	Mean		0.021
			(0.050)
CT*CFC- F	Mean		0.036
			(0.057)
Models fit			
BIC/N[2]		1.511	1.514
AIC/N[3]		1.473	1.470

[1] Standard errors in parentheses

[2] BIC: Bayesian information criterion

[3] AIC: Akaike information criterion

Note: *, **, and *** indicate the coefficients statistically significant at the 10%, 5%, and 1% level, respectively.

Figure 1

Example of a Choice-Set.

Figure 2. Scree Plot from PCA

Appendix A

Cheap Talk Script

The results of recent similar studies have highlighted that sometimes people give a certain answer, but then behave differently in real life. A possible explanation is that being in a hypothetical context might lead people to give less importance to their choices because these do not have a concrete impact on their life. Instead, when in a real buying situation, consumers have to face their budget constraint because they really have to pay for the product. We ask you to behave exactly as if you were in a real store, getting groceries for yourself or your family, and give real responses. Please, keep this in mind while answering.

Appendix B

Table 1B. Descriptive statistics of the scores of CFC-I and CFC-F

		CFC-I	**CFC-F**
Mean		0.000	0.000
Median		0.005	-0.035
Standard deviation		1.000	1.000
Variance		1.000	1.000
Interval		5.694	6.407
Min		-1.821	-3.671
Max		3.873	2.735
Percentile	25	-0.692	-0.712
	50	0.005	-0.035
	75	0495	0.686
Frequency		91	82
Percentage of total		*52.6*	*47.4*
	N	*6228*	*6228*

Figure 2B: Histogram of the distribution of the CFC-I factor

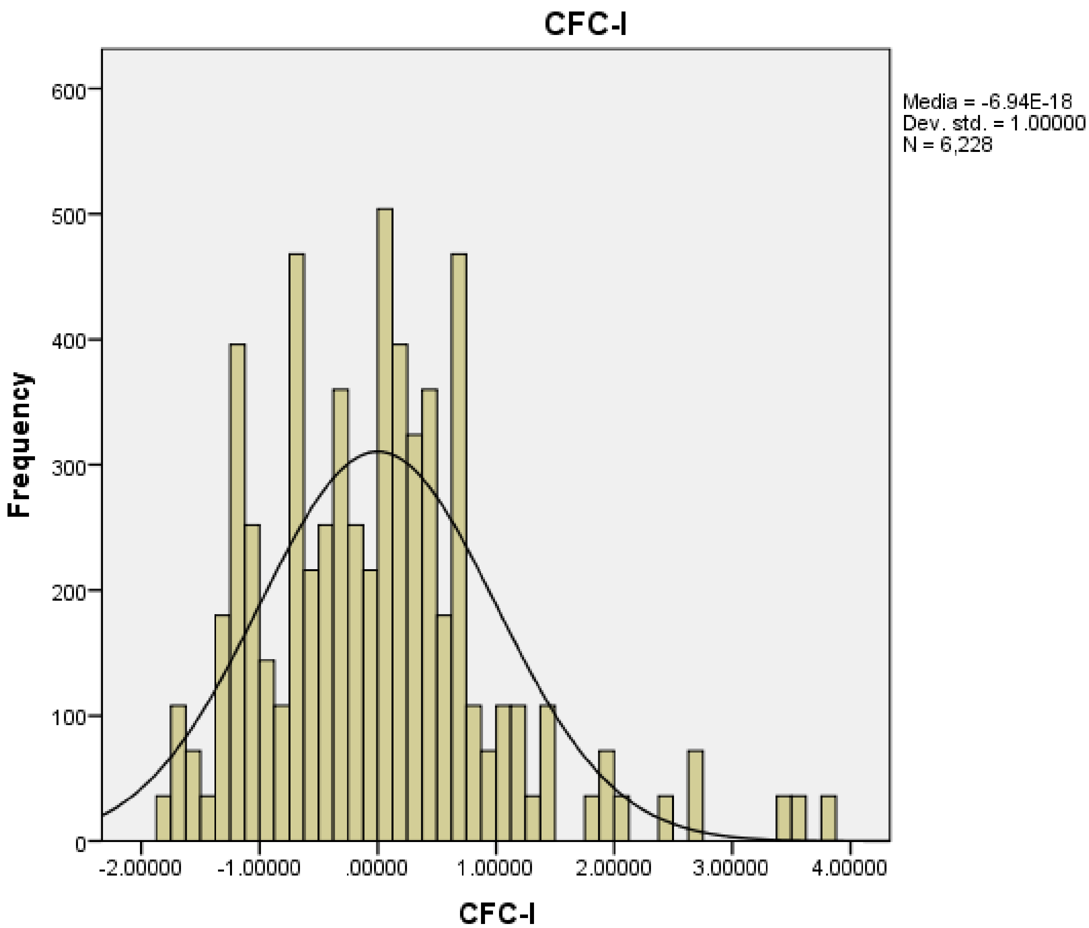
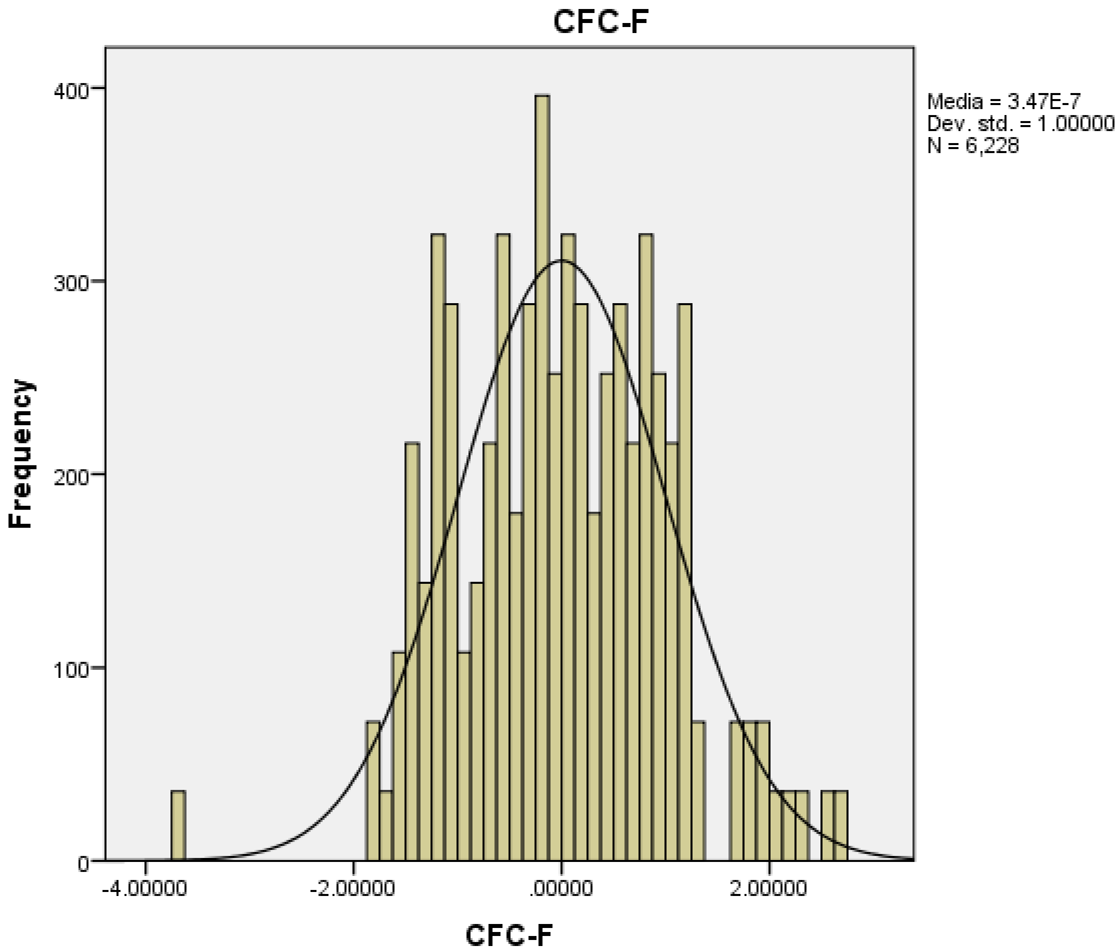


Figure 3B: Histogram of the distribution of the CFC-F factor



Highlights:

- Healthy and environmentally-friendly labels influence food choices;
- People with different time preferences have different food preferences;
- Time preferences affect the evaluation of organic, health claims and calorie labels.