Is local and organic produce less satiating?

Some evidence from a field experiment

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Abstract: We investigate consumers' preferences towards local and organic food via a framed field experiment involving revealed multiple discrete-continuous choices. Participants were endowed with a cash amount as a budget to purchase any desired quantity of different products. We modelled choices via the Multiple Discrete-Continuous Nested Extreme Value model. Central to our investigation is the test of the hypothesis of constant effect of attitudes across consumption doses, which is normally an assumption invoked a-priori and without testing in discrete-choice analyses. Our results support the hypothesis and reveal a strong preference towards organic and local products, associated with both the highest baseline utility and the lowest satiation effect.

Key-words: Multiple Discrete-Continuous choices; revealed preferences; field experiment; local organic food; attitudinal traits.

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1. Introduction

Consumers demand for local and organic products has substantially increased in recent years, due to issues concerning food safety, food security and health and environmental concerns (de Magistris and Gracia, 2014; Aprile et al., 2016; Bazzani et al., 2017; Gustavsen and Hegnes, 2020). In parallel with this trend, an increasing body of literature has dealt with the analysis of preference towards local and organic foods and its determinants. Several qualitative and quantitative methods have been adopted for this purpose, such as focus groups (Wirth et al., 2011; Hersleth et al., 2012), sensory analysis (Costanigro et al., 2014), experimental auctions (Bernard and Bernard, 2009; Grebitus et al., 2013; Costanigro et al., 2014), conjoint analysis (Annunziata and Vecchio, 2016), hedonic pricing (Connolly and Klaiber, 2014) and contingent valuation (Brugarolas et al., 2010). Among such methods, the discrete choice experiment (DCE) approach has gained increasing popularity over the last years (Scarpa and Thiene, 2011; Meas et al., 2014; Kamphuis et al., 2015; Thiene et al., 2018; Denver et al., 2019; Malone and Lusk, 2019; Muller et al., 2019; Scarpa et al., 2020; Caputo and Scarpa, 2022). In spite of its popularity and advantages, the DCE approach has important drawbacks. To list but a few, it is often applied to hypothetical choice data, which makes it vulnerable to hypothetical bias (Ready et al., 2010; Vossler et al., 2012; Fifer et al., 2014; Gschwandtner and Burton, 2020); its focus is on a single selection of preferred choice from a pre-defined and given set of options (thus not allowing for multiple selection), and choices are often framed with the impossibility for respondents to choose the desired consumption level for the preferred alternative (Corsi, 2007). Together, the above drawbacks impose serious limitations to the credibility and external validity of food choice analyses. In fact, in real choice contexts it is most likely to observe the simultaneous selection of multiple products and in varying quantities. Over the last decades, different streams of literature have emerged to address such shortcomings. Hypothetical bias has been addressed by DCE studies (Lusk and Schroeder, 2004; Olesen et al., 2010; Moser and Raffaelli, 2012; Gracia, 2014; Bazzani al., 2017) that used “real choice experiments”. These are framed field experiments in which respondents actually purchase the selected products from a choice set, spending real money, often obtained, as in this study, from an endowment which is part of the experiment design. Comparisons between welfare estimates obtained with real choice experiments found these to be significantly lower than those retrieved from the analysis of hypothetical choices (Moser et al., 2014; Liebe et al., 2019), a difference often generically attributed to "hypothetical bias". The second and third shortcomings have been addressed by studies dealing with multiple discrete choices (or MDC also referred as basket choices, Russel and Petersen, 2000; Caputo and Lusk, 2022) and multiple discrete-continuous choices (or MDCC), respectively. To the best of our knowledge, Caputo and Lusk (2022) is, to date, the only empirical study adopting this approach within a DCE in food economics. In MDC experiments, respondents are allowed to choose multiple food items in each choice occasion, while in MDCC they can also choose the quantity of each selected food type in the bundle. These methods allow researchers to account for the complementarity/substitution patterns between different products and for satiation effects at increasing consumption levels (Hendel, 1998; Van der Lans, 2018; Caputo and Lusk, 2022).

In this paper we report results from a framed field experiment based on a real MDCCs concerning selected categories of products. The experiment took place in Padua (Veneto region, Italy) and involved 186 participants who could use real cash endowments to purchase food items in any desired quantity to take home after the experiment, along with the cash left over. Four variants of each food item were made available: i) organic local, ii) organic non-local, iii) non-organic local, iv) non-organic non-local. The choice of selected products and purchased quantities were analysed via the multiple discrete continuous extreme value (MDCEV) model proposed by Bhat (2005; 2008) and its nested version, introduced by Pinjari and Bhat (2010) and referred as the MDCNEV model.

Our approach allows us to contribute to the existing literature in three main ways: i) by exploring the advantages of analysing revealed discrete-continuous choices via the MDCEV and the MDCNEV models in the context of organic and local foods; ii) by investigating satiation effects for local and organic products; iii) by explicitly testing whether the effects of attitudes and beliefs on preferences are constant across consumption levels.

With regards to the first contribution, despite their popularity in other fields (e.g. transportation and energy), where they have become the state-of-the-art approach for analysing multiple-discrete continuous choices, there is still a paucity of empirical applications of these categories of models in the analysis of food choices. The only papers we found were based on scanner data and were directed to a marketing audience, explaining brand effect of apple varieties (Richards et al., 2012) and demand for food-away-from-home (Richards and Mancino, 2014). To the best of our knowledge, there are no studies that use the MDCEV model to investigate preferences towards organic and local products. To account for naturally occurring correlation patterns among products with the same combination of local and organic features, we also estimate the nested version of the MDCEV model. To date, only a few studies addressed nesting by means of such model and it would appear that none of these dealt with food purchase decisions. As such, we contribute to the exploration of the potential advantages afforded by nesting also in the forecast of consumption levels using as benchmark those obtained with the MDCEV model.

Related to our second contribution, we choose to estimate a MDCEV model over alternative options (e.g. multivariate logistic distribution, Cox, 1972) as it allows us to conveniently account for satiation effects, thereby relaxing the assumption of constant marginal utility (i.e. a. marginal utility that remains unchanged when consumed quantity changes), a common ad implicit assumption in discrete choice models. The satiation effect is related to the notion of diminishing marginal utility. Everything else equal, it measures the rate at which marginal utility decreases as consumption levels increase. In other words, the highest is the satiation effect, the lowest is the number of units of a given good required to reach the point where marginal utility approaches the satiation value of zero. In turn, this implies that – ceteris paribus - the lowest is the satiation effect of each additional dose, the highest is the number of units that an individual desires to consume. Accounting for satiation effects allows us to better describe the demand for local and organic foods, compared to alternative models (including discrete choice models), which ignore dose effects on utility. In turn, this allows us to provide more complete information to firms and policymakers of the food supply sector.

The main point of our investigation (and our third contribution) is to explicitly test the effects of attitudes and beliefs at various purchase levels of the food products, i.e. whether attitudes and beliefs affect satiation. Accounting for such aspects is particularly important in our empirical application given the extensive body of literature highlighting how attitudes and beliefs influence preferences towards organic and local food products (e.g. Scarpa and Del Giudice, 2004; Zepeda and Li, 2006; Grebitus and Dumortier, 2016; Ditvlesen and Hegnes, 2020). Despite the fact that it has become standard practice to include covariates relating to attitudes and beliefs in discrete choice models of food selection (Nocella et al., 2012; Greiner, 2015), the use of such variables in MDCEV models has yet to receive serious attention. The advantage offered by incorporating attitudinal covariates in MDCEV and MDCENV models is that their effects on satiation can be explicitly tested. Do attitudes have utility effects that vary from the first dose of purchase -- say the first apple -- to the subsequent doses? While constant effects are held a-priori as an untested assumption in discrete choice data analyses, these can be subject of testing in MDCC data. There are various reasons as to why this can be of interest, since different foods might be interpreted by consumers differently when seen as vehicles to satisfy certain attitudinal stances. When purchasing a food bundle a certain degree of give and take between food types might occur in satisfying such stances---a sort of "mixing" effect. This would naturally occur in real food choice situations, when typically, more than one food type is bought, but it is automatically unobserved in standard preferred choice experiments based on a single hypothetical choice per choice task.

Compared to some of the previous studies on multiple discrete-continuous choice, we did not account for complementarity and substitution patterns, given our specific focus on satiation effects in real choices and the sample size we could afford. While this may lead to a less accurate representation of preferences towards local and organic products, we feel it does not necessarily detract from our main contributions.

The remainder of the paper is structured as follows: section 2 describes previous works related to our study; section 3 illustrates our experimental approach; section 4 formally describes the econometric model we used to analyse choice data; section 5 reports the results and section 6 draws the conclusions of the paper.

2. Related previous work

2.1. Preferences towards local and organic food

Preferences towards local and organic foods have been investigated by an extensive body of literature. Studies on this topic consistently found consumers to value local and organic products on average more than non-local/conventional ones (Hu et al., 2012; de Magistris and Gracia, 2014; Bazzani et al., 2017; Gustavsen et al., 2020). Typically, products which are both local and organic are associated with highest willingness to pay estimates (e.g. Scarpa and Del Giudice, 2004; Costanigro et al., 2014).

Consumers' characteristics, such as socio-demographic variables, have been found to influence preferences towards local and organic foods (Nie and Zepeda, 2011; Ditvlesen et al., 2020). Other variables with these effects include attitudes, views and beliefs (Costanigro et al., 2014; Ditvlesen et al., 2020), personality/psychological traits (Onozaka et al., 2011; Scarpa and Thiene; 2011; Gustavsen and Hegnes, 2020) and environmental (Nie and Zepeda, 2011; Srinieng and Thapa, 2018) and health (Denver and Christensen, 2015) concerns.

More in detail, Nie and Zepeda (2011) investigated the role of socio-demographics and health concern on US consumers' preferences towards organic and local food. They found race, gender, age, education and income to significantly affect such preferences. Women and lower middle-income consumers, in particular, were strongly interested in organic products. Their findings also suggest that environmental and health concerns positively correlate to consumption of local and organic products. The latter result was also found in Srinieng and Thapa (2018) in a survey study on

Vietnamese consumers and in Denver and Christensen (2015) among Danish households. Ditvlesen et al. (2020) used survey data on consumers from Denmark to investigate how individuals' characteristics affect preferences towards local and organic products. They found consumers of organic products to be better educated than consumers of local products, and gender to be insignificant in that regard. Results also suggest that preferences are affected by a variety of attitudinal traits (e.g. consumers who believe that organic products are safer and healthier are more likely to purchase them). Costanigro et al. (2014) used an experimental auction to explore preferences towards organic and local apples and found willingness to pay for such products to be affected by consumers' trust in governmental food agencies. Onazaka et al. (2011) used the Theory of Planned Behavior (Fishbein e Ajzen, 1975) as a framework to investigate preferences of US consumers for organic and local products. They found consumers who see a personal role in improving sustainability to value more such claims. Similarly, Scarpa and Thiene (2011) linked the preference structure for local and organic carrots to the Protection Motivation Theory (Rogers, 1975), by using data from a survey addressing Italian consumers. Gustavsen and Hegnes (2020), instead, explored how consumption of organic food is affected by the Big Five Personality Traits, by using data on Norwegian consumers. They found that Openness to experience and Agreeableness are positively related to consumption of such products, while Extroversion and Conscientiousness are negatively related.

When comparing preferences for local versus organic claims, the literature provides mixed evidence. Some studies found consumers to value local production more (Scarpa and Del Giudice, 2004; Aprile et al., 2012; de Magistris and Gracia, 2014) while other studies suggest the opposite (Hu et al., 2012; Bazzani et al., 2017) or found consumers to value similarly the two claims (Costanigro et al., 2014).

Other work (e.g. Scarpa et al., 2005) found preferences between the two production methods to be food-specific, i.e. organic production is preferred for some items and local origin for others.

While the above studies provide a comprehensive picture on preferences towards local and organic products and on the factors affecting them, none of them accounts for satiation effects and how they are potentially affected by attitudinal traits, which is the focus and main contribution of our paper.

2.2 Multiple discrete and continuous choices

Over the last decades, some studies moved from collecting a single discrete choice per choice task, typical of discrete choice experiments, to approaches that allow respondents to choose multiple alternatives per choice task. Such approach has been sometimes referred to as basket choice (Russel and Petersen, 2000; Caputo and Lusk, 2022). For example, Venkatesh and Mahajan (1993) carried out a survey in which respondents could choose to participate in multiple entertainment events among those proposed to them, thus creating bundles of tickets. Ben-Akiva and Gershenfeld (1998) presented to respondents several calling services (each with its own price) and allowed them to select multiple services to form their own plan. The total cost of the bundle was given by the sum of the prices over chosen features. Russel and Peterson (2000) used data from a purchase panel of 170 households in Toronto, Canada, concerning basket choices for four paper goods categories: paper towels, toilet paper, facial tissue, and paper napkins. These authors found significant complementarity and substitution effects among the four categories. Kim et al. (2002) used purchase data to estimate demand for alternative bundles of yogurt flavours. More recently, Caputo and Lusk (2022) carried out a Basket-Based Choice Experiment via a survey of around 1,200 US consumers in which respondents could choose multiple entries to be combined into a meal from a list of 21 food items. Results from a multivariate logit model highlighted the existence of complementarity and substitution patterns among food items.

An increasing body of literature focuses on the simultaneous modelling of both alternative selection and quantity decisions, i.e. choice occasions concerning the selection of multiple goods as well as their respective consumption level. In what follows we first restrict our review to studies that model multiple discrete-continuous choices without adopting the influential random utility model proposed by Bhat (2005, 2008), the MDCEV. Studies adopting the MDCEV model are reviewed in the following section.

Hendel (1998) analysed demand for personal computers (PC) using data from a survey addressing US firms. Firms' representatives were asked to state the total number of PCs their firm owned, the PC models and, for each model, the sub-total number of PCs. The author used such data to predict PC purchases for each firm as a function of PC attributes and firms' characteristics. Phaneuf et al. (2000) investigated angler trip behaviour by using data from two surveys carried out in the US. The information used included each anglers' number of trips to each destination and salient anglers' characteristics, such as socio-demographics and preferred angling mode. The Kuhn-Tucker model developed and used by these authors to analyse trip data has since been generalized into the MDCEV model. Dubè (2004) is the first study of this type in the food and beverage sector, and modelled data from a survey on US consumers concerning choices among 26 soft drink types. The dataset included information about chosen products and their quantities. Kwak et al. (2015) analysed choices among different brands and flavours of yogurts by using retail data. They focused specifically on the effect of brand quality perception on choice probabilities for each flavour and on the number of chosen flavours. Van der Lans (2018) analysed choices from two different datasets: the first involved yogurt purchases and included information about variety and quantity choices between six different flavours; the second concerned sales data from an ice-cream shop and included information about chosen flavours and the number of consumed scoops. We note that none of the above studies included attitudinal variables to explain heterogeneity of choices.

2.3 Applications of multiple discrete-continuous extreme value models

Since its introduction by Bhat (2008), the MDCEV has become the go-to, state-of-the-art, and workhorse model to analyse multiple discrete-continuous data in three fields: time allocation among different activities, transportation mode and energy consumption.

Concerning time allocation across activities, Chikaraishi et al. (2010) used data from the German travel survey Mobidrive to investigate how different days of the week affect the likelihood of allocating time to different activities. Calastri et al. (2020) used a subset of the same data to investigate correlation between time allocations to various activities within-day and between-days. Castro et al. (2012) modelled survey data collected in the US to investigate how time, money and capacity constraints affect time use. Kuriyama et al. (2020) analysed survey data concerning trips to national parks in Japan, with the aim of estimating leisure time value of weekends and long holidays. Results suggest that such values are substantially different and that there is low substitution effect between weekends and long holidays. Lloyd-Smith et al. (2020) used data from a survey of recreational anglers in the Gulf of Mexico to estimate how value of time varies seasonally. Watanabe et al. (2021) explored variations of time use in leisure activities during non-working days by using GPS-based data collected in two Japanese cities (Matsuyama and Yokoyama). They found significant differences between the two cities in terms of relationship between non-working time allocation and workday time use. More recently, Pellegrini et al. (2021) integrate monetary and time constraints into a single economic constraint coupled with a non-additively separable utility form to capture complementarity and substitution patterns in recreational activities in Netherlands.

Moving to the second field of MDCEV applications, that of transportation analysis, Sobhani et al. (2013) analysed data from the 2009 National Household Travel Survey (NHTS) for the New York region to investigate vehicle type and usage decisions in relation to activity type. Jian et al. (2017) used revealed preference data provided by an Australian carsharing company to model vehicle choices in the context of carsharing. They found that vehicle choice and satiation effect across vehicle types are affected by a variety of factors, such as age, income level and insurance plan. Khan and Machemehl (2017) analysed time of day choice behaviour of commercial vehicles by using data drawn from the 2005–2006 Austin Commercial Vehicle Survey. Results suggest that commercial vehicle choice behaviour is influenced by several factors, such as vehicle class, commodity type, total unloading weight and frequency of stops. Tapia et al. (2020) used combined stated preference and revealed preference data to evaluate the societal impact of rail infrastructure investment in Argentina. Specifically, they modelled destination port and transport mode choice for freight. Augustin et al. (2015) implement the MDCEV model in conjunction with a Stochastic Frontier (SF) regression to accommodate household ownership and utilization, noting that the SF approach is preferable over econometric models for measuring the unobserved mileage budget (see also Pellegrini et al., 2020).

In the field of energy choices, Jeong et al. (2011) used survey data collected from households in Seoul, South Korea, to investigate residential energy consumption patterns. They found gas boilers and electric heaters to have the highest baseline utility and the lowest satiation effect among heating systems. They also found a significant effect on choices of consumers' socioeconomic characteristics and environmental impact of technologies. Yu and Zhang (2015) also used household survey data to model domestic energy use in China, which they found to be strongly affected by socio-demographics. More recently, Frontuto (2019) used survey expenditure data from Italian households to estimate residential energy demand. The author found such demand to be relatively inelastic. In a simulated scenario related to climate change, he found that for an increase in temperature of 2 degree Celsius the energy demand would decrease by 4%. Acharya and Marhold (2019) investigated the determinants of households' energy choices and found education to have a substantial effect: households with low education tend to consume more firewood and kerosene, while those more educated are likely to prefer liquefied petroleum gas and electricity.

Few studies adopted the MDCEV model in other fields. For example, as previously mentioned, Richards et al. (2012) analysed demand for different apple varieties by using panel survey data from households in New York State. Han et al. (2016) investigated how preferences and consumption patterns related to mobile apps vary across demographic groups. Dekker et al. (2019) investigated data collected via an online survey in which respondents selected a portfolio of public sector projects given a governmental budget constraint. Finally, Pellegrini et al. (2021) propose a MDCEV model to assess herbicide use decisions in the context of weed control strategies in Australia. While the inclusion of individuals' sociodemographic characteristics in the utility function is common practice in the above literature, none of the studies used attitudinal variables to explain heterogeneity of either baseline utility or, crucially for our contribution, satiation effects.

2.4 Applications of the nested multiple discrete-continuous extreme value model

Aggregation of alternatives into groups with similar degree of substitutability is often defined as "nesting" in choice models. The most famous such model is the nested logit model introduced by Williams (1977), but often attributed to McFadden (1978). The nesting in the MCDNEV was developed from the baseline MDCEV model by Pinjari and Bhat (2010). Since then, only few studies applied it to data analysis, for example Ferdous et al. (2010) used it to explore data from the Consumer Expenditure Survey carried out in the US to analyse households' income allocation between alternative expenditure categories. Their model specification included four nests: i) housing, utilities, business services and welfare activities; ii) food, alcohol/tobacco, entertainment and recreation: iii) clothing, apparel and personal care; iv) vehicle, fuel and motor oil, vehicle insurance, maintenance and operation. Bernardo et al. (2015) used MDCNEV to study data from the 2010 American Time Use Survey and investigate time-use patterns of adults with and without children. The nesting structure adopted in their study consisted of a single nest, which included out-of-home activities. Similarly, Calastri et al. (2017) used it to model survey data collected in Chile and investigate time allocation among different activities. Their specification included two nests, one for in-home activities, the other for out-of-home activities. To the best of our knowledge, there are no MDCNEV applications incorporating attitudinal variables in the utility function.

3. Our experimental approach

3.1 Food items in the experiment

Our experiment includes seven food items, namely: i) apples; ii) pears; iii) tomatoes; iv) salad; v) red wine (Cabernet); vi) white wine (Chardonnay) and vii) olive oil. For each product, four variants were made available to participants, and described to them in relation to the four combinations of the two production methods under investigation: i) organic local; ii) organic non-local; iii) non-organic local; iv) non-organic non-local. We chose to include only seven food items due to the available budget for the experiment, but the same design can be applied to experiments including a larger number of products.

We classified as local those food items produced in the Veneto region, and as non-local products from other Italian regions. We choose to not specify the origin region for non-local products to avoid possible confounding effects, as different participants may react differently to a given origin region, an effect that would be difficult to control. Given our focus on local and organic products, we chose to include in the study only foods for which organic production is commercially widespread in the Veneto region. Among these, we chose the most traded fruits and vegetables in the region and wine rather than grapes, since the former has a more relevant role in the agri-food sector of the Veneto region. We note, however, that previous studies with similar sample sizes modelled a larger number of alternatives.

Table 1 reports the full list of prices for each product. Price amounts were based on price averages recorded across the main grocery shops of Padua, to ensure the realism of the experiment. For wine, the unit referred to the standard 0.75 litre bottles, whereas for olive oil to the standard 0.50 litre bottles. For fruit and vegetables, the prices were defined per item (e.g. for one tomatoes or one apple). While this choice may somewhat decrease the realism of the experiment (since the prices of such products are typically indicated per kilogram), weighting the selected quantities during the experiment would have been impractical. Furthermore, many purchasers do determine the buying amounts for these standard-sized products on the basis of items, which is then weighted at the till.

The price ranges (with non-organic non-local products being the cheapest and organic local products being the most expensive) we used are: €0.30 - €0.70 for apples; €0.40 – €0.90 for pears; €0.30 – €0.60 for tomatoes; €0.50 - €1.00 for salad; €7.50 - €8.50 for both red and white wine; €9.20 – €12.50 for olive oil. Given our primary focus on satiation effects, and the relatively small sample size used, the design of this framed field experiment excluded price variation within specific items. That is, the same combination of food type-mode of production-origin was always offered for purchase at the same price.

3.2 Experimental procedure

The experiment was designed to mirror as closely as possible consumers' experience in a real shopping scenario when purchasing food for home consumption. For this purpose, we created a setting similar to the one commonly found in supermarkets, or in large grocery stores. The premises fitted out for the purpose are located in two University buildings in Padua (Veneto region, North-East Italy).

To make the experimental market more natural and realistic, we placed the food items in tables that mirror typical supermarket stands for fruit and vegetables. Apples, pears, tomatoes and salad were placed in units in baskets similar to those present in supermarkets. Wine and oil bottles were placed on the tables, with brand labels concealed by paper tags, so as to ensure that brand did not play any role in participants' choices. Prices were reported in front of baskets and bottles, to mirror price tags found in supermarkets. Figure 1 reports a picture of our experimental setting.

A total of 186 participants took part in the framed field experiment over two days in October 2019. Among those, 143 were recruited by a market research firm among households of the Veneto region, whereas the remaining 45 were recruited among personnel of the University of Padua. In view of their larger travel cost to participate, subjects recruited by the market research firm were paid travel expenses.

As they entered the venue of the experiment, all participants received the instructions for the experiment in written form. More than one participant could access the room at the same time. The full instruction text is reported in Appendix A. The instructions included information about the purpose of the study and outlined the rules of the experiment: i) a €25 cash endowment (approximately $27.50 in USD) was provided to each participant to purchase any food item available in the stands; ii) participants could choose to spend all of it or more if they desired. In the latter case, the difference had to be covered with their own money; iii) at the end of the experiment participants took home all purchased products and the cash left over if there was any. Subjects were allowed not to spend all the €25 cash endowment to avoid forcing them to purchase products they were not interested in (or products in a larger quantity than desired), which would result in a biased representation of their preferences.

After reading the instructions, respondents were informed they would be asked to fill a questionnaire at the end of the experiment and then they were left to choose their products. After shopping, they left the products to the experimenter, who registered the items chosen, calculated the balance and the change if any was due, while the participant filled the questionnaire. After handing in the questionnaire, participants were given their shopping and their cash change when this was due. The baskets and tables were refilled after each purchase to ensure to maintain the same conditions across participants.

3.3 The questionnaire

The questionnaire was designed to collect information about respondents' socio-demographics, food purchasing habits, and - importantly - attitudes towards food origin (local vs non-local) and production modes (organic vs conventional), environmental concerns and other self-reported personality traits. Specifically, the questionnaire started with a series of attitudinal questions on views and beliefs concerning organic and local products. Respondents were asked to express their agreement with a series of statements on a Likert scale from 1 to 5 (1 = totally disagree; 5 = totally agree). Then, respondents were asked how frequently and since when they had purchased organic and local products, as well as which organic and local foods they usually purchase (if any). The subsequent section included attitudinal questions designed to measure environmental concern. Responses to such questions were also elicited with a Likert scale. Afterwards, the Ten Item Personality Inventory (TIPI) scale (Gosling et al., 2003) was included to measure respondents' personality traits. Respondents’ socio-demographic characteristics were collected at the end.

4. Econometric approach

This section describes the econometric approach used to model produce purchases. Given that consumption patterns of fruits/vegetables and olive oil and wine substantially differ (especially in terms of consumed quantities), in this paper we present the results of models which only investigate choices of fruit and vegetables.

We firstly formally describe the MDCEV (4.1) and MDCNEV models (4.2) and then, in subsection (4.3), we describe the procedure used to investigate the effect of the attitudinal variables on satiation effects.

4.1 The multiple discrete continuous extreme value model

Both the MDCEV and the MDCNEV models are based on a direct utility function $U(x)$ that individuals maximise by consuming a vector x of quantities of each of the K products, $x = (x_1, \ldots, x_k)$. 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 vector of prices. In our case, the vector $\mathbf{x}$ includes a unit-priced outside good (Lu et al., 2017) which represent the expenditure on goods other than the food products included in the experiment (and also includes the expenditure for olive oil and wine). 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, $U(\mathbf{x})$ 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 baseline and utility levels for other alternatives are estimated relative to that of the 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 part V_k and by a stochastic one ε_k, so that it can be expressed as:

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

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

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 not choosing one (or more) of the food 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 $\alpha_k \to -\infty$ 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 satiation effect. For this reason, it is necessary to normalise one of the two in order to identify the other. This leads to different MDCEV (and MDCNEV) 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[1]. As such, the γ_k coefficients allow us to measure satiation effects for the different variants for fruit a vegetable, an information which is not obtainable with traditional discrete choice models.

In this profile, the utility function expressed in equation 1 becomes:

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

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

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

$$P(x_1^*, x_2^*, \dots, x_M^*, 0, \dots, 0) = \frac{1}{p_1} \frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m\right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m}\right) \left(\frac{\prod_{m=1}^{M} \exp\left(V_i/\sigma\right)}{\left(\sum_{k=1}^{K} \exp\left(V_k/\sigma\right)\right)^M} \right) \qquad \text{(Eq. 4)}$$

where $p_1, \dots, p_m$ 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).

4.2 The nested multiple discrete continuous extreme value model

In the nested version of the MDCEV, the MDCNEV, the expenditure allocation problem is solved by assuming that the stochastic part of utility has a joint extreme value distribution given by (Panjari and Bhat, 2010):

$$F(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_K) = \exp\left[-\sum_{s=1}^{S_k} \left(\sum_{i \in s^{th} nest} \exp\left(-\frac{\varepsilon_i}{\theta_s}\right)\right)^{\theta_s}\right] \qquad \text{(Eq. 5)}$$

Where s represents one of the S_k nests to which the K products belong to, with $S_k < K$ (i.e. at least two alternatives are nested together). The θ_s parameter measures the correlation between the stochastic components of the alternatives within a nest, with $0 < \theta_s \leq 1$.

Next, let $1, 2, \dots, S_M$ be the nests including the M chosen alternatives and $q_1, q_2, \dots, q_{S_M}$ the number of chosen products in each of the S_M nests, so that $q_1, q_2, \dots, q_{S_M} = M$. Assuming the distribution of the stochastics components specified in equation 3, the consumption probability can be expressed as:

$$P(x_1^*, x_2^*, \dots, x_M^*, 0, \dots, 0) = |J| \frac{\prod_{i \in chosenalts} \exp\left(\frac{V_i}{\theta_i}\right)}{\prod_{S=1}^{S_M} \left(\sum_{i \in s^{th}nest} \exp\left(\frac{V_i}{\theta_s}\right)\right)^{q_s}} \cdot$$

$$\sum_{r_1=1}^{q_1} \cdots \sum_{r_s=1}^{q_s} \cdots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{s=1}^{S_M} \left[\frac{\left(\sum_{i \in s^{th}nest} \exp\left(\frac{V_i}{\theta_s}\right)\right)^{\theta_s}}{\sum_{s=1}^{S_k} \left\{ \left(\sum_{i \in s^{th}nest} \exp\left(\frac{V_i}{\theta_s}\right)\right)^{\theta_s} \right\}} \right]^{q_s - r_s + 1} \left(\prod_{s=1}^{S_M} sum(X_r S)\right) \left(\sum_{s=1}^{S_M} (q_s - r_s + 1) - 1\right)! \right\} \quad \text{(Eq. 6)}$$

where $sum(X_r S)$ is the sum of the elements of a row matrix $X_r S$. A detailed description of the form of such matrix is provided in Pinjari and Bhat (2010). Compared to the MDCEV model, the estimation of a MDCNEV model entails an additional set of nesting parameters (the θ_s), one for each nest.

The general expression above represents the MDCNEV consumption probability for a two-level nested extreme value error structure. This expression can be used in the log-likelihood formation and subsequent maximum likelihood estimation of the parameters for any dataset with mutually exclusive groups (or nests) of interdependent multiple discrete–continuous choice alternatives. In our case these are the four origin-production modes combinations. To be explicit, we estimated a MDCNEV model with four nests, each including the same variant of the four food products: i) conventional non-local products nest; ii) conventional local products nest; iii) organic non-local products nest; iv) organic local products nest. The outside good was left out of the nesting structure related to production mode-place of origin and treated as a degenerate branch with one alternative. Such nesting structure led to the estimation of four additional nesting parameters compared to the MDCEV specification (the θ_s), which allowed us to explore whether preferences for fruit and vegetables of the same variant are correlated.

4.3 Inclusion of attitudinal variables in the utility function

One of the advantages on the MDCEV (and MDCNEV) model is that it allows researchers to investigate how attitudinal variables affect both the baseline utility (i.e. the utility of the first dose of consumption of a selected alternative) and the satiation effect (i.e. the utility of subsequent doses of consumption of a selected alternative). Importantly, the latter allows researchers to empirically test the standard maintained assumption in discrete choice models that attitudinal variables have the same effect on utility at any given consumption level, which is one of the main objectives of our paper. Attitudinal variables can be included in the utility function by parameterizing ψ_k and either γ_k or α_k (depending on the estimated profile) to be function of such variables.

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

$$\psi_k = \exp(V_k + \varepsilon_k) = \exp(\vartheta_k + \boldsymbol{\beta}'_k \boldsymbol{z}_k + \varepsilon_k) \qquad \text{(Eq. 7)}$$

where ϑ_k is a constant, $\boldsymbol{z}_k$ is a vector of covariates (sociodemographic characteristics and attitudinal traits) 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 attitudinal covariates on satiation. In the case of the hybrid profile (the one we estimated), this is done by expressing the satiation parameter γ_k as:

$$\gamma_k = \exp\,(\omega_k + \boldsymbol{\lambda}'_k \boldsymbol{w}_k) \qquad \text{(Eq. 8)}$$

where ω_k is a constant, $\boldsymbol{w}_k$ is a vector of covariates associated to the vector of coefficients $\boldsymbol{\lambda}'_k$. One may choose to use the same covariates to investigate heterogeneity of both baseline utility and satiation effect, in which case $\boldsymbol{z}_k$ = $\boldsymbol{w}_k$.

Given the parameterizations reported in equations 7 and 8, a positive element of $\boldsymbol{\beta}'_k$ would imply that the associated attitudinal trait 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 attitudinal trait increases the chosen consumption level of product k. The typical assumption of discrete choice models of homogeneity of attitudinal effects at varying consumption levels, instead, would be confirmed by statistically insignificant estimates of the elements in $\boldsymbol{\lambda}'_k$.

In our model specification, we used the same covariates in $\boldsymbol{z}_k$ and $\boldsymbol{w}_k$, namely: i) number of family members; ii) regular consumption of organic products; iii) thinking it is right to support local farmers; iv) thinking organic products are more ethical; v) thinking organic products are too expensive. The latter three covariates, which refer to attitudinal traits, were retrieved from the Likert scale statements described in section 3.3. For the analysis, we transformed the ordinal scores in dummy variables (taking the value of 1 is the score is greater than 3, i.e. the middle point of the scale). Given our focus on preferences towards local and organic products and to avoid over-parametrization of the model, we included the covariates only on baseline utility and satiation effect for local organic products. For the other variants only the constants ϑ_k and ω_k were estimated.

5. Results

This section is organized as follows: at first, we report descriptive statistics for our sample and for the observed choices. Then, we compare the MDCEV and MDCNEV models and report the estimates from the MDCNEV model. Finally, we describe results of testing the attitudinal effects on satiation as obtained from the MDCNEV parameters.

5.1 Descriptive statistics

Table 2 reports the descriptive statistics for our sample. The sample is balanced in terms of gender, with around 45% men and 55% women. With regards to education attainments, most of the sample achieved a high school diploma (48%) or a university degree (35%). The relatively high share of participants with high education is in part influenced by the recruitment of participants among the University personnel, who consisted mostly of professors, researchers and PhD students. Nearly half of the sample declared a yearly income between €15,001 and €35,000, while the lowest income class (less than €15,000) includes around 20% of respondents. Finally, the sample is well distributed in terms of age, with the highest frequency (26%) class being aged between 18 and 29.

Table 3 reports the descriptive statistics for the observed choices. The organic local variant of each product was consistently chosen more frequently than the others, with percentages ranging from 40% of the sample for salad to 45% for tomatoes. At the opposite range of the selection spectrum, non-organic non-local products are consistently associated with the lowest choice frequency. The average purchase levels of the products are reported in the last column of Table 3. For apples, the highest values are for non-organic non-local and organic local (3.79 in both cases). Similarly, for pears, the non-organic non-local variant has the highest average consumption level (3.73), possibly due to its lower price. However, for tomatoes, the organic local ones have a substantially higher consumption level (7.44), compared to the other mode-origin combinations. For salad, the two variants with the highest average purchase levels, with almost identical values, are non-organic local and organic local (1.32 and 1.30, respectively).

With regards to the amount of money spent by participants, only around 7% of them purchased products for less than €10, while the majority spent more than €20, with 34.6% of the participants spending more than the €25 cash endowment.

5.2. Models comparison

The log-likelihood of the MDCEV model is -2289.94, whereas for the MDCNEV model equals -2216.39, with four additional parameters (the nesting ones). Both the Akaike (AIC) and Bayesian (BIC) information criteria strongly favour the MDCNEV model (for AIC 4586.78 vs 4725.88 and for BIC 4833.49 vs 4959.77 for the MDCNEV and MDCEV, respectively).As such, it seems that accounting for correlation patterns across products via a nesting structure provides a better statistical fit of the model to consumers choice behaviour. Table 5 shows the predicted average consumption levels for the two models. Overall, the predictions are quite similar, with the MDCNEV providing better predictions for organic local products and the MDCEV for the others.

In the remainder of the section, we focus on estimates from the MDCNEV model, due to its superior goodness of fit and capability to capture possible correlation among alternatives.

5.3 Nested multiple discrete-continuous extreme value model estimates

This section reports the estimated coefficients of our MDCNEV model. Table 6 reports the nesting parameters, then Table 7 the estimates for the constants of baseline utility and the satiation parameters and finally Table 8 and Table 9 those capturing covariates' effect on baseline utility and satiation parameters, respectively.

The θ nesting parameters are all statistically significant at 95%, with value between 0 and 1, in accordance with the theory. Values for the organic non-local, non-organic local and non-organic non-local nests are quite similar, ranging from 0.63 to 0.69. The nesting parameter for organic local products, instead, is much closer to 0 (0.37), thus suggesting stronger correlation within such nest compared to the others. This implies that individuals which favour local organic production are likely to do so for all food items. Interestingly, within-nest correlation for local organic products is higher than correlations found in other studies carried out in different fields, such as travel behaviour (Pinjari and Bhat, 2010; Bernardo et al., 2015; Calastri et al., 2017).

Moving to the baseline utility parameters ϑ, we remind that we set the outside good as the reference alternative to identify the parameters for the other products. All the estimated coefficients are statistically significant at 95% level and negative, thus suggesting that – at zero consumption level – consumers benefit more from consuming the outside good compared to the food items included in our experiment. We note that such result is common in MDCEV applications using the outside good as the baseline alternative (e.g. Calastri et al., 2017). Looking at the estimates, it can be noticed how the values are consistently higher (i.e. less negative/closer to zero) for organic local products, compared to the other product methods; this suggests consumers prefer such variant. For all products, we then have the following order of preferences: organic non-local, non-organic local and finally non-organic non-local, which seems to consistently be the least preferred production method. Interestingly, these results suggest that baseline utility for organic products is higher than that for local ones.

With regards to the effects of the satiation parameters, we first note that the α coefficient is statistically insignificant, as found in other studies (Calastri et al., 2017). The γ parameters, instead, are all different from zero in a statistically significant manner (at least 95% level). We remind the reader that the higher the estimated value of such coefficient, the lower is the satiation effect. As such, it can be noticed how utility for organic local food items is decreasing as quantity purchased increases, but compared to the other production methods, it does so at a lower rate. This holds true for all products. In contrast to the findings for the baseline utility, we found that satiation effects have an order that varies across the other three production methods. For apples, tomatoes and salad the second highest value was retrieved for organic non-local, while for pears non-organic non-local production was associated with the second-lowest satiation effect.

Overall, such results suggest a strong preference for organic and local products among study participants, a result consistent with previous studies. Importantly, compared to the previous literature, that generally focused solely on utility associated with different food production methods, our results provide evidence that items that are both local and organic produced not only have the highest utility, but also the lowest satiation effect. Accounting for satiation effect also allowed us to better disentangle preferences for foods that are only organic or only local. Specifically, we found that for some products, non-organic non-local variants have lowest satiation effect compared to products that are only local or only organic. Limiting the analysis to baseline utilities (as in the case of discrete choice models) would have not allowed us to obtain this information, since only organic and only local product have consistently higher utility that non-organic and non-local ones. This further corroborates the importance of accounting for satiation effects when analysing the demand for local and organic food items.

5.4 Socio-demographic and attitudinal variables' effects on baseline utilities and satiation

We now turn our attention to describing the effects of socio-demographic and attitudinal covariates on baseline utility and our estimates of satiation parameters for local organic products. To facilitate the comparison of effects across different products, we computed the money metric utility (MMU) for each of the covariates. Based on equation 7 and considering that all *z* covariates were dummy coded, we computed MMU as:

$$MMU_{zk} = \frac{\exp(\vartheta_k + \boldsymbol{\beta}_{zk}) - \exp(\vartheta_k)}{p_k} \qquad \text{(Eq. 10)}$$

The MMU values for the effects of baseline utilities reported in the last column of Table 8 are multiplied by 100 to ease numerical comparisons. Table 9, instead, does not report MMU values, as none of the covariates were found to significantly affect satiation (as described more in detail in the second part of this section).

Living with family members has a significant (at 90% level) and positive effect on the baseline utility of all products, with the exception of tomatoes. This suggests that subjects in charge of making food choices for their family tend to choose products generally considered healthier more frequently than the other products. By looking at the MMU values, it appears that this covariate has a stronger effect for pears compared to the other food items.

As expected, individuals who regularly consume organic food (i.e. at least once per week) have a stronger preference for all four organic local foods. This effect seems to be stronger in the case of apples and pears compare to salad and tomatoes.

Next, we found attitudes to generally be reflected in the observed choice behaviour. Subjects who believe it is important to support local farmers have a stronger preference for organic local products, except for salad whose utility was found not to be significantly affected by such covariate. In terms of magnitude of the effect, the MMU values are quite similar for the three products with significant coefficients, with apples having a slightly larger value compared to pears and tomatoes. Those who believe that organic products are more ethical are also more likely to choose organic local products as well. We found this effect to be consistent across the four products. When comparing the specific effect on utility across products, it can be seen how the MMU are very close in all cases. Finally, thinking that organic products are too expensive has a significant effect only on baseline utility for organic local tomatoes. Such effect is negative, thus suggesting that individuals who think organic products are too expensive are less likely to purchase organic local tomatoes than the others. We remind the reader that organic local tomatoes were the most expensive of the four products, which may at least partially explain why this covariate significantly affects only such product.

With regards to the effect of covariates on preferences for each product, the strongest effect on utility for organic local apples and pears was found to be "regular consumption". For organic local tomatoes and salad, instead, the highest MMU values were retrieved for thinking that "such products are more ethical than non-organic ones". Overall, the above results highlight how preferences towards organic and local food items are strongly affected by attitudinal aspects but also how the effect of such traits is highly heterogeneous across different products.

Moving to the effect of the covariates on satiation parameters, we recall that finding significant effects would invalidate the commonly held assumption in standard discrete choice experiments of a constant effect on baseline utility, because it would suggest that such variables affect utility differently in quantity purchased after the first unit. As shown in Table 9, none of the effects was found to be statistically significant. This seems to imply that attitudinal aspects only affect baseline utility (and in turn only the probability of choosing to purchase a given product) and do not affect satiation (and in turn the chosen purchased quantity of a given product). This is an important result as it corroborates the standard assumption of discrete choice models that attitudinal covariates have the same effect on utility across all quantities purchased.

5.5 Consistency of estimates of attitudinal effects on satiation

To obtain some information on sample size effect on significance of the estimates of covariates effect on satiation, we adopted a bootstrapping approach, a method introduced by Efron and Tibshirani (1993). Specifically, we simulated samples of size N = 364 (twice our observations) by resampling our observations with 50 repetitions. We then obtained the variance-covariance matrix of the estimated parameters across repetitions, from which we computed the standard error of the parameters (as the squared root of the diagonal of the matrix). Finally, the standard errors were used to compute the t-values for each parameter. The results are illustrated in Figure 1 (absolute values of the t-values are reported to ease visualization). At N = 364, only two covariates have statistically significant effect at 95% level, namely number of family members in the case of apples, and regularly purchasing organic product for tomatoes. None of the approximated t-values for attitudinal covariates has an absolute value higher than 1.96 (the threshold for 95% significance level). When considering a 90% significance level, only thinking that organic products are too expensive reaches the threshold (1.64) in the case of tomatoes. While such results provide some support to the consistency of our estimates, sample size requirements for specific effects should be assessed in future research via proper Monte Carlo simulations.

6. Discussion and conclusions

In this paper we investigated consumers' preferences towards local and organic food products by means of a framed field experiment involving multiple discrete-continuous choices. The experiment simulated a real grocery market situation in which participants were provided with a cash endowment they could choose to spend on the desired quantities of different food items. Each food item was available in four variants related to the production origin (local/non-local) and production method (organic/conventional). Observed choices were used to estimate MDCEV and MDCNEV random utility models, which, to date, have yet to receive in-depth attention in food economics.

The results of the MDCEV model allowed us to highlight how food products which are both local and organic are not only associated with the highest utility (in accordance with previous studies, Costanigro et al., 2014), but also with the lowest satiation effect, suggesting that consumption doses following the first maintain comparatively high levels of satisfaction. This result is consistent across all four types of produce (apple, pears, salad and tomatoes) included in our analysis and it is not obtainable with standard discrete choice models based on preferred or ranked choice, as these do not allow to model satiation. We also found that when the contrast is limited between local and organic produce, the latter is generally preferred by consumers. This is especially expressed by demand for organic non-local food items being higher than demand for non-organic local ones. We find, however, one exception to this pattern, in the case of pears. This provides further evidence that preferences for place and mode of production may be product-specific, as previously shown by other studies (e.g. Scarpa et al., 2005). Compared to the existing knowledge, our results allowed to highlight how preferences are item-specific particularly in terms of satiation effects, rather than baseline utility.

The estimation of the MDCNEV model provide evidence of correlation among different food items belonging to the same variant. The correlation is particularly strong across local organic products, suggesting how consumers who favour both these features are also likely to do so for all food items. Finally, we found preferences for local and organic products to be affected by consumers' socio-demographics, attitudes and beliefs. More specifically, we found attitudinal traits, such as believing that "organic products are more ethical" and that "it is important to support local farmers" to affect the baseline utility for organic and local produce, while they fail to have a specific satiation effect. This suggests that attitudes and beliefs may affect consumers propensity to buy organic local foods but do not necessarily affect the purchased quantity. This has important repercussions for the entire literature that uses preferred choice data, such as discrete choice experiments, in which this assumption is made but never explicitly tested. Importantly, we also found the effect of attitudes and beliefs to be heterogenous across different products.

To summarize, from a methodological perspective our study adds to the existing literature in several ways. First of all, results show how the MDCEV model is a promising approach for better describing food choice behaviour in real transactions. The results also provide evidence of the advantages of adopting its nested version, the MDCNEV model, when the existence of correlation in preference is strong. Overall, the results support the inclusion of nesting structures in the analysis of multiple-discrete continuous choices, especially when preferences are likely to be correlated within groups of alternatives sharing specific features (e.g. organically and locally produced). Finally, our results support the inclusion of attitudinal covariates in the utility function of MDCEV/MDCNEV models, which so far have seldom been accounted for in empirical applications of such models and are especially lacking in studies based on real transactions.

There are clear implications of our results for the food supply sector in the Veneto Region, as they seem to support investments in production, marketing and logistics for local agricultural products that are organically grown, as their demand is higher than that of products missing these features.

The main limitation of our study lies in the lack of analysis of complementarity and substitution patterns between different food items and their variants. To enable such an investigation, it would have been necessary to deploy a different experimental design including price variations and obtain substantially more observations, something that was beyond the available budget. Future research should focus on the analysis of such effects, given their relevance in the evidence provided by previous basket choice studies (e.g. Caputo and Lusk, 2022). The relatively small sample size could also affect the accuracy of the estimates, an issue that we assessed via bootstrapping. It may be interesting for future research to investigate this issue via a proper Monte Carlo simulation study, to define the sample size needed to reliably measure satiation effects and how these may be influenced by attitudes and beliefs.

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Tables and figures

Table 1 – Food items prices

Food item	Non-organic non-local	Non-organic local	Organic non-local	Organic local
Apples	€0.30	€0.40	€0.60	€0.70
Pears	€0.40	€0.50	€0.80	€0.90
Tomatoes	€0.50	€0.60	€0.80	€1.00
Salad	€0.30	€0.40	€0.50	€0.60
Red wine	€7.50	€8.00	€8.20	€8.50
White wine	€7.50	€8.00	€8.20	€8.50
Olive oil	€9.20	€10.50	€11.20	€12.50

Table 2 – Sample's descriptive statistics

	n.	%
Gender		
Man	84	45.16
Woman	102	54.84
Education		
Middle school or lower	13	6.99
High school	89	47.85
Degree	66	35.48
PhD/Master	18	9.68
Yearly income (€)		
Less than 15.000	37	19.89
15,001 - 25,000	52	27.96
25,001 - 35,000	40	21.51
35,001 - 45,000	17	9.14
More than 45,000	10	5.38
No answer	30	16.13
Age (years)		
18-29	49	26.34
30-39	37	19.89
40-49	42	22.58
50-59	28	15.05
60-69	21	11.29
>70	9	4.84

Table 3 – Descriptive statistics of observed choices

Product	Choice frequency	Average consumption when chosen (units)
Apples		
Non-organic non-local	10%	3.79
Non-organic local	17%	3.23
Organic non-local	11%	3.35
Organic local	41%	3.79
	$\chi^2 = 39.79$; p-value = *<0.001*	*F = 21.36; p-value = <0.001*
Pears		
Non-organic non-local	6%	3.73
Non-organic local	12%	3.18
Organic non-local	8%	3.27
Organic local	42%	3.34
	$\chi^2 = 60.38$; p-value = *<0.001*	*F = 32.93; p-value = <0.001*
Tomatoes		
Non-organic non-local	4%	4.29
Non-organic local	8%	4.71
Organic non-local	10%	5.42
Organic local	45%	7.44
	$\chi^2 = 75.85$; p-value = *<0.001*	*F = 41.46; p-value = <0.001*
Salad		
Non-organic non-local	4%	1.00
Non-organic local	6%	1.32
Organic non-local	12%	1.23
Organic local	40%	1.30
	$\chi^2 = 63.75$; p-value = *<0.001*	*F = 59.74; p-value = <0.001*
Distribution of the endowment spent by participants		
Less than €5.00	3.3%	
€5.00 - €10.00	3.8%	
€10.01 - €15.00	11.0%	
€15.01 - €20.00	13.7%	
€20.01 - €25.00	33.5%	
More than €25	34.6%	

Table 4. Information criteria for MDCEV and MDCNEV models

	MDCEV	MDCNEV
Log-likelihood	-2289.94	-2216.39
Akaike Information Criterion (AIC)	4725.88	4586.78
Bayesian Information Criterion (BIC)	4959.77	4833.49
Number of estimated parameters	73	77

Table 5. Average consumption predictions for MDCEV and MDCNEV models

Product	Observed consumption	MDCEV predictions	MDCNEV predictions
Apples			
Non-organic non-local	0.40	0.66	0.69
Non-organic local	0.55	0.87	0.95
Organic non-local	0.37	0.48	0.55
Organic local	1.56	2.11	1.89
Pears			
Non-organic non-local	0.23	0.35	0.42
Non-organic local	0.38	0.58	0.59
Organic non-local	0.27	0.36	0.42
Organic local	1.41	1.82	1.69
Tomatoes			
Non-organic non-local	0.16	0.29	0.37
Non-organic local	0.36	0.52	0.69
Organic non-local	0.57	0.69	0.82
Organic local	3.31	3.68	3.41
Salad			
Non-organic non-local	0.04	0.11	0.10
Non-organic local	0.08	0.17	0.21
Organic non-local	0.15	0.29	0.26
Organic local	0.52	0.93	0.71

Table 6. MDCNEV estimates – θ nesting parameters

Nest	value	|t|
Organic local	0.37	7.39
Organic non-local	0.63	8.43
Non-organic local	0.69	7.13
Non-organic non-local	0.65	9.27

Table 7. MDCNEV estimates – baseline utility and satiation parameters

ϑ baseline utility constants	**value**	**|t|**	**γ satiation parameters**	**value**	**|t|**
Apples			**Apples**		
Non-organic non-local	-6.15	27.86	Non-organic non-local	3.92	4.79
Non-organic local	-5.31	29.71	Non-organic local	3.11	8.22
Organic non-local	-5.29	25.65	Organic non-local	4.03	5.19
Organic local	-4.81	10.28	Organic local	5.32	6.37
Pears			**Pears**		
Non-organic non-local	-6.33	22.80	Non-organic non-local	4.84	4.88
Non-organic local	-5.44	27.82	Non-organic local	3.68	6.27
Organic non-local	-5.24	21.24	Organic non-local	4.73	5.84
Organic local	-4.50	9.30	Organic local	4.94	2.19
Tomatoes			**Tomatoes**		
Non-organic non-local	-6.94	20.39	Non-organic non-local	6.01	7.37
Non-organic local	-6.02	23.68	Non-organic local	6.10	5.68
Organic non-local	-5.55	24.92	Organic non-local	7.25	4.66
Organic local	-5.28	10.90	Organic local	22.97	3.05
Salad			**Salad**		
Non-organic non-local	-6.47	19.81	Non-organic non-local	1.43	7.07
Non-organic local	-5.80	24.22	Non-organic local	1.71	5.40
Organic non-local	-4.95	26.86	Organic non-local	1.51	8.84
Organic local	-4.76	10.70	Organic local	2.88	3.14
α satiation parameter	-15.00	0.10			

Table 8. MDCNEV estimates – covariates effect on baseline utility (β parameters)

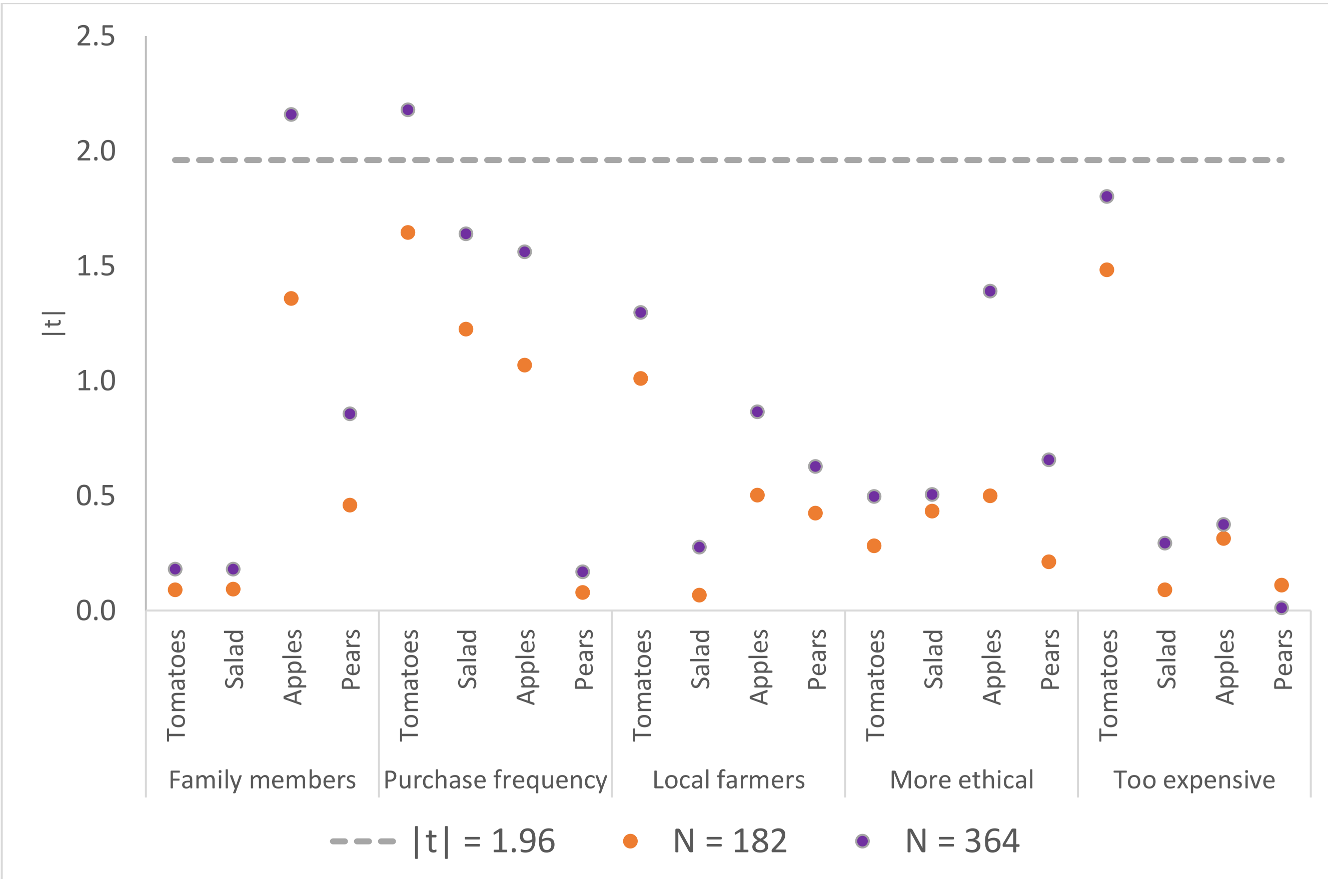
Covariate	Value	|t|	MMU x 100
Living with family members			
Organic local apples	0.33	1.71	0.46
Organic local pears	0.56	2.57	0.93
Organic local tomatoes	0.32	1.58	0.32
Organic local salad	0.37	2.49	0.38
Consuming regularly organic products			
Organic local apples	0.81	2.55	1.45
Organic local pears	0.79	3.17	1.49
Organic local tomatoes	0.61	4.35	0.71
Organic local salad	0.69	3.85	0.85
Thinking it is right to support local farmers			
Organic local apples	0.43	1.93	0.63
Organic local pears	0.37	0.98	0.55
Organic local tomatoes	0.45	2.29	0.48
Organic local salad	0.24	1.89	0.23
Thinking organic products are more ethical			
Organic local apples	0.71	2.25	1.20
Organic local pears	0.72	1.97	1.30
Organic local tomatoes	0.93	1.69	1.30
Organic local salad	0.90	1.79	1.25
Thinking organic products are too expensive			
Organic local apples	0.01	0.04	0.01
Organic local pears	-0.11	0.53	-0.13
Organic local tomatoes	-0.38	1.88	-0.27
Organic local salad	-0.24	1.14	-0.18

Table 9. MDCNEV estimates – covariates effect on satiation parameters (λ parameters)

Covariate	Value	|t|
Living with family members		
Organic local apples	2.15	1.36
Organic local pears	0.72	0.46
Organic local tomatoes	0.25	0.09
Organic local salad	-0.05	0.09
Consuming regularly organic products		
Organic local apples	1.97	1.07
Organic local pears	-0.11	0.08
Organic local tomatoes	-5.82	0.64
Organic local salad	-0.73	1.22
Thinking it is right to support local farmers		
Organic local apples	0.76	0.50
Organic local pears	0.68	0.42
Organic local tomatoes	-3.77	1.01
Organic local salad	-0.04	0.07
Thinking organic products are more ethical		
Organic local apples	-2.54	0.50
Organic local pears	0.53	0.21
Organic local tomatoes	1.62	0.28
Organic local salad	-0.48	0.43
Thinking organic products are too expensive		
Organic local apples	0.51	0.31
Organic local pears	0.18	0.11
Organic local tomatoes	-9.21	1.48
Organic local salad	-0.05	0.09

Figure 1: Experimental setting

Figure 2. Absolute values of t-values for estimates of coviariates effects on satiation at different sample size (bootstrapping)



Appendix 1 – Field 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 €25. During the experiment, you can use this amount to make real purchases, if you wish. The products that can be purchased are: white wine, red wine, oil, apples, pears, salad and tomatoes. Each of the products is available in four variants: i) local and organic, ii) local and non-organic, iii) non-local and organic, iv) non-local and non-organic.

At the end of the experiment, you will be given the products you have chosen and the cash left over. If you wish, you can purchase products for more than €25 and cover the difference with your own money. 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 €25 entirely in cash.

Once you made your purchases, we will record your choices and afterwards you will be given a short questionnaire to fill out.

We ask you to make your purchases and to fill in the questionnaire independently, without communicating with the other participants and trying not to be influenced by their choices.