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Ecosystem Services in Food Labels: The Role of Different Information Layers in Shaping Consumers Preferences

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Abstract

Information on the provision of ecosystem services has the potential to contribute to an integrative food labelling framework. This study examines that potential by explicitly communicating ecosystem services provided by agricultural producers. The research analyzes how different label formats-ranging from generic references to ecosystem services to specific indicators-influence consumer preferences. An on field Discrete Choice Experiment was conducted with 552 Italian consumers of extra virgin olive oil. A Latent Class Model identified consumer heterogeneity, and to address the endogeneity of environmental attitudes in class allocation, a two-stage Control Function approach was applied. Two consumer segments emerged. The first, showed a consistently higher and statistically significant willingness to pay for sustainability attributes. Their willingness to pay increased with the level of informational detail. However, a negative halo effect was observed when ecosystem services labels appeared alongside organic certification, suggesting a perception of redundancy. The second segment was more price-sensitive and resistant to additional information. From a policy perspective, the results indicate how ecosystem service labeling strategies, particularly when linked to measurable environmental outcomes, can stimulate market-based incentives.

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Introduction

Today's global food system has a significant impact on both the environment and climate. It accounts for approximately 29.7% of total greenhouse gas emissions (FAO, 2024) and is a major driver of biodiversity loss and ecosystem degradation (O'Brien *et al.*, 2024). At the same time, food systems play a central role in achieving key social goals, including reducing hunger and poverty (Searchinger *et al.*, 2019). Due to this dual role – both contributing to and being affected by environmental and social challenges – there is a pressing need to transition toward more sustainable and resilient models (Schulze *et al.*, 2024).

Policymakers have a wide range of interventions and tools at their disposal. From the producers' perspective, strategies to internalize the negative externalities of food production have primarily focused on conditional subsidy payments, as exemplified by the European Union's Common Agricultural Policy (CAP) (Pe'er *et al.*, 2019). On the consumer side, policy efforts have largely aimed at influencing purchasing choices (Just & Byrne, 2019). Understanding public attitudes toward various policy options is essential for designing effective interventions (De-loyde *et al.*, 2025; Reisch & Sunstein, 2016). Governments have access to a wide range of tools to achieve consumer-focused food policy goals, including information campaigns, behavioral nudges, financial incentives (such as taxes or subsidies), and regulatory approaches. In general, consumers are more likely to support less intrusive measures – such as informational tools and nudges – than stricter options like taxes or bans, despite the latter often proving more effective (Ammann *et al.*, 2025).

Among the less intrusive measures, front-of-pack (FOP) labels are increasingly used to help consumers make healthier and more environmentally responsible food choices (Hallström *et al.*, 2015; Canavari *et al.*, 2002). These labels aim to bridge the information gap between producers and consumers by highlighting product characteristics that are difficult to observe (Canavari & Coderoni, 2020), even after purchase – specifically, credence attributes such as environmental impact and sustainability performance (Lin & Nayga Jr, 2022). By enhancing awareness, reducing search costs, and encouraging more sustainable consumption, FOP labels also have the potential to incentivize environmentally responsible production (Carlsson *et al.*, 2022). Gorton *et al.* (2021) examined the use of eco-labels – especially organic certifications in the EU – and found that they play a key role in transforming unobservable product attributes into actionable market signals.

However, many existing labels focus on broad standards, such as organic production, and fail to communicate specific environmental contributions –

for instance, efforts by agricultural producers to conserve pollinator habitats or sequester carbon in soils, which more generally can be described as agriculture's contribution to the provision of ecosystem services (ES). These services, defined as the benefits people obtain from nature, are receiving increasing attention in both EU policy and academic research (Bouwma *et al.*, 2018; Costanza, 2020; Nes & Ciaian, 2022). Yet despite their growing significance, ES remain absent from current food labeling and consumer communication frameworks.

This study contributes to the literature on ES labelling along three complementary dimensions. First, it moves beyond treating ES labelling as a homogeneous attribute by explicitly focusing on the design of ES-related information. The analysis compares alternative communication strategies, ranging from a generic reference to ES to a specific and measurable representation of a single service, articulated across different levels of informational detail. Second, the study situates ES labelling within a broader information environment by jointly analyzing on-pack labels and complementary off-pack communication aimed at explaining the meaning and relevance of ES. Third, integrating multiple attitudinal scales into a latent class framework while explicitly addressing the associated endogeneity concerns, the study provides a parsimonious and empirically robust alternative to hybrid choice models, enabling attitudes to inform preference heterogeneity and yielding stable and interpretable welfare measure estimates.

Helping consumers understand the environmental role of agriculture – particularly through the lens of ES – may encourage more sustainable consumption patterns. Labels that clearly convey these contributions could motivate consumers to reward producers for their efforts, enhancing the effectiveness of sustainability policies (Laksmawati *et al.*, 2024). If consumers value these practices, targeted financial incentives could be more impactful, especially in encouraging change among less sustainable producers (Just & Byrne, 2019).

1. Background

Emerging research has started to examine novel food labeling schemes that incorporate ES. Schulze *et al.* (2024) explored how information on ES provision could inform future labeling practices in the EU's Farm to Fork Strategy, identifying three potential label types: producer-driven, consumer-oriented, and EU-wide sustainability labels, based on expert input from multiple countries. Their work highlights the importance of integrating diverse stakeholder perspectives in label design. The study by Voglhuber-Slavinsky *et al.* (2023) explores private valorization options for biodiversity and ES in the agri-food value chain and confirm that labeling has the potential to complement or even substitute public policy instruments by operating beyond the production stage and actively shaping consumer demand. Altmann and Berger Filho (2020) examined the potential of certification and labeling as economic instruments to promote biodiversity conservation and ES in the Pampa Biome, using grassland beef certified under the "Alianza del Pastizal" scheme as a case study, demonstrating that such mechanisms can create market incentives through premium pricing, though their effectiveness depends on system design and consumer responsiveness.

Other studies have investigated how ES certification can influence market dynamics through direct consumer surveys. Jaung *et al.* (2019), through a DCE on bottled water with ES claims in Indonesia, found that certification improved brand equity but struggled to outperform established competitors, emphasizing the role of branding and market positioning. Borrello *et al.* (2022) demonstrated that cultural ES from traditional agricultural landscapes could be valued through labeling: consumers expressed willingness to pay (WTP) for products certified as linked to terraced olive groves, particularly when combined with organic and protected designation of origin (PDO) certifications.

Nevertheless, the literature has not yet explored the optimal communication strategy for ES labels-specifically, how consumers perceive, interpret, and value them, both in terms of visual design and informational content.

Individuals differ in how they interpret and use labels: some rely on general food knowledge, while others depend on label familiarity (Sørensen *et al.*, 2012; Silva *et al.*, 2018), making effective label design a complex challenge (Boncinelli *et al.*, 2023; Duckworth *et al.*, 2022). Van Loo *et al.* (2015) outline the importance of label salience and consumer education, noting that visibility and clarity are essential to converting credence attributes into meaningful decisions. Informational framing is equally important: clear explanations, and eco-metrics help reduce information asymmetries and build consumer trust (Canavari *et al.*, 2016; Aprile & Punzo, 2022). However, the complexity and multidimensional nature of ES increase the risk of information overload, which may impede consumers' ability to effectively process and act on label information (Grunert & Wills, 2007). This is further supported by a recent study on extra virgin olive oil (EVOO) across Italy, Greece, and Israel, which highlights that the abundance of certifications (e.g., PDO, organic, carbon footprint) can cause consumer confusion, ultimately diminishing the communicative effectiveness of labels (Paffarini *et al.*, 2025). These elements are particularly relevant in the context of ES labeling, as ES are, by definition, a diverse set of benefits provided by nature. In the case of agriculture, these services can include provisioning services such as food, fiber, and biomass production; regulating services such as carbon sequestration, pollination, water purification, erosion control, and climate regulation; supporting services including soil fertility and nutrient cycling; and cultural services such as landscape aesthetics, cultural heritage, and recreational value (United Nations *et al.*, 2021). Given the variety of services involved, communication through labeling can take two different approaches: a generic label that certifies the overall provision of ES, or a targeted label that highlights a specific ES delivered by the farm. For example, a farm could adopt a targeted labeling strategy to communicate its contribution to pollination services. In this case, a possible indicator could be Net Pollination Index, which quantifies the contribution of on-farm practices such as the maintenance of wildflower strips, hedgerows, or pollinator habitats to pollinator activity and crop yield (Martínez-López *et al.*, 2019). Together, this body of evidence suggests that effective ES labels should balance visual clarity, meaningful content, and credible certification to foster informed choices and reward environmentally responsible production – especially considering that these new labels may appear alongside existing environmental (e.g., organic) or quality certifications (e.g., PDO) on the product.

2. Materials and method

2.1. *Data and Survey Design*

Survey was conducted from May to August 2024, through a face-to-face field experiment approach at a supermarket chain store in Brescia, Italy. The focus of the survey was a DCE on EVOO for consumption at home. In Italy, EVOO is a widely consumed product and plays a key role in the Mediterranean diet, being therefore often chosen for reasons related to health, culture, and product quality (Del Giudice *et al.*, 2015; Perito *et al.*, 2019).

The sample consisted of 552 people, aged eighteen years and older, regular consumers of EVOO (at least 2 times a week) and main responsible for their household's food expenditure. Subjects were recruited at the entrance of the supermarket store. We promoted a brief collaboration with a store belonging to a national supermarket chain present in Brescia, Italy, in a middle- to high-income neighborhood. In Mompiano, the median household annual income was estimated at €31.835, with residents accounting for 3.84% of total taxpayers in the municipality (Dipartimento delle Finanze, 2022). The reference population of the study is therefore defined as adult, frequent consumers of extra virgin olive oil who are primarily responsible for household food purchases and who shop in large-scale retail outlets.

Given the single-store setting and the socio-economic characteristics of the neighbourhood, the sample reflects a specific segment of Italian consumers and should not be interpreted as statistically representative of the national population.

A preliminary pilot study of 52 students was conducted to test the clarity of the experiment, the quality of the responses and to optimize the experimental design.

The survey was conducted in a standardized face-to-face setting using a tablet, with interviewers following a fixed script and simultaneously presenting and reading aloud all information shown on the screen. The questionnaire was structured into four main sections. The first investigated awareness and attitudes related to sustainability of food supply chains. The second section contained the DCE. To ensure data quality, before presenting the set of choice tasks, we asked respondents whether they had "devoted their full attention to the questions up to that point" and whether, in their honest opinion, they felt we should have used their answers for the study (Meade & Craig, 2012). We strategically placed this question immediately before more important ones, such as choice tasks (Asioli *et al.*, 2022). Prior to the DCE tasks respondents were also instructed on how to complete the DCE and given a cheap talk script to mitigate hypothetical bias (Cummings and Taylor, 2009). For transparency and replicability, the full text of the cheap talk script provided to respondents is reported in the Supplementary material (S1).

The third section of the questionnaire investigated respondents' knowledge and usage habits related to food labels and ES. Prior knowledge was measured through self-reported familiarity. Specifically, respondents were asked whether they had previously seen selected food labels (Organic, Eco-label, PDO/PGI, Carbon Footprint) and whether they had ever heard of ecosystem services, using dichotomous response options (Yes/No/Don't know). Objective knowledge was assessed using performance-based measures. For food labels, respondents answered multiple-choice questions asking them to identify the correct meaning of each label, with one correct option among several alternatives (Grunert *et al.*, 2014). For ES, objective knowledge was measured through a set of true/false statements covering core ES concepts (e.g. the role of biodiversity, human dependence on ES, and the possibility of quantifying ES). Objective knowledge scores were constructed as the number of correct answers provided by each respondent. In addition, self-reported label use was measured through Likert-scale questions asking how frequently different types of information typically available on food packages are considered during purchase decisions, using a 7-point scale ranging from 1 ("Never") to 7 ("Always"). The last section, with socio-demographic questions, concluded the questionnaire.

2.2. *Experimental Design*

Different labeling strategies have been investigated using DCEs, which allows the estimation of a welfare measure in terms of citizens' marginal willingness to pay (mWTP) for different labeled information options (Bazzani *et al.*, 2025; Lusk *et al.*, 2018; Thiene *et al.*, 2018; Van Loo *et al.*, 2014). Some of the most relevant studies evaluating how environmental impact information drives consumer choices have implemented this approach (Lin & Nayga Jr, 2022; Mameno *et al.*, 2023). Hypothetical DCE was also used to elicit preferences for different qualities of EVOO (Panico *et al.*, 2014; Scarpa & Del Giudice, 2004). DCEs allow to decompose the good into different attributes, estimating preferences for each of them and representing the decision-making mechanisms that individuals enact in a context such as the supermarket (Canavari *et al.*, 2023; Caputo *et al.*, 2023; Cerroni *et al.*, 2019; Grebitus *et al.*, 2013; Muller *et al.*, 2019).

The first step in designing the experiment was to define the product, which is an EVOO in a one-liter bottle. EVOO was selected as case study because in Italy EVOO production represents one of the main permanent tree productions, occupying about 8 percent of the national utilised agricultural area (ISTAT, 2021). Second, areas designated for EVOO production generally represent an ecosystem with important potential for the conservation and maintenance of biodiversity (Salazar-Ordóñez *et al.*, 2021). Moreover, in Italy, EVOO production has been abandoned in some areas in the last 5 years (Mediobanca - Area Studi, 2024), representing the potential case study of the effective capacity of a labeling strategy on the provision of ES as an incentive for a premium price to make production economically viable.

Second phase involved the selection of attributes and related levels to describe the EVOO bottle proposed in the experiment (Table 1).

Table 1 - Attributes and relative levels used in the choice experiment

Attributes	**Levels considered**	**Logo**
Ecosystem Services	• None • ES logo	
Organic	• None • EU Organic logo	

ES Maintenance of Biodiversity (preservation of pollinator species)	• None • Farming for Biodiversity • Farming for Biodiversity + Bees • Farming for Biodiversity + Bees + Net pollination index
Designation of origin	• None • PGI • PDO
Price	• 9,1 € • 10,6 € • 12,1 € • 13,6 € • 15,1 €

Given the intention to also investigate the effect of co-occurrence with the most common labeling types associated with EVOO, labels for organic certification and designation of origin were selected (Čehić *et al.*, 2021). For the former, levels indicating the presence or absence of the logo were included. For the latter, levels corresponding to absence, Protected Geographical Indication (PGI), and PDO were selected.

Regarding the provision of ES two hypothetical attributes were employed. The attributes were selected based on the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin-

Young, 2018). In particular, the generic ES logo does not correspond to a specific CICES service but represents an aggregate and hypothetical signal of ES-oriented agricultural management. By contrast, the 'ES maintenance of biodiversity' attribute refers to regulating ES related to habitat provision, with a specific focus on farming practices supporting pollinators (CICES v5 code 2.2.2.1). For this specific attribute, levels of increasing informational detail were selected: an absence level, an initial informational level labeled "Farming for Biodiversity", an enhanced level "Farming for Biodiversity + Bee", which includes the image of a bee to represent the service being provided, and a further detailed level, "Farming for Biodiversity + Bee + Net Pollination Index", which introduces a value scale based on the Net Pollination Index (Martinez-Lopez *et al.*, 2019). The idea that communicating to consumers the efforts and services that producers can potentially offer to the community may provide producers with new opportunities for product differentiation motivated the selection of these attributes. Finally, based on data from the Italian bottled EVOO market and current literature, the price attribute for one liter bottle of EVOO was constructed with five levels (9.1€, 10.6€, 12.1€, 13.6€ and 15.1€) selected on the basis of price monitoring in the supermarket where the survey was conducted and the results of the pilot study.

In designing the DCE, we initially developed an optimal orthogonal in differences design. This design was employed in a pilot study involving a sample of 52 students, following the design principles outlined by Street *et al.* (2001, 2005). Subsequently, the parameter estimates obtained from the pilot study were used to generate a Bayesian D-efficient design aimed at minimizing the average D-error. Design simulations were conducted using 500 Halton draws, resulting in a design comprising 36 choice tasks (Bliemer *et al.*, 2008; Ferrini & Scarpa, 2007; Rose & Bliemer, 2013; Scarpa & Rose, 2008). The 36 choice sets were orthogonally divided into four blocks, each consisting of nine tasks. This means that each respondent was randomly assigned to one block and asked to evaluate nine purchase scenarios. Each scenario presented two product alternatives and a third opt-out alternative (no purchase).

2.3. Choice Tasks and Treatment Design

As an introduction to the DCE, respondents were instructed on the mechanism of the experiment. They were asked to imagine themselves in a real-life choice situation within the supermarket and that they would have to select one liter bottle of EVOO for home consumption under nine different scenarios. Respondents were asked to indicate their preferred option based on the label information provided or to opt-out if none of the alternatives were considered acceptable.

In addition, respondents were randomly assigned to one of two treatment groups that differed in the presence of an additional informational component external to the product label. In detail, in the control treatment (Info = 0), participants were presented with choice tasks preceded by a brief and generic introduction to ES. In contrast, in the information treatment (Info = 1), respondents were provided with an explanation prior to the choice tasks detailing how ES are measured, and what the information on the hypothetical labels really represents. For example, the Net Pollination Index was explained, as an index that ranges from –1 to +1 and measures how well an ecosystem supports crop pollination. Habitats such as forest edges and flowering hedgerows help pollinating insects. An olive grove that preserves these habitats and reduces pesticide use will have a positive index (0 to +1). Conversely, a field that does not preserve these habitats and reduces the availability of shelter and protection for pollinator species will have a negative index (0 to –1) (Martínez-López *et al.*, 2019). This information covered both the general informational levels of the labels and the more detailed information levels, elaborating on the methods used for measuring and representing the ES. This approach was intended to simulate a potential external informational campaign – distinct from product labeling – as a form of nudging, assessing the effect of additional off-label information and information asymmetry gap filling on consumer preferences.

2.4. Econometric Approach

2.4.1. Latent Class Model

From DCEs data, estimates of discrete choice models (DCMs) can be obtained. DCMs are consistent with random utility theory (McFadden, 1974), which states that the utility that individual *n* gets from alternative *j* in the set of choices *t* can be decomposed into an observed, deterministic part (V_{njt}) and an unobserved, random part (ε_{njt}):

$$U_{njt} = V_{njt} + \varepsilon_{njt} = ASC_j + x'_{njt}\beta + \varepsilon_{njt} \quad (1)$$

where x'_{njt} is a vector containing attributes of the asset to be evaluated, β is the vector of corresponding parameters, ASC_j are the alternative specific constants. This structure of utility is consistent with Lancaster's (1966) theory, which assumes total utility resulting from the choice of a product as a decomposition of additive utilities arising from the attributes of the product itself.

The literature on consumer behavior in relation to food labels shows that consumers have heterogeneous preferences (Lusk *et al*., 2003). Heterogeneity of preferences (e.g., taste variation) in sustainability claims must also be considered for correlation between utilities and between taste parameters (Van Loo *et al*., 2014). Heterogeneity can be assumed to be continuous or discrete, and recent literature has shown that taste variation has asymmetric and multimodal distributions (Caputo *et al*., 2018; Scarpa *et al*., 2021).

An initial approach on the continuous and discrete nature of heterogeneity was conducted using Mixed Logit models in WTP space (Scarpa *et al*., 2008; Train & Weeks, 2005). The results showed a multimodality of preferences distributed in subgroups that supports our latent class model (LCM) approach (Yagi *et al*., 2025).

LCM consists of a structural equation for the choice model (Equation 1) and a class allocation function (Greene & Hensher, 2003). In LCMs, individuals are indirectly allocated into q classes, and the researcher is unable to know which class an individual belongs to. The probability that an individual n will choose an alternative i is the logit probability conditional on membership in class q. The probability of sequence of choices of individual n is then represented as:

$$P_n(i|q) = \prod_{t=1}^{T} P_{nit}\,(i|q) = \prod_{t=1}^{T}\left(\frac{\exp\left(ASC_i + x'_{nit}\beta_q\right)}{\sum_{j=1}^{J} \exp\,(\,ASC_i + x'_{nit}\beta_q)}\right) \tag{2}$$

The probability Ψ_{nq} that individual n belongs to class q is modeled as a logit probability:

$$\Psi_{nq} = \frac{\exp\,(\gamma_{0q} + z'_n\gamma_{1q})}{\sum_{q=1}^{Q} \exp\,(\gamma_{0q} + z'_n\gamma_{1q})} \tag{3}$$

where z'_n are observable exogenous characteristics (e.g., sociodemographic), γ_{1q} is the corresponding parameter vector, and γ_{0q} are constant terms.

The unconditional probability that individual n will make the set of choices will be given by the sum of the conditional probabilities on the q classes (Equation 2), weighted by the probability of membership in each class (Equation 3) (Mariel *et al*., 2025). It is not possible to estimate the number of classes a priori, but it is necessary to orient based on informative criteria about the model fit, as well as the researcher's judgment (Scarpa & Thiene, 2005).

2.4.2. Endogeneity in the allocation function of an LCM and the two-step Control Function approach

A growing body of literature describes the influence of individual attitudes toward an environmental good or service on environmental valuation (Hess *et al.*, 2013). Heterogeneity of preferences, particularly in an LCM, shows its best representation with the inclusion of such attitudes. While generally the problem related to endogeneity concerns the structural equation (Equation 1) (Guevara, 2018), it can also occur in the allocation function of an LCM (Equation 3). As described in Mariel and Arata (2022) this function can be seen as the propensity to belong to a specific class q, and can be described as:

$$F_{nq} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \xi_{nq} \quad (4)$$

where z_n is a vector of observable exogenous characteristics (e.g., sociodemographic), s_n is a vector of individual attitudes (e.g., attitudinal scale) and γ_{0q}, γ_{1q} and γ_{2q} are the corresponding parameters.

Assuming that s_n is defined as:

$$s_n = \alpha_0 + c_n'\alpha_1 + \eta_n \quad (5)$$

where c_n is a vector of exogenous variables independent of error terms ξ_{nq} (Eq. 4) and η_n, and α_0 and α_1 are unknown parameters. The vector c_n may contain all or some of the observable exogenous variables z_n (Eq. 4).

Therefore, assuming the influence of individual attitudes related to the environmental good or service ($\gamma_{2q} \neq 0$), we could have endogeneity in Equation (4) due to the omission of the relevant variable (s_n); due to the measurement error of the attitude itself (under appropriate assumptions); or in the case where the error terms ξ_{nq} in Equation (4) is correlated to the error term η_n in the Equation (5). In the latter case, s_n in Equation (4) is endogenous by definition (Alcorta & Mariel, 2025).

Our case study evaluates the inclusion of an endogenous indicator (s_n) representing individuals' attitudes toward the sustainability of the agribusiness supply chain. This is the case where, as the classes defined by equation (4) are representative of preferences for label information regarding the environmental sustainability of EVOO production, the error terms ξ_{nq} and η_n are correlated.

To address this potential endogeneity problem, we apply the two-stage Control Function (CF) approach (Guevara & Polanco, 2016). In the first stage, the attitudinal indicator is regressed on the exogenous variables z_n, on an instrumental variable (Instr_{1n}) for which typical instrument assumptions apply (Guevara, 2018), and on two additional instruments formed by seven additional statements on sustainability of agrifood supply chain collected and used to define the two main factors from an exploratory factor analysis ($Fact_{1n}$, $Fact_{2n}$):

$$s_n = \alpha_0 + z_n'\alpha_1 + \alpha_2 Instr_{1n} + \alpha_3 Fact_{1n} + \alpha_4 Fact_{2n} + \eta_n \quad (6)$$

where η_n is assumed to be i.i.d. normally distributed. Equation (6) is estimated by ordinary least squares regression to obtain the residuals $\hat{\eta}_n$. The second step of the CF approach is to include in equation (4):

$$F_{nq}^{CF} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \gamma_{3q}\hat{\eta}_n + \xi_{nq} \quad (7)$$

where $\hat{\eta}_n$ residuals collect the part of s_n that generates correlation with the error term in equation (4).

The entire DCM was estimated using Equation 7 in the LCM allocation function.

To verify the necessary condition that the instruments used in Equation (6) are exogenous, the test of refutability of instrument exogeneity was used (Guevara, 2018). The test is based on the condition of overidentification and first estimates the LCM using Equation (7) in the allocation function, then recalculates the model with a modified allocation function that includes Equation (7) with all instruments except one. The test statistic is defined as:

$$S_{ref} = -2\,(LL^{CF} - LL^{CFinstr}) \sim \chi^2_{df} \quad (8)$$

where *df* are the degrees of freedom equal to the number of instruments minus the number of endogenous variables. The null hypothesis of the test is that the instruments are exogenous, while the alternative hypothesis is that one or both instruments are endogenous, and it is repeated for all possible combinations of instruments.

2.5. *Empirical Model*

The random utility discrete choice model (Eq. 1) is specified as:

$$\begin{aligned} U_{nit|q} = {} & ASC_q[1 + 1(Inf)_n] + \alpha p_{nit} + \tilde{\beta}_q' x_{nit} + \delta_q[x_{nit} \times 1(Inf)_n] \\ & + \gamma_q\left[x_{nit}^{ES} \times Organic\right] + \vartheta_q\left[x_{nit}^{ES} \times PDO\right] + \varepsilon_{nit|q} \end{aligned} \quad (9)$$

where *ASC* denotes the alternative-specific constant for the opt-out alternative, it takes the value 1 when respondents choose not to purchase any of the proposed products. The model also includes interaction effects between *ASC* and an external information variable, which equals 1 if the respondent received additional information processing. The variable p_{nit} is a continuous measure representing the five price levels used in the experiment. The vector x_{nit} comprises non-price attributes, including:

1. Organic production certification, treated as dummy variable (1 if the logo is present, 0 otherwise).
2. Indicator for generic ES provision, treated as dummy variable (1 if the logo is present, 0 otherwise).
3. A variable for the specific ES attribute concerning the maintenance of biodiversity preserving pollinator species, modeled as dummies across three experimental levels reflecting increasing information content (the absence of a label serves as the reference level with a value of 0).
4. The designation of origin attribute, also represented by dummy variables for each experimental level and associated logo presence (PGI and PDO).

The parameter α denotes the marginal utility of income (i.e., the price coefficient). The vector $\tilde{\beta}_q$ includes coefficients for non-price attributes specific to class q, which are assumed to vary randomly and continuously among respondents in that class according to a normal distribution. The vector δ_q captures class-dependent, within-class fixed parameters reflecting the effects of information on the quality attributes represented by the treatment dummy variable *Inf.* The vector γ_q comprises class-specific fixed parameters describing the interaction effects between ES-related logos (x_{nit}^{ES}) and the "Organic" dummy. Similarly, ϑ_q represents the interaction effects between ES-related logos (x_{nit}^{ES}) and the PDO dummy. The parameters γ_q and ϑ_q describe the potential halo effect of well-recognized and widely adopted certifications (Organic and PDO) on the perception of ES-related information.

The class allocation function corresponding to Equation 4 is defined as:

$$\begin{aligned} F_{nq} = \gamma_{0q} + \gamma_{1q} Female_n + \gamma_{2q} Age_n + \gamma_{3q} Education_n + \gamma_{4q} Income_n \\ + \gamma_{5q} Full\ time_n + \gamma_{6q} Household_n + \gamma_{7q} Children_n \\ + \gamma_{8q} Environmental\ damage_n + \xi_{nq} \end{aligned} \tag{10}$$

where the attitudinal statement *Environmental damage* is added to the sociodemographic variables to assess the potential role that attitudes toward the relationship between food production and the environment may have on individual class allocation. We applied the CF approach to consistently estimate the model defined above being this additional explanatory variable endogenous by definition (Mariel and Arata, 2022).

Finally, the negative ratio between the estimated average value of the coefficient associated with the quality attribute of the EVOO and the price coefficient was used to estimate the marginal WTP.

3. Results

3.1. *Descriptive analysis*

Data were collected on a sample of 750 respondents from the adult population who frequented the supermarket in question in the Mompiano neighborhood in the city of Brescia. Final sample consisted of 552 correct responses, representing 4968 observations.

Table 2 reports the summary statistics of the sociodemographic variables.

Table 2 - Sociodemographic variables

Category	**Variable**	**Mean[a] Control**	**Mean[a] Treatment**	**No diff. in proportion** *p-value*	**No diff. in distribution** *p-value*
Gender					
	Male	48.1%	42.2%	0.187	0.107
	Female	51.1%	57.8%	0.135	
	Prefer not to answer	0.8%	0.0%	//	
Age class					
	18-24	12.2%	12.1%	0.953	0.812
	25-34	18.5%	15.6%	0.425	
	35-44	10.7%	13.8%	0.330	
	45-54	20.0%	20.9%	0.871	
	55-64	27.4%	24.8%	0.553	
	65+	11.1%	12.8%	0.641	
Education					
	High School	46.7%	48.2%	0.778	0.597
	Graduate	42.2%	42.6%	0.937	
	Post Graduate	11.1%	9.2%	0.552	
Employment					
	Unemployed	14.4%	12.1%	0.483	0.522
	Retired	9.3%	12.8%	0.239	
	Part-time Employed	14.4%	12.1%	0.483	
	Full-time Employed	61.9%	63.1%	0.826	

Household Gross Income					
	≤15,000€	10.7%	6.4%	**0.091**	0.281
	15,001-29,000€	27.8%	29.1%	0.807	
	29,001-55,000€	38.9%	39.7%	0.912	
	55,001-100,000€	16.7%	18.4%	0.664	
	>100,000€	5.9%	6.4%	0.965	
Household Composition					
	Household Size	2.211 (1.340)	2.131 (1.266)	//	0.382
	Children Under 15	0.267 (0.646)	0.309 (0.705)	//	0.428
Environmental association membership		15.2%	11.7%	0.282	
Sample Size	N. of respondents	270	282		

Note: [a] Refers to proportions for dummy variables; for all other variables, values represent means, with standard errors reported in parentheses.

A total of 270 people were assigned to the Inf = 0 group and 282 to the Inf = 1 group. We conducted equilibrium checks to assess whether the two treatment groups differed systematically in their sociodemographic characteristics. Chi-squared tests and Nonparametric Mann-Whitney U-tests were applied to test for significant differences between the distributions in the two subsamples with and without information, as well as *p*-values for the test of no difference between the proportions was reported. Overall, the sample appears well balanced. Gender differences are not statistically significant, although the Inf = 1 group includes a slightly higher proportion of female respondents (57.8%) than Inf = 0 (51.1%). The age distribution is similar, with the largest shares concentrated in the 45-64 age group. There are no significant differences in education or employment status. Household income levels are also comparable, although the Inf = 0 group includes a marginally higher proportion of low-income respondents (≤ 15,000 euros, p = 0.091), which falls short of conventional levels.

Table 3 shows the relative frequency of scores given by respondents to attitudinal questions regarding concern about the sustainability of food production (adapted from Grunert *et al*., 2014).

Table 3 - Attitudinal questions and relative frequency (%) (1 = only slightly concerned; 7 = extremely concerned)

	Label	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Environmental damage caused by human use of land and water in food production	env_damage	6.9%	10.0%	15.9%	11.1%	15.6%	17.6%	23.0%
The use of pesticides used in food production	pest	6.0%	9.1%	15.4%	10.0%	12.5%	17.4%	29.7%
Poor treatment of animals in food production	animals	8.9%	10.7%	15.8%	10.1%	14.3%	9.2%	31.0%
The process of deforestation related to food production	deforestation	4.7%	6.5%	16.3%	7.6%	13.4%	19.0%	32.4%
Using too much of the world's natural resources for food production	resources	6.3%	8.5%	15.2%	9.8%	13.2%	19.0%	27.9%
The amount of non-recyclable packaging	packages	4.5%	6.9%	15.4%	10.3%	12.5%	19.9%	30.4%
The amount of CO_2 emissions during the transportation of food products	transport	7.1%	9.2%	15.2%	11.1%	18.1%	18.7%	20.7%
The amount of energy used when cooking food products	energy	16.1%	14.5%	13.9%	15.0%	17.6%	13.6%	9.2%

The respondents were asked to rate their level of concern for various issues on a 7-point Likert scale, where 1 indicates very low concern and 7 indicates very high concern. The results reveal distinct patterns in public perception across different environmental dimensions.

Overall, respondents express relatively high levels of concern for several issues. The highest levels of concern are observed for deforestation (32.4% selecting 7), poor animal treatment (31.0%), and non-recyclable packaging (30.4%). These issues are also characterized by low percentages at the lower end of the scale (4.5-8.9% selecting 1), suggesting broad consensus around their perceived severity. Similarly, pesticide use (29.7% scoring 7) and excessive use of natural resources (27.9%) are considered pressing problems by a substantial share of respondents.

In contrast, concern about energy consumption during cooking shows a markedly different pattern. This is the only item for which the most frequent response is at the lower end of the scale (16.1% selecting 1, compared to only 9.2% selecting 7), indicating that respondents perceive this issue as less environmentally relevant. CO_2 emissions from food transport also rank lower in relative concern, with 20.7% selecting 7, and more evenly distributed responses across the scale.

Responses regarding environmental damage from land and water use and resource overuse are relatively moderate, with around one-quarter of respondents selecting the highest concern level (23.0% and 27.9%, respectively), and notable proportions scoring in the mid-range (categories 4 and 5).

Table 4 reports respondents' levels of both prior and objective knowledge regarding four food-related labels – Organic, Eco-label, PDO, and Carbon Footprint – as well as their knowledge of ES. The table displays mean values across the two treatment groups, with minimal differences observed between the groups.

Table 4 - Prior and objective knowledge regarding four food-related labels and ES

Variable	**Mean[a] Control**	**Mean[a] Treatment**	**Labels**
Labels prior knowledge declaration			
Organic label prior knowledge	78.1%	75.9%	
Eco-label prior knowledge	33.3%	28.7%	
PDO label prior knowledge	64.1%	62.4%	
Carbon foot-print label prior knowledge	17.0%	16.3%	
Labels objective knowledge			
Organic label objective knowledge	42.6%	35.1%	
Eco-label objective knowledge	40.0%	41.1%	
PDO label objective knowledge	77.0%	77.0%	

Carbon foot-print label objective knowledge	60.4%	56.4%	
Labels knowledge score (0-4)	2.200 (1.091)	2.096 (1.086)	
Ecosystem Services knowledge			
ES prior knowledge declaration	37.0%	33.7%	
ES knowledge score (0-5)	4.056 (1.145)	4.018 (1.156)	

Note: [a] Refers to proportions for dummy variables; for all other variables, values represent means, with standard errors reported in parentheses.

Overall, self-reported prior knowledge ("*Have you ever seen this label?*") is highest for the Organic label, with 78.1% of respondents in the control group and 75.9% in the Information treatment group reporting recognition. PDO follows, with roughly 64% of respondents indicating familiarity. In contrast, the Eco-label and Carbon Footprint label show considerably lower recognition levels, with fewer than 35% of respondents reporting prior exposure (Hartikainen *et al.*, 2014). These results suggest that while organic and origin-related certifications are widely recognized, environmental indicators such as eco- and carbon-labels remain less familiar to the public (Gorton *et al.*, 2021).

Objective knowledge presents a different picture. While recognition of the PDO label is high, only 77% correctly identified its meaning, indicating some consistency between familiarity and understanding. In contrast, only 35.1% (Treatment) to 42.6% (Control) correctly answered questions about the Organic label, revealing a potential gap between perceived and actual understanding. Carbon Footprint label knowledge is moderate (around 58%) (Rondoni & Grasso, 2021), while Eco-label understanding remains low, with only 40–41% correct answers. The composite label knowledge score averages just above 2 out of 4 in both groups, suggesting moderate overall comprehension.

Regarding ES, 37.0% of the control group and 33.7% of the treatment group reported prior knowledge. However, the objective ES knowledge scores are relatively high, averaging around 4 out of 5 in both groups, suggesting that even among those unfamiliar with the term, conceptual understanding is strong when prompted with specific content. This is also due to the basic information received from the whole sample at the beginning of the DCE.

In summary, while prior exposure to food and environmental labels varies widely, objective knowledge tends to be lower, particularly for eco- and organic labels, highlighting potential gaps in consumer understanding.

3.2. *Estimation results*

This section reports the estimates of an LCM incorporating the potentially endogenous variable *Environmental damage* within the allocation function. To address endogeneity, suitable instruments were required for the auxiliary equation specified in Equation (6) the results of which are reported in the supplementary material (S4). These instruments must be correlated with the endogenous variable but uncorrelated with the error term in the allocation function.

Based on this theoretical framework, the primary instrument selected is a dummy variable indicating whether the respondent is a member of an environmental association. To strengthen the identification strategy, two additional instruments – *Factor1* and *Factor2* – were derived from an exploratory factor analysis conducted on the remaining seven attitudinal statements. The key results of this analysis are presented in Table 5.

Table 5 - Exploratory factor analysis

Eigenvalues and variability				**Factor loadings**		
Factor	**Eigenvalue**	**Variance**	**Cumulative**	**Item**	**Factor1**	**Factor2**
Factor1	5.116	88.1%	88.1%	pest	0.835	0.229
Factor2	0.343	5.9%	94.0%	animals	0.813	0.320
Factor3	0.209	3.6%	97.6%	deforestation	0.910	0.123
Factor4	0.109	1.9%	99.5%	resources	0.907	0.036
Factor5	0.025	0.4%	100.0%	packages	0.829	–0.257
Factor6	0.003	0.1%	100.0%	transport	0.891	–0.267
Factor7	0.000	0.0%	100.0%	energy	0.792	–0.184

Factor loadings indicate that Factor 1 captures the largest portion of shared variance across all statements, with high positive loadings for issues such as deforestation (0.910), resource use (0.907), and transport emissions (0.891). These high loadings suggest that Factor 1 reflects a general dimension of concern about the environmental impact of food production. Factor 2, while accounting for a smaller proportion of the variance, shows relatively stronger loadings for the statements related to animal treatment (0.320) and pesticide use (0.229), suggesting a secondary dimension possibly linked to ethical concerns in food production. However, the overall strength of loadings for Factor 2 is weaker, indicating that it plays a more marginal role. The validity of the results is conditioned by the assumption that the instruments used in the estimation are exogenous. The null hypothesis of the refutability test is that all instruments included in Equation (6) are exogenous. The p-values of the refutability test in all cases are greater than 0.92, which leads to the non-reject of the null hypothesis.

Table 6 reports the estimation of the two classes LCM with indicator. While more complex specifications (e.g., three-class models with additional interaction terms) achieve better fit according to the AIC, both the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC), which impose stronger penalties for over-parameterization, consistently favor more parsimonious two-class specifications. Furthermore, the three-class model generated some classes with behavioral overlap. A summary table reporting the number of estimated parameters, log-likelihood values, and model selection criteria (AIC, BIC, CAIC) has been added to supplementary materials (S2). Therefore, the allocation function is composed of two additional variables to the observable exogenous variables (sociodemographic). The first is the *Environmental damage* indicator, and the second contains the residuals of the auxiliary regression defined in equation (6).

Table 6 - Estimation of the LCM with indicator

Variable	**Class 1**	**Class 2**
Main Effects		
ASC	–2.800*** (0.271)	0.764 (0.637)
Ecosystem Services	1.285*** (0.227)	0.615* (0.343)
Organic	1.535*** (0.249)	0.910** (0.452)
Farming for Biodiversity	0.459*** (0.155)	–0.066 (0.447)
Farming for Biodiversity + Bee	1.090*** (0.152)	–0.322 (0.489)
Farming for Biodiversity + Bee + Net Pollination Index	1.265*** (0.163)	0.418 (0.432)
PGI	0.437*** (0.081)	0.572* (0.296)

PDO	0.575*** (0.172)	–0.306 (0.451)
Price	–0.190*** (0.012)	–0.176*** (0.037)
Interaction Effects Organic		
Ecosystem Services × Organic	–1.220*** (0.410)	–0.099 (0.348)
Farming for Biodiversity × Organic	–0.365* (0.192)	0.518 (0.461)
Farming for Biodiversity + Bee × Organic	–0.526*** (0.191)	0.286 (0.455)
Farming for Biodiversity + Bee + Net Pollination Index × Organic	–1.144*** (0.209)	0.071 (0.447)
Interaction Effects PDO		
Ecosystem Services × PDO	–0.054 (0.161)	0.292 (0.338)
Farming for Biodiversity × PDO	0.570*** (0.182)	0.382 (0.487)
Farming for Biodiversity + Bee × PDO	–0.199 (0.206)	1.082** (0.502)
Net Pollination Index × PDO	–0.307 (0.236)	0.858* (0.512)
Treatment Effects		
ASC × Information	–0.769** (0.301)	–1.721*** (0.541)
Ecosystem Services × Information	–0.158** (0.075)	–0.947*** (0.284)
Organic × Information	0.055 (0.080)	–0.257 (0.340)
Farming for Biodiversity × Information	0.026 (0.124)	–0.605 (0.407)
Farming for Biodiversity + Bee × Information	0.025 (0.128)	0.003 (0.449)
Farming for Biodiversity + Bee + Net Pollination Index × Information	0.222* (0.124)	–0.646* (0.389)
PGI × Information	–0.079 (0.109)	–0.370 (0.356)
PDO × Information	–0.091 (0.107)	–0.807** (0.385)

Parameter of the Class 2 Allocation Function	
Constant	–2.159*** (0.759)
Female	0.268 (0.258)
Age	0.355*** (0.093)
Education	0.030 (0.208)
Income	0.167 (0.130)
Full-Time Employment	0.030 (0.273)
Household Size	–0.295*** (0.104)
Children in Household	1.098*** (0.315)
Environmental damage	–0.251*** (0.075)
Residuals	0.258* (0.142)

*, **, *** indicate 10%, 5%, 1% significance level, respectively.
Standard errors of the estimated parameters are shown in parentheses.

First, it's interesting to note that the coefficient associated with the residuals in the allocation function is significant, showing that the *Environmental damage* indicator is endogenous. Second, the coefficient of the indicator is negative and significant (–0.251; p-value < 0.000). This points to the fact that individuals' attitudes of concern toward the role of the agribusiness supply chain in damaging the environment through overuse of land and water have significance in distinguishing groups (Hess *et al.*, 2013; Mariel & Arata, 2022). A lower score for this indicator increases the likelihood of belonging to class 2. This is in line with the result that WTP values for the adoption of ES-related labels are lower in class 2 (Table 7) (Califano *et al.*, 2025). Class 2 is thus characterized by less interest in the proposed labeling and less concern about whether food production has a negative impact on the environment.

The model distinguishes two distinct behavioral profiles. Class 1, in which there is a higher probability of belonging accounting for about 82.5 percent of the sample, displays a clear preference for the purchase alternatives presented in the experiment. This is reflected in the negative and significant ASC, suggesting that these respondents value the attributes of the alternatives and actively engage in trade-offs. The probability of belonging to this class increases as age decreases, if no children are present in the household, and if the attitude of concern about the environmental impact of food production supply-chain increase. Class 2 represents a smaller segment that prefers generic information labels, is price sensitive, and is not interested in additional information.

For a detailed comparison we report the WTP values (Table 7) recognizing the marginal utility of the two groups with respect to the specific information levels, the interaction between logos and the information treatment outside the labels.

Table 7 - Mean WTP values

Variable	**Class 1**	**Class 2**
Main Effects		
ASC	–14.748*** [–17.197, –12.299]	4.342 [–3.903, 12.587]
Ecosystem Services	6.767*** [4.281, 9.253]	3.495* [–0.520, 7.510]
Organic	8.084*** [5.442, 10.725]	5.171* [–0.204, 10.546]
Farming for Biodiversity	2.417*** [0.829, 4.006]	–0.375 [–5.348, 4.598]
Farming for Biodiversity + Bee	5.741*** [4.165, 7.316]	–1.829 [–7.311, 3.653]
Farming for Biodiversity + Bee + Net Pollination Index	6.662*** [4.933, 8.390]	2.376 [–2.436, 7.189]
PGI	2.300*** [1.427, 3.173]	3.252* [–0.272, 6.776]
PDO	3.030*** [1.232, 4.827]	–1.737 [–6.906, 3.432]
Interaction Effects Organic		
Ecosystem Services × Organic	–6.423*** [–10.728, –2.118]	–0.562 [–4.461, 3.338]
Farming for Biodiversity × Organic	–1.924* [–3.899, 0.051]	2.947 [–2.168, 8.062]

Farming for Biodiversity + Bee × Organic	–2.770*** [–4.702, –0.838]	1.628 [–3.452, 6.709]
Farming for Biodiversity + Bee + Net Pollination Index × Organic	–6.022*** [–8.102, –3.943]	0.406 [–4.584, 5.395]
Interaction Effects PDO		
Ecosystem Services × PDO	–0.285 [–1.957, 1.386]	1.659 [–2.164, 5.482]
Farming for Biodiversity × PDO	3.000*** [1.086, 4.915]	2.174 [–3.415, 7.762]
Farming for Biodiversity + Bee × PDO	–1.046 [–3.159, 1.068]	6.148* [–0.328, 12.625]
Farming for Biodiversity + Bee + Net Pollination Index × PDO	–1.619 [–4.055, 0.817]	4.874 [–1.427, 11.175]
Treatment Effects		
ASC × Information	–4.050** [–7.237, –0.862]	–9.781*** [–16.336, –3.227]
Ecosystem Services × Information	–0.834** [–1.620, –0.048]	–5.383*** [–8.958, –1.808]
Organic × Information	0.288 [–0.535, 1.111]	–1.461 [–5.235, 2.313]
Farming for Biodiversity × Information	0.138 [–1.143, 1.419]	–3.436 [–8.094, 1.222]
Farming for Biodiversity + Bee × Information	0.131 [–1.188, 1.451]	0.020 [–4.977, 5.016]
Farming for Biodiversity + Bee + Net Pollination Index × Information	1.168* [–0.115, 2.450]	–3.674 [–8.110, 0.762]
PGI × Information	–0.417 [–1.542, 0.707]	–2.104 [–6.097, 1.888]
PDO × Information	–0.480 [–1.583, 0.623]	–4.588** [–9.064, –0.111]

*, **, *** indicate 10%, 5%, 1% significance level, respectively.

Lower and upper limits of the 95% confidence intervals are given in square brackets.

Class 1 demonstrates consistently higher and statistically significant WTP values across most sustainability attributes, while Class 2 shows lower and often statistically not significant valuations, consistent with a more price-sensitive and information-averse profile.

Class 1 exhibits robust positive preferences for Organic production (8.084, $p < 0.000$) and the generic ES provision logo (6.767, $p < 0.000$). For the specific ES the first information level Farming for biodiversity presents a WTP of 2.417 ($p < 0.000$), while the addition of increased information levels further increases WTP, with Farming for Biodiversity + Bee (5.741, $p < 0.000$) and Farming for Biodiversity + Bee + Net Pollination Index (6.662, $p < 0.000$) both yielding highly significant effects. Geographical Indications (PGI: 2.300, $p < 0.000$; PDO: 3.030, $p < 0.000$) are also positively valued.

In contrast, Class 2 values are lower and more varied. In relation to main effects, this group shows that they exclusively prefer the generic level of ES provision (3.495, $p < 0.1$) and Organic certification (5.171, $p < 0.1$), but their confidence intervals include zero, suggesting weaker statistical reliability.

Interaction effects with Organic reveal important halo effects in Class 1. Ecosystem Services × Organic (–6.423, $p < 0.000$), Farming for Biodiversity × Organic (–1.924, $p < 0.1$), Farming for Biodiversity + Bee × Organic (–2.770, $p < 0.000$) and Farming for Biodiversity + Bee + Net Pollination Index × Organic (–6.022, $p < 0.000$), are all significantly negative. These interactions suggest that when the Organic logo is present, the additional value of ES labels diminishes, possibly due to consumer perception that organic production already subsumes these environmental benefits (Jean *et al.*, 2025). In Class 2, none of the Organic-based interactions are significant, implying the absence of such a halo effect in this group.

PDO interactions provide mixed results. In Class 1, Farming for Biodiversity × PDO is positive and highly significant (3.000, $p < 0.000$), supporting the idea that biodiversity attributes gain credibility when paired with PDO. Other PDO interactions are not insignificant.

Treatment effects from information provision show divergent impacts across classes. In Class 1, Ecosystem Services × Information is negative (–0.834, $p < 0.05$), while Farming for Biodiversity + Bee + Net Pollination Index × Information is positive (1.168, $p < 0.1$). This suggests that in this group, the external information layer, which introduces a specificity of service measurement information, increases WTP only in the case of the introduction of the Net Pollination index, while decreasing the marginal utility for the generic ES supply logo. For Class 2, the effect of Ecosystem Services × Information is highly negative (–5.383, $p < 0.000$). These consumers respond poorly to additional information, reflecting skepticism or confusion towards detailed environmental claims. The PDO × Information interaction is also negative and significant (–4.588, $p < 0.05$), suggesting that even established quality cues may lose value when overloaded with information.

Discussion and conclusion

This study explored the potential of ES-related labels to influence consumer preferences in the food system, using EVOO as a case study. The analysis contributes to the growing literature on sustainable food labeling by assessing how varying label designs and levels of informational detail shape consumer choices. In addition, the moderating role of an external informational treatment – designed to simulate a public awareness campaign – was examined to evaluate whether providing contextual information enhances consumer valuation of ES.

The LCM estimates identified two distinct consumer segments with significantly different preferences. First group showed consistently strong preferences for sustainability attributes. These consumers demonstrated a WTP for a range of ES-related labels, with higher values associated with increasing levels of specificity – from general references to biodiversity, to a visual indicator (bee image), and ultimately to a quantified scientific metric (Net Pollination Index). This group exhibited high engagement with sustainability themes and responded positively to detailed, transparent information (Borrello *et al.*, 2021; Johnson & Geisendorf, 2022). In contrast, a minority segment, displayed lower WTP values and limited responsiveness to detailed ES labels, regardless of the external informational treatment. This group tended to be older, more likely to have children at home, and less concerned about the environmental impacts of food production. Their choices suggest greater price sensitivity and a preference for generic information level, indicating a degree of disengagement or skepticism towards detailed environmental labeling.

The inclusion of the external informational treatment produced differentiated effects across segments. While self-reported and objective knowledge levels did not vary substantially between treated and untreated respondents, preferences modeling indicated that the additional information enhanced WTP in the most involved segment. For this group, the treatment acted as a reinforcing mechanism, validating the relevance of ES-related claims and amplifying consumer trust and valuation. This finding suggests that supplementary communication tools – such as in-store educational materials, QR codes linking to explanatory content, or public campaigns – may increase the effectiveness of ES related labels, particularly when targeted at already receptive consumers (Marchi *et al.*, 2024).

However, the treatment had no observable effect on the more skeptic group (Casati *et al.*, 2023). This is consistent with findings in the behavioral economics and psychology literature, which highlight that information-based interventions may fail when not aligned with individuals' values, motivations, or perceived relevance (Grunert *et al.*, 2014; Reisch & Sunstein, 2016). For this segment, information alone is insufficient to modify behavior, pointing to the potential need for alternative strategies, such as more intrusive policy tools related to prices.

One of the key findings is the importance of label specificity in driving consumer preferences. The highest WTP was recorded for the most detailed labeling option ("Farming for Biodiversity + Bee + Net Pollination Index"), indicating that consumers value clarity, credibility, and precision in sustainability communication. The inclusion of visual and quantified elements improved perceived product quality and producer trustworthiness (Aprile & Punzo, 2022). These results suggest that vague or generic sustainability claims may be less effective, whereas detailed, verifiable, and visually engaging labels are more likely to influence consumer behavior.

Nonetheless, attention must be paid to potential information overload or attribute redundancy. The observed negative interaction between organic certification and ES labels among Class 1 respondents suggests a possible halo effect, whereby the presence of multiple overlapping sustainability claims may dilute the perceived incremental value of additional labels (Janßen & Langen, 2017). This underscores the importance of coherent and complementary label design, where different claims are clearly differentiated in terms of meaning and function (Fresacher & Johnson, 2023).

While these results indicate that metric-based information on ES can affect consumer preferences, the use of a quantitative indicator such as the Net Pollination Index also raises important questions regarding certifiability and verification. While the index provides a scientifically grounded measure of pollination services, its use in a labelling context would require clearly defined protocols for data collection, independent verification, and auditing. In practice, measurement could be carried out by accredited third-party bodies or research institutions, potentially building on existing agri-environmental monitoring schemes. However, such processes would entail non-negligible costs and may pose challenges for smaller producers. Moreover, without standardized verification procedures, the risk of strategic use or greenwashing cannot be excluded. For these reasons, in this study the Net Pollination Index should be interpreted as a proof-of-concept illustrating how metric-based information on ES may be perceived by consumers, rather than as a fully developed certification proposal. Future research should explicitly assess the institutional feasibility and cost-effectiveness of certifying ES indicators at farm level.

From a policy perspective, the results point to the potential of ES labeling strategies – particularly those linked to measurable environmental outcomes – to stimulate market-based incentives for biodiversity conservation and other ES. As agricultural systems play a dual role in contributing to and mitigating environmental degradation, enhancing the visibility of their environmental contributions through credible labels could serve as a promising lever for sustainable consumption.

The heterogeneity in consumer responses also suggests the need for differentiated policy approaches. For highly engaged consumers, information-based nudges and detailed labeling schemes may be sufficient to drive behavioral change. For more disengaged segments, however, regulatory tools, price mechanisms, or default options may be necessary to shift preferences. Policymakers should therefore consider hybrid frameworks that combine voluntary and mandatory elements, tailored to different levels of consumer engagement (Huang *et al.*, 2024).

Several limitations of the study should be noted. First, while the DCE included measures to mitigate hypothetical bias and the econometric approach is based on managing respondents' latent attitudes (Czajkowski *et al.*, 2017), external validity remains low. In addition, data were collected in a single supermarket located in a middle-to-high income urban area, and participation was voluntary, which may have resulted in self-selection of consumers more interested in food quality or sustainability-related issues. Future research should validate these findings using incentivized experiments or observational data conducted in different retail and socio-economic contexts. Second, the analysis focused on EVOO, a culturally salient product in the Italian context; generalizability to other products or countries may be limited. Third, although the price levels were grounded in observed retail prices, the use of non-rounded decimal values, derived from constant percentage increments, may appear less representative of actual shelf prices, potentially affecting perceived realism; future studies could test alternative price framings to assess their influence on choice behaviour. Fourth, all respondents received a brief, generic introduction to ES to ensure a minimum level of understanding, as pilot testing showed that participants with no prior information produced inconsistent or erratic responses. While this may reduce the contrast between treatment and control, it was necessary to maintain comprehension and the reliability of WTP estimates. Finally, the study did not examine interactions between ES labels and other marketing elements such as branding or packaging, which may influence consumer interpretation and valuation.

In conclusion, the results demonstrate that ES-related food labeling can influence consumer preferences, particularly when labels are specific, visual, and supported by credible information. While most consumers are willing to reward sustainability efforts with price premiums, a notable minority remains unresponsive to information-based strategies. To enhance the market uptake of ES-related labels and their contribution to sustainability goals, future interventions should account for the diversity of consumer motivations, the design of complementary communication strategies, and the broader policy environment in which labeling initiatives are embedded.

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Declaration of Generative AI Use

During the preparation of this article, the author(s) used ChatGpt to improve writing and grammatical structure. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Alcorta, P., & Mariel, P. (2025). Beyond biases: Exploring endogeneity in the allocation function of latent class models for environmental valuation. *Resource and Energy Economics*, *83*, 101498. Doi: 10.1016/j.reseneeco.2025.101498.

Altmann, A., & Berger Filho, A. G. (2020). Certification and labeling for conservation of ecosystem services in the Pampa Biome: Case study of the Aliança do Pastizal scheme. *Ecosystem Services*, *46*, 101209.

Ammann, J., Arbenz, A., Mack, G., & Siegrist, M. (2025). Consumer support of policy measures to increase sustainability in food consumption. *Food Policy*, *131*, 102822.

Aprile, M. C., & Punzo, G. (2022). How environmental sustainability labels affect food choices: Assessing consumer preferences in southern Italy. *Journal of Cleaner Production*, *332*, 130046.

Asioli, D., Fuentes-Pila, J., Alarcón, S., Han, J., Liu, J., Hocquette, J.-F., & Nayga, R. M. (2022). Consumers' valuation of cultured beef Burger: A Multi-Country investigation using choice experiments. *Food Policy*, *112*, 102376.

Bazzani, C., Scarpa, R., Begalli, D., & Capitello, R. (2025). Reporting nutritional information on wine packaging: Does it affect consumers' choices? Evidence from a choice experiment in Italy. *Food Policy*, *131*, 102800.

Bliemer, M. C., Rose, J. M., & Hess, S. (2008). Approximation of Bayesian efficiency in experimental choice designs. *Journal of Choice Modelling*, *1*(1), 98-126.

Boncinelli, F., Gerini, F., Piracci, G., Bellia, R., & Casini, L. (2023). Effect of executional greenwashing on market share of food products: An empirical study on green-coloured packaging. *Journal of Cleaner Production*, *391*, 136258. Doi: 10.1016/j.jclepro.2023.136258.

Borrello, M., Cecchini, L., Vecchio, R., Caracciolo, F., Cembalo, L., & Torquati, B. (2022). Agricultural landscape certification as a market-driven tool to reward the provisioning of cultural ecosystem services. *Ecological Economics*, *193*, 107286.

Borrello, M., Cembalo, L., & Vecchio, R. (2021). Role of information in consumers' preferences for eco-sustainable genetic improvements in plant breeding. *PLOS ONE*, *16*(7), e0255130. Doi: 10.1371/journal.pone.0255130.

Bouwma, I., Schleyer, C., Primmer, E., Winkler, K. J., Berry, P., Young, J., Carmen, E., Špulerová, J., Bezák, P., & Preda, E. (2018). Adoption of the ecosystem services concept in EU policies. *Ecosystem Services*, *29*, 213-222.

Califano, G., Vita, G. D., Raimondo, M., Spina, D., D'Amico, M., & Caracciolo, F. (2025). Premium pricing for zero residue certification: The role of environmental concern and health consciousness in consumer preferences for eco-labels on fresh tomatoes. *Journal of Cleaner Production*, *518*, 145928. Doi: 10.1016/j.jclepro.2025.145928.

Canavari, M., Castellini, A., & Xhakollari, V. (2023). *A short review on willingness to pay for novel food. Case Studies on the Business of Nutraceuticals, Functional and Super Foods*, 21-30.

Canavari, M., & Coderoni, S. (2020). Consumer stated preferences for dairy products with carbon footprint labels in Italy. *Agricultural and Food Economics*, *8*(1), 4. Doi: 10.1186/s40100-019-0149-1.

Canavari, M., Wongprawmas, R., & Di Muro, M. (2016). Consumers' preferences and willingness-to-pay for misfit vegetables. *Economia agro-alimentare*, *XVIII*(2), 133-154.

Canavari, M., Bazzani, G.M., Spadoni, R., Regazzi, D. (2002). Food safety and organic fruit demand in Italy: a survey. *British Food Journal*, *104*(3-4-5), 220-232. Doi: 10.1108/00070700210425688.

Caputo, V., Lagoudakis, A., Shupp, R., & Bazzani, C. (2023). Comparing experimental auctions and real choice experiments in food choice: A homegrown and induced value analysis. *European Review of Agricultural Economics*, *50*(5), 1796-1823. Doi: 10.1093/erae/jbad033.

Caputo, V., Van Loo, E. J., Scarpa, R., Nayga Jr, R. M., & Verbeke, W. (2018). Comparing serial, and choice task stated and inferred attribute non-attendance methods in food choice experiments. *Journal of Agricultural Economic*s, *69*(1), 35-57.

Carlsson, F., Kataria, M., & Lampi, E. (2022). Sustainable food: Can information from food labels make consumers switch to meat substitutes? *Ecological Economics*, *201*, 107567.

Casati, M., Soregaroli, C., Rommel, J., Luzzani, G., & Stranieri, S. (2023). Please keep ordering! A natural field experiment assessing a carbon label introduction. *Food Policy*, *120*, 102523. Doi: 10.1016/j.foodpol.2023.102523.

Čehić, A., Canavari, M., Oplanić, M., & Cerjak, M. (2021). The importance of intrinsic and extrinsic local olive oil attributes for tourists: Evidence from a Mediterranean destination. *European Journal of Tourism, Hospitality and Recreation*, *11*(2), 280-295.

Cerroni, S., Watson, V., Kalentakis, D., & Macdiarmid, J. I. (2019). Value-elicitation and value-formation properties of discrete choice experiment and experimental auctions. *European Review of Agricultural Economics*, *46*(1), 3-27. Doi: 10.1093/erae/jby014.

Costanza, R. (2020). Valuing natural capital and ecosystem services toward the goals of efficiency, fairness, and sustainability. *Ecosystem Services*, *43*, 101096.

Cummings, R. G., & Taylor, L. O. (1999). Unbiased Value Estimates for Environmental Goods: A Cheap Talk Design for the Contingent Valuation Method. *American Economic Review*, *89*(3), 649-665. Doi: 10.1257/aer.89.3.649.

Czajkowski, M., Vossler, C. A., Budziński, W., Wiśniewska, A., & Zawojska, E. (2017). Addressing empirical challenges related to the incentive compatibility of stated preferences methods. *Journal of Economic Behavior & Organization*, *142*, 47-63. Doi: 10.1016/j.jebo.2017.07.023.

Del Giudice, T., Cavallo, C., Caracciolo, F., & Cicia, G. (2015). What attributes of extra virgin olive oil are really important for consumers: A meta-analysis of consumers' stated preferences. *Agricultural and Food Economics*, *3*, 1-15.

De-loyde, K., Pilling, M. A., Thornton, A., Spencer, G., & Maynard, O. M. (2025). Promoting sustainable diets using eco-labelling and social nudges: A randomised online experiment. *Behavioural Public Policy*, *9*(2), 426-442. Doi: 10.1017/bpp.2022.27.

Dipartimento delle Finanze (2022). *Redditi e principali variabili Irpef su base Sub-Comunale (CAP)* [Dataset]. -- https://www1.finanze.gov.it/finanze/analisi_stat/public/index.php?opendata=*yes*.

Duckworth, J. J., Randle, M., McGale, L. S., Jones, A., Doherty, B., Halford, J. C. G., & Christiansen, P. (2022). Do front-of-pack 'green labels' increase sustainable food choice and willingness-to-pay in U.K. consumers? *Journal of Cleaner Production*, *371*, 133466. Doi: 10.1016/j.jclepro.2022.133466.

FAO (2024). *Greenhouse gas emissions from agrifood systems – Global, regional and country trends, 2000-2022* (94; FAOSTAT Analytical Brief Series, p. 11).

Ferrini, S., & Scarpa, R. (2007). Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study. *Journal of Environmental Economics and Management*, *53*(3), 342-363.

Fresacher, M., & Johnson, M. K. P. (2023). Designing climate labels for green food choices. *Journal of Cleaner Production*, *430*, 139490. Doi: 10.1016/j.jclepro.2023.139490.

Gorton, M., Tocco, B., Yeh, C.-H., & Hartmann, M. (2021). What determines consumers' use of eco-labels? Taking a close look at label trust. *Ecological Economics*, *189*, 107173.

Grebitus, C., Lusk, J. L., & Nayga Jr, R. M. (2013). Effect of distance of transportation on willingness to pay for food. *Ecological Economics*, *88*, 67-75.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681-698.

Grunert, K. G., Hieke, S., & Wills, J. (2014). Sustainability labels on food products: Consumer motivation, understanding and use. *Food Policy*, *44*, 177-189.

Grunert, K. G., & Wills, J. M. (2007). A review of European research on consumer response to nutrition information on food labels. *Journal of Public Health*, *15*, 385-399.

Guevara, C. A. (2018). Overidentification tests for the exogeneity of instruments in discrete choice models. *Transportation Research Part B: Methodological*, *114*, 241-253. Doi: 10.1016/j.trb.2018.05.020.

Guevara, C. A., & Polanco, D. (2016). Correcting for endogeneity due to omitted attributes in discrete-choice models: The multiple indicator solution. *Transportmetrica A: Transport Science*, *12*(5), 458-478.

Haines-Young, R. and Potschin-Young, M. (2018). *Common international classification of ecosystem services (CICES) v5. 1. guidance on the application of the revised structure.*

Hallström, E., Carlsson-Kanyama, A., & Börjesson, P. (2015). Environmental impact of dietary change: A systematic review. *Journal of Cleaner Production*, *91*, 1-11. Doi: 10.1016/j.jclepro.2014.12.008.

Hartikainen, H., Roininen, T., Katajajuuri, J.-M., & Pulkkinen, H. (2014). Finnish consumer perceptions of carbon footprints and carbon labelling of food products. *Journal of Cleaner Production*, *73*, 285-293. Doi: 10.1016/j.jclepro.2013.09.018.

Hess, S., Shires, J., & Jopson, A. (2013). Accommodating underlying pro-environmental attitudes in a rail travel context: Application of a latent variable latent class specification. *Transportation Research Part D: Transport and Environment*, *25*, 42-48. Doi: 10.1016/j.trd.2013.07.003.

Huang, L., Solangi, Y. A., Magazzino, C., & Solangi, S. A. (2024). Evaluating the efficiency of green innovation and marketing strategies for long-term sustainability in the context of Environmental labeling. *Journal of Cleaner Production*, *450*, 141870. Doi: 10.1016/j.jclepro.2024.141870.

ISTAT (2021). *Censimento Agricoltura 2020 – Superfici e Produzione [Dataset].* -- https://esploradati.istat.it/databrowser/#/it/dw/categories/IT1,Z1000AGR,1.0/AGR_CRP/DCSP_COLTIVAZIONI/IT1,101_1015_DF_DCSP_COLTIVAZIONI_2,1.0.

Janßen, D., & Langen, N. (2017). The bunch of sustainability labels – Do consumers differentiate?. *Journal of Cleaner Production*, *143*, 1233-1245. Doi: 10.1016/j.jclepro.2016.11.171.

Jaung, W., Putzel, L., & Naito, D. (2019). Can ecosystem services certification enhance brand competitiveness of certified products? *Sustainable Production and Consumption*, *18*, 53-62.

Jean, I. R., Canavari, M., Cerdan, C., Consentino, F., & Peri, I. (2025). Integrating biodiversity information into consumer preferences for extra virgin olive oil: Evidence from a real choice experiment in France. *Journal of Cleaner Production*, *497*, 145121. Doi: 10.1016/j.jclepro.2025.145121.

Johnson, D., & Geisendorf, S. (2022). Valuing ecosystem services of sustainable urban drainage systems: A discrete choice experiment to elicit preferences and willingness to pay. *Journal of Environmental Management*, *307*. Doi: 10.1016/j.jenvman.2022.114508.

Just, D. R., & Byrne, A. T. (2019). Evidence-based policy and food consumer behaviour: How empirical challenges shape the evidence. *European Review of Agricultural Economics*. Doi: 10.1093/erae/jbz010.

Laksmawati, W. K., Hsieh, C.-M., & Yang, S.-H. (2024). Social influence and climate change issues affecting consumer behavioral intention toward carbon footprint label: A study of Taiwanese consumers. *Journal of Cleaner Production*, *444*, 141092. Doi: 10.1016/j.jclepro.2024.141092.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2), 132-157.

Lin, W., & Nayga Jr, R. M. (2022). Green identity labeling, environmental information, and pro-environmental food choices. *Food Policy*, 106, 102187.

Lusk, J. L., McFadden, B. R., & Wilson, N. (2018). Do consumers care how a genetically engineered food was created or who created it? *Food Policy*, *78*, 81-90. Doi: 10.1016/j.foodpol.2018.02.007.

Lusk, J. L., Roosen, J., & Fox, J. A. (2003). Demand for beef from cattle administered growth hormones or fed genetically modified corn: A comparison of consumers in France, Germany, the United Kingdom, and the United States. *American Journal of Agricultural Economics*, *85*(1), 16-29.

Mameno, K., Kubo, T., Ujiie, K., & Shoji, Y. (2023). Flagship species and certification types affect consumer preferences for wildlife-friendly rice labels. *Ecological Economics*, *204*, 107691. Doi: 10.1016/j.ecolecon.2022.107691.

Marchi, E. D., Scappaticci, G., Banterle, A., & Alamprese, C. (2024). What is the role of environmental sustainability knowledge in food choices? A case study on egg consumers in Italy. *Journal of Cleaner Production*, *441*, 141038. Doi: 10.1016/j.jclepro.2024.141038

Mariel, P., & Arata, L. (2022). Incorporating attitudes into the evaluation of preferences regarding agri-environmental practices. *Journal of Agricultural Economics*, *73*(2), 430-451.

Mariel, P., Campbell, D., Sandorf, E. D., Meyerhoff, J., Vega-Bayo, A., & Blevins, R. (2025). *Environmental Valuation with Discrete Choice Experiments in R: A Guide on Design, Implementation, and Data Analysis (Vol. 17).* Springer Nature.

Martínez-López, J., Bagstad, K. J., Balbi, S., Magrach, A., Voigt, B., Athanasiadis, I., Pascual, M., Willcock, S., & Villa, F. (2019). Towards globally customizable ecosystem service models. *Science of the Total Environment*, *650*, 2325-2336.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Fontiers in Econometrics*, 105-142.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*(3), 437.

Mediobanca - Area Studi (2024). *L'industria dell'olio d'oliva in Italia*. -- https://www.areastudimediobanca.com/en/product/28031.

Muller, L., Lacroix, A., & Ruffieux, B. (2019). Environmental Labelling and Consumption Changes: A Food Choice Experiment. *Environmental and Resource Economics*, *73*(3), 871-897. Doi: 10.1007/s10640-019-00328-9.

Nes, K., & Ciaian, P. (2022). EU marketing standards and sustainability. *Applied Economic Perspectives and Policy*, *44*(4), 1844-1863.

O'Brien, K., Garibaldi, L., & Agrawal, A. (2024). *IPBES Transformative Change Assessment: Full report (Version 4.0.0).* Zenodo. Doi: 10.5281/ZENODO.11382215.

Paffarini, C., Torquati, B., & Cecchini, L. (2025). The impact of multiple labeling on consumer choices for extra virgin olive oil: A cross-country study. *Agricultural and Food Economics*, *13*(1), 1-28.

Panico, T., Del Giudice, T., & Caracciolo, F. (2014). Quality dimensions and consumer preferences: A choice experiment in the Italian extra-virgin olive oil market. *Agricultural Economics Review*, *15*(2), 100-112.

Pe'er, G., Zinngrebe, Y., Moreira, F., Sirami, C., Schindler, S., Müller, R., Bontzorlos, V., Clough, D., Bezák, P., Bonn, A., Hansjürgens, B., Lomba, A., Möckel, S., Passoni, G., Schleyer, C., Schmidt, J., & Lakner, S. (2019). A greener path for the EU Common Agricultural Policy. *Science*, *365*(6452), 449-451. Doi: 10.1126/science.aax3146.

Perito, M. A., Sacchetti, G., Di Mattia, C. D., Chiodo, E., Pittia, P., Saguy, I. S., & Cohen, E. (2019). Buy local! Familiarity and preferences for extra virgin olive oil of Italian consumers. *Journal of Food Products Marketing*, *25*(4), 462-477.

Reisch, L. A., & Sunstein, C. R. (2016). Do Europeans like nudges? *Judgment and Decision Making*, 11(4), 310-325.

Rondoni, A., & Grasso, S. (2021). Consumers behaviour towards carbon footprint labels on food: A review of the literature and discussion of industry implications. *Journal of Cleaner Production*, *301*, 127031. Doi: 10.1016/j.jclepro.2021.127031.

Rose, J. M., & Bliemer, M. C. (2013). Sample size requirements for stated choice experiments. *Transportation*, *40*, 1021-1041.

Salazar-Ordóñez, M., Rodríguez-Entrena, M., & Villanueva, A. J. (2021). Exploring the commodification of biodiversity using olive oil producers' willingness to accept. *Land Use Policy*, *107*, 104348.

Scarpa, R., & Del Giudice, T. (2004). Market segmentation via mixed logit: Extra-virgin olive oil in urban Italy. *Journal of Agricultural & Food Industrial Organization*, *2*(1).

Scarpa, R., Franceschinis, C., & Thiene, M. (2021). Logit mixed logit under asymmetry and multimodality of WTP: a Monte Carlo evaluation. A*merican Journal of Agricultural Economics*, *103*(2), 643-662.

Scarpa, R., & Rose, J. M. (2008). Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. *Australian Journal of Agricultural and Resource Economics*, *52*(3), 253-282.

Scarpa, R., & Thiene, M. (2005). Destination choice models for rock climbing in the Northeastern Alps: A latent-class approach based on intensity of preferences. *Land Economics*, *81*(3), 426-444.

Scarpa, R., Thiene, M., & Train, K. (2008). Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps. *American Journal of Agricultural Economics*, *90*(4), 994-1010.

Schulze, C., Matzdorf, B., Rommel, J., Czajkowski, M., García-Llorente, M., Gutiérrez-Briceño, I., Larsson, L., Zagórska, K., & Zawadzki, W. (2024). Between farms and forks: Food industry perspectives on the future of EU food labelling. *Ecological Economic*s, *217*, 108066. Doi: 10.1016/j.ecolecon.2023.108066.

Searchinger, T., Waite, R., Hanson, C., Ranganathan, J., Dumas, P., Matthews, E., & Klirs, C. (2019). *Creating a sustainable food future: A menu of solutions to feed nearly 10 billion people by 2050. Final report.*

Silva, A., Canavari, M., & Wander, A. (2018). Consumer preferences and willingness-to-pay for integrated production label on common beans. *Economia agro-alimenatre*, 11-28. Doi: 10.3280/ECAG2018-001002.

Sørensen, H. S., Clement, J., & Gabrielsen, G. (2012). Food labels – an exploratory study into label information and what consumers see and understand. *The International Review of Retail, Distribution and Consumer Research*, *22*(1), 101-114.

Street, D. J., Bunch, D. S., & Moore, B. J. (2001). Optimal designs for 2 k paired comparison experiments. *Communications in Statistics-Theory and Methods, 30*(10), 2149-2171.

Street, D. J., Burgess, L., & Louviere, J. J. (2005). Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. *International Journal of Research in Marketing*, *22*(4), 459-470. Doi: 10.1016/j.ijresmar.2005.09.003.

Thiene, M., Scarpa, R., Longo, A., & Hutchinson, W. G. (2018). Types of front of pack food labels: Do obese consumers care? Evidence from Northern Ireland. *Food Policy*, *80*, 84-102.

Train, K., & Weeks, M. (2005). *Discrete choice models in preference space and willingness-to-pay space*. Springer.

United Nations *et al*. (2021). *System of Environmental-Economic Accounting – Ecosystem Accounting (SEEA EA). White cover publication, pre-edited text subject to official editing*. -- https://seea.un.org/ecosystem-accounting.

Van Loo, E. J., Caputo, V., Nayga Jr, R. M., Seo, H.-S., Zhang, B., & Verbeke, W. (2015). Sustainability labels on coffee: Consumer preferences, willingness-to-pay and visual attention to attributes. *Ecological Economics*, *118*, 215-225.

Van Loo, E. J., Caputo, V., Nayga Jr, R. M., & Verbeke, W. (2014). Consumers' valuation of sustainability labels on meat. *Food Policy*, *49*, 137-150.

Voglhuber-Slavinsky, A., Lemke, N., MacPherson, J., Dönitz, E., Olbrisch, M., Schöbel, P., Moller, B., Bahrs, E., & Helming, K. (2023). Valorization for biodiversity and ecosystem services in the agri-food value chain. *Environmental Management*, *72*(6), 1163-1188.

Yagi, K., Maesano, G., Li, G., & Canavari, M. (2025). *Olive Oil Preferences Among Japanese Consumers: Best-Worst Scaling on Country of Origin and Consumer Heterogeneity*. Agribusiness.