Reporting nutritional information on wine packaging: does it affect consumers' choices? Evidence from a Choice Experiment in Italy.

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Abstract:

At the end of 2023, in EU Commission mandated the adoption of nutritional labelling on alcoholic beverages. This was intended to tackle irresponsible drinking behaviour and excessive energy intake from alcohol, but the alcohol industry stakeholders have remained skeptical. In this study, we seek clarification on: (1) whether nutritional labelling on alcoholic beverages can nudge consumers toward lower alcohol and hence lower calorie choices, (2) whether it can affect consumers' evaluations for quality attributes, and (3) whether it beneficially affects choices by those who are most vulnerable. We conduct an online Choice Experiment on Italian consumers with a between-subjects approach, to simulate pre- and post-policy scenarios and observe choices by consumers who are informed about nutritional features (i.e. calorie content) and contrast these to those by uninformed consumers (i.e. the control group). We focus on red wine since, in Italy, wine is part of the traditional food diet and, at the same time, quality attributes represent a major component of product distinctiveness. Results from a Latent Class Random Parameter Logit Model (LC-RPL) weakly support nutritional labelling being an effective nudge toward low-alcohol wines, specifically in the case of less vulnerable consumers who are health-conscious, with lower BMI, who enjoy red wine during social gatherings and don't typically read wine labels. Nutritional labelling on wine bottles either did not affect or enhanced mWTP for quality attributes. Consumers generally valued calorie content on wine packaging. This supports the implementation of nutritional labelling policies.

Keywords: Choice Behaviour; Choice Experiment; Latent Class Random Parameter Logit Model; Nutritional Labelling; Wine.

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1. Introduction

Alcohol can be a significant source of calories in individuals' diets. The energy density of ethanol is 7 kcal/g, second only to that of fat, which is a macronutrient. Energy intake via alcohol consumption adds to that from other dietary sources, resulting in a net increase of the total intake of calories, which is often ignored or discounted (Barry, Whiteman, & Cremeens-Matthews, 2016; Battista & Leatherdale, 2017; Yeomans, 2010).

The link between energy intake from alcohol and obesity is confounded by the impact of other factors such as age, gender, and alcohol consumption habits (Butler et al., 2016; Dumesnil et al., 2013; White et al., 2019). However, recent studies have highlighted that, besides addiction and cognitive disorders, alcohol can be a risky factor for obesity due to the calorie intake and its associated nutritional and metabolic disorders (Booranasuksakul et al., 2019; Knai et al., 2018; Kwok et al., 2019; Traversy & Chaput, 2015; White et al., 2019).

Being overweight or obese are major risk factors for a number of chronic diseases, such as diabetes, cardiovascular diseases, and cancer, representing important health issues with potential long-term impact on public health and economic outcomes (Biener et al., 2020; OECD, 2017; The World Bank Group, 2020; WHO, 2020). Nutritional food labelling which makes contributed calories explicit is a major policy measure in the strategy to curb unhealthy dietary patterns and obesity (Barreiro-Hurlé et al., 2010; Kelly & Jewell, 2018; Thiene et al., 2018; Van Wezemael et al., 2014; WHO, 2019). However, the labelling of alcoholic beverages with nutritional information was proposed in the early '10s, mostly via voluntary agreements within the industry. Examples are the American Voluntary Nutrient Content Statements in the Labelling and Advertising of Wines, Distilled Spirits, and Malt Beverages (US Department of Treasury, 2013) and the English Public Health Responsibility Deal (UK Department of Health, 2011).

In Europe, most countries have adopted mandatory nutritional labelling on foods since 2016 under Regulation (EU) No 1169/2011. However, the regulation exempted alcoholic beverages containing more than 1.2% alcohol by volume, generating a lack of information on ingredients and key nutrients. In the following years, the exemption of alcoholic beverages from compulsory nutritional labelling generated a fierce debate among policymakers, industry practitioners, and scientists regarding the need and usefulness of informing consumers about the nutritional content of alcoholic beverages (Annunziata et al., 2016; Eurocare, 2014; European Commission, 2017; Martin-Moreno et al., 2013; Pabst et al., 2019; Petticrew et al., 2017). In alignment with the goals of Europe's Beating Cancer Plan and the Farm to Fork Strategy, which aim to empower consumers to make more informed and health-conscious choices, the European Commission has encouraged the adoption of nutritional labelling on alcoholic beverages. This would address the health and nutrition information gap between alcohol and other pre-packed foods (European Commission, 2022). Accordingly, in order to accommodate the opposition of the alcoholic beverage industry, instead of proposing a regulation, in 2017 the European Commission produced a report inviting the European trade associations of such industry to present by March 2018 a joint self-regulatory proposal with specific annexes for beer, wine, spirits, and cider (European Commission, 2018). Specifically, the alcoholic industry proposed different ways of nutritional information communication, namely on-label (i.e., reported on the packaging) or off-label (i.e., a web link, QR code, bar code, or other smart technologies). With the EU regulation No. 2021/2117, nutritional labelling of alcoholic beverages was made mandatory by the end of 2023. The format of nutritional labelling will follow the industry suggestions, and it will consist of (1) the on-label declaration of energy value per 100 ml, and (2) the use of off-labelling for ingredients list with full nutritional information per 100 ml of wine, and of a standard serving when relevant.

Given the adoption of the mandatory nutritional labelling of alcoholic beverages, an increasing number of studies explored how nutritional information on alcoholic beverages may be perceived by consumers (Annunziata et al., 2016b; Grunert et al., 2018; Walker et al., 2019). Particularly, some studies have raised the important question of how this policy implementation might affect consumer evaluation and choice behaviour toward alcoholic beverages (Annunziata et al., 2016a; Bui et al., 2008; Grunert et al., 2018; Hayward & McSweeney, 2020; Pabst et al., 2019; Vecchio et al., 2018*)*. In this study, we focus on answering this question. Specifically, we aim at deepening the knowledge of nutritional labelling on alcoholic beverages as an effective nudge to guide consumers toward lower calories and, hence, healthier choices.

However, contradictory results have been obtained regarding the extent to which the effects of nutritional labelling on alcohol consumption patterns have been positive (Bui et al., 2008; Martin-Moreno et al., 2013). Bui et al. (2008), for instance, found unintended effects of reporting serving facts information, such as a decreased perception of calories and carbohydrates in wine resulting in an increased intention to consume. Hence, the assumption that nutritional labelling may prevent excessive energy intake from alcohol remains to be corroborated. Previous studies investigated both consumer attitudes (e.g. Bui et al., 2008; Grunert et al., 2018) and purchase behaviour (e.g. Annunziata et al., 2016a; Popovoch & Velikova, 2023; Vecchio et al., 2018) toward alcoholic products, be they labelled or not with nutritional information. Given the controversial findings to date, determining whether nutritional labelling may be an effective strategy toward healthier consumption patterns still requires further exploration. The research gap seems particularly evident in consumer choice behaviour toward product alternatives which may differ in terms of nutritional information. As Thiene et al. (2018) explain, policymakers would benefit from an improved understanding of whether a targeted labelling policy can affect the behavior of most vulnerable individuals, such as those subject to excessive body weight, or those with low health awareness. To our knowledge, this aspect is yet to be adequately investigated in this context.

Our aim is to contribute to the academic discussion on the effects of nutritional labelling by investigating wine consumer choice behaviour from a policy and marketing perspective. Wine is an interesting alcoholic beverage to study since its consumption is predominantly motivated by hedonistic and aesthetic reasons (Charter & Pettigrew, 2005; Neeley et al., 2010; Samoggia, 2016). Pleasure and enjoyment have been found as one of the main quality dimensions by both high-involved and low-involved consumers in the study by Charters & Pettigrew (2007). At the same time, when consumed in moderation, wine is often seen as a "healthy indulgence" (Higgins & Llanos, 2015). This leads to significant market value generated by the consumer's attraction toward the combination of health aspects and well-being that can be attributed to wine when combined with responsible consumption behaviours (Pitt, 2017; Jaud et al., 2023). These joint motivations for consumption (health perception, moderation and hedonism) may add to the uncertainty regarding the net potential impact of a nutritional labelling intervention.

Additionally, wine is one of the most consumed alcoholic beverages worldwide, and it is distinctive for its high variety of quality cues (Scarpa, Thiene, & Galletto, 2009; Mueller et al., 2010; Lockshin & Corsi, 2012; Costanigro et al., 2019; Pomarici & Vecchio, 2019). In this regard, Pabst et al. (2019a; 2019b) discussed further some controversial aspects of nutritional labelling and noted that producers fear the potential decline in demand. As such, one of wine producers' concerns is whether adding nutritional information may affect consumer evaluations for quality attributes (Pabst et al., 2019a).

While awaiting the availability of revealed preference data from real market transactions with different nutritional labels, some interim insight can be derived from a hypothetical choice analysis. This study presents results from an online survey of Italian red wine consumers using Discrete Choice Experiment (DCE) data. We use red wine, rather than white, due to its content of polyphenols and other antioxidants (e.g. resveratrol), which make it a healthier option than white wine (Sabila & Carmen 2010; Higgins & Llanos, 2015; Deroover et al., 2021). (Sabila & Carmen 2010; Higgins & Llanos, 2015; Deroover et al., 2021). The perceived benefits associated with moderate red wine consumption align with consumption patterns in traditional wine-producing countries, such as Italy, where wine holds significance as a cornerstone of culinary heritage and is frequently consumed during regular meals (Vecchio et al., 2017) .

By means of a between-subjects experimental design, we compare the outcomes between an uninformed control group of consumers and a group that is provided with nutritional information (specifically, energy value expressed in kj and kcal) in order to observe how this information impacts wine choice behaviour. In this way, we are able to simulate scenarios representing the situation pre-policy, in the form of no nutritional information (i.e. the current market situation before the application of the EU regulation), and post-policy when the disclosure of such information is made mandatory in various forms (i.e. the market situation from 8th December 2023). Accordingly, we directly test the effect of the additional nutritional information on the consumer's decision-making process. The calorie content of dry wines is strictly proportional to the percent volume of alcohol. So, in our DCE the profiles of wine bottles are characterized by different levels of alcohol content, and the implied calories are disclosed to respondents who are randomly assigned to the information treatment. The line of reasoning is straightforward: the lower the alcohol content of the bottle, the lower the caloric content. To our knowledge, we test for the first time in the literature whether nutritional information can make product characteristics directly connected with the unhealthiness of wine (i.e. its alcohol content) more salient in individual decisions and drive choice toward lower alcohol (and calories) bottles.

In our DCE we also explore the role of certification labelling of other quality attributes, such as those relative to sustainable (and trendy) wine production practices associated with the “natural” and "clean" supply chains. Often, these wine characteristics are also associated with healthiness (Bazzani et al., 2024; Staub et al., 2020, Vecchio et al., 2017). Moreover, food and beverage products with clean production and labelling characteristics have recently experienced an increased market demand (Asioli et al., 2017; Capitello & Sirieix, 2019; Galati, et al., 2019; Pomarici & Vecchio, 2019). Wines characterized by eco-labels have undeniably gained market value from both the perspectives of consumers and experts (Capitello et al., 2021; Delmas & Gergaud, 2021; Moscovici & Reed, 2018). Hence, the use of wine qualities pertaining to sustainable practices allows us to determine whether consumer evaluations for quality cues are affected by the additional nutrition information. While the complex relationship between wine quality cues and nutritional information is yet to be fully understood, to our knowledge, only the study by Hayward & McSweeney (2020) investigated whether calorie information significantly interacted with consumer perceptions of wine quality. That study focused on sensory cues, noting that they were not perceived differently by consumers when the calories of a glass of rosé wine were reported. Whether and how consumers process information claims remains to be studied. Would their processing be affected by the mandatory nutritional labelling? Would nutritional information affect consumers' preferences for quality attributes?

The paper is articulated as follows. We first summarize the current literature exploring the nexus between nutritional labelling and the consumer's consumption pattern of alcoholic beverages, highlighting the knowledge gaps that our research aims to fill. Secondly, we explain our hypotheses, survey design, data, and used methods of analysis. Finally, we discuss our results, and we give recommendations for policy, marketing strategies, and future research.

2. Nutritional labelling of alcoholic beverages and consumer behaviour: a literature review

In order to investigate consumer perceptions and preferences for nutritional labelling, past studies generally used data from surveys or experiments. As previously discussed, it is yet unclear whether information about nutritional values of alcoholic beverages effectively nudges consumers toward healthier consumption choices. A couple of studies showed that, with respect to consumer's perception of alcoholic beverages, the adoption of nutritional labelling had an unexpected impact. Wright et al. (2008) conducted a survey in different wineries and breweries in the USA. Respondents were asked to rank different non-alcoholic and alcoholic beverages, including beer and wine, based on their perceived healthiness. Respondents were asked to perform the ranking task both before and after they were shown the attendant nutritional information. Surprisingly, beer and wine were generally perceived as healthier than non-alcoholic beverages, and especially when nutritional information was provided, heavy beer drinkers perceived beer to be even healthier. Similar results were observed by Bui et al. (2008) in a study on a sample of university students in a campus in the US. The authors investigated the students' subjective and objective knowledge concerning nutritional facts of alcoholic beverages (i.e. beer, light beer, red wine, and distilled liquor). They tested the effect of providing students with factual information on their perception of the products and on their future consumption intentions. Results showed that students tended to lack knowledge of objective nutritional information on alcoholic beverages, generally overestimating the content of calories, carbohydrates, and fats. When they became aware of the nutritional information, their intentions to consume alcohol in the future increased. The fact that consumers generally have little or no knowledge of nutritional information about alcoholic products has been discussed and reported elsewhere in the literature (GfK Belgium, 2014; Annunziata et al., 2016b; Grunert et al., 2018). Results from different studies in several countries (Europe, US, and Australia) showed that consumers were generally interested in nutritional labelling on alcoholic beverages and that they claimed this information to be reported on the product packaging (Thomson et al., 2012; GfK Belgium, 2014;

Annunziata et al., 2016a; Annunziata et al., 2016b; Grunert et al., 2018). Consistently with food consumer studies (Drichoutis et al., 2006), nutritional knowledge of alcoholic beverages has been recognized as a relevant factor in shaping consumer perception toward ingredients and nutritional information, as well as product involvement (Annunziata et al., 2016b; Grunert et al., 2018). Grunert et al. (2018) observed that compared with health attitudes, product involvement was a more relevant driver in the search for nutritional information, while the former factors were found to be affecting consumer interest toward the ingredients of the product. Their results partially confirmed previous findings by Annunziata et al. (2016a), who showed, from a conjoint analysis study of wine, that a graphical representation of a glass with calorie information was generally preferred to a detailed nutritional panel.

Vecchio et al. (2018) further explored preferences toward different kinds of labelling formats by means of an experimental auction on nearly one hundred Italian students. Specifically, the authors tested four different formats of wine nutritional labels, namely: (1) *back label* with the indication of kcal per glass of wine of 100ml, (2) with the *nutritional panel* referred to 100 ml, (3) without nutritional information, but with a *weblink to information*, (4) and with the *indication of key nutrients*. Their findings showed that the weblink was the least preferred labelling format, while the nutritional panel received the highest bids.

Regarding how to report nutritional information, focus groups on consumers in New Zealand revealed that participants expressed preference for more information on alcoholic beverages, rather than not having any, but they agreed that this information should be reported in a visually engaging and easy-to-read fashion (Walker et al., 2019). On the other hand, focus groups with German consumers suggested that wine was perceived to be less natural when nutritional information and ingredient lists were reported (Pabst et al., 2019b). In a subsequent study, Pabst et al. (2021) conducted an online choice experiment in three different countries (Australia, Italy, and Germany) and observed a general preference for detailed nutritional information. They found that ingredient information had a positive effect on utility only in the case of the Italian market. However, in all three countries, those consumers who received negative information from a mass-media source regarding certain ingredients in wine, tended to have a higher preference for ingredient labelling with respect to consumers who had received no information. Popovich and Velikova (2023) observed from a series of four experiments that nutritional labelling altered perceptions of healthiness and likelihood of purchasing wine only when consumers were prompted to read the labels. Specifically, their results showed that consumers who read the labels tended to perceive the wine as less healthy and to have a lower purchasing likelihood when nutritional information were provided. Moreover, Meyerding et al. (2019) used the claim “calorie-reduced” in a conjoint analysis study on beer and observed that it had a negative effect on choice frequency. This result contrasts with the findings by Marinez et al. (2015), who showed that consumers tended to prefer alcoholic beverages with such claims. Finally, Hayward & McSweeney (2020) tested the effect of reporting a glass of rosé wine calories on consumer sensorial perceptions, which were found to be unaffected by consumers being provided with information about calorie contents.

This review of studies on nutritional labelling in wine shows that most studies focused on consumer's attitudes and choice behaviour (e.g. Bui et al., 2008; Annunziata et al., 2016a; Grunert et al., 2018; Vecchio et al., 2018) toward nutritional information labelling. Few studies, instead, investigated consumers’ trade-offs toward products varying in terms of calorie content (e.g. Hayward & McSweeney, 2020; Martinez et al., 2015; Meyerding et al., 2019). Among these, only Hayward & McSweeney (2020) tested the effect of nutritional information on quality cues. However, their research focused on sensory attributes and did not explore the effects of nutritional information on purchase behaviour. Similarly, they did not test whether nutritional labelling affects vulnerable individuals.

Our study is, to the best of our knowledge, the first that looks at whether the presence of a nutritional label informing on calorie content affects consumer's choice of wines differing in calorie content and quality attributes. Given our intention to provide information from policy makers' and business' perspectives, our study also provides a novel contribution in addressing the role played by attitudinal characteristics relating to individual health and body weight status.

3. Survey Design

3.1 <u>Sample and survey design</u>

DCE data were collected in November 2018, through an online survey administered to a panel of Italian respondents from a reputable panel provider company. The core of the survey was a DCE on red wine to consume at home. In Italy, most wine is consumed during meals and at home (Vecchio et al., 2017). This aligns with most food choice labelling studies, which generally focus on the use of nutritional labels in food purchases for home consumption (Drichoutis et al., 2005; Gracia et al., 2007; Nayga, 1996; Nayga et al., 1998; Thiene et al., 2018). Our sample consisted of Italian consumers aged at least eighteen (i.e., the legal drinking age in Italy) and who reported having consumed red wine at home at least once a month. To adequately capture the effects of covariates, the sample was stratified by gender, age, and region of residence.

The questionnaire and DCE design were tested in two preliminary pilot studies (on 81 and 80 respondents, respectively) to assess the clarity of our questions and the quality of DCE responses. More details on this aspect are given in the later section on experimental design.

The survey questionnaire was structured in four main sections. The first contained questions investigating wine involvement, consumption habits, and use of wine labels. These questions were followed by the DCE and then by the section with some manipulation tasks to capture respondents' attendance to attributes, health attitudes, wine consumption consciousness[1], and wine nutritional knowledge. The last section, with socio-demographic questions, concluded the questionnaire.

3.2 The Design of the Experiment

DCEs are widely used in food policy studies since they allow the estimation of welfare effects of a policy implementation and individuals' marginal utilities and Marginal Willingness to Pay (mWTP) for different labelling strategies (Costanigro et al., 2019; Lusk et al., 2018; Maples, Lusk, & Peel, 2018; Ortega et al., 2011; Thiene et al., 2018; Van Loo et al., 2014; Van Wezemael et al., 2014). Hypothetical DCEs, like ours, have been conducted to elicit consumer preferences for wine label information (Costanigro et al., 2019; Lockshin et al., 2006; Mueller et al., 2010; Piracci et al., 2022). Relevant studies exploring the impact of wine nutritional information on consumer choice have also implemented this approach (i.e. Annunziata et al., (2016a) and Pabst et al. (2021)). Moreover, compared to other preference elicitation methods, such as contingent valuation and experimental auctions, DCEs have the advantage of allowing for the simultaneous estimation of preferences for different attributes and resemble the decision mechanism that individuals may experience in real purchase situations (Caputo et al., 2023; Cerroni et al. 2019; Gracia, Loureiro, & Nayga, 2011; Grebitus, Lusk, & Nayga, 2013; Shi et al., 2015).

As a first step in the design of our DCE, we selected the product in question, namely red wine in a standard-sized 750 ml bottle. The choice of wine is explained by the fact that this product is suitable for answering our research questions. First, in Italy wine is the alcoholic beverage most frequently consumed during home meals (Istat, 2023). Second, wine is an alcoholic beverage with a wide variety of quality cues. We selected red rather than white wine since red wine is often considered a healthier product if consumed in moderation, given the presence of antioxidants and other beneficial compounds (Annunziata et al., 2016b). Moreover, red wines on the market generally have a wider

[1] The questionnaire also contained questions related to environmental attitudes and objective knowledge of CE attributes. This part of the questionnaire is not reported since this is not the focus of the present study.

range of alcohol content, which is one of the key attributes of our study. Red wine was described as still (not sparkling) and not associated with geographical indications (e.g., Protected Designation of Origin and Protected Geographical Indication), even though in the Italian market, wine bottles generally carry some indication of place of origin. We used a generic red wine to avoid potential home-bias effects on choice by respondents (Scarpa et al., 2005).

The second step concerned the selection of the attributes and levels needed to describe our red wine bottle profiles (see Table 1). Given the relationship between alcohol and calories, alcohol content (by volume) was used as one of our attributes. Four levels were selected, i.e. 11%, 12%, 13%, and 14%, aiming at implementing values commonly present in the market, easily understandable and distinguishable by respondents. Regarding the other quality attributes, we used labels related to "environmental sustainability" and "naturalness". As mentioned in the introduction, the selection of these attributes was motivated by the fact that demand for environment-friendly and "natural" claims on wine has significantly increased in the last decade, providing producers with new product differentiation options (Galati et al., 2019; Pomarici & Vecchio, 2014, 2019; Sogari, Corbo, Macconi, Menozzi, & Mora, 2015; Sogari, Mora, & Menozzi, 2016). Moreover, these labels are often perceived as an indication of a comparatively healthier alternative (Amato et al., 2017; Vecchio et al., 2017). Specifically, we used the attribute "Sustainable Production Certification", described by three levels of certifications, namely (1) organic certification, visually represented by the 'European Leaf' logo; (2) biodynamic certification, using the logo of the private protocol 'Demeter®'; and (3) a certification aimed at communicating the adoption of agricultural practices that protect or enhance biodiversity (i.e., the private protocol 'Biodiversity Friend®', supported by the WBA World Biodiversity Association); a fourth level indicated the absence of any sustainability certification. These levels were selected on the basis of the most recent literature about sustainable wine, aiming at capturing different aspects of sustainability (Amato et al., 2017; Mazzocchi, Ruggeri, & Corsi, 2019; Pomarici & Vecchio, 2019; Schäufele & Hamm, 2017). As Asioli et al. (2017) explained, clean labelling, and therefore naturalness, can also be related to traditional production methods and low levels of automation and processing. Accordingly, we have selected the attributes "hand-picked grapes" (present/absent) and "unfiltered wine" (present/absent). These claims have been gaining in popularity in the Italian wine market (Dominici et al., 2019; Dreßler & Paunovic, 2023).

Table 1. Attributes and attribute levels used in the choice experiment.

Attributes	Attribute Levels
Sustainable production certification	• Organic • Biodynamic • Biodiversity friend® • None (reference level)
Hand-picked grapes	• Present Uva raccolta a mano • Absent (reference level)
Unfiltered wine	• Present Vino non filtrato • Absent
Alcoholic strength/energy value	• 11% vol – 252 kJ / 62 kcal • 12% vol – 275 kJ / 66 kcal • 13% vol – 297 kJ / 72 kcal • 14% vol – 320 kJ / 77 kcal
Price	• 2.10 € • 3.60 € • 5.10 € • 8.10 € • 11.10 € • 14.10 €

Finally, the price attribute was described by six levels (€2.10, €3.60, €5.10, €8.10, €11.10, and €14.10). These levels were selected based on the current literature and data from the Italian market for bottled red wine to provide a sufficiently wide price range to adequately reflect the cost of a bottle of red wine sourced from stores where wine for home consumption is typically bought (Contini et al., 2019; IRI Infoscan, 2017). The final set of price levels has been adjusted based on responses collected in the two pilot studies both from the DCE and from a question investigating individuals' reference price for a bottle of still red wine to consume at home (Bazzani et al., 2017; Caputo, Lusk, & Nayga, 2018). In the first pilot study, a narrower price range was implemented, but estimates from a Multinomial Logit Model (MNL) implied a positive marginal effect of a price increase on selection. This suggested the need to increase the price range. So, the second pilot used a wider range of six prices, and estimates from an MNL revealed a negative coefficient of the price coefficient, as expected. This latter range was then implemented in the final design. The two pilot studies were also used to test the appropriateness of the selected quality cues as attributes of interest. In both pilots, the MNL estimates for the preference parameters of all quality attributes were statistically significant at 10%, confirming their relevance on consumers' choice probabilities of red wine bottles.

A Bayesian efficient design approach was used to generate a set of choice tasks differing in terms of the attributes and attribute levels described above. The software package Ngene was implemented (Choice Metrics, Ngene v1.0.1, 2011), which is a standard in this field. Efficient experimental designs have come to the fore in recent years. In particular, Bayesian efficient designs accommodate uncertainty over population values of parameters by assuming distributions over prior parameter values and are expected to improve estimate efficiency at a given sample size (Rose & Bliemer, 2013; Scarpa & Rose, 2008). Different criteria can be used to determine the efficiency of the design. In this study, a WTPb efficient design was implemented (Scarpa & Rose, 2008; Vermeulen at al., 2011; Thiene et al., 2019), which consisted of sixty choice tasks divided into five blocks of twelve choice tasks each, minimizing the total correlation values between all of the attributes and the blocking variable. This means that each respondent was randomly assigned to answer twelve choice questions from one of the five blocks. So, for every five respondents, a full design was covered. Each choice task presented two product alternatives and an opt-out alternative (buy neither). In the experimental design used for the pilot DCE, parameters of the non-price attributes were specified assuming a uniform distribution, defining the lower bound as the lowest price level of the chosen range and the upper bound as the highest price level. This pilot design was tested on 80 more respondents in a second pilot. Then, the implied marginal WTP values were estimated and used as Bayesian priors with normal distribution to generate the final WTPb efficient design, preserving the same dimension as before.

3.3 Choice Tasks and Treatments design

3.3.1 *Choice Tasks design*

Before engaging in the DCE, respondents were informed that they would be asked to make a series of twelve purchasing decisions concerning red wine. Specifically, in each choice task, they were asked to imagine being in the store where they usually buy wine and facing the choice of buying a 750 ml bottle of red wine for home consumption from the available choice set. In each choice task, they would be asked to indicate either the preferred wine bottle or opt-out if neither of the bottles on offer was deemed desirable. To mitigate the hypothetical bias, the choice experiment was introduced by a ‘cheap talk’ script. This was designed to be generic, short, and neutral (Cummings & Taylor, 1999; Penn & Hu, 2018; Silva et al., 2011). The script warned respondents about the potential problem of hypothetical bias, asking them not to overstate their true WTP and to provide truthful responses as if they were in a real-life setting (List, 2001; Van Loo et al., 2011).

In an attempt to mimic a real purchasing situation, the product alternatives were represented by mock-ups of red wine bottles developed by a graphic designer with a particular focus on their back labels. We used back-pack labels since the wine labelling legislation mandates back labels to contain all mandatory product information, inclusive of nutritional information. Hence, all mandatory information was reported (e.g., presence of sulfites, place of bottling, batch number), including alcohol content and those respondents were subject to the information treatment---also the calorie content. Information on quality attributes was represented by the respective logos for sustainable production certifications, while for “Hand-picked grapes” and “Unfiltered wine” we used purpose-developed logos conceived anew for this study. Prices were indicated under the pictures displaying the back labels. The order of appearance of the choice tasks was randomized, and so was the order of display of the two product alternatives in each choice card.

3.3.2 *Treatments design*

Respondents were randomly assigned to two treatments differing in terms of the presence of calories in the nutritional information. Specifically, in the “Without Calories Information Treatment” (*Inf=0*), respondents were shown choice tasks containing attribute information reported in Table 1 (without displaying energy and calorie content). On the other hand, in the “With Calories Information Treatment” (*Inf=1*), respondents were presented with choice tasks that also displayed information regarding the energy and calorie content. Figure 1 and Figure 2 show examples of *Inf=0* and *Inf=1* treatments, respectively.

Figure 1: Example of a *Inf* = 0 choice task

Figure 2: Example of a *Inf* = *1* choice task

We limited the nutritional information to the energy value content, i.e. the calorie content, because it is the piece of information that must be reported on-label. Energy value information was described in terms of kJ/kcal per 100 ml, in line with Article 30(4) of Regulation (EU) No 1169/2011, as indicated in the EU regulation No. 2021/2117. We calculated the alcohol to calories conversion suggested in the wine and aromatized wines appendix of the Joint Self-Regulatory proposal[2] and

[2] The energy value calculation has been based on the following formula assuming the absence of any carbohydrate residual and setting the volume at 100 ml.

computed respective energy values for each alcohol degree level: 252kJ/62kcal (11%Vol), 275kJ/66kcal (12%Vol), 297kJ/72kcal (13%Vol), 320kJ/77kcal (14%Vol). Our red wine was a dried red wine with no residual sugars. So, the increase in calorie content was directly and exclusively related to an increase in alcohol percentage.

4 Research questions and Data Analysis

4.1 Research hypotheses

Using our experimental data, we test three hypotheses. Two hypotheses test the effectiveness of nutritional labelling first as an information vehicle and secondly as a nudge to induce consumers toward making more health-oriented choices, i.e. selecting wine bottles with lower alcohol and hence lower calories. A third hypothesis allows us to consider the unintended effects of nutritional labelling on quality wine valuation. The hypotheses are formulated in a way that rejection of the null implies is the expected outcome of the policy.

We first test the "effective information vehicle" hypothesis. That is, whether reporting calorie information affects consumers' awareness of its calorie content. The expected outcome is that the policy implementation would increase the fraction of respondents who correctly identify the direct correlation between wine calorie content and alcohol degree, something we measure with the indicator $I = CalAlc,$ which is a dummy variable equal to 1 if the respondent reported knowing the direct relationship between alcohol and calorie content and 0 otherwise (European Commission, 2018; OIV, 2022). We hence test the following hypotheses:

$$H_0^1: I|Inf = 1 \leq I|Inf = 0$$

$$H_A^1: I|Inf = 1 > I|Inf = 0.$$

The beneficial effect of the policy forcing nutritional labels to include calorie amounts would result in a negative preference for wines with comparatively higher alcoholic degrees. This would result in

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$$E = Alc. \times \rho_{etOH} \times \frac{V_w}{100} \times Cf_{etOH} + \frac{m_{sug}}{1000} \times V_w \times Cf_{Carb}$$

E: Energy value (kJ or kcal/ml); Alc. : Alcoholic strength by volume (%); ρ_{etOH}:Density of ethanol (0,789 g/l); V_w: Volume of wine (ml); Cf_{etOH} : Conversion factor for alcohol (29 kJ/g – 7kcal/g) (Wilfred W. Westerfeld, 1959); m_{sug}: mass of sugar per litre of wine (g); Cf_{Carb}: Conversion factor for carbohydrates (17 kJ/g – 4kcal/g) (Westerfeld, 1959).

lower calorie intakes (European Commission, 2018). Given that our preference structure allows us to estimate the marginal WTP for alcohol content, we frame the second set of hypotheses as follows:

$$H_0^2: mWTP_{Alcohol\ Content}|Inf = 1 \geq mWTP_{Alcohol\ Content}|Inf = 0$$

$$H_A^2: mWTP_{Alcohol\ Content}|Inf = 1 < mWTP_{Alcohol\ Content}|Inf = 0$$

However, other quality aspects of wine matter too. So, the effect of marginal WTP for other quality attributes is something to preserve for the benefit of the operators of the entire wine supply chain. Potential unintended effects of nutritional labelling would be a decreased valuation for a quality wine attribute by consumers. This might be a source of discontent and criticism by the wine industry operators who strive to increase production quality (Pabst et al., 2019a). We then test our final hypotheses:

$$H_0^3: mWTP_{Quality\ Attribute}|Inf = 1 < mWTP_{Quality\ Attribute}|Inf = 0$$

$$H_A^3: mWTP_{Quality\ Attribute}|Inf = 1 \geq mWTP_{Quality\ Attribute}|Inf = 0.$$

4.2 Data Analysis

To test the first hypothesis, we use non-parametric tests based on descriptive statistics of consumer attitudes. Specifically, we have asked respondents a true/false question exploring whether they are aware of the direct relationship between alcohol and calorie content[3]. This survey question was asked after the DCE to observe whether the display of nutritional information in the *Inf*=1 treatment was an efficient nudging strategy in terms of increasing knowledge of the relationship between alcohol and calorie content.

To test H_0^2 and H_0^3, estimates of structural Discrete Choice Models (DCMs) are obtained from DCE data. We use DCMs that are consistent with Random Utility Theory (Luce, 1959; McFadden, 1974) based on the assumption that, from the researcher's perspective, the probability of a respondent choosing a wine bottle alternative can be modelled as a function of two utility components: one observed and deterministic, and a second unobserved and random. Of course, from the perspective of each respondent, the utility of each alternative is completely known. Further, our utility structure

[3] In other to elicit objective knowledge regarding nutritional information, previous research directly asked the amount of calories of a glass of wine (e.g., Annunziata et al., 2016 and Bui et al., 2008). We rather controlled for the simple relationship between alcohol degree and calories since the amount of calories in a glass of wine depends on the alcohol content and we used this relationship to determine the attributes in the CE wine bottles.

is consistent with Lancaster Theory (1966), which is based on the assumption that the total utility derived from choosing a product can be segregated into additive utilities derived from the product attributes. Literature on wine consumption behaviour shows that consumers have heterogeneous preferences for wine attributes (Lockshin et al., 2006). Preference heterogeneity (e.g., taste variation across consumers) can be assumed to occur continuously or discretely. Recent studies have highlighted that taste variations have asymmetric and multimodal distributions, suggesting that preferences are distributed in sub-groups of varying size even when they are assumed to be continuously random across individuals (Bansal et al. 2018, Caputo et al., 2018; Scarpa et al., 2021). A preliminary investigation on the continuous v/s the discrete nature of heterogeneity was conducted using Mixed Logit (Train and Weeks, 2005; Scarpa et al., 2008) and Logit Mixed Logit (Train 2016) models in WTP space, with a focus on the implied distributions of marginal WTP. The results are consistent with a clustering and multimodality of preferences, which corroborate our subsequent latent class approach (refer to Figure A1 and Figure A2 in the online appendix).

For this reason, we use a Latent Class Random Parameter Logit Model (LC-RPL), which can accommodate both forms of preference mixing, continuous and discrete (Bujosa et al., 2010; Greene and Hensher, 2013; Hess et al., 2012). The assumption is that respondents' preferences for wine attributes vary randomly and continuously within latent distinctive segments (classes). However, the assumption of a random distribution of the price coefficient introduces complexities for the computation of WTP values. WTP measures linear in the coefficient utilities are derived by computing the negative ratio between the non-price and the price coefficient. Therefore, treating the price variable as random would imply that WTP is the ratio between two random variables. This complication can be overcome by imposing a price coefficient with a constant marginal utility of money across participants. At the same time, the fixed marginal utility of money contradicts economic intuition, as the value of the last unit of money may differ among participants with diverse income constraints (Scarpa et al., 2007). Morey et al. (2003) suggested a straightforward method to account for diverse marginal income effects into discrete choice models. Acknowledging income as the primary determinant of the marginal utility of money, they assumed that alterations in the marginal utility of money, namely the price coefficient, follow a piece-wise function based on income levels. This permits the marginal utility of income to vary across income groups while remaining consistent within each group. The theoretical expectation is that the marginal utility of money decreases (WTP increases) in higher-income groups. Accordingly, in our model specification, we include the marginal utility of income as a constant across all respondents ($-\alpha$) with an additive positive effect for those with high income (α^{HI}), expecting this to be $\alpha + \alpha^{HI} < 0$. In our analysis, we postulate that the indirect utility that the n^{th} respondent in class *C* derives in choosing alternative *i* out of *J* alternatives in the t^{th} choice task can be described as:

$$U_{nit|c} = ASC_c[1 + 1(Inf)_n] + \alpha p_{nit} + \alpha^{HI}1(High\_Inc)p_{nit} + \widetilde{\beta_c}'x_{nit} + \delta_c[x_{nit} \times 1(Inf)_n] + \varepsilon_{nit|c} \quad (1)$$

Where ASC is the alternative-specific constant of the opt-out alternative taking value of 1 if the respondent chooses to buy neither of the bottles on offer, 0 otherwise; for the ASC variable, the model specifies both main and interaction effects with the *Inf* treatment variable, that takes value equal to 1 if the respondent received the information treatment (i.e. belongs to the *Inf*=1 treatment), 0 otherwise; p_{nit} is a continuous variable represented by the six experimentally designed price levels; *High_Inc* is a dummy variable taking the value of 1 when the participant belongs to the high income group (in our case defining respondents with income level higher than the median sample value) and 0 otherwise; x_{nit} is a vector denoting the non-price attributes, namely: (1) the sustainable production variables which are treated as dummy variables equal to one if the respective certification logo is present, 0 otherwise (the no-label level was fixed to 0 as reference level); (2) the hand-picked grapes attribute; and (3) the unfiltered wine claim; while (4) alcohol content is treated as a continuous variable described by the four experimental levels; α is the marginal utility of income (i.e. the price coefficient) and α^{HI} is the coefficient of the interaction term between the price and the indicator function for high income effects; both price coefficients are specified as fixed and constant across the latent classes; $\widetilde{\beta_c}$ is the vector of non-price attribute coefficients specific to class *C*, which are assumed to vary randomly and continuously across respondents in this class following a normal distribution; δ' is the parameter vector dependent on class *C* and fixed within the class. These are describing the information effects with the quality attributes from the treatment dummy variable *Inf*. Finally, $\varepsilon_{nit|c}$ is the stochastic unobserved utility term, which is assumed to be independently and identically distributed Gumbel (Extreme Value Type I).

Finally, marginal WTP values are calculated as a negative ratio, where the nominator is the estimated mean value of the coefficient associated with a wine attribute and the denominator is the price coefficient α in the case of respondents with income below the median and $\alpha + \alpha^{HI}$ for the others. The coefficient α explains a baseline marginal price effect, which refers to taste common to all participants, while α^{HI} is the coefficient of the interaction term between the price and the dummy variable *High_Inc*. Data were analysed using Latent Gold Choice 5.1 with specific syntax.

Further, to provide an understanding of latent preference class composition, posterior probabilities of individual membership to each of the latent classes are calculated for each respondent. To explore whether individual characteristics can explain these membership probabilities, we used a regression specification suitable to explain a vector of dependent variables (the posterior class probabilities of the n[th] respondent) taking values between zero and one and collectively summing to unity. The Dirichlet regression has this property. We hence follow Hu et al. (2004) and Thiene et al. (2019) who used this regression tool for this purpose. In practice, for each individual probability of class membership obtained a-posteriori, the regression can take the form $\pi_{ns}^{P} = g_s(\Phi,\chi_n) + v_{ns}$ which are bounded in (0,1) and $\sum_s \pi_{ns}^{P} = 1$; g_s is a linear additive function of the individual variables χ_n defined up to a set of coefficients Φ to be estimated; and v_{ns} is the error term. We focus on explanatory variables capturing higher/lower degree of vulnerability of the respondent in terms of health attitudes and knowledge of the calories/alcohol relationship. Individual posterior membership probabilities can be defined as compositional data, since they can be interpreted as non-negative proportions of disjoint categories (i.e. the latent classes) adding up to one. Assuming that individual membership probabilities are described by a Dirichlet distribution, Dirichlet regression models can be implemented to estimate the ratio in which explanatory variables can be distributed among the multiple dependent variables (Paolino, 2001; Smithson & Verkuilen, 2006), namely the different latent classes. The log-likelihood function of the Dirichlet regression used in this study can be specified as follows:

$$LL_n = \ln\Gamma(H) - \sum_{s=1}^{S} \ln\Gamma\left[H g_s(\Phi,\chi_n)\right] + \sum_{s=1}^{S}\left[H g_s(\Phi,\chi_n) - 1\right]\ln(\pi_{ns}^{P}) \qquad (2)$$

where π_{ns}^{P} are the posterior individual probabilities for each latent class (s), H is a constant to be estimated and $\Gamma(\cdot)$ is the gamma function. The Dirichlet regression was estimated in RStudio 4.1.2 by using the package DirichletReg (Maier, 2014).

5. Results

5.1 Data description

A total sample of 559 red wine consumers completed the online survey, 278 respondents were randomly assigned to the treatment *Inf*=0 and 281 to *Inf*=1. As is good practice in experiments involving between-subject treatments, we conduct tests to determine whether the two treatments are balanced in terms of individual characteristics that might influence choice behaviour. Since the existing literature shows that wine consumption and wine involvement can be relevant factors affecting wine choice behaviour (Annunziata et al., 2016a; Brown et al., 2007; Bruwer & Huang, 2012; Grunert et al., 2018), we particularly focus on socio-demographic variables and attitudinal variables concerning wine consumption and wine involvement. We also control for health awareness and weight-related information, as they may affect calorie content evaluation (Drichoutis et al., 2005; Thiene et al., 2018; Vecchio et al., 2018).

In Table 2 we report the socio-demographic information. Nonparametric Mann-Whitney U tests were applied for age, education and income, and Chi-squared tests for gender, to test for significant differences across distributions in the two sub-samples with and without information, as well as the p-values for test of no difference across proportions.

Table 2: Socio-demographic information across *Inf*=0 and *Inf*=1

Variable	***Inf=0*** **(n=278)**	***Inf*=1 (n=281)**	***No diff in Prop*** ***p*-value**	***No diff in distr*** ***p*-value**
Age (%)				
18–24 years	13.31	11.74	0.978	
25–34 years	18.71	21.71	0.108	
35–44 years	17.63	15.66	0.239	
45–54 years	15.47	15.30	0.210	0.817
55–64 years	16.55	15.66	0.185	
65–74 years	17.63	18.15	0.177	
Older than 74 years	0.72	1.78	0.711	
Gender (%)				
Man	47.48	49.47	0.966	
Woman	52.52	50.17	0.310	0.610
Prefer not to answer	-	0.36		
Education (%)				
Comprehensive school	0.36	0.36	0.996	
Intermediate school	12.23	8.54	**0.000**	
High school	51.44	48.75	**0.026**	**0.038**
University degree	20.22	31.67	0.384	
More than University degree	5.76	10.68	0.982	
Total annual household gross income (%)				
Less than €10,000	14.75	12.46	0.977	
€10,000–€20,000	21.22	16.73	0.974	
€20,001–€30,000	23.74	23.84	0.971	
€30,001–€40,000	14.39	11.74	0.977	
€40,001–€50,000	4.68	7.83	0.984	
€50,001–€60,000	2.52	5.34	0.987	**0.045**
€60,001–€70,000	2.88	2.85	0.989	
€70,001–€80,000	1.80	3.56	0.989	
€80,001–€90,000	2.88	2.14	0.989	
More than €90,000	2.52	3.91	0.988	
Prefer not to answer	8.63	9.61	0.981	

The p-values reported in the fourth column of Table 2 show that statistical differences are found across distributions in education and income at the 3.8% and 4.5% levels of significance, respectively. Specifically, the *Inf*=0 has a significantly higher percentage of respondents with high school or intermediate diploma, while in the case of *Inf*=1, a higher fraction (but not significant) of respondents have a university degree or a higher level of education. This asymmetry is consistent with the statistics related to the income levels, which are lower the sub-sample treated with the *Inf*=0. The two sub-samples are balanced in terms of age, with the highest percentage of individuals belonging to the 25 to 34 years segment, and gender, with a nearly equal percentage of men and women. There are no official statistics at the national level concerning red wine drinkers, which prevents us to compare our sample statistics with those of the national population for consumers.

In appendices Table A1 and Table A2, further descriptive statistics are reported, which describe: (1) wine consumption and wine involvement[4] attitudes (Bruwer & Huang, 2012; Thach, 2012); (2) awareness of wine/alcohol intake effect on health (Yoo et al., 2013); (3) health consciousness (*HealthC*) (Gould, 1988; Hassan, 2008); and (4) weight-related information (Thiene et al., 2018), taking into account the self-body image (*SBody*) (respondents were asked whether they felt a 'lot over', a 'little over', 'about equal', a 'little under', or a 'lot under' their ideal body weight), the Body Mass Index (*BMI*) (obtained from the weight and height self-reported in the survey), and whether respondents controlled for their body weight status (*WeightCtrl*). We observe that the hypothesis of equality across the two treatments can be rejected only in the case of the BMI variable (the *t*-test shows a significant difference at 9.6% level), indicating that respondents from the *Inf*=0 have, on average, a higher BMI.

5.2 <u>Effect of nutritional labelling on wine nutritional knowledge (H_0^1)</u>

The hypotheses H_0^1 was tested by comparing across the two sub-samples the descriptive statistics for *CalAlc*. *CalAlc* is a dummy variable that takes a value of 1 if the respondent correctly indicated a direct relation between alcohol and calorie content, 0 otherwise. *CalAlc* was found not to be significantly different across information treatment (48.56% for the *Inf=0* treatment, 46.98% for the *Inf=1* treatment, Chi-square test (*p*-value of 0.707)). We conclude that H_0^1 can not be rejected. This suggests that providing nutritional information on the wine bottles in the DCE did not nudge

[4] A seven-point Likert scale, adapted from Bruwer & Huang (2012), was used to measure the respondents' levels of agreement on statements capturing wine involvement. To capture frequency level of wine consumption in the different occasions, a five-point itemized scale, adapted from Thach (2012), was implemented ("Never", "Rarely", "Sometimes", "Often", "Always or almost Always").

consumers toward increased knowledge of the relationship between alcohol degree and calorie content.

To better understand the reasons behind such a result, we use survey answers to the Attribute Non-Attendance (ANA) questions. These questions were posed right after the sequence of DCE choice tasks. 18% of respondents with *Inf*=1 stated non-attendance of some attributes while executing the DCE choice tasks, 65% of whom reported non-attendance of calorie content information. We have then looked at whether body weight information and health awareness can explain this behaviour (Table A1 and Table A2). The correlation matrix (results are reported in Table A3) indicates that ignoring the nutritional information positively and significantly correlates with the BMI values (10% significance level) and with the perceived distance from ideal body weight (*SBody*) (5% significance level). This suggests that respondents who have ignored the calorie content attribute tend to have a higher BMI and to perceive their current weight over the ideal one. On the other hand, respondents who score highly on the health-conscious scale tend to pay more attention to nutritional information, as suggested by the significant (10% significance level) and negative correlation.

5.3 Nutritional labelling and preference for wine attributes (H_0^2 and H_0^3)

To accommodate preference variation, we estimate a latent class model and test our hypotheses on the effect of nutritional labelling on consumer wine preference structure (H_0^2 and H_0^3). Preliminary evidence on the existence of the effect of information treatment on the mWTP distributions derived from mixed logit models strongly corroborates its significance. Table A4 of the online appendix reports the Kolmogorov-Smirnov test scores for the hypothesis of equal distributions of the posterior individual means of marginal WTP for the various attributes for the untreated and treated subsamples (*Inf*=0, *Inf*=1) reported in Figure A1. The null is rejected for all distributions, so in the structural random utility model we pay particular attention to the interaction effects between wine attributes and information treatment.

Significance and coefficient sign of the interaction effect between alcohol content and exposure to information treatment provide a direct test of H_0^2. A significant and negative sign implies that informed respondents prefer low-alcohol wines, thereby rejecting H_0^2. On the other hand, a significant and positively signed estimates suggest that nutritional labelling might not be an effective nudge toward low-calorie wine choices.

The effect of the interaction coefficient between treatment and all other quality attributes allows us to test H_0^3, which is rejected in the presence of insignificant or positive coefficients.

The definition of the optimal number of classes in finite mixing models is always problematic. To obtain guidance on this issue for our data, we proceeded by implementing a DCMs with flexible distributions that can accommodate multiple modal values (Scarpa et al., 2021). The Logit Mixed Logit (LML) specification is capable of uncovering the multimodality and asymmetry of continuous taste distributions (Train, 2016). Hence, we estimated a diagnostic LML model[5] in WTP space (Train, 2016), and observed that random mWTP values in the data are characterized by a multimodal distribution, varying between three and four modal values per attribute (results are reported on Figure A2). This suggests the presence of three or four latent preference classes, so both three and four LC-RPL models were estimated. Information Criteria (AIC3) indicate a better fit to the data by the four-class model, and we report here the salient results in Table 3 (Utility coefficients are reported in Appendix, Table A5). We report mWTP values, taking into account observed income heterogeneity by recognizing the differential marginal utility of income of high-income groups from that of baseline respondents. WTP were derived using the bootstrapping technique introduced by Krinsky and Robb (1986). This method yielded a distribution comprising 1,000 WTP values for each parameter. Specifically, these 1,000 observations were generated from a multivariate normal distribution, using the estimated means and the variance-covariance matrix obtained from the 4-class LC-RPL model. The estimates are based on a slightly reduced sample size of 508 observations given that 51 respondents had missing income data. Note that class-specific parameters for "Biodynamic" and "Biodiversity" attributes have been treated as non-random within classes, since the class-specific standard deviations of their respective utility coefficients were found to be insignificant at 10% level in most of the classes when tried as random.

5.3.1 *Latent class results*

In Table 3 WTP value derived from the LC-RPL model are reported. In terms of membership probabilities, respondents show a 40% probability of belonging to Class 1, 33% of belonging to Class 2, 22% to Class 3, and, finally, a residual 5% to Class 4. As expected, the high-income group[6] is associated with greater WTP. When mWTP is negative, this group displays a more negative value than the baseline, reflecting the need for higher compensation due to the lower marginal utility of money.

[5] A 8-degree polynomial function was specified.

[6] Individual-specific mWTP for the wine attributes are derived from a 4 LC-RPL model excluding the interaction term with the high-income variable on the price attribute. These estimates are then used as dependent variables in a Seemingly Unrelated Regression to test the effect of annual income on individual-specific mWTP. Results show that income has a positive and significant effect on high-segment attributes, namely organic, biodynamic, and biodiversity friendly labels. These findings support the inclusion of the step-function in the LC-RPL model.

Table 3: Mean WTP values

	Class 1 (40%)		Class 2 (33%)		Class 3 (22%)		Class 4 (5%)	
Main Effects	***Low Income***	***High Income***	***Low Income***	***High Income***	***Low Income***	***High Income***	***Low Income***	***High Income***
Hand-picked	**4.558*****	**7.925*****	**3.606*****	**6.268*****	**11.945*****	**20.773*****	**71.851*****	**124.825*****
	[2.081;7.003]	[3.579;12.335]	[1.703;5.523]	[2.946;9.631]	[7.323;16.629]	[12.423;29.429]	[29.440;113.821]	[52.932;196.289]
Unfiltered	**3.541*****	**6.158*****	-0.797	-1.388	0.336	0.592	0.758	1.357
	[1.585;5.653]	[2.616;10.416]	[-2.444;0.923]	[-4.391;1.580]	[-4.092;4.959]	[-7.143;8.713]	[-10.831;12.772]	[-19.094;22.559]
Organic	**4.749*****	**8.259*****	1.350	2.351	**15.744*****	**27.411*****	**46.286*****	**80.522*****
	[2.244;7.348]	[3.749;13.126]	[-0.664;3.414]	[-1.148;6.015]	[11.691;20.082]	[19.101;37.050]	[23.128;70.883]	[38.663;128.339]
Biodynamic	-1.835	-3.197	**-3.446*****	**-5.998*****	**14.513*****	**25.247*****	-3.183	-5.558
	[-4.321;0.569]	[-7.873;1.069]	[-6.015;-0.966	[-10.847;-1.713]	[9.781;19.513]	[16.291;35.519]	[-17.687;10.569]	[-31.987;18.492]
Biodiversity	**3.407*****	**5.923*****	-1.302	-2.271	**12.776*****	**22.231*****	**-78.684*****	**-136.570*****
	[1.062;5.899]	[1.787;10.420]	[-3.701;1.068]	[-6.506;1.878]	[8.745;16.930]	[14.414;30.812]	[-149.252;-6.956]	[-265.108;-12.083]
Alc. Content	**-1.007*****	**-1.752*****	0.188	0.328	**2.112*****	**3.675*****	2.640	4.584
	[-1.748;-0.332]	[-3.164;-0.570]	[-0.527;0.904]	[-0.981;1.636]	[0.748;3.519]	[1.289;6.386]	[-1.437;6.511]	[-2.519;11.406]
ASC_{nobuy}	**-40.546*****	**-70.591*****	0.565	0.992	14.683	25.515	-9.784	-17.037
	[-53.357;-30.186]	[-96.493;-49.347]	[-8.837;9.126]	[-15.180;16.726]	[-3.819;32.106]	[-6.641;56.816]	[-58.800;34.929]	[-102.309;62.945]
Treatment Effects								
Hand-picked*Inf	-1.359	-2.370	-1.066	-1.854	3.436	5.984	**-62.533*****	**-108.635*****
	[-4.288;2.019]	[-7.897;3.503]	[-3.309;1.488]	[-6.080;2.619]	[-3.482;11.396]	[-5.998;19.459]	[-102.705;-21.279]	[-181.162;-38.479]
Unfiltered*Inf	0.033	0.050	**3.089*****	**5.375*****	0.451	0.777	-3.720	-6.488
	[-2.855;3.009]	[-4.895;5.152]	[0.816;5.457]	[1.400;9.577]	[-5.618;6.823]	[-10.352;11.773]	[-17.278;9.461]	[-30.660;16.155]
Organic*Inf	-1.190	-2.074	-1.883	-3.283	2.895	5.049	-13.223	-22.982
	[-4.881;2.182]	[-8.498;3.885]	[-4.962;1.108]	[-8.640;1.897]	[-3.307;8.734]	[-5.689;15.664]	[-32.122;5.136]	[-56.191;8.870]
Biodynamic*Inf	1.948	3.388	-0.417	-0.714	1.682	2.958	8.746	15.230
	[-1.710;5.471]	[-2.912;9.963]	[-3.954;3.097]	[-6.777;5.419]	[-4.427;7.932]	[-7.722;14.648]	[-8.416;26.373]	[-14.936;46.506]
Biodiversity*Inf	-1.622	-2.827	1.194	2.072	-0.014	-0.031	**72.527*****	**125.837*****
	[-5.014;1.806]	[-8.844;3.264]	[-2.061;4.428]	[-3.495;7.532]	[-6.799;6.072]	[-12.231;10.717]	[1.174;144.820]	[2.146;253.706]
Alc. Content*Inf	**1.054****	**1.826****	-0.318	-0.558	-1.504	-2.618	3.314	5.759
	[0.115;2.025]	[0.212;3.613]	[-1.326;0.674]	[-2.360;1.226]	[-3.392;0.326]	[-5.913;0.551]	[-1.229;8.067]	[-2.352;14.344]
ASC_{nobuy}*Inf	-0.034	-0.220	-6.023	-10.524	**-20.665***	**-35.937***	34.000	59.057
	[-19.774;18.553]	[-35.961;35.106]	[-18.727;7.284]	[-33.466;12.859]	[-44.265;2.537]	[-78.887;4.805]	[-19.305;92.181]	[-33.598;160.901]

***, **, * indicate significance at 1%, 5%, 10% level

Latent *Class 1* (the largest segment with 40% membership probability) is characterized by a negative mWTP for an increase in alcohol content, hence a negative mWTP for low-calorie wines (Table 3). The positive interaction effect between alcohol content and information treatment indicates that respondents tend to prefer wines with higher alcohol content when they are informed about the calorie content. So, we cannot reject H_0^2. On the other hand, we do reject H_0^3. In fact, the information treatment effect on mWTP for wine quality attributes is statistically insignificant at 10% level. We note that the magnitude of the significant and negative WTP for *Alc.content* common to all group in row six (main effects) is basically counter-balanced by the mWTP for those who are informed, which is a negative and surprising result for the effect of such information, also considering the large probability of belonging to this cluster.

Main effects estimates show that consumers with high membership probability to *Class 1* tend to pay a price premium for the “clean” and "environmentally sustainable" attributes (only mWTP for the *Biodynamic* attribute fails to be significant). *Class 1* stands out as the only class with a negative WTP for the "no-buy" option. This suggests that respondents in this class would rather purchase a red wine than opt-out. Because of this, *Class 1* can be defined as the “Red wine enthusiasts”.

H_0^2 cannot be rejected in *Class 2* (with 33% of membership probability) as well. Here the interaction effect between the calorie content attribute and the information treatment is insignificant. However, we observe positive and statistically significant interaction coefficients with "*Unfiltered*" wine attribute. This suggests rejection of H_0^3, as we did for *Class 1*. When we examine the main effects, we find positive and significant mWTP only for *Hand-picked* attribute. *Biodynamic* is even disliked. So, this class tends to cluster consumers who were indifferent about the role of most investigated attributes. Hence, *Class 2* can be referred to as the class of consumers who are "Uninterested in red wine".

Class 3 (22% of probability) can be labeled as “Wine quality lovers”. With the only exception of *Unfiltered* wine, this class displays positive and statistically significant mWTPs for all the quality attributes, including for *Alc.Content* (Ma et al., 2024), which is insignificant in Classes 2 and 4. None of the interactions with information treatment are statistically significant. This implies, respectively, failure to reject H_0^2 and outright rejection of H_0^3. We note a negative and significant information treatment effect on the opt-out alternative, suggesting that respondents tend to be willing to pay more for wine when provided with nutritional information. The negative interaction effect between the ASC_{nobuy} and the treatment may be interpreted as the price premium respondents would be willing to pay to have access to nutritional information.

Class 4 is the residual and lowest probability class (5% of probability), characterized by statistically significant high mWTP. Structural results in small probability classes need to be evaluated with caution, especially in terms of magnitudes of implied mWTP estimates. Given the small probability of membership of this residual class, we abstain from providing an interpretation of the resulting utility structure. We simply note that these consumers are likely random choosers, not making the necessary trade-offs between wine attributes.

5.4 Exploring latent preference class composition

We explore the correlation of selected socio-economic variables on posterior probabilities of membership to the four preference classes by means of a Dirichlet regression (Paolino, 2001; Smithson & Verkuilen, 2006). This enables us to behaviourally validate the results of the LCM model. Amongst the explanatory variables, we have carefully selected those with information that may identify vulnerable respondents. For example, by using individuals' susceptibility to health, inattentiveness to weight status, ignorance of wine nutritional information and awareness of health effects from wine consumption (see Table A1 for a description of the implemented variables) .

The selected variables are: (1) a dummy variable with value 1 if the respondent is knowledgeable of the direct relationship between alcohol and calorie content, 0 otherwise (*CalAlc*); (2) wine labels use frequency (*WineLabel*); (3) computed *BMI*; (4) degree of health consciousness (*HealthC*); (5) a dummy variable with a value equal to 1 if the individual controls for her weight status, 0 otherwise (*WeightCtrl*); (6) a dummy variable with a value equal to 1 if the respondent perceives herself overweight, 0 otherwise (*dSBody*); (7) the eight variables capturing the degree awareness of wine/alcohol intake effect on health (from 1= totally disagree to 7=totally agree). We have also assessed information regarding the hedonistic aspect of wine consumption since this can be a determinant of wine choices. The degree of importance participants assign to the taste attribute when purchasing wine (*Taste*), the frequency of red wine consumption at home (*WineCons*) and in convivial occasions (*Conviviality*)[7] were also included, as well as the information treatment dummy variable. Finally, we have included the education level (*Education*) and annual income class (*Income*) since we observed statistically significant differences in these variables across the two subsamples (*Inf*=0 and *Inf*=1 in Table 2).

[7] A 7-point likert scale has been used to capture the degree of importance of taste in purchasing wine. The "Conviviality" variable has been generated as mean value of the variables "FRestaurant", "HomeFriends", "CRestaurant", "Aperitif" which can represent the convivial special occasions when to consume wine.

We comparatively identify as more vulnerable those respondents who are less health-conscious (*HealthC*), those with higher BMI (*BMI*), those who do not actively monitor their bodyweight status (*WeightCtrl*) or with low knowledge of nutritional information on wine (*CalAlc*). The Dirichlet regression estimates are reported in Table 4.

Table 4: Dirichlet regression estimates

	Class 1		**Class 2**		**Class 3**		**Class 4**	
Constant	-0.720	*	-0.923	**	-2.131	***	-1.948	***
	(0.462)		(0.416)		(0.493)		(0.417)	
CalAlc	-0.062		0.102		-0.090		-0.012	
	(0.100)		(0.097)		(0.097)		(0.094)	
WineLabel	-0.188	***	0.016		-0.060		-0.017	
	(0.064)		(0.065)		(0.063)		(0.062)	
BMI	-0.018	*	0.004		0.003		-0.001	
	(0.011)		(0.006)		(0.012)		(0.007)	
HealthC	0.146	**	-0.135	**	0.182	***	0.007	
	(0.067)		(0.061)		(0.064)		(0.062)	
WeightCtrl	-0.092		-0.143		0.125		0.090	
	(0.130)		(0.129)		(0.121)		(0.120)	
dSBody	-0.015		0.002		-0.153		-0.023	
	(0.111)		(0.100)		(0.112)		(0.098)	
WHB_Property	-0.030		-0.006		-0.015		-0.007	
	(0.071)		(0.064)		(0.064)		(0.061)	
WineCure	0.015		0.014		0.007		-0.028	
	(0.061)		(0.051)		(0.057)		(0.052)	
RedDesease	-0.006		-0.004		-0.042		0.035	
	(0.066)		(0.059)		(0.062)		(0.059)	
LimAlc	-0.081		0.040		-0.033		0.022	
	(0.057)		(0.052)		(0.052)		(0.051)	
ModWine	0.066		0.022		-0.027		-0.012	
	(0.063)		(0.061)		(0.062)		(0.059)	
RWHB_Property	0.074		0.021		0.064		0.019	
	(0.070)		(0.070)		(0.069)		(0.067)	
StDrink	-0.035		0.008		-0.046		-0.024	
	(0.057)		(0.050)		(0.053)		(0.052)	
HealthyWine	-0.038		0.009		-0.005		-0.013	
	(0.066)		(0.056)		(0.060)		(0.056)	
Taste	0.039		-0.086	*	0.062		0.005	
	(0.054)		(0.051)		(0.052)		(0.050)	
WineCons	-0.008		0.034		0.013		-0.013	
	(0.036)		(0.036)		(0.035)		(0.034)	
Conviviality	0.087	**	-0.071	*	0.048		0.020	
	(0.039)		(0.040)		(0.038)		(0.038)	
Education	-0.004		-0.032		0.037		-0.018	

	(0.047)		(0.046)	(0.043)	(0.044)	
Income	0.015		0.023	-0.017	0.009	
	(0.024)		(0.023)	(0.023)	(0.022)	
Inf	-0.166	*	0.072	-0.091	0.125	
	(0.100)		(0.097)	(0.096)	(0.093)	
Model Fit Statistics						
N° Observations						507[1]
LL						-4,148
AIC						8,120
BIC						7,748

***, **, * indicate significance at 1%, 5%, 10% level; numbers in parenthesis are standard errors; 1 = one respondent did not report his/her weight, making not possible the calculation of the BMI index.
Variable definitions can be found on Table A1 and Table A2 in the online appendix.

Significant determinants of the most likely class (i.e. Class 1 "Red wine enthusiasts") include those who read wine labels only infrequently (*WineLabel* is negative) and those with lower BMI. The higher probability membership of respondents with lower BMI is of extreme interest, since *Class 1* is the only class where being informed (*Inf*) increases the probability of choosing wine with higher alcohol content. The Dirichlet regression also shows a lower likelihood of membership into this class by those treated with information. We note this is a positive effect of information as in the other classes, but a higher likelihood for those with high health consciousness scores (*HealthC*) and conviviality-related consumption (*Conviviality*). The similarity of impacts on the conviviality and health consciousness variables in Class 1 corroborates findings from previous studies (Pitt, 2017; Higgins & Llanos, 2015; Samoggia, 2016), which highlighted health and hedonistic motives as being joint drivers of wine consumption. Class 1 resembles the cluster identified in Samoggia's study (2016) and named the "Optimistic", who are inclined to consume wine because they perceive it as a "healthy" indulgence. The positive interaction effect between the alcohol content and the information treatment (Table 3) may then be explained by the fact that individuals who tend to be part of this class are also those who use fewer wine labels and, therefore, might give less attention to the calorie content. Another perspective is that the more health-conscious individuals consider the calorie content of higher-alcohol wines acceptable for the special occasions during which they typically consume wine, particularly because they have low BMI.

The interplay between health and hedonistic reasons for consuming wine is also confirmed by the explanation of Class 2 membership, namely the “Uninterested in red wine” group (column two of Table 4). In fact, we observe that respondents who tend to be less health conscious, who do not tend to drink wine on convivial occasions, and who care less about the taste when selecting a wine, are those with higher membership probability to this class.

Column three shows that health consciousness is the main driver of membership in Class 3. The more a respondent is health-conscious, the higher her membership probability to Class 3, the "Wine quality lovers". The preference for clean labels from health-conscious consumers is actually in line with the current literature (Staub et al., 2020; Bazzani et al., 2024) that shows that those who are more health-conscious are generally willing to pay a premium for "natural" and "clean" wines. The results on preference for higher alcohol wines are actually in line with the study by Samoggia (2016) who showed that health-oriented consumers (the so-called "medical" cluster) prefer red wine with a higher alcohol degree since they perceive this as a heathier alternative to white wine, even when the latter has a lower alcohol content. Health consciousness can explain the negative interaction effect between the treatment and the no-buy alternative. This finding aligns with the existing literature that shows that more health-conscious individuals are those who tend to value nutritional information on food products (Drichoutis et al., 2005).

Finally, none of the variables explains for likelihood of membership to Class 4.

6. Discussion and policy implications

In the present work, we addressed the issue of policy measures imposing nutritional labelling on wine as an eminent example of an alcoholic beverage. We drafted three hypotheses concerning the effects of such a policy measure and developed a stated choice web-survey with information treatments that provided us with suitable data to test these.

Our first hypothesis pertains to consumer's knowledge of the relationship between alcohol degree and calorie content. Consistently with previous research (Bui et al., 2008), we observe a notably low level of objective knowledge of this relationship in our sample: less than half of the sample correctly answered a question regarding such a relationship. We further note that placing nutritional information on the label did not produce an effective nudge in terms of increasing consumers' knowledge of the relationship between alcohol and calorie content.

Our second hypothesis regards the effect of nutritional labelling on wine selection focusing on a potentially unhealthy wine characteristic, that is, its alcohol content. We reject the null hypothesis that proving calorie content information encourages the selection of low-alcohol options, thereby reducing calorie intake. On the contrary, we observe an increased preference for wines with higher alcohol for individuals who had been exposed to the calorie content information. In our latent class random utility model, this effect is apparent in the largest preference class (40% of membership probability). However, in preference Class 3 we observe that respondents tend to have higher WTP for wine bottles displaying calorie information, given the negative interaction effect between the information treatment and the "opt-out" alternative.

We reject the third null hypothesis on information treatment having a negative effect on respondents' evaluation of wine quality attributes. This result should reassure those stakeholders in the wine industry who feel their quality efforts are threatened by the implementation of the nutritional labelling policy (Pabst et al., 2019a).

Together these findings indicate that the display of calorie content was generally appreciated by respondents, suggesting that the adoption of nutritional labelling policy is positively valued. This is in line with the studies by Annunziata et al. (2017) and Vecchio et al (2018). The observed interest of respondents toward the calorie information supports the relevance of empowering consumers to make more informed decisions, even when it comes to wine products. This emphasizes the need to bridge the gap between alcohol and food through policy measures mandating nutritional labelling. Moreover, although we do not observe an increased preference for lower calorie wines in case of the informed consumers, nutritional labelling has generally a positive effect on mWTP for "clean" labels that are generally associated with healthiness (Bazzani et al., 2024; Staub et al., 2020). This implies a higher WTP for healthier options when nutritional information is provided. Also, note that in the "Red wine Enthusiast" cluster, calorie information did not deter respondents from selecting higher calorie wine options. This cluster is inclined to seek healthier wines with "clean" production claims and low alcohol content (Table 3) and correlates with health-conscious individuals. However, they may perceive red wine consumption as a "healthy indulgence" (Higgins & Llanos, 2015; Samoggia, 2016), particularly during social gatherings. This tendency to prioritize health but still occasionally indulge may contribute to their overall tendency to disregard wine label information and, therefore, wine calorie content. This latter aspect may imply that employing easy-to-read and visually engaging nutritional labels, as recommended by Walkers et al. (2019), could serve as a more effective communication strategy. This could reduce the cost associated with accessing and retaining information for consumers. Consequently, this could facilitate an effective nudge toward making lower-calorie choices. This finding may also indicate the need for additional educational policy measures to enhance consumers' utilization and comprehension of nutritional information. Pabst et al. (2021b) highlight the important role that communication may play in increasing consumers' awareness of alcohol consumption. We then suggest that adequate communication of wine's nutritional properties by mass media and policymakers should support and supplement the implementation of nutritional labelling in nudging consumers toward healthier choices (Diaconeasa et al., 2021).

A significant finding for policymakers is that more vulnerable individuals, namely those with higher BMI, have lower membership probability to Class 1, namely the group of consumers who selected higher calorie wine options when nutritional information was provided. Our study presents positive implications for the wine industry as well. Consumers who prioritize quality attributes in wine (Class 1 and Class 3) show either insignificant or positive effects of nutritional labelling on preference structure for wine quality attributes. Similarly, nutritional labelling does not (negatively) influence the choices of consumers who place less importance on the quality aspects of wine (Class 2). Hence, our findings indicate no adverse effect of nutritional labelling on consumer preference for wine qualities, contrary to the concerns expressed by certain stakeholders in the wine industry (Pabst et al., 2019a).

7. Conclusions, limitations, and future research

In the last decade in Europe, there has been a much participated policy debate regarding nutritional labelling in the alcoholic beverage industry. While stakeholders from such industry have been skeptical, the European Commission has encouraged the adoption of nutritional labelling in order to align the information gap between alcoholic beverages and food products (European Commission, 2017; OIV, 2022). In this study, we focused on wine consumers and tested the potential of the policy on nutritional labelling for alcoholic beverages on wine consumer choice in a traditional wine-consuming country like Italy.

In line with some studies (Bui et al., 2008; Meyerding et al., 2019; Wright et al., 2008), our results scarcely support the hypothesis that reporting calorie content on wine packaging would encourage the selection of lower-alcohol options and an increased wine nutritional knowledge. However, our research reveals that nutritional labelling either has no effect or positively influences how consumers value wine quality attributes. Overall, consumers showed appreciation for the presence of calorie content on wine labels, supporting the adoption of nutritional labelling policies.

It is important to note that strong policy recommendations should not be predicated on the basis of stated preference studies alone, and that further testing is needed. First of all, this study is limited to the use of calorie content, assuming that this will be the only on-label mandatory nutritional information (OIV, 2022). However, the EU regulation also imposes the use of off-label formats (QR code) containing ingredient information and the nutritional fact panel. Given the digital nature of our experiment, we were unable to test consumers' use of the QR code and the effect of off-label nutritional information on their preference structure. This is something we suggest as the subject of future studies. We also recommend corroborating our results using different labelling formats to help determine what communication strategy is the most effective in nudging consumers toward healthier choices. While we have focused on only one type of alcoholic beverage (i.e. dry red wine), we also suggest extending this research to different types of alcoholic beverages, such as different types of wine, beer, etc. An additional aspect worth studying would be the use of products with different sugar contents (not only with different alcohol content) and to assess individuals' choice behaviour toward product alternatives with a larger variation of calories and/or nutritional content. While our study is limited to Italian consumers, it is clear that the implementation of a nutritional labeling policy on alcoholic products is worth exploring in different countries to account for different cooking and drinking cultures.

Finally, an important limitation of our work is the hypothetical nature of our survey. We hope that our study can be replicated in non-hypothetical settings or in real-choice contexts, such as stores or restaurants. Besides this, it is important to point out that the choice of alcoholic beverage, especially for wine, is influenced by food choices and vice versa. Recently, the food choice literature has shown some interest in "basket choices" (Caputo & Lusk, 2022; Franceschinis et al., 2022; Neill & Lahne, 2022). Hence, we believe that future research investigating the effect of nutritional labelling on consumers' alcoholic beverage preferences should also account for food alternatives that consumers may trade-off when choosing something to drink.

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Appendix

Table A1: Wine consumption behaviour and wine attitudes across *Inf*=0 and *Inf*=1 treatments

Variable	*Inf*=0 (n=278)	*Inf*=1 (n=281)	P-value
Red wine home consumption at home (WineCons)			
	Frequency (%)	Frequency (%)	
Once a month	8.27	7.47	
Two or three times a month	6.83	3.56	0.808
Once a week	10.43	10.32	
Two or three times a week	16.55	21.71	
More than three times a week	22.30	22.06	
Everyday	35.61	34.88	
Wine label use (WineLabel)	Mean	Mean	
	4.91	4.96	0.515
Wine servings (glasses) normally consumed in a setting (WineServing)			
	Frequency (%)	Frequency (%)	
Half glass	8.99	9.61	
1	30.22	31.67	
2	39.57	41.64	
3	16.19	11.74	0.399
4	2.88	2.85	
5	1.08	0.71	
More than 5	1.08	1.78	
Wine Involvement (WineInv)	Mean	Mean	
	4.82	4.77	0.666
Wine consumption occasion			
	Median	Median	
Wine with meals at restaurants during important occasion (e.i. birthday, business meeting) (FRestaurant)	3	3	0.661
Wine with meals at a friend's house (HomeFriends)	4	4	0.672
Wine with meals at casual restaurants (CRestaurant)	3	3	0.446
At bars during aperitif (Aperitif)	3	3	0.421
Wine with meals at home alone (HomeAlone)	4	4	0.666
Wine with meals at home with family (HomeFamily)	5	5	0.297
Awareness of wine/alcohol intake effect on health			
	Mean	Mean	
Wine can reduce the risk of certain disease (RedDisease)	5.007	5.021	0.861
I think wine is a healthy alcoholic beverage (HealthyWine)	5.191	5.043	0.183

It is important to limit the amount of alcohol you consume (LimAlc)	5.881	5.819	0.676
I know what moderate wine drinking is (ModWine)	5.752	5.665	0.411
I understand how many standard drink of wine is healthy (StDrink)	5.428	5.242	0.266
Wine can cure certain diseases (WineCure)	4.953	4.858	0.439
Wine has better health properties than other alcoholic beverages (WHB_Property)	5.428	5.455	0.855
Red wine has more health enhancing property (RWHB_Property)	5.424	5.43	0.997
Perceived adequate number of wine servings (glasses) consumed in a setting (serving)			
	Frequency (%)	Frequency (%)	
Half glass	8.63	8.19	
1	28.42	30.96	
2	38.49	39.5	0.473
3	15.47	13.52	
4	4.32	5.34	
5	2.52	1.42	

Table A2: Health consciousness and weight-related information across INF=0 and INF=1

Variable	*Inf=0* (n=278)	*Inf=1* (n=281)	P-value
Self-body perception (SBody)			
A lot under	0.72%	2.14%	
A little under	8.27%	6.41%	
About ideal	37.77%	43.06%	0.185
A little over	39.57%	39.15%	
A lot over	13.67%	9.25%	
BMI (mean)	25.09	24.11	0.096
Weight status control (WeightCtrl)			
I'm trying to lose weight	35.25%	32.03%	
I'm trying to maintain my weight	44.24%	49.11%	0.514
I don't do anything to regulate my weight	20.50%	18.86%	
Health consciousness (HealthC)	5.41	5.40	0.895

Table A3: Correlation matrix of non-attended nutritional information and attitudinal variables in *Inf=1*

Correlation	*CalAlc*	*WineLabel*	*BMI*	*HealthC*	*WeightCtrl*	*SBody*	*Non-attended nutritional info*
CalAlc	1						
WineLabel	-0.020	1					
BMI	-0.017	0.118*	1				
HealthC	0.105*	0.400*	-0.053	1			
WeightCtrl	0.053	0.109*	0.177*	0.035	1		
SBody	0.082	0.007	0.634*	0.011	0.210*	1	
Non-attended nutritional info	-0.036	-0.056	0.127*	-0.161*	-0.012	0.125**	1

Table A4: Two-sample Kolmogorov-Smirnov test for equality of distribution functions across the information treatments (*Inf*=0, *Inf*=1)

	H_0: Treat = Control	
	Δ	p-values
Handpicked	0.238	<0.001
Unfiltered	0.360	<0.001
Organic	0.209	<0.001
Biodynamic	0.130	<0.001
Biodiversity	0.163	<0.001
Alcohol	0.291	<0.001

Table A5: Estimates from LC-RPL model

	Class 1 (40%)			Class 2 (33%)			Class 3 (22%)			Class 4 (5%)		
Parameters	*Coeff.*	*SE*	*P-value*	*Coeff.*	*SE*	*P-value*	*Coeff.*	*SE*	*P -value*	*Coeff.*	*SE*	*P-value*
Intercept	0.692	0.118	<0.001	0.508	0.098	<0.001	0.089	0.143	0.530	-1.289	0.178	<0.001
Mean: Hand-picked	0.622	0.162	<0.001	0.492	0.123	<0.001	1.630	0.310	<0.001	9.789	2.707	<0.001
St. Dev.: Hand-picked	0.882	0.135	<0.001	0.150	0.126	0.240	0.505	0.231	0.029	0.733	0.776	0.340
Mean: Unfiltered	0.477	0.147	0.001	-0.115	0.120	0.340	0.027	0.322	0.930	0.059	0.844	0.940
St. Dev.: Unfiltered	0.847	0.121	<0.001	0.187	0.140	0.180	1.498	0.226	<0.001	1.897	0.622	0.002
Mean: Organic	0.645	0.182	<0.001	0.184	0.147	0.210	2.152	0.290	<0.001	6.288	1.664	<0.001
St. Dev.: Organic	0.721	0.141	<0.001	0.288	0.159	0.070	0.332	0.191	0.083	5.367	1.765	0.002
Biodynamic	-0.244	0.178	0.170	-0.464	0.178	0.009	1.999	0.337	<0.001	-0.380	1.018	0.710
Biodiversity	0.470	0.173	0.007	-0.173	0.168	0.300	1.753	0.294	<0.001	-10.691	4.935	0.030
Mean: Alc. Content	-0.140	0.050	0.005	0.023	0.050	0.640	0.287	0.099	0.004	0.352	0.271	0.190
St. Dev.: Alc. Content	0.011	0.031	0.730	0.055	0.011	0.000	0.167	0.026	<0.001	0.939	0.229	<0.001
ASC_{nobuy}	-5.575	0.752	<0.001	0.039	0.644	0.950	1.972	1.268	0.120	-1.435	3.311	0.660
Price	-0.137	0.008	<0.001	-0.137	0.008	<0.001	-0.137	0.008	<0.001	-0.137	0.008	<0.001
*Price * Higher Income*	0.057	0.011	0.000	0.057	0.011	0.000	0.057	0.011	0.000	0.057	0.011	0.000
Treatment effects												
*Hand-picked*Inf*	-0.190	0.219	0.390	-0.148	0.167	0.370	0.462	0.496	0.350	-8.535	2.663	0.001
*Unfiltered*Inf*	0.004	0.203	0.990	0.425	0.161	0.008	0.065	0.433	0.880	-0.474	0.942	0.620
*Organic*Inf*	-0.157	0.251	0.530	-0.252	0.209	0.230	0.409	0.419	0.330	-1.775	1.279	0.170
*Biodynamic*Inf*	0.265	0.247	0.280	-0.059	0.243	0.810	0.227	0.421	0.590	1.141	1.176	0.330
*Biodiversity*Inf*	-0.228	0.232	0.330	0.158	0.222	0.480	-0.018	0.444	0.970	9.850	4.915	0.045
Alcohol content Inf*	0.146	0.070	0.038	-0.040	0.070	0.570	-0.200	0.131	0.130	0.461	0.330	0.160
*ASCnobuy*Inf*	0.071	1.396	0.960	-0.774	0.889	0.380	-2.734	1.599	0.087	4.761	3.942	0.230
Model fit Statistics					***, **, * indicate significance at 1%, 5%, 10% level							
N° Obs												508
LL												-5090.42
BIC												10660.5779
AIC												10334.8309
AIC3												10411.8309

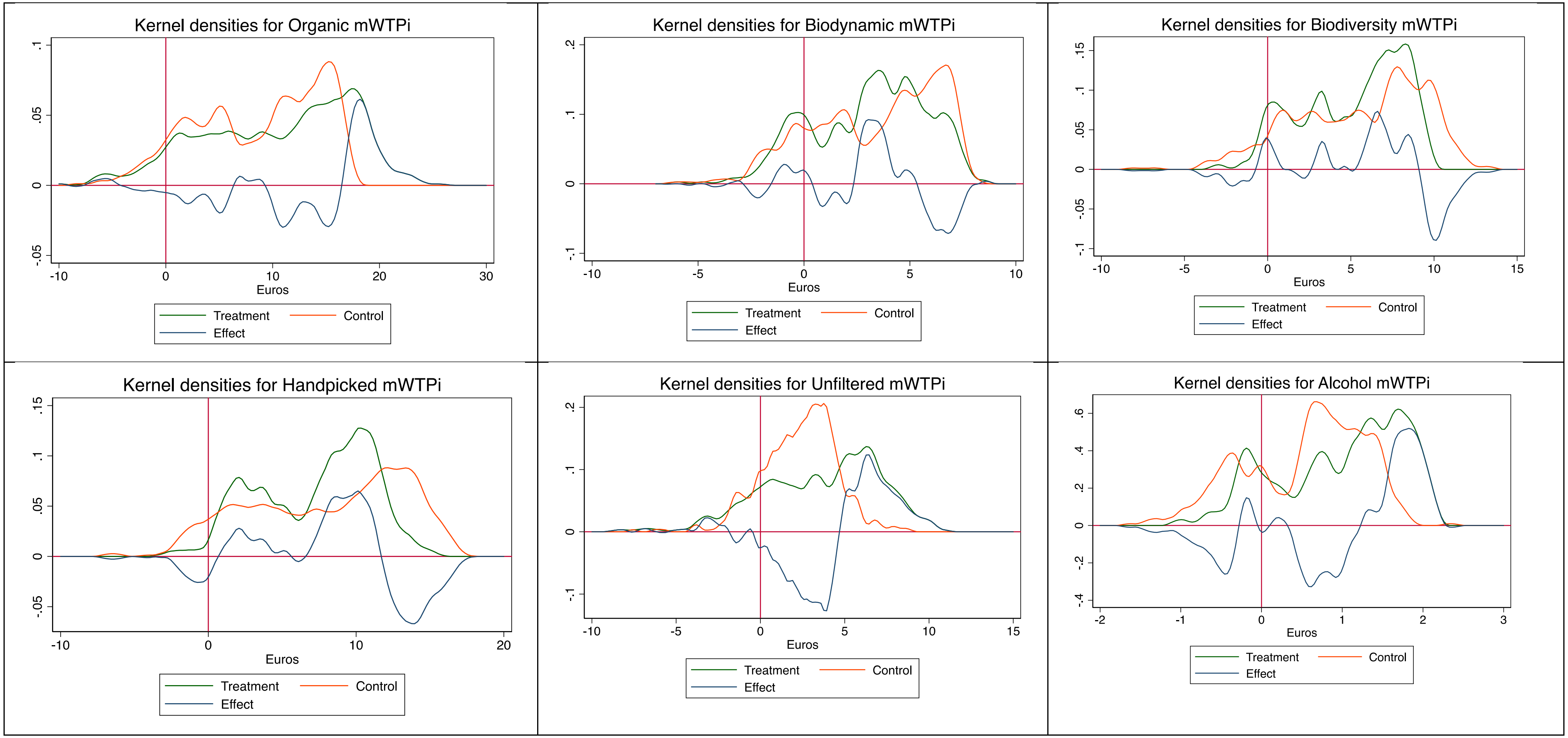

Figure A1: Distributions of individual mean mWTP value estimates from Mixed Logit Models in WTP space

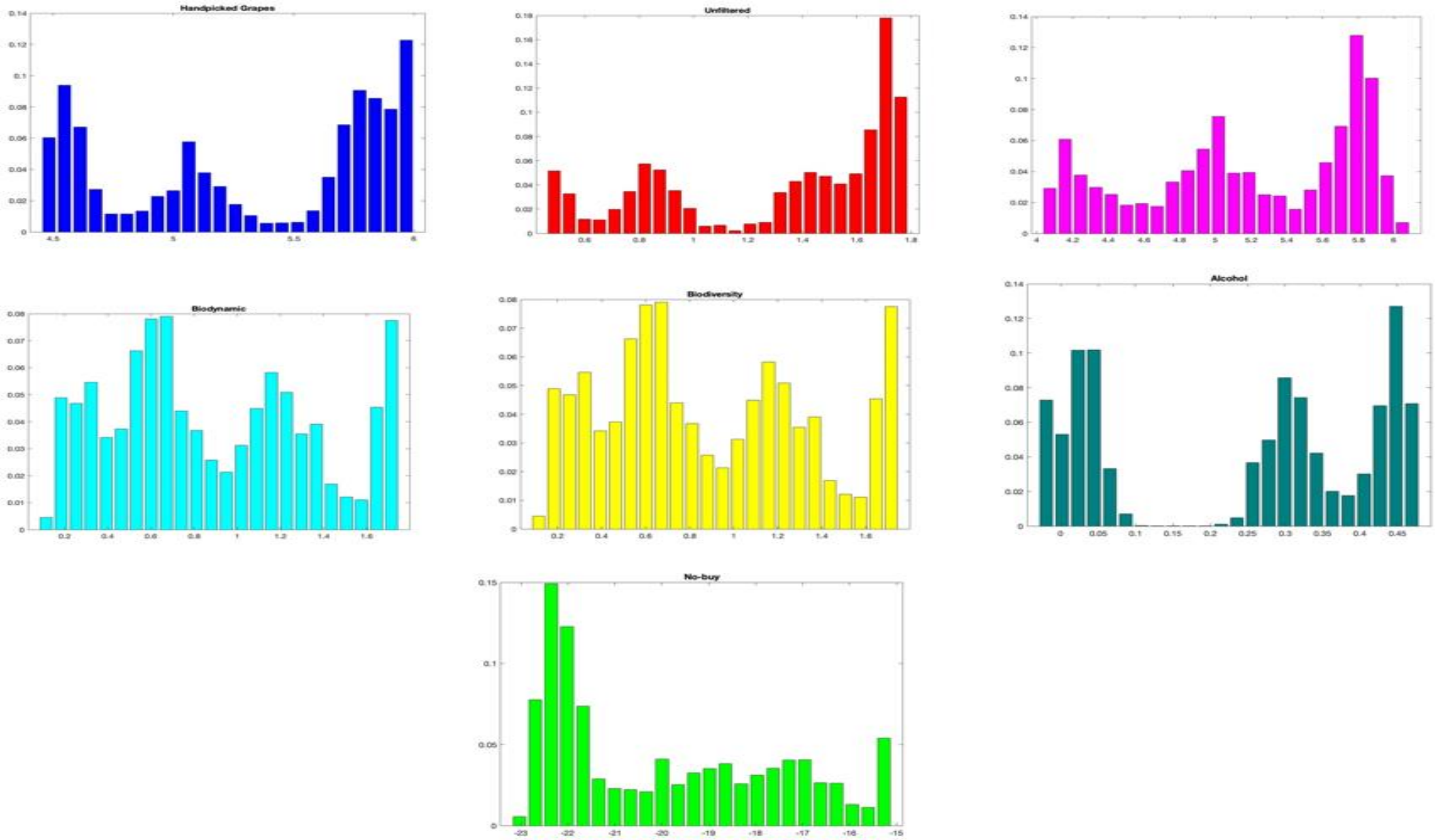

Figure A2: Distributions of mWTP value estimates from LML model in WTP space