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Consumers WTP for wine with certified origin: Latent classes based on attitudinal responses

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Abstract

This paper investigates preference heterogeneity of wine consumers by using latent class models based on attitudinal questions. Such responses turn out to be an important source of additional information when the goal is to identify different groups of people with a similar wine preference structure. We assume that preferences are latent and the responses to attitudinal questions are the visible effect of this latent heterogeneity. We find evidence of 4 different classes of respondents with similar response patterns. We focus on preferences for a well-known wine, the Prosecco, and sample the population in the area of production. For each preference-class we estimate a class-specific WTP equation for this wine, so as to estimate the class responsiveness of WTP to various determinants. Estimates for a 4-class model are discussed in detail to illustrate the potential of this approach in characterizing the preferences of local consumers for the two most common certifications of origin.

Key words: Latent Class Attitudinal model, consumer preferences, organic products, WTP, unobserved heterogeneity.

1 Introduction

The European wine market is becoming increasingly globalized. As a result locally produced wines need to compete with a much wider set of alternative wines produced the world over. In this market setting consumers perceptions and evaluation of local production and certification of origin take a much more important role than ever before, especially in countries with a traditionally strong wine industry. The empirical characterization of preference heterogeneity is at the basis of every successful marketing operation, and the main concern of this study.

Market research analysts are often interested in understanding the sources of systematic differences in consumer preferences. Survey data often include responses to questions regarding the importance placed by the respondent on product attributes, the outlet of purchase outlet and venue of wine consumption (home, bar, restaurant, winery, etc.). Often the information conveyed by responses to these questions, often does not enter the structure of econometric models of standard consumer's behavior. Sometimes this kind of 'attitudinal data' are considered as a mere 'warm-up exercise', leading the respondents into a suitable frame of mind adequate to formulate answers to questions which are considered more important, such as product choice or willingness-to-pay. Nevertheless, attitudinal data can be an important source of additional information, especially when the goal is to identify different groups of people with a similar preference structure, the so-called preference 'classes' (or groups, or segments).

In this paper we assume that the answers to these questions reflect exogenous well-behaved preferences for wine. We assume that preferences are latent or unobserved and that the responses to these attitudinal questions are the visible effect of this latent heterogeneity. Our ultimate objective is to derive the sample stated WTP for Prosecco wine and characterize them differently by means of class-specific WTP equations.

The estimated marginal effects on class-specific WTPs are then used to validate the latent preference-class structure, and the expected behavior of respondents belonging to each of the identified classes. We develop a latent class model of preferences based on responses to what we—following Morey et al. (2006)—broadly termed 'attitudinal responses'. Although latent-class models are not novel in the literature (Titterington et al. 1985, Bartholomew & Knott 1999, Wedel & Kamakura 2000), this model, denoted as latent-class attitudinal (LCA) has not seen wide implementation (Clogg & Goodman 1984, McCutcheon & Nawojcyzk 1995, Eid et al. 2003). In this application we first explore the kind of information one can obtain from this approach by using attitudinal data on wine purchase and consumption in the North-East of Italy. We use our analytical findings to speculate about the appeal of different labelling strategies of the Prosecco wine, that is the CDO label and the TGI label (Alfnes & Rickertsen 2003, Steiner 2004, Cuyno et al. 2001).

The rest of this paper is articulated as follows. In the next section (2) we provide the motivation and the background for this applied study. In section (3) we describe briefly the latent-class attitudinal approach and its application to the case at hand. A description of the data and of the most relevant features of the sample are reported in section (4). A discussion of the conduct and results of the statistical analysis are reported in section (5). Section (6) concludes and summarizes the main findings.

2 Prosecco wine and certification of wine origin

In Italy the most common form of public certification for quality wines are CDOs (Controlled Denomination of Origin) and TGIs (Typical Geographic Indication). In order to be able to market a wine under either of these systems of certification of origin a wine producer must comply with a specific Production Regulation. CDO wines are produced in areas with specific climatic, historical and soil characteristics, from grapes of a given grapevine type cultivated in a prescribed fashion. The combination of these factors with a specific production protocol result in a typical set of well-recognized and stable wine characteristics. Each CDO trademark is ruled by a decree that defines the production area, the authorized cultivars, vineyard management and wine making techniques. A CDO guarantees the wine origin, the method of production and the product's final characteristics which must comply with those stated by the Regulation.

TGI trademarks are governed by less restrictive production rules than those that apply to CDO ones. In our production context—that of Venetian wines based on the 'Prosecco' grapevine cultivar—there are three TGIs and two CDOs wines. Of the CDO the Conegliano-Valdobbiadene (henceforth abbreviated as C-V) is by far the most economically important one. The success of C-V has been continuously growing for the last fifteen years, in terms of both expansion of vineyard area and volume of grape and wine production, reaching 15% of the total of Venetian CDO wines. During the period 1994-2004 the volume of bottled wines increased by a remarkable 60%, but still more remarkable has been the increase in the quantity of bottled sparkling wine (+80%). This means that, within the boundaries of the area of Denomination'sparkling wine production' is establishing progressively stronger roots. As a percentage of the toal bottled wine production the share of sparkling wine has shifted from 72% in 1994 to 81% in 2004. Exports of C-V CDO Prosecco have also grown, jumping from 23% in 1994 to 35% of the total production in 2004, demonstrating the increased popularity of this wine abroad. The main foreign market destination has been Germany, with a current 70% export quota (Galletto 2005).

Despite these extraordinary results, some rain clouds have been gathering on the horizon. While most other well-established wines are identified by and often named after their geographical area of production (e.g. Chianti, Champaign, Valpolicella, etc.), C-V CDO Prosecco is distinctive in its linkage to the name of the name of the grapevine variety. This trait makes it more vulnerable to imitation and competition with Prosecco wines produced in areas outside the original boundaries defined by the current production protocols, making its distinction in the retail market more difficult. In an international market place where 'Italian-sounding' products, produced and marketed abroad, are costing Italian industry billions of Euros worth of trade every year, this is a major concern.

Therefore, while the market features of Prosecco brands have been well studied (see Barisan et al. 2005, for a recent survey), there is a real interest among Prosecco producers to have a better understanding of the determinants of market value belonging to their collective brand compared with the Prosecco TGI ones. In order to start to investigating these determinants a survey has been carried out at a local level, specifically in the C-V Prosecco CDO production zone, where knowledge of this wine should be greater than in other places.

3 Explaining WTP for the Prosecco wine in a LCA framework

Despite the name 'Prosecco' having achieved the status of household brand-name in most of northern Italy, customers are likely to differ in terms of their knowledge about the different types of Prosecco wines. Currently, Prosecco wine is sold in a number of different outlets which operate a differential form of pricing, a fact which implies the existence of willingness to pay (henceforth WTP) heterogeneity amongst consumers.

Despite this observed diversity in WTP, there is limited knowledge of the determinants of the difference in value between IGT and DOC. In this study we assume that Prosecco wine consumers segregate into groups (or classes) with similar WTP structure on the basis of various factors determining their attitudes towards wine consumption. The main aims of the econometric analysis are therefore to derive the individual membership probabilities to classes with homogeneous preferences, and to identify for each class parameter estimates for the determinants of WTP for Prosecco wine.

3.1 Membership probabilities and WTP equations

Individual membership probabilities to each attitudinal class c for wine purchase (or $\pi(c)$) are informed by the individual-specific patterns of responses (Likert scores) to 'attitudinal questions' or x_{iqs}, where i denotes the individual, q the question and s the Likert score given as a response to questions about the above mentioned factors. The result is a (discrete) mixed density of estimated equation errors for each individual respondent, or $\hat{\varepsilon_i}$, where the mixing variables are the individual membership probabilities conditional on x_i, or $\pi(c|x_i)$. The underlying equation structure is linear $\hat{\varepsilon}_i = \sum_{c=1}^{C} \pi(c|x_i)\hat{\varepsilon}_{i|c}$ where: $\hat{\varepsilon}_{i|c} = \phi(WTP_i - \hat{\beta}_c'\mathbf{x}_i)$ and $\phi(\cdot)$ denotes the standard normal density function, so that $E[\varepsilon_{i|c}] = 0$.

The ML estimate for the marginal effect for each determinant k conditional on the class c is $\hat{\beta}_{ck}$. The estimated average marginal effect for the individual consumer i in the sample is given by the weighted average $\sum_{c=1}^{C} \pi(c|x_i)\beta_{ck}$. The derivation of the individual probability of membership to a class for i, or $\pi(c|x_i)$, is explained in what follows.

3.2 Attitudinal latent classes from response patterns

A latent class attitudinal model allows the analyst to identify groups of people having different preferences, as reflected by their self-reported attitudes. Typically, questions used in a survey are Likert-scale attitudinal questions. Here is an example of one such question we asked in the survey:

> On a scale from 1 to 5 where 1 means "Not interested at all" and 5 means "Very much interested", answer the following question. When you buy a bottle of wine, how important is the brand of the wine to you?

Basically, with this particular question we expected to identify segments of people who place much importance on the wine brand, as well as others who do not care so much or do not care at all. Each of these groups will be characterized by other peculiar characteristics, which tend to vary among groups but not much within the group. People with a high probability of being placed in the same group are homogenous with respect to their attitude scores. As a result they are expected to have similar underlying preferences.

The assumption of latent class models is that a person belongs to a specific group, but that the class membership is unknown or latent. As a consequence, people belonging to different classes will have different preferences and will therefore answer in different ways to attitudinal questions. The interesting thing is that the number of classes is estimated by the model without the imposition of any restriction, hence allowing for a wider range of preference heterogeneity. This implies that the researcher does not have to assume a single distribution for the parameters or a specific functional form.

The LCA model estimates the conditional probability for a person to belong to a group c, expressed as a function of specific answers given to attitudinal questions (Morey et al. 2006). Let's assume that the population can be divided into C groups having different preferences. The researcher does not know the preference class to which the individual belong since this is latent. The model provide estimates of the conditional membership probabilities $\pi(c|x_i)$. These are the probabilities that a single person belongs to a certain class conditional on his answers to the attitudinal questions.

The key note of the latent class attitudinal model is the response probabilities $\pi_{qs|c}$, that is the probability that an individual in group c answers s to attitudinal question q. The goal of the LCA model is to estimate the response probabilities and the number of preference classes that best describe the observed response patterns. Given these assumptions, the probability that an individual has a given response pattern x_i can be considered as part of a discrete mixture of C multinomials (Morey et al. 2006):

$$\pi(x_i) = \sum_{c=1}^{C} \pi(c)\pi(x_i|c) = \sum_{c=1}^{C} \pi(c) \prod_{q=1}^{Q} \prod_{s=1}^{S} (\pi_{qs|c})^{x_{iqs}}, \tag{1}$$

where $\pi(x_i|c) = \prod_{q=1}^{Q} \prod_{s=1}^{S} (\pi_{qs|c})^{x_{iqs}}$ is the probability of the individual's response pattern conditional on being in group c.

As usual, the issue is to find the parameter values that best explain the response patterns, that is to find the conditional probabilities $\pi_{qs|c}$ and marginal probabilities $\pi(c)$ maximizing the log-likelihood function

$$\mathcal{L} = \sum_{i=1}^{N} \ln[\pi(x_i)] = \sum_{i=1}^{N} \ln \left[\sum_{c=1}^{C} \pi(c) \prod_{q=1}^{Q} \prod_{s=1}^{S} (\pi_{qs|c})^{x_{iqs}} \right], \tag{2}$$

subject to $\sum_{s=1}^{S} \pi_{qs|c} = 1$ and $\sum_{c=1}^{C} \pi_c = 1$. The $\pi_{qs|c}$ that maximize equation 2 are

$$\pi_{qs|c} = \frac{\sum_{i=1}^{N} \pi(c|x_i) x_{iqs}}{\sum_{i=1}^{N} \pi(c|x_i)}. \tag{3}$$

The denominator in equation 3 estimates the number of individuals in group c, while the numerator provides an estimation of the number of individuals in group c that answered level s to question q.

It can be observed that, $\pi_{qs|c}$ depends on the conditional membership probabilities $\pi(c|x_i)$, which are unknown. Hence there is insufficient information to maximize the likelihood function. The E-M (expectation-maximization) algorithm is a technique that can be used to obtain maximum likelihood estimation whenever there is incomplete information (Dempster et al. 1977, Bartholomew & Knott 1999). Basically, in the algorithm unobserved information is replaced by expected values and followed by a search for the maximum of the log-likelihood function as if these expectations were correct. Subsequently, the maximum likelihood estimates are used to update the original expectations. The process is reiterated until convergence according to some criterion.

4 The data

The data on stated WTP and attitudinal responses were obtained by a questionnaire-based survey administered to a sample of the population of local consumers, specifically in the C-V Prosecco CDO production zone, where knowledge of this wine should be greatest. The survey gathered data on the socio-economic characteristics of respondents' commonly used for market segmentation (place of residence, gender, profession, educational level, knowledge of wine), wine consumption and purchase (places, frequency, etc.), the respondents' knowledge of the wines made from Prosecco grapes and their denominations and, finally, the respondents' WTP for a single standard (75 cc) bottle of Prosecco —CDO and TGI—in the four most popular outlet categories, namely supermarkets, wineries, restaurants and wine shops. Eight of these venues (two of each kind) were chosen as data collection places, where we obtained between 40 to 55 completed questionnaires per venue. The total sample included 372 sets of consumer responses all randomly chosen at intercept point.

The sample statistics indicate that the selected sample is a good representation of the local population and—more generally—that of wine consumers in Italy. The sample included a broad majority of men (75%), who were mostly middle aged (41% within the 30-44 year class and 32% within the 45-60 class). Half of them live within the boundaries of the C-V CDO Prosecco; a second group (31%) dwells in other parts of the province of Treviso, in which knowledge of Prosecco is supposed to be greatest, 11% comes from other Veneto provinces and 8% from outside Veneto. Most of respondents (87%) are working and 35% are self-employed. Their educational level is good, with 57% having a high school diploma and 25% with some kind of university education.

The majority (57%) have families with 3 to 4 persons, and earn more than 2000Euro/month, an amount which can be translated into sufficient purchasing power available for partially luxury good such as many CDO Proseccos. Most of them (69%) are 'generic' consumers, hence not deeply interested in wines, but who usually drink it. Only 8% of them are self-reporting as 'expert tasters' (e.g. wine stewards or similar) and 10% carry out activities in wine-related fields, and so may be expected to know more than most people about wines, including the local Prosecco wine.

Wine purchase is common in all the sale channels, except in supermarkets where three fifths of the sample never buy wine. The highest frequencies occur in restaurants, bars and taverns. Similar percentages were found for those consumers who often visit wine shops and those who never go in these sale points, 30% and 31% respectively. Only 10% never buys at a winery.

Among factors that influence the choice of a wine, taste or sensorial quality ranks first, while at the bottom we find advertising, which is a promotion tool little used by many Italian wine firms. A low level of attention is paid to label and TGI certification, while CDO and price appear quite important.

As expected, respondents who come from a wine growing area were found to have quite good knowledge of local wine. The CDO acronym appear fairly well-known. In fact, 57% correctly answer that CDO is 'the guarantee of origin from a specific territory' and 35% stated that CDO indicates 'a wine of superior quality with respect to a TGI one,' which is not always true, but in most cases it would be. The exact meaning of TGI instead, was correctly indicated by only 65% of the sample. One fifth of respondents has no idea about the quality relationship between CDO and TGI wines.

A similar level of knowledge was recorded for the correct classification of the Prosecco wines. Four fifths of the sample identified each brand correctly as CDOs or TGIs. Conegliano Valdobbiadene is the most commonly known wine, while the other CDO wines are the least known. A little less than 60% knows the three TGIs but it is worth noting that 22.6% made no mistake in classifying all the five denominations, revealing a very widespread familiarity with Proseccos' winebrands.

5 The latent groups

5.1 Response selection

As previously indicated, the survey instrument included a large number of attitudinal questions. The venue i which wine consumption takes place of from which wine is purchased is often considered to be an important aspect of the experience and so in our investigation we examined the potential connection between type of wine outlet and consumer preference.

To investigate attitudes towards wine outlets, intensity of attitudinal responses were expressed on a 4-point Likert scale by respondents who purchased wine in restaurants, bars, supermarkets, wineries and wine shops. However, consumer attitudes on price, taste, brand, TGI or CDO label, advertising, and suggestions from friends or the seller were scored in a 5-point Likert scale.

A total of 14 responses were initially considered. However, interpreting the 45 plus 916 combinations produced by 14 sets of 4 and 5 Likert scale responses is quite a complicated endeavor, even when limited to 4-6 latent classes. We eventually reduced the number of variables by dropping in turn each set of responses to a given question and using as a criterion the impact of such an exclusion of the log-likelihood value at convergence ($\mathcal{L}$) (Table n. 1). If dropping a given set produced a relatively small reduction of the log-likelihood in equation 2, compared to the effects of dropping others, then this was taken as an indication that the set of responses was relatively uninformative. As a consequence the responses to these questions were eliminated. Using these variables we maximize equation 2 varying the number of classes from 2 to 5. This procedure enabled us to select responses to those attitudinal questions included in the appendix (results are reported in Table 2).

5.2 Characterizing the latent groups

To determine the appropriate numbers of preference groups, we followed a two-step procedure, as suggested by Bandeen-Roche et al. (1997). We first identified preference groups without socio-economics co-variates—such as age, sex, dependents, etc.—and then we included these to explore their explanatory power, which was found to be statistically insignificant. Hence the final models excluded these.

We estimated two, three and four group models with the selected responses to attitudinal questions. Preference groups can be analyzed by examining the predicted response probabilities for each class, which ranks the importance of characteristics within a group, and comparing average responses across groups.

Figures 1, 2 and 3 illustrate the average responses to the attitudinal questions for the wine consumers most likely to belong to each group. The figures emphasize differences across models with a different number of preference classes. By increasing the number of classes variability seems to increase for all the attitudinal questions considered, demonstrating an increase in taste heterogeneity in the models.

The form of heterogeneity varies within each model and across preference groups within the same model. The highest variability in terms of average scores across groups are recorded for brand, the TGI and CDO label and for the importance of advice from friends' and sellers'. At the other end of the across-groups variability range for the average scores to attitudinal questions we recorded the importance of price and the frequency of visits to wine shops.

No respondent indicated a score of one (the lowest point in the importance scale), providing evidence that the selected questions addressed attitudes of importance. The factor emerging as the most important in purchasing wine and in its consumption is the CDO label. Although its average score values vary quite a lot across groups and models, its average value is never lower than 3.8. The least important attribute is associated with the TGI label. Quite surprisingly, in only one of the four groups model is price rated as the most important across wine attributes, on average.

The average scores of the two and three class models show quite a similar pattern, for the frequency of visits to wine shops and for the importance attributed to price. Group one and two from the two-class model (figure 1) are similar to groups one and two in the three-class model. For example, in both cases, people belonging to these groups gave good scores of attendance to wine shops and they attribute a moderate relevance to price. The third and additional group of the three-class model (figure 2) shows similar responses to group 1 in the 2-class model, with the exception of attitude to brand, which records the lowest score across the three groups in this model.

The four-class model (figure 3) allows the segregation of yet another group, and preserves the other three. Thus new group (group 4) differs from the others as consumers in this class only seem to care for brand and the vendor's suggestions. By carefully inspecting figure 3 one can be persuaded that group four is probably a splinter from group two in the previous two models.

5.3 Choosing the number of classes

The number of classes with different preferences is exogenous to the estimation procedure. To establish the appropriate number of classes for a given sample the literature suggests using general information criteria based on the log-likelihood of the model and penalized for the increase in the number of parameters to be estimated. A general formulation (Wedel & Kamakura 2000) is $C = 2\mathcal{L} + \kappa J$ where $\mathcal{L}$ is the value of the log-likelihood function at convergence, J is the number of estimated parameters in the model, and κ is a penalty constant. For $\kappa = 2$ we obtain the Akaike Information Criteria (AIC); for $\kappa = \ln(N+1)$ we obtain the consistent AIC (cnAIC); for $\kappa = \ln(N)$ we obtain the Bayesian Information Criteria (BIC), which by construction is very similar to the cnAIC. Finally, for = 2+2(J+1)(J+2)/(NJ 2) we have the *corrected* AIC (crAIC) (Hurvich & Tsai 1989), which increases the penalty for the number of extra parameters estimated. However, this criterion also fails some of the regularity conditions for a valid test under the null (Leroux 1992). Asymptotically the AIC is reported to be biased towards an over-estimate of the number of preference classes, while the BIC is not, although in small sample sizes the BIC tends to favor too few classes (McLachlan & Peel 2000).

Another criterion that can be used is the entropy score which ranges from 0 to 1.

$$E_s = 1 - \frac{\sum_{i=1}^{N}\sum_{i=c}^{C} - \Pr(c|x_i)\ln(\Pr(c|x_i))}{N\ln(C)} \tag{4}$$

A value close to 1 suggests good segregation of individuals into preference groups (Wedel & Kamakura 2000).

Typically, as the number of classes increases the precision of the single parameter estimates of each class decreases (i.e. the standard errors become broader), especially when they are associated with classes with an overall low probability of membership. Therefore the selection criterion for the number of classes inevitably implies value judgements about the significance and meaningfulness of parameter estimates and signs.

Over the range of 2-5 classes models that we estimated, using the criteria described above, we fail to identify clear evidence in support of any particular number of classes (Table n. 2). After considering the results reported in the previous section in terms of plausibility of interpretation and provision of useful findings we decided that the four-class model was more appropriate for the purpose of this study. In what follows we focus on the implications of such a model.

5.4 Results and discussion

In what follows, we will try to discuss the implications of the differences in the preference structure observed across the four groups, and their shares. (Table n. 3) shows predicted response probabilities of ‘attending wine shops four times or more per year’ (the wine shop response variable) and for all the other response variables it reports the probability of observing a score value of 4 (‘considered important’) or 5 (‘considered very important’), for each of the four preference groups.

The predicted population probabilities of belonging to classes are 19.5%, 44.4%, 21.0% and 15.0% for classes

1 to 4 respectively. In terms of significance of the variables used to explain variation in stated WTP (Table n. 4) we notice that all classes show a significant effect (baseline was TGI wine bought in a supermarket) for both types of label indicating geographical origins for wines bought in restaurants and wine shops. The only exception is for a bottle of TGI labeled wine bought in wineries for members of class as 1 and 3.

5.5 Classes 1 and 2

Classes 1 and 2 share a more similar behavior than that observed by comparing classes 3 and 4 (Table n. 3). Consumers belonging to class 1 show lowest visits to wine shops and have a high probability (37%) of placing a high importance to price. They show the highest probability of attributing importance to the brand (51%) and to both TGI and CDO certification, where the latter displays a much higher score respect the former (23% and 74% respectively). People in this group also show a high probability of taking into account advice from acquaintances and sellers in wine selection. Therefore, consumers in this class seem to deliberate quite carefully, but at the same time they show a strong preference towards a brand product with either a typical geographical indication (TGI) or a controlled denomination of origin (CDO) in the label. Perhaps they are inclined to buy high-quality wines, but do not posses the specific knowledge required, and hence rely on acquaintances' and sellers' advice. Note that wine-shops are places where one can find the widest variety of choice and often reliable advice from shop attendants.

Consumers belonging to class 2 share a similar preference pattern with those in class 1. However, they seem to place slightly lower importance on brand and price (30% probability a high score), having probably slacker income constraints and are among those who show the highest frequency of attendance of wine shops (56%).

In terms of the respective stated WTP equations, both classes share a similar structure in terms of signs and significance of the marginal effects, but the magnitudes show a different responsiveness of stated WTP to types of geographical certification. The differences worth noticing are that:

1. class 2 shows a significant effect of gender on stated WTP, with men showing a higher WTP, while in class 1 men appear to be WTP less;
2. class 2 members seem to possess specific knowledge of wines;
3. class 2 shows a higher stated WTP for both types geographical certification, in the region of 3.5 Euro for the TGI, and of 4 Euro for CDO wines in restaurants and wine shops.

5.6 Classes 3 and 4

Some similarities can also be found between the preference structure of members of class 3 and class 4, although for individuals belonging to these two the results indicate the existence of a quite distinct preference structure (Table n. 3).

Consumers in these classes place very little interest in wines with a specific brand and a TGI label, although the presence of a CDO label still remains of some importance. Class 3 members show the highest probability (46%) of assigning high scores to price. These people have probably the tightest income constraints and as a consequence the price factor seems to be the only one playing an important role in wine choice. Marketing strategies neglecting price reduction might fail to entice these people into buying wine. Finally, it is of some interest to look at members of class 4 as they display a peculiar pattern of responses. This group places the lowest importance on price, jointly with all other factors. They seem not to be affected in their purchasing behavior by any of the investigated elements and they probably represent a market segment that is difficult to interest in purchasing wine.

In terms of determinants of stated WTP (Table n. 4) the results for class 3 reinforces the notion that members of this class are cautious spenders, as they are significantly sensitive to budget constraints imposed by income and the number of dependants, and at the same time appear to be quite discerning as they show similar low WTP both for CDO and TGI labels in different outlets. As expected, people in class 4 show highest values for most of the TGI and CDO labels, with a WTP quite often over 10 Euro per bottle. They are also the only group where age has a positive sign, indicating that older people tend to state higher WTP.

6 Conclusions

In this study the use of latent classes—as constructed on the basis of response patterns to wine-purchase attitudinal questions—was linked to WTP for Prosecco wine. This has been shown to produce quite an articulated picture.

To summarize our findings, we identified 4 different classes of respondents with similar response patterns, and each was then linked to a class-specific WTP equation to estimate the class responsiveness of stated WTP for a bottle of Prosecco wine to various determinants.

As one would expect, the stated WTP varies as a function of where it is purchased or consumed and it also changes in relation to the age of respondents (Table n. 5). Comparing 70 and 40 years old consumers, younger people state higher WTP (by about one Euro) for all types of Prosecco wines.

We found evidence of quite a high WTP for CDO Prosecco purchased in restaurants (8.91 Euro) and for purchase in wine shops (8.08 Euro). These moved down to 7.16 Euro and 6.16 Euro, respectively, for Prosecco with TGI certification.

Despite these averages in stated WTP, the latent classes identified by means of the patterns of responses based on wine purchasing attitudes allowed us to find evidence of an articulated set of differences across classes. In our sample respondents have 21% probability of belonging to a class with a less-than-average WTP for Prosecco, and 15% Probability of belonging to a higher-than-average WTP class.

Finally, they have a 44% probability of belonging to a group of very sensitive, yet discerning spenders, who nevertheless display a higher-than-average WTP. The remainder of probability is assigned to a group with a generally low sensitivity to wine purchasing.

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7 Appendix

Selected attitudinal questions included in the analysis:

- Do you purchase or drink wine in wine shops? Never, 1-3 times per year, 4-6 times a year, more than 6 times per year.
- On a scale from 1 to 5, where 1 means “not at all important” and 5 means “very important”, answer the following question. When you buy some wine, how much importance do you place on price, brand, TGI label, CDO label and suggestions from friends and the seller?

Table 1: Log likelihood with dropping of each variable for 2-5 class models .

Variable	Class 2	Class 3	Class 4	Class 5
Restaurant	–6,611.7	–6,507.6	–6,415.7	–6,357.6
Wine shop	–6,554.9	–6,462.4	–6,375.1	–6,317.2
Supermarket	–6,661.1	–6,553.2	–6,463.3	–6,372.7
Winery	–6,572.8	–6,468.3	–6,388.3	–6,302.8
Pub	–6,601.9	–6,495.2	–6,435.6	–6,366.4
Price	–6,541.0	–6,424.3	–6,336.5	–6,249.3
Taste	–6,727.7	–6,631.2	–6,511.4	–6,444.6
Brand	–6,514.1	–6,397.1	–6,315.2	–6,232.9
TGI label	–6,529.1	–6,411.6	–6,325.6	–6,267.4
Bottle shape	–6,610.9	–6,492.3	–6,405.4	–6,348.5
CDO label	–6,525.1	–6,407.0	–6,314.5	–6,248.3
Friend suggestion	–6,494.6	–6,390.5	–6,281.8	–6,223.5
Seller suggestion	–6,533.4	–6,419.0	–6,322.1	–6,269.1
Adverstising	–6,670.2	–6,568.0	–6,460.7	–6,409.1

Table 2: Criteria for the models.

	$\mathcal{L}$	Parameters	Akaike IC	Bayes IC	cn Akaike IC	cr Akaike IC	Entropy
Model 2	–3,745.0	55	7,600	7,815	7,815	7,620	0.84
Model 3	–3,670,6	83	7,507	7,832	7,832	7,557	0.69
Model 4	–3,631.5	111	7,485	7,920	7,920	7,582	0.59
Model 5	–3,593.9	139	7,465	8,010	8,010	7,636	0.52

Table 3: Predicted response probabilities of 'attending wine shops four times or more per year' and of observing a score value of 4 ('considered important') or 5 ('considered very important') for all the other response variables.

	Class 1	Class 2	Class 3	Class 4
Wine shop	35.9	56.0	54.2	39.4
	(n=26)	(n=92)	(n=34)	(n=22)
Price	37.3	29.8	46.3	18.8
	(n=27)	(n=49)	(n=37)	(n=10)
Brand	51.4	30.7	4.1	19.1
	(n=37)	(n=51)	(n=3)	(n=11)
TGI label	22.9	17.8	1.5	15.7
	(n=16)	(n=30)	(n=1)	(n=9)
CDO label	73.8	67.7	14.1	45.9
	(n=54)	(n=112)	(n=11)	(n=26)
Friend suggestion	50.4	55.3	7.5	20.1
	(n=37)	(n=92)	(n=6)	(n=11)
Seller suggestion	33.3	28.3	2.4	2.2
	(n=24)	(n=47)	(n=2)	(n=1)
Class membership	19.5	44.4	21.0	15.0
	(n=73)	(n=165)	(n=78)	(n=56)
$S.E.$	[0.03]	[0.04]	[0.03]	[0.02]

Table 4: Maximum likelihood estimates of finite mixing WTP.

	Class 1		Class 2		Class 3		Class 4	
	$\hat{\beta}$	St. Error	$\hat{\beta}$	St. Error	$\hat{\beta}$	St. Error	$\hat{\beta}$	St. Error
INT	8.29	0.248	15.99	0.108	5.16	0.316	5.81	0.315
TGI_Restaurant	4.51	0.100	8.60	0.049	4.04	0.099	10.99	0.103
TGI_Wine shop	4.18	0.102	7.11	0.051	3.62	0.105	9.70	0.104
TGI_Winery	0.10	0.117	0.83	0.057	0.16	0.113	–1.03	0.126
CDO_Restaurant	6.56	0.098	10.71	0.048	4.75	0.103	12.76	0.104
CDO_Wine shop	5.88	0.100	9.55	0.052	5.23	0.100	10.81	0.103
CDO_Winery	1.17	0.112	2.79	0.052	0.97	0.122	2.27	0.119
CDO_Supermarket	1.23	0.112	0.50	0.068	1.11	0.124	1.02	0.128
Age	–0.19	0.010	–0.75	0.005	–0.08	0.015	1.05	0.016
Age_SQ×100	0.23	0.012	0.89	0.007	0.07	0.019	–1.90	0.022
MALE	–1.28	0.044	0.45	0.027	1.10	0.058	–0.68	0.096
Family comp.	–0.36	0.016	–0.16	0.011	–0.05	0.022	–1.73	0.021
Income	0.33	0.013	1.16	0.009	–0.16	0.018	–0.42	0.013
Knowledge	–0.16	0.054	6.78	0.039	3.91	0.087	–5.21	0.071
Class Prob.	0.19		0.44		0.21		0.15	

Table 5: Predicted WTP for types of Prosecco and outlet.

AGE	70	40
TGI Restaurant	4.95	5.77
TGI Wine Shop	4.79	5.61
TGI Winery	4.09	4.90
TGI Supermarket	4.05	4.87
CDO Restaurant	5.30	6.12
CDO Wine Shop	5.13	5.95
CDO Winery	4.33	5.15
CDO Supermarket	4.15	4.97

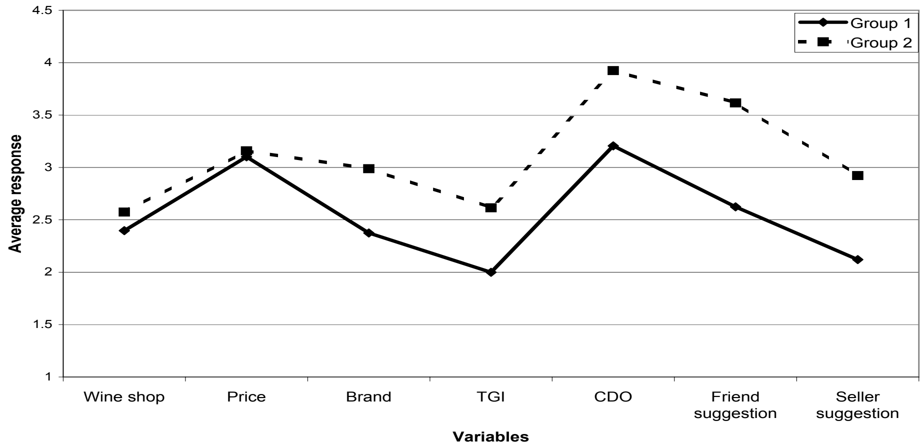

Figure 1: Average scores by Class. Model with 2 classes.

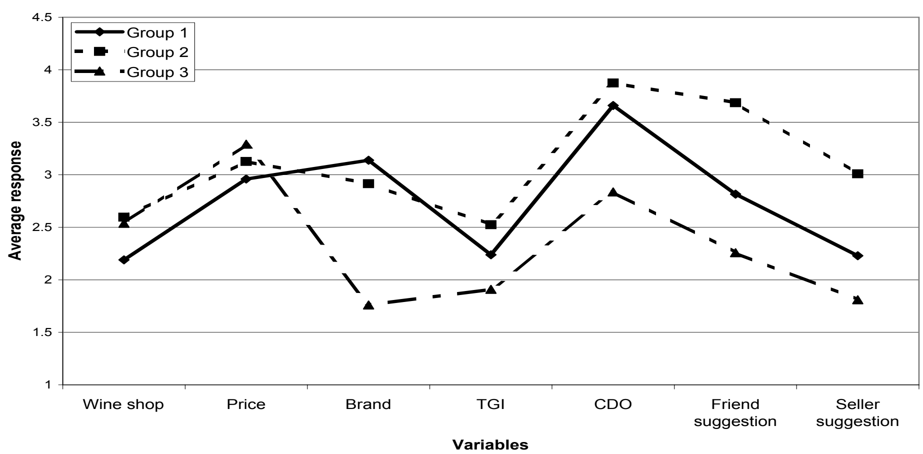

Figure 2: Average scores by Class. Model with 3 classes.

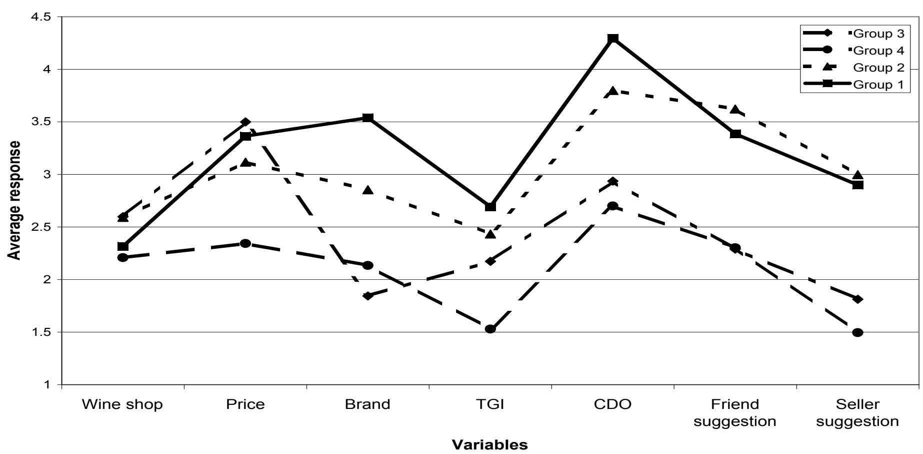

Figure 3: Average scores by Class. Model with 4 classes.