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Palma, D orcid.org/0000-0002-1276-8469, Ortúzar, JDD, Rizzi, LI et al. (1 more author) (2018) Modelling consumers' heterogeneous preferences: a case study with Chilean wine consumers. Australian Journal of Grape and Wine Research, 24 (1). pp. 51-61. ISSN 1322-7130

https://doi.org/10.1111/ajgw.12297

Modelling consumers' heterogeneous preferences: a case study with Chilean wine consumers

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Short title: Modelling wine consumers' heterogenous preferences

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Background and Aims: Understanding consumers' preferences is key to making a successful product, but preferences are heterogenous. We compare three approaches to consider preference heterogeneity in discrete choice models: (i) systematic preference variations based on sociodemographic characteristics; (ii) latent classes; and (iii) hybrid choice models with latent variables measuring consumers' attitudes.

Methods and Results: Data from a stated choice survey of Chilean wine consumers was analysed using three different approaches; these agreed on average trends, but differed in fit and implied different trade-offs. For example, sociodemographic characteristics correlate poorly with preferences. Latent classes offer a good fit but do not link preference heterogeneity to consumer characteristics. The hybrid choice model provides the best fit, but requires more data, making it more difficult to use this approach in forecasting.

Conclusions: The best approach might depend on the research objectives. Using latent classes on a representative sample is the best approach if forecasting is paramount. Modelling attitudes is helpful when more insight into consumers' preferences is sought. Systematic preference variations based on sociodemographic characteristics are a good choice when only average trends are relevant.

Significance of the Study: We make recommendations on how to model preference heterogeneity when studying wine preferences, an issue often overlooked.

Keywords: discrete choice, hybrid choice models, latent classes, preference heterogeneity, wine

Introduction

The consumption of food and beverages can be conceptualised as a two-stage process (Grunert, 2005). In the first stage, consumers decide whether or not to buy a product based on their expectations of the product's quality. This expected quality is constructed from available cues, such as the packaging or friends' advice, as consumers cannot taste or smell the product at this point. The second stage is when consumers actually taste the product and can fully appreciate its (subjective) quality. This process induces a dichotomous classification of the product's attributes: those that can be appreciated before buying are called extrinsic (e.g. price, packaging and advertising), and those that can only be appreciated after purchase are called intrinsic (e.g. colour, taste and aroma).

But the perception and valuation of attributes is not homogenous among consumers. This is particularly true in the case of food and beverages, where even the valuation of extrinsic attributes varies between consumers. For example, some consumers may be willing to pay more for health certification or for organic food, while others may not (Angulo and Gil 2007, Scarpa and Thiene 2011).

In this research, we attempt to identify the best way of modelling preference heterogeneity in the first stage of food choice,that is when only extrinsic attributes are considered. We use wine as a case study due to its complexity (Ferreira et al. 2007, Mouret et al. 2013, McIntyre et al. 2015), which leads to increased preference heterogeneity among consumers (Dodd et al. 2005, Terrien and Steichen 2008, D'Alessandro and Pecotich 2013, Velikova et al. 2015) and even some confusion among expert judges (Gawel and Godden 2008). To make the study manageable, we focus on a specific wine-drinking context, that of an informal dinner with friends. This way we control (to a certain degree) the influence of context, and reduce a problem of multiple choice-purchase decisions to only one choice-purchase decision. With this simplification we are able to apply a discrete choice modelling approach, notably simplifying both the data requirement and modelling complexity. Selecting a special occasion as the consumption context is an approach followed by several authors (Lockshin et al. 2006, Mtimet and Albisu 2006, Jarvis et al. 2010, Mueller et al. 2010a).

To account for heterogeneity in consumers' preferences, we used three alternative approaches: (i) systematic preference variations; (ii) latent classes; and (iii) latent variables. The first approach explains preference heterogeneity based on consumers' observable sociodemographic characteristics. This approach assumes, for example, that female consumers of a certain age behave more similarly among themselves than a group composed of both males and females of various ages. The second approach classifies consumers in a finite number of groups with homogenous preferences, assigning each individual a probability of belonging to each group (which may be common), as opposite to being classified in a deterministic manner. Finally, the last approach explains preference heterogeneity based on a set of consumers' unobservable characteristics. These characteristics represent consumers' attitudes or opinions, and therefore are not directly observable. We measure these latent variables using a novel short questionnaire, and also link them to observable sociodemographic characteristics and consuming habits.

To accomplish our goals, we designed a stated choice survey where respondents faced a hypothetical choice between four wines for an informal dinner with friends. The survey was designed to also provide the information required for the estimation of the latent variables. The survey was implemented through the web and was answered by members of a wine club.

Data was collected in Chile, a relevant New World wine producing country. In the last few years, wine consumers in developing nations have become increasingly involved and more knowledgeable about wine; this has shifted industry focus on local markets from mass production to premium quality. Yet, quality is often understood only from the expert's perspective. In this research, we attempt to understand expected quality from the consumer's standpoint, as derived from extrinsic attributes.

The rest of the paper is organised as follows. The second section describes the experimental design, sample selection and modelling strategy. The third section presents the modelling results and the fourth closes the paper with a discussion on the various models and their appropriateness for modelling heterogeneity in preferences.

Materials and methods

Sample description

The experiment was performed in two steps. In the first, 842 respondents answered a web survey concerning their socio-demographic characteristics, wine consuming habits and attitudes. In the second step, they were invited to participate in a Stated Choice (SC) survey, but only 254 responded. All participants were clients of a Chilean wine specialty store and represent the richer end of the wine consumers’ spectrum, that is 80% of respondents belong to the richest 20% of Chilean households (Ministerio de Desarrollo Social 2012). Table 1 summarises the main characteristics of each sample. The distribution of data from both samples is statistically equivalent, except for the purchase frequency and level of education.

Modelling

Discrete choice models (DCM) are a particular class of econometric models used to explain and predict choices among a set of finite alternatives. These models have become common in the food and beverages preferences literature lately [see Ortúzar (2010) for a review, and Grisolía et al. (2012), Adamowicz and Swait(2013) and O'Neill et al. (2014) for some recent examples]. There are also several applications of these models to wine consumption (Lockshin et al. 2006, Mtimet and Albisu 2006, Barreiro-Hurlé et al. 2008, Jarvis et al. 2010, Mueller et al. 2010a, Costanigro et al. 2014).

Using DCM to study consumer preferences has several advantages. First, it is an indirect method to assess the importance of a product's attribute in relative terms, without rating them directly (Mueller et al. 2010b). Secondly, the methodology requires consumers to do nothing else than what they normally do when buying, i.e. choosing among a set of alternatives.

Discrete choice models are mathematical representations of the choice process followed by individuals, based on the Random Utility Theory (Lancaster 1966). Alternatives (i.e. bottles of wine) are defined as a set of attributes and their particular levels, while consumers hold preferences for these attributes. The interaction between the products' attributes and consumers' preferences gives rise to utility, as perceived by consumers. Consumers are assumed to behave in a compensatory way, that is a poor level on one attribute can be compensated by a good level on other/s.

One of the most popular random utility models is the Multinomial Logit (MNL) model (McFadden 1973, Train 2009, Ortúzar and Willumsen 2011). The MNL model assumes that each alternative i provides a particular level of utility U_{int} for consumer n in choice situation t. This utility Equation 1 is assumed to depend linearly on both observed alternative's attributes x_{kit} (k enumerating attributes) and unobserved consumers' preferences, which are assumed to be homogenous among the population; β_k are coefficients (marginal utilities) to be estimated. As the modeller does not possess as much information as the consumer, an additional random error term ε_{itn}, representing all those attributes perceived only by the consumer, is added to the utility. This random component is assumed to distribute IID Extreme Value Type-I in the MNL, allowing to derive an analytical form for the probability of choosing a particular alternative Equation 2[2].

$$U_{int} = \sum_k \beta_k x_{kit} + \varepsilon_{itn} \tag{1}$$

$$P_{jnt} = \frac{e^{\sum_k \beta_k x_{kjt}}}{\sum_i e^{\sum_k \beta_k x_{kit}}} \tag{2}$$

[2] Note that in Equation 2 we have omitted the scale factor inversely related to the unknown standard deviation (σ) of the errors ε as it is unestimable in this case; this means that estimated parameters β are deflated by σ.

There are several ways to introduce preference heterogeneity in the modelling. The first and simpler approach, often called systematic preference variations (SPV) [Ortúzar and Willumsen (2011), page 279], consists in adding new terms to the utility, in the form of interactions between the products' attributes (x_{kit}) and consumers' characteristics (z_{rn}, where r enumerates characteristics of consumer n), as shown in Equation 3. This method has the benefit of maintaining the analytical form of the probability of choosing an alternative Equation 2 and is a simple and easy to interpret form of relaxing the assumption of equal preferences for all individuals. The main limitation of this approach is that consumers' characteristics must be observable, therefore consumers' demographic factors are often used.

$$U_{int} = \sum_{k} \beta_k x_{kit} + \sum_{r} \sum_{k} \beta_{kr} x_{kit} z_{rn} + \varepsilon_{itn} \qquad (3)$$

Another approach to consider preference heterogeneity is the use of latent classes (LC) [Hensher et al. (2015), chapter 16]. The approach consists in assuming a fixed number of different classes of consumers within the sample, with homogenous preferences within each class, but different preferences between them. Consumers are not assigned to a class in a deterministic way, but each of them has a probability of belonging to each class. This probability can be assumed to be equal for every consumer (as we do in this study), or can depend on consumers' observable characteristics. Equations 4 - 6 show the utility of alternative j, the probability of choosing alternative j, and the probability of an individual belonging to class c, respectively; where c enumerates classes and α_c is a parameter, to be estimated, proportional to the size of class c. If the modeller wants p_c to depend on respondents' characteristics, then they only need to make α_c a function of respondents' characteristics. We assumed α_c fixed and equal for all individuals, as we measured the effect of sociodemographic characteristics using the SPV approach instead.

$$U_{int}^{c} = \sum\nolimits_{k} \beta_k^c x_{kit} + \varepsilon_{int}^{c} \tag{4}$$

$$P_{jnt} = \sum\nolimits_{c} p_c \frac{e^{\sum_k \beta_k^c x_{kjt}}}{\sum_i e^{\sum_k \beta_k^c x_{kit}}} \tag{5}$$

$$p_c = \frac{1}{1 + e^{-\alpha_c}} \tag{6}$$

A third alternative to model preference heterogeneity is the use of latent variables (LV) [Walker and Ben-Akiva (2002), Bahamonde-Birke and Ortúzar (2012)]. This approach is similar to SPV, but this time the attributes interact with consumers' unobservable characteristics, instead of observable ones. This provides a wider range of possibilities, as preference variations can depend, for example, on consumers' attitudes or opinions towards the product, or consumers' psychological characteristics, such as personality traits. These unobservable characteristics are modelled as latent variables.

The LV approach requires more information than the previous approaches. Besides requiring the record of choices by each consumer, it requires indicators or measurements of the LV. As these represent unobservable characteristics, more than one indicator for each LV is recommended. These indicators are often consumers' answers to questionnaires about their attitudes, opinions and general behaviour; the most common type of questions are asking for the level of agreement with a set of phrases (e.g. using a scale from 1 to 5, what is your level of agreement with the phrase 'I like trying new wines').

There are several ways of estimating the LV, but one of the most popular approaches is using the Multiple Indicators Multiple Causes (MIMIC) model (Bollen 1989). We wish to measure something that we cannot observe, that is one or more latent variables η_{ln}. The model assumes that the indicators (m_{lqn}, where l enumerates latent variables and q the indicators associated with each of them, for consumer n) are caused by the LV and a random error term ν_{lqn}; this allows us to write measurement Equation 7, where γ_{lq}^{0} and γ_{lq} are coefficients to be estimated. The measurement equations do not need to be linear, and may take an ordinal logit form [Hensher et al. (2015), chapter 18] if the indicator is of ordinal nature. If possible, we would also like to explain the value of the LV using observable characteristics, therefore allowing prediction. This leads to posing structural Equation 8, where ζ_{rl} are parameters to be estimated and ε_{ln} are further error terms.

$$m_{lqn} = \gamma_{lq}^{0} + \gamma_{lq}\eta_{ln} + \nu_{lqn} \tag{7}$$

$$\eta_{ln} = \sum\nolimits_{r} \zeta_{rl} z_{rn} + \varepsilon_{ln} \tag{8}$$

Once the LV are estimated, they can be included in the choice model. But as the value of the latent variables is estimated with a level of error (ε_{ln}), this additional source of noise must be incorporated when estimating the probability of choosing an alternative. Equations 9, 10 and 11 present the new forms of the utility and of the probability of choosing an alternative in this case. Note that the LV interact with every observable variable in Equation 9. The probability may not have a closed analytical form anymore, depending on the distribution $f(\varepsilon_{ln})$ of the latent variable's random error term.

$$V_{int} = \sum\nolimits_{k} \beta_k x_{kit} + \sum\nolimits_{l} \sum\nolimits_{k} \beta_{kl} x_{kit} \left(\sum\nolimits_{r} \zeta_{rl} z_{rn} + \varepsilon_{ln} \right) \tag{9}$$

$$U_{int} = V_{int} + \varepsilon_{int} \tag{10}$$

$$P_{jnt} = \int \frac{e^{V_{jnt}}}{\sum_i e^{V_{int}}} f(\varepsilon_{ln}) d\varepsilon_{ln} \tag{11}$$

The combination of LV and discrete choice models is often called a Hybrid Choice Model (HCM). These can be estimated sequentially or simultaneously (Raveau et al. 2010). Sequential estimation means that the MIMIC model is estimated first, and then its output is used on a second stage as input for the DCM estimation. Simultaneous estimation, instead, makes use of Full Information Maximum Likelihood to estimate both models in a single process. Both estimation methods assure parameters' consistency, even though the second one is more efficient. We used sequential estimation in this case to make easier use of the larger first stage dataset (842 respondents) when estimating the MIMIC model; afterwards, we used the smaller second stage dataset (254 respondents) for the choice model.

Experimental design of the Stated Choice survey

A Stated Choice survey (SC) [Ortúzar and Willumsen (2011), section 3.4] considers a series of hypothetical but realistic situations where individuals are asked their choices. We set up an SC survey on an on-line survey platform, and sent it to the 842 consumers who had previously answered the first (descriptive) survey. This allowed us to reduce the time required to complete the SC survey, as the demographic and attitudinal data were already available. In the SC component, each person faced six hypothetical choice scenarios with four alternatives each. All scenarios included a non-purchase alternative (Figure 1).

There is an ample literature identifying the most relevant attributes of wine from the consumers' standpoint [Lockshin and Corsi (2012) present a review; Schnettler and Rivera (2003); Jiménez et al.(2006); Mora et al. (2010); and Cerda et al. (2010) studied the subject in Chile]. We complemented the literature search with our own qualitative study of local consumers (not reported in this document).

Six attributes were selected for inclusion in the experiment: Label design, Grape variety, Alcoholic content, Price, Discount and Advice. Although six is not considered a large number of attributes in many DCM studies, it is bordering the limit in the Chilean case (Caussade et al. 2005). Table 2 presents the levels for all attributes. A maximum of four levels was allowed to keep the number of choice situations from growing excessively, while maintaining level balance.

As measuring the effect of particular brands was not one of our objectives, we used a fixed fictional brand for all alternatives. Consumers were made aware that the brand was fictional. Unlike consumers from other parts of the world (Verdonk et al. 2015), Chilean consumers displayed little knowledge of local wine-producing valleys during a focus groups (not reported), therefore, we did not include the wine's origin as a descriptive attribute. In contrast, although alcohol concentration is not considered as one of the most relevant attributes of wine (Goodman 2009), we included it as it was of much current interest to Chilean winemakers. Context (consuming occasion) is also an important attribute (Martínez-Carrasco et al. 2006), so it was fixed for all exercises as 'an informal dinner with friends'.

We pivoted prices to avoid consumers disregarding alternatives because they were either too expensive or cheap, which would violate the compensatory behaviour assumption. Before being presented with the choice exercises, consumers were asked to declare the maximum amount of money they were willing to spend on a bottle of wine for an informal dinner with friends. This value was scaled using the percentages on the Price column of Table 2, and discounts were later applied over the scaled price. When modelling, we included only the price after discount in the utility function. Therefore, the discount parameters capture only the psychological effect of discount, that is how much attractive an alternative becomes because of being advertised as discounted, not because it has a lower price.

The four red grape cultivars included are those most common in Chile (Oficina de Estudios y Politicas Agrarias 2012). The alcohol concentrationt was made to vary enough to consider 8.5° Gay-Lussac (G.L), a level that was inexistent in the Chilean market at the time of the study. The levels used for Label design were taken from Orth and Malkewitz (2008), where five classes of wine label designs are identified, but only three of them were considered to describe the Chilean market well enough. These are delicate (muted, sleek and delicate), contrast (stark, not harmonic) and natural (representative, archetypical). To measure the effect of the design classes, and not of a particular label design, three different labels were constructed for each level of the Label design attribute, and they were assigned randomly as needed. All labels were designed following Orth and Malkewitz (2008) parameters, by a professional designer. In Figure 1, from left to right, the first and second are of type contrast, while the third and fourth are natural and delicate, respectively.

A D-efficient balanced design [Rose and Bliemer (2009); Ortúzar and Willumsen (2011), section 3.4) was built using N-gene (http://choice-metrics.com/). A simple logit model structure was assumed, using priors from a pilot study with 19 participants. The design was divided into two blocks of six scenarios each. Every respondent was randomly assigned to one of these blocks. To avoid order bias, the presentation order of alternatives and choice scenarios was randomized across respondents.

We asked respondents to rank the various grape cultivars at the beginning of the survey. This ranking was exploded generating three additional fictional choices, where the only difference among alternatives was Grape Cultivar. For example, if a respondent indicated the following ranking: (i) Cabernet Sauvignon, (ii) Carménère, (iii) Merlot; and (iv) Syrah, we could create three fictional choices. In the first, the four alternatives would be available, and the first fictional choice would be Cabernet Sauvignon, as it was the respondent's first preference. In the second, only three alternatives would be available (omitting Cabernet Sauvignon) and the fictional choice would be Carménère. In the third, only the Merlot and Syrah wines would be available and the fictional choice would be Merlot. A scale factor [Ortúzar and Willumsen (2011) section 8.7.3) was used to integrate the 'fictional choices' and the real choices.

Results

We estimated three models with the same dataset (although the third model uses additional information on consumers' attitudes), each of them using a different approach to model and explain preference heterogeneity. The first model considers systematic preference variations (SPV and explains differences in preferences based on consumers' sociodemographic characteristics. The second model uses latent classes (LC) to capture preference heterogeneity but not to explain it. Finally, the third model uses latent variables (LV) representing consumers' unobserved attitudes to explain preference heterogeneity. All models were estimated using BIOGEME (Bierlaire 2003).

Models SPV and LC consider a pseudo panel effect as proposed by Daly and Hess (2010). This method consists in adding a different Normal independent and identically distributed random error component (with mean zero and a standard deviation to be estimated) to each alternative in order of presentation, from left to right, in every choice situation for each respondent. This effectively introduces correlation between the observations of the same respondent depending on the presentation order of alternatives (i.e. all 'alternatives A' are correlated). For the LV model this procedure is not necessary as it already induces correlation between observations through each respondent's latent variables' levels. Preferences for label style were not significant in any model, and therefore were removed from their specifications.

SPV model

The SPV model includes interactions between all attributes and four consumers' characteristics: gender (a dummy with value one if the consumer was female), age (a dummy with value one if the consumer was 39 years old or younger), level of education (a dummy with value one if the consumer was not a professional), and per capita income. All main effects were kept in the model, despite their level of significance. Interactions, in contrast, were removed if they were not significant at the 95% confidence level considering a two-sided test (i.e. $\alpha \leq 0.05$); robust t-tests are reported in Table 3. No interaction with income turned out to be significant, even though we tested different transformations for this variable (linear, logarithm and exponential).

Concerning preferences for grape cultivar, the SPV reveals a significance difference between young and older consumers. The latter's favourite grape cultivars are Carménère and Cabernet Sauvignon, with no difference among them, while younger consumers favour Carménère over Cabernet Sauvignon. The relevance of advice also varies depending on consumer characteristics. While many favour friends' over critics' advice, young and non-professional consumers trust of friends is lower than of critics. Among the least relevant advice, men value more the advice of salesmen than nothing at all, but women seem to distrust recommendations made by salesmen. There are no differences among consumers regarding the effect of alcohol, with a higher level being preferred by all consumers. Price shows an insignificant negative effect for every consumer (α = 0.15), probably due to its use as a cue for quality (see the discussion section). Different levels of discount do not appear to differ significantly on their level of attractiveness to consumers, except among young consumers. Finally, the scale factor for the grape ranking observations is close to zero, indicating much greater variability across respondents for this kind of observations than for wine choices.

LC model

A model with two LCs was found to have the best trade-off between fit and interpretability (see Table 4). Each class considers only the main effect of each attribute, and no interactions are included. The probability of belonging to a class does not depend on any consumer characteristics, but instead is assumed to be constant for every respondent. This allows the model to identify classes of consumers based only on their preferences, without forcing preferences to correlate with any consumer characteristic. In other words, this approach considers preference heterogeneity but does not explain it.

The first class (39% of the sample) appears to have more experienced consumers. They prefer the Shiraz grape cultivar over more traditional Chilean cultivars, such as Cabernet

Sauvignon, Carménerè and Merlot; they value more the advice from critics than from friends and dislike wines with low alcohol content. Their price coefficient is negative and significant, probably indicating that they do not see price as a strong cue for quality, which would also explain the insignificance of discount, as its effect is completely captured by the reduced price.

The second class represents a more traditional—and maybe casual—consumer. They favour Carménerè—the Chilean flag cutlivar—over all others, value friends' advice the most, and they are not influenced by the alcoholic content of the wine. Price does not appear to influence their choice, probably because they use price as a cue for quality. Discounts are attractive to them: the higher the better, though the attractiveness does not grow linearly. These last two observations are consistent, as consumers who use price as a cue for quality also value discounts as an opportunity to buy better wines.

The scale factor for observations coming from the grape cultivar ranking is lower than one, and significantly different from both one and zero. This means that individuals' grape cultivar rankings have more variability across respondents than wine choices, implying that the high preference heterogeneity for particular attributes nets out—at least to some degree—when choosing bottles.

Hybrid choice model

The HCM is more complex to interpret than the others. First, we must begin by examining the MIMIC model that measures consumers' attitudes (i.e. latent variables). The structure of this model component is shown in Figure 2. The links between latent variables and indicators (i.e. the measurement equations) are assumed to be of ordered logit form, while links between consumers' observable characteristics and their latent variables (i.e. the structural equations) are assumed to be linear.

Two latent variables were identified: Social drinking and Wine enthusiasm. This two-factor solution is corroborated by confirmatory factor analysis (CFI = 0.914, RMSEA = 0.067) and even though the Cronbach's alpha is low for both factors (0.43 and 0.46, respectively), it is still acceptable due to the small number of indicators (Cortina 1993).

Table 5 presents the MIMIC model's coefficients and main fit indices. The sign of the indicators' coefficients allows interpreting the factors. The Social drinking latent variable alludes to a way of drinking that is mainly social: the individual feels overwhelmed by choosing a wine, often relying on price as a cue for quality, and perceives wine as a social drink for weekends. High levels of this latent variable correlate with (or may be caused by) drinking wine at social gatherings but not on working days; buying less frequently and in less volume; being slightly older and having a high level of education. The Wine enthusiasm latent variable, instead, represents a relevant level of cognitive engagement with wine. Consumers high on Wine enthusiasm see wine as a drink to share (similarly to Social drinking), but they feel knowledgeable about it. They also feel that drinking wine is something inherited from their families and they enjoy exploring new wines. High levels of this latent variable correlate with (or may be caused by) higher consumption and buying frequency, buying several bottles at once, buying expensive bottles, and buying at specialty stores more often; also with keeping a stock of bottles (i.e. a cellar) at home, giving wine to friends as gifts and having a slightly lower level of education.

The MIMIC model exhibits a low level of fit, with a CFI of only 0.805. Given that the confirmatory factor analysis (i.e. the analysis with only the indicators, and no structural equations) showed a higher fit (CFI = 0.9), the problem appears to be due to weak explanatory variables. In other words, respondents' purchase and consuming behaviour do not appear to explain their latent variables in a satisfactory way.

Once the MIMIC model is estimated, the latent variables are calculated for each participant based on their structural equations, and then used as exogenous (but noisy) characteristics of the respondents. Table 6 shows the estimated parameters and main fit indices of the choice component of the HCM. As described in Equation 9, all attributes were interacted with the latent variables; however, only significant interactions were kept in the final model (i.e. $\alpha \leq 0.05$ under a two-tailed test). Note that given the sequential estimation of the complete HCM, the log-likelihood reported in this table is directly comparable to those in Table 3 and Table **4**.

The level of Social drinking is more useful than the level of Wine enthusiasm in explaining consumers' preferences. Interestingly, and contrary to their assertions, consumers high on Social drinking appear to be less prone to using price as a cue for quality than consumers high on Wine enthusiasm, as their significant and negative price coefficient shows. This is in line with how Social drinking lowers the relevance of discounts. However, it could also be that higher levels of Social drinking imply lower willingness to pay for wine and its attributes. The level of Wine enthusiasm, on the other hand, boost the preference for Shiraz grape cultivar and the amount of alcohol in wine.

The scale parameter for the grape ranking data is not significantly different from one (α = 0.07). This indicates that grape cultivar ranking observations are just as noisy as wine choice observations.

Comparison of models

Figure 3 presents a graphical comparison of preferences for grape cultivars among the three models. All coefficients were normalised by dividing them by the model's alcohol content coefficient, so their magnitude is comparable across models. Each graph compares the coefficients of two models: if coefficients are similar across models, the dots will be close to the diagonal. Each dot represents the coefficient of one participant for one attribute. In general, it can be seen that the SPV and LC models' coefficients are slightly correlated, but the LV model parameters have little correlation with the other models' parameters. This difference is partly due to a higher variability in the LV coefficients, but it is also caused by the normality assumption on the latent variables. This assumption forces the coefficients to distribute symmetrically and other assumptions could be tested. In summary, each model provides different preference profiles.

All models are superior to a base model neglecting preference heterogeneity (the coefficients of which are available upon request). The base model neglecting preference heterogeneity achieves a log-likelihood of -3014 (i.e. 26, 98 and 129 points worse than the SPV, LC and HCM models, respectively). All differences in fit are significant ($p \leq 0.05$) according to a Likelihood Ratio test.

Discussion

We estimated three models with the same choice dataset using three different approaches to explain preference heterogeneity. The first model used Systematic Preference Variations (SPV), and attempted to explain differences in preferences based on respondents' sociodemographic characteristics. The second model used Latent Classes (LC) and only captured but did not attempt to explain preference heterogeneity. Finally, the last model used Latent Variables (LV) representing consumers' attitudes towards wine to explain variations in preferences, and a mix of consumers' sociodemographic characteristics and consumption habits to explain the level of consumers' attitudes.

All models agree on average trends: Carménère is the most popular grape cultivar; friends' and critics' recommendations are most valuable for most consumers; higher alcohol content is not perceived negatively; discounts effectively attract the attention of most consumers; and the overall effect of price on choice probability is negative, though tenuous at times.

The effect of price is difficult to measure using traditional choice models, because it has a double and opposite effect in the choice probability. It has, first, a negative effect because, as any (non-Giffen) good, consumers will be more prone to choose an alternative if its price is lower. In contrast, price can also have a positive effect if it acts as a cue for quality (e.g. consumers tend to assume that a US$20 wine is better than a US$5 one). The use of price as a cue for quality is well documented, especially in products with strong vertical (quality) differentiation (Leavitt 1954, Dodds et al. 1991). In the case of wine, it has even been observed at a neurological level (Plassman et al. 2007). A way to deal with this issue was presented by Palma et al. (2016).

Despite the alignment on average trends, the three estimated models differ on how they distribute preferences among the sample (Figure 3). The SPV model suggests that there are two groups of people; both like Shiraz almost the same, but their appreciation of Carménère differs. The LC also shows two groups of people, whose preference for both Shiraz and Carménère differ, but not as strongly as in the SPV model. Finally, the HCM reveals a broader range of variation, and -contrary to both the SPV and LC models—suggests that preferences for Shiraz and Carménère are positively correlated. These differences are caused by the structure and type of variables used to explain preference heterogeneity: demographics in the SPV model, none in the LC model, and attitudes in the HCM. Each model's level of fit can help to identify the most reliable one.

The HCM achieved the best fit, followed by the LC model, while the SPV model lagged behind. All differences are significant at the 99% confidence level according to Horowitz's test for non-nested models (Horowitz 1983). This implies that, at least in this dataset and with these formulations, consumers' attitudes are better at explaining consumers' preferences than two latent classes and consumers' sociodemographic characteristics.

That the SPV achieves the lowest fit is not surprising. This model simply averages preferences over a priori defined groups (e.g. all males, young or professionals). Yet, most of the wine segmentation literature [Spawton (1991), Lockshin et al. 1997, Brunner and Siegrist (2011), to name a few] has focused on consumers' attitudes rather than sociodemographic characteristics, hinting to attitudes correlating more strongly with consumers' purchase habits and preferences than demographic characteristics. O'Neill et al. (2014) also found significant improvements of fit when attitudes were used instead of only demographic characteristics. Unlike the other approaches, the scale parameter associated with the grape cultivar ranking observations was close to zero in the SPV model, indicating a great variability in this kind of observations, meaning that the SPV model's ability to explain respondents' grape cultivar rankings is poor. One could argue that using more demographic characteristics could significantly improve fit, as we only had gender, age, education and income available. Not much more information, however, is usually available at the population level. This is not to say that demographic characteristics are useless when explaining preference heterogeneity, but only that there are better alternatives than this approach.

The LC model achieves second place in terms of fit, much closer to the top than to the bottom. The LC model does not try to explain consumers' preferences based on any of their demographic features, but simply produces a grouping of consumers based on their preferences. This approach greatly improves fit, as the model does not force preference heterogeneity to correlate with any consumers' characteristic. Fit could be improved further if individual level parameters were estimated [Train (2009), chapter 11], potentially matching or even surpassing the fit of the HCM. The downside of this approach is that it does not provide any guidance on how to identify the preference groups outside the sample. Even though these groups are homogeneous in term of their preferences, they may be reasonably heterogeneous when it come to their characteristics, becoming difficult to identify and measure their size in the population. Mueller and

Szolnoki (2010) make a post-hoc characterisation of wine consumers on previously detected latent classes, finding that classes correlate mainly with consuming habits (preferred sweetness levels, drink and purchase frequency and subjective knowledge) and not with demographic characteristics (only age seems to differ among classes). Therefore, we recommend this approach when the sample is sufficiently representative of the population under study, and the researcher is not interested in explaining preferences, but only measuring them. This makes the LC approach particularly interesting for forecasting.

The hybrid choice model achieves the best fit in our sample, matching results by O'Neill et al. 2014 and Scarpa and Thiene (2011). This approach attempts to explain preferences based on consumers' attitudes, and attitudes on consumers' observable characteristics. As most of the segmentation literature suggests (Spawton 1991, Lockshin et al. 1997, Brunner and Siegrist 2011), attitudes appear to be a useful tool explaining behaviour and preferences. Even though we used a relatively weak questionnaire to measure consumers' attitudes, this approach obtained the highest fit. It is also interesting that attitude levels are better explained by respondents' consuming habits, such as consuming frequency and number of bottles bough per purchase, rather than by demographic characteristics (age and education were the only significant ones), matching results by Mueller and Szolnoki (2010). This result reinforces the idea that demographic characteristics weakly correlate with preferences.

Despite its superior fit, the HCM requires much more information than the previous alternatives. First, a good attitude-measuring questionnaire must be answered by each respondent, and some of these can be close to 100 questions [e.g. Brunner and Siegrist (2011)], though there are shorter alternatives (Ogbeide and Bruwer 2013). Second, a reasonable amount of personal information is required to explain the levels of the latent variables, such as consuming habits, personal background, and demographic characteristics. While the second set of data could be omitted by not explaining the level of the attitudes [i.e. a structural equation model with no structural equation (Bollen 1989)], this would make it impossible to forecast with the model, as attitude levels could not be inferred out of sample. Nevertheless, the large amount of data necessary to explain the attitude levels makes it difficult to forecast with this kind of model. Therefore, our advice is to use the HCM approach when seeking a deeper understanding of how preferences are formed. For example, in this case study the hybrid choice model revealed two tendencies of wine consumers: Social drinking and Wine enthusiasm; this could be relevant for advertising purposes (e.g. advertising less expensive wines with images of friends happily sharing a meal, and more expensive ones with images of a single person discovering a less-well known grape cultivar). A recent discussion on the benefits of hybrid choice models can be found in Vij and Walker (2016).

Our comparison helps characterising three approaches when dealing with preference heterogeneity: (i) explaining preferences based on sociodemographic characteristics (SPV); (ii) avoid explaining preference heterogeneity and only measuring it (LC); and (iii) explaining preferences based on consumers' psychological characteristics (LV). Each approach has its own trade-offs. Using demographic characteristics is the simplest approach in terms of model estimation, and forecasting is also easy as these types of characteristics are often available at the population level; however, its fit is significantly poorer than that of the other alternatives. The LC approach can be estimated with relatively less information than other approaches, as only choices are necessary, and provides an acceptable level of fit (maybe even the best if individual level parameters were estimated), but it does not link preferences to consumers' characteristics. Finally, the use of attitudes provides the higher fit and the maximum amount of insight, but it is arguably the most difficult approach to estimate and the one requiring larger amounts of information, making it more appropriate for in-depth studies where forecasting is not the main objective.

Our list of approaches is by no means exhaustive, as more complex structures could also be used. For example, Scarpa et al. (2005) compared a random parameters (RP) logit model with the SPV approach, concluding that the random parameters model provided a higher fit – however, a more appropriate comparison would be testing the RP logit against an error components mixed logit allowing for SPV; this comparison has shown in several cases to be in favour of the SPV model (not least because of the much better interpretation of results). More interestingly, Scarpa et al. (2009) used a mixed approach: an LC model where the membership probability was a function of participants' responses to a psychometric questionnaire. This is one possible way of mixing the LC and LV approaches. This mixture harvests both the benefits and limitations of the two approaches: results are easy to interpret but quite difficult to extrapolate out of sample. A simpler mixture of models could be a LC model with class probability functions depending on participants' sociodemographic characteristics (i.e. make α_c in Equation 6 a function of participants' observable characteristics). We did not test this approach as the SPV model already showed that the participants' observable characteristics did not correlate strongly with preferences.

Some limitations of our study must be acknowledged. We used a novel, self-developed, short questionnaire to measure consumers' attitudes towards wine, based on information from focus groups and in-depth interviews with consumers. However, the questionnaire did not perform quite right, as suggested by the low fit of the MIMIC model. For this reason, we are not in a position to recommend it for future research. Instead, using validated questionnaires (also called instruments) to measure wine-related attitudes appears more appropriate. There is a well-developed literature on this subject (Lockshin et al. 1997, Brunner and Siegrist 2011, Bruwer and Huang 2012, Ogbeide and Bruwer 2013), although the length of some of these questionnaires makes their inclusion in choice experiments difficult. Another limitation of our results is that no random parameter model or individual-level parameters were estimated. We decided not to include these to avoid excessive length of the paper and because they could be considered as extensions of the LC model. A random parameter model is equivalent to a LC model with infinite classes and a functional form attached to them, and an individual-level parameter model is equivalent to a LC model with as many classes as respondents.

Finally, the inclusion of an extremely low level of alcohol content (8.5°GL) may have influenced the positive perception of higher alcohol content captured in all models. However, (non-reported) models with dummy variables for each level of alcohol also show a positive, though milder, perception of wines with higher alcohol levels.

Future research should focus on how recommendations about the different approaches to preference heterogeneity apply to other product categories.

Acknowledgements

We are grateful to the Chilean Fund for the Development of Scientific and Technological Research (FONDECYT) through Project 1121058. Thanks are also due to the Millennium Institute in Complex Engineering Systems (ICM: P05-004F; FONDECYT: FB8016) for having partially financed this work.

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Table 1. Sample mean of participant's characteristics, for the first and second stage samples.

Category	Item	1st	2nd
Sample size	Number of individuals	842	254
Consumption habits	Weekly number of consuming occasions †	2.70	2.63
	Drink wine at lunch on weekdays (%)‡	12	14

Purchasing habits	Number of purchases during a month	3.45	3.13
	Number of bottles per purchase †	7.78	8.19
	Buy bottles of more than US$50 (%) ‡	22	20
	Keeps a stock of wine at home (%) ‡	88	93
Use of distribution channels	Supermarket ‡ (Likert scale from 0/never to 3/always)	2.31	2.33
	Specialty store ‡ (Likert scale from 0/never to 3/always)	1.85	1.85
	Internet ‡ (Likert scale from 0/never to 3/always)	1.36	1.37
Attitudes (Agreement level with each phrase on a 1 to 7 Likert scale)	I know a lot about wine ‡	4.68	4.78
	I like trying new wines ‡	6.33	6.37
	There are expensive wines I don't like ‡	5.27	5.22
	Wine is a family tradition for me ‡	5.14	5.02
	Choosing wine at the supermarket can be difficult ‡	3.87	3.85
	Wine is for weekends ‡	3.10	3.11
	Wine is a social drink ‡	5.28	5.25
	To make sure I get a good wine, I choose an expensive one ‡	3.67	3.47
Demographics	Female (%) ‡	24	30
	Age †	41.80	43.11
	Number of people in household †	3.19	3.20
	Number of adults in household †	2.49	2.51
	Highest level of formal education (3=university)	2.90	2.95
	Monthly income (1000 US$) †	4.14	3.97

† Data from both samples are statistically equivalent under the Kolgomorov-Smirnov two-sided test at 5% significance

‡ Data from both samples are statistically equivalent under the chi-square test at 5% significance

Table 2. Attribute levels in the stated choice (SC) design.

	Label design	Grape cultivar	Alcohol concentration	Advice	Price	Discount
1	Delicate	Cabernet Sauvignon	8.5° G.L.	None	100%	0%
2	Contrast	Merlot	11.0° G.L.	Salesman	120%	10%
3	Natural	Carménère	12.5° G.L.	Friend	130%	20%
4		Shiraz	14.5° G.L.	Critic	160%	

Table 3. Parameter estimates and goodness of fit indicators of the systematic preference variations (SPV) model.

Attribute	**Level**	**Coefficient**	***t*-test†**
Grape	Merlot	-0.703	-3.45
cultivar	*x* Young	0.650	2.93
	Carménère	0.134	0.86
	x Young	0.388	1.89
	Shiraz	-0.541	-3.45
	x Young	0.488	1.98
Advice	Salesman	0.106	1.01
	x Female	-0.375	-2.15
	Friend	0.575	4.50
	x Young	-0.273	-1.90
	x Non professional	-0.266	-1.53
	Critic	0.394	3.21
	x Female	-0.315	-1.69
Alcohol concentration		0.071	4.48
Price	After discount	-0.012	-1.45
Discount	10%	0.477	5.14
	x Young	-0.247	-2.05
	20%	0.434	4.56
Constant	Base	0.492	1.10
	x Female	0.314	0.75
	x Young	-0.377	-0.92
	x Non professional	1.320	2.56
Scale	Grape ranking	0.026	4.15‡
Panel effect	Standard deviation	-0.455	-4.41
Fit	Observations		2286
indices	Individuals		254
	Number of parameters		26
	Log-likelihood		-2988
	Rho2		0.10
	Adjusted Rho2		0.09

† Robust t-tests reported

‡ Robust *t*-test with respect to 1.

Table 4. Coefficients and fit indices of the latent class (LC) model

		Class 1		Class 2	
Attribute	**Level**	**Coeff.**	***t*-test†**	**Coeff.**	***t*-test†**
Grape	Merlot	-1.400	-5.66	-0.184	-1.07
cultivar	Carménère	-0.518	-2.24	0.435	2.61
	Shiraz	0.354	1.53	-0.642	-3.62
Advice	Salesman	0.153	0.75	-0.046	-0.36
	Friend	0.447	2.01	0.471	3.71
	Critic	0.693	2.61	0.227	1.51
Alcohol concentration		0.291	5.50	-0.017	-0.87
Price	After discount	-0.064	-3.18	0.001	0.14
Discount	10%	0.221	1.11	0.454	4.19
	20%	0.170	0.89	0.575	4.54
Constant		0.221	1.11	0.454	4.19
Scale	Grape ranking	0.635	-2.38‡	0.635	-2.38‡
Panel effect	Standard deviation	0.581	3.07	0.000	0.15
Class size		39%		61%	[50,99]
Fit	Observations (individuals)			2286 (254)	
indices	Number of parameters			26	
	Log-likelihood			-2916	
	Rho2			0.12	
	Adjusted Rho2			0.12	

† Robust t-test reported

‡ Robust t-test with respect to 1. The scales of both classes were constrained to be equal.

Table 5. Parameters of the multiple indicators multiple causes (MIMIC) model [part of the latent variable model (LV)]

		Coefficient	***t*-test**
Social cohesion	Consumption frequency	-0.118	-4.10
	Number of bottles per purchase	-0.010	-2.01
	Drinks at social gatherings	0.350	2.08
	Drinks at dinner in working days	-0.510	-4.00
	Age	0.012	2.67
	Education	0.092	1.94
Wine enthusiast	Buying frequency	0.178	4.41
	Consumption frequency	0.102	3.40
	Number of bottles per purchase	0.014	2.20
	Specialty store purchase frequency	0.157	2.62
	Buys bottles over US$40	0.292	2.24
	Maintains a cellar at home	0.789	4.58
	Gifts wine to friends	0.570	2.56
	Education	-0.125	-2.69
Fit indices	RMSEA†	0.048	
	P value of RMSEA ≤ 0.05	0.686	
	CFI	0.805	

† Root mean square error of approximation

Table 6. Parameter estimates and fit indices of the choice component of the latent variable model (LV).

Attribute	**Level**	**Coefficient**	***t*-Test†**
Grape cultivar	Merlot	0.048	0.27
	x Social cohesion	-1.090	-4.35
	Carménère	0.711	3.65
	x Social cohesion	-1.120	-5.57
	Shiraz	-1.660	-5.34
	x Social cohesion	-0.649	-3.29
	x Wine enthusiast	0.827	6.96
Advice	Salesman	0.103	1.05
	Friend	0.527	5.31
	Critic	0.491	4.49
Alcohol concentration	Main effect	-0.206	-4.41
	x Wine enthusiast	0.139	6.33
Price	After discount	-0.013	-0.94
	x Social cohesion	-0.045	-1.97
Discount	10%	0.541	5.01
	x Social cohesion	-0.346	-3.01
	20%	0.640	5.03
	x Social cohesion	-0.410	-2.82
Constant	Base	10.200	4.93
	x Social cohesion	0.797	0.50
	x Wine enthusiast	-3.780	-5.42
Scale	Grape ranking	0.760	1.81‡
Fit indices	Observations		2286
	Individuals		254
	Number of parameters		22
	Log-likelihood		-2885
	Rho2		0.13
	Adjusted Rho2		0.13

† Robust t-test reported

‡ Robust t-test with respect to 1.

Wine A	Wine B	Wine C	Wine D
			
Carménère	Merlot	Syrah	Cabernet Sauvignon
14.5° GL	12.5° GL	8.5° GL	14.5° GL
You remember reading a favouring critic about this wine	You don't remember reading or hearing about this wine	You remember reading a favouring critic about this wine	The salesman recommended this wine to you
US$ 8.00	~~US$ 10.40~~ US$ 8.32 -20%	~~US$ 12.80~~ US$ 11.52 -10%	~~US$ 9.60~~ US$ 7.68 -20%

Which wine would you buy?

○ Wine A ○ Wine B ○ Wine C ○ Wine D ○ I would not buy any

Figure 1. Example of choice exercise. Participants had to choose only one wine, or none of them. Each respondent answered six exercises.

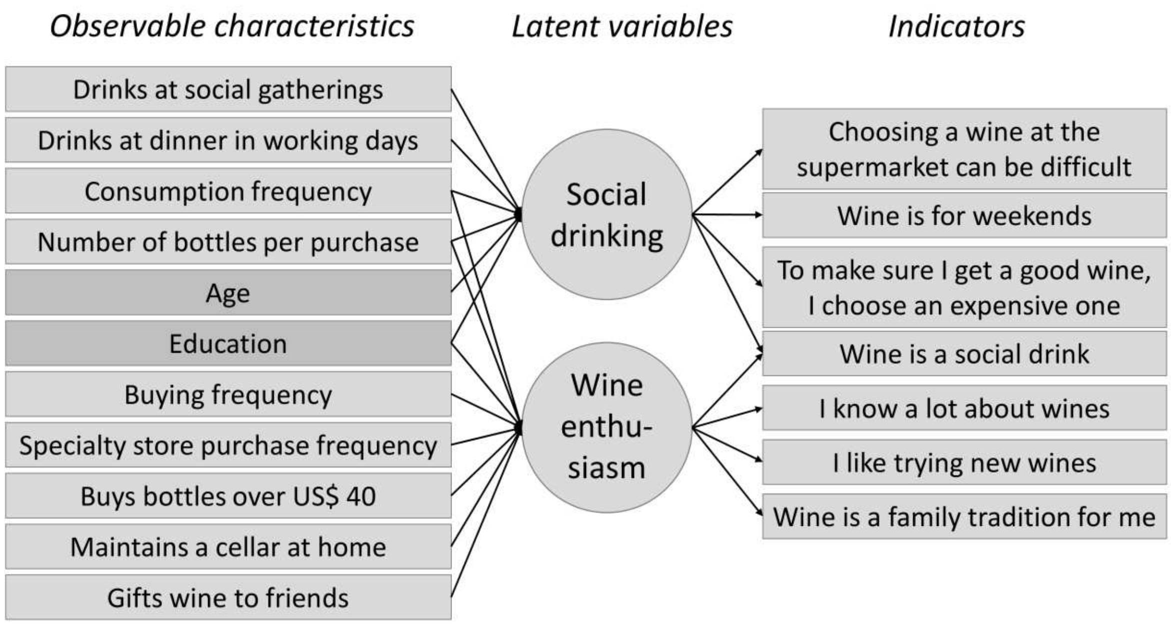

Figure 2 Structure of the multiple indicators multiple causes (MIMIC) model [part of the latent variable (LV) model]

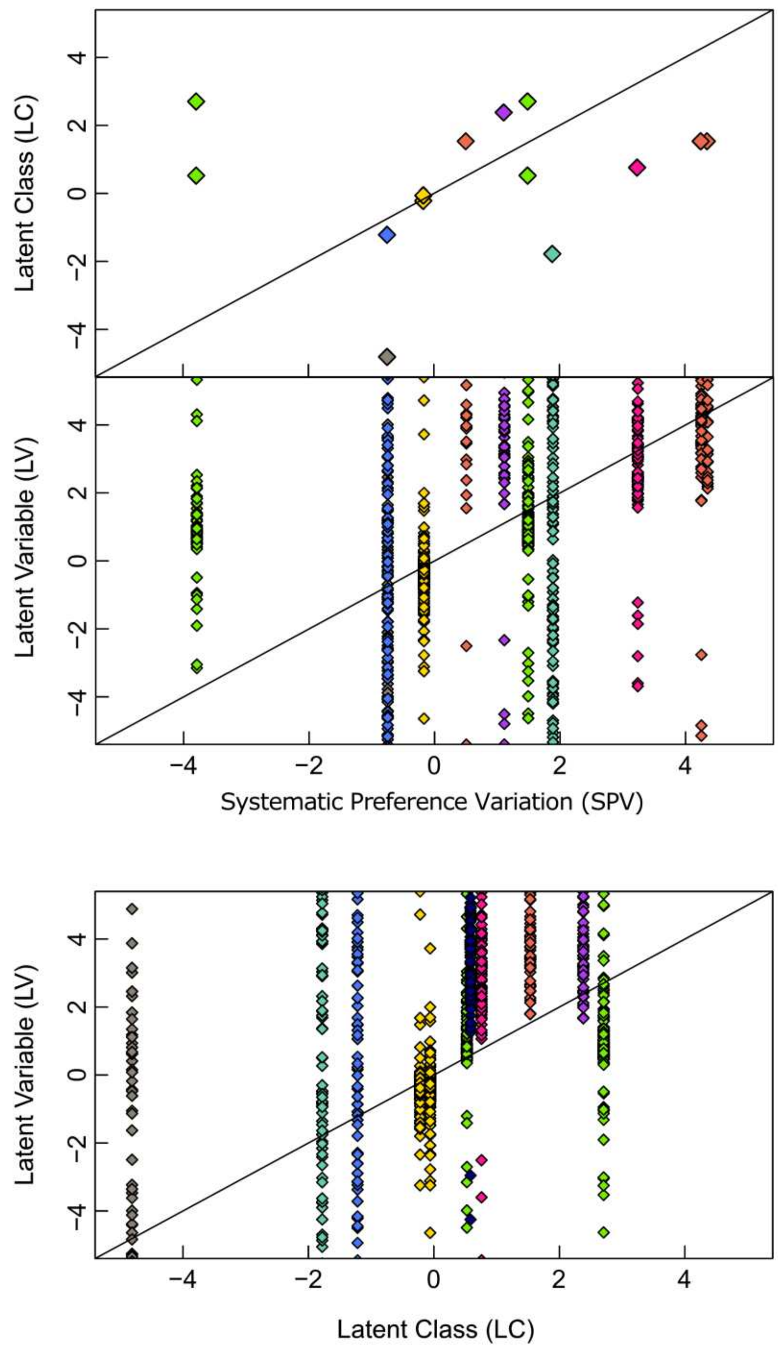

Figure 3. Graphical comparison of preferences profiles between models. Each graph compares normalised coefficients between pairs of models, if data points are near the diagonal, then models preference patterns are similar. Merlot (●); Carménère (●); Shiraz

(●); salesman’s advice (●); friend’s advice (●); critic’s advice (●);price (●); 10% discount (●); and 20% discount (●).