Modelling food and beverages purchase process combining sensory science and advanced discrete choice: A wine case study.

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Abstract

Purchasing any food or beverage product is a multi-stage, multi-attribute process. During the first purchase, consumers rely only on extrinsic (i.e. visual) attributes. Only after purchase can consumers taste the product, perceiving its intrinsic (i.e. sensory) attributes. When re-purchasing the product, consumers have full information about it. Most attempts to model consumers' choices of food and beverages either focus on only one stage of the process, one kind of attributes, or are limited in terms of their complexity or forecasting possibilities.

We present a novel experimental and modelling framework to study the choice of food and beverages in three stages: (i) purchase, (ii) tasting, and (iii) re-purchase on a controlled yet incentive-compatible setting. Our framework links all stages in a tractable and statistically correct way: it avoids endogeneity issues due to price-quality association, allows consumers to buy more than one product at a time, and is flexible enough to accommodate several methods of data analysis.

We study the purchase decisions of 130 Chilean wine consumers. They are equally influenced by visual perception and sensory liking of wines, though some sensory attributes (bitterness and astringency) can further increase sales. Visual perception is positively influenced by Cabernet Sauvignon and Shiraz grape varieties, and delicate label designs. Bitterness, astringency, and aromas of sweet spices and wood drive sensory liking, but preferences for them are too heterogeneous across the sample to identify any relevant average trend.

1 Introduction

As proposed by Grunert (2005) in his *Total Food Quality Model*, the purchase process of food and beverage products has three stages: (i) the first time a product is purchased, i.e. before tasting it; (ii) the tasting (consumption) of the product; and (iii) the decision to re-purchase the product in future occasions. However, this processes is seldom studied in its full complexity, as most research efforts tend to focus on a single stage of the process. This has led to a segmented literature about consumer preferences for food and beverages, with each segment using different tools and approaches. Recently, several authors have acknowledge this situation and called for new methodologies that encompass the full complexity of the purchase process (Simeone & Marotta 2010, Grunert 2015, Lockshin et al. 2017, Asioli et al. 2017).

Few studies focus on the joint effect of *extrinsic* and *intrinsic* attributes on consumers' purchase process. Extrinsic attributes are those consumers can perceive before tasting the product (e.g. packaging, price and health claims), and intrinsic attributes are those that can only be perceived during tasting (i.e. mainly taste and aroma). Asioli et al. (2017) offer a review of these kind of research during the last decade. They identify three approaches: (i) *conjoint hedonic methods*, (ii) *"classic" hedonic tasting*, and (iii) *alternative descriptive approaches*.

1.1 Conjoint hedonic methods

Conjoint hedonic methods are experiments where consumers face a series of samples described by both extrinsic and intrinsic attributes simultaneously, taste the samples, and then rate their level of liking for each of them. Even though these kind of studies can offer valuable

insight into new product development, they do not provide enough information for demand forecasting, as they are focused on consumers' liking instead of purchase decisions.

Using *conjoint hedonic methods*, Johansen et al. (2010) and Endrizzi et al. (2015) use traditional ANOVA methods to explain the level of liking of yoghurt and apples, respectively. Their greatest contribution is their way of reducing the complexity of intrinsic attributes' representation, from a full sensory profile to just dichotomous variables. They begin by representing the sensory space of a large sample of products on just two dimensions (i.e. two principal components). Then they select four samples covering as much of the sensory space as possible, and classify each of them as low or high on each principal component, therefore effectively representing the whole sensory profile with two dichotomous variables. This simplification allows them to build orthogonal designs. However, their methodology assumes linear responses to intrinsic attributes, and limits the analysis to only a few samples. Menichelli et al. (2012) expands the methodology by allowing for continuous intrinsic attributes and a bigger number of samples by presenting different samples to different groups of consumers.

Within the *conjoint hedonic methods* Asioli et al. (2017) also include choice based experiments. Unlike studies asking only for level of liking, choice studies do allow forecasting probabilities of choice, and through it, demand (under certain assumptions). However, these kind of studies tend to use very simple representations of intrinsic attributes, usually represented by discrete levels of one or two very specific attribute (e.g. sweetness, fat, and colour). Enneking et al. (2007) uses this approach to study preferences for price, label and sweeteners on soft drinks, noting that the approach is useful, but significantly demanding for participants. Grunert et al. (2015) studies preferences of Chinese consumers for fresh

pork, considering fat content, meat colour, packaging, branding and quality certification, but they do not include tasting in their experiment; instead, only pictures of the product are shown to participants.

1.2 "Classic" hedonic tasting

"Classic" hedonic tasting is the most popular, and probably more promising, approach to measuring the influence of both intrinsic and extrinsic attributes on purchase decision. The basic idea behind this approach is to measure the liking or willingness to buy a product under three different conditions or stages. In the first stage -blind tasting- participants taste samples with no additional information, therefore only perceiving their intrinsic attributes. In the second stage -expectations- participants evaluate products based only on their extrinsic attributes. In the third stage -informed tasting- participants have available both intrinsic and extrinsic attributes of the product for its evaluation. While most studies consider the three stages, some include only the blind and informed stages, assuming that the difference in evaluation between the two is due to the influence of extrinsic attributes.

The *"classic" hedonic tasting* approach has the benefit of representing the food and beverage purchase process more accurately than the conjoint hedonic approach. However, in its traditional form it still focuses on measuring liking or purchase intent for samples, two measures that do not allow for demand forecasting. This limitation could be overcome by using actual or hypothetical purchase decisions as a dependent variable in the third stage, as this measurement allows forecasting demand.

The "classic" hedonic tasting approach has a statistical difficulty that is often overlooked. In the traditional approach, the informed tasting rating is explained by the blind tasting rating and the expectations rating. However, both of these explanatory variables are endogenous

with the informed tasting rating, i.e. they correlate with the error term of the informed tasting rating. To see this more clearly, consider the following representation of the true model underlying the "classic" hedonic tasting approach.

$$R_{blind} = \propto blind + \delta \tag{1}$$

$$R_{expectations} = \beta\ expectations + \varepsilon \tag{2}$$

$$R_{informed} = \gamma\ informed + \zeta \tag{3}$$

$$informed = \lambda_1 blind + \lambda_2 expectations + \eta \tag{4}$$

R_{blind}, $R_{expectations}$ and $R_{informed}$ are the ratings provided by consumers in the blind tasting, the expectation, and the informed tasting stage, respectively. Equations (1), (2), and (3) show that ratings are noisy measures of the true levels of liking during each stage, i.e. the unobserved or latent variables *blind*, *expectations*, and *informed*. α, β, and γ are scale factors, and δ, ε, and ζ are random error components. It is assumed (equation 4) that the true level of informed liking (*informed*) is determined by a weighted combination of the blind and expected liking (i.e. *blind*, *expectations*), with weights λ_1 and λ_2, and a random error term η.As *blind*, *expectations*, and *informed* are not observed, λ_1 and λ_2 cannot be estimated directly, and instead we can only estimate the θ_1 and θ_2 parameters in equation (5). Furthermore, as both R_{blind} and $R_{expectations}$ correlate with ν –the new error component- the estimators of θ_1 and θ_2 will be biased. In fewer words, R_{blind} and $R_{expectations}$ are endogenous to $R_{informed}$.

$$\begin{gathered} \frac{R_{informed} - \zeta}{\gamma} = \lambda_1 \frac{R_{blind} - \delta}{\alpha} + \lambda_2 \frac{R_{expectations} - \varepsilon}{\beta} + \eta \\ R_{informed} = \frac{\lambda_1 \gamma}{\alpha} R_{blind} + \frac{\lambda_2 \gamma}{\beta} R_{expectations} + \left(\gamma\eta - \zeta - \frac{\lambda_1 \gamma}{\alpha}\delta - \frac{\lambda_2 \gamma}{\beta}\varepsilon\right) \\ R_{informed} = \theta_1 R_{blind} + \theta_2 R_{expectations} + \nu \end{gathered} \tag{5}$$

There are several approaches to analysing data from *"classic" hedonic tasting* experiments. The most common approach is based on ANOVA, studying the difference of evaluations between stages. Di Monaco et al. (2004), Varela et al. (2010), Hersleth et al. (2011), and Almli & Hersleth (2013) use this methodology for studying consumer preferences for pasta, powdered juice, dry ham and smoked salmon. They find an *assimilation effect*, i.e. expectations about the product quality before tasting it influence the evaluation of the product after tasting.. Only Almli & Hersleth (2013) include price among the evaluated extrinsic attributes. Once again, these applications make use of very simple intrinsic attributes, such as amount or type of salt, or measure preferences for whole products instead of intrinsic attributes of those products. This last issue could be overcome by using the sample selection technique by Johansen et al. (2010) and Menichelli et al. (2012).

Other studies using the *"classic" hedonic tasting* canvas employ more sophisticated methods to analyse the data. Guinard et al. (2001) use preference mapping to study beer preferences. Preference mapping has the benefit of considering the full sensory profile of products, but it does not allow for clear hypothesis testing on underlying factors (i.e. intrinsic attributes before the data reduction step is applied), therefore hindering the reliability of its results. As the authors only measured intention to buy among consumers, they are not able to forecast demand. Mueller & Szolnoki (2010) use seemingly unrelated regression with latent classes to study preferences for white wine. However, they only focus on the effect of extrinsic attributes on informed liking, as participants taste only one sample whose extrinsic attributes are systematically varied. Their results are potentially biased as they ignore the endogeneity of the blind tasting rating when estimating its impact on informed liking.

The work by Mueller *et al.* (2010) –even though not listed by Asioli et al. (2017)- could also be classified in the "*classic" hedonic tasting* group, as they studied preferences for wine in a two stage experiment. They simulated the expectation stage through an online best-worst exercise, followed by an informed tasting session where respondents provided their liking and purchase intent. However, the study faces some limitations. First, they only measure expectations at the product level, without analysing the impact of specific extrinsic attributes. Secondly, they did not account for the endogeneity of expectations on purchase intent (which is analogous to the informed rating in equations 1 to 5). Finally, their experiment was not incentive-compatible.

Another interesting study is by Combris et al. (2009). The study considers three stages: blind tasting, expectations, and informed tasting. The difference with the other experiments is that instead of reporting liking, participants had to reveal their willingness to pay for the product through an incentive-compatible bidding system. Later, willingness to pay data is analysed using ANOVA. The benefit of this methodology is that it reveals willingness to pay for products, but allows only for a limited set of samples, and sets the purchase decision in a fairly uncommon setting, which may alter the decision process.

Finally, Asioli et al. (2017) discuss new sensory descriptive methods that mix both extrinsic and intrinsic attributes, most notably Projective Mapping (PM) and Check All That Apply (CATA). PM, also called Napping®, asks consumers to place products close or far away from each other in a piece of paper based on their similarity of extrinsic and/or intrinsic attributes. The main advantage of this method is that consumers' responses are spontaneous, but it can be quite demanding on consumers and its results have to be complemented with more traditional profiling techniques to increase interpretability (Varela & Ares 2012).

CATA gives consumers a pre-defined list of sensory attributes, and ask them to use these attributes to describe a series of samples, one at a time. This method easily provides a consumer-based sensory profile, but it is hard to determine how the list of attributes influences consumer responses.

In this paper, we propose a novel experimental framework allowing to consistently measure the effect of both extrinsic and intrinsic attributes in the whole purchase process of food and beverages product. We do this in a realistic and incentive compatible environment, using a methodology that allows forecasting demand. We also use a simple yet highly flexible approach to data analysis, allowing researchers to use the tools they regard as more appropriate, while maintaining statistical consistency.

We use wine as a case study, as it is a very representative product of the food and beverages categories, highlighting its multi-stage, multi-attribute purchase process. Wine is a complex product, both from a subjective (Charters, 2006) as well as an objective (Ferreira *et al*. 2008) perspective. This complexity makes it difficult to determine wine's quality, therefore forcing consumers to strongly rely on extrinsic quality cues during the first purchase, and also tasting experience on consecutive occasions. At the same time, the vast diversity in the wine market forces consumers to constantly face new alternatives, making wine a remarkable product to study consumers' purchasing behaviour within the food and beverages' category.

Our framework aims to reproduce the whole purchase process of wine or any other food and beverage product. To do this, we use an experiment in three stages: (i) first purchase, analogous to measuring expectations (ii) blind tasting, and (iii) re-purchase, analogous to informed tasting. In the first stage, participants face a shelf full of products, and make a hypothetical purchase decision based only on what they can see. In the second stage,

participants blindly taste some of the products they chose in the previous stage, plus some other products selected by the researchers. Consumers are asked to provide an indicator of overall liking for each tasted product. Finally, in the third stage, we reveal to participants the extrinsic attributes of the wines they tasted, therefore providing them with full information about the products. Then, we allow participants to actually purchase any of the products they have full information for.

Our experimental design allows us studying consumers' decision making when facing a new product (i.e preferences for extrinsic attributes alone); measuring consumers' sensory preferences (i.e. preferences for intrinsic attributes alone); measuring the relative weight of extrinsic and intrinsic attributes in a real re-purchase decision; and predict demand for the products under study.

Section 2 describes the experiment, summarizes the sample's main characteristics, and presents the models used to analyse each stage of the experiment. Section 3 presents the main results of the experiment, and section 4 discusses them.

2 Materials and methods

In this section, the experiment's design is presented (section 2.1), followed by a summary of the sample's main characteristics (section 2.2) and a description of the models used to analyse the data (section 2.3).

2.1 Design of the experiment

The experiment had three stages: choice on shelf (stage 1), blind tasting (stage 2) and re-purchase (stage 3). There was also a registering stage (stage 0). All data was recorded using

an online survey system. A tablet PC was handed to each participant so they could input their answers.

2.1.1 Stage 0: Registration

Participants could register before arriving to the testing site through a link in the invitation to participate in the experiment. They could also register at the testing location. In this stage participants had to complete a questionnaire indicating some of their socio-demographic characteristics, as well as some details about their wine purchasing and consuming habits. After registering, participants went on to the choice on shelf stage.

2.1.2 Stage 1: Choice on shelf

In the choice on shelf stage, participants were randomly assigned to an available shelf, each with 24 wines (see Figure 1). Even though the wines were the same between shelfs, their price, discount and position varied. Participants had to build a ranking of the six wines they would like to buy the most. In first place, they had to place the wine they would buy if they could buy only one bottle. In second place, they had to place the wine they would buy if their first preference was not available, and so on until the sixth position. Participants could make shorter rankings if they did not find six wines they would like to buy in their assigned shelf.

Figure 1 - Participants during the choice on shelf stage

The purpose of this stage was to capture participants' preferences for wine when only extrinsic attributes were available, i.e. to capture their behaviour during a first buy. We attempted to use mostly unknown brands so participants would not be familiar with them. We could not explicitly ask participants' level of familiarity with each wine, as this would have made the experiment excessively tedious (we tested it during a pilot study, and most participants complained).

For modelling purposes, each wine was assumed to be described by five attributes: type of label, grape variety, alcohol content, price, and price discount. There were three types of label: delicate, natural and contrast, following the definitions by Orth & Malkewitz (2008). Grape variety had four possible levels: Cabernet Sauvignon, Merlot, Carmenere, and Shiraz; the most common grape varieties in Chile. Alcohol content had three possible levels: 13.5, 14.0 and 14.5 percent of alcohol. Price (before discount) was determined by each wine's market price. Additional to their listed price, wines could have a discount, with three possible levels: 0, 10 and 20 percent. Furthermore, we considered the vertical and horizontal position of wines in the shelf as two additional attributes. A summary of attributes and their levels is

presented in Table 1. The 24 wines were available in the market at the time of the experiment, and they were selected to represent every combination of label design (three levels), grape variety (four levels) and alcohol content (assuming only two levels: low at 13.5, and high at 14.0 or 14.5), while being priced within the 7 to 18 USD price range.

Table 1 - Extrinsic attributes and their levels

Type of label	Grape variety	Alcohol content	Price	Discount	Horizontal position	Vertical position
Delicate	Cabernet Sauvignon	13.5	(market price, approx. from 7 to 18 USD)	0%	Left	Down
Contrast	Merlot	14.0		10%	Centre	Centre
Natural	Carménère	14.5		20%	Right	Up
	Shiraz					

We used a D-efficient experimental design for this stage of the experiment (Rose & Bliemer, 2009). We used priors from a pilot study with ten participants, and assumed a simple MNL model with a linear utility function considering only attributes main effects. The full design had a single block with 24 choice situations. And even though we set up the 24 shelves, each respondent only faced one of them. We did four sessions of data collection, each of them with six different shelves. Each consumer was randomly assigned to one of the six available shelves. After completing the shelf choice, participants moved on to the tasting stage, on a different room.

2.1.3 Stage 2: Blind tasting

Before the beginning of data collection, all wines used in the study were profiled by a trained panel, according to the ISO 13299:2003 standard. A total of 27 different attributes (including colour) were identified and valued for each wine using a one to nine intensity scale. Using

principal component analysis (PCA) on the sensory profiles of wines, we obtained two different solutions: one with only two principal components (PC) explaining approximately 40% of the variation in the dataset, and another with four PCs accounting for approximately 60% of data variation. We only used the two components solution for design purposes, but the four components solution for analysis purposes.

When participants arrived to the second stage, they were assigned a set of five wines to taste under blind conditions (Figure 3), which were selected using a technique similar to the one described by Menichelli et al. (2012). Three of these five wines were the first three positions of each participant's ranking in the previous stage. The other two wines were selected based on each participant's first choice during the previous stage, in such a way that they would provide the maximum possible coverage of the sensory space between the 24 wines. This "maximization" was done by visual inspection, as shown in **Error! Reference source not found.**. In the graph, each dot represents a wine in sensory space (as described by two principal components of their sensory profile). To select the additional two wines to taste, each participant's first choice was found in the graph, and then a triangle was built with the chosen wine as one of its vertexes, and two additional wines in the other two vertex, in such a way that the triangle would cover the maximum possible area of the graph.

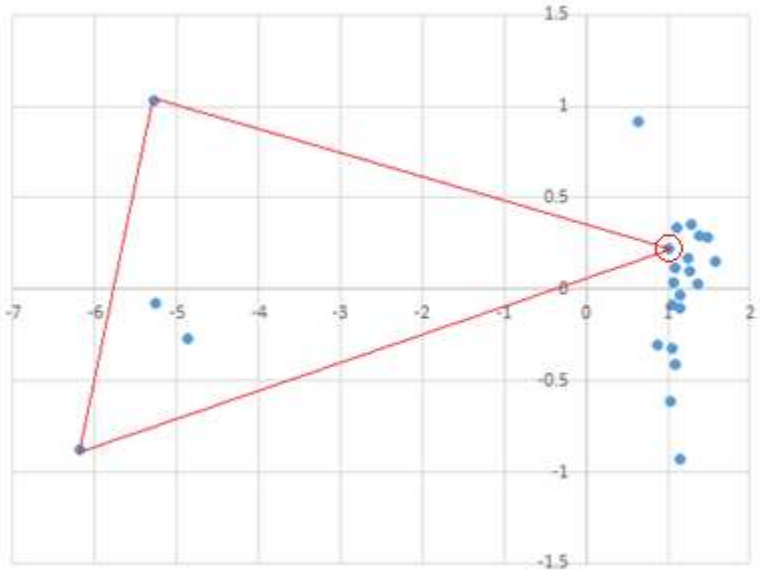

Figure 2 - Sensory space of all wines, as described by the two principal components used for designing the third stage of the experiment. Given the first wine chosen by the participant in the previous stage (circled in red), a triangle is built to maximize coverage. These two other wines (as given by the two other vertexes of the triangle) would provide two other samples for the tasting stage.

Figure 3 - Participants during the tasting stage

After tasting each wine, participants had to provide their level of liking on a 7-point Likert scale and complete a Check All That Apply (CATA) question concerning each sample. The

descriptors or *adjectives* used in the CATA exercise were non-technical wine descriptors collected during focus groups conducted before the experiment. Participants could select some, none, or all of the attributes for each wine if they so preferred. The adjectives were: *sweet, fruity, tastes like red berry, wood, chocolate, bitter, sour, dry, tastes like leather, tastes like alcohol, tastes flat, thick*. Tasting was done blindly to isolate the effect of intrinsic attributes on participants' perception of the product. After completing the tasting stage, participants could proceed to the final stage of the experiment: the re-purchase.

2.1.4 Stage 3: Re-purchase

During the re-purchase stage participants saw in their tablet's screen the full information of the five wines they had just tasted, i.e. all their extrinsic attributes as well as the level of liking they reported themselves (Figure 4). Then, participants were given the opportunity to purchase up to three bottles of any of the five wines they had previously tasted, in any possible combination. For example, they could buy three bottles of the same wine, or three different bottles, or just two bottles, or none at all. This was an actual purchase decision (Figure 5), as participants had to pay for the wines they wanted to buy. Prices and discounts were the same that respondents had faced at the first stage of the experiment.

Participants could not buy any wine other that the five wines they had tasted. Among those five wines, there were the three top choices of each participant during the "choice on shelf" stage. The goal of this stage is to measure the re-purchase decision, i.e. when consumers have seen the products' extrinsic attributes as well as tasted its intrinsic attributes, so it was of upmost importance that consumers had full information about all the available alternatives. Therefore, we could not allow them to choose a wine they had not tasted at the previous stage. We did not used any predetermined efficient design for the re-purchase stage, as its

alternatives were fully determined by each participant's choices during the two previous stages.

Wine A	Wine B	Wine C	Wine D	Wine E
Odjfell	ChateauLosBoldos	Apaltagua	ValleSecreto	ViuManent
Cabernet Sauvignon	Syrah	Cabernet Sauvignon	Carmenere	Cabernet Sauvignon
13.5° G.L.	14° G.L.	14° G.L.	14.5° G.L.	13.5° G.L.
Tasting score: 6	Tasting score: 4	Tasting score: 7	Tasting score: 3	Tasting score: 5
~~USD 9.60~~ USD 7.70 -20%	~~USD 6.80~~ USD 6.20 -10%	~~USD 7.40~~ USD 5.90 -20%	~~USD 11.60~~ USD 9.30 -20%	~~USD 6.60~~ USD 5.90 -10%

Considering only the wines shown on the table above. Which wines do you want to buy?
You can purchase up to three bottles. You can buy more than one bottle of each wine.
If you do not want to buy, select the alternative "I will not buy". *

1st wine to buy -- Please Select --
2nd wine to buy -- Please Select --
3rd wine to buy -- Please Select --

Figure 4 - Example of choice during the re-purchase stage

2.2 Sample

130 people participated on the experiment. Half of them (49%) were students aged between 18 and 25 years old, representing the Millennial group. The overrepresentation of this group was due to the experiment being performed in a university campus, so many students participated spontaneously. Table 2 presents more details about the sample characteristics.

Invitations to participate were sent to members of a Chilean wine social network (wineCLR). The main incentive for participating was the possibility of buying discounted wines; however, we also made a lottery among those who participated with six prizes of 12 bottles of wine each.

Figure 5 - A happy participant takes home his wines after purchasing them in the last stage of the experiment

2.3 Modelling

We first make a detailed presentation of the behavioural model inspiring the mathematical modelling, and then describe the specific modelling approach for each stage.

2.3.1 Behavioural model

During the first purchase, consumers cannot taste the product, therefore their *intention to buy* is mostly based on its *expected quality*. This expectation of quality is formed based on available quality cues, such as packaging, recommendations, and advertising. All attributes perceivable by consumers before purchase are called *extrinsic*. Price can also act as a cue for quality (Leavitt 1954, Dodds *et al.* 1991), therefore having a positive effect on *expected*

quality and through it, on *intention to buy*. However, as consumers also face budget restrictions, price has a direct negative effect on *intention to buy*, as consumers tend to select more economic alternatives. This leads to price having a double effect on *intention to buy*: an indirect positive effect due to consumers assuming that higher prices indicate higher quality, and a direct negative effect due to consumers' budget constraints.

Table 2 - Main characteristics of the sample

		Male	Female	Total
Number of people		78	52	130
Consuming Frequency	Almost never	0	6	6
	Few times a year	8	8	16
	Once a month	12	5	17
	Two times a month	23	10	33
	Once a week	12	12	24
	Two times a week	14	8	22
	Almost everyday	7	3	10
	Everyday	0	0	0
	More than one time a day	2	0	2
Average number of bottles per purchase		1.95	1.73	1.84
Always or almost always buys wine at…	Supermarket	54	34	88
	Specialty store	6	5	11
	Liquor store	15	8	23
	Web store (internet)	2	1	3
	Catalogue	3	0	3
Maximum buying range (USD)	Less than 5	5	4	9
	Between 5 and 7	31	25	56
	Between 8 and 14	34	17	51
	Between 15 and 21	4	3	7
	Between 22 and 29	2	2	4
	30 or more	2	1	3
Maintains a cellar at home		39	23	62
Age	18 to 25	44	30	74
	26 to 35	23	12	35
	36 to 45	4	5	9
	46 to 55	2	2	4
	56 to 65	3	3	6
	66 or more	2	0	2
Education	No higher education	7	3	10
	Incomplete university	37	27	64
	Complete university	23	13	36
	Complete postgrad	11	9	20

Household size (average)	Number of people	4.03	3.60	3.81
	Number of adults	3.54	3.06	3.30
Household income (USD)	Less than 1429*	16	15	31
	Between 1430 and 4285**	30	18	48
	More than 4286	32	19	51

** approx. one million Chilean Pesos; ** approx. three million Chilean pesos*

When consumers taste the product, they perceive its taste and aroma, determining their perception of the product's *experienced sensory quality*. All attributes that can only be perceived during the tasting stage are called *intrinsic*. Consumers' previous expectations about the product do influence their experience with it, i.e. *expected quality* does influence the *experienced sensory quality*.

Finally, during future purchase occasions, the consumers' *intention to buy* will be influenced by both the recalling of *experienced quality* and the effect of extrinsic attributes through an updated *expected quality*. The whole process is represented in Figure 6.

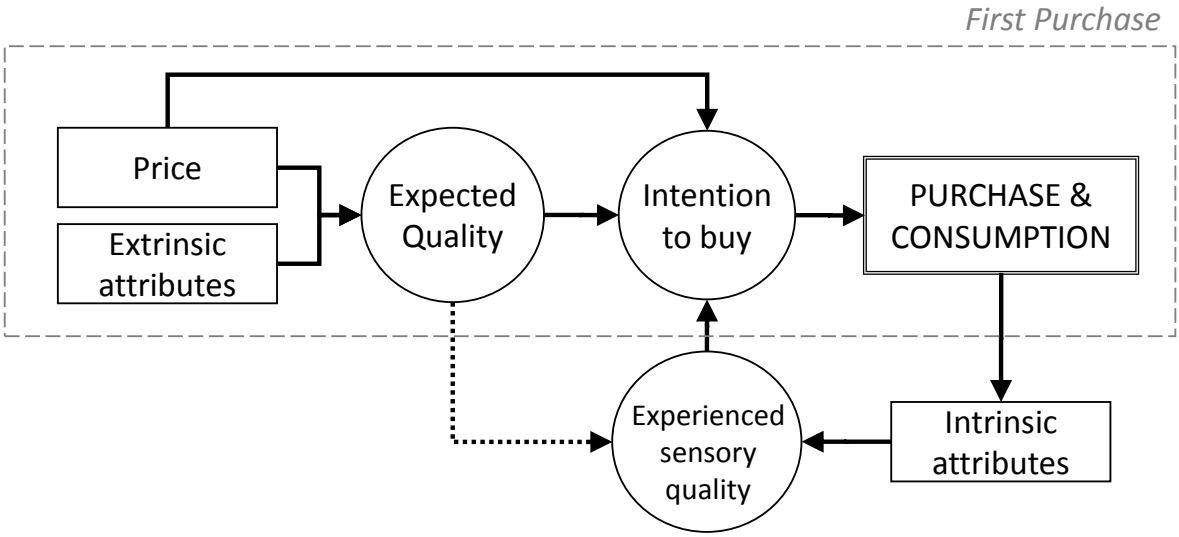

Figure 6 - Behavioural model for food and beverages consumption

Because of the complexity of modelling the whole purchase process described in Figure 6, in this application we decided to ignore the influence of *expected quality* on *experienced sensory* quality (the dotted line in Figure 6). Therefore, we assumed that *experienced sensory quality* is determined only by intrinsic attributes. In accordance to this assumption, we asked participants to rate their *experienced sensory quality* under blind conditions.

2.3.2 Stage 1: Choice on shelf stage

The objective of this stage was to measure participant's *intention to buy* when only extrinsic attributes were available. We modelled respondent's answers using an ordered logit (Train 2009, chapter 7).

The dependant variable was the inverted position in the ranking assigned by participants to each wine. Figure 7 presents one example of how to calculate the inverted ranking for a respondent who selected her six preferred wines out of a larger set and ranked these six wines in decreasing order, from most preferred to least preferred. All wines left out of the ranking (not selected) were assigned an inverse ranking value of 1, even though during the analysis of this stage, we only considered the wines actually included in the ranking (i.e. those whose inverted ranking value were two or higher). The wine that was ranked in sixth place in stage 1 is assigned an inverted ranking value of 2; the wine that was ranked in fifth place is assigned an inverted ranking value of 3, and so on; finally, the wine ranked in the first place is given an inverted ranking of 7. This coding makes coefficients easier to interpret, as the ordered logit's utility becomes the *expected quality*, and a higher expected quality leads to a higher inverted ranking.

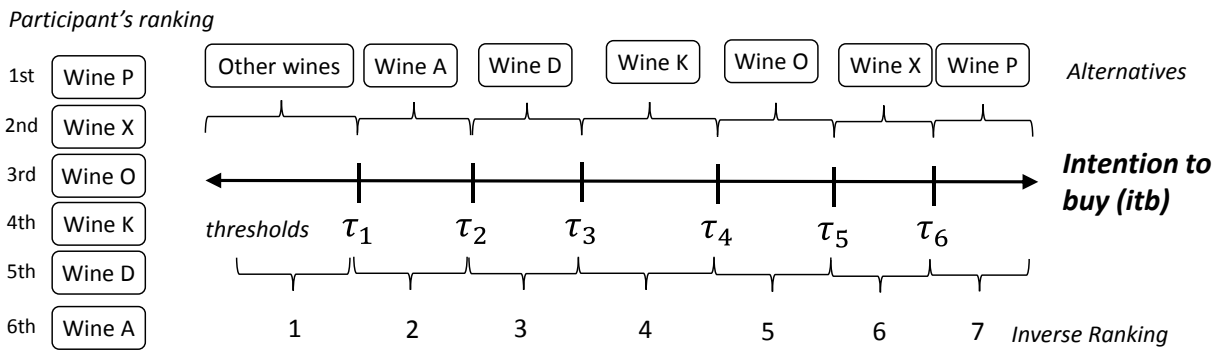

Figure 7 - Example of inverse ranking coding assuming respondents select six wines out of larger set and rank these six wine from most preferred to least preferred.

Expected quality was explained by each wine's attributes (Table 1). We tested systematic taste variations, i.e. interactions between alternative's attributes and participant's characteristics, but none was significant. Equations (6) to (8) describe the model.

$$itb_{nj} = X_j\alpha + \sigma_\zeta \zeta_n + \varepsilon_{nj} \tag{6}$$

$$\begin{aligned} P\left(invRnk_{nj} = r_j | \zeta_n\right) &= P\left(\tau_{r_j-1}^{invRnk} < itb_{nj} < \tau_{r_j}^{invRnk}\right) \\ &= \frac{1}{1+e^{X_j\alpha+\sigma_1\zeta_n-\tau_{r_j}^{invRnk}}} - \frac{1}{1+e^{X_j\alpha+\sigma_1\zeta_n-\tau_{r_j-1}^{invRnk}}} \end{aligned} \tag{7}$$

$$P(invRnk_n = r) = \int_{-\infty}^{+\infty} \prod_j P\left(invRnk_{nj} = r | \zeta_n\right) \phi(\zeta) d\zeta \tag{8}$$

itb_{nj} is product's j *intention to buy* by participant n, when only extrinsic attributes are available; X_j is a row vector of product's j extrinsic attribute levels; α is a column vector of taste parameters to be estimated; σ_ζ is a scalar parameter to be estimated; ζ_n is a random error component with standard normal distribution, its objective is introducing correlation among all observations j of the same individual n; ε_{nj} is an independent identically distributed (i.i.d.) standard logistic random error term. $invRnk_{nj}$ is the inverted ranking position of wine j

according to participant n's ranking; τ_r^{invRnk} ($r = 1, 2, ..., 6$) are parameters to be estimated, except for $\tau_1^{invRnk}=-\infty$ and $\tau_6^{invRnk}=+\infty$, which are fixed to allow identification of the model's parameters. The integral in (8) is solved using Monte Carlo methods (Train 2009, Chapter 10).

2.3.3 Stage 2: Blind tasting stage

The tasting stage was modelled as an ordered logit with random parameters, using the overall liking rating as dependant variable and the sensory profile of the wines and some of its physical attributes (alcohol content and grape variety) as explanatory variables. Each participant blindly tasted five wines. Overall liking was measured using a 1 to 7 Likert Scale, while the sensory profile was provided by the trained panel, using 27 descriptors, which were reduced to four factors using Principal Component Analysis (PCA).

Equations (9) to (11) describe the modelling of the blind tasting stage. The modelling is similar to the one used for the first stage, but now we considered preference heterogeneity in the form of Normally distributed preference parameters (β) across the population.

$$s_{nj} = Z_j\beta_n + \nu_{nj} \tag{9}$$

$$\begin{aligned} P\left(ove_{nj} = l_j \middle| \beta_n\right) &= P\left(\tau_{l-1}^{ove} < s_{nj} < \tau_l^{ove}\right) \\ &= \frac{1}{1 + e^{Z_j\beta_n - \tau_l^{ove}}} - \frac{1}{1 + e^{Z_j\beta_n - \tau_{l-1}^{ove}}} \end{aligned} \tag{10}$$

$$P(ove_n = l) = \int_{-\infty}^{+\infty} \prod_j P\left(ove_{nj} = l \middle| \beta_n\right) \phi\left(\beta_n \middle| \beta_\mu, \beta_\sigma\right) d\beta_n \tag{11}$$

Where s_{nj} is product j's *experienced sensory quality* as perceived by participant n; Z_j is a row vector of wine j's intrinsic attributes; β_n is a vector of normally distributed random taste parameters to be estimated, with mean β_μ and variance-covariance matrix β_σ (a diagonal matrix). As β_n is individual-specific, it correlates all observations from the same individual.

v_{nj} is an i.i.d. standard logistic error term. ove_{nj} is the overall liking score that participant n provided for wine j. Equation (10) presents the probability of wine j scoring l_j on average liking according to participant n, conditional on participant n's vector of preferences β_n; τ_l^{ove} ($l = 0, 1, ..., 7$) are thresholds to be estimated, except for τ_0^{ove}=-∞ and τ_7^{ovek}=+∞, which are fixed to allow identification of the model's parameters. Equation (11) presents individual n's unconditional probability of evaluating all wines j presented to her with the vector of scores l, where $\phi(\cdot \mid \beta_\mu, \beta_\sigma)$ is the multivariate normal distribution with mean β_μ and variance-covariance matrix β_σ.

2.3.4 Stage 3: Re-purchase stage

The re-purchase stage was modelled using Bhat (2008)'s Multiple discrete continuous extreme value (MDCEV) model. This family of models combine a discrete choice, i.e. what products to buy, with a continuous one, i.e. how much to buy of each product. Additionally, they take consumers' budget constraint into explicit consideration.

In accordance with classical economic theory, the MDCEV model assumes that individuals determine their consumption by optimizing their utility, subject to their budget constraint. In other words, individuals solve the following optimization problem.

$$\max_{x_n} U(x_n, e_n) = \sum_{j=1}^{J} \psi_{nj}\gamma_{nj} ln\left(\frac{x_{nj}}{\gamma_{nj}} + 1\right) + \varphi_n ln(e_n) \tag{12}$$

$$\sum_{j=1}^{J} p_{nj}x_{nj} + e_n = I_n \tag{13}$$

Where x_n is a vector with the amount consumed of each product j by individual n, and e_n is the amount consumed of the outside good. The outside good is an artificial product that captures the slack in constraint (13), i.e. weekly expenditures in everything that is not the

experiments' wine bottles, e.g. rent, food, transportation, etc. ψ_{nj} is the base utility of product j for individual n, i.e. the marginal utility of product j at zero consumption. γ_{nj} is a parameter determining the level of satiation for product j, i.e. the higher this value, the faster individual n gets satiated of consuming product j. φ_n is the base utility of the outside good. This particular form of the utility function is based on identification recommendations given by Pinjari & Sivaraman (2012). Equation (13) represents the budget constraint. p_{nj} is the price of product j for individual n, and I_n is her budget, which we set to the weekly household's per-capita income (i.e. a fourth of the household's monthly per capita income).

To ease interpretation, we assume ψ_{nj} determines the discrete part of the choice (i.e. what to buy), and γ_{nj} determines the continuous part of it (i.e. how much to buy). While this is not exactly true, as the purchase decision is determined by a complex non-linear interaction between all parameters, it is a useful simplification to interpret the results.

For $U(x_n, e_n)$ to be a valid utility function, ψ_{nj}, γ_{nj} and φ_n must be positive, which we attain using exponential functional forms. As we are interested in contrasting the effect of extrinsic and intrinsic attributes in the purchase decision, we would like ψ_{nj} and γ_{nj} to depend on *expected quality* (q) and *experienced sensory quality* (s), i.e. $\psi_{nj} = e^{\delta_q q_{nj} + \delta_s s_{nj} + \eta_{nj}}$ and $\gamma_{nj} = e^{\kappa_q q_{nj} + \kappa_s s_{nj}}$. However, we do not observe *expected quality* nor *experienced sensory quality*, which forces us to use indicators of them ($invRnk_{nj}$ and ove_{nj}) instead of their real values. But indicators are endogenous (Guevara & Polanco, 2016). To solve this, we resort to the Control Function Approach (Petrin & Train 2010).

The *Control Function* approach requires us to perform two auxiliary linear regressions: one to explain *invRnk* and another to explain *ove* based on a set of exogenous instruments (we can use different instruments for each variable). Instruments must fulfil two requirements: (i)

be independent of the purchase error term, and (ii) correlate with the endogenous variable. In the case of *invRnk*, we use product *j*'s extrinsic attributes as instruments, and for <u>*ove*</u> we use

We achieve this using the following functional forms.

$$\psi_{nj} = e^{\delta_s ove_{nj} + \delta_{Rs} resOve_{nj} + \eta_{nj}} \quad (14)$$

$$\gamma_{nj} = e^{\kappa_q invRnk_{nj} + \kappa_s ove_{nj} + \kappa_{Rq} resInvRnk_{nj} + \kappa_{Rs} resOve_{nj}} \quad (15)$$

Where ove_{nj} is the overall liking rating assigned to product *j* by individual *n*, $resOve_{nj}$ is the residual of a linear regression the δs, δRs,

Assuming a multiplicative i.i.d. Extreme value Type I error term in ψ_{nj}, Bhat (2008) shows that the probability of a given consumption (x_n, e_n) has the closed form showed in equation (14).

The *Control Function* approach requires us to perform two auxiliary linear regressions: one to explain *invRnk* and another to explain *ove* based on a set of exogenous instruments (we can use different instruments for *invRnk* and *ove*). Instruments must comply with two requirements: (i) be exogenous to the dependant variables (*invRnk* and *ove*, respectively), and (ii) correlate with their dependant variable. In the case of *invRnk* we used wine's observable (i.e extrinsic) attributes as instruments, as they are exogenous to participants' *invRnk*, but correlate with it. In the case of *ove*, we used the adjectives provided by each consumer to describe each wine as instruments. The adjectives are another indicator of

experienced quality, as discussed in the Results section, and are therefore exogenous to *ove*, but correlated with it because they both are caused by the same underlying factor, i.e. *perceived sensory quality* (see Guevara & Polanco 2016 for a discussion on using indicators as instruments, a special implementation of the Control Function approach called Multiple Indicator Solution).

The *Control Function* approach also requires us to include the residual of both auxiliary regressions in the definition of ψ_{nj}. Therefore, the final definition of these parameters is as presented in equation (11).

$$\psi_{nj} = e^{\beta_q invRnk_{nj} + \beta_s ove_{nj} + \beta_{Rq} resInvRnk_{nj} + \beta_{Rs} resOve_{nj} + \varepsilon_{nj}} \tag{11}$$

Where $invRnk_{nj}$ is the *inverse ranking* position of wine *j* for participant *n*, and ove_{nj} is its *overall liking*. $resInvRnk_{nj}$ and $resOve_{nj}$ are the residuals from the *invRnk* and *ove* auxiliary regressions, respectively. All β's are scalar parameters to be estimated. Among them, β_q and β_s are the most relevant, as they are proxies for the impact of *expected quality* and *experienced sensory quality* in the purchase decision. As both *invRnk* and *ove* are on a 1 to 7 scale, comparing β_q and β_s is straightforward. β_{Rq} and β_{Rs} are only necessary for the endogeneity correction and are of no particular interest, other than having to be negative, as required by the *Control Function* approach.

The likelihood function of the model has a closed form, and is the one presented in equation (12), with additional definitions in equations (13) and (14).

$$P(x_n, e_n, b_n) = \frac{1}{\sigma^M} |J| \frac{M! \prod_{j=1}^{M} e^{\frac{Vnj}{\sigma}}}{\left(1 + \sum_{j=1}^{J} e^{\frac{Vj}{\sigma}}\right)^{M+1}} \tag{12}$$

$$V_{nj} = -\ln(\psi_{nj}) + \ln\left(\frac{x_{nj}}{\gamma_{nj}} + 1\right) + ln\left(\frac{p_j}{e_n} + \frac{1}{b_n}\right) \tag{13}$$

$$J_{ih} = \frac{\frac{p_i p_h}{e_n^2} + \frac{1}{b_n^2}}{\frac{p_h}{e_n} + \frac{1}{b_n}} + \frac{\mathbb{I}_{i=h}}{b_n + \gamma_i} \qquad i,h=1\ldots M \tag{14}$$

Where σ is the scale parameter of the model's error component (ς_n and ε_{nj}), and it must be estimated. M is the number of different wines purchased. $|J|$ is the determinant of the Jacobian matrix whose ih^{th} element is as described in equation (14). Matrix J only considers purchased wines, so it is an M x M matrix. $II_{i=h}$ is equal to one if $i=h$, and zero otherwise. V_{nj} is described in equation (13). The product on equation (12)'s numerator only consider the wines that are purchased by the participant n. If participant n does not buy any inside good, then the numerator becomes 1 and $|J|$ disappears from equation (12).

Unlike more traditional choice models, the PS-MDC model does not have a price parameter, therefore demand price elasticities must be estimated by changing prices in the data base, forecasting for the new situation, and comparing the number of purchases in the forecast to a base scenario. Forecasting requires solving the optimization problem described in equations (5) to (7) for each participant. We solved this problem through enumeration, i.e. we enumerated all possible purchase combinations (e.g. do not buy any wine; buy one bottle of alternative A and none of the rest; buy one bottle of alternative A and one bottle of alternative B and none of the rest; etc.), then we calculated the utility for each purchase combination, and we finally assumed that the participant bought the purchase combination with the highest associated utility. We repeated this process for each participant. To account for the stochasticity of the problem, we simulated draws for ς_n and ε_{nj}, repeated the whole process for each set of draws, and then average the solution across all draws. For comparative

purposes, we also "forecasted" for a base situation with the original prices. We cannot use the observed purchases as base, as that would require us conditioning draws on observed behaviour, something we cannot do in the forecasting scenarios (see Pinjari & Bhat 2011, section 2, and von Haefen *et al.* 2004). When only one constraint is considered, enumeration of alternatives is not necessary, as more efficient algorithms exist (Pinjari & Bhat 2011, section 4.2).

All models were estimated using R (R Core Team 2015) and the maxLik package (Henningsen *et al.* 2011). The standard errors were obtained using the hessian of the loglikelihood function calculated by the package numDeriv (Gilbert & Varadhan, 2016).

3 Results

In this section, results from the three stages of the experiment are presented.

3.1.1 Choice in shelf stage

In this first stage, we measure *intention to buy* when only extrinsic attributes were available. We used the inverted ranking (*invRnk*) as a proxy for *intention to buy*. We only measured the net effect of price, i.e. we did not separated the positive (price as a cue for quality) and negative effect (due to the budget constraint) of price. However, we did controlled for the most popular winemaker brands included in the experiment. Brand images strongly correlate with expected quality, and therefore might have helped avoiding any endogeneity issues with the price parameter. See Palma et al. (2016) for a deeper discussion on how to separate both effects of price. Controlling for brand also allowed us to capture any systematic bias due to participants having tasted the available wines previous to the experiment. We attempted

several formulations with systematic taste variations based on available demographic characteristics of the participants, but none turned out to be significant.

Results for this stage are presented in Table 3. The utility function was linear, i.e. the functional form of *intention to buy* was assumed to be linear in parameters. Threshold parameters (τ) are not reported.

Table 3 - Estimates of the impact of extrinsic attributes on intention to buy when only extrinsic attributes are available.

Attribute	Level	Coefficient	t-value
Grape variety	Merlot	-0.741	-3.45
	Carmenere	-0.549	-2.77
	Shiraz	-0.064	-0.31
Label design	Contrast	-0.621	-3.22
	Natural	-0.416	-2.39
Alcohol content		-0.055	-0.25
ln(price after discount)		-3.127	-3.00
Discount	10%	-0.267	-1.34
	20%	-0.004	-0.01
Position	lower shelf	-0.256	-1.86
Winemaker	Group 1	2.347	4.20
	Group 2	1.283	3.23
Fit indices	Loglikelihood		-1355.14
	Number of parameters		17
	Number of observations		768
	Number of respondents		130
	ρ^2		0.250

Results reveal a strong preference towards Cabernet Sauvignon (the base grape variety) and Shiraz. Preference for these two grape varieties is statistically equivalent. Concerning label design, the preferred style is delicate, i.e. a traditional design without elaborated nor abstract

pictures or drawing. Alcohol content does not seem to influence participants' intention to buy. On the other hand, the net effect of price is negative and highly significant, as expected. Discount, on the other hand, is not relevant for consumer. The effect of discount measured here is only psychological, as its effect in price is already considered by making intention to buy depend on price after discount. The effect of position on the shelf is not significant, though being in the lower part of it has a marginally significant negative effect (p=0.06). Finally, two relatively homogenous groups of winemaker brands were identified, both with positive effects on intention to buy.

3.1.2 Tasting stage

This stage aimed at measuring *experienced sensory quality* when only intrinsic attributes were available to participants. We used the overall liking indicator (*ove*) as a proxy for *experienced sensory quality*. We tested several forms of representing the intrinsic attributes, but due to high preference heterogeneity, we could not find any significant average trend in the sample. In other words, as tastes are so different among the sample, their net (i.e. average) effect on the sample is zero.

We tested the effect of principal components through a four and an eight factor solution accounting for 60% and 80% of the data variability, respectively. We directly tested the effect of the 27 sensory descriptors on overall liking. We also tested formulations with the grape variety and the alcohol content as explanatory variables, but none of these turned out to have a significant average effect on the sample. This, however, does not mean that they are irrelevant, but that participants have very dissimilar tastes.

Taste heterogeneity is reflected in the best model found for this stage. In it, the mean effects of intrinsic attributes are not significant, but the variability of some of them are. Particularly,

preferences for PC2 and PC4 vary significantly across the sample. PC2 is mainly related to bitterness and astringency, while PC4 is linked to sweet spices and wood aromas. We also included fixed effects for the presentation order, most of which were highly significant, revealing that the first wine was evaluated more positively than the rest. Table 4 presents the best model's parameters, excluding thresholds (τ).

Table 4 - Estimate of the impact of intrinsic attributes in experienced sensory quality when only intrinsic attributes are available. Coefficients were considered random across the sample, except for order of presentation.

Attribute	Level	Coefficient	t-value
Sensory profile	Colour (mean)	0.159	1.03
	Colour (s.d.)	0.035	0.60
	PC 1 (mean)	-0.069	-0.79
	PC 1 (s.d.)	0.095	0.84
	PC 2 (mean)	-0.030	-0.40
	PC 2 (s.d.)	0.101	2.08
	PC 3 (mean)	-0.087	-1.47
	PC 3 (s.d.)	0.051	0.38
	PC 4 (mean)	0.009	0.19
	PC 4 (s.d.)	0.149	3.12
Presentation order	Second (mean)	-0.694	-3.04
	Third (mean)	-0.371	-1.62
	Fourth (mean)	-0.546	-2.39
	Fifth (mean)	-0.540	-2.35
Fit indices	Loglikelihood		-1187.45
	Number of parameters		20
	Number of observations		650
	Number of respondents		130
	ρ^2		0.221

Data from the CATA exercise, where participants described each sample based on a set of pre-defined adjectives, was not suitable to build a participant-based sensory profile of the wines. Instead, participants seem to have used the adjectives as indicators of liking. Participants seem to have classified the adjectives into two groups: positive adjectives (sweet,

fruity, tastes like red berry, wood, chocolate) and negative adjectives (bitter, sour, dry, tastes like leather, tastes like alcohol, tastes flat, thick), assigning positive adjectives to the wines they liked, and negative ones to the wines they did not liked.

Adjectives could not be used to build a participant-based sensory profile of wines due to lack of consensus in their use. Consensus is assumed to be reached when the number of times a given {wine, adjective} pairing is observed in the data is significantly different from zero. Table 5 shows the percentage of times a given pairing was selected by participants, when such pairing was available to select (i.e. when participants tasted the wine in the pairing). None of those values is significantly different from zero based on a t-test at 95% confidence, indicating that no consensus was reached, and therefore making any attempt to create a sensory profile from the data futile.

At a more aggregate level, Chi-Squared tests of independence indicate significant correlation between the wine samples and the selection of adjectives in only three cases: chocolate, sour and dry. The p-values of these tests are reported in the last row of Table 5. However, these cases reveal a negative association, i.e. no wine in the sample should be described as having chocolate aroma, or having sour or dry tastes. But only negative associations are not useful for building a consumer-defined sensory profile.

The high correlation between the use of some adjectives and overall liking reveals that participants used adjectives as another indicator of quality. Table 6 shows adjectives “sweet”, “fruity”, “berry”, “wood” and “chocolate” being positive and significantly correlated with overall liking. Instead, adjectives “bitter”, “sour” and “flat” have a negative significant correlation with overall liking.

Table 5 – Percentage (in 0-1 scale) of times each {wine, adjective} pairing was observed. Last row presents p-values of Chi-squared test of independance between adjectives and samples (rejection of independence is highlighted).

wine	n	sweet	fruity	berry	wood	choc.	bitter	sour	dry	leather	alcohol	flat	thick
1	41	0.15	0.32	0.22	0.29	0.10	0.29	0.17	0.15	0.15	0.10	0.07	0.22
2	27	0.19	0.37	0.19	0.22	0.11	0.07	0.56	0.19	0.07	0.19	0.22	0.07
3	27	0.26	0.44	0.15	0.33	0.04	0.11	0.22	0.26	0.11	0.11	0.22	0.04
4	33	0.18	0.21	0.21	0.36	0.09	0.33	0.27	0.27	0.24	0.24	0.09	0.24
5	9	0.22	0.22	0.33	0.11	0.11	0.22	0.44	0.33	0.11	0.22	0.11	0.00
6	22	0.18	0.14	0.18	0.27	0.00	0.14	0.32	0.23	0.05	0.18	0.23	0.05
7	55	0.18	0.33	0.16	0.45	0.24	0.25	0.18	0.24	0.18	0.18	0.11	0.25
8	44	0.23	0.23	0.20	0.27	0.02	0.16	0.27	0.20	0.07	0.16	0.18	0.14
9	34	0.15	0.29	0.24	0.35	0.18	0.24	0.09	0.12	0.15	0.15	0.15	0.21
10	17	0.06	0.24	0.12	0.35	0.00	0.29	0.24	0.18	0.35	0.24	0.12	0.12
11	15	0.27	0.20	0.27	0.20	0.07	0.20	0.33	0.13	0.07	0.40	0.20	0.13
12	48	0.06	0.17	0.17	0.19	0.08	0.25	0.46	0.23	0.13	0.38	0.15	0.19
13	30	0.17	0.37	0.20	0.30	0.03	0.23	0.37	0.07	0.17	0.30	0.23	0.20
14	38	0.26	0.18	0.29	0.34	0.03	0.24	0.26	0.05	0.18	0.18	0.08	0.11
15	17	0.18	0.24	0.24	0.35	0.18	0.12	0.18	0.53	0.12	0.24	0.06	0.12
16	18	0.11	0.22	0.17	0.33	0.11	0.28	0.17	0.22	0.22	0.44	0.11	0.17
17	17	0.35	0.24	0.12	0.24	0.18	0.41	0.29	0.24	0.24	0.18	0.06	0.18
18	25	0.16	0.40	0.12	0.40	0.24	0.20	0.32	0.20	0.12	0.28	0.08	0.24
19	17	0.29	0.41	0.41	0.18	0.24	0.24	0.24	0.29	0.12	0.18	0.06	0.24
20	30	0.27	0.23	0.17	0.27	0.03	0.27	0.27	0.30	0.17	0.30	0.20	0.10
21	11	0.09	0.09	0.18	0.27	0.00	0.45	0.27	0.18	0.09	0.09	0.00	0.55
22	30	0.20	0.37	0.23	0.27	0.03	0.23	0.40	0.43	0.10	0.30	0.13	0.23
23	11	0.09	0.09	0.18	0.64	0.09	0.09	0.09	0.27	0.09	0.00	0.00	0.18
24	31	0.23	0.39	0.29	0.26	0.03	0.19	0.26	0.19	0.13	0.13	0.19	0.16
Chi Squared		0.685	0.252	0.923	0.435	**0.004**	0.550	**0.000**	**0.040**	0.674	0.068	0.465	0.127

Table 6 - Results of a linear regression between overall liking (ove) and descriptive adjectives

Attribute	Coeff.	t-value
Intercept	4.142	30.86
Sweet	0.362	2.30
Fruity	0.684	5.04
Berry	0.713	4.84
Wood	0.559	4.31
Chocolate	0.444	2.16
Bitter	-0.659	-4.49
Sour	-0.445	-3.24
Dry	-0.105	-0.74
Leather	-0.160	-0.95
Alcohol	-0.235	-1.59
Flat	-0.414	-2.39
Thick	0.185	1.17
R2		0.23
adjusted R2		0.22

3.1.3 Re-purchase stage

The objective of this stage was to measure the effect of price, intrinsic and extrinsic attributes in the re-purchase decision under real conditions, i.e. on real purchase data. We used the inversed ranking (*invRnk*) collected in the first stage as a proxy for *expected quality*, and the

overall liking (*ove*) rating obtained in the second stage as a proxy for *sensory experienced quality*. As these indicators are endogenous, we used the Control Function Approach (CFA) to correct for it. Results of the first stage of the CFA for each endogenous variable are presented on Table 7. The residuals of these linear regressions are later used in the main model for the re-purchase stage.

Table 7 – Third stage's auxiliary linear regressions (1st stage of CFA)

	Overall liking				Inverted Ranking		
	Coeff.	t value			Coeff.	t value	
Intercept	4.065	34.71	**Intercept**		-21.030		-4.76
Sweet	0.385	2.46	**Grape**	Merlot	0.674		2.51
Fruty	0.727	5.43	**Variety**	Carmenere	0.184		0.72
Berry	0.739	5.07		Shiraz	0.493		1.80
Wood	0.565	4.40	**Label**	Contrast	-0.681		-3.07
Chocolate	0.471	2.31	**design**	Natural	-1.535		-5.58
Bitter	-0.685	-4.75	**Alcohol content**		1.690		4.79
Sour	-0.463	-3.42	**ln(price before discount)**		0.636		1.16
Flat	-0.431	-2.53	**Winemaker**	Group C	1.400		4.58
				Group D	2.955		9.03
R2		0.224	**Fit Indices**	R2			0.142
adjusted R2		0.215		adjusted R2			0.129

Unlike result from the first stage (Table 3), where *price* had a negative and significant effect, *price* has a positive but insignificant effect on the auxiliary linear regression of *inverted ranking* (Table 7). This is probably due to price's double effect: both as a cue for quality (positive effect on *intention to buy*) and a strain to the budget constraint (negative effect on *intention to buy*). When only respondents' favourite wines are considered, (as in Table 3) the negative effect of price after discount dominates, as respondents consider all those wines to have an acceptable level of quality, and therefore prefer those with lower prices. However, when all wines are considered, including those left out of the ranking (as in Table 7), the positive effect of price is stronger, as participants tend to exclude the cheaper wines from

their rankings. This last trend can be observed directly in the data, as the average price before discount of wines included in the ranking ($8.61) is higher than the average price of wines excluded from the ranking ($8.12). Both averages, however, are not significantly different, just like the price effect in the auxiliary linear regression is not significant either.

Table 8presents the estimated parameters of the PS-MDC model for re-purchase. We used participants' weekly per capita income as the monetary Budget, i.e. I_n is equal to the household's per capita income divided by four. Nevertheless, parameters show little variability if other budgets are used, e.g. monthly household income or per capita monthly income (not reported).

Table 8 - Impact of price, extrinsic and intrinsic attributes in intention to buy

		Coeff.	t-value
Discrete choice (ψ)	Inverse ranking (invRnk)	0.160	4.25
	Overall liking (ove)	0.134	3.85
	Residual of invRnk	-0.135	-3.29
	Residual of ove	-0.164	-3.93
Continuous choice (γ)	Intercept	-2.090	-6.51
	Wineyard Group D	0.314	3.77
	PC2	0.064	1.71
Other	σ	0.248	12.05
Fit indices	Loglikelihood		-41.10
	Number of parameters		8
	Number of observations		130
	Number of respondents		130

Both extrinsic and intrinsic attributes –as represented by *inverse ranking* and *overall liking* respectively– have a positive, significant, and statistically equivalent influence (p = 0.61) on the choice of what to buy. Both residuals have a negative coefficient, as required by the CFA, and are also significant at 95% confidence. How much to buy is only influenced by the

winemaker, while some intrinsic attributes of the wine (PC2, associated to bitterness and astringency) is only marginally significant ($p = 0.09$).

The equivalence of extrinsic and intrinsic attribute's influence is aligned with participants' observable behaviour, though only when price is considered. If price is ignored, blind tasting seems to determine purchase: among those participants who bought, only one third (33%) purchased the wine they ranked better in the first (shelf) stage, while 83% of them purchased the wine they rated best at the blind tasting stage. However, if we take price into account, things change. If we consider each wine's *expected quality* and *sensory quality* per unit of price (or more precisely, a proxy for it using *inverse ranking* and *overall liking* divided by *price*), we find that half of the participants who bought purchased the wine with best *expected quality* / *price* ratio, and also half of the sample got the wine with best experienced *sensory quality* / *price* ratio.

Sensitivity to price is highly dependent on the definition of participants' constraints. Table 9 shows how own price – demand elasticity changes under different definitions of the two constraints (hereafter called *forecasting scenarios*). All elasticities were calculated by increasing the price of the first alternative by five percent, while keeping the other alternatives' price fixed. We forecasted for the base and price-increased scenario, calculating the elasticity based on the sales difference of the altered alternative in both scenarios.

The first constraint defining each scenario is the budget constraint (equation 6). As is to be expected, increases in budget lead to decreases in price sensitivity. We estimated three different models, one for each budget considering: 25%, 50% and 100% of the household per capita income. Only the first of these models is reported in Table 8. We do not report the

others as their parameters and t-test are very similar. We used the corresponding model parameters when forecasting under each scenario.

The second constraint (equation 7), determines the maximum number of bottles that participants could purchase during the experiment. This is an exogenous and artificial constraint. While this constraint was imposed to limit the stock of wines necessary to run the experiment, it also had the side-effect of truncating demand. This means that for some participants the number of bottles constraint was more restrictive than the budget constraint, therefore making them appear to be insensitive to price. To avoid this pitfall, we estimated the price – demand elasticity under simulated conditions limiting the maximum number of bottles to purchase to 12, 24 and infinite (i.e. we dropped this restriction).

When the number of bottles constraint is kept at three (just as in the actual experiment) price sensitivity is very low, ranging from -0.04 to -0.14 depending on the budget constraint. However, as the number of bottles constraint is relaxed, sensitivity to price increases to -1. This estimate, however, is only a rough approximation of the true value, as an experiment without restricting the maximum number of bottles would have to be conducted to obtain a more reliable estimate. Interestingly, when the number of bottles constraint is dropped, the price – demand elasticity is almost insensitive to the budget definition.

The aggregated demand for wine, i.e. the demand for all alternatives, is insensitive to increases in price of just one alternatives (values not reported). This means that an increase of price in an alternative just make participant choose a different wine, but their overall wine consumption remains the same.

Table 9 - Price elasticity under different constraints

	Money budget	Maximum number of bottles

(per capita income)	3	12	24	∞
25%	-0.10	-0.19	-0.33	-1.02
50%	-0.06	-0.09	-0.18	-1.01
100%	-0.02	-0.04	-0.08	-1.00

4 Discussion

We designed and executed a three-stage experiment to improve the understanding of wine's purchase and repurchase process, and the influence of extrinsic and intrinsic attributes on it. Starting from a well stablished behavioural model (section 2.3.1), we proposed a tractable econometric approach to study the whole process (sections 2.3.2 to 2.3.4).

4.1.1 About the first purchase

Concerning the modelling of the first purchase, we used a ranking exercise which we analysed using an ordered logit model. Similar results can be obtained using a linear regression with *inverted ranking* as the dependent variable, and wines' extrinsic attributes as independent variables.

We identified respondents' preferred extrinsic attributes: Cabernet Sauvignon and Shiraz grape variety, and delicate label design (see Orth & Malkewitz 2008). As expected, we also find a negative effect of price, but estimating a reliable price-demand elasticity is difficult due to data being a ranking exercise. Discounts do not seem to have any psychological effect, instead they only influences *willingness to buy* through the price reduction. Discount's lack of influence may be due to participants not having any time constraint to complete the experiment; if rushed, consumers may focus on discounted wines first, instead of searching through all alternatives, as participants seem to have done in our experiment (data collection was during the weekend). The lower shelf negatively influenced the probability of choosing

a wine, though the effect was not significant (p=0.06). Despite our effort on using mostly unknown brands in the experiment, controlling for the winemaker was fundamental in obtaining significant results, pointing to respondents' familiarity with some of the brands used in the experiment. This highlight how consumers strongly rely on previous experience and recommendation when choosing a wine.

Our results are consistent with global and local literature on the effect of extrinsic attributes on wine purchase decisions. Agreeing with the "clear accepted knowledge" enumerated by Lockshin & Corsi (2012), we find price and brand to be relevant, and grape variety to play a major role, as in other New World countries. We also found discount to have no positive effect, similarly to what Lockshin & Corsi (2012) report. Concerning other studies with Chilean samples of wine consumers, we find brand and price to be relevant, and preferences not to vary significantly due to participants' sociodemographic characteristics, just as in Schnettler & Rivera (2003). Also, in accordance with Cerda et al. (2010), we find grape variety to be relevant and an average preference toward Cabernet Sauvignon over Carmenere and Merlot.

In light of our results, we recommend two improvements to future implementations of our experimental design. First, we recommend dropping the use of rankings on the shelf stage in favour of a multi-purchase, i.e. allowing participants to choose as many bottles as they want from the shelf. To increase the amount of observations, respondents could be asked to choose from several shelfs, and then randomly select one of them as the actual purchase. Secondly, we recommend making this stage incentive-compatible by asking consumers to immediately pay for the wines they choose in the randomly selected shelf. After the transaction, participants can be invited to the blind tasting, and after that (in the third stage) they can be

allowed to change their purchase decision, making for a more realistic re-purchase stage. These changes would increase participants' involvement with the first stage purchase, and would also allow for more reliable calculations of price-demand elasticities. However, removing the ranking in this stage also implies removing the indicator of *expected quality* used in the third stage, so it should be replaced by at least one new indicator of *expected quality*. One possible type of indicator are participant-provided quality rankings for each wine. Asking for two indicators would be better, as one of them could be used as an instrument when applying the Control Function Approach on the third stage modelling (Guevara & Polanco 2016).

Additionally, using a smaller set of wines could be advisable. This would reduce the similarity between the experimental setting and a supermarket, and would not allow measuring the effect of shelf position. However, using a smaller number of wines would also greatly ease stock-keeping logistics. Additionally, it might allow for a better sensory design, as participants could taste a bigger proportion of available wines.

4.1.2 About the tasting

Concerning the modelling of sensory preferences, we attempted to explain respondents' *overall liking* based on wines' sensory profile, as determined by a trained panel, using once again an ordered logit model. This stage could also be modelled using linear regression.

Results of the second stage were not as satisfactory as the ones from the first stage, mainly due to high heterogeneity in preferences. Only two out of four sensory factors (i.e. principal components) had a significant effect on liking, but this effect was so heterogeneous among respondents that their net effect on the sample was zero. Instead, presentation order had a significant effect, with the first wine being evaluated more liberally.

It is possible that consumers' sensory perception is not aligned with the trained panel's perception. Principal Components summarize wines' differences as perceived by the trained panel, but these differences need not be drivers of consumers' linking. We attempted to avoid this problem by building a sensory profile of the wines directly from participants' responses, using a Check All That Apply (CATA) exercise with consumer-defined adjectives as descriptors, which were drawn from a focus group. But participants interpreted the adjectives as indicators of liking, i.e. as an either positive or negative judgement of liking over the wine, and not as sensory descriptors.

Despite the described difficulties, we obtained some valuable results from the second stage of our experiment. We found two principal components whose effect is significant, relating to bitterness, astringency and wood and spicy aromas. This result is in line with focus groups, where wood, bitterness and astringency were some of the most mentioned sensory attributes of wine. Preferences for these attributes, though, are highly heterogeneous among the sample, and therefore no general trend of preferences could be identified.

Our results concerning intrinsic attributes are only partially aligned with the published literature. Just as Francis & Williamson (2015) state, we find bitterness and astringency to be relevant drivers of liking, but we cannot confirm their negative effect, as preferences for these attributes are too heterogeneous in our sample. We also found wood and sweet spice aromas to be relevant, but there is not much literature highlighting the relevance of these attributes.

For future implementations of our experimental design, we recommend using sensory descriptive methods based on consumers' responses where no explicit *a priori* enumeration of attributes is made. A thoroughly description of new methods can be found on Varela &

Ares 2012, and Valentin et al. 2012. In particular, a promising profiling method using regular consumers is *Projective Mapping* or *Napping* (Pagès 2005). In it, consumers are given a blank sheet, a set of products, and are asked to place the products in the sheet in such a way that similar products are close, and dissimilar products are far away. Even though the method is based on consumers' perception and does not use a predefined set of attributes, it has several disadvantages. First, it is significantly demanding and therefore time consuming for regular consumers, making it unsuitable to implement as part of the second stage of our experiment. Secondly, it requires several samples to be evaluated simultaneously, making it mostly unsuitable to use with alcoholic products. Finally, unlike more traditional profiling techniques, Napping's sensory profiles do not provide a clear-cut set of attributes, but instead tend to cluster products together, limiting the generalization of results. Modelling sensory perception to explain consumers' level of liking is one of the most challenging aspects of modelling food and beverages demand.

Another possible improvement to the second stage's experimental design is asking for two indicators of liking, instead of just one. So in addition to asking for overall liking, a question about participants' relative willingness to pay could be included (e.g. ask if they would be willing to pay more or less for that wine than what they usually pay for a bottle of wine), or asking about how tasty the wine was. The second indicator could be used as a more precise instrument for the first one when applying the control function approach on the third stage (i.e. using the MIS approach, as described by Guevara & Polanco 2016).

4.1.3 About the re-purchase

Concerning the modelling of the re-purchase, we used the multiple discrete continuous model with two constraints described by Pinjari & Sivaraman (2012) (PS-MDC). This model

allowed us considering consumers' budget restriction, as well as the artificial constraint of purchasing a maximum of three bottles. Multiple discrete continuous models allow consumer to behave just as they would on the marketplace, i.e. to choose several (or none) alternatives and to buy one or more units of each. These characteristics are hard to replicate with simpler models, such as linear regressions, traditional choice models, or count models alone.

In the third stage we focus on the effect of *expected quality* and *experienced sensory quality* on purchase, as they condense the influence of extrinsic and intrinsic attributes, respectively. This approach free us from measuring the influence of particular attributes on the purchase decision, gaining efficiency and obtaining a more parsimonious model. This is important, as in this stage we only captured one observation per respondent. This approach also provides more flexibility as each stage can be analysed independently. As we do not directly observe *expected* nor *experienced sensory* quality, we used *inversed ranking* and *overall liking* as proxies, correcting for their endogeneity using the Control Function approach.

We found the influence of extrinsic and intrinsic attributes to be statistically equivalent when choosing what wine to purchase. In other words, the appearance of a bottle of wine seems to be just as important as its content. Nevertheless, some intrinsic attributes –bitterness and astringency, in particular- can positively influence the number of bottles purchased. The winemaker (i.e. the brand) can also influence the number of bottles purchased, indicating that previous experience or recommendations play a relevant role on the purchase process. Finally, we estimated price-demand elasticity to be close to -1. However, this value is only referential, as constraining the maximum number of bottles that consumers could purchase did not allowed us to obtain a reliable elasticity estimate.

We tested for interactions between the proxies of *expected quality* and *experienced sensory quality* (i.e. between *inverse ranking* and *overall liking*), but could not find any significant one. It is possible that we did not observe any significant interaction due to the tasting stage being performed under blind conditions. If the tasting was not blind, we might had observe some significant interaction. We also tested for differences on the importance of *expected* and *experienced sensory* quality for different groups of participants based on age, gender and income, but could not find any significant difference.

It is possible that the relevance of *experienced quality* and *experienced sensory quality* may change as time between the tasting and the re-purchase elapses. The direction of this change, however, is hard to predict, as time may make experienced sensory quality hard to remember and therefore less relevant, or memory may idealize wines over time, increasing the relevance of experienced sensory quality. More research is necessary on this subject.

Results from the third stage are aligned with the literature. Concerning price sensibility, a meta-analysis by Wagenaar et al. (2009) estimated price-demand elasticity for wine at -0.69, but other studies have estimated values ranging from -0.586 (Gruenewald 2006) to -0.9 (Collis et al. 2010) and -1.60 (Lu et al. 2017, using hypothetical purchase data). Considering that wines used in the experiment belonged to an upper price niche, an elasticity of -1 seems reasonable.

Concerning the weight of extrinsic and intrinsic attributes in consumers purchase decision, not many studies explicitly measure it. However, many studies acknowledge the influence of both extrinsic and intrinsic attributes in the liking of a product during re-purchase (Di Monaco et al. 2004, Varela et al. 2010, Hersleth et al. 2011, Almli & Hersleth 2013). More particularly, and unlike our results, Enneking et al. (2007) finds that sweetness is more

relevant than label information when choosing soft drinks. Grunert et al. (2015) also finds that fat content and colour are more relevant than other extrinsic attributes when choosing fresh pork, among Chinese consumers. But concerning wine, Mueller & Szolnoki (2010) find that packaging cues and brand are stronger influencers than sensory liking on purchase intent for white wine (though these results may be biased due to sensory liking endogeneity). Therefore, the relative weight of extrinsic and intrinsic attributes seems to depend on the product under study. It is likely that as the sensory complexity of the product increases, extrinsic attributes gain influence on the purchase decision, though this is a hypothesis that needs to be tested rigorously.

On future implementations of our experimental design we recommend removing the constraint on the maximum amount of bottles participants can purchase, as this would allow easier and more accurate calculations of price elasticities.

4.2 Conclusions

From a methodological perspective, our approach solves most of the problems identified in the literature on current approaches to jointly measure the effect of extrinsic and intrinsic attributes. Our approach is based on the well stablished multi-stage measurement of expectations (i.e extrinsic attributes), blind tasting (i.e. intrinsic attributes), and informed tasting (i.e. extrinsic and intrinsic attributes available together). The use of the Control Function Approach in the third stage allows separating the problem in smaller ones, significantly reducing complexity. Our approach allows for using complex intrinsic attributes, such as sensory profiles and a large number of samples, using an experimental design similar to the one by Menichelli et al. (2012). Our approach uses real purchases as response variable, therefore assuring reliability. And finally, the use of the PS-MDC model

allows forecasting demand and estimating reliable price-demand elasticities, something uncommon in the literature.

We recommend focusing future research on improving the proposed methodology, for which we already suggested several recommendations. However, the most critical aspect probably is improving the interface between sensory profiling and its use on econometric models. We still cannot determine the influence of intrinsic attributes with the same precision than we measure extrinsic attributes' influence on purchase. This is probably because we have not found the most efficient way to represent intrinsic attributes in an econometric modelling context. The inclusion of the passage of time between tasting and purchasing is another important aspect that is currently excluded from our experiment, but could be of great importance.

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