Spanish wine consumer behaviour: A stated and revealed preferences analysis

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Abstract: Overall wine consumption in Spain is decreasing while, at the same time, Designation of Origin (DO) wine consumption is increasing gradually. This study examines Spanish DO wine consumer behaviour through stated preferences (SP) and revealed preferences (RP) data. Part-worth utilities are calculated and results from both analyses are compared to look for similarities and differences between what respondents say on surveys and what they really do on real purchases. Consumer segmentation is undertaken based on purchase frequencies. In a second step, we try to pool the two data sources in order to get more meaningful and robust results. Results indicate similarities in the consumer choice process when comparing the two data sources, especially for the preference of the DO and wine aging attributes. The only difference detected is the price variable, where a concave price-utility function is obtained with the SP analysis and a negative linear price coefficient is obtained with the RP analysis. Likelihood ratio statistic indicates that equal parameters hypothesis is rejected, meaning that it is not possible to merge the two data sources. This is mainly due to the difference on consumers price perception which could be explained by the different purchase occasion selected in each case.

Key words: wine, consumer behaviour, Spain, stated preference, revealed preference, DO.

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1. Introduction

Modern distribution channels have incorporated new technologies (lasers, specific digital codes for each item, etc.) to collect data which helps to understand better consumers behaviour and their preferences. In contrast with data gathered through consumer surveys, known as stated preferences (SP), scanner data reveal real purchases and are referred to as revealed preferences (RP). Combining SP and RP data, whenever possible, allows exploiting strengths of each data source and ameliorate their weaknesses, which lead to more robust estimations (Louviere et al., 2000).

The objective of this work is to estimate Designation of Origin (DO) wine consumers preferences with the use of wine sales data from hypermarkets, showing revealed preferences, and data from a survey undertaken to DO wine consumers, showing stated preferences. In a second step, results obtained from each data source are compared, to check between what consumers declare on the survey and what they really do on their real purchase. Both data sources are combined to explore the advantages of a joint analysis.

The paper is structured as follows. In section two there is a brief description of the data used in the analysis; the next section explains the methodology; results are presented in the fourth section and conclusions are reported in the last section.

2. Data

In order to undertake the revealed preference analysis, wine purchases data were used from two hypermarkets located in the city of Zaragoza (Spain) during 2004. Purchase of table wines plus DO white and rosé wines were not taken into consideration. The reason was to concentrate only on DO red wines. The same decision was undertaken for customers who did not participate in the SP survey or did not purchase any bottle of DO wine from Cariñena, Rioja or Somontano. The new data base contained 299 transactions, corresponding to 86 clients, 107 SKUs (Stock Keeping Units) and 631 bottles sold.

Regarding the stated preference process, a questionnaire was undertaken in 2005 and directed to DO wine consumers living in Zaragoza. The survey included questions about DO wine consumption and purchase and it also included an experimental choice experiment design. A total sample of 357 respondents, aged between 21 and 82 years old, agreed to participate to the experiment. Nevertheless, in this research only responses from the 86 respondents as well present in the RP database are analysed. The selected attributes and their corresponding levels used in the choice set for each data source are shown in table1.

Table1. Selected wine attributes and their corresponding levels for each data source

	Survey Data (SP)	Scanner Data (RP)
Wine attribute	Attribute levels	Attribute levels
Designation of Origin	Cariñena	Cariñena
	Rioja	Rioja
	Somontano	Somontano
Price	2.5 €	Unit price for the chosen alternative
	5 €	Mean price for the non chosen alternatives
	7.5 €	
Wine aging	Joven	Joven
	Crianza	Crianza
	Reserva	Reserva + Gran reserva
Grape variety	Cabernet Sauvignon	---
	Garnacha	---
	Tempranillo	---

In the SP choice experiment, consumers were asked to make a choice between four alternatives: three alternatives related to three different bottles of wine and a fourth constant alternative of no choice (no buy). Each bottle of wine was described by a combination of different levels of the four attributes previously introduced. A sample choice experiment set is illustrated in figure 1.

Which bottle of red wine would you buy for dinner at home with guests?

➔ Please check (X) on the corresponding option

Bottle 1	Bottle 2	Bottle 3	No bottle
Rioja 5 € Crianza Tempranillo	Cariñena 2.5 € Joven Garnacha	Somontano 7.5 € Reserva Cabernet Sauvignon	I will not buy any of these 3 bottles
☐	☐	☐	☐

Figure 1. A Choice Experiment Sample Card

This class of choice experiment is referred to as unlabelled or generic (Louviere et al., 2000) since the alternatives have no specific name or label. The purchase occasion was highlighted, indicating that respondents wanted to buy a bottle of red wine for dinner having guests at home. A purchase occasion evokes an involvement level of a particular purchase situation and it is influenced by product attributes as well as the situation (Houston and Rothschild, 1978). Laurent and Kapferer (1985) stated that the level of involvement influences the consumer choice process. In this experiment the purchase occasion was specified in order to avoid possible consumers misspecifications, such as each respondent thinking of a specific occasion, which could result in biased responses. In total, each respondent was asked to complete 9 choice sets.

3. Methodology

A choice experiment technique was selected to analyse the two data bases. Choice experiments derive from the theory of Lancaster (1966) as well as from Random Utility Theory (RUT). The former postulated that utility is derived from the characteristics that goods possess (bundles of attributes), rather than the good per se. Random Utility Theory states that the overall utility U_{ij} can be expressed as the sum of a systematic (deterministic) component V_{ij}, which is expressed as a function of the attributes presented (wine characteristics in this study), and a random (stochastic) component ε_{ij}. Individual i chooses alternative j rather than alternative k if $U_{ij} \succ U_{ik}$. On probabilistic terms it can be expressed by the following equation:

$$P_{ij} = \Pr(V_{ij} + \varepsilon_{ij} \geq V_{ik} + \varepsilon_{ik} ; \forall\, j \neq k \in C_i) \tag{1}$$

where C_i is the choice set for respondent i. In this study the choice set is constant and it includes 4 alternatives for the SP data and 6 alternatives for the RP data. Equation (1) means that consumers will choose an option, from among a number of choices, trying to achieve their highest utility.

Different discrete choice models are obtained from different specifications of the density function of the error term, which correspond to different assumptions about the distribution of the unobserved portion of utility (Train, 2003). In this research it has been assumed that the random components are identically and independently distributed, type-I extreme value, across the j alternatives and N individuals, leading to the following multinomial logit model (McFadden, 1974):

$$\Pr(j) = \frac{e^{\mu V_{ij}}}{\sum_{k \in C_n} e^{\mu V_{ij}}} \tag{2}$$

Where, μ is the scale parameter known to be inversely related to the variance (Ben-Akiva and Lerman, 1985). It is widely recognized that when operating in a random utility context, the scale parameter is arbitrarily assumed to be unity (Adamowicz et al., 1994). However, when combining two data sources (or more), the scale factor differences must be isolated, and it is possible to identify the ratio of the scale parameters by equalling to unity one scale parameter from a data source (generally the RP scale) and estimating the other relative scale parameter of the second data source. Swait and Louviere (1993) proposed a method to estimate this ratio by maximizing the standard likelihood ratio statistics of the combined model. Thus, for each data source equation (2) could be written as:

For revealed preference data:

$$\Pr(j) = \frac{e^{\mu_r V_{ij}^r}}{\sum_{k \in C_n^r} e^{\mu_r V_{ij}^r}} \tag{3}$$

with, $V_{ij}^{r} = \alpha_{ij}^{r} + \beta^{r} X_{ij}^{r} + \omega Z_{ij} + \varepsilon_{ij}^{r}$, $\forall\, j \in C_{i}^{r}$ (4)

For stated preference data: $$\Pr(j) = \frac{e^{\mu_s V_{ij}^{s}}}{\sum_{k \in C_n^{s}} e^{\mu_s V_{ij}^{s}}} \quad (5)$$

with, $V_{ij}^{s} = \alpha_{ij}^{s} + \beta^{s} X_{ij}^{s} + \delta W_{ij} + \varepsilon_{ij}^{s}$, $\forall\, j \in C_{i}^{s}$ (6)

where, j is an alternative from the choice set of the RP C_i^{r} or of the SP C_i^{s} ; the coefficients α represent specific constants for each data source, β^{r} y β^{s} are the coefficients of the common attributes levels, ω and δ are the coefficients of specific attributes for each data source.

The method proposed by Swait and Louviere (1993) for the joint estimation of both data sources consists, in a first step, to estimate separately the two models derived from SP data and RP data. Then, the two data sources are combined and the maximum likelihood statistics is reported for each new chosen value of the SP scale parameter μ_s. The estimation ends when a maximum coefficient of the likelihood statistic is obtained. Finally, the obtained likelihood statistic is compared to the sum of the likelihood statistics of the two separated models. The hypothesis of parameters equality is accepted when there is no significant difference between likelihood statistics. Otherwise, the parameters equality hypothesis is rejected.

4. Results and discussion

4.1. Separate estimates for each data source

The first step, in the estimation process, was to estimate each data source separately by the use of the multinomial logit model (MNL). In both models, the price variable is considered continuous and its linear form (price) and quadratic form (price^2) are estimated (Table 2).

The values of the log likelihood ratio test (LR1) indicate the overall significance of both models including all explicative variables comparatively to a model including only a constant. All coefficients of both models are statistically significant (except the constant and Garnacha level in model 1). The estimated coefficients of the Designation of Origin attribute, in the two models, show that consumers allocate higher utility to wines from the Aragon designation Somontano. Although Rioja wines come from another region, respondents are more likely to buy these wines than Cariñena wines. Similar results are obtained for both models when considering the wine aging attribute. In that sense, consumers have higher probabilities to buy Reserva wines than Crianza and Joven wines. The more aged the wine is the more likely consumers will choose it.

Table 2. Parameters estimates of the MNL model for each data source

	SP data		RP data	
Variable	Model 1	Std. Error	Model 2	Std. Error
ASC[a]	0.3181	0.3231	---	---
Cariñena	-0.1201**	0.0556	-1.6835***	0.1487
Somontano	0.1910***	0.0520	1.5787***	0.1807
Rioja	-0.0709[b]	---	0.1048[b]	---
Price	0.6431***	0.1248	-1.5771***	0.1061
$Price^2$	-0.0641***	0.0123	---	---
Joven	-0.4253***	0.0612	-1.5984***	0.1534
Crianza	0.1768***	0.0527	-0.2604**	0.0931
Reserva	0.2485[b]	---	1.8588[b]	---
Garnacha	0.0278	0.0537	---	---
Cabernet Sauvignon	0.0898*	0.0530	---	---
Tempranillo	-0.1176[b]	---	---	---
N. Obs.[c]	3096		3786	
LL0[d]	-968.4		-680.7	
LL1[e]	-920.4		-539.2	
LR1 = -2(LL0- LL1)	96***		283***	
Pseudo R^2	0.14		0.52	

[a] Alternative specific constant (ASC). Coded as dummy variable that takes the value of 1 if one of the first three alternatives is chosen, and 0 when the no purchase alternative is preferred.

[b] Represents the base level. Effects codes have been used rather than dummy variables for coding the attributes. The parameter value of the base level is equal to the negative of the sum of the estimated coefficients from the other levels.

[c] For the SP data, the number of observations is equal to the product of the number of respondents (86) by the number of choice sets (9) by the number of alternatives (4). For the RP data, the number of observations is equal to the product of bottles sold (631) by the number of alternatives (6).

[d] Maximum likelihood statistic for a model with only a constant.

[e] Maximum Likelihood statistic for a model with all explicative variables.

*** significant at 1%, ** significant at 5%, * significant at 10%.

Concerning the grape variety variable, SP coefficients show that consumers allocate higher utility to Cabernet Sauvignon, which is a foreign variety in the Spanish market.

Finally, the only difference detected between the two models is related to the price coefficients. In the first model (SP data), the linear price coefficient is positive whereas the quadratic form is negative indicating a concave shape of the utility function curve (Figure 2). In model 2 (RP data), the negative coefficient of the linear price form indicates that consumers utility decrease when price increases, ceteris paribus.

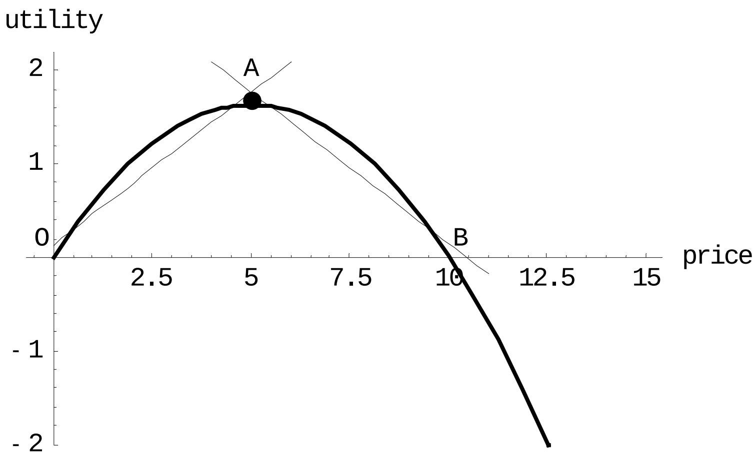

Figure 2. Utility function along price values for the SP data

This price difference between the RP model and the SP model could be due to the wine buying process in hypermarkets (RP data), which implies a particular choice approach, and to the consumption occasion in mind when buying a bottle of wine. It could be assumed that the RP data generally are related to ordinary consumption circumstances, which are different from the choice process and consumption occasion specified in the SP survey.

4.2. Consumer segmentation

From previous questions on the survey and based on consumers' purchase frequency, the consumer sample was segmented into two segments: frequent DO wine consumers, who drink wine every day or some days during the week, and occasional consumers, whose wine consumption is restricted to weekend days or sporadically within the month. The consumer segmentation variable "heavy" (coded as a dummy variable) was interacted with different levels of some attributes in the two models.

Table3. Parameter estimates of the consumer segmentation model for each data source

	SP data		RP data	
Variable	Model 3	Std. Error	Model 4	Std. Error
Cariñena	-0.1500**	0.0747	-1.7563***	0.1664
Somontano	0.3074***	0.0679	1.7509***	0.1963
Price	0.8361***	0.0847	-1.5330***	0.1173
$(\text{Price})^2$	-0.0873***	0.0094	---	---
Joven	-0.4341***	0.0617	-1.5801***	0.1516
Crianza	0.1804***	0.0532	-0.2568***	0.0932
Garnacha	0.0290	0.0542	---	---
Cabernet S.	0.0927*	0.0535	---	---
Heavy x Cariñena	0.0745	0.1132	0.3749*	0.2089
Heavy x Somontano	-0.2756**	0.1073	-0.7705**	0.3116
Heavy x Price	-0.2009	0.1275	-0.0585	0.1256
Heavy x $(\text{Price})^2$	0.0302**	0.0141	---	---
N. Observations	3096		3786	
LL0	-968.4		-680.7	
LL2	-913.4		-533.2	
LR2 = -2(LL0 – LL2)	110***		295***	
LR12 = -2(LL1 – LL2)	14***		12***	
Pseudo R^2	0.15		0.53	

*** significant at 1%, ** significant at 5%, * significant at 10%.

The addition of the variable “heavy”, and its interaction with the wine attributes, improves the overall explanatory power of model 3 and model 4 compared respectively to model 1 and model 2. The heavy-DO interaction coefficients have the same signs in the two models confirming the similarities between both data sources. These coefficients values indicate that heavy consumers allocate lower utility to the DO attribute than light consumers do, as DO level differences are lower in the former consumer group.

4.3. Joint estimation of the two data sources

Before pooling the two data sources and the estimation of the composite model, the coefficients of the common variables in the two sources were plotted (Figure 3), as an easy and rapid way to verify whether parameters equality hypothesis holds or not.

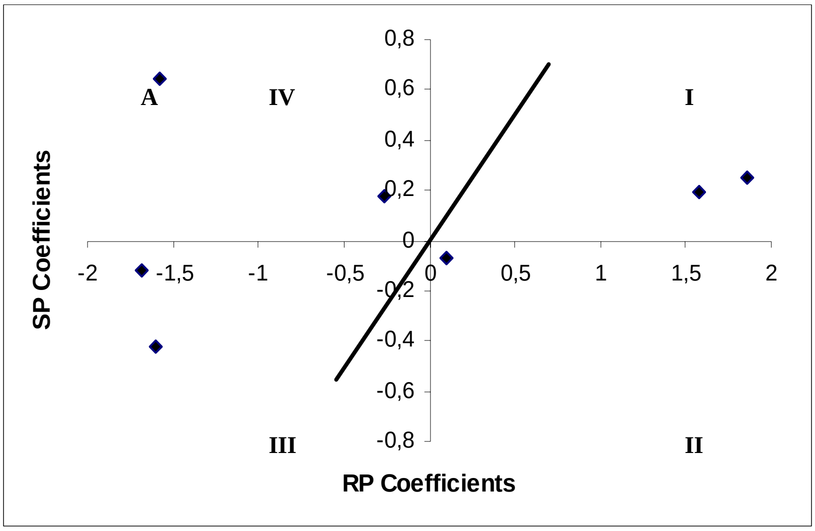

Figure 3. Plot of the of the SP and the RP coefficients

If the hypothesis of equal parameters holds, a graph of one parameter vector against the second should exhibit a positive, proportional relationship, the slope of which should equal the ratio of variances between the data sources (Hensher et al., 1999). This implies that all points should be situated in regions I and III. However, three points are situated outside these areas, especially point A which represents the linear price coefficients for each data source. Thus, this graphic distribution implies that the equal parameters hypothesis is rejected. However, it is important to confirm this assumption with the composite estimation of the two data sources and to compare the likelihood ratio obtained with the Chi squared statistic.

Following the method of Swait and Louviere (1993), two different joint-models (Table 4) were estimated. In the first model (model 5) the same linear price coefficient for both data sources was considered, whereas in model 6, two separate linear price coefficients were introduced, each one specific for each data base. In model 5, equalling the RP scale parameter to one, a SP scale parameter $\mu_s = 0.01$ was obtained, indicating higher variance of the latter data. Almost all variables coefficients are significant (except Garnacha level). However, it is important to emphasis that the obtained pseudo R^2 is less than the pseudo R^2 when considering only the RP data (model 2), and that the variety attribute has coefficients levels higher than the other attributes coefficients.

Table 4. Joint estimation of both data sources

	SP	RP	SP-RP	SP-RP
Variable	Model 1	Model 2	Model 5	Model 6
ASC	0.3181	---	---	---
	(0.3231)			
Cariñena	-0.1201**	-1.6835***	-1.6873***	-1.6480***
	(0.0556)	(0.1487)	(0.1485)	(0.1278)
Somontano	0.1910***	1.5787***	1.5834***	1.5577***
	(0.0520)	(0.1807)	(0.1803)	(0.1553)
Rioja	-0.0709[a]	0.1048[a]	-0.1039[a]	0.0903[a]
Price	0.6431***	-1.5771***	-1.5743***	5.3697*** / -1.5704***
	(0.1248)	(0.1061)	(0.1058)	(0.4475) (0.0925)
$Price^2$	-0.0641***	---	1.2118***	-0.5307***
	(0.0123)		(0.1566)	(0.0496)
Joven	-0.4253***	-1.5984***	-1.6070***	-1.6091***
	(0.0612)	(0.1534)	(0.1532)	(0.1317)
Crianza	0.1768***	-0.2604***	-0.2625***	-0.1988**
	(0.0527)	(0.0931)	(0.0928)	(0.0873)
Reserva	0.2485[a]	1.8588[a]	1.8695[a]	1.8079[a]
Garnacha	0.0278	---	3.0388	0.1978
	(0.0537)		(5.7088)	(0.3838)
Cabernet Sauvignon	0.0898*	---	10.0138*	0.6404*
	(0.0530)		(5.6162)	(0.3787)
Tempranillo	-0.1176[a]	---	-13.0526[a]	-0.8382[a]
μ_s			0.01	0.14
N. Observations	3096	3786	6882	6882
LL0	-968.4	-680.7	-2203.6	-2203.6
LL3	-920.4	-539.2	-1589.3	-1471.0
LR3 = -2(LL0- LL3)	96***	283***	1228.6***	-1465.2***
LR(PE/PR) = $-2[LL3_{PE\text{-}PR} - (LL3_{PE} + LL3_{PR})]$			259.4	22.8

N. parameters	9	5	8	9
Pseudo R^2	0.14	0.52	0.51	0.55

Standard errors within brackets

[a] Represents the base level. Effects codes have been used rather than dummy variables for coding the attributes. The parameter value of the base level is equal to the negative of the sum of the estimated coefficients from the other levels.

*** significant at 1%, ** significant at 5%, * significant at 10%.

The likelihood ratio statistic equals to 259.4 and it is higher than the Chi-squared critical value $\chi^2_{0,05;6} = 12.6$ indicating the rejection of the hypothesis of equal parameters. Thus, it is not possible to merge both data bases because there are differences in the consumers' choice process between the SP and RP data. However, the high likelihood statistic is surprising since, in the two cases, purchasing data of the same product were used. That is why, in a second step, it was decided to estimate a model considering a separate estimate of the linear price coefficient for each data source since the separate estimates of this variable (model 1 and model 2) have shown significant differences between the two sources (point A in Figure 3).

The results obtained from this estimation (model 6) indicate that all variables are significant, excepting the Garnacha coefficient. The overall model fit is very good with pseudo R^2 equals 0.55. The scale parameter $\mu_s = 0.14$, less than one, indicates higher variance of the SP data. Chi-square statistic equals 22.8 and it is higher than the critical value $\chi^2_{0,05;5} = 11.1$, indicating in this case also the rejection of the equal parameters hypothesis at 95% confidence level.

However, although the parameters equality hypothesis was rejected, it is important to emphasise that the likelihood statistic diminished considerably comparatively with the same statistic when considering a unique linear price coefficient. These results indicate that consumers' choice difference between the two data has an effect on the price attribute. In figure 4, the tendency line which better approximates the correlation between SP and RP coefficients is plotted. In the first case, when including the price coefficients (point A), a weak linear correlation ($R^2 = 0.056$) is obtained. However, after dropping the price coefficients, the R^2 coefficient raises to 0.67 indicating a strong linear correlation and the slope coefficient (0.139) is equal to the scale parameter ($\mu_s = 0.14$) in model 6.

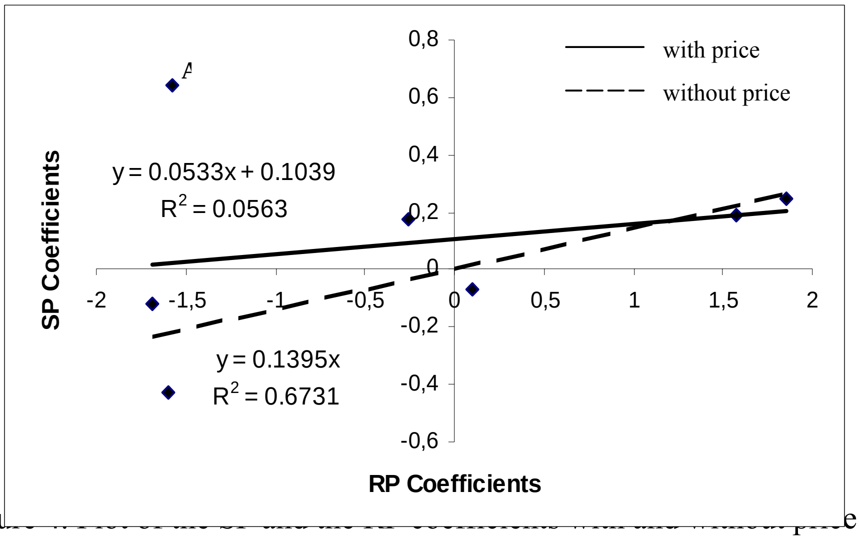

Fig e

These results confirm that consumers choose wine differently mainly because of their price perception. In the SP data collected by the survey, consumers were asked to choose a bottle of wine for a special occasion (dinner with guests at home), while the RP data are from wine purchases in hypermarkets where the purpose of the purchase is unknown (could be dinner with friends, meal at home, gift, ordinary consumption, etc.) and where consumers are price oriented.

5. Conclusions

In this work there were two main objectives. The first objective was to compare between what consumers state in surveys and what they really do when confronted to real purchase situation. The second objective was to pool both data sources (SP and RP data) to obtain robust results and enhance the predictive power of our model.

The obtained results mainly show similarities in the choice process between the two data sources. Designation of Origin and wine aging coefficients obtained with RP data confirmed the results obtained with SP data. Accordingly, consumers prefer wines from the Somontano region rather than wines from Rioja or Cariñena. The wine aging variable has shown that consumers allocate higher utility to Reserva wines (more mature wines) followed by Crianza and Joven wines. Different results have been obtained with each data base concerning the price variable. The estimation of the SP data with linear and quadratic price levels results in respectively positive and negative coefficients, showing a concave price-utility curve and indicating an increase in consumers' utility when price increases until a price level. Above this price consumers' utility decreases when price increases. This confirms recent results obtained by Lockshin et al. 2006 and Lockshin and Halstead (2005) on wine consumption. However, when estimating the RP data with a linear price level, a negative coefficient is obtained indicating a decrease in consumers' utility when price increases, which confirms previous expectations since RP data comes from hypermarket wine purchases very sensitive to price. The negative sign of the linear price coefficient confirms the results obtained using RP data by others researches (Blamey et al., 2001; Bonnet and Simioni, 2001; Swait and Andrews, 2003).

Consumers' segmentation based on consumption frequency showed in both cases (SP and RP) that light consumers allocate higher utility to the DO attribute compared to heavy consumers. These results indicate also a relative degree of coherence between what consumers declare and what they really do.

The data enrichment process of estimating both data sources together has failed due to differences between consumers' price perception. The chi-squared test rejected the parameters equality hypothesis. This result is not very surprising because previous research combining SP and RP data found similar results concerning the incompatibility of data (Swait and Adamowicz, 1996; Adamowicz et al., 1997; Earnhart, 2001; Earnhart, 2002; Swait y Andrews, 2003). In this work, the SP data linked to the purchase occasion (dinner with guests at home) could explain the difference between price perceptions in each data source.

REFERENCES

Adamowicz W., Louviere J., Williams M., 1994. Combining revealed and stated preference methods for valuing environmental amenities. Journal of Environmental Economics and Management, 26(3), 271-292.

Adamowicz W., Swait J., Boxall P., Louviere J., Williams M., 1997. Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation. Journal of Environmental Economics and Management, 32(1), 65-84.

Ben-Akiva M., Lerman S., 1985. Discrete choice analysis: theory and application to travel demand. Cambridge, Mass: MIT Press.

Blamey R., Bennett J., Louviere J., Morrison M., 2001. Green product choice. In J. Bennett y R. Blamey (Ed.). The choice modelling approach to environmental valuation. Northampton: Edward Elgar Publishing.

Bonnet C., Simioni, M., 2001. Assessing consumer response to Protected Designation of Origin Labelling: a mixed multinomial logit approach. European Review of Agricultural Economics, 28(4), 433-449.

Earnhart D., 2001. Combining revealed and stated preference methods to value environmental amenities at residential locations. Land Economics, 77(1), 12-29.

Earnhart D., 2002. Combining revealed and stated data to examine housing decision using discrete choice analysis. Journal of Urban Economics, 51(1), 143-169.

Hensher D., Louviere J., Swait J., 1999. Combining sources of preference data. Journal of Econometrics, 89(1-2), 197-221.

Houston M., Rothschild M., 1978. Conceptual and methodological perspectives on involvement, Educators Proceedings, Ed., S.C. Jain, Chicago: American Marketing Association, 184-187.

Lancaster K., 1966. A new approach to consumer theory. Journal of Political Economy, 74, 132-157.

Laurent G., Kapferer J., 1985. Measuring consumer involvement profiles. Journal of Marketing Research, 22, 41-53.

Lockshin L., Halstead L., 2005. A comparison of Australian and Canadian wine buyers using discrete choice analysis. Paper presented at the International Wine Marketing Symposium, Sonoma, California.

Lockshin L., Jarvis W., D´Hauteville F., Perrouty J. P., 2006. Using simulations from discrete choice experiments to measure consumer sensitivity to brand, region, price, and awards in wine choice. Food Quality and Preference, 17(3-4), 166-178.

Louviere J., Hensher D., Swait J., 2000. Stated choice methods: Analysis and application. Cambridge: Cambridge University Press.

McFadden D., 1974. Conditional logit analysis of qualitative choice behavior. In Zarembka, P. (Eds). Frontiers in econometrics. New York: Academic Press.

Swait J., Louviere J., 1993. The role of the scale parameter in the estimation and comparison of multinomial logit models. Journal of Marketing Research, 30(3), 305-314.

Swait J., Adamowicz W., 1996. The effect of choice complexity on random utility models: An application to combined stated and revealed preference models or tough choices: Contribution or confusion? Presented at the 1996 Association of Environmental and Resource Economists Summer Workshop, Lake Tahoe, CA.

Swait J., Andrews R. L., 2003. Enriching scanner panel models with choice experiments. Marketing Science, 22(4), 442-460.

Train K.E., 2003. Discrete choice methods with simulation. Cambridge: Cambridge University Press.