Wine Label Descriptors and Shelf Price Paid by Argentine Consumers

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Abstract

A wide variety of wines are sold in the Argentine retail wine market, both in specialized stores and supermarkets. There are several wine segments according to their degree of vertical differentiation, each with additional differentiation strategies. One of them centers on the information provided in the bottle label to attract consumers, which can be characterized as objective information (type of grape, color, age, alcoholic content, region of origin) and additional information (food pairing, sensorial and environmental characteristics, wine making process, serving temperature suggestions). The question arises about the relationship, if any, between those descriptors and the price paid by the consumer. To answer it, an empirical study was conducted for Santa Fe city, an important consumption center. A hedonic price model was estimated, with the results showing that within the lower-priced wine segment, the additional information had a positive impact on prices; this situation was not the same for the higher-priced wines. Statistically significant differences were also found between provinces of origin, type of wine and purchase place.

Keywords: **Hedonic Prices *Retail Market * Attributes * Differentiation**

1. Introduction

Argentina is a major grape wine producer, with an annual average of 14.4 millons hectoliters between 2002 and 2012. The main wine producing areas are: a) traditional Mendoza and San Juan provinces, in the Andean Region, with about 93 percent of the country total vineyard area, and the presence of large wineries producing a wide range of table and fine wines; b) Salta province in the north, with a 2% planted land and smaller size wineries; and c) new producing areas in La Rioja province, in the Andean region, as well as the Patagonian Rio Negro and Neuquen provinces, developed in the last two decades, mostly with smaller wineries specialized in premium or fine wines.

Approximately 63%-83% of total production is consumed domestically, with an average of 24.9 liters per capita (2011) and a downward trend. Wines without varietal mention represent 75%, varietal wines 20% and others (sparkling and dessert wines)

5%. By color, the largest share corresponds to red wines (84%), followed by white wines (15%) and rosé wines (1%).

The remaining volume is exported with over 2300 brands to around 122 countries, being U.S. the largest buyer. Imports are very low, amounting to 67 thousand hectolitres in 2011, almost 98% coming from Chile.[1]

The 2008 international crisis negatively affected Argentine exports, forcing local producers to concentrate sales in the domestic market. As a result, there was an oversupply of some types of wines, increased competition among the 973 wineries which market their products with 4,000 labels and saturation in some price ranks (USDA 2012).

After the international crisis, a reduction in the cheaper table wines´ consumption was more than compensated with an increase in the purchases of fine wines (FVM, 2010). Further changes included the opening of a wide number of specialized wine stores all over the country´s major cities as well as the proliferation of brands.

The wineries´ increased competition for local consumers´ purchases drove them to adopt several differentiation strategies. One of them was to try to influence their choice with additional labeling information (*AI*), such as s taste descriptors, food pairing, serving temperatures recommendations, environmental characteristics and descriptions about wine manufacturing process, or more standard information about the wine objective characteristics such as grape type, age, etc. At least two questions arise from this situation: 1) Has the additional labeling information been relevant to consumers in their decision to buy wine?; and 2) Did it have any relationship with the selling price?.

Taking into account that label establishes the identity of the product and gives clues to purchasers about what they should expect to find inside the bottle, label information appears to be crucial to selling wine (Corduas, et al., 2013); therefore, answers to previous questions are expected to be positive. Nonetheless, the empirical literature findings are not unanimous.

Most of the existing literature about the influence of wine attributes and/or label descriptors on market prices is focused on objective characteristics (*OC*), with minor attention to *AI*. To fill this vacuum, the primary objective of this paper is to estimate the impact on shelf prices of such additional descriptors included in wine bottle labels for an Argentine market, where empirical studies on wine economics are very scarce. Specifically, for Argentine wines, previous researches have mostly centered on the behavior of international prices (San Martin et al., 2005; Berrios y Saens, 2012), but the domestic market, wich is growing in importance, deserves an effort to better appretiate it. So, this study contributes to understand retail wine price determination in an unexplored market, making it possible the comparison with the global wine market. It also increases the knowledge of variables affecting consumers´ wine purchase decisiones to be used by the wineries´own private strategies as well as the government to design programs to promote the industry in the major producer provinces.

In the next section, a review of the international literature regarding descriptors is made and impact on prices is outlined, followed by the methodology selected. Results are discussed in the third section and finally, some conclusions are drawn.

[1] All calculations are based on data from the Instituto Nacional de Vinicultura (2014).

2. Literature Review

Differentiated goods such as wines can be seen through their specific attributes and the observed equilibrium market price as a function of the implicit prices of each attribute of differentiation. In this context, Rosen´s hedonic pricing model (1974) is applicable to study price determination, with objective characteristics and other attributes placed on label by wineries as marketing strategy.

A profuse literature exists on hedonic price models showing the relevance of different wine characteristics or attributes on average market prices. For example, Oczkowski (1994) used the effect of wine quality, grape type, harvest year, region and winery size; Nerlove (1995) concentrated on wine´s chemical composition and consumers´ taste evaluation. More recent research focused on objective characteristics, easily perceived by the consumer (Lutzeyer, 2008: 6) such as region of origin (Panzone y Simoes, 2009), wine variety (Schamel and Anderson, 2003; Steiner, 2004a; Davis y Ahmadi-Esfahani, 2005) and harvest year; as well as sensory quality ratings given by experienced judges or wine experts (Combris et al. 2000; Schamel and Anderson, 2003; Bentzen and Smith, 2008, Lutzeyer, 2008; Bentary et al., 2011, among others). Steiner (2004b) included objectives attributes and retailer traits (measured by name of the retailer) as an additional choice variable. Recently, price differentials in organic wines have been studied using the hedonic price equation (Corsi and Strøm, 2013; Hong et al., 2014).

For the *AI*, concentration has been on the consumers´ evaluation of some descriptors associated with the *AI*. For example, Barber et al. (2006) evaluated the influence of wine packaging and label descriptors on purchasing consumers' decision, incorporating taste descriptors, food paring history of the wine region, wine making process, among others. Charters et al. (1999) explored the responses of Australian consumers, finding that sensorial or tastes descriptors were the most valued attributes among other back label information. Mueller et al. (2009) found that the label content could be crucial to the consumer in the shelf selection process, the reason being that more information reduces the buyer's "perceived purchase risk". Mueller et al. (2010) examined which back label attributes were the highest valued to Australian consumers using a discrete choice experiment. They included taste descriptors, manufacturing and history related statements, consumption advice about cellaring, food pairing, ingredients, environmental characteristics and the website. They found that the presence of these *AI* descriptors was very important to explain the likelihood of a wine being chosen, but they did not study their relevance on wine prices. Mora and Livat (2013) studied the role of the vineyards' storytelling as a mean of corporate communication. But this information was provided in a guidebook, not on label. According to Mora and Livat (2013) in experience-oriented goods such as wine, image and reputation are involved in pricing decisions, so additional information could explain price differences. Storytelling enables consumer to integrate the history of a wine brand or a wine estate.

Lockshin et al. (2009), in turn, found that it was possible to identify different consumer segments driven by particular wine attributes specified in labels. Therefore, it was expected that not all consumers would react in the same way to changes in wine packaging and price. Whereas such preference heterogeneity could be observed at the individual level, it would be possible that these differences cancel each other out over the total market. So, it was uncertain that the previously observed impact of wine labeling on individual consumer preferences translated into different market prices (Mueller y Szolnoki, 2010).

Among the hedonic price model applications that include *AI* or packaging attributes beyond the objective characteristics, Costanigro *et al.* (2007) analyzed whether or not labeling information availability impacted on catalog wine prices. Melo *et al.* (2005) incorporated label descriptors and analyzed the length of the brand name. Mueller and Szolnoki (2010; 2012) studied the prices effects of packaging characteristics employing a hedonic pricing model using scanner data of red wine sales in two US markets. They focused on label design (style and color) and bottle form, taking some objective attributes such as grape variety and origin, including additional information in a single dummy variable. They showed that additional information on the label was related to price premiums.

This review realizes the absence of hedonic wine price models focalized in each specific additional label descriptors. The related literature shows that their presence has an impact on prices, leading to further inquire which of them has the greater influence.

This paper contributes to the literature in several ways. First, the focus is on *AI*, which received minor attention in previous studies. Second, the effects of label descriptors are analyzed in two models. One of them includes each particular *AI* descriptor in separate form, to know its specific marginal price. The other consideres the label effect through the total number of *AI* descriptors is considered, where the effect of the amount of additional information on the label is emphasized. Third, price segments are considered in order to capture possible different label effects between lowerand higher priced wines. Forth, different types of stores´ shelf prices are used, in contrast to the specialized guides and magazine prices of most previous studies. Finally, this paper gives new empirical evidence fot the Argentine wine market, adding to the scarce literature related to label characteristics, which can be compared with other countries or regions.

3. Methodology

Consumer theory postulates that the utility that an individual derives from a good could be thought of as depending on its attributes (Nelson, 1970). A good x can be represented as a vector $\mathbf{a}_x$ of attributes, i.e. $\mathbf{a}_x = (a_{1x},\ldots,a_{Ax})$, which enters into the individual utility function. The market price of x, therefore, is a function of those attributes (Rosen 1974):

$$p_x = p(\mathbf{a}_x) \equiv p(a_{1x},\ldots,a_{Ax}) \tag{1}$$

where $\partial p / \partial a_{jx}$ is the marginal effect of the j characteristic over the final price of x. Equation (1) conforms the general hedonic price model. In the wine case, the attributes can be separated into: a) those objective characteristics (*OC*) that can be easily perceived by the consumer (Lutzeyer, 2008; Lecocq y Viser, 2006): such as color, grape variety, vintage or aging (i.e. the difference between the date of releasing the wine to the market and the vintage year) and alcoholic content[2] b) label descriptors with additional information (*AI*), such as reccomendations of serving temperatures and food pairing; c) region of origin (*O*), attribute which might also be included as an objective characteristic.[3]

Therefore, the shelf price of wine v is determined by

$$p_v = p(OC_v, AI_v, O_v, \varepsilon_v) \quad (2)$$

With ε_v standing for the "non observed" characteristics. Since the economic theory does not require a specific functional form for (2), the search of an adequate specification has persisted in empirical studies. The semi-logarithmic form has been extensively used because of two advantages: first, it allows an easy and straightforward interpretation of the estimated parameters; and secondly, the non-negativity and right-skewness are features consistent with the log-normal distribution (Costanigro and McCluskey, 2011). In wine studies, logarithmic transformations have prevailed (Oczkowski 1994; Nerlov, 1995; Schamel, 2003; San Martin *et al.*, 2008; Panzone and Simoes, 2009; Brentari *et al.*, 2011, among others). Costanigro (2007) used the inverse of the square root of price as an alternative to the logarithmic transformation and the left-hand-side Box-Cox model. Benfratello (2009) tried several Box-Cox transformation variants. The semi-logarithmic form is adopted in this paper because it facilitates the results interpretation. When some cuadratic effect is observed, this is included in the model as covariate.

For a sample of *V* wines, the model (2), in its empirical form, is:

$$\ln(E(p_v \mid \mathbf{x})) = \alpha + OC_v'\beta_{OC} + AI_v'\beta_{AI} + O_v'\beta_O \qquad v = 1,\ldots,V \quad (3)$$

Where $\mathbf{x} \equiv (OC_v, AI_v, O_v)$ and $\alpha = \ln E(p_v \mid OC_v = AI_v = O_v = 0)$. Due to the fact that not only wineries participate in the price determination process, but retailers also do,[4] an additional variable is included in (3): the type of store where wine is bought (*TS*).

The model is:

$$\ln(E(p_v \mid \mathbf{x})) = \alpha + OC_v'\beta_{OC} + AI_v'\beta_{AI} + O_v'\beta_O + TS_v'\beta_{TS} \quad (4)$$

The model (4) is estimated by maximum quasi-likelihood following Manning and Mullay (2001) algorithm for log models based on generalized linear models framework (GLM) of McCullagh and Nelder (1989). Especifically, in GLM modeling the conditional mean-variance relationship is specified by $\mathrm{var}(p_v \mid \mathbf{x}) = \sigma^2 v(\mathbf{x})$, being $v(p_v \mid \mathbf{x}) = k(E(p_v \mid \mathbf{x}))^\lambda$ the variance function, where λ must be finite and non-negative. If $\lambda = 0$, the usual nonlinear least-squares estimator is obtained. In the case $\lambda = 1$, the Poisson-like class is obtained. When $\lambda = 2$, a gamma-class model is specified. In the case $\lambda = 3$, the inverse Gaussian (or Wald) distribution is obtained. In a first stage, a gamma model with log link is estimated. Then the modified 'Park test' on the

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2 The alcoholic content belongs to wine chemical attributes (Oczkowski, 1994).

3 Wine expert ratings or scores are not information available in shelf. So to reflect the real market condition, this is not including in the model (Mueller and Szolnoki, 2010).

4 The influence on Price of the grape producers is reflected by the regiόn of origin.

raw-scale residuals is used to select one of the GLM [5].

Because an incorrect specification of the variance function or the distribution function for GLM leads to efficiency losses, the inference will be corrected using robust (sandwich) estimators for the variance-covariance matrix (Hardin and Hilbe, 2012). Thus, the quasi-likelihood approach protects against some problems –inconsistency and inefficiency- that can arise from mis-specified distribution function (Manning and Mullay, 2001: 469).

Following Kennedy (1981), for dummy variables the percent impact can be estimated by $[\exp(\hat{\beta}_{Hk} - Var(\hat{\beta}_{Hk})/2) - 1] \times 100$ where in this case $a_{Hk} \in$ (OC, AI, O, TS) is dichotomic. For continuous descriptors, the coefficients can be interpreted as the percent impact of *Hj*-th variable on average wine bottle prices (i.e., $\hat{\beta}_{Hj} \times 100$ with *H=OC,AI,O,TS*). Although this interpretation may be approximately correct over a very small range, it is incorrect outside it (Thornton y Innes, 1989). Therefore, for non-dummy variables with an integer domain such as *age* or *oak barrique storage*, the Kennedy correction is adopted. For variables with real domain like *alcohol content* where infinitesimal changes occur, the percentual impact is estimated by $\hat{\beta}_{Hj} \times 100$.

The selected area where the study was conducted was Santa Fe city, with 350,000 inhabitants, located in the Humid Pampas, the richest country region. The data comes from a sample [6] of 1,015 varietal wines produced by 49 Argentine wineries, in the 750 mililiter (ml) glass bottle segment. It was collected in three supermarkets, three hypermarkets and two specialized wine stores in Santa Fe city, all of them offering a wide variety of wines in their shelves. The collection occurred in April of 2011 in supermarkets and specialized stores, and in May in hypermarkets. The “wine” included corresponds to that product defined by Article 17 of National Wine Law No. 14.878, legally considered genuine grape wine. Each observation contained variables characterizing the type of wine (color, harvest year, grape variety, alcoholic graduation, etc), the region of origin, and additional labeling information (*AI*).

All prices (in Argentine pesos) were deflacted to April 2011 using the Santa Fe Consumer Price Index published by the Santa Fe Statistical Unit (IPEC)[7] and then translated into U.S. dollars. The final average price was 6.4 dollars per bottle,[8] with a standard deviation of 3.9 dollars.

To analyze the differences of wineries’ strategies related to labeling information, several criteria could be used: type or color of wine (Thrane, 2004; Noev, 2006; Ling and Lockshin, 2003; Carew y Florkowski, 2010), grape varieties (Ling and Lockshin, 2003), region of origin (Ling and Lockshin, 2003), quality (Panzone y Simoes, 2009), distribution channels (Brentari *et al.*, 2011; González y Melo, 2008) or price itself

5 Manning and Mullay (2001) recommend this procedure when there is no kurtosis on the log-scale residuals (coefficient of kurtosis about 3 r less). In the present case, the coefficient of kurtosis is about 1.

6 Data collected by Lic. Julio Cesar Monzón for his undergraduate final paper for the Economics degree (FCE-UNL), directed by Gustavo Rossini (Ph.D) and Rodrigo García Arancibia (MSc.).

7 IPEC statistics are more precise to this purpose than those from the national organism (INDEC). The use of the General index instead of the Food and Beverages category does not introduce biases since the difference is minimal (The Food and Beverages category represents 65% of it).

8 The Exchange rate in April 2011 was 1 U$S = 4.07 AR$

(Angulo et al., 2000; Costanigro et al., 2007). For the present study, two segments were defined according to price: a) segment of varietal wines with prices below 6.14 dollars per bottle, named here on "Lower-Priced Wines" (LPW) (Área del Vino, 2011); b) higher 6.14 dollars per bottle, from here on "Higher-Priced Wines" (HPW), with the following subcategories: b.1) "Premium" (between US$ 6.14 and US$ 8.6; b.2) "Super Premiums" (from US$ 8.6 to US$ 12.3 per bottle); b.3) 'Ultra Premium' (from US$ 12.3 to US$ 18.5); b.4) 'Icon' (from US$ 12.3 to US$ 30.7 inclusive) and lastly b.5) 'Uber' (larger than US$ 30.7).

Table 1 illustrates that LPW represented 65% of the sample, with an average price of 4.45 dollars per bottle. In the HPW category the average price was 9.96 dollars, falling into the subcategory of 'Super Premium' wines. Both 'Icon' and 'Uber' represented just 1.5% of the total, but 36% in the higher priced category. For each segment, the model (4) is estimated.

The following variables were defined with the data collected: a) For the wine objective and chemical characteristics (*OC*): 1) *age*: indicates the number of years that passed since the grape was harvested (vintage) until the product was on the shelf (2011). Also a squared of age variable was incorporated to analyze the non linear effects of the harvest year. 2) *alcoholic content*: measured through the percentage volumen-volume. 3) *aging in oak barrique*: number of months that the wine was stored in oak barrels. [9] 4) *red wine* (*base*): binary variable that assume value 1 when wine is produced with red grapes; 5) *white*: with value 1 when is elaborated with white grapes, 0 otherwise; 6) *rose*: binary variable with value 1 when comes from rose grapes, 0 otherwise; 7) *varietal*: with value 1 when the wine is made from a single grape variety and 0 for blended wines[10]. Some papers include the specific variety, but since there were not significant differences in this case, they were left out.

b) We considerer five descriptors of *AI* defined by the following dummy variables: 1) *Food pairing*, with value 1 when recommendations about adequate combination with specific food come in the label, 0 otherwise; 2) *sensorial description*: with value 1 when information about aspect, color, texture, aroma or fragance, tastes or other were present; 3) serving *temperature*: with value 1 when recommendations about the right temperature to be served were found; 4) *environmental characteristics*: with value 1 when the label presents some information about the environment in which grapes are produced such as type of soil, altitude, climate, geological characteristics; 5) *wine making process*: with value 1 when some information about wine making process was offered.

To establish hypothesis about the label information impact on wine shelf price is not simple given the heterogeneity of consumers´ tastes. In general 'search' attributes commonly available to a consumer on the shelf are of limited help for the most typical wine purchasers in order to reduce their perceived purchase risk. Nontheless, some may be ready to asume it paying a differentiated price. For example, if the label sensorial or taste description is understandable, credible and relevant to the consumer, and reflects his of her likely perception of the wine (Mueller *et al.*, 2009) a positive effect on price is expected. Similar result would occur with environmental characteristics and the wine making process.

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[9] A quadratic form of the term was also tried as well as a binary variable indicating whether the wine was stored in oak barrels or not. In neither cases they were statistically significant.

[10] In the sample, blended wines correspond to wines made from two or three grape varieties.

Table 1. *Statistic summary of variables used in the model (N_T=1.015; N_B=650; N_C=365)*

	TOTAL SAMPLE				LOWER-PRICED WINES (LPW)				HIGHER-PRICED WINES (HPW)			
VARIABLE	Average	SD	Min	Max	Average	SD	Min	Max	Average	SD	Min	Max
Price (US dollars per bottle)	6.43	3.94	2.08	37.38	4.45	0.84	2.08	6.12	9.96	4.75	6.19	37.38
Wine Characteristics												
Age	1.89	1.26	0	13	1.5	0.8	0	5	2.64	1.54	1	13
Alcoh_content	13.47	0.55	10	14.9	13.3	0.5	10	14.8	13.76	0.46	12	14.9
Oak barrique stor	3.28	4.59	0	16	0.9	2.4	0	12	7.46	4.59	0	16
Red wine	0.76	0.43	0	1	0.7	0.4	0	1	0.81	0.39	0	1
Rose wine	0.02	0.15	0	1	0.03	0.2	0	1	0.01	0.09	0	1
White wine (base)	0.22	0.41	0	1	0.2	0.4	0	1	0.18	0.39	0	1
Varietal	0.86	0.35	0	1	0.85	0.36	0	1	0.87	0.34	0	1
***AI* Descriptors**												
Food pairing	0.41	0.49	0	1	0.51	0.50	0	1	0.23	0.42	0	1
Sensorial descrip.	0.83	0.38	0	1	0.90	0.31	0	1	0.70	0.46	0	1
Serving temperatura	0.57	0.50	0	1	0.68	0.47	0	1	0.38	0.48	0	1
Environmental	0.17	0.37	0	1	0.14	0.35	0	1	0.21	0.41	0	1
Wine making process	0.36	0.48	0	1	0.34	0.47	0	1	0.41	0.49	0	1
Purchase store												
Supermarket	0.51	0.50	0	1	0.56	0.50	0	1	0.44	0.50	0	1
Hypermarket	0.27	0.45	0	1	0.22	0.42	0	1	0.36	0.48	0	1
Specialized wine store (base)	0.21	0.41	0	1	0.22	0.41	0	1	0.14	0.34	0	1
Origen (province)												
San Juan province	0.15	0.35	0	1	0.17	0.38	0	1	0.10	0.31	0	1
Salta province	0.05	0.22	0	1	0.06	0.24	0	1	0.03	0.17	0	1
La Rioja province	0.01	0.003	0	1	0.01	0.04	0	1	s/d			
Patagonian	0.04	0.20	0	1	0.05	0.22	0	1	0.02	0.16	0	1
Mendoza province (base)	0.76	0.43	0	1	0.71	0.46	0	1	0.84	0.37	0	1

Food pairing and *serving temperature*, on the other hand, suggest behaviors that might be relevant and well-taken by some consumers while completely ignored by others.

Two models were run. The first one included each one of the five previous additional descriptors; and the second one replacing them with a sole variable: *total number of descriptors*, constructed counting the number of additional descriptors found.

For the *type of store* (*TS*) where the wine was for sale, three binary variables were considered: 1) specialized wine stores (base), 2) supermarkets, and 3) hypermarkets.

Five *regions of origin* (provinces) were selected: 1) *Mendoza* province (base); 2) S*an Juan* province. 3) *Salta* province; 4) *La Rioja* province. 5) *Patagonian* provinces: comprising Neuquen and Rio Negro provinces, grouped together because of their very low relevance in the sample.

The descriptive statistics for each variable are in Table 1. First, it can be seen that some type of additional information prevails in the LPW segment. An average of 2.5 additional descriptors was found in each LPW label but only 1.9 in HPW. Recommendations about serving temperature were included in 68% of LPW labels against 38% of HPW; with corresponding figures of 51% versus 23% for recommendatios on food pairing; a larger percentage for the first group was also detected for the sensorial characteristics. On the other side, more information related to region of origin and the wine making process appears in the HPW segment.

4. Results

Results of the pooled model with five label descriptors (*food pairing, sensorial description, serving temperature recommendation, environmental characteristics and wine making process*) are presented in Table 2, and those with the number of descriptors are in Table 3.

From the modified Park test, an inverse Gaussian model is selected for pooled sample and the HPW segment. On the contrary, a gamma model is selected for LPW. In both cases, the variance function is modeled as proportional to some power (cubic or cuadratic) of mean function.

The tables include robust standard errors using the White heterocedastic variance-covariance matrix, the Akaike information criterion (AIC), the log of pseudolikelihood and the correlation between p and $\hat{p}$ as a simple measure of predictive power (R-square type measure) for a GLM (Zheng and Agresti, 2000).

In the pooled model (Table 2) *food pairing* was statistically significant just for HPW, with a negative association with price. On average, they were 9% cheaper than those without it. It might respond to the intent to attract better off less educated wine drinkers.

Something similar occurs with *serving temperature* recommendations, significant in the total sample and the HPW only. The estimated coefficients show that they were priced 13% lower in the total sample and 20% lower in the HPW segment.

The *sensorial description* was positively associated with price in HPW segment and negatively associated in LPW and the total sample. In all of them the impact was statistically significant. Therefore, the hypothesis is corroborated for HPW only.

Table 2. *Results of the Hedonic Price Models with Specific Label Descriptores*

	Pooled Model		LPW		HPW	
VARIABLES	Parameters	Impact %	Parameters	Impact %	Parameters	Impact %
Age	0.124***	10.22	0.0426	3.53	0.0833***	6.81
	(0.0168)		(0.0312)		(0.0230)	
age2	-0.00580***		-0.00250		-0.00287	
	(0.00184)		(0.00717)		(0.00198)	
Alcoh content	0.103***	10.30	0.0521***	5.21	0.0680**	6.80
	(0.0180)		(0.0126)		(0.0288)	
Oak barrique	0.0516***	5.30	0.0168***	1.69	0.0194***	1.96
	(0.00262)		(0.00240)		(0.00316)	
Red wine	-0.0851***	-8.18	-0.0348**	-3.43	-0.0802**	-7.76
	(0.0220)		(0.0142)		(0.0332)	
Rose wine	-0.0545	-5.37	0.0333	3.35	-0.343***	-29.25
	(0.0375)		(0.0252)		(0.0769)	
Varietal	0.0583**	5.97	0.0372*	3.77	-0.00919	-1.00
	(0.0246)		(0.0193)		(0.0422)	
Food pairing	-0.0201	-2.01	-0.00239	-0.25	-0.0922***	-8.87
	(0.0194)		(0.0159)		(0.0355)	
Sensorial desc.	-0.0800***	-7.73	-0.0922***	-8.84	0.167***	18.10
	(0.0294)		(0.0274)		(0.0366)	
Serv. Temperature	-0.139***	-13.00	0.0170	1.70	-0.217***	-19.56
	(0.0214)		(0.0159)		(0.0365)	
Environmental	0.112***	11.82	0.0397**	4.03	0.0237	2.34
	(0.0224)		(0.0198)		(0.0342)	
Making Process	-0.0199	-1.99	0.133***	14.21	-0.199***	-18.08
	(0.0212)		(0.0163)		(0.0312)	
Supermarket	0.177***	19.33	0.165***	17.93	0.149***	16.00
	(0.0229)		(0.0152)		(0.0352)	
Hipermarket	0.227***	25.44	0.167***	18.16	0.127***	13.46
	(0.0248)		(0.0167)		(0.0382)	
San Juan prov	-0.0435*	-4.29	0.0411**	4.17	-0.198***	-18.04
	(0.0261)		(0.0204)		(0.0444)	
Salta prov	0.0845***	8.78	0.0908***	9.46	-0.258***	-22.84
	(0.0276)		(0.0281)		(0.0517)	
La Rioja	-0.289***	-25.22	-0.0200	-2.05		
	(0.0568)		(0.0365)			
Patagonian	-0.0148	-1.54	0.165***	17.90	-0.184***	-17.01
	(0.0379)		(0.0263)		(0.0702)	
Constant	1.438***		1.990***		2.448***	
	(0.236)		(0.168)		(0.377)	
Obs.	1,015		650		365	
Park Test: $v(\mu)=$	μ^3		μ^2		μ^3	
$corr(p,\hat{p})$	0.743		0.508		0.703	
AIC	11.32		7.84		12.84	
Log -pseudolikelihood	-5729.27		-2527.93		-2324.79	

Note: Robust Standard Errors in brackets ***Statistically Significant at 1% level; **significant at 5% level; * significant at 10 % level *.

The inclusion of *environmental characteristics* was positively associated with price and statistically significant in the total sample and the LPW. In the first case wines with the presence of this label information were 12% more expensive than those without it; and 4% in the second group, confirming the specified hypothesis.

Information about the *wine making process* was statistically significant for all three cases. In the LPW segment it increased the average price in 14%, while in the HPW decreased it in 18%. In the total was a 2% negative.

The wine objective variable *age* and its quadratic form were statistically significant in the total sample. Evaluated at the sample mean of age, each additional year increased, on average, 10% the wine bottle value. *Age* was also significant for HPW; however, for LPW the variable was not statistically significant.

Alcoholic content was positively related to price and statistically significant in the three models. Storage in oak barrels (measured in months) showed that on average increased the price by 5% per month.

Red and rose wines exhibited significant lower prices than *white* ones with a larger difference in HPW. The significant consumption of beef in the argentine diet and its pairing preferences with red wines causes a larger production of them, stronger competition among wineries and lower prices compared to the white and rose wines.

Varietal wines for the total sample and the LPW received on average higher prices (6%) than wines made with two or three grape varieties. However, the coefficient was negative for the HPW, although not statistically significant.

Differences also appeared with respect to the type of store where wine was purchased. In supermarkets the price was on average 19% more expensive than in specialized wine stores, and in hypermarkets that difference increased to 25.5%.

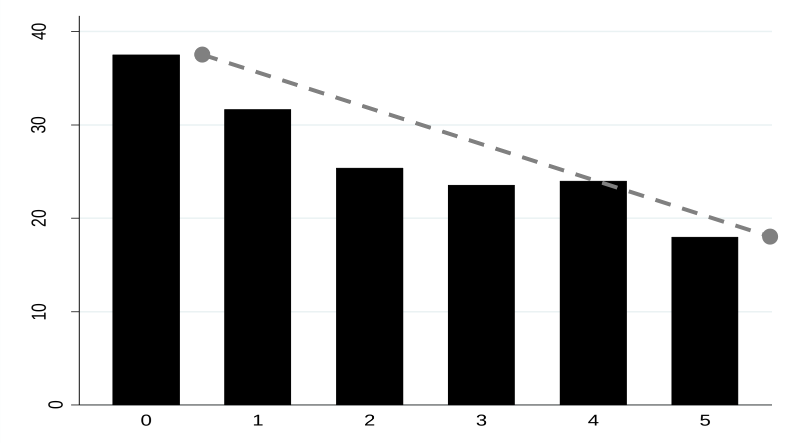
Respect to the *region of origin*, for the total sample the higher prices corresponded to Salta province, followed by Mendoza province and the Patagonian ones (Neuquen and Rio Negro). Compared to Mendoza province, San Juan and La Rioja wines carried lower prices, between 4% and 25% on average.

However, the results changed when each segment was analyzed. For the LPW, those from Mendoza province carried the lowest prices, except for La Rioja wines; for the HPW (from where 85% of the sample came, Table 1), Mendoza exhibited the highest prices.

When only one variable: *Total number of AI descriptors* was used in the model, similar results were obtained (Tabla 3, Annex). For the pooled sample a negative relationship with prices was found, with a larger decrease up to a number of 3 descriptors (Figure 1).

For the LPW segment, the larger the number of *AI*, the higher the price, findings consistent with those of Mueller and Szolnoki (2010). The addition of each label descriptor increased the bottle price in almost 1,5%, and began with 3 descriptors (Figure 2 a).

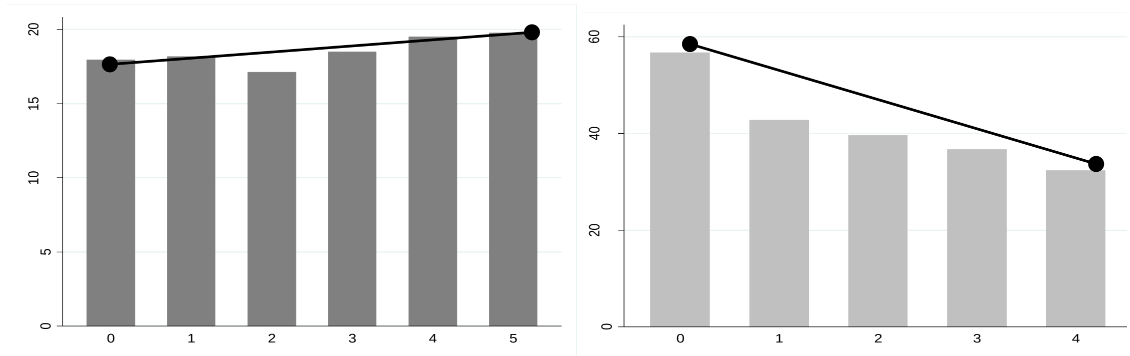
On the contrary, for the HPW, the relationship was negative and each additional descriptor was associated with a 9% decrease in price (Figure 2 b).



Source: Predicted wine prices from model of Table 3.

Figure 1. *Relation between Number of Descriptors and Wine Average Price. Total sample*

(a) LPW (b) HPW



Source: Predicted wine prices from model of Table 3.

Figure 2. *Relation between label information and wine average price. Wine segments according to price.*

5. Discussion

The general results found in this paper show that *AI* descriptors are significant to explain wine prices paid by consumers. But the signs of their impacts are different, with varying results among price segments.

About food pairing information, our results indicate that for the LPW segment, this descriptor is not relevant, whereas in HPW, its presence is negatively associated with the wine prices. This result is opposite to the consumer preference analysis of Barber et al. (2006) and Mueller et al. (2010), considering that shelf price reveals demand and supply side. Mueller et al. (2010) found that food pairing information had a positive effect on consumers' valuation and it is strongly by consumer who prefers lower prices. Barber et al. (2006) also found that such food pairing is highly evaluated by consumers. Nevertheless, the negative association between food pairing and wine price in the Argentine retail market could be explained by the reputation or fame gained by traditional argentine wineries whose wines are in the top of the HPW segment. So they do not need to put food pairing information in order to increase their market share. Therefore we can interprete that food pairing information on label is more present in cheaper wines as differentiation strategy of the wineries that compete in a more atomized market with an increasing numbers of brands.

The recommendation about serving temperature of wine is not included in previous studies to compare. But the results appear to support the negative effect of food pairing in the HPW segment. Even with temperature recommendation, the negative association with prices is stronger.

Our results about taste or sensorial description show a positive association with prices only for the HPW segment. This is in congruence with the findings of Charters (1999) that sensory descriptions constituted the most valued attribute of back label in a sample of highly involved and experienced consumers, who in general look for wines in the HPW segment. Additionally, in this segment, the sensorial description constitutes the only one *AI* that has a significant positive effect on wine prices, and this relevance is consistent with findings by Mueller et al. (2010). For LPW and in the pooled sample, we find that sensorial descriptor influences negatively on prices. To understand this result, it is necessary to take into account that we do not differentiate between simple or complex description of wine taste. But in general, if LPW have a sensory description on the label, it is simpler in comparison with that used in more fine wines, which search for more understanding consumers. So, for the LPW segment, the sensory description is more present in wines with lower prices. This could happen in the case of unknown wineries without market positioning or selling a wine with lower quality, and need to add value by such differentiation strategy.

Geographic and geological information (here, the *enviromental* variable) show to be relevant for LPW segment with a positive coefficient. Mora and Livat (2013) found the opposite for geographic description (i.e. a negative effect).

For wine making process information our results for LPW segment concur with the findings of Beverland (2004), Mora and Livat (2013) and Mueller et al. (2010) and Mueller and Szolnoki (2012). Mora and Livat (2013) explain that the positive link between "winemaking" and some higher prices may be due to the fact that this type of storytelling is aimed at a more educated consumer segment and therefore more involved in wine than average. However, in the argentine HPW segment, this descriptor has a negative influence on prices; food pairing or recommendation of serving temperature follow the same pattern for luxury wines, where they appear not to need additional information to compete in the shelf.

Finally, as in Mueller and Szolnoki (2010), we find that a variable with the number of descriptors was useful to explain price spreads. However, in this paper it gave further information about the relationship between *total number of AI descriptors* and wine price segments, being positive for LPW and negative in HPW.

6. Conclusions

The 2008 international economic crisis adversely affected Argentine wine exports. In the following years, the domestic market supply of fine wines increased as did wineries´ competition to gain market share. At retail level many specialized wine stores opened in most populated centers, adding new outlets for this product. Competitive prices favored the consumption of better quality wines in detriment of the traditional cheaper table wines. Wineries adopted different strategies to attract consumers, including additional labeling information. This paper aimed to look into the effect of labeling information on average prices paid for wine bottles on the shelf, applying the study to Santa Fe city. A hedonic price model was estimated for label information on objective wine characteristics and *AI* descriptors.

All objective wine characteristics (color, alcoholic content, age, aging in barrique, varietal) were statistically significant and with the expected sign in the model. Differences were found between LPW and HPW, which reaffirmed and helped to understand that both segments continued increasing their domestic differentiation.

AI descriptors were also found statistically significant to explain price differences, although with opposite impact in each wine price segment.

In the pooled model and for HPW segment the *AI* association was negative, indicating that wineries relied on other factors such as quality, reputation or consumers' previous knowledge. For LPW, *AI* was positively associated with higher prices. In this way the effects of additional labelling information on shelf price was found to be opposite between price segments.

Finally, a few suggestions for future studies. First, to try other criteria to analyze the sample, such as grape color, sale stores or quality. Second, to replicate the study in a wine producing province to search for the influence of local availability and cultural differences on the wine market. And third, to explore alternative methodologies such as other than logarithmic transformations to allow for a parsimoneous interpretation of results, or different estimation models such as quantile regression to identify more price segments.

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ANNEX

Table 3. *Results of the Hedonic Price Model with Number of AI Descriptors*

	Pooled Model		LPW		HPW	
VARIABLES	Parameters	Impact %	Parameters	Impact %	Parameters	Impact %
Age	0.107***	10.02	-0.00476	1.73	0.0850***	7.89
	(0.0175)		(0.0325)		(0.0269)	
age2	-0.00423*		0.00813		-0.00374	
	(0.00216)		(0.00718)		(0.00283)	
Alcoh content	0.106***	11.9	0.0726***	7.24	0.0417	4.24
	(0.0186)		(0.0137)		(0.0373)	
Oak barrique	0.0509***	5.42	0.0185***	1.88	0.0240***	2.41
	(0.00240)		(0.00307)		(0.00356)	
Red wine	-0.0805***	-8.98	-0.0400**	-3.94	-0.0577	-6.84
	(0.0219)		(0.0157)		(0.0414)	
Rose wine	-0.0246	-2.05	0.0737*	7.06	-0.324*	-29.79
	(0.0606)		(0.0393)		(0.166)	
Varietal	0.0383	5.66	0.0441**	4.47	0.0315	-2.19
	(0.0253)		(0.0187)		(0.0464)	
#AI descriptors	-0.0690***	-6.09	0.0187**	1.43	-0.0941***	-9.11
	(0.00885)		(0.00726)		(0.0161)	
supermarket	0.172***	19.93	0.154***	16.87	0.145***	15.27
	(0.0225)		(0.0166)		(0.0407)	
hipermarket	0.233***	25.19	0.156***	16.40	0.151***	14.46
	(0.0256)		(0.0204)		(0.0414)	
San Juan prov	-0.0724***	-7.30	-0.00128	-0.70	-0.147***	-13.47
	(0.0258)		(0.0187)		(0.0483)	
Salta prov	0.108***	11.58	0.0920***	9.32	-0.183**	-16.89
	(0.0410)		(0.0294)		(0.0872)	
La Rioja prov	-0.0327***	-26.77	-0.0503	-6.45		
	(0.0980)		(0.0603)			
Patagonian	0.0259	-3.60	0.149***	14.89	-0.231**	-20.99
	(0.0452)		(0.0311)		(0.0967)	
Constant	1.481***		1.669***		2.896***	
	(0.245)		(0.185)		(0.489)	
Obs.	1,015		650		365	
Park Test: $v(\mu)$	μ^3		μ^2		μ^3	
$corr(p, \hat{p})$	0.733		0.568		0.698	
AIC	11.33		7.83		12.82	
Log-pseudolikelihood	-5729.38		-2529.08		-2324.84	

Nota: Robust Standard Errors between brackets. ***Statistically Significant at 1% level; **significant at 5% level; * significant at 10 % level *.