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A hedonic price analysis for the Italian wine in the domestic market

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Abstract Price formation in the domestic market has not been widely studied in spite of the importance of the Italian wine market in terms of sales. We use a unique dataset to estimate the hedonic price function for Italian wine sold on the Italian market in the period 2005–2011. For each bottle considered, the dataset records several characteristics such as the price by retail channel (on the mass market and in wine shops), label characteristics, chemical analysis, sensory evaluations and experts' opinions. The objective of the analysis is to examine price setting on the mass market and in wine shops and to explore the differences in price formation for red and white wines. Our results have been obtained using an innovative technique that consists of combining hedonic price techniques with dimensionality reduction tools.

Keywords Price formation mechanism · Hedonic price function · Canonical correlation analysis · Latent factors

1 Introduction

Italian wine is becoming increasingly popular and Italy has overtaken France as the world's largest wine producer[1]. Italian wine is exported around the world and is also extremely popular among domestic consumers. In Italy, the market for wine has very specific characteristic that influence price and distribution strategies. On the production side, a few large producers

[1] http://www.telegraph.co.uk/foodanddrink/wine/8571222/Italy-overtakes-France-to-become-worlds-largest-wine-producer.html.

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coexist with small ones that still have an artisan approach to wine making. On the demand side wine is sold mainly through the mass market outlets (GDO); only about 7.5 %[2] of the total volume is sold through wine shops (ENO). The level of consumer literacy and purchasing habits is very heterogeneous Ismea (2009a, b), which implies that pricing strategies should be channel-dependent (Brentari and Levaggi 2014). In this paper we study price formation for red and white wines and use an innovative estimation procedure to overcome some of the problems related to the lack of theory behind hedonic pricing estimation techniques. As in Brentari et al. (2011) we preliminarily carry out a dimensionality reduction by means of canonical correlation analysis, in order to replace the original chemical and sensory variables with some latent factors globally accounting for quality.

The plan of the paper is as follows: in the following section we present a brief review of the literature; after a review of the literature (Sect. 2), in Sect. 3 we describe our database and the methodology used; in Sect. 4 we present the results of our analysis. Finally, Sect. 5 concludes.

2 Review of the literature

Since the Combris et al. (1997) seminal paper, several authors have studied how quality is perceived by consumers in the wine market. Attributes written on the label, reputation and sensory characteristics are certainly very important, but from a marketing point of view it is fundamental to know their relative importance.

In the literature, the problem has been studied from several perspectives and with reference to several markets (for a review, see Orrego et al. 2012). Most literature agrees that consumer willingness to pay depends on observable characteristics and reputation (what is written on the label matters), while sensory variables and jury grades usually have a rather limited explanatory power. Market segmentation also seems to exist (Steiner 2004; Costanigro and McCluskey 2007).

Few studies are available on the hedonic price of Italian wine. Benfratello et al. (2009) use a hedonic price approach to study price formation of Barbaresco and Barolo, two high quality wines produced in Piedmont; Galizzi (2007) and Galizzi and Miniaci (2009) propose a similar analysis for Franciacorta Bollicine while Corsi and Strom (2013) use a hedonic price function approach to assess whether organic wines benefit from a price premium. Roma et al. (2013) and Brentari and Levaggi (2014) show that sensory variables and jury grades have a marginal role in price formation. One of the most important shortcomings faced by this literature is the absence of a reference model as regards the functional form and the variables that should be used to determine the price of the wine. For this reason, as suggested by Combris et al. (1997), the dataset should include a large number of variables, especially in terms of sensory characteristics. Only few databases have such requirements and even when the data requirement is fulfilled, estimation problems may arise. To overcome these problems, we propose to use an innovative approach to the traditional literature that consists of combining a latent variables approach with hedonic price estimation. As explained in Brentari and Levaggi (2014) our dataset has exactly all the Combris et al. (1997) requirements, but through canonical correlation analysis (Brentari and Zuccolotto 2011) we can reduce the number of variables by summarizing them into latent factors accounting for quality.

[2] http://www.confcommercioverona.it/index.php?option=com_content&view=article&id=1868:vinitaly-2012-cambiano-i-consumi-di-vino-nei-supermercati-o-il-prezzo-o-la-qualita&catid=52&Itemid=22.

3 Description of the dataset and methodology

We use the dataset that Altroconsumo uses for its guide (2006–2012). Each year about 300 wines (red and white) in the low to medium/high price range are bought and their characteristics are evaluated using a panel of experts. Within this range, wines are chosen in order to represent the variety of Italian wines in terms of vineyards, producers and region of origin. The sensory analysis is carried out using a detailed protocol and the price of each wine is observed using a specific market analysis. For our estimation we use the prices of red and white wines for the period 2005–2011. Our database comprises 1,077 observations from 45 denominations for red wines and 724 from 48 denominations for white wines. The descriptive statistics for the sample are presented in Appendix 1. The dataset is fully described in Brentari et al. (2011); we recall here its most important characteristics. For each wine several variables were recorded and grouped into three main categories, namely *Label*, *Chemical* and *Sensory* variables.

Label variables comprise geographical origin marking (*DOC*, *Denominazione di Origine Controllata*, Controlled Designation of Origin: *DOCG*, *Denominazione di Origine controllata e Garantita*, Controlled and Guaranteed Designation of Origin: *IGT*, *Indicazione Geografica Tipica*, Geographical Denomination); appellation (*AP*); the Region of production (*REG)*; the declared alcoholic content (*Alcdic*).

Chemical variables are represented by the verified alcoholic content (*Alcver*); residual sugar (*Sugar*); volatile acidity (*Acivol*); total acidity (*Acitot*); sulphur anhydrides (*SO2*); the ratio between free and total sulphur anhydrides (*RS02*).

Sensory variables are derived from the assessment by the Brescia Centro Studi Assaggiatori [Taster Study Centre].[3] The judges were asked to grade the most important visual, olfactory and gustatory sensory variables, such as the appearance of the wine described by the intensity of the colour (*Colour—V1*); the presence of specific reflections (*Violet—V2*, *Orange—V3*, for red wines, *Green—V2*, *Gold—V3*, for white wines); the attraency (*Attraency—ATT*) which measures how pleasant the aspect of the wine is; the bouquet which is represented by the intensity of the bouquet (*Intolf—O1*) and by the several perfumes that can be perceived in the wine (*Floral—O2*, *Fruits—O3*, *Spicy—O4, Vegetal—O5*), how well they are perceived (*Clean—OF*) and how well they are harmonized (*Quality—OQ*); the flavour which is described by its structure (*Structure—G1*); the harmony of the different components (*Persfe—G2* and *Harmony—GA*), the taste and mouth feel (*acidity—G3*, *bitterness—G4* and, for red wines only, *astringency—G5*) and finish (*Ricarom—GO*, *Persistency—PAI*, *Retclean—ROF*, *Retquality—ROQ*); an overall evaluation of the wine (*Overall*). The perception of each descriptor was recorded using a 0–9 scale where 0 denotes the lowest and 9 the highest score. The datasets presents three scores of the sensorial analysis that are summarised by the following indices: Hedonic Index (IE) which determines the score as the average of Attraency, Clean, Quality, Harmony, Retclean, Retquality and Overall; ZOB Index which determines the score as the average of: Colour, Persfe, Structure, Flower, Fruit, Spicy (Zironi et al. 2003); Competition Index (IC) which determines the quality level as the average of the scores obtained on Structure, Finish, Attraency, Cleanness, Harmony. Finally for each bottle in the sample the price when sold on the mass market (p_{GDO}) and in wine shops (p_{ENO}) is recorded. If the wine is sold using only one channel we have one price.

[3] For further information see http://www.assaggiatori.com. The authors wish to thank *Altroconsumo*, the main and most widespread Italian consumer association with over 300,000 members, and Luigi Odello, chairman of *Centro Studi Assaggiatori*, for the datasets used in this work.

A hedonic price estimation approach was used to determine the most important factors in price formation. The aprioristic nature of hedonic price estimation makes it necessary for the dataset to have a great number of explanatory variables, none of which can be excluded *a priori*. This may be a serious impairment to the use of these techniques when they are carried out with the aim of a more refined analysis than a simple investigation into the main determinants of price formation. For this reason in this paper we used two approaches to reduce the number of explanatory variables. For red wines with more than 20 observations and white wines with more than 10 observations a specific dummy variable was created; the others were grouped into four appellations: *OsupN*, *OsupC*, *OsupS* which comprises *DOC* and *DOCG* appellations divided by Region of origin (North, Centre, South) and *Ainf* which comprises lesser known and more generic appellations.

The same grouping was done for Regions. In this case the cut-off point was having more than 65 observations for red wines and more than 55 for white wines; all the others were grouped into three variables, according to the geographical position of each region (*North*, *Centre*, *South*).

As regards chemical and sensory variables, different choices are possible. On the one hand, we can try to model their influence on price by considering them one by one. As pointed out in Brentari et al. (2011), with this choice, only few sensory and chemical variables enter the model, their inclusion is not stable from one dataset to another and their role is usually marginal. Ultimately, this leads to a fragmented result, where the impact of the single variables on the outcome is difficult to interpret. On the other hand, we can construct composite indicators in order to summarize chemical and sensory variables into a few variables able to account for all the information contained in the sets $\boldsymbol{C} = (Alcver, Sugar, Acivol, Acitot, SO2, RS02)$ and $\boldsymbol{S}$ = (V1, V2, V3, O1, O2, O3, O4, O5, G1, G2, G3, G4, G5, GO, PAI, ATT, OF, OQ, GA, ROF, ROQ). Different dimensionality reduction techniques are available for this purpose. For example, principal component analysis (PCA) or canonical correlation analysis (CCA) may be used. In this context, PCA usually results in meaningful and easily interpretable latent factors in terms of sensory variables, but the interpretability of the chemical principal components is typically hard and, moreover, there is no guarantee that they account for the wine quality. Following Brentari et al. (2011) and Brentari and Zuccolotto (2011), we prefer CCA, a multivariate statistical technique introduced by Hotelling (1936), aimed at defining the coordinate system that describes the maximum cross–covariance between two datasets, because we argue that forcing chemical and sensory latent factors to be correlated to each other should hopefully result in latent factors globally correlated to the wine's quality, from two different perspectives.

Another possibility, which we leave to future research, is to use Co-inertia Analysis (Chessel and Mercier 1993) in order to improve CCA. In fact, CCA creates highly correlated linear combinations but they are not necessarily the most explicative ones. Co-inertia Analysis, based on the covariance criterion, has been proposed to improve the Correlation Analysis. However, it is worth noting that Co-inertia Analysis and CCA should not be considered as competing techniques due to their different goals (Cherry 1996, 1997; Amenta 2007).

The first and the second chemical and sensory latent factors obtained by CCA, *LFC1*, *LFC2*, *LFS1*, *LFS2,* were then added to the database and used as explanatory variables in place of the single variables composing the sets $\boldsymbol{C}$ and $\boldsymbol{S}$. The main features of these latent factors and the details of the CCA analysis are summarized in Sect. 4.1.

As in Brentari and Levaggi (2014) we restricted the choice to linear and log-linear equations and performed a RESET test, which showed that a log-linear form is preferable also in this case. The results are presented in Appendix 1.

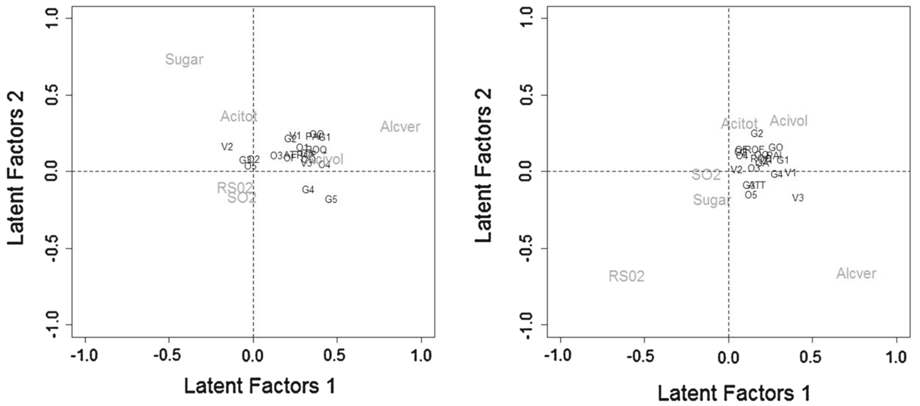

Fig. 1 Linear correlation coefficients of the single variables in the sets C (*gray*) and S (*black*) with the first and second (chemical and sensory, respectively) latent factors—*left* red wines; *right* white wines. (Color figure online)

4 Results

4.1 Sensory and chemical latent factors

We denote with X_1 and X_2 the vectors containing the p_1 chemical variables and the p_2 sensory variables in the set $\boldsymbol{C}$ and $\boldsymbol{S}$ respectively. With CCA we find, successively for $k = 1, 2, \ldots, \min[p_1, p_2]$, pairs of linear functions of X_1 and X_2, $\{\alpha_{k1}X_1, \alpha_{k2}X_2\}$ respectively, such that the correlation between $\alpha_{k1}X_1$ and $\alpha_{k2}X_2$ is maximized, subject to $\alpha_{k1}X_1$ and $\alpha_{k2}X_2$ both being uncorrelated with $\alpha_{jh}X_h$, $j = 1, 2, \ldots, (k-1)$; $h = 1, 2$. The linear functions $\{\alpha_{k1}X_1, \alpha_{k2}X_2\}$ are called canonical variables and in this context are interpreted as variables able to describe, using chemical and sensory features, some latent trait concerning the analyzed wines. For this reason we will call them chemical ($\alpha_{k1}X_1$–*LFCk*) and sensory ($\alpha_{k2}X_2$–*LFSk*) latent factors. The correlation coefficient $\rho_k = \mathrm{Corr}(\alpha_{k1}X_1, \alpha_{k2}X_2)$ is called the k-th canonical correlation coefficient and informs us about the extent to which the pairs of canonical variables are able to describe the same latent trait. In fact, we rely on the conjecture that forcing chemical and sensory latent factors to be correlated with each other should hopefully result in latent factors globally correlated with the wine's quality, which should be the latent trait we try to describe with this method. We performed CCA separately for red and white wines. In both cases we decided to retain only the first two latent factors ($k = 1, 2$), with canonical correlation coefficients given by $\rho_1 = \mathrm{Corr}(\mathit{LFC1}, \mathit{LFS1}) = 0.7027$ and $\rho_2 = \mathrm{Corr}(\mathit{LFC2}, \mathit{LFS2}) = 0.4504$ for red wines and $\rho_1 = \mathrm{Corr}(\mathit{LFC1}, \mathit{LFS1}) = 0.5222$ and $\rho_2 = \mathrm{Corr}(\mathit{LFC2}, \mathit{LFS2}) = 0.4125$ for white wines. For interpretation purposes, it is useful to inspect the graphics displayed in Fig. 1, showing the linear correlation coefficients of the single variables in the sets C and S with the first and second latent factors, separately for red and white wines.

In both cases the first sensory latent factors tend to be positively correlated with almost all the sensory variables, thus they can account for a global sensory quality of wines. Globally, also the second sensory latent factors tend to summarize all the sensory variables, thus accounting for an overall sensory quality of wine, with some differences between red and white wines. In fact, in the former case, the overall sensory quality described by the second latent factor is negatively correlated with variables $G4$ (*bitterness*) and G5 (*astringency*),

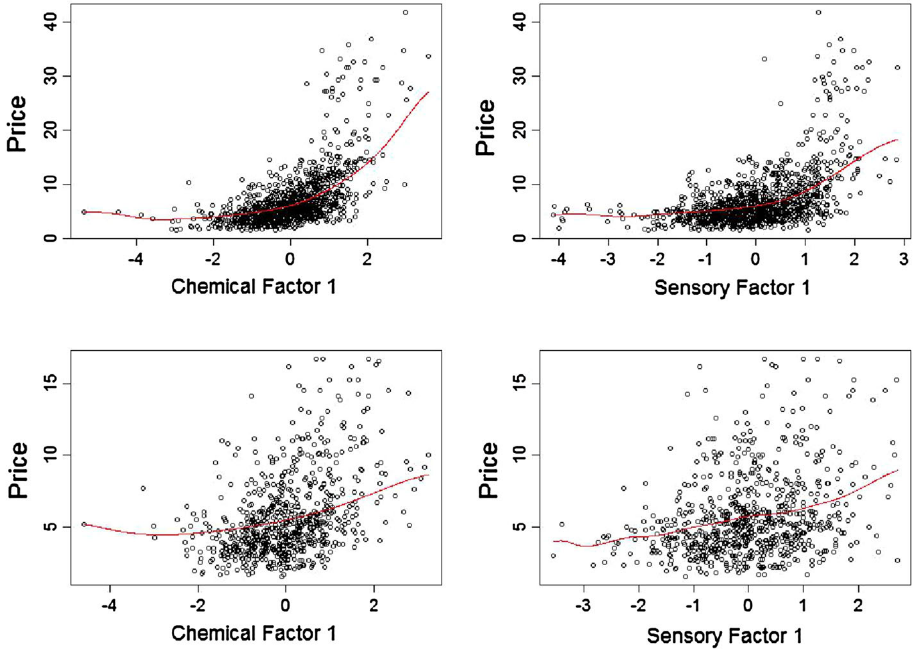

Fig. 2 Scatterplot of the first latent factors versus wine price factors—*top* red wines; *bottom* white wines. (Color figure online)

thus meaning that these two features can turn out to be considered unpleasant with respect to this latent trait. In the case of white wines, the same happens for variables $G3$ (*acidity*), *ATT* (*attraency*), $O5$ (*vegetal*), $V3$ (*gold*). From the point of view of the chemical variables, it is interesting to note that forcing correlation to the sensory latent factors tells us about the chemical features distinguishing wines with high sensory quality. In both cases we have a positive correlation of high sensory quality with the alcoholic content of the wine, and a negative one with residual sugar and variables related to the presence of sulphur anhydrides. Different behaviour can be observed as regards the variables describing acidity.

Figure 2 shows that *LFC1* and *LFS1* exhibit some association with the wine price, both in the case of red and white wines, thus allowing us to proceed in the hedonic price analysis by replacing the original variables in the sets C and S with the latent factors. On the other hand, *LFC2* and *LFS2*, beyond being less informative, exhibit a considerably weaker association with price, but we decided to retain them anyway.

4.2 Price formation in the mass market

For the mass market, we fitted the following model:

$$\ln p_{GDO} = k + aDOC + bDOCG + \sum_{i=1}^{z} c_i AP_i + \sum_{i=1}^{w} d_i REG_i + \\ + \sum_{i=1}^{2} k_i LFC_i + \sum_{i=1}^{2} l_i LFS_i + mENOp + nVINT + \varepsilon_i$$

Table 1 Censored Stepwise regression

	pGDO		*pENO*	
	Estimate	t statistic	Estimate	t statistic
Constant	−1.723	−5.770	0.0150	0.03606
IGT	0.303	2.026		
DOC	0.363	2.423		
DOCG	0.506	3.976	0.3157	9.066
Amarone	0.5729	9.006		
Barolo	0.5413	7.954	0.3158	3.537
Castel del Monte	−0.3404	−5.372		
Chianti	−0.2732	−6.120	−0.1498	−2.192
Dolcetto	0.1684	3.859		
Grignolino	0.2279	4.009		
Montepulciano	−0.2253	−4.985		
Nebbiolo	0.3194	4.572		
Nero d'Avola	−0.1126	−2.754		
Primitivo di Manduria	−0.3748	−5.708	−0.2780	−2.593
Rosso di Montalcino	0.4808	8.852	0.5443	10.89
Sangiovese	−0.1621	−4.105		
Terre di Franciacorta	0.3713	5.380	0.5116	6.382
Valpolicella	0.1863	3.039		
Valtellina Superiore	0.2416	4.092		
OsupN	0.1183	3.381	0.2190	4.08
OsupS	−0.2348	−5.888	−0.1601	−2.942
Piedmont			0.1986	4.819
Tuscany	0.0877	2.536		
Sicily			−0.0957	−2.234
Veneto			0.2233	2.502
Centre	−0.0783	−2.274		
Alcdic	0.219	10.37	0.1436	4.409
LFC1	0.0902	6.050	7.47E−02	3.078
LFS1			6.34E−02	3.436
S_{Eno}	0.27498	13.280		
R^2	0.7911		0.7376	
N	973		416	
LL	−38.028		5.0400	

Dependent variable: prices of red wines in large distribution (*pGDO*) and in wine shops (*pENO*)

where $z = 27$ and $w = 9$ for red wines and $z = 34$ and $w = 8$ for white wines. The baseline for this estimation is an ordinary wine without any appellation denomination.

The results are presented in Tables 1 and 2 for red and white wines respectively. The models explain about 80 % of the price variance for red wines and 66 % for white wines. The price for white wines is either more or less volatile depending on the variables we considered. Below we highlight the main common characteristics and the main differences in the results of the two models.

Table 2 Censored Stepwise regression

	p_{GDO}		p_{ENO}	
	Estimate	t statistic	Estimate	t statistic
Constant	−1.6692	−7.825	−0.1287	−0.5389
DOCG	0.0805	2.157		
Alcamo	−0.2009	−3.109	−0.1675	−2.094
Bianco di Custoza	−0.1707	−2.813		
Castelli Romani	−0.4524	−5.537	−0.7055	−3.341
Est Est Est	−0.2542	−3.284	−0.6463	−6.089
Frascati	−0.1923	−2.95		
Gavi	0.1939	2.607		
Grillo	−0.3654	−5.287	−0.1745	−2.438
Greco di Tufo	0.4058	5.338	0.3371	5.182
Locorotondo	−0.1844	−2.361		
Isola di Nuragus	−0.2827	−3.498		
Orvieto	−0.2365	−4.722		
Pinot Grigio	0.1394	3.049		
Soave	−0.1645	−3.081		
Terre di Franciacorta	0.2486	3.682	0.2355	3.183
Tocai			−0.4949	−3.889
Trebbiano	−0.4132	−9.331		
OsupCS			0.3065	4.277
Friuli V.G	0.1227	3.206	0.4154	8.553
Trentino Alto Adige			0.1518	4.005
Veneto			0.1756	2.546
Nord	0.1533	4.524	0.4405	9.791
Alcdic	0.2471	14.07	0.1527	8.095
LFS2	$4.72E-02$	4.44	0.0310	2.482
S_{Eno}	0.3186	13.66		
S_{Gdo}			0.0473	1.532
R^2	0.6635		0.6166	
N	652		280	
LL	−12.5251		54.5087	

Dependent variable: prices of white wines in large distribution (p_{GDO}) and in wine shops (p_{ENO})

4.2.1 The common characteristics

The alcohol content and label characteristics are driving factors in determining the price. In particular the appellation can increase the price as in the case of wines with a higher reputation or it may decrease it for wines with a lower reputation or with a strong taste. Only variables that can, to some extent, be verified are valued by the consumer. In fact geographical origin markings enter the model while other less verifiable characteristics (such as "Superior" or "Reserve") are not significant. For red wines all the appellation denominations are significant while for white wines only DOCG has a positive impact on the price. Selling using both channels has a positive impact on the price; the mark-up is however higher for white wines

(37.5 % against 31.65 %).[4] This factor is even more important if we observe that the price for white wines is on average lower. The region of production has no particular impact on the price of the wine; in both cases only the Region that is relatively more represented in the sample (Tuscany for red wines and Friuli Venezia Giulia for white wines) is significant. For Tuscan red wine the positive effect is fairly strong, given that wines coming from Regions in the same area (Centre) receive a negative mark-up.

4.2.2 The distinguishing features

The data fit the regression for red wines better (80 % against 66 %). This difference may derive from the absence of robust driving factors in determining the price of white wines. For example, while for red wines appellation is important in price formation, the same does not seem to happen for white wines. In both cases the signs are as expected, but the impact on the price is higher for some "top class" red appellations (Amarone, Rosso di Montalcino). This result may reflect several factors; whatever the reason, our estimations point out that this process seems to be more important for red rather than white wines.

For red wines also "pooled" appellations are important with northern wines having a positive mark-up, while southern ones have a negative sign. This is not the case for white wines where only specific appellations are significant.

Both sensory and chemical quality latent factors enter the model. For red wines chemical characteristics seem to be more important than sensory ones. In fact in this case the first chemical factor is significant. For white wines only the second sensory latent variable is significant.

4.3 Price formation in wine shops

For wine shops, we estimated the following model:

$$\ln p_{ENO} = k + aDOC + bDOCG + \sum_{i=1}^{z} c_i AP_i + \sum_{i=1}^{w} d_i REG_i + \\ + \sum_{i=1}^{2} k_i LFC_i + \sum_{i=1}^{2} l_i LFS_i + mGDOd + nVINT + \varepsilon_i$$

For white wines *OsupC* was merged with *OSupS* because of their relative small importance. The baseline is an ordinary IGT wine, since in our sample only wines with a geographical origin marking are sold in wine shops.

4.3.1 The common characteristics

The explanatory power of the model is lower than for GDO and the gap is about the same. For both models, the number of appellations that enter the regression is lower than for GDO; there also seems to be more homogeneity in the price of appellations deriving from the same Region, as shown by the significance of "pooled" appellations in both regressions; for the same reason few dummies representing the region of production are significant in explaining the difference in price. For white wine a clear North/South divide exists: most of the northern Regions enter the model (either as a single entity or through the pooled variable "North"), and they all have a positive sign. It is interesting to note that in this case Veneto and Trentino

[4] For a log-linear specification, Halvorsen and Palmquist (1980) propose estimating the effect of a binary variable on the price as follows: $\Delta p/p = e^c - 1$, where c is the coefficient of the parameter obtained through OLS. When two variables interact, their combined effect is: $\Delta p/p = e^{c+d} - 1$.

Alto Adige are the Regions with the lowest mark-up (around 20 % instead of the 55 % for "Other" northern Regions). In both cases, the sensory latent factors enter the model: for red wine it is the first latent factor, while for white it is the second.

4.3.2 The distinguishing features

Geographical origin markings are not significant explanatory variables for white wine while for red wines DOCG is important and has a mark-up of about 37 %. The difference in this case may derive from a different sample composition. For white wines about 70 % of those sold in this channel are DOC and, as noted before, the price is increasing in the geographical origin marking, but the variance is quite high. The chemical quality latent factors are not significant for white wines, while sensory indicators are important, more for red than white wines (see Sect. 5).

Finally it is interesting to note that selling using both channels has no impact on the price of the red wine whereas it adds a small mark-up to the price of the white wine.

5 Discussion and conclusions

Although internal consumption is decreasing through time, the domestic market is still the most important outlays for the majority of Italian wine-makers. The present economic recession, the increased competition and the change in consumption habits has increased the pressure on the industry to think more carefully about their selling strategies.

In this paper we have used the richness of the Altroconsumo dataset to infer the value that consumers attach to specific characteristics of the wine from its price. We have compared the hedonic characteristics of the market for red and white wines in the mass market and in wine shops.

Our results show that label characteristics and appellations are the variables that consumers perceive as important to determine the quality (hence their willingness to pay) for a specific wine. This result is in line with the findings of Corduas et al. (2013). Consumers do not seem to distinguish between appellations that characterize a specific grape (Nebbiolo, Barolo) from those that characterize a blend (Rosso di Montalcino, Sangiovese). Selling using both channels has a positive impact on the price in GDO, but it does not seem to have a bad reputation effect on the price in wine shops: in fact for white wines there is a positive (although small) increase in the price. Selling the wine using both channels may derive from different strategies. According to Ismea (2009a, b) a substantial proportion of consumers buy wines using both channels. They make a first purchase in a wine shop (perhaps following the advice of the shopkeeper) and, if they like the wine, they may decide to buy it again on the mass market. In fact, consumers who have noted that a specific label was also on the wine shop shelves may interpret this as a signal of higher quality and may, then, be willing to pay a price higher than the average for that wine. In order to differentiate between these behaviours we would need to have information about the quantity sold in each channel, and this information is missing in our dataset. However, if we interpret together the evidence deriving from our models, we can conclude that double channel strategy for the white market may be dominated by producers of top wines (the average price of their wine is higher both on the mass market and in the wine shops).

Appendix

See Tables 3, 4 and 5.

Table 3 Descriptive statistics of the sample for red wines

Binary variables (1 = presence of the specific characteristic)				Other variables			
AP	Sample composition				Mean	Min	Max
Chianti	0.0613			pENO	10.432	3	45
Nero D'Avola	0.0604	Superiore	0.0288	pGDO	6.116	1.4	34
Montepulciano	0.0539	DOC	0.5557	Alcdic	12.797	10	16.5
Barbera	0.0511	DOCG	0.2115	Alcver	12.852	10.25	16.44
Siangiovese	0.0483	IGT	0.2180	Sugar	3.935	1.1	27.6
Chianti Classico	0.0474	Riserva	0.0074	Acitot	5.514	4.1	8.1
Dolcetto	0.0455			Acivol	0.445	0.17	0.95
Merlot	0.0353			RSO2	0.206	0	1.444
Rosso di Montalcino	0.0334	REG		SO2	72.284	3	166
Valtellina Superiore	0.0334	Toscana	0.1977				
Aglianico	0.0316	Piemonte	0.1578				
Rosso Toscano	0.0297	Veneto	0.1049	Colour	7.066	4	9
Grignolino	0.0232	Sicilia	0.0854	Violet	4.922	0	8
Bardolino	0.0223	Lombardia	0.0770	Orange	3.178	0	8
Barolo	0.0213	Puglia	0.0585	Intolf	6.893	5	8
Nebbiolo	0.0213			Floral	3.985	1	6
Refoscolo dal Peduncolo Rosso	0.0204			Fruits	5.230	3	7
Cabernet Sauvignon	0.0195	Nord	0.1133	Spicy	3.513	1	6.5
Amarone	0.0186	Centre	0.1300	Vegetables	2.771	0	5
Castelli Romani	0.0186	Sud	0.0743	Structure	6.717	5	8
Primitivo di Manduria	0.0186			Roundness	5.895	4	8
Terre di Franciacorta	0.0186			Acidity	4.219	2.5	6
Valpolicella	0.0186			Bitterness	2.080	0	5
Ainf	0.0650			Astringency	4.332	0	7
Vino Rosso				AromRich	6.504	4	8
Sicilia				Persistency	6.482	4	9
Negramaro				Attraency	6.987	5	8
Isola dei Nuraghi				Clean	6.818	4	8
Syrah				Quality	6.752	4	8
OsupN	0.0714			CleanRet	6.427	4	8
Barbaresco				QualityRet	6.845	4	8
Bonarda				Giuglo	6.595	4	8.5
Cabernet				Zob	6.630	4	8.5
Lagrein				IE	7.381	4.7	8.8
Marzemino				IC	0.549	0.4	0.7
Oltrepò				Vintage		2003	2010
Teroldego							
Valcalepio							
OsupC	0.0483						
Sagrantino di Montefalco							

Table 3 continued

Binary variables (1 = presence of the specific characteristic)		Other variables		
AP	Sample composition	Mean	Min	Max
Rosso del Conero				
Rosso Piceno				
Morellino di Scansiano				
OsupS	0.0575			
Cirò				
Cannonau				
Monica				
San Severo				
Salice Salentino				

Table 4 Descriptive statistics of the sample for white wines

Binary variables (1 = presence of the specific characteristic)				Other variables			
AP	Sample composition				Mean	Min	Max
Trebbiano	0.0608			pENO	7.978	3.50	16.0
Vermentino	0.0608	DOC	0.6989	pGDO	4.8513	1.40	14.5
Chardonnay	0.0552	DOCG	0.1133	Alcdic	12.256	9.5	14.5
Pinot Grigio	0.0539	IGT	0.1796	Alcver	12.327	9.6	14.9
Verdicchio	0.0483			Sugar	3.9849	0	16.9
Soave	0.0414			Acitot	5.3968	4.01	8.29
Orvieto	0.0401			Acivol	0.2301	0	0.58
Pinot Bianco	0.0331			RSO2	0.3257	0.02	80
Terre di Franciacorta	0.0331	REG		SO2	97.127	0.09	176
Sauvignon	0.0318	Trentino A.A.	0.11602				
Sicilia	0.0318	Veneto	0.10635				
Bianco di Toscana	0.0290	Friuli VG	0.09254	Colour	5.9551	2.5	8
Vernaccia	0.0290	Sicilia	0.08011	Green	3.3833	1	6
Bianco di Custoza	0.0276	Toscana	0.07458	Gold	4.5953	1	7
Muller Thurgau	0.0276			Intolf	6.6091	4.5	8
Cirò	0.0249			Floral	4.7169	2.5	7
Alcamo	0.0235	Nord	0.15746	Fruits	4.7859	2.5	7
Frascati	0.0221	Centro	0.20166	Spicy	2.0829	0	5
Gavi	0.0221	Sud	0.10635	Vegetables	2.8267	0	6
Gewurtztraminer	0.0221			Structure	6.3384	4	7
Grillo	0.0221			Roundness	5.9185	4	7
Greco di Tufo	0.0221			Acidity	4.6347	3	7
Isola di Nuragus	0.0166			Bitterness	1.826	0	4
Roero	0.0166			AromRich	6.2949	4	8
Castelli Romani	0.0152			Persistency	6.2424	4	8
Est Est Est	0.0152			Attraency	6.721	0	8
Locorotondo	0.0152			Clean	6.6844	4	8

Table 4 continued

Binary variables (1 = presence of the specific characteristic)		Other variables			
AP	Sample composition		Mean	Min	Max
Tocai	0.0152	Quality	6.5905	3.5	8
Falanghina	0.0138	Harmony	6.4254	3	8
Pinot Nero	0.0138	CleanRet	6.7459	4	8
Sylvaner	0.0138	QualityRet	6.4869	3	8
Ainf	0.0235	IE	7.262	4.6	8.41
Salento		ZOB	0.4896	0.3	0.64
Galestro		IC	72.208	48.89	84.44
Pecorino		Vintage		2003	2010
Friulano					
Colline Pescaresi					
OsupN	0.0469				
Pigato					
Lugana					
Traminer					
Riesling					
Valcalepio					
Erbaluce					
Cortese del Monferrato					
OsupC	0.0069				
Pomino Bianco					
Pitigliano					
OsupS	0.0249				
Fiano di Avellino					
Castel del Monte					
San Severo					

Table 5 Choice of the functional form

	Red wine		White wine	
	Lin	Loglin	Lin	Loglin
p_{GDO}				
RESET	252.57***	0.108	67.261***	1.48
R^2	0.8035	0.8128	0.637	0.689
BP	504.22***	51.44	294.131***	38.57
p_{ENO}				
RESET	57.022***	0.776	17.503*	6.14
R^2	0.786	0.710	0.648	0.652
BP	516.22***	20.573	48.19	14.58

For each estimated equation (p_{GDO} and p_{ENO}) we have recorded the following statistics:
RESET which is the Ramsey (1969) RESET specification test; R^2;
BP Breusch-Pagan (1980) test for heteroschedasticity;
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

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