AMERICAN ASSOCIATION OF WINE ECONOMISTS

AAWE WORKING PAPER
No. 211
Economics

VERTICAL DIFFERENTIATION, PERCEPTIONS RESTRUCTURING, AND WINE CHOICES: THE CASE OF THE GRAN SELEZIONE IN CHIANTI WINES

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Feb 2017

www.wine-economics.org

Vertical differentiation, Perceptions Restructuring, and Wine choices: the case of the Gran Selezione in Chianti Wines.

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Working paper

Abstract

We conduct a choice experiment where the number of labels vertically differentiating Chianti wines (Chianti, Chianti Classico, Chianti Classico Riserva, Chianti Classico Gran Selezione) is augmented incrementally in a between-subject design, eliciting both quality perceptions and wine choices. We find that quality expectations are endogenous to the labeling regime, and adding a high-quality label (e.g., Chianti Gran Selezione) decreases the perceived quality of all other Chianti wines (comparative stigma). A model conditioning on subjective quality perceptions with heterogeneous WTP for quality is then proposed, and estimated via random parameter multinomial logit. The endogeneity problem arising from using subjective beliefs as regressors is addressed by means of a control-function approach. Results are compared to reduced form approaches where the marginal utility of quality and subjective perceptions are confounded in a single label-specific estimate, and the model is used to determine how much of the cannibalization observed after introducing higher-tier quality standards is attributable to restructuring of perceptions and comparative stigma.

Introduction

What happens when a new food label signaling higher quality is released to market? The theory of vertical product differentiation (e.g Giannakas and Yiannaka 2008) explains that quality labels provide consumers with more options, and consumers' willingness to pay (WTP) for high quality products will determine market shares under the new labeling regime. But quality improvements are often hard to verify, either at first (experience attributes, Nelson 1970) or even in the longer term (credence attributes, Darby and Karni 1973); so consumers' reaction to a new label will often depend on subjective interpretations of the quality signal. The appearance of a new high-quality signal may also alter how other products are perceived, just like the release of a "new and improved" phone suddenly changes how much we like the one we hold in our pocket. This suggests that, while WTP for a given level of quality may plausibly be independent of the labeling regime, quality perceptions may not be.

In this article we present a choice experiment where subjective quality perceptions and product choices are jointly elicited; and the market share captured by a new quality label is decomposed into a portion attributable to "choice availability" effects (i.e. consumers who are WTP for higher quality), and one owed to restructuring of perceptions. The context is the highly segmented market for Tuscan wines made from Sangiovese grapes, and the recent addition of the "Gran Selezione" (Great Selection,) to the previously established Chianti, Chianti Classico and Chianti Classico Riserva quality labels. While most directly related to the empirical literature on Geographical Indications and quality standards, our work also contributes to the nascent food economics literature attempting to differentiate preferences from beliefs ((Teisl and Roe 2010) (Lusk, Schroeder, and Tonsor 2013) (Costanigro, Deselnicu, and Kroll 2015)), and how vertical differentiation via quality labels affects consumers' perceptions of "conventional"/unlabeled products (e.g. Costanigro and Lusk, 2014 and Kanter, Messer, and Kaiser 2009).

Related literature

The literature leveraging choice data to estimate consumer preferences and WTP for food attributes is extensive and well-established; and the most advanced work in this arena has acknowledged the need to model heterogeneous consumers (e.g.(Onozaka and Mcfadden 2011; Meas et al. 2015)), which is often accomplished via random parameter specifications of the utility function (see D. McFadden and Train 2000). Until recently however, this literature has paid little attention to the distinction between preferences and perceptions (also referred to as beliefs or subjective expectations) and, more in general, the identification issue raised by Manski (2004). Put simply, choice data alone allow measuring the premium (or discount) consumers will pay for a labeled attribute, but tell us little about why people are willing to pay more (or less, or are indifferent). In the current context, one may not be willing to pay more for a Gran Selezione wine because they are happy with the quality of a lower tier Chianti Classico (suggestive of market saturation), or because they don't think that a Gran Selezione will differ that much from a Classico (implying a need for further differentiation or consumer messaging)[1]. This confounding of preferences and beliefs weakens the usefulness of choice data in drawing policy or even marketing recommendations, as identical choices can be justified on the basis of multiple combinations of preferences and beliefs.

[1] Lusk and colleagues (2013) raised a similar point while considering consumers' motivations to buy organics or not: a person not willing to pay a premium for organics may either not care much about better environmental and health outcomes, or simply doubt that there is any difference between organics and conventional products.

As economists begin to develop choice models incorporating subjective perceptions, several practical issues need to be addressed. The first one relates to how beliefs should be measured and incorporated into a credible model of choice. A strategy adopted in the risk literature and advocated by Manski is the elicitation of subjective probabilities for possible outcomes tied to different choices, such as the probability of losing a job, or getting pregnant (Delavande 2008). This approach is appealing because it fits naturally within the von Neumann-Morgenstern expected utility maximization framework, and has been recently adopted in the food choice literature (e.g. Lusk, Schroeder, and Tonsor 2013), yet some weaknesses appear evident. The first one (as the cited authors concede) is that some cognitive psychologists have been skeptical of people's ability to express subjective beliefs in a probabilistic form, as humans tend to process information in a verbal rather than numerical way[2] (Zimmer 1983). Subjective probabilities/beliefs appearing in the right-hand side of a choice model or regression equation are also potentially endogenous, even though the empirical relevance of this issue appears to be case-specific[3]. When endogeneity of subjective beliefs is a concern, the typical solution relies on finding appropriate observational instruments or randomized experimental treatments (or both, as in Teisl and Roe 2010).

A perhaps more problematic issue that became evident while designing this experiment is that the probabilistic approach is well-suited for measuring beliefs about discrete, mutually exclusive events that can be evaluated independently of the other available choices; but less

[2] Anecdotally, in an online consumer survey Costanigro and Lusk (2014) inquired about the "chance of eventually becoming ill from repeatedly consuming genetically engineered food" and "repeatedly consuming ethylene ripened fruit". The most frequent (mode) answer to both questions was a (rather large) 50%, but it seems plausible that "50/50" may in fact be a heuristic way of expressing uncertainty rather than an attempt to guess about the chance of illness.

[3] Lusk, Schroeder, and Tonsor 2013 or Zafar 2011 did not find evidence of belief endogeneity in their specific applications.

useful with vertically differentiated products. For example, the subjective probability of graduating in 4 years (a binary outcome) when choosing a certain major (as in Zafar 2011) can be assessed independently of other career choices. Similarly, the perceived chance of getting pregnant (yes vs. no) using a given contraceptive method (Delavande 2008) does not directly depend on the effectiveness of other available devices. Conversely, it is difficult to express the probability that organic products are environmentally friendly, because perceived quality (e.g. taste, environmental friendliness, convenience, or overall quality assessments) is a comparative rather than an absolute concept (Steenkamp 1990). That is, it is much easier to say whether organic is (a little, somewhat, a lot) better than something else (e.g. conventional) than evaluating quality in a vacuum.

This suggests that the use of likert scales, while not exempt from flaws (most notably framing effects), might be more congruent to eliciting perceptions related to specific quality dimensions or overall quality assessments, as the typical practices of wine rating magazines (Wine Spectator, Wine Enthusiast, Decanter etc.) seem to confirm. The use of spatial scales is also consistent with mainstream economic models of vertical differentiation and/or quality expectations, which represent quality (implicitly or explicitly) as a linear spectrum over which consumers compare products. The literature on product quality, expectations, and asymmetric information originating with Akerlov (1970) follows this paradigm (e.g. Mussa and Rosen 1978), and so does the theoretical literature on minimum quality standards (Leland 1979, Shapiro 1983, Bockstael 1984, Boom 1995) and Geographical Indication labeling (Winfree and McCluskey 2005, Moschini, Menapace, and Pick 2008 Menapace and Moschini 2012), which is particularly relevant to our application. However, perhaps because of the innate hesitation to using subjective data in economics (Manski, 2004), this literature on quality differentiation typically assume that quality is an objective trait, leaving no room for subjectivity and individual perceptions[4], so that introducing a new label can never affect how existing products are perceived—a major point of departure from this paper.

The marketing literature on the other hand has tackled the issue of quality perceptions as a subject-object interaction, postulating that objective product cues, such as a label, are internalized by consumers in the form of subjective perceptions. Examples includes the lens model (Brunswik 1956) and its reformulation for quality perceptions by Dudycha and Naylor (1966), the conceptual model of the quality perception process by Steenakmp (1990), or the total quality model by Grunert (2005). While these models are often conceptual in nature, we argue that the framework they propose is a better fit for studying product differentiation in food markets, where many labels signal quality improvements inherently prone to subjective interpretation (Messer, Costanigro and Kaiser, forthcoming).

The idea that introducing a higher-tier certification may damage how lower tier labels are perceived is novel to the Geographical Indications literature (which was developed under an "objective quality" assumption), but marketing work on product line extension and umbrella branding did point out how upward or downward brand extensions may change consumers' perceptions of all the products marketed by the same brand (Chintagunta 1996; Heath, DelVecchio, and McCarthy 2011). The introduction of higher quality products is generally thought to increase brand equity (Randall, Ulrich, and Reibstein 1998) and possibly market power (Kadiyali, Vilcassim, and Chintagunta 1998), but it is also possible that introducing premium products may hinder the perceived quality of the other products in the line, and

[4] This interpretation of quality is most directly pertinent to the study of technical traits, such as the "engineering" quality of a building, or the specs of a computer.

ultimately damage the differentiating brand (Caldieraro, Ling-Jing Kao, and Cunha Jr. 2015). In the end, consumers' response to the introduction of a new label is largely an empirical question.

In this article we test one main hypothesis, and two related ancillary propositions: H_1, (restructuring of perceptions and comparative stigma) the perceived quality of labels signaling minimum quality standards is not independent of the presence/absence of other labels. That is, consumer interpretation of a labeled quality standard is endogenous to the labeling regime. We further hypothesize that introducing higher quality labels (i.e. with more stringent standards) can damage the perceived quality of lower tier or unlabeled products, a phenomenon we refer to as *comparative stigma*.

After providing evidence in support of H_1, we investigate how models controlling for endogenous quality perceptions compare to the reduced form (i.e. confounded) random parameter models typically estimated for marketing purposes. More formally: H_{11}) models of choice not controlling for subjective quality perceptions confound heterogeneity in WTP for quality and variation in subjective quality expectations. It follows that choice models controlling for quality perceptions should provide better fit and generality than confounded random parameter models.

Lastly, we investigate the empirical relevance of preference restructuring and comparative stigma in determining market shares, by examining the following proposition: H_{12}: observed changes in market shares after the introduction of a quality label can be traced to two distinct mechanisms: 1) a "*choice availability*" effect, whereby choice-constrained consumers can manifest their preference for a previously unavailable quality level; and 2) a "*restructuring of perceptions*" effect, whereby changes in the labeling regime modify quality perceptions for all available options.

In the next section, we provide a brief description of the market institutions relative to the Chianti designation of origin and its competitors. Then, we illustrate the experimental design, which involved four levels of vertical differentiation, two randomized quality rating scales and a number of information treatments. In the results section, we first document that quality perceptions are endogenous to the labeling regime, and then briefly present the model of quality perceptions we estimated for instrumentation purposes (i.e. a control function, see Petrin and Train 2010). Two random parameter models of wine choice are then presented, estimated and compared: a reduced form specification serving as benchmark; and a model controlling for quality perceptions. We use the latter model to predict market shares and investigate the effect of comparative stigma on consumer wine choices.

Empirical application and relevance: A brief history of Chianti Labeling

Chianti producers have been pursuing a strategy of quality standards and product differentiation for centuries; and this is no hyperbole. The *Lega del Chianti* was founded in Florence in the thirteenth century[5] to regulate administrative relations with the leading producers of a red wine made with Sangiovese grapes from the Chianti region. In 1716 the Grand Duke Cosimo III de' Medici issued a decree in Florence specifying the boundaries of the areas in which Chianti wines could be produced, and set up a *Congregation* to oversee the production, shipping, fraud-control and marketing of wine.

As the popularity of Chianti wines increased through the centuries, so the acreage and region of production expanded beyond the traditional boundaries, but in 1932 the modern Consortium protecting the authenticity of Chianti wines established the Chianti Classico label

[5] The first notarial document in which the name Chianti is used to refer the wines produced in that region appears dates to 1398.

(Chianti2) and its distinctive red rooster trademark to identify the wines produced within the historical (1716) region, and differentiate them from the more generic wines produced in the broader Chianti region[6] (Chianti1). Table 1 shows the main production differences between the two denominations. Chianti wines with higher alcohol content (>12.5%) with at least two years of aging may be further qualified as Reserve (Chianti Classico Riserva, which we indicate as Chianti3).

In 2013 the Chianti Classico Consortium issued the "Gran Selezione" label (Great Selection) to identify a limited number of wines meeting very stringent quality standards (including approval by a tasting commission—see table 1). The stated objective was an "upward expansion of the oenological offer of the Chianti territory"[7], but the decision to introduce the new quality label raised some controversies among the members of the Consortium (Brook 2015). Would the new label bring real value to Chianti producers or just increase bureaucratic costs? Would the Gran Selezione advantage some producers while damaging others? While in this paper we abstract from the interactions between regional and winery reputations (see Costanigro, McCluskey, and Goemans 2010; and Costanigro, Bond, and McCluskey 2012), a quote from a Chianti producer sceptical about the Gran Selezione pins down the central role of consumer perceptions. According to the wine magazine Decanter (Brook 2015), Giovanni Poggiali of Felsina Winery, was "… concerned that if we present our single-vineyard Rancia as Gran Selezione, then consumers will assume our other top wines such as our pure-Sangiovese Fontalloro

[6] In 1984, Chianti obtained the DOCG designation (*Denominazione di Origine Controllata e Garantita* - Denomination of Controlled and Guaranteed Origin), which is awarded to wines of certified origin with codified production processes and guaranteed wine quality; while in 1996 the Chianti Classico became a DOCG independent of the broader Chianti DOCG

[7] http://www.chianticlassico.com/chianti-classico-gran-selezione/

are not as good”. That is, the new label may damage consumer perceptions of the wines *not* included in the Gran Selezione, even if production standards remained the same.

Survey Description and Experimental Design: Choice Experiment

The experimental design was first obtained for a scenario including a full palette of differentiated Chianti wines (Chianti1-Chianti4), a competitor wine (either Rosso di Montalcino DOC or Brunello di Montalcino DOCG, at random), and a “none of the above” option. The Montalcino wines were chosen as ideal competing products for a number of factors. First, both Rosso and Brunello are Sangiovese-based Tuscan wines with a long tradition. The Montalcino wines also follow labelling practices and quality standards similar to Chianti: both wines are produced exclusively in the territory of the Municipality of Montalcino, but quality standards are much more stringent for Brunello than for Rosso (see table 1), so that the two wines are sold at very different price points.

To maintain a reasonable level of complexity, two attributes were included: the wine (as defined by the PDO label) and its price. As the price range of a Brunello and an entry-level Chianti1 will never overlap in the real world, we opted for a labeled choice experiment with price levels specific to each PDO label (see de Bekker-Grob et al. 2010, for a discussion of labeled vs. unlabeled or generic experiments). Median market prices were obtained using scanner data (Chianti1 €6, Chianti2 €13, Chianti3 €20, Chianti4 €25, Rosso €9, Brunello €30, IRI Infoscan, 2015), and price levels in the experiment varied above and below each median (4 levels: median+/- 20% and median +/- 30%). Based on these attributes and levels, a fractional factorial orthogonal design of 12 choice sets was obtained using Ngene©.

Four between-subject, randomized experimental treatments were implemented with the purpose of simulating choices under increasing vertical differentiation. In treatment I (150 participants) all Chianti options were eliminated, with the exception of Chianti1, treatment II (250 participants) included both Chianti1 and Chianti2, treatment III (300 participants) had Chianti1, Chianti2 and Chianti3, and treatment IV (500 participants) presented the full palette of four Chianti wines. In all treatments, each choice sets included one or more Chianti options, a competitor wine (Rosso or Brunello), and the opt-out "none of these wines" alternative.

Wine marketing research has shown that consumers may value different attributes/qualities depending on the occasion of consumption (Pascale G. Quester and Justin Smart 1998) and price segment (Costanigro, McCluskey, and Mittelhammer 2007). Given the extent of differentiation between the wines included in our experiment, it is quite plausible that a wine preferred for an everyday consumption situation would not be selected for a special occasion, and vice versa. To provide additional context to the choice scenario, two purchasing questions were posed in each choice set: 1) which wine would one purchase for everyday consumption (*consumo quotidiano*) and 2) which wine would one purchase for a special occasion (*occasione speciale*). A choice set extracted from the design for Treatment IV is presented in figure1.

Survey Description and Experimental Design: Survey Flow

The sample of consumers was stratified to match, within the limits of an online survey, the statistics on gender, age and region of residence of the Italian population. Given the nature of our experiment, we limited participations to consumers who purchased or consumed red wine at least once a week.

<u>Randomized information treatment</u>: after the initial screening questions, participants were exposed to a randomized information treatment. The main intent of this treatment was introducing exogenous variation in perceived quality, thereby creating a set of instrumental

variables. The full information set comprised a total of eight screenshots, presenting formal descriptions and definitions of the wine labels to appear in the choice experiment. This included a definition of a Protected Designation of Origin (Denominazione di Origine Controllata e Garantita, or DOCG), the meaning and use of the term “riserva” (reserve) in Chianti wines, and one statement describing the region of production, allowed grape varieties and the production/selection process of each wine label appearing in the choice experiment. Finally, the schematic summary of the production protocols adopted for each label in table 1 was also used as an information treatment. The total number of treatments assigned to each participant, the specific information bullets presented and their ordering were all randomized, while the information set to draw from was kept consistent with the extant labeling regime (treatment I-treatment IV)[8]. To stimulate participants’ attention to the information treatments, each screenshot was displayed for a minimum of 20 seconds, as in McFadden and Lusk (2015).

Elicitation of quality expectations: after the information treatment, participants were asked to rate the quality of the wines assigned by their labeling regime treatment. The main objective here is not so much obtaining a cardinal assessment of the quality of each wine (which is irrelevant in a choice model), but rather eliciting how products are perceived to differ along the quality spectrum. As such, participants located each product on a scale ranging from lower to higher quality (minore qualita’, maggiore qualita’), with no other numerical markings, and numerical values in partitioning the quality spectrum were assigned only later for econometrical purposes only.

[8] For example, for participants in treatment III Table 1 would not include the information about Chianti4

To account and control for possible framing effects, perceptions were elicited using one of two survey tools (at random). In one case, participants used label-specific sliding bars going from lower to higher quality (see figure 2, upper panel). In the second case, participants were instructed to represent their perceptions by dragging and dropping each wine label on a single line representing the quality spectrum, from lower to higher (see figure 2, lower). Participants who used this rating tool were also informed that, if two wines were similar in quality, the labels could be overlapped. With both tools, the order in which the wines were presented on the screen was randomized to avoid suggesting an implicit ordering in the quality of the wines.

Choice experiment and closing questions: after eliciting quality perceptions, each subject answered the 12 choice sets of the previously described experiment. The last section of the survey asked a series of questions related to an individual's typical wine consumption, his or her familiarity with the wines presented in the experiment, a self-assessment of wine expertise (1-10, low to high), family income and food expenditure.

Perceptions restructuring and comparative stigma

Table 2 presents the average quality perceptions (elicited with the tools presented in figure 2 and projected to a 0-100 numerical scale) across labeling regime, and their correlation matrix. For the entry level Chianti (Chianti1), elicited perceptions decline from an average of 71 (Treat. I) to 64 (Treat. II), 59 (Treat. III) and finally 53 (Treat. IV). The same, unequivocal declining pattern across treatments can be also discerned for Chianti2 and Chianti3. The variation in the perception of Rosso and Brunello, on the other hand, appears erratic for the case of Rosso, and minor for Brunello. Nonparametric fits comparing quality perceptions for Chianti1 and Brunello across treatment 1 and 4 display a notable change in the distribution of perceptions for Chianti1 (figure 3), but not Brunello. A nonparametric k-sample test for equality of medians[9] strongly rejects (see table 2) the null hypothesis for all Chianti wines (Chianti1-Chianti4), while the same hypothesis is rejected at $\alpha = 0.05$ for the Rosso wines (but not at $\alpha = 0.01$), and not rejected at any conventional level of significance for Brunello. These findings are unchanged across the elicitation tools employed (drag and drop vs. slider bar) and in full accordance with the hypothesis that introducing higher-tier quality labels causes a restructuring of perceptions hampering lower tier wines. The bottom part of table 2 presents pairwise correlations between quality perceptions, and the interpretation is quite straightforward: if a person perceives the quality of a Chianti($\#$) to be high (or low), they will also tend to rate high (or low) a Chianti($\#\pm 1$). Correlations between perceptions of Chianti wines and competing wines (Rosso, Brunello) are generally weaker and less clearly structured, even though some positive correlation in perceptions is detected between higher tier Chianti wines and Brunello.

Table 3 presents the choice shares for everyday consumption vs. special occasion, broken down by the randomized competitor (Rosso or Brunello). As price levels fluctuated above and below real median market prices and the experimental design is balanced (for all wines, each of the four price levels occurs three times), the choice shares do have reasonable external validity. Several facts are worth of note. First, everyday consumption and special occasion choices have a very different distribution of shares, as one would expect. When purchasing a wine for a meal at home, the preferred wines are Chianti1 and Rosso, with very few consumers willing to pay the high prices of Chianti4 and Brunello. To the contrary, special occasion choices tend to gravitate towards the higher quality wines available (e.g. Chianti3, Chianti4, Brunello), even though they

[9] Results for parametric tests of equality of means are analogous, but they rely on the stronger and unrealistic assumption of multivariate normality, so we don’t report them.

are generally more expensive. It is also clear that Rosso can compete (i.e., gain significant shares) with Chianti wines in both every day and special occasion purchases, while Brunello is often preferred for special occasions, but is probably considered too expensive for an everyday meal.

The second point worth noticing is that introducing higher tier Chianti labels causes minimal changes in the shares of everyday consumption choices. Indeed, Chianti2, Chianti3 and Chianti4 obtain relatively small shares in all scenarios, especially when Rosso is available as competitor. The one discernible pattern is the reduction in opt-out choices as the number of available choices increases, but the Chianti1 and Rosso jointly maintain about 70% of the shares across scenarios, irrespective of the presence of the higher quality wines. Things are quite different for special occasion choices. In this case, for all labeling treatments the preferred Chianti wine is consistently the highest tier available, implying that consumers felt somewhat constrained in the treatments with fewer choices. Given the nature of our hypotheses and the need to be succinct, we focus our modeling efforts and ensuing analysis on the special occasion choices, as they are more likely to be influenced by both the *choice availability* and *perception restructuring* effects we aim to isolate.

Instrumentation of quality perceptions

Consistent estimation of discrete choice models requires the explanatory variables to be independent of the disturbance term, implying that that the use of subjective quality perceptions as right-hand-side variables may produce biased estimates[10]. To amend the problem, we adopt the control function approach proposed by Petrin and Train (2010), where residuals obtained by

[10] When we did not control for endogeneity, model estimates implied a negative (and significant) WTP for a marginal increase in quality perceptions, which obviously points to systematic bias in the estimation results.

regressing the potentially endogenous variable on a set of instruments are included as an additional explanatory variable in the choice model.

A model of quality perceptions was first estimated via seemingly unrelated regressions (i.e. SUR, Zellner 1962) where the perceived quality of each wine was regressed on the randomized experimental information and framing treatments, plus a set of descriptor capturing a participant's knowledge about wine (Gustafson et al. (2016) find that wine knowledge is an important driver of how information is processed, and a determinant of WTP for wine). This is similar to Teisl and Roe (2010), who instrumented the subjective (and potentially endogenous) assessments of contracting a food-borne illness using randomly assigned information treatments, age, and attitudes towards eating raw food. Results for the preferred model specification are presented in table 4.

As all regressors were standardized, the constants represent quality perceptions predicted at data centroid. In concordance with the results presented in table 2, predicted quality perceptions for lower-tier Chianti wines decrease as we move from Treatment I to Treatment IV. Increasing the number of informational facts presented (InfoNum) decreased perceived quality for lower tier wines (Chianti1 and Chianti2), leaving perceptions of Chianti3 and Chianti4 unaltered. Participants who were randomly assigned to the drag-and-drop (Frame1=1) elicitation tool (see lower panel of figure 2) tended to assign much lower quality scores to all wines than those who used the likert scale (Frame1=0). Participants with greater general knowledge of wine

(WineKnowledge[11]) tended to appreciate more the lower tier Chianti wines but, at parity of general knowledge, previous experience with Chianti lowered perceived quality[12].

Reduced form and quality perceptions models: alternative parameterizations and estimation results

Having established that introducing higher-quality signals can alter consumers' perceptions of other labels, we turn our attention to developing a model accounting for subjective quality expectations. The ultimate intent is to obtain a model useful in evaluating how the availability of new choices and perception restructuring effects interact in determining market shares after the release of a new label. As we develop the specification and estimate the model, it is useful to compare results with those obtained from the more typical reduced-form estimation approach. Here we present the results relative to "special occasion" choices in Treatment IV, the most complex scenario (Chianti1-4 plus competitor), as they are the most insightful. In the context of Treatment IV, the <u>reduced form</u> (i.e. <u>Model 1</u>, not controlling for quality perceptions) specification of the choices of consumer *i* between the alternatives *j* takes the form:

$$
\begin{aligned}
U_{ij} &= \mathbf{x}_j^{1}{}'\boldsymbol{\beta} + \varepsilon_{ij} \\
&= \beta_0(\text{NONE})_{\text{j}} + \beta_{02}\text{Chianti2}_j + \beta_{03}\text{Chianti3}_j + \beta_{04}\text{Chianti4}_j + \beta_{05}\text{Brunello}_j \\
&\quad + \beta_{06}\text{Rosso}_j + \beta_1\text{PriceA}_j + \beta_2\text{PriceB}_j + \varepsilon_{ij};
\end{aligned}
\tag{1}
$$

[11] The WineKnowledge variable is the principal component score obtained using the first component of the decomposition of the data from a series of wine knowledge questions presented in Appendix 1. Participants having higher values for this variable tend to purchase and consume red wine more often (both at home and outside of home), state a higher degree of certainty in assigning quality rankings, and think they are more knowledgeable about wine.

[12] The predicted qualities for Brunello and Rosso (not presented here) were obtained in separate runs of analogous models using only half of the dataset (recall that only one competitor wine was randomly assigned to each participant)

where β_0 is the "opt-out" alternative (which, as suggested by Haaijer, Kamakura, and Wedel, 2001, should not be used as omitted category), and $\beta_{0j} \quad j = 2,...,6$ are alternative-specific constants contrasting the choice of a given wine label (indicated by the associated dummy variable) and a bottle of Chianti1 (the reference label). Given the wide price range spanned by the products in the experiment, we defined the two variables

$\text{PriceA}_j\text{=Price}_j * \left[\text{Chianti1}_j\text{+Chianti2}_j\text{+Rosso}_j\right]$ and

$\text{PriceB}_j\text{=Price}_j * \left[\text{Chianti3}_j\text{+Chianti4}_j\text{+Brunello}_j\right]$, so that two separate price coefficients where estimated for the lower-priced and higher-priced wines: β_1 for Chianti1, Chianti2 and Rosso and β_2 for Chianti3, Chianti4 and Brunello[13]. The specification for the quality perceptions model (Model 2) is completely analogous, except it includes the perceptions elicited in the experiment (QualExp) and the control function (Petrin and Train 2010) variable "Resid":

2) $U_{ij} = \mathbf{x}_j^1{}'\boldsymbol{\beta} + \beta_3\text{QualExp}_{ij} + \beta_4\text{Resid}_{ij} + \varepsilon_{ij}$

Both models were first estimated as conditional logits (D. McFadden 1973) to determine the preferred model specification before proceeding to the estimation via random coefficient MNL (D. McFadden and Train 2000). The well-known conditional logit is obtained by assuming that ε_{ij} is distributed iid extreme value, which yields the logistic choice probabilities

$P_j = \dfrac{\exp\left(\mathbf{x}_j{}'\boldsymbol{\beta}\right)}{\sum_j \exp\left(\mathbf{x}_j{}'\boldsymbol{\beta}\right)}$. As for the random parameter models, the error component presentation (adapted here from Brownston and Train, 1998) is particularly instructive in our case. The

[13] This specification, which simply allows the marginal (dis) utility of a price increase to change across the two broad price segments, produced the most stable and sensible results across several attempted specifications.

random parameter model can be obtained by decomposing the error term ε_{ij} in (1) and (2) in two parts, both having zero mean: ν_{ij} is again iid extreme value (independent over individuals and alternatives), and η_{ij} is a random term not necessarily independent across choices and/or people. Assuming that the *J*-dimensional, zero-mean random vector $\boldsymbol{\eta}$ has density $f(\boldsymbol{\eta}|\boldsymbol{\Omega})$, $\boldsymbol{\Omega}$ being parameters of the distribution, then the choice probabilities can be obtained by integrating over all values of $\boldsymbol{\eta}$, $P_j = \int \frac{\exp(\mathbf{x}_j{}'\boldsymbol{\beta} + \eta_j)}{\sum_j \exp(\mathbf{x}_j{}'\boldsymbol{\beta} + \eta_j)} f(\boldsymbol{\eta}|\boldsymbol{\Omega}) d\boldsymbol{\eta}$, which is generally accomplished numerically simulating the probabilities SP_j . Estimation involves maximizing the resulting (simulated) log-likelihood function $\sum_i \ln(SP_{ij})$ over the unknowns $\boldsymbol{\beta}$ and $\boldsymbol{\Omega}$. The extension to the case of multiple choices for each participant is straightforward.

Correlations between alternatives and/or heteroskedasticity can be modeled by appropriately specifying $\boldsymbol{\eta}$ to be a function of a vector of attributes/individual characteristics $\mathbf{z}_j$, and a zero-mean conformable random vector $\boldsymbol{\mu}$. Omitting the model-specific superscripts, the implied utility model is $U_{ij} = \mathbf{x}_j{}'\boldsymbol{\beta} + \eta_j + \nu_{ij} = \mathbf{x}_j{}'\boldsymbol{\beta} + \mathbf{z}_j{}'\boldsymbol{\mu} + \nu_{ij}$, and the resulting correlation structure between two alternatives, say choice one and two, becomes $E\left[(\mathbf{z}_1{}'\boldsymbol{\mu} + \nu_{i1})(\mathbf{z}_2{}'\boldsymbol{\mu} + \nu_{i2})\right] = \mathbf{z}_1{}'V(\boldsymbol{\mu})\mathbf{z}_2$. In the present context, a model of consumer preferences for Tuscan wines with unexplained heterogeneity over labels and fixed price coefficients (i.e. a “random labels” model, as in Onozaka and Mcfadden (2011), Hu et al. 2012, and many other applications) is obtained by setting $\mathbf{z}_j^{(1)} = \{\text{None}_j, \text{Chianti2}_j, \text{Chianti3}_j, \text{Chianti4}_j, \text{Rosso}_j, \text{Brunello}_j\}$ in Model 1. This model was first estimated with a diagonal $V(\boldsymbol{\mu})$ matrix, and then fully unconstrained variance-covariance matrix. As for Model 2, we note that the alternative-specific constants lose most of their original economic interpretation once we control for the (label-specific) quality perceptions[14], so it would make little sense to make the label-specific coefficients random. As such, the alternative-specific intercepts were estimated as fixed constants, while allowing for heterogeneity in the valuation of quality improvements and price responsiveness: $\mathbf{z}^{(2)} = \left\{ \text{PriceA}_j, \text{PriceB}_j, \text{QualExp}_j, \text{Resid}_j \right\}$, and the model was estimated parsimoniously by imposing a diagonal $V(\boldsymbol{\mu})$ matrix. We find this model appealing because the study of heterogeneity is focused on two broader, generalizable concepts: i.e. how people value quality and how responsive they are to prices. A competing model with heterogeneous valuation of quality but fixed price parameters produced inferior fit results [15], so we do not present it here; but such specification could be preferable if the main intent was calculating WTP, rather than predicting market shares, as in our case.

Conditional logit estimates are presented in the he first two columns of table 5. For model 1, the estimated label specific constants are all significant, and imply the following average ordering of preferences (holding price constant): Brunello is the most favorite choice for special occasion purchases, followed by Chianti4, Chianti3, Rosso, Chianti2 and Chianti1. The fact that all alternative-specific constants are different from zero obviously signifies that the labels signal important non-price factors that have not been included in the model. Results from model 2 suggest that such differences are largely imputable to varying quality expectations. When

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[14] For example, β_{02} represents the utility premium/discount of a Chianti2 vs. Chianti 1, holding constant any difference in quality perceptions and prices.

[15] In terms of AIC and BIC, the fixed-price model was superior to Model1 with constrained v-cov, but inferior to both the unconstrained v-cov specification and the Model2 specification we present.

QualExp is introduced in the model (table 5, second column), the associated coefficient is positive and significant, all measures of model fit (AIC, BIC) improve, and the alternative (label)–specific constants get closer to zero, some of them becoming non-significant. The remaining differences between labels could perhaps be ascribed to the different "prestige" of each each wine, perhaps a relevant factor in special occasion purchases.[16] Price coefficients are non-significant in both model 1 and 2, perhaps because of heterogeneity in how people interpret prices in a special occasion purchase.

Results for the random parameter specifications are presented in the columns 3, 4 and 5 of table 5. In all cases, estimation was accomplished via the mixlogit procedure in STATA (Hole 2007), which assumes that $f\left(\boldsymbol{\eta}\,|\,\boldsymbol{\Omega}\right)$ is multivariate normal, and 300 Halton draws at each iteration of the simulated log-likelihood function in the maximization process. For the random label model with constrained v-cov (third column), the significance of all estimated standard deviations and the large increase in model fit implied by the AIC and BIC statistics document a substantial amount of heterogeneity in label valuations, but once again price coefficients are not significant. The random parameter specification of the quality perception model produced results qualitatively consistent with *a priori* expectations: both price coefficients have negative and significant means, and quality expectations have a positive and significant estimate. Estimated standard deviations of the error components are also significant, signaling heterogeneity in how much participants value quality improvements and their price responsiveness. Information

[16] Prestige can be conceptualized as one's perception of how other people or "experts" evaluate the wine, which does not necessarily coincide with an individual's perceptions of quality. We considered eliciting the perceived prestige of a wine at the early stages of the design, but then decided to omit this construct from the final version of the survey because of collinearity and survey length concerns.

criteria show that this specification, while relatively parsimonious, produces sizable gains in fit over all other models we estimated.

The last sets of results refer to the random label model with fully unconstrained variance covariance matrix[17]. Estimates of the means and fit statistics are reported in the last column of table 5, while the full variance-covariance matrix of the random parameter estimates is shown in table 6. Despite the large number of parameters estimated and the increased flexibility of this specification, the measures of fit show negligible differences with Model2, and again non-significant price effects. The diagonal elements of the estimated variance covariance matrix (table 6) once again suggest substantial heterogeneity in label valuation, but the most insightful results relate to the off-diagonal correlations between the random label parameters and how they compare to the correlations in quality perceptions presented in table 2. On one hand, there are clear similarities: participants with a stronger-than-average preference for Chianti2 also tend to have a more marked preference for Chianti3, and similar relationships hold for the Chianti3-Chianti4 pair—a structure recognizable in the correlation of quality perceptions. On the other hand, table 6 also shows that people who tend to choose more often higher tier Chianti wines also tend to prefer Brunello, and preference for Rosso correlate more strongly with lower-tier wines. A similar relationship can be traced to table 2 for the case of Brunello, but not for Rosso. The core result here ties back with the confounding of preferences and perception hypothesis: as the random label model does not control for quality expectations, the error-component part of the model confounds correlations in perceptions and WTP for quality.

[17] The estimates in column 1 were used as starting values in the maximization procedure.

Separating choice availability from restructuring of preferences: the effect of comparative stigma

We now leverage the distinctive features of model 2 to determine the extent to which the substitutions observed after introducing a higher-quality product can be traced to choice availability effects and/or restructuring of perceptions (hypothesis H_{12}). As the motivation for this study was the recent introduction of the Gran Selezione by the Chianti Consortium, we focus the presentation on the comparison between Treatments III (without Chianti4) and IV (with Chianti4). Our approach is the following: first, we estimate Model 2 for treatment III (point estimates are reported in Appendix 2), and predict market shares at the mean QualExp elicited under the same regime (and median prices). Estimates and quality expectations from estimating Model 2 in treatment IV are then similarly used to predict market shares after the introduction of the Gran Selezione (second, fifth and height rows of table 6). To isolate the effect of perceptions restructuring, we then re-calculate market shares, but hold the quality expectations constant at the levels observed in Treat. III (with the obvious exception of Chianti4, which was evaluated only in Treat. IV). The intent is to simulate a scenario where perceptions are not allowed to adjust in response to the introduction of a new label.

Shares are presented in table 6 for different competitor scenarios: Rosso (rows 1-3), Brunello (rows 4-6) or both (rows 7-4). Cannibalization effects (inclusive of availability and restructuring of perceptions effects) can be measured by comparing the total market share captured by Chianti1, Chianti2 and Chianti3 (penultimate column of table 6) when we move from treatment III to treatment IV. Results shows that these effects are large: for example, in the case of Brunello as a competitor (row 4), Chianti 4 captures a total of 19.1% of the special occasion choices, with 15.9% (49.9%-34.0%) cannibalized from lower tier Chiantis and the remaining 3.2% captured from the Brunello and the No Choice categories. When we hold the quality perceptions of the Chianti1-3 wines constant at Treat. III levels, the total market share of the lower-tier Chiantis bounces back from 34.0% to 38.2%. These numbers shouldn't obviously be taken too literally (framing effects might still play a role despite the dual elicitation approach), but the main result is that perception restructuring effects can be sizable: more than a quarter $\left(\frac{38.2\% - 34.0\%}{15.9\%} = 0.26\right)$ of the cannibalized market share is owed to preference restructuring and comparative stigma effects.

Conclusions and limitations and future research

Following the structure laid out in the introduction, our conclusions can be categorized under three general research hypotheses. The first relates to the restructuring of perceptions occurring after a high-quality label is introduced. We started from the observation that, to explain consumption decision, understanding people's subjective interpretation of quality signals is just as important as measuring WTP. In our experiments the introduction of a higher-tier quality certification for Chianti wines consistently decreased the perceived quality of lower-tier products from the same region (a phenomenon we referred to as comparative stigma) while non-chianti wines remained generally unaffected.

A reasonable objection to this result is that, given our use of Likert scales, participants who evaluated more Chianti labels simply had to divide the quality spectrum in more segments, which lowered measurements of perceived quality. There is no doubt that the robustness of our result should be put to test with alternative elicitation methods[18], but we also note that this

[18] For example, an approach alternative to the use of likert scales could be the use of validated psychometric questionnaires, (e.g. Verdú Jover, Lloréns Montes, and Fuentes Fuentes 2004). The biggest challenge to using such methods is, again, maintaining a reasonable survey length.

segmentation process is completely rational, and could very well be a good representation of consumers' heuristics. After all, if the best Chianti Classico are re-classified as Gran Selezione, then it must be that the average quality of a Chianti Classico decreases after the new label is introduced; and this updating of quality expectations is in many ways similar to what Akerlof (1970) modeled in his celebrated "lemons" paper.

The second set of results relates to the estimation of choice models controlling for quality perceptions, and the comparison of such models to more traditional reduced form approaches where perceived quality and its valuation are confounded in label or attribute specific estimates. We illustrated how introducing quality perceptions in the systematic part while addressing endogeneity by means of a control function approach eliminate a source of confounding, allowing a more direct study of consumers' heterogeneous preference for quality. Our results show that, while more parsimonious, the quality perception model produced fit statistics comparable or even superior to the most sophisticated random label approaches. The model comparison also shows that the correlation structure captured in the error component of random parameter models can be explained as correlation in quality perceptions, rather than preferences.

We then used the quality perceptions model to differentiate between choice availability vs. perception restructuring effects after the introduction of a new quality certification. Comparing the two scenarios with (treatment IV) and without (treatment III) the Chianti Gran Selezione, we observed that the Chianti Classico Gran selezione captured 19.1 % of the special occasion choices, but almost 16% is cannibalized from other Chianti Wines. In our application, about three quarters of these reallocated purchase choices is attributable to consumers' desire for higher quality in special occasions, while the rest is due to comparative stigma—introducing the Gran Selezione cheapens the perceived quality of other Chianti wines.

We have no doubt that the results presented here are far from addressing all the important questions surrounding the issue of subjective quality perceptions and beliefs in analyzing consumer choices. Indeed, the most exciting part is perhaps how much is still left to be resolved. The fundamental point we raised and attempted to establish is that consumers interpret quality signals (including food labels) in a contextual rather than absolute manner; and in most cases introducing new quality signals will lead to a reassessment of the meaning and usefulness of other related cues. As we are not aware of any theoretical model addressing this type of mechanism within the context of vertical differentiation and quality standards/ Geographical Indications this could be a fruitful area for future work.

Another natural next step is establishing how models accounting for quality perceptions perform in out of sample forecasting (as in, for example Provencher and Bishop 2004), a topic we are pursuing in a companion paper. The idea is that, if perceptions are endogenous to the labeling regime, the parameters of a reduced form model elicited under a certain regime (e.g. Treatment IV) cannot be used to forecast behavior under a different one (Treatment III). A limitation of this paper is that we only measured one overall assessment of quality, which we treated as a synonym of taste expectations. While we believe that this is reasonable for wine choices, other applications may require investigating other quality dimensions whose perceptions may be influence by labeled information, such as convenience (Steenkamp 1990). We can also expect that the role of perceptions will be fundamental when credence, public good aspects of quality (e.g. environmental and societal impact, food safety, animal welfare) come into play. Does introducing a "humanly raised" label lead people to think that other products are raised "inhumanly"? Are changes in perceptions always congruent with the labeled improvements? How can we measure the welfare implication of potentially misconstrued quality perceptions?

Applied economists are not (yet) fully equipped to address these types of questions, but it seems clear that simple answers based on what people choose to buy can only provide, at best, partial answers.

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Table 1: minimum quality standards and median prices for Chianti and Montalcino wines

(label)	Chianti D.O.C.G. (Chianti1)	Chianti Classico D.O.C.G. (Chianti2)	Chianti Classico D.O.C.G. Riserva (Chianti3)	Chianti Classico D.O.C.G. Gran Selezione (Chianti4)	Rosso di Montalcino D.O.C. (Rosso)	Brunello di Montalcino D.O.C.G (Brunello)
Area (Hectares)	71,800	7,000	7,000	700	3,600	3,600
Maximum Production (Ton/Hectare)	9	7.5	7.5	7.5	9	8
% Sangiovese grapes (min)	70%	80%	80%	80%	100%	100%
Alcohol % (min)	12%	12%	12.5%	13%	12%	12.5%
Aging (min)	3 Months	10 Months	24 Months	30 Months	12 Months	60 Months
Mandatory Bottling on Premises	No	No	No	Yes	No	No
Approval by Tasting Commission	No	No	No	Yes	No	Yes
Median Market Price (IRI)	€6	€13	€20	€25	€9	€30

Table 2: mean quality perception (by treatment), test of equality of medians, and correlations

		Chianti 1	Chianti 2	Chianti 3	Chianti 4	Rosso	Brunello
Treat I	Mean	71.49				69.69	81.80
	S.E. Mean	1.65				2.74	2.07
Treat II	Mean	64.26	69.67			75.01	81.32
	S.E. Mean	1.48	1.41			2.03	1.84
Treat III	Mean	59.24	65.45	78.63		72.09	77.95
	S.E. Mean	1.32	1.13	1.08		1.98	1.89
Treat IV	Mean	53.77	58.79	74.36	77.16	66.71	78.49
	S.E. Mean	1.13	1.01	0.92	0.89	1.64	1.40
K Samples Median Test	Chi2	47.28	28.09	9.08	-	8.30	1.32
	p	0.000	0.000	0.003		0.040	0.725
		Chianti1	Chianti2	Chianti3	Chianti4	Rosso	Brunello
Chianti 1	Corr.	1					
Chianti 2		0.67	1				
Chianti 3		0.38	0.40	1			
Chianti 4		0.25	0.34	0.52	1		
Rosso		0.06	0.14	0.09	0.10	1	
Brunello		0.11	0.21	0.32	0.32	-	1

Table 3: Survey Choice shares for special occasion

Occasion	Treat.	N*	Chianti 1	Chianti 2	Chianti 3	Chianti 4	Comp. Rosso	None	Chianti 1	Chianti 2	Chianti 3	Chianti 4	Comp. Brunello	None
Every Day Cons.	1	75	56.7	-	-	-	18.2	25.1	76.3	-	-	-	3.1	20.6
	2	125	54.3	4.8	-	-	22.0	18.9	67.2	8.6	-	-	1.7	22.5
	3	150	57.8	5.8	1.9	-	19.1	15.3	69.9	10.7	4.3	-	2.3	12.8
	4	250	50.6	5.0	2.2	2.4	23.4	16.3	70.3	8.3	3.0	1.2	1.3	16.0
Special Occ.	1	75	29.1	-	-	-	58.4	12.4	10.9	-	-	-	80.7	8.4
	2	125	9.5	48.7	-	-	37.9	3.9	5.7	31.9	-	-	56.1	6.2
	3	150	5.7	16.2	57.8	-	16.1	4.1	6.4	12.7	25.1	-	53.3	2.6
	4	250	5.4	10.3	25.4	40.9	14.4	3.5	4.3	9.8	14.5	24.2	44.1	3.1

*each of the N respondents answered 12 choice sets.

Table 4. Instrumentation of quality perceptions via Seemingly Unrelated Regression

Wine	Variable	Treat I	Treat II	Treat III	Treat IV
Chianti1	InfoNum	-1.462	-2.343	-1.603	-3.024***
	Frame1	-4.010	-11.516***	-13.256***	-13.018***
	Chianti1Know	2.219	-0.509	-1.038	-2.015**
	WineKnowledge	3.258*	6.398***	3.324**	4.431***
	_cons	72.460***	68.784***	66.297***	61.630***
R-sq		0.0577	0.1422	0.1076	0.1203
Chi2		2.22*	42.34***	36.75***	68.69 ***
Chianti2	InfoNum		-0.583	-0.148	-2.152**
	Frame1		-13.263***	-9.354***	-10.378***
	Chianti1Know		2.898**	1.711*	-0.497
	WineKnowledge		4.558***	0.009	3.721***
	_cons		75.585***	70.505***	64.913***
Adj R2			0.1807	0.0702	0.0907
Chi2			53.96***	22.59***	50.65***
Chianti3	InfoNum			1.725	-0.804
	Frame1			-4.808**	-9.691***
	Chianti1Know			1.119	1.537*
	WineKnowledge			1.553	1.439
	_cons			81.223***	79.446***
Adj R2				0.0384	0.076
Chi2				11.81**	39.88***
Chianti4	InfoNum				0.195
	frame1				-7.545***
	Chianti1Know				0.576
	WineKnowledge				0.782
	_cons				80.703***
Adj R2					0.041
Chi2					20.58***

Table 5: parameter estimates model 1 and model 2 (coefficient estimates, standard errors and p-values). Data relates to treatment IV, special occasion choices.

Variable	Model 1 Cond. Logit	Model 2 Cond. Logit	Model 1 Rand. Par. Constr. Vcov		Model 2 Ran. Par Constr. Vcov		Model 1 Rand. Par. Uncostr. Vcov
	Coef	**Coef**	**Coef/Mean**	**SD**	**Coef/Mean**	**SD**	**Coef/Mean**
Chianti2	0.619	0.414	-3.404	1.596	0.620	-	-4.392
	(.143)	(.151)	(.555)	0.158	(.873)		(.494)
	0.000	0.006	0.000	0.000	0.478		0.000
Chianti3	1.473	0.564	-0.339	1.567	0.585	-	1.823
	(.216)	(.294)	(.245)	0.135	(.188)		(.257)
	0.000	0.055	0.165	0.000	0.002		0.000
Chianti4	1.953	0.917	1.384	2.122	2.818	-	4.521
	(.217)	(.317)	(.285)	0.141	(.42)		(.339)
	0.000	0.004	0.000	0.000	0.000		0.000
Rosso	0.851	0.235	1.946	2.159	3.096	-	5.057
	(.16)	(.205)	(.296)	0.263	(.452)		(.354)
	0.000	0.250	0.000	0.000	0.000		0.000
Brunello	2.485	1.400	2.420	2.911	3.486	-	5.518
	(.236)	(.329)	(.347)	0.223	(.473)		(.394)
	0.000	0.000	0.000	0.000	0.000		0.000
None	-0.283	2.259	-0.103	3.328888	0.452	-	1.303
	(.245)	(.584)	(.238)	0.341	(.261)		(.38)
	0.248	0.000	0.665	0.000	0.083		0.001
PriceA	0.015	0.016	0.023	-	-0.064	0.185	0.024
	(.012)	(.012)	(.018)		(.03)	0.019	(.016)
	0.193	0.193	0.192		0.035	0.000	0.119
PriceB	0.002	0.002	0.003	-	-0.024	0.207	0.003
	(.005)	(.005)	(.008)		(.011)	0.012	(.004)
	0.711	0.711	0.711		0.027	0.000	0.510
QualExp	-	0.047	-	-	0.070	0.055	-
		(.01)			(.014)	0.004	
		0.000			0.000	0.000	
Resid	-	-0.033	-	-	-0.035	0.064	-
		(.01)			(.014)	0.005	
		0.001			0.013	0.000	
ll	-8,892	-8,722	-6,694		-6,310		-6,298
aic	17,800	17,464	13,416		12,647		12,654
bic	17,868	17,549	13,535		12,766		12,900
chi2	398	463	262		454		5,188

Table 6: Variance-Covariance Matrix for unconstrained random label random parameter model (model 5)

Variable		Nochoice	Chianti2	Chianti3	Chianti4	Brunello	Rosso
No Choice	Coef.	**17.174**	-0.434	-0.178	-1.641	**-2.846**	**-4.753**
	Std.err	**3.382**	0.919	1.037	0.982	**1.034**	**0.960**
	p	**0.000**	0.637	0.864	0.095	**0.006**	**0.000**
Chianti2	Coef.		**6.862**	**7.775**	**6.186**	**5.068**	**3.081**
	Std.err		**1.315**	**1.031**	**0.968**	**0.837**	**0.679**
	p		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Chianti3	Coef.			**15.793**	**17.057**	**17.372**	**3.119**
	Std.err			**1.547**	**1.722**	**1.906**	**1.019**
	p			**0.000**	**0.000**	**0.000**	**0.002**
Chianti4	Coef.				**20.740**	**21.802**	**1.463**
	Std.err				**2.119**	**2.401**	**1.253**
	p				**0.000**	**0.000**	**0.243**
Brunello	Coef.					**26.079**	2.654
	Std.err					**3.050**	1.464
	p					**0.000**	0.070
Rosso	Coef.						**5.616**
	Std.err						**1.350**
	p						**0.000**

Table 7. Market shares for special occasion purchases at median prices under different labeling regimes and scenarios

Param. Estimates from Treat.	QEXP from Treat:	Chianti 1	Chianti 2	Chianti 3	Chianti 4	Rosso	Brunello	No Choice	Chianti1-Chianti3 Total	Total Chianti
III	III	4.3%	17.5%	60.2%	-	12.9%	-	5.2%	82.0%	82.0%
IV	IV	3.5%	10.0%	23.1%	46.9%	11.4%	-	5.1%	36.6%	83.4%
IV	III*	3.6%	10.7%	27.2%	41.8%	11.6%	-	5.1%	41.5%	83.3%
III	III	6.0%	23.5%	20.4%	-	-	45.1%	4.9%	49.9%	49.9%
IV	IV	5.4%	15.0%	13.5%	19.1%	-	41.6%	5.3%	34.0%	53.1%
IV	III*	5.5%	16.0%	16.7%	17.6%	-	38.9%	5.2%	38.2%	55.8%
III	III	4.0%	16.3%	18.6%	-	12.1%	44.5%	4.6%	38.8%	38.8%
IV	IV	3.3%	9.5%	12.4%	18.3%	10.8%	41.0%	4.6%	25.2%	43.5%
IV	III*	3.4%	10.2%	15.4%	17.0%	11.0%	38.4%	4.6%	29.0%	46.0%

*: for Chianti4, quality expectations are always obtained from treatment 4.

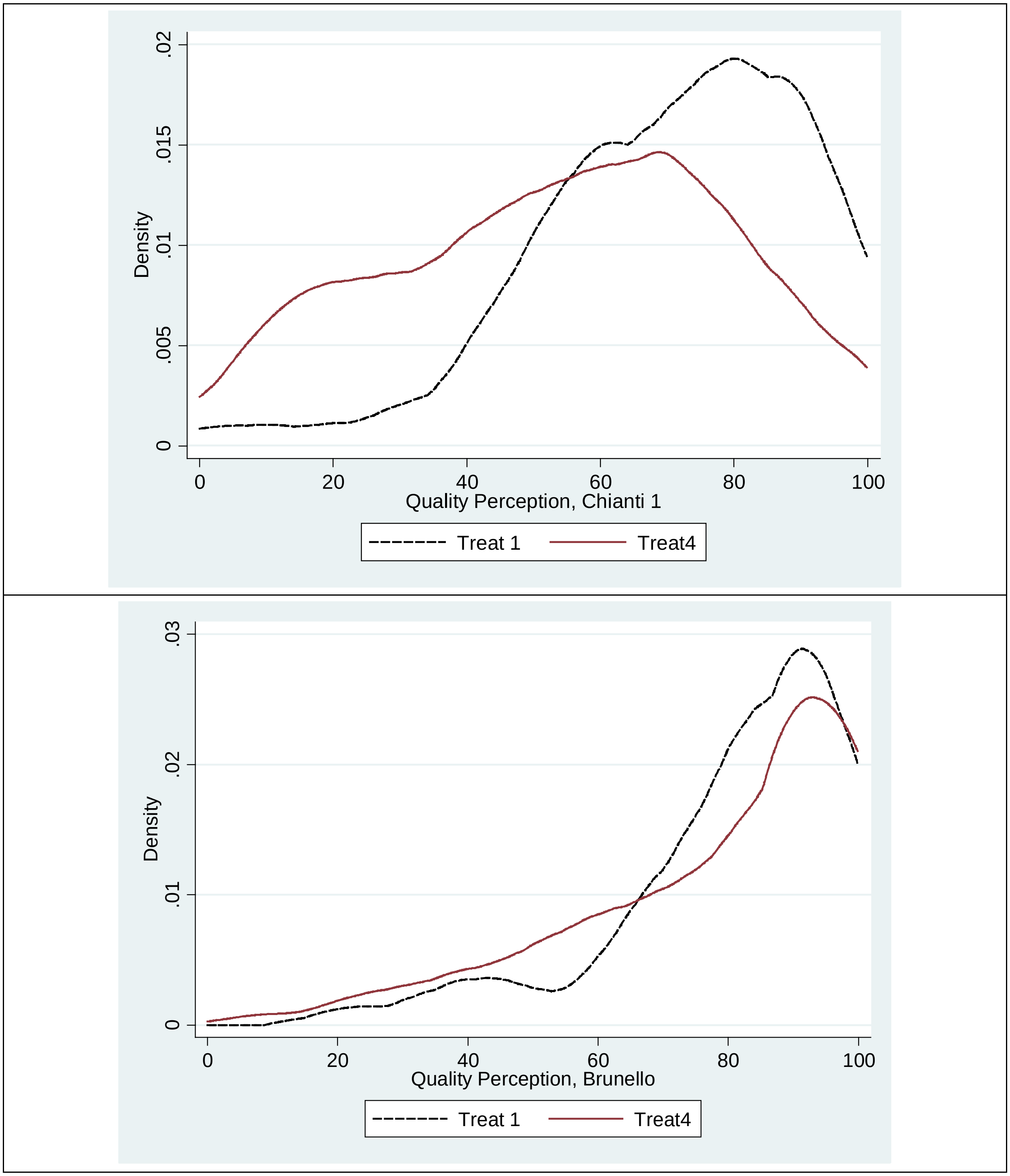
Figures

Figure 1. A screenshot showing a choice set including four Chianti labels (Chianti1-Chianti4) (treatmentIV) and Brunello as competitor wine.

	Chianti Classico D.O.C.G. Gran Selezione € 27.50	Brunello di Montalcino D.O.C.G. € 33.00	Chianti D.O.C.G. € 6.60	Chianti Classico D.O.C.G €11.70	Chianti Classico Riserva D.O.C.G € 22.00	Nessuno
Consumo quotidiano						
Consumo per occasione speciale (anniversario, regalo, compleanno, ecc.)						

Figure 2. Quality perception elicitation tools: Frame 1 and Frame 2.

Figure 3. Nonparametric density estimation for quality expectations for Chianti1 (upper panel) and Brunello (lower panel). Solid lines are obtained from participants in Treatment 1 (only Chianti1 and competitor are present), while the dashed line represents Treatment 4 (Chianti1-Chianti4 and competitor).



Appendix 1

Principal component decomposition of wine knowledge (first three components).

Question	Coding	Comp1	Comp2	Comp3
How often do you consume red wine?	1-5 (rarely-daily)	0.41	-0.34	0.11
How often do you consume wine at home?	1-5 (rarely-often)	0.49	-0.33	0.03
How often do you consume wine outside of home?	1-5 (rarely-often)	0.35	0.34	-0.45
How often do you purchase wine for everyday consumption?	1-5 (never-often)	0.47	-0.35	-0.01
How often do you purchase wine for a special occasion?	1-5 (never-often)	0.29	0.43	-0.51
How certain are you of your (quality) rankings?	1-4 (not at all-very)	0.20	0.45	0.63
How do you rate your overall knowledge of wine?	"1-10"	0.34	0.39	0.35
	Eigenvalue	2.67	1.36	0.99
	Difference	1.32	0.36	0.35
	Proportion	0.38	0.19	0.14
	Cumulative	0.38	0.58	0.72

Appendix 2. Estimated parameter for Model 1 and Model 2 across all treatments (standard errors available upon request).

	Model 1 (random par, constrained v-cov)				Model 2 (random par, constrained v-cov)			
Mean	Treat I	Treat II	Treat III	Treat IV	Treat I	Treat II	Treat III	Treat IV
Price_A	0.143(b)	0.121(a)	0.012	0.023	0.159(b)	0.118a	-0.025	-0.064(b)
Price_B	-0.205(a)	-0.132(a)	-0.059(a)	0.003	-0.087(b)	-0.115(a)	-0.068(b)	-0.024(b)
None	-1.836(a)	-4.036(a)	-3.392	-3.404(a)	3.948	1.446	0.467	0.62
Chianti2		1.198(a)	0.537(c)	-0.339		0.995(a)	0.855(a)	0.585(a)
Chianti3			3.665(a)	1.384(a)			3.597(a)	2.818(a)
Chianti4				1.946(a)				3.096(a)
Brunello	12.840(a)	7.829(a)	5.452(a)	2.420(a)	9.034(a)	6.531(a)	4.329(a)	3.486(a)
Rosso	0.577(b)	1.416(a)	0.491	-0.103	0.792(a)	0.865(a)	0.191	0.452(c)
QualExp					0.087(c)	0.091(a)	0.077(b)	0.070(a)
Resid					-0.035	-0.045(b)	-0.042	-0.035(b)
SD								
Price_A					0.411(a)	0.316(a)	0.175(a)	0.185(a)
Price_B					0.175(a)	0.152(a)	0.256(a)	0.207(a)
None	3.994(a)	5.001(a)	3.476(b)	3.329(a)				
Chianti2		2.476(a)	2.049(a)	1.596(a)				
Chianti3			2.863(a)	1.567(a)				
Chianti4				2.122(a)				
Brunello	5.370(a)	4.775(a)	3.822(a)	2.911(a)				
Rosso	2.084(a)	1.808(a)	2.041(a)	2.159(a)				
QualExp					0.054(a)	-0.067(a)	-0.060(a)	0.055(a)
Resid					0.068(a)	0.063(a)	0.066(a)	0.064(a)
Ll	-895	-2,050	-2,954	-6,694	-860	-2,009	-2,879	-6,310
Aic	1,806	4,121	5,933	13,416	1,741	4,043	5,784	12,647
Bic	1,859	4,195	6,026	13,535	1,814	4,132	5,885	12,766
chi2	110	194	191	262	129	282	256	454

(a): significant at $\alpha = 0.01$; (b) significant at $\alpha = 0.05$; (c)significant at $\alpha = 0.1$