How Emotions Affect Choices: The Case of Wine

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Abstract

In this paper, we assess the role of emotions in choices. We elicited emotions using an innovative facial expression analysis approach, and we compared the results to those for a traditional hedonic rating scale. To this end, we conducted an experiment combining surveys and actual wine tasting. The results show that for wines with credence attributes (organic and selected vintage organic wines), there exists a significant relationship between positive emotions (joy) and experiences (valence) and wine choices; whereas this relationship is not found in the case of regular wines.

Keywords: wine-evoked emotions, facial expression analysis, discrete choice experiment, organic wine, experience and credence attributes

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1 Introduction

Traditional economic models assume that consumers behave rationally to maximize their utility when making choices. This theory of reasoned action (Stanovich and West, 2000) is applied to many public policies (e.g., resource allocation decisions, taxation, subsidies, public health policies) and market strategies (e.g., price formation, fixation, and change; consumer demand; marketing). However, research has illustrated that consumers are not fully rational and that many behaviors are intuitive rather than reasoned or planned (Ekman, 2007; Kahneman, 2003; Keltner and Lerner, 2010; Keltner et al., 2014; Köster, 2009; Loewenstein et al., 2001). Emotions can affect decision-making, inducing behavioral biases (Lerner et al., 2004; Schunk and Betsch, 2006) or improving decision-making performance (Hopfensitz and Mantilla, 2019; Seo and Barrett, 2007).

During the mid-1980s, research on the role of emotions in complementing cognitive theories became more predominant, explaining more mysteries of consumer choice behavior (Hansen and Christensen, 2007; van Raaij, 2008). However, the role of emotions in behavior has been not effectively addressed in neoclassical theory because, among other reasons, emotions have been perceived as unimportant or unpredictable (Elster, 1998; Elster, 1996; Hansen et al., 2004).

New applications in behavioral economics (Hsee and Rottenstreich, 2004; Ifcher and Zarghamee 2011; Kőszegi, 2006; Loewenstein and Lerner, 2003; Loewenstein, 2000; Rick and Loewenstein, 2008; Rottenstreich and Hsee, 2001; Schade et al., 2012; van Winden et al., 2011), psychology (Keltner and Lerner, 2010; Lerner et al., 2015), and neuroscience (Phelps et al., 2014) have demonstrated the important role of emotions in economic decision-making processes. Loewenstein (2000) illustrated that emotions are determinant drivers of behavior and systematically predictable. Virlics' review (2013) concluded that the role of emotions in the decision-making process is important and influential. She highlighted the need to combine behavioral economics, psychology, and neuroeconomics to better understand the decision-making process. Kahneman described two complementary ways of making decisions: rationally and emotionally (Kahneman, 2003). He reported that people make decisions upon unconsciously consulting their emotions (Kahneman, 2011).

According to Rick and Loewenstein's (2008) review, both expected and immediate emotions influence economic behavior. Expected emotions are anticipated feelings about the consequences of decisions, and they are experienced after making a choice. Immediate emotions are experienced at the moment of making a decision, and they are categorized into two types: (1) integral immediate emotions, which are feelings about the consequences of a decision experienced at the moment of that choice decision, and (2) incidental emotions, which are also experienced at the moment of the decision but evoked by other sources unrelated to that decision. Rick and Loewenstein's (2008) review showed how considering the role of expected emotions rectified many inconsistencies of the basic axioms (monotonicity, transitivity, etc.) assumed by the economic models of risky decision-making, intertemporal choice, and social preferences. They also illuminated the role that both integral and incidental immediate emotions can potentially play in explaining behavioral phenomena. Rick and Loewenstein (2008) concluded that expected emotions receive far more research attention than immediate emotions and highlighted the need for more research on the role of immediate emotions in the production of behavior. Loewenstein (2000) warned that economists have mostly investigated expected emotions (regret, disappointment), while psychologists have been interested in immediate emotions. Loewenstein et al. (2001) reported that, together with expected emotions, immediate emotions should also be involved in decision-making models.

Researchers have also demonstrated the role of positive and negative emotions in various economic behaviors. Tamarit and Sánchez (2016) reported that incorporating emotions in the utility function improves the prediction of players' strategic behavior in experimental economics games (the ultimatum game). Alempaki et al. (2019) stated that positive emotions make people more accepting of risk. Ifcher and Zarghamee (2011) showed that happiness significantly reduces time preferences. Induced happiness was found to increase gambling and framing effects (Stanton et al., 2014), while Guven (2012) revealed that happiness leads people to save more, spend less, and consume less. Schade et al. (2012) found that the degree of worry about potential losses increases subjects' intention to buy and willingness to pay for insurance. Baillon et al. (2016) reported that emotional states influence subjects' economic behavior through their effects on ambiguity preferences. Lerner et al. (2004) showed that disgust eliminates the endowment effect, while sadness reverses it. Enachescu et al. (2019) found that positive and negative emotions experienced by individuals when paying taxes affect tax compliance decisions, with positive emotions leading to higher levels of compliance than negative ones. Richards et al. (2018) demonstrated that investors' intuitive emotional reactions lead to a high disposition effect bias, which may be reduced by using an effective strategy for controlling emotions. Biel et al. (2011) stated that the observed gap between willingness to accept and willingness to pay for public goods may be explained by emotions and moral perceptions. In the context of brand choices, Lin et al. (2006) reported that the endowment effect is absent when negative emotions (sadness) are induced, while it occurs when positive emotions (happy) are induced. Hansen et al. (2004) showed that net emotional response strength is a good predictor of consumer choices and brand equity and loyalty.

Some studies (Dalenberg et al., 2014; Gutjar et al., 2015; Thomson et al., 2010) have focused on the role of immediate product-evoked emotions in product choice. Gutjar et al. (2015) used the EsSense Profile method to test whether emotional responses to intrinsic (sensory) and extrinsic (packaging) cues predict actual product choices. They found that emotions motivated by intrinsic and extrinsic product properties were different and that combining evoked emotions and liking ratings improved predictions of consumers' product choice behavior. Dalenberg et al. (2014) used a verbal method and non-verbal method (EsSense Profile and PrEmo, respectively) to test whether food-evoked emotions improve food choice prediction. They demonstrated that food-evoked emotions overcame traditional perceived liking measures in predicting food choices, although the best predictions where made after combining both measures. Moreover, they showed that non-verbal (PrEmo) food-evoked emotions better predict food choices than verbal (EsSense Profile) food-evoked emotions. Thomson et al. (2010) analyzed the role of product-evoked emotions, measured using an appropriate lexicon of conceptual descriptors, in consumers' food choices in a best-worst scaling task. They suggested that considering food-evoked emotions would improve understandings of consumer food choices and provide the food industry with useful information for product development and marketing. In recent years, emoji have been included to measure emotions related to food (Jaeger et al., 2017; Schouteten et al., 2018). Emoji are able to discriminate between different food samples and they are associated with liking score measured by the widely used hedonic rating scale (Jaeger et al., 2017; Schouteten et al., 2018).

Neuroeconomics has likewise contributed to an improved understanding of the drivers of the consumer decision-making process (Glimcher et al., 2009), especially by identifying the specific parts of the brain activated by emotions and measuring emotions with positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) scans (Hansen and Christensen, 2007). However, despite these advances regarding the role of emotions in decision-making processes, little is known about how consumer choices are influenced by emotions, especially in multi-attribute choices. Elster (1998) considered attempts to understand how emotions influence behavior as insufficient and highlighted the need for more research.

There is a particular need for research focusing on how to actually measure emotions. Emotions are usually measured by self-reported measures, which are subject to various problems, including social desirability bias and the difficulty of verbalizing emotions (Kaneko et al., 2018). The review done by Lagast et al. (2017) concluded that explicit measures are more used to assess the emotional reactions to food than implicit ones. They argued that implicit measures are mainly applied in consumer and sensory research, however, they highlighted the increase of development of innovative implicit techniques to capture emotional reactions. de Wijk and Noldus (2020) concluded that implicit measures provide little added value in laboratory food studies, however, they offer insights in mechanisms underlying food choice and acceptance. They reported that explicit measures capture mainly sensory aspects of the food, while implicit measures capture mainly the food experience from pre- to post- consumption which is related to both the food itself and the physical and social context. They argued that implicit and explicit measures capture complementary information and they suggested to apply implicit measures outside the conventional laboratory habitat. Niedziela and Ambroze

(2020) argued that neuroscience and psychological research methodologies should be applied to complement the cognitive surveys rather than to replace them. Very few studies (Danner et al., 2014; He et al., 2016) have used implicit methods to measure product-evoked emotions. Results based on implicit methods – early autonomic nervous system (ANS) responses and facial expressions – were associated with relatively fast arousal emotions. He et al. (2016) also found an association between later ANS responses and slower food odors' valence. However, Danner et al. (2014) and He et al. (2016) did not explore or analyze the relationship between evoked emotions and product choices. In our literature review, we did not find any study that measured evoked emotions using facial expressions and associated them with product choices.

These research gaps motivated us to assess the role of immediate product-evoked emotions on wine purchasing decisions in an experimental setting. We took advantage of a unique experimental setting by combining two approaches to measuring emotions, sophisticated facial recognition technologies and the classical hedonic score rating. Moreover, new interest in the role of emotions in economic behavior focused on the role of valence rather than specific emotions (Zeelenberg and Pieters, 2006). Our research focuses on the role of both valence and specific emotions in the decision-making process. Furthermore, we tested whether the role of emotions is more important in the choice of credence attributes (organic or selected vintage organic wines) or experience attributes (conventional wine).

Economic information theory categorizes goods into three groups: search, experience, and credence goods (Darby and Karni, 1973; Nelson, 1970). Nelson (1970) distinguished between *search qualities* (identified by inspection prior to purchase) and *experience* *qualities* (identified only after a purchase), and Darby and Karni (1973) identified a third category called *credence qualities* (cannot be judged even after a purchase). Schiffman et al. (2008) reported that when they make emotional purchases, decision-makers do not search for pre-purchase information or evaluate alternatives.

We find a positive relationship between positive emotions (joy) and experience (valence) and the choice of wines with credence attributes (organic or selected vintage organic wines). This relationship is not found for regular wines. We find that facial recognition methods sometimes outperform classical hedonic ratings. Hence, despite existing efforts, understanding the role of emotions in choices remains challenging.

2. Material and methods

We analyzed consumers' preferences in the context of regular wine purchases. A survey, containing a labeled discrete choice experiment (DCE), combined with a blinded wine tasting, was conducted among 178 regular red wine drinkers. Participant recruitment was carried out by a research recruitment agency. Two similar groups of consumers were recruited, and each was representative of the population of reference in terms of sex and age. All participants were responsible for their household's food purchasing, and were regular (at least three times per month) buyers and drinkers of red wine.

Figure 1 shows the main steps of the experiment. First, participants were welcomed, briefed about the objectives of the experiment, and asked to sign a consent form. Then, participants were informed about the type (young red wine), origin (Catalonia), grape variety (Tempranillo), and year of harvest (2017) of the wines. They were informed that the differences between the considered wines in the experiment regarded prices and the production systems. The differences between the three wine types (conventional, organic, and selected vintage organic wines) were then explained. Second, participants took part in a blind wine tasting where they tested (in different order) the wines without receiving information about the wine types that were being tasted (production system). Third, they rated their actual liking of the wines using a nine-point hedonic scale of liking (1 = "very unpleasant" to 9 = "very pleasant"). Fourth, participants were informed about the wines' production system and were asked to complete a survey containing a DCE.

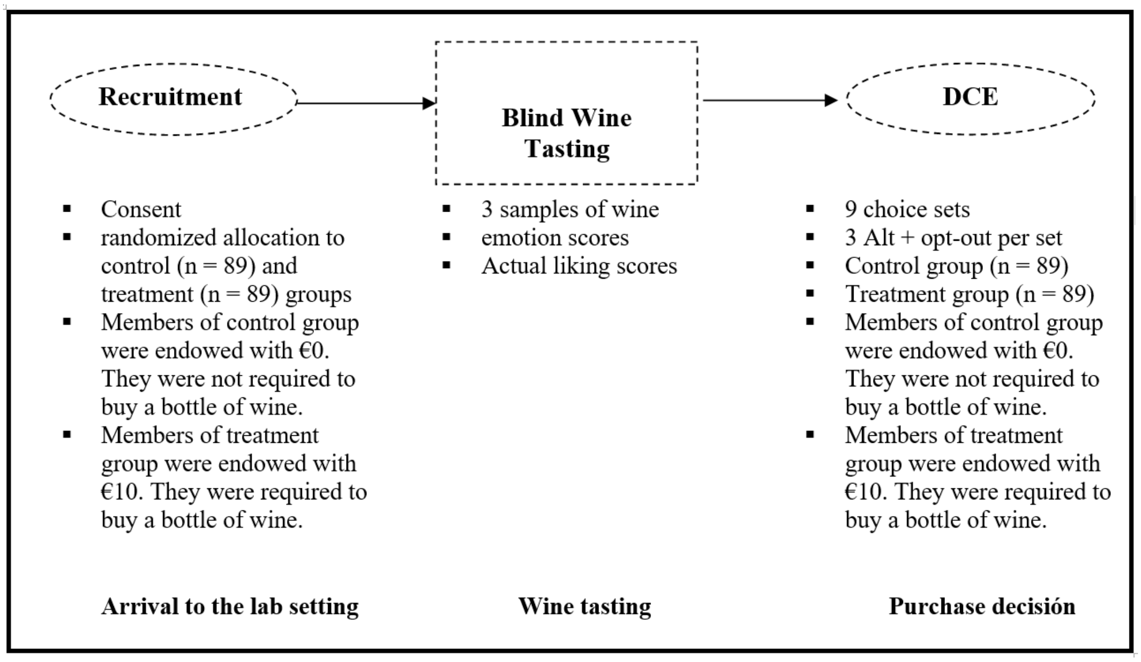

Figure 1: Experiment protocol

Each respondent was required to answer a total of nine choice sets. In each choice set, participants were asked to choose from among three wine types (conventional, organic, and selected vintage organic) and an opt-out option (no choice). Figure 2 provides an example of a choice card used in the experiment. The considered wines were experimental wines produced for this study and only differed in two attributes: the production system (conventional, organic, and selected vintage organic wines[1]) and the corresponding prices (€3.50, €5.00, €6.50, €8.00). Three price levels were identified for conventional wines (€3.50, €5.00, €6.50) and for the two organic wines (€5.00, €6.50, €8.00) following market information. These price levels correspond to the market prices of young red wines from Catalonia made with Tempranillo grapes. We also considered the context of frequent consumption when the price levels were selected. We generated a D-efficient (D-error = 0.40) design resulting in nine choice sets.

	Conventional wine	Organic wine	Selected vintage organic wine	None
Price	€3.5	€5	€8	None of the first three wines
I choose	☐	☐	☐	☐

Figure 2: Example of a purchase occasion (choice set)

To check for hypothetical bias, half of the participants (n = 89) were randomly assigned to a non-hypothetical treatment (treatment group), and the other half (n = 89) were then assigned to a hypothetical one (control group). Participants in the non-hypothetical treatment group received €10 to be used in the experiment and were informed that at the end of the DCE task, a choice set would be randomly selected and they would have to pay for a bottle of the wine originally selected on that particular choice occasion. Members of the control group did not receive money, nor were they required to buy a bottle of wine. Instead, they were given a brief talk explaining the problem of hypothetical bias in consumer studies and were invited to behave as they would in a shop or supermarket in real life.

[1] They are organic wines made with the best quality grapes of the 2017 harvest. A careful selection is done during the harvest to select the best quality grapes. It is a wine category typical from Spain.

With respect to emotion measurement, we recruited a specialized private firm (called Imotion Analytics), which uses its own technology to capture facial emotions and provides companies of different sectors (leisure and culture, hotels, banks, transport) with high-value information, including traffic at a store, the gender and age range of customers, wait and customer service times, emotional state, and emotional valence. Several systems based on the shape and movement of specific facial regions (facial muscle, edge of the mouth, eyes and eyebrows have been proposed for facial-expression-based emotion recognition (Ekman and Friesen, 1978; Yacoob and Davis, 1994). The technology we used applies the Internet of Things by using sensors that record consumers' facial emotions in two main streams: infrared and video. The combination of video plus infrared of great precision (FHD RGB + IR signals) provides a data stream with depth. From this information, "objects" are detected, which, following a pattern defined by applied algorithms, identify and differentiate the human body through a three-layer analysis: (1) human bodies: detection and differentiation of people against other objects or living beings; (2) extremities and joints: motion capture and follow-up; and (3) micro facial expressions: analysis of demographic profile and emotions. The sensors used for the present work incorporate two cameras (FHD RGB + IR) that recognize people while capturing subjects' biometric features, collecting raw data that is automatically transferred to a data-processing server (cloud server) to extract participants' emotions. The data processing works in the following way: once the raw biometric information is uploaded, several processes are run. These processes are responsible for identifying and extracting key signs on people's faces. The key signs are, for example, the corners of the eyebrows, the tip of the nose, and the corners of the mouth. The aim is detecting and classifying facial expressions[2].

[2] The facial coding system used is the highly accurate Facial Action Coding System developed by Carl-Herman Hjortsjö and adopted by Ekman and Friesen (Ekman and Friesen, 1978).

The moments of interest selected for emotion analysis were the 10 seconds right after the wine tasting. We organized participants (Figure 3) at three separate tables, with five participants per table. At each table, one sensor had been set up, since a given sensor can capture the facial emotions of five participants. The sensors take five measurements (five images) per second, which means that 10 recording seconds contain 50 measurements. For each individual, 50 measurements were recorded for each wine sample. We used the average values of the facial emotions in the analysis. The use of this technology required compliance with the technical conditions related to the distribution and separation of the participants (see Figure 3) to avoid contagion of emotions. For coordination purposes, a signal was given to participants to start tasting each wine sample at the same time. Six sessions of 15 participants each (alternating between the control and treatment groups) were organized per day during two consecutive days in June 2018.

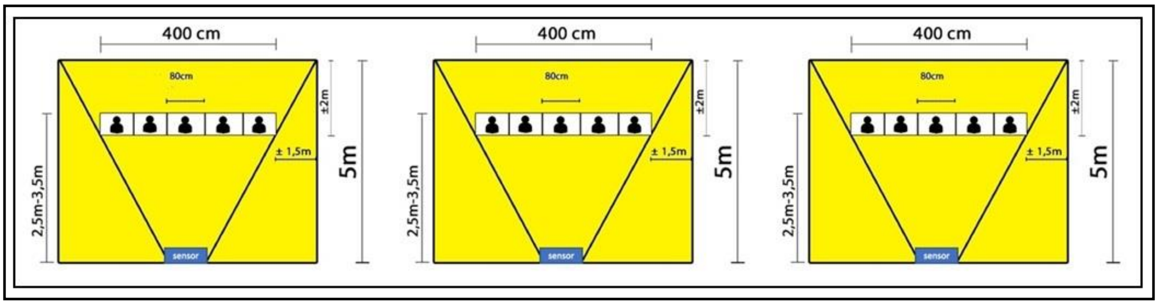

Figure 3: Distribution of group members in the room

After this procedure, the seven basic emotions (anger, contempt, disgust, fear, joy, sadness, and surprise) and emotional valence were identified. Ekman et al. (1987) confirmed the universality of these seven facial expressions of emotions. The software also provides the intensity (0 = "not present at all" to 100 = "maximum intensity") of the seven emotions. Emotional valence is a ratio between positive and negative emotions (Danner et al., 2014) that indicates the nature (positive or negative) and intensity (-100 = "very negative experience" to +100 = "very positive experience") of the emotional experience. Elster (1998) has suggested using valence (positive and negative experiences) to describe emotions.

3 Model specification

To analyze the role of emotions in consumers' choices in the DCE, we specified a random parameter logit (RPL) model. According to the assumption of random utility theory, an individual will behave rationally in choosing the wine that provides them with the highest utility on each choice occasion. The utility derived from each alternative *j* by each individual *i* in choice situation *t* is expressed as follows (Revelt and Train, 1998):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where V_{ijt} is the systematic component and ε_{ijt} are the random terms and are independent and identically distributed (iid) following an extreme value distribution. Assuming linearity, the systematic component can be written as follows:

$$V_{ijt} = \beta_i . x_{ijt}, \tag{2}$$

where x_{ijt} is a vector of observed variables and β_i is a vector of parameters associated with x_{ijt}, capturing individual's tastes or preferences for the attributes. These parameters are specific to the individual and vary in the population following the density $f(\beta_i|\theta^*)$, where θ are the moments of this distribution. The unconditional probability can be represented as

$$P_{ijt}(\theta^*) = \int L_{ijt}(\beta_i) f(\beta_i|\theta^*) d\beta_i, \qquad (3)$$

where $L_{ijt}(\beta_i)$ is the conditional probability that an individual i chooses an alternative j on choice occasion t.

$$L_{ijt}(\beta_i) = exp^{V_{ijt}(\beta)} / \sum_{j=1}^{J} exp^{V_{imt}(\beta)} \qquad (4)$$

The integral in Equation 3 needs to be approximated by simulation (see the procedure in Hensher and Greene, 2001; Revelt and Train, 1998). This model allows for different substitution patterns and for unobserved factors to be correlated over time because it overcomes the problem of the independence of irrelevant alternatives (IIA) assumption (Hensher and Greene, 2001). The specifications of the estimated models are detailed below.

We first estimated a baseline RPL model (M0) using the combined (aggregated) data from the two groups (control and treatment groups). In this model (M0), wine choices were modeled using the price (*Price*) and wine-specific constants: conventional wine (*ASC1*) and organic wine or selected vintage organic wine (*ASC2*), as well as two cross-products between the wine constants and a dummy variable "*TREATMENT*" (1 if the participant was from the treatment group and 0 if otherwise). The model (M0) was estimated with a nonrandom price parameter, and the wine-specific constants were random and normally distributed because consumers could like (positive preference) or dislike (negative preference) each of the three wine types. Next, a second model was estimated (M1) including the cross-product ($HVALENCE_j$, where j = 1, 2) between the wine-specific constants (*ASC1* and *ASC2*) and the evoked valence ($valence_j > 0$). The mean valence evoked by the organic wine and selected vintage organic wine was used. Third, the next model (M2) was estimated including the product ($HLIKING_j$, where j = 1, 2) between the wine constants ($ASC1$ and $ASC2$) and high actual hedonic scores ($LIKING_j$ > 6) of each wine. The mean actual hedonic scores of the organic wine and selected vintage organic wine were used. Fourth, a model (M3) including both previous products was estimated. Fifth, we re-estimated model M1 (M4) substituting the overall valence with joy ($HJOY_j$, where j = 1, 2) and contempt ($HCONTEMPT_j$, where j = 1, 2). In the model, $HJOY_j$ represented the cross-products between the wine-specific constants ($ASC1$ and $ASC2$) and the JOY_j dummy variables (JOY_j > 5); $HCONTEMPT_j$ represented the cross-products between the wine-specific constants ($ASC1$ and $ASC2$) and the $CONTEMPT_j$ dummy variables ($CONTEMPT_j > 5$). The mean scores of *JOY* and *CONTEMPT* for the organic wine and selected vintage organic wine were used. Sixth, we re-estimated model M3 (M5) substituting valence with joy and contempt. Table 1 shows the descriptive statistics of the variables used.

	Control group (Hypothetical DCE)		Treatment group (Non-hypothetical DCE)		Sample	
	Mean	*SD*[3]	Mean	*SD*	Mean	*SD*
Average age	46.97	13.24	46.50	12.54	46.73	12.89
FEMALE (%)	.49	.50	.52	.50	.51	.50
HVALENCE1[4]	.09	.29	.13	.34	.11	.31
HVALENCE2[5]	.09	.29	.13	.34	.11	.32
HLIKING1	.25	.43	.35	.48	.30	.46
HLIKING2	.44	.50	.58	.49	.51	.50
HJOY1	0.12	0.33	0.20	0.40	0.16	0.37
HJOY2	0.15	0.35	0.19	0.39	0.17	0.37
HCONTEMPT1	0.29	0.45	0.22	0.42	0.26	0.44
HCONTEMPT2	0.27	0.44	0.35	0.48	0.31	0.46

Table 1: Descriptive statistics of the explanatory variables

4 Results and discussion

Eighty-nine individuals participated in each treatment (control vs. treatment). Table 1 shows the descriptive statistics of some characteristics of the sample. The percentages of women in the control (49%) and treatment (52%) groups were similar, $X^2(1, 178) = 0.20$, $p = .653$. The *F-test* shows that there are no statistically significant differences in age across groups, $F(1,175) = 0.06$, $p = 0.814$, namely, 46 years. Members of the two groups were representative of the local population in terms of sex and age (see Table 1). Thirty-three percent of each of group belonged to households with a monthly income greater

[3] SD refers to standard deviation.
[4] The number 1 refers to conventional wine
[5] The number 2 refers to organic wine or selected vintage organic wine.

than €2,500. The average household size was three persons in both groups. Forty percent of the control group had completed their university studies, while this level of study was reached 25% of the members of the treatment group. The two groups were sufficiently similar to compare their behaviors.

Table 2 provides the means of the actual hedonic scores and emotion intensities. The selected vintage organic wine (6.07) received the highest actual hedonic liking score, followed by the organic wine (5.87) and conventional wine (5.19). The three wines had negative valences, which means that, in general, participants did not like any of them. It should be noted that the wines were experimental wines produced only for this study. Emotions such as anger, fear, and sadness had means not far from zero, which implies that many participants did not express them clearly.

	Conventional wine		Organic wine (OW)		Selected vintage OW	
	Mean	*SD*[6]	Mean	*SD*	Mean	SD
Actual liking score	5.19	0.02	5.87	0.02	6.07	0.02
Valence	-11.35	0.23	-14.17	0.23	-11.20	0.25
Anger	0.37	0.01	0.56	0.02	0.59	0.02
Contempt	5.01	0.12	6.01	0.15	7.24	0.18
Disgust	9.24	0.20	11.99	0.26	10.43	0.21
Fear	0.27	0.01	0.16	0.01	0.51	0.06
Joy	5.15	0.15	3.46	0.10	4.30	0.16
Sadness	0.21	0.01	0.34	0.01	0.39	0.02
Surprise	3.05	0.08	2.82	0.08	3.69	0.14

Table 2: Means of actual hedonic scores and emotion intensities

[6] SD refers to standard deviation.

The descriptive analyses of the data from the DCE demonstrated many similarities in the preferences of the control and treatment groups. Figure 4 illustrates the percentage of choices per wine type. The selected vintage organic wine was the most preferred wine by members of both groups, followed by the organic wine and conventional wine. The choice percentages for each wine were similar for the two groups, and practically identical for the selected vine organic wine. The percentage of participants selecting the opt-out option (selecting none of the wines) was also highly similar between the two groups.

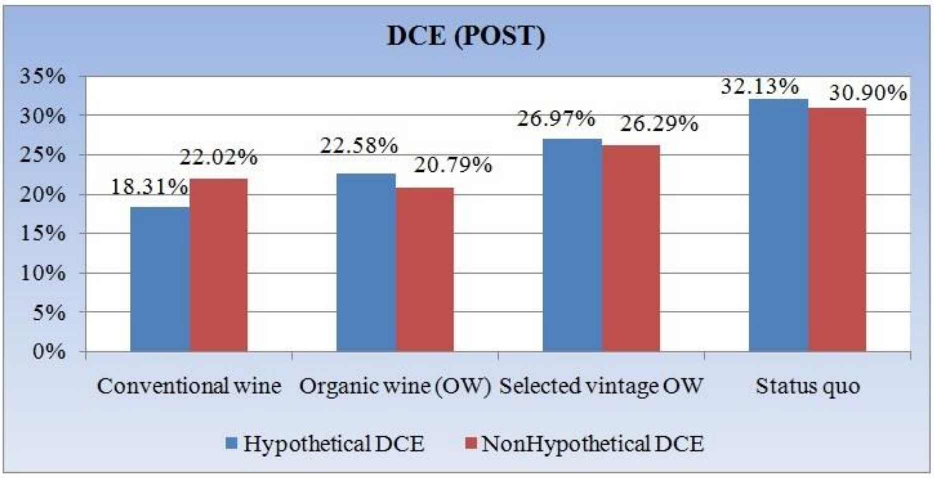

Figure 4: Percentage of participants choosing wine alternatives after wine tasting (per group)

Table 3 offers the results of all the estimated RPL models. In all models, price has a negative effect on choices, which is expected and in line with consumer theory and previous studies (Lockshin et al., 2006; Mann et al., 2012). The organic wines (selected vintage organic wine or organic wine) were the most preferred wine types (providing a higher marginal utility), followed by the conventional wines, in line with previous findings (Mann et al., 2012). The standard deviations of the wine-specific constants were highly statistically significant, meaning that there was heterogeneity in the preferences for each wine. However, there was more heterogeneity in preferences for the organic wines than for the conventional wines.

None of the included cross-products between wine type and the *TREATMENT* variable in model M0 were statistically significant. Thus, the condition to which each group (control or treatment) was subjected did not have a significant effect on participants' preferences for the wines. This result supports the descriptive analysis confirming the absence of hypothetical bias, which is similar to the findings reported by Carlsson and Martinsson (2001) but different from those by Lusk and Schroeder (2004). Consequently, providing a brief talk may mitigate hypothetical bias in hypothetical DCEs, resulting in reliable results similar to those of non-hypothetical DCEs.

Comparing the fit of models M1, M2, and M3, model M2 had the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC), so it is the best statistical model. However, when comparing the fit of models M2, M4, and M5, model M4 was the best (lowest BIC). These results mean that model M4, which only includes emotions, fits the best our data. This differs from previous research (Dalenberg et al., 2014; Gutjar et al., 2015) stating that the best predictions were achieved when combining both measures. This disparity may be due to different methods for measuring emotions (implicit vs. explicit measures).

The results for models M1 and M3 show that participants expressing a more positive emotion toward the organic wine or selected vintage organic wine (*HVALENCE2* > 0) were more likely to select them, while participants who had an overall positive experience with the taste of the conventional wine *(HVALENCE1 > 0)* were not more likely to choose the conventional wine. Models M2 and M5 point to a positive and significant relationship between high hedonic scores associated with the taste of each organic wine ($HLIKING_j$, j = 2), and the choice of these wine types. This means that valence and hedonic scores were good predictors for the choice of the organic wine and selected vintage organic wine, while neither measure predicted the choice of the conventional wine.

The results of models M4 and M5 show a positive relationship between higher joy (*Hjoy)* and the choice of the organic wine and selected vintage organic wine and a negative relationship between contempt *(Hcontempt*) and the choice of the organic wine and selected vintage organic wine. No statistical relationship was found between contempt and joy, and the choice of the conventional wine. Our findings illustrate that emotions are more relevant for credence goods (organic wines) than experience goods (regular wine).

	RPL (M0)	RPL (M1)	RPL (M2)	RPL (M3)	RPL (M4)	RPL (M5)
Parameters in utility functions						
PRICE	-0.82***[7]	-0.81***	-0.82***	-0.82***	-0.80***	-0.80***
	(0.04)[8]	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*
ASC1 (CW)	2.91***	3.13***	2.87***	3.07***	3.41***	3.06***
	(0.37)	*(0.27)*	*(0.34)*	*(0.29)*	*(0.36)*	*(0.39)*
ASC2 (OW)	4.62***	4.62***	4.21***	4.44***	5.11***	4.53***
	(0.51)	*(0.35)*	*(0.43)*	*(0.38)*	*(0.43)*	*(0.47)*
Standard deviations of random parameters						
NsASC1 (CW)	2.36***	2.54***	2.44***	2.54***	2.64***	2.56***
	(0.27)	*(0.22)*	*(0.27)*	*(0.25)*	*(0.28)*	*(0.27)*
NsASC2 (OW)	3.56***	3.63***	3.54***	3.45***	3.33***	3.32***
	(0.55)	*(0.37)*	*(0.34)*	*(0.36)*	*(0.32)*	*(0.30)*
Nonrandom parameters in utility functions						
*ASC1 * TREATMENT*	0.09					
	(0.54)					
*ASC2 * TREATMENT*	0.79					
	(0.91)					
ASC1 HVALENCE1*		-0.87		-0.57		
		(0.82)		*(0.47)*		
ASC2 HVALENCE2*		2.54***		2.10**		
		(0.67)		*(0.65)*		
ASC1 HLIKING1*			0.71	0.06		*0.48*
			(0.49)	*(0.43)*		*(0.51)*
ASC2 HLIKING2*			1.54**	0.50		*1.18**
			(0.57)	*(0.42)*		*(0.47)*
ASC1 HJOY1*					-0.75	-0.47
					(0.67)	*(0.53)*
ASC2 HJOY2*					0.05*	0.06**
					(0.02)	*(0.02)*
ASC1 HCONTEMPT1*					-0.79	-0.99
					(0.57)	*(0.53)*
ASC2 HCONTEMPT2*					-.05*	-0.05
					(0.02)	*(0.02)*
Number of participants	178	178	178	178	178	178
Number of observations	1,602	1,602	1,602	1,602	1,602	1,602
Log likelihood function	-1,459.1	-1,455.4	-1,450.6	-1,454.6	-1,322.9	-1,317.5
AIC	2,932.2	2,924.7	2,915.3	2,927.2	2,664.0	2,656.9
BIC	2,969.8	2,962.4	2,952.9	2,975.6	2,712.4	2,716.1
McFadden pseudo R^2	0.34	0.34	0.35	0.34	0.34	0.34

Table 3: Results of the estimated RPL models

3

[7] *, **, and * indicate $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.*

[8] *Standard errors in parentheses.*

5. Policy implications

Research in consumer behavior is usually used to establish public policies, so, any improvement in consumer behavior understanding will be of great help to the success of public policies (e.g., public policies to support organic farming). The present work showed that positive experience and emotions have a greater influence on the choice of organic wines. In particular, wine-evoked emotions measured using an innovative facial expression analysis approach and incorporated in stated preference discrete choice models improved our understanding and prediction of consumers' organic wine choices. These findings imply that researchers and product developers should consider product-evoked emotions when conducting sensory evaluations or developing new products to increase the product's acceptability and success. Moreover, existing traditional self-reported techniques for product sensory evaluation should be complemented with new technologies such as facial-expression-based recognition softwares to go further in the analysis of consumer acceptability. Controlling for emotions in consumer behavior modeling will improve predictions and the impact of public policies (e.g., subsidies).

6 Conclusion

Economists have often observed a gap between consumers' self-reported attitudes and their real behaviors. This gap is partially due to the fact that economists consider consumers to often arrive at their decisions using a rational decision-making process. Over the years, behavioral economics and psychology have demonstrated that a large part of behavior is influenced by our emotional experiences.

Our paper presents an application to assess how emotions influence consumers' wine purchasing decisions. Consumers' growing health and environmental awareness has been increasing demand for healthy and sustainable foods. This tendency provides a market opportunity for organic foods. This upward trend in demand has also been experienced in the wine industry, which is adopting organic production systems. Our paper has analyzed consumer interest in buying wines produced via different systems: conventional, organic, and selected vintage organic wines. It has evaluated whether and to what extent consumers are willing to buy organic wines versus conventional wines. Moreover, we tested whether the choice of credence products (organic wines) comprises a more affective decision than the choice of experience products (conventional wines).

Having in mind these research aims, we combined a labeled DCE, a blind wine tasting, and a facial expression analysis. We measured facial expressions of emotions evoked by tasting different wine types (conventional, organic, selected vintage organic) using an innovative implicit method, and we incorporated these emotions in stated preference discrete choice models to improve our understanding and prediction of consumers' wine choices. The present work has assessed the role of emotions in wine choices, and we conclude that a positive relationship exists between valence and the choice of the organic wine and selected vintage organic wine, and between joy and the choice of the organic wine and selected vintage organic wine. Overall we find that experienced positive and negative emotions have a greater influence on the choice of environmentally superior wines, or wines with credence attributes. However, much remains unknown about the impact of emotions on overall choices and the best way to assess emotions.

Moreover, we conclude that facial recognition mechanisms predict choices better than actual hedonic liking scores. Future research should investigate why positive emotions influence only the choice of specific attributes and the best way to measure emotions. Facial recognition and facial expressions are critical for better understanding economic behaviors. However, the economic literature has not evaluated this new way of perceiving emotions. Companies use these approaches to identify consumers' emotions in shopping malls, hotels, shops, and similar locations. Economists should pay attention to these innovative techniques by incorporating them into choice experiment applications and other methods to better understand human behavior.

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