Does 'price framing' influence empirical estimates in Discrete Choice Experiments: The case study for the South African wine industry

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Abstract

The approach and survey used to examine non-market value in a stated preference study can influence the outcomes and impact the validity and reliability of value estimates. While prior research has investigated the impact of 'price framing' on decision-making in other disciplines, (i.e. marketing & psychology), little is known about its validity and reliability in Discrete Choice Experiments (DCEs) and environmental valuation. The study explores the effect of 'price framing' on DCE measurements. The tests are carried out using data from a choice experiment on preferences for natural preservatives in wine. The same respondents completed a nearly identical DCE survey, one with a *real price* and another with a *percentage price change* as cost attribute. 611 respondents completed the survey, and a panel mixed logit model was used for the analysis. Results demonstrate that 'price framing' remarkably influenced respondents WTP changes in attributes. The data reveals that while the rank order of importance of attributes, signs, and significance levels are similar for the two samples, they differ in the parameter magnitudes. The study sheds light on the establishment of guidelines for developing valid cost attributes in DCEs studies.

Keywords: Price framing, Discrete Choice Experiment, Mixed Logit Model

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1 Introduction

Discrete choice experiments (DCEs) are increasingly being used to estimate value for environmental goods and services. The theory behind choice experiments (CE) is that participants derive utility from valued goods or services. Participants' choices determine the amount or quality of multiple attributes that describe the characteristics of that good or service (Kragt and Bennett, 2010). Central to choice experiments is using surveys in which alternative (hypothetical) scenarios are defined by varying non-market attributes and cost levels. The survey participants are then asked to choose their preferred option from a list of options. Since its introduction by Batsell and Lodish (1981) and Louviere and Woodworth (1982), the Choice Experiments technique has been frequently employed (1983). Furthermore, the technique has been applied to a variety of fields, including transportation and services (e.g. Hensher and Rose, 2007; Rose and Bliemer 2009; Alberini and Ščasný 2018), human health (e.g. O'Hara, 2016; Ryan and Wordsworth, 2000) and environmental valuations (Chikumbi et al. 2021, Gibson et al., 2016; Hanley et al., 2006).

Because the contextual information offered in expressed preference surveys can affect both the validity and reliability of value estimations, how CEs are designed and how attributes are explained to respondents plays a vital role in DCEs investigations (Samples et al. 1986; Bergstrom et al. 1990; Ajzen et al. 1996; Schlapfer 2008). Furthermore, because the findings of choice experiments studies are increasingly being utilized to inform policy formation, it is critical to assess the method's validity and the accuracy of value estimates. (Kragt and Bennett (2012).

The validity of various stated preference techniques has been tested in numerous studies. Even though most studies have demonstrated that the way cost information is presented, referred to as "price framing," has a major impact on value judgements (Anderson and Simester 2003; Gourville 1998; Heath, Chatterjee, and France 1995; Russo 1977; Bertini & Wathieu, 2006) little is known about their validity and reliability in DCE and environmental valuations. A detailed examination of DCE studies (Veldwijk et al. (2016; Determann et al., 2017; Norman et al., 2016; Cornelsen et al., 2020; Howard and Salkeld, 2009; Kragt and Bennett, 2010; Murwirapachena and Dikgang, 2019) has shown that changes in attribute framing have unanticipated effects on obtained estimates which could lead to biased results. Little is known on the effects of 'price framing' on DCE measurements. The study answers the research question, "does 'price framing' influence empirical estimates in DCEs?" and contributes to the literature by explicitly assessing whether or not the use of either *real price* or *percentage price* affects empirical estimates in DCEs concerning parameter' magnitude; sign; significance level; rank order of attribute importance; and the willingness to pay (WTP) estimates. The study hypothesizes that since the cost attribute values are similar and only differ when presented as either *real price* or *percentage price,* they should give similar outcomes.

The study uses choice experiment data on preferences for natural preservatives in wine from a South African wine industry case study. A split sample survey was administered to 611 respondents and only differed on whether the cost attribute was presented as *real price* or *percentage price*. The results of a mixed logit model revealed that 'price framing' had a substantial impact on respondents' WTP changes in attributes. In addition, the findings suggest that while the attribute's rank order of importance, sign and significance level are similar for the two samples, they were differences in their parameter magnitude.

The following section, 2, provides a theoretical and empirical literature review. Then, section 3 presents the modelling framework, and section 4 presents the case study. Finally, section 5 presents the results and concludes with a discussion of the findings in section 6.

2 Literature Review

Framing refers to the setting in which decisions are made (Rolfe et al., 2002). There is much evidence that the way questions are framed, and the information offered in a survey influences respondents' responses (Ajzen et al., 1996). Likewise, there is much evidence that the way questions are phrased and the information offered in a survey affects respondents' responses (Ajzen et al., 1996). Therefore, it is critical to understand how respondents' choices are affected by the survey setting when employing choice experiments to value non-market products and services. Not all survey participants have pre-existing preferences for the non-market products presented in a choice experiment survey, but those preferences are formed based on the data collected in the survey, for example, see Tversky and Simonson (1993), Bateman et al. (2004) or Braga and Starmer (2005) on setting-dependent preferences. In this situation, rather than the nature of the good or service, preferences are more likely to change due to the information offered and the settings specified in the questionnaire. As stated-preference techniques rely on the information provided in the survey, it is safe to argue that framing effects are inherent.

Attribute framing occurs when decisions are influenced by how attributes are described to survey participants (Levin and Gaeth, 1988). Minor modifications in how attributes are presented or framed can have an impact on the decisions made. For example, Kahneman and Tversky (1979) discovered that changing the presentation of probabilities and results changes individuals' information translation and decision-making behaviour. They discovered that the more attractive choice was based on whether outcomes were framed as lives saved or lives lost, as explained in their famous "Asian disease" example (Tversky and Kahneman, 1981). As a result, the choices differed significantly in terms of how the problem was framed.

Similar framing effects have been demonstrated in other fields, such as environmental policy, public policy, contract negotiations, taxation, health, and political (Frederickson and Waller, 2005; Ovaskainen and Kniivila, 2005; McCaffery and Baron, 2004; Druckman, 2004; Rege and Telle, 2004; Park, 2000; Miller, 2000; Sonnemans, Schram and Offerman, 1998; Johannesson and Johansson, 1997). Thus, there is suggestive evidence that attribute framing does influence the choices made by respondents.

To reduce the different types of bias resulting from framing, Johnston et al. (2017) provide some guiding principles for stated preference studies. These recommendations, when addressed, reduce uncertainty surrounding the use of State Preference (SP) methods to inform decisions and to assist researchers and practitioners in understanding best practices when considering designing, implementing, or using the estimates from SP studies. They are divided into five groups: (a) survey development and implementation, (b) value elicitation, (c) data analysis, (d) validity assessment, and (e) study reporting (Johnston et al. 2017). There seems to be substantial agreement on many of the details under each step. For example, few question the desirability of subjecting survey drafts to qualitative research and pretesting. A broad consensus has also developed regarding appropriate econometric approaches (see, for example, Haab and McConnell 2002). Researchers in the field would agree on the basic procedures involved in doing a state-of-the-art study, including the general efficacy of properly defining the changes to be valued, deciding whose values are to be counted, determining a suitable sample size, and so on (Johnston et al. 2017).

A few DCE studies have tested the effects of attribute framing on empirical estimates (e.g., Veldwijk et al.,2016; Determann et al., 2017; Murwirapachena and Dikgang, 2019; Norman et al., 2016; Cornelsen et al., 2020; Howard and Salkeld, 2009; Kragt and Bennett, 2010). They discovered that changes in attribute framing have unfavourable effects on generated estimations, potentially leading to skewed findings. Veldwijk et al. (2016), for example, used a survey in the Netherlands to see if attribute framing in a discrete choice experiment influences respondents' decision-making behaviour and preferences. The DCE included four factors to consider when deciding whether to participate in colorectal cancer genetic screening. The risk factor was interpreted in two ways: positively as the likelihood of surviving cancer and negatively as the likelihood of dying from cancer. The relative relevance of the qualities was estimated using mixed-logit models. Most respondents (56%) ranked survival as the most significant feature in the positively framed DCE, but only roughly 8% ranked mortality as the most important attribute in the negatively framed DCE. They discovered that how risk is framed impacts how people value it (Veldwijk et al., 2016).

Determann et al. (2017) investigated whether paper or electronic administration causes measurement effects in a DCE. Participants were selected from the same sample frame (an Internet panel) and were asked to complete a virtually identical DCE survey on the web or paper simultaneously. They used mixed logit models and a DCE on preferences for basic health insurance as a case study. From both means, they received a total of 898 responses. There were no significant differences in sociodemographic variables between the participants in both samples. However, the median response time for the paper sample was more significant than for the web sample, and a smaller proportion of web participants were satisfied with the quantity of choice combinations. Even though some WTP estimates for the web sample were higher, the elicited preferences for essential health insurance criteria were identical in both modes of delivery.

Murwirapachena and Dikgang (2019) investigated the effects of three presentation formats, namely text, visuals and a combination of the two formats using data collected from a household survey in Gauteng province, South Africa. They found that visual presentations generate more efficient estimates than the other two formats using the mixed logit model. A comparison of attribute parameters across all three experiments showed some differences in the signs of each parameter, with the WTP estimates showing that households were willing to pay for more attributes in the visuals experiment than in the other two experiments. Comparing the magnitude of the WTP estimates across the three experiments showed that the text-and-visuals experiment had larger estimates than the other two experiments in absolute terms. Overall, the WTP estimates were largely different in terms of sign, significance and magnitude across the three presentation formats.

Norman et al. (2016) investigated the possibility of using a discrete choice experiment (DCE) to value health wellbeing in the QLU-C10D, a utility instrument derived from the QLQC30, and to assess clarity, difficulty, and participants' preference between two presentation forms using the QLU-C10D. They employed an online survey in which participants replied to 16 choice pairs; half of these had variations between dimensions highlighted, while the other half had standard dimensions explained in the text and differences in attributes calculated. They utilized a conditional logit model to evaluate the DCE data by format and Chi-squared tests to compare other responses by format. Respondents' cognitive methods to the valuation task were investigated through semi-structured telephone interviews. The findings revealed that participants considered 10 domains challenging but workable, with many using simplifying heuristics.

Cornelsen et al. (2020) studied whether signalling and framing a sugar-sweetened beverage (SSB) tax increase explicitly as a health-related, designated action reduces SSB demand more than an equivalent price rise. Many nations have imposed SSB taxes to prevent obesity, with evidence that they effectively reduce SSB purchases. A discrete choice experiment (DCE) was given online to a randomly selected set of 603 families with children in Great Britain who routinely purchase SSBs to estimate demand for non-alcoholic beverages. They discovered compelling evidence that when a price rise is signalled as a tax and framed as a health-related and designated policy, it leads to a greater reduction in the likelihood of choosing SSBs. Furthermore, individuals who did not support an SSB tax, who were also more inclined to use SSBs in the first place, were on average more receptive to a price rise portrayed as an allocated tax than those who did support the tax. The findings suggest that a well-publicized and earmarked levy on SSBs could be more effective at reducing demand.

Howard and Salkeld (2009) used a discrete choice experiment to investigate the impact of attribute framing on marginal rates of substitution and the WTP in the context of colorectal cancer screening preferences. They surveyed in NSW, Australia, and interviewed 1157 people. Respondents were randomly assigned to one of four different information "frames." A mixed logit model was used to estimate preferences, and results show that attribute framing had a considerable impact on WTP estimates.

Kragt and Bennett (2012) investigated the effects of two attribute level descriptions. They first employed positive versus negative contextual descriptions of attribute levels to characterize non-market qualities as absolute levels or relative terms. These experiments were carried out utilizing data from an Australian choice experiment on catchment management. Unlike derived expectations, stated preferences are unaffected by clear data indications regarding relative attribute levels in the choice sets. However, when attribute levels are described as a 'loss' versus a 'presence,' the data reveals significant differences in value estimates.

Hess et al. (2006) examined whether positive and negative changes in journey time attribute levels from a "current trip" reference choice were balanced. They discovered that attribute level increments and decreases were valued differently, suggesting that gains and losses from a predetermined reference point did not have the same value.

The focus of this chapter is 'price framing'. The two commonly used 'price framing' in DCE studies are *real price* and *percentage price* as cost attribute (see Regier et al., 2015; Michaud, 2012; Chau et al., 2010; Masiero et al., 2015; Balogh et al., 2016; Fecke et al. 2018). While prior research has investigated the impact of 'price framing' on decision-making in other disciplines, i.e. marketing and psychology (e.g., Bertini & Wathieu, 2006; Anderson and Simester 2003; Gourville 1998; Heath, Chatterjee, and France 1995; Russo 1977), little is known about their validity and reliability in DCEs and environmental valuation studies. What makes DCE and environmental valuation unique is its ability to assign monetary values to non-market goods, as the case for the current study. The study contributes to the literature by exploring whether *real* or *percentage price change* as a cost attribute in DCE studies affects empirical estimates. This decision is critical since the contextual information provided in stated preference surveys affect results that ultimately influence policy development. Further, the study sheds light on establishing guidelines for developing valid cost attributes in DCE evaluations.

3 Modelling Framework

The theory of Choice Experiment is vested in the random utility theory and Lancaster's characteristics theory of value (Lancaster, 1966). It assumes the utility that individuals derived from choice situations are a function of a vector of attributes in the choice set and individual characteristics and an unobserved stochastic component:

$$U_{njt} = X_{njt}\alpha_n + \beta_n \cdot (Y_n - PRICE_{njt}) + \varepsilon_{njt} \qquad (1)$$

where X represents a vector of alternative specific attributes (PRESERVATIVES, VITICULTURE PRODUCTION, QUALITY SCORE), Y is income, and PRICE is the price of wine, the vector of coefficients α and coefficient β is estimated and is a stochastic component identically and independently distributed with a constant variance k_n^2 (π^2 /6), with k_n^2, being an individual-specific scale parameter. An individual will choose alternative *j* if $U_{njt} > U_{nkt}$, $\text{for all } k \neq j$, and the probability that a particular alternative *j* is chosen from a set of *C* alternatives is given and can be estimated using different econometric models (Louviere et al. 2000; Alpízar et al. 2001; Bennett and Adamowicz, 2001):

$$P(j|C) = \frac{exp\,(X_{njt}\alpha_n + \beta_n \cdot (Y_n - PRICE_{njt}))}{\sum_{k=1}^{C} exp\,(X_{nkt}\alpha_n + \beta_n \cdot (Y_n - PRICE_{nkt}))} \qquad (2)$$

The study uses a mixed logit model specification with random, freely and fully correlated factors to account for unobserved heterogeneity across respondents (Revelt and Train 1998). The model is evaluated using the simulated maximum likelihood technique because the mixed logit probability does not have a closed-form solution. The use of a mixed logit model has the advantage of allowing for correlations throughout the series of choices made by individual n by specifying an individual specific error component. The conditional probability of seeing a sequence of individual choice t from the choice sets is the product of the conditional probabilities (Carlsson et al., 2003). Per procedure is to estimate the utility coefficients' distribution and then estimate the willingness-to-pay as a ratio of two utility parameter estimates, as $-\frac{\hat{\alpha}}{\hat{\beta}}$.

3.1 Case Study: Measuring premium price for natural preservatives in wine. A Discrete Choice Experiment

The effects of 'price framing' on DCE measurements was tested using data from a choice experiment on preferences for natural preservatives in wine in the South African (SA) wine industry. SA wines have been successful globally, achieving significant production and export sales growth since 1994 (VinPro, 2018). However, since 2005, the industry has undergone major setbacks that have negatively impacted growth. As a survival mechanism, industry policy-makers are increasingly exploring ways to mitigate the negative trends.

One such way is through product innovation. Innovation is widely accepted as a driving force for agricultural development, and scientists recognize innovative farmers' key role (Chambers and Thrupp, 1994; Klerkx and Leeuwis, 2008; Reij and Waters-Bayer, 2014). In the same context, SA wines could explore product innovation as a potential revenue source to support itself and enhance competition.

The South African wine industry introduced the world's first "no sulphite added" wine in 2014, created from indigenous Rooibos and Honeybush toasted wood chips. This wood chip is high in anti-oxidants, which help to keep the wine from oxidizing. Sulphur dioxide (SO2), on the other hand, is commonly considered by wine drinkers as a headache-inducing preservative. Drawing attention to consumer behaviour in the marketplace has highlighted the trend of consumers choosing healthy food products. Most consumers, particularly in recent times, are attentive to artificial additives and prefer to buy organic foods (Hoffman et al., 2014). Since 'no sulphite added' wines seem attractive to health-conscious consumers, it is interesting to explore this potential niche market in-depth to gauge consumers' perceptions of the importance of these wines. Determining whether consumers choose such wines is essential, as it would reveal whether wine players can exploit this source of avenue to save the struggling industry. Key indicators that would inform wine players are how valuable 'no sulphite added' wine is to consumers and what consumers would consider such a trait necessary in their purchasing decisions.

3.2 Experiment design and randomized treatment

Designing a DCE involves selecting and combining the attributes and their levels to construct the alternatives in hypothetical choice situations presented to respondents (Hoyos, 2010). Respondents are then asked to think about the situation in which they would be making their choices. Identifying the attributes and levels (see Table 1) in the experiment was facilitated by the literature review as well as findings from qualitative pre-testing conducted in focus groups with wine consumers from the Cape Town area.

Table 1. Attributes and levels of the discrete choice experiment

Attributes	No. levels	Levels
Preservatives	2	SO_2-based, Rooibos & Honeybush
Type of viticulture production	2	Conventional, Organic
Wine quality score	6	60, 75, 82, 88, 92, 100
Real Price	5	Rands: 0, 30,45,60,75 (Euro:0, 1.77, 2.66, 3.54, 4.43)
Percentage Price	5	0, 20%, 30%, 40, 50%

The same respondents completed a nearly identical DCE survey, one presented a *real price,* and another presented a *percentage price* as a cost attribute. The study uses four price increase levels in the DCE design in both options, with zero in the Status Quo. While in the former case, the price increase was given by design, the levels in percentage value were respondent-specific in the latter variant. Thus, each respondent was presented with eight (8) choice situations where half the cards cost attribute was presented as *real price,* and the other half was presented as *percentage price*. An example of a choice card presented to respondents is shown in Figures 1 and 2, respectively.

The wine price was shown as an increment of what a consumer typically pays for a bottle of wine, and the premium included *real price*: 30, 45, 60, and 75, and Euro equivalents are also shown on the cards in brackets. In *percentage price*, the offered bids represented 0, 20%, 30%, 40% and 50% of the average price of the status-quo wine.

The choice task included three alternatives, one referred to as wine typically purchased (i.e., the status quo). The status quo option described a typical wine sold on the South African market (in the Western Cape Province): a 750ml bottle of conventional wine with SO_2-based preservatives, graded by a 75-point quality score, whilst the price in the status quo was respondent-specific. Specifically, before the valuation part, the study asked each respondent the question, "What is the average price for which you typically buy a bottle of wine most often?". As a result, approximately respondents typically paid on average R184 for a bottle of wine, with a minimum at R33.60 and a maximum at R848. It then asked, "Which of the three alternatives do you prefer?" and repeated the valuation question four times for each different choice situation.

Using NGENE software, a Bayesian-efficient design was generated. The Bayesian approach for optimal experimental design has become more prominent in the literature (e.g., Muller, 1999; Han and Chaloner, 2004; Amzal et al., 2006; Muller et al., 2006; Collins and Rose, 2006; Ferrini and Scarpa, 2007; Scarpa and Rose, 2008; Cook et al., 2008; Huan and Marzouk, 2013) due to its ability to optimize design criteria that are functions of the posterior distribution and can easily be tailored to the experiments' objectives. The design contains twenty-four (24) unique choice combinations grouped into three, giving us eight choice cards per respondent. In total, the study obtained 4,888 responses (from 611 respondents) for both choice tasks, half presented with *real price* and another half with *percentage price change.*

Figure 1. Real Price choice scenario

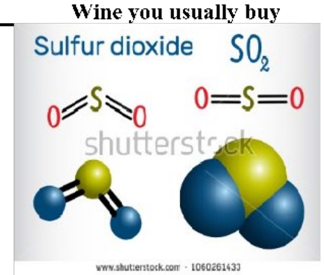
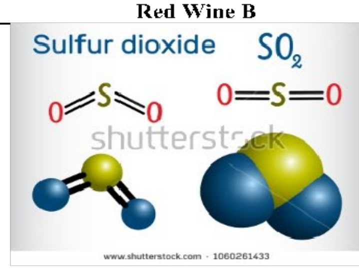
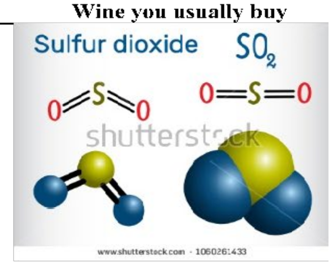
	Red Wine A	Red Wine B	Wine you usually buy
Preservatives	Rooibos & honeybush 		
Viticulture production	Conventional 	Organic 	Conventional 
Wine quality Score	100 (great top wine)	60 (not recommended)	75 (a drinkable wine that may hav minor flaws)
Additional cost per bottle	R45 (€2.8) more	R60(€3.75) more	as you usually pay
Which option do you prefer?	◯	◯	◯

Figure 2. Percentage Price choice scenario

	Red Wine A	Red Wine B	Wine you usually buy
Preservatives	Rooibos & honeybush 		
Viticulture production	Conventional 	Organic 	Conventional 
Wine quality Score	100 (great top wine)	60 (not recommended)	75 (a drinkable wine that may hav minor flaws)
Additional cost per bottle	30% more	40% more	as you usually pay
Which option do you prefer?	◯	◯	◯

3.3 Experimental data

Multistage sampling was used to select areas and places to conduct the interviews. No incentive was offered to the survey participants. The interview was conducted in English, and the enumerators used a pen-and-paper mode of interviewing. Prior to the final survey, the questionnaire was comprehensively pre-tested in two waves of testing, and the survey instrument was modified to improve its readability and comprehension. The questionnaire consisted of four sections. The first section contained a brief explanation of the purpose of the study without getting into details about what the study was all about to minimize a potential framing bias. The second section dealt with consumer information and knowledge about SO_2 content in wine, perceived health effects, cultivar production types and quality score of wine. The discrete choice experiment was presented in the third section. If respondents choose no change (status quo), they were asked to provide their main reason to identify protest responses. The final section collected socio-economic and other relevant information about the respondents. Visual information was included to facilitate understanding and make the survey more pleasant to respondents (see Figures 1 and 2).

The primary survey was conducted between July 8–22, 2019, and 611 participants completed the survey. The demographic characteristics of the sample are reported in Table 2. While the sample may not represent the South Africa population, the recruiting strategy successfully targeted respondents in areas where most wine consumers reside. Almost everyone was buying at least a bottle of wine in a typical month. The majority of respondents (78%) are between the age of 21-50 years. There are 42% males and 51% females, while 7% choose not to provide information about their gender.

Table 2. Socio-demographic characteristics of the sample (n = 611).

Variable	Per cent
Gender	
Males	42%
Females	51%
Age	
18-20	4%
21-30	32%
31-40	24%
41-50	22%
51-60	15%
61-70	3%
Education	
High (secondary) school	12%
Some technical certificate/diploma	19%
Bachelor's degree	22%
Honours degree	18%
Professional/Master degree	16%
Doctorate	11%
Income	
R50,000 and less (€3,125 and less)	12%
R50,000 to R100,000 (€3,125 - €6,250)	5%
R100,000 to R150,000 (€6,250 - €9,375)	5%
R150,000 to R200,000 (€9,375 - €12,500)	5%
R200,000 to R350,000 (€12,500 - €21,875)	7%
R350,000 to R500,000 (€21,875 – €31,250)	9%
R500,000 to R750,000 (€31,250 – €46,875)	8%
R750,000 to R1,000,000 (€46,875 - €62,500)	5%
R1,000,000 to R2,000,000 (€62,500 - €125,000)	5%
R2,000,000 and more (€125,000 and more)	4%
I prefer not to answer	33%

Wine Consumption	
Almost daily	15%
Several times a week	19%
Once a week	27%
Once a fortnight	22%
Once a month	12%
Very rarely	5%
Headache	68%

The majority of the respondents reside in Africa (80%), some in Europe (10%), 4% and 3% came from Northern America and Asia, respectively, and the rest (3%) come from other parts of the world. Regarding race, our sample included 33% Caucasian, 31% African, 23% coloured (mixed race), and the minority being Indian and Asian (5% each). In addition, over 66% held a university degree. The median net annual household income is between R200,000 and R350,000 (€12,500–€21,875), coinciding with the average annual household income for South Africa at R270,000 (StatsSA, 2019). However, one-third of the respondents preferred not to provide information about their income.

In order to understand how respondents perceive SO_2 in wine, the study asked several questions. First, question asked, "*do you have allergies on sulphur contained foods and beverages such as wine*?" followed by a question ", *do you know, or have you heard of someone who suffers from sulphite allergies in wine*?" Final and the key question was, *"do you believe that drinking even moderate amounts of wine give you a headache?*" About 25% of respondents reported being allergic to SO_2 in foods and beverages; 61% claim to know someone who suffers from SO_2 effects. In addition, about 68% believed that drinking even a moderate volume of some type of wine may result in headaches.

4 Estimation results

Results for the mixed logit model estimated in the preference space with all factors random and freely correlated are presented in Table 3. The study estimates the utility function and WTP estimates for the experiment. The rationale of these two fundamental analyses is to compare estimates of the experiments and see if there are variations in terms of the rank order of importance of the attributes, statistical level of significance; sign; the magnitude of parameters; and the WTP estimates. Results from pooled data (see column) show all coefficients are statistically significant at any convenient level and have expected signs, conforming to a priori expectations. It implies that respondents are willing to pay a premium for each of the three wine attributes, and the likelihood of purchasing a wine bottle decreases with a price increase. It also discovered large unobserved preference heterogeneity for each of the four random attributes, indicated by the means' extensive and robust statistically significant standard deviations.

Table 3. Parameter estimates for the all MXL model

	Total sample (1)		Real price (2)		Percentage price (3)	
Variable	*mean*	*(s.e)*	*mean*	*(s.e)*	*mean*	*(s.e)*
Random parameter mean						
Rooibos	1.9691***	(0.1538)	2.5318***	(0.2506)	1.9247***	(0.2100)
Organic	0.6175***	(0.1139)	0.8156***	(0.1868)	0.6219***	(0.1549)
Quality	0.0553***	(0.0054)	0.0649***	(0.0092)	0.0599***	(0.0086)
Price	-0.022***	(0.0022)	-0.0419***	(0.0047)	-0.017***	(0.0031)
Random parameter standard deviation						
Rooibos	2.9365***	(0.1745)	3.3372***	(0.3045)	3.5630***	(0.3004)
Organic	1.7764***	(0.1340)	1.7835***	(0.2792)	2.1299***	(0.2147)
Quality	0.0784***	(0.0061)	0.0920***	(0.0117)	0.0932***	(0.0118)
Price	0.0391***	(0.0027)	0.0546***	(0.0052)	0.0336***	(0.0040)
likelihood	-3415.14941		-1834.5272		-1915.819	
LR Chi2	2973.51		1128.75		1069.15	
n(observations)	14,640		7,332		7,308	
r(respondents)	611		306		305	
k(parameters)	10		10		10	

*Notes: *, **, and *** represent coefficients significantly different from zero at 0.1, 0.05, and 0.01 significance level, respectively. Standard errors are provided in parentheses. All parameters are freely correlated, with 1000 draws for simulations.*

When the sample was split between *real price* and *percentage price change*, the test statistics indicate significant differences in the coefficient means for the two samples, 4.23 (p =0.0398) for Rooibos; 5.23 (p = 0.0211) for organic; and 5.32 (p = 0.0147) for quality, implying that the two samples give different estimates (see, column 2 & 3 of Table 3).

While the signs and significance levels are similar for the two samples, the study finds differences in the parameter magnitudes. *For example, real price* had a higher likelihood of choosing all its attributes (Rooibos, organic, and quality score) than *percentage price*, whilst the likelihood of choosing the cost attribute was lower for the *real price* than *percentage price*, an indication that the model fit for *real price* sample was more efficient than that of *percentage price* sample. Furthermore, the statistically significant estimates for derived SD for all parameters suggest the existence of heterogeneity around the mean parameter over the two samples.

There is strong evidence that willingness to pay (WTP) estimates are different for the two samples. WTP for natural preservatives as well as that for quality is at least two times larger for *percentage price* sample, R109.24 vs R60.39 for Rooibos and R3.40 vs R1.54 for quality, whilst their WTP for organic attribute does not statistically differ from the other, R35.30 vs 19.45, with Wald=1.05 (p = 0.3059). Further, the rank order of importance of attributes and importance scores were similar across both samples. *Rooibos & Honeybush* was considered the most important attribute, followed by organic, price and quality, respectively.

Table 4. WTP estimates in Rands per 750ml wine bottle.

	Total sample (1)		Real price (2)		Percentage price (3)	
Rooibos	88.3248***	(11.1016)	60.3993***	(6.2265)	109.2448***	(20.551)
Organic	27.6996***	(5.6485)	19.4582***	(4.4825)	35.3001***	(9.9298)
Quality	2.4845***	(0.3256)	1.5497***	(0.2132)	3.4046***	(0.6929)

*Notes: *, **, and *** indicate the significance of the WTP mean estimates at 10%, 5%, and 1%. Standard errors are provided in parentheses. Wald statistics for the quality test of the WTP means for real price vs percentage price is 9.09 (p = 0.0026) for Rooibos; 1.05 p=0.3059) for organic; and 6.92 (p=0.0085) for quality.*

5 Discussion and Conclusion

There is enough evidence that the way information is framed in choice experiment surveys can impact respondents' decision behaviour. Therefore, if choice experiment surveys are to be used and trusted to value environmental goods and services, it is crucial to determine how sensitive value estimates are to 'price framing'. This chapter contributes to the literature by investigating the impacts of 'price framing' on respondents' choices and welfare estimates using data from a DCE survey on preferences for natural preservatives in wine in the South African wine industry.

The effect examined was the impact of 'price framing' on DCE empirical estimates, presenting the cost attribute to respondents as either *real price* or *percentage price change*. A split sample survey was administered to the same respondent who answered 8 choice scenarios - half of the cards were assigned in *real price,* and another half was presented in *percentage price*. The study hypothesized that since the cost attribute values were similar and only presented to respondents as either *real price* or *percentage price,* they should give similar outcomes. However, the mixed logit model results show that estimated parameters were significantly different in the split sample. The test statistics indicates significant differences in the coefficient means for the two samples, 4.23 ($p = 0.0398$) for Rooibos; 5.23 ($p = 0.0211$) for organic; and 5.32 ($p = 0.0147$) for quality.

Data also indicates that while the signs and significance levels are similar for the two samples, it reveals differences in the parameter magnitudes. *For example, real price* had a higher likelihood of choosing all its attributes (Rooibos, organic, and quality score) than *percentage price*, whilst the likelihood of choosing the price attribute was lower for *real price* than *percentage price*, an indication that the model fit for *real price* sample was more efficient than that of *percentage price* sample. Additionally, the statistically significant estimates for derived SD for all parameters suggest heterogeneity around the mean parameter over the two samples.

There is strong evidence that WTP estimates are different for the two samples. WTP for natural preservatives and quality is at least two times larger for *percentage price*, whilst their WTP for organic attribute does not statistically differ from the other. Additionally, the rank order of importance of attributes was similar across both samples. *Rooibos & Honeybush* was considered most important, followed by organic, price and quality scores, respectively.

These findings suggest that presenting the cost attribute in *real price* will give more efficient results than the *percentage price change.* Because this study is rare, there is limited literature to compare these findings with. However, similar experimental studies on the effects of framing on empirical estimates in DCEs have shown that changes in attribute framing have unintended influences on obtained estimates, resulting in biased conclusions. This study confirms these findings, and DCE practitioners need to be cautious when designing experimental tools. There is a need for well-defined instruments that match individuals' decision environments when making the actual policy choice considered in the CE studies.

In order to reveal people's real preferences for the resources under consideration, DCE practitioners must have a good understanding of individual decision behaviour and the scientific settings of the study. The cost attribute in a CE questionnaire should not only fit the decision context but should also be communicated to participants in a relevant and understandable way. CE practitioners should be mindful that how cost attributes are presented, such as *real price* vs *percentage pricing*, can affect how respondents interpret survey data. Focus group discussions and pilot studies are recommended beforehand to gauge participants' prior beliefs and assess how the cost attribute framing may influence participants' choices.

There are no clear standards for communicating pricing attributes in a DCE scenario or how 'price framing' decisions influence study outcomes. As a result, more research into 'price framing' implications in additional DCE scenarios is advised. This will determine whether these effects exist in other decision situations, and ongoing research on appropriate designs will further quantify the extent of 'price framing' influence in DCE investigations.

The study's main limitation is that it used a DCE on preferences for natural preservatives in the South Africa context as a case study for this methodological research. In addition, this DCE was administered on a sample representative of the generalized adult wine consumer population in Cape Town, South Africa. This generalization and a small population sample may be limiting. More research is needed to test the generalizability of the findings to other populations and other environmental valuation settings. Nevertheless, the results provide insight into the validity and reliability of 'price framing' effects in DCE and environmental valuations. DCE practitioners need to be cautious when designing experimental tools considering that the contextual information provided in stated preference surveys affect results that ultimately influence policy development.

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