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The importance of efficient designs in discrete choice experiments for environmental valuation

Master Thesis

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Abstract

Discrete Choice Experiments (DCEs) are considered to be an appealing approach that is nowadays frequently used among researchers in many fields. No exception is their application in the field of environmental valuation, where we usually deal with relatively small sample sizes. This Master thesis analyzes the efficiency of different experimental designs used in DCEs. Moreover, it tries to examine the effect of prior parameter values in generation of efficient designs for a DCE. All the results are applied on a real case study devoted to climate change adaptations of winemakers in the Rioja region, Spain. The results are obtained through simulation exercises, which are emphasized to be crucial for checking our statistical design before conducting a DCE. The conclusions highlight the use of a specific method to set the prior parameter values necessary for the generation of an efficient design. Finally, the simulation exercises also draw conclusions regarding the trustworthiness of results obtained in the real case study.

Keywords

discrete choice experiments, experimental design, multinomial logit model, simulation exercise

Contents

1 Introduction

In recent years, Discrete Choice Experiments (DCEs) have been experiencing a considerable rise in popularity among researchers. Being used for eliciting the preferences of individuals, the wide applicability of DCEs settles them among powerful tools for a systematic analysis of different markets and fields, such as health economics, marketing and transportation. Moreover, they are widely used with regards to labor and energy markets, education or food choice. In this work, we are going to focus on the use of DCEs in environmental valuation, describing a real case study that analyzes climate change adaptation options of winemakers.

When studying the preferences of individuals, two main approaches are usually considered. Firstly, having been introduced by Samuelson (1948), revealed preference (RP) valuation techniques are based on the actions (choices) of people in the market (what they purchase), through which they reveal their preferences. On the other hand, stated preference (SP) valuation techniques are based on asking people (consumers) to reveal their preferences through hypothetical choices (e.g. in questionnaires). Then, if we are considering DCEs, we are basically focusing on analyzing SP data based on specific hypothetical choice tasks. However, in environmental valuation we work many times with small samples. Nonetheless, it is our goal to obtain as high parameter estimates precision as possible. And this is where we put emphasis on the fundamental part of DCEs – the experimental design.

History of experimental designs has gone through many changes, mainly with respect to the technological development, as it is explained by Kuhfeld (1997). Originally, the so-called orthogonal designs were used, having been accessible in form of tables for researchers. Not only they were available with relatively simple formulas, but also orthogonality usually implied that the parameter estimates would have minimum variance and hence maximum precision. However, this approach worked well in linear models, but in order to avoid possible loss of efficiency in non-linear models, different approaches have emerged. Being based on maximization of the precision of parameter estimates, the efficient designs are nowadays considered to be the cornerstone of DCEs.

The aim of this paper can be then summarized into three main points. Firstly, to analyze the efficiency of different experimental designs used in DCEs. In other words, we are going to compare the performance of selected experimental designs in terms of their efficiency. This will be done through simulation exercises and the consequent display of the distributions of parameter estimates. Secondly, we will analyze the effect of prior parameter values in generation of an efficient experimental design for a DCE. This will be done using a recent method of Bliemer and Collins (2016) for determining the prior parameter values for the generation of efficient designs. In addition to that, we will perform the simulation exercises again using priors that are set deliberately inferior, in order to draw conclusions about the possible differences and the importance of determining the priors correctly. Finally, we are going to apply the results on a real case study devoted to climate change adaptations of winemakers in the Rioja region.

Regarding the structure of this work, in Chapter 2 we are going to introduce the theoretical framework behind DCEs and experimental designs. The theoretical approaches described in this section form a foundation for the empirical application and results presented in the remaining chapters. Chapter 3 presents the context of the stated preference survey conducted for the purposes of the case study to which the results will be applied, but it also serves as a connection between the theoretical aspects described in Chapter 2 and their applications. The results of this paper will be then provided in Chapter 4. All of the above-mentioned issues and consequent conclusions will be summarized and discussed in Chapter 5.

2 Methodological framework

In this chapter, the theoretical framework behind the DCEs is introduced by focusing mainly on the topic of statistical designs as well as on the econometric approach. The differences between Orthogonal, A-efficient and D-efficient designs are explained. The latter two are categorized as efficient designs and they are based on a definition of prior parameter values. The approach devoted to checking the appropriateness of a particular statistical design proposed in this section is based on simulation exercises.

2.1 Discrete choice experiments

A DCE could be formally defined for instance by Ryan, Gerard and Amaya-Amaya (2008) as an attribute-based approach (a survey method) that involves SP data collection. Respondents are presented with a series of choice tasks, while it is crucial to understand that these choice tasks were selected based on the statistical design principles. Apart from many other issues related to DCE, there is a debate in literature regarding the optimal number of choice tasks presented to a respondent, since we have to take into account a question of fatigue. More on this topic can be found for example in Hess et al. (2012).

Since in DCEs we are interested in eliciting the preferences of individuals, this approach has found numerous applications in the literature. On application of DCEs in marketing is elaborated thoroughly for instance in Zwerina (1997), while in transportation McNamara et al. (2013) analyzed the factors that affect older people's decision to relinquish their driver's licence. Moreover, DCEs are applied increasingly in health economics since the mid-1990s and the current state of knowledge as well as potentially fruitful areas for further research regarding this field are studied deeply by Louviere and Lancsar (2009).

No exception to the above-mentioned fields is labor economics, where for example Scotland et al. (2011) analyzed women's preferences for aspects of labor management. Application of DCEs involves a huge variety of other fields, such as energy markets, food choice and education. As indicated in the Introduction section, this work is focused on the environmental valuation field. More precisely, we will aim at the preferences of individuals with regards to climate change adaptation options, but more details will be explained in Chapter 3 devoted to the description of the case study.

Mariel et al. (2021a) address other important issues regarding DCEs, such as the question of dimensionality – the number of alternatives and also the number of attributes. We have to understand that respondents are choosing in each choice task presented between two or more alternatives and this number of alternatives negatively influences their response efficiency, since the complexity increases with a greater number of alternatives. Moreover, the number of alternatives also influences the frequency of choosing the alternative representing the current situation (statu quo). More about the conclusions on this issue is presented by Oehlmann et al. (2017).

Last but not least, the differences between alternatives in a choice task are characterized by the attributes we are interested in. For this reason, the number of attributes is another important issue that is deeply discussed in literature. As opposed to number of alternatives, Meyerhoff et al. (2015) concluded that there is no negative effect of an increase in the number of attributes on response efficiency. Moreover, taking into account that an attribute is determined by its levels, they found that an increase in the number of attribute levels tends to positively affect the consistency of choices.

It can be summarized that DCEs are based on choice tasks that propose two or more alternatives and individuals have to choose one of them. Each alternative is defined by certain characteristics called attributes, which are determined by their levels. Then, given the choice of an individual, we can estimate various econometric models (usually Logit-type models) that are based on different assumptions. The econometric approach used for the purposes of this Master thesis is the subject of discussion in the following section.

2.2 Econometric approach

Let us consider the McFadden (1974) Random Utility Maximization (RUM) model, which assumes the utility-maximizing behavior of individuals. Moreover, let us consider that the individual n ($n = 1,2,\dots,N$) faces a choice task s (where $s = 1,2,\dots,S$) with three alternatives ($j = 1,2,3$). Then, the indirect utilities U_{sn1}, U_{sn2} and U_{sn3} defined in (2.1) represent the utility obtained by individual n in each of the three alternatives in a given choice task s:

$$U_{sn1} = V_{sn1} + \varepsilon_{sn1} = ASC_1 + \sum_{k=1}^{K} \beta_k x_{sn1k} + \varepsilon_{sn1},$$

$$U_{sn2} = V_{sn2} + \varepsilon_{sn2} = ASC_2 + \sum_{k=1}^{K} \beta_k x_{sn2k} + \varepsilon_{sn2}, \qquad (2.1)$$

$$U_{sn3} = V_{sn3} + \varepsilon_{sn3} = \sum_{k=1}^{K} \beta_k x_{sn3k} + \varepsilon_{sn3},$$

where ASC_j is an alternative-specific constant (which is omitted from the third equation in (2.1) due to identification issues), ε_{snj} is a random error term, K is the number of attributes, V_{snj} is the deterministic utility linear in unknown parameters β_k ($k = 1,2,\dots,K$) and x_{snjk} represents the level of attribute k, corresponding to respondent n, alternative j and choice situation s.

McFadden (1974) explains that alternative i is chosen in a choice situation s by individual n, if and only if for every alternative j such that $j \neq i$ holds that $U_{sni} > U_{snj}$. Moreover, the RUM model also assumes that the individual's utility is not observed by researcher – only some individual characteristics and some alternative-related attributes. For this reason the random factors are represented by the error term ε_{snj} in (2.1), while different assumptions about the random error term lead to different models.

In case of the Multinomial logit (MNL) model, the random error terms are assumed to be *i.i.d.* (independently identically distributed) type I extreme values (Gumbel distribution) over time, people and alternatives. Then, the probability of choosing alternative j by individual n in choice situation s, P_{snj}, is defined for instance by Train (2009, Ch. 3) in equation (2.2):

$$P_{snj} = \frac{exp\left(\sum_{k=1}^{K} \beta_k x_{snjk}\right)}{\sum_{j \in J_{sn}} exp\left(\sum_{k=1}^{K} \beta_k x_{snjk}\right)}. \tag{2.2}$$

However, it is crucial to understand that true parameter values, β_k, are unknown. Therefore, if we want to compute choice probabilities defined in (2.2) it is necessary to set parameters β_k to specific values. These are usually obtained in the literature by a maximum-likelihood-based estimation method.

Finally, Mariel et al. (2021a) state that in RP studies, values of the variables x_{snjk} are determined by the collected revealed preference data, while in SP studies, these values are artificially generated by a statistical design. Hence, in the following section we will focus on the topic of statistical designs, explaining the differences between Orthogonal, A-efficient and D-efficient statistical design.

2.3 Statistical design of the choice tasks

This section follows closely Mariel et al. (2021a, Ch. 3.2) and Ngene manual (ChoiceMetrics 2021, Ch. 5-8). Firstly, we should mention that the advantage of conducting an SP survey, as opposed to RP, is the ability to control the choice tasks that are presented to respondents. However, not only we have to make sure that these presented choice tasks are relevant, but also that by choosing a particular statistical design we will maximize its informational content. To put it in other way, we have to set up the alternatives in a choice task in such a way that we would be able to learn as much as possible about the preferences of the respondents.

Starting with orthogonal designs, these ensure mutual independence of the attribute levels. Since the correlation between the attribute levels is removed, we can more easily determine the effect of each of the attributes on the dependent variable. However, it is crucial to understand that when we are considering the discrete choice models, where the choice probabilities are highly non-linear, the statistical optimality of the orthogonal design might no longer hold. Moreover, it is pretty common that alternatives which are more expensive and at the same time are worse with respect to a qualitative point of view can appear in a generated design if no restrictions to make the experimental design realistic are used. In addition, as it is explained by Yao et al. (2015), even though orthogonal designs are robust with regards to the modelling assumptions, we have to cope with the problem of the loss of efficiency. Thus, in the following paragraphs we will focus more on the efficient designs.

The definition of efficient designs is related to the minimization of standard errors obtained as a result of the corresponding estimation of parameters from the data yielded by the design. We know that standard errors are given as the square root of the diagonal terms of the asymptotic variance-covariance (AVC) matrix of parameter estimates, whose consistent estimator written in the formula (2.3) is given as the negative inverse of the matrix of second-order derivatives of the log-likelihood function (the Hessian matrix):

$$\Omega_N\left(X,Y,\tilde{\beta}\right) = -\left[\frac{\partial^2 L_N\left(X,Y,\tilde{\beta}\right)}{\partial\beta\,\partial\beta'}\right]^{-1}, \tag{2.3}$$

where N is the number of respondents in the sample, X is the experimental design, Y is representing the outcomes of the survey and $\tilde{\beta}$ are the parameter estimates, since the true parameter values β are unknown. In case of the MNL model, the log-likelihood function can be formulated in equation (2.4) as following:

$$L_N(X, Y, \tilde{\beta}) = \sum_{n=1}^{N} \sum_{s=1}^{S} \sum_{j=1}^{J} y_{snj} \ln\left(P_{snj}(X, \tilde{\beta})\right), \quad (2.4)$$

where y_{snj} equals one in case alternative j is chosen in choice situation s by respondent n and $P_{snj}(X, \tilde{\beta})$ is the corresponding choice probability already defined in (2.2). As it was stated earlier, by selecting a certain statistical design we are trying to maximize the informational content in our survey (and therefore minimize the uncertainty). However, in that case it would be preferable to assess a design according to a single number, not a matrix. Therefore, we can reduce the dimensionality of the AVC matrix using the efficiency measures.

A-efficiency measure minimizes the so-called A-error[1] given by the formula (2.5), which is determined by the trace of the AVC matrix, and hence excludes the covariances between parameter estimates from the computation:

$$A_p\text{-} error = \frac{tr\left(\Omega_N(X, Y, \tilde{\beta})\right)}{K}, \quad (2.5)$$

where K is the number of estimated parameters. When the A-error is low enough, we can call the design as A-efficient. It should be noted that because of the large number of possible design combinations we might not be able to find the design with the lowest possible A-error (also called the A-optimal design). The most popular measure in literature, however, is the D-efficiency measure that takes into account also the covariances between parameters estimates. This measure minimizes the D-error given by the determinant of the AVC matrix, as it is shown in the formula (2.6):

$$D_p\text{-} error = det\left(\Omega_N(X, Y, \tilde{\beta})\right)^{1/K}. \quad (2.6)$$

Then, analogically as above, the design with sufficiently low D-error is called D-efficient, while we might not always be able to find the D-optimal design with the lowest possible D-error due to the dimensionality of the design setting.

[1] The subindex "p" represents "priors" or more precisely the fact that we are assuming our priors, $\tilde{\beta}$, to be good approximation of the true unknown parameters. We will talk more about the issue of priors further in the text.

2.4 On determining priors for the generation of efficient designs

The aim of the Chapter 2.4 is to generally introduce a possible strategy on determining priors for the generation of efficient designs which is based on the article of Bliemer and Collins (2016). As showed in the formula (2.3), the AVC matrix depends on the parameters of the model (e.g. MNL) and thus the prior parameter values need to be set, if we want to generate an efficient design. According to Bliemer and Collins (2016), we can either search for the prior parameter values in literature or conduct a pilot study (with the latter being probably more costly) or use a specific strategy they propose that is described below.

Let us assume that a prior parameter value, $\tilde{\beta}_k$, has normal distribution with mean μ_k and standard deviation σ_k. Then, the scaled prior, $\tilde{\beta}_k^*$, has normal distribution as it is shown in (2.7), where $\tilde{\lambda}$ is the scaling parameter.

$$\tilde{\beta}_k^* \sim \mathbb{N}\big(\tilde{\lambda}\mu_k, \tilde{\lambda}\sigma_k\big). \tag{2.7}$$

First of all, before conducting any computation, it is important to rank the attribute levels with respect to the expected preferences, taking into account that the range of these levels needs to be determined. Secondly, using analyst's educated guesses, we would like to set reasonable values for μ_k and σ_k.

For this we need to determine the base attribute (subindex "b"), which should have ideally continuous levels (e.g. price attribute such as subsidy). Then, each attribute is compared with the base attribute by making trade-offs between the two attributes (remember, one is the base attribute and the other is selected from the remaining attributes). To put it more clearly, by making the trade-offs we would like to set two alternatives – Option 1 and Option 2 – such that these alternatives are utility-balanced (or in other words, that these options are equally preferred).

An example on how to set these two options in case the attribute that is compared with the base attribute is qualitative and has only two levels (which are coded as 0 and 1) follows. Bliemer and Collins (2016) explain that in Option 1 we set the base attribute to its midpoint and the other attribute to 0. However, in Option 2 we change its value from 0 to 1, while for the base attribute an analyst has to provide (using his educated guess) a range of values for which there is utility balance between the two options considered. Having done this, we can then easily compute the minimum and maximum tradeoffs for each of the two attributes:

Δ_k^{min}, Δ_k^{max}, Δ_b^{min} and Δ_b^{max}. Consequently, we get the reasonable values for μ_k and σ_k by applying the formulas (2.8) and (2.9) below:

$$\mu_k = \frac{\Delta_b^{min} + \Delta_b^{max}}{\Delta_k^{min} + \Delta_k^{max}}, \tag{2.8}$$

$$\sigma_k = \frac{1}{1.96}\left|\frac{\Delta_b^{max}}{\Delta_k^{max}} - \mu_k\right|. \tag{2.9}$$

Finally, we need to determine the scale, $\tilde{\lambda}$, in order to obtain the prior parameter value as in the formula (2.7). Bliemer and Collins (2016) propose to (randomly) construct sample choice tasks with two alternatives (hence $J = 2$) and provide (using an educated guess) the probability of choosing each alternative, denoted as f_{s1} and f_{s2}, where $f_{s2} = 1 - f_{s1}$. With higher number of choice tasks constructed, the reliability of calibration of $\tilde{\lambda}$ increases. Then, we find $\tilde{\lambda}$ that best fits the expected probabilities by solving the maximization problem of the log-likelihood function shown in (2.10):

$$L(\tilde{\lambda}) = \sum_{s=1}^{S}\sum_{j=1}^{J=2} f_{sj}\, log(P_{sj}), \tag{2.10}$$

where P_{sj} is the choice probability of choosing alternative j in a choice situation s that was defined earlier in (2.2). The solution can be found for instance by using Excel solver (as it was done also later in the following chapters when applying this method to a particular case study), with the starting value of $\tilde{\lambda}$ equal to 0.

The strategy of Bliemer and Collins (2016) on determining the priors for the generation of efficient designs described above has already been used in the literature. De Marchi, Cavaliere and Banterle (2021) for instance used the method with regards to the cisgenic food and identifying motivations for its acceptance. Another example from the literature could be Nthambi et al. (2021), who applied the strategy in a discrete choice experiment with farmers in Kenya in order to study how poor governance can affect the process of implementing climate change adaptation measures.

2.5 Checking your statistical design

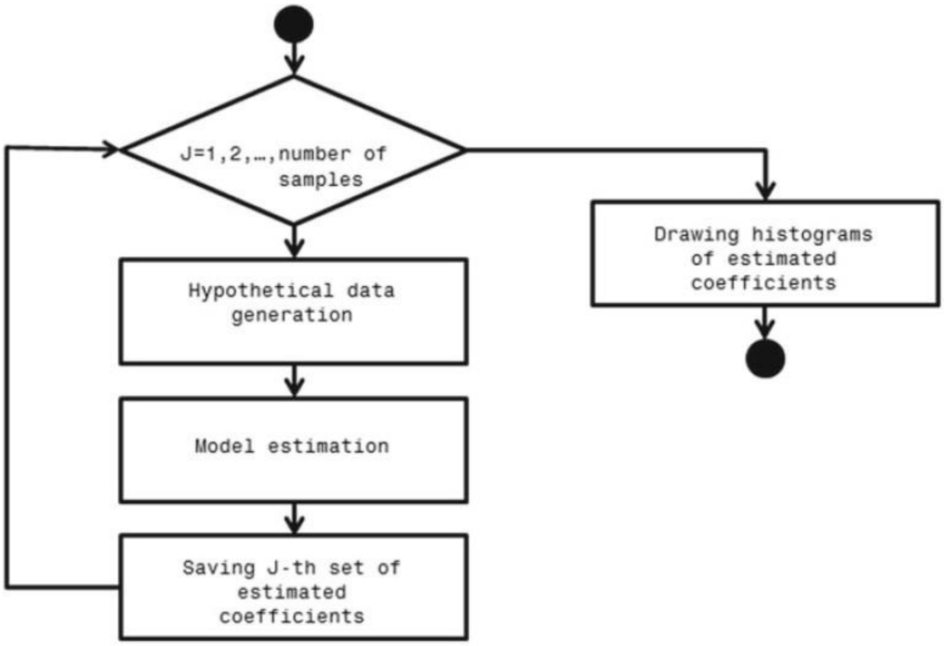
The last section of the Chapter 2 follows closely Mariel et al. (2021a, Ch. 3.3) and tries to describe the ideas behind the simulation exercise performed for the purposes of this Master thesis. We know that in a linear regression, the explanatory variables form the so-called right-hand side matrix. However, considering what has been said so far in the previous chapters, it is clear that this matrix is in a discrete choice model determined by the variables shaping the deterministic utility, V_{snj}, which has been defined earlier in equation (2.1) when discussing the RUM model. Hence, we see that what defines the right-hand side matrix in a DCE is the chosen experimental design.

For the above-mentioned reasons, we would be interested in checking the appropriateness of an experimental design, or in other words, of the right-hand side matrix. This can be done through a simulation exercise, whose process is summarized in Figure 2.1 below. For each simulation exercise performed, we have to set the number of samples. Moreover, as the figure suggests, hypothetical data sets need to be generated for this exercise. This can be done for instance by using the Ngene software, according to the instructions thoroughly described in Ngene manual (ChoiceMetrics, 2021) and also according to the theory explained throughout the previous chapters. Hence, we can generate an Orthogonal, A-efficient and D-efficient statistical design, setting the prior parameter values in case of the efficient designs to those computed using the approach of Bliemer and Collins (2016).

As we have already indicated in Chapter 2.2, we will estimate the MNL model, where we assume the errors, ε_{snj}, to be Gumbel-distributed. Hence, in order to perform a simulation exercise, we would need to generate J times (where J is the number of samples) three sets of Gumbel-distributed errors (since we have three alternatives) for each sample size considered. It should be noted that we will analyze the efficiency of different experimental designs also for different sample sizes, while more about this issue will be provided in the Chapter 3 with regards to the case study.

Moreover, in each simulation exercise, regardless of the sample size or the statistical design generated, we will assume the priors computed using the approach of Bliemer and Collins (2016) to be hypothetical population parameter values. As we mentioned earlier, we will repeat the estimation process J times, for each sample size and each statistical design considered, while in each iteration we will save the parameter estimates. The iterated estimation process together with the generation of errors can be done for example in R.

Figure 2.1 Simulation exercise flowchart



Source: Mariel et al. (2021a, Ch. 3.3)

To put things more clearly, let us provide the following example. Imagine we have 50 individuals and each faces one choice situation (for simplicity) with three alternatives. Then, having generated certain statistical design in Ngene software, we would like to perform a simulation exercise to check the generated design, setting $J = 1000$. Consequently, we would generate 1000 times three sets of Gumbel-distributed errors according to the sample size. Hence, for each individual n (where $N = 50$), we would generate 1000 utilities U_{n1}, U_{n2} and U_{n3} and thus, 1000 hypothetical choices. Then, it would be possible to estimate MNL model 1000 times, while saving the parameter estimates in each iteration. We remind the reader that for all these actions described in this small example, the prior parameter values should have been computed beforehand, for example using the method suggested in section 2.4. Finally, by drawing the distribution of the parameter estimates, we can analyze properties and appropriateness of the generated design.

To conclude section 2.5, we will be interested in displaying the distribution of estimated parameters using boxplots and by comparing the distributions across statistical designs as well as different sets of priors used when generating the D-efficient design in Ngene, not only we can graphically compare the efficiency of different statistical designs used in a DCE, but also we can analyze the effect of priors in generation of an efficient experimental design. These issues will be subject of detailed discussion in Chapter 4.

3 Case study

All the theoretical concepts explained in this work will be applied to a particular case study, which is going to be described in the following paragraphs of the Chapter 3. The case study follows closely Mariel et al. (2021b), who conducted a discrete choice experiment aimed to analyze the preferences of winemakers in the Spanish Rioja wine appellation with regards to adaptation strategies to climate change.

3.1 Description of the context

The Rioja wine region, being famous across Spain for the production of still red wines, spans an area including three autonomous regions of the Northern Spain: La Rioja, Navarre and the Basque province of Álava. Unsurprisingly, the global phenomenon – climate change – affects considerably also the Rioja region, taking into account that changes in temperature can influence the quality and quantity of wine produced, which is concluded for instance also by Ashenfelter and Storchmann (2016).

Therefore, different adaptation strategies varying in costs and longevity of the solution can be considered. The case study focuses on the following strategies: use of different clones of authorized grape varieties (authorized in a sense that the Regulatory council of Rioja region explicitly defines the varieties that can be used), relocation of existing vineyards to a higher altitude or a different orientation, implementation of a full irrigation system in all vineyards of a winemaker, different ways of covering the grape (such as different pruning methods or by using vegetative or artificial structures that help to shade the vines) and oenological adaptations. According to Naulleau et al. (2021), better solutions are obtained through a combination of the adaptation strategies, rather than applying only one of them.

3.2 Stated preference survey

The questionnaire presented to winemakers in the Rioja region consisted of two parts – short introductory questions regarding basic information about the vineyard, type of wine produced and also regarding their beliefs about climate change, while the second part was a discrete choice experiment, where each winemaker was shown five choice cards with three alternatives. One of the alternatives represented business-as-usual option (statu quo) and the remaining two were hypothetical alternatives including a combination of aforementioned strategies to counter climate change.

Table 3.1 Attributes and their levels

Attribute	Levels
Grape	No change
	Different clones
Relocation	No change
	Relocation to higher altitude or different orientation
Irrigation	No change
	Implementation of a full irrigation system
Grape coverage	No change
	Implementation of specific pruning or driving
	Implementation of a structural cover (vegetal or artificial)
Oenological adaptations	No change
	Implementation of specific adaptations (reverse osmosis, spinning cone, etc.)
Subsidy	0 €/ha, 1000 €/ha, 3000 €/ha, 5000 €/ha, 7000 €/ha, 9000 €/ha

Source: Mariel et al. (2021b)

These strategies determined the levels of five attributes, which described, together with monetary attribute *Subsidy*, the two hypothetical alternatives. An overview of the attributes and their levels, based on the adaptation strategies mentioned above are being shown in the Table 3.1. As it is explained in Mariel et al. (2021b), the attributes and their corresponding levels stated in Table 3.1 were selected according to the literature recommendations on this particular topic of a DCE. Moreover, it is important to mention that the five non-price attributes were dummy-coded with value zero representing the *No change* level. Therefore, two dummy variables needed to be created regarding the *Grape coverage* attribute, each one representing the corresponding implementation attribute level. The monetary attribute *Subsidy* is a hypothetical amount of money received from local authorities for implementation of an adaptation strategy.

Figure 3.1 presents an example of a choice card based on the description of adaptation strategies, attributes and their levels provided in the previous paragraphs. Mariel et al. (2021b) explained that wineries that shaped the target sample were randomly drawn from the list of wineries made by the Regulatory Council (2021). The administration of the questionnaire including five choice cards was in form of the in-person pencil-and-paper individual home interviews. In the final sample, 32 questionnaires were deemed valid and this means, keeping in mind that each respondent filled five choice cards, that the number of observations was 160.

Figure 3.1 Choice task example

	NO CHANGE	STRATEGY A	STRATEGY B
GRAPE	No change	Different clones	Different clones
RELOCATION	No change	No change	Change in location (in orientation, higher altitudes)
IRRIGATION	No change	Full irrigation	No change
GRAPE COVERAGE	No change	Pruning methods, conduction systems	Structural coverage (vegetative or artificial)
ENOLOGICAL ADAPTATIONS	No change	No change	Specific adaptations (reverse osmosis, spinning cone)
SUBSIDY	*0€/ha*	*4,000€/ha*	*7,000€/ha*
I choose (only one option)	☐	☐	☐

Source: Mariel et al. (2021b)

In the last paragraphs of section 3.2 the results obtained in the case study will be briefly summarized. These results were obtained using the econometric approach introduced in Chapter 2.2. As it was concluded by Mariel et al. (2021b), relatively high willingness is shown by the Rioja winemakers towards adopting the changes. Moreover, implementation of the strategies regarding irrigation, grape coverage and oenological adaptations increases the utility of the winemakers as well as an increase in the subsidy received (as expected).

The preferences concerning the use of different clones of authorized grape varieties were unclear. On the other hand, relocation to a higher altitude or a different orientation was viewed negatively by the Rioja winemakers, with this adaptation strategy decreasing their utility. This conclusion is not surprising, since a change in the vineyard location is not only costly, but also time-demanding. Moreover, the winemakers were even willing to pay (hypothetically) their own money in order to avoid this adaptation strategy.

3.3 Applying the theoretical concepts to the case study example

The last section of this chapter adjusts some of the general equations and approaches presented in Chapter 2 with regards to the case study of winemakers in Rioja region. Starting with the econometric approach, it should be noted that the number of attributes equals seven ($K = 7$), since the attribute regarding grape coverage has 3 possible levels and two dummy coded variables were created. This has already been discussed when describing the attributes and their levels in Table 3.1.

Then, the deterministic utility defined in (2.1), V_{snj}, linear in unknown parameters β_k, is for each alternative j (where $j = 1,2,3$) given by alternative-specific constant, by six dummy coded variables stating whether or not the corresponding adaptation strategy is hypothetically chosen to be implemented and, finally, by continuous variable representing the subsidy attribute, according to the Table 3.1. The deterministic utility V_{snj} can be written as:

$$\begin{aligned} V_{snj} = ASC_j &+ \beta_1 grape_{snj} + \beta_2 relocation_{snj} + \beta_3 irrigation_{snj} \\ &+ \beta_4 cover\_pruning_{snj} + \beta_5 cover\_structure_{snj} \\ &+ \beta_6 oenology_{snj} + \beta_7 subsidy_{snj}. \end{aligned} \tag{3.1}$$

Regarding the simulation exercise, we have already indicated in Chapter 2.5 that different sample sizes would be considered. Since each winemaker was shown five choice cards, the sample size is then obtained by multiplying the number of winemakers by five. For the purposes of the simulation exercise as well as checking the statistical designs generated in Ngene software, we considered four sample sizes given by: 32, 64, 128 and 256 winemakers. In this way we obtained the hypothetical data sets needed for the model estimation and consequent save of the estimated parameters in each iteration.

4 Results

In Chapter 4 the results that were obtained by applying the concepts introduced in the methodological framework are going to be described. We will start by displaying the computed prior parameter values, with this process being explained in detail. Consequently, we will focus on analyzing and comparing the efficiency of selected statistical designs, according to the concepts discussed earlier in the previous chapters (regarding the simulation exercises). Moreover, the effect of priors in generation of the D-efficient design will also be studied. The results section will be then concluded with the application of the results on a real case study devoted to climate change adaptations of winemakers in the Rioja region.

4.1 Determining priors in the case study paradigm

The following paragraphs describe the application of the strategy of Bliemer and Collins (2016) on determining prior parameter values for the generation of efficient designs to the real case study of winemakers in Rioja region. This method was introduced generally in Chapter 2.4 and now we will correspondingly follow those steps and formulas to obtain the priors, since they are essential for the simulation results discussed later. In addition, Appendix A includes all the necessary computations carried out in Excel.

As it was mentioned earlier, before applying any formula, we need to determine the range of attribute levels, while ranking them with regards to the expected preferences. This is shown in the Table 7.1 in Appendix A. Since all the attributes except for *Subsidy* are dummy-coded, the ranking and range determination of the attribute levels then become trivial. In case of the subsidy attribute, the values displayed (in thousands of euros per ha) were determined in consultation with experts in Rioja wine region and range between 0 €/ha (status quo) and 9000 €/ha.

Second step is to set reasonable values for μ_k and σ_k according to formulas (2.8) and (2.9). Firstly, we determine the base attribute with continuous levels – *Subsidy*. Then, we will compare each of the dummy-coded attributes with the base attribute by making trade-offs between the two attributes. This is done in Table 7.2 in Appendix A by constructing two equally preferred alternatives – Option 1 and Option 2. Since there are six dummy-coded attributes to be compared with Subsidy, we have to construct these options under six comparison situations.

As Table 7.2 suggests, each of the dummy-coded attributes changes its value from zero to one when we move from Option 1 to Option 2. Hence, the minimum and maximum tradeoff, Δ_k^{min} and Δ_k^{max}, in this simple case will be always one. With regards to the base attribute, the situation is different. In Option 1 we have to set the base attribute to its midpoint – in our case, the value 5000 €/ha was selected, while in Option 2 we have to set the range of values for which there is utility balance between the two options. This was again done using educated guess and expert judgements of the researchers.

To interpret the meaning of the values set in Option 1 and Option 2, let's consider for instance the second comparison including *Relocation* attribute in Table 7.2. We notice that relocation of existing vineyards (changing the value of *Relocation* variable from zero to one) is viewed so negatively by the winemakers that they would be even willing to pay between 2000 €/ha and 3000 €/ha of their own money (hypothetically) to avoid it. In other words, there exists no such positive value of subsidy potentially received that would compensate the application of this adaptation strategy and what is more, such value is even negative as a sign of high unwillingness towards this strategy. Similarly, the same applies for the *Grape* attribute. The interpretation of the remaining comparisons is simpler, since the ranges of subsidy values in Option 2 just represent the amount of money which the winemakers consider to be appropriate for application of a corresponding adaptation strategy. Then, the minimum (resp., maximum) subsidy tradeoffs are computed as a difference between the minimum (resp., maximum) value in Option 2 and the midpoint 5000 €/ha in Option 1. Consequently, by using formulas (2.8) and (2.9) we get reasonable values for μ_k and σ_k, which are displayed on the right side of the table.

Finally, the remaining step is to determine the scale, $\tilde{\lambda}$. Following the steps described in Chapter 2.4, we randomly constructed 16 sample choice tasks with two alternatives, which are displayed in Table 7.3 in Appendix A. Setting up the starting value of scale parameter to zero ($\tilde{\lambda} = 0$), we computed for each alternative under each choice situation the deterministic utility, V_{sj}, as in formula (3.1) and also the MNL choice probabilities, P_{sj}, as in (2.2). Moreover, relying again on educated guess of experts, we determined the probabilities of choosing each alternative, f_{sj}. Then, using the Excel solver we solved the maximization problem of the log-likelihood function shown in (2.10) to get the optimal value of the scale parameter, $\tilde{\lambda}$, with the maximum value of the log-likelihood function being -7.106, as it is shown in the right bottom corner of Table 7.3. The optimal value of $\tilde{\lambda}$ is equal to 0.313 and the values of scaled priors were consequently computed as $\tilde{\beta}_k^* = \tilde{\lambda}\mu_k$, according to formula (2.7). The computed values are displayed at the top of Table 7.3, but we include them separately also in the Table 4.1 below.

Table 4.1 Computed prior parameter values by applying the strategy of Bliemer and Collins (2016)

Attribute:	Grape	Relocation	Irrigation	Coverage (pruning)	Coverage (structure)	Oenological adaptations	Subsidy
Scaled prior $\tilde{\boldsymbol{\beta}}_k^*$	-0.625	-0.782	0.782	0.469	0.469	0.234	0.313

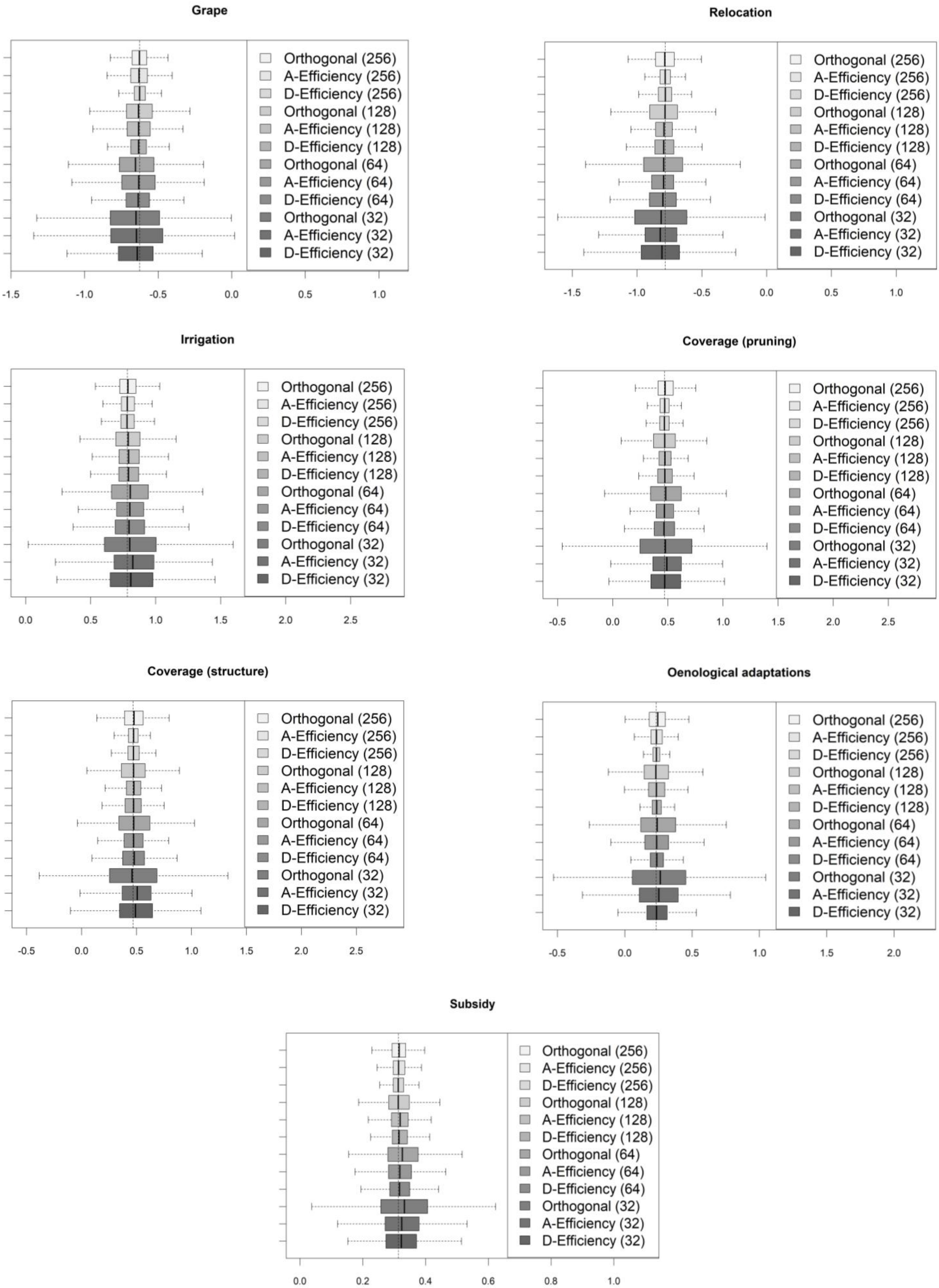
4.2 Analyzing the efficiency of selected statistical designs

Having computed the priors in Table 4.1, we were consequently able to generate in Ngene software the orthogonal, A-efficient and D-efficient statistical design for each sample size considered, according to what was explained in Chapter 3.3. It should be mentioned that not only are the above-computed prior parameter values necessary for the generation of the statistical designs considered, but also we will assume these priors to be the hypothetical population values when performing the simulation exercises according to the process explained in Chapter 2.5, setting the number of samples to 1000. In this way we estimated MNL model 1000 times for each sample size and statistical design considered and we were thus able to display using boxplots the parameter estimates distributions based on different designs. The results are shown in the Figure 4.1.

Each of the seven displayed subplots in Figure 4.1 represents the corresponding parameter β_k from the equation (3.1). Since we are considering three statistical designs and four sample sizes (given by the number of winemakers written in brackets in the legend of a subplot in the Figure 4.1), each subplot contains 12 boxplots of the parameter estimates distributions from the simulation exercises. Several conclusions can be drawn.

Firstly, we notice that the orthogonal design can be considered the least efficient design out of the three statistical designs, since for six out of seven attributes (excluding *Grape* attribute), the interquartile range of the distributions of their corresponding parameter estimates is clearly the widest regardless of the sample size. This result can be viewed as expected, since we have already explained in Chapter 2.3 that orthogonal designs work well in linear models, but in discrete choice models where the choice probabilities are highly non-linear, we might face a loss of efficiency.

Figure 4.1 Comparing the distributions of parameter estimates across statistical designs



However, from the Figure 4.1 we cannot conclude that using D-efficient design instead of A-efficient design leads to a higher efficiency of parameter estimates. If we look at the distributions of parameter estimates corresponding to the attributes *Coverage (pruning)*, *Coverage (structure)* and *Relocation*, we would favor the A-efficient design regardless of the sample size. Having observed these results, the following conclusions can be drawn.

As far as the efficient designs concerned, their use in DCEs leads to a higher efficiency of the parameter estimates, compared to using the orthogonal design. Secondly, we notice that whether A-efficient or D-efficient design leads to a higher efficiency depends on the attributes considered and the choice would be most probably dependent on a particular case. Therefore, the most important message of the section 4.2 would be that when preparing our DCE, then in search of a higher efficiency of parameter estimates it is recommended to perform a simulation exercise to determine the statistical design to be used.

4.3 Effect of priors in generation of the D-efficient design

Since one of the purposes of the thesis is to analyze the effect of priors in generation of an efficient design, we generated in this section three additional D-efficient designs, each time using a different set of prior parameter values. This simulation exercise is, therefore, devoted to the comparison of four cases. The first case is the D-efficient design generated by the Bliemer-Collins (2016) approach, while the second is a D-efficient design generated by the use of Bliemer-Collins (2016) priors whose signs were reverted. In the third and fourth case relatively small priors close to zero with reverted signs were used. These three additional sets of priors represent clearly non-adequate priors that should have a negative impact on the design efficiency. All the analyzed sets in this section are presented in Table 4.2.

The labels used in Table 4.2 as well as later in the results are as follows: priors obtained by the method of Bliemer and Collins (2016) are labeled as “B&C”, while these exact same priors, but with reverted signs, are labeled as “B&C signs”. The sets containing relatively small priors (0.100) with signs corresponding to B&C priors are labeled as “All 0.1” and finally, the relatively small priors with reverted signs are labeled as “All 0.1 signs”.

Hence, the purpose of this section is clear – by performing the simulation exercises again with different sets of prior parameter values and by saving the parameter estimates in each iteration, we would be able to compare the distributions of the parameter estimates using boxplots and consequently draw conclusions whether priors of Bliemer and Collins (2016) lead to a higher efficiency of parameter estimates.

Table 4.2 Alternative sets of prior parameter values for the generation of D-efficient design

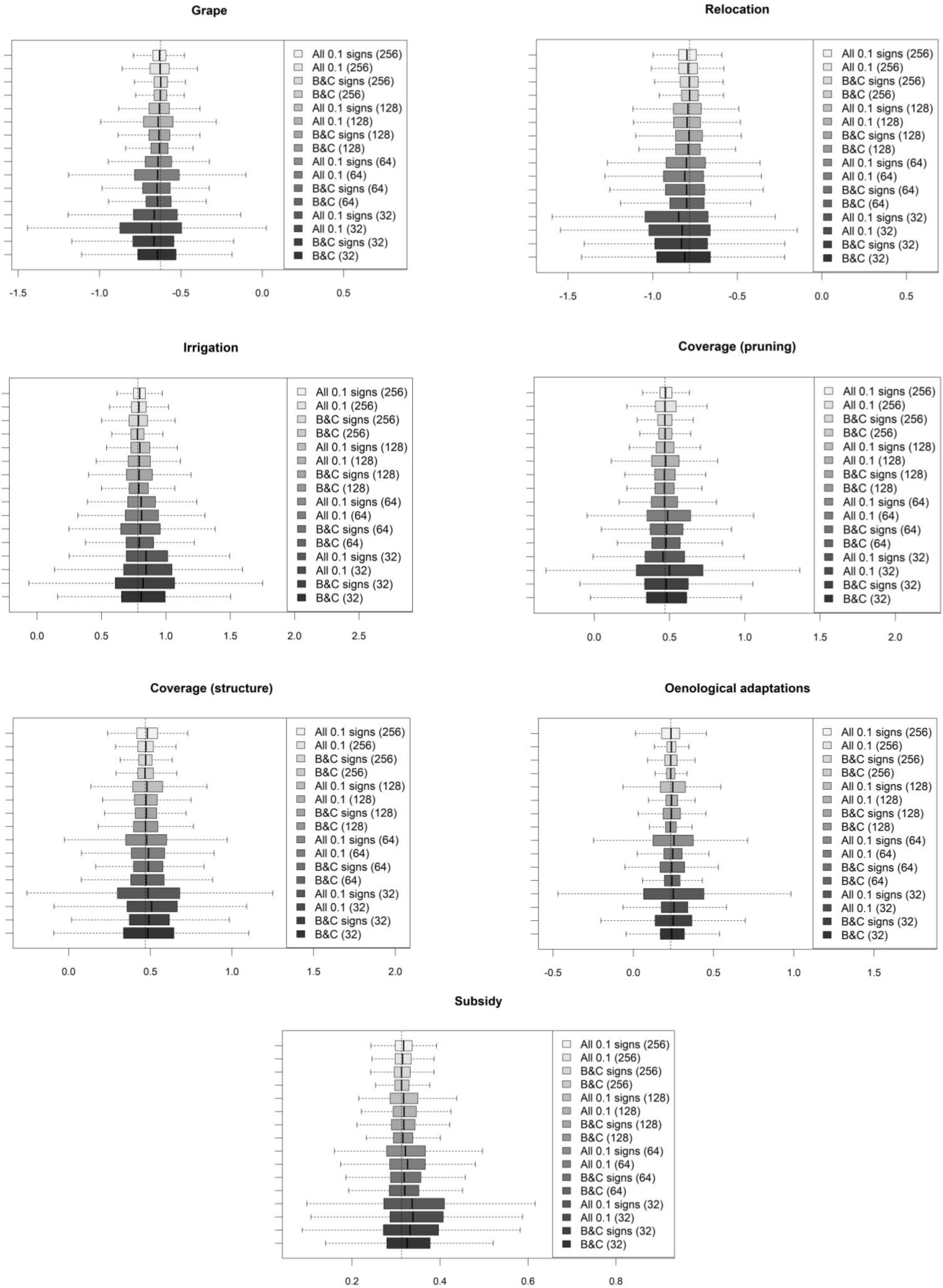
Attribute:	Grape	Relocation	Irrigation	Coverage (pruning)	Coverage (structure)	Oenological adaptations	Subsidy
B&C	-0.625	-0.782	0.782	0.469	0.469	0.234	0.313
B&C signs	0.625	0.782	-0.782	-0.469	-0.469	-0.234	-0.313
All 0.1	-0.100	-0.100	0.100	0.100	0.100	0.100	0.100
All 0.1 signs	0.100	0.100	-0.100	-0.100	-0.100	-0.100	-0.100

It is very important to understand that even though different sets of priors were used in the process of generation of the D-efficient designs in Ngene, we still assumed the priors of Bliemer and Collins (2016) to be the hypothetical population values when performing the simulation exercises in R. Then, the distributions of the parameter estimates are displayed in the Figure 4.2, where analogically as before the numbers in brackets represent the number of winemakers determining the sample sizes.

To analyze the results obtained from the Figure 4.2, we notice that using the priors of Bliemer and Collins (2016) has not always led to a higher efficiency of parameter estimates. This is the case for the parameter estimates corresponding to attributes *Coverage (pruning)* or *Coverage (structure)*. However, it can be clearly seen that on average, "B&C" priors help to improve the efficiency of parameter estimates, since the interquartile ranges of the displayed distributions are in majority of cases smaller than those of "All 0.1" and "All 0.1 signs" priors regardless of the sample size considered. Moreover, as Figure 4.2 suggests, setting the "correct" signs of the prior parameter values increases the design efficiency on average.

Nevertheless, the conclusion drawn from this particular analysis has pretty much in common with the one drawn in the Chapter 4.2. It seems that we cannot use the suggested methods and approaches automatically, since it might not be applied to all possible cases, but it is recommended to run simulation exercises before constructing our DCE.

Figure 4.2 Comparing the distributions of parameter estimates using different sets of priors



4.4 Comparing the results with the case study

This section compares the computed prior parameter values from the Table 4.1 with the estimated parameter values from the case study. The reasoning behind this approach is clear. We have concluded in the previous section of this chapter that even though it cannot be taken literally, determining priors according to Bliemer and Collins (2016) leads to a higher efficiency of parameter estimates. What is more, we then assumed these computed scaled priors to be the hypothetical population values in our simulation exercises.

Hence, if we trust these prior parameter values, we might be interested in comparing them with the estimated parameter values from the case study in order to draw conclusions whether they are close enough to be trusted. Table 4.3 displays the estimated values of the coefficients that appeared in Mariel et al. (2021b), where the sample size was given by 32 winemakers.

Also, we have already discussed the conclusions about willingness of winemakers regarding the adaptation strategies, who are in favor of implementation of the strategies regarding irrigation, grape coverage and oenological adaptations, while being reluctant towards the strategies involving relocation to a higher altitude. The preferences towards the use of different clones of grapes remain unclear, since we do not reject the null hypothesis at 5 % significance level that the estimated coefficient of *Grape* attribute equals zero.

Table 4.3 Estimated parameter values from the real case study

	MNL		
	Estimate	*Robust st. err.*	
Grape	0.003	0.41	
Relocation	-0.556	0.33	*
Irrigation	0.821	0.44	*
Grape coverage – pruning	0.721	0.44	*
Grape coverage – structure	0.985	0.58	*
Oenological adaptations	0.396	0.22	*
Subsidy	0.228	0.11	**
LogL	-160.07		
N	160		
AIC	338.14		
BIC	365.82		

*,**, and *** indicate 10, 5 and 1 % significance levels respectively

Source: Mariel et al. (2021b)

It is crucial to understand that these conclusions are based primarily on the signs of the estimated parameter values from the Table 4.3. Therefore, by comparing the displayed results with the computed scaled priors of Bliemer and Collins (2016) from the Table 4.1, we can conclude that the estimated parameters are generally close to the priors, being the *Grape* parameter an exception. Moreover, focusing on the expected parameter estimates precision presented in Figure 4.2 by the label B&C (32), we can conclude that the number of winemakers in the real case study by Mariel et al. (2021b) is sufficient to yield results that can be considered trustworthy, at least regarding the signs of the parameters. This is because the corresponding distributions in this case stay generally on the positive or negative side of the x-axis.

5 Conclusions and discussion

The purpose of this work was to describe different aspects of experimental designs in DCEs, putting emphasis on the importance of efficient designs, which are nowadays the cornerstone of DCEs. Firstly, the aim was to analyze the efficiency of selected experimental designs used in DCEs. Considering that discrete choice models are highly non-linear, we tried to compare the performance of the orthogonal, A-efficient and D-efficient design by doing simulation exercises and consequently displaying the distributions of parameter estimates using boxplots.

Secondly, we wanted to analyze the effect of prior parameter values in generation of an efficient experimental design for a DCE. These priors were computed using a specific method of Bliemer and Collins (2016), which was explained both theoretically as well as empirically in great detail throughout the work. In order to draw conclusions about the effect of priors on the generation of efficient designs, the simulation exercises were repeated using different sets of priors in generation of the D-efficient design in Ngene software that were determined deliberately inferior to the priors of Bliemer and Collins (2016). Lastly, all of these concepts were applied on the real case study devoted to climate change adaptation options of winemakers in Spanish wine appellation Rioja that was conducted by Mariel et al. (2021b).

The main results show that the orthogonal design can be considered the least efficient design out of the three statistical designs used. Regardless of the sample size with which the simulation exercise was done, the interquartile range of the displayed distributions of the parameter estimates was concluded to be the widest out of the three designs considered for orthogonal design in six out of seven cases that are corresponding to the attributes explained in the thesis. This result clearly suggests the importance of efficient designs in DCEs, since orthogonality approach directly yields the loss of efficiency in non-linear models. Hence, we conclude that the use of efficient designs in DCEs indeed leads to a higher efficiency of parameter estimates.

Moreover, from the results we can conclude that the signs of the computed priors using the method of Bliemer and Collins (2016) are corresponding to the signs of the estimated coefficients from the real case study. Considering also the displayed distributions, it means that not only we can trust the conclusions drawn in the real case study towards the preferences of the winemakers in Rioja region regarding the climate change adaptation options, but more importantly it suggests that the sample size given by 32 winemakers in the case study is sufficient to draw trustworthy conclusions. Regardless of the aforementioned conclusions, there are several issues, however, which deserve deeper discussion.

One such issue is the comparison between the efficient designs. As we indicated in the results section, we cannot conclude that using D-efficiency design leads generally to a higher efficiency of parameter estimates than if using A-efficiency design. The answer to the question regarding the statistical design to be used is dependent on the particular case study, meaning that general rule is difficult to define. This clearly puts emphasis on the importance of doing simulation exercises before designing our DCE.

Second issue worth deeper understanding are the prior parameter values used in generation of statistical designs. Our results are corresponding to the recommendations of Bliemer and Collins (2016) that highlight the use of more sophisticated method to determine the priors, since it leads on average to a higher efficiency of the parameter estimates. Nevertheless, it is important not to apply these sophisticated methods automatically, without checking the statistical design generated through the simulation exercises.

Hence, the above-discussed issues basically lead to a general conclusion of this work. We have presented, explained and consequently applied in this paper many sophisticated approaches and methods that assist us in the overall preparation of our DCE as well as that help us to appropriately set our experimental design and determine the prior parameter values such that it leads to a higher efficiency of parameter estimates. However, in environmental valuation we work many times with a low number of respondents yielding small sample sizes. Therefore, as we have seen above, it is of high importance to simulate the right-hand side matrix, given the sample size, before automatically applying these methods. Hence, performing simulation exercises is crucial since the application of these methods is dependent on a particular case study and its attributes, which can vary across different setups. In other words, it is merely impossible to draw general conclusions about which method should be always used.

Finally, we strongly believe that this work offers plenty of room for further research. For instance, it might be very interesting to apply the methods and approaches described in this thesis to other fields of DCEs, such as health economics and transportation economics and analyze the results of the simulation exercises. Also, different models other than MNL model can be considered, such as for example Random parameter logit model or Latent class model.

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7 Appendix A

Table 7.1 Determined ranges of the corresponding attribute levels

Attribute	Range of the attribute levels					
Grape	0	1				
Relocation	0	1				
Irrigation	0	1				
Coverage – pruning	0	1				
Coverage – structure	0	1				
Oenological adaptations	0	1				
Subsidy (€000/ha)	0	1	3	5	7	9

Table 7.2 Calculation of μ_k and σ_k through construction of the two utility-balanced options

1	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	2.5	3.5	-2.5	-1.5	-2.00	0.26
Grape	0	1		1	1		
2	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	2	3	-3	-2	-2.50	0.26
Relocation	0	1		1	1		
3	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	7	8	2	3	2.50	0.26
Irrigation	0	1		1	1		
4	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	6	7	1	2	1.50	0.26
Coverage (pruning)	0	1		1	1		
5	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	6	7	1	2	1.50	0.26
Coverage (structure)	0	1		1	1		
6	Option 1	Option 2		Δ^{min}	Δ^{max}	μ_k	σ_k
Subsidy	5	5.5	6	0.5	1	0.75	0.13
Oenological adaptations	0	1		1	1		

Table 7.3 Computation of the scaled priors $\tilde{\beta}_k^*$ based on Bliemer and Collins (2016)

	μ_k	-2	-2.5	2.5	1.5	1.5	0.75	1	$\boldsymbol{\tilde{\lambda} = 0.313}$				
	$\tilde{\beta}_k^* = \tilde{\lambda}\mu_k$	**-0.625**	**-0.782**	**0.782**	**0.469**	**0.469**	**0.234**	**0.313**					
Choice situation (s)	Alternative $(j = 1,2)$	Grape	Relocation	Irrigation	Coverage (pruning)	Coverage (structure)	Oenological adaptations	Subsidy	V_{sj}	P_{sj}	$log(P_{sj})$	f_{sj}	$f_{sj}\ log(P_{sj})$
1	1	1	1	0	1	0	1	7	1.485	0.331	-1.106	0.1	-0.111
1	2	0	0	1	1	0	0	3	2.189	0.669	-0.402	0.9	-0.362
2	1	0	1	1	0	0	0	5	1.563	0.281	-1.268	0.1	-0.127
2	2	0	1	0	1	0	0	9	2.501	0.719	-0.330	0.9	-0.297
3	1	1	0	0	1	0	1	5	1.641	0.777	-0.252	0.5	-0.126
3	2	0	1	0	0	0	1	3	0.391	0.223	-1.502	0.5	-0.751
4	1	0	1	0	1	0	1	5	1.485	0.101	-2.295	0.2	-0.459
4	2	1	0	1	1	0	1	9	3.674	0.899	-0.106	0.8	-0.085
5	1	0	0	0	1	0	1	5	2.267	0.815	-0.204	0.9	-0.184
5	2	0	1	1	1	0	0	1	0.782	0.185	-1.689	0.1	-0.169
6	1	1	1	0	1	0	1	3	0.234	0.049	-3.020	0.01	-0.030
6	2	0	0	1	0	0	1	7	3.205	0.951	-0.050	0.99	-0.050
7	1	1	1	1	1	0	0	1	0.156	0.162	-1.819	0.2	-0.364
7	2	0	1	1	0	0	1	5	1.798	0.838	-0.177	0.8	-0.142
8	1	1	0	1	0	0	1	1	0.703	0.422	-0.862	0.4	-0.345
8	2	1	0	0	1	0	1	3	1.016	0.578	-0.549	0.6	-0.329
9	1	1	0	1	0	0	1	9	3.205	0.539	-0.618	0.6	-0.371
9	2	1	0	1	0	1	1	7	3.048	0.461	-0.774	0.4	-0.310
10	1	0	1	1	1	0	1	1	1.016	0.266	-1.325	0.4	-0.530
10	2	1	1	1	1	0	0	7	2.032	0.734	-0.309	0.6	-0.185
11	1	1	1	1	1	0	1	1	0.391	0.066	-2.725	0.01	-0.027
11	2	0	0	0	0	0	1	9	3.048	0.934	-0.068	0.99	-0.067
12	1	1	1	0	0	0	1	3	-0.234	0.197	-1.626	0.3	-0.488
12	2	1	0	0	0	0	1	5	1.172	0.803	-0.219	0.7	-0.153
13	1	1	1	0	1	0	1	7	1.485	0.173	-1.753	0.2	-0.351
13	2	0	1	1	0	0	1	9	3.048	0.827	-0.190	0.8	-0.152
14	1	0	1	0	0	0	1	1	-0.234	0.025	-3.699	0.05	-0.185
14	2	0	0	1	1	0	0	7	3.439	0.975	-0.025	0.95	-0.024
15	1	1	0	0	0	0	0	7	1.563	0.061	-2.799	0.01	-0.028
15	2	0	0	1	1	0	1	9	4.299	0.939	-0.063	0.99	-0.062
16	1	0	0	1	1	0	0	5	2.814	0.858	-0.153	0.95	-0.146
16	2	1	0	0	1	0	1	3	1.016	0.142	-1.951	0.05	-0.098

$$L(\tilde{\lambda}) = \sum_{s=1}^{16}\sum_{j=1}^{2} f_{sj}\ log(P_{sj}) = \mathbf{-7.106}$$