Interpreting correlated random parameters in choice experiments

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Abstract

The random parameter logit (RPL) model with uncorrelated coefficients is a restrictive version of the mixed logit model, but it is one of the most frequently used models for analysing stated choice data in environmental valuation. The body of applied literature using a more flexible version, the RPL model with correlated coefficients, has been noticeably growing in the last years, but it has still been used less frequently due to its computational complexity and non-trivial interpretation. The correlation matrix of the coefficients in this model captures not only the correlation due to a behavioural phenomenon but also the correlation caused by scale heterogeneity. These two effects cannot be identified empirically. Nevertheless, this paper proposes a simple procedure that enables an interpretation of some of the estimated correlations, which can help to disentangle the unobserved preference heterogeneity. The proposed procedure consists of two simple steps. Firstly, the signs of the attributes corresponding to the utility coefficients that have a negative mean coefficient are reversed. Secondly, only negative correlations are interpreted. We propose a theoretical model accounting for correlations induced both by hypothetical behavioural phenomena and by scale heterogeneity and apply the proposed procedure to three typical cases of environmental valuation.

Keywords: choice experiment; correlated parameters; random parameter logit; scale heterogeneity

1. Introduction

The random parameter logit (RPL) model with uncorrelated utility coefficients is probably the most frequently applied model in environmental valuation in spite of the fact that it is a relatively restrictive model. The assumption of uncorrelated random coefficients leads to a specific and restricted correlation structure of the willingness-to-pay (WTP) values (Train and Weeks, 2005) and a fixed scale across individuals (Hess and Rose, 2012; Hess and Train, 2017). The practitioners applying this RPL model usually cite McFadden and Train's (2000) work to justify their model choice, as it shows that any choice model, with any distribution of preferences, can be approximated to any degree of accuracy by a mixed logit model and its most widely used derivation, based on random coefficients. However, this is not true if the assumed variance−covariance matrix of the utility coefficients in the RPL is diagonal, as is the case in an RPL model with uncorrelated utility coefficients.

A more flexible version, the RPL model with correlated utility coefficients, is used less frequently, probably due to different issues related to the estimation (local maxima) and non-trivial interpretation. The correlation matrix of the utility coefficients captures not only the correlation of the random parameters but also the correlation caused by scale heterogeneity, and these two effects cannot be identified empirically (Hess and Train, 2017).

Indeed, the RPL model with correlated coefficients is closely related to the widely discussed topic of scale heterogeneity. As stressed by Hess and Rose (2012), scale heterogeneity cannot be identified separately from other sources of heterogeneity and represents a specific type of correlation among utility coefficients. Scale heterogeneity is usually introduced in the literature as the influence of unobserved factors on an individual's choices, which can differ between them. An individual's choices can mainly be determined by the included factors and thus are less influenced by unobserved heterogeneity, leading to utility coefficients that are large in magnitude. On the contrary, the choices influenced mainly by unincluded factors are expected to be small in magnitude. This is called scale heterogeneity, because the scale of the specific utility differs between individuals. For some individuals, all their coefficients are larger (or smaller) than their corresponding means and are therefore correlated.

However, the correlation between utility coefficients can also appear due to behavioural phenomena. For example, people who support flora protection can also be supportive of fauna protection, creating a positive correlation between random flora and fauna coefficients. On the contrary, people who support flora protection can disapprove of the building of new recreational parks, creating a negative correlation between the random coefficients of fauna and recreational parks.

The RPL models with full correlation among utility coefficients allow for all sources of correlation, including both scale heterogeneity and heterogeneity due to behavioural phenomena. These sources, however, cannot be empirically disentangled in any model. The RPL models with correlated random parameters require the estimation of a significantly higher number of parameters and thus increase not only the computation time but also the risk of local maxima. The estimation of the full variance–covariance matrix of the random coefficient can also increase the number of estimated parameters to the point that simulation-based methods become impractical, because the number of draws required for estimation grows exponentially with the number of parameters (Cherchi and Guevara, 2012).

Due to the computational burden, the estimated model can be restricted, avoiding the estimation of a full covariance matrix. These restrictions might be defensible in a specific case study, but the interpretation of the results needs to recognize the implications of the restrictions. For example, in a scaled multinomial logit model, the utility coefficients are allowed to vary only because of scale heterogeneity. Therefore, the scale parameter will capture any other existing source of variation in the utility coefficients. The generalized multinomial logit model was proposed to capture scale heterogeneity. However, given that it cannot be disentangled from other sources, the model estimates include the combined impact of all the sources of correlation of the parameter representing scale heterogeneity. The interpretation of the estimated coefficients must take this fact into account, and, as stated by Hess and Train (2017), that is not undertaken properly in many papers in the environmental valuation literature.

The research question of this paper is whether the estimated correlations in the RPL model, which include not only the correlation due to behavioural phenomena but also the correlation caused by scale heterogeneity, can be used for the interpretation of the results, allowing deeper insights into the analysed data. The empirical identification of the two concepts is not possible, but, under some assumptions, we can at least draw a conclusion regarding the sign of the correlation caused by the behaviour phenomena.

Therefore, this paper seeks to propose a procedure that allows for the interpretation of some of the estimated correlations. To achieve this goal, we propose a theoretical setting accounting for correlation due to a behavioural phenomenon and correlation induced by scale heterogeneity. Then, we define a very simple procedure to interpret the estimated correlations that consists of two steps. Firstly, the signs of the attributes corresponding to the negative mean coefficients are reversed so that the re-estimated RPL has all positive mean coefficients. Secondly, only negative correlations are interpreted. This interpretation obviously depends on the reversed signs of the attributes. If one of the pair of attributes of which the correlation is being analysed has a reversed sign, the estimated correlation must be interpreted with the opposite sign. If neither of the two attributes has a reversed sign, their estimated correlation is interpreted with the estimated sign. The proposed procedure is applied to three typical cases of environmental valuation carried out in the Basque Country.

Focusing on the environmental literature, the use of the RPL model in discrete choice model applications is overwhelming. Nevertheless, the application of the restrictive version of the RPL with uncorrelated utility coefficients clearly prevails. There are numerous examples of that approach in outdoor recreation (Murdock, 2006), environmental aspects of food production systems and environmental labelling (Bjørner et al., 2004; Carlsson et al., 2007; Lusk et al., 2007), landscape creation and conservation (Birol et al., 2006; Campbell, 2007; Scarpa et al., 2007) and hazard waste management (Layton, 2000).

In spite of the computational complexity and non-trivial interpretation, the body of work based on the use of the RPL model with correlated parameters has grown markedly in the last years. Revelt and Train's (1998) study represents one of the first applications to estimate the impact of rebates and loans on US residential customers' choice of efficiency level for refrigerators. Table 1 presents examples of environmental valuation studies using the RPL model with correlated parameters. These studies apply this approach because of its flexibility, but they do not focus on the estimation and interpretation of scale heterogeneity and generally do not pay attention to the interpretation of the estimated correlations.

Table 1. Environmental valuation studies using the RPL model with correlated parameters

Topic	References
Angler site destination	Von Haefen and Domanski (2018)
Climate change mitigation	Layton and Brown (2000), Ščasný et al. (2017), Alberini et al. (2018)
Fauna conservation	Hanley et al. (2010), Wakamatsu et al. (2018)
Green pricing programme	Bae and Rishi (2018)
Landscape and forest management	Giergiczny et al. (2015), Czajkowski et al. (2016a), Valasiuk et al. (2018), Frontuto et al. (2020), Tyrväinen et al. (2020)
Protection of cold-water coral marine ecosystems	Aanesen et al. (2015), Tuhkanen et al. (2016), Armstrong et al. (2017)
Waste treatment and household recycling	Woldemariam et al. (2016), Czajkowski et al. (2019b)
Wetland protection	Carlsson et al. (2003), Glenk and Martin-Ortega (2018), Glenk et al. (2019)
Recreation behaviour	Provencher and Bishop (2004), Scarpa et al. (2008), Thiene et al. (2017)
Sustainable agricultural practices	Waldman et al. (2017)

There are some applications of the RPL with correlated parameters that focus on the non-trivial interpretation of scale heterogeneity (Hess and Train, 2017). Examples of this approach focusing on forest management can be found in the studies by Czajkowski et al. (2014a, 2014b, 2015, 2016b). Some authors include the correlation of the parameters in other structures. Hybrid choice models based on RPL can include this feature easily, but the computational burden, which is already very high for this kind of model, increases even more. Examples of this approach can be found in the studies by Zawojska et al. (2019) and Faccioli et al. (2020), which focus on peatland restoration and renewable energy development, respectively.

Examples of the use of the RPL model with correlated parameters in transport economics include, for example, the studies by O'Neill and Hess (2014), who study the decision of workplace location of one member of a two-person household that affects the travel time and salary of both members, Hess et al. (2017), who analyse travellers' choices of route by car and public transport in Singapore, and Hou et al. (2018), who analyse crash frequency in freeway tunnels.

In other areas, the use of the RPL model with correlated parameters has also been increasing steadily. In education, Czajkowski et al. (2019a) study the preferences of young people for higher education, in labour economics, Eriksson and Kristensen (2014) estimate individuals' willingness-to-pay values for fringe benefits and job amenities and, in cultural economics, Morey and Greer Rossmann (2003) focus on the preservation of marble monuments.

The rest of the paper is organized as follows. Section 2 presents the theoretical model, which is followed by a description of the analysed case studies in Section 3. The last section concludes.

2. The model

Let the utility that individual n obtains from alternative j in choice situation t be denoted as follows:

$$U^*_{njt} = \alpha_{1n} ATTR1_{njt} + \alpha_{2n} ATTR2_{njt} + \varepsilon^*_{njt} \tag{1}$$

where $ATTR1_{njt}$ and $ATTR2_{njt}$ are observed attributes, α_{1n} and α_{2n} are their corresponding utility coefficients, which vary randomly over individuals, and ${\varepsilon_{njt}}^*$ is a random term that represents the unobserved component of utility.

Sometimes, some explanatory factors that influence respondents' choices are not included in the model. These factors can differ over respondents, and some respondents might be more affected by these factors than others such that their choices appear to be more random. This phenomenon, called scale heterogeneity, can be modelled by rewriting the utility function (1) as follows:

$$U_{njt}^* = \alpha_{1n} ATTR1_{njt} + \alpha_{2n} ATTR2_{njt} + \frac{1}{\varphi_n} \varepsilon_{njt}, \tag{2}$$

where φ_n varies over people and is inversely proportional to the standard deviation of the error term. Equation (2) can be written as

$$\begin{aligned} \varphi_n U_{njt}^* &= \varphi_n \alpha_{1n} ATTR1_{njt} + \varphi_n \alpha_{2n} ATTR2_{njt} + \varepsilon_{njt} \\ U_{njt} &= \beta_{1n} ATTR1_{njt} + \beta_{2n} ATTR2_{njt} + \varepsilon_{njt}. \end{aligned} \tag{3}$$

Let us assume that φ_n and α_n are independent and α_{1n} and α_{2n} are normally distributed according to

$$\alpha_n = \begin{pmatrix} \alpha_{1n} \\ \alpha_{2n} \end{pmatrix} \sim N \left[\begin{pmatrix} \mu_{\alpha_{1n}} \\ \mu_{\alpha_{2n}} \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha_{1n}}^2 & \\ \sigma_{\alpha_{1n}\alpha_{2n}} & \sigma_{\alpha_{2n}}^2 \end{pmatrix} \right]. \tag{4}$$

Let us also assume that the parameter representing scale heterogeneity φ_n is lognormally distributed with $E(\varphi_n) = \mu_{\varphi_n}$ and $Var(\varphi_n) = \sigma_{\varphi_n}^2$. Thus, $\varphi_n = \exp(\varphi_n^*)$, where $\varphi_n^* \sim N(\mu_{\varphi_n}^*, {\sigma_{\varphi_n}^*}^2)$ and $E(\varphi_n) = e^{\left(\mu_{\varphi_n}^* + \frac{{\sigma_{\varphi_n}^*}^2}{2}\right)}$, $Var(\varphi_n) = \left(e^{{\sigma_{\varphi_n}^*}^2} - 1\right) e^{\left(2\mu_{\varphi_n}^* + {\sigma_{\varphi_n}^*}^2\right)}$.

If the original coefficients α_{1n} and α_{2n} in (2) are normally distributed according to equation (4), then the expected values of β_{1n} and β_{2n} are

$$E\begin{pmatrix}\beta_{1n}\\ \beta_{2n}\end{pmatrix} = E\begin{pmatrix}\varphi_n\alpha_{1n}\\ \varphi_n\alpha_{2n}\end{pmatrix} = \begin{pmatrix}\mu_{\varphi_n}\,\mu_{\alpha_{1n}}\\ \mu_{\varphi_n}\,\mu_{\alpha_{2n}}\end{pmatrix} \tag{5}$$

and the variance−covariance matrix (proofs are in the Appendix)

$$Var\begin{pmatrix}\beta_{1n}\\ \beta_{2n}\end{pmatrix} = Var\begin{pmatrix}\varphi_n\alpha_{1n}\\ \varphi_n\alpha_{2n}\end{pmatrix} = \begin{pmatrix}\sigma^2_{\varphi_n}\sigma^2_{\alpha_{1n}} + \sigma^2_{\varphi_n}\left(\mu_{\alpha_{1n}}\right)^2 + \sigma^2_{\alpha_{1n}}\left(\mu_{\varphi_n}\right)^2 & \sigma_{\alpha_{1n}\alpha_{2n}}\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right) + \sigma^2_{\varphi_n}\mu_{\alpha_{1n}}\mu_{\alpha_{2n}}\\ \sigma_{\alpha_{1n}\alpha_{2n}}\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right) + \sigma^2_{\varphi_n}\mu_{\alpha_{1n}}\mu_{\alpha_{2n}} & \sigma^2_{\varphi_n}\sigma^2_{\alpha_{2n}} + \sigma^2_{\varphi_n}\left(\mu_{\alpha_{2n}}\right)^2 + \sigma^2_{\alpha_{2n}}\left(\mu_{\varphi_n}\right)^2\end{pmatrix}. \tag{6}$$

As the estimated utility coefficients are β_{1n} and β_{2n}, we do not estimate the covariance $Cov(\alpha_{1n}, \alpha_{2n}) = \sigma_{\alpha_{1n}\alpha_{2n}}$, which we assume to be caused by a behavioural phenomenon, but we estimate instead the transformed covariance affected by scale heterogeneity:

$$Cov(\beta_{1n}, \beta_{2n}) = \sigma_{\alpha_{1n}\alpha_{2n}}\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right) + \sigma^2_{\varphi_n}\mu_{\alpha_{1n}}\mu_{\alpha_{2n}}. \tag{7}$$

As can easily be seen, $Cov(\beta_{1n}, \beta_{2n}) = Cov(\alpha_{1n}, \alpha_{2n}) = \sigma_{\alpha_{1n}\alpha_{2n}}$ only if there is no scale heterogeneity, that is, if $\sigma^2_{\varphi_n} = 0$ and $\mu_{\varphi_n} = 1$.

The first term $\sigma_{\alpha_{1n}\alpha_{2n}}\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right)$ in (7) can be positive or negative, because the positive term $\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right)$ magnifies or diminishes the original (positive or negative) covariance $\sigma_{\alpha_{1n}\alpha_{2n}}$. The second term $\sigma^2_{\varphi_n}\mu_{\alpha_{1n}}\mu_{\alpha_{2n}}$ can be positive or negative, depending on the signs of the means $\mu_{\alpha_{1n}}$ and $\mu_{\alpha_{2n}}$. As the parameters of scale heterogeneity ($\sigma^2_{\varphi_n}$ and μ_{φ_n}) cannot be identified, there is no possibility of extracting the original covariance $\sigma_{\alpha_{1n}\alpha_{2n}}$ from an estimation of the transformed $Cov(\beta_{1n}, \beta_{2n})$ for interpretational purposes.

Nevertheless, the means $\mu_{\alpha_{1n}}$ and $\mu_{\alpha_{2n}}$ are to a certain extent under the control of the researcher. For example, if the sign of attribute $ATTR1$ is reversed, the sign of the mean of the distribution of its coefficient would be reversed. The main idea of our proposed procedure is as follows. If the two attributes are defined so that the signs of the corresponding means are both positive, then the second term $\sigma^2_{\varphi_n}\mu_{\alpha_{1n}}\mu_{\alpha_{2n}}$ of the transformed covariance $Cov(\beta_{1n}, \beta_{2n})$ defined in (7) is always positive. In this case, we know that a positive constant is added to the first term $\sigma_{\alpha_{1n}\alpha_{2n}}\left(\sigma^2_{\varphi_n} + \left[\mu_{\varphi_n}\right]^2\right)$. Therefore, if the estimated $Cov(\beta_{1n}, \beta_{2n})$ is negative in this case, it must be due to the fact that the original covariance $\sigma_{\alpha_{1n}\alpha_{2n}}$ is negative. Obviously, if the sign of one attribute is reversed, the sign of the original covariance $\sigma_{\alpha_{1n}\alpha_{2n}}$ is also reversed.

To describe all the concepts analysed above in a more numerical way, let us assume different specific numerical values of scale and preference heterogeneity to identify the cases in which the original covariance $\sigma_{\alpha_{1n}\alpha_{2n}}$ deviates more from the estimated covariance defined in (7) and the cases in which it deviates less. Assuming that $E(\alpha_{in}) = \mu_{\alpha_{in}} = 0.5,\ i = 1{,}2$, we generate two cases of low ($V(\alpha_{in}) = 0.1^2,\ i = 1{,}2$) and high ($V(\alpha_{in}) = 0.5^2,\ i = 1{,}2$) preference heterogeneity for the two attributes. These cases are combined with low ($E(\varphi_n) = 1, Var(\varphi_n) = 0.01$) and high levels of scale heterogeneity ($E(\varphi_n) = 1,\ Var(\varphi_n) = 0.4$) and with six different correlations between the two parameters representing low, medium and high negative and positive correlations ($-0.9, -0.5, -0.1, 0.1, 0.5, 0.9$).

Table 2. Differences between transformed and original correlations

		Low level of pref. heterogeneity $E(\alpha_1) = 0.5$ $E(\alpha_2) = 0.5$ $Var(\alpha_1) = 0.1^2$ $Var(\alpha_2) = 0.1^2$		High level of pref. heterogeneity $E(\alpha_1) = 0.5$ $E(\alpha_2) = 0.5$ $Var(\alpha_1) = 0.5^2$ $Var(\alpha_2) = 0.5^2$	
		Small scale $E(\varphi) = 1$ $Var(\varphi) = 0.01$	Large scale $E(\varphi_n) = 1$ $Var(\varphi) = 0.4$	Small scale $E(\varphi) = 1$ $Var(\varphi) = 0.01$	Large scale $E(\varphi) = 1$ $Var(\varphi) = 0.4$
Low positive correlation	$Corr(\alpha_1, \alpha_2) = 0.1$	0.18	0.79	0.01	0.20
Medium positive correlation	$Corr(\alpha_1, \alpha_2) = 0.5$	0.10	0.44	<0.01	0.11
High positive correlation	$Corr(\alpha_1, \alpha_2) = 0.9$	0.02	0.09	<0.01	0.02
Low negative correlation	$Corr(\alpha_1, \alpha_2) = -0.1$	0.22	0.96	0.01	0.24
Medium negative correlation	$Corr(\alpha_1, \alpha_2) = -0.5$	0.30	1.32	0.02	0.33
High negative correlation	$Corr(\alpha_1, \alpha_2) = -0.9$	0.38	1.67	0.02	0.42

Table 2 presents the differences between the population correlation $Corr(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ and the population assumed value of $Corr(\alpha_{1n}, \alpha_{2n})$.[1] The specific cases presented in Table 2 are obtained by combinations of low and high levels of preference and scale heterogeneity. A low level of preference heterogeneity (third and fourth columns) is represented by low standard deviations of the utility coefficients (0.1), and a high level of preference heterogeneity (fifth and sixth columns) is represented by a high standard deviation (0.5). These two cases are combined with a low level of scale heterogeneity ($E(\varphi) = 1$, $Var(\varphi) = 0.01$) presented in the third and fifth columns and with a high level of scale heterogeneity ($E(\varphi) = 1, Var(\varphi) = 0.4$) presented in the fourth and sixth columns. These combinations of low and high levels of preference and scale

[1] The detailed numerical values of these correlations together with a graphical explanation of the change in the original correlations into the transformed correlations (which are finally estimated in an RPL model) are presented in Tables A2.1–A2.4 in the Appendix.

heterogeneity are analysed for low (0.1 and -0.1), medium (0.5 and -0.5) and high (0.9 and -0.9) positive and negative correlations (of the original parameters, ($Corr(\alpha_1, \alpha_2)$) presented in the rows of Table 2.

As explained above, $Cov(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ = $Cov(\alpha_{1n}, \alpha_{2n}) + c$, where $c \geq 0$ for $\mu_{\alpha_{1n}}, \mu_{\alpha_{2n}} > 0$. That is why the differences $Corr(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ - $Corr(\alpha_{1n}, \alpha_{2n})$ are always positive, as $\alpha_{1n} = \alpha_{2n} = 0.5 > 0$. The maximum value of this difference is two for the extreme case in which the correlations differ completely, $Corr(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ - $Corr(\alpha_{1n}, \alpha_{2n}) = 1 - (-1) = 2$, and the minimum value is zero for the case in which the two correlations are equal, $Corr(\varphi\alpha_{1n}, \varphi\alpha_{2n}) = Corr(\alpha_{1n}, \alpha_{2n})$.

The main and expected conclusion that can be drawn from Table 2 is that the columns corresponding to low-level scale heterogeneity (third and fifth columns) represent smaller differences than the columns of high-scale heterogeneity (fourth and sixth columns). The second conclusion is that the differences are generally smaller for high levels of preference heterogeneity (fifth and sixth columns).

The last row in the fourth column of Table 2 presents the largest difference. In this case, the original $Cov(\alpha_{1n}, \alpha_{2n}) = -0.9$ is transformed by large-scale heterogeneity into a positive correlation of 0.77. The difference is therefore $1.67 = 0.77 - (-0.9)$. The bottom-right corner of Table A2.2 in the Appendix shows graphically this transformation of a large negative original correlation of -0.9 (behavioural phenomenon) by large-scale heterogeneity into a positive correlation of 0.77 of the estimated parameters. The right-hand side of Table A2.2 shows the more severe transformations of the original negative correlations among all the analysed cases. The left-hand side of the same Table A2.2 shows that even a low level ($Var(\varphi) = 0.01$) of scale heterogeneity can have a big impact on the original correlations if the preference heterogeneity is small ($Var(\alpha_{1n}) = Var(\alpha_{2n}) = 0.1^2$). In this case, the corresponding differences in the low part of the third column of Table 2 range from 0.22 to 0.38. The other cases with low preference heterogeneity but with positive original correlations are presented in Table A2.1 and the upper part of the third and fourth columns of Table 2. The differences are relatively small for low levels of scale heterogeneity and range from 0.02 to 0.18. For high levels of heterogeneity, the differences increase and range from 0.09 to 0.79, as can also be observed in Table A2.1.

Given that only cases with $\mu_{\alpha_{1n}}, \mu_{\alpha_{2n}} > 0$ are considered, according to (7), if the transformed $Cov(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ is negative, the original $Cov(\alpha_{1n}, \alpha_{2n})$ must also be negative. On the other hand, if $Cov(\varphi\alpha_{1n}, \varphi\alpha_{2n})$ is positive, the original $Cov(\alpha_{1n}, \alpha_{2n})$ can be either negative or positive. Therefore, the proposed conservative rule is to interpret only the estimated negative correlations that must correspond to the original negative correlations.

The proposed rule is based on the idea that the original covariance that we would like to interpret is always "shifted" by scale heterogeneity "to the right-hand side". A small shift of a negative correlation keeps the final correlation negative, and a large skip changes its sign. That is why, we propose to interpret only the negative correlations.

3. Case studies

Our empirical results are based on data from three stated preference choice experiments, described in Table 3. These three case studies have been already published and described in detail in the literature (Hoyos et al., 2009, 2012; de Ayala et al., 2015). The objective of their use here is to show the applicability of the proposed procedure, as they can be considered typical environmental valuation case studies.

The first case study (Hoyos et al., 2009) presents an economic valuation of Mount Jaizkibel, a natural area located in the Basque Country. Mount Jaizkibel is a 2400 ha natural site in the Basque Country that contains 15 zones declared to be of high ecological interest by the European Union, and it was incorporated into the European Natura 2000 network in 2004. A discrete choice experiment was conducted to determine the non-market values of the main environmental attributes of this natural site. The proposed programmes of protection aimed to prevent future environmental degradation at the site provoked by human activities. The attributes and levels considered in this study are presented in Table 3. The levels with asterisks represent the status quo scenario. The four non-cost attributes considered in the study were (1) landscape, measured by the percentage of surface area on which today's landscape could be seen in the future; (2) flora, measured by the future level of protection of today's population of *armeria euskadiensis endemism*; (3) avifauna, measured by the future level of protection of today's population of lesser and peregrine falcons; and (4) seabed, measured by the future level of protection of today's extension of red algae. The proposed payment vehicle was an annual contribution by all Basque citizens to a foundation exclusively dedicated to protecting Mount Jaizkibel.

The second environmental valuation case study, described in detail by Hoyos et al. (2012), focuses on the area called Garate-Santa Barbara, which is located in the Basque province of Gipuzkoa. It covers about 142 ha of private property and was proposed as part of the Natura 2000 network in 2003 as a site of community importance due to the presence of five forests and other environmentally valuable ecological habitats. The objective of the study was to evaluate the social preferences of the wider population on the regional scale for the key attributes of the protected site. These attributes were associated with the use value of agricultural development (vineyards), commercial forestry and recreation and the non-use values linked to the conservation of the natural forest remnants and biodiversity (endangered species). The resulting evaluation of social preferences was then used to assess the social desirability of potential future management plans. The information included in the discrete choice experiment referred to the potential effects of various levels of protection in terms of the following attributes: (1) native forest, represented by the percentage of land area covered by cork oak woodland; (2) the percentage of land area covered by vineyards; (3) exotic tree plantations, represented by the land area covered by productive pine forest plantations; (4) biodiversity, based on the number of endangered species of flora and fauna; (5) the level of conservation of recreational and cultural facilities; and (6) a cost attribute regarding the price of the conservation programme. Similar to the previous case study, the proposed payment vehicle was an annual contribution by all Basque citizens to a foundation exclusively dedicated to protecting the site.

The last study, described by de Ayala et al. (2015), is a multidimensional landscape valuation applied to an area called *Llanada Alavesa*, located in the south of the Basque Country. Different types of landscapes, natural habitats and human activities coexist in this area, including forests, farming activities, industry, urban areas, infrastructure and swamps. The Basque Country adopted the European Landscape Convention (ELC) in 2011; thus, the Basque authorities made a commitment to promoting the ELC's principles and objectives. Therefore, the Basque authorities should protect, manage and plan the different landscapes so that their quality is preserved and improved. In this context, this study tried to promote these principles and a future landscape law, choosing the landscapes of a specific area of the Basque province of Araba, which is suffering from different alterations. The attributes and levels considered in the study are presented in Table 3 and include (1) native forests, represented by the percentage of the area covered by native forests; (2) intensive farming, represented by the percentage of the land devoted to this activity; (3) organic farming, measured by the percentage of the land taken up by organic farming; (4) cemented surface, represented by the percentage of the surface occupied by urban, industrial and economic activity sites as well as by infrastructure; and (5) recreation areas, measured by the level of conservation and protection of recreation areas (e.g. swamps and picnic areas) and cultural heritage sites (e.g. megalithic monuments and the branch of the way of St James). The proposed payment vehicle was an annual payment through a new tax to be paid to an organization exclusively dedicated to coordinating the action plans.

Table 3 presents the basic information regarding the three studies. All three studies used a three-alternative setting, and the number of choice occasions that each person faced in the experiment varied between two and six. The number of respondents was also relatively low (from 218 to 358), and the number of observations varied from 687 to 1326. The attributes listed in Table 3 can be considered typical in environmental studies described by non-cost attributes with levels set on a particular percentage or Likert scale level.

Table 3. Empirical data sets

Case study #1: Mount Jaizkibel				Attributes	Levels
				Landscape	40%*, 60%, 80%, 100%
Number of				*Flora*	50%*, 70%, 85%, 100%
alternatives	**choice occasions**	**respondents**	**observations**	*Fauna*	25%*, 50%, 75%, 100%
3	2	358	687	*Seabed*	50%*, 70%, 85%, 100%
				Annual payment (€)	0*, 5, 10, 15, 20, 30, 50, 100

Case study #2: Garate-Santa Barbara				Attributes	Levels
				Native forest	2%*, 10%, 20%, 30%
Number of				*Biodiversity*	25*, 15, 10, 5
alternatives	**choice occasions**	**respondents**	**observations**	*Recreation*	Low*, medium, high, very high
3	6	221	1326	*Exotic tree plantations*	40%*, 30%, 25%, 15%
				Vineyards	40%*, 30%, 20%, 10%
				Annual payment (€)	0*, 5, 10, 30, 50, 100

Case study #3: Llanada Alavesa				Attributes	Levels
				Intensive farming	15%, 20%, 29%*, 35%
Number of				*Organic farming*	8%, 16%*, 25%, 30%
alternatives	**choice occasions**	**respondents**	**observations**	*Native forests*	39%*, 45%, 50%, 30%
3	6	218	1308	*Cemented surface*	14%*, 16%, 20%, 25%
				Recreation areas	Very high, high, medium*, low
				Annual payment (€)	0*, 5, 15, 30, 50

Sources: Hoyos et al. (2009, 2012), de Ayala et al. (2015). Levels with asterisks represent the status quo scenario.

Table 4. Case study #1: Mount Jaizkibel

MNL	Coef.	Std Error		RPL with correlated parameters	Coef.	Std Error	
Alternative specific constants				*Alternative specific constants*			
ASC1	0.630	0.304	**	ASC1	13.774	4.909	***
ASC2	0.505	0.326		ASC2	13.618	4.870	***
Attributes				*Attributes (means)*			
Landscape	0.016	0.003	***	Landscape	0.044	0.018	**
Flora	0.008	0.004	*	Flora	0.026	0.017	
Avifauna	0.008	0.002	***	Avifauna	0.023	0.011	**
Seabed	0.008	0.002	***	Seabed	0.016	0.009	*
Payment	-0.014	0.002	***	Payment (sign reversed)	-3.449	0.442	***
				Attributes (std deviations)			
				Landscape	0.077	0.036	**
				Flora	0.114	0.046	**
				Avifauna	0.061	0.026	**
				Seabed	0.040	0.020	**
				Payment (sign reversed)	2.022	0.268	***
Log-likelihood	-587.1				-512.6		
Number of parameters	7				22		
Observations	687				687		
AIC	1188.2				1069.1		
BIC	1219.9				1168.8		

AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.
***, ** and *: significance at the 1%, 5% and 10% levels.

Tables 4, 6 and 8 present the estimation results of the standard MNL and RPL models with correlated random parameters for the three data sets analysed. Both the MNL and the RPL models are presented with LogL, AIC and BIC values, so, for the RPL models, an important increase in fit can be observed. The random coefficients of the non-cost attributes are assumed to be normally distributed and the cost attribute is assumed to be log-normally distributed, but the sign of the attribute is reversed, which is the usual and recommended (Daly et al., 2012) approach in the literature.

As can be seen in Table 4, all the estimated means of the non-cost attributes are positive in this case, so no auxiliary RPL model is needed for the interpretation of the correlation matrix of the random coefficients. Tables 6 and 8 present, apart from the standard RPL model, an auxiliary RPL model in which the signs of the non-cost attributes' corresponding negative estimated mean coefficient in the standard RPL are reversed.

The interpretation of the estimated standard RPL models is not a key objective of this paper and can be found in already-published works (Hoyos et al., 2009, 2012*;* de Ayala et al., 2015). These papers present the estimations and interpretations of the same models with slight variations, which include some interactions with sociodemographic variables. In this paper, we focus on the application of the proposed procedure for interpreting the estimated correlation matrices of the random coefficients, and that is why we analyse only the RPL model without interactions. Tables 5, 7 and 9 present these matrices for the three case studies.

Table 5. Case study #1: Mount Jaizkibel − Estimated correlation matrix

		Signs of the non-cost attributes unchanged				
CV		*Landscape*	*Flora*	*Avifauna*	*Seabed*	*Payment* (sign reversed)
175%	*Landscape*	1.00	0.88	0.70	0.62	-0.27
438%	*Flora*	0.88	1.00	0.81	0.55	-0.50
265%	*Avifauna*	0.70	0.81	1.00	0.00	-0.23
250%	*Seabed*	0.62	0.55	0.00	1.00	-0.38
59%	*Payment* (sign reversed)	-0.27	-0.50	-0.23	-0.38	1.00

Table 5 presents the estimated correlation matrix corresponding to the RPL estimation included in Table 4 based on the first case study: Mount Jaizkibel (Hoyos et al., 2009). The positive correlations between the coefficients of non-cost attributes cannot be interpreted according to the proposed rule. We can interpret only the negative correlations between the coefficients of *Payment* and all the non-cost attributes. As the sign of the *Payment* attribute was reversed, the interpretation of these correlations must be made with a reversed sign. A positive correlation between the coefficients of *Payment* and all the non-cost attributes indicates that people with a high coefficient of a non-cost attribute (that is, people who are in favour of protecting the landscape, flora, avifauna or seabed) have a low (in absolute values) cost coefficient, that is, a higher WTP for these attributes. This is not an unexpected result, and we can conclude, that, in this case study, the interpretation of the correlations did not offer valuable additional information on people's preferences regarding our environmental attributes.

Table 6. Case study #2: Garate-Santa Barbara

MNL				RPL with correlated parameters Signs of some non-cost attributes changed				RPL with correlated parameters			
	Coef.	Std Error			Coef.	Std Error			Coef.	Std Error	
Alternative specific constants				*Alternative specific constants*				*Alternative specific constants*			
ASC1	-0.172	0.254		ASC1	3.449	0.636	***	ASC1	3.466	0.635	***
ASC2	-0.266	0.258		ASC2	3.278	0.641	***	ASC2	3.269	0.643	***
Attributes				*Attributes (means)*				*Attributes (means)*			
Native forest	0.046	0.005	***	Native forest	0.099	0.014	***	Native forest	0.079	0.012	***
Vineyards	0.007	0.005		Vineyards	-0.012	0.012		Vineyards (sign reversed)	0.005	0.011	
Exotic tree plantations	-0.007	0.006		Exotic tree plantations	0.005	0.016		Exotic tree plantations	0.000	0.014	
Biodiversity	-0.043	0.010	***	Biodiversity	-0.123	0.033	***	Biodiversity (sign reversed)	0.118	0.032	***
Recreation	0.015	0.023		Recreation	0.012	0.061		Recreation	0.006	0.017	
Payment (sign reversed)	-0.017	0.001	***	Payment (sign reversed)	-3.351	0.236	***	Payment (sign reversed)	-3.392	0.206	***
				Attributes (std deviations)				*Attributes (std deviations)*			
				Native forest	0.075	0.018	***	Native forest	0.065	0.017	***
				Vineyards	0.065	0.019	***	Vineyards (sign reversed)	0.058	0.016	***
				Exotic tree plantations	0.084	0.023	***	Exotic tree plantations	0.074	0.019	***
				Biodiversity	0.232	0.039	***	Biodiversity (sign reversed)	0.217	0.035	***
				Recreation	0.156	0.095		Recreation	0.145	0.083	*
				Payment (sign reversed)	2.611	0.215	***	Payment (sign reversed)	2.379	0.294	***
Log-likelihood	-1208.7				-807.4				-808.2		
Number of parameters	8				29				29		
Observations	1326				1326				1326		
AIC	2433.4				1672.8				1674.5		
BIC	2474.9				1823.3				1825.0		

AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.
***, ** and *: significance at the 1%, 5% and 10% levels.

Table 7. Case study #2: Garate-Santa Barbara – Estimated correlation matrix

Signs of the non-cost attributes unchanged

	Native forest	*Vineyards*	*Exotic tree plantations*	*Biodiversity*	*Recreation*	*Payment* (sign reversed)
Native forest	1.00	-0.33	-0.45	-0.22	0.12	0.05
Vineyards	-0.33	1.00	0.01	0.00	-0.23	-0.59
Exotic tree plantations	-0.45	0.01	1.00	0.24	-0.25	0.45
Biodiversity	-0.22	0.00	0.24	1.00	0.11	-0.16
Recreation	0.12	-0.23	-0.25	0.11	1.00	-0.34
Payment (sign reversed)	0.05	-0.59	0.45	-0.16	-0.34	1.00

Signs of some non-cost attributes changed

	Native forest	*Vineyards* (sign reversed)	*Exotic tree plantations*	*Biodiversity* (sign reversed)	*Recreation*	*Payment* (sign reversed)
Native forest	1.00	0.27	-0.84	0.28	0.41	-0.46
Vineyards (sign reversed)	0.27	1.00	0.19	0.03	0.47	0.44
Exotic tree plantations	-0.84	0.19	1.00	-0.06	-0.02	0.53
Biodiversity (sign reversed)	0.28	0.03	-0.06	1.00	-0.06	0.07
Recreation	0.41	0.47	-0.02	-0.06	1.00	-0.46
Payment (sign reversed)	-0.46	0.44	0.53	0.07	-0.46	1.00

Table 7 presents the estimated correlation matrices corresponding to the RPL estimations included in Table 6, based on the second case study, which focuses on the region of Garate-Santa Barbara (Hoyos et al., 2012). Table 6 is in this case divided into two blocks. The left-hand block presents the RPL estimation with the original definition of all the attributes. As can be seen, two of the non-cost mean coefficients are negative (*Vineyards* and *Biodiversity)*, and that is why an auxiliary RPL estimation is needed for the application of the proposed procedure. The signs of the two attributes (*Vineyards* and *Biodiversity*) are reversed in the RPL estimation presented in the right-hand block of Table 6. As expected, the outcomes in the two blocks of Table 6 are very similar (only the estimated mean coefficients of *Vineyards* and *Biodiversity* are reversed), but their corresponding correlation matrices, presented in Table 7, are very different.

The correlations in the first correlation matrix in Table 7, denoted as *Signs of the non-cost attributes unchanged*, are, according to (7), affected positively or negatively by the (positive and negative) means of the assumed distributions, and their direct interpretation is therefore impossible. The second correlation matrix in Table 7 presents the correlation based on (7), and all the means of the non-cost attributes are positive.

There are three large negative correlations. These are *Native forest−Exotic tree plantations, Native forest−Payment* and *Recreation−Payment.* The signs of these correlations are perfectly in line with our a priori hypotheses. The first correlation (*Native forest−Exotic tree plantations*), for example, is negative, because people with an above-average WTP value for *Native forest* are likely to have a below-average WTP for *Exotic tree plantations*. This is because people who are in favour of *Native forest* are expected to dislike policies supporting *Exotic tree plantations*, which are usually devoted to the timber business. The sign of the second (and the third) correlation between *Native forest* (*Recreation*) and *Payment* must be reversed, because the sign of the attribute payment has been reversed for the estimation. The inverted positive correlation of the two attributes indicates that people who are in favour of *Native forest* and *Recreation areas* are expected to have a lower negative payment coefficient (in absolute values), leading to a higher WTP value for the other environmental attributes.

Table 8. Case study #3: Llanada Alavesa

MNL

	Coef.	Std Error	
Alternative specific constants			
ASC1	0.690	0.121	***
ASC2	0.657	0.119	***
Attributes (means)			
Intensive farming	0.016	0.012	
Organic farming	0.056	0.013	***
Native forests	0.036	0.013	***
Cemented surface	0.008	0.016	
Recreation area	0.256	0.042	***
Payment (sign reversed)	-0.051	0.003	***
Log-likelihood	-1228.3		
Number of parameters	8		
Observations	1308		
AIC	2472.6		
BIC	2514.0		

RPL with correlated parameters
Signs of some non-cost attributes changed

	Coef.	Std Error	
Alternative specific constants			
ASC1	1.662	0.182	***
ASC2	1.589	0.182	***
Attributes (means)			
Intensive farming	0.017	0.020	
Organic farming	0.090	0.023	***
Native forests	0.049	0.021	**
Cemented surface	-0.007	0.027	
Recreation area	0.398	0.072	***
Payment (sign reversed)	-2.444	0.121	***
Attributes (std deviations)			
Intensive farming	0.119	0.028	***
Organic farming	0.154	0.029	***
Native forests	0.138	0.027	***
Cemented surface	0.073	0.036	**
Recreation area	0.330	0.123	***
Payment (sign reversed)	1.223	0.127	***
Log-likelihood	-1091.4		
Number of parameters	29		
Observations	1308		
AIC	2240.8		
BIC	2390.9		

RPL with correlated parameters

	Coef.	Std Error	
Alternative specific constants			
ASC1	1.662	0.182	***
ASC2	1.589	0.182	***
Attributes (means)			
Intensive farming	0.017	0.020	
Organic farming	0.090	0.027	***
Native forests	0.049	0.021	**
Cemented surface (sign reversed)	0.007	0.027	
Recreation area	0.398	0.072	***
Payment (sign reversed)	-2.444	0.121	***
Attributes (std deviations)			
Intensive farming	0.119	0.028	***
Organic farming	0.154	0.029	***
Native forests	0.138	0.027	***
Cemented surface (sign reversed)	0.073	0.036	**
Recreation area	0.330	0.123	***
Payment (sign reversed)	1.223	0.117	***
Log-likelihood	-1091.4		
Number of parameters	29		
Observations	1308		
AIC	2240.8		
BIC	2390.9		

AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.
***, ** and *: significance at the 1%, 5% and 10% levels.

Table 9. Case study #3: Llanada Alavesa – Estimated correlation matrix

Signs of the non-cost attributes unchanged

	Intensive farming	*Organic farming*	*Native forests*	*Cemented surface*	*Recreation area*	*Payment* (sign reversed)
Intensive farming	1.00	0.83	0.77	-0.09	-0.30	-0.13
Organic farming	0.83	1.00	0.86	-0.24	-0.19	-0.14
Native forests	0.77	0.86	1.00	-0.66	-0.79	-0.28
Cemented surface	-0.09	-0.24	-0.66	1.00	-0.09	0.42
Recreation area	-0.30	-0.19	-0.13	-0.09	1.00	0.48
Payment (sign reversed)	-0.13	-0.14	-0.28	0.42	0.48	1.00

Signs of some non-cost attributes changed

	Intensive farming	*Organic farming*	*Native forests*	*Cemented surface* (sign reversed)	*Recreation area*	*Payment* (sign reversed)
Intensive farming	1.00	0.83	0.77	0.09	-0.31	-0.13
Organic farming	0.83	1.00	0.85	0.24	-0.19	-0.14
Native forests	0.77	0.85	1.00	0.66	-0.13	-0.28
Cemented surface (sign reversed)	0.09	0.24	0.66	1.00	0.09	-0.42
Recreation area	-0.31	-0.19	-0.13	0.09	1.00	0.48
Payment (sign reversed)	-0.13	-0.14	-0.28	-0.42	0.48	1.00

Table 9 presents the estimated correlation matrix corresponding to the RPL estimation included in Table 8, based on the third case study of *Llanada Alavesa*, described in the original study by de Ayala et al. (2015). The left-hand block of Table 8 presents the RPL estimation with the original definition of all the attributes. One of the non-cost mean coefficients (*Cemented surface*) is negative, and that is why the auxiliary RPL estimation is presented in the right-hand block of Table 8. In this case, the corresponding correlation matrices presented in Table 9 are relatively similar.

If we focus on the highest negative correlations between coefficients of non-cost attributes, we can easily see that there is a negative correlation between *Recreation* *area* and *Intensive farming*, *Organic farming* and *Native forests*. That means that people with high positive preferences for recreation areas are likely to have negative preferences for farming and forests. This differentiating behaviour of people with high preferences for recreational areas can also be observed in the correlations with the *Payment* attribute. The attributes *Intensive farming*, *Organic farming* and *Native forests* present a negative correlation with *Payment*, which, similar to the two previous cases (*Payment*'s sign is reversed), means that people with high preferences for these attributes are likely to have a lower coefficient for *Payment*, leading to a higher WTP for these attributes. This outcome is, however, not observed for the *Recreation area* and *Cemented surface* (sign reversed) attributes, confirming that people with high preferences for recreational and cemented surface areas are likely to present lower WTP values in general.

4. Conclusions

The random parameter logit model has been widely used in the last two decades to analyse data from stated choice surveys, and it has become a relatively standard approach because it accounts for unobserved taste heterogeneity. The main goal of this paper is to try to disentangle, at least partially, the unobserved preference heterogeneity estimated by an RPL model, because any additional information on differences between people's preferences can help to set better environmental policies. Therefore, we propose a procedure that helps to interpret the estimated correlations between utility random coefficients, correlations that arise due to a behavioural phenomenon. The proposed procedure is based on a standard RPL model in which the signs of the attributes are adjusted so that the means of the estimated distributions are positive. Three typical cases of environmental valuation carried out in the Basque Country are used to show its application.

The proposed procedure is limited, because only some of the correlations are interpreted, but this limitation assures that any incorrect interpretation is avoided. Another limitation could be the specific theoretical setting of our model. However, the proposed theoretical model is relatively flexible and only the first and second moments of the assumed distributions affect the main results. We tested our procedure on dozens of hypothetical data sets assuming normal and lognormal distributions of the utility coefficients mimicking the real data sets described in Section 3. The main result of the shift of the original correlation "to the right-hand side" by scale heterogeneity remains valid in spite of the use of different distributions.

The interpretation of only the negative estimated correlations seems to be a shortcoming of the proposed procedure. Nevertheless, it does not mean that only negative correlations due to a behavioural phenomenon will be interpreted. A positive correlation can be related to two random coefficients with opposite signs of the mean parameters, and then one of the corresponding attributes will be included in the auxiliary RPL estimation with a reversed sign. This change will also invert the original positive correlation that would be estimated as negative so that it is eventually interpreted as positive. Which correlations will therefore remain without interpretation is highly case dependent. The three cases presented in Section 3 show this fact, and, in the first application, based on Hoyos et al. (2009), the interpretation of the correlations of the random parameters is very limited. However, in the remaining two studies, the interpreted correlations reveal interesting patterns of preference heterogeneity.

Another issue of the interpretation can be related to the nature of the original correlation. If there is more than one behavioural phenomenon and they cause opposite effects on the correlation, these cannot be identified separately, and the proposed procedure obviously identifies the final combined effect (Hess and Train, 2017). Suppose that two sources of correlation exist for people's choices among environmental programmes in a landscape valuation study that involves native forest and recreational area attributes. On the one hand, people who are in favour of native forest can also be in favour of recreational areas, as these are usually located in native forests, creating a positive correlation between these two coefficients. On the other hand, some people who are in favour of native forest tend to dislike recreational areas, because their construction and use lead to degradation of native forest, creating a negative correlation. The researcher would estimate a combined effect of a specific sign depending on which of these two effects prevails. The researcher's case study expertise should help to identify these cases.

The policy implications of this paper are twofold. Firstly, any application of an RPL model should include correlated utility coefficients. Any possible restrictions imposed on these correlations should be based on a proper statistical test. A non-justified estimation of an RPL model with uncorrelated utility coefficients can imply biased estimation of the parameters, and this can lead to biased estimation of the WTP values. Secondly, the correlations of the utility coefficients in the estimated RPL model must not be interpreted directly. A direct interpretation could lead to incorrect policy setting. An incorrectly interpreted positive correlation between the coefficients of, for example, landscape and seabed could lead to a completely erroneous conclusion that people who like landscape also like seabed and that they are willing to pay more for both attributes.

The proposed approach helps to interpret correctly at least part of these correlations, which can lead to important policy implications. These interpretations can help to disentangle the preference heterogeneity by determining whether a high preference for one attribute is related to a high or a low preference for another attribute.

More research using other data sets will be needed to confirm the gains of our procedure. Nevertheless, researchers should start to use the RPL model with correlated utility coefficients more broadly. Researchers' expertise in the setting in which the model is applied should also allow for the definition of a priori hypotheses regarding the correlations that can be confirmed or rejected by the proposed procedure. The extent to which the proposed procedure allows the interpretation of the majority of the correlations in line with these hypotheses is still an open question.

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Appendix A1. Proofs

Given that φ_n and α_n are independent:

$$E(\varphi_n \alpha_{1n}) = E(\varphi_n)E(\alpha_{1n}) = \mu_{\varphi_n}\,\mu_{\alpha_{1n}}$$

$$E(\varphi_n \alpha_{2n}) = E(\varphi_n)E(\alpha_{2n}) = \mu_{\varphi_n}\mu_{\alpha_{2n}}$$

$$\begin{aligned}
Var(\varphi_n \alpha_{1n}) \quad &= E\big(\varphi_n \alpha_{1n} - E(\varphi_n \alpha_{1n})\big)^2 \\
&= E(\varphi_n \alpha_{1n})^2 - 2E(\varphi_n \alpha_{1n})E(\varphi_n \alpha_{1n}) + [E(\varphi_n, \alpha\beta_{1n})]^2 \\
&= E(\varphi_n \alpha_{1n})^2 - [E(\varphi_n, \alpha_{1n})]^2 = E({\varphi_n}^2 {\alpha_{1n}}^2) - [E(\varphi_n, \alpha_{1n})]^2 \\
&= E({\varphi_n}^2)E({\alpha_{1n}}^2) - [E(\varphi_n)E(\alpha_{1n})]^2 \\
&= E({\varphi_n}^2)E({\alpha_{1n}}^2) - [E(\varphi_n)]^2[E(\alpha_{1n})]^2 \\
&= [Var(\varphi_n) + [E(\varphi_n)]^2][Var(\alpha_{1n}) + [E(\alpha_{1n})]^2] \\
&- [E(\varphi_n)]^2[E(\alpha_{1n})]^2 \\
&= Var(\varphi_n)\, Var(\alpha_{1n}) + Var(\varphi_n)[E(\alpha_{1n})]^2 + Var(\alpha_{1n})[E(\varphi_n)]^2 \\
&+ [E(\varphi_n)]^2[E(\alpha_{1n})]^2 - [E(\varphi_n)]^2[E(\alpha_{1n})]^2 \\
&= Var(\varphi_n)\, Var(\alpha_{1n}) + Var(\varphi_n)[E(\alpha_{1n})]^2 + Var(\alpha_{1n})[E(\varphi_n)]^2 \\
&= \sigma^2_{\varphi_n}\sigma^2_{\alpha_{1n}} + \sigma^2_{\varphi_n}\big(\mu_{\alpha_{1n}}\big)^2 + \sigma^2_{\alpha_{1n}}\big(\mu_{\varphi_n}\big)^2
\end{aligned}$$

$$\begin{aligned}
Cov(\varphi_n \alpha_{1n}, \varphi_n \alpha_{2n}) &= E[\varphi_n \alpha_{1n} - E(\varphi_n \alpha_{1n})][\varphi_n \alpha_{2n} - E(\varphi_n \alpha_{2n})] \\
&= E[\varphi_n \alpha_{1n} \varphi_n \alpha_{2n}] - E(\varphi_n \alpha_{1n})E(\varphi_n \alpha_{2n}) \\
&= E({\varphi_n}^2 \alpha_{1n}\alpha_{2n}) - E(\varphi_n \alpha_{1n})E(\varphi_n \alpha_{2n}) \\
&= E({\varphi_n}^2)E(\alpha_{1n}\alpha_{2n}) - E(\varphi_n \alpha_{1n})E(\varphi_n \alpha_{2n})
\end{aligned}$$

$$= \Big((Var(\varphi_n) + [E(\varphi_n)]^2) \big(Cov(\alpha_{1n}, \alpha_{2n}) + E(\alpha_{1n}) E(\alpha_{2n}) \big) \Big)$$

$$- E(\varphi_n \alpha_{1n}) E(\varphi_n \alpha_{2n})$$

$$= \Big((Var(\varphi_n) + [E(\varphi_n)]^2) \big(Cov(\alpha_{1n}, \alpha_{2n}) + E(\alpha_{1n}) E(\alpha_{2n}) \big) \Big)$$

$$- [E(\varphi_n)]^2 E(\alpha_{1n}) E(\alpha_{2n})$$

$$= \left(\left(\sigma_{\varphi_n}^2 + \left[\mu_{\varphi_n}\right]^2 \right) \left(\sigma_{\alpha_{1n}\alpha_{2n}} + \mu_{\alpha_{1n}} \mu_{\alpha_{2n}} \right) \right) - \left[\mu_{\varphi_n}\right]^2 \mu_{\alpha_{1n}} \mu_{\alpha_{2n}}$$

$$= \sigma_{\alpha_{1n}\alpha_{2n}} \left(\sigma_{\varphi_n}^2 + \left[\mu_{\varphi_n}\right]^2 \right) + \sigma_{\varphi_n}^2 \mu_{\alpha_{1n}} \mu_{\alpha_{2n}}$$

Appendix A2. Tables

Table A2.1. Low-preference heterogeneity, positive correlation

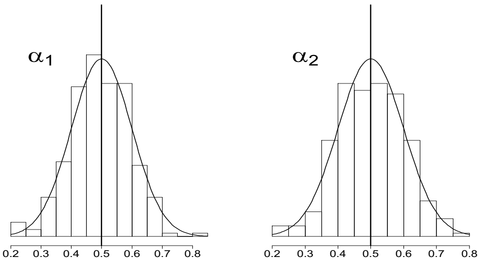
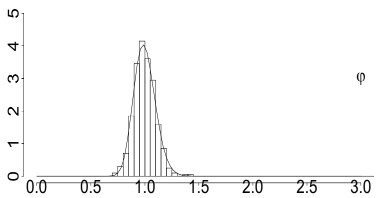
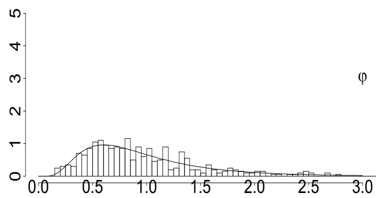
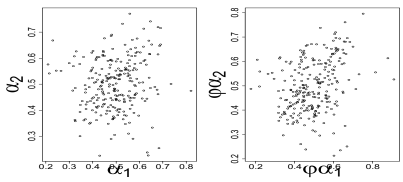
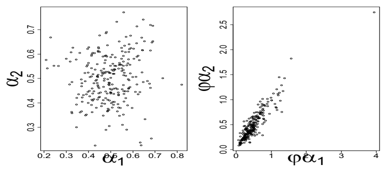
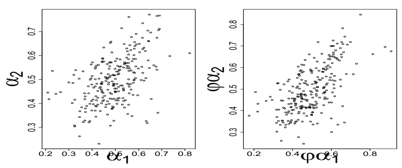
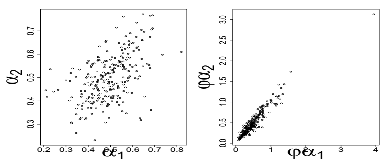
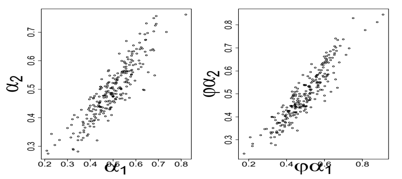
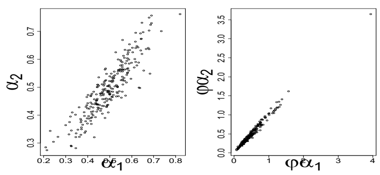
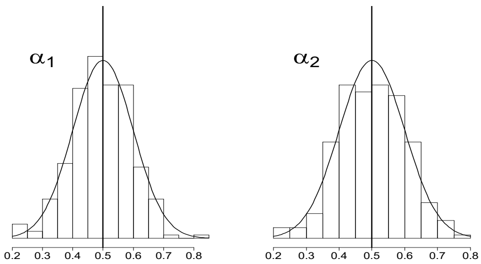
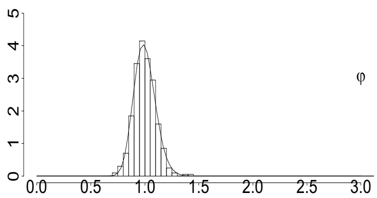
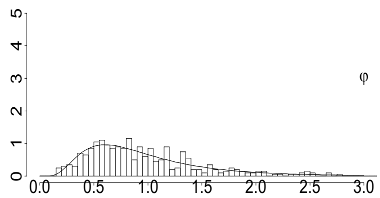
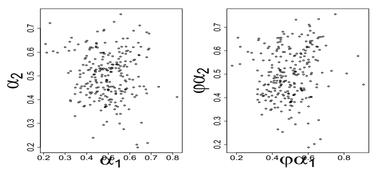
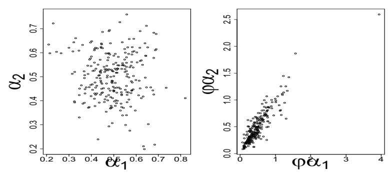
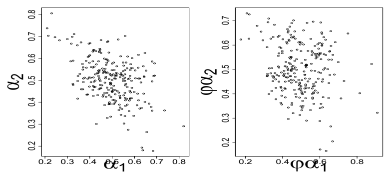
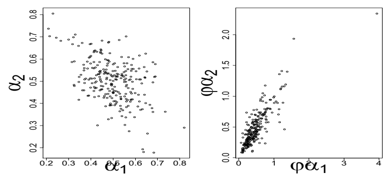
<table>
<tr><td></td><td colspan="2">$E(\alpha_1) = 0.5, Var(\alpha_1) = 0.1^2$
$E(\alpha_2) = 0.5,\ Var(\alpha_2) = 0.1^2$
</td></tr>
<tr><td></td><td>$E(\varphi) = 1, Var(\varphi) = 0.01$
</td><td>$E(\varphi_n) = 1, Var(\varphi) = 0.4$
</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2)$
$= 0.1$</td><td>
$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.28$</td><td>
$Corr(\varphi\alpha_1, \varphi_n\alpha_2) = 0.89$</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2)$
$= 0.5$</td><td>
$Corr(\varphi\alpha_1, \varphi\alpha_2) =$0.60</td><td>
$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.94$</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2) =$
0.9</td><td>
$Corr(\varphi\alpha_1, \varphi\alpha_2) =$0.92</td><td>
$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.99$</td></tr>
</table>

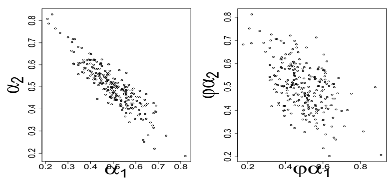
Table A2.2. Low-preference heterogeneity, negative correlation

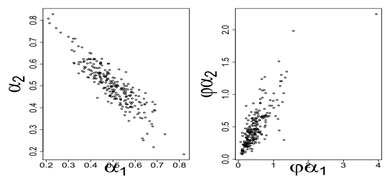
<table>
<tr><td rowspan="3"></td><td colspan="2">$E(\alpha_1) = 0.5, Var(\alpha_1) = 0.1^2$
$E(\alpha_2) = 0.5, Var(\alpha_2) = 0.1^2$</td></tr>
<tr><td colspan="2">
</td></tr>
<tr><td>$E(\varphi) = 1, Var(\varphi) = 0.01$

</td><td>$E(\varphi_n) = 1, Var(\varphi) = 0.4$

</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2)$
$= -0.1$</td><td>

$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.12$</td><td>

$Corr(\varphi\alpha_1, \varphi_n\alpha_2) = 0.86$</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2)$
$= -0.5$</td><td>

$Corr(\varphi\alpha_1, \varphi\alpha_2) =$ -0.20</td><td>

$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.82$</td></tr>
<tr><td>$Corr(\alpha_1, \alpha_2) =$
-0.9 ()</td><td>

$Corr(\varphi\alpha_1, \varphi\alpha_2) =$ -0.52</td><td>

$Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.77$</td></tr>
</table>

Table A2.3. High-preference heterogeneity, positive correlation

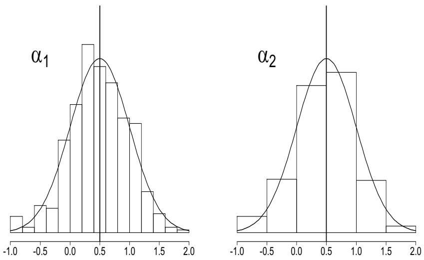
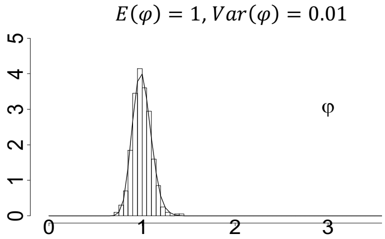
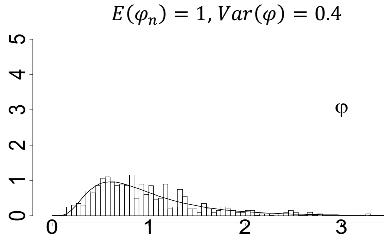
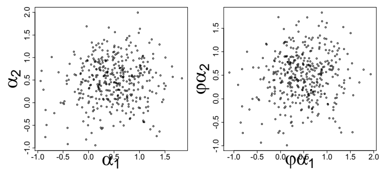
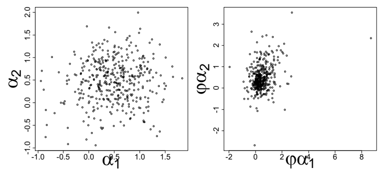
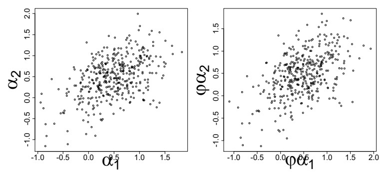
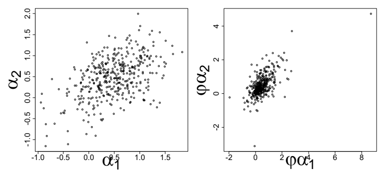
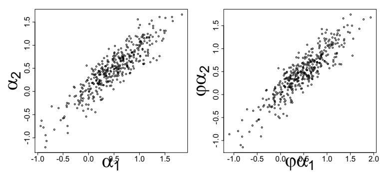
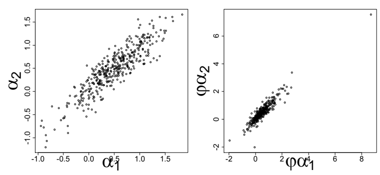
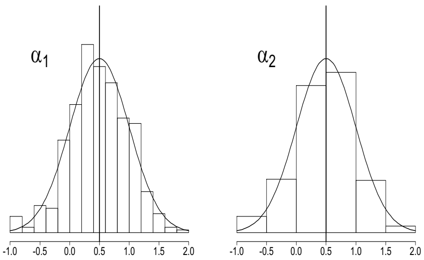
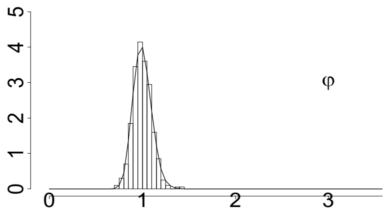
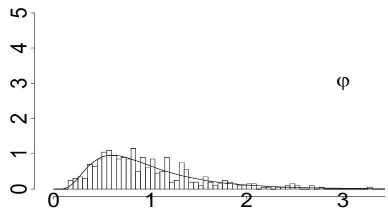
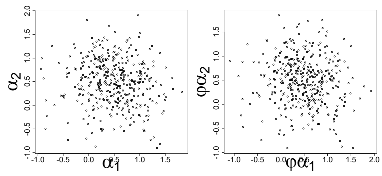
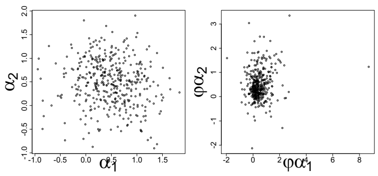
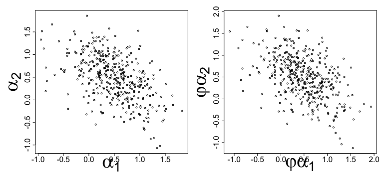
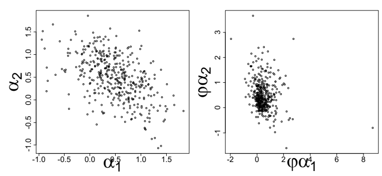
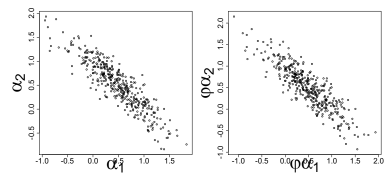
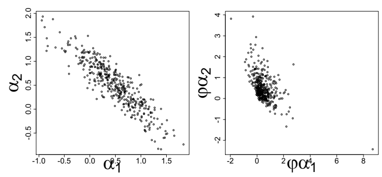
	$E(\alpha_1) = 0.5, Var(\alpha_1) = 0.5^2$ $E(\alpha_2) = 0.5, Var(\alpha_2) = 0.5^2$	
		
	$E(\varphi) = 1, Var(\varphi) = 0.01$ 	$E(\varphi_n) = 1, Var(\varphi) = 0.4$ 
$Corr(\alpha_1, \alpha_2)$ $= 0.1$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.11$	 $Corr(\varphi\alpha_1, \varphi_n\alpha_2) = 0.30$
$Corr(\alpha_1, \alpha_2)$ $= 0.5$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.50$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.61$
$Corr(\alpha_1, \alpha_2) =$ 0.9	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.90$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = 0.92$

Table A2.4. High-preference heterogeneity, negative correlation

	$E(\alpha_1) = 0.5, Var(\alpha_1) = 0.5^2$ $E(\alpha_2) = 0.5, Var(\alpha_2) = 0.5^2$	
		
	$E(\varphi) = 1, Var(\varphi) = 0.01$ 	$E(\varphi_n) = 1, Var(\varphi) = 0.4$ 
$Corr(\alpha_1, \alpha_2)$ $= -0.1$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = -0.09$	 $Corr(\varphi\alpha_1, \varphi_n\alpha_2) = 0.14$
$Corr(\alpha_1, \alpha_2)$ $= -0.5$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = -0.48$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = -0.17$
$Corr(\alpha_1, \alpha_2)$ $= -0.9$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = -0.88$	 $Corr(\varphi\alpha_1, \varphi\alpha_2) = -0.48$