A More Flexible Model or Simply More Effort? On the Use of Correlated Random Parameters in Applied Choice Studies

Petr Mariel

Department of Applied Economics III (Econometrics and Statistics), University of the Basque Country

Avda. Lehendakari Aguirre, 83

E48015 Bilbao, Spain

E-mail: petr.mariel@ehu.es

Tel: +34.94.601.3848

Fax: +34.94.601.3754

Jürgen Meyerhoff

Institute for Landscape Architecture and Environmental Planning

Technische Universität Berlin

D-10623 Berlin, Germany

E-mail: juergen.meyerhoff@tu-berlin.de

Abstract

The random parameter logit model has become the dominating model for analyzing stated choice data in environmental valuation. The unrestricted version of the model with correlated random parameters, however, is rarely applied. An important advantage of this specification is that the correlations between the parameters are not restricted to zero. These correlations can arise due to a behavioural phenomena or scale heterogeneity. One consequence of this might be that derived willingness-to-pay or to-accept estimates are under- or overestimated, providing decision makers with incorrect estimates. We compare both model specifications using data from a study about farmers' willingness to accept compensation for implementing agri-environmental measures in Brandenburg, Germany. For this data both model specifications - with and without correlated random parameters - provide similar willing-to-accept estimates, but the model with correlations performs better despite the higher number of parameters. As our findings could be case study specific, we want to encourage especially applied researchers to estimate also specifications with correlated random parameters. Applying only models with uncorrelated random parameters can result in biased estimates and thus provide incorrect information to decision makers.

Keywords: agri-environmental measures, choice experiment, correlated parameters, random parameter logit model

1. Introduction

The random parameter logit (RPL) is currently the most often used model to analyze stated choice data in environmental valuation. The motivation for this is that researchers are in general keen on investigating unobserved taste heterogeneity and the extent to which it drives recorded choices. To achieve this goal, the coefficients are usually assumed to be normally distributed and the cost coefficient is kept fixed for numerical convenience or is assumed to be log-normally distributed, since this is in line with microeconomic reasoning. However, the most important simplification adopted by the researchers is to assume that the parameters are not correlated as can be seen, for example, in recent articles by Rid et al., (2018) or Subroy et al., (2018).

McFadden and Train (2000) have shown that any choice model, with any distribution of preferences, can be approximated to any degree of accuracy by a mixed logit. The mixed logit probability can be derived in different ways that are formally equivalent, but provide distinct interpretations; the most widely used derivation is based on random coefficients. From a theoretical point of view, only a specification with correlated random parameters is correct, as this does not impose constraints on the model. The standard application of mixed logit models, however, imposes constraints on the model assuming that the variance-covariance matrix of the parameters is diagonal. The use of correlated random parameters has also gained attention in the debate concerning scale heterogeneity (Hess and Rose, 2012; Hess and Train, 2017). Scale causes correlation among coefficients as a respondent's choice can be more random (with all of the coefficients being smaller in magnitude) or more deterministic (with all of the coefficients being larger in magnitude). The scale of utility, that is the magnitude of all utility coefficients, generally differs over people.

Scale heterogeneity, as was shown in the debate mentioned above, cannot be separated from the variation in the utility coefficients. What can be done, however, to capture scale heterogeneity is to specify random parameters as being correlated, thus preventing scale heterogeneity from being picked up by the estimated taste parameters when scale is fixed at one. Seen the other way around, taste heterogeneity is picked up in scale parameters when taste preferences are assumed to be the same across respondents, and only scale differences are investigated in a heteroskedastic logit model, for example. In both cases, the parameter estimates could be severely biased. The use of correlated random parameters is also important because uncorrelated utility-random coefficients lead to a specific and restricted correlation structure of the willingness to pay (WTP) values (Train and Weeks, 2005). The advantages of using correlated random parameters and, therefore, a more flexible approach, are that no correlation structure is imposed on the WTP estimates and scale heterogeneity can be captured. Drawbacks, in contrast, are the increasing number of parameters leading to significantly higher computational burdens and that the interpretation of the model results becomes more cumbersome.

For our case study, we use choice data from a survey among farmers in Germany concerning their willingness to accept compensation for implementing agri-environmental measures on their farms. The literature on this topic recently has been growing rapidly as environmental problems such as high nitrogen loads deteriorate water quality in many countries. One way to get farmers to reduce nitrogen loads is by compensating them for the implementation of agri-environmental measures. Examples are the establishment of buffer zones or organic production. For decision makers it is thus important to know which factors influence the willingness of farmers to implement agri-environmental measures on the farmland they cultivate. Choice experiments are increasingly applied for investigating farmers' willingness to accept compensation in exchange for implementing these measures (e.g., Franzén et al., 2016; Santos et al., 2015). They are similarly employed for investigating farmers' willingness to carry out afforestation (Lienhoop and Brouwer, 2015) or forest owners' willingness to accept contracts for the provision of ecosystem services (e.g., Vedel et al., 2015). Common attributes are the amount of required compensation as well as the amount of land offered for implementing the measures by the farmer, but also whether the duration of a contract and whether it is possible to cancel contracts.

The majority of studies concerned with compensation payments for agri-environmental measures investigates the presence of unobserved taste heterogeneity by applying RPL models.

Although the number of studies recently increased significantly, we are not aware of any study that has applied a RPL specifications with correlated random parameters. Results presented in the literature regarding the requested compensation might thus be impaired by over- or under-estimation providing decision makers, who have to design the agri-environmental measures, with incorrect estimates. This could result a) in offering too low compensations to farmers, leading subsequently to too low supply, or b) in paying too much to farmers for the amount of measures demanded.

Not applying models with correlated random parameters is, however, not a unique feature of the literature concerned with agri-environmental measures. A review of studies employing RPL models to analyze choice data from stated preference studies, provided in Section 2, shows that models with uncorrelated random parameters are rather the norm than the exception. The main objective of this study is thus to present the more flexible approach with correlated random parameters and compare the results from this specification to a model with uncorrelated random parameters. We want to raise awareness among applied researchers that the so far routinely used specification of the RPL suffers from some severe theoretical limitations. This is especially unfortunate as standard software packages offer an easy implementation of the RPL model with correlated random parameters. Among them are NLogit (Greene 2016), the mixed logit model for Stata provided by Hole (2007), and a comprehensive R-package for analyzing choice data by Sarrias et al. (2017). In the following we thus hope to raise awareness for adding this specification of the RPL model to the suite of models used to investigate data gained from stated choice experiments. Whether this specification indeed results in a better model is, however, an empirical question that can only be answered by estimating RPL models with correlated random parameters.

2. Correlated Random Parameters

2.1 Literature review

In the following we briefly present those studies we have identified as applying correlated random parameters.[1] As all these studies haven't compared the performance of models with and without correlated random parameters, but "simply" used them as part of their model specification, the review also only mentions findings with respect to the each application. One of the first studies using correlated random parameters was presented by Revelt and Train (1998). They estimate the impact of rebates and loans on US residential customers' choice of efficiency level for refrigerators. In their application of a RPL model with correlated coefficients, they show that consumers who respond greatly to rebates tend also to respond greatly to attractive financing, such that the rebate and financing coefficients are positively correlated. Another study using specification with correlated random parameters is from Scarpa et al. (2008) who analyze destination choices among Alpine hiking sites in the northeast of Italy, showing that recreationists who value warming huts at the site tend also to prefer sites with easier trails. On the other hand, people who prefer difficult trails also tend to like having rope assists on the trails.

In a recent analysis, Alberini et al. (2018) seek to estimate the benefits of climate change mitigation, as measured by the public's willingness to pay for such policies. They find evidence of considerable heterogeneity in WTP driven by income, but also an important dependency of the income elasticity of WTP on the RPL specification. Another recent study applying correlated random parameter in a RPL model is by Waldman et al. (2017). They evaluate farmers' preferences for perennial attributes of pigeon pea intercropped with maize in central and southern Malawi. Adoption of annual pigeon pea

[1] We conducted a search on Scopus using different combinations of the words "random", "parameter", "logit" and "correlated", "random", "parameters" as well as "mixed" and "logit" in Titles, Abstracts, and Keywords. We do not claim that we found all studies that report results from a RPL specification with correlated random parameters, as results might only be described in the main text of a paper, but we think that the low number of studies we found reflects the rare use of the model specification with correlated random parameters.

in the area under study is relatively low, but perennial production of pigeon pea may be more appealing to farmers due to some of the ancillary benefits associated with perenniality. While maize yield is approximately twice as valuable to farmers as pigeon pea yield, the authors find positive but heterogeneous demand for perenniality driven by soil fertility improvements and pigeon pea grain yield. Further, Wakamatsu et al. (2018) use correlated random parameters to value whale conservation using data collected from anti-whaling populations in Australia and Japan. They find higher economic valuation for a ban on whaling than for conventional protection actions in Australia. However, the results do not indicate whether a ban or conventional protection is preferred among those against whaling in Japan. The results, therefore, show a significant difference between both countries, even when only the anti-whaling populations are taken into account, suggesting a high bar for reaching international consensus over whaling.

Looking at studies outside of environmental economics, a specific application from transportation is presented by O'Neil and Hess (2014). They study the decision of workplace location of one member of a two-person household affecting the travel time and salary of both members. Using data of Swedish couples, they apply a bargaining discrete choice model allowing for correlated random parameters showing significant heterogeneity across individuals, not just in their underlying sensitivities, but also in the relative weight they assign to their partner. It concludes that male respondents place more weight on their partner's travel time, while female respondents place more weight on their partner's salary. Another, more recent example from transportation literature is Hess et al. (2018), who analyze travellers' choices of route by car and public transport in Singapore, finding complex correlation patterns between the sensitivities to the different time, cost, quality of service and safety attributes.

Finally, Eriksson and Kristensen (2014) present an application in labor economics. They estimate individuals' willingness-to-pay values for fringe benefits and job amenities, comparing a RPL model with correlated and uncorrelated parameters. They analyze a data set on Danish respondents within the age range 25–64 who were likely to hold jobs and to receive job offers where remuneration potentially includes fringe benefits and other non-monetary rewards. As one of the results of their study, they conclude that the non-monetary job attributes can be monetized. This conclusion implies that models of incentives and pay can be applied also to non-monetary rewards, like benefits and job amenities.

2.2 Econometric Approach

As it is generally done, we assume the basic setting of a Random Utility Model (McFadden, 1974), i.e., the utility from alternative j in choice occasion t by person n is:

$$U_{njt} = \beta' x_{njt} + \varepsilon_{njt} = V_{njt} + \varepsilon_{njt}, \tag{1}$$

where ε_{njt} is an independently, identically distributed type I extreme value over time, people and alternatives. In this equation, x_{njt} represents a vector of K attribute levels, β is a vector of unknown paramaters and V_{njt} is called representative utility. Under this assumption we get the Multinomial Logit Model (MNL). The probability that decision-maker n, in a choice occasion t chooses alternative i is:

$$P_{nit} = \frac{exp(x_{nit}' \beta)}{\sum_{j=1}^{J} exp(x_{njt}' \beta)}.$$

The main limitations of the MNL is the independence of errors between alternatives, its implication of proportional substitution across alternatives and the independence of the unobserved factors over time in repeated choice situations. There has been a huge development of different modifications of this basic MNL. Since the mentioned contribution by McFadden and Train (2000), the RPL has been one of the most applied models across different fields due to its flexibility, allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time or distribution of preferences.

Mixed logit probabilities are the integrals of standard logit probabilities over a density of parameters β. The choice probabilities of a mixed logit model are defined as:

$$P_{nit} = \int L_{nit}(\beta) f(\beta) d\beta,$$

where $f(\beta)$ is a density function and $L_{nit}(\beta)$ is the standard logit probability evaluated at parameters β; that is:

$$L_{nit}(\beta) = \frac{exp(V_{nit}(\beta))}{\sum_{j=1}^{J} exp(V_{njt}(\beta))} = \frac{exp(x_{nit}^{'}\beta)}{\sum_{j=1}^{J} exp(x_{njt}^{'}\beta)}.$$

The mixed logit probability can be derived in different ways that are formally equivalent but provide distinct interpretations. The most widely used derivation is based on random coefficients. In this case, the utility from alternative j in choice occasion t by person n is:

$$U_{njt} = x_{njt}^{'}\beta_n + \varepsilon_{njt},$$

where ε_{njt} is *iid* over time, people and alternatives, and coefficients β_n are distributed with density $f(\beta|\Omega)$. The vector of random coefficients can be decomposed into:

$$\beta_n = \beta + \Lambda z_n + \Gamma v_n, \tag{2}$$

where β is a parameter vector representing the fixed means of the random parameter distribution, z_n is the vector of observed individual-specific characteristics that affect the mean of the random parameter distribution and Λ is the associated parameter matrix. The random unobserved taste variation is represented by v_n, a vector of uncorrelated random variables with mean zero and covariance matrix with known values on the diagonal, fixed by identification restrictions. The matrix of parameters Λ allows for different mean shiftings among the means β and the lower triangular matrix Γ-possible covariance structures among K random parameters. The vast majority of published papers based on MXL assume $\Gamma = diag(\gamma_{11}, \gamma_{22}, \ldots, \gamma_{KK})$, which corresponds to the case of uncorrelated random parameters. In the case of freely correlated parameters, the full variance-covariance matrix of the random parameters is:

$$Var(\beta_n) = \Gamma\,\Sigma\,\Gamma^{'}. \tag{3}$$

Conditional on β_n, the probability that the decision-maker n makes a sequence of alternatives $\{i_{n1}, i_{n2}, \ldots, i_{nT}\}$ is:

$$L_{ni}(\beta) = \prod_{t=1}^{T} \left(\frac{exp(x_{ni_{nt}t}^{'} \beta_n)}{\sum_{j=1}^{J} exp\left(x_{njt}^{'} \beta_n\right)} \right)$$

assuming that ε_{njt} are independent over time. The unconditional probability of the sequence of choices $\{i_{n1}, i_{n2}, \ldots, i_{nT}\}$ is the mixed logit probability formula:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta.$$

The log-likelihood function is, therefore, defined as:

$$LL(\Omega) = \quad = \sum_{n=1}^{N} ln \left(\int \left(\prod_{t=1}^{T} \left(\frac{exp(x_{ni_{nt}t}^{'} \beta_n)}{\sum_{j=1}^{J} exp\left(x_{njt}^{'} \beta_n\right)} \right) \right) f(\beta|\Omega) d\beta \right)$$

Given that there is no closed form of $LL(\Omega)$, the probabilities are approximated through simulation for any given value of Ω. The simulated log-likelihood function is, therefore, defined as:

$$SLL(\Omega) = \sum_{n=1}^{N} ln \left(\frac{1}{R} \sum_{r=1}^{R} \left(\prod_{t=1}^{T} \left(\frac{exp(x_{ni_{nt}t}^{'} \beta_r)}{\sum_{j=1}^{J} exp\left(x_{njt}^{'} \beta_r\right)} \right) \right) \right).$$

The maximum simulated likelihood estimator (MSLE) is the value of Ω that maximizes $SLL(\Omega)$. Choosing the correct distribution to reproduce the heterogeneity in underlying population preferences has been, in past years, one of the major research interests in discrete choice modeling literature, but the question of choosing the correct distribution still seems to remain unanswered (Daly, Hess and Train, 2012).

The fact that taste and scale heterogeneity cannot be determined separately from each other (Hess and Rose, 2012; Hess and Train, 2017) makes it also impossible to interpret the estimated variance-covariance (or correlation) matrix of the random parameters defined in (3). It is shown in a following simple simulation exercise. Let us assume that the utility defined in (1) depends only on two attributes $X1_{njt}$ and $X2_{njt}$ and α_{1n} and α_{2n} are their corresponding utility coefficients that vary randomly over individuals. Thus,

$$U_{njt} = \alpha_{1n}X1_{njt} + \alpha_{2n}X2_{njt} + \frac{1}{\varphi_n}\varepsilon_{njt}, \tag{4}$$

where $\varphi_n$varies over people and is inversely proportional to the standard deviation of the error term. This utility function can be rewritten as

$$\varphi_n U_{njt} = \varphi_n\alpha_{1n}X1_{njt} + \varphi_n\alpha_{2n}X2_{njt} + \varepsilon_{njt},$$

that is

$$U_{njt}{}^{*} = \beta_{1n}X1_{njt} + \beta_{2n}X2_{njt} + \varepsilon_{njt.} \tag{5}$$

Let us assume that φ_n and α_n are independent and

$$\begin{pmatrix}\alpha_{1n}\\ \alpha_{2n}\end{pmatrix} \sim N\left[\begin{pmatrix}0.5\\ -0.5\end{pmatrix}, \begin{pmatrix}0.00250 & 0.00225\\ 0.00225 & 0.00250\end{pmatrix}\right] \tag{6}$$

and φ_n is lognormally distributed with $E(\varphi_n) = 1$ and $Var(\varphi_n) = 0.4$. The covariance 0.00225 (corresponding to the correlation coefficient $\rho = 0.9$) between the original parameters α_{1n} and α_{2n} indicates very high correlation that arises due to a behavioural phenomenon. Nevertheless, if scale heterogeneity is present (φ_n), the model is not capturing this correlation between α_{1n} and α_{2n} but the correlation between β_{1n} and β_{2n} in equation (5).

The left hand side panel of Figure 1 shows 400 draws from the multivariate distribution defined in (6). It shows very high positive correlation among the random parameters for the case without scale heterogeneity (e.g., respondents with higher preferences for attribute $X1$ are likely to have higher preferences for attribute $X2$). In contrast, the right hand side panel of Figure 1 shows the correlation between β_{1n} and β_{2n}, that is the correlation between the original taste parameters affected by scale ($\varphi_n\alpha_{1n}$ and $\varphi_n\alpha_{2n}$). As can be easily seen, the original high positive correlation is inverted by scale to a high negative correlation. That illustrates the confounding between taste heterogeneity represented by α_{1n} and α_{2n} and scale heterogeneity represented by φ_n. It also shows that the estimated correlation cannot be directly interpreted as correlation arising from respondents choices reflecting their preferences.

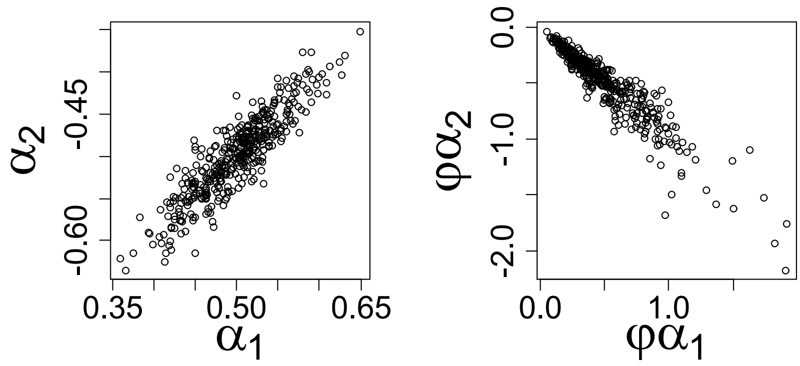

Fig. 1. Scatter plots

3. Survey Design and Data Collection

Instead of presenting farmers with a generic choice experiment, we opted for a labelled experiment with the labels reflecting the three main types of agri-environmental measures that were on offer in Brandenburg (Germany) when the survey was conducted: i) greening, i.e., arable land, which is used as extensive grassland, will be subsidized when kept as arable land, ii) water protection, i.e., compliance with a given nitrogen, and iii) organic farming. Each of these three labelled alternatives, which were accompanied by an opt-out alternative, was described by the attributes reported in Table 1. The selection of the attributes was done after consulting experts from the region, as well as consulting prior studies conducted in similar contexts.

Table 1
Attributes and levels.

Attribute	**Definition**	**Levels**
Contract duration	Run-time of the contract	3 / 5 / 12 years
Monitoring	Share of farmers that will be controlled by the authorities	3% / 10% / 30%
Cancellation	Whether it is possible to cancel the contract during the term	no / yes

Minimal share of farmland under contract	Minimum share of the available farmland that will be subject of the contract	10% / 40% / 100%
Effort on administration	Number of hours per months spent on administrative tasks	low (0 -10 hours) medium (10 – 20 hours) high (> 20 hours)
Compensation	Yearly payment per hectare if the farmer participates	40 / 65 / 120 / 170 / 240 / 370 Euros

To allocate the attribute levels to alternatives, we used a Bayesian D-efficient design optimized for an MNL model.[2] The resulting 18 choice sets were grouped into two blocks, in which each respondent had to answer nine choice sets. The order of the choice sets was randomized. Figure 2 shows an example of a choice set. The survey was conducted online and the questionnaire contained, in addition to the choice sets, questions regarding farm characteristics and the farmers' attitudes towards, among other things, agri-environmental measures and environmental protection in general.

	Greening	**Water protection**	**Organic farming**	**No measures**
Contract duration	5 years	3 years	12 years	I will not sign a contract
Cancellation	No	No	Yes	
Minimal share of farmland	100%	100%	40%	
Monitoring	10%	3%	30%	
Effort administration	Medium	Low	Medium	
Compensation	65€	370€	370€	
I choose	□□	□□	□□	□□

Fig. 2. Example choice set.

[2] As stated in Bliemer and Rose (2010, 2011), designs for MNL models seem to perform well when more advanced models are used. However, an experimental design specifically tailored for the model might have performed better with respect to the statistical efficiency. Currently, only a very few studies have used design based on other than the MNL model, and too little is known about the pros and cons of optimizing a design for a specific model such as the RPL model. What has been raised, however, is that efficient design might not be neutral (Yao et al., 2015, Olsen and Meyerhoff, 2017) because it can also affect the so called respondent efficiency. Without further evidence that increasing statistical efficiency does not negatively impact on choice behavior and subsequently model estimates we withhold from using more efficient statistical designs.

The survey took place in February 2015. A list with the addresses of all farms in Brandenburg at that time was provided by the State Office for Rural Development, Agriculture and Land Consolidation (LELF; https://lelf.brandenburg.de), Brandenburg, for use in the research project Nitrolimit[3]. All 5,400 farmers listed were invited to participate in the survey. Since the data base from the LELF contained the email addresses of 2,730 farms, those were invited by email, i.e., the link to the survey webpage was sent to them. The remaining farmers were invited by surface mail. Two weeks after the initial invitation, all farmers received a reminder asking them to participate if they had not already responded. The reason all farmers were reminded is that the link sent to farmers was anonymous, and thus we could not determine who had already participated. This resulted finally in 565 useable interviews, slightly below a 10% share of those who were invited.

Table 2 reports some of the characteristics of the farms in our sample and compares them to the registered farms in Brandenburg, i.e., the 5,400 that were invited to the survey. Interestingly, we have a slightly higher response from farms organized as business partnerships or legal entities compared to individual companies. Due to this effect, on average farms in the sample have significantly more land (438ha) than the average farm in Brandenburg has (238ha). In the sample, there are also fewer arable farms and farms that have specialized in fodder crops, while farms that do both fodder and livestock farming are slightly overrepresented; organic farms are slightly overrepresented, too. In Brandenburg, 12% of the farms are run as organic farms, while in the sample, 16% of the farms are organic. Overall, those who responded are not completely representative for all farms in Brandenburg, but since we use this sample first of all to demonstrate methodological aspects, this is of minor importance here.

[3] The overall objective of this project was to investigate whether nitrogen reduction in freshwaters is ecologically meaningful and economically feasible. More information is available at www.nitrolimit.de.

Table 2
Characteristics of farms in the sample

	Variable	Mean farms in sample (N = 565)	Mean all farms* (N = 5400)
Legal form %	Individual companies	64	69
	Business partnership (GbR, OHG KG)	15	13
	Legal entities (e.g., GmbH)	21	19
Company form %	Arable farming	26	33
	Fodder crops	29	37
	Fodder and livestock farming	29	17
	Other	16	13
Area arable land in ha		438	238
Share of arable land in %		53	78
Share organic farming (%)		16	12

Note: * Figures are from “Agrarbericht Brandenburg - Online” (https://agrarbericht.brandenburg.de).

Table 3 presents definition, description and descriptive statistics of farm-specific variables used in the estimation. First, soil quality is measured using a measure of the productivity of agriculture land (Ackerzahl, see for more information below Table 3) of the interviewed farms. It’s average value is 30 and thus slightly lower than the average value of 33 for Brandenburg (MLUL 2016). However, it varies between 45 and 23 (median 32) indicating that conditions are different for the farms in the sample. The average size of the farmland is, as already mentioned, 438 ha in our sample. As it varies strongly across farms in the sample - from 1ha to 12,000 ha -, the median with 89ha is also reported here. The other statistics show that only 16% completely own the farmland they cultivate, that 64% of the farms had previously participated in agri-environmental measures, and that 45% of the farmers are members of a farmers’ association.

Table 3

Descriptive statistics of farm specific variables.

Name	Description	Mean	Median	St. Dev.	Min	Max
*SoilQuality**	Soil quality measured by *Ackerzahl*, an indicator ranging from 100 (very good) to 0 (very poor)	30.1	32	6.5	23	45
Farmland	Size of the farmland (ha)	438.4	89	874.2	1	12,000
		Value	**Frequency**			
Property	Farm land is completely private property (=1)	0	83.6%			
		1	16.3%			
PriorAgriEnv	Prior participation in agri-environmental measures (=1)	0	36.2%			
		1	63.8%			
NoMember	Farm is not a member of any farmer association (=1)	0	55.1%			
		1	44.9%			

Note: *Soil quality was measured by requesting the category of agricultural land (Landbaugebiet) to which the farm belongs to. Categories are defined by a measure of the productivity of agriculture land (Ackerzahl) that ranges in Brandenburg from 45 and less to more than 23 (MLUL 2016). The best soil quality is indicated by a value of 100. When this measure (Ackerzahl), was introduced, farmland in the Magdeburg Börde, today a central landscape unit of the state of Saxony-Anhalt in Germany, that is known for its very fertile Chernozem soils, was chosen as a reference.

4. Results

4.1 Model Results

The estimates from both RPL models with and without correlated random parameters are reported in Table 4. The simulated log-likelihood was each time maximized using 2000 Halton draws. The underlying distribution of all random parameters is the normal, with the exception of the parameter of attribute *Compensation*, which is assumed to be log-normally distributed. The reason behind this is that basic economic theory states that the sign for the requested compensation by farmers should always be positive. The coefficients in Table 4 reflect the estimated means of the normal distribution denoted β in (2), and the standard deviations were calculated according to (3). Their standard errors are obtained directly from the lower triangular matrix Γ in the case of uncorrelated parameters, as in this case Γ is a diagonal matrix. For the model with correlated parameters, the standard errors are computed using the delta method. Hensher et al. (2015) discuss in detail the applied Cholesky decomposition used in the case of correlated parameters. The standard deviations of all parameters for the correlated case are computed by the means of estimated Γ presented in Table A1 (Appendix) according to (3), and all of them are significant, indicating strong preference heterogeneity among respondents. After reporting the coefficients for the three ASCs, Table 4 reports the estimates for the main effects of each attribute and the estimated standard deviations – labeled *Attributes (means)* and *Attributes (sd. Deviations)* in the Table. The last section of Table 4 is devoted to the interaction effects representing the mean-shifters included in the matrix Λ of (2).

Overall, the model with correlated random parameters clearly performs better, even when we penalize for the increased number of estimated parameters. Both the AIC and the BIC indicate that adding the correlations to the model is worth the effort. However, the estimates of both the uncorrelated and correlated model are close to each other. Looking first at the ASCs for the three labelled alternatives, we find that in the model with uncorrelated random parameters, only the ASC for water protection is significant. Its negative sign indicates that, on average, this alternative is less preferred than signing no contract. In the model with correlated random parameters, we also see that the other alternatives are relevant for the farmers' choices. Greening and organic farming are, on average, preferred over not signing a contract.

The first attribute is then *Compensation*, reflecting the amount of money farmers request for implementing agri-environmental measures on their farms. Since the mean of the underlying Normal distribution for the *Compensation* coefficient is assumed to be log-normally distributed, its median for the uncorrelated case is $exp(-4.894) = 0.0075$, and the mean is $exp(-4.894 + 0.866/2) =$

0.0116, and the standard deviation is $\sqrt{(exp(2(-4.894)+0.866)[exp(0.866)-1])} = 0.0002$. Thus, both models clearly indicate unobserved heterogeneity with respect to the requested compensation above the variation captured by the mean shifters. Other attributes relevant to the recorded choices are cancellation, contract duration and time spent on administrative tasks. The opportunity to cancel the contract regarding the agri-environmental measure is seen as highly positive, because it would allow farmers to switch to more intensive farming when market prices increase, for example. Contract duration is similar, but, valued negatively on average; longer-running contracts mean less flexibility for farmers. Finally, time spent on administrative tasks is also highly important and valued strongly negative by farmers. For these attributes both models reveal very similar results; only the standard errors for contract duration are smaller in the correlated model. The corresponding standard deviations indicate high levels of unobserved heterogeneity. Not all farmers seem to value contract duration and time spent on administrative tasks as negative as the average, and not all value the opportunity to cancel a contract as positively as the average. This applies, of course, also in the reverse. At first glance, both attributes monitoring and minimal share of land seem to be irrelevant for farmers' choices among the alternatives. In both models the mean parameter for these attributes is insignificant. However, in each case the standard deviation is highly significant in the correlated model. In the uncorrelated model, only the standard deviation for minimal share of farmland is significant. Having a not-significant mean and highly significant standard deviations, as in the correlated model, indicates that these two attributes are probably valued very differently by groups of farmers.

In addition to unobserved heterogeneity, we also investigate the influence of a set of mean shifters comprising different farm characteristics. These are: the quality of the soil of the farm (*SoilQuality*), the amount of farmland (*Farmland*), whether the farmland is private property or rented (*Property*), whether a farmer has participated in an agri-environmental measure program before (*PriorAgriEnv*), and whether a farmer is a member of a farmers' association (*NoMember*). Strikingly, we find that two farm characteristics are highly relevant to the way the amount of required compensation is valued. Farms with higher soil quality require, on average, less compensation, while farms with more farmland require on average more compensation per hectare. Next, the valuation of the attribute monitoring depends on the amount of farmland. Farmers with larger farms are even more negative toward monitoring than farmers with less farmland. Regarding the preference toward cancellation, the property has some relevance, i.e., farmers who own their farmland completely value the opportunity to cancel the contract less positively. The reason behind this might be that farmers who have to lease land might not have contracts with their landlords for the whole period the agri-environmental measure contract will run, and thus need more flexibility. The valuation of the minimum share of farmland is again mainly influenced by soil quality and farmland. Having better soil quality shifts farmers slightly toward higher minimum shares and more farmland leads farmers to a more negative valuation of the minimum share. On the other hand, time spent on administrative tasks is not affected by any of the farm characteristics, which is reasonable since the paperwork required by agencies does not depend on the amount of farmland under contract.

Table 4

RPL model estimation.

	Uncorrelated RPL			**Correlated RPL**		
	Coef.	Std. Error		Coef.	Std. Error	
Alternative specific constants						
ASC_greening	-0.031	0.084		0.189	0.084	**
ASC_water	-0.609	0.086	***	-0.430	0.087	***
ASC_organic farming	-0.114	0.084		0.140	0.085	*
Attributes (means)						
Compensation	-4.894	0.348	***	-4.910	0.337	***
Monitoring	0.013	0.014		0.012	0.014	
Cancellation	0.475	0.233	**	0.441	0.220	**
Minimal share of farmland	-0.004	0.005		-0.004	0.005	
Contract duration	-0.094	0.056	*	-0.099	0.044	**
Time spent on administrative tasks	-0.459	0.148	***	-0.464	0.156	***
Attributes (sd. deviations)						
Compensation	0.866	0.069	***	0.763	0.097	***
Monitoring	0.013	0.008		0.018	0.004	***
Cancellation	0.320	0.095	***	0.186	0.092	**
Minimal share of farmland	0.012	0.001	***	0.015	0.001	***
Contract duration	0.181	0.015	***	0.123	0.011	***
Time spent on administrative tasks	0.130	0.088		0.267	0.041	***

Interaction effects						
Compensation						
- SoilQuality	-0.027	0.010	***	-0.024	0.010	**
- Farmland	0.202	0.054	***	0.177	0.055	***
- Property	0.135	0.176		0.077	0.174	
- PriorAgriEnv	0.067	0.138		0.122	0.133	
- NoMember	0.095	0.133		0.124	0.125	
Monitoring						
- SoilQuality	0.001	0.001		-0.001	0.001	
- Farmland	-0.014	0.004	***	-0.012	0.004	***
- Property	0.001	0.007		0.002	0.007	
- PriorAgriEnv	-0.005	0.006		-0.005	0.006	
- NoMember	0.002	0.005		0.001	0.006	
Cancellation						
- SoilQuality	-0.007	0.007		-0.008	0.007	
- Farmland	-0.081	0.062		-0.093	0.057	
- Property	-0.205	0.118	*	-0.196	0.110	*
- PriorAgriEnv	-0.001	0.095		0.007	0.090	
- NoMember	0.011	0.092		0.011	0.086	
Minimal % of agriculture area						
- SoilQuality	0.001	0.001		0.001	0.001	**
- Farmland	-0.007	0.001	***	-0.007	0.002	***
- Property	0.004	0.002	*	0.005	0.003	*
- PriorAgriEnv	0.003	0.002		0.004	0.002	*
- NoMember	-0.001	0.002		0.000	0.002	
Contract duration						
- SoilQuality	-0.003	0.002		-0.002	0.001	
- Farmland	-0.030	0.015	**	-0.024	0.012	**
- Property	0.036	0.028		0.037	0.022	*
- PriorAgriEnv	0.034	0.023		0.025	0.018	
- NoMember	-0.013	0.022		-0.012	0.017	
Time spent on administrative tasks						
- SoilQuality	0.003	0.004		-0.001	0.005	
- Farmland	0.001	0.040		0.004	0.040	
- Property	0.022	0.075		0.074	0.079	
- PriorAgriEnv	0.080	0.061		0.097	0.064	
- NoMember	0.015	0.058		0.019	0.061	
Log-likelihood	-5533.7			-5383.8		
Number of parameters	45			60		
Observations	5085.0			5085.0		
AIC	11157.4			10887.6		
BIC	11451.4			11279.6		

Note: ***, **, * stands for significance at 1%, 5% and 10%, respectively.

The implied correlation matrix of the random parameters in the model with correlated random parameters is presented in Table 5. We find high correlations among some of the attributes. For example, *Monitoring* and *Minimum share*, *Contract duration* as well as *Time spent on administrative tasks* are highly correlated. We can test the null hypothesis that all out-of-diagonal elements of the matrix Γ are zero, that is, the correlation matrix of the random parameters (Table 5) is an identity matrix. If this hypothesis is not rejected, the use of the RPL with uncorrelated parameters is justified. The Likelihood ratio statistics is $LR = -2 \cdot ((-5533.7) - (-5383.8)) = 299.8 > 25 = \chi^2_{(15)}{}^{0.05}$, leading to rejection of the null hypothesis. The RPL with correlated parameters is thus the preferred model.

Table 5

Estimated correlation matrix of the random parameters.

	Compensation	*Monitoring*	*Cancellation*	*Min. % of agr. area*	*Contract duration*	*Time spent on admin. tasks*
Compensation	1.00					
Monitoring	-0.24	1.00				
Cancellation	0.81	0.13	1.00			
Min. % of agr. area	0.00	0.95	0.43	1.00		
Contract duration	-0.08	0.98	0.32	0.99	1.00	
Time spent on admin. tasks	-0.04	0.93	0.43	0.99	0.98	1.00

4.2 Willingness to Accept Estimates

In a classic choice experiment (CE), marginal WTP values are typically calculated as the change in one non-monetary attribute with respect to the monetary attribute (Hanemann, 1984; Train, 1998). This is in the present case the required *Compensation*. Note, however, that since we are dealing with requested compensations, the sign is reversed compared to the classical WTP calculation. Thus, the marginal willingness to accept (WTA) estimates are calculated as:

$$WTA = \frac{\beta_{attribute}}{\beta_{Compensation}}. \quad (3)$$

For the WTA marginal estimates, we need to take into account the random nature of the coefficients. For this purpose, the values in (3) are generated following the Krinsky and Robb (1986) procedure. The generated marginal WTA distribution for the *Monitoring* attribute, with its parameter distribution as normal and the *Compensation* attribute parameter as log-normal, is specified, for example, as:

$$\widehat{WTA}_{Monitoring} = \frac{\hat{\beta}_{Monitoring} + \hat{\sigma}_{Monitoring} \cdot \nu_{Monitoring}}{\exp\,(\hat{\beta}_{Compensation} + \hat{\sigma}_{Compensation} \cdot \nu_{Compensation})},$$

where $\hat{\beta}_{Monitoring}$ and $\hat{\beta}_{Compensation}$ are the estimated means (Table 4) of the *Monitoring* and $Compensation$ random-attribute parameters, respectively; and $\hat{\sigma}_{Monitoring}$ and $\hat{\sigma}_{Compensation}$ are their corresponding estimated standard deviations (Table 4), and $\nu_{Monitoring} \sim N(0{,}1)$, $\nu_{Compensation}$ $\sim N(0{,}1)$ in the uncorrelated case. In the correlated case, the corresponding multivariate joint distribution must be used.

The inclusion of interaction effects representing the mean-shifters included in Λ of (2) allows for a more detailed analysis of preference heterogeneity using observed data. If we denote $\hat{\beta}_{M \times SoilQuality}$, $\hat{\beta}_{M \times Area}$, $\hat{\beta}_{M \times Prop}$, $\hat{\beta}_{M \times Agri}$ and $\hat{\beta}_{M \times Noor}$, as the corresponding interactions of the attribute *Monitoring* with *SoilQuality*, *Farmland*, *Property*, *PriorAgriEnv* and *NoMember*, using a similar notation for the interactions with *Compensation* attribute ($\hat{\beta}_{C \times SoilQuality}$, $\hat{\beta}_{C \times Farmland}$, $\hat{\beta}_{C \times Prop}$, $\hat{\beta}_{C \times Agri}$ and $\hat{\beta}_{C \times Noor}$), then the marginal WTA distribution for the attribute *Monitoring* with interaction effects is as follows:

$$\widehat{WTA}_{MonitoringInteract} = \frac{\begin{gathered}(\hat{\beta}_{Monitoring} + \hat{\beta}_{M \times SoilQuality} \cdot SoilQuality + \hat{\beta}_{M \times Farmland} \cdot Farmland \\ + \hat{\beta}_{M \times Property} \cdot Property + \hat{\beta}_{M \times PriorAgriEnv} \cdot PriorAgriEnv \\ + \hat{\beta}_{M \times NoMember} \cdot NoMember + \hat{\sigma}_{Monitoring} \cdot \nu_{Monitoring})\end{gathered}}{\begin{gathered}\exp\,(\hat{\beta}_{Compensation} + \hat{\beta}_{C \times SoilQuality} \cdot SoilQuality + \hat{\beta}_{C \times Farmland} \cdot Farmland \\ + \hat{\beta}_{C \times Property} \cdot Property + \hat{\beta}_{C \times PriorAgriEnv} \cdot PriorAgriEnv \\ + \hat{\beta}_{C \times NoMember} \cdot NoMember + \hat{\sigma}_{Compensation} \cdot \nu_{Compensation})\end{gathered}}. \tag{4}$$

We define benchmark values of the farm characteristics used in (4) to perform our detailed analysis of marginal WTA values. The selected benchmark values are the median values for $SoilQuality$ ($median = 32$) and $Farmland$ ($median = 89$). All remaining dummy variables are set to zero, i.e., $Property = 0$, $PriorAgriEnv = 0$ and $NoMember = 0$. Subsequently, we perform two comparisons based on the simulated marginal WTA values defined in (4). The first is focused on the methodological contribution of the paper and the second on the interpretational part of the results regarding the specific case study.

The first comparison in Figure 3 presents the simulated marginal WTA values for all attributes obtained for the mixed logit estimated without and with correlated parameters. The spreads of all distributions are very similar, except for the attribute *Cancelation*. This can be due to the fact that it is the only dummy-coded attribute. Similar to the classical linear regression model, the precision of estimations of coefficients related to dummy-coded attributes in discrete choice model (DCM) studies is usually lower than the precision of coefficients with continuous attribute levels, due to the fact that they contain much less variation. Nevertheless, what effect the nature of an attribute can have on the estimation of coefficients in a RPL model with correlated coefficients with respect to an estimation with uncorrelated coefficients is not straightforward and can be case specific.

Focusing on the median values from the correlated RPL, we can see that median WTA for all attributes are as follows: monitoring (a 10% change) 16.9 €, cancellation -43.1 €, minimal share of farmland (a 10 % change) 42.9 €, contract duration 43.2 € and time spent for office 136.2 €.

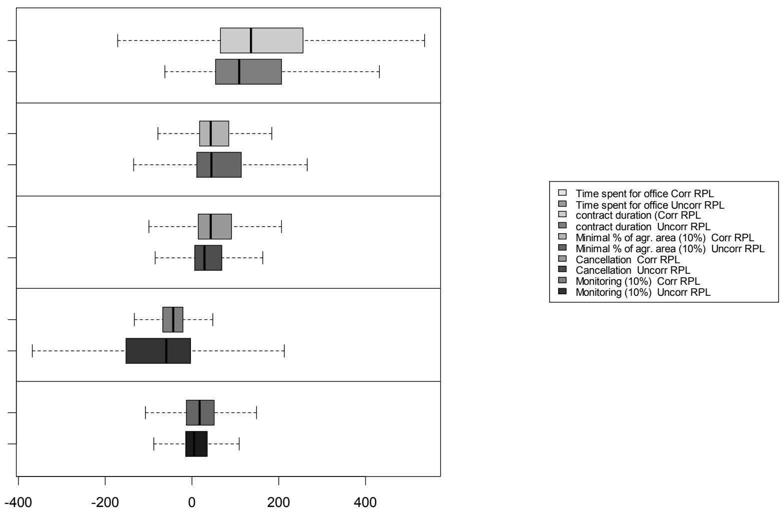

Fig. 3. Comparison of simulated WTA values of correlated and uncorrelated RPL.

The second comparison is about the coefficients representing the observed preference heterogeneity (mean-shifters included in the matrix Λ). We focus on the significant mean shifters of the attributes presented in Table 4, and analyze the effect of changing soil quality (*SoilQuality*), the amount of farmland (*Farmland*) and whether the farmland is completely private property or not (*Property)*. The WTA distribution of all attributes with interaction effects has been simulated by the use of (4), which can be straightforwardly updated for the other attributes.

Figure 4 presents the effect of the change from 5th percentile to 95th percentile value of $Farmland$; that is, from $Farmland = 4$ (ha) to $Farmland = 2{,}150$ (ha) and leaving other farm specific variables on the previously defined benchmark values ($SoilQuality = 32$ and zero for the remaining dummy variables, that is $Property = 0$, $PriorAgriEnv = 0$ and $NoMember = 0$). The distributions of all simulated WTAs for farmland set at 5th and 95th percentile generally overlap for all attributes, except for cancellation. The median value for the 5th percentile is -45.8 €, but the 95th percentile is 1.7 €. This means that small farms are asking for less compensation per hectare than large farms, i.e., those at the 95th percentile.

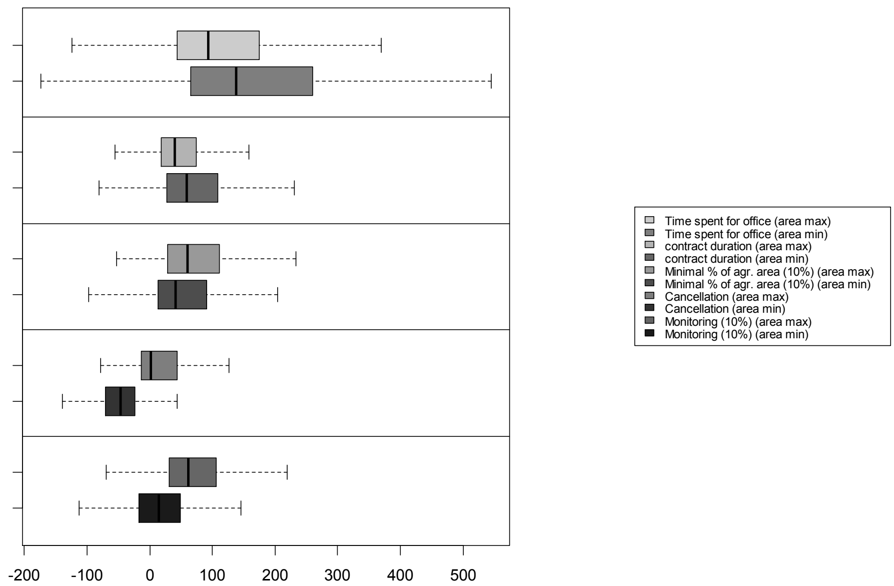

Fig. 4. Simulated WTA values. Effect of farmland. RPL with correlated parameters.

The effect of the change from the 5th percentile to the 95th percentile to the maximum value of $SoilQuality$ was also investigated, but the simulated distributions of the WTA values overlap almost perfectly for all attributes, showing that the effect of that variable on the WTA distribution is negligible.

Finally, the effect of the dummy variable $Property$, changing its value from $Property = 0$ to $Property = 1$, leaving all other farm specific variables at the benchmark value ($SoilQuality = 32$ and $Farmland = 89$ and zero for the remaining dummy variables, that is $PriorAgriEnv = 0$ and $NoMember = 0$), is depicted in Figure 5. In this case, the two distributions overlap for the attribute minimum % of agriculture area but clearly differ for cancellation. The median value for farms with farmland completely owned by the farmer is 3.5 €, but for farms not owning all farmland this reduces the overall requested compensation (-43.1 €). We assume that farmers who leased land require more flexibility, given potential uncertainty about whether contracts will be extended, and thus are not able to guarantee that they will provide the agri-environmental measure for the whole time span.

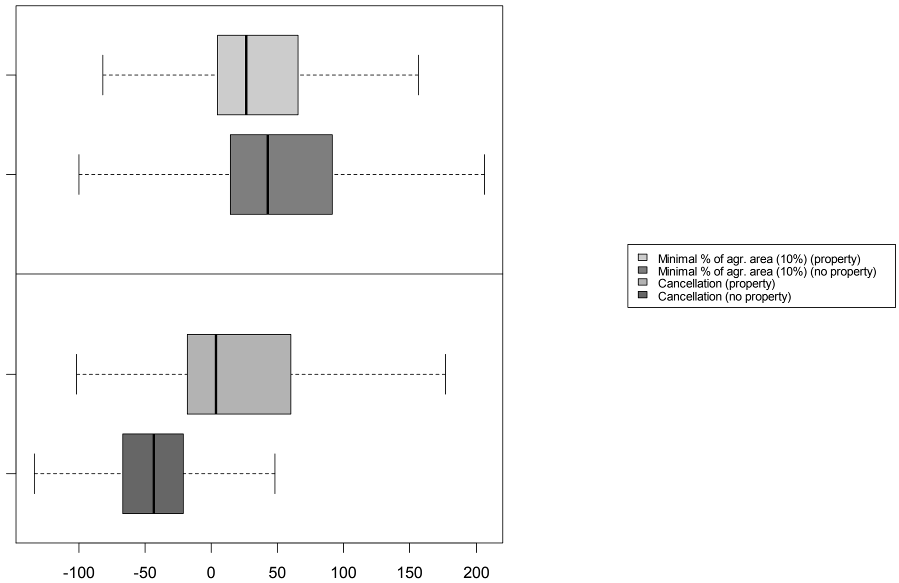

Fig. 5. Simulated WTP values. Effect of property. RPL with correlated parameters.

5. Conclusions

The Random Parameter Logit (RPL) model has become the standard approach to analyze data from stated choice surveys. A main reason in favor of this model is probably that it easily enables researchers to account for unobserved taste heterogeneity. Rarely applied is a model specification of the mixed RPL that comes with less restrictions: the RPL with correlated random parameters. According to McFadden and Train (2000), a mixed logit model can approximate any choice model, but a prerequisite for this is that no constraints are imposed on the model. This takes place when a RPL with uncorrelated random parameters is estimated. An unconstrained model is beneficial as no correlation structure is imposed on the WTP or WTA estimates and scale heterogeneity is captured. Given these advantages and easily available software for estimating unconstrained models, we want to raise awareness particularly among applied researchers that estimating the RPL with uncorrelated random parameters can lead to biased estimates.

Our data are from a survey among farmers regarding their willingness to accept implementation of agri-environmental measures on their farms in order to increase water quality in open-surface water bodies. Participants were presented choice sets with three labelled alternatives and an option not to sign any contract. Concerning the choice attributes, we find a similar relevance of changes in their levels as reported in other studies (e.g., Broch and Vedel, 2012; Christensen et al., 2011; Ruto and Garrod, 2009; Santos et al., 2015). Increasing contract duration, for example, is valued negatively; while the opportunity to cancel the contract before it expires is valued positively. Required compensation is, of course, positive, since increasing compensations paid will increase the probability that a certain alternative is chosen. We also find two farm characteristics, soil quality and amount of farmland, to be significant shifters of the mean parameter values.

Any comparison among the models, however, has to mention also the increasing computational burden. A significantly higher number of parameters have to be estimated, increasing not only the computation time but also the risk of local maxima. Thus, models with correlated random parameters *are no free lunch*. Regarding the outcome obtained in our case study, both models lead to very similar estimations of the coefficients and, therefore, to very similar simulated WTA distributions. This can lead to a question whether the entire computational burden is worth it. Our response is, nevertheless, simple: any imposed restriction in an econometric model must be tested before it is finally included in the model. Similar results of two models, as in our case, might just be case specific and cannot be generalized. As we have seen in the simulation exercise above, even in a case in which a definition of the attributes indicates a behavioral phenomenon leading to a positive correlation of their corresponding coefficients, the correlation estimated in the RPL can be negative due to the scale heterogeneity.

Overall, we conclude that our findings point toward the model specification with correlated random parameters and we would therefore encourage more researchers to also estimate RPL without constraining these correlations. And, we would also like to encourage people to report in their articles whether they have tested this specification, informing readers that using constrained models does not result in biased models estimates and subsequently WTP or WTA values.

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Appendix

Table A1. Estimation of the Cholesky matrix in the correlated RPL model

	Coef.	Std. Error	
γ_{11}	-0.763	0.097	***
γ_{21}	0.004	0.004	
γ_{31}	-0.150	0.068	**
γ_{41}	0.001	0.002	
γ_{51}	0.010	0.015	
γ_{61}	0.010	0.052	
γ_{22}	0.018	0.004	***
γ_{32}	0.063	0.070	
γ_{42}	0.014	0.001	***
γ_{52}	0.121	0.012	***
γ_{62}	0.253	0.045	***
γ_{33}	-0.089	0.185	
γ_{43}	-0.003	0.003	
γ_{53}	-0.013	0.031	
γ_{63}	-0.073	0.090	
γ_{44}	-0.001	0.004	
γ_{54}	-0.012	0.036	
γ_{64}	-0.039	0.115	
γ_{55}	-0.001	0.021	
γ_{65}	-0.001	0.053	
γ_{66}	0.005	0.053	

Note: ***, **, * stands for significance at 1%, 5% and 10%, respectively.

According to Table A1, the estimation of the RPL model with correlated coefficients leads to

$$\Gamma = \begin{bmatrix} -0.763 & & & & & \\ 0.004 & 0.018 & & & & \\ -0.150 & 0.063 & -0.089 & & & \\ 0.001 & 0.014 & -0.003 & -0.001 & & \\ 0.010 & 0.121 & 0.013 & -0.012 & -0.001 & \\ 0.010 & 0.253 & 0.073 & -0.039 & -0.001 & 0.005 \end{bmatrix}.$$

Therefore, according to (3) and given that $\Sigma = I$,

$$\widehat{Var}(\hat{\beta}_n) = \hat{\Gamma}\,\Sigma\,\hat{\Gamma}^{'} =$$

$$\begin{bmatrix} 0.5821 & -0.0033 & 0.1144 & 0.0001 & -0.0074 & -0.0072 \\ -0.0033 & 0.0003 & 0.0004 & 0.0002 & 0.0021 & 0.0045 \\ 0.1145 & 0.0004 & 0.0344 & 0.0012 & 0.0073 & 0.0211 \\ 0.0001 & 0.0002 & 0.0011 & 0.0002 & 0.0018 & 0.0039 \\ -0.0074 & 0.0021 & 0.0074 & 0.0018 & 0.0151 & 0.0321 \\ -0.0073 & 0.0045 & 0.0211 & 0.0039 & 0.0321 & 0.0710 \end{bmatrix}.$$

The estimated standard deviations of the random coefficients are presented in Table 4 - Section: Attributes (sd. deviations), and are computed as square roots of the main diagonal of the above matrix, that is $D = \sqrt{diag(\widehat{Var}(\hat{\beta}_n))}$. The standard errors for these estimators are computed using the delta method. The correlation matrix is obtained in a standard way by $D^{-1}\widehat{Var}(\hat{\beta}_n)D^{-1}$.