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Ordered Response Models and Non-Random Personality Traits: Monte Carlo Simulations and a Practical Guide

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Abstract

The paper compares different estimation strategies of ordered response models in the presence of non-random unobserved heterogeneity. By running Monte Carlo simulations with a range of randomly generated panel data of differing cross-sectional and longitudinal dimension sizes, we assess the consistency and efficiency of standard models such as linear fixed effects, ordered and conditional logit, and several different binary recoding procedures. Among the binary recoding procedures analyzed are the conditional ordered logit estimator proposed by Ferrer-i-Carbonell and Frijters (2004) that recently has gained some popularity in the analysis of individual well-being, as well as the new developed "Blow-Up and Cluster" (BUC) estimator of Baetschmann et al. (2011). The Ferrer-i-Carbonell and Frijters estimator (FCF) performs best if the number of observations is large and the number of categories on the ordered scale is small. However, the BUC method performs similarly well and even outperforms the FCF estimator if the number of categories on the ordered scale is large. If the researcher is only interested in the relative size of coefficients with respect to a baseline, however, the easy-to-compute linear fixed effects model delivers essentially the same results as the more elaborate binary recoding schemes.
Keywords: fixed effects ordered logit, ordered responses, happiness

JEL classifications: C230, C250, I310

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1 Introduction

When estimating models for ordinal response data, researchers typically face the problem of accounting for unobserved personality traits that may be correlated with explanatory variables, while at the same time accommodating the ordinal nature of the dependent variable. Since there is no consistent estimator for an ordered logit or probit model that can explicitly incorporate individual fixed effects, different estimation strategies have been pursued in the literature.

Authors such as Winkelmann and Winkelmann (1998), Senik (2004), Clark (2003) and Kassenböhmer and Haisken-DeNew (2009) recode the ordinal dependent variable into a binary variable and subsequently apply the conditional logit estimator by Chamberlain (1980). This approach has the advantage that it maintains the non-linear character of the dependent variable. However, recoding ordinal responses into binary responses requires the researcher to more or less arbitrarily define a threshold above which the dependent binary variable takes the value one. As a consequence, potentially important variation in the original ordinal response variable is disregarded.

A second approach taken, for example, by Di Tella et al. (2001), Scheve and Slaughter (2004), and Senik (2004), attempts to avoid this problem by assuming cardinality of the ordered response variable and by estimating a simple first difference or within-transformed linear model. However, this approach is equally problematic since theoretically there is no guarantee that an equal distance between any two points on the ordinal scale of the dependent variable indeed corresponds to an equal distance between the values of the corresponding latent variable. Although certain applications, such as studies of subjective well-being, have shown that the cardinality assumption does not severely bias estimates (see Ferrer-i-Carbonell and Frijters (2004)), it is difficult to generalize this finding to other applications. The severity of the cardinality assumption in such models probably depends on the number of ordinal categories among which the respondent can choose, that is, on the aggregation level of the ordinal scale.

A third method proposed by van Praag and Ferrer-i-Carbonell (2008) is using the "probit-adapted OLS" technique. Their estimation procedure is used, e.g., by

Clark et al. (2010), Cornelissen (2009), Luechinger et al. (2010), Luechinger (2009), and Stevenson and Wolfers (2008). Its strategy is to rescale the ordered dependent variable to a normal distributed variable centred around zero, whereby the outcomes of the rescaled variable depend on the relative frequencies of the ordered categories in the original dependent variable. This "probit-adapted" variable is then used in a simple fixed effects OLS regression.

In a fourth approach proposed by Ferrer-i-Carbonell and Frijters (2004), the binary conditional logit estimator of Chamberlain (1980) is extended to accommodate ordered response variables. Unlike in the above-mentioned simple binary recoding, where one arbitrary threshold is applied, Ferrer-i-Carbonell and Frijters propose an individual specific binary recoding procedure using the individual specific information of the second derivative of the log likelihood function for the conditional logit estimator.

Compared to the simple binary case, the estimation strategy of Ferrer-i-Carbonell and Frijters (2004) makes use much more of the variation in the ordinal response variable. However, since this procedure requires calculation of the individual Hessian for each binary recoding possibility, it is computationally very expensive. Nevertheless, the estimator has gained some popularity and has been employed in a number of recent empirical studies, such as Frijters et al. (2006), Frijters et al. (2004), Knabe and Rätzel (2009) and Clark et al. (2010).

Baetschmann et al. (2011) have recently shown, that the estimation strategies of Ferrer-i-Carbonell and Frijters (2004) can produce biased parameter estimates. In a theoretical and empirical proof they show, that the individual-mean recoding may result in inconsistent estimates. The reason behind is a endogeneity problem of the individual threshold, which is by itself a function of the original ordered variable. And since there are cases where the individual-mean and the FCF have the same recoded binary variable, they postulate that the FCF estimator must be inconsistent as well. In addition, they developed a new estimator, called the "Blow-Up and Cluster" (BUC) estimator, which we also include in our Monte Carlo Simulations and will be more discussed in section 2.

Choosing from the existing estimation strategies is not an easy task, since apart from rough comparisons of the alternatives discussed in the context of concrete applications (e.g. Ferrer-i-Carbonell and Frijters (2004)), there is little comparative evidence on their finite sample properties and performance that can be generalized. In the present paper, we aim to fill this gap by performing Monte Carlo simulations that yield measures of bias and efficiency of standard models such as linear fixed effects, ordered and conditional logit, and several different binary recoding procedures, among which is the conditional ordered logit estimator proposed by Ferrer-i-Carbonell and Frijters.

The contribution of the paper is twofold. First, the paper presents a systematic evaluation of the Ferrer-i-Carbonell and Frijters estimator's properties in finite samples, which so far are unknown. Second, the paper functions as a guide to applied researchers who typically face data for which asymptotic theory is not applicable and who need to choose between the different proposed estimation strategies.

The remainder of the paper is structured as follows: Section 2 revisits the proposed estimation strategies more formally with a focus on providing more detail on the FCF estimator over and above what is published in Ferrer-i-Carbonell and Frijters (2004). Section 3 describes the Monte Carlo experiment, including the data generation process, and presents the results of our simulations for different variants of the discussed estimation strategies. Section 4 concludes.

2 Estimation Strategies in Detail

We want to estimate a latent variable model with ordered response data. The model is given by:

$$y_{it}^* = \beta' x_{it} + \alpha_i + \epsilon_{it} \tag{1}$$

where y_{it}^*, for example, represents general well-being of individual $i = 1, \ldots, I$ at time $t = 1, \ldots, T$ and is a continuous variable that cannot be observed. x_{it} is a vector of independent explanatory variables, α_i is the individual personality trait assumed to be correlated with the vector of explanatory variables x_{it}. Finally ϵ_{it} is the logistically distributed error term. Since the continuous latent variable y_{it}^*

cannot be observed, an ordered categorical response variable y_{it} is measured with $k = 1, \dots, K$ categories and individual-specific thresholds λ_k^i, where $\lambda_k^i < \lambda_{k+1}^i$:

$$y_{it} = k \Leftrightarrow \lambda_k^i \leq y_{it}^* < \lambda_{k+1}^i. \tag{2}$$

As previously discussed, one estimation strategy for ordered response data with unobserved personality traits is to transform the ordered response variable such that it can be estimated with a conditional logit estimator. The conditional logit estimator was first introduced by Chamberlain (1980). He showed that simply applying the methods for fixed effects estimation of the linear case to the nonlinear case, e.g., logit models, leads to inconsistent estimators. This is especially an issue if the numbers of observations per group are small, as in almost every panel data setup. For the binary logit model, he used a conditional likelihood approach, conditioning on the sum of ones in the dependent variable per group. This sum is a sufficient statistic for the time-invariant unobserved effects, and ensures that the incidental parameters drop out of the likelihood function. Hence, Chamberlain (1980) established a consistent estimator for a binary fixed effects logit framework that avoids any incidental parameter problem.

To generate the required binary response variable one common approach is to apply what is considered a meaningful threshold (Y) to the whole data set (e.g., Winkelmann and Winkelmann, 1998; Clark, 2003) such that:

$$B_{it} = \begin{cases} 0 & \text{if } y_{it} \leq Y \\ 1 & \text{if } y_{it} > Y \end{cases} \tag{3}$$

The conditional logit statistic corresponding to this simple coding scheme then is:

$$P\left[B_{it} | \sum_t B_{it} = c_i\right] = \frac{e^{\sum_{t=1}^T B_{it} x_{it} \beta}}{\sum_{y \in S(k_i, c_i)} e^{\sum_{t=1}^T B_{it} x_{it} \beta}} \tag{4}$$

This represents the probability that the dependent variable is above Y, conditional on the sum c_i. More precisely, c_i denotes the number of times the dependent variable per group exceeds the threshold Y, $0 < c < T$. S describes the set of all possible combinations of $y_{i1}, \ldots, y_{iT}$ that sum up to $\sum_t B_{it} = c_i$. In the following, we refer to this estimation strategy as naive conditional logit (NCLOG).

Clearly the NCLOG ignores all variation in y_{it} that takes place below or above Y. Furthermore and most importantly, the applied naive coding scheme also abstracts from the possibility that the thresholds λ_k^i in equation 2 indeed vary in i. As an example, consider ordered responses on life satisfaction. Our sample may include a happy life long enthusiast and an equally happy life-long sceptic. While the enthusiast's self reported life satisfaction scores may tend to be on the high side, responses of the equally happy sceptic may tend to be on the low side. Accordingly, in this example, a common threshold crossing cannot capture changes in the self-reported life satisfaction of the sceptic and the enthusiast equally well. Thus, this strategy does not in fact address personality traits in any satisfactory way.

A somewhat more sophisticated coding scheme takes account of such personality traits by constructing a binary response variable (E) that takes the value one if the score of the ordered categorical response variable is above the individual-specific mean of all ordered categorical responses:

$$E_{it} = \begin{cases} 0 & \text{if } y_{it} \leq E(y_{it}) \\ 1 & \text{if } y_{it} > E(y_{it}) \end{cases} \tag{5}$$

To stay with the example, our enthusiast and sceptic now have different thresholds that reflect that the responses of the former tend to be on the high side of the ordered scale while the responses of the latter tend to be on the low side. Recent applications of this approach include Kassenböhmer and Haisken-DeNew (2009). In the following, we refer to this approach as individual mean conditional logit (IMCLOG).

Ferrer-i-Carbonell and Frijters (2004) further develop the IMCLOG in order to take into account more variation in individuals' ordered responses. Their method uses the conditional logit approach combined with a fairly complex individual-specific coding of the dependent variable. In doing so, they use the information from the second derivative of the log likelihood function, the Hessian matrix, per individual to choose which coding is appropriate for the final conditional logit estimation. This procedure consists of three steps.

In the first step the ordered scaled dependent variable y_{it} with K categories is split into $K-1$ new binary coded variables D_{ik} capturing all possible threshold crossings.

The first newly generated variable D_{i1} equals one if the original dependent variable y_{it} is at least one category greater than the minimum of y_{it} for each i:

$$D_{itk} = \begin{cases} 0 & \text{if } y_{it} \leq min_i\{y_{it}\} \\ 1 & \text{if } y_{it} > min_i\{y_{it}\} \end{cases} \tag{6}$$

The next newly generated variable D_{i2} equals one if the original dependent variable is at least two categories greater than the minimum of y_{it} for each i and so forth. A more detailed example can be found in the appendix of Ferrer-i-Carbonell and Frijters (2004).

In a second step, the following conditional log likelihood function is estimated for the first threshold crossing to derive the coefficients (β) that are used to calculate the Hessian matrix for each individual for each D_{ik}.

$$\ln L_{ik} = \ln L\left(D_{ik} \mid \sum_{t=1}^{T} D_{itk}, \beta, x_i\right) = \ln \frac{e^{\sum_{t=1}^{T} D_{itk} x_{it}\beta}}{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it}\beta}} \tag{7}$$

The derivations of the first and second derivatives of the log likelihood function used for these calculations can be found in the appendix to this paper. On this basis, the sum of the diagonal elements, the so called "trace," for each individual Hessian is calculated for each D_{ik}. The final binary dependent variable is then generated by choosing the specific D_{ik} that corresponds to the minimum trace per individual i. Since the variance of the estimated conditional logit coefficient is the negative of the inverse of the sum over i of the Hessian H_i this yields the maximum likelihood estimator with minimal variance:

$$Var(\widehat{\beta}) = \left[-\sum_{i=1}^{I} H_i\right]^{-1} \tag{8}$$

In a third step, the binary variable constructed as described above, which reflects the optimal choice of D_{ik} for all i, is fed into a conditional logit estimation to obtain the final coefficients. In the following, we refer to this estimation strategy as the Ferrer-i-Carbonell Frijters estimator (FCF). Since the FCF estimator requires calculation of individual-specific Hessian matrices for each possible threshold D_{ik}, it is computationally expensive, particularly if T is large.[1]

Note that the individual-specific coding procedure based on minimum-trace individual Hessian matrices is initially based on the assumption of knowing the "true" parameter estimates of the latent variable model. It is debatable how these initial parameters should be obtained. We test whether the FCF estimation results differ when using the individual mean coding procedure (IMCLOG), that is, whether the FCF estimates are sensitive to replacing D_{it1} in Equation 7 with E_{it} from Equation 5. Furthermore, we also estimate an iterated version of the FCF, continuously updating the initial parameters. However, there are only subtle differences between the corresponding final FCF parameters. Thus, the FCF method is robust with respect to the choice of the first-step estimation routine.

As noted above, Baetschmann et al. (2011) introduced a new estimation strategy to obtain a consistent fixed effects ordered logit model. It is called the "Blow-Up and Cluster" (BUC) estimator. They recode the original dependent variable with k categories into $k-1$ different dichotomizations using $k-1$ different thresholds. Each observation of the original data is then duplicated $k-1$ times, one for each dichotomization. After "blowing up" the data, a standard conditional logit estimation with clustered standard errors is then applied to the whole sample. For more details we refer to the paper of Baetschmann et al. (2011).

A previously discussed alternative estimation strategy assumes cardinality and makes use of all variation in individuals' ordered responses, while also accounting for non-random personality traits. Accordingly, the ordered response categories $k = 1, \ldots, K$ of y_{it} are interpreted as continuous values of the latent variable $y*_{it}$, which lends itself to linear regression methods. Personality traits can then be addressed

[1]For example, a data setup of 3,000 individuals with 15 observations each can take about half an hour computation time.

by, for instance, within-transformation of Equation 1, such that α_i cancels out:

$$y_{it}^* - \overline{y}_{it}^* = \beta'(x_{it} - \overline{x}_{it}) + \epsilon_{it} - \overline{\epsilon}_{it} \tag{9}$$

In the following we refer to this estimation strategy as the fixed effects estimator (FE).[2] The FE has the advantage that it is fast and very easy to implement. However, assuming cardinality of ordered responses may be too strong an assumption, potentially yielding severely biased estimates. Nevertheless, as previously discussed, numerous studies have used this approach (e.g., Scheve and Slaughter, 2004; Di Tella et al., 2001) and at least in the context of life satisfaction studies, there is some evidence that the associated bias is only moderate (Ferrer-i-Carbonell and Frijters, 2004).

The probit-adapted OLS (POLS) method by van Praag and Ferrer-i-Carbonell (2008) tries to cardinalize the data, such that it can be applied to simple OLS without the above mentioned problems of the FE estimator. Compared with the standard ordered probit, the POLS is easier and faster to implement and is more flexible for more advanced models and can, without any drawbacks, applied within a fixed effects environment. The original ordered dependent variable is bounded by the lower and upper category. Applying linear models on the bounded dependent variable may lead to predictions outside the category boundaries. The POLS estimator circumvents this problem by first calculating the relative frequencies of the different outcome categories and then putting the frequencies into a standard normal distribution function to obtain N(0;1) distributed, "cardinal scaled", and unbounded conditional means of the dependent variable. This variable can then be used for simple (fixed effect) OLS. For more details on this procedure, see van Praag and Ferrer-i-Carbonell (2008).

Regardless, from a theoretical perspective, assuming cardinality of ordered responses is unsatisfactory, and our Monte Carlo simulations will show whether this pragmatic approach frequently employed in the life satisfaction literature is justified in a more general setting.

[2]First difference transformation of the model yields equivalent results.

3 Monte Carlo Simulation and results

Our data generating process is designed in line with the standard Monte Carlo simulation literature for panel data (e.g., Honoré and Kyriazidou, 2000; Greene, 2004). The latent variable y_{it}^* is generated by the following model:

$$y_{it}^* = x_{it}\beta + \alpha_i + \epsilon_{it}$$

The individual fixed effect α_i is generated as $\alpha_i = \sqrt{T}\bar{x}_i$. The idiosyncratic error ϵ_{it} is i.i.d. logistically distributed, and the exogenous variables x_{it} are i.i.d. normally distributed. Both error and exogenous variables have the same standard deviation of $\sigma = \pi/\sqrt{3}$.

We define the categories for the discrete dependent variable y_{it} by splitting the generated latent variable y_{it}^* into K even parts. As a result, every category has the same number of observations. To evaluate consistency of the different estimators under investigation, we focus on the mean of the estimated coefficients, the mean squared error (MSE), and as a more robust performance measure to possible outliers, the median absolute error (MAE). To assess efficiency we compare coefficients' standard errors as well as their 95 % confidence interval. For the different specification settings, the size of our panel data setup varies in both dimensions for individual i and time t. All simulations are performed 1000 times[3]

We start with only one exogenous variable x_{it} and set the coefficient to $\beta = 1$. The dependent variable consists of three categories on an ordinal scale with $y_{it} \in \{1, 2, 3\}$. To compare the asymptotic properties of the estimators under consideration we start with a small panel and subsequently increase the cross-sectional and longitudinal dimension sizes.

Table 1 presents estimation results where we fix the longitudinal dimension to $T = 3$ and raise the cross-sectional dimension size from $I = 100$ to $I = 3,000$ while $K = 3$. In accordance with asymptotic theory, all estimators gain consistency and precision with increasing I. The MSE as well as the MAE continuously decrease as the standard error and the corresponding confidence interval become

[3]We use the statistical software STATA to run our simulations. The corresponding STATA ado-file for the FCF estimator is available from the authors' website: http://www.uni-goettingen.de/en/199539.html.

smaller. The same asymptotic properties can be seen when subsequently increasing the longitudinal dimension size from $T = 3$ to $T = 15$, as reported in Tables 2 to 4.[4]

In the first two rows of Tables 1 to 4, the means of the linear fixed effects OLS estimation are listed. It is easy to see that the coefficients are significantly smaller than the true parameters. However, this is due to the different functional forms of the FE, which assumes cardinality. As a consequence, with only one explanatory variable, the FE cannot be compared with the other estimators, and we do not report performance measures other than the mean coefficients and standard errors. However, when later including more than one explanatory variable, we will compare the consistency and efficiency of coefficient ratios to reflect on the relative size of coefficients. The probit adapted OLS (POLS) method, which should handle the ordinal scaled data better, results in very similar outcomes.

From the set of nonlinear estimators it is the standard ordered logit estimator without controlling for unobserved heterogeneity that performs worst. The potential bias from ignoring unobserved heterogeneity is clearly noticeable for all panel data configurations. In Tables 1 to 4, the means of the simple ordered logit coefficients are always furthest away from the true parameter $\beta = 1$, and from $T = 10$ and $I = 500$ onwards the true parameter is not even in the 95% confidence interval. This discrepancy corresponds to the advice given by Ferrer-i-Carbonell and Frijters (2004), who argue that allowing for individual fixed effects is more important than taking into account the ordinal data structure.

Comparing the nonlinear models that take the individual fixed effects into account leads to several important insights. The naive binary coding procedure NCLOG is very sensitive to small sample sizes since the simple coding procedure already disregards a large part of the available variation in the dependent variable.[5] For example, with $T = 3$ and $I = 100$, more than 50 percent of all observations were ignored because of no variation in the dependent variable. With real survey data and less homogeneous categories, the loss of data may be even more serious. This probably results in unreliable outcomes. We therefore recommend not using

[4]We also perform simple t-tests to compare the means of the respective estimators' coefficients when I and T increase. The differences of the means are statistically significant when starting from small T and small I and become insignificant when both dimension sizes are large.

[5]For our data set with $y_{it} \in \{1, 2, 3\}$ we did the following binary recoding: $y_{it}^n = 1$, if $y_{it} > 2$.

the NCLOG method under any circumstances.

Regarding the IMCLOG and FCF, both estimators perform similarly well in terms of consistency and efficiency but are outperformed by the BUC method for all panel data configurations except for the smallest data set with $T = 3$ and $I = 100$. Even though the means of the parameter estimates of the FCF and IMCLOG deviate more or less distinctly from the true value, more so than the means of the NCLOG method, the smaller mean squared errors (MSE) and median absolute errors (MAE) of the FCF and IMCLOG indicate, that they are both better than the NCLOG in terms of consistency.

As a first conclusion, these simulations clearly show the asymptotic properties of the estimation methods: All gain consistency and precision from increasing observations in both panel data dimensions, I and T.

We proceed by comparing the set of estimators when including more than one explanatory variable in the model, which is more informative for real data analysis. With three explanatory variables, Table 5 reports the performance measures for the coefficient estimates and their ratios. In practical research, coefficient ratios are frequently employed to interpret the size of coefficients relative to a baseline effect. In the analysis of individual well-being, for instance, it is common to calculate compensating income variations, that is, the well-being effect of certain events expressed in percentage changes in income that would generate the same well-being effect (see Winkelmann and Winkelmann, 1998). Accordingly, it is not necessarily the absolute size of coefficients that researchers are interested in, but their ratios.

For the following simulation, the total number of observations is 18,000 consisting of $I = 3000$ and $T = 6$. We choose $\beta_1 = 1$, $\beta_2 = -3.5$ and $\beta_3 = 7$ so we can also evaluate the correct sign of the parameter estimates as well as their ratios $\beta_2/\beta_1 = -3.5$ and $\beta_3/\beta_1 = 7$.

As previously argued, the coefficients of the linear fixed effects models (FE, POLS) reported in the first two rows of Table 5 cannot be compared to the ones from out non-linear estimators. However, the estimated coefficient ratios of the FE, as well as the ratios of the POLS, are very close to the ratios of the true parameters, that is, $\widehat{\beta_2}/\widehat{\beta_1}$ is almost exactly -3.5 and $\widehat{\beta_3}/\widehat{\beta_1}$ is nearly 7. At the same time, of all estimators, the MSE and the MAE of the FE and the POLS are smallest, indicating highly consistent estimations of the parameter ratios. Accordingly, if the researcher is only interested in ratios of parameter estimates and not in absolute values, ignoring the ordinal structure of the dependent variable and applying linear fixed effects models is indeed a recommendable method.

Of all the nonlinear estimators controlling for unobserved heterogeneity in Table 5, both the BUC and the FCF method outperform the others in terms of consistency and efficiency. Compared to the NCLOG and the IMCLOG, the means of the BUC and FCF parameter estimates come closest to the true parameters in conjunction with the smallest standard errors and lowest values for MSE and MAE.

When it comes to the ratios of the parameter estimates the means of the FCF, BUC, naive (NCLOG) and individual mean conditional logit (IMCLOG) estimators are altogether relatively close to the true values. Nevertheless we again get the lowest values for the MSE and MAE with the BUC and the FCF, which implies an improved consistency of the BUC and the FCF method over the other estimators.

In comparison, ignoring unobserved individual heterogeneity by applying the simple ordered logit estimator leads to severely biased coefficients and coefficient ratios in Table 5. This becomes apparent when looking at the 95% interval of the ordered logit estimates for β_2 and β_3, in which the true parameters are not included and the large MAE. Thus, of all non-linear estimators with more than one covariate, the BUC and the FCF are the most consistent and are therefore the method of choice. However, due its simplicity, the FE has its merits if the researcher is only interested in the coefficient ratios.

So far we have assumed that the ordinal response variable is fairly aggregated and lies on a three-point scale ($K = 3$). However, various types of ordinally scaled data consist of more than three categories. For example, in the U.S. National Survey of Families and Households (NSFH) and the German Socio-Economic Panel (SOEP), information on individual well-being is captured on a seven- and eleven-point scale, respectively. Against this backdrop, we want to test the extent to which the performance of the estimators under consideration varies with respect to the ordinal structure of the dependent variable. Table 6 lists the simulation results for a three-, seven- and eleven-point scale ordered response variable. All simulations are performed with two exogenous variables with the true parameters $\beta_1 = 1$ and $\beta_2 = -2$. The panel data dimensions are $I = 3,000$ and $T = 12$.

Interestingly, it seems that the FCF method responds rather sensitively to the number of ordered categories in the dependent variable. Beginning with $K = 3$ in Table 6, the FCF parameter estimates of β_1 and β_2 are very accurate, with low MSE and MAE compared to the other non-linear methods. However, from $K = 7$ to $K = 11$, the estimated parameters diverge more and more from the true values, although the β_2/β_1 relations remain highly consistent.

The downward bias of the FCF parameter estimates for increasing ordinal categories can be the result of a misspecification of the distribution in the conditional logit model. Baetschmann et al. (2011) argue, that the individual-specific cutoffs are chosen endogenously. Hence, the conditional distribution of the binary dependent variable for the FCF estimation differs from the conditional logit model, which leads to inconsistent estimates. However, our empirical result of biased FCF slope coefficients but consistent coefficient ratios is in line with the kind of misspecification, like e.g., in Ruud (1983), Cramer (2007) and Wooldridge (2010). They show cases for logit and probit models, where misspecification leads to parameter estimates which are biased towards zero. Nonetheless, as demonstrated by the above authors, the bias is symmetric. That is, all coefficients are multiplied by a common scaling factor, such that the coefficient ratios, are still correct. We find evidence for such a bias in our Monte Carlo simulations for ordered response data.

In comparison, BUC, and NCLOG are not sensitive with respect to the size of K; there is no significant change in either consistency as expressed in the MSE and MAE or in efficiency as captured by the mean standard error and the confidence interval. We find the BUC method to perform best when K increases. For $K = 7$ and $K = 11$, it clearly outperforms all nonlinear estimators.

The FE and the POLS perform well regarding the consistency and efficiency of coefficient ratios, irrespective of the size of K. Furthermore, the FE parameter estimates as such improve slightly in terms of consistency in K, but still remain distant from the true parameters even for $K = 11$, which still does not constitute a continuous dependent variable.

Summarizing, for small K, the BUC and FCF outperforms all other methods in terms of consistency and efficiency. However, for larger K, that is, for more disaggregated ordinal scales, we recommend the BUC. However, as long as the researcher is only interested in the ratios of the parameters, the linear fixed effect (FE) provides the same results with considerably less computational effort.

4 Conclusion

We compare linear and non-linear ordered response estimators in terms of consistency and efficiency by running Monte Carlo simulations while varying the sample size, the number of covariates, and the number of ordinal response categories. The estimators under consideration are linear fixed effect, simple ordered logit, and four binary recoded conditional logit estimators.

In line with the literature, we find that not controlling for individual unobserved heterogeneity leads to severely biased estimates. Of all estimators suitable to control for unobserved personality traits, we find the binary recoding schemes of Baetschmann et al. (2011) and Ferrer-i-Carbonell and Frijters (2004) to perform equally well in terms of consistency and efficiency, at least as long the number of ordinal response categories is low. However, for a more disaggregated ordinal structure with a higher number of response categories, the BUC is the method of choice, since it is more consistent and computationally less expensive than the Ferrer-i-Carbonell and Frijters estimator.

Furthermore, if the researcher is more interested in the ratios of the parameter estimates, the linear fixed effects model that is commonly employed in the analysis of ordered response problems, e.g., subjective and objective well-being, essentially delivers the same results as the more elaborate binary recoding schemes and is much easier to compute.

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Appendix

Loglikelihood equation of the conditional logit model:

$$\ln L_{ik} = \sum_{t=1}^{T} D_{itk} x_{it} \beta - \ln \sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}$$

Gradient function of the conditional logit model:

$$\frac{\partial \ln L_{ik}}{\partial \beta} = \sum_{t=1}^{T} D_{itk} x_{it} - \frac{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}$$

Hessian function of the conditional logit model:

$$H = \frac{\partial^2 \ln L_{ik}}{\partial \beta^2}$$

$$H = \frac{\left(\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}\right) \left(\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}\right)}{\left(\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}\right)^2}$$

$$- \frac{\left[\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}\right] \sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}{\left(\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}\right)^2}$$

$$= A * A - \frac{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}$$

With $A = \frac{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} \left(\sum_{t=1}^{T} D_{itk} x_{it}\right) e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}{\sum_{S\left(\sum_{t=1}^{T} D_{itk}\right)} e^{\sum_{t=1}^{T} D_{itk} x_{it} \beta}}$ corresponding to the second term of the gradient function.

Table 1: Monte Carlo simulation results for $K = 3$, $T = 3$

	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
I = 100						
FE OLS	0.19899	0.01977				
POLS	0.21641	0.02150				
ordered logit	1.18576	0.10533	0.04664	0.18445	0.97901	1.41583
Naive clogit	1.05566	0.24753	0.07954	0.15683	0.64239	1.73361
FCF	0.99069	0.17932	0.03794	0.12780	0.67118	1.43929
Indiv. Mean clogit	0.99128	0.18281	0.04034	0.12424	0.67039	1.45750
BUC	1.02201	0.17227	0.03691	0.11845	0.70515	1.44283
I = 500						
FE OLS	0.19839	0.00878				
POLS	0.21576	0.00955				
ordered logit	1.17926	0.04680	0.03422	0.17855	1.08925	1.27688
Naive clogit	1.00264	0.10255	0.01090	0.06833	0.81899	1.22389
FCF	0.96569	0.07735	0.00725	0.05880	0.82559	1.13177
Indiv. Mean clogit	0.96781	0.07892	0.00719	0.06011	0.82568	1.13476
BUC	1.00075	0.07577	0.00576	0.05331	0.86747	1.15025
I = 1000						
FE OLS	0.19821	0.00620				
POLS	0.21557	0.00674				
ordered logit	1.17846	0.03299	0.03296	0.17729	1.11813	1.24220
Naive clogit	1.00044	0.07233	0.00544	0.04885	0.86150	1.15537
FCF	0.96420	0.05460	0.00424	0.04818	0.86095	1.07516
Indiv. Mean clogit	0.97921	0.05570	0.00427	0.04775	0.85826	1.08004
BUC	0.99988	0.05383	0.00286	0.03576	0.89692	1.10606
I = 3000						
FE OLS	0.19858	0.00358				
POLS	0.21597	0.00389				
ordered logit	1.18000	0.01908	0.03296	0.18003	1.14076	1.21792
Naive clogit	1.00255	0.04168	0.00171	0.02695	0.92311	1.08820
FCF	0.96447	0.03147	0.00225	0.03707	0.90506	1.02847
Indiv. Mean clogit	0.96661	0.03211	0.00215	0.03575	0.90370	1.03128
BUC	1.00083	0.03104	0.00093	0.01965	0.94302	1.06448

Note: All simulations were performed 1000 times

Table 2: Monte Carlo simulation results for $K = 3$, $T = 5$

	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
I = 100						
FE OLS	0.20526	0.01416				
POLS	0.22324	0.01540				
ordered logit	1.03623	0.06999	0.00671	0.05192	0.89769	1.20035
Naive clogit	1.01140	0.14563	0.02093	0.09346	0.76928	1.32656
FCF	0.98475	0.11516	0.02538	0.08207	0.78009	1.24946
Indiv. Mean clogit	0.98594	0.11772	0.01531	0.07952	0.78337	1.25336
BUC	1.00708	0.10682	0.01238	0.06708	0.80646	1.25820
I = 500						
FE OLS	0.20555	0.00632				
POLS	0.22355	0.00687				
ordered logit	1.03423	0.03124	0.00215	0.03322	0.97628	1.10259
Naive clogit	1.00433	0.06419	0.00446	0.04419	0.88182	1.14270
FCF	0.97926	0.05102	0.00314	0.03892	0.88404	1.08702
Indiv. Mean clogit	0.98090	0.05218	0.00310	0.03846	0.88357	1.08989
BUC	1.00330	0.04780	0.00242	0.03409	0.91493	1.11028
I = 1000						
FE OLS	0.20477	0.00446				
POLS	0.22270	0.00485				
ordered logit	1.03298	0.02206	0.00163	0.00840	0.98943	1.07798
Naive clogit	1.00183	0.04529	0.00225	0.03235	0.91389	1.09804
FCF	0.97711	0.03600	0.00193	0.03270	0.91003	1.05655
Indiv. Mean clogit	0.97921	0.03684	0.00191	0.03224	0.90987	1.06044
BUC	1.00080	0.03390	0.00124	0.02508	0.93906	1.07563
I = 3000						
FE OLS	0.20492	0.00258				
POLS	0.22286	0.00280				
ordered logit	1.03253	0.01275	0.00122	0.00835	1.00751	1.05610
Naive clogit	0.99857	0.02603	0.00064	0.01767	0.95139	1.05082
FCF	0.97514	0.02073	0.00103	0.02561	0.93725	1.01506
Indiv. Mean clogit	0.97694	0.02121	0.00096	0.02343	0.93794	1.01708
BUC	0.99912	0.01953	0.00037	0.01362	0.96365	1.03747

Note: All simulations were performed 1000 times

Table 3: Monte Carlo simulation results for $K = 3$, $T = 10$

	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
I = 100						
FE OLS	0.21295	0.00961				
POLS	0.23160	0.01046				
ordered logit	0.91143	0.04376	0.00982	0.09136	0.82890	1.00717
Naive clogit	1.00733	0.08749	0.00771	0.05621	0.85282	1.19424
FCF	0.99290	0.07352	0.00531	0.04695	0.85449	1.14367
Indiv. Mean clogit	0.99367	0.07461	0.00522	0.04637	0.86381	1.14545
BUC	1.00561	0.06551	0.00429	0.04174	0.88374	1.13851
I = 500						
FE OLS	0.21238	0.00429				
POLS	0.23098	0.00467				
ordered logit	0.90890	0.01950	0.00871	0.09106	0.87070	0.94932
Naive clogit	0.99905	0.03878	0.00160	0.02738	0.92061	1.08111
FCF	0.98788	0.03268	0.00130	0.02402	0.91985	1.05746
Indiv. Mean clogit	0.98829	0.03316	0.00130	0.02422	0.92179	1.05703
BUC	1.00016	0.02924	0.00091	0.02033	0.94109	1.05774
I = 1000						
FE OLS	0.21262	0.00304				
POLS	0.23124	0.00330				
ordered logit	0.90834	0.01379	0.00859	0.09168	0.88139	0.93454
Naive clogit	0.99986	0.02741	0.00074	0.01834	0.94901	1.05545
FCF	0.98763	0.02310	0.00070	0.01823	0.94010	1.03268
Indiv. Mean clogit	0.98774	0.02343	0.00071	0.01835	0.93772	1.03382
BUC	0.99917	0.02063	0.00043	0.01415	0.95767	1.04011
I = 3000						
FE OLS	0.21245	0.00175				
POLS	0.23105	0.00191				
ordered logit	0.90865	0.00797	0.00841	0.09133	0.89299	0.92537
Naive clogit	0.99936	0.01582	0.00024	0.01075	0.96966	1.02985
FCF	0.98680	0.01333	0.00036	0.01493	0.96154	1.01522
Indiv. Mean clogit	0.98724	0.01353	0.00036	0.01422	0.96177	1.01522
BUC	0.99966	0.01193	0.00014	0.00818	0.97662	1.02232

Note: All simulations were performed 1000 times

Table 4: Monte Carlo simulation results for $K = 3$, $T = 15$

	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
I = 100						
FE OLS	0.21672	0.00779				
POLS	0.23570	0.00847				
ordered logit	0.86096	0.03505	0.02057	0.14017	0.79509	0.93255
Naive clogit	1.00385	0.06774	0.00452	0.04424	0.87780	1.15030
FCF	0.99237	0.05824	0.00345	0.04111	0.88325	1.10978
Indiv. Mean clogit	0.99243	0.05883	0.00353	0.04113	0.88649	1.11326
BUC	1.00094	0.05088	0.00255	0.03404	0.90907	1.10613
I = 500						
FE OLS	0.21627	0.00348				
POLS	0.23521	0.00378				
ordered logit	0.85991	0.01564	0.01988	0.13983	0.82853	0.89196
Naive clogit	0.99996	0.03019	0.00092	0.02111	0.94309	1.06048
FCF	0.99154	0.02603	0.00077	0.01870	0.93848	1.04893
Indiv. Mean clogit	0.99174	0.02629	0.00078	0.01929	0.93978	1.04672
BUC	1.00025	0.02284	0.00054	0.01517	0.95427	1.04599
I = 1000						
FE OLS	0.21602	0.00246				
POLS	0.23493	0.00267				
ordered logit	0.85903	0.01103	0.01999	0.14065	0.83816	0.88044
Naive clogit	1.00004	0.02135	0.00050	0.01496	0.95837	1.04591
FCF	0.99102	0.01839	0.00045	0.01476	0.95502	1.02925
Indiv. Mean clogit	0.99116	0.01858	0.00044	0.01507	0.95451	1.02742
BUC	0.99956	0.01614	0.00028	0.01139	0.96684	1.03459
I = 3000						
FE OLS	0.21599	0.00142				
POLS	0.23491	0.00154				
ordered logit	0.85881	0.00637	0.01997	0.14125	0.84630	0.87183
Naive clogit	0.99938	0.01232	0.00015	0.00813	0.97517	1.02285
FCF	0.99068	0.01062	0.00025	0.01033	0.96972	1.01234
Indiv. Mean clogit	0.99085	0.01072	0.00021	0.01422	0.96919	1.01443
BUC	0.99951	0.00931	0.00009	0.00607	0.98052	1.01686

Note: All simulations were performed 1000 times

Table 5: Monte Carlo simulation results for $K = 3, I = 3000, T = 6$

	Beta1 = 1					
	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
FE OLS	0.04989	0.00173				
POLS	0.05426	0.00188				
ordered logit	1.00502	0.02422	0.00068	0.01774	0.95783	1.05935
Naive clogit	1.01026	0.07765	0.00647	0.05167	0.87179	1.18344
FCF	1.00660	0.05627	0.00328	0.03852	0.89728	1.11986
Indiv. Mean clogit	1.00880	0.06541	0.00463	0.04600	0.88757	1.14603
BUC	1.00679	0.05469	0.00313	0.03851	0.90407	1.12268

	Beta2 = -3.5					
	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
FE OLS	-0.17453	0.00173				
POLS	-0.18981	0.00188				
ordered logit	-2.97515	0.05386	0.27842	0.52604	-3.08677	-2.87015
Naive clogit	-3.53246	0.21114	0.04740	0.14399	-4.02147	-3.15602
FCF	-3.51850	0.15444	0.02460	0.10461	-3.85379	-3.23361
Indiv. Mean clogit	-3.52683	0.17752	0.03407	0.12809	-3.92360	-3.21833
BUC	-3.51849	0.14827	0.02262	0.09718	-3.84610	-3.24138

	Beta3 = 7					
	Mean	**S.E.**	**MSE**	**MAE**	**95% Interval**	
FE OLS	0.34927	0.00173				
POLS	0.37985	0.00188				
ordered logit	6.31452	0.10850	0.48139	0.68670	6.11651	6.52682
Naive clogit	7.06639	0.41294	0.17659	0.27514	6.33672	8.03934
FCF	7.03928	0.30238	0.09304	0.21048	6.48856	7.65859
Indiv. Mean clogit	7.05319	0.34703	0.12856	0.24591	6.41916	7.79776
BUC	7.03928	0.28989	0.08506	0.19120	6.48744	7.64819

	Beta2/Beta1 = -3.5				
	Mean	**MSE**	**MAE**	**95% Interval**	
FE OLS	-3.50254	0.01688	0.09059	-3.77135	-3.26882
POLS	-3.50255	0.01688	0.09047	-3.77223	-3.26900
ordered logit	-2.96128	0.29334	0.54159	-3.07308	-2.85501
Naive clogit	-3.50610	0.03664	0.12148	-3.92625	-3.16180
FCF	-3.50022	0.01837	0.08657	-3.78670	-3.23716
Indiv. Mean clogit	-3.50289	0.02615	0.10578	-3.85568	-3.21248
BUC	-3.49951	0.01807	0.08461	-3.78585	-3.24382

	Beta3/Beta1 = 7				
	Mean	**MSE**	**MAE**	**95% Interval**	
FE OLS	7.00921	0.06358	0.17499	6.55400	7.54091
POLS	7.00924	0.06358	0.17470	6.55289	7.54045
ordered logit	6.28513	0.52405	0.71975	6.07888	6.51445
Naive clogit	7.01410	0.13999	0.24292	6.33485	7.85700
FCF	7.00274	0.06840	0.17344	6.51613	7.55918
Indiv. Mean clogit	7.00530	0.09721	0.19735	6.43982	7.68614
BUC	7.00133	0.06733	0.17449	6.52065	7.54664

Note: All simulations were performed 1000 times

Table 6: Monte Carlo simulation results for $I = 3000, T = 12$

	Mean	S.E.	MSE	MAE	95 % Interval	
			Beta1 = 1			
K = 3						
FE OLS	0.16148	0.00248				
POLS	0.17563	0.00270				
ordered logit	0.92901	0.01586	0.00529	0.07188	0.89849	0.96411
Naive clogit	0.99994	0.02903	0.00090	0.01946	0.94103	1.06088
FCF	0.99330	0.02656	0.00074	0.01819	0.94225	1.04474
Indiv. Mean clogit	0.98699	0.02651	0.00094	0.02148	0.93630	1.04430
BUC	0.99976	0.02110	0.00045	0.01412	0.96138	1.04181
K = 7						
FE OLS	0.42420	0.00500				
POLS	0.20693	0.00235				
ordered logit	0.92531	0.01208	0.00572	0.07466	0.90169	0.94856
Naive clogit	0.99972	0.02784	0.00075	0.01826	0.94528	1.05358
FCF	0.95820	0.02539	0.00239	0.04203	0.90878	1.00931
Indiv. Mean clogit	0.99042	0.02635	0.00080	0.01979	0.93930	1.04363
BUC	0.99932	0.01645	0.00026	0.01100	0.96783	1.03000
K = 11						
FE OLS	0.67823	0.00761				
POLS	0.21344	0.00225				
ordered logit	0.92525	0.01138	0.00573	0.07483	0.90294	0.94886
Naive clogit	0.99906	0.02766	0.00078	0.01933	0.94290	1.05466
FCF	0.93817	0.02481	0.00449	0.06286	0.89028	0.99085
Indiv. Mean clogit	0.98989	0.02628	0.00081	0.01933	0.93778	1.03975
BUC	0.99942	0.01575	0.00027	0.01090	0.96750	1.03096

	Mean	S.E.	MSE	MAE	95% Interval	
			Beta2 = -2			
K = 3						
FE OLS	-0.32337	0.00248				
POLS	-0.35169	0.00269				
ordered logit	-1.50856	0.02589	0.24219	0.49096	-1.56013	-1.45887
Naive clogit	-2.00233	0.04700	0.00242	0.03288	-2.10216	-1.90702
FCF	-1.98814	0.04479	0.00226	0.03063	-2.07914	-1.89968
Indiv. Mean clogit	-1.97595	0.04291	0.00265	0.03646	-2.06764	-1.89027
BUC	-2.00110	0.03390	0.00124	0.02316	-2.07578	-1.93391
K = 7						
FE OLS	-0.84926	0.00500				
POLS	-0.41421	0.00235				
ordered logit	-1.50239	0.02181	0.24808	0.49766	-1.54547	-1.46093
Naive clogit	-2.00188	0.04511	0.00197	0.02853	-2.09208	-1.91451
FCF	-1.91857	0.04403	0.00865	0.08329	-2.01559	-1.83207
Indiv. Mean clogit	-1.98281	0.04264	0.00213	0.03225	-2.06524	-1.89991
BUC	-1.99984	0.02595	0.00070	0.01730	-2.05347	-1.94883
K = 11						
FE OLS	-1.35736	0.00761				
POLS	-0.42709	0.00225				
ordered logit	-1.50084	0.02107	0.24960	0.49944	-1.54128	-1.45818
Naive clogit	-2.00034	0.04480	0.00201	0.02971	-2.08792	-1.91651
FCF	-1.87649	0.04313	0.01711	0.12460	-1.96627	-1.79364
Indiv. Mean clogit	-1.98237	0.04254	0.00219	0.03074	-2.06710	-1.89292
BUC	-1.99987	0.02479	0.00067	0.01746	-2.05021	-1.94826

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Table 6: ... continued

	Beta2/Beta1 = -2				
	Mean	**MSE**	**MAE**	**95% Interval**	
K = 3					
FE OLS	-2.00295	0.00114	0.02251	-2.06771	-1.93409
POLS	-2.00295	0.00114	0.02261	-2.06770	-1.93408
ordered logit	-1.62404	0.14204	0.37591	-1.67641	-1.57123
Naive clogit	-2.00323	0.00201	0.02935	-2.09963	-1.91360
FCF	-2.00207	0.00137	0.02585	-2.07552	-1.93191
Indiv. Mean clogit	-2.00268	0.00175	0.02665	-2.08529	-1.92115
BUC	-2.00198	0.00106	0.02066	-2.06850	-1.93866
K = 7					
FE OLS	-2.00229	0.00074	0.01871	-2.05785	-1.95103
POLS	-2.00200	0.00067	0.01766	-2.05361	-1.95338
ordered logit	-1.62376	0.14202	0.37563	-1.66442	-1.58330
Naive clogit	-2.00312	0.00172	0.02757	-2.08770	-1.92411
FCF	-2.00270	0.00117	0.02266	-2.07857	-1.94011
Indiv. Mean clogit	-2.00266	0.00168	0.02766	-2.08324	-1.91922
BUC	-2.00146	0.00067	0.01700	-2.05403	-1.95221
K = 11					
FE OLS	-2.00159	0.00070	0.01795	-2.05382	-1.95094
POLS	-2.00119	0.00059	0.01666	-2.04767	-1.95443
ordered logit	-1.62222	0.14322	0.37818	-1.66620	-1.58054
Naive clogit	-2.00295	0.00183	0.02941	-2.09252	-1.92420
FCF	-2.00071	0.00130	0.02393	-2.07339	-1.93461
Indiv. Mean clogit	-2.00328	0.00170	0.02745	-2.08487	-1.92772
BUC	-2.00130	0.00068	0.01717	-2.05481	-1.95115

Note: All simulations were performed 1000 times

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