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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 analyzed binary recoding procedures is 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. 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, a much simpler individual mean based binary recoding scheme performs similarly well and even outperforms the FCF estimator if the number of categories on the ordered scale becomes large. If the researcher is, however, only interested in the relative size of coefficients with respect to a baseline the easy to compute linear fixed effect model essentially delivers 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 a model 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 exists no consistent estimator for an ordered logit or probit model that explicitly can incorporate individual fixed effects three main estimation strategies have been followed 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 by, e.g., Di Tella et al. (2001), Scheve and Slaughter (2004), and Senik (2004), tries 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 in certain applications such as studies of subjective well being it is known that the discussed cardinality assumption does not severely bias estimates (see Ferrer-i-Carbonell and Frijters, 2004) it is, however, difficult to generalize this finding to other applications particularly as the severity of the cardinality assumption in such models probably depends on the number of ordinal categories between the respondent can choose, that is the aggregation level of the ordinal scale.

In a third 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 Chamberlain (1980) makes use of all variation in the ordinal response variable. However, as 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).

Choosing from the existing estimation strategies is not an easy task since apart from eye ball comparisons of the discussed alternatives 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 that so far are unknown. Second, the paper functions as a guide to applied researchers that 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 than published in Ferrer-i-Carbonell and Frijters (2004). Section 3 describes the Monte Carlo experiment including the data generating 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, $\alpha_i$ is the individual personality trait assumed to be correlated with the vector of explanatory variables $x_{it}$. Finally $\epsilon_{it}$ 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 $k = 1, \ldots, K$ categories and individual specific thresholds $\lambda_k^i$, 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 effect 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 is small like 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 effect logit framework avoiding 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 what follows 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 $\lambda_k^i$ in equation 2 indeed vary in $i$. As an example, consider ordered responses on life satisfaction. Our sample may include an happy life long enthusiast and a 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 self reported life satisfaction of the sceptic and the enthusiast equally well. Thus, this strategy does in fact not 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 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 responses of the former tend to be on the high side of the ordered scale while responses of the latter tend to be on the low side. Recent applications of this approach include Kassenböhmer and Haisken-DeNew (2009). In what follows 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 all variation in individuals' ordered responses into account. Their method is using the conditional logit approach combined with an fairly evolved individual specific coding of the dependent variable. In doing so, they use the information of the second derivative of the log likelihood function, the so called 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 extensive example can be found in the appendix of Ferrer-i-Carbonell and Frijters (2004).

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

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

The derivations of the first and second derivatives of the log likelihood function used for these calculations can be found in the appendix at the end of 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 correspond 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 so constructed binary variable, that reflects the optimal choice of $D_{ik}$ for all $i$ is fed into a conditional logit estimation to obtain the final coefficients. In what follows we refer to this estimation strategy as Ferrer-i-Carbonell Frijters estimator (FCF). As the FCF estimator requires calculation of individual specific Hessian matrices for each possible threshold $D_{ik}$ it is computational very 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.

[1] For example a data setup of 3000 individuals with 15 observations each can take about one hour of computational time.

A previously discussed alternative assumes cardinality and makes use of all variation in individuals' ordered responses while 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. As previously discussed, personality traits can then be addressed by for instance within transformation of Equation 1 such that $\alpha_i$ cancels out:

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

In what follows we refer to this estimations strategy as 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). 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 can be justified in a more general setting.

# 3 Monte Carlo Simulation and results

Our data generating process is designed according to standard Monte Carlo simulation literature for panel data (e.g., Honoré and Kyriazidou, 2000). The latent variable $y^*_{it}$ is generated by the following model:

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

The individual fixed effect $\alpha_i$ is generated as $\alpha_i = (x_{i1} + x_{i2} + \cdots + x_{iT})/T$. The idiosyncratic error $\epsilon_{it}$ is i.i.d. logistically distributed and the exogenous variables

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

$x_{it}$ 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 concerning 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 500 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 $I = 3000$. In accordance with asymptotic theory all estimators gain consistency and precision with increasing $I$. The MSE as well as the MAE continuously decrease while the standard error and the corresponding confidence interval become 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 row 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 that assumes cardinality. As a consequence, with only one explanatory variable the FE cannot be compared with the other estimators and we do not re-

[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 upon request.

[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.

port performance measures other than the mean coefficients and standard errors. However, when later including more than one explanatory variables we will compare the consistency and efficiency of coefficient ratios to reflect on the relative size of coefficients.

From the set of nonlinear estimators it seems to be the standard ordered logit estimator without controlling for unobserved heterogeneity which performs best for $T = 3$. Its estimated coefficients are the closest to the true parameter values, the standard errors, as well as the MSE and MAE, are the lowest among all the other estimation methods. However, since in the data generating process $\alpha_i$ can be chosen fairly arbitrarily this finding cannot be generalized. Furthermore, the potential bias from ignoring unobserved heterogeneity is clearly noticeable for $T = 5$ and above. In Tables 2 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 of Ferrer-i-Carbonell and Frijters (2004) that allowing for individual fixed effects is more important than taking into account the ordinal data structure.

Comparing the nonlinear models which 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 $B_{it}$. With real survey data and less homogeneous categories the loss of data may be even more serious. This likely results in unreliable outcomes so that we recommend not to use the NCLOG method.

Regarding the IMCLOG and FCF, both estimators perform similarly well and dominate all other estimators in terms of consistency and efficiency for all $I \geq 500$ and $T \geq 5$.

As a first conclusion after these simulations regarding the asymptotic properties of the estimation methods it is clear that they all gain consistency and precision from increasing observations in both panel data dimensions $I$ and $T$.

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

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. For instance in the analysis of individual well-being 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 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 model (FE) reported in the first row of Table 5 cannot be compared to the ones from out non-linear estimators. However, the estimated coefficient ratios of the FE 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, off all estimators the MSE and the MAE of the FE is smallest indicating highly consistent estimations of the parameter ratios. Accordingly, if the researcher is only interested in ratios of parameter estimates and not into absolute values, ignoring the ordinal structure of the dependent variable and applying linear fixed effects models is indeed a commendable method.

Of all the nonlinear estimators controlling for unobserved heterogeneity in Table 5 it is the FCF model which performs best in terms of consistency and efficiency. Compared to the NCLOG and the IMCLOG the means of the 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, naive (NCLOG) and individual mean conditional logit (IMCLOG) estimators are altogether relatively close to the true values. Nevertheless we still get the lowest values for the MSE and MAE with the FCF, which implies an improved consistency of 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 can becomes apparent by looking at the 95% interval of the ordered logit estimates for $\beta_2$ and $\beta_3$ in which the true parameters are not included and the large MAE. Thus, of all non-linear estimators with more than one covariate the FCF is the method of choice as it is the most consistent one. 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 ordinally scaled micro survey 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 (GSOEP) information on individual well-being is captured on an seven and eleven point scale, respectively. Against this backdrop we want to test to what extent 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 3, 7 and 11 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 $I = 3000$ and $T = 12$.

Interestingly, it seems that the FCF method responses rather sensitively to the number of ordered categories in the dependent variable. Beginning with $K = 3$ in Table 6 the FCF parameter estimates of $\beta_1$ and $\beta_2$ 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 $\beta_2/\beta_1$ relations remain highly consistent. In comparison the NCLOG and IMCLOG are not sensitive with respect to the size of $K$, consistency as expressed in the MSE and MAE as well as efficiency as captured by the mean standard error and the confidence interval do not significantly change. Since NCLOG suffers from ignoring a large part of the variation in the dependent variable we find the

IMCLOG to perform comparatively best when $K$ increases. For $K = 7$ and $K = 11$ its performance dominates that of all nonlinear estimators.

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

Summarizing, for small $K$ the FCF dominates in terms of consistency and efficiency. However, for larger $K$, that is for more disaggregated ordinal scales, we recommend the individual mean coded conditional logit approach (IMCLOG). 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 three 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 scheme of the Ferrer-i-Carbonell and Frijters (2004) estimator to perform best 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 individual mean based binary recoding scheme is the method of choice as 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 effect 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:

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

Gradient function:

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

Hessian function:

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

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

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

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

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 $T = 3$

| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
|---|---|---|---|---|---|---|
| **I = 100** | | | | | | |
| **FE** | 0.14711 | 0.00978 | | | | |
| **ordered logit** | 0.99356 | 0.08272 | 0.00750 | 0.05436 | 0.83684 | 1.17915 |
| **FCF** | 1.02721 | 0.21002 | 0.05801 | 0.13159 | 0.69986 | 1.56390 |
| **NCLOG** | 1.73327 | 53896.2 | 52.0970 | 0.17936 | 0.64208 | 2.97807 |
| **IMCLOG** | 1.03710 | 0.21969 | 0.07406 | 0.13168 | 0.69404 | 1.77980 |
| **I = 500** | | | | | | |
| **FE** | 0.14623 | 0.00432 | | | | |
| **ordered logit** | 0.99047 | 0.03682 | 0.00146 | 0.02591 | 0.92106 | 1.07088 |
| **FCF** | 0.98936 | 0.08734 | 0.00858 | 0.06259 | 0.82509 | 1.18874 |
| **NCLOG** | 1.02945 | 0.12070 | 0.01615 | 0.08245 | 0.82487 | 1.32031 |
| **IMCLOG** | 0.99051 | 0.08949 | 0.00904 | 0.06285 | 0.81752 | 1.20715 |
| **I = 1000** | | | | | | |
| **FE** | 0.14606 | 0.00341 | | | | |
| **ordered logit** | 0.99123 | 0.02675 | 0.00079 | 0.01908 | 0.94113 | 1.05008 |
| **FCF** | 0.98367 | 0.06040 | 0.00391 | 0.04397 | 0.87313 | 1.11747 |
| **NCLOG** | 1.00959 | 0.08237 | 0.00799 | 0.05778 | 0.86919 | 1.21730 |
| **IMCLOG** | 0.98356 | 0.06252 | 0.00417 | 0.04424 | 0.86440 | 1.11947 |
| **I = 3000** | | | | | | |
| **FE** | 0.14624 | 0.00177 | | | | |
| **ordered logit** | 0.98939 | 0.01505 | 0.00035 | 0.01424 | 0.95975 | 1.02211 |
| **FCF** | 0.98050 | 0.03505 | 0.00161 | 0.02880 | 0.90824 | 1.05609 |
| **NCLOG** | 1.00229 | 0.04687 | 0.00217 | 0.02901 | 0.91211 | 1.09916 |
| **IMCLOG** | 0.98090 | 0.03586 | 0.00160 | 0.02851 | 0.90953 | 1.05563 |

Note: All simulations were performed 500 times

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

| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
|---|---|---|---|---|---|---|
| **I = 100** | | | | | | |
| **FE** | 0.16163 | 0.00714 | | | | |
| **ordered logit** | 0.95499 | 0.06101 | 0.00596 | 0.05720 | 0.84292 | 1.08775 |
| **FCF** | 0.99886 | 0.12126 | 0.01688 | 0.08010 | 0.78577 | 1.30027 |
| **NCLOG** | 1.04222 | 0.15784 | 0.03308 | 0.09881 | 0.78571 | 1.47499 |
| **IMCLOG** | 1.00052 | 0.12424 | 0.01675 | 0.08120 | 0.78490 | 1.31254 |
| **I = 500** | | | | | | |
| **FE** | 0.16119 | 0.00319 | | | | |
| **ordered logit** | 0.95220 | 0.02746 | 0.00302 | 0.04877 | 0.90246 | 1.00996 |
| **FCF** | 0.98770 | 0.05305 | 0.00300 | 0.03736 | 0.89002 | 1.09438 |
| **NCLOG** | 1.00232 | 0.06590 | 0.00446 | 0.04196 | 0.87939 | 1.14024 |
| **IMCLOG** | 0.98671 | 0.05415 | 0.00314 | 0.03933 | 0.88846 | 1.10267 |
| **I = 1000** | | | | | | |
| **FE** | 0.16100 | 0.00258 | | | | |
| **ordered logit** | 0.95109 | 0.01853 | 0.00274 | 0.04976 | 0.91564 | 0.99237 |
| **FCF** | 0.98515 | 0.03592 | 0.00151 | 0.02612 | 0.91419 | 1.05910 |
| **NCLOG** | 1.00285 | 0.04661 | 0.00232 | 0.03255 | 0.90989 | 1.10275 |
| **IMCLOG** | 0.98487 | 0.03696 | 0.00159 | 0.02636 | 0.91146 | 1.06181 |
| **I = 3000** | | | | | | |
| **FE** | 0.16101 | 0.00130 | | | | |
| **ordered logit** | 0.95134 | 0.01117 | 0.00250 | 0.04853 | 0.92826 | 0.97437 |
| **FCF** | 0.98357 | 0.02154 | 0.00075 | 0.01885 | 0.94109 | 1.02861 |
| **NCLOG** | 1.00128 | 0.02683 | 0.00079 | 0.01967 | 0.94789 | 1.05848 |
| **IMCLOG** | 0.98402 | 0.02202 | 0.00077 | 0.01972 | 0.94182 | 1.03088 |

Note: All simulations were performed 500 times

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

| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
|---|---|---|---|---|---|---|
| **I = 100** | | | | | | |
| **FE** | 0.17576 | 0.00493 | | | | |
| **ordered logit** | 0.95288 | 0.04401 | 0.00404 | 0.05073 | 0.87204 | 1.04101 |
| **FCF** | 0.99385 | 0.07125 | 0.00531 | 0.05098 | 0.86952 | 1.15154 |
| **NCLOG** | 1.00390 | 0.08191 | 0.00681 | 0.05408 | 0.84928 | 1.17568 |
| **IMCLOG** | 0.98860 | 0.07205 | 0.00539 | 0.05229 | 0.86206 | 1.14846 |
| **I = 500** | | | | | | |
| **FE** | 0.17562 | 0.00220 | | | | |
| **ordered logit** | 0.95309 | 0.01976 | 0.00257 | 0.04746 | 0.91454 | 0.99024 |
| **FCF** | 0.99142 | 0.03166 | 0.00099 | 0.02162 | 0.93114 | 1.05918 |
| **NCLOG** | 1.00350 | 0.03648 | 0.00119 | 0.02248 | 0.93800 | 1.07435 |
| **IMCLOG** | 0.99071 | 0.03220 | 0.00101 | 0.02285 | 0.93721 | 1.04831 |
| **I = 1000** | | | | | | |
| **FE** | 0.17551 | 0.00158 | | | | |
| **ordered logit** | 0.95102 | 0.01342 | 0.00258 | 0.04846 | 0.92516 | 0.97645 |
| **FCF** | 0.98807 | 0.02000 | 0.00054 | 0.01652 | 0.95044 | 1.03164 |
| **NCLOG** | 1.00004 | 0.02566 | 0.00062 | 0.01716 | 0.95347 | 1.05255 |
| **IMCLOG** | 0.98765 | 0.02171 | 0.00062 | 0.01683 | 0.94559 | 1.03323 |
| **I = 3000** | | | | | | |
| **FE** | 0.17554 | 0.00090 | | | | |
| **ordered logit** | 0.95136 | 0.00806 | 0.00243 | 0.04848 | 0.93527 | 0.96907 |
| **FCF** | 0.98882 | 0.01287 | 0.00028 | 0.01290 | 0.96373 | 1.01524 |
| **NCLOG** | 0.99930 | 0.01480 | 0.00021 | 0.00938 | 0.97103 | 1.02771 |
| **IMCLOG** | 0.98751 | 0.01309 | 0.00032 | 0.01298 | 0.96233 | 1.01335 |

Note: All simulations were performed 500 times

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

| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
|---|---|---|---|---|---|---|
| **I = 100** | | | | | | |
| **FE** | 0.18197 | 0.00401 | | | | |
| **ordered logit** | 0.96310 | 0.03677 | 0.00263 | 0.03981 | 0.89864 | 1.04024 |
| **FCF** | 0.99042 | 0.05505 | 0.00305 | 0.03880 | 0.89632 | 1.10614 |
| **NCLOG** | 0.99898 | 0.06120 | 0.00386 | 0.04269 | 0.89139 | 1.13139 |
| **IMCLOG** | 0.99132 | 0.05605 | 0.00315 | 0.04026 | 0.88598 | 1.11441 |
| **I = 500** | | | | | | |
| **FE** | 0.18144 | 0.00179 | | | | |
| **ordered logit** | 0.96073 | 0.01639 | 0.00181 | 0.03903 | 0.92771 | 0.99158 |
| **FCF** | 0.99071 | 0.02460 | 0.00070 | 0.01761 | 0.94394 | 1.03802 |
| **NCLOG** | 0.99988 | 0.02739 | 0.00078 | 0.01921 | 0.95022 | 1.05868 |
| **IMCLOG** | 0.99027 | 0.02500 | 0.00073 | 0.01904 | 0.94151 | 1.04022 |
| **I = 1000** | | | | | | |
| **FE** | 0.18138 | 0.00133 | | | | |
| **ordered logit** | 0.96075 | 0.01087 | 0.00166 | 0.03956 | 0.94135 | 0.98417 |
| **FCF** | 0.99091 | 0.01707 | 0.00037 | 0.01261 | 0.95927 | 1.02732 |
| **NCLOG** | 0.99975 | 0.01937 | 0.00034 | 0.01319 | 0.96588 | 1.03591 |
| **IMCLOG** | 0.98938 | 0.01773 | 0.00043 | 0.01446 | 0.95340 | 1.02354 |
| **I = 3000** | | | | | | |
| **FE** | 0.18137 | 0.00073 | | | | |
| **ordered logit** | 0.96016 | 0.00672 | 0.00163 | 0.03972 | 0.94593 | 0.97349 |
| **FCF** | 0.99083 | 0.01004 | 0.00018 | 0.00979 | 0.96968 | 1.00894 |
| **NCLOG** | 0.99959 | 0.01118 | 0.00013 | 0.00775 | 0.97762 | 1.02318 |
| **IMCLOG** | 0.98952 | 0.01019 | 0.00021 | 0.01085 | 0.96831 | 1.01043 |

Note: All simulations were performed 500 times

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

| | **Beta1 = 1** | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
| **FE** | 0.02792 | 0.00093 | | | | |
| **ordered logit** | 0.98511 | 0.02704 | 0.00095 | 0.02074 | 0.93026 | 1.04027 |
| **FCF** | 1.01914 | 0.08215 | 0.00710 | 0.05105 | 0.87224 | 1.22135 |
| **NCLOG** | 1.03795 | 0.11894 | 0.01724 | 0.07777 | 0.84756 | 1.34663 |
| **IMCLOG** | 1.02589 | 0.10253 | 0.01116 | 0.06250 | 0.84640 | 1.26099 |

| | **Beta2 = -3.5** | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
| **FE** | -0.09758 | 0.00101 | | | | |
| **ordered logit** | -3.21216 | 0.07591 | 0.08860 | 0.28694 | -3.37413 | -3.06152 |
| **FCF** | -3.56367 | 0.26134 | 0.07222 | 0.15694 | -4.22692 | -3.11057 |
| **NCLOG** | -3.62448 | 0.38030 | 0.19138 | 0.23968 | -4.65269 | -2.98323 |
| **IMCLOG** | -3.58944 | 0.32179 | 0.11134 | 0.20280 | -4.30434 | -3.06970 |

| | **Beta3 = 7** | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
| **FE** | 0.19519 | 0.00119 | | | | |
| **FCF** | 6.58101 | 0.15462 | 0.19941 | 0.41810 | 6.28138 | 6.90170 |
| **ordered logit** | 7.13022 | 0.52083 | 0.28767 | 0.32358 | 6.21890 | 8.40571 |
| **NCLOG** | 7.25259 | 0.75595 | 0.75895 | 0.46455 | 5.99978 | 9.28319 |
| **IMCLOG** | 7.18041 | 0.63893 | 0.43995 | 0.40480 | 6.12934 | 8.62187 |

| | **Beta2/Beta1 = -3.5** | | | | |
|---|---|---|---|---|---|
| | **Mean** | **MSE** | **MAE** | **95% Interval** | |
| **FE** | 6.99840 | 0.05611 | 0.16076 | 6.54920 | 7.47032 |
| **FCF** | 6.68180 | 0.10965 | 0.31315 | 6.50494 | 6.85143 |
| **ordered logit** | 7.03820 | 0.06101 | 0.16257 | 6.54165 | 7.50587 |
| **NCLOG** | 7.00110 | 0.11975 | 0.21563 | 6.33132 | 7.76580 |
| **IMCLOG** | 7.01260 | 0.09134 | 0.19880 | 6.48967 | 7.69938 |

| | **Beta3s/Beta1 = 7** | | | | |
|---|---|---|---|---|---|
| | **Mean** | **MSE** | **MAE** | **95% Interval** | |
| **FE** | -3.49850 | 0.01463 | 0.08540 | -3.73833 | -3.26905 |
| **FCF** | -3.26140 | 0.05905 | 0.23709 | -3.35002 | -3.17465 |
| **ordered logit** | -3.51270 | 0.01617 | 0.08866 | -3.75794 | -3.26046 |
| **NCLOG** | -3.49900 | 0.03017 | 0.10449 | -3.88651 | -3.14615 |
| **IMCLOG** | -3.50560 | 0.02410 | 0.10576 | -3.83643 | -3.23671 |

Note: All simulations were performed 500 times

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

| | **Beta1 = 1** | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.E.** | **MSE** | **MAE** | **95 % Interval** | |
| **K = 3** | | | | | | |
| **FE** | 0.09647 | 0.00119 | | | | |
| **ordered logit** | 0.97994 | 0.01757 | 0.00074 | 0.02196 | 0.94474 | 1.01800 |
| **FCF** | 0.99964 | 0.03013 | 0.00089 | 0.02099 | 0.94214 | 1.06309 |
| **NCLOG** | 1.00127 | 0.03398 | 0.00122 | 0.02421 | 0.93632 | 1.07487 |
| **IMCLOG** | 0.99775 | 0.03085 | 0.00099 | 0.02153 | 0.93600 | 1.05969 |
| **K = 7** | | | | | | |
| **FE** | 0.25361 | 0.03189 | | | | |
| **ordered logit** | 0.97699 | 0.01147 | 0.00066 | 0.02317 | 0.95326 | 0.99771 |
| **FCF** | 0.97477 | 0.02926 | 0.00152 | 0.02734 | 0.91801 | 1.03524 |
| **NCLOG** | 0.99928 | 0.03223 | 0.00095 | 0.02104 | 0.94548 | 1.06179 |
| **IMCLOG** | 0.99581 | 0.03065 | 0.00095 | 0.02098 | 0.93367 | 1.05437 |
| **K = 11** | | | | | | |
| **FE** | 0.40537 | 0.00311 | | | | |
| **ordered logit** | 0.97476 | 0.01017 | 0.00074 | 0.02522 | 0.95430 | 0.99525 |
| **FCF** | 0.94709 | 0.02839 | 0.00367 | 0.05449 | 0.89303 | 1.00454 |
| **NCLOG** | 0.99862 | 0.03195 | 0.00108 | 0.02113 | 0.93602 | 1.07116 |
| **IMCLOG** | 0.99561 | 0.03057 | 0.00103 | 0.02051 | 0.93865 | 1.06310 |

| | **Beta2 = -2** | | | | | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.E.** | **MSE** | **MAE** | **95% Interval** | |
| **K = 3** | | | | | | |
| **FE** | -0.19315 | 0.00119 | | | | |
| **ordered logit** | -1.84427 | 0.03061 | 0.02528 | 0.15652 | -1.91277 | -1.78198 |
| **FCF** | -2.00065 | 0.05661 | 0.00315 | 0.03670 | -2.11609 | -1.89609 |
| **NCLOG** | -2.00430 | 0.06253 | 0.00372 | 0.04242 | -2.13357 | -1.88532 |
| **IMCLOG** | -1.99786 | 0.05680 | 0.00326 | 0.03862 | -2.11217 | -1.88445 |
| **K = 7** | | | | | | |
| **FE** | -0.50776 | 0.05860 | | | | |
| **ordered logit** | -1.83763 | 0.02024 | 0.02683 | 0.16292 | -1.88024 | -1.79289 |
| **FCF** | -1.95065 | 0.05607 | 0.00592 | 0.05426 | -2.06452 | -1.83298 |
| **NCLOG** | -2.00103 | 0.05935 | 0.00344 | 0.04180 | -2.12783 | -1.88990 |
| **IMCLOG** | -1.99160 | 0.05631 | 0.00319 | 0.03813 | -2.10690 | -1.87616 |
| **K = 11** | | | | | | |
| **FE** | -0.81148 | 0.00311 | | | | |
| **ordered logit** | -1.83329 | 0.01810 | 0.02813 | 0.16650 | -1.87146 | -1.79826 |
| **FCF** | -1.89545 | 0.05459 | 0.01407 | 0.10499 | -2.00788 | -1.78824 |
| **NCLOG** | -1.99969 | 0.05885 | 0.00389 | 0.04111 | -2.12906 | -1.88069 |
| **IMCLOG** | -1.99412 | 0.05629 | 0.00364 | 0.04133 | -2.11658 | -1.88387 |

| | **Beta2/Beta1 = -2** | | | | |
|---|---|---|---|---|---|
| | **Mean** | **MSE** | **MAE** | **95% Interval** | |
| **K = 3** | | | | | |
| **FE** | -2.00218 | 0.00082 | 0.01838 | -2.05898 | -1.94394 |
| **ordered logit** | -1.88202 | 0.01430 | 0.11891 | -1.92477 | -1.84434 |
| **FCF** | -2.00137 | 0.00069 | 0.01689 | -2.05049 | -1.95083 |
| **NCLOG** | -2.00175 | 0.00124 | 0.02439 | -2.07020 | -1.93398 |
| **IMCLOG** | -2.00238 | 0.00090 | 0.02096 | -2.05945 | -1.94991 |
| **K = 7** | | | | | |
| **FE** | -2.00211 | 0.00039 | 0.01355 | -2.04032 | -1.96307 |
| **ordered logit** | -1.88091 | 0.01437 | 0.11912 | -1.90826 | -1.85379 |
| **FCF** | -2.00113 | 0.00052 | 0.01420 | -2.05036 | -1.95795 |
| **NCLOG** | -2.00248 | 0.00101 | 0.01932 | -2.06808 | -1.93918 |
| **IMCLOG** | -1.99998 | 0.00089 | 0.01924 | -2.05674 | -1.94110 |
| **K = 11** | | | | | |
| **FE** | -2.00185 | 0.00032 | 0.01220 | -2.03805 | -1.96969 |
| **ordered logit** | -1.88077 | 0.01437 | 0.11867 | -1.90717 | -1.85575 |
| **FCF** | -2.00134 | 0.00049 | 0.01547 | -2.04453 | -1.95963 |
| **NCLOG** | -2.00246 | 0.00106 | 0.02109 | -2.07182 | -1.93873 |
| **IMCLOG** | -2.00292 | 0.00107 | 0.02268 | -2.06778 | -1.93913 |

Note: All simulations were performed 500 times

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