

Ensuring the cross-group comparability of latent variable models for ranking data with the EPC-interest

–BLINDED VERSION–

ABSTRACT

Many variables crucial to the social sciences are not directly observed but instead are latent and measured indirectly. When an external variable of interest affects this measurement, estimates of its relationship with the latent variable will then be biased. Such violations of “measurement invariance” may, for example, confound true differences across countries in postmaterialism with measurement differences. To deal with this problem researchers commonly aim at “partial measurement invariance”, i.e. to account for those differences that may be present and important. To evaluate this importance directly through sensitivity analysis, the “EPC-interest” was recently introduced for continuous data. However, latent variable models in the social sciences often use categorical data. The current paper therefore extends the EPC-interest to latent variable models for categorical data and demonstrates its use in example analyses of US Senate votes as well as respondent rankings of postmaterialism values in the World Values Study.

Program inputs and data for the examples discussed in this article are provided in the electronic appendix ([http://\[blinded\]](http://[blinded])).

1. INTRODUCTION

The assumption that groups are comparable in measurement is often called “measurement equivalence” or “measurement invariance”, and evaluating measurement invariance is therefore a concern in any comparative study (see Steenkamp and Baumgartner, 1998; Vandenberg and Lance, 2000; Schmitt and Kuljanin, 2008, for reviews). Recently, Oberski (2014) introduced a measure to evaluate measurement invariance in terms of the substantive parameters of interest, the “EPC-interest”. The researcher initially fits a model that assumes full measurement invariance; EPC-interest then estimates the expected change in the parameters of interest that would occur if assumptions of measurement invariance were (partially) relaxed. To continue the previous example, EPC-interest might indicate how much of the substantive mean difference in “materialism” between Costa Rica and Russia is contaminated by possible measurement differences, and whether this contamination is capable of reversing the conclusions or not. While useful, currently EPC-interest is only available for linear structural equation models for continuous data. Categorical observed and latent variables are, however, commonly found in the social sciences. Ranking data, moreover, have never been examined for cross-group equivalence in this sense.

This paper therefore develops the EPC-interest in more generality. This allows for application of the EPC-interest approach to measurement equivalence evaluation in, for example, IRT models (see also Oberski and Vermunt, 2013), ordinal factor analysis, latent class analysis, and to models for ranking data.

2. MEASUREMENT INVARIANCE IN CATEGORICAL DATA

2.1. *The problem of measurement invariance*

Many important variables in the social sciences are not or cannot be directly observed, but are instead latent (Bollen, 2002) and measured using a vector of multiple indicators, \mathbf{y} , say. This measurement of the latent variable ξ is defined by a “measurement model”,

$$p(\mathbf{y}|\xi). \tag{1}$$

The latent ξ variable could, for example, be a “random effect”, a person’s unobserved utility for a choice, a general attitude, or a variable measured with error such as voter turnout. Often the measurement model in Equation 1 is not, however, of primary interest to the researcher, but rather the relationship between the latent variable and some covariate vector \mathbf{x} is, i.e. the “structural model”,

$$p(\xi|\mathbf{x}). \tag{2}$$

Figure 1 shows this relationship as an arrow between the observed covariate \mathbf{x} and latent variable ξ . For example, \mathbf{x} could contain a set of dummy variables indicating a respondent’s country or gender, so that Equation 2 simply compares values of ξ across countries or genders. Alternatively, interest could focus on the influence of continuous covariates such as GDP or age on the latent ξ . Of course, the problem is that ξ is not observed, but only \mathbf{y} and \mathbf{x} are.

Latent variable models generally attack this problem by making two key assumptions about how ξ is measured (Skrondal and Rabe-Hesketh, 2004). The first assump-

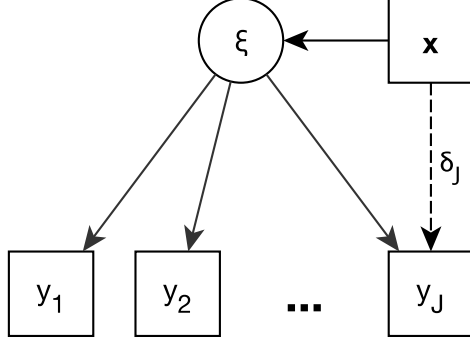


Figure 1: Graph of a latent variable model. The latent variable ξ is shown in a circle to indicate that it is unobserved.

tion is necessary to identify the measurement model. It states that, given the latent variable, the indicators y_j are “locally independent”:

$$p(\mathbf{y}|\xi) = \prod_{j \in \{1 \dots J\}} p(y_j|\xi), \quad (3)$$

where J is the number of indicators use to measure ξ ; typically J will be at least three. In Figure 1, the absence of relationships among the observed variables except those due to their common cause ξ implies local independence.

The second assumption is necessary to identify the structural model. It states that, while the latent variable may depend on the covariate, its *measurement* should not, i.e. the indictors should be “measurement invariant”:

$$p(y_j|\xi, \mathbf{x}) = p(y_j|\xi). \quad (4)$$

When Equation 4 holds for *all* J indicators this is called “full measurement invariance” (Meredith, 1993). A violation of measurement invariance is sometimes termed “differential item functioning” (DIF), since the “items” y_j have differing conditional probability distributions given ξ for differing values of \mathbf{x} (Mellenbergh, 1989). Intuitively, measure-

ment invariance is necessary to identify the structural model of Equation 2 because if all indicators are caused by both ξ and \mathbf{x} , then there is no way of knowing whether an observed indicator difference over values of the covariate is due to a covariate effect on ξ or to a difference over the covariate in the way ξ is measured. For example, when comparing countries, an observed cross-country difference in anti-immigrant attitudes might be a substantive difference or it might equally well be explained as differing answer tendencies over countries.

This identification problem only occurs, however, when there are no measurement invariant indicators at all. A single invariant indicator can disentangle measurement from substantive differences in the other, non-invariant, indicators. Full measurement invariance is therefore not necessary to identify the structural model, but “partial measurement invariance” is (Byrne, Shavelson and Muthén, 1989). The standard practice is to search for non-invariant indicators and either remove them or parameterize their differential functioning (Holland and Wainer, 1993). A common way of doing so when the observed variables are categorical with K categories is a logistic regression,

$$P(Y_j = k) = \frac{\exp(\tau_{jk} + \lambda_{jk}\xi + \delta_{jk}\mathbf{x})}{\sum_{m \in \{1..K\}} \exp(\tau_{jm} + \lambda_{jm}\xi + \delta_{jm}\mathbf{x})}, \quad (5)$$

(Mellenbergh, 1989; Kankaraš, Moors and Vermunt, 2010), where some restriction is imposed on the parameters for identification purposes such as “effect coding”, $\sum_k \tau_{jk} = \sum_k \lambda_{jk} = \sum_k \delta_{jk} = 0$, or dummy coding, $\tau_{j1} = \lambda_{j1} = \delta_{j1} = 0$. It can be seen in Equation 5 that setting $\delta_{jk} = 0$ corresponds to measurement invariance¹. This means that it is possible to estimate a model in which $\delta_{jk} \neq 0$ for *some* indicators, while δ_{jk} is kept at zero, i.e. partially measurement invariant, for others. Figure 1 shows this possible direct effect from covariate to indicator as a dashed arrow.

¹An interaction term $\delta_{jk}^* \mathbf{x} \xi$ could be added to Equation 5 but has been omitted for clarity.

2.2. Existing solutions

In short, some form of measurement invariance is needed to estimate the structural model of interest: deciding which form, that is, selecting a model, is therefore crucial. Currently, there are broadly four existing approaches to doing so:

1. Selecting one indicator as the reference indicator or “anchor item” *a priori*;
2. Imposing a strong prior on the differential functioning parameters;
3. Testing the null hypothesis of full measurement invariance;
4. Evaluating the size and statistical significance of the differential functioning parameters to obtain a partially invariant model.

Each of these four procedures has its merits and drawbacks.

A priori reference indicators are often selected implicitly. In multiple group confirmatory factor analysis (MGCFA), for example, when one loading is fixed to unity in each group, the corresponding indicator is implicitly assumed to be measurement invariant over groups (Hancock, Stapleton and Arnold-Berkovits, 2009). Recently, Muthén and Asparouhov (2014) refined this approach by suggesting to rotate the *a priori* reference indicator MGCFA solution towards the fully invariant solution. A disadvantage of the *a priori* approach, however, is that all models choosing exactly one *a priori* single reference indicator per latent variable and group will fit the data equally well (are equivalent). Thus, it is impossible to select the reference indicator based on the data (Hancock, Stapleton and Arnold-Berkovits, 2009).

Recently, Muthén and Asparouhov (2012) introduced a Bayesian approach to dealing with lack of measurement invariance: estimate a single model in which all the

“direct effects” are allowed to differ somewhat from zero by imposing a strongly informative prior on them. When the prior is chosen adequately, this allows for a modest level of violation of measurement invariance while still identifying the structural model. For this reason Muthén and Asparouhov (2012) termed this approach “approximate measurement invariance”. This new approach is promising, but has some drawbacks as well:

An key issue with this approach, however, is that of choosing an adequately informative prior. At current, this issue remains unresolved, although future research may bring more clarification.

Testing for full measurement invariance is done by comparing a full measurement invariance model is compared with a model imposing no invariance besides an *a priori* reference indicator (Steenkamp and Baumgartner, 1998; French and Finch, 2006). If full measurement invariance is not rejected, the structural relationships of interest is then estimated under this model. Criteria used to accept or reject full measurement invariance include likelihood ratio (chi square) testing, information criteria such as AIC and BIC, and fit measures such as CFI, RMSEA, and gamma-hat (Hu and Bentler, 1998; Cheung and Rensvold, 2002; Chen, 2007). This approach has three serious disadvantages, however. First, the misfit may be due to only a few misspecifications, which could be accounted for in a partially invariant model (Byrne, Shavelson and Muthén, 1989). Second, when the full invariance model fits badly, this need not have a strong substantive impact on the parameter of interest (Saris, Satorra and Van der Veld, 2009). And third, when the full invariance model fits well, Oberski (2014) showed that there may still be violations of invariance in certain items that substantially bias the parameters of interest.

Evaluating size and significance of the direct effect solves the first of these problems by essentially performing a series of tests like the ones described for each possible

misspecification, $\delta_{jk} \neq 0$, separately. The size of the direct effect δ_{jk} may be assessed by estimating J separate models or by use of the “expected parameter change” (EPC). After fitting a full invariance model, the EPC estimates the size of δ_{jk} itself if that parameter were freed (Saris, Satorra and Sörbom, 1987). For this reason, we will refer to this well-known measure as the “EPC-self”. While this approach solves the first problem with omnibus measurement invariance testing, it suffers from the second and third problems, just as omnibus testing does. That is, even when significant and/or large misspecification are found these do not necessarily have a strong substantive impact on the parameters of interest; and, conversely, when the misspecification appears to be small in terms of, for instance, EPC-self, its effect on the parameters of interest may still be considerable (Oberski, 2014). In short, the problem with measurement invariance testing is that it does not account for the effect that violations of measurement invariance have on the parameters of interest.

The EPC-interest was recently introduced by Oberski (2014) for continuous data structural equation models. Similar to the EPC-self, it assesses what would happen if a particular possible direct effect were freed. Rather than assessing the size of this direct effect itself, however, it assesses its impact on the parameter of interest. However, this measure is only available for continuous data, whereas many important measures of latent variables in the social sciences are categorical. Examples include the votes (Yea/Nay) of senators indicating their ideology, how respondents rank their value priorities (1 through 4), or answers (correct/incorrect) to political knowledge questions. The following section therefore explains the rationale of the EPC-interest in more detail, extending it to the case of categorical indicators.

2.3. *EPC-interest*

The “EPC-interest” estimates the change in a free parameter estimate of the model that one can expect to observe if a particular restriction were freed. It is therefore a method of sensitivity analysis. However, the researcher is not forced to estimate all possible alternative models, but can evaluate the sensitivity of the results after fitting the restrictive full invariance model. The EPC-interest is based on the work of Saris, Satorra and Sörbom (1987), who introduced the expected parameter change in a fixed parameter for linear structural equation models (SEM), and Bentler and Chou (1993), who introduced the expected parameter change in a free parameter after freeing a fixed parameter for SEM. It was applied to invariance testing with continuous data by Oberski (2014).

In models for categorical data, the EPC-interest can be derived, as shown below, by applying general results of maximum likelihood analysis. An additional problem with categorical data, however, is that there is usually a large set of parameters relating to a particular variable. For example, in Equation 5, there will be K “loadings” λ_{jk} , K “intercepts” τ_{jk} , K “direct effects” δ_{jk} , and, if present, K “interaction effects” δ_{jk}^* for each variable. These parameters will, moreover, be strongly dependent on one another, so that the impact of freeing one of them cannot be seen separately from the impact of freeing another parameter relating to the same variable. For this reason, when extending EPC-interest to the categorical case, it also becomes necessary to allow for the consideration of *sets* of parameters to free rather than just investigating the effect of single restrictions.

In deriving the EPC-interest, the key concept is considering the likelihood not only as a function of the free parameters of the model, but also as a function of the parameters that are fixed to obtain the full invariance model. Collecting the free

parameters in a vector $\boldsymbol{\theta}$ and the fixed parameters in a vector $\boldsymbol{\psi}$, we assume the likelihood can be written as an explicit function of both sets of parameters, $L(\boldsymbol{\theta}, \boldsymbol{\psi})$. The maximum-likelihood estimates $\hat{\boldsymbol{\theta}}$ of the free parameters can then be seen as obtained under the full invariance model that sets $\boldsymbol{\psi} = 0$, i.e. $\hat{\boldsymbol{\theta}} = \arg \max_{\boldsymbol{\theta}} L(\boldsymbol{\theta}, \boldsymbol{\psi} = 0)$. Further, define the parameters of substantive interest as $\boldsymbol{\pi} := \mathbf{P}\boldsymbol{\theta}$, where \mathbf{P} is typically a logical (0/1) selection matrix, although any linear function of the free parameters $\boldsymbol{\theta}$ may be taken. Interest then focuses on the likely value these free parameters $\boldsymbol{\pi}$ would take if the fixed $\boldsymbol{\psi}$ parameters were freed in an alternative model, $\hat{\boldsymbol{\pi}}_a = \mathbf{P} \arg \max_{\boldsymbol{\theta}, \boldsymbol{\psi}} L(\boldsymbol{\theta}, \boldsymbol{\psi})$.

We now show how these changes in the parameters of interest as a consequence of freeing the fixed parameters $\boldsymbol{\psi}$ can be estimated without fitting the alternative model. Let the Hessian $\hat{\mathbf{H}}_{\mathbf{ab}}$ be the matrix of second derivatives of the likelihood with respect to vectors \mathbf{a} and \mathbf{b} , evaluated at the maximum likelihood solution of the full invariance model, $\hat{\mathbf{H}}_{\mathbf{ab}} := (\partial^2 L / \partial \mathbf{a} \partial \mathbf{b}')|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}}$. The expected change in the parameters of interest is then measured by the EPC-interest,

$$\text{EPC-interest} = \hat{\boldsymbol{\pi}}_a - \hat{\boldsymbol{\pi}} = \mathbf{P} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}} \mathbf{D}^{-1} \left[\frac{\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})}{\partial \boldsymbol{\psi}} \Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} \right] + O(\boldsymbol{\delta}'\boldsymbol{\delta}), \quad (6)$$

where $\mathbf{D} := \hat{\mathbf{H}}_{\boldsymbol{\psi}\boldsymbol{\psi}} - \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}}' \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}}$ and the deviation from the true values is $\boldsymbol{\delta} := \boldsymbol{\vartheta} - \hat{\boldsymbol{\vartheta}}$, with $\boldsymbol{\vartheta}$ collecting the free and fixed parameters in a vector, $\boldsymbol{\vartheta} := (\boldsymbol{\theta}', \boldsymbol{\psi}')'$. Note that, apart from the order of approximation term $O(\boldsymbol{\delta}'\boldsymbol{\delta})$, Equation 6 contains only terms that can be calculated after fitting the invariance model. Thus, it is not necessary to fit the alternative model to obtain the EPC-interest.

In the structural equation modeling literature, the expected change in the fixed parameters $\boldsymbol{\psi}$ is commonly found and implemented in standard SEM software. This measure is commonly known as the ‘‘EPC’’, but to avoid confusion we term it ‘‘EPC-self’’ here. The EPC-self and EPC-interest both consider the impact of freeing restrictions,

but differ in the target of this impact: the EPC-self evaluates the impact on the restriction itself, whereas the EPC-interest evaluates the impact on the parameters of interest. In spite of these differences, the two measures are related: this can be seen by recognizing that $-\mathbf{D}^{-1} \left[\frac{\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})}{\partial \boldsymbol{\psi}} \Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} \right] = \text{EPC-self} \approx \boldsymbol{\psi} - \hat{\boldsymbol{\psi}}$ so that, from Equation 6,

$$\text{EPC-interest} = -\mathbf{P} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}} \text{EPC-self} \approx -\mathbf{P} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}} (\boldsymbol{\psi} - \hat{\boldsymbol{\psi}}) \quad (7)$$

Furthermore, since $\hat{\boldsymbol{\psi}}$ and $\hat{\boldsymbol{\theta}}$ are implicitly related by the fact that they are both solutions to the equation $\partial L / \partial \boldsymbol{\vartheta} = \mathbf{0}$, invoking the implicit function theorem yields $-\hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}} = \partial \boldsymbol{\theta} / \partial \boldsymbol{\psi}'$, so that

$$\text{EPC-interest} = \mathbf{P} \left(\frac{\partial \boldsymbol{\theta}}{\partial \boldsymbol{\psi}'} \right) (\boldsymbol{\psi} - \hat{\boldsymbol{\psi}}), \quad (8)$$

that is, the EPC-interest can be seen simply as the coefficient of a linear approximation to the relationship between the free and fixed parameters, multiplied by the change in the fixed parameters. This demonstrates the difference with the sensitivity analysis approach common in econometrics (Magnus and Vasnev, 2007, p. 168) and applied to SEM by Yuan, Marshall and Bentler (2003), in which only $\partial \boldsymbol{\theta} / \partial \boldsymbol{\psi}'$ is considered: the EPC-interest combines both the direction $(\partial \boldsymbol{\theta} / \partial \boldsymbol{\psi}')$ and the magnitude $(\boldsymbol{\psi} - \hat{\boldsymbol{\psi}})$ of the misspecification.

The derivation of the EPC-interest given in Equation 6 starts from the full invariance solution. We then find a hypothetical new maximum of the likelihood by setting the gradient of a Taylor expansion of the likelihood around the full invariance solution to zero:

$$\frac{\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})}{\partial \boldsymbol{\vartheta}} = \mathbf{0} = \begin{pmatrix} \frac{\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})}{\partial \boldsymbol{\theta}} \Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} \\ \frac{\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})}{\partial \boldsymbol{\psi}} \Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} \end{pmatrix} + \begin{pmatrix} \hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}} & \hat{\mathbf{H}}_{\boldsymbol{\psi}\boldsymbol{\theta}} \\ \hat{\mathbf{H}}_{\boldsymbol{\psi}\boldsymbol{\theta}} & \hat{\mathbf{H}}_{\boldsymbol{\psi}\boldsymbol{\psi}} \end{pmatrix} \begin{pmatrix} \boldsymbol{\theta} - \hat{\boldsymbol{\theta}} \\ \boldsymbol{\psi} - \hat{\boldsymbol{\psi}} \end{pmatrix} + O(\boldsymbol{\delta}'\boldsymbol{\delta}). \quad (9)$$

A similar device was used to derive the so-called “modification index” or “score test” for the significance of the hypothesis $\boldsymbol{\psi} = \mathbf{0}$ by Sörbom (1989, p. 373). Equation 6 follows directly by noting that $(\partial L(\boldsymbol{\theta}, \boldsymbol{\psi})/\partial \boldsymbol{\theta})|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} = \mathbf{0}$ and applying the standard linear algebra result on the inverse of a partitioned matrix $(\hat{\mathbf{H}}^{-1})_{\boldsymbol{\theta}\boldsymbol{\psi}} = -\hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{-1}\hat{\mathbf{H}}_{\boldsymbol{\theta}\boldsymbol{\psi}}\mathbf{D}^{-1}$ (e.g. Magnus and Neudecker, 2007, p. 12).

The accuracy of the approximation of the EPC-interest as a measure of the change in the parameters of interest is reflected in the order of approximation term, $O(\boldsymbol{\delta}'\boldsymbol{\delta})$. It can be seen that this accuracy is quadratic in the overall change in parameters, so that the approximation can be expected to work best when the misspecifications are not “too large”. This result corresponds to results on the score test (“modification index”) and “EPC-self” in the literature on structural equation modeling, which can be shown to be exact under a “sequence of local alternatives”, i.e. when $\boldsymbol{\vartheta} = \lim_{n \rightarrow \infty} \hat{\boldsymbol{\vartheta}} + n^{-\frac{1}{2}}\boldsymbol{\delta}$ (Satorra, 1989, p. 135). It is important to note here that $\boldsymbol{\delta}$ is the deviation from the “true” value of $\boldsymbol{\vartheta}$, rather than the deviation from the limit of the parameter estimates under the alternative model. Therefore another view on the accuracy is that it will be better when the alternative model is not strongly misspecified. For this reason it is also important to consider freeing sets of very strongly related parameters simultaneously, since a change in one of them will then imply a change in the others, and, consequently, a misspecified alternative model.

2.4. *Small simulation study*

To demonstrate the extent of the approximation bias in the EPC-interest, we performed a small simulation study. In this study, we specified a latent variable model for four binary indicators:

$$P(Y_j = 1|x) = [1 + \exp(-x)]^{-1},$$

with $j \in \{2, 3, 4\}$, and structural model

$$x = \gamma z + \epsilon$$

with $\gamma = 1$ and $\epsilon \sim N(0, 1)$. We then introduced a violation of measurement invariance for the first indicator,

$$P(Y_1 = 1|x) = [1 + \exp(-x - \delta_1 z)]^{-1}.$$

Nine conditions varied the following experimental factors:

- Sample size: $n = 250, 500$, or 1000 ;
- The size of the invariance violation: $\delta = 0$ (no violation), 0.5 (moderate), or 1 (extreme).

Data were generated using R 3.1.2 and analyzed using Latent Gold 5.0.0.14161. The results over 200 samples under the nine conditions are shown in Table 1. The first two rows of this table show the average point estimate of the parameter of interest $\hat{\gamma}$, and its deviation from the true value $\gamma = 1$, respectively. It can be seen that a modest violation $\delta = 0.5$ can still have a substantively important impact on bias. Under this condition, that bias is reasonably well approximated by the EPC-interest, which has average values close to the true bias. When the violation is extreme, however, the approximation causes the EPC-interest to somewhat overestimate the bias: for example, in the last column of the table the true bias is -0.327 but EPC-interest estimates it at about -0.448 . This effect appears to be strongest with the smallest sample size, a phenomenon that can be explained by the approximation term being more likely to take on large values in small samples.

n	250			500			1000		
True δ_1	0	0.5	1	0	0.5	1	0	0.5	1
Est. $\hat{\gamma}$	1.010	1.151	1.353	0.980	1.152	1.330	1.013	1.163	1.327
Bias $\hat{\gamma}$	-0.010	-0.151	-0.353	0.020	-0.152	-0.330	-0.013	-0.163	-0.327
EPC-int.	0.003	-0.166	-0.494	-0.001	-0.180	-0.486	0.004	-0.182	-0.448

Table 1: Simulation study of EPC-interest. Shown is the average point estimate for the γ parameter of interest under full measurement invariance (“Est”), its difference from the true value $\gamma = 1$ (“Bias”), and the average EPC-interest.

Overall, the results of this very limited simulation study demonstrate the analytic results discussed above. As expected, for small samples and very large violations of invariance, the EPC-interest will overestimate the bias caused somewhat. In these cases, the researcher may wish to verify that after freeing the violation in question, the results of interest do indeed change substantially. Alternatively, where this is feasible, one may also resort to estimating all alternative models and examining the results. In other conditions, the EPC-interest performs as expected: when there is no bias, it estimates zero on average, and when there is moderate bias in the parameter of interest, EPC-interest approximates this bias adequately.

3. EXAMPLE APPLICATION #1: 90TH US SENATE ROLL CALL DATA

To exemplify the use of the EPC-interest using a relatively simple latent variable model with categorical variables that is well-known in political science, we estimate an ideal point model on roll call data (Jackman, 2010) for senators in the 90th US Senate, which met from 1967 to 1969 during the Lyndon B. Johnson Administration.

The probability that senator i votes “Yea” on motion j is modeled as a logistic regression on the motion’s (unobserved) utility,

$$P(\text{“Yea” on motion } j | x_i) = [1 + \exp(-\beta_j u_{ij})]^{-1}, \quad (10)$$

where the utility u_{ij} of the motion to that senator is simply the Euclidean distance between the senator’s position x_i and the motion’s position τ_j ,

$$u_{ij} = (x_i - \tau_j)^2. \quad (11)$$

The latent variable x_i is known in the literature as an “ideal point”. This model is equivalent to the well-known unidimensional Poole and Rosenthal (1985) (W-NOMINATE) model, and can be estimated in specialized software (e.g. Poole et al., 2008) or by software capable of factor analysis with quadratic factors (Maraun and Rossi, 2001).

The Poole-Rosenthal model can be extended to incorporate covariates that predict the latent variable x_i , for example using the party of the senator as a predictor:

$$x_i = \alpha + \gamma \cdot \text{Party} + \epsilon_i. \quad (12)$$

Using party (Democratic or Republican) as a predictor allows the researcher to see how strongly party membership relates to the senator’s ideological position, which ultimately influences their votes. A higher value of γ thus indicates more ideological homogeneity within parties in the Senate: we therefore call γ the “polarization coefficient”.

The usual choice $\epsilon_i \sim \text{Normal}(0, \sigma^2)$ leads to a quadratic structural equation model (SEM) for categorical data, or, equivalently, a quadratic 2PL IRT model with a covariate (Rabe-Hesketh, Skrondal and Pickles, 2004). Alternatively, the distribution of x can be estimated from the data by choosing some number K of categories for x (“latent classes”) and modeling the probability of belong to class k as an ordered multinomial regression,

$$P(x_i = k | \text{Party}) = \frac{\exp(\alpha_k + \gamma \cdot x^{(k)} \cdot \text{Party})}{\sum_{m=1}^K \exp(\alpha_m + \gamma \cdot x^{(m)} \cdot \text{Party})}, \quad (13)$$

where $x^{(k)}$ is a latent score assigned to the k -th category of x . For this arbitrary choice of latent scale, we choose $x^{(k)}$ to go from 0 to 1 in equally spaced intervals (following Vermunt and Magidson, 2013). The latent category intercepts α_k allow the distribution of the latent dimension to be freely estimated rather than assumed Normal. This leads to the “latent class factor model” (Vermunt and Magidson, 2004), for which the Likelihood is

$$P(\text{Voting pattern of senator } i) = \sum_{m=1}^K P(x_i = m) \prod_{j=1}^J P(\text{Senator's vote on motion } j | x_i). \quad (14)$$

A possible problem when using ideal point models to investigate polarization is that it is assumed that this polarization is the same on all motions the Senate votes on. If there is some motion on which the votes of senators from the same party are significantly more tight-knitted than usual, there will be an effect of Party over and above that of the senator’s utility for this motion. A vote model with a direct covariate effect,

$$P(\text{“Yea” on motion } j | x_i) = [1 + \exp(-\beta_j u_{ij} - \delta_j \cdot \text{Party})]^{-1}, \quad (15)$$

then replaces Equation 10. In other words, the usual ideal point model assumes measurement invariance with respect to the covariate, an assumption that can be expressed as $\delta_j = 0$. In the current application, where such direct effects do exist they are relevant to the investigation of polarization insofar as ignoring them biases the estimate of the Senate’s overall polarization. Thus, we investigate whether the assumption of measurement invariance $\delta_j = 0$ seriously affects the estimate of interest $\hat{\gamma}$ using the EPC-interest.

Maximum likelihood estimates of the parameters were obtained using the software Latent Gold, taking $K = 4$ and the first 20 motions introduced in the 90th Senate

as an example. The model appears to fit the data well, with an L^2 bootstrapped p -value of 0.14. The factor scores \hat{x}_i obtained from this simple model correlated highly (0.79) with those obtained from W-NOMINATE (Poole et al., 2008) and from Optimal Classification Roll Call Scaling (0.81; Poole et al., 2012). Based on the full invariance model, the polarization coefficient $\hat{\gamma}$ was estimated at 4.164 (s.e. 1.3077). Since γ is a logistic regression coefficient, this means that a Republican senator has a $\exp(\hat{\gamma}) = \exp(4.164) \approx 64$ times higher odds of being one category above a Democratic senator than of being in the same category. There was therefore considerable polarization in the 90th Senate.

However, violations of measurement invariance could conceivably bias this conclusion. To investigate this, Figure 2 plots the EPC-interest values of freeing the direct effects δ_j on the parameter estimate of interest $\hat{\gamma}$. Each number in Figure 2 corresponds to a motion number introduced in the Senate. The vertical axis, labeled “EPC-interest”, estimates the change from the current estimate ($\hat{\gamma} = 4.164$) under full measurement invariance that one can expect to observe in $\hat{\gamma}$ when freeing the direct effect of Party for that motion. The horizontal axis shows the p -value for the null hypothesis that the corresponding $\delta_j = 0$, adjusted for false discovery rate (Benjamini and Hochberg, 1995). The idea behind plotting both of these quantities at the same time is that the researcher will likely be interested in violations of measurement invariance that are both statistically and substantively significant (Saris, Satorra and Van der Veld, 2009).

Figure 2 shows that, of the statistically significant violations of measurement invariance, motion #03 violates measurement invariance in a manner that augments the estimated polarization (EPC-interest is positive). Motions #04 and #13, violate measurement invariance in an approximately opposite manner (EPC-interests are negative). However, one motion, #20, clearly stands out as an important violation of measurement invariance. After introducing the direct effect of party on voting “Yea”

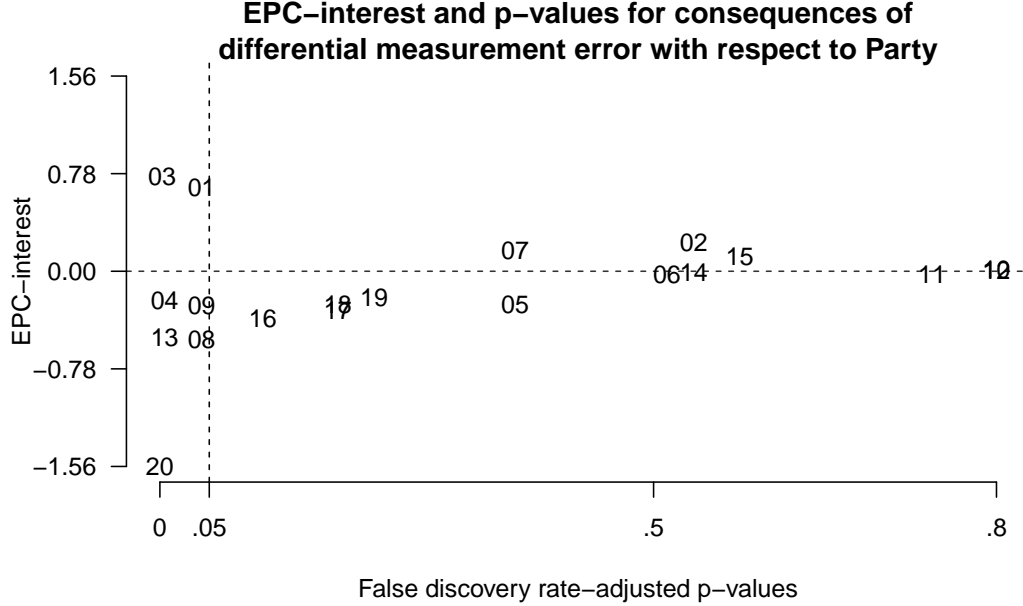


Figure 2: The effect of twenty measurement invariance assumptions on the polarization parameter of interest γ , plotted against the p-values for each violation.

to Motion #20 (freeing δ_{20}), no other measurement invariance violations are statistically significant (all false discovery rate-adjusted p -values ≥ 0.05). Thus, it seems that Motion #20 (HR4573, which increased the public debt limit) was an issue on which the ranks were closed more than usual. Indeed, the 1967 CQ Almanac² specifically reports on this motion, remarking that “Republicans launched their first major attacks in the 90th Congress on the Administration’s fiscal policies”, with no Republicans voting in favor.

After adjusting for this event, the polarization coefficient is estimated at 3.422 (s.e. 1.0630): the tight-knittedness between party membership and voting pattern is therefore somewhat loosened, but still strong. The partial invariance model after accounting for this one violation becomes acceptable, in the sense that those violations that are present do not substantially change the results of interest regarding polarization. The model fit the data well with an L^2 bootstrapped p -value of 0.11. Its BIC (1379) indicates

²<http://library.cqpress.com/cqalmanac/document.php?id=cqal67-1314297>

Unidimensional ideal point estimates of Senators in the 90th US Senate

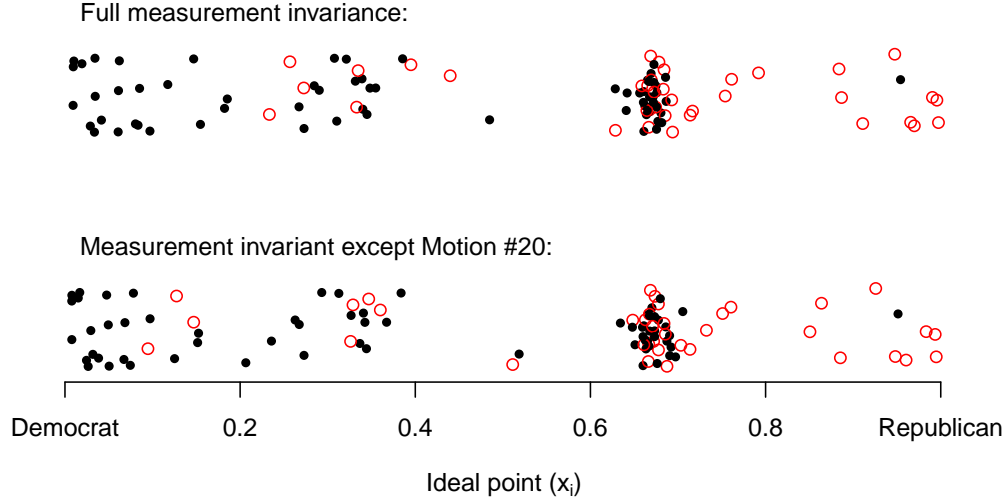


Figure 3: Posterior point estimates of the latent variable “ideal point” score \hat{x}_i for all senators (points), jittered vertically for visual clarity. Black points are Democrats, red circles Republicans. Top: estimates under the fully invariant model; Bottom: estimates allowing for the direct effect $\delta_{20} \neq 0$.

an improvement over that of the full invariance model (1405). Overall, the difference between the fully and partially invariant models are modest. Figure 3 shows the effect of freeing δ_{20} on the “ideal point” estimates, i.e. the latent variable estimates \hat{x}_i .

The top part of Figure 3 shows the ideal point estimates under the full invariance model. These estimates range from zero to one; since Democrats, shown as black dots, are predominantly on the lower side of the scale, zero has been labeled “Democrat” and the score 1 has been labeled “Republican”, since most Republicans (red circles) can be found here. To make the points more visible, they have been jittered randomly in the vertical direction. The bottom part of Figure 3 shows the ideal point estimates for the same senators, but this time while accounting for the partial violation of measurement invariance $\delta_{20} \neq 0$. It can be seen that Republicans are more spread out into the “Democratic” side of the scale. Especially the three Republican senators with a score

below 0.2 experience a rather large shift in position. On the whole, therefore, the differences between the two distributions are modest, but the differences for individual senators’ ideal point estimates can be quite substantial.

In this section we investigated measurement invariance assumptions in the well-known “ideal point” model for example binary roll call data. The example demonstrated that even when the model appears to fit the data well initially, it is still possible for violations of measurement invariance to bias the conclusions. The EPC-interest was used here as a tool to detect such bias. After accounting for one violation of measurement invariance, the final model differed somewhat from the original conclusions: the estimated amount of polarization in the 90th Senate was lower and several Republican senators’ estimated ideological positions were considerably more liberal.

4. EXAMPLE APPLICATION #2: RANKING VALUES IN THE WVS

Our second, more complex, example application employs the 2010–2012 World Values Survey³ (WVS) comprising $n = 67,568$ respondents in 48 different countries (Appendix A provides a full list of countries). The WVS questionnaire includes Inglehart (1977)’s extended (post)materialism questions, developed to measure political values priorities. This extended version includes three sets of four priorities (Table 2) to be ranked by the respondents. Of these, set B in Table 2 is known as the “short scale” that is commonly used in research on values priorities.

Based on the “dual hypothesis model” (Inglehart, 1981, p. 881), previous authors have suggested a structural relationship of interest between, on the one hand, (post)materialism, and socio-economic (Inglehart and Welzel, 2010) as well as socio-

³<http://www.worldvaluessurvey.org/>

Table 2: Value priorities to be ranked for the three WVS 2010–2012 ranking sets. “Materialist” concerns are marked “M” , “postmaterialist” concerns are marked “P”.

Option #	M/P	Value wording
<i>Set A</i>		
1.	M	A high level of economic growth
2.	M	Making sure this country has strong defense forces
3.	P	Seeing that people have more say about how things are done at their jobs and in their communities
4.	P	Trying to make our cities and countryside more beautiful
<i>Set B</i>		
1.	M	Maintaining order in the nation
2.	P	Giving people more say in important government decisions
3.	M	Fighting rising prices
4.	P	Protecting freedom of speech
<i>Set C</i>		
1.	M	A stable economy
2.	P	Progress toward a less impersonal and more humane society
3.	P	Progress toward a society in which ideas count more than money
4.	M	The fight against crime

Wording: “People sometimes talk about what the aims of this country should be for the next ten years. On this card are listed some of the goals which different people would give top priority. Would you please say which one of these you, yourself, consider the most important?”; “And which would be the next most important?”.

cultural (Inglehart, Norris and Welzel, 2002) variables, on the other. We will follow these authors and examine the aggregate relationship of values priorities with log-GDP per capita (Z_1) and the percentage of women in parliament (Z_2)⁴.

We model the probability that unit i in country c belongs to category x of the latent (post)materialism variable using the multilevel multinomial logistic regression

$$P(X_{ic} = x | Z_{1ic} = z_{1ic}, Z_{2ic} = z_2, G_c = g) = \frac{\exp(\alpha_x + \gamma_{1x}z_1 + \gamma_{2x}z_2 + \beta_{gx})}{\sum_t \exp(\alpha_t + \gamma_{1t}z_1 + \gamma_{2t}z_2 + \beta_{tg})}, \quad (16)$$

where the country-level random effect variable G has been introduced. We take the “random effects” variable G to be a country-level latent class variable with S classes and a freely estimated (nonparametric) distribution. Overall, then, our model can be seen as a multilevel multinomial regression of (post)materialism on country-level covariates, in which the nominal dependent variable is latent, and the random effects distribution is nonparametric. The main parameters of substantive interest in Equation 16 are therefore the multinomial logistic regression coefficients γ_{mx} . This “structural” part of the model is shown in the top part of Figure 4.

The latent (post)materialism variable is measured by respondents’ rankings of value priorities. Each respondent in the 48 countries has ranked only their first and second choice on three ranking tasks A, B, and C (see Table 2). We assume that each value priority has a particular “utility” (Luce, 1959; Böckenholt, 2002, p. 171) dependent on the latent class variable (Croon, 1989; Böckenholt, 2002, p. 172). For example, for ranking task A in country c , respondent i ’s choices for first and second place are

⁴These country-level variables were obtained from the World Bank database⁵ using the WDI package (Arel-Bundock, 2013) in R 3.0.2 (R Core Team, 2012).

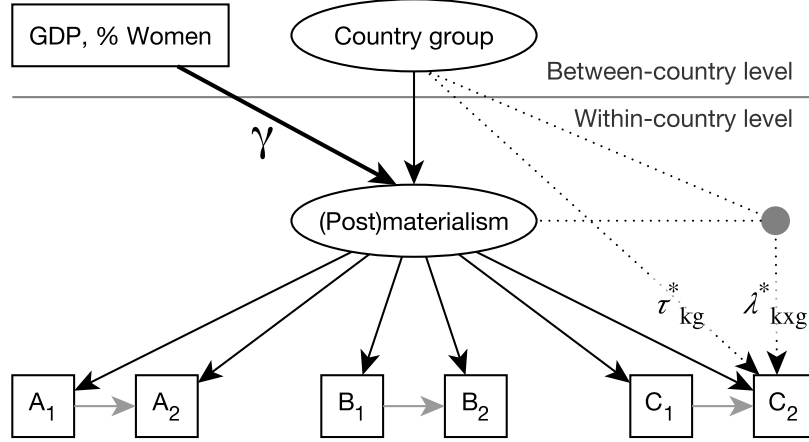


Figure 4: Graphical representation of the multilevel latent class regression model for (post)materialism measured by three partial ranking tasks. Observed variables are shown in rectangles while unobserved (“latent”) variables are shown in ellipses.

modeled as

$$P(A_{1ic} = a_1, A_{2ic} = a_2 | X_{ic} = x) = \frac{\exp(\tau_{a_1} + \lambda_{a_1x})}{\sum_k \exp(\tau_k + \lambda_{kx})} \frac{\exp(\tau_{a_2} + \lambda_{a_2x})}{\sum_{k \neq a_1} \exp(\tau_k + \lambda_{kx})}, \quad (17)$$

Crucially, the choice for second place, A_{2ic} , is modeled while excluding the alternative already chosen for first place, A_{1ic} . In other words, we model a sequential ranking process in which first place is chosen from all options, then second place is chosen from the remaining options. This dependency intrinsic to ranking tasks makes the model used here different from standard models for qualitative dependent variables such as multinomial regression. The measurement model for (post)materialism is shown in the bottom part of Figure 4, using gray arrows to indicate that the choice for second place is modeled conditionally upon that for first place.

As shown in Section 2, Equation 17 is a full measurement invariance model: it excludes potential direct main effects and direct interaction effects of the grouping variable. Instead of considering main and interaction effects from the countries directly, we consider these for the country random effects (G) (see De Jong, Steenkamp and Fox,

2007; Fox and Verhagen, 2011; Jak, Oort and Dolan, 2014). Thus, measurement invariance violations could be parameterized by extending Equation 17 to include country group class (g) effects:

$$P(A_{1ic} = a_1, A_{2ic} = a_2 | X_{ic} = x) = \frac{\exp(\tau_{a_1} + \lambda_{a_1x} + \delta_{a_1g} + \delta_{a_1xg}^*)}{\sum_k \exp(\tau_k + \lambda_{kx} + \delta_{kg} + \delta_{kxg}^*)} \dots \quad (18)$$

The base invariance model above can then be seen as fixing the intercept deviations $\delta_{kg} = 0$ and slope deviations $\delta_{kxg}^* = 0$. An example of this parameterization of measurement non-invariance for the second ranking of Set C (C_2) is shown in Figure 4 as the dotted main effect and interaction effects for scalar and metric invariance, respectively. In line with Section 2, we now investigate whether the possible misspecifications in the measurement invariance model, $\delta_{kg} \neq 0$ and $\delta_{kxg}^* \neq 0$, substantially affect the parameters of interest γ_{mx} using EPC-interest for categorical data.

The model as well as EPC-interest measures were implemented by one of the authors in the software Latent Gold Choice version 5.0.0.14157 and higher (Vermunt and Magidson, 2005, 2013, pp. 135–136). Program input for this analysis can be found in Appendix B, while output and data are included in the online Appendix at [http://\[BLINDED\]](http://[BLINDED]). We select three classes for both the latent “(post)materialism” variable and the country group class variable. For BIC values and the rationale behind these choices, please see Appendix C. Since class selection is not the focus of this example analysis, we will not discuss it here further.

After estimating the full invariance model, we calculated the EPC-interest for the δ and δ^* parameters, of which our three-class model has four: two for each of the two independent variables. Measurement invariance violations can potentially take the form of 6 direct main effects (δ_{jkg}) and 12 direct interaction effects (δ_{jkxg}^*) for each of the three ranking tasks, totaling 54 possible misspecifications in the full invariance

Table 3: Full invariance multilevel latent class model: parameter estimates of interest with standard errors (columns 3 and 4), as well as expected change in these parameters measured by the EPC-interest when freeing each of six sets of possible misspecifications (columns 5–10).

		EPC-interest for...							
		Estimates		δ_{jkg}			δ_{jkxg}^*		
		Est.	s.e.	Ranking task			Ranking task		
				1	2	3	1	2	3
Class 1	GDP	-0.035	(0.007)	-0.013	0.021	-0.002	0.073	0.252	0.005
Class 2	GDP	-0.198	(0.012)	-0.018	-0.035	0.015	-0.163	-0.058	0.002
Class 1	Women	0.013	(0.001)	-0.006	0.002	0.000	-0.003	0.029	0.002
Class 2	Women	-0.037	(0.001)	0.007	-0.003	0.002	-0.006	-0.013	0.002

model. These misspecifications are strongly correlated and should not be considered separately. Rather, we consider the probable impact of freeing the direct main effects for each ranking task separately and of freeing the direct interactions for each ranking task separately. Thus, rather than consider the direct and interaction effects for each of the 48 countries on each of the 3 unique categories of each of the three ranking tasks, making for 5076 potential EPC-interest values, we evaluate direct effects of the country group random effect and consider their impact jointly for strongly correlated misspecifications, reducing the problem to 24 EPC-interest values of interest.

Table 3 shows these 24 EPC-interest values calculated from the full invariance model. These EPC-interest values estimate the likely change from the maximum likelihood estimates (column 3 in Table 3) in the four parameters of substantive interest after freeing the direct main or interaction effects for each of the three ranking tasks (columns 5–10 in Table 3). In the full invariance model, Class 1 corresponds to a “post-materialism” class. The estimate -0.035 (s.e. 0.007) shown in Table 3) would therefore suggest that more prosperous nations tend to be less postmaterialist. This directly contradicts the theory of Inglehart and Welzel (2010), which suggests that this coefficient should be positive.

Since the theory specifies only that certain coefficients should be positive or negative, the key focus of substantive interest is whether misspecifications in the invariance model can potentially change the sign of a parameter of interest. In Table 3, we therefore look for EPC-interest values that, when added to the estimates in column 3, would change the sign of those estimates. It can be seen in the Table that two such EPC-interest are indeed present, namely the direct interaction effect of the country group class with the postmaterialism class on ranking tasks 1 and 2. This means that the attribute parameters that define the classes for these two tasks differ over country groups, and that after accounting for these differences the effect of GDP on postmaterialism is estimated to be positive rather than negative. This set of misspecifications is thus of substantive interest and should be amended in the model.

Following the common practice of partial invariance models, we therefore free these two sets of measurement invariance violations, allowing for differences in the parameters of ranking tasks 1 and 2 across country groups. Table 4 shows the substantive parameter estimates and EPC-interest interest values for the resulting partial invariance model, which has 63 parameters and a log-likelihood of -418610.0 ($\text{BIC} = 837920.5$). The likelihood ratio test of improvement in model fit is highly significant ($\chi^2_{\text{df}=28} = 24607$). Moreover, the substantive logistic regression coefficient for the effect of GDP on the postmaterialism class (Class 2 in Table 4), is indeed positive after freeing the detected misspecifications. Re-calculating EPC-interest values for the remaining possible misspecifications reveals that none of the possible misspecifications in this partial invariance model has the potential to change the substantive conclusions. In this sense, we therefore conclude that the partial invariance model fits “approximately”, since none of the substantive conclusions based on it are threatened by measurement invariance violations.

□

Table 4: Partially invariant multilevel latent class model: parameter estimates of interest with standard errors (columns 3 and 4), as well as expected change in these parameters measured by the EPC-interest when freeing each of four sets of remaining possible misspecifications (columns 5–7 and 10).

		EPC-interest for non-invariance of...							
		δ_{kg}				δ_{kxg}^*			
				Ranking task			Ranking task		
		Est.	s.e.	1	2	3	1	2	3
Class 1	GDP	-0.127	(0.008)	-0.015	-0.003	0.002			0.097
Class 2	GDP	0.057	(0.011)	-0.043	-0.013	0.002			0.161
Class 1	Women	0.008	(0.001)	-0.002	0.000	0.002			0.001
Class 2	Women	0.020	(0.001)	-0.007	-0.001	0.002			0.007

5. DISCUSSION AND CONCLUSION

Whenever groups are compared, measurement equivalence is a concern. Particularly, it should be verified that substantive conclusions of interest are uncontaminated by possible cross-group differences in measurement. The EPC-interest, a measure introduced by Oberski (2014) for this purpose in the context of linear structural equation models, was extended in this paper to apply to categorical observed and latent variables as well as rankings and other types of data often encountered in the social sciences. An example application looked at the relationship between latent (post)materialism on the one hand and, on the other, log-GDP per capita and the percentage of women in parliament using data from 67,568 respondents in 48 countries. A violation of measurement invariance existed that, when unaccounted for, could reverse substantive conclusions. The EPC-interest allowed us to detect this problem and account for those violations of assumptions that were indeed influential on the substantive conclusions of interest. Finally, we provided user-friendly software implementing the EPC-interest; program input and data for the example application is available in the online Appendix.

The EPC-interest fits within the recent literature on “approximate measurement

invariance”. That is, the goal of incorporating important measurement differences in the model while ignoring unimportant ones. Invariance testing using “approximate” fit measures such as the CFI and RMSEA (e.g. Cheung and Rensvold, 2002; Chen, 2007) can be thought of as such a method, since the fit of the model is thought to be “approximate”, and relative to model complexity. Model-based approaches include random effects modeling (De Jong, Steenkamp and Fox, 2007; Jak, Oort and Dolan, 2014), Bayesian priors on measurement differences (Muthén and Asparouhov, 2012), and factor rotation towards an invariant solution (Muthén and Asparouhov, 2014). An advantage of these last three approaches is that a middle ground may be found between exact equality of measurement processes over groups and complete independence (Van De Schoot et al., 2013). However, a current problem is that there is no agreed-upon definition of “approximate”. At the same time, the EPC-interest approach does not offer a middle ground, but it does solve the problem of defining what “approximate” fit might be (Van De Schoot et al., 2013, p. 12): for example, in the current application it was taken to be any measurement difference that cannot reverse the sign of the regression parameters of substantive interest. An interesting direction for future work is therefore to combine the sensitivity analysis approach of the EPC-interest with the approaches to approximate measurement invariance of Muthén and Asparouhov (2012, 2014), for example by weighting the cross-group measurement differences to be aligned by the possible change in parameters of interest.

The scope of the paper was limited to an application of the EPC-interest to a model with categorical observed and latent variables. While we consider this a useful contribution, we did not further investigate the performance of this measure. We do note that the actually observed change in the parameters of interest after freeing the suggested invariance restrictions was very close to that predicted by the EPC-interest in this particular application. The Monte Carlo simulation using linear structural equa-

tion models in Oberski (2014) demonstrates that this is the case for linear structural equation models with relatively simple setups. However, an investigation of whether this is the case for categorical latent class models under a wider range of hypothetical conditions in a simulation study remains work for the future.

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A. COUNTRIES INCLUDED IN THE STUDY

ISO3 code	Country name	ISO3 code	Country name
DZA	Algeria	MAR	Morocco
ARM	Armenia	NLD	Netherlands, The
AUS	Australia	NZL	New Zealand
AZE	Azerbaijan	NGA	Nigeria
BLR	Belarus	PAK	Pakistan
CHL	Chile	PER	Peru
CHN	China	PHL	Philippines
COL	Colombia	POL	Poland
CYP	Cyprus	QAT	Qatar
ECU	Ecuador	RUS	Russian Federation
EGY	Egypt	RWA	Rwanda
EST	Estonia	SGP	Singapore
DEU	Germany	SVN	Slovenia
GHA	Ghana	ESP	Spain
IRQ	Iraq	SWE	Sweden
JPN	Japan	TTO	Trinidad and Tobago
JOR	Jordan	TUN	Tunisia
KAZ	Kazakhstan	TUR	Turkey
KOR	Korea, Republic of	UKR	Ukraine
KGZ	Kyrgyzstan	USA	United States
LBN	Lebanon	URY	Uruguay
LBY	Libya	UZB	Uzbekista
MYS	Malaysia	YEM	Yemen
MEX	Mexico	ZWE	Zimbabwe

B. LATENT GOLD CHOICE INPUT FOR THE FULL INVARIANCE MODEL

The input below fits the full invariance model described in the paper, setting the possible violations of invariance to zero (0). The option “score test” in the output section (only available in Latent Gold or Latent Gold Choice ≥ 5) is then used to obtain the EPC-interest values. Output and data for this example can be obtained from the online appendix at <http://>.

options

```
maxthreads=all;
algorithm
  tolerance=1e-008 emtolerance=0.01
  emiterations=450 nriterations=70 ;
startvalues
  seed=0 sets=30 tolerance=1e-005 iterations=50;
bayes
  categorical=0 variances=0 latent=0 poisson=0;
missing  excludeall;

// NOTE: The option "scoretest" for output is used to obtain
//       the EPC-interest. This will also produce the score test ("MI")
//       and EPC-self for the measurement invariance restriction
```

output

```
parameters=effect  betaopts=wl standarderrors profile
probmeans=posterior
frequencies bivariateresiduals estimatedvalues=regression
predictionstatistics setprofile setprobmeans
iterationdetails scoretest ;

// There are several ways of modeling ranking data using LG or LGChoice.
//   The most computationally efficient is to use the so-called "3-file"
//   setup in LGChoice employed here (see LGChoice manual).
```

choice = 3

```
alternatives 'inglehart_wvs6_long.alt' quote = single
id=alt
choicesets 'inglehart_wvs6_long.set' quote = single
```

```

id=set;

variables
  groupid country;
  caseid id;
  choicesetid set ;
  dependent value ranking;
  independent NY_GDP_PCAP_CD, SG_GEN_PARL_ZS;
  attribute int1 nominal, int2 nominal, int3 nominal;
  latent
    GClass group nominal 3,
    Class nominal 3;

equations
  // Group class intercept
  GClass <- 1 ;

  // Parameters of interest are logistic regression coefficients of
  //      NY_GDP_PCAP_CD and SG_GEN_PARL_ZS.
  Class <- 1 + GClass + NY_GDP_PCAP_CD + SG_GEN_PARL_ZS;

  // Below, sets of possible violations of measurement invariance have been
  //      explicitly restricted to equal zero using "(0)". This will
  //      produce EPC-interest, EPC-self, and Score test output.
  value <- int1 + int2 + int3 +
    int1 Class + int2 Class + int3 Class +
    (0) int1 GClass + (0) int2 GClass + (0) int3 GClass +
    (0) int1 Class GClass +
    (0) int2 Class GClass +
    (0) int3 Class GClass ;

```

Table 5: Log-likelihood, number of parameters, and Bayesian Information Criterion (BIC) for models with different numbers of classes for the (post)materialism (within-country) and country group (between-country) latent class variables.

(Post)materialism (X) classes, $ \{G\} = 1$				Country group (G) classes, $ \{X\} = 3$			
#Classes	Log-lik	#Par	BIC(L^2)	#Classes	Log-lik	#Par	BIC
1	-460512.7	9	-10346.1	1	-447646.2	29	895616.3
2	-449836.9	19	-31586.2	2	-444754.8	32	889867.0
3	-447646.2	29	-35855.8	3	-443216.6	35	886824.1
4	-446211.1	39	-38614.4	4	-442734.2	38	885892.8
5	-445246.3	49	-40432.4	5	-442436.5	41	885330.9
6	-444776.4	59	-41260.3	6	-442110.5	44	884712.3
7	-444384.0	69	-41933.4	7	-441946.2	47	884417.3

C. MODEL SELECTION FOR THE EXAMPLE APPLICATION

In choosing the number of classes for the (post)materialism (within-country) and country group (between-country) latent class variables, we follow the advice of Lukočienė, Varriale and Vermunt (2010) to first fix the number of country-group classes to unity and choose a number of within-country classes, subsequently fixing the number of within-country classes to this chosen number and determining the number of country-group (between-country) classes. The left-hand side of Table 5 shows the log-likelihoods, number of parameters and Bayesian Information Criterion (BIC) values based on the L^2 for the model with one country-group class and an increasing number of (post)materialism classes. It can be seen that the BIC, which penalizes model complexity, decreases with each additional latent (post)materialism class. In fact, the BIC does not stop decreasing even when incrementing the number of classes to 14 (not shown in Table 5 for brevity).

In the literature on (post)materialism (e.g. Inglehart and Welzel, 2010), the number of (post)materialism classes is typically fixed to three: “postmaterialist”, “materialist”, and “mixed”. Clearly, using the WVS ranking tasks and imposing full invariance, many

more qualitative (post)materialism classes can be distinguished than the traditional three classes. This corresponds to findings by Moors and Vermunt (2007); however, these authors also argued that “one can safely interpret the results (...) if adding another class does not result in important changes of the latent class weights for the other classes” (p. 637). While this is a somewhat subjective criterion, the three-class solution found in the data does correspond to the theoretical “postmaterialist”, “materialist”, and “mixed” classes, whose parameters appear to change little in the models with a greater number of classes. Moreover, the greatest reduction in BIC seen in Table 5 takes place when moving from a one-class to a two-class model, with relatively small improvements after three or more classes. We therefore follow the theoretical literature in selecting the three-class model.

While selecting the number of country-group classes, we find that the BIC improves little after three classes (right-hand side of Table 5), so that our initial full invariance model has three (post)materialism (within-country) and three country group (between-country) classes.

D. WVS RANKING DATA MODEL ESTIMATES

Table 6 shows the sizes of the three (post)materialism classes (third row) as well as the “attribute parameters”, i.e. each class’s average log-utility. Thus, when reading each row horizontally, the class with the highest log-utility represents respondents who value that object highest. For example, priorities A.1, A.2, B.1, B.3, and C1 have the highest log-utilities in Class 1. Since all of these priorities are “materialist” (labeled “M” in Table 6), we also labeled Class 1 “materialist”. A caveat with this label is that the materialist priorities that are most strongly related to this class also happen to be the first item in each set, so that a primacy effect may play a role here as

Table 6: Estimated log-utilities under the final model. In each row, the highest log-utility has been printed in **bold face** to facilitate interpretation of the classes.

		Class 1	Class 2	Class 3
Class label		“Materialist”	“Postmater.”	“Mixed”
Class size		0.569	0.213	0.218
(s.e.)		(0.0114)	(0.0179)	(0.0280)
Set A				
M	1. Economic growth	2.1102	0.4837	0.4156
M	2. Strong defense	-0.5285	-1.4984	-0.9249
P	3. More say	-0.5519	1.4683	0.4643
P	4. More beauty	-1.0298	-0.4536	0.0449
Set B				
M	1. Order in the nation	1.0016	-0.5898	0.0435
P	2. More say	-0.4592	0.6902	-0.2763
M	3. Rising prices	0.4281	-0.2269	0.3719
P	4. Freedom of speech	-0.9705	0.1266	-0.1390
Set C				
M	1. Stable economy	2.0086	0.0789	0.1715
P	2. Humane society	-0.7919	0.4450	-0.0943
P	3. Ideas	-1.1402	-0.0593	-0.4550
M	4. Fight crime	-0.0765	-0.4646	0.3778

well. Class 2 is labeled “postmaterialist” because it has the highest log-utilities for all of the postmaterialist priorities (labeled “P” in Table 6), with the exception of A.4. Preferences in the third class appear to be for the most part in-between those of Classes 1 and 2. At the same time, however, this class has the highest log-utilities for A.4 (a “postmaterialist” object) and C.4 (a “materialist” object). For this reason we apply the label “mixed” to Class 3.