EPC-interest for categorical data with an application to the Inglehart values ranking

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ABSTRACT

Social science is often concerned with comparing groups such as countries, regions, time periods, the genders, or ethnicities. Because such substantive comparisons may be threatened when measurement parameters differ across the groups, it is common practice to test the hypothesis of exact equality of measurement parameters across groups: "measurement invariance testing". However, not all measurement differences are substantively relevant. At the same time, it was recently shown that not all substantively relevant differences are necessarily detected by the current best practices of invariance testing. Therefore, it was recently suggested to detect the relevant set of violations of measurement invariance using sensitivity analysis. This approach, recently introduced in this journal, uses the "EPC-interest", a measure of the change in the parameters of substantive interest due to violations of invariance. So far, however, EPC-interest was limited to continuous linear structural equation models and did not consider the impact of freeing several restrictions at the same time.

Since categorical data are common in the social sciences and measurement invariance restrictions may be highly correlated, this paper extends the "EPC-interest" to models with categorical observed and latent variables. Moreover, we explicitly consider freeing (potentially large) sets of equality restrictions simultaneously. The advantages of the extended EPC-interest are demonstrated using a 48 country analysis of "materialism/postmaterialism" values measured by three partial ranking tasks using multilevel latent class regression. Some corroboration for hypotheses on postmaterialism from the literature are found when employing the EPC-interest, while without its application some of the findings contradict these hypotheses.

The newly developed methods discussed in this paper have been implemented in commercial software for latent variable modeling. Program inputs and data for the examples discussed in this article are provided in the electronic appendix (`http://`) [included as zip file in blinded version].

1. INTRODUCTION

The logic of measurement invariance testing is that groups may safely be compared when their measurement parameters are exactly equal: in that case, conclusions of substantive interest are uncontaminated by measurement differences. While this logic is sound, it does not follow that comparison is never warranted when measurement parameters are not exactly equal. Moreover, in practical applications exact equality is not often plausible. These observations have led to the concept of "approximate" measurement invariance, in which a certain, "small" amount of non-invariance is permitted.

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

Table 1: Options to be ranked for the three Inglehart values ranking sets in the World Values Survey 2010–2012. The wording of the question is "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?".

However, while these methods ensure that measurement differences are "small", even "small" measurement differences could, in principle, still contaminate the conclusions of interest. Conversely, those measurement differences allowed for may not necessarily affect the conclusions of interest.

(Muthén and Asparouhov, 2012) (Van De Schoot et al., 2013)

(Muthén and Asparouhov, 2014)

2. EPC-INTEREST

3. DATA

4. MODEL

There are several approaches to modeling ranking data. (...) Different approaches to modeling ranking data can be found in Maydeu-Olivares and Böckenholt (2005); Brown and Maydeu-Olivares (2011, 2012).

(Moors and Vermunt, 2007)

$$P(A_1 = a_1, A_2 = a_2 | X = x) = \frac{\omega_{a_1 x}}{\sum_k \omega_{kx}} \frac{\omega_{a_2 x}}{\sum_{k \neq a_1} \omega_{kx}} \tag{1}$$

where ω_{kx} is the utility ($0 < \omega_{kx} < 1$) of response option k (McFadden, 1974). Crucially, the choice for second place, A_2, is modeled while excluding the alternative already chosen for first place, A_1. In other words, we model a sequential ranking process in which first place is chosen first, then second place is chosen from the remaining options. The utilities ω_{kx} may differ over persons due to the latent class variable X (Böckenholt, 2002, pp. 171–3), which in our case will represent "(post)materialism". This latent class variable is typically chosen to have a fixed number of categories, T. To restrict the utilities to their allowed range and facilitate model interpretation, it is convenient instead of the utilities ω_{kx} to estimate the log-linear parameters,

$$\ln \omega_{kx} = \tau_k + \lambda_{kx}. \tag{2}$$

Choosing effects coding for identification (Vermunt and Magidson, 2013), the attribute parameter λ_{kx} can then be interpreted as the deviation from option k's average log-utility in latent class x.

Primary interest focuses on how the probabilities of belonging to these latent (post)materialism classes differ as a function of the country-level covariates log-GDP per capita (Z_1) and percentage of women in parliament (Z_2). At the same time, it has become common practice to control for country effects using a multilevel approach. We therefore model the latent class probabilities using the multinomial logistic regression,

$$P(X = x|Z_1 = z_1, Z_2 = z_2, G = g) = \frac{\exp(\alpha_x + \gamma_{1x}z_1 + \gamma_{2x}z_2 + \beta_{gx})}{\sum_t \exp(\alpha_t + \gamma_{1t}z_1 + \gamma_{2t}z_2 + +\beta_{tg})}, \qquad (3)$$

where the country-level latent variable G has been introduced. The country-level effects β_{tx} in Equation 3 could be modeled as normal, leading to a standard multilevel model. However, since in the past very differing classes of countries have been observed (Moors and Vermunt, 2007), making the normality assumption rather implausible, we instead take G to be a country-level latent class variable with a freely estimated distribution. This model was introduced as the "multilevel latent class regression" model by Vermunt (2003). The main parameters of substantive interest in Equation 3 are the $2(T-1)$ regression coefficients γ_{mx}.

Combining the three ranking tasks, each modeled according to Equation 1, with the multilevel latent class regression model in Equation 3 leads to the casewise likelihood

$$L(\boldsymbol{\theta}) = P(A_1, A_2, B_1, B_2, C_1, C_2|Z_1, Z_2) = \sum_G P(G) \sum_X P(X|Z_1, Z_2, G)P(A_1, A_2|X)P(B_1, B_2|X)P(C_1, C_2|X), \qquad (4)$$

where the realizations of variables have been dropped for clarity, and $\boldsymbol{\theta}$ is a vector

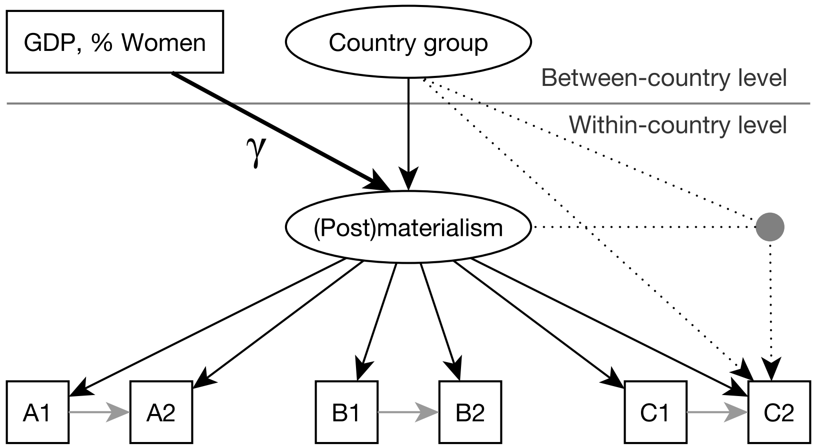

Figure 1: Graphical representation of the multilevel latent class regression model for (post)materialism measured by three partial ranking tasks. Observed variables are shown in rectangles while unobserved ("latent") variables are shown in ellipses.

collecting the free parameters of the model. Note that values of the within-country variables $X, A_1, A_2, B_1, B_2, C_1$, and C_2 may differ over persons, whereas the between-country variables G, Z_1, and Z_2 can differ only over countries.

Figure 1 shows a graphical representation of the model in Equation 4. The parameters of primary substantive interest are the effect-coded logistic regression coefficients for the effect of GDP per capita and percentage of women in parliament on the latent postmaterialism class (the stronger line labeled γ in Figure 1). These effects of interest are controlled for the country random effects. Since these are modeled using a latent class variable, the top part of the model in Figure 1 is a multilevel latent class regression. The gray arrows between indicators are meant to show that a fixed conditional relationship is specified between the first and second choice within each set (Equation 1).

Not modeled in Equation 4 are the potential violations of "scalar" and "metric" measurement invariance. These can be conceptualized as, respectively, a direct main effect and a direct interaction effect of the grouping variable (Mellenbergh, 1989;

		EPC-interest for non-invariance of...							
				Set main effects			Set × Class effects		
		Estimates		Set			Set		
		Est.	s.e.	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

Table 2:

Kankaraš, Moors and Vermunt, 2010; Kankaraš, Vermunt and Moors, 2011). Since we do not employ multiple groups (fixed effects) to deal with country effects, but a latent class multilevel (random effects) approach, 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, for applications in multilevel IRT). An example of this parameterization of measurement non-invariance for the second ranking of Set C (C_2) is shown in Figure 1 as the dotted main effect and interaction effects for scalar and metric invariance, respectively .

5. RESULTS

Latent Gold Choice 5.0.0.14157 (Vermunt and Magidson, 2005, 2013)

LL = -418609.9616

Number of parameters (Npar) 63

				EPC-interest for non-invariance of...					
		Estimates		Set			Set		
				Set			Set		
		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

Table 3:

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

Table 4: Attribute parameter estimates for the final model.

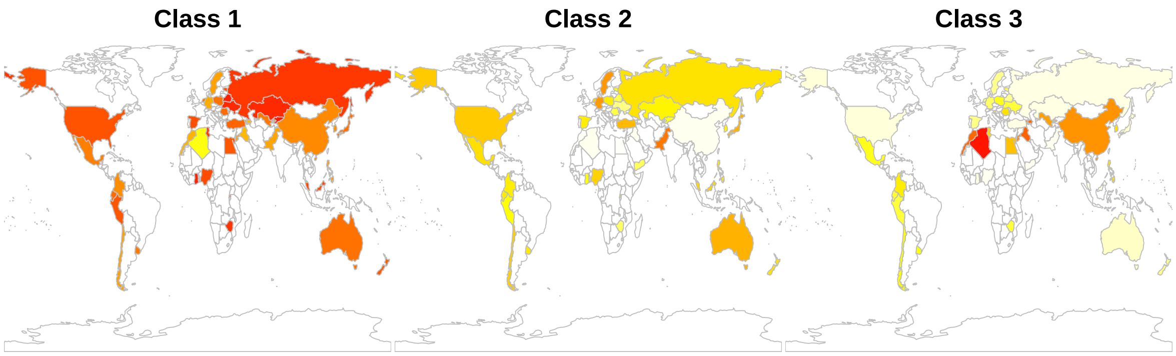

Figure 2:

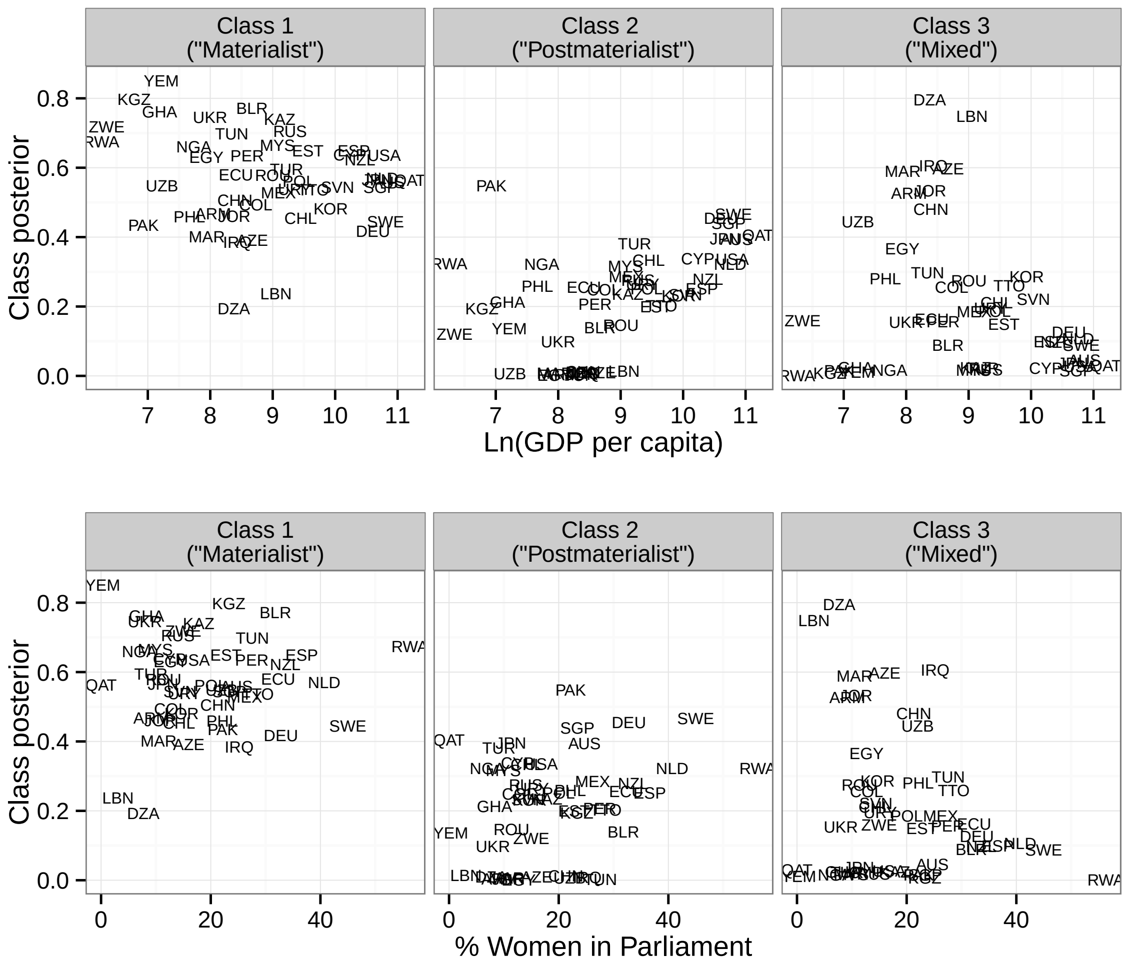

Figure 3:

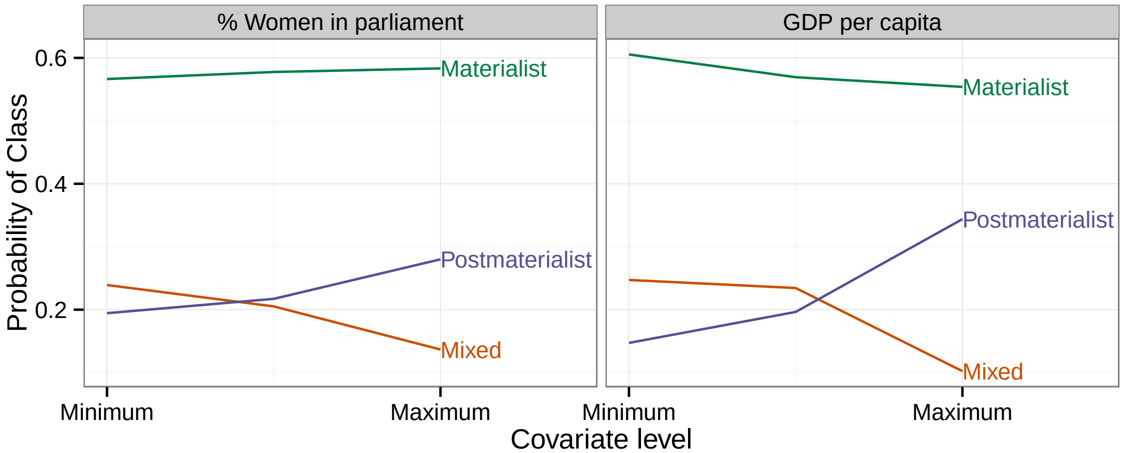

Figure 4: Estimated probability of choosing each class as a function of the covariates of interest under the final model.

6. DISCUSSION

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