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# Modeling the correct level of analysis in non-aggregated household panel data: A simulation approach

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**Abstract** Multilevel models can deal with nested structures in household panel data to derive unbiased regression coefficients and standard errors for predictors from multiple hierarchical levels, e.g., households, products, or stores. Within the framework of multilevel modeling, researchers can apply purely nested models or cross-classified random effects models (CCREM). This paper explains the partially cross-classified structure in household panel data. Simulation study 1 demonstrates that standard errors for level-two predictors are severely downward biased when applying a nested three-level model to partially crossed data. Furthermore, the hierarchical location of interactions between predictors associated with two crossed levels is explained. Simulation study 2 demonstrates that with unbalanced real-world data, both standard errors and regression coefficients for interaction-level predictors can be biased when the "artificial" random interaction level is omitted from a CCREM. The simulation studies are followed by a discussion of implications for the application of multilevel models to household panel data.

**Keywords** Multilevel modeling · Cross-classified model · Panel data · Simulation

## 1 Introduction

Hierarchical or multilevel modeling (Raudenbush and Bryk 2002; Snijders and Bosker 2012) comprises a group of methodologies suited for application to panel data owing to the nested structure of such data (Steele 2008). In non-aggregated household panel data, repeated observations are not only nested within households but also within products and stores[1]. When researchers simultaneously investigate random samples of two (or more) of these higher-order levels, either purely nested three- (or more) level

[1]Household panel often contain information on trade chains. The term store is used for brevity.

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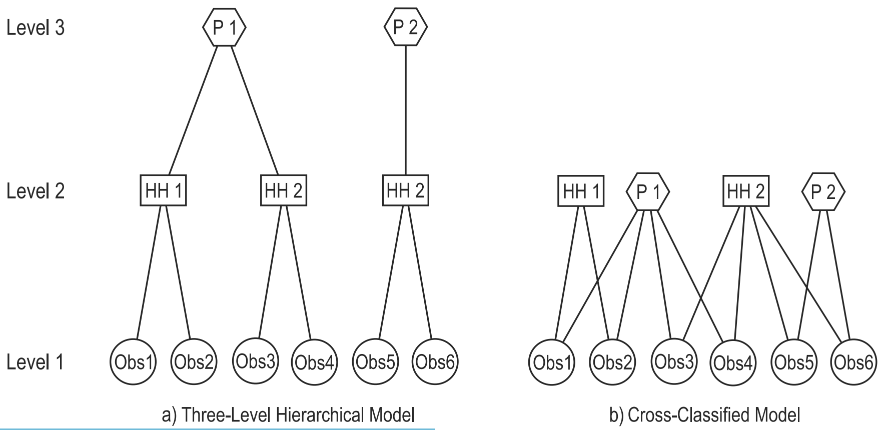
models or cross-classified random effects models (CCREMs) can be applied within the framework of multilevel modeling. Nested models are suitable when lower-level units are nested within a single unit at the next higher level. In contrast, CCREM are special multilevel models that are applied when lower-level units are simultaneously nested within units from two or more higher-order levels, but these higher-order level units are not nested within each other (Snijders and Bosker 2012). The structures of a purely nested model compared with a CCREM applied to household panel data, including the observation, household, and product levels, are illustrated in Fig. 1.

In general, multilevel models are specifically focused on splitting variance to the modeled levels and drawing correct inferences for predictors associated with *different* hierarchical levels (Rabe-Hesketh and Skrondal 2012). However, accounting for these different hierarchical levels require correctly formulating a random part of a multilevel model. Some previous studies have investigated the biasing effects when the random parts of nested models (e.g., Moerbeek 2003, 2004) and CCREMs (Luo and Kwok 2009; Meyers and Beretvas 2006) are misspecified through the omission of one hierarchical level (random factor). Most notably, these studies concluded that the standard error of a predictor's regression coefficient is underestimated when the associated hierarchical level is omitted from the model's random part. The standard error bias increases with the variance associated with the ignored factor. For CCREM, the bias decreases with increasing correlation between the residuals of the crossed factors. Furthermore, the variances of ignored factors are redistributed to the adjacent levels, while the redistribution depends on factors such as whether the data structure is more crossed or more nested.

While these studies provide valuable insights into the consequences of misspecifying a multilevel model's random part, they ignore two important issues for modeling household panel data. First, they focused on the omission of nested or crossed factors, but ignored the possibility of formulating a nested three-level model when two higher-order factors are partially cross-classified. Especially in household panel data, the structure is neither fully crossed nor fully nested. Thus, it is attractive for researchers




P: product; HH: household; Obs: observation

**Fig. 1** Comparison of model structures for a three-level model and a cross-classified model to apply the simpler nested model to data that lie between nesting and cross-classification. Second, previous studies ignored cross-level interactions despite their being an inherent part of multilevel modeling. Especially in marketing, many research questions cannot be answered without interaction effects. Thus, it is important to extend existing research by incorporating cross-level interactions. Beyond these limitations, it should also be possible to draw more generalizable conclusions about the data structure and the best performing multilevel model for household panel data. Since the data structures are similar in most cases, and generally at least include household and product information, it should be possible to provide practical guidance for researchers and managers wishing to apply similar models to their data.

Motivated by the described limitations, section 2 of this manuscript aims to clarify the data structure of household panel data from a hierarchical perspective. The associated simulation study in section 2.2 demonstrates standard error bias when nested models are mistakenly applied to partially crossed data. Next, section 3 describes the cross-level interactions between predictors from higher-order levels in CCREMs and the simulation study 2 in section 3.1 aims to highlight the biases of regression coefficients and standard errors for these cross-level interactions within an unbalanced real-world data structure. Finally, section 4 provides a general discussion of the major findings as well as implications for researchers and managers.

## 2 The data structure in the household panel data

### 2.1 Nesting or cross-classification

If interest is limited to predictors from only one higher-order level, for example the household level, a two-level hierarchical linear model (HLM) can be applied to household panel data in which observations are nested within households. However, if predictors from two higher-order levels are included, a nested three-level model or CCREM can be formulated. In the case of nesting, the assumption is that every observation at level one is associated with exactly one unit at level two, and each level-two unit in turn is nested within a unit at level three (Raudenbush and Bryk 2002). Such a model for household panel data was proposed by Gielens and Steenkamp (2007), who modeled households at level two and products at level three (see Fig. 1a). However, this model assumes that each household at level two is nested within *exactly one product* at level three, which equals the assumption that each household is loyal to a single product that they always choose. However, especially for consumer packaged goods (CPGs), this seems extremely unrealistic since even loyal or habitual consumers are forced to select alternatives from time to time. Theoretically, every household has the chance to buy any product, or alternatively, every product has the chance to attract customers from any household, meaning the data structure could be fully crossed. Since the real data structure lies between these two extremes of pure nesting and full cross-classification, the underlying data structure can be described as partially cross-classified and thus should be modeled as a CCREM in which a single observation is described by a household-product combination (see Fig. 1b).

The choice of a CCREM for this kind of data is essential because in a three-level model, the number of independent observations for an intermediate-level predictor (i.e., household-level predictors in the Gielens and Steenkamp model) is assumed to be too large. For example, if each household buys two different products, a three-level model would double the assumed household sample size when modeling households at the intermediate level (see household 2 in Fig. 1a). Consequently, the standard errors for household-level predictors are likely to be downward biased. Meanwhile, if each product is bought by two households and products are modeled at the intermediate level, standard errors for product-level predictors would be downward biased because the product sample size is assumed to be twice the true sample size. Thus with a three-level HLM, incorrect assumptions concerning the level-two sample sizes make it impossible to be sure that standard errors for level-two predictors are unbiased. In contrast, by applying a CCREM, predictors associated with both the household and product levels coexist at level two. Consequently, a CCREM should reveal unbiased standard errors for household- and product-level predictors since its assumptions do not result in overstated sample sizes for both levels. In summary, when analyzing non-aggregated panel data, higher-order levels (households, products, and stores) are partially cross-classified rather than purely nested. Thus, a CCREM is the correct choice when dealing with predictors of two or more higher-order levels.

## 2.2 Study 1

### *2.2.1 Description*

This simulation study aims to demonstrate standard error biases when applying two- and three-level HLMs to balanced and partially cross-classified data. Results of a correct CCREM and three misspecified nested models are compared in terms of the biases of regression coefficients, standard errors, and variance components. First, a two-level HLM is estimated, in which the product level is omitted. Results for this model are expected to resemble those of previous studies that tested the effects of omitting a level of nesting (Moerbeek 2004) or a crossed factor (Luo and Kwok 2009) in multilevel models. Those studies found regression coefficients to be unaffected within a balanced data structure, but that the standard errors for predictors at the omitted levels and random effects were biased.

Second, two three-level models are formulated, in which either the household or product levels are modeled as nested within the other partially crossed factor. Both models consider all relevant hierarchical levels, but we expect standard errors of level-two predictors to be downward biased because level-two sample sizes are overstated as a result of incorrect assumptions. To test different levels of nesting versus cross-classification, these models are applied to household purchase data, where each household bought four different products, while each product was bought by eight different households. Thus, households are more nested in products than vice versa. We expect the standard error bias to be larger if products are modeled at level two because the product sample size is overstated by a factor of eight, while the household sample size is only overstated by a factor of four in the other model with households nested in products. However, compared with the two-level HLM, in which the product level is omitted, biases are expected to be lower since level-two predictors are not assumed to vary at the lowest level, meaning overstating the product sample size should have less dramatic effects in the three-level than the two-level model.

*2.2.2 Data generation and analysis*

The CCREM and the three HLMs were applied to a simulated household panel data set including 500 households and 250 products. As described, for the various possible household-product combinations, each household was assumed to buy only four products and each product was assumed to be bought by eight households. The data structure was partially cross-classified, with 98.4 % of cells being empty. Each household-product combination appeared five times in the data set, resulting in 10,000 observations in total. The data-generating model included the level-one predictor *Time*, a product-level predictor, and a household-level predictor. The level-one model is as follows:

$$Y_{tij} = \beta_{0ij} + \beta_1 * Time_{tij} + e_{tij}$$

The variation of the random intercept was captured by a level-two model, which appears as follows:

$$\beta_{0ij} = \gamma_0 + \gamma_1 * W_i + \gamma_2 * Z_j + b_{00i} + c_{00j},$$

where $t$ denotes time, $i$ denotes households, and $j$ denotes products. $W_i$ and $Z_j$ are predictors at the household and product levels, respectively. The conditional random effects for the observation, household, and product levels, $e_{tij}$, $b_{00i}$, and $c_{00j}$, respectively, were drawn from a multivariate normal distribution and had means of zero and variances of $\sigma_e^2$, $\sigma_b^2$, and $\sigma_c^2$. The correlations between these random effects were set to zero. The simulated population effects for generating the outcome variable $Y_{tij}$ are reported in Table 1. The population effects for the household- and product-level predictors were set to the same value, as were the household- and product-level variances, to ensure possible parameter biases are due to overstated sample sizes rather than differences in these simulated population effects. Relative biases for the regression coefficients $B(\widehat{\gamma})$ , variance components $B(\widehat{\sigma})$ , and standard errors $B(\widehat{S}_{\widehat{\gamma}})$ were calculated as follows:

$$B(\widehat{\gamma}) = \frac{\widehat{\gamma} - \gamma_{popul}}{\gamma_{popul}}; B\left(\widehat{\sigma^2}\right) = \frac{\widehat{\sigma^2} - \sigma^2{}_{popul}}{\sigma^2{}_{popul}}; B(\widehat{S}_{\widehat{\gamma}}) = \frac{\widehat{S}_{\widehat{\gamma}} - S_{emp}}{S_{emp}}$$

These formulas indicate that estimates for the regression coefficients and variances were compared with the simulated population effects, while standard errors were compared with the empirical standard errors, which were calculated as the standard deviations of standard error estimates over the 1,000 model runs.

Data generation was conducted with Stata 13[2]. The models were formulated with runmlwin (Leckie and Charlton 2013). Thus, all the models were estimated using the multilevel modeling software MLwiN (Rasbash et al. 2013) by applying its Markov Chain Monte Carlo (MCMC) functionality[3].

[2] The Stata do-file is available from the authors on request.

[3] The MCMC approach within MLwiN was used because of the ease of incorporating (multiple) cross-classifications, rather than based on an ideological preference for Bayesian over frequentist approaches.

### 2.2.3 Results and discussion

The results of the CCREM and the three different nested models are reported in Table 1. Within the balanced partially cross-classified data structure used in this study, fixed effects regression coefficients were not affected by the model type ($-.02<B<.01$). The standard errors for the level-one predictor *Time* were also unaffected for the CCREM and the three-level HLMs ($-.01<B<.02$). For the two-level HLM, the standard error for *Time* was upward biased ($B=.19$) while that for the product-level predictor was downward biased ($B=-.74$) because it omitted the product level. Based on a cut-off value of .10 for acceptable standard error biases (Hoogland and Boomsma 1998), these biases were unacceptably high for both standard errors. The product-level variance was also redistributed to both level one and the remaining crossed household level. These findings for the two-level HLM confirm the results of previous studies (e.g., Luo and Kwok 2009) when a crossed factor is omitted from the model.

The application of three-level HLMs to cross-classified data also led to biased standard errors for level-two predictors. The bias appeared larger when products were modeled as nested in households ($B=-.58$) than when households were nested in products ($B=-.44$). These results indicate that the real underlying data structure was better reproduced in the latter case because of the higher nesting of households in products than vice versa, as described in Section 2.2.2. Overstating level-two sample sizes thus became less problematic with more nesting. However, the standard error bias far exceeded the acceptable range even for the better model. This result implies that three-level models cannot account for the underlying partially crossed data structure, though they outperformed a two-level HLM.

The results of this study confirm that only a CCREM can assume correct sample sizes for the partially crossed level-two factors, households and products. Omitting one of these factors or modeling the structure as purely nested leads to incorrect conclusions

**Table1** Results for study 1

| | Simulated population effect | CCREM | 2-level HLM omission of product level | 3-level HLM households nested in products | 3-level HLM products nested in households |
|---|---|---|---|---|---|
| Sample sizes | | | | | |
| Households | | 500 | 500 | 2000 | 500 |
| Products | | 250 | 10,000 | 250 | 2000 |
| Fixed effects | $\gamma_{popul}$ | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) |
| Time | .2 | .20 (.016) | .20 (.019) | .20 (.016) | .20 (.016) |
| Household-level predictor | .4 | .39 (.057) | .40 (.062) | .40 (*.033*) | .40 (.061) |
| Product-level predictor | .4 | .40 (.079) | .40 (*.022*) | .40 (.081) | .40 (*.034*) |
| Random effects | $\sigma^2_{popul}$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ |
| Level-one residual variance | 5.0 | 5.00 (.072) | *7.35* (*.107*) | 5.00 (.079) | 5.00 (.078) |
| Household-level variance | 3.0 | 3.01 (.210) | *3.62* (.248) | 2.99 (*.137*) | 3.00 (.261) |
| Product-level variance | 3.0 | 3.02 (.295) | | 3.02 (.321) | 2.98 (*.145*) |

Note: numbers in italics indicate unacceptable parameter bias for predictors associated with the omitted factor or level-two factor, respectively. Generally, it can be concluded that the data structure in household panel data is not purely nested because households will not purchase just one product over time and products will not attract just one customer. Thus, a CCREM seems to be the most appropriate modeling option.

## 3 Modeling cross-level interactions in CCREM

While in study 1, we clarified the structure of household panel data and identified a CCREM as the best performing model, this section examines the consequences of these findings for modeling cross-level interactions between predictors associated with two crossed factors. Cross-level interactions originate from interactions between predictors associated with two different hierarchical levels. These interactions are modeled when researchers expect the effect of a lower-level predictor to be contingent on a higher-level predictor (Aguinis et al. 2013). From a hierarchical perspective, such interactions vary at the lower of the two respective levels and thus can be seen as lower-level predictors. Consequently, when purely nested models are applied, it is sufficient to model the lower-level random factor to derive unbiased standard errors for cross-level interactions. However, unlike for nested models, no lower-level factor exists when interactions are formed by predictors associated with two crossed factors in a CCREM, for example when household-product interactions, household-store interactions, or product-store interactions are formed. In a CCREM, such interactions vary between the crossed factors at an "artificial" level. For this level, it is possible to estimate a so-called random interaction effect. Raudenbush and Bryk (2002, p. 378) stated that such random interaction effects were omitted in most CCREMs because within-cell sample sizes were insufficient for reliable estimations of the associated variance component. However, to date, it is unclear whether it is better to incorporate or omit the interaction level to derive (more) reliable regression coefficients and associated standard errors for cross-level interactions.

We argue that without modeling the random interaction effect, interaction-level predictors in CCREM are assumed to vary at level one. As for omitting one of the main crossed factors, not modeling the random interaction effect overstates the interaction-level sample sizes and thus causes downward-biased standard errors for interaction-level predictors. Additionally, regression coefficients for interaction-level predictors may be biased because real-world household panel data are likely to be unbalanced (Baltagi 2013). Such unbalance means some households, products, and stores appear more often in the data than others. To summarize, the omission of the random interaction effect could result in bias of both standard errors and regression coefficients for the interaction-level predictor.

### 3.1 Study 2

#### *3.1.1 Description*

This study aims to demonstrate that within a real-world data structure, regression coefficients and standard errors for interaction-level predictors formed by predictors from two crossed levels are biased when the associated random interaction effect is not incorporated into the model. To this end, we employ household panel data on yoghurt purchases from Germany for 2008. Such real-world data have the advantage that the degrees of unbalance and cross-classification do not have to be created by an artificial process. Compared to real-world data, the advantage of simulated data is that population effects are known and thus biases of estimated parameters can be evaluated. In order to combine these two advantages, the population effects are simulated within the given real-world data structure.

In this study, we are interested in a level-one, household-level, store-level, and household-store interaction-level predictor. Similar to the household-product relationship illustrated in Fig. 1b, households and stores are also cross-classified because each household can theoretically shop in any store and each store can attract any household.

We apply three different CCREMs with different random parts. While the first model incorporates all random factors, the second model does not estimate the product-level variance. Since we are not interested in an associated product-level predictor, we expect the fixed part of the model to be unaffected by this restriction and the interaction-level predictor to be unbiased because the model includes the random interaction level. The third model omits the household-store interaction level. Consequently, we expect the regression coefficient and the standard error of the interaction-level predictor to be biased.

### *3.1.2 Descriptive statistics, data generation, and analysis*

The household panel data used in this study included 154,237 purchases of 1876 different yoghurt products. These purchases were made by 2996 households in 30 different stores. Since we focused on the household-store interaction-level predictor, we were mainly interested in the degree of crossing and unbalance of households and stores. The household-store interaction level involved 11,922 units. Thus, more than 86 % of cells were empty, indicating partial cross-classification. The average household bought yoghurt in 3.98 different stores, with 8.78 % of households shopping in only one store and less than 5 % shopping in more than seven stores. Meanwhile, the average store attracted 394.4 households, with 36.67 % attracting less than 100 households and 10 % attracting more than 1000 households. In terms of unbalance, the average number of household-store interaction observations was 12.9. The structure thus was clearly unbalanced, with 32.23 % of interaction units having cell sizes of one or two, and only 4.81 % having cell sizes of more than 50.

Within the given data structure, population effects were simulated (see Table 2). The level-one and level-two models appear as follows:

$$\begin{aligned} Y_{tijk} &= \beta_{0ijk} + \beta_1 * Time_{tijk} + e_{tijk} \\ \beta_{0ijk} &= \gamma_0 + \gamma_1 * W_i + \gamma_2 * V_k + \gamma_3 * W_i * V_k + b_{00i} + c_{00j} + d_{00k} + r_{0ik} \end{aligned}$$

The additional index $k$ denotes the store level. $V_k$ is the store-level predictor and $W_i$* $V_k$ is the interaction between the household- and store-level predictors. The simulated variances $\sigma_e^2$, $\sigma_b^2$, $\sigma_c^2$, $\sigma_d^2$, and $\sigma_r^2$ are located at the observation, household, product, store, and household-store interaction levels, respectively. As in study 1, random effects were drawn from a multivariate normal distribution and were not correlated.

### *3.1.3 Results and discussion*

Table 2 presents the results of the three different CCREMs applied in simulation study 2. The standard error bias for the level-one, household- and store-level predictors did not exceed the acceptable range in the three models (-.05<$B$<.05). Thus, the different formulations of the random part did not significantly affect these parameters. For the interaction-level predictor, the standard error biases were acceptable in the full model ($B$=.01) and the restricted model ($B$=.02), both of which included the random interaction effect. However, the standard error was unacceptably downward biased in the model without the random interaction effect ($B$=−.69). As for omission of one of the main random factors, the omission of the interaction-level predictor's hierarchical level thus led to overstatement of the interaction-level sample size.

Besides the standard error bias, we also expected the regression coefficient for the interaction-level predictor to be biased in the misspecified model because of the unbalance in the data. This bias in the misspecified model cannot be evaluated using the coefficient reported in Table 2 because the bias appears in single model runs and can add up to zero over the 1000 model runs in this study. Therefore, we compared the correlations of the regression coefficients for the interaction-level predictor in the three models and found a high correlation of .92 between the full and restricted models, but smaller correlations of .65 between the full and misspecified models and .62 between the restricted and the misspecified models. The difference between .92 and .65 (.61)

**Table 2** Results for study 2

| | Simulated population effects | Full model | Restricted model without product level variance | Misspecified model without random interaction effect |
|---|---|---|---|---|
| Sample sizes | | | | |
| Households | | 2996 | 2996 | 2996 |
| Products | | 1876 | 154,237 | 1876 |
| Stores | | 30 | 30 | 30 |
| Household-store interactions | | 11,922 | 11,922 | 154,237 |
| Fixed effects | $\gamma_{popul}$ | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) | $\hat{\gamma}$ ($\hat{S}_{\hat{\gamma}}$) |
| Time | .2 | .20 (.001) | .20 (.001) | .20 (.001) |
| Household-level predictor | .4 | .40 (.027) | .40 (.029) | .40 (.029) |
| Store-level predictor | .3 | .41 (.188) | .39 (.194) | .39 (.197) |
| Household-store interaction level predictor | .3 | .30 (.011) | .30 (.013) | .30 (*.005*) |
| Random effects | $\sigma^2_{popul}$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ | $\hat{\sigma}^2\left(\hat{S}_{\hat{\sigma}^2}\right)$ |
| Level-one residual variance | 5.0 | 5.00 (.001) | *7.32* (*.001*) | *6.78* (*.001*) |
| Household-level variance | 4.0 | 3.00 (.119) | 3.10 (.129) | *5.20* (.141) |
| Product-level variance | 3.0 | 3.00 (.115) | | 3.14 (.122) |
| Store-level variance | 2.0 | 2.10 (.616) | *2.18* (.637) | *2.28* (.668) |
| Household-store interaction variance | 4.0 | 4.00 (.080) | *4.53* (*.095*) | |

Note: numbers in italics indicate unacceptable parameter bias was significant at the $p<.01$ level. This result confirmed our expectation that the omission of the random interaction level resulted in biased regression coefficients for the interaction-level predictor given unbalanced data.

Regarding the random effects of the three models, we found that only in the full model were the variances correctly apportioned to the different levels ($B<.05$), while for the restricted and misspecified models, the variances of the omitted levels were redistributed to the adjacent levels. However, in the restricted model, the redistribution did not affect the fixed part of the model, which suggests the product level can be omitted for reasons of parsimony, given that the interest is not in a product-level predictor and/or specifically in the random model part. This is consistent with the conclusion of Meyers and Beretvas (2006) that it is unnecessary to model cross-classifications if researchers are not interested in predictors from all cross-classified factors.

## 4 General discussion and conclusions

The first purpose of this study has been to clarify the data structure in non-aggregated household panel data and the consequences for modeling when researchers simultaneously incorporate predictors from two or more higher-order levels, for example the household, product, and store levels. For (most) household panel data, the structure is not purely nested, with households nested in products or vice versa, but rather is partially crossed. Study 1 demonstrated that a CCREM performs best for this kind of data, even when the number of empty cells is substantial and the use of a nested model for simplicity appears attractive. Even though a nested three-level model performs better than a two-level model, the results of study 1 clearly indicate that even three-level models overstate intermediate-level sample sizes, leading to downward-biased standard errors for intermediate-level predictors. Thus, researchers should prefer a CCREM to ensure that correct sample sizes for *both* crossed levels are assumed.

The consequences of applying CCREMs to model cross-level interactions between predictors from two crossed levels were demonstrated in study 2. In a CCREM, such interactions are located at a separate level between the two crossed main levels. Results of study 2 show that this random interaction level must be modeled to derive unbiased standard errors for interaction-level predictors. Otherwise, the interaction-level predictors are assumed to vary at the lowest hierarchical level which leads to overstated interaction-level sample sizes. Thus, the consequences of ignoring the random interaction level are similar to those of omitting a main crossed factor.

Study 2 further demonstrated that not only can standard errors be biased, but regression coefficients for predictors associated with an omitted crossed factor can also be incorrect when employing *unbalanced* real-world data. Although Luo and Kwok (2009) noted that the mechanisms underlying biased regression coefficients within unbalanced data remain unclear, there are reasons to expect that regression coefficients are biased toward units that appear more often in the data. Such units are incorrectly assumed to be independent and thus are likely to more strongly influence regression coefficients. Generally, biased regression coefficients are particularly problematic when the focus of a study is less on hypothesis testing than accurate prediction of an outcome variable. For example, an incorrect interaction effect between "average store shelf price" and "household income" that affects purchase quantities could lead to incorrect conclusions regarding the optimal composition of high- and low-priced products in a store since the true interaction effect could differ in magnitude from that estimated in the misspecified model. Interactions between household- and product-level predictors as well as direct effects are also at risk of being misinterpreted if their associated levels are omitted and regression coefficients are biased. For example, managers targeting a certain trial rate for their new products may allocate too much or too little to the advertising budget of a new product when the direct effect of "advertising intensity" and/or its interactions with household-level predictors are biased. Thus, misspecifying the random part of a CCREM can ultimately cause economic losses for a company. Researchers thus must carefully consider the hierarchical location of every model variable and include the associated random factor in the random part of a multilevel model.

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