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Comments on Article by Yin

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We would like to congratulate the author for a nice development of the Bayesian Generalized Method of Moments (BGMM). BGMM is a natural extension of the classical GMM. On the one hand, BGMM enjoys asymptotic properties and estimation efficiency of GMM; on the other hand, BGMM has a better computational property due to the recent advance in Markov chain Monte Carlo (MCMC) sampling. Therefore, BGMM is potentially very useful when the parameter estimation is of primary interest especially in statistical analysis of correlated, longitudinal or repeated measurement data.

The BGMM is primarily based on the moment conditions, instead of the likelihood. Thus, the "likelihood" used in constructing the "posterior distribution" in the BGMM is not the usual model-based likelihood function. This may be advantageous when the true likelihood is difficult to derive. However, in the BGMM framework, formal Bayesian model comparisons cannot be carried out as the likelihood function or the predictive distribution is not defined. Since the construction of the BGMM is primarily based on the marginal distribution model, the success of the BGMM in estimating the regression coefficients for the correlated data heavily relies on an adequate specification of the moment conditions. An immediate practical question is: how many moment conditions or what moment conditions need to be specified in order to capture the true correlation matrix? We suspect that when the moment conditions are not correctly specified, the standard deviations of Bayesian estimators based on the BGMM can be over-stated or under-stated especially when the sample size is relatively small. As the models cannot be compared via a usual Bayesian model comparison criterion such as the Bayes factor or the Deviance Information Criterion (Spiegelhalter et al. (2002)) and the true correlation structure is unknown in the BGMM, it becomes quite challenging and difficult to know how many $\mathbf{C}_{(j)}$'s are needed in order to achieve reliable standard deviations of the Bayesian estimators. Although the author has proposed several possible choices of $\mathbf{C}_{(j)}$'s, this issue has not been fully addressed. A BGMM estimator is asymptotically unbiased. However, the BGMM may fail to accurately estimate the certainty of a Bayesian estimator, which may be a major concern for using the BGMM.

To gain a better understanding of the BGMM and to further examine the performance of this method, we have conducted three simulation studies. In all simulations, we consider the similar regression model used in Section 3.3 with $K = 4$ and two covariates (Z_{1ik}, Z_{2ik}), i.e.,

$$Y_{ik} = \beta_0 + \beta_1 Z_{1ik} + \beta_2 Z_{2ik} + \epsilon_{ik}.$$

The covariate distributions for (Z_{1ik}, Z_{2ik}) are the same as those given in Section 3.3. That is, $Z_{1ik} \sim N(0,1)$ and $Z_{2ik} \sim$ Bernoulli(0.5). The true parameter values are $\beta_0 = 0.2$, $\beta_1 = 0.5$ and $\beta_2 = -0.5$. Also, 500 data sets of sample size $n = 50$ were

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