

One- vs. Two-Step Approach in Regularized Bayesian Confirmatory Factor Analysis (CFA)

Research Proposal

Michael Koch (6412157)

Methodology and Statistics for the Behavioral, Biomedical, and Social Sciences

Supervisor: Dr. Sara van Erp

Email: j.m.b.koch@students.uu.nl

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A common model-constraint in *Confirmatory Factor Analysis (CFA)* is fixing all cross-loadings to zero. This is done to identify the model, and to achieve an easy-to-interpret factor structure. However, this practice often leads to poor model fit. Consequently, researchers commonly free some cross-loadings based on modification indices to improve model fit. This practice, however, is flawed for a variety of reasons, among which risking capitalization on chance (Jacobucci, Grimm, & McArdle, 2016; Muthen & Asparouhov, 2012).

As solution, Muthen and Asparouhov (2012) proposed that rather than fixing all cross-loadings to zero, one should assume that *most* cross-loadings are zero. Formally, this is achieved by setting the so-called *Small Variance Prior* for the cross-loadings, which is a normal distribution with mean zero and a very small variance (e.g.: $\sigma = 0.01$, $\sigma = 0.001$). Such prior gives cross-loadings of zero large prior density, but cross-loadings that are far from zero almost zero prior density (see Figure 1 for an example with $\sigma = 0.01$). Consequently, all cross-loadings in the model are shrunk substantially, those close to zero to zero, and those far from zero towards zero. The larger the prior's variance, the more admissible the model is in the amount of deviation from zero it allows. Hence, by tuning the variance of the prior, one is able to fit a systematically and continuously varying sequence of models. This allows for a much more continuous process of model identification and model selection than classical CFA.

However, an issue with this method is that not only the cross-loadings close to zero that are considered irrelevant are shrunk to zero, as desired. Also the cross-loadings that are further from zero are shrunk towards zero, which introduces bias. The method thus requires a two-step approach. First, the model is estimated with shrinkage. Then the model is re-estimated, with cross-loadings that have been shrunk to zero in the previous step fixed to zero, and the remaining cross-loadings estimated without shrinkage. To overcome this, alternative priors need to be identified that can outperform the small-variance prior *in*

a single step.

Lu, Chow, and Loken (2016) pointed out that the Bayesian CFA approach by Muthén and Asparouhov (2012) can be viewed as a form of *Regularization*, where rather than selecting variables that are relevant as predictors in a regression model, cross-loadings that are relevant in modeling a factor structure are selected. The literature on regularization in regression (see Van Erp, Oberski, & Mulder, 2019 for an overview) can thus provide alternative priors. Here, the *Regularized Horseshoe Prior* (Piironen & Vehtari, 2017), an extension of the *Horseshoe prior* (Carvalho, Polson, & Scott, 2010), appears as particularly promising. Both priors are characterized by a *global* shrinkage component ω , shrinking all parameters towards zero (explaining the steep peak at $\lambda_j = 0$ in Figure 1), and a *local* component τ_j , which gives the prior its heavy tails and thereby allows large parameters to escape the shrinkage entirely¹. Although being one of the core qualities of the original Horseshoe Prior, in practice not shrinking large coefficients at all can lead to computational issues in the MCMC sampling of the model (Ghosh, Li, & Mitra, 2018; Piironen & Vehtari, 2017). To avoid this, the *Regularized Horseshoe Prior*² is designed to ensure that there is always a little shrinkage, even for large parameters (Piironen & Vehtari, 2017):

$$\lambda_j | \hat{\tau}, \omega \sim \mathcal{N}(0, \hat{\tau}^2 \omega), \text{ with } \hat{\tau}^2 = \frac{c^2 \tau_j^2}{c^2 + \omega^2 \tau_j^2}$$

$$\omega | \omega_0^2 \sim \mathcal{N}(0, \omega_0^2), \text{ with } \omega_0 = \frac{p_0}{p - p_0} \frac{\sigma}{\sqrt{N}}$$

$$\tau_j \sim \mathcal{C}^+(0, 1)$$

$$c^2 | \nu, s^2 \sim \mathcal{IG}(\nu/2, \nu s^2/2),$$

¹ We deviate from the common notation of the global shrinkage parameter as λ , as that letter is commonly reserved for factor loadings in CFA.

² Following previous research, we set the hyper-parameters $\nu = 4$ and $s^2 = 2$ (Piironen & Vehtari, 2017; Van Erp et al., 2019).

where p_0 represents a prior guess of the number of relevant cross-loadings.

While the Regularized Horseshoe Prior has been shown to perform well in the selection of relevant predictors in regression (Piironen & Vehtari, 2017; Van Erp et al., 2019), no previous research has validated its performance in selecting relevant cross-loadings in CFA. To fill this gap, the aim of this study is to compare the Regularized Horseshoe Prior to the Small Variance Prior in their performance in selecting the true factor structure in Confirmatory Factor Analysis (CFA).

Analytic Strategy

A Monte Carlo simulation study is conducted using stan (Stan Development Team, 2021). True Positives vs. False Positives in estimating truly non-zero cross-loadings as non-zero are considered as main outcome. Conditions are based on Lu et al. (2016) and will include two factor structures (1 non-zero cross-loading, several non-zero cross-loadings), three sample sizes (100, 200, 300), and three magnitudes of the cross-loadings (0.1, 0.2, 0.3), yielding a total of $2 \times 3 \times 3 = 18$ main conditions. All models will be sampled using the No-U-Turn-sampler (Betancourt, 2018; Homan & Gelman, 2014), where each time four chains are sampled for 1000 iterations, following a burn-in period of 1000.

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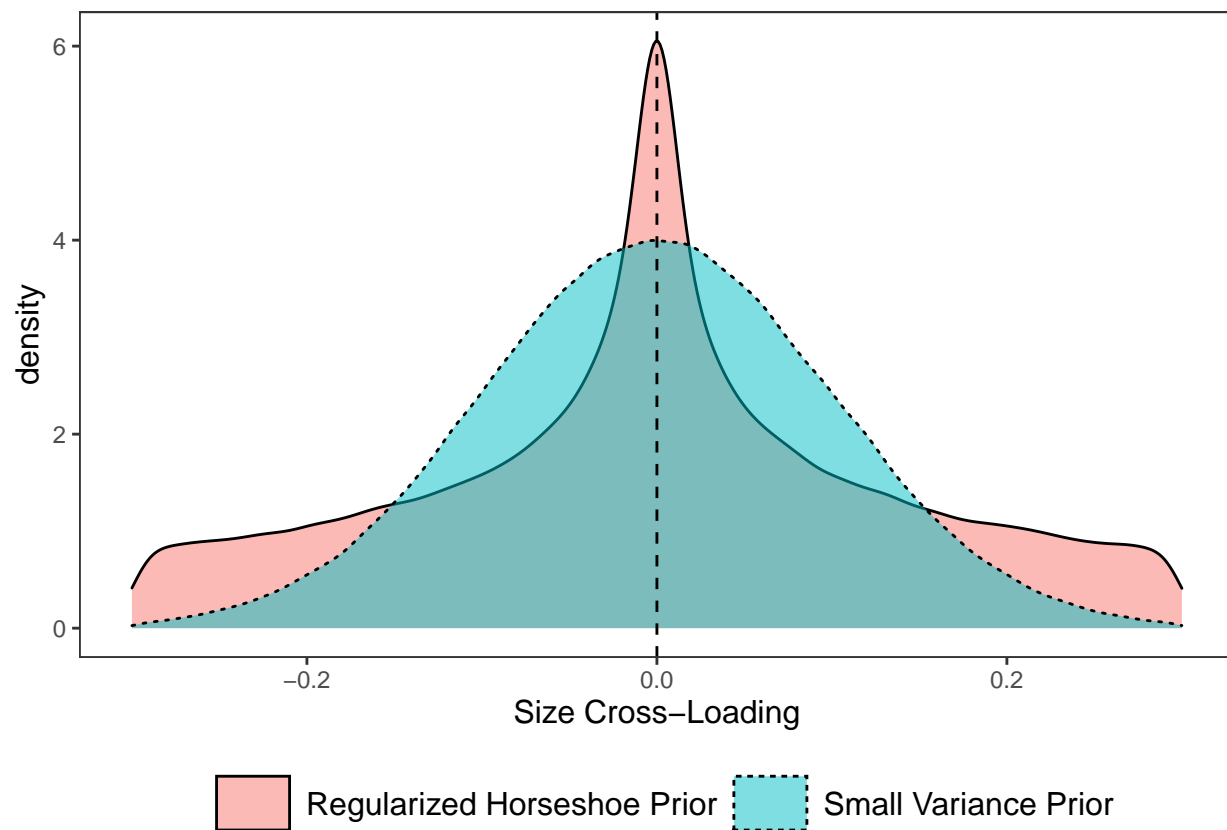


Figure 1. Density Plots of the Regularization Priors of Interest