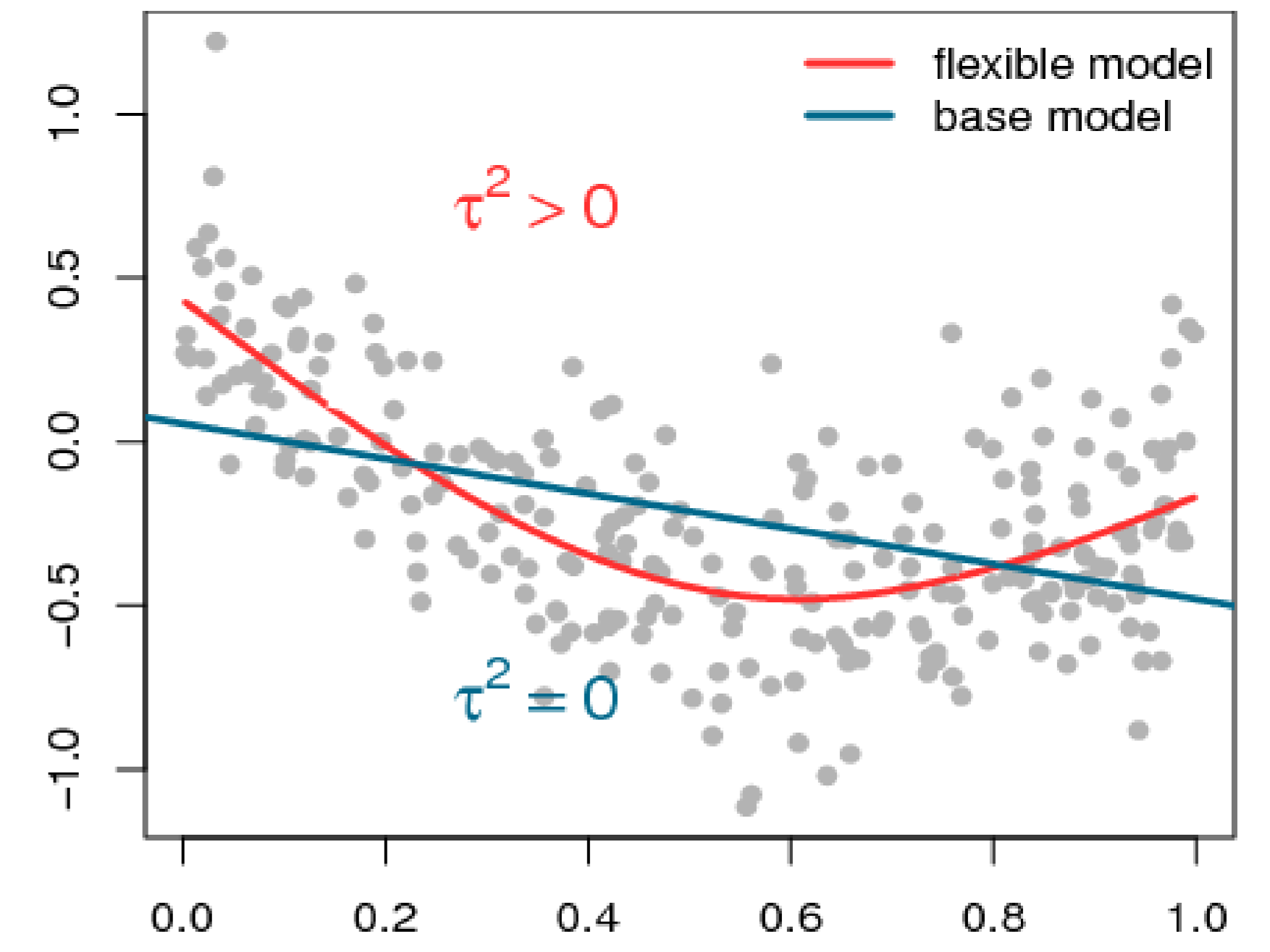


## Base Models and Increased Complexity

- Nested structure inherent in many model components.
- Hyperparameter  $\tau^2$  to determine the deviation of a flexible alternative to the base model.
- **Aims:** Construct principled prior distributions for variances of additive components in structured additive distributional regression (motivated from penalised complexity priors<sup>2</sup>). Develop Bayesian inference and elaborate similar approach for other priors from the literature.



- Alternative priors for  $\tau^2$  include half-normal (HN), half-Cauchy (HC) and uniform (U) priors for  $\tau$ .
- HN priors for  $\tau$  correspond to gamma, HC to generalised beta priors for  $\tau^2$ .

## Distributional Regression

**M1:**  $y | x \sim F$  with parametric density  $f(y | \vartheta_1, \dots, \vartheta_K)$

**M2:**  $\vartheta_k(x) = h_k(\eta_k)$ ,  $k = 1, \dots, K$  with structured additive predictors

$$\eta_k = \sum_j g_j(x) = \sum_j Z_j \beta_j$$

## Standard Prior Specifications

- Regularisation or smoothness can be achieved via  $p(\beta | \tau^2) \propto \exp(-1/(2\tau^2)\beta'K\beta)$  with prior precision  $K$  (specific to  $j, k$ , often rank deficient).
- For variances  $\tau^2$  inverse gamma (IG( $a, b$ )) priors are used:

$a, b = \varepsilon$ , small (flat on log-scale)  
 $a = -1, b = 0$  (flat for  $\tau^2$ )

$a = 1, b = \varepsilon$  (flat for  $1/\tau^2$ )  
 $a = -0.5, b = 0$  (flat for  $\tau$ ).

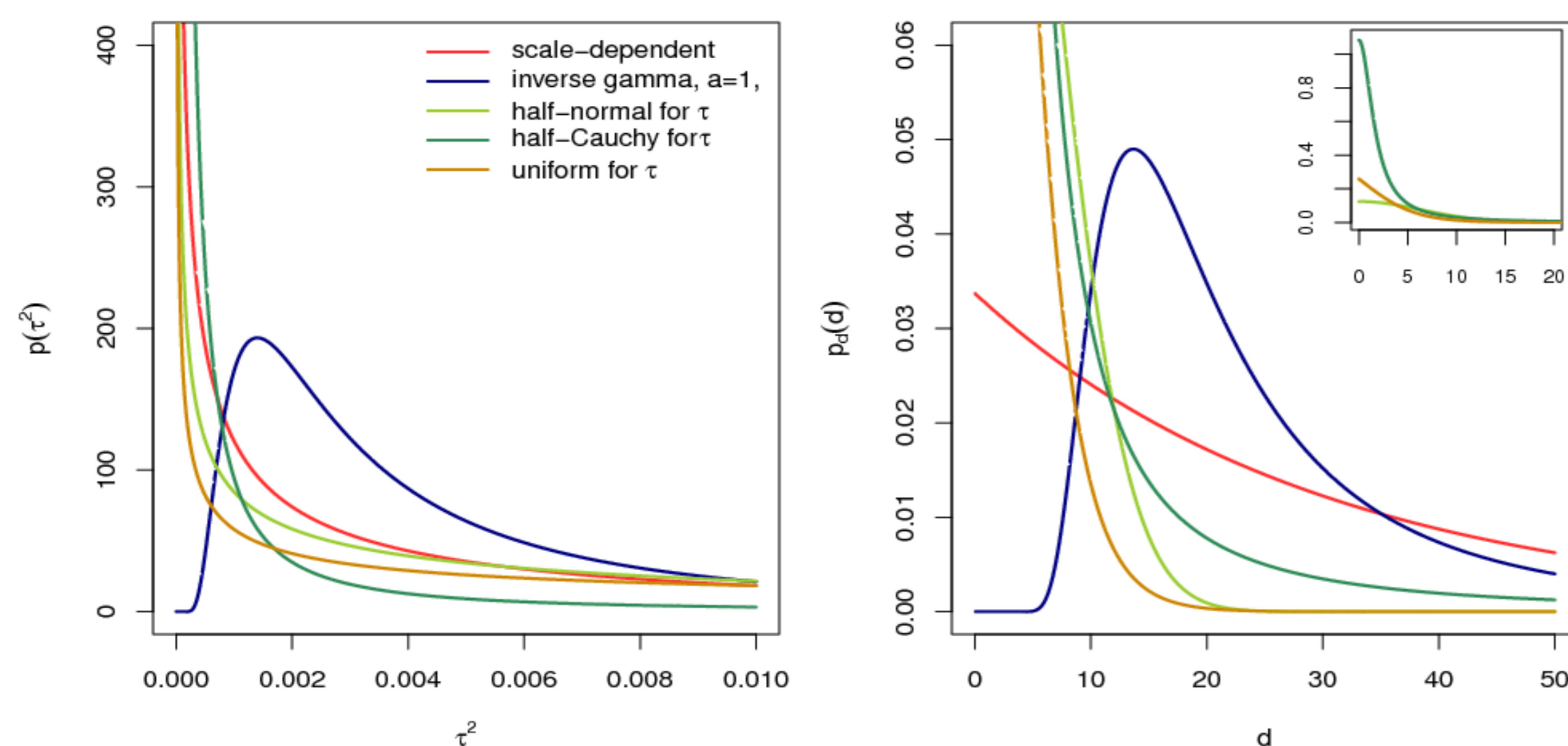
## Scale-Dependent (SD) Priors

SD prior for  $\tau^2$  has density of a Weibull distribution with shape parameter  $a=0.5$  and scale parameter  $\theta$  resulting from three construction principles<sup>2</sup>:

*Occam's razor:* Prior should invoke principle of parsimony.

*Measure of complexity:* Increased complexity between base model  $p_b$  and flexible alternative  $p$  is measured by  $d(p || p_b) = \sqrt{2\text{KLD}(p || p_b)}$ .

*Constant rate penalisation:* Implies exponential prior on distance scale  $d$ , i.e. constant rate of decay in the distance prior from the base model to stronger deviations.



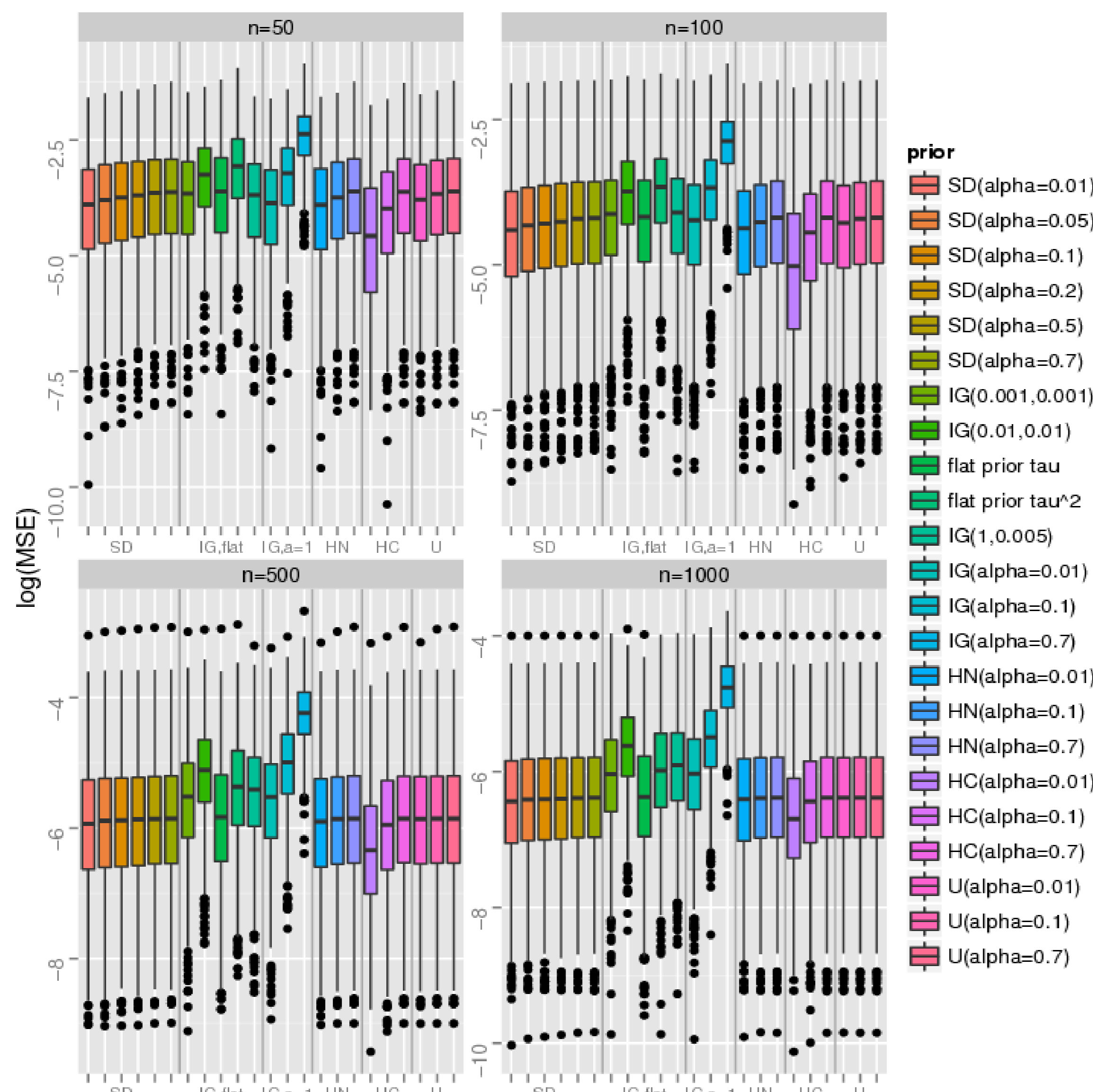
## User-Defined Scaling

- Decay rate  $\exp(-\lambda)$  in the exponential prior is controlled implicitly through scale parameter  $\theta$  of the prior for  $\tau^2$  by  $P(q(\tau^2 \leq c)) = 1 - \alpha$ .
- Prior knowledge on effects  $g = Z\beta$  allows to specify interval with high marginal probability,  $P(|g(x)| \leq c \forall x \in D) \geq 1 - \alpha$ . Resulting integral can be approximated numerically.
- User-defined scaling has been transferred to HN, HC and U priors for  $\tau$  (and IG priors for  $\tau^2$  when  $a=1$ ).
- Optimising  $\theta$  for given  $Z$  and  $K$  is implemented in the R-package **sdPrior** on CRAN.

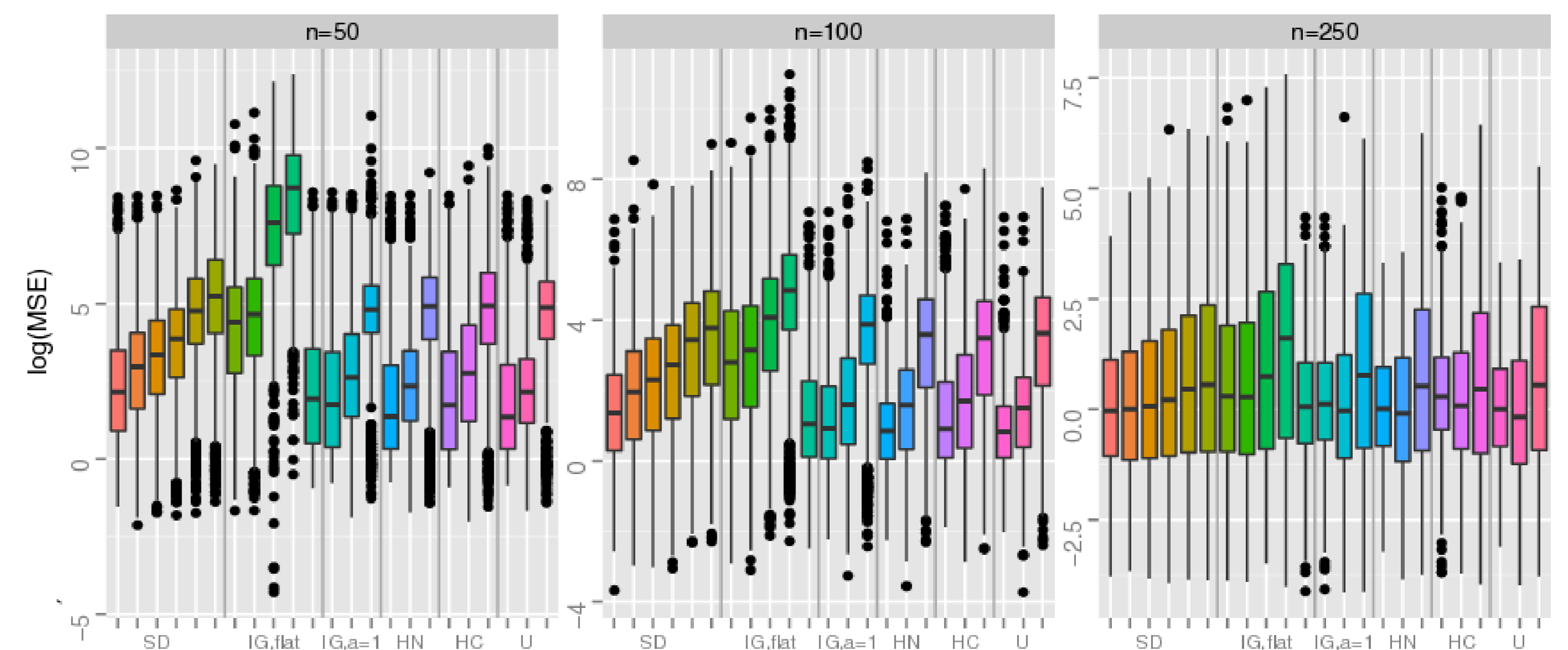
## MCMC Inference

- Full conditional  $p(\tau^2 | \cdot)$  has no closed form when  $p(\tau^2)$  is SD prior or priors derived from HN, HC and U for  $\tau$ .
- Still feasible with Metropolis-Hastings steps, similar as for  $\beta$ .
- Construction of proposal densities based on approximations to  $\log(p(\log(\tau^2) | \cdot))$ .
- Empirically, MCMC chains have good convergence behaviour.
- Conditions for propriety of joint posterior with SD prior are derived.
- Implementation in open software BayesX ([www.bayesx.org](http://www.bayesx.org)).

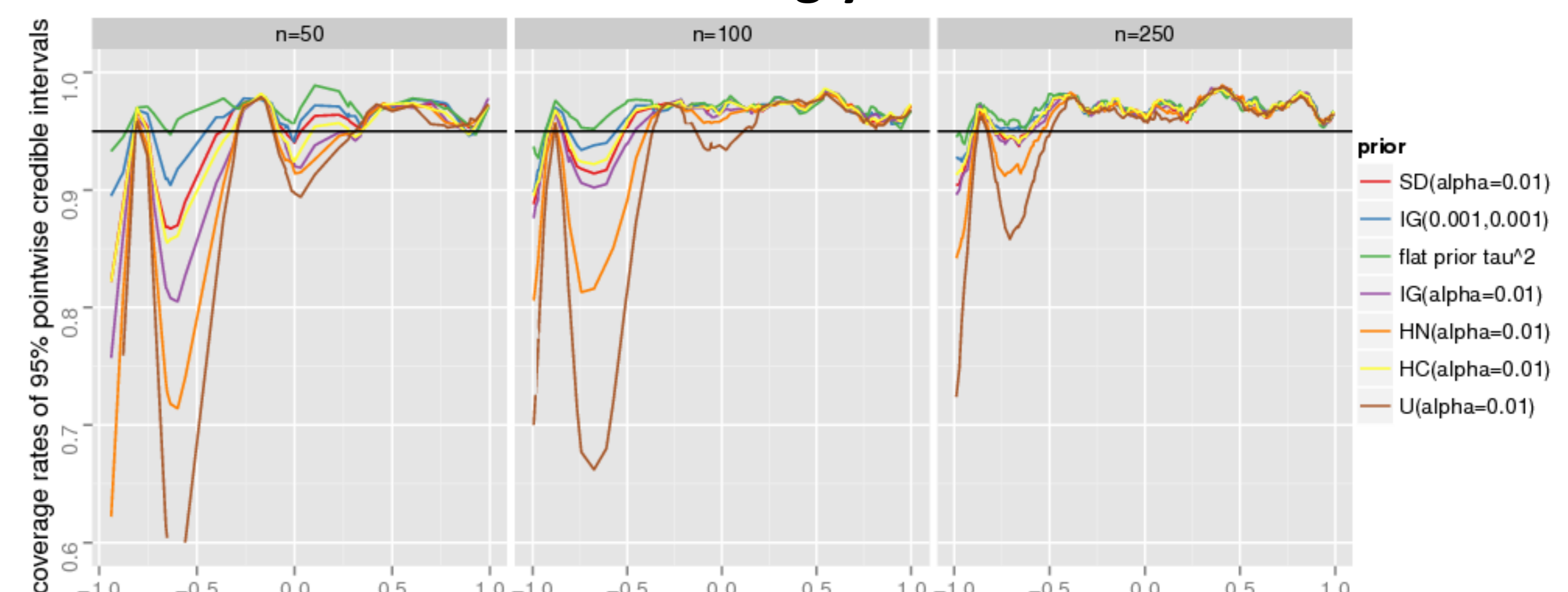
## Simulation 1: Close to the Base Model



## Simulation 2: Flat Likelihood



## Simulation 3: Strongly Nonlinear Effect



**Overall:** SD priors are fairly robust in all considered scenarios.