

# Adventures in Bayesian Structural Time Series Part 3: Structural Time Series in Bayesian Context Andrew Bates, Josh Gloyd, Tyler Tucker



Without Regression:



- Without Regression:
  - Prior



- Without Regression:
  - Prior
  - Posterior



- Without Regression:
  - Prior
  - Posterior
- With Regression:



- Without Regression:
  - Prior
  - Posterior
- With Regression:
  - Prior



- Without Regression:
  - Prior
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- Spike: prior for probability of regression coefficients being zero



- © Consider coefficients fixed through time
  - If not, include as state variables
- Spike: prior for probability of regression coefficients being zero
- Slab: prior on nonzero regression coefficients and variance



#### Spike

$$\ \ \ \ \ \ \gamma_k = 1 \ \text{if} \ \beta_k \neq 0. \ \gamma_k = 0 \ \text{if} \ \beta_k = 0$$



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#### Spike

- $\ \ \ \ \gamma_k = 1 \ \text{if} \ \beta_k \neq 0. \ \gamma_k = 0 \ \text{if} \ \beta_k = 0$
- $\ \ \ \ \beta_{\gamma}$ : subset of  $\beta$ s with  $\beta_{k} \neq 0$

$$\gamma \sim \prod_{i=1}^K \pi_k^{\gamma_k} (1-\pi_k)^{1-\gamma_k}$$



#### Slab

 $\otimes \Omega^{-1}$ : symmetric matrix



#### Slab

- $\otimes \Omega^{-1}$ : symmetric matrix
  - $\Omega_{\gamma}^{-1}$ : submatrix corresponding to  $\gamma_k = 1$



#### Slab

- $\otimes \Omega^{-1}$ : symmetric matrix
- © Conjugate prior:

$$\beta_{\gamma} \big| \sigma_{\varepsilon}^2, \gamma \sim \textit{N}(\textit{b}_{\gamma}, \sigma_{\varepsilon}^2 \Omega_{\gamma}) \qquad \frac{1}{\sigma_{\varepsilon}^2} \big| \gamma \sim \operatorname{Gamma}\left(\frac{\textit{v}}{2}, \frac{\textit{ss}}{2}\right)$$



#### Full Prior

$$f(\beta, \gamma, \sigma_{\varepsilon}^2) = f(\beta_{\gamma}|\gamma, \sigma_{\varepsilon}^2)f(\sigma_{\varepsilon}^2|\gamma)f(\gamma)$$

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