Minnesota BART

Hedibert Freitas Lopes[1]
INSPER Institute of Education and Research

Annual Conference of the Banco Central do Brasil
Setor Bancário Sul Quadra 3 Bloco B
May 13th-15th 2026

[1] https://arxiv.org/abs/2503.13759 Joint with Lima, Carvalho and Herren. FAPESP-2023/02538-0.

An helicopter view on VARs

- Vector autoregressive (VAR) models are the main workhorse in empirical macroeconomics: forecasting, impulse response and policy analysis.

- For m-dimensional y_t and p lags, the standard Gaussian VAR model is defined as

$$y_t = \sum_{l=1}^{p} \Phi_l y_{t-l} + \epsilon_t, \quad \epsilon_t \text{ iid } N(0, \Sigma_t),$$

  for $t = 1, \ldots, T$.

- mp regressors per equation.

- $m^2 p$ parameters in $(\Phi_1, \ldots, \Phi_p)$.

Evolution of Bayesian VAR models

- Small/medium size VAR
  - Doan, Litterman and Sims (1984/1986) - Minnesota prior
  - Kadiyala and Karlsson (1993/1997) - MC + MCMC
  - Lopes, Moreira and Schmidt (1999) - VAR + TVP via SIR
  - Primiceri (2005) - Structural VAR + TVP + SV
- Large/huge size VAR
  - Bańbura et al. (2010) - Large VAR
  - Koop and Korobilis (2013) - Large VAR + TVP
  - Carriero et al. (2019) - Large VAR + SV
  - Kastner and Huber (2020) - Huge VAR (sparsity)
- Nonparametric VAR
  - Huber and Rossini (2022) - BART
  - Clark et al. (2023) - BART
  - Huber and Koop (2024) - Dirichlet process mixture (DPM)
  - Hauzenberger et al. (2024) - Gaussian processes (GP)

Learning $(\Phi_1, \ldots, \Phi_p)$ via Minnesota Prior

Let us focus on the first equation of the VAR(p) model

$$y_{t1} = \sum_{l=1}^{p} \sum_{j=1}^{m} \phi_{l,1j} y_{t-l,j} + \epsilon_{t1}$$

The Minnesota prior induces a random walk behavior for y_{t1}:

$$E(\phi_{1,11}) = 1 \quad \text{and} \quad E(\phi_{l,1j}) = 0 \;\; \forall l, j \neq 1$$

and

$$V(\phi_{l,1j}) = \begin{cases} \frac{\lambda_1}{l^{\lambda_3}} & j = 1 \\ \frac{\lambda_2}{l^{\lambda_3}} & j \neq 1 \end{cases}$$

Doan, Litterman and Sims (1984) Forecasting and conditional projection using realistic prior distributions. *Econometric reviews*, 3(1),1-100. Litterman (1986) Forecasting with Bayesian vector autoregressions - five years of experience. *JBES*, 4(1), 25-38.

Learning Σ_t via Factor Stochastic Volatility (FSV)

Recall the VAR(p) structure

$$y_t = \sum_{l=1}^{p} \Phi_l y_{t-l} + \epsilon_t, \quad \epsilon_t \text{ iid } N(0, \Sigma_t),$$

We model Σ_t via a factor stochastic volatility (FSV) framework:

$$\Sigma_t = \Lambda \Omega_t \Lambda + H_t$$

where Λ is an equation matrix $m \times r$ factor loadings ($r \ll m$), with components r and m of the diagonal matrices Ω_t and H_t following univariate SV models.

Chan (2023) argue that for BVAR with FSV structure, SV specifications for Ω_t and H_t are crucial for producing accurate density forecasts.

FSV models: Pitt and Shepard (1999), Aguilar and West (2000), Lopes (2000), Lopes and Carvalho (2007) and Kastner, Fruehwirth-Schnatter and Lopes (2017) and Kastner (2019), among many others.

Our contribution: Minnesota BART

Three-fold extension of Huber and Rossini (2022) and Clark et al. (2023):

- Allowing for high-dimensional data and variable selection via the approach by Linero (2018), and
- Introducing a Minnesota-type shrinkage specification into the BART node splitting selection.
- Factor SV specification for Σ_t.

m BART strutures

Let us introduce the following notation:

- $y_t = (y_{t1}, \ldots, y_{tm})'$.
- $x_t = (y'_{t-1}, \ldots, y'_{t-p})$.
- $G(x_t) = (g_1(x_t), \ldots, g_m(x_t))'$ is a n-dimensional vector BART mean functions.

We replace the linear AR structure by a nonlinear, nonparametric one:

$$y_t = G(x_t) + \epsilon_t, \quad \epsilon_t \sim \text{iid } N(0, \Sigma_t)$$

The full (hierarchical) model

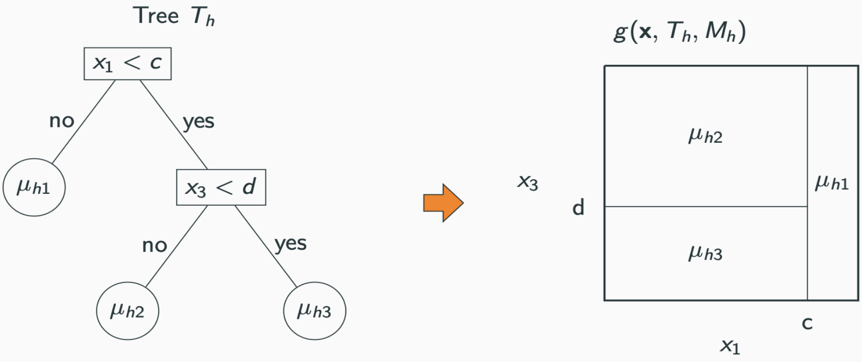
$$\begin{aligned} y_t &= G(x_t) + \Lambda f_t + \eta_t \\ f_t &\sim N(0, \Omega_t) \\ \eta_t &\sim N(0, H_t), \end{aligned}$$

where the components of H_t and Ω_t follow standard SV models.

Our MCMC scheme will cycle through the following blocks:

- Sampling Λ,
- sampling the components of Ω_t and $H_t \;\; \forall t$,
- Sampling the common factors $f_t \;\; \forall t$,
- Sampling $g_i(x_t) \;\; \forall i = 1, \ldots, m$.

A brief introduction to a tree model



Leaf/End node parameters
$M_h = (\mu_{h1}, \mu_{h2}, \mu_{h3})$

Partition $\mathcal{A}_h = \{\mathcal{A}_{h1}, \mathcal{A}_{h2}, \mathcal{A}_{h3}\}$

$g(\mathbf{x}, T_h, M_h) = \mu_{ht}$ if $\mathbf{x} \in \mathcal{A}_{ht}$ (for $1 \leq t \leq b_h$).

The vector of mean functions, $G(x_t)$

Each component of $G(x_t)$ is modeled as a decision tree ensemble:

$$g(x_t) = \sum_{n=1}^{N} g_n\left(x_t; \mathcal{T}_n, \mathcal{M}_n\right),$$

where

- $\mathcal{T}_n$ denotes a *decision tree* shape,
- $\mathcal{M}_n$ denotes a collection of *leaf node parameters*, and
- $g_n(x_t; \mathcal{T}_n, \mathcal{M}_n)$ is a *regression tree function* that returns the prediction associated to x_t for the pair $(\mathcal{T}_n, \mathcal{M}_m)$.

Prior specification:

$$\pi(\mathcal{T}_m, \mathcal{M}_m) \sim \pi_{\mathcal{T}}(\mathcal{T}_m)\, \pi_{\mathcal{N}}(\mathcal{M}_m \mid \mathcal{T}_m)$$

BART prior

BART proceeds by placing a prior on the regression trees.

Prior independence, given the model hyperparameters θ:

$$\pi\left((\mathcal{T}_1, \mathcal{M}_1), \ldots, (\mathcal{T}_M, \mathcal{M}_M) \mid \theta\right) = \prod_{m=1}^{M} \pi_{\mathcal{T}}(\mathcal{T}_m \mid \theta) \pi_{\mathcal{M}}(\mathcal{M}_m \mid \mathcal{T}_m).$$

The prior distribution for the trees $\pi_{\mathcal{T}}$ consists of three steps:

1. A prior on the shape of the tree $\mathcal{T}$;
2. A prior for the splitting rules that first selects a predictor by sampling $k_b \sim \text{Categorical}(s)$ where $s = (s_1, \ldots, s_k)^\top$ is a probability vector.
3. A prior on the splitting rules $[x_{k_b} \leq C_b]$ for each branch node of the tree, given k_b

UT Austin gang

Antonio & Jared

Hill, Linero, and Murray (2020) Bayesian Additive Regression Trees: A Review and Look Forward, *Annual Review of Statistics and Its Application*, Volume 7, pages 251-278 - https://doi.org/10.1146/annurev-statistics-031219-041110

Carlos, Drew, Rafael & Pedro

`stochtree` (short for "stochastic trees") - https://stochtree.ai

Boosted decision tree models (like xgboost, LightGBM, or scikit-learn's HistGradientBoostingRegressor) are great, but often require time-consuming hyperparameter tuning. stochtree can help you avoid this, by running a fast Bayesian analog of gradient boosting (called BART – Bayesian Additive Regression Trees).

BART splitting rule

- Select a predictor by sampling $k_b \sim \text{Categorical}(s)$, where
$$s = (1/k, \ldots, 1/k).$$

- What if $m = 100$ and $p = 5$, such that $k = mp = 500$?
BART breaks down with larger number of irrelevant features (Linero (2018)).

- Bias will increase as k increases (again $k = mp$ for VAR's equations).

- Credible intervals will widen as well.

Linero (2018): Exercise high dimension

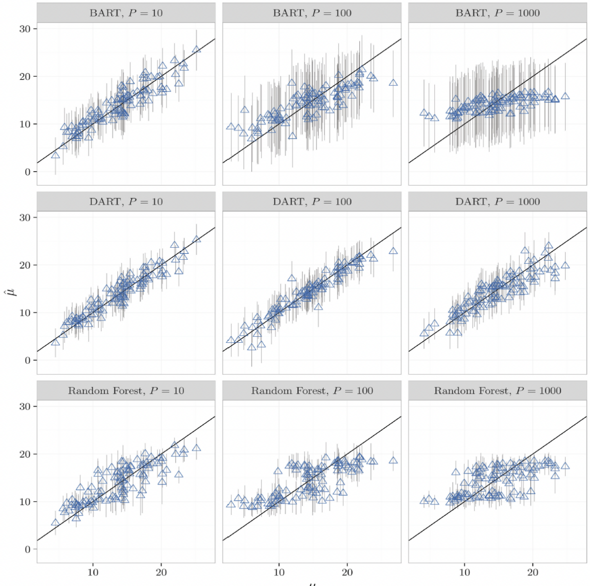
Consider the following nonlinear regression

$$\begin{aligned} y_t &= g(x_t) + \epsilon_t, \\ g(x_t) &= 10sin(\pi x_{t1} x_{i2}) + 20(x_{t3} - 0.5)^2 + 10x_{t4} + 5x_{t5}, \end{aligned}$$

where

- $\epsilon_t \sim \mathcal{N}(0, 1)$,
- $T = 100$ observations,
- 5 relevant predictors,
- $k - 5$ irrelevant predictors,
- $k = \{10, 100, 1000\}$.

Predictions degrade as k increases



DART prior

If many predictor are potentially irrelevant, why should s_k constant over k?

Linero (2018) propose a solution when k is close or much larger than T:

$$s \sim \text{Dirichlet}(\alpha/k, \dots, \alpha/k)$$

Full Bayesian variable selection:

$$\frac{\alpha}{\alpha + k} \sim \text{Beta}(0.5, 1).$$

Minnesota BART

For equation m, the prior for the split probability is defined as

$$(s_{1m}, \ldots, s_{km}) \sim \text{Dirichlet}(\phi_{1n}, \ldots, \phi_{kn}). \quad (1)$$

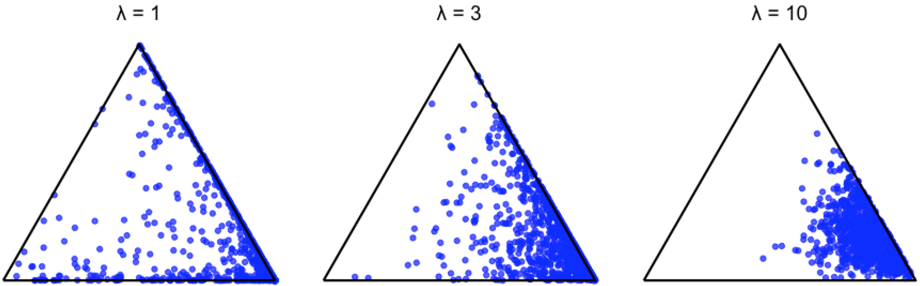
The scale parameters of the Dirichlet distribution are defined as

$$\phi_{im} = \begin{cases} \frac{\lambda_1}{l^2}, & \text{for the scale on the } l\text{-th lag of variable } i, \\ \frac{\lambda_2 \cdot \rho}{l^2}, & \text{for the coefficient on the } l\text{-th lag of variable } j, \ j \neq i, \end{cases}$$

Minnesota BART: *Dirichlet* $\left(\lambda, \frac{\lambda}{4}, \frac{\lambda}{9}\right)$

The figure illustrates the effect of varying λ on the concentration parameters of the *Dirichlet* prior on the simplex for $\lambda = (1, 3, 10)$.

The vertices of the simplex correspond to one-sparse probability vectors, the edges represent two-sparse vectors, and the interior points indicate denser probability distributions.



Bayesian inference

- **Prior features (in a nutshell)**
  - Choice of prior and hyperparameters from BART literature.
  - Horseshoe prior used for any linear conditional mean coefficients

- **MCMC features (in a nutshell)**
  - Standard MCMC steps from BVAR and BART.
  - Novel updating step for the split probabilities:

$$s_1, \ldots, s_k | \phi, \text{data} \sim \text{Dirichlet}(\phi_1 + n_1, \ldots, \phi_k + n_k)$$

where n_k are the number of splits on predictor k over the ensemble.

Posterior inclusion probability

- In order to illustrate the properties of the proposed priors we conduct a simulation study where we aim to assess the efficacy of DART-VAR and Minnesota DART in recovering the sparsity pattern.

- We use *posterior inclusion probability* as metric for variable selection.

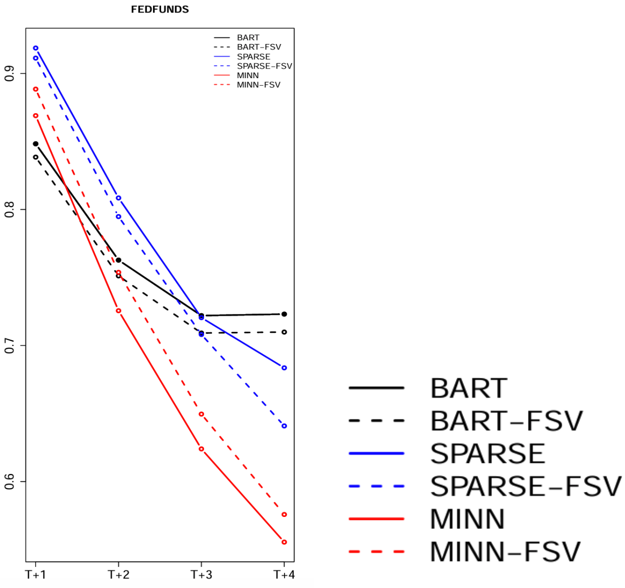
$$\text{PIP}_k = \Pr(\text{predictor } k \text{ appears in the ensemble} \mid \text{data})$$

- We will report the results of the **first equation** of the estimated dynamic system.

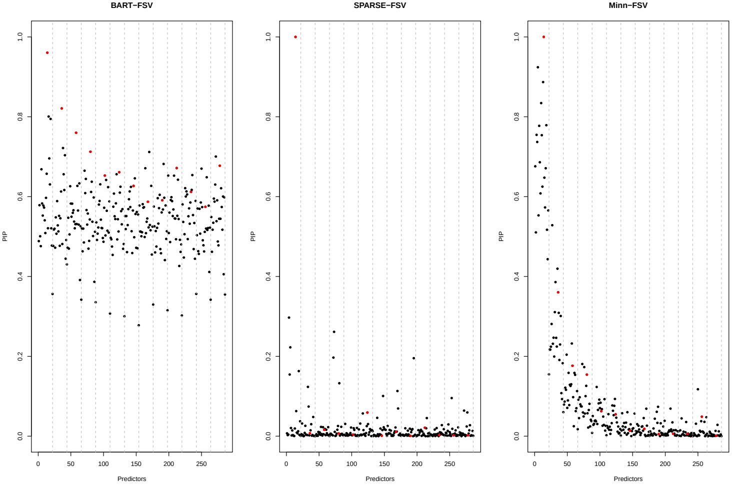
Real data exercise

- Data: 22 series from FRED-QD, McCracken and Ng (2016).
- Time span: 1965Q1 - 2019Q4.
- Expanding window: 2005Q1 to 2019Q4.
- Horizons: $h = 1, 2, 3, 4$.
- Evaluation metric: Root mean squared predictive error (RMSPE)
- Baseline model: BVAR-FSV with Minnesota prior

Root mean squared predictive error - FEDFUNDS



Posterior inclusion probabilities - CPI



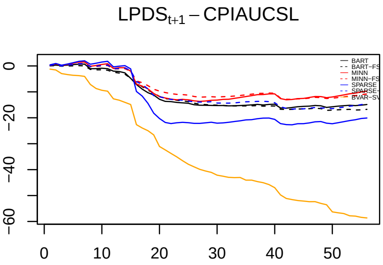
Predictive density scores

- The log predictive density score (LPDS) measures the ability to predict higher-order moments of the posterior predictive distribution.

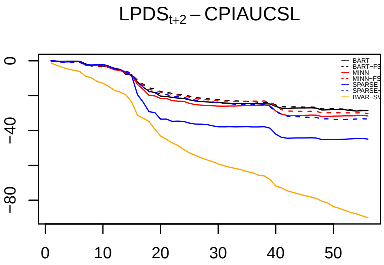
$$\text{LPDS} = \log p(y_{t_0+1}, \ldots, y_T \mid y_1, \ldots, y_{t_0}) = \sum_{t=t_0+1}^{T} \log p(y_t \mid y^{t-1})$$

- In what follows, each probability split prior specification for the mean function is shown under both homoskedastic and heteroskedastic (SV) settings, where the former is represented by a continuous line and the latter by a dashed line.

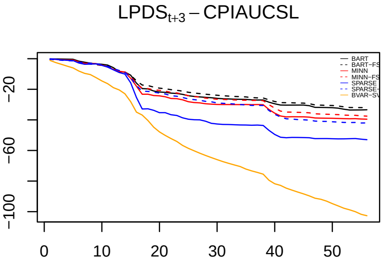
CPI



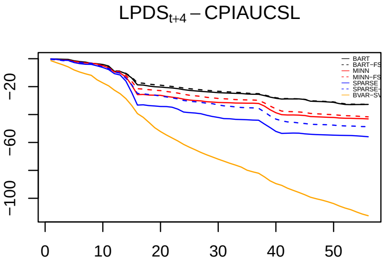
LPDS$_{t+1}$ – CPIAUCSL
BART
BART–FS
MINN
MINN–FS
SPARSE
SPARSE-
BVAR–SV
0
–20
–40
–60
0 10 20 30 40 50



LPDS$_{t+2}$ – CPIAUCSL
BART
BART–FS
MINN
MINN–FS
SPARSE
SPARSE-
BVAR–SV
0
–40
–80
0 10 20 30 40 50



LPDS$_{t+3}$ – CPIAUCSL
BART
BART–FS
MINN
MINN–FS
SPARSE
SPARSE-
BVAR–SV
–20
–60
–100
0 10 20 30 40 50



LPDS$_{t+4}$ – CPIAUCSL
BART
BART–FS
MINN
MINN–FS
SPARSE
SPARSE-
BVAR–SV
–20
–60
–100
0 10 20 30 40 50

Sensitivity to the prior

- The choice of λ is of critical importance, as it plays a central role in determining the expected level of shrinkage in the model.

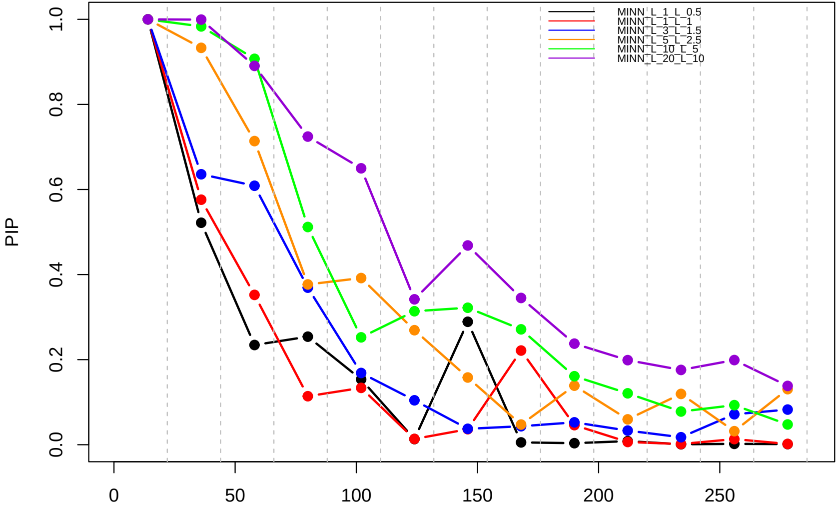
- Higher values of λ lead to a more gradual decline in PIPs, preserving the influence of lags and cross-lags over a longer range. This highlights the importance of carefully selecting λ, as it directly affects variable selection, model interpretability, and forecast accuracy.

- We considered different levels of λ using a grid of values

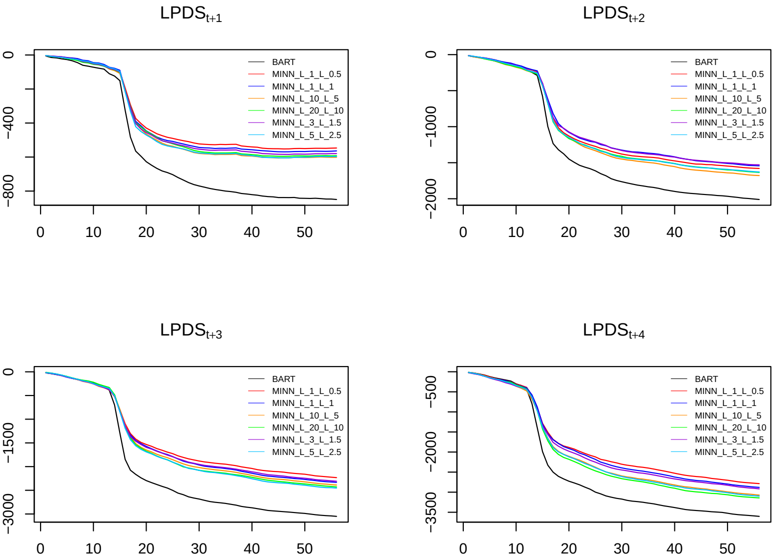
$$\lambda_1 = \{1, 3, 5, 10, 20\} \text{ and } \lambda_2 = \{0.5, 1, 1.5, 2.5, 5, 10\}$$

and assessed their impact on the LPDS relative to the standard BART prior.

PIP - CPI own lags



Cumulative LPDS



Final Remarks

- **Advancing Multivariate BART for High-Dimensional Analysis:** We introduce a structured prior that enables shrinkage in split probabilities, addressing sparsity and time dependence limitations in high-dimensional VARs.

- **Empirical Validation & Forecasting Gains:** Our priors improve forecast accuracy, particularly for higher-order moments, with the Minnesota specification outperforming the sparse alternative.

- **Broader Applications & Future Directions:** The framework extends to structural analysis (GIRFs, LP) and can be further improved through scalable sampling methods and time-varying parameters.

Bibliography I

Bańbura, M., D. Giannone, and L. Reichlin (2010). Large bayesian vector auto regressions. *Journal of applied Econometrics 25*(1), 71–92.

Carriero, A., T. E. Clark, and M. Marcellino (2019). Large bayesian vector autoregressions with stochastic volatility and non-conjugate priors. *Journal of Econometrics 212*(1), 137–154.

Chan, J. C. (2023). Comparing stochastic volatility specifications for large bayesian vars. *Journal of Econometrics 235*(2), 1419–1446.

Clark, T. E., F. Huber, G. Koop, M. Marcellino, and M. Pfarrhofer (2023). Tail forecasting with multivariate bayesian additive regression trees. *International Economic Review 64*(3), 979–1022.

Hauzenberger, N., F. Huber, M. Marcellino, and N. Petz (2024). Gaussian process vector autoregressions and macroeconomic uncertainty. *Journal of Business & Economic Statistics*, 1–17.

Bibliography II

Huber, F. and G. Koop (2024). Fast and order-invariant inference in bayesian vars with nonparametric shocks. *Journal of Applied Econometrics*.

Huber, F. and L. Rossini (2022). Inference in bayesian additive vector autoregressive tree models. *The Annals of Applied Statistics 16*(1), 104–123.

Linero, A. R. (2018). Bayesian regression trees for high-dimensional prediction and variable selection. *Journal of the American Statistical Association 113*(522), 626–636.

McCracken, M. W. and S. Ng (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics 34*(4), 574–589.

Bibliography III

- Doan, Litterman and Sims (1984) Forecasting and conditional projection using realistic prior distributions, *Econometric Reviews*, 3, 1-100.
- Litterman (1986) Forecasting with BVARs: Five Years of Experience, *Journal of Business and Economic Statistics*, 4(1), 25-38.
- Kadiyala and Karlsson (1993) Forecasting with generalized BVARs. *Journal of Forecasting*, 12, 365-78.
- Kadiyala and Karlsson (1997) Numerical methods for estimation and inference in BVAR models, *Journal of Applied Econometrics*, 12, 99-132.
- Lopes, Moreira and Schmidt (1999) Hyperparameter estimation in forecasting models, *Computational Statistics and Data Analysis*, 29, 387-410.
- Primiceri (2005) Time varying structural VARs and monetary policy. *The Review of Economic Studies*, 72(3), 821-852.
- Koop and Korobilis (2013) Large time-varying parameter VARs, *Journal of Econometrics*, 177, 185-198.
- Kastner and Huber (2020) Sparse Bayesian vector autoregressions in huge dimensions, *Journal of Forecasting*, 39(7), 1142-1165.