Large SVARs

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SVARs with Sign Restrictions and Large Models

- Increasing availability of large datasets $\rightarrow$ resurgence of large VARs
- Bayesian methods allow estimation of large VARs (Bańbura et al., 2010)
- SVARs benefit from broader information sets for
  - Shock Identification
  - Number of shocks
- Sign restrictions widely used (Uhlig, 2005; Rubio-Ramírez et al., 2010)
- Conventional approach: Accept-reject methods
- The bottleneck
  - Tight identification
  - Large number of shocks

  } **These are two sides of the same coin**

Need: Efficient inference methods under tight identification and large models.

Gibbs Sampler with Elliptical Slice Sampling

- Recent work (Chan et al., 2025) tries to solve the problem (more efficient Accept-reject methods)
- The bottleneck appears later, but still there.
- We propose a **Gibbs sampler with embedded elliptical slice sampling**.
- Avoids the bottleneck $\rightarrow$ enables tractable inference even under tight identification.
- Supports several priors.
  - Natural conjugate
  - Independent
  - Asymmetric

Result: Substantial computational gains.

Applications and Benchmarking

- **Application 1:** (Kilian and Murphy, 2014) oil market SVAR
  - Combination of signs and rankings restrictions to identify
    - Flow supply
    - Flow demand
    - Speculative demand
  - They use the efficient Accept-reject methods of (Chan et al., 2025)
  - As we add ranking restrictions the method becomes impracticle
- **Application 2:** (Chan et al., 2025) large SVAR with 35 variables and 8 shocks
  - Even efficient Accept-reject methods become impractical as shocks increase
  - Our ESS-based Gibbs sampler is robust to the number of shocks
- **Related work:** Read and Zhu (2025) use slice sampling under conditionally uniform priors

Our algorithm: General, efficient, scalable.

This Paper in a Nutshell

- We break apart with the accept-reject tradition and show that embedding an elliptical slice sampling within a Gibbs sampler approach can deliver dramatic gains in speed and turn previously infeasible applications into feasible ones
- The objective is to obtain draws from the posterior distribution of the orthogonal reduced-form parameters conditional on the sign restrictions
- To accomplish such a goal, we iteratively draw from the posterior distributions conditional on the sign restrictions, making the accept-reject step unnecessary

The Objective

- Consider the SVAR with the general form,

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \boldsymbol{\varepsilon}_t'$$

- Let $[\boldsymbol{S}_S(\mathbf{A}_0, \mathbf{A}_+) > 0]$ equal 1 if the sign restrictions are satisfied and 0 otherwise.
- The orthogonal reduced-form parameterization is

$$\mathbf{y}_t' = \mathbf{x}_t'\mathbf{B} + \boldsymbol{\varepsilon}_t'\mathbf{Q}'h(\boldsymbol{\Sigma})$$

- Mapping is $f(\mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q}) = (h(\boldsymbol{\Sigma})^{-1}\mathbf{Q}, \mathbf{B}h(\boldsymbol{\Sigma})^{-1}\mathbf{Q}) = (\mathbf{A}_0, \mathbf{A}_+)$.
- Let $[\boldsymbol{S}_R(\mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q}) > 0]$ in terms of the orthogonal reduced-form parameterization
- The objective is to draw from and transform to parameterization of interest.

$$p(\mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q} \mid \mathbf{y}_{1:T}, \boldsymbol{S}_R(\mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q}) > 0)$$

- Use following class of prior

$$p(\mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q}) = p(\mathbf{B}, \boldsymbol{\Sigma})\kappa \text{ if } \mathbf{Q} \in \mathbb{Q}_n, \text{ where} \int_{\mathbb{Q}_n} \kappa d\mathbf{Q} = 1.$$

- We call it uniform prior and it is justified by Arias et al. (2025).

The Prior

- Uniform prior

$$p(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) = p(\mathbf{B}, \mathbf{\Sigma})\kappa \text{ if } \mathbf{Q} \in \mathbb{Q}_n, \text{ where } \int_{\mathbb{Q}_n} \kappa d\mathbf{Q} = 1.$$

- For Accept-Reject approach we need
  - $p(\mathbf{B}, \mathbf{\Sigma}) \sim$ direct sampling
  - $p(\mathbf{Q}) \sim U(\mathbb{Q}_n)$
- This includes
  - Natural Conjugate
  - Independent
  - Asymmetric Prior

  } **All combined with Uniform with respect to Haar Measure over the orthogonal matrices**
- We focus on Natural Conjugate for $p(\mathbf{B}, \mathbf{\Sigma})$
- With $p(\mathbf{Q}) \sim U(\mathbb{Q}_n)$ we get uniform natural conjugate prior.
- Because of conjugate, we draw from uniform natural conjugate posterior.

The Accept-Reject Algorithm

Algorithm

The following algorithm independently draws from the uniform natural conjugate posterior distribution over parameterization to interest conditional on the sign restrictions.

1. *Draw* $(\mathbf{B}, \mathbf{\Sigma})$ *independently from* $NIW(\tilde{\nu}, \tilde{\mathbf{\Phi}}, \tilde{\mathbf{\Psi}}, \tilde{\mathbf{\Omega}})$.
2. *Draw* $\mathbf{Q}$ *independently from the uniform over* $\mathcal{O}(n)$.
3. *Keep* $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ *if the sign restrictions are satisfied:* $[\boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0] = 1$.
4. *Return to Step 1 until the required number of draws has been obtained.*
5. *Transform to parameterization of interest.*

The Accept-Reject Algorithm Eventually Fails

A Simple Example

- Consider an example similar to the one explored by Granziera et al. (2018):

$$\mathbf{y}_t' = (y_{t,1}, y_{t,2}) = \boldsymbol{\varepsilon}_t' \mathbf{Q}' \boldsymbol{\Sigma}_{tr}$$

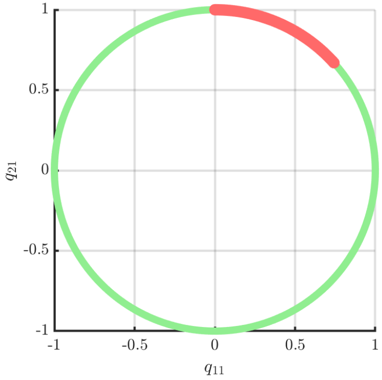
- We set $\boldsymbol{\Sigma}_{tr,11} = \boldsymbol{\Sigma}_{tr,22} = 1$ and $\boldsymbol{\Sigma}_{tr,21} = -0.9$. Note that the contemporaneous impact matrix $\mathbf{L}_0$ is defined as $\mathbf{L}_0 = \boldsymbol{\Sigma}_{tr}\mathbf{Q}$. Thus, the impact of the first shock on $y_{t,1}$ and $y_{t,2}$ is:

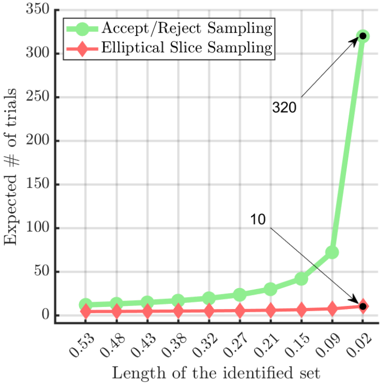
$$\ell_{11} = q_{11} \text{ and } \ell_{21} = -0.9q_{11} + q_{12},$$

respectively, where ℓ_{ij} and q_{ij} are the i-th row and j-th column entry of $\mathbf{L}_0$ and $\mathbf{Q}$, respectively, and $\mathbf{q}_i$ represents the i-th column of $\mathbf{Q}$.

- If we impose sign restrictions such that both impacts are nonnegative, then $q_{11} \geq 0$ and $q_{12} \geq 0.9q_{11}$

The Accept-Reject Algorithm Eventually Fails





- The size of the set depends:
  - Tightness/number of restrictions
  - Number of shock

Elliptical Slice Sampling (ESS)

- ESS is a **rejection-free** Markov chain Monte Carlo (MCMC) algorithm designed to sample from posteriors of the form:

$$p(\boldsymbol{\theta}) \propto L(\boldsymbol{\theta})\,\mathcal{N}(\boldsymbol{\theta}; \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

  where $L(\boldsymbol{\theta})$ is a likelihood function and the prior is Gaussian.

- The key idea is to treat the prior as defining an **ellipse**, and sample from the likelihood-restricted posterior along that ellipse.

- ESS is efficient and automatically tunes step sizes — no need for tuning parameters or gradient evaluations.

Our Proposed Algorithm

- For ESS we need
  - $\mathbf{B} \mid \mathbf{\Sigma}, \mathbf{Q} = g_{\mathbf{B}}(\mathbf{X}, \mathbf{\Sigma}, \mathbf{Q}) f_{\mathbf{B}}(\mathbf{X})$ with $\mathbf{X}$ normal
  - $\mathbf{\Sigma} \mid \mathbf{B}, \mathbf{Q} = g_{\mathbf{\Sigma}}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) f_{\mathbf{\Sigma}}(\mathbf{X})$ with $\mathbf{X}$ normal
  - $\mathbf{Q} = f_{\mathbf{Q}}(\mathbf{X})$ with $\mathbf{X}$ normal
- The algorithm will be written using a uniform natural conjugate prior, but they could be written using an independent and asymmetric prior
- The objective can be written as

$$p(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q} \mid \mathbf{y}_{1:T}, \boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0) \propto [\boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0] N_{(\tilde{\mathbf{\Psi}}, \mathbf{\Sigma} \otimes \tilde{\mathbf{\Omega}})}(\mathbf{B}) IW_{(\tilde{\nu}, \tilde{\mathbf{\Phi}})}(\mathbf{\Sigma})$$

- We will use Gibbs Sampler.

Algorithm

The following algorithm independently draws from the natural conjugate posterior distribution over parameterization to interest conditional on the sign restrictions.

1. *Draw* $\mathbf{Q}^i$ *from*

$$p(\mathbf{Q} \mid \mathbf{B}^{i-1}, \boldsymbol{\Sigma}^{i-1}, \mathbf{y}_{1:T}, \boldsymbol{S}_R(\cdot) > 0) \propto [\boldsymbol{S}_R(\cdot) > 0]$$

2. *Draw* $\boldsymbol{\Sigma}^i$ *from*

$$p(\boldsymbol{\Sigma} \mid \mathbf{B}^{i-1}, \mathbf{Q}^i, \mathbf{y}_{1:T}, \boldsymbol{S}_R(\cdot) > 0) \propto [\boldsymbol{S}_R(\cdot) > 0] N_{(\tilde{\boldsymbol{\Psi}}, \boldsymbol{\Sigma} \otimes \tilde{\boldsymbol{\Omega}})}(\mathbf{B}^{i-1}) IW_{(\tilde{\nu}, \tilde{\boldsymbol{\Phi}})}(\boldsymbol{\Sigma})$$

3. *Draw* $\mathbf{B}^i$ *from*

$$p(\mathbf{B} \mid \boldsymbol{\Sigma}^i, \mathbf{Q}^i, \mathbf{y}_{1:T}, \mathbf{S}_R(\cdot) > 0) \propto [\mathbf{S}_R(\cdot) > 0] N_{(\tilde{\boldsymbol{\Psi}}, \boldsymbol{\Sigma}^i \otimes \tilde{\boldsymbol{\Omega}})}(\mathbf{B})$$

Drawing from $p(\mathbf{Q} \mid \mathbf{B}, \mathbf{\Sigma}, \mathbf{y}_{1:T}, \boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0)$

- Use a transformation from a matrix normal to via the QR-decomposition.
- Let $\mathbf{X} \sim \mathcal{N}_{n\times n}(\mathbf{0}, \mathbf{I}_n, \mathbf{I}_n)$.
- Define the mapping $\mathbf{Q} = \gamma(\mathbf{X})$, where γ extracts the orthogonal matrix from the QR-decomposition of $\mathbf{X}$.
- Then $\mathbf{Q}$ is distributed uniformly according to the Haar measure.
- Sampling procedure:
  1. Draw $\mathbf{X}$ from:
  $$[\boldsymbol{S}_R(\mathbf{B}, \mathbf{S}, \gamma(\mathbf{X})) > 0] N_{(\mathbf{0}, \mathbf{I}_n, \mathbf{I}_n)}(\mathbf{X}).$$
  2. Transform via $\mathbf{Q} = \gamma(\mathbf{X})$ to obtain a draw from the desired conditional distribution.
- Since $\mathbf{X}$ is Gaussian, we use Elliptical Slice Sampling (ESS) to draw efficiently from the truncated Gaussian.

Drawing from $p(\mathbf{\Sigma} \mid \mathbf{B}, \mathbf{Q}, \mathbf{y}_{1:T}, \boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0)$

- Use a transformation from a matrix normal to an inverse Wishart via a quadratic mapping.
- Let $\mathbf{R} \sim \mathcal{N}_{n\times\tilde{\nu}}(\mathbf{0}, \tilde{\mathbf{\Phi}}^{-1}, \mathbf{I}_{\tilde{\nu}})$.
- Define the mapping $\mathbf{S} = \varsigma(\mathbf{R}) = (\mathbf{R}\mathbf{R}')^{-1}$.
- Then $\mathbf{S}$ is distributed as inverse Wishart: $\mathbf{S} \sim \mathcal{IW}(\tilde{\nu}, \tilde{\mathbf{\Phi}})$.
- Sampling procedure:
  1. Draw $\mathbf{R}$ from:

$$[\boldsymbol{S}_R(\mathbf{B}, \varsigma(\mathbf{R}), \mathbf{Q}) > 0] N_{(\tilde{\mathbf{\Psi}}, \varsigma(\mathbf{R})\otimes\tilde{\mathbf{\Omega}})}(\mathbf{B}) N_{(\mathbf{0}, \tilde{\mathbf{\Phi}}^{-1}, \mathbf{I}_{\tilde{\nu}})}(\mathbf{R}).$$

  2. Transform via $\mathbf{S} = \varsigma(\mathbf{R})$ to obtain a draw from the desired conditional distribution.
- Because $\mathbf{R}$ is Gaussian, we use Elliptical Slice Sampling (ESS) to efficiently draw from the truncated Gaussian.

Small SVAR of the World Oil Market

- In the first application, we replicate Kilian and Murphy (2014). This paper adds oil inventories to the model Kilian and Murphy (2012) in order to identify speculative demand shocks. The tight restrictions used in this paper render the identified set small and the typical algorithm becomes infeasible

- To get around this infeasibility, Kilian and Murphy (2014) consider an approach similar to the one in Chan et al. (2025) by exploiting permutations and sign alternation. As we will show below, our algorithm can handle this application in about half the time it takes when using Chan et al.'s (2025) accept-reject algorithm

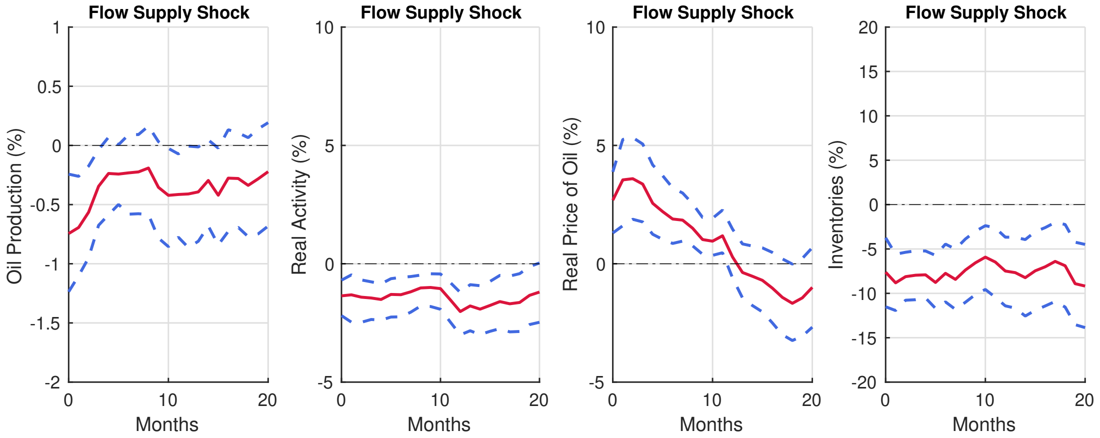
Small SVAR of the World Oil Market

Identifying Restrictions

	Sign Restrictions on Impact Impulse Responses		
Variable/Shock	Flow supply	Flow demand	Speculative demand
Oil production	-1	$+1$	$+1$
Real activity	-1	$+1$	-1
Real price of oil	$+1$	$+1$	$+1$
Inventories			$+1$
	Elasticity Bounds		
	Flow supply shock	Flow demand shock	Speculative demand shock
Price Elasticity of Oil Supply		0.025	0.025
	Sign Restrictions on Impulse Responses at Horizons 0 through 12		
	Flow supply shock	Flow demand shock	Speculative demand shock
Real activity	-1		
Real price of oil	$+1$		

Small SVAR of the World Oil Market

Impulse Responses to Flow Supply Shock



Computation Time: Gibbs vs Accept-Reject

Specification	Benchmark Model	Benchmark Model + Additional Restriction
Gibbs Sampler	0.03	
Accept-Reject	0.33	

Table: Time (Hours) Per 1,000 Effective Draws

Small SVAR of the World Oil Market

Identifying Restrictions

	Sign Restrictions on Impact Impulse Responses		
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Oil production	-1	$+1$	$+1$
Real activity	-1	$+1$	-1
Real price of oil	$+1$	$+1$	$+1$
Inventories			$+1$
	Elasticity Bounds		
	Flow supply shock	Flow demand shock	Speculative demand shock
Price Elasticity of Oil Supply	$(-0.09, -0.07)$	0.025	0.025
	Sign Restrictions on Impulse Responses at Horizons 0 through 12		
	Flow supply shock	Flow demand shock	Speculative demand shock
Real activity	-1		
Real price of oil	$+1$		

Specification	Benchmark Model	Benchmark Model + Additional Restriction
Gibbs Sampler	0.03	0.10
Accept-Reject	0.33	7.92

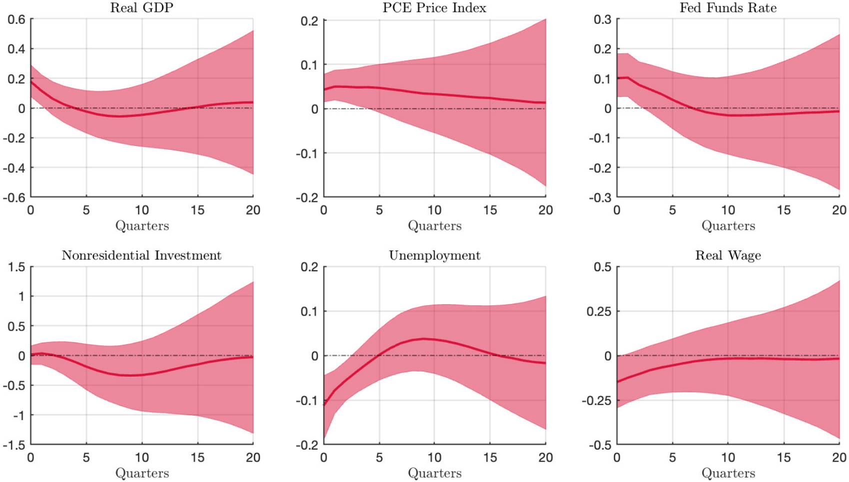
TABLE: Time (Hours) Per 1,000 Effective Draws

A Large SVAR of the U.S. Economy

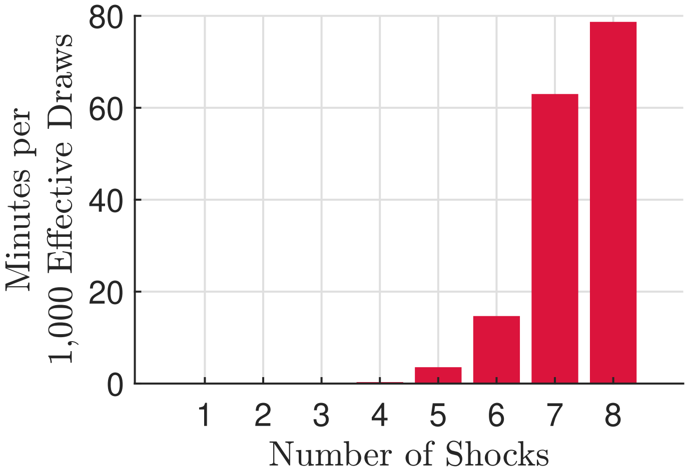
- We re-visit the structural analysis in Chan et al. (2025) who use Crump et al.'s (2025) large SVAR model of the U.S. economy to identify 8 structural shocks
- The model includes 35 variables typically monitored at the Federal Reserve System. The SVAR is specified at quarterly frequency (1973:Q2–2019:Q4)
- We assume a Minnesota prior for the reduced-form parameters and we set the hyper-parameters following Giannone et al. (2015). We follow the conventional approach and impose a Haar distribution over the set of orthogonal matrices
- For identification purposes, Chan et al. (2025) use sign restrictions on the contemporaneous impulse responses as well as by ranking restrictions. In total, there 105 sign restrictions are imposed

A Large SVAR of the U.S. Economy

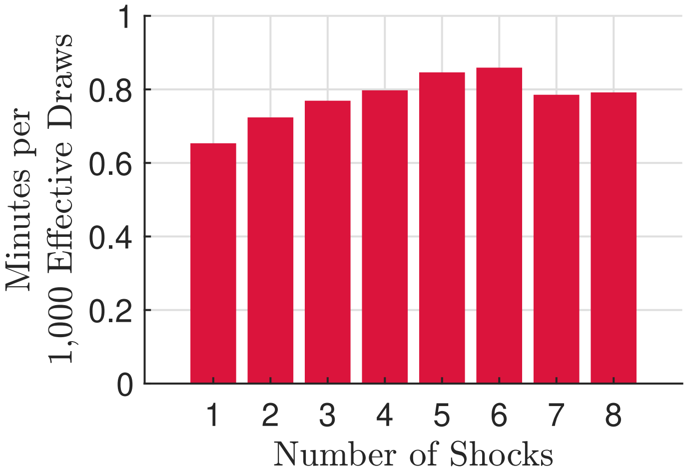
Impulse Responses to a Demand Shock



Accept-Reject

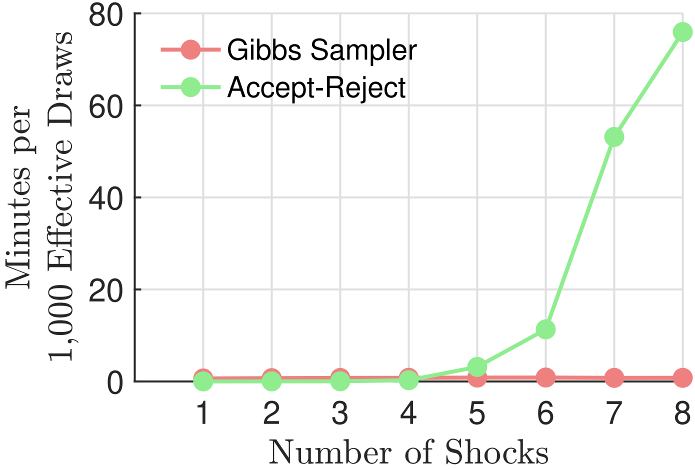


Gibbs

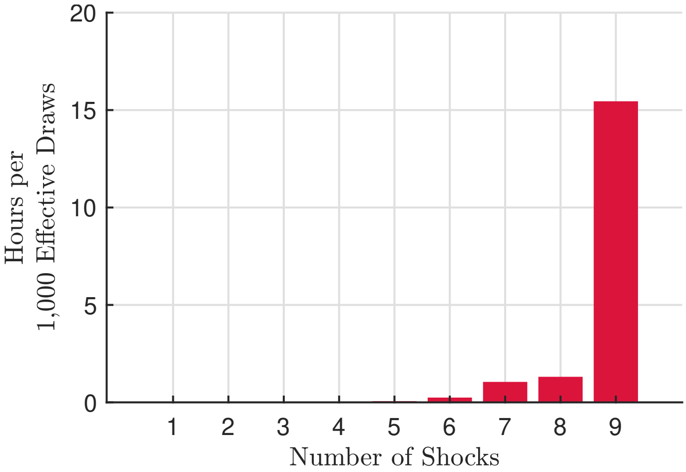


Minutes per
1,000 Effective Draws
1
0.8
0.6
0.4
0.2
0
1
2
3
4
5
6
7
8
Number of Shocks

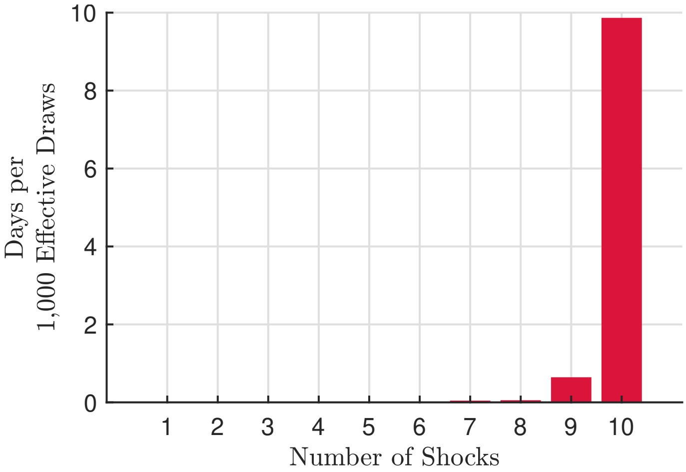
Accept-Reject vs Gibbs



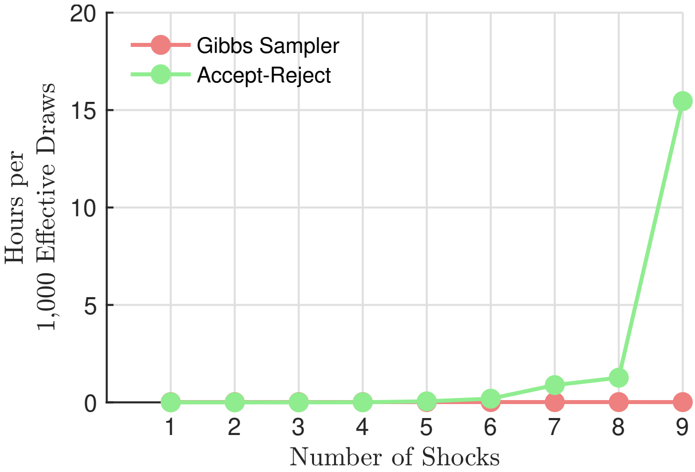
Accept-Reject



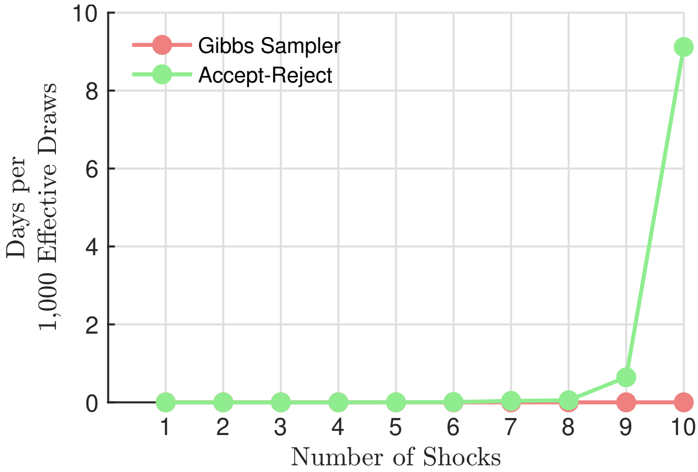
Accept-Reject



Accept-Reject vs Gibbs



Accept-Reject vs Gibbs



Beyond Gibbs

- Gibbs sampling can be costly in large models due to autocorrelation of draws.
- Temptation: use conditionally uniform (CU) prior:
  - Like accept–reject, typically yields independent draws.
  - Lower computational burden.

Setup and Notation

- Define the set:

$$\mathbb{Q}_n(\mathbf{B},\mathbf{\Sigma}) = \{\mathbf{Q} \in \mathbb{Q}_n : \mathbf{S}_R(\mathbf{B},\mathbf{\Sigma},\mathbf{Q}) > 0\}.$$

- Choose a normalizing constant $\kappa(\mathbf{B},\mathbf{\Sigma})$ such that:

$$\int_{\mathbb{Q}_n(\mathbf{B},\mathbf{\Sigma})} \kappa(\mathbf{B},\mathbf{\Sigma})\, d\,\mathbf{Q} = 1.$$

- The Conditional Uniform Normal-Inverse-Wishart (CU) prior is defined as:

$$\text{CUNIW}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{B},\mathbf{\Sigma},\mathbf{Q}) = \begin{cases} \kappa(\mathbf{B},\mathbf{\Sigma})\,\mathrm{NIW}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{B},\mathbf{\Sigma}), & \mathbf{Q} \in \mathbb{Q}_n(\mathbf{B},\mathbf{\Sigma}), \\ 0, & \text{otherwise.} \end{cases}$$

- **Key Feature:** $\kappa(\mathbf{B},\mathbf{\Sigma})$ depends on $(\mathbf{B},\mathbf{\Sigma})$, so reduced-form parameters with:
  - Smaller identified sets (i.e., larger $\kappa(\mathbf{B},\mathbf{\Sigma})$)
  - Receive more prior mass.

Conditional Prior on $\mathbf{Q}$

- Under the CU prior, the conditional prior on $\mathbf{Q}$ is uniform over the restricted set:

$$\pi(\mathbf{Q} \mid \mathbf{B}, \mathbf{\Sigma}) = \begin{cases} \kappa(\mathbf{B}, \mathbf{\Sigma}), & \mathbf{Q} \in \mathcal{O}(n)(\mathbf{B}, \mathbf{\Sigma}), \\ 0, & \text{otherwise.} \end{cases}$$

- Note that $\kappa(\mathbf{B}, \mathbf{\Sigma})$ depends on the imposed restrictions.
- **Implication:**
  - Changing the restrictions alters $\kappa(\mathbf{B}, \mathbf{\Sigma})$.
  - This in turn changes the implied prior on derived quantities like $\mathbf{L}_0$ (impact IRFs).

Posterior under Sign Restrictions

- Given data $\mathbf{y}_{1:T}$ and sign restrictions $\mathbf{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0$, the posterior is:

$$p(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q} \mid \mathbf{y}_{1:T}, \mathbf{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0) = \frac{[\mathbf{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0]\ \text{CUNIW}(\tilde{\nu}, \tilde{\mathbf{\Phi}}, \tilde{\mathbf{\Psi}}, \tilde{\mathbf{\Omega}})}{\Pr(\mathbf{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0 \mid \mathbf{y}_{1:T})}.$$

- **Sampling Strategy:**
  - Draws can be obtained using a simple accept–reject scheme on $\mathbf{Q}$.
  - Some people are using EES on this step (see)readzhu2025

Modified Accept-Reject Algorithm

Algorithm

The following algorithm does independently draws posterior under sign restrictions (CU prior).

1. *Draw* $(\mathbf{B}, \mathbf{\Sigma})$ *independently from* $NIW(\tilde{\nu}, \tilde{\mathbf{\Phi}}, \tilde{\mathbf{\Psi}}, \tilde{\mathbf{\Omega}})$.
2. *Draw* $\mathbf{Q}$ *independently from the uniform over* $\mathcal{O}(n)$ *until* $[\boldsymbol{S}_R(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) > 0] = 1$.
3. *Return to Step 1 until the required number of draws has been obtained.*
4. *Transform to parameterization of interest.*

Comparison of Sign Restrictions

Identification A

	S1	S2	S3
Var 1	$+1$	$+1$	$+1$
Var 2	$+1$	-1	$+1$
Var 3	$+1$		-1

Identification B

	S1	S2	S3
Var 1	$+1$	$+1$	$+1$
Var 2	$+1$	-1	$+1$
Var 3	$+1$	-1	-1

- Any IRFs satisfying **Identification B** also satisfy **Identification A**.
- **Identification B** is stricter (more restrictive) than A.

How the Implied Prior Shifts Under CU

- Fix hyperparameters:
  - $\nu = 100$
  - $\mathbf{\Phi} = \mathbf{I}_n$
- Consider ten matrices $\{\mathbf{\Sigma}^i\}_{i=1}^{10}$:
  - Each has equal prior density under $\mathrm{IW}_{(\nu,\mathbf{\Phi})}$
  - Each has the same determinant
- Let $\{\mathbf{L}_0^i\}_{i=1}^{10}$ be the corresponding impact IRFs that satisfy Identification B.
- Since the Jacobian from $(\mathbf{\Sigma}, \mathbf{Q})$ to $\mathbf{L}_0$ depends only on $\det(\mathbf{\Sigma})$:
  - The unrestricted prior treats all $\mathbf{L}_0^i$ equally.
- Under the CU prior with identification scheme $j \in \{A, B\}$:

$$\frac{\pi^j(\mathbf{L}_0^i)}{\pi^j(\mathbf{L}_0^{i'})} = \frac{\kappa^j(\mathbf{\Sigma}^i)}{\kappa^j(\mathbf{\Sigma}^{i'})}.$$

- Differences in the prior over $\mathbf{L}_0$ arise solely from the sign restrictions via $\kappa^j(\mathbf{\Sigma})$.

Empirical illustration: prior ratios

Draw i	1	2	3	4	5	6	7	8	9	10
$\pi^A(\mathbf{L}_0^i)/\pi^A(\mathbf{L}_0^1)$	1.00	1.29	0.89	0.62	1.45	1.52	0.46	0.07	1.24	0.41
$\pi^B(\mathbf{L}_0^i)/\pi^B(\mathbf{L}_0^1)$	1.00	1.60	1.88	0.25	0.58	0.83	0.26	0.03	1.00	0.31

Table: Different schemes ⇒ different implied priors over IRFs under CU.

Example contrasts:

- Under A: $\mathbf{L}_0^5$ favored $1.45\times$ over $\mathbf{L}_0^1$.
- Under B: $\mathbf{L}_0^1$ favored $\sim 4\times$ over $\mathbf{L}_0^4$; $\mathbf{L}_0^3$ favored $2\times$ over $\mathbf{L}_0^1$.

Summary

- CU prior offers computational simplicity, but at a conceptual cost.
- It reweights parameter regions based on identified set size.
- Different sign schemes $\Rightarrow$ different implied priors.
- Prefer priors with $\mathbf{Q} \perp (\mathbf{B}, \mathbf{\Sigma})$ and uniform over $\mathcal{O}(n)$.

Conclusion

- We develop a new algorithm for inference based on sign-identified SVARs
  - The key insight is to break apart from the accept-reject tradition associated with sig-identified SVAR
  - We show that embedding an elliptical slice sampling within a Gibbs sampler approach can deliver dramatic gains in speed and turn previously infeasible applications into feasible ones
- We provide a tractable example to illustrate the power of the elliptical slice sampling applied to sign-identified SVARs
- We demonstrate the usefulness of our algorithm by applying it to a well-known small-SVAR model of the oil market featuring a tight identified set as well as to large SVAR model with more than 100 sign restrictions

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