A Narrative Approach To A Fiscal DSGE Model

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Why a narrative approach to a DSGE model?

1. Structural DSGE models are widely used in business cycle analysis.
2. Narrative studies also purport to identify structural shocks. Is the DSGE model misspecified compared to narrative studies?
It may be an advantage of VAR’s that they restrain our impulse to take our story-spinning too seriously. If Bayesian DSGE’s displace methods that try to get by with weak identification and in the process reinforce the excess weight we give to story-spinning, they may set us back.

Chris Sims (p. 2, 2005)

Before we use these [DSGE] models in the Solow-style mode of helping to organize our thinking and refine our trained intuitions, it seems only sensible that we check first where the models reflect and where they contradict common understanding.

Jon Faust (p. 63, 2009)
This paper

- Do narrative and structural methods agree?
  1. Theoretically: Yes. For DSGE models with Taylor-type policy rules identifying shocks with narrative variables as instruments is correct. Stock & Watson (2012), Mertens & Ravn (2013)
  2. Empirically: No. The data likes DSGE model dynamics, but not the covariance structure implied by the identification scheme. Del Negro & Schorfheide (2004)

- Implications:
  - Different policy rules?
  - Policy foresight?
  - Question narrative policy measures, e.g. the monetary policy shock.
DSGE-VAR framework

- State space representation of DSGE model:

\[
Y_t = B^* X^*_{t-1} + A^* \epsilon_t \\
X^*_t = D^* X^*_{t-1} + C^* \epsilon_t.
\]

\( (DSGE-Y) \)
\( (DSGE-X) \)

- VAR(p) approximation:

\[
Y_t = BX_{t-1} + A \epsilon_t \\
X_t = [Y_t, \ldots, Y_{t-(p-1)}].
\]

\( (VAR-Y) \)
\( (VAR-X) \)

- VAR problem: Observe \( A^* (A^*)' \approx AA' \), but not \( A \).

- Use DSGE model rotation to identify shocks.
Narrative DSGE-VAR framework

- State space representation of DSGE model:
  \[ Y_t = B^* X^*_{t-1} + A^* \epsilon_t \]  
  \[ X^*_t = D^* X^*_{t-1} + C^* \epsilon_t. \]  

- VAR(p) approximation:
  \[ Y_t = B X_{t-1} + A \epsilon_t \]  
  \[ X_t = [Y_t, \ldots, Y_{t-(p-1)}]. \]

- VAR problem: Observe \( A^*(A^*)' \approx AA' \), but not \( A \).
- Use DSGE model rotation to identify shocks.
- Use “narrative” instruments \( Z_t \) to recover 1st columns of \( A \):
  \[ Z_t = F X^*_t + G \epsilon_{1,t} + 0 \times \epsilon_{2,t} + \text{noise}_t. \]
What I will show today

1 Narrative BVAR
   1.1 Shock identification conditional on parameters.
   1.2 SUR-type inference over parameters.

2 Narrative DSGE-V AR
   2.1 Taylor-type policy rules allow partial identification.
   2.2 Implement DSGE-V AR prior.

3 Application: Fiscal and monetary policy.
   3.1 Vary weight on DSGE models and compare via marginal likelihoods.
   3.2 Additional moments: IRFs, historical shock correlations.
Narrative BVAR: Setup and assumptions

Consider VAR(1) in $Y_t$, $m_z$ instruments $Z_t$:

\[
\begin{bmatrix}
Y_t \\
Z_t
\end{bmatrix}
\sim \mathcal{N}
\left(
\begin{bmatrix}
B_y Y_{t-1} \\
B_z X_{t-1}^z
\end{bmatrix},
\begin{bmatrix}
\Sigma & \Gamma' \\
\Gamma & \Omega
\end{bmatrix}
\right)
\]

\[
\Sigma \equiv \text{Var}_{t-1}[Y_t] = AA' \\
\Gamma \equiv \text{Cov}_{t-1}[Z_t, Y_t] \\
A \equiv \begin{bmatrix} A_{IV} & A_{other} \end{bmatrix}
\]

Standard SUR Gibbs sampler for reduced form parameters:

1. Vector of coefficients $B_y, B_z$ is conditionally Normal distributed given covariance.
2. Inverse covariance matrix is conditionally Wishart given coefficients.
Identification given parameters

Assumption
Assume that for some invertible matrix $G$:

$$\Gamma \equiv \begin{bmatrix} G & 0 \end{bmatrix} \begin{bmatrix} A_{IV} & A_{other} \end{bmatrix} = GA'_{IV}$$

Proposition (Mertens & Ravn, 2013)
Given $\Gamma, \Sigma, A_{IV}$ is identified up to a factorization of $S_1S'_1$.

$$A_{IV} = \left[ (I - \eta\kappa)^{-1} \right] \left[ (I - \kappa\eta)^{-1} \kappa \right] S_1$$

where

- $\eta, \kappa$ are functions of $\Sigma \equiv AA', \Gamma$,
- $S_1S'_1$ is the residual variance of $v_{1,t}$ unexplained by $v_{2,t}$.
Identification: Overview

Standard VAR identification problem
Need $\frac{m(m-1)}{2}$ restrictions

$m_z$ narrative instruments
Mertens & Ravn (2013)

Lower-dimensional identification problem
Need $\frac{m_z(m_z-1)}{2}$ restrictions

Conditional Choleski
Mertens & Ravn (2013)

Partially identified VAR
$m_z$ shocks identified

Conditional max FEVD
Uhlig (2003)
1. Provide conditions when VAR and DSGE model agree on $A_{IV} = A_{IV}^*$. 
2. Incorporate DSGE model prior.
Identifiable policy rules

Definition
A simple Taylor-type rule in the (DSGE) economy for $y_{p,t}$ is of the form:

$$y_{p,t} = \sum_{i=m_p+1}^{m} \psi_{p,i} y_{i,t} + \lambda_p X_{t-1} + \sigma_p \epsilon_{p,t}, \quad \epsilon_{p,t} \subset \epsilon_t \sim iid, y_{i,t} \subset Y_t, i > m_p. $$

Example
Consider the following Taylor-rules for interest rates $r_t$:

$$r_t = (1 - \rho_r) (\gamma_\pi \pi_t + \gamma_y (y_t - y_{t-1})) + \rho_r r_{t-1} + \omega_r \epsilon^r_t. \quad \text{(a)} $$

$$r_t = (1 - \rho_r) (\gamma_\pi \pi_t + \gamma_y (y_t - y^f_t)) + \rho_r r_{t-1} + \omega_r \epsilon^r_t. \quad \text{(b)} $$

$$r_t = (1 - \rho_r) (\gamma_\pi \pi_t + \gamma g g_t) + \rho_r r_{t-1} + \omega_r \epsilon^r_t. \quad \text{(c)} $$

If $[y_t, \pi_t] \subset Y_t$ and $y^f_t \not\subset Y_t$: (a) is a simple Taylor rule, but not (b) or (c).
Narrative VAR consistent with DSGE models

Proposition
If $A^*(A^*)' = AA'$ then (up to sign) $S_1 = \text{chol}(S_1S_1')$ if:

(a) (DSGE) has $m_p = m_z$ simple Taylor rules with $m_z$ instruments, or

(b) (DSGE) has $m_p = m_z - 1$ simple Taylor rules ordered first and $\psi_{p,m_z} = 0, p = 1, \ldots, m_p$ with $m_z$ instruments.

Corollary
If $A^*(A^*)' = AA', \Gamma = GA'_{IV}, G^{-1}$ exists, and (a) or (b) hold:

$$A_{IV} = \left[ (I - \eta\kappa)^{-1} \right] (I - \kappa\eta)^{-1} \kappa \left[ (I - \eta\kappa)^{-1} \right] S_1 = A^*_{IV}$$

up to sign normalization.

Sketch of proof
DSGE-VAR

Statistical background

▸ Prior for VAR via artificial observations from DSGE model (Del Negro & Schorfheide, 2004):
  ▸ Priors over DSGE model parameters $\theta$ standard to elicit.
  ▸ Approximate DSGE model with VAR based on model moments given $\theta$.
  ▸ Parameterize prior precision via number of dummy observations.

▸ Measure fit via marginal likelihood $p(Y, Z|T_0^B, T_0^V)$
  ▸ If $p(Y, Z|T_0^B, T_0^V)$ increases in $T_0^V$, evidence in favor of DSGE model identification.
  ▸ If $p(Y, Z|T_0^B, T_0^V)$ increases in $T_0^B$, evidence in favor of DSGE model dynamics.
Generating DSGE-model instruments

\[ Z_t = F X_{t-1}^z + G \epsilon_1, t + 0 \times \epsilon_2, t + \text{chol}(\Omega) \mathcal{N}(0, I_{m_z}) \quad (\text{VAR-Z}) \]

\[ Z_t = 0 + \text{diag}([c_i]_i) \epsilon_1, t + 0 \times \epsilon_2, t + \text{diag}([\omega_i]_i) \mathcal{N}(0, I_{m_z}) \quad (\text{DSGE-Z}) \]
Dummy variable DSGE prior

Use (DSGE) economy to generate prior for $B, \Sigma, \Gamma$ given (DSGE) parameters $\theta$.

\[
\begin{bmatrix}
\bar{B}_y^0 \\
\bar{B}_z^0
\end{bmatrix} = \begin{bmatrix}
\mathbb{E}[X_0'X_0]^{-1}\mathbb{E}[X_0'Y_0]^{-1} \\
0
\end{bmatrix}
\]

\[
\bar{V}_0 = \begin{bmatrix}
(A^*)(A^*)' \\
[I_{mz}, 0](A^*)' & \bar{\Omega}_0(A_1^*)
\end{bmatrix}
\]

Vectorize as $\bar{\beta}_0$.

Implement $\beta \sim \mathcal{N}(\bar{\beta}_0, N_{XX}(\bar{V}_0))$ via dummy observations:

\[
\text{vec}([Y_0^B, Z_0^B]) = \bar{X}_{0, SUR}(\theta)\bar{\beta}_0(\theta) + 0,
\]

\[
\text{vec}([Y_0^B, Z_0^B]) \sim \mathcal{N}(\bar{X}_{0, SUR}(\theta)\bar{\beta}_0(\theta), \bar{V}_0(\theta) \otimes I_{T_0^B})
\]

Implement $V^{-1} \sim \mathcal{W}(\bar{V}_0 T_0^V, T_0^V)$ via dummy observations:

\[
[Y_0^V, Z_0^V] = 0 \times \beta + \text{chol}(\bar{V}_0(\theta)) \otimes I_{T_0^V},
\]

\[
\text{vec}([Y_0^V, Z_0^V]) \sim \mathcal{N}(0, V \otimes I_{T_0^V})
\]
Inference with DSGE-VAR

Random-Blocking Metropolis-Hastings-within-Gibbs sampler
(Chib & Ramamurthy, 2010).

1. Draw $B(i) | V_{i-1}^{-1}, \theta_{i-1}$ from Normal distribution.

2. Draw $V^{-1}_{i} | B(i), \theta_{(i-1)}$ from Wishart distribution.

3. Draw $\theta_{(i)} | B(i), V^{-1}_{(i)}$ from $\pi(\theta|V^{-1}, B, Y, Z) \propto \pi(V^{-1}, B|\theta)\pi(\theta)$.

Intro Narrative VAR Narrative DSGE-VAR Application: Fiscal and monetary policy rules Conclusion
Inference with DSGE-VAR

Random-Blocking Metropolis-Hastings-within-Gibbs sampler (Chib & Ramamurthy, 2010).

1. Draw $B(i)|V_{(i-1)}^{-1}, \theta(i-1)$ from Normal distribution.
2. Draw $V_{(i)}^{-1}|B(i), \theta(i-1)$ from Wishart distribution.
3. Draw $\theta(i)|B(i), V_{(i)}^{-1}$ from $\pi(\theta|V^{-1}, B, Y, Z) \propto \pi(V^{-1}, B|\theta)\pi(\theta)$:
   3.1 Randomly permute parameter indices $j \rightarrow j'$.
      $\forall j' = 1, \ldots, \#(\theta)$: Assign $\theta_{j'}$ to new block $s$ with iid probability.
   3.2 $\forall s = 1, \ldots, S_{(i)}$:
      Set $\theta_{(i-1),s} \equiv [\theta(i), \ldots \theta(i,s-1), \theta(i-1,s+1), \ldots, \theta(i-1), S_{(i)}]$.
      Draw $\vartheta_s$ from proposal density $q(\vartheta_s|\theta(i-1), s, \theta_{c(i-1),s})$.
      Compute $\alpha = \min \left\{ 1, \frac{\pi(\vartheta_s|V_{(i)}^{-1}, B(i), \theta_{c(i-1),s})q(\theta(i-1), s|\vartheta_s, \theta_{c(i-1),s})}{\pi(\theta(i-1), s|V_{(i)}^{-1}, B(i), \theta_{c(i-1),s})q(\vartheta_s|\theta(i-1), s, \theta_{c(i-1),s})} \right\}$
      Set $\theta(i), s = \begin{cases} \vartheta_s & \text{Pr} = \alpha \\ \theta(i-1), s & \text{Pr} = 1 - \alpha. \end{cases}$
Application: Fiscal and monetary policy rules

1. DSGE and VAR comparison by Bayes factors.
2. Informal model comparison: IRFs and historical shocks.
Empirical DSGE model

  - Complete markets.
  - Habit formation in consumption.
  - Monopolistic labor and final goods markets.
  - Fixed cost in production.
  - Working capital.
  - Calvo-sticky prices and wages.
  - Investment adjustment costs. Variable capacity utilization.
  - Linear consumption, capital, and labor taxes.

Estimate 40 parameters (+some calibrated values).

- Taylor-type policy rules.
Taylor-type policy rules

► Fiscal rules for government spending $g_t$ and labor income taxes $d\tau^n_t$: (Leeper et al., 2010, and Fernandez-Villaverde et al., 2013)

$$\hat{g}_t = r_g \hat{g}_{t-1} - (1 - r_g) (\psi_{g,y} \hat{y}_t + \psi_{g,b} \bar{b} \hat{b}_t) + \xi^g_t$$

$$d\tau^n_t = r_{\tau} d\tau^n_{t-1} + (1 - r_{\tau}) (\psi_{\tau,y} \hat{y}_t + \psi_{\tau,b} \bar{b} \hat{b}_t) + \xi^{\tau}_t$$

► Monetary policy rule for Federal Funds Rate:

$$\hat{FFR}_t = r_{FFR} \hat{FFR}_{t-1} + (1 - r_{FFR}) (\psi_{FFR,\pi} \hat{\pi}_t + \psi_{FFR,y} \hat{y}_t) + \xi^{FFR}_t$$
Data: 1948:Q1 to 2007:Q4

- **Narrative signals**

  Set missing narrative data to zero.

- **VAR: NIPA and FoF data**
  
  $G$, personal income tax, output, investment, gov. debt to GDP, FFR, inflation.

- **Quadratic detrending before estimation.**
Bayes factors

Bayes factors based on estimates of marginal likelihood (Chib (1995) + Geweke (1999)).

Application: Fiscal and monetary policy rules
Bayes factors

Bayes factors: Increasing weight on dynamics $T_0^B$ vs covariance structure $T_0^V$

![Graph showing Bayes factors for different (T0^B, T0^V) values.]

- Raise $T_0^B$ by 0.5
- Raise $T_0^V$ by 0.5

Application: Fiscal and monetary policy rules
Developing intuition for model comparison

Sample moments matter for fit ⇒ focus on results with weak prior.

1. Flat prior narrative VAR.
   - Very wide confidence intervals; mostly qualitative results.
   - Similar results with conditional Choleski and max FEVD decompositions.

2. Narrative DSGE-VAR.
   - IRF comparisons: Inflation and tax dynamics not well captured.
   - Historical shocks: FFR shocks does best, tax shocks the noisiest.
   - VAR Taylor rule estimates: Imprecise without prior information.
   - DSGE parameter estimates: Sensible Taylor rule estimates

Conclusion
Effects on output

$G$ to $G$ shock

Tax rate to Tax

Real rate to FFR shock

$Y$ to $G$ shock

$Y$ to Tax

$Y$ to FFR shock

- posterior median
- 68% posterior band
- 90% posterior band
Moderate amounts of prior information go a long way

- Output response to government spending shock with prior information

**Benchmark**

- Flat prior
- Weak prior $T_0 = \frac{1}{5}T$
- $T_0 = \frac{1}{2}T$

**Intro Narrative VAR**

**Narrative DSGE-V AR**

**Application:** Fiscal and monetary policy rules

**Conclusion**
Effects of $G$ shocks: Comparison with DSGE model

Government spending

Tex rate

FFR

Inflation

Output

Investment

narrative DSGE-V AR

pure DSGE

posterior median

68% posterior band

90% posterior band

Application: Fiscal and monetary policy rules

Conclusion
Effects of tax shocks

Government spending

Tax rate

FFR

Inflation

Output

Investment

narrative DSGE-V AR

pure DSGE

posterior median

68% posterior band

90% posterior band

Application: Fiscal and monetary policy rules

Conclusion
Effects of monetary policy shocks

Government spending

Tax rate

FFR

Inflation

Output

Investment

-8 -6 -4 -2 0 2 4%

-1 -0.5 0 0.5 1%

-1.5 -1 -0.5 0 0.5 1 p.p.

-6 -5 -4 -3 -2 -1 0 1 2%


narrative DSGE-V AR

pure DSGE

posterior median 68% posterior band 90% posterior band

Best fit

Intro Narrative VAR Narrative DSGE-V AR Application: Fiscal and monetary policy rules Conclusion
Implied shocks: $G$

**1949Q2 – 1969Q4**
- G shock correlation = 0.74

**1970Q1 – 1989Q4**
- G shock correlation = 0.66

**1990Q1 – 2007Q4**
- G shock correlation = 0.69

<table>
<thead>
<tr>
<th>Shock</th>
<th>Posterior median</th>
<th>(90% band)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G'$</td>
<td>0.62</td>
<td>(0.43, 0.73)</td>
</tr>
<tr>
<td>Tax</td>
<td>0.55</td>
<td>(0.37, 0.69)</td>
</tr>
<tr>
<td>FFR</td>
<td>0.82</td>
<td>(0.74, 0.88)</td>
</tr>
</tbody>
</table>

Overview

Application: Fiscal and monetary policy rules

Conclusion
## Instruments and historical shocks

(a) **Weak prior:** \( T_0 = \frac{1}{5} T \)

<table>
<thead>
<tr>
<th>Shock</th>
<th>DSGE-VAR vs DSGE Median (90% band)</th>
<th>DSGE-VAR vs IV Median (90% band)</th>
<th>DSGE vs IV Median (90% band)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( G )</td>
<td>0.62 (0.43, 0.73)</td>
<td>0.50 (0.37, 0.59)</td>
<td>0.40 (0.37, 0.43)</td>
</tr>
<tr>
<td>Tax</td>
<td>0.55 (0.37, 0.69)</td>
<td>0.56 (0.39, 0.69)</td>
<td>0.30 (0.19, 0.40)</td>
</tr>
<tr>
<td>FFR</td>
<td>0.82 (0.74, 0.88)</td>
<td>0.65 (0.63, 0.67)</td>
<td>0.58 (0.55, 0.60)</td>
</tr>
</tbody>
</table>

(b) **DSGE-VAR vs DSGE**

<table>
<thead>
<tr>
<th>Shock</th>
<th>Median (90% band)</th>
<th>Median (90% band)</th>
<th>Median (90% band)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_0 = \frac{1}{5} T )</td>
<td>( T_0 = 2 \times T )</td>
<td>( T_0 = 4 \times T )</td>
<td></td>
</tr>
<tr>
<td>( G )</td>
<td>0.62 (0.43, 0.73)</td>
<td>0.77 (0.70, 0.83)</td>
<td>0.81 (0.75, 0.86)</td>
</tr>
<tr>
<td>Tax</td>
<td>0.55 (0.37, 0.69)</td>
<td>0.73 (0.60, 0.82)</td>
<td>0.79 (0.67, 0.86)</td>
</tr>
<tr>
<td>FFR</td>
<td>0.82 (0.74, 0.88)</td>
<td>0.83 (0.75, 0.88)</td>
<td>0.87 (0.82, 0.91)</td>
</tr>
</tbody>
</table>

**Intro Narrative VAR**

**DSGE-VAR**

**Application:** Fiscal and monetary policy rules

**Conclusion**
Monetary Taylor rule: Estimated loadings

**Weak prior:**
\[ T_0 = \frac{1}{5}T \]

**Best fitting model:**
\[ T_0 = 2 \times T \]

**Dogmatic prior:**
\[ T_0 = \infty \]
Estimated signal to noise ratios

The graph shows the signal-to-noise ratio (square root) for different parameters $T_0^V = T_0^B$. The graph compares three scenarios: G, FFR, and Tax. The signal-to-noise ratio decreases as $T_0^V = T_0^B$ increases.

The application section discusses fiscal and monetary policy rules.
This paper

- **Method**
  1. Bayesian narrative VAR via SUR.
  2. Narrative DSGE-VAR in SUR framework:

- **Theoretical result:**
  Narrative identification valid for DSGE model with class of policy rules.

- **Empirical results:**
  1. Overall, intermediate weight on DSGE model optimal.
  2. Evidence against DSGE identification – but even weak prior sharpens inference.

- **Empirical caveats:**
  1. Narrative information is noisy.
  2. Potentially problematic $FFR$ instrument: Policy foresight?
What’s next?

1. Fiscal policy application
   - Relax statistical assumptions (with P. Amir-Ahmadi and C. Matthes)
     1.1 Impute missing proxy variables
     1.2 Allow for time varying parameters
     1.3 Include forward-looking macroeconomic factors
   - Use Wieland et al. (2012) model data base to compare different DSGE models.

2. Entrepreneurship and local labor markets (with G. Carlino)
   - Systematically generate instruments using Bartik (1991) idea
   - Spatial Panel VAR
   - Compare effects of shocks to startups and established firms
Labor demand shocks in low density areas

“Are Startups Special?” (with G. Carlino)

Startup labor demand

Overall labor demand

Intro Narrative VAR Narrative DSGE-VAR Application: Fiscal and monetary policy rules Conclusion
Startup labor demand shocks

“Are Startups Special?” (with G. Carlino)

Low density

 Employment/Pop (log, BDS) to entry job creation shock - group 1

 Employment/Pop (log, BDS) to entry job creation shock - group 2

Medium density

 Pop growth to entry job creation shock - group 1

 Pop growth to entry job creation shock - group 2

Intro
Narrative VAR
Narrative DSGE-VAR
Application: Fiscal and monetary policy rules
Conclusion
Which structural shocks do narrative shocks reflect?

- Test identifying assumption within DSGE model.
- Compare flexible model with baseline: $c_{ij} = 0 \forall i \neq j$?

$$z^i_t = c_{ii} \epsilon^i_t + \sum_{j \neq i} c_{ij} \epsilon^j_t + \text{noise}_t$$

- Priors: $c_{ij} \sim N(0, 1), i \neq j$ and $c_{ii} \sim N(1, 1)$.

Bayes factor relative to best model

<table>
<thead>
<tr>
<th>Narrative shock</th>
<th>violated</th>
<th>satisfied</th>
<th>satisfied with $c_{ii} = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defense spending $G$</td>
<td>-10.6</td>
<td>0</td>
<td>-3.0</td>
</tr>
<tr>
<td>Personal income tax</td>
<td>-12.1</td>
<td>0</td>
<td>-2.8</td>
</tr>
<tr>
<td>Money shock, R&amp;R</td>
<td>-5.6</td>
<td>0</td>
<td>-28.4</td>
</tr>
<tr>
<td>Money shock, R&amp;R extended</td>
<td>0</td>
<td>-3.8</td>
<td>-68.2</td>
</tr>
<tr>
<td>Money shock, R&amp;R CPI</td>
<td>-4.7</td>
<td>0</td>
<td>-79.5</td>
</tr>
<tr>
<td>Money shock, Kuttner</td>
<td>-7.3</td>
<td>0</td>
<td>-0.9</td>
</tr>
<tr>
<td>Money shock, TBill</td>
<td>-23.3</td>
<td>0</td>
<td>-191.4</td>
</tr>
</tbody>
</table>

Overview

Conclusion

Intro Narrative VAR Narrative DSGE-VAR Application: Fiscal and monetary policy rules Conclusion