## Structural Vector Autoregressions with Markov Switching

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## Motivation

- Identifying shocks is a central problem in SVAR models.
- Previous proposals:
- Restrictions on instantaneous effects of shocks (Sims, 1980).
- Restrictions on long-run effects of shocks (Blanchard/Quah, 1989; King/Plosser/Stock/Watson, 1991).
- Sign restrictions (Canova/DeNicoló, 2002; Uhlig, 2005).
- Bayesian methods (Koop, 1992).
- Using statistical data properties
- Heteroskedasticity (Rigobon, 2003; Lanne/Lütkepohl, 2008)
- Nonnormal residual distribution (Lanne/Lütkepohl, 2009)
- This paper:

Use Markov regime switching

## Overview

(1) Model setup
(2) Estimation
(3) Inflation, Unemployment, Interest Rate
(4) Conclusions

## Overview

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## Reduced form VAR model

## Variables of interest: $\quad y_{t}=\left(y_{1 t}, \ldots, y_{K t}\right)^{\prime}$

$$
y_{t}=D d_{t}+A_{1} y_{t-1}+\cdots+A_{p} y_{t-p}+u_{t}
$$

- $d_{t}$ - deterministic term.
- $u_{t} \sim\left(0, \Sigma_{u}\right)$.


## Structural form VAR model

AB-model à la Amisano \& Giannini (1997):
$A y_{t}=D^{(s)} d_{t}+A_{1}^{(s)} y_{t-1}+\cdots+A_{p}^{(s)} y_{t-p}+B \varepsilon_{t}$

- A typically has ones on its main diagonal.
- $A$ or $B$ may be identity matrix.
- $\varepsilon_{t} \sim\left(0, \Sigma_{\varepsilon}\right)$.
- $\sum_{\varepsilon}$ diagonal.
- $\Sigma_{u}=A^{-1} B \Sigma_{\varepsilon} B^{\prime} A^{-1 \prime}$.


## Markov Switching

Markov process

$$
s_{t} \in\{1, \ldots, M\}(t=0, \pm 1, \pm 2, \ldots)
$$

Transition probabilities

$$
p_{i j}=\operatorname{Pr}\left(s_{t}=j \mid s_{t-1}=i\right), \quad i, j=1, \ldots, M
$$

Conditional distribution of $u_{t}$

$$
u_{t} \mid s_{t} \sim \mathcal{N}\left(0, \Sigma_{s_{t}}\right)
$$

## Identification of Shocks

Assumption: $M=2$
A matrix decomposition result
$\Sigma_{1}, \Sigma_{2}$ positive definite
$\Rightarrow \exists \mathrm{a}(K \times K)$ matrix $B$ and $\Lambda=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{K}\right)$ such that $\Sigma_{1}=B B^{\prime}$ and $\Sigma_{2}=B \wedge B^{\prime}$

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Identification assumption
Instantaneous effects of shocks are the same across all states

## More than two states I

Assumption: $M>2$
Matrix decomposition

$$
\Sigma_{1}=B B^{\prime}, \quad \Sigma_{i}=B \wedge_{i} B^{\prime}, \quad i=2, \ldots, M
$$

imposes restrictions on covariance matrices which can be tested.

Test for state invariant $B$
LR test has asymptotic $\chi^{2}$-distribution with $\frac{1}{2} M K(K+1)-K^{2}-(M-1) K$ degrees of freedom.

## More than two states II

Uniqueness of $B$
$B$ is (locally) unique if for each pair of equal diagonal elements, for example, in $\Lambda_{2}=\operatorname{diag}\left(\lambda_{21}, \ldots, \lambda_{2 K}\right)$ there is a corresponding pair of distinct diagonal elements in one of the other $\Lambda_{i}=\operatorname{diag}\left(\lambda_{i 1}, \ldots, \lambda_{i K}\right), i=3, \ldots, M$.

Alternative decomposition

$$
\Sigma_{i}=A^{-1} \Lambda_{i}^{*} A^{-1 \prime}, \quad i=1, \ldots, M
$$

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## ML estimation

Use EM algorithm to optimize (pseudo) log likelihood.

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## Research question and data

## Question of interest

Has US monetary policy changed or just the volatility of shocks?
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Data and variables
quarterly US data
Sample period: 1953Q1 - 2001Q3

## Variables:

- $\pi_{t}$ - inflation rate based on chain weighted GDP price index
- $u_{t}$ - unemployment rate
- $r_{t}$ - yield on three-months treasury bills


## Primiceri's identifying restrictions

$$
A=\left[\begin{array}{lll}
* & 0 & 0 \\
* & * & 0 \\
* & * & *
\end{array}\right] \quad\left[\begin{array}{l}
\pi_{t} \\
u_{t} \\
r_{t}
\end{array}\right]
$$

Table: Estimates of Structural Parameters of MS Models for $\left(\pi_{t}, u_{t}, r_{t}\right)^{\prime}$ with Lag Order $p=2$ and Intercept Term (Sample Period: 1953Q1-2001Q3)

|  | unrestricted model |  | restricted model |  |
| :--- | :---: | :---: | :---: | :---: |
| parameters | estimates | std.dev. | estimates | std.dev. |
| $\lambda_{1}$ | 2.708 | 0.790 | 3.989 | 1.007 |
| $\lambda_{2}$ | 8.230 | 2.381 | 7.956 | 1.979 |
| $\lambda_{3}$ | 16.57 | 3.889 | 12.87 | 2.382 |
| $\log L_{T}$ | -148.12 |  | -156.35 |  |

Note: Standard errors are obtained from the inverse Hessian of the log likelihood function.

Table: Wald Tests for Equality of $\lambda_{i}$ 's for Unrestricted Model from Table 1

| $H_{0}$ | test value | $p$-value |
| :--- | :---: | :---: |
| $\lambda_{1}=\lambda_{2}$ | 4.85 | 0.028 |
| $\lambda_{1}=\lambda_{3}$ | 11.70 | 0.001 |
| $\lambda_{2}=\lambda_{3}$ | 2.83 | 0.092 |

## Test of Primiceri's identifying restrictions

Estimated $B$ matrix

$$
\hat{B}=\left[\begin{array}{rrr}
0.193(0.024) & -0.105(0.026) & 0.008(0.029) \\
-0.104(0.027) & -0.101(0.025) & -0.066(0.026) \\
0.022(0.049) & -0.085(0.086) & 0.286(0.031)
\end{array}\right]
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$$

LR test of lower triangularity

$$
16.47 \text { (0.001) }
$$

## Inflation responses to monetary policy shock



## Unemployment responses to monetary policy shock



## Interpretation of states

$$
\begin{gathered}
\hat{A}=\left[\begin{array}{rrr}
1 & 1.041 & 0.029 \\
-0.537 & 1 & -0.230 \\
0.115 & 0.841 & 1
\end{array}\right], \\
\hat{\Lambda}_{1}^{*}=\left[\begin{array}{ccc}
0.037 & 0 & 0 \\
0 & 0.010 & 0 \\
0 & 0 & 0.082
\end{array}\right] \text { and } \hat{\Lambda}_{2}^{*}=\left[\begin{array}{ccc}
0.101 & 0 & 0 \\
0 & 0.084 & 0 \\
0 & 0 & 1.356
\end{array}\right] .
\end{gathered}
$$

## Probabilities of State $2\left(\operatorname{Pr}\left(s_{t}=2 \mid Y_{T}\right)\right)$ for the unrestricted model for $\left(\pi_{t}, u_{t}, r_{t}\right)^{\prime}$.



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## Conclusions

## Identification assumptions:

- MS in the reduced form residuals.
- The impulse responses are invariant across regimes.


## Advantages:

- Identifying assumptions in standard SVAR framework become overidentifying and can be tested.
- MS structure can be investigated with statistical methods.


## Extensions

## Remaining problems:

- Tests for number of states.
- Confidence intervals for impulse responses.
- Models with many variables and regimes are computationally difficult to handle because of difficult likelihood function.
- Theory for asymptotic inference for models with cointegrated variables is not complete.

