Macroeconometrics

Lecture 6 Macroeconometrics research themes

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Assessing policy effects with Structural VARs

Trend and cycle analysis with Unobserved Component models

Baseline model: Vector Autoregression

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \mu_0 + \epsilon_t$$

 $\epsilon_t | Y_{t-1} \sim iid (\mathbf{0}_N, \Sigma)$

System modelling — all variables are endogenous

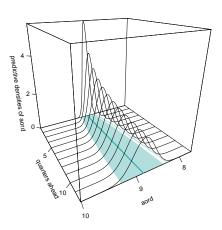
Dynamics — captures system dynamics of the variables

Forecasting — a go to model for predictive applications

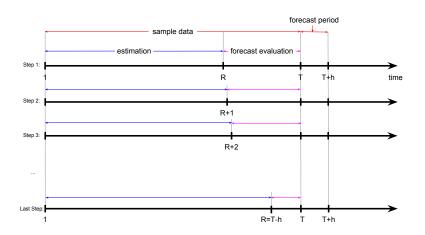
Extensions capturing important data features improve forecasting precision

Objective: Density forecasting performance evaluation

$$p(y_{T+h} \mid Y_T)$$



Method: Recursive forecasting exercise



Data set examples.

Fat data of 117 quarterly macro variables for Australia Bond yield curve modelling using daily/monthly interest rates Small-open economy forecasting with a foreign sector

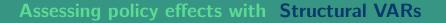
Examples of possible model extensions.

Common heteroskedasticity for all variables

Non-normal error term via gamma-scale mixtures

Estimated prior shrinkage of the Minnesota prior

Regime change to capture time-variation in parameters



Structural Vector Autoregressions.

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \mu_0 + \epsilon_t$$
 $B\epsilon_t = u_t$ $u_t | Y_{t-1} \sim iid(\mathbf{0}_N, I_N)$

Structural relationships are explicitly modelled

Economic theory informs identification of structural shocks

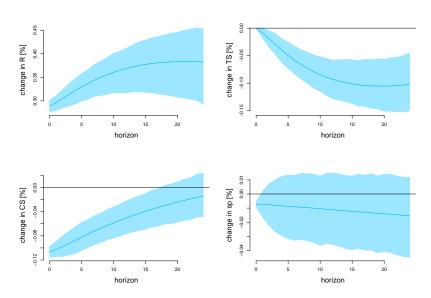
Dynamic causal effects can be estimated and interpreted

Policy decision-making is based on evidence provided by SVARs

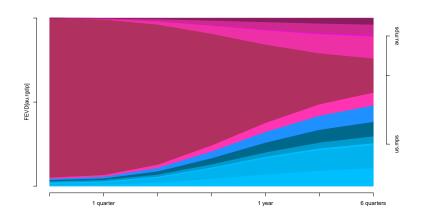
Objective: identification of a structural shock and its effects

Identification via restrictions leading to fast estimation Identification via sign restrictions that are less controversial Identification via heteroskedasticity using data properties

Method: impulse response analysis



Method: forecast error variance decomposition





Unobserved Component Models.

$$egin{aligned} y_t &= au_t + \epsilon_t \ & au_t &= \mu + au_{t-1} + \eta_t \ &\epsilon_t &= lpha_1 \epsilon_{t-1} + \dots + lpha_p \epsilon_{t-p} + e_t \ &\eta_t | Y_{t-1} \sim \textit{iid} \mathcal{N}\left(0, \sigma_\eta^2\right) \ &e_t | Y_{t-1} \sim \textit{iid} \mathcal{N}\left(0, \sigma_e^2\right) \end{aligned}$$

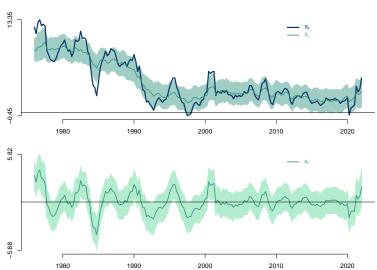
Trend and cycle decomposition of a variable

Long-run trend is highly-persistent

Oscillating cycle captures short-term dynamics

Inflation trend analysis and output gap estimation are the main applications

Objective: inflation trend and cycle analysis.



Heteroskedastic Model.

$$\begin{aligned} y_t &= \tau_t + \epsilon_t \\ \tau_t &= \mu + \tau_{t-1} + \eta_t \\ \epsilon_t &= \alpha_1 \epsilon_{t-1} + \dots + \alpha_p \epsilon_{t-p} + e_t \\ \eta_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_{\eta,t}^2 \right) \\ e_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_{e,t}^2 \right) \end{aligned}$$

Time-varying trend.

$$\begin{aligned} y_t &= \tau_t + \epsilon_t \\ \tau_t &= \mu_t + \tau_{t-1} + \eta_t \\ \mu_t &= \mu_{t-1} + m_t \\ \epsilon_t &= \alpha_1 \epsilon_{t-1} + \dots + \alpha_p \epsilon_{t-p} + e_t \\ \eta_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_\eta^2 \right) \\ e_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_e^2 \right) \\ m_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_m^2 \right) \end{aligned}$$

Common factor.

$$\begin{aligned} y_{n.t} &= \tau_t + \epsilon_{n.t} \\ n &= 1, \dots, N \\ \tau_t &= \mu + \tau_{t-1} + \eta_t \\ \epsilon_t &= \alpha_1 \epsilon_{t-1} + \dots + \alpha_p \epsilon_{t-p} + e_t \\ \eta_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_\eta^2 \right) \\ e_t | Y_{t-1} &\sim \textit{iid} \mathcal{N} \left(0, \sigma_e^2 \right) \end{aligned}$$

The choice is yours!