Impulse Responses by Local Projections: Practical Issues

by

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Motivation

- Impulse Responses are important statistics that substantiate models of the economy

- Is the DGP a VAR? Very likely it is not:

    - Zellner and Palm (1974) and Wallis (1977): a subset from a VAR follows a VARMA
    - Cooley and Dwyer (1998): many standard RBC models follow a VARMA
    - New solution techniques for nonlinear DSGE models produce polynomial difference equations

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Disadvantages of VARs

- VARs approximate the data *globally*: best, linear, one-step ahead predictors.
- Impulse responses are functions of multi-step forecasts
- Standard errors for impulse responses from VARs are complicated: they are highly nonlinear functions of estimated parameters

What this paper does

Because any model is a *global* approximation to the DGP in the sample, consider instead local approximations for each forecast horizon of interest

Use local projections!

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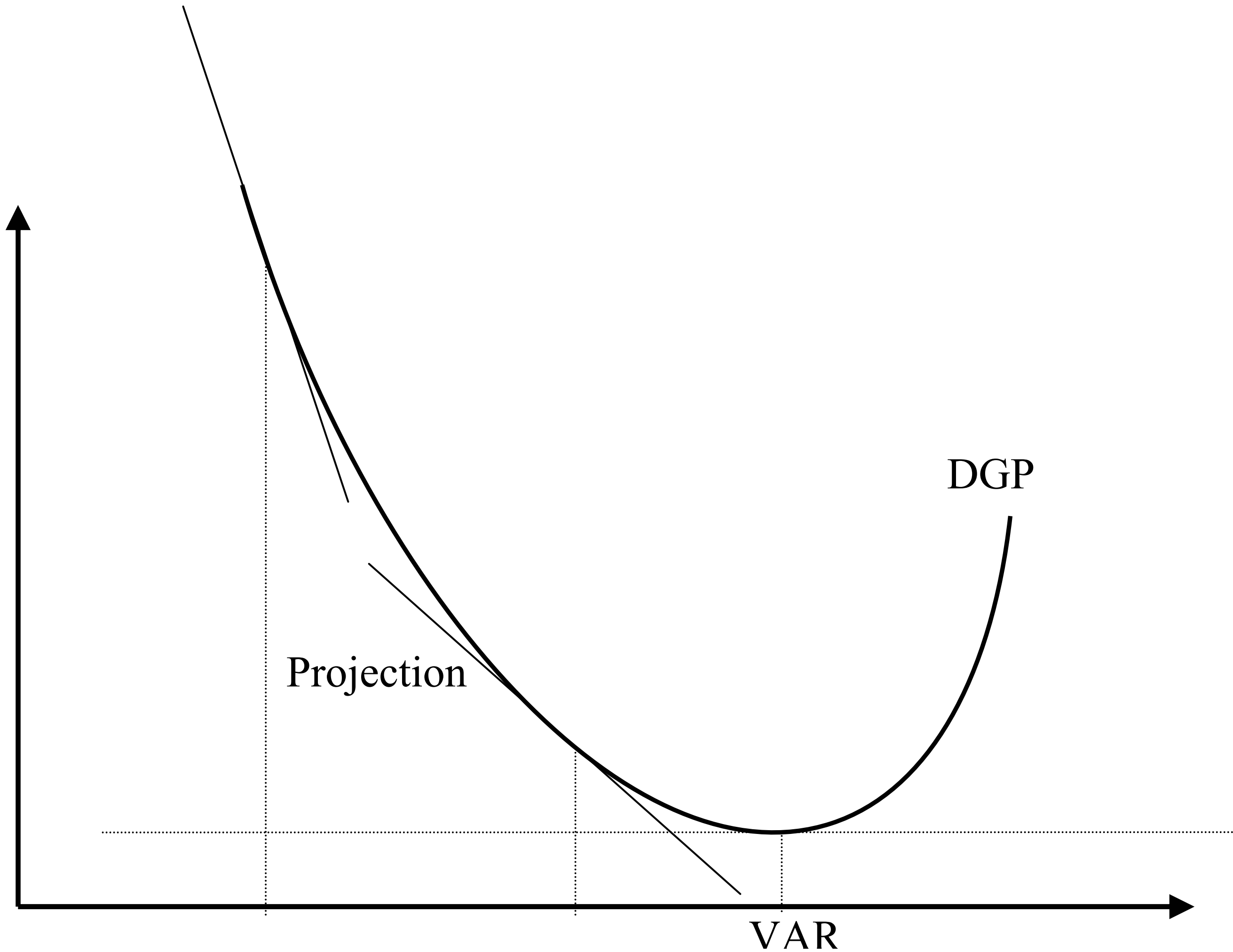
Intuition



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Advantages of Local Projections

- Can be estimated by single-equation OLS with standard regression packages
- Provide simple, analytic, joint inference for impulse response coefficients
- They are more robust to misspecification
- Experimentation with very nonlinear and flexible models is straight-forward

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Estimation

A definition of impulse response (Hamilton, 1994, Koop et al. 1996):

$$IR(t,s,\mathbf{d}_i) = E(\mathbf{y}_{t+s} \mid \mathbf{v}_t = \mathbf{d}_i; X_t) - E(\mathbf{y}_{t+s} \mid \mathbf{v}_t = 0; X_t)$$

$\mathbf{y}_t$ is $n \times 1$

$X_t = (\mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \ldots)'$

$E(\mathbf{v}_t \mathbf{v}_t') = \Omega$

$D = [\mathbf{d}_1 \ldots \mathbf{d}_i \ldots \mathbf{d}_n];$

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Hence, consider

$$\mathbf{y}_{t+s} = \alpha^s + B_1^{s+1}\mathbf{y}_{t-1} + \ldots + B_p^{s+1}\mathbf{y}_{t-p} + \mathbf{u}_{t+s}^s$$

so that

$$IR(t, s, \mathbf{d}_i) = \hat{B}_1^s \mathbf{d}_i \qquad s = 0,1,2,\ldots h$$

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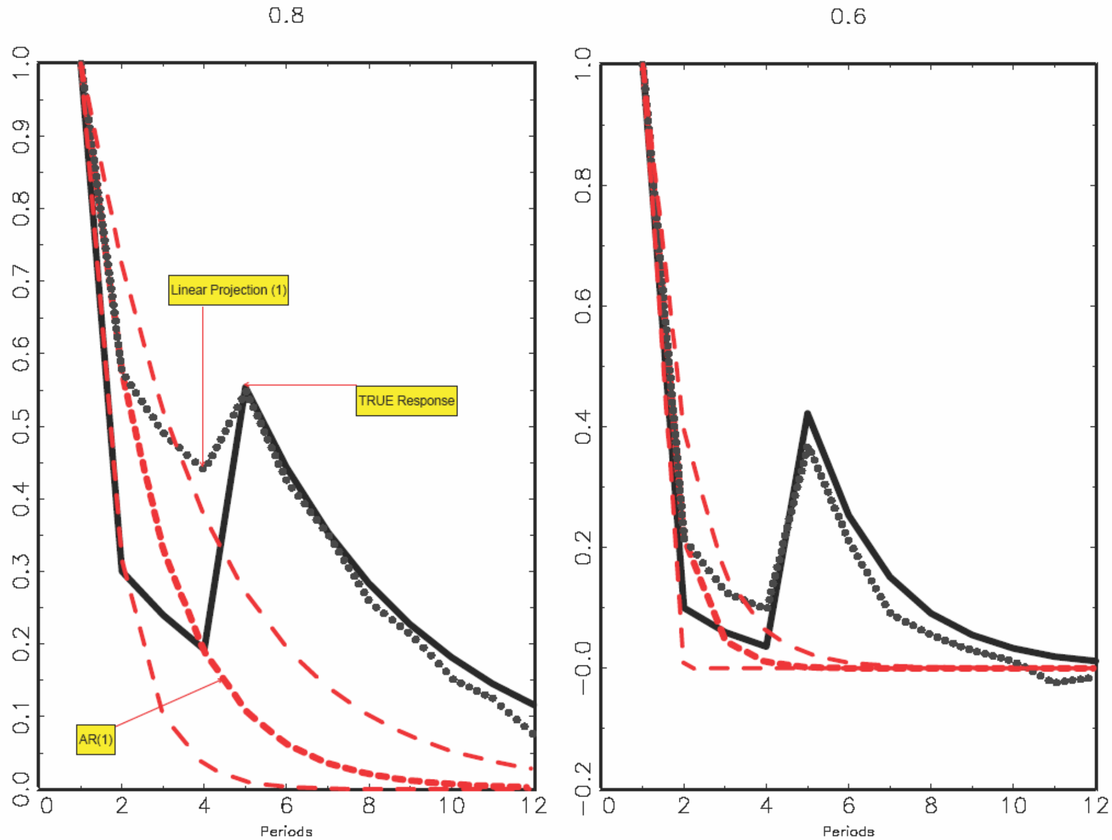
Example: AR(1) vs. Local Projection



$$y_t = \rho y_{t-1} + \varepsilon_t - 0.5\varepsilon_{t-1} + 0.4\varepsilon_{t-4}; \; T = 180; \; p = 1, \; 100 \text{ reps}$$

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Practical Comments

- The maximum lag p need not be common to all s projections (e.g. VMA(q))
- The lag length and the IR horizon impose degree-of-freedom constraints for very small samples
- Consistency does not require that all $n \times h$ regressions be estimated jointly. It can be done by univariate regression for each n, and h.

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Variance Decompositions

$$\mathbf{y}_{t+s} - E(\mathbf{y}_{t+s} \mid X_t) = \mathbf{u}_{t+s}^{s} \quad s = 0,1,\ldots,h$$

$$MSE_u(E(\mathbf{y}_{t+s} \mid X_t)) = E(\mathbf{u}_{t+s}^{s}\mathbf{u}_{t+s}^{s}{}')$$

$$MSE(E(\mathbf{y}_{t+s} \mid X_t)) = D^{-1}E(\mathbf{u}_{t+s}^{s}\mathbf{u}_{t+s}^{s}{}')D'^{-1}$$

Structural Identification for Linear Projections

Example: Cholesky Decomposition

Estimate a VAR (also, the first projection):

$$\mathbf{y}_t = \alpha^0 + B_1^1 \mathbf{y}_{t-1} + \ldots + B_p^1 \mathbf{y}_{t-p} + \mathbf{u}_t^0$$

$$E\mathbf{u}'\mathbf{u} = \Omega = A'\Lambda A$$

Then $D = A^{-1}$. This is the D for all subsequent projections.

Alternatively:

When available instruments can be used to resolve endogeneity, structural impulse responses can be calculated directly:

$$\mathbf{y}_{t+s} = \alpha^s + A_0^{S+1}\mathbf{y}_t + A_1^{s+1}\mathbf{y}_{t-1} + \ldots + A_p^{s+1}\mathbf{y}_{t-p} + \varepsilon_{t+s}^s$$

so that the response to the i^{th} variable is simply

$$IR(t,s,i) = \hat{A}(.,i)_1^{s+1} \qquad s = 0,1,2,\ldots h$$

Inference and Relation to VARs

$$\mathbf{y}_t = \mu + \Pi' X_t + \mathbf{v}_t \qquad \text{VAR(p)}$$

$$W_t \equiv \begin{bmatrix} \mathbf{y}_t - \mu \\ \vdots \\ \mathbf{y}_{t-p+1} - \mu \end{bmatrix}; F \equiv \begin{bmatrix} \Pi_1 & \cdots & \Pi_{p-1} & \Pi_p \\ I & \cdots & 0 & 0 \\ \vdots & \dots & \vdots & \vdots \\ 0 & \dots & I & 0 \end{bmatrix}$$

$$\nu = \begin{bmatrix} \mathbf{v}_t \\ \vdots \\ 0 \end{bmatrix}; \text{hence} \quad W_t = FW_{t-1} + \nu_t \ \ \text{VAR(1)}$$

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From the VAR(1) representation of the VAR(p),

$$\mathbf{y}_{t+s} - \mu = \mathbf{v}_{t+s} + F_1^1 \mathbf{v}_{t+s-1} + \ldots + F_1^s \mathbf{v}_t + F_1^{s+1}(\mathbf{y}_{t-1} - \mu) + \ldots + F_p^{s+1}\left(\mathbf{y}_{t-p} - \mu\right)$$

hence, as $s \to \infty$

$$\mathbf{y}_t = \gamma + \mathbf{v}_t + F_1^1 \mathbf{v}_{t-1} + \ldots + F_1^s \mathbf{v}_{t-s} + \ldots$$

and therefore

$$\boxed{IR(t, s, \mathbf{d}_i) = F_1^s \mathbf{d}_i}$$

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IR coefficients from a VAR(p)

$$F_1^1 = \Pi_1$$

$$F_1^2 = \Pi_1 F_1^1 + \Pi_2$$

$$\vdots$$

$$F_1^s = \Pi_1 F_1^{s-1} + \Pi_2 F_1^{s-2} + \ldots + \Pi_p F_1^{s-p}$$

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Compare this with the linear projection

$$\mathbf{y}_{t+s} = \alpha^s + B_1^{s+1}\mathbf{y}_{t-1} + \ldots + B_p^{s+1}\mathbf{y}_{t-p} + \mathbf{u}_{t+s}^s$$

then

$$\alpha^s = (I - F_1^s - \ldots - F_p^s)$$

$$B_1^{s+1} = F_1^{s+1}$$

$$\mathbf{u}_{t+s}^s = \left(\mathbf{v}_{t+s} + F_1^1\mathbf{v}_{t+s-1} + \ldots + F_1^s\mathbf{v}_t\right)$$

Define $Y_t \equiv (\mathbf{y}_{t+1},\ldots,\mathbf{y}_{t+h})'; V_t \equiv (\mathbf{v}_{t+1},\ldots,\mathbf{v}_{t+h})'; X_t$

Under the assumption that the DGP is a VAR(p), consider the system:

$$Y_t = X_t \Psi + V_t \Phi$$

with

$$\Psi = \begin{bmatrix} F_1^1 & \ldots & F_1^h \\ \vdots & \vdots & \vdots \\ F_p^1 & \ldots & F_p^h \end{bmatrix}; \Phi = \begin{bmatrix} I_n & \ldots & F_1^h \\ \vdots & \vdots & \vdots \\ 0 & \cdots & I_n \end{bmatrix}$$

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Further define:

$$E(\mathbf{v}_t\mathbf{v}_t') = \Omega_v, \text{ then } E(V_tV_t') = \Phi\left(I_h \otimes \Omega_v\right)\Phi' \equiv \Sigma$$

then

$$vec(\hat{\Psi}) = \left[(I \otimes X)'\Sigma^{-1}(I \otimes X)\right]^{-1}(I \otimes X)'\Sigma^{-1}vec(Y)$$

The usual impulse responses and their correct standard errors are rows 1-n and columns 1-nh of $\hat{\Psi}$

What does all this math mean?

- It establishes the equivalence between the IR coefficients from a VAR and from local projections

- It shows how to impose the VAR constraints to jointly estimate the local projections by block-GLS

- The GLS estimates deliver efficient analytic inference for IR coefficients through time and across responses.

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Other remarks

- Monte Carlos show little loss of efficiency in estimating *univariate* local projections and using HAC robust standard errors (such as Newey-West)
- Denote $\hat{\Sigma}_L$ the HAC, VCV matrix of $\hat{B}_1^s$ in the linear projection, then a 95% CI is $1.96 \pm \left(\mathbf{d}_i'\hat{\Sigma}_L\mathbf{d}_i\right)$
- Also, could use the *s-1* stage residuals as regressors in the *s* stage projection
- Linear projections are a type of general misspecification test!

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The Constrains of Linearity

- *Symmetry*
- *Shape invariance*
- *History independence*
- *Multidimensionality*

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Flexible Local Projections

Generally,

$$\mathbf{y}_t = \Phi(\mathbf{v}_t, \mathbf{v}_{t-1}, \ldots)$$

A Taylor series approximation to Φ is the Volterra series expansion (the non-linear Wold):

$$\mathbf{y}_t = \sum_{i=0}^{\infty} \Phi_i \mathbf{v}_{t-i} + \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \Phi_{ij} \mathbf{v}_{t-i} \mathbf{v}_{t-j} + \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \sum_{k=0}^{\infty} \Phi_{ijk} \mathbf{v}_{t-i} \mathbf{v}_{t-j} \mathbf{v}_{t-k} + \ldots$$

It is natural to use polynomials for the local projections as well, for example:

$$\mathbf{y}_{t+s} = \alpha^{s} + B_1^{s+1}\mathbf{y}_{t-1} + Q_1^{s+1}\mathbf{y}_{t-1}^{2} + C_1^{s+1}\mathbf{y}_{t-1}^{3} + B_2^{s+1}\mathbf{y}_{t-2} + \ldots + B_p^{s+1}\mathbf{y}_{t-p} + \mathbf{u}_{t+s}^{s}$$

Hence

$$IR(t,s,\mathbf{d}_i) = \left\{ \begin{array}{l} \hat{B}_1^{s}\mathbf{d}_i + \hat{Q}_1^{s}\left(2\mathbf{y}_{t-1}\mathbf{d}_i + \mathbf{d}_i^{2}\right) + \\ \hat{C}_1^{s}\left(3\mathbf{y}_{t-1}^{2}\mathbf{d}_i + 3\mathbf{y}_{t-1}\mathbf{d}_i^{2} + \mathbf{d}_i^{3}\right) \end{array} \right\}$$

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Remarks

- IRs no longer symmetric nor shape invariant

- IRs no longer history independent – they depend on $\mathbf{y}_{t-1}$. Evaluate at $\mathbf{y}_{t-1} = \bar{\mathbf{y}}$ to evaluate at linearity.

- Define $\lambda_i \equiv (\mathbf{d}_i \;\; 2\mathbf{y}_{t-1}\mathbf{d}_i + \mathbf{d}_i^2 \;\; 3\mathbf{y}_{t-1}^2\mathbf{d}_i + 3\mathbf{y}_{t-1}\mathbf{d}_i^2 + \mathbf{d}_i^3)'$ then a 95% CI is approximately

$$1.96 \pm \left(\lambda_i' \hat{\Sigma}_C \lambda_i\right)$$

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Flexible projections in general

Since what matters are the terms associated with $\mathbf{y}_{t-1}$ (but not the remaining lags), then

$$\mathbf{y}_{t+s} = m^{s}(\mathbf{y}_{t-1}; X_{t-1}) + \mathbf{u}_{t+s}^{s}$$

Thus, any parametric, semi-parametric and non-parametric conditional mean estimator will do.

Notice this can be done *univariately*.

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Monte Carlo Simulations

Two experiments:

1. Robustness to lag-length misspecification, consistency and efficiency: Christiano, Eichenbaum and Evans (1996)

2. Robustness to nonlinearities: Jordà and Salyer (2003)

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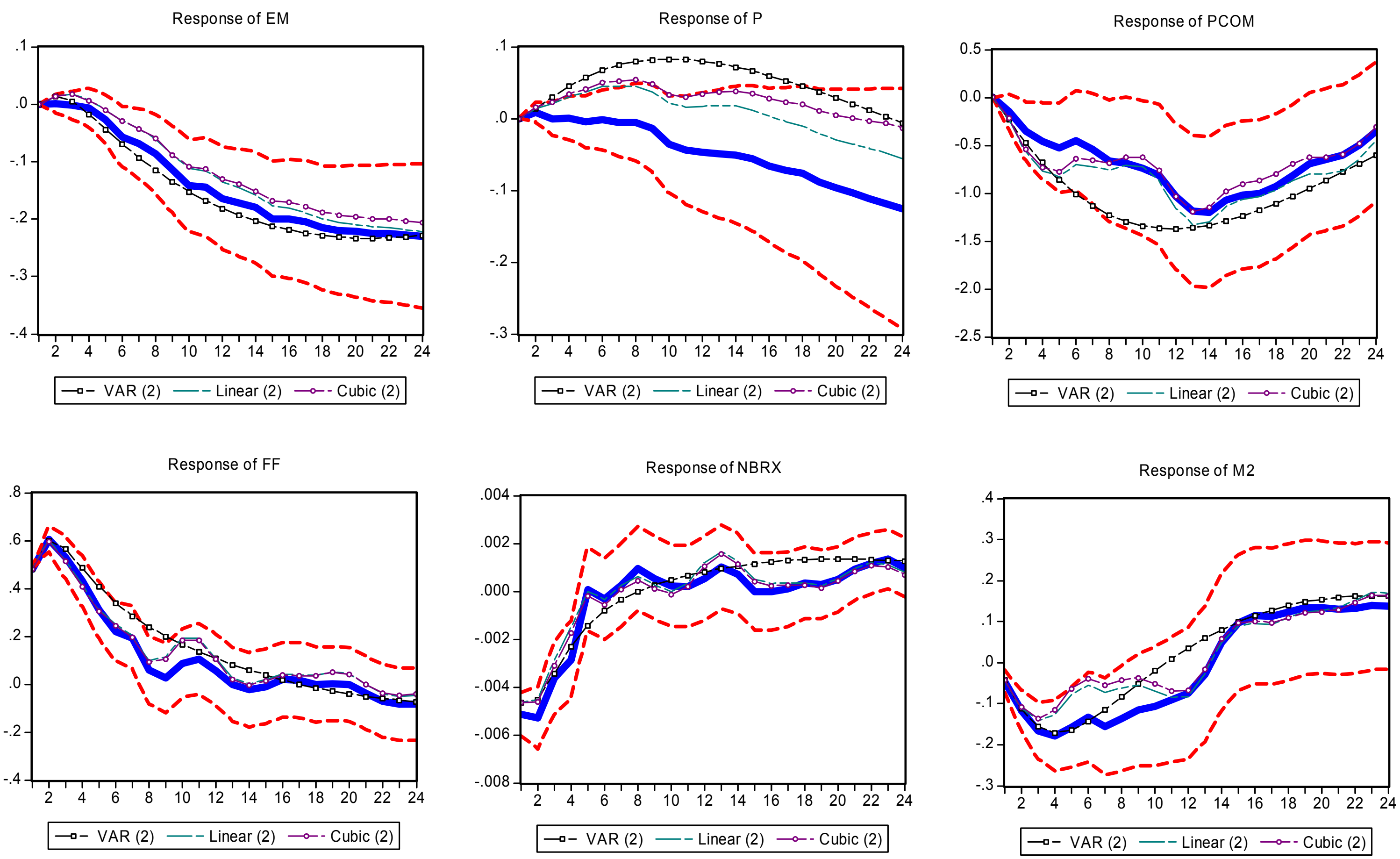
Robustness, Consistency and Efficiency

- Estimate the CEE VAR with 12 lags. Save the coefficients to produce the Monte Carlos

- Three experiments:

1. Fit a VAR(2) and local-linear and –cubic projections: Robustness
2. Fit local-linear and –cubic projections with 12 lags: Consistency
3. Check standard errors from 2: Efficiency

Experiment 1



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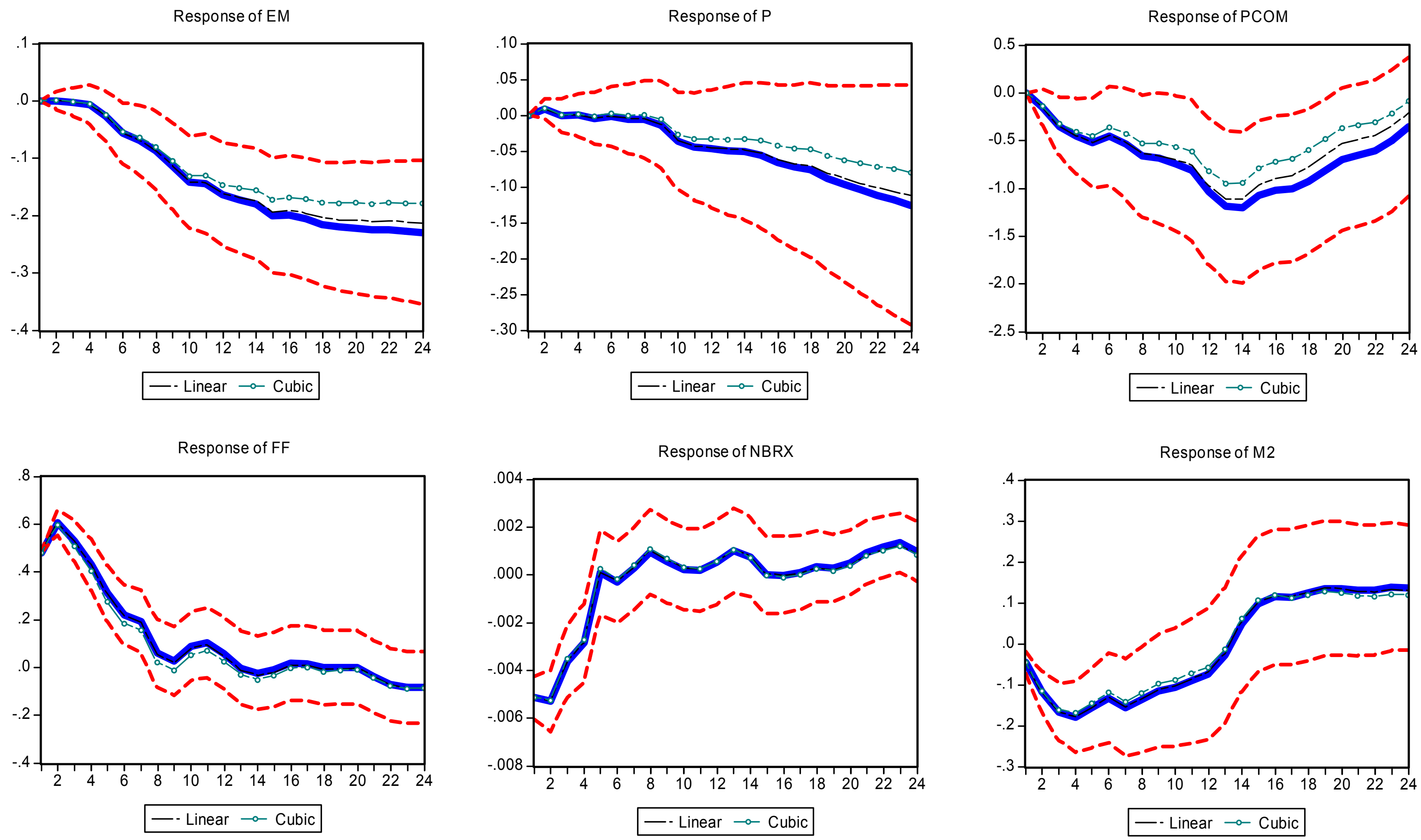
Experiment 2



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Experiment 3

	EM			P			PCOM		
s	True-MC	Newey-West (Linear)	Newey-West (Cubic)	True-MC	Newey-West (Linear)	Newey-West (Cubic)	True-MC	Newey-West (Linear)	Newey-West (Cubic)
1	0.000	0.007	0.008	0.0000	0.007	0.007	0.000	0.089	0.096
…	…	…	…	…	…	…	…	…	…
12	0.046	0.044	0.048	0.042	0.042	0.045	0.390	0.380	0.416
…	…	…	…	…	…	…	…	…	…
24	0.064	0.063	0.068	0.086	0.081	0.086	0.371	0.431	0.484
	FF			**NBRX**			**ΔM2**		
1	0.000	0.022	0.024	0.0005	0.0005	0.0005	0.014	0.012	0.014
…	…	…	…	…	…	…	…	…	…
12	0.077	0.075	0.083	0.0009	0.0009	0.0010	0.082	0.077	0.085
…	…	…	…	…	…	…	…	…	…
24	0.077	0.087	0.095	0.0006	0.0009	0.0010	0.078	0.088	0.096

Nonlinearities

Simulate:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = A \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{bmatrix} + Bh_{1t} + \begin{bmatrix} \sqrt{h_{1t}}\varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}; \; \varepsilon_t \sim N(0, I)$$

$$h_{1t} = 0.5 + 0.3u_{t-1}^2 + 0.5h_{1,t-1}; \; u_t = \sqrt{h_{1t}}\varepsilon_{1t}$$

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Compare:

- A VAR(1)
- Local-linear projections with one lag
- Local-cubic projections with one lag
- A Bayesian, time-varying parameter/volatility VAR à la Cogley and Sargent (2001,2003) - TVPVAR

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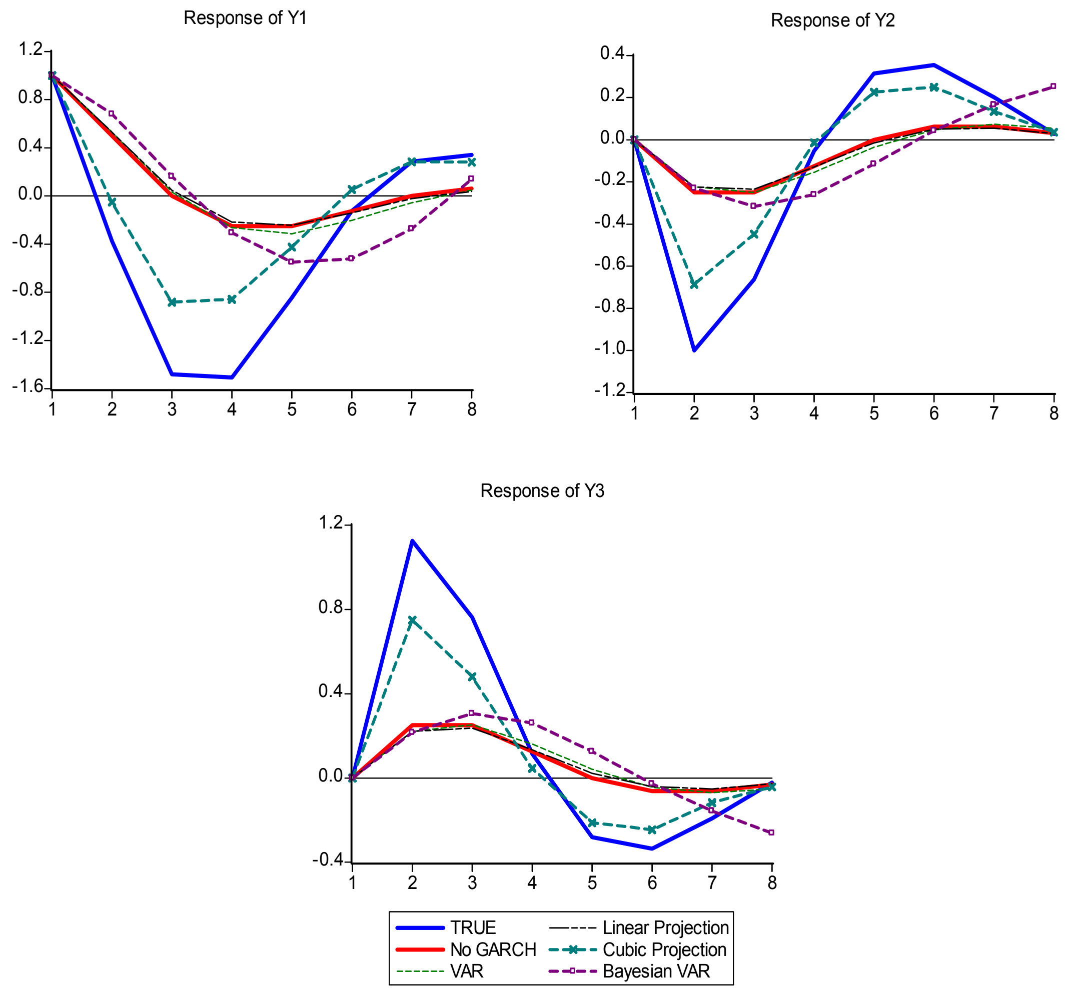
The Monte-Carlo design for the TVPVAR:

- 100 obs. used to calibrate the prior
- Gibbs-sampler initialized with 2,000 draws
- Additional 5,000 draws to ensure convergence
- Select the quintiles of the distribution of the residuals of the first equation to identify 5 dates.
- Given the local histories of the 5 dates, calculate 100 Monte Carlo forecasts 1-8 steps ahead
- Obtain 5 impulse responses as the average of each 100 replications.
- Time of run: 9 days, 2 hours, 17 min. on a Sun Sunfire with 8, 900 Mhz processors and 16GB RAM

Nonlinearities



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A New-Keynesian-Type Model of the Economy

Rudebusch and Svensson (1999) model:

- percentage gap between real GDP and potential GDP (from CBO)
- quarterly inflation in the GDP, chain-weighted price index in percent, annual rate
- quarterly average of the federal funds rate in percent at annual rate

Asymmetries and Thresholds

Does the effectiveness of monetary policy depend on:

- The stage of the business cycle
- Whether inflation is high or low
- Whether interest rates are close to the zero bound or not.

I test for threshold effects with Hansen's (2000) test.

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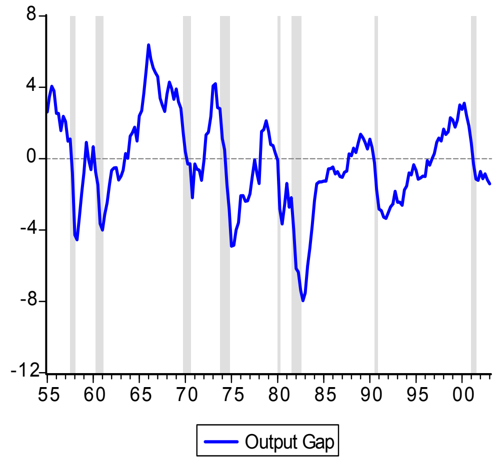
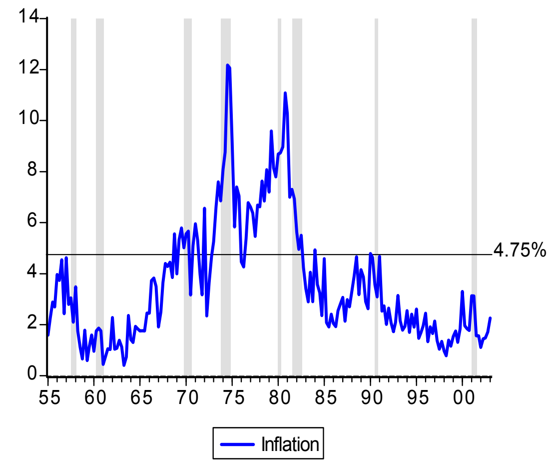
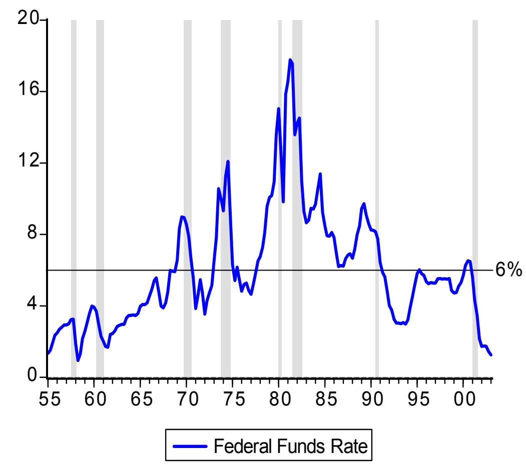
The Data







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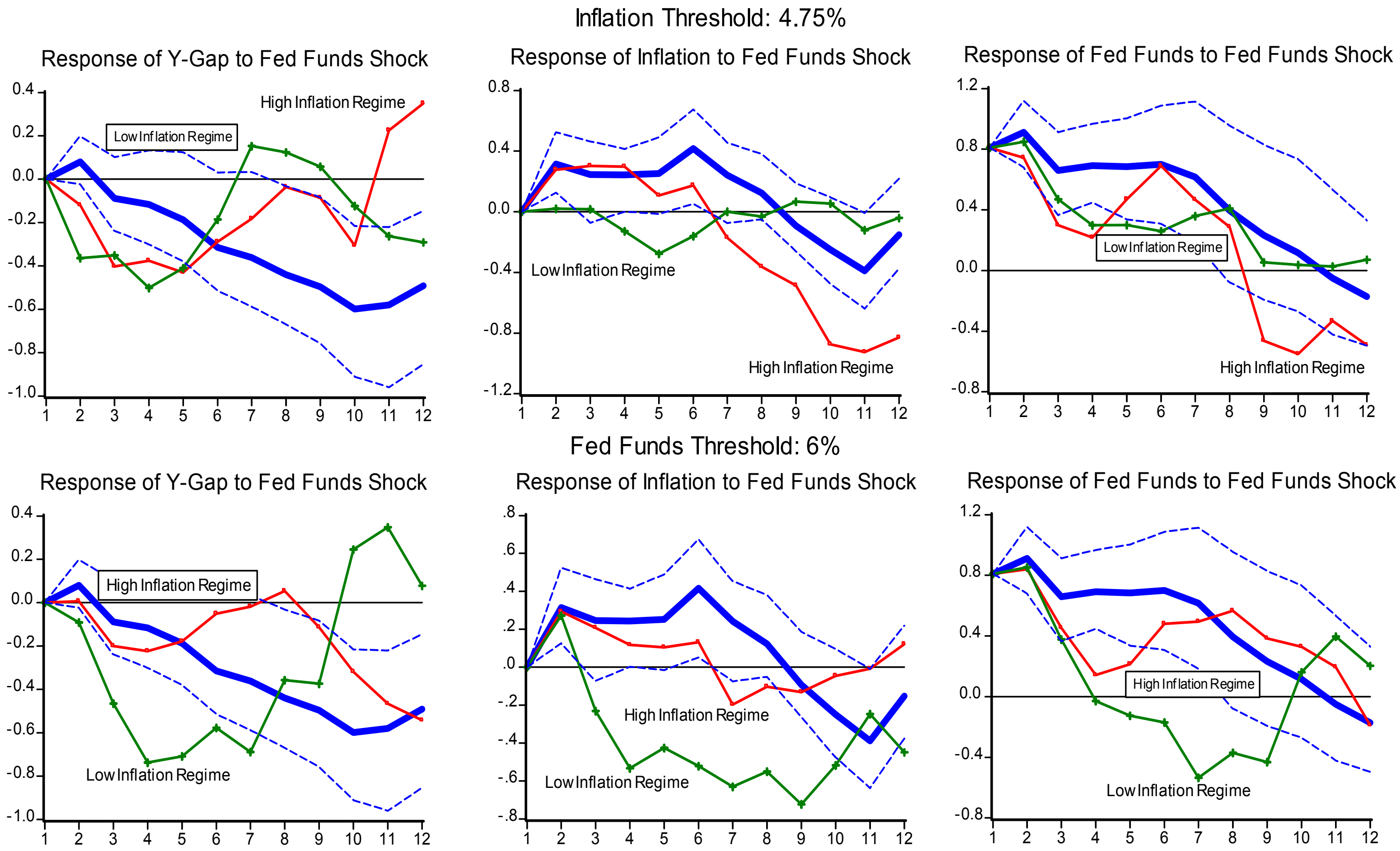
Thresholds in the New-Keynesian Model



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Future Research

- Estimation of deep parameters in rational expectations models by efficient matching of MA coefficients.
- Applications to Panel Data and treatment effects.
- Efficiency improvements: using stage *s-1* residuals as regressors in stage *s* projections
- Applications to non-Gaussian data

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An Efficient Moment-Matching Estimator for RE models

Example (Fuhrer and Olivei, 2004):

$$z_t = \mu z_{t-1} + (\beta - \mu)E_t z_{t+1} + \gamma E_t x_t + \varepsilon_t$$

- z and x are the structural and driving processes
- ε is the stochastic shock
- For IS curve set z the output gap x the interest rate
- For AS curve set z inflation, x the output gap

The usual solution approach

Assume: $$x_t = \alpha x_{t-1} + u_t$$

Conjecture: $$z_t = bz_{t-1} + cx_{t-1} + d\varepsilon_{t-1}$$

Undetermined Coeffs.: $$d = 1$$

$$c = \frac{\gamma\alpha}{1-(\beta-\mu)(b+\alpha)}$$

$$-(\beta-\mu)b^2 + b - \mu = 0$$

An alternative

Assume: $$x_t = \sum_{i=0}^{\infty} \rho_i \varepsilon_{t-i} + \sum_{i=0}^{\infty} \theta_i u_{t-i}$$

Conjecture: $$z_t = \sum_{i=0}^{\infty} a_i \varepsilon_{t-i} + \sum_{i=0}^{\infty} b_i u_{t-i}$$

U.C.:

$$a_0 = (\beta - \gamma)a_1 + 1; \quad b_0 = (\beta - \mu)b_1$$

...

$$a_s = \mu a_{s-1} + (\beta - \mu)a_{s+1} + \gamma\rho_s$$
$$b_s = \mu b_{s-1} + (\beta - \mu)b_{s+1} + \gamma\theta_s$$

Define:

$$Y = \left(a_0 - 1, a_1, \ldots, a_h, b_0, \ldots, b_h\right)'$$

$$X_1 = \left(0, a_0, \ldots, a_{h-1}, 0, b_0, \ldots, b_{h-1}\right)'$$

$$X_2 = \left(a_1, \ldots, a_{h+1}, b_1, \ldots, b_{h+1}\right)'$$

$$X_3 = \left(0, \rho_1, \ldots, \rho_{h-1}, 0, \theta_{1,} \ldots, \theta_{h-1}\right)'$$

Notice that the reduced form coefficients and the structural coefficients are related by:

$$Y - \left(X_1\mu + X_2(\beta - \mu) + X_3\gamma\right) = \omega$$

Let the covariance matrix of the impulse responses be:

$$VAR(Y) = \Omega_Y$$

Then, an efficient estimator for $\beta, \mu,$ and γ is:

$$\min \omega' \Omega_Y \omega$$

This also gives a natural metric for model fit even for models that would be rejected by FIML.

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Identification with Long-Run Restrictions

Blanchard and Quah

Let $\mathbf{y}_t = A(L)\varepsilon_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ with $E\varepsilon'\varepsilon = I$.

B-Q impose zero coefficient restrictions on $A(1)$.

Using the reduced form $\mathbf{y}_t = C(L)\mathbf{u}_t = \sum_{i=1}^{\infty} C_i \mathbf{u}_{t-i}$ and $E\mathbf{u}'\mathbf{u} = \Sigma$ we can recover the matrix D.

How to estimate an approximation to $C(1)$ with linear projections?

Option 1: Add the estimated linear projection coefficients,

$$\hat{C}(1) \cong \sum_{s=1}^{h} B_1^s$$

for h "large."

Option 2:

Define: $\mathbf{Y}_{t+h} = \sum_{s=0}^{h} \mathbf{y}_{t+s}$.

Then

$$\mathbf{Y}_{t+h} = G_1^h \mathbf{y}_{t-1} + \ldots + G_p^h \mathbf{y}_{t-p} + \mathbf{u}_{t+h}^h$$

from which $\hat{G}_1^h$ is an estimate of $\sum_{i=1}^{h} C_i$. Choose h "large."

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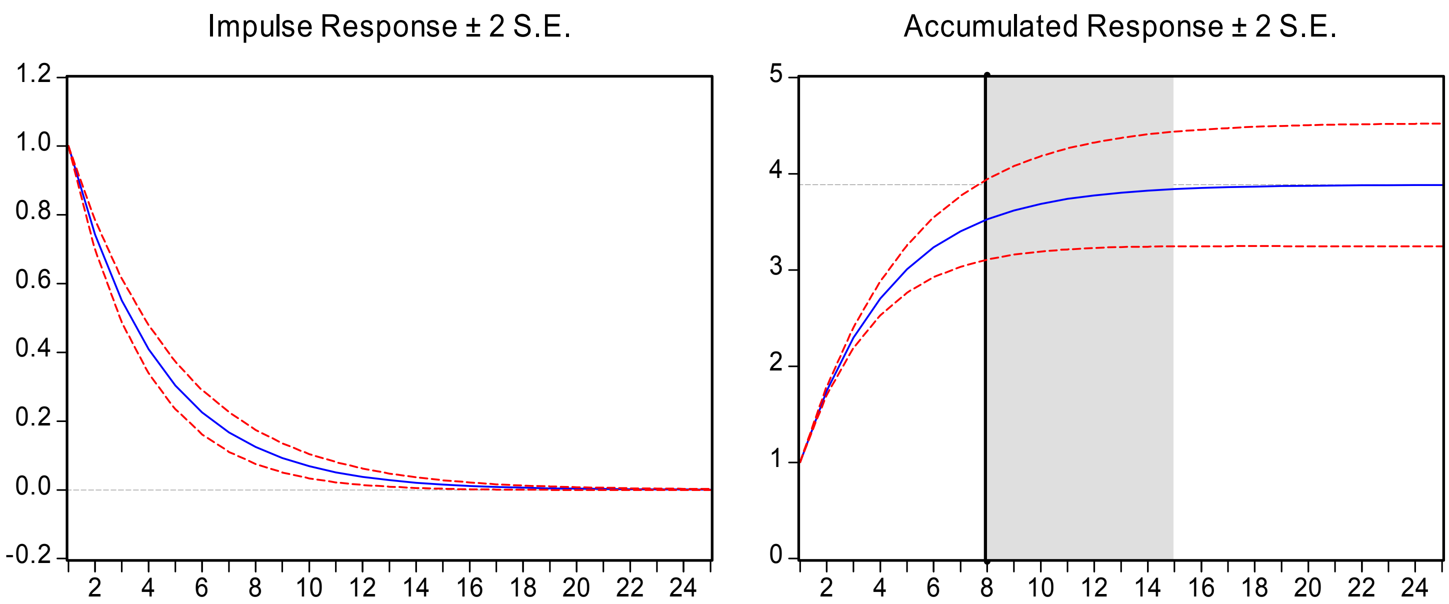
Example:

$$y_t = 0.75 y_{t-1} + \varepsilon_t$$



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A Panel Data Application

Example: Measuring the dynamic effect of a treatment.

"*European Union Regional Policy and its Effects on Regional Growth and Labor Markets*" by Florence Bouvet (Econ Dept, Graduate Student)

How does a poor region's growth and unemployment respond to fund allocation from the European Regional Development Fund?

Data: panel of 111 regions from 8 EU countries, 1975-1999.

Instruments: political alignment between the regions, the national government and the EU Comission.

Estimation: TSLS with fixed country effects and fixed time effects.

Two examples: Response of Growth and Unemployment

Table 5: Explaining regional growth disparities

	OLS	OLS	2SLS	2SLS
Initial income per capita	-1.663***	-1.52***	-1.65*	-1.21*
	(0.26)	(0.27)	(0.9)	(0.7)
ERDF per capita	-0.063***	-0.032**	-0.173	-0.094
	(0.01)	(0.01)	(0.12)	(0.08)
ERDF *poor	0.084***			-0.109
	(0.03)			(0.10)
Agriculture	-0.038***	-0.033***	0.024	0.01
	(0.01)	(0.01)	(0.018)	(0.016)
Capital stock per worker	0.034	0.031	-0.051	-0.054
	(0.03)	(0.04)	(0.05)	(0.04)
Adjusted R-square	0.185	0.183	0.188	0.204
Instruments			political alignment	political alignment
Partial R-square of the 1st stage of the IV estimation			0.232	0.272
Number of regions	98	98	75	75
Number of observations	2450	2450	1408	1408

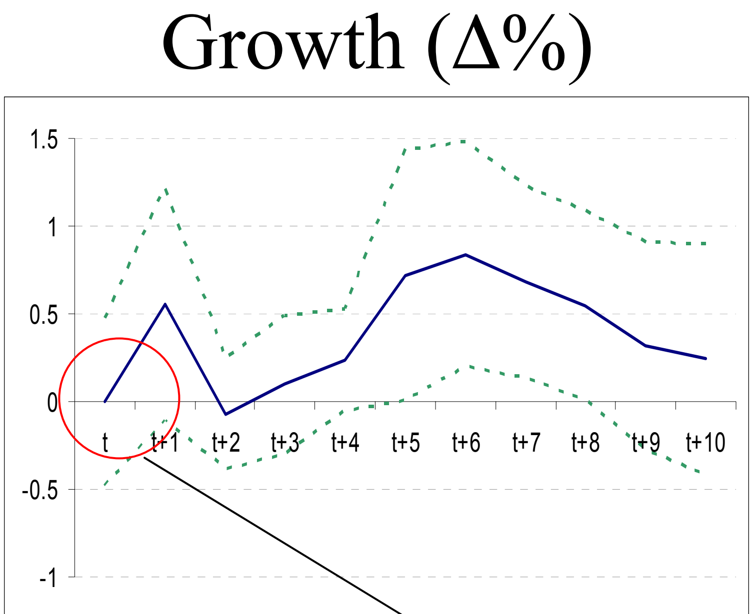
$$Growth_{i,t} = \beta_o + \beta_1 GVA_{i,1975} + \beta_2 ERDF_{i,t-1} + \beta_3 Agriculture_{i,t-1} + \beta_4 Capital_{i,t-1} + D_c + D_t + \varepsilon_{i,t}$$

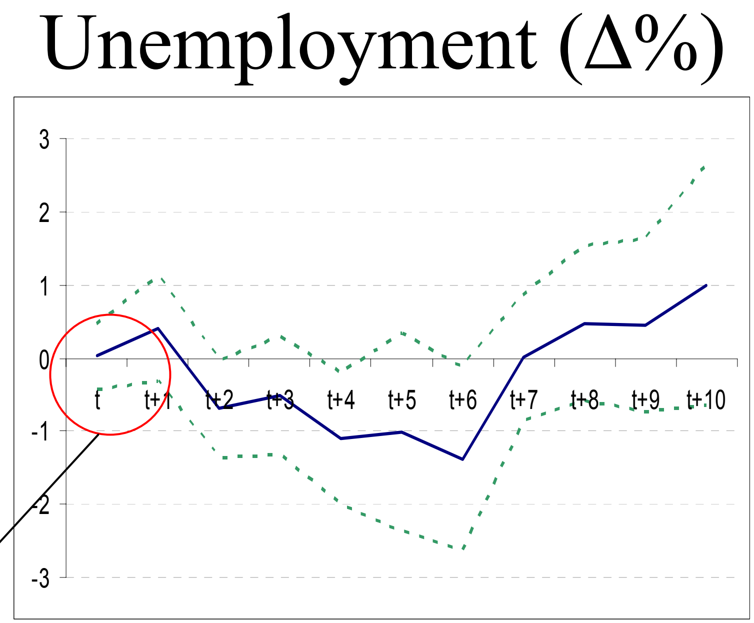
Table 9: Explaining regional unemployment disparities

	OLS	OLS	2SLS	2SLS	OLS	2SLS
Lagged unemployment					0.952***	1.00***
					(0.01)	(0.02)
Growth rate of income per capita	0.151***	0.165***	0.019	-0.004	-0.025**	-0.019*
	(0.04)	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
ERDF per capita	0.242***	0.324***	1.25***	0.173	0.300***	0.03
	(0.06)	(0.06)	(0.335)	(0.33)	(0.008)	(0.06)
ERDF*poor	0.327***		0.249		-0.02*	-0.384***
	(0.11)		(0.37)		(0.01)	(0.14)
Agriculture	-0.013	-0.004	-0.118	0.222	0.012***	0.056***
	(0.04)	(0.04)	(0.12)	(0.15)	(0.005)	(0.02)
Capital stock per worker	-0.253	-0.27	-0.157	-0.269	-0.032	-0.049
	(0.25)	(0.25)	(0.28)	(0.31)	(0.03)	(0.03)
Adjusted R-square	0.540	0.529	0.157	0.532	0.935	0.929
Instruments			political alignment	political alignment		political alignment
R-square of the 1st stage of the IV estimation			0.241	0.180		0.262
number of regions	105	105	77	77	105	77
number of observations	2287	2287	1349	1349	2240	1343

$$Unemployment_{i,t} = \beta_o + \beta_1 Growth_{i,t-1} + \beta_2 ERDF_{i,t-1} + \beta_3 Agriculture_{i,t-1} + \beta_4 Capital_{i,t-1} + D_c + D_t + \varepsilon_{i,t}$$

However,





These are the same coefficients as in the Tables!

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Conclusions

- If the IR is the object of interest, concentrate on fitting the long-horizon forecasts rather than fitting the data one-period ahead.
- Projections can be estimated univariately – simplifies IR estimation and inference for panel/longitudinal data and non-Gaussian data.
- Consider graph analysis to resolve contemporaneous causality (Demiralp and Hoover)