DSGE models: problems and some personal solutions

Fabio Canova

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Outline of the talk

- Identification problems.
- Singularity problems.
- External information problems.
- Data mismatch problems.
- Model evaluation problems.

References

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All available at http://www.eui.eu/Personal/Canova/

What are DSGE models?

$$E_t[A_\theta x_{t+1} + B_\theta x_t + C_\theta x_{t-1} + D_\theta z_{t+1} + F_\theta z_t] = 0 \quad (1)$$

$$z_{t+1} - G_\theta z_t - e_t = 0 \quad (2)$$

Their stationary (log-linearized) rational expectation solution is:

$$x_t = K_\theta + W_\theta z_{t-1} + J_\theta x_{t-1} + R_\theta e_t \quad (3)$$

$$z_t = G_\theta z_{t-1} + e_t \quad (4)$$

where $K_\theta, W_\theta, J_\theta, R_\theta$ are functions of $A_\theta, B_\theta,$ $C_\theta, D_\theta, F_\theta$ and θ are the structural parameters.

Benchmark in academics for:

- Understanding generation and propagation of business cycles.

- Conduct policy analyses.

Popular in central banks/policy circles because:

- Give a coherent story with all general equilibrium interactions.

- Give sharp and easy to communicate optimal policy actions.

- Can use them to forecast (OK when compared to time series models).

- Same language and same tools of academics - no misunderstandings.

Big drive to use Bayesian methods. Why?

- Existence of specialized software (Dynare) makes estimation easy.

- Can incorporate external information in the form of a prior - sophisticated interval calibration.

- Classical estimates make sense only if the model is (asymptotically) the DGP of the data up to a set of serially correlated errors. Posterior estimates valid even when the model is not the DGP; and in small samples.

- Estimates make (economic) sense (not always the case with classical methods).

General problems

- The likelihood of a DSGE is generally ill-behaved.

- Severe population identification difficulties.

- Misspecification.

- Fundamental mismatch about the nature of the models and the data.

- General singularity issues.

1. Identification issues

- Crucial DSGE parameters face identification problems.
- Problems are compounded in large scale models.
- Standard fixup are problematic.
- Bayesian methods are a mixed blessing.

Where could identification problems be?

• The **solution mapping**, linking the θ to the (reduced form) coefficients of the decision rule (K_θ, W_θ, etc.) Additional problem: numerical solution.

• The **objective function mapping**, linking the solution to the population objective function (likelihood or posterior) - multiple peaks, flat areas.

• The **data mapping**, linking the population to the sample objective functions - small samples, error in variables, omitted variables.

Example 1: Observational equivalence, under-identification and weak identification

$$y_t = k_1 + a_1 E_t y_{t+1} + a_2(i_t - E_t \pi_{t+1}) + e_{1t} \quad (5)$$

$$\pi_t = k_2 + a_3 E_t \pi_{t+1} + a_4 y_t + e_{2t} \quad (6)$$

$$i_t = k_3 + a_5 E_t \pi_{t+1} + e_{3t} \quad (7)$$

where y_t is the output gap, π_t the inflation rate, i_t the nominal interest rate, e_{1t}, e_{2t}, e_{3t} iid contemporaneously uncorrelated shocks and k_1, k_2, k_3 are constants. The solution is:

$$\begin{bmatrix} y_t \\ \pi_t \\ i_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} 1 & 0 & a_2 \\ a_4 & 1 & a_2 a_4 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \equiv \mu_\theta + P_\theta e_t \quad (8)$$

where $\mu(\theta)$ function of k_i, a_i.

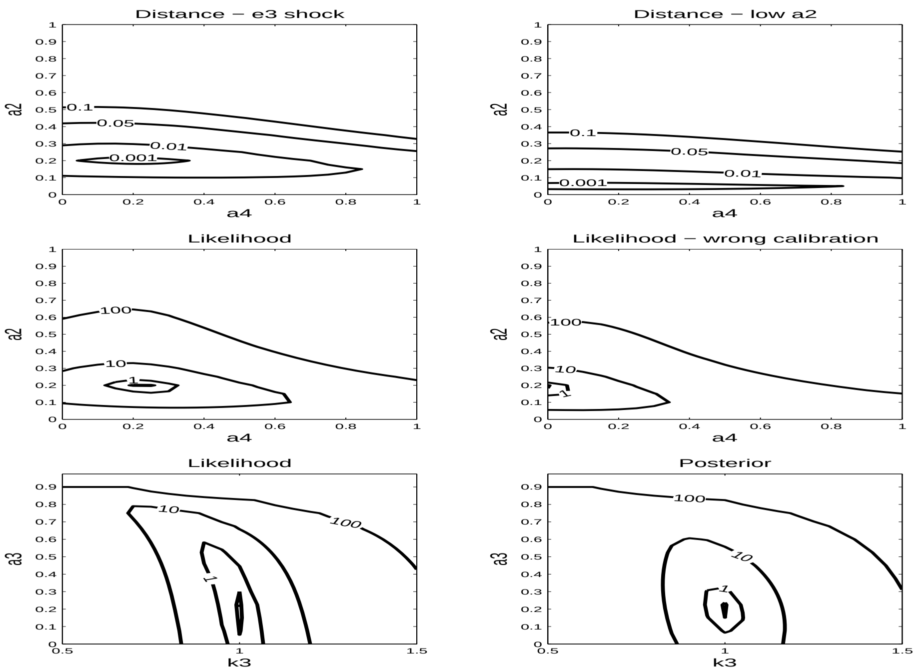
- a_1, a_3, a_5 disappear from the dynamics.

- Observational equivalence: can't study determinate vs. indeterminate solutions; Sticky vs. non-sticky information.

- Different shocks identify different parameters.

- ML and distance function (based on impulse responses) have different identification properties. Steady state information matters!

Example 2: RBC model: Distortions



Distance function, Likelihood and Posterior.

- Identification is local (depends on true parameter values, if they exist).

- Calibrating difficult parameters may lead to gross mistakes.

- Prior can cover up identification problems (convexify the likelihood).

Example 3: Standard NK model with frictions: wrong inference

	ζ_p	γ_p	ζ_w	γ_w
Case 1	0.887	0.862	0.620	0.221
max	0.979	0.910	0.884	0.980
median	0.845	0.515	0.641	0.657
min	0.034	0.015	0.028	0.009
Case 5	0.887	0.862	0.620	0.221
max	0.989	0.989	0.986	0.987
median	0.873	0.406	0.906	0.563
min	0.046	0.001	0.122	0.008

Population intervals producing objective functions in the 0.01 contour.

- Wrong inference (confuse price and wage indexation).

- Wrong policy advise.

What can one do to solve problems?

- Always use all possible information (add steady states or the covariance matrix of the shocks information). Limited information procedures likely to have worse identification properties.

- Partial identification problems (ridges) difficult to deal with. Need to reparametrize the model.

- Add sufficient internal dynamics (see Sargent 1978).

2. Singularity issues

- DSGE models typically singular. Does it matter which variables are used to estimate the parameters? Yes.

i) Omitting relevant variables may lead to distortions in parameter estimates.

ii) Adding variables may improve the fit, but also increase standard errors if added variables are irrelevant.

iii) Different variables may identify different parameters (e.g. with aggregate consumption data and no data on who own financial assets may be very difficult to get estimate the share of rule-of-thumb consumers).

Recall solution of example 1:

$$\begin{bmatrix} y_t \\ \pi_t \\ i_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & a_2 \\ a_4 & 1 & a_2 a_4 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} + \mu_\theta$$

iv) Likelihood function may change shape depending on the variables used. Multimodality may be present if important variables are omitted (e.g. if y_t is excluded in above example).

- Levin et al. (2005, NBER macro annual): habit in consumption is 0.30; Fernandez Villaverde and Rubio Ramirez (2008, NBER macro annual): habit in consumption is 0.88. Same model and same sample. But use different data to estimate the model!

Guerron Quintana (2010); use Smets and Wouters model and different combinations of observable variables.

Parameter	Wage stickiness	Price Stickiness	Slope Phillips
Data	Median (90%)	Median (90%)	Median (90%)
Basic	0.62 (0.54,0.69)	0.82 (0.80, 0.85)	0.94 (0.64,1.44)
Without C	0.80 (0.73,0.85)	0.97 (0.96, 0.98)	2.70 (1.93,3.78)
Without Y	0.34 (0.28,0.53)	0.85 (0.84, 0.87)	6.22 (5.05,7.44)
Without C,W	0.57 (0.46,0.68)	0.71 (0.63, 0.78)	2.91 (1.73,4.49)
Without R	0.73 (0.67,0.78)	0.81 (0.77, 0.84)	0.74 (0.53,1.03)

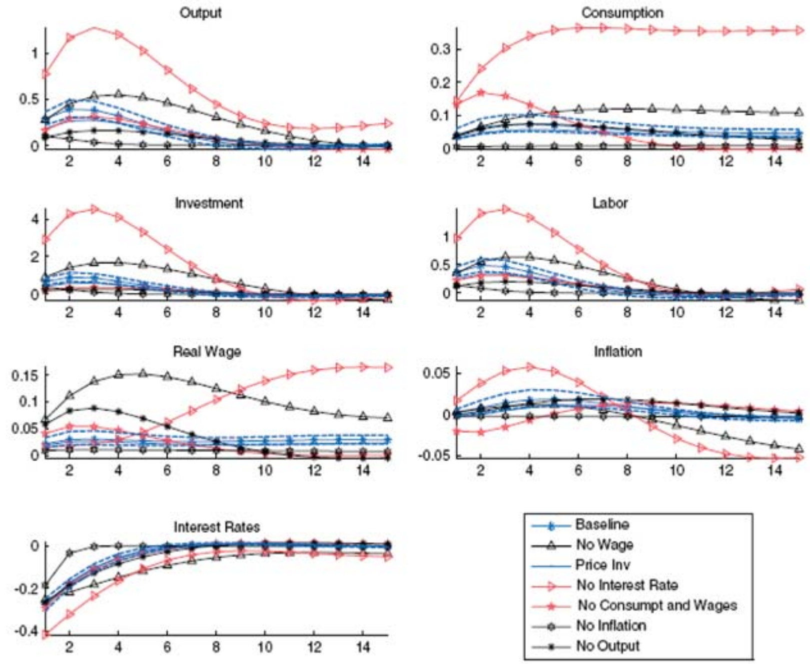


Figure 1. Responses to an expansionary monetary shock. This figure is available in color online at www.interscience.wiley.com/journal/jae

Solutions:

- Solve out variables from the FOC before you compute the solution. Which variables do we solve out? Problem: solution is a restricted VARMA - not a VAR.

- Add measurement errors to complete probability space. How many? Where? Need to restrict time series properties of measurement error (see Altug,1989, Ireland, 2004).

- Invent structural shocks. Nuisance parameter problem!

Canova, Ferroni and Matthes (2013):

- Use formal criteria to select variables to be used in estimation

1) Choose vector that maximize the identifiability of relevant parameters. Use Komunjer and Ng (2011) tools. Compare the curvature of the convoluted likelihood in the singular and the non-singular systems in the dimensions of interest to eliminate ties and explore weak identification issues

2) Choose vector that minimize the information loss going from the larger scale to the smaller scale system. Information loss is measured by

$$p_t^j(\theta, e^{t-1}, u_t) = \frac{\mathcal{L}(W_{jt}|\theta, e^{t-1}, u_t)}{\mathcal{L}(Z_t|\theta, e^{t-1}, u_t)} \tag{9}$$

where $\mathcal{L}(.|\theta, y_{1t})$ is the likelihood of Z_t, W_{jt} which are defined by

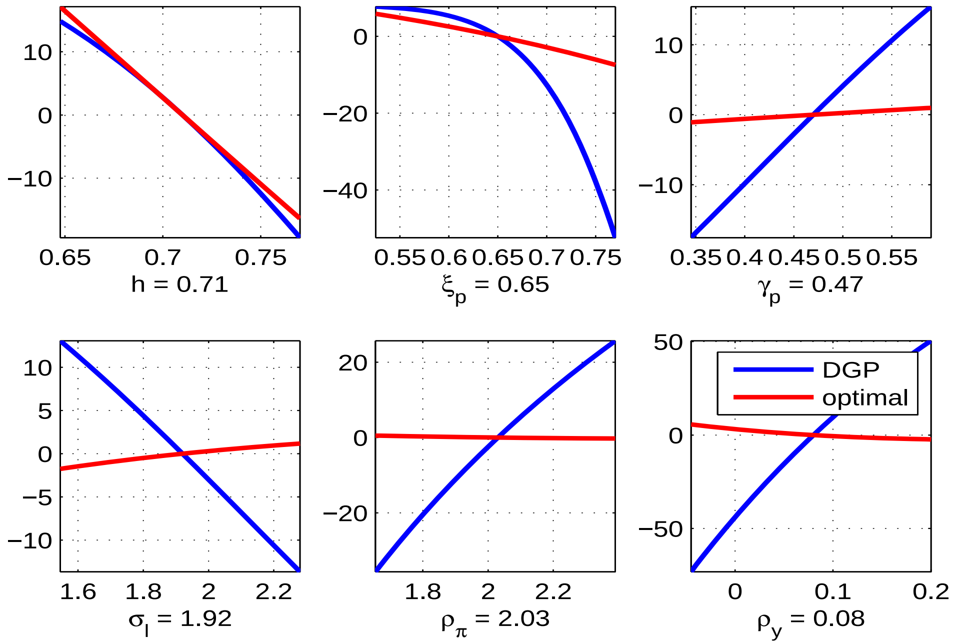
$$\begin{aligned} Z_t &= y_t + u_t && (10) \\ W_{jt} &= Sy_{jt} + u_t && (11) \end{aligned}$$

u_t is an iid convolution error, y_t the original set of variables and y_{jt} the j-th subset of the variables producing a non-singular system.

- Apply procedures to SW model driven with 4 shocks and 7 potential observables.

Vector	Unrest Rank(Δ)	SW Restr Rank(Δ)	SW Restr and Sixth Restr
y, c, i, w	186	188	ψ
y, c, i, π	185	188	ψ
y, c, r, h	185	188	ψ
y, i, w, r	185	188	ψ
c, i, w, h	185	188	ψ, σ_c, ρ_i
c, i, π, h	185	188	ψ
c, i, r, h	185	188	$\zeta_\omega, \zeta_p, i_\omega$
y, c, i, r	185	187	
...			
c, w, π, r	183	187	
c, w, π, h	183	187	
i, w, π, r	183	187	
w, π, r, h	183	187	
c, i, π, r	183	186	
Ideal	189	189	

Rank conditions for all combinations of variables in the unrestricted SW model (columns 2) and in the restricted SW model (column 3), where $\delta = 0.025$, $\varepsilon_p = \varepsilon_w = 10$, $\lambda_w = 1.5$ and $c/g = 0.18$. The fourth columns reports the extra parameter restriction needed to achieve identification; a blank space means that there are no parameters able to guarantee identification.



Likelihood curvature

Order	Basic Vector	Basic Relative Info	T=1500 Vector	T=1500 Relative info	$\Sigma_u = 0.01 * I$ Vector	$\Sigma_u = 0.01 * I$ Relative Info
1	(y, c, i, h)	1	(y, c, i, h)	1	(y, c, i, h)	1
2	(y, c, i, w)	0.89	(y, c, i, w)	0.87	(y, c, i, w)	0.86
3	(y, c, i, r)	0.52	(y, c, i, r)	0.51	(y, c, i, r)	0.51
4	(y, c, i, π)	0.5	(y, c, i, π)	0.5	(y, c, i, π)	0.5

Ranking based on the information statistic. The first two column present the results for the basic setup, the next six columns the results obtained altering some nuisance parameters. Relative information is the ratio of the $p(\theta)$ statistic relative to the best combination.

- How different are good and bad combinations?

- Simulate 200 data points from the model with four shocks and estimate structural parameters using

(1) Model A: 4 shocks and (y, c, i, w) as observables (best rank analysis).

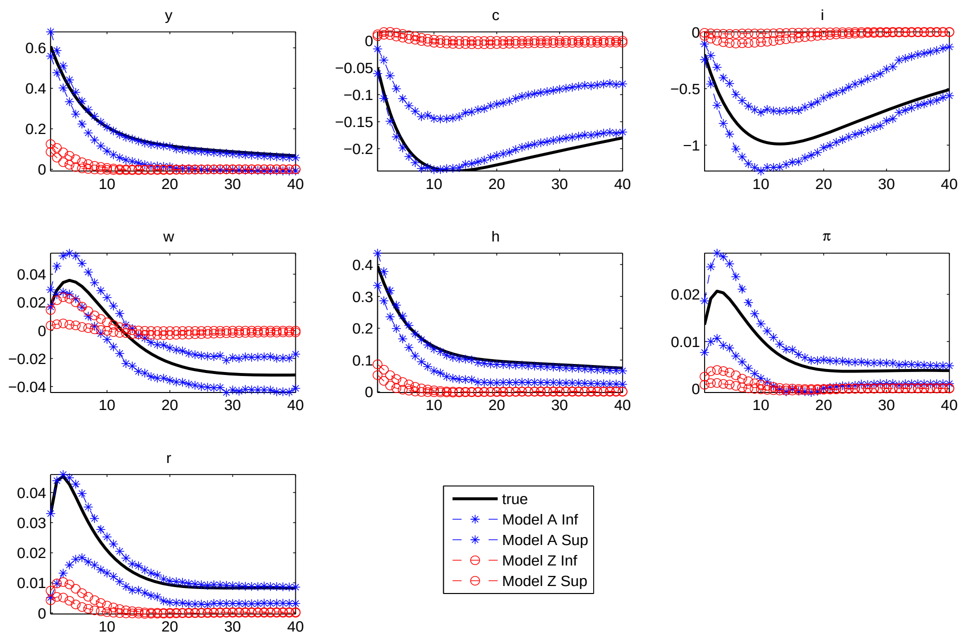
(2) Model B: 4 shocks and (y, c, i, w) as observables (best information analysis).

(3) Model Z: 4 shocks and (c, i, π, r) as observables(worst rank analysis).

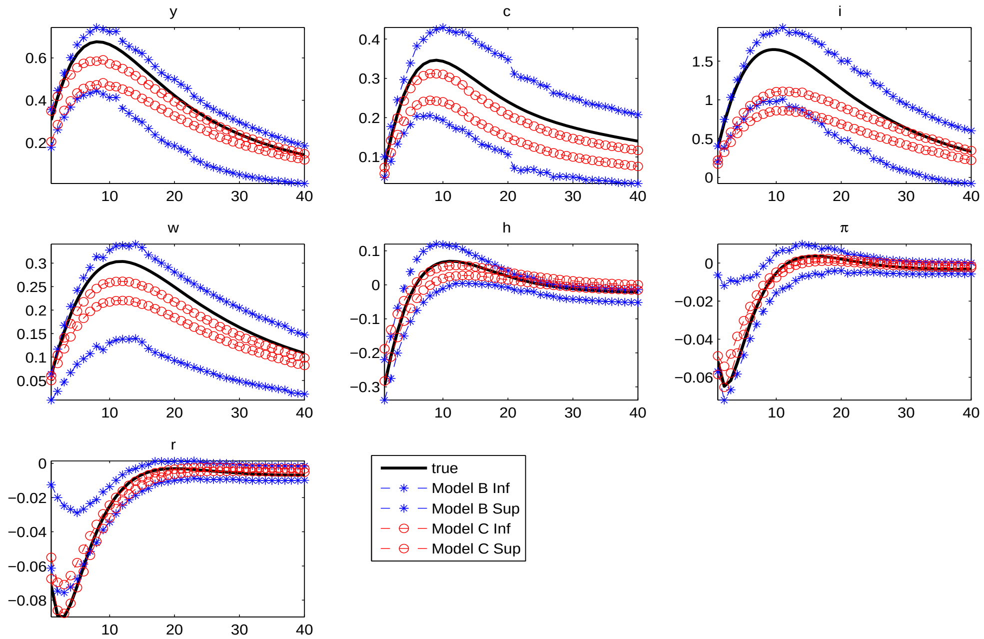
(4) Model C: 4 structural shocks, three measurement errors and $(y_t, c_t, i_t, w_t, \pi, r_t, h_t)$ as observables.

(5) Model D: 7 structural shocks (add price and wage markup and preference shocks) and $(y_t, c_t, i_t, w_t, \pi, r_t, h_t)$ as observables.

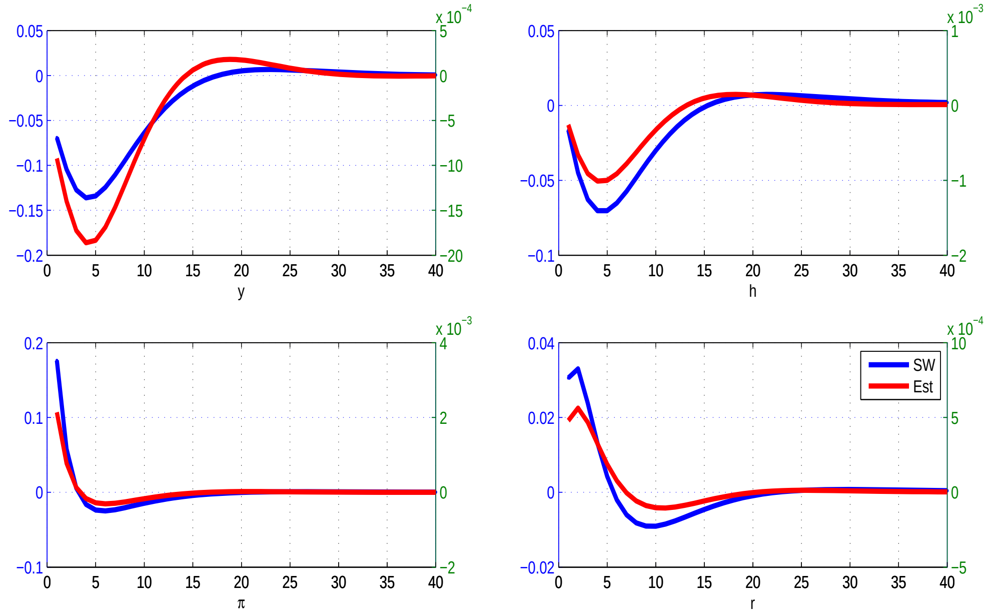
	True	Model A	Model B	Model Z	Model C	Model D
ρ_a	0.95	(0.920 , 0.975)	(0.905 , 0.966)	(0.946 , 0.958)	(0.951 , 0.952)	(0.939 , 0.943)*
ρ_g	0.97	(0.930 , 0.969)	(0.930 , 0.972)	(0.601 , 0.856)*	(0.970 , 0.971)	(0.970 , 0.972)
ρ_i	0.71	(0.621 , 0.743)	(0.616 , 0.788)	(0.733 , 0.844)*	(0.681 , 0.684)*	(0.655 , 0.669)*
ρ_{ga}	0.51	(0.303 , 0.668)	(0.323 , 0.684)	(0.010 ,0.237)*	(0.453 , 0.780)	(0.114 , 0.885)*
σ_n	1.92	(1.750 , 2.209)	(1.040 , 2.738)	(0.942 , 2.133)	(1.913 , 1.934)	(1.793 , 1.864)*
σ_c	1.39	(1.152 , 1.546)	(1.071 , 1.581)	(1.367 , 1.563)	(1.468 , 1.496)*	(1.417 , 1.444)*
h	0.71	(0.593 , 0.720)	(0.591 , 0.780)	(0.716 , 0.743)	(0.699 , 0.701)*	(0.732 , 0.746)*
ζ_ω	0.73	(0.402 , 0.756)	(0.242, 0.721)*	(0.211 ,0.656)*		(0.806 , 0.839)*
ζ_p	0.65	(0.313 , 0.617)*	(0.251 , 0.713)	(0.512 , 0.616)*	(0.317 , 0.322)*	(0.509 , 0.514)*
i_ω	0.59	(0.694 , 0.745)	(0.663 , 0.892)*	(0.532 ,0.732)	(0.728 , 0.729)*	(0.683 , 0.690)*
i_p	0.47	(0.571 , 0.680)*	(0.564 , 0.847)*	(0.613 , 0.768)*	(0.625 , 0.628)*	(0.606 , 0.611)*
ϕ_p	1.61	(1.523 , 1.810)	(1.495 , 1.850)	(1.371 , 1.894)	(1.624 , 1.631)*	(1.654 , 1.661)*
φ	0.26	(0.145 , 0.301)	(0.153 , 0.343)	(0.255 , 0.373)	(0.279 , 0.295)*	(0.281 , 0.306)*
ψ	5.48	(3.289 , 7.955)	(3.253 , 7.623)	(2.932 , 7.530)	(11.376 , 13.897)*	(4.332 , 5.371)*
α	0.2	(0.189 , 0.331)	(0.167 , 0.314)	(0.136 , 0.266)	(0.177 , 0.198)*	(0.174 , 0.199)*
ρ_π	2.03	(1.309 , 2.547)	(1.277 , 2.642)	(1.718 , 2.573)	(1.868 , 1.980)*	(2.119 , 2.188)*
ρ_y	0.08	(0.001 , 0.143)	(0.001 , 0.169)	(0.012 , 0.173)	(0.124 , 0.162)*	
ρ_R	0.87	(0.776 , 0.928)	(0.813 , 0.963)	(0.868 , 0.916)	(0.881 , 0.886)*	
$\rho_{\Delta y}$	0.22	(0.001 , 0.167)*	(0.010, 0.192)*	(0.130 ,0.215)*	(0.235 , 0.244)*	
σ_a	0.46	(0.261 , 0.575)	(0.382 , 0.460)	(0.420 ,0.677)	(0.357 , 0.422)*	(0.386 , 0.455)*
σ_g	0.61	(0.551 , 0.655)	(0.551 , 0.657)	(0.071 ,0.113)	(0.536 , 0.629)	(0.585 , 0.688)*
σ_i	0.6	(0.569 , 0.771)	(0.532 , 0.756)	(0.503 ,0.663)	(0.561 , 0.660)	(0.693 , 0.819)*
σ_r	0.25	(0.100 , 0.259)	(0.078 , 0.286)	(0.225 ,0.267)	(0.226 , 0.265)	(0.222 , 0.261)



Responses to a goverment spending shock



Responses to a technology shock



Responses to an price markup shock

3. Practical issues

• How do you estimate DSGE models when:

a) the variables are mismeasured relative to the model quantities?

b) there are multiple observables that correspond to model quantities?

c) have information about variables not included in the model.

For a): add measurement errors to model variables

Observables x_{1t}. Model based quantities $x_t^m(\theta) = Sx_t$, S is a selection matrix.

$$x_{1t} = x_t^m(\theta) + u_t \tag{12}$$

where u_t is iid measurement error.

- Estimate θ, σ_u^2 jointly.

- Use properties of σ_u^2 to assess misspecification.

- How do you measure hours? Use establishment survey series? Household survey series? Employment?

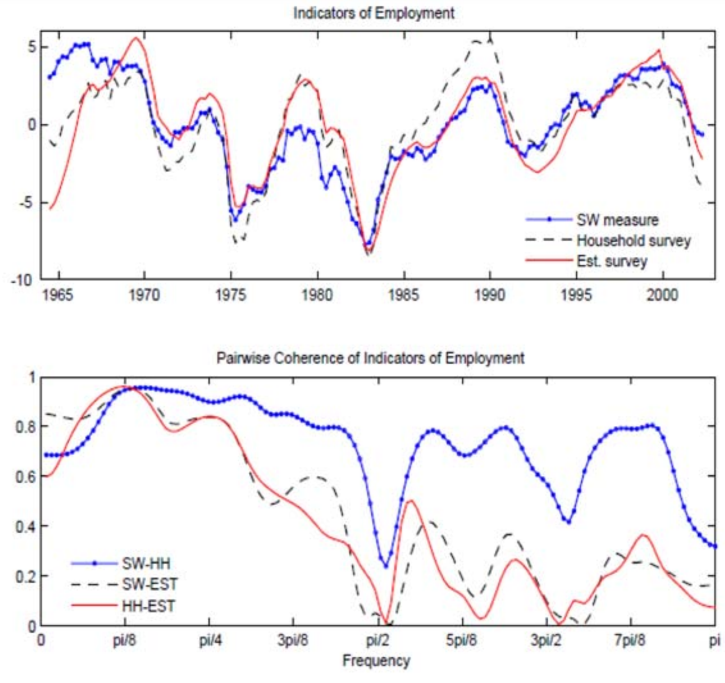


Figure 1: Indicators of employment (de-trended) and pairwise coherence.

• For b) Let x_{2t} be a $k \times 1$ vector of observables and $x_t^m(\theta)$ be of dimension $N \times 1$ where dim(N) $<$dim(k). Then:

$$x_{2t} = \Lambda_1 x_t(\theta)^m + u_{1t} \tag{13}$$

where the first row of Λ_1 is normalized to 1 and u_t is iid measurement error.

- Estimate $\theta, \sigma_u^2, \Lambda_1$ jointly. $\Lambda_{1j}, j = 2, ldots$ measures the relative informational content of various indicators.

- Can reduce the noise (var$[x_t(\theta)^m]$ will be asymptotically of the order $1/k$ time the variance obtained when only one indicator is used (see Stock and Watson (2002)).

- Estimates of θ more precise, see Justiniano et al. (2012).

Many cases fit in c):

- Proxy measures for the unobservable states: commodity prices used as proxies for future inflation shocks, stock market shocks used as proxies for future technology shocks, see Beaudry and Portier (2006).

- Sometimes we have survey data, conjunctoral information providing information for unobserved states (e.g. business cycles).

- Mixed frequency data

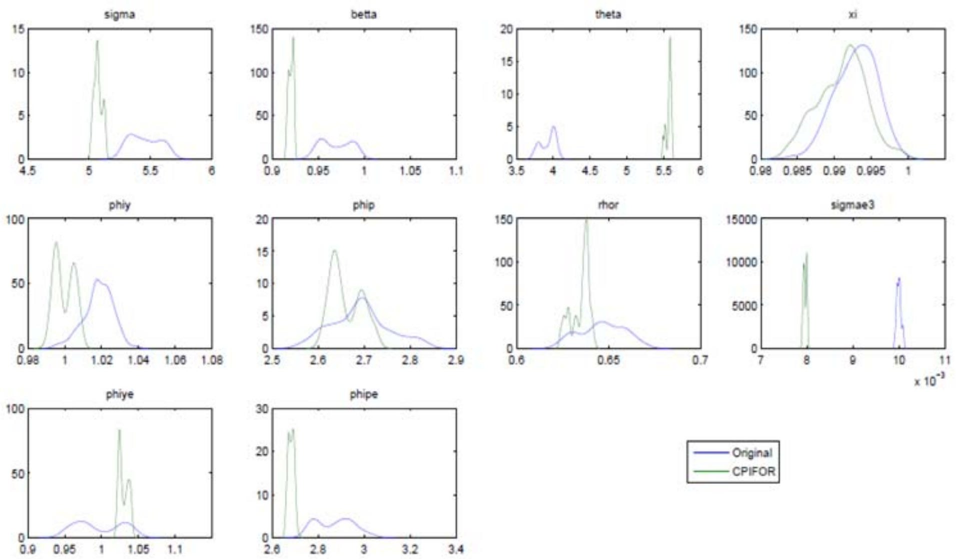
Specification:

$$x_{3t} = \Lambda_2 y_t + u_{2t} \tag{14}$$

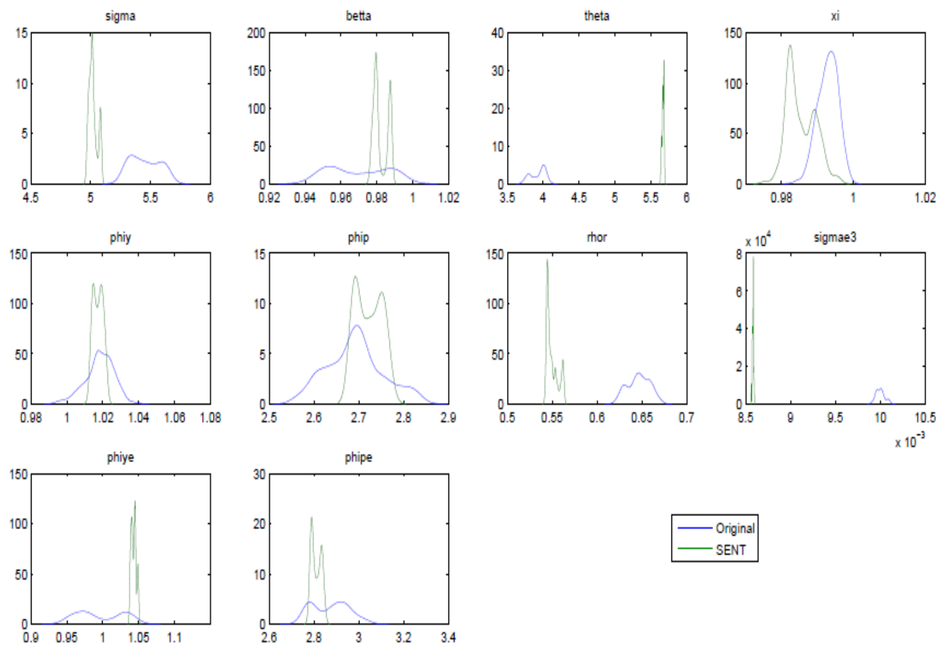
where Λ_2 is unrestricted and y_t a $q \times 1$ vector of states and x_{3t} are measures of future states (inflation, output) at different horizons, financial information (oil prices, stock prices, term structure, etc.) or quarterly sampling of e.g. monthly observation (see Foroni and Marcellino (2013)).

A. Tryphonides: How external information can contribute to structural analysis?

Comparison of original Posterior and Posterior with CPI forecast:



Comparison of original Posterior and Posterior with SENT:



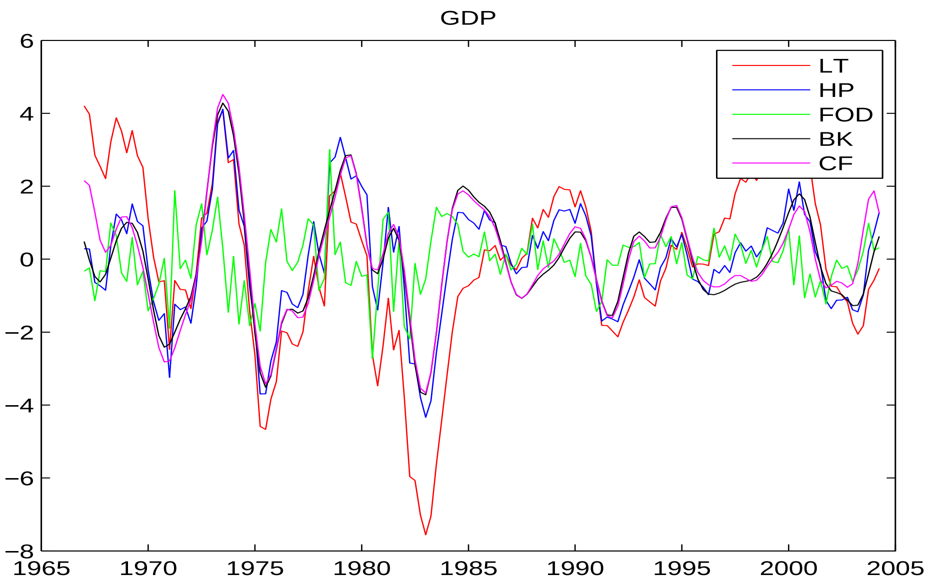
4. Data mismatch issues

- Most of models available for policy are stationary and cyclical.

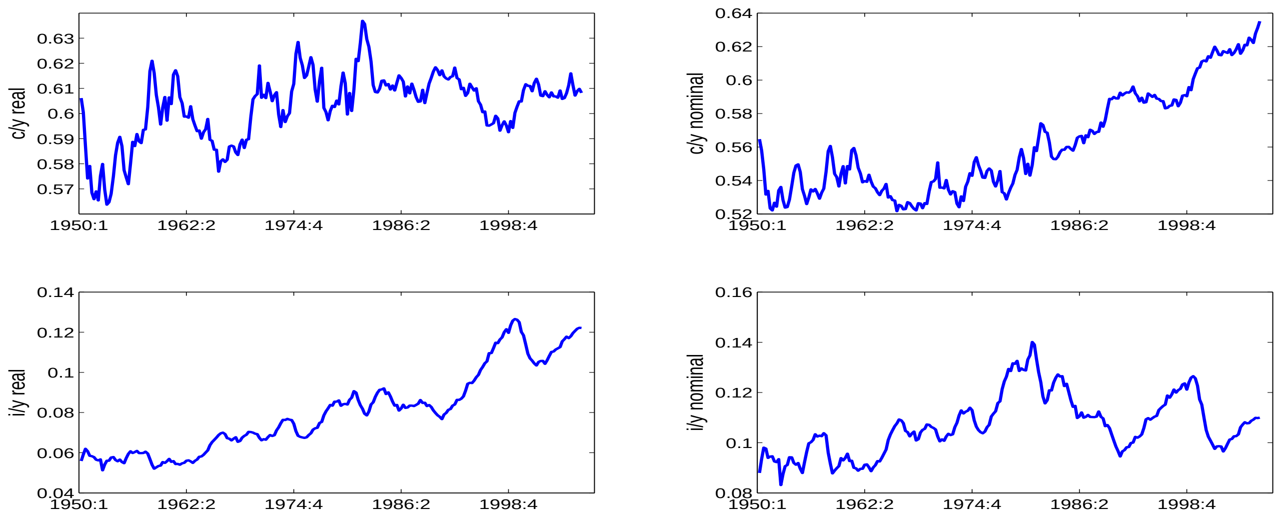
- Data is close to non-stationary; it has trends and displays breaks.

- How to we match models to the data?

a) Detrend actual data: the model is a representation for detrended data. Problem: which detrended data is the model representing?


GDP
LT
HP
FOD
BK
CF
6
4
2
0
−2
−4
−6
−8
1965
1970
1975
1980
1985
1990
1995
2000
2005

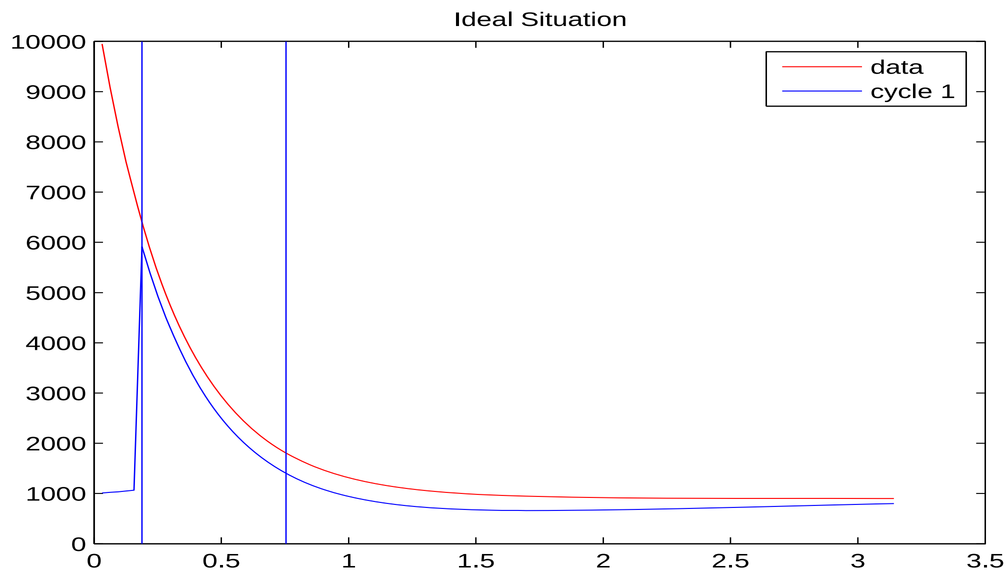
b) Take ratios in the data and in the model - will get rid of trends if variables in the ratio are cointegrated. Problem: data does not seem to satisfy balanced growth.



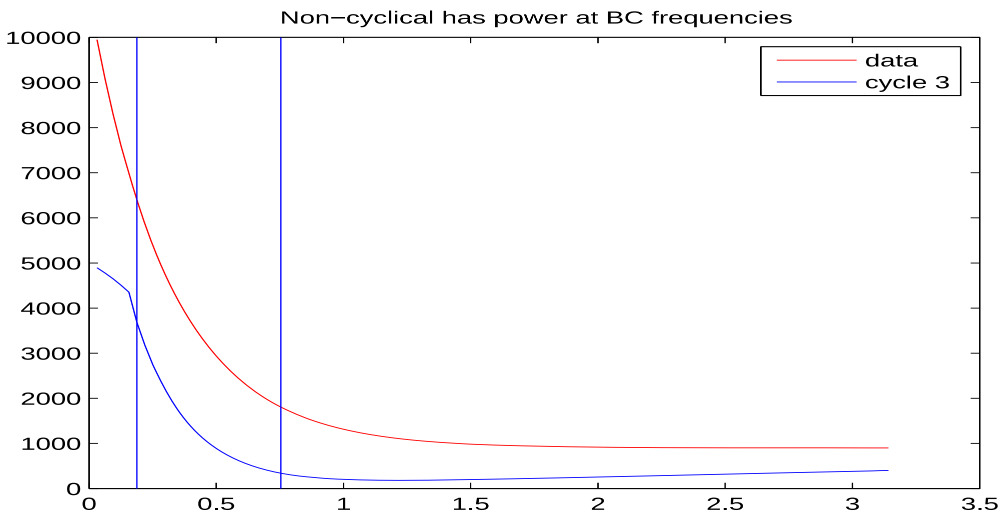
Real and nominal Great ratios in US, 1950-2008.

c) Build-in a trend into the model. Detrend the data with model-based trend. Problems: Specification of the trend is arbitrary (deterministic? stochastic?); where you put the trend (TFP? preference?) matters for estimation and inference.

• General problem: statistical definition of a cycle is different from the economic definition. All statistical approaches are biased, even in large samples.


Ideal Situation
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0
0.5
1
1.5
2
2.5
3
3.5
data
cycle 1

Ideal case



General case

- In developing countries most of cyclical fluctuations driven by trends (permanent shocks), see Aguiar and Gopinath (2007).

Example 4: The log linearized equilibrium conditions of basic NK model are:

$$\lambda_t = \chi_t - \frac{\sigma_c}{1-h}(y_t - hy_{t-1}) \tag{15}$$
$$y_t = z_t + (1-\alpha)n_t \tag{16}$$
$$w_t = -\lambda_t + \sigma_n n_t \tag{17}$$
$$r_t = \rho_r r_{t-1} + (1-\rho_r)(\rho_\pi \pi_t + \rho_y y_t) + v_t \tag{18}$$
$$\lambda_t = E_t(\lambda_{t+1} + r_t - \pi_{t+1}) \tag{19}$$
$$\pi_t = k_p(w_t + n_t - y_t + \mu_t) + \beta E_t \pi_{t+1} \tag{20}$$
$$z_t = \rho_z z_{t-1} + \iota_t^z \tag{21}$$

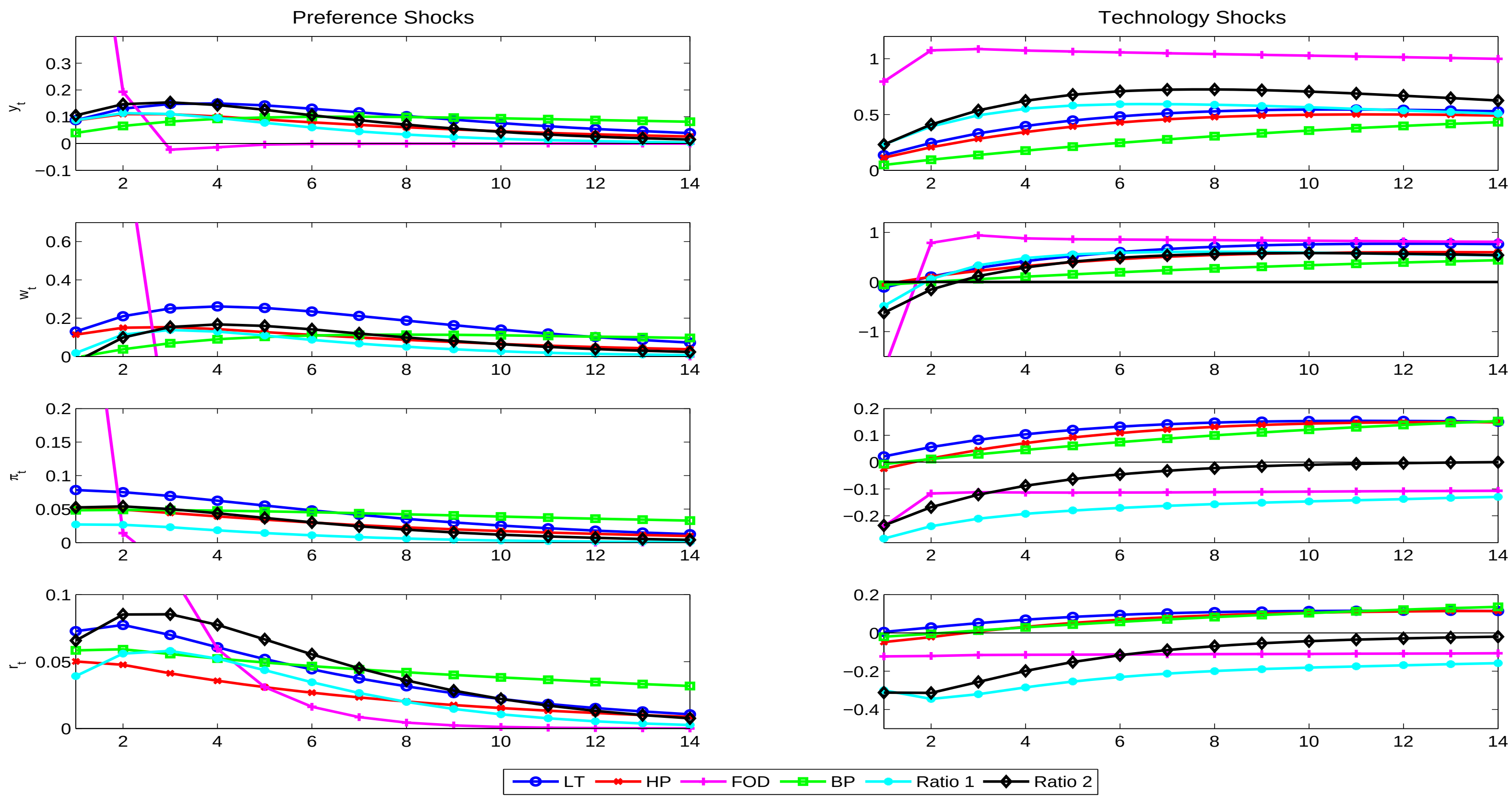
where $k_p = \frac{(1-\beta\zeta_p)(1-\zeta_p)}{\zeta_p}\frac{1-\alpha}{1-\alpha+\varepsilon\alpha}$, λ_t is the Lagrangian on the consumer budget constraint, z_t is a technology shock, χ_t a preference shock, v_t is an iid monetary policy shock and ϵ_t an iid markup shock.

Estimate this model with different detrending transformations. Do we get different estimates?

	Prior	LT	HP	FOD	BP	Ratio 1	Ratio2
		Median (s.e.)	Median (s.e.)	Median (s.e.)	Median (s.e.)	Median(s.e.)	Median (s.e.)
σ_c	$\Gamma(20, 0.1)$	1.90 (0.25)	1.41 (0.21)	0.04 (0.01)	0.96 (0.11)	2.33 (0.27)	0.81 (0.15)
σ_n	$\Gamma(20, 0.1)$	1.75 (0.16)	1.37 (0.13)	5.23 (0.08)	1.19 (0.09)	3.02 (0.24)	2.68 (0.19)
h	$B(6, 8)$	0.83 (0.02)	0.88 (0.02)	0.45 (0.01)	0.96 (0.01)	0.72 (0.05)	0.88 (0.02)
α	$B(3, 8)$	0.07 (0.04)	0.09 (0.05)	0.42 (0.01)	0.07 (0.03)	0.05 (0.04)	0.03 (0.01)
ρ_r	$B(6, 6)$	0.19 (0.05)	0.11 (0.04)	0.62 (0.01)	0.09 (0.02)	0.38 (0.06)	0.28 (0.04)
ρ_π	$N(1.5, 0.1)$	1.33 (0.08)	1.37 (0.05)	1.53 (0.02)	1.51(0.06)	1.92 (0.06)	1.80 (0.05)
ρ_y	$N(0.4, 0.1)$	-0.16 (0.03)	-0.18 (0.03)	0.06 (0.00)	-0.22 (0.03)	0.16 (0.02)	-0.03 (0.02)
ζ_p	$B(6, 6)$	0.82 (0.02)	0.80 (0.03)	0.63 (0.01)	0.86 (0.01)	0.82 (0.02)	0.80 (0.02)
ρ_χ	$B(18, 8)$	0.69 (0.04)	0.40 (0.05)	0.52 (0.01)	0.70(0.02)	0.67 (0.03)	0.66 (0.02)
ρ_z	$B(18, 8)$	0.96 (0.02)	0.95 (0.02)	0.99 (0.01)	0.97(0.01)	0.97 (0.01)	0.96 (0.01)
σ_χ	$\Gamma^{-1}(10, 20)$	0.53 (0.19)	0.47 (0.11)	4.96(0.13)	0.23 (0.05)	3.41 (0.74)	0.97 (0.13)
σ_z	$\Gamma^{-1}(10, 20)$	0.20 (0.04)	0.23 (0.04)	2.00 (0.22)	0.19 (0.03)	0.06 (0.01)	0.06 (0.01)
σ_r	$\Gamma^{-1}(10, 20)$	0.11 (0.01)	0.08 (0.01)	2.30(0.23)	0.07 (0.01)	0.10 (0.01)	0.11 (0.18)
σ_μ	$\Gamma^{-1}(10, 20)$	25.06 (0.97)	14.25 (0.93)	7.17 (0.13)	18.19 (0.66)	22.89 (1.91)	15.94 (0.49)

	Prior	Ratio 3	TFP	Preferences	TFP FD		
		Median (s.e.)	Median (s.e.)	Median (s.e.)	Median (s.e.)		
σ_c	$\Gamma(20, 0.1)$	0.12 (0.03)	1.0	1.0	1.0		
σ_n	$\Gamma(20, 0.1)$	2.09 (0.14)	2.24 (0.26)	2.43 (0.20)	0.50 (0.28)		
h	$B(6, 8)$	0.10 (0.03)	0.08 (0.04)	0.78 (0.03)	0.54 (0.29)		
α	$B(3, 8)$	0.03 (0.02)	0.17 (0.03)	1.0	0.49 (0.29)		
ρ_r	$B(6, 6)$	0.20 (0.06)	0.30 (0.04)	0.61 (0.02)	0.49 (0.28)		
ρ_π	$N(1.5, 0.1)$	1.51 (0.07)	1.74 (0.06)	1.69 (0.05)	1.69 (2.13)		
ρ_y	$N(0.4, 0.1)$	0.77 (0.04)	0.49 (0.03)	0.38 (0.07)	0.25 (1.97)		
ζ_p	$B(6, 6)$	0.81 (0.01)	0.41 (0.03)	0.84 (0.01)	0.47 (0.29)		
ρ_χ	$B(18, 8)$	0.75 (0.03)	0.63 (0.03)		0.49 (0.28)		
ρ_z	$B(18, 8)$	0.62 (0.03)		0.59 (0.02)			
σ_χ	$\Gamma^{-1}(10, 20)$	0.26 (0.04)	0.21 (0.03)	0.06 (0.008)	3.49(0.48)		
σ_z	$\Gamma^{-1}(10, 20)$	0.08 (0.01)	0.05 (0.006)	0.15 (0.02)	2.09 (0.89)		
σ_r	$\Gamma^{-1}(10, 20)$	2.68 (0.27)	0.10 (0.01)	0.07 (0.007)	0.79(0.55)		
σ_μ	$\Gamma^{-1}(10, 20)$	15.98 (1.09)	0.25 (0.04)	36.68 (1.42)	8.34(0.44)		

Table 2: Posterior estimates. LT refers to linearly detrended data, HP to Hodrick and Prescott filtered data, FOD to demeaned growth rates, BP to band pass filtered data. For Ratio 1 the observables are $\log(y_t/n_t), \log(w_t), \pi_t, r_t$, all demeaned, for Ratio 2 they are $\log(y_t/w_t), \log(n_t), \pi_t, r_t$, all demeaned, For Ratio 3, the observables are $\log((w_t n_t)/y_t), \log(w_t/y_t), \pi_t, r_t$, all demeaned. For TFP trending, the observable are linearly detrending output and real wages and demeaned inflation and interest rates. For Preference trending, the observable are demeaned growth rate of output, demeaned log real wages, demeaned inflation and demeaned interest rates. When frequency domain estimation is used, only information in the band $(\frac{\pi}{32}, \frac{\pi}{8})$ is employed. The sample is 1980:1-2007:4.



Estimated impulse responses.

Two approaches to deal with mismatch problem:

1) Data-rich environment: Canova and Ferroni (2011). Let y_t^i be the actual data filtered with method i and $y_t^d = [y_t^1, y_t^2, \ldots]$. Assume:

$$y_t^d = \lambda_0 + \lambda_1' y_t(\theta) + u_t \tag{22}$$

where $\lambda_j, j = 0, 1$ are matrices of parameters, measuring the bias and correlation between the filter data y_t^d and model based quantities $y_t(\theta)$; u_t are measurement errors and θ the structural parameters.

- Same setup as before: model based quantities are non-observable.

- Jointly estimate θ, σ_u^2 and λ's. Can obtain a more precise estimates of the unobserved $y_t(\theta)$ if measurement error is uncorrelated across filtering methods.

2) Bridge cyclical model and the data (Canova, 2012)).

$$y_t^d = c + y_t^T + y_t^m(\theta) + u_t \tag{23}$$

where $y_t^d \equiv \tilde{y}_t^d - E(\tilde{y}_t^d)$ the log demeaned vector of observables, $c = \bar{y} - E(\tilde{y}_t^d)$, y_t^T is the non-model component, $y_t^m(\theta) \equiv S[y_t, x_t]'$, S is a selection matrix, is the model based component, u_t is a iid $(0, \Sigma_u)$ (measurement) noise, $y_t^T, y_t^m(\theta)$ and u_t are mutually orthogonal.

- Model (linearized) solution:

$$\begin{aligned} y_t &= RR(\theta)x_{t-1} + SS(\theta)z_t && (24) \\ x_t &= PP(\theta)x_{t-1} + QQ(\theta)z_t && (25) \\ z_{t+1} &= NN(\theta)z_t + \epsilon_{t+1} && (26) \end{aligned}$$

$PP(\theta), QQ(\theta), RR(\theta), SS(\theta)$ functions of the structural parameters $\theta = (\theta_1, \ldots, \theta_k)$, $x_t = \tilde{x}_t - \bar{x}$; $y_t = \tilde{y}_t - \bar{y}$; and z_t are the disturbances, $\bar{y}, \bar{x}$ are the steady states of $\tilde{y}_t$ and $\tilde{x}_t$.

-Non model-based component:

$$y_t^T = \rho_1 y_{t-1}^T + \bar{y}_{t-1} + e_t \qquad e_t \sim \ iid\ (0, \Sigma_e^2) \tag{27}$$

$$\bar{y}_t = \rho_2 \bar{y}_{t-1} + v_t \qquad v_t \sim \ iid\ (0, \Sigma_v^2) \tag{28}$$

$\Sigma_v^2 > 0$ and $\Sigma_e^2 = 0$, y_t^T is a vector of I(2) processes. $\rho_1 = \rho_2 = I, \Sigma_v^2 = 0$, and $\Sigma_e^2 > 0$, y_t^T is a vector of I(1) processes. $\rho_1 = \rho_2 = I, \Sigma_v^2 = \Sigma_e^2 = 0$, y_t^T is deterministic. $\rho_1 = \rho_2 = I, \Sigma_v^2 > 0$ and $\Sigma_e^2 > 0$ and $\frac{\sigma_v^2}{\sigma_e^2}$ is large, y_t^t is smooth (as in HP). $\rho_1 \neq I, \rho_2 \neq I$ or both, non-model based component has power at particular frequencies

- Jointly estimate structural θ and non-structural parameters $(\rho_1, \rho_2, \Sigma_e, \Sigma_u)$.

Advantages of suggested approach:

- No need to take a stand on the properties of the non-cyclical component and on the choice of filter to tone down its importance - specification errors and biases limited.

- Estimated cyclical component not localized at particular frequencies of the spectrum.

- Account for trend uncertainty in estimates of θ.

- Provides a measure of model misspecification.

DGP1: Trend is important							
	True value	LT	HP	FOD	BP	Ratio1	Flexible
σ_n	0.50	0.04	0.08	0.00	0.11	0.05	0.04
h	0.70	0.00	0.00	0.00	0.01	0.07	0.10
α	0.30	0.00	0.04	0.00	0.06	0.04	0.06
ρ_r	0.70	0.05	0.05	0.01	0.06	0.13	0.01
ρ_π	1.50	0.00	0.00	0.00	0.01	0.02	0.00
ρ_y	0.40	0.17	0.20	0.17	0.19	0.15	0.00
ζ_p	0.75	0.03	0.04	0.03	0.03	0.02	0.03
ρ_χ	0.50	0.00	0.04	0.00	0.00	0.00	0.07
ρ_z	0.80	0.03	0.05	0.00	0.05	0.00	0.05
σ_χ	1.12	1.60	0.45	3.89	0.64	8.79	1.00
σ_z	0.50	1.47	0.01	3.18	0.03	0.02	0.16
σ_r	0.10	1.37	0.03	3.75	0.03	0.00	0.00
σ_μ	1.60	13.14	18.81	17.68	38.52	38.36	1.94
Total1		0.30	0.40	0.21	0.48	0.49	0.24
Total2		17.91	19.79	28.71	39.75	47.66	3.45

MSE. In DPG1 there is a unit root component to the preference shock and $\frac{\sigma_\chi^{nc}}{\sigma_\chi^T} = [1.1, 1.9]$.

DGP2: Trend unimportant							
	True value	LT	HP	FOD	BP	Ratio1	Flexible
σ_n	0.50	0.04	0.11	0.17	0.12	0.12	0.06
h	0.70	0.01	0.00	0.00	0.03	0.08	0.17
α	0.30	0.00	0.05	0.00	0.06	0.02	0.07
ρ_r	0.70	0.05	0.05	0.04	0.05	0.13	0.02
ρ_π	1.50	0.00	0.00	0.00	0.00	0.01	0.00
ρ_y	0.40	0.16	0.21	0.08	0.19	0.15	0.00
ζ_p	0.75	0.03	0.04	0.02	0.05	0.04	0.03
ρ_χ	0.50	0.00	0.04	0.00	0.00	0.01	0.08
ρ_z	0.80	0.04	0.05	0.03	0.03	0.00	0.06
σ_χ	1.12	10.41	0.87	2.80	0.69	9.43	0.97
σ_z	0.50	9.15	0.06	1.91	0.06	0.01	0.17
σ_r	0.10	9.35	0.00	1.05	0.03	0.00	0.00
σ_μ	1.60	10.41	20.72	20.33	57.03	40.17	1.90
Total1		0.29	0.46	0.32	0.51	0.55	0.35
Total2		39.65	22.20	26.44	58.34	50.17	3.54

MSE. In DGP2 all shocks are stationary but there is measurement error and $\frac{\sigma_u}{\sigma_\chi^T} = [0.09, 0.11]$ The MSE is computed using 50 replications.

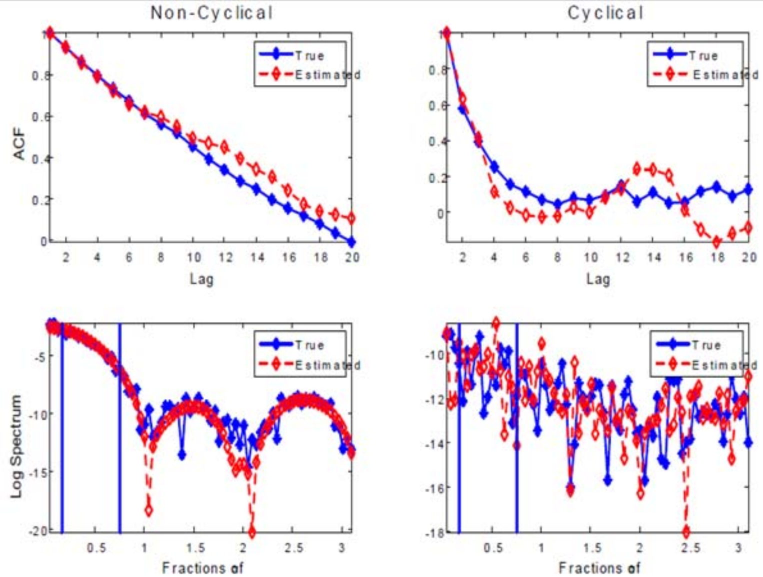
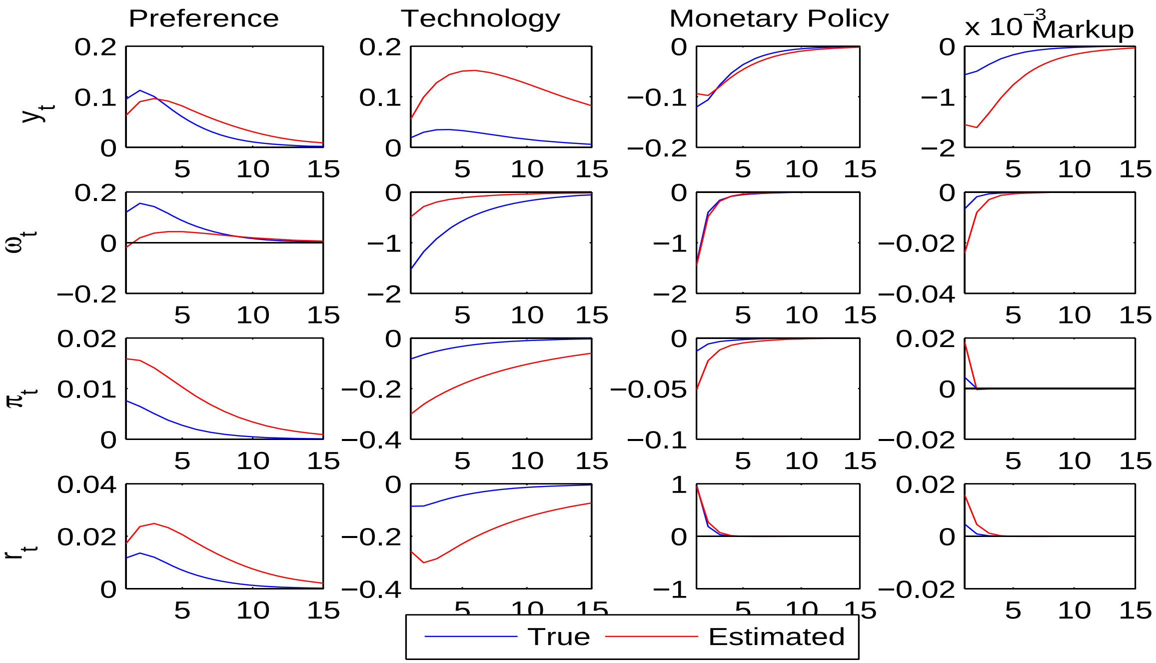


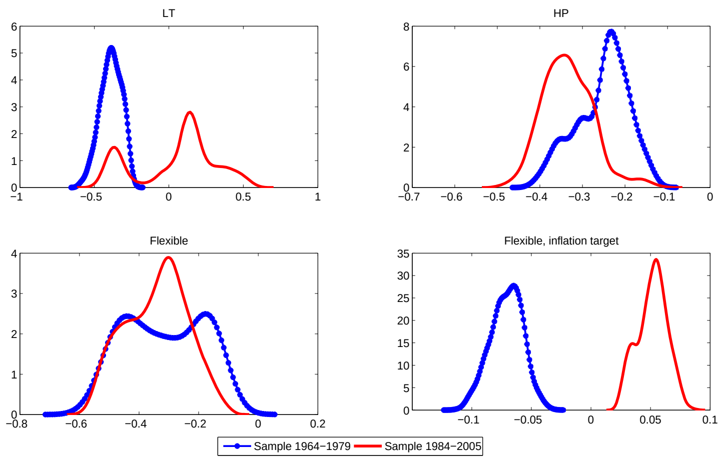
Figure 3: Output decomposition, true and estimated with a flexible approach. Vertical bars indicate business cycle frequencies

- The true and estimated log spectrum and ACF close.

- Both true and estimate cyclical components have power at all frequencies.



Model based IRF, true and estimated.



Posterior distributions of the policy activism parameter, samples 1964:1-1979:4 and 1984:1-2007:4. LT= linearly detrended, HP=Hodrick and Prescott filtered data and Flexible to the approach of the paper

	LT		FOD		Flexible	
	Output	Inflation	Output	Inflation	Output	Inflation
TFP shocks	0.01	0.04	0.00	0.01	0.01	0.19
Gov. expenditure shocks	0.00	0.00	0.00	0.00	0.00	0.02
Investment shocks	0.08	0.00	0.00	0.00	0.00	0.05
Monetary policy shocks	0.01	0.00	0.00	0.00	0.00	0.01
Price markup shocks	0.75(*)	0.88(*)	0.91(*)	0.90(*)	0.00	0.21
Wage markup shocks	0.00	0.01	0.08	0.08	0.03	0.49(*)
Preference shocks	0.11	0.04	0.00	0.00	0.94(*)	0.00

Variance decomposition at the 5 years horizon, SW model. Estimates are obtained using the median of the posterior of the parameters. A (*) indicates that the 68 percent highest credible set is entirely above 0.10. The model and the data set are the same as in Smets Wouters (2007). LT refers to linearly detrended data, FOD to growth rates and Flexible to the approach this paper suggests.

5. Evaluation problems

- Validation problematic when the model is not the DGP of the data. Standard econometric procedures inapplicable.

- Bridging procedure (Canova, 2012) can be used to measure how much the model leaves unexplained without requiring the model to be the DGP.

Del Negro and Schorfheide (2004), (2006), Del Negro, et. al. (2006)

• Model can be used as a prior for the data.

• Can verify the quality of model's restrictions by checking how much simulated data must be added to a VAR to improve its fit.

Problems:

1) Condition on a single model. What if the model is wrong?

2) Look at the model as a whole: can't measure discrepancy in one equation.

3) Not much to say about cyclical properties of the model.

Canova and Paustian (2011): address problems 1) and 2).

Basic idea:

- Find a set of robust dynamic implications in the model.

- Impose some of them on the data to identify shocks.

- Compare other dynamics implications of model and data in response to robustly identified shocks.

- Use qualitative rather than quantitative evaluation. Can make the evaluation probabilistic.

Results with experimental data

- Can recognize *qualitative* features of the DGP with high probability.

- Can separate models which are close to each other with high probability.

- Can get a good handle of *quantitative* features of DGP if:

a) Restrictions are abundant (can't be too agnostic).

b) Identified shocks have "relative" large variance.

- Good even in small samples; median response tracks true one well.

Measuring the effects of government spending on consumption

- Models predict that consumption falls after increased government spending: negative wealth effect.

- VAR evidence generally the opposite: Blanchard and Perotti (2002), Fatas and Mihov (2001), Perotti (2007), Pappa (2008).

- Gali et al. (2007): sticky prices and non-Ricardian consumers can produce a rise in consumption following a government spending shock.

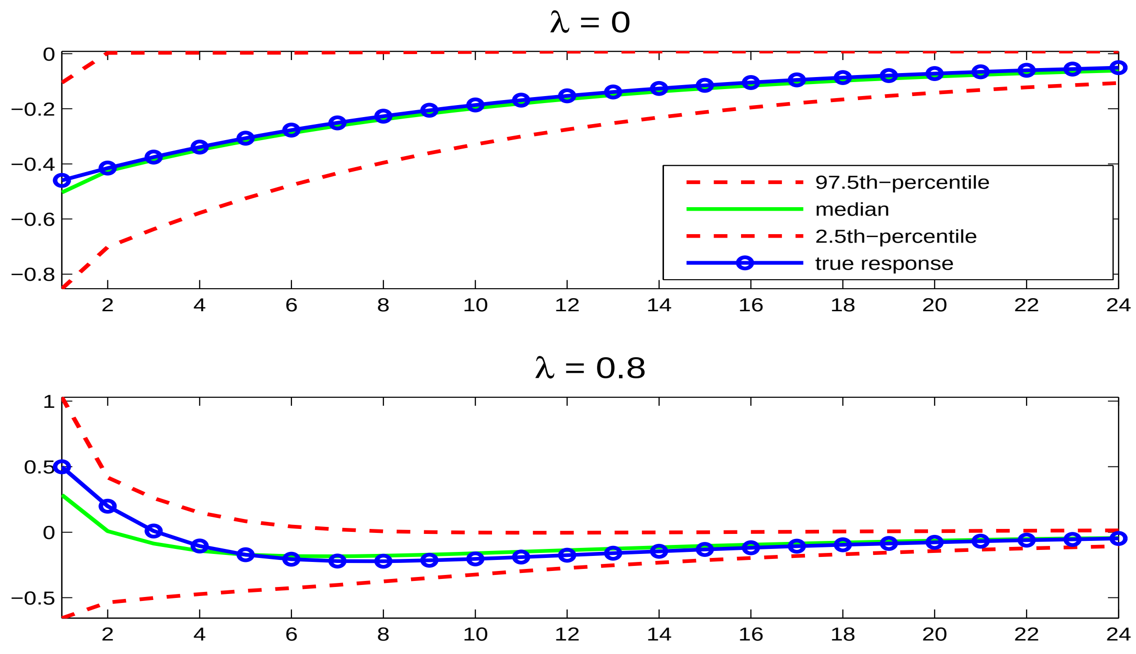
- Derive robust restrictions from this class of models. Check if conditioning on the class of models, consumption increases or falls. (Test of sticky price setup plus presence of rules of thumb consumers).

Robust restrictions: Gali et al (2007)

	markup	monetary	**spending**	technology
r	?	?	$+$	-
w	-	-	?	?
π	?	-	**+**	-
y	-	-	$+$	$+$
l	-	-	**+**	-
i	?	?	-	$+$
c	-	-	?	$+$

Signs of impact response (10^5 draws, 95 % bands).

Question: Can the procedure recover the truth?



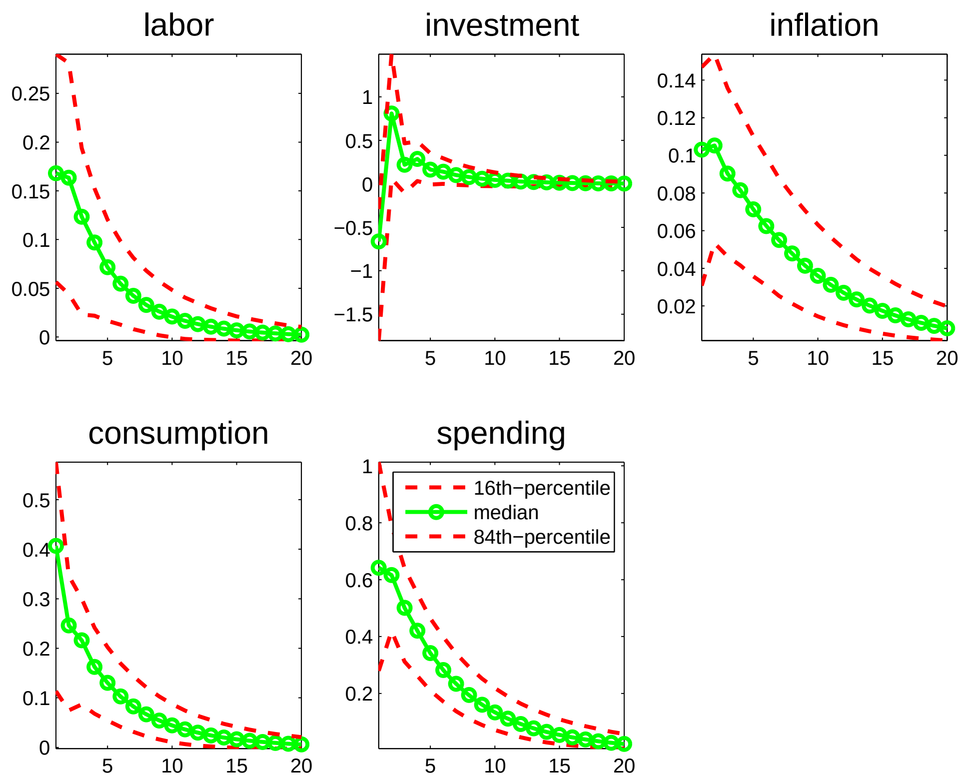
Consumption responses to government spending shock.

U.S. data: 1954:1-2007:1.

- Estimate a 5 variable VAR, $(g_t, \pi_t, l_t, c_t, i_t)$.

- Data is in log differences (except inflation in log levels).

- Identify spending shock $(\pi_t > 0, l_t > 0, i_t < 0, g_t > 0)$ and generic technology shock $(\pi_t < 0, l_t < 0, i_t > 0, c_t > 0)$



Response to a government spending shock in U.S. data, 1954-2007

Future challanges

- Dealing with time variations in the structure.

- Dealing with generic misspecification.

- Dealing with non-linear frameworks

Large Thanks for your attention and patience!