Now-casting and the real time data-flow

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Background: forecasting at central banks

- Obtain a good number for the short-term outlook
- Tell a story about the medium run

How important is the short run?

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Background

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Very !!!!

Forecasting GDP in real time

Horizon	0	1	2	3	4
GB	0.87	1.03	1.16	1.23	1.29
SPF	0.85	1.03	1.00	1.06	1.06

Evaluation sample 1992Q1 through 2001Q4
MSFE relative to constant growth
(Source: D'Agostino, Giannone and Surico, 2007)

KEY: Exploitation of early releases throughout the quarter (real time data-flow)

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KEY: Exploitation of early releases throughout the quarter (real time data-flow)

Background: Early estimates

Early estimates: exploit monthly information becoming available at different dates throughout the quarter to continuously update your estimate of current quarter GDP

Key concepts:

- Staggered monthly data releases $\rightarrow$ panel with missing of observations at the end of the sample
- Bridging monthly and quarterly data

Data release calendar for the euro area in the 2nd quarter of 2008

Release Day	Indicators	Reference Period	Source
30 April 2008	European Commission Surveys	Apr-08	Commission
16 May 2008	New Passenger Car Registrations	Apr-08	ACEA
29 May 2008	Monetary aggregates	Apr-08	ECB
30 May 2008	Unemployment rate	Apr-08	Eurostat
30 May 2008	European Commission Surveys	May-08	Commission
4 June 2008	Retail Trade Turnover	Apr-08	Eurostat
12 June 2008	Industrial Production	Apr-08	Eurostat
13 June 2008	New Passenger Car Registrations	May-08	ACEA
17 June 2008	External Trade	Apr-08	Eurostat
18 June 2008	Production in Construction Index	Apr-08	Eurostat
26 June 2008	Monetary aggregates	May-08	ECB
30 June 2008	European Commission Surveys	Jun-08	Commission
1 July 2008	Unemployment rate	May-08	Eurostat
3 July 2008	Retail Trade Turnover	May-08	Eurostat
14 July 2008	Industrial Production	May-08	Eurostat
16 July 2008	New Passenger Car Registrations	Jun-08	ACEA
18 July 2008	Production in Construction Index	May-08	Eurostat
18 July 2008	External Trade	May-08	Eurostat
25 July 2008	Monetary aggregates	Jun-08	ECB
31 July 2008	Unemployment rate	Jun-08	Eurostat
5 August 2008	Retail Trade Turnover	Jun-08	Eurostat
13 August 2008	Industrial Production	Jun-08	Eurostat
14 August 2008	*GDP flash estimate*	2008 Q2	Eurostat

Background: Early estimates

Traditional tools:

Bridge Equations

Average of bridge equations (pooling)

New tool:

Bridging with factors: Giannone, Reichlin, Small (2005, Forthcoming JME)

Bridge equations and pooling

Step 1 : Use monthly variables and forecast missing monthly observations over the remainder of the quarter to obtain x_{it}^{Q}

Step 2 :

• BE with few selected indicators (ECB):

$$y_t^Q = \mu + \sum_{i=1}^{k} \beta_i^j(L) x_{it}^{jQ} + \varepsilon_t^{jQ}$$

• BE with pooling (we will show results):

Average of the j equations:

$$y_t^Q = \mu_j + \beta_1^j(L) x_{1t}^{jQ} + \varepsilon_t^{jQ}.$$

Remark: Missing data forecasted using univariate AR model

Bridging with factors (GRS model)

Monthly Factor Model

$$\begin{aligned} X_t &= \Lambda f_t + e_t, & e_t &\sim \mathbb{N}(0, \Sigma_e) \\ f_t &= \sum_{i=1}^{p} A_i f_{t-i} + B u_t, & u_t &\sim \mathbb{N}(0, I_q) \end{aligned}$$

Aggregate quarterly

$$\begin{aligned} f_t^Q &= \frac{1}{3}(f_t + f_{t-1} + f_{t-2}) \\ y_t^Q &= \beta' f_t^Q + \varepsilon_t^Q \end{aligned}$$

f_t ... 3-month growth rates

Bridging with factors (GRS model)

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f_t ... 3-month growth rates

Bridging with factors: estimation

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Estimate	**Obtain**
Principal components to x_t	$\widehat{f}_t$, $\widehat{\Lambda}$, and $\widehat{\Sigma}_e$
$\widehat{f}_t = \sum_{i=1}^{p} A_i \widehat{f}_{t-i} + v_t$	$\widehat{A}_i$ and $\widehat{\Sigma}_v$
Principal components on $\widehat{v}_t$	$\widehat{B}$
$y_t^Q = \beta' \widehat{f}_t^Q + \varepsilon_t^Q$	$\widehat{\beta}$

Bridging with factors: estimation

$$\begin{aligned} x_t &= \Lambda f_t + e_t, & e_t \sim \mathbb{N}(0, \Sigma_e) \\ f_t &= \sum_{i=1}^{p} A_i f_{t-i} + B u_t, & u_t \sim \mathbb{N}(0, I_q) \end{aligned}$$

Estimate	**Obtain**
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Principal components on $\widehat{v}_t$	$\widehat{B}$
$y_t^Q = \beta' \widehat{f}_t^Q + \varepsilon_t^Q$	$\widehat{\beta}$

Bridging with factors: forecasting and Kalman filter

$$
\begin{aligned}
x_t &= \Lambda f_t + e_t, & e_t \sim N(0, \Sigma_e) \\
f_{t+1} &= A_1 f_t + v_t, & v_t \sim N(0, BB')
\end{aligned}
$$

For **any** data set $\mathcal{Z}$ (i.e. missing data)
the Kalman filter and smoother provide MMS estimates

$$
\begin{aligned}
\widehat{f}_{t+h|t} &= \mathbb{E}\left[f_{t+h}|\mathcal{Z}\right] \\
P_{t+h|t} &= \mathbb{E}\left[\widehat{f}_{t+h|t} - f_{t+h}\right]\left[\widehat{f}_{t+h|t} - f_{t+h}\right]'
\end{aligned}
$$

Efficient treatment of publication lags

Contributions and forecast uncertainty

Interpolation

Bridging with factors: forecasting uncertainty

From

$$y_t^Q = \beta' f_t^Q + \varepsilon_t^Q$$

forecast uncertainty is given by

$$\mathrm{var}(y_{t+h|t}^Q - y_{t+h}^Q) = \beta' P_{t+h|t} \beta + \sigma_\varepsilon^2$$

$\beta' P_{t+h|t} \beta$ Filter uncertainty
σ_ε^2 Residual uncertainty

Theory: Doz, Giannone and Reichlin, 2006 and 2007

Bridging with factors: filter weights and contributions

Filter weights:

express $\widehat{y}^Q_{t+h|t}$ as weighted sum of available data

$$\widehat{y}^Q_{t+h|t} = \sum_{k=0}^{t-1} \sum_{i=0}^{n+1} \omega_{k,i}(h) x_{i,t-k}$$

with weights $\omega_{k,i}(h)$ for series i at lag k.

Cumulative forecast weights $\sum_{k=0}^{t-1} \omega_{k,i}(h)$ for series i

Contribution of series i to $\widehat{y}^Q_{t+h|t}$ is $\sum_{k=0}^{t-1} \omega_{k,i}(h) x_{i,t-k}$

[see Banbura and Runstler, 2007]

Euro area (ECB) evaluation (Angelini et al., 2008):

• Models:

Bridging with factors
Pool of bridge eqns.
ECB bridge equations: average of 12 equations, each with selected variables

• Period of evaluation:

1998q3-2005q4

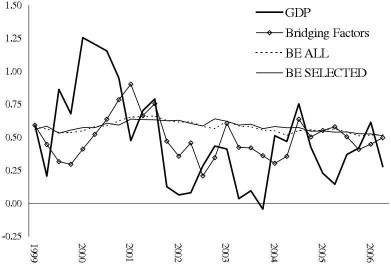
• Real Time Design

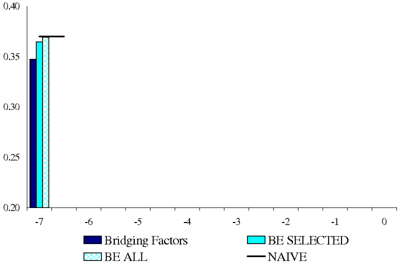
Update twice a month (hard and soft) and replicate pattern of data availability
Each time re-estimate model parameters

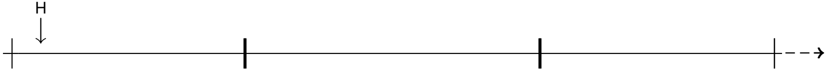
• Data:

85 variables: hard, soft, international, financial

Nowcasting GDP growth







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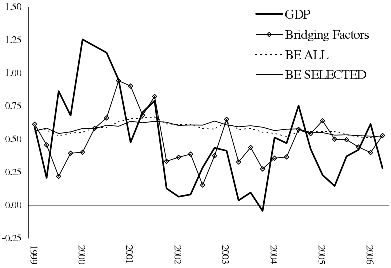

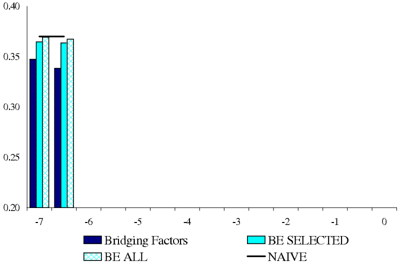

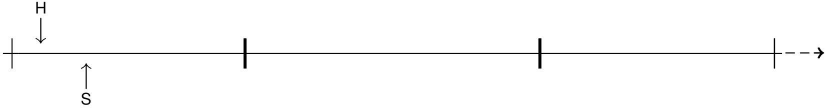

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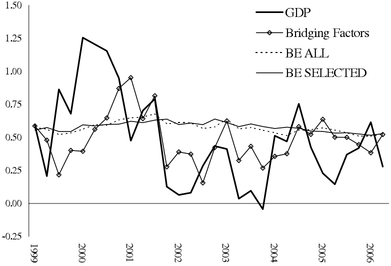

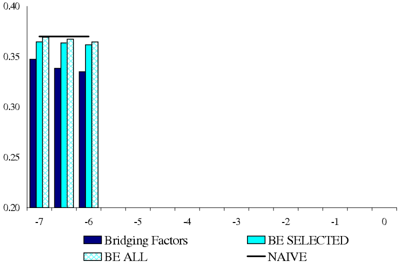

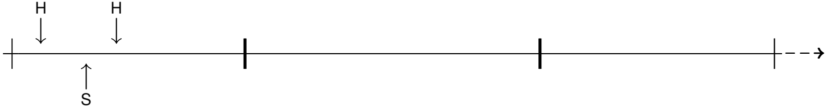

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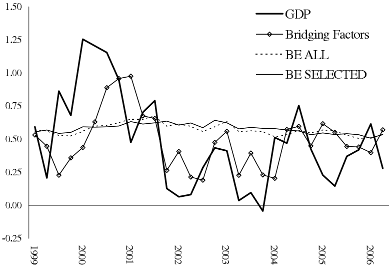

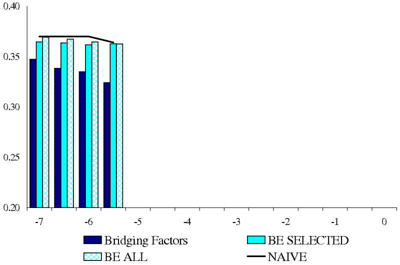

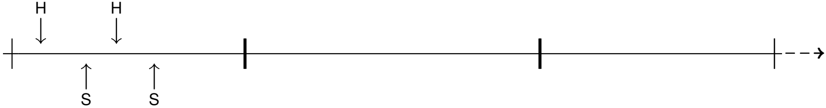

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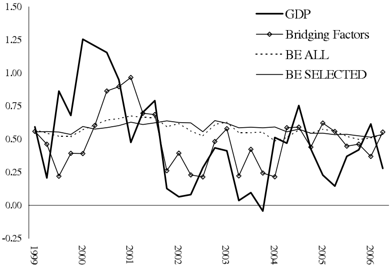

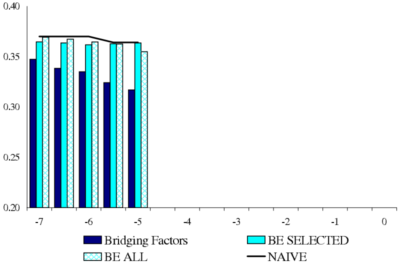

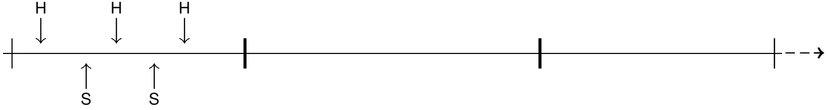

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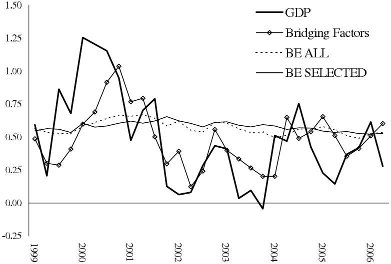

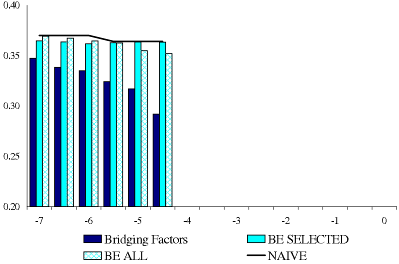

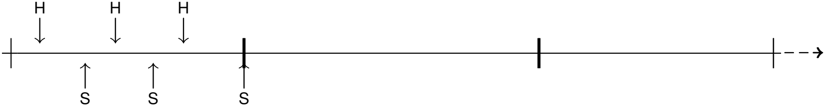

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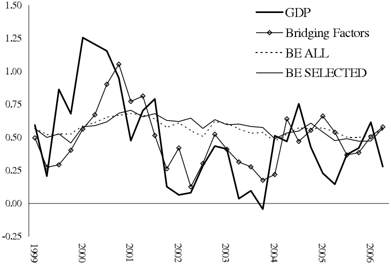

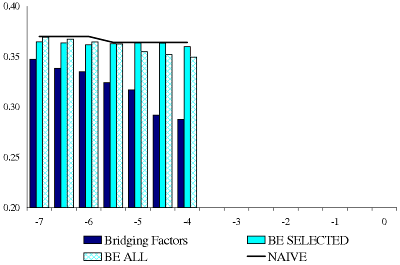

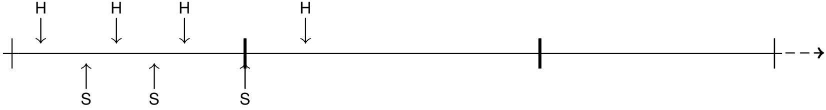

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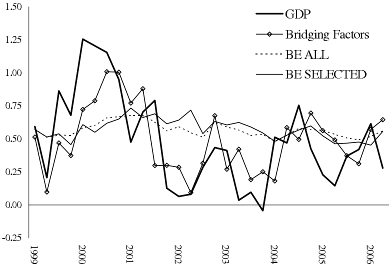

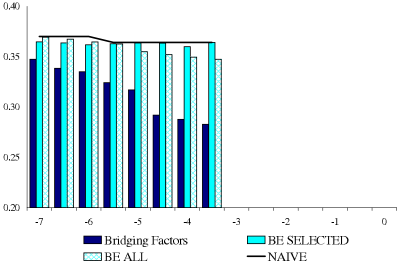

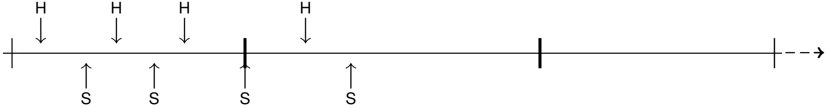

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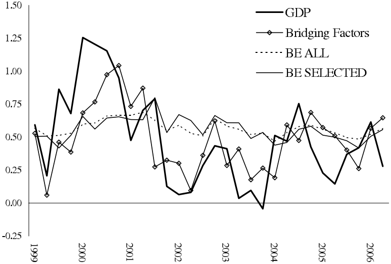

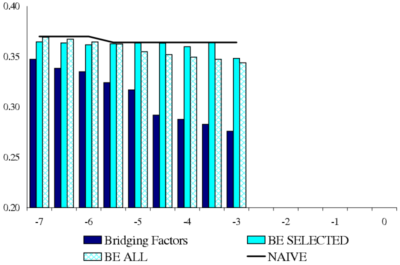

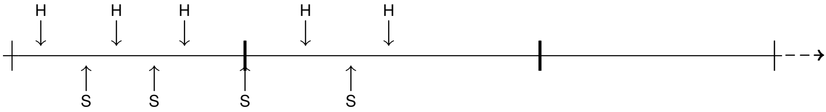

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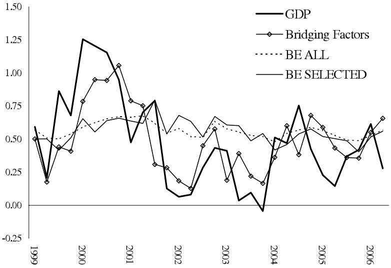

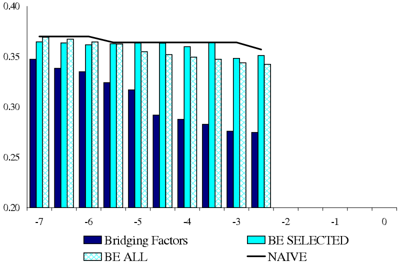

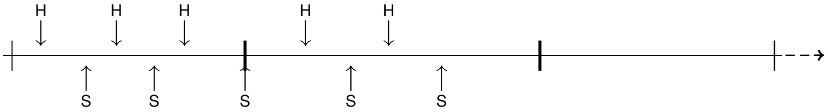

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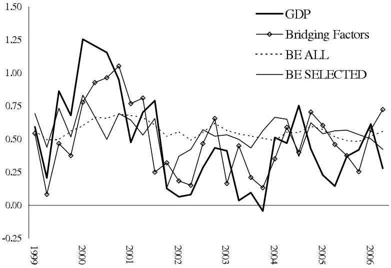

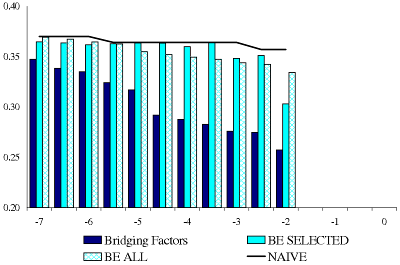

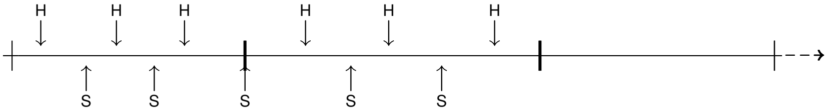

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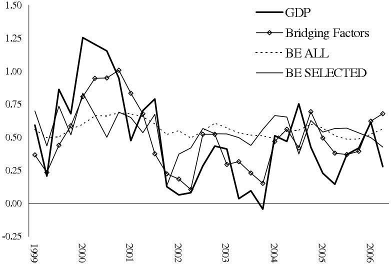

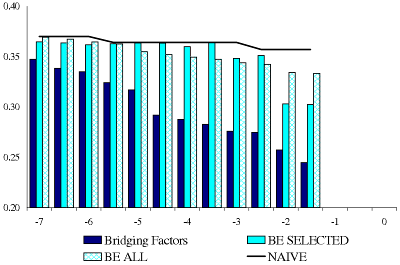

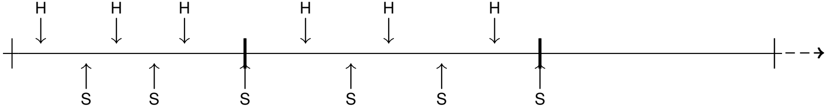

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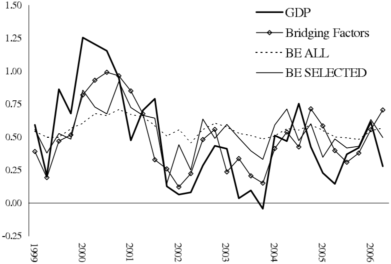

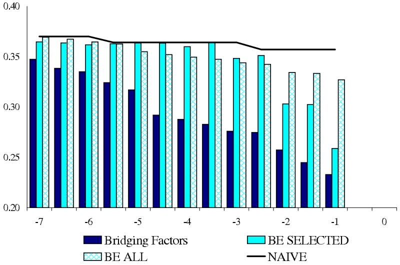

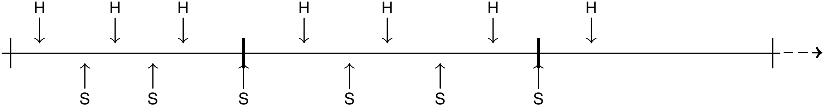

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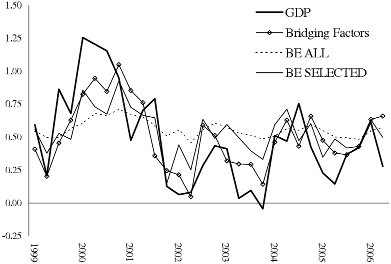

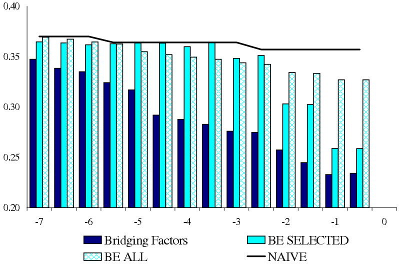

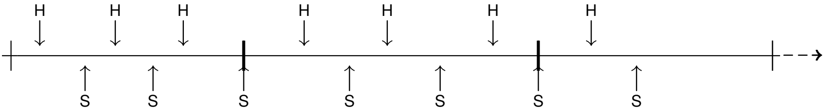

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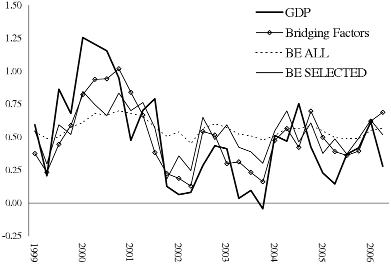

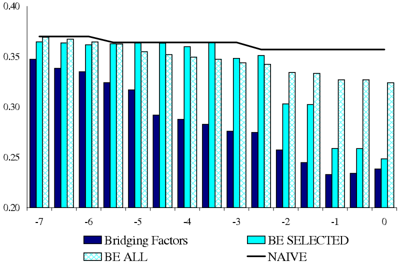

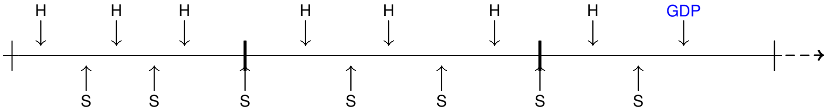

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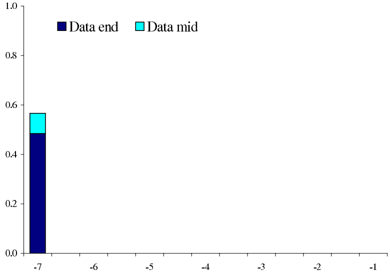

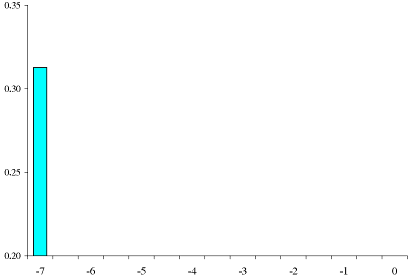

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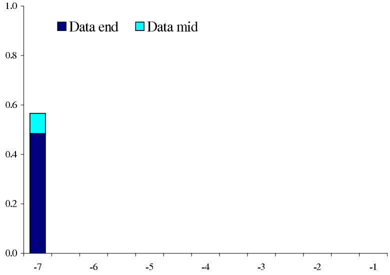

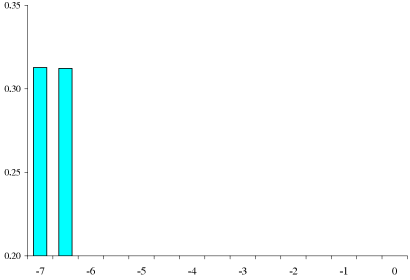

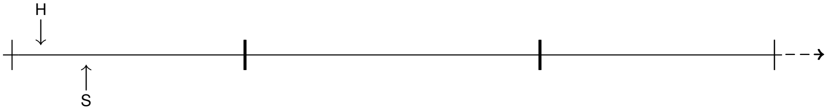

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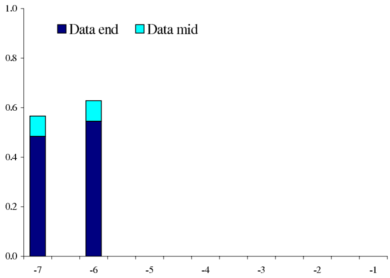

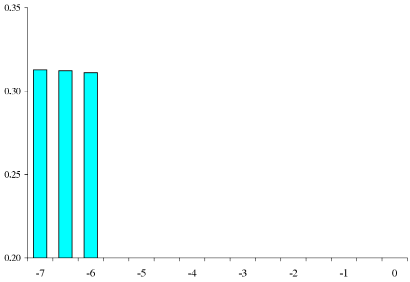

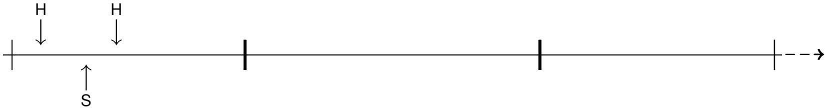

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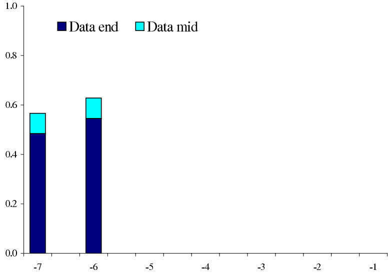

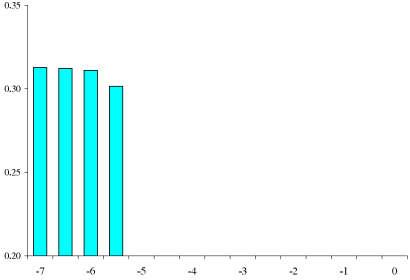

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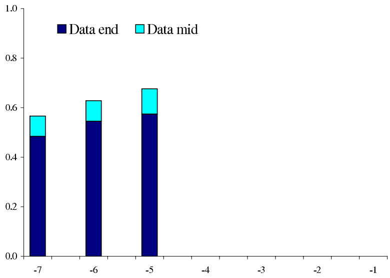

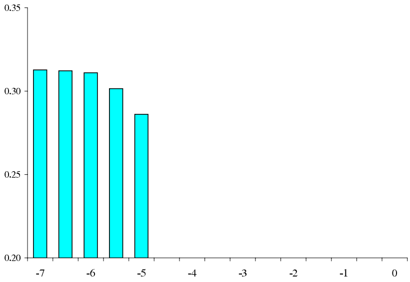

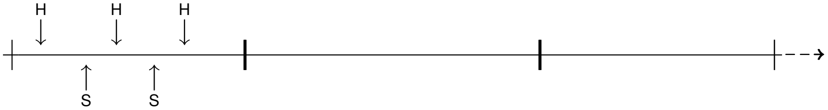

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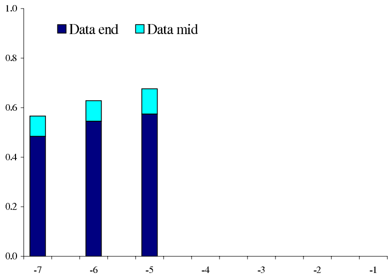

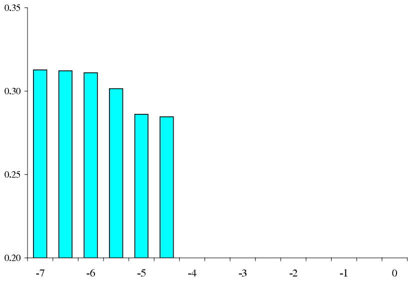

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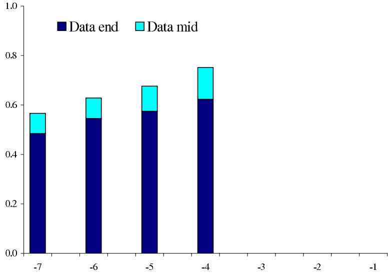

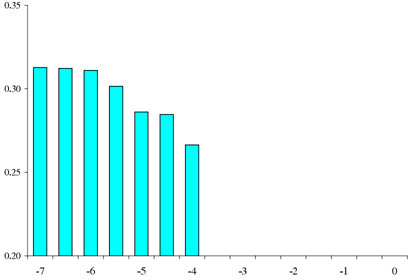

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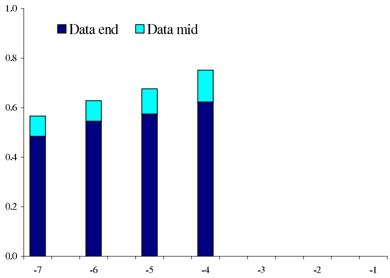

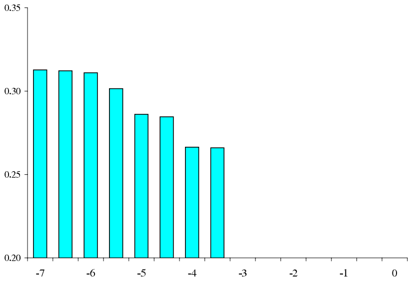

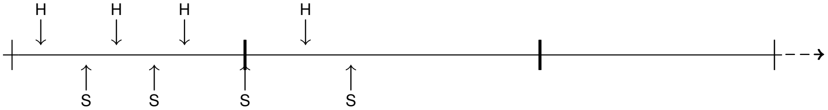

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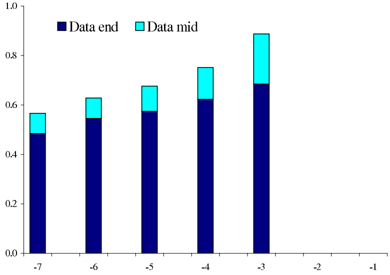

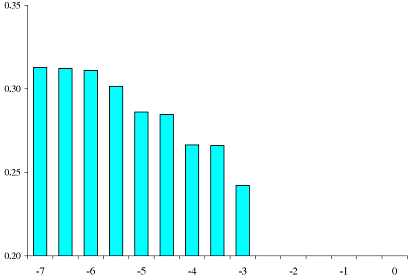

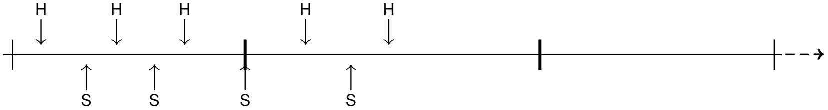

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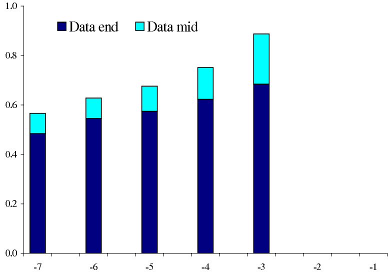

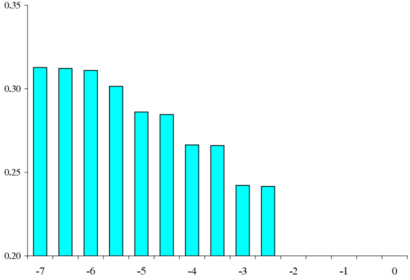

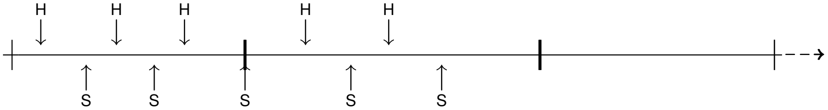

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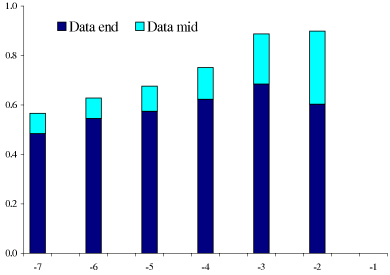

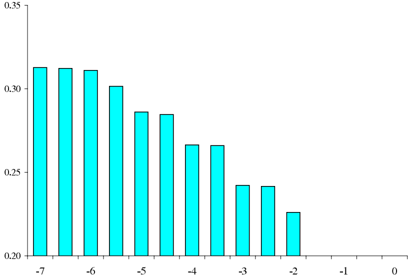

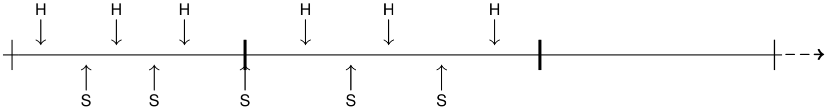

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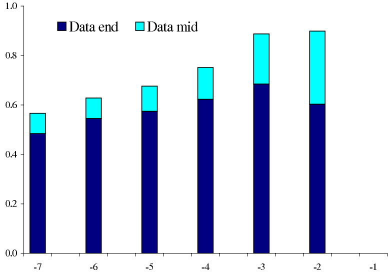

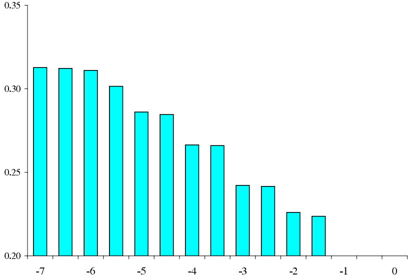

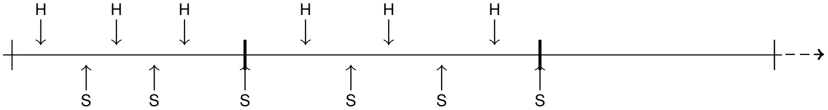

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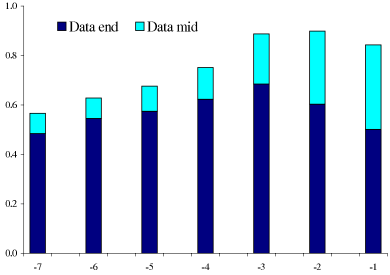

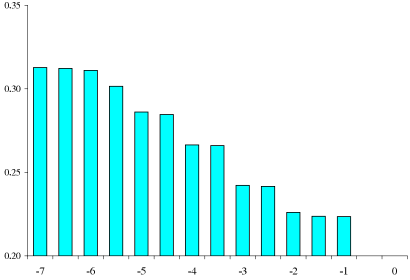

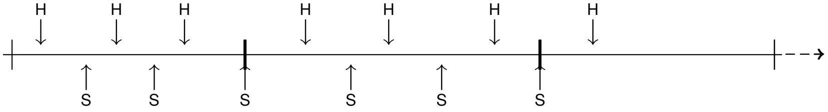

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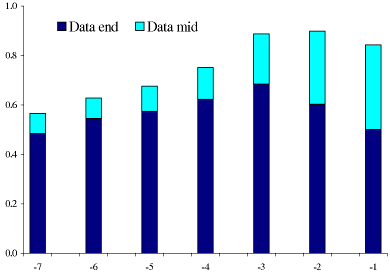

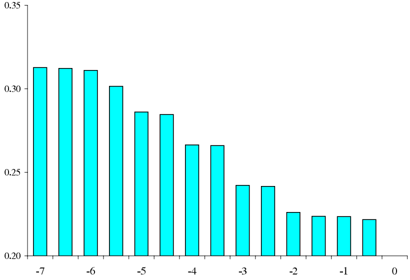

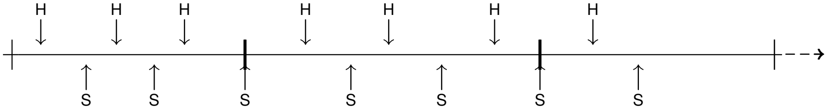

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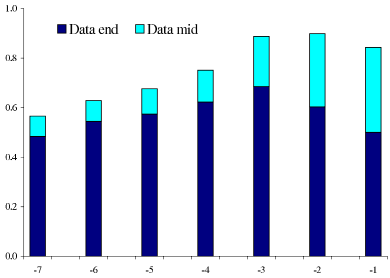

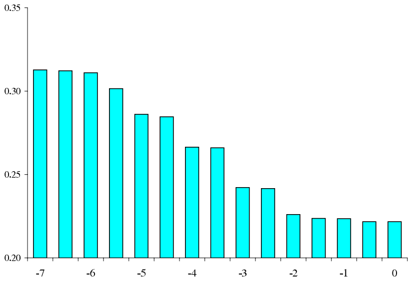

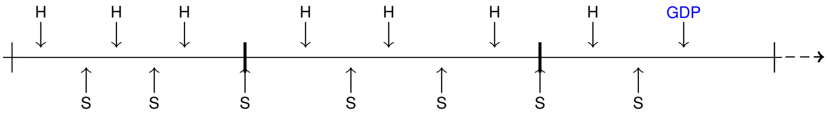

Problem: these are reduced form models

Can we bridge with structural quarterly models?

⇒ Giannone, Monti and Reichlin, 2008 [GMR]

Problem: these are reduced form models

Can we bridge with structural quarterly models?

$\Rightarrow$ Giannone, Monti and Reichlin, 2008 [GMR]

GMR: The problem

With a traditional (balanced, quarterly) structural micro-founded model we are **unable** to exploit any information on the current quarter coming from the early releases.

Is there a way to **exploit of timely information**, as done in judgmental (GB, SPF) and reduced-form bridge forecasts, and still **tell a story**?

Giannone, Monti and Reichlin, 2008

The method we propose aims at combining short-term/conjunctural analysis with structural micro-founded models.

- Take a structural model (estimated elsewhere)
- Exploit the timely information coming from the monthly releases [monthly in the model and monthly auxiliary]

→ to obtain more accurate forecasts of the observables and, more importantly, **real-time estimates** of concepts such as output gap, the natural rate of interest, etc....

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Giannone, Monti and Reichlin, 2008

Related literature
Hybrid reduced-form/structural models
$\downarrow$
Del Negro and Schorfheide, 2004;
Del Negro, Schorfheide, Smets and Wouters, 2005;
Boivin and Giannoni, 2006

Our objective (and method) is different

Integrating conjunctural and micro-founded models

Structural model (log-linearized)

$$
\begin{array}{llcll}
\text{quarterly variables} & y_{t_q} & = & \mathcal{M}_\theta(L)\ s_{t_q-1} & \\
\text{states} & s_{t_q} & = & \mathcal{T}_\theta\ s_{t_q-1} & +\ B_\theta\ \varepsilon_{t_q}
\end{array}
$$

$\mathcal{M}_\theta$: the observation equation
$\mathcal{T}_\theta$: transition equation

$\mathcal{M}_\theta$, $\mathcal{T}_\theta$: linear functions;
θ: deep parameters
(estimated or calibrated by the structural modeler)

model is estimated and defined at a quarterly frequency.

Integrating conjunctural and micro-founded models

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Integrating conjunctural and micro-founded models

1. Derive monthly state space:

Transform monthly indicators so that they correspond to a quarterly quantity when observed at the end of the quarter: $y_{t_m} = y_{t_q}$ at the end of the quarter.

$\rightarrow$ Irregular Sampling Problem

$$X_{t_m} = \Lambda y_{t_m} + \nu_{t_m} \qquad \text{(conjunctural model)}$$

$$\Downarrow$$

$$X_{t_m} = \Lambda \mathcal{M}_\theta^m(L) s_{t_m} + \nu_{t_m}$$

$$\Downarrow$$

$$s_{t_m} = \mathcal{T}_\theta^m \; s_{t_m - 1} + B_\theta^m \; \varepsilon_{t_m}^m \qquad \text{(monthly state space)}$$

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Bridging monthly and quarterly

2. Expand the monthly state-space with the auxiliary variables

$$\begin{bmatrix} y_{t_m} \\ X_{t_m} \end{bmatrix} = \begin{bmatrix} \mathcal{M}_\theta^m(L) \\ \Lambda \mathcal{M}_\theta^m(L) \end{bmatrix} s_{t_m} + \begin{bmatrix} u_{t_m} \\ \nu_{t_m} \end{bmatrix}$$

expand the state-space

$var(u_{it_m}) =$ 0 *if available* / ∞ *if not available*

$var(\nu_{jt_m}) =$ R_j *if available* / ∞ *if not available*

Empirics - Structural model

Small scale New-Keynesian model
e.g. Del Negro and Schorfheide (IER, 2004)

It reduces to a three-equations model:

$$\begin{aligned}
\hat{y}_t - \hat{g}_t &= E_t\left[\hat{y}_{t+1} - \hat{g}_{t+1}\right] - \frac{1}{\tau}\left(\hat{r}_t - E_t\hat{\pi}_{t+1} - \rho_z \hat{z}_t\right) \\
\hat{\pi}_t &= \beta E_t \hat{\pi}_{t+1} + \kappa(\hat{y}_t - \hat{g}_t) \\
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\end{aligned}$$

the bridge model $\rightarrow X_{t_m} = f(\hat{z}_t, \hat{g}_t, \hat{r}_t) + \nu_t$

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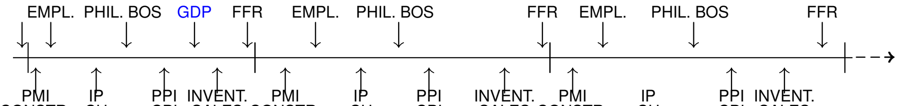

Empirics

We evaluate the model's out-of-sample performances with a pseudo real time forecasting exercise

- evaluate the model over the sample 1997q1-2007q4
- the deep parameters θ of the structural model are estimated only once at the beginning of the evaluation sample (1997q1)
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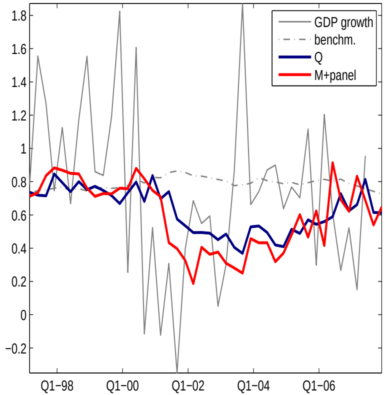

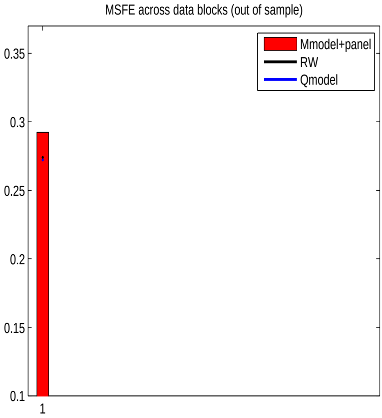

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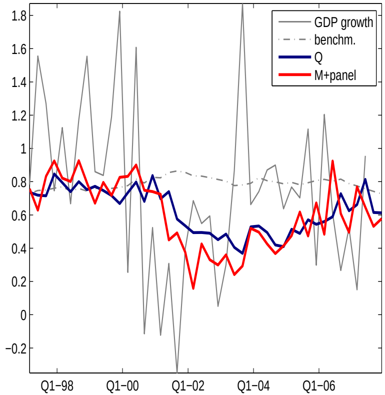

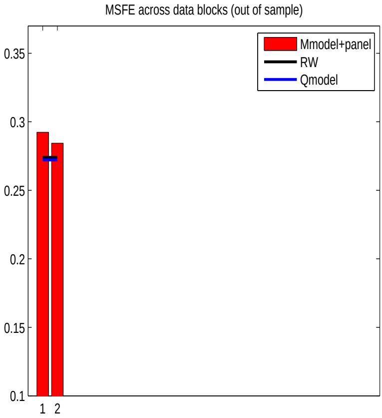

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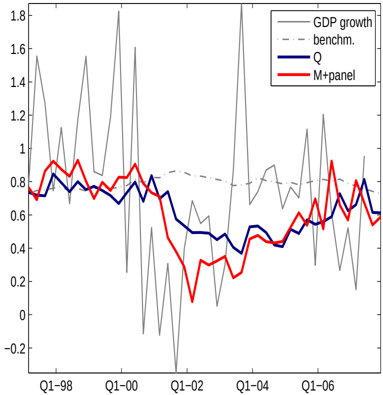

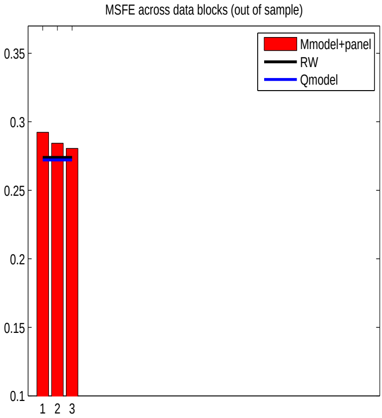

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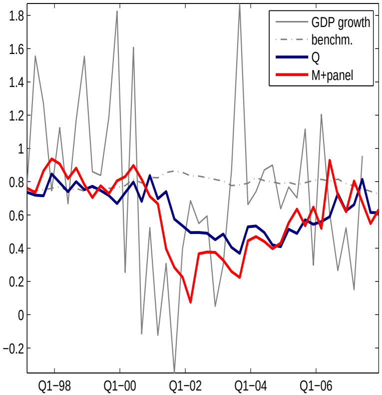
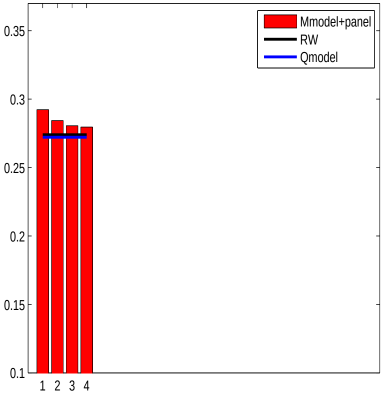
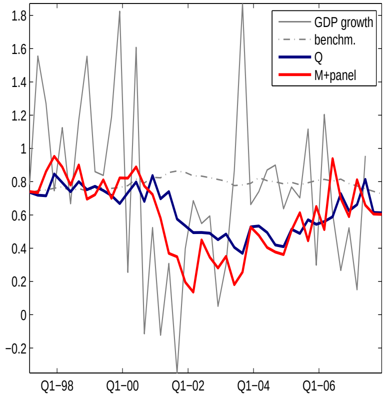
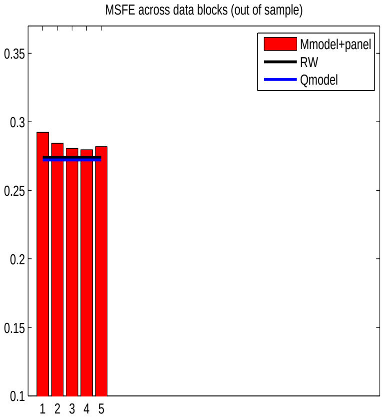


MSFE across data blocks (out of sample)



Nowcasting GDP growth





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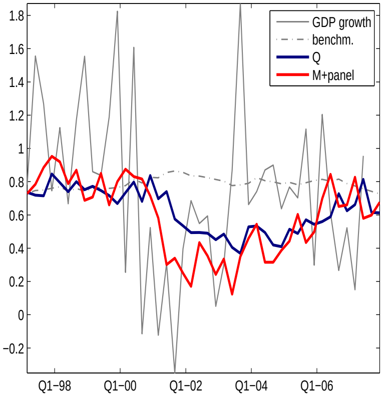

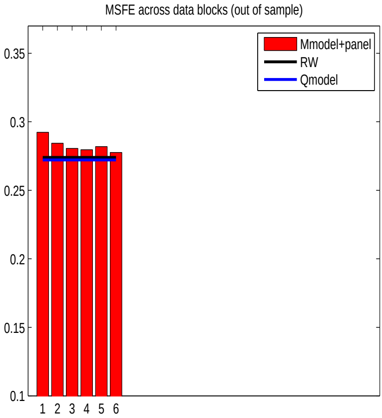

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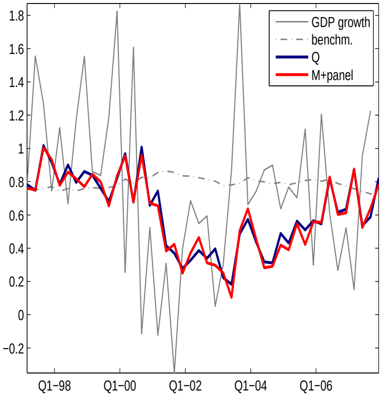
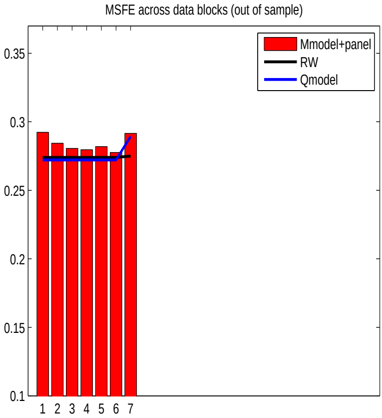
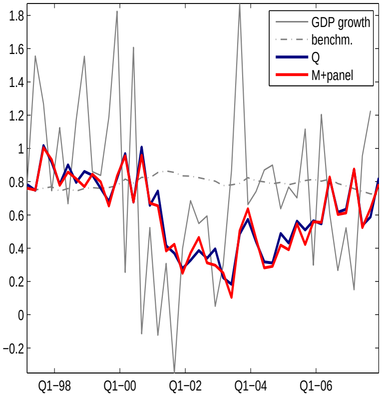
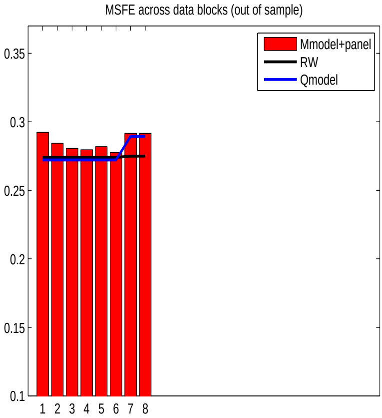




Nowcasting GDP growth





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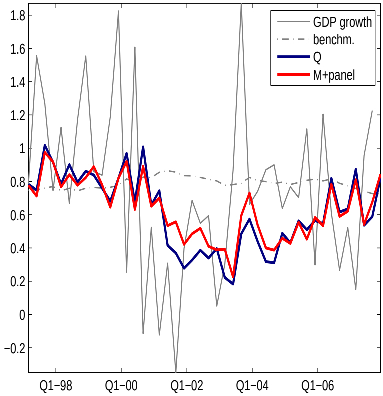

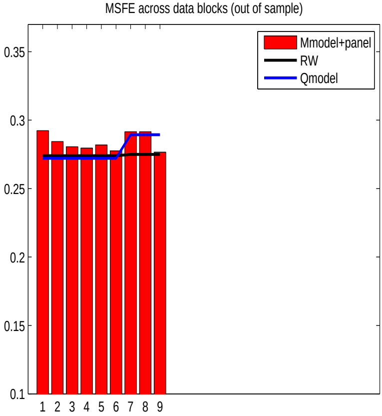

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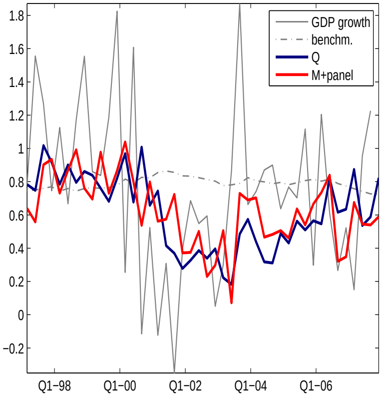
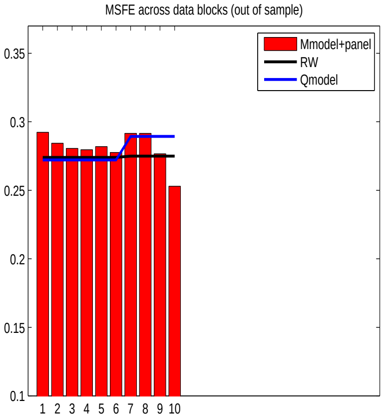
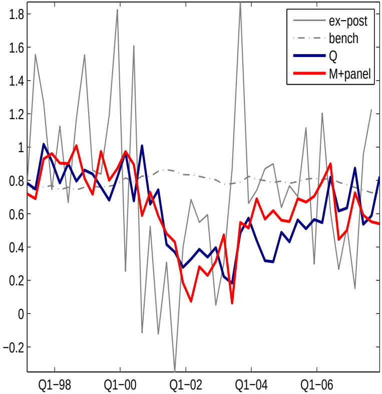
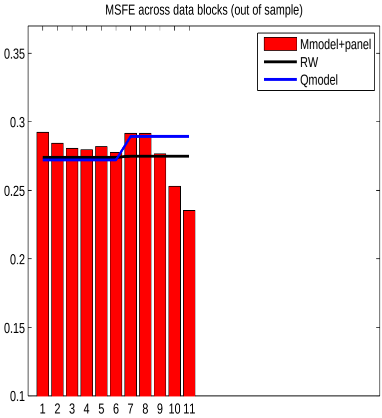




Nowcasting GDP growth





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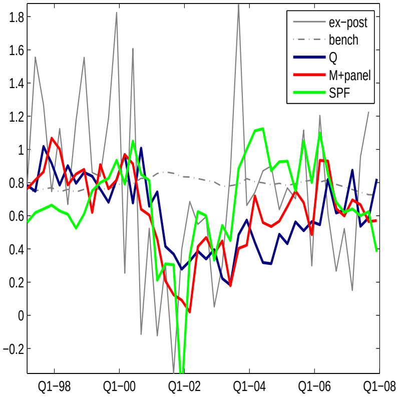

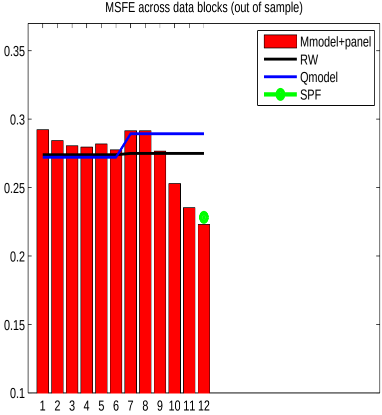

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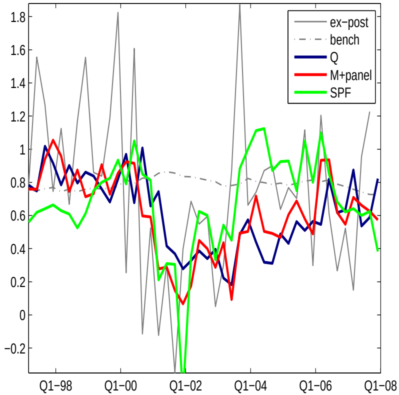

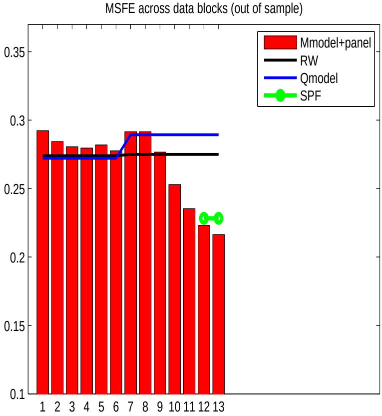

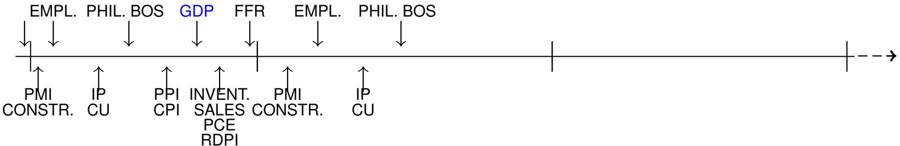

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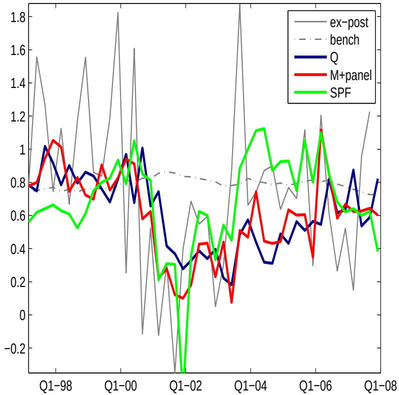

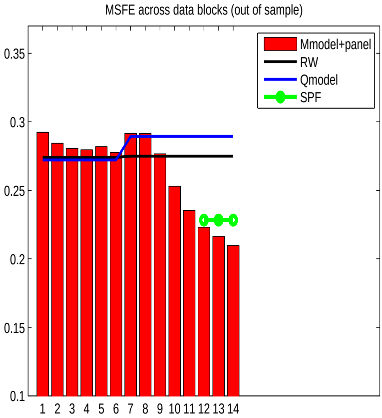

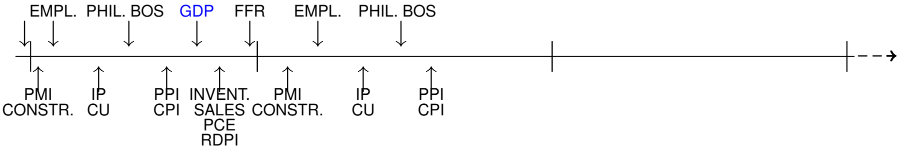

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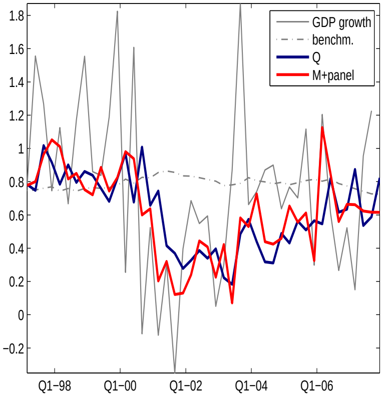

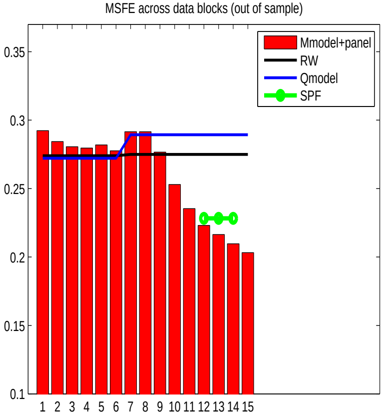

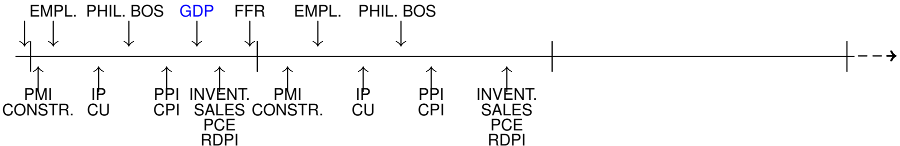

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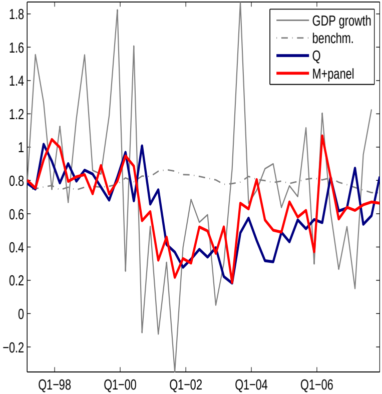
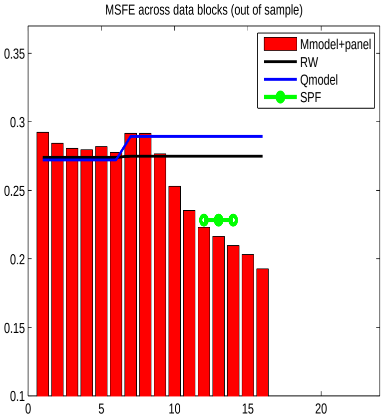
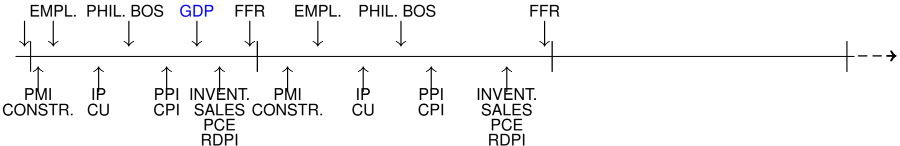
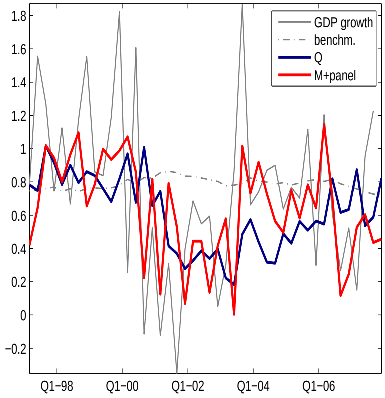
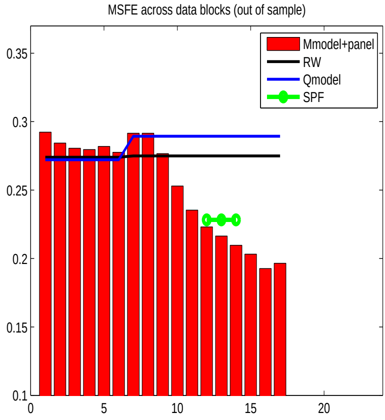


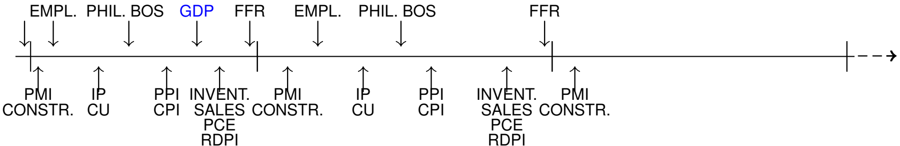




Nowcasting GDP growth







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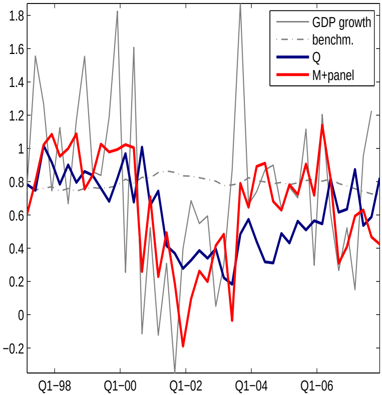

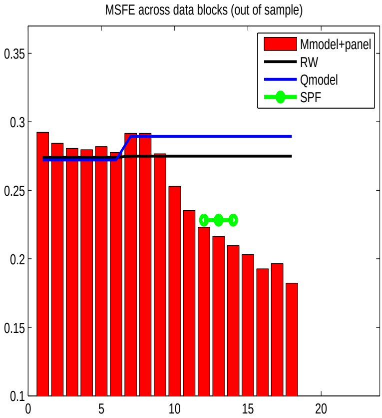

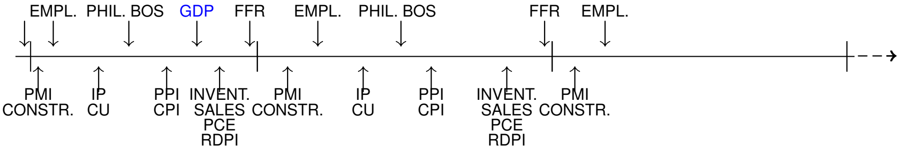

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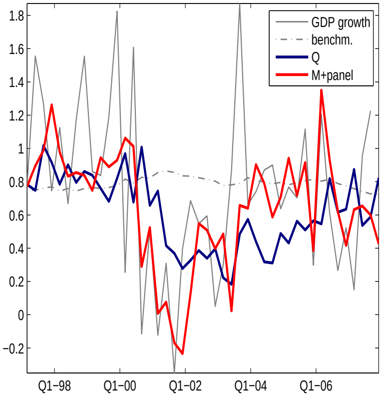

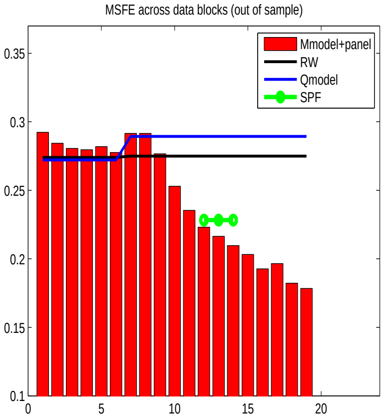

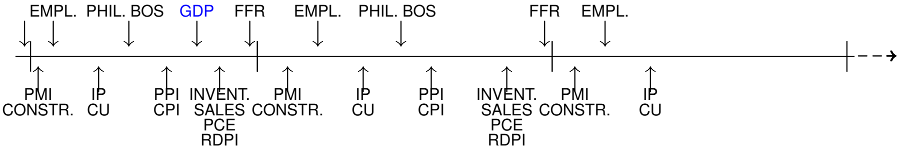

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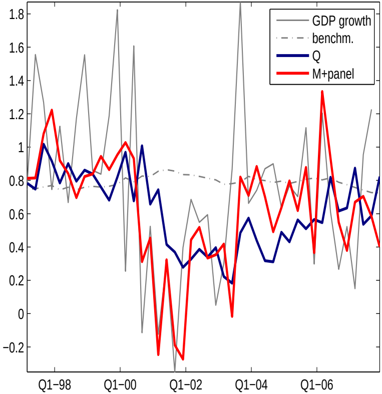

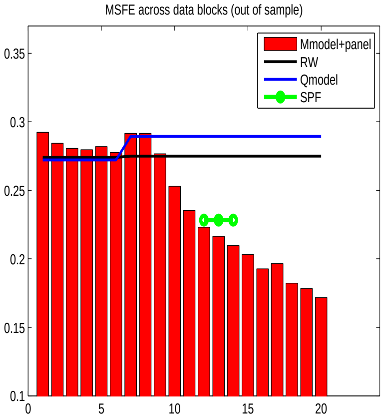

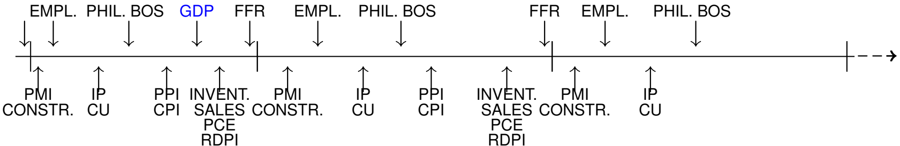

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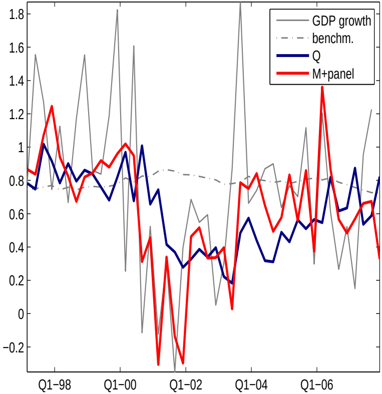

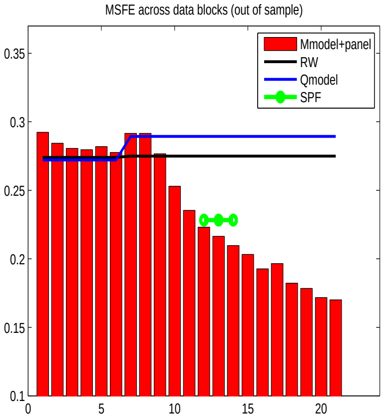

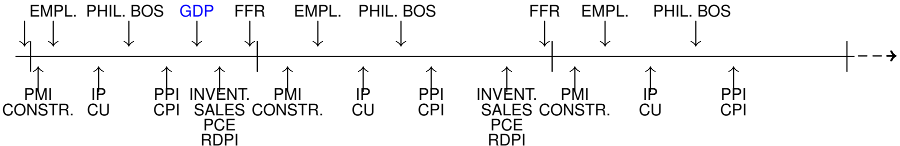

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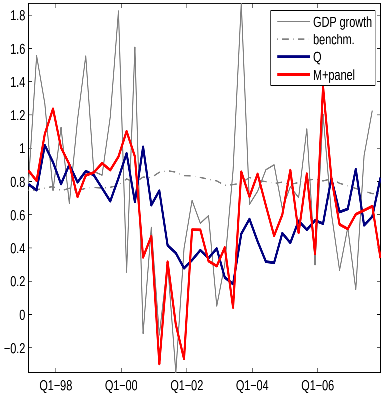

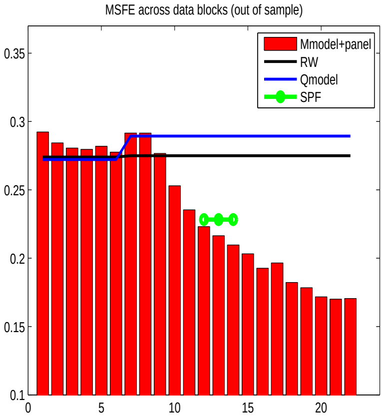

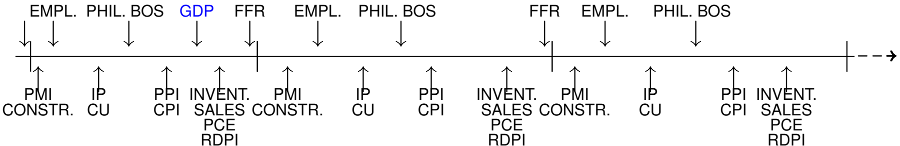

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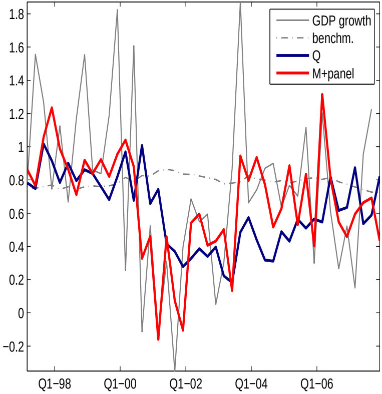

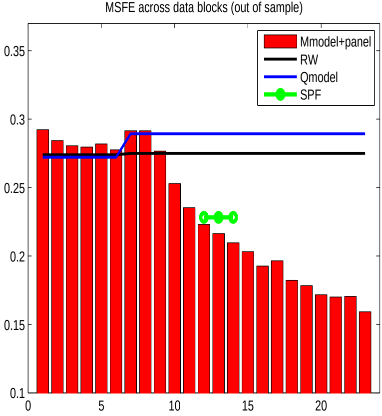

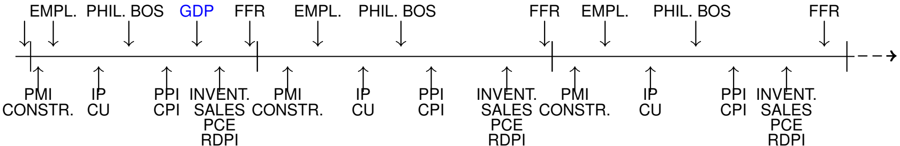

Taking advantage of the structure

Ok, we have greater forecasting accuracy for the observables

More importantly, we are able to

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- show how each release affects these estimates

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$$\ln A_t = \ln \gamma + \ln A_{t-1} + \hat{z}_t \quad (1)$$

In this simple framework $\hat{rr}^*_t = \rho_z \hat{z}_t$

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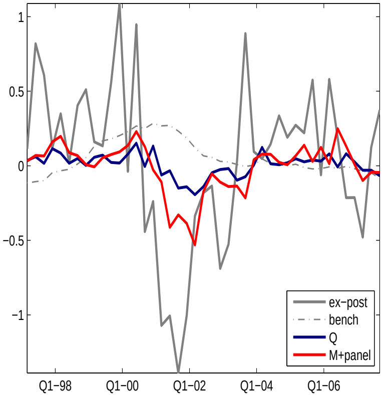

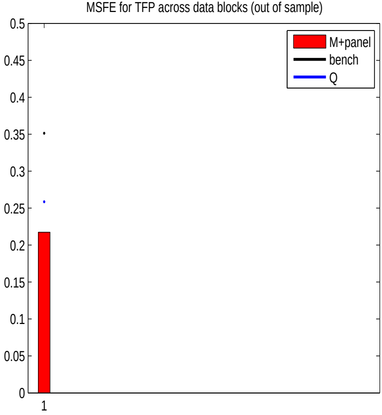

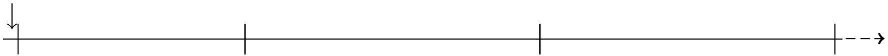

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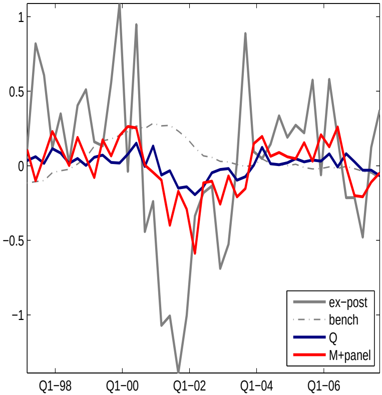

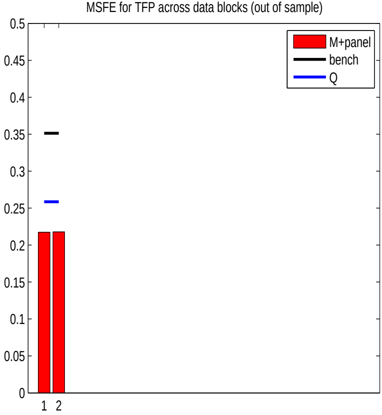

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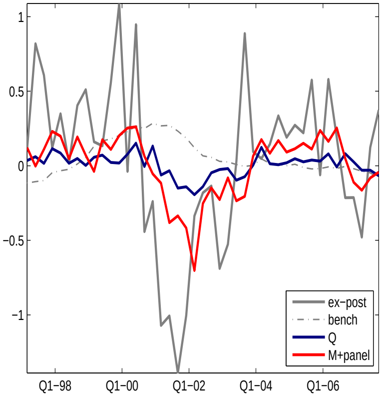

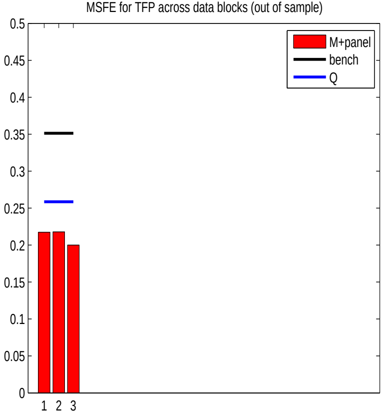

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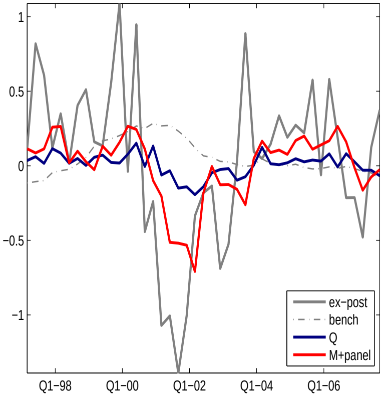

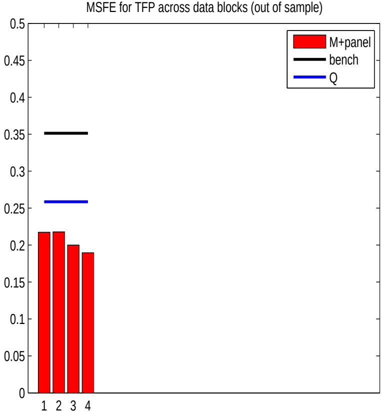

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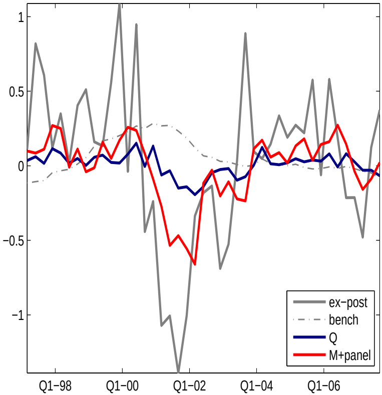

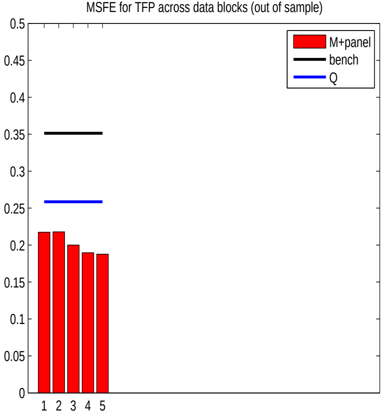

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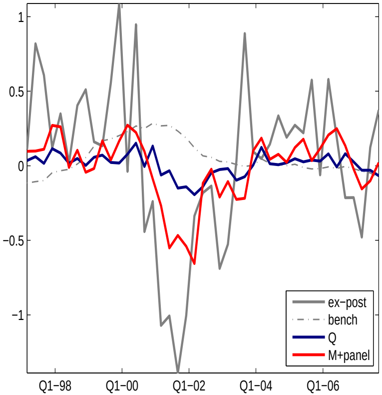

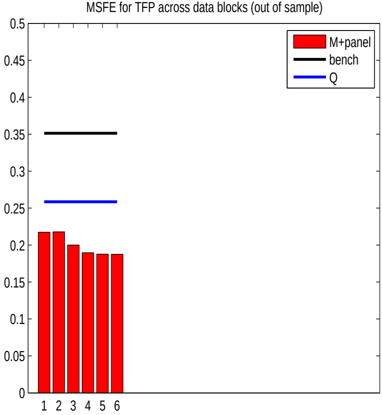

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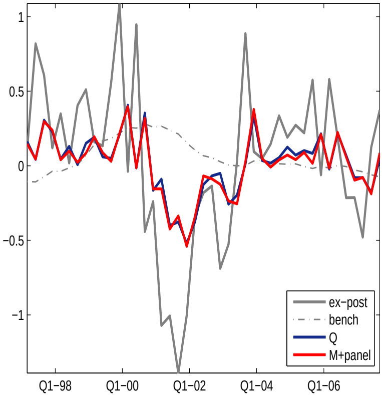

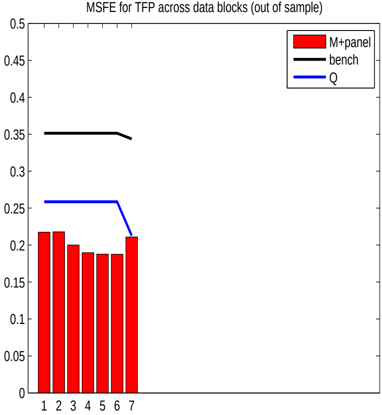

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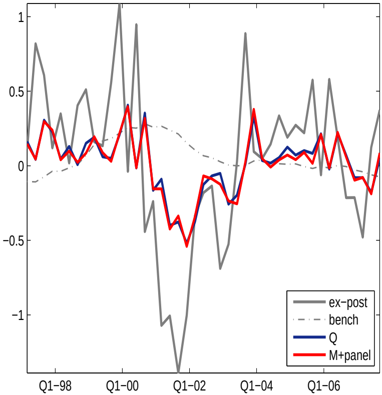

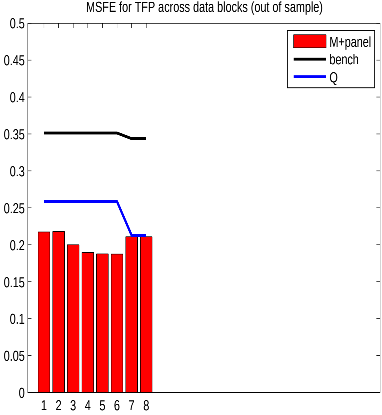

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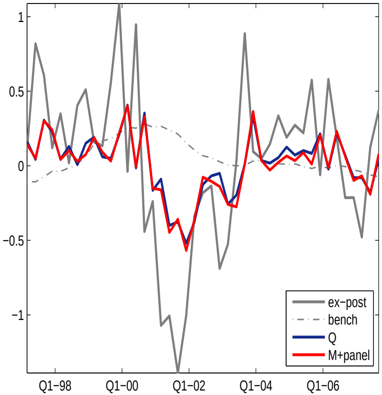

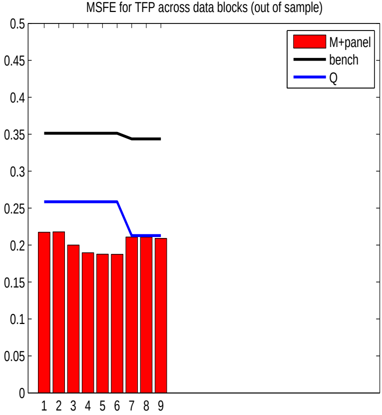

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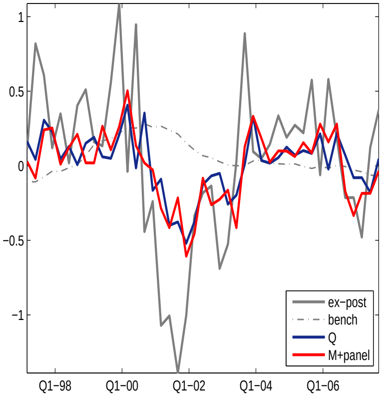
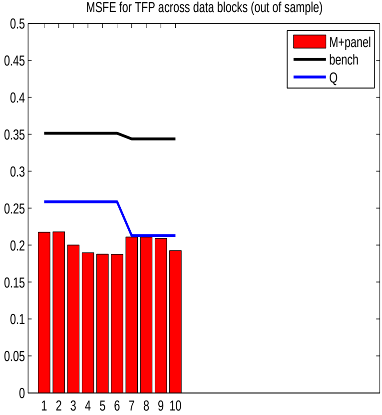
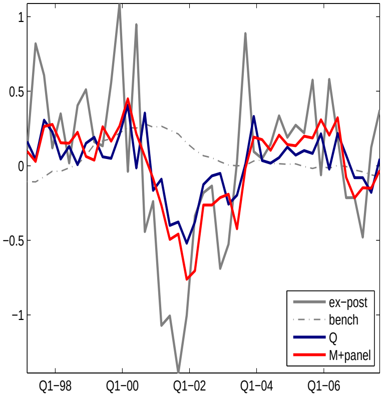
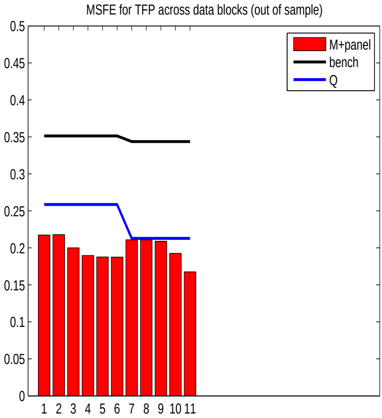


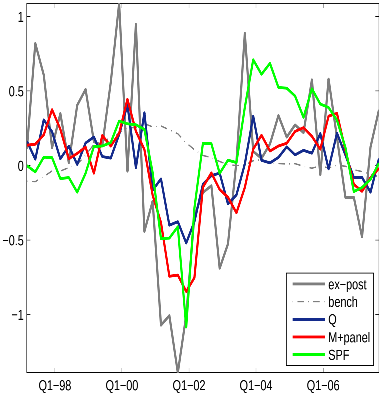


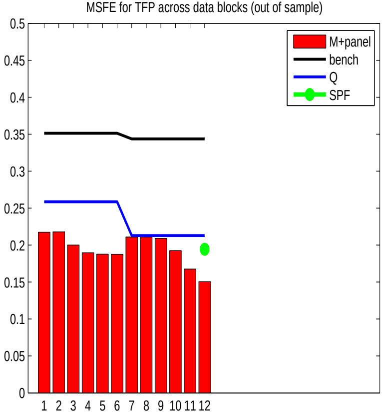
Nowcasting TFP growth





Nowcasting TFP growth





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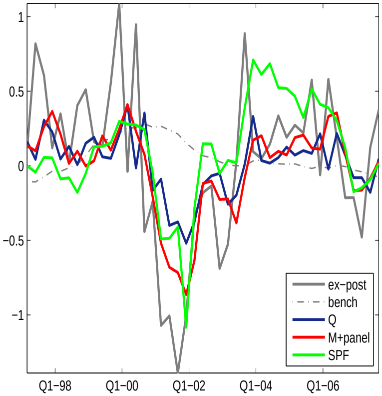

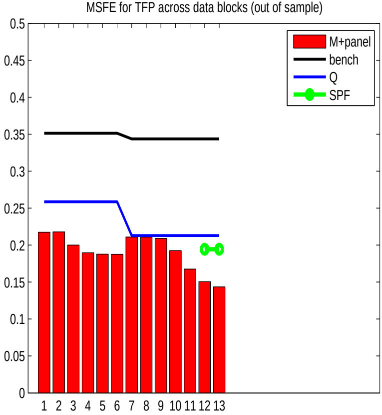

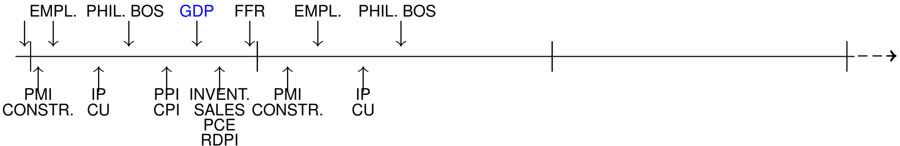

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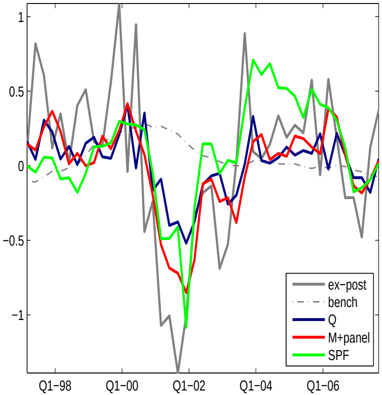

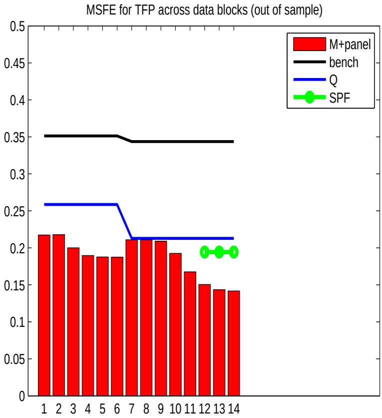

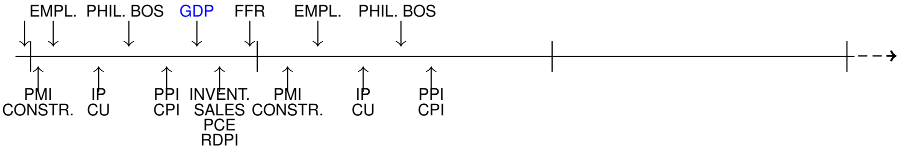

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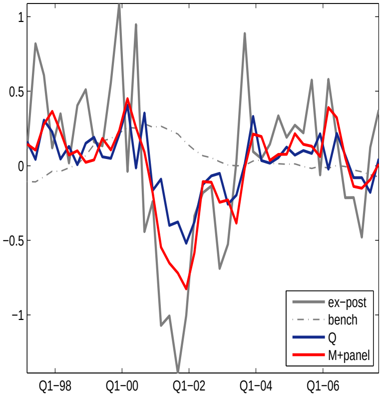

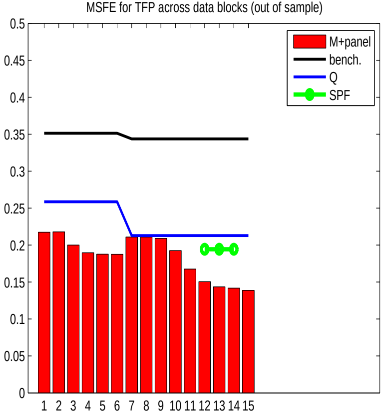

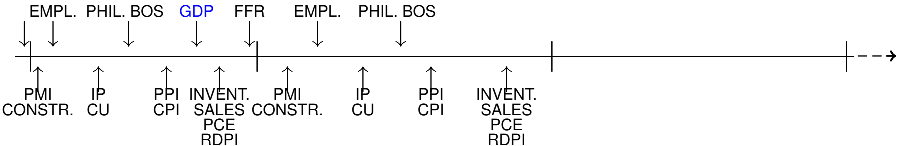

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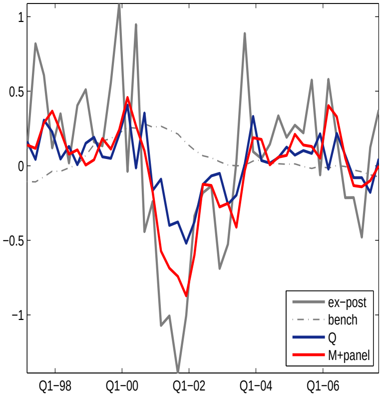
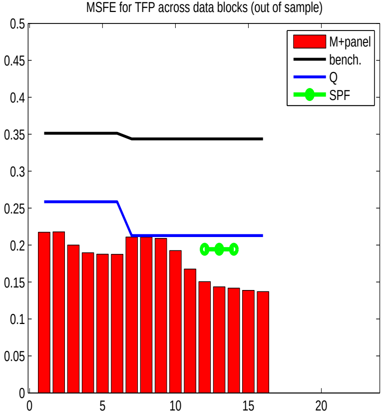
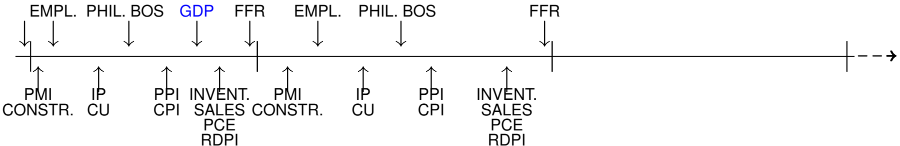
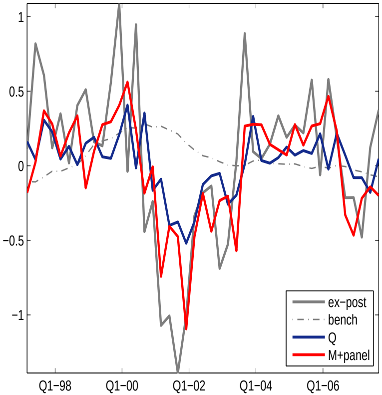
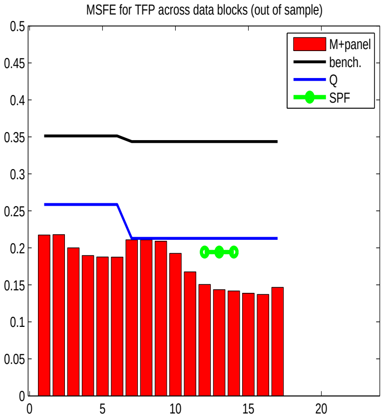


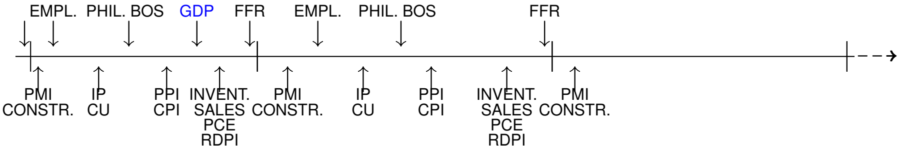




Nowcasting TFP growth







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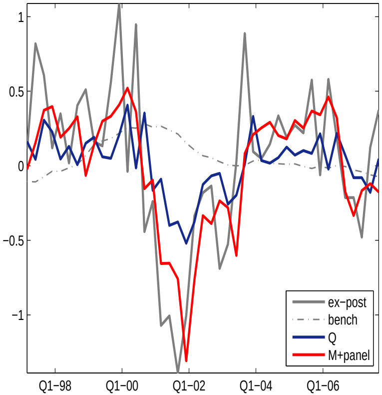

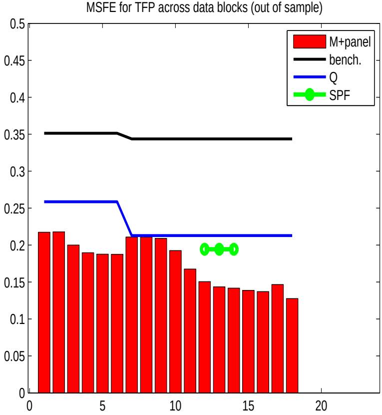

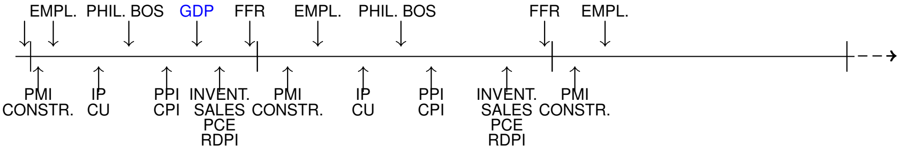

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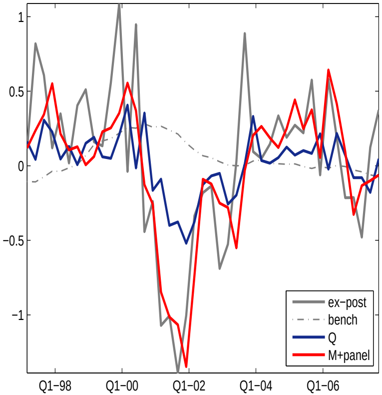

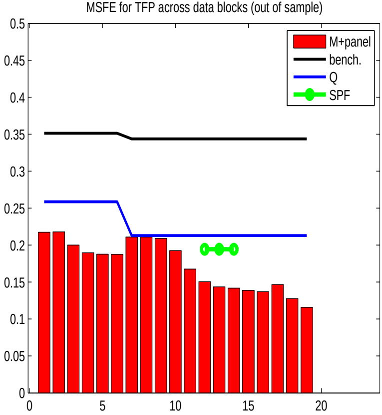

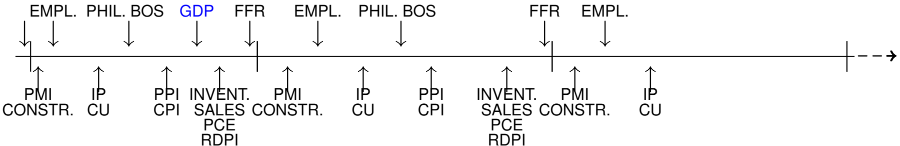

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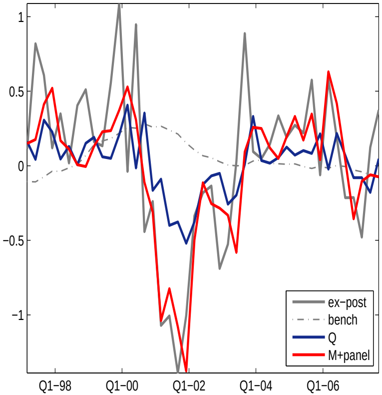

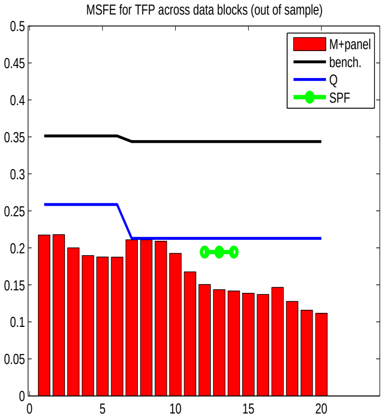

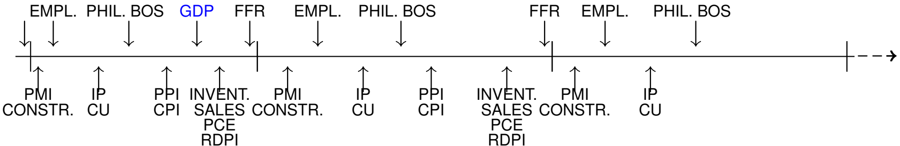

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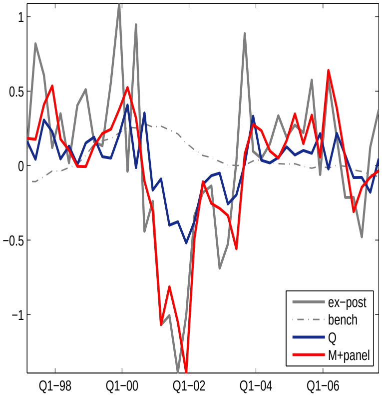

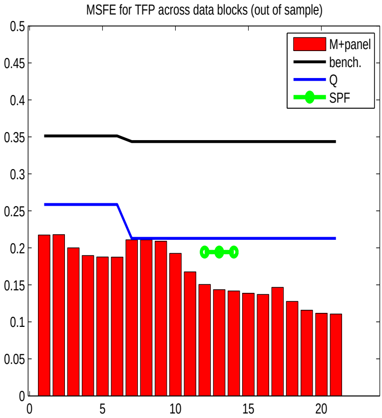

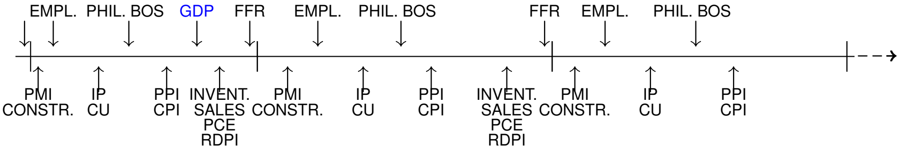

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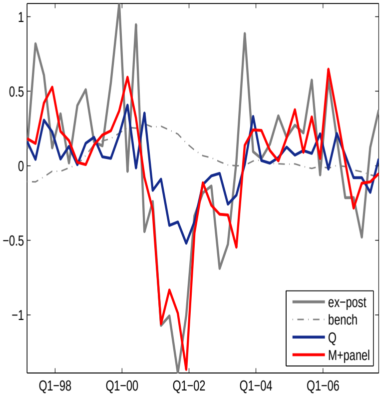

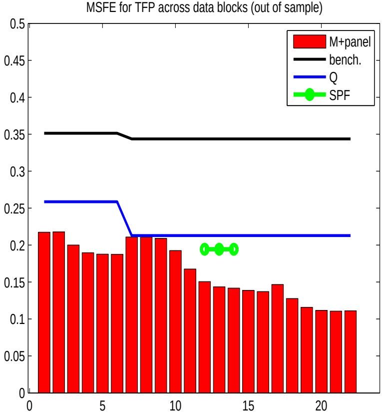

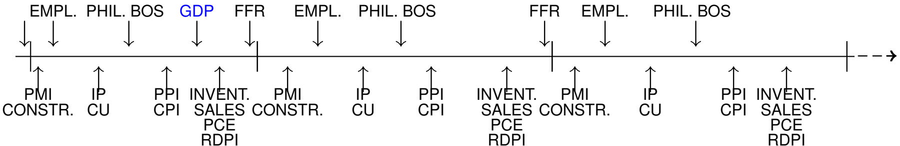

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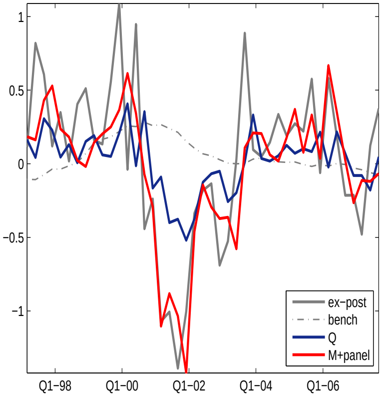
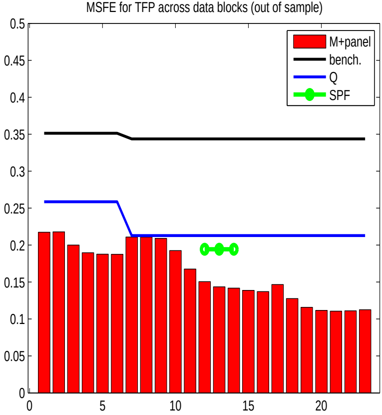
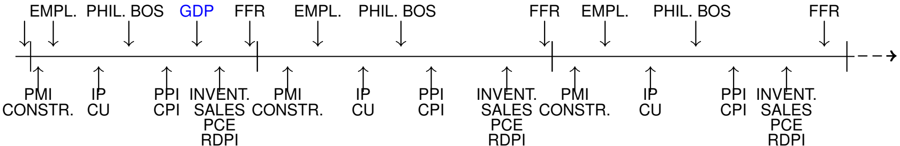






Conclusions

• Now-casting important
• Key is to take into account the real time data flow: need methods to handle panels of many data with jagged edge [GRS and ECB projects, other applications at central banks (New Zealand, Federal Reserve, Norway)]

• Also relevant to combine conjunctural analysis with structural micro-founded models [GMR]

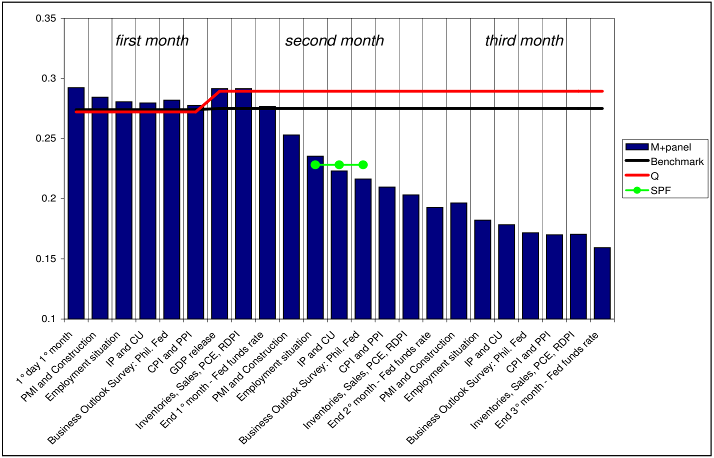
Our ideas:

- exploit timely information within a structural model
- without interfering with the estimation of the structural model

In this way we able able to make better forecasts of the variables of interest and of model-based concepts

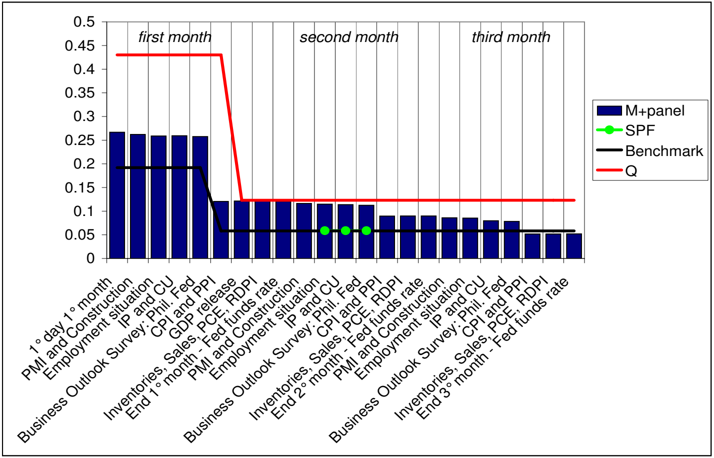
MSFE at various release dates

GDP growth nowcast



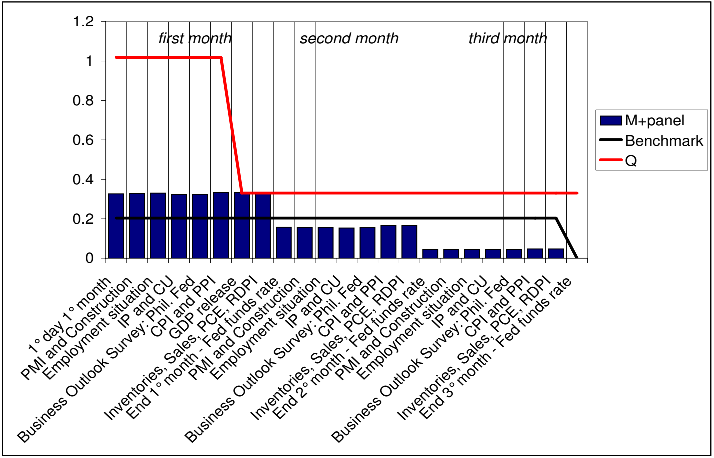
MSFE at various release dates

CPI inflation growth nowcast



MSFE at various release dates

Fed Funds rate nowcast



Nowcasting GDP growth

MSFE relative to constant growth model

Greenbook	1.03
Structural model alone	0.88
Structure + judgement	0.82