Forecasting with the Help of Survey Information

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  - Access to extensive data
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This paper: Can we efficiently combine surveys and models to improve *real time* forecasts?

In the literature: combining survey and model forecasts

Ex-post adjustment: estimate a model, produce forecasts with it, *then* adjust them with external information. Examples include:

- *Entropic tilting:* Galvão et al. (2021), Ganics and Odendahl (2021), Robertson et al. (2005), and Tallman and Zaman (2020)
- *Optimal pooling:* Ang et al. (2007) and Bańbura, Brenna, et al. (2021)
- *Incorporate survey forecasts in structural models:* Monti (2010) and Svensson (2005)

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This paper: incorporate the survey forecasts *directly into* a reduced form model in order to get more precise estimates, and, therefore, improve forecasts.

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- We combine SPF forecasts (multiple variables & horizons) with observed data to estimate more precise *model parameters*.
- We run a recursive out-of-sample forecasting exercise using a BVAR model with stochastic volatility (SV), **augmented with SPF forecasts**.
- We assess gains over a standard BVAR+SV **without** survey info — considering both *point forecasts* and *density forecasts*.

VAR augmented with the term-structure of SPF forecasts

Starting point is a **VAR(p)+SV**:

$$y_t = c + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + A_0^{-1} \boldsymbol{\Lambda_t} e_t \quad (1)$$

SV

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To which we add *SPF forecasts* done at **time** t (latest obs is $t-1$)

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To which we add *SPF forecasts* done at **time** t (latest obs is $t-1$)

$$\textit{for nowcast} \qquad y_{t|\mathbf{t}} = c + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + A_0^{-1}\Lambda_{t|\mathbf{t}} e_{t|\mathbf{t}} \tag{2}$$

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for nowcast $$y_{t|t} = c + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + A_0^{-1} \Lambda_{t|t} e_{t|t} \quad (2)$$

$$\vdots$$

for horizon ***h*** $$y_{t+\boldsymbol{h}|t} = c + \beta_1 y_{t+\boldsymbol{h}-1|t} + \ldots + \beta_p y_{t+\boldsymbol{h}-p|t} + A_0^{-1} \Lambda_{t+\boldsymbol{h}|t} e_{t+\boldsymbol{h}|t} \quad (3)$$

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To which we add *SPF forecasts* done at time t (latest obs is $t-1$)

$$\textit{for nowcast} \qquad y_{t|t} = c + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + A_0^{-1} \Lambda_{t|t} e_{t|t} \tag{2}$$

$$\vdots$$

$$\textit{for horizon } h \qquad y_{t+h|t} = c + \beta_1 y_{t+h-1|t} + \dots + \beta_p y_{t+h-p|t} + A_0^{-1} \Lambda_{t+h|t} e_{t+h|t} \tag{3}$$

$e_{t|t}, \dots, e_{t+h|t}$ represent i.i.d. *judgement* as in Brenna and Budrys (2024)

Matrix form

SV

ECB Survey of Professional Forecasters and **ECB Real-Time Database**

- Sample 1990q1-2024q3
- **4 variables:** real GDP growth, unemployment rate, HICP inflation, 3-m Euribor
- At each quarter q, observed data (four variables) and forecasts (*only* for GDP and HICP) at different horizons. 4q-ahead always present, fixed event forecast with varying horizons.
- We run the model for the average ("consensus") forecast.

Data, Specifications and Evaluation

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Evaluation:

- Recursive estimation from **2007q2**; forecast evaluation from **2007q3 to 2024q3**
- Comparison of two models:
  - *Baseline:* standard BVAR with stochastic volatility (SV)
  - *S-BVAR (Proposed):* BVAR with SV + **survey information**

Average relative scores: S-BVAR/BVAR

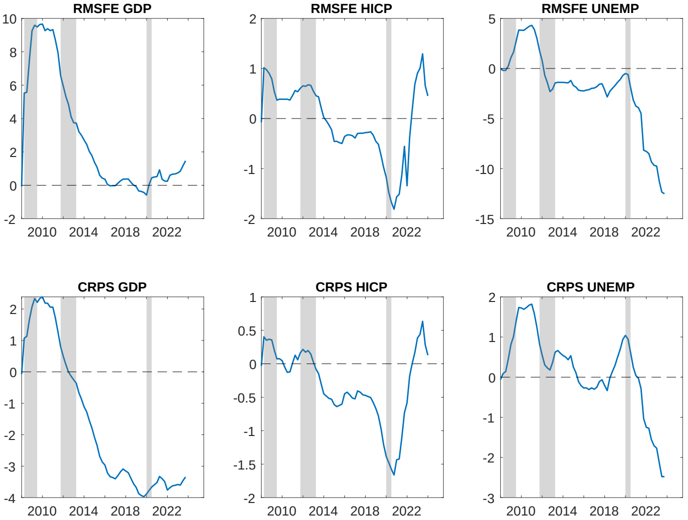
Horizon	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
					GDP				
RMSFE	1.05	**0.99**	1.01	**0.99**	1.00	1.00	**0.99**	**0.99**	**0.98**
CRPS	**0.98**	**0.95**	**0.94**	**0.90**	**0.94**	**0.94**	**0.91**	**0.89**	**0.92**
					HICP				
RMSFE	1.23	1.05	1.03	**0.96**	1.01	**0.98**	**0.98**	**0.97**	**0.98**
CRPS	1.13	1.03	1.00	**0.96**	1.01	**0.97**	**0.95**	**0.94**	**0.95**
					Unemployment				
RMSFE	1.07	1.03	**0.96**	**0.91**	**0.90**	**0.90**	**0.90**	**0.90**	**0.90**
CRPS	1.02	1.04	**0.98**	**0.94**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**

Note: The table shows accuracy metrics in relative terms, with the BVAR model at the denominator and the Survey-augmented BVAR (S-BVAR) at the numerator. Values smaller than one indicate that the latter model is more accurate on average over the sample for the respective horizon.

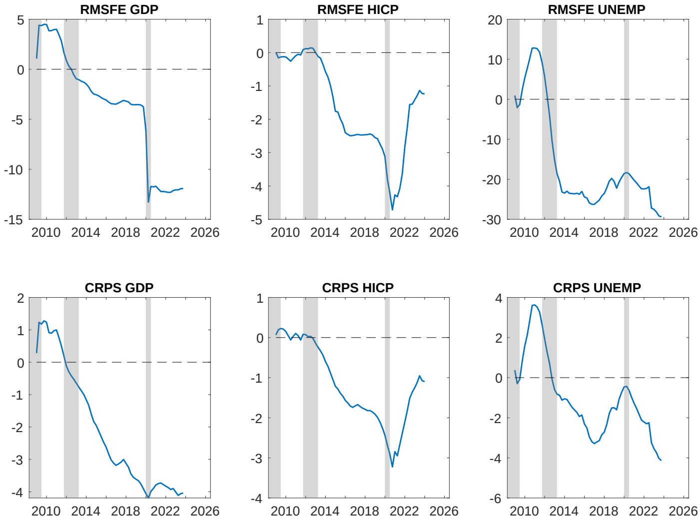
Alternative

Forecast performance at 1-year-ahead

Alternative



Forecast performance at 2-year-ahead



Conclusions

- We use a parsimonious and efficient way to incorporate survey forecasts into a VAR model with stochastic volatility;
- The added information content allows for sharper parameter estimates;
- In particular, larger gains using:
  - SPF average point forecasts between nowcast and four quarters ahead;
  - SPF GDP and HICP forecast;
- S-BVAR does best:
  - for horizons between four and eight quarters ahead;
  - from density perspective;
  - for GDP and unemployment forecasts.

Thank you!

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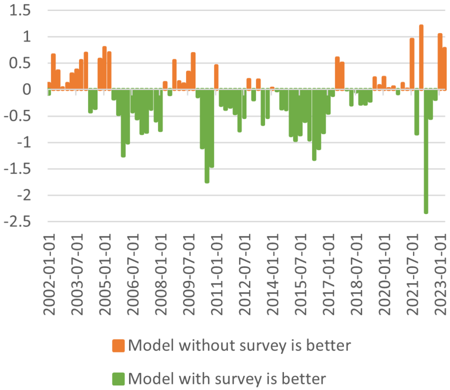
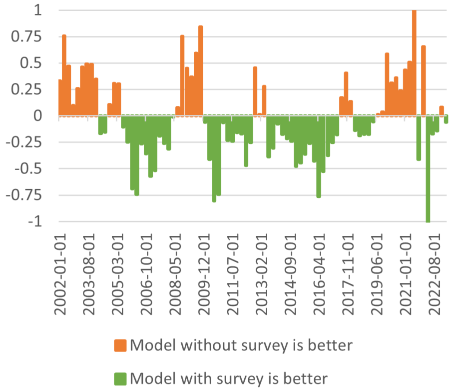
Background slides



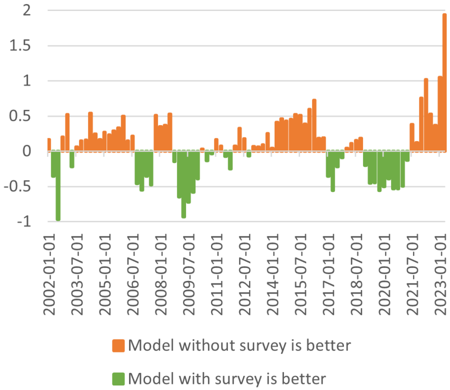
(a) Differences in RSFE



(b) Differences in CRPS

Back

Forecast performance at 1-year-ahead: HICP



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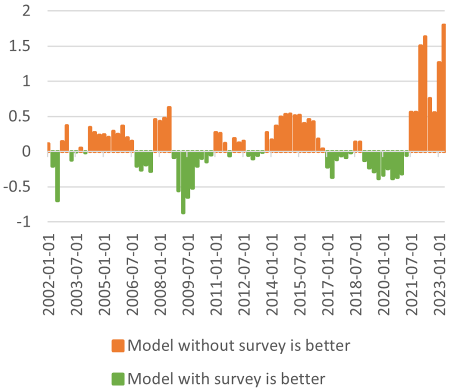
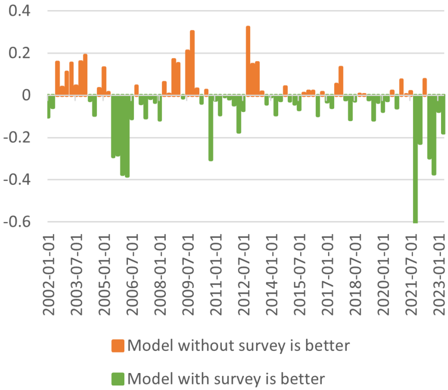


(b) Differences in CRPS

Back

Forecast performance at 1-year-ahead: Unemployment

(a) Differences in RSFE



(b) Differences in CRPS

Back

Toy Model in Companion Form: n=2, p=1, h=1

$$
\begin{bmatrix} y_{t+1|t} \\ \pi_{t+1|t} \\ y_{t|t} \\ \pi_{t|t} \\ y_{t-1} \\ \pi_{t-1} \end{bmatrix} = \begin{bmatrix} \boldsymbol{c}_{*,2} \\ \\ \boldsymbol{c}_{*,1} \\ \\ \boldsymbol{c}_{*,0} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & \boldsymbol{B}_{*,3}^{[1:6,1:2]} \\ 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & \end{bmatrix} \begin{bmatrix} y_{t|t-1} \\ \pi_{t|t-1} \\ y_{t-1|t-1} \\ \pi_{t-1|t-1} \\ y_{t-2} \\ \pi_{t-2} \end{bmatrix}
$$

$$
+ \begin{bmatrix} 1 & 0 & \beta_{11} & \beta_{12} & \\ 0 & 1 & \beta_{21} & \beta_{22} & \\ 0 & 0 & 1 & 0 & \\ 0 & 0 & 0 & 1 & \boldsymbol{B}_{*,2}^{[1:6,1:2]} \\ 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & \end{bmatrix} \begin{bmatrix} A_{0,11}^{-1} & A_{0,12}^{-1} & 0 & 0 & 0 & 0 \\ A_{0,21}^{-1} & A_{0,22}^{-1} & 0 & 0 & 0 & 0 \\ 0 & 0 & A_{0,11}^{-1} & A_{0,12}^{-1} & 0 & 0 \\ 0 & 0 & A_{0,21}^{-1} & A_{0,22}^{-1} & 0 & 0 \\ 0 & 0 & 0 & 0 & A_{0,11}^{-1} & A_{0,12}^{-1} \\ 0 & 0 & 0 & 0 & A_{0,21}^{-1} & A_{0,22}^{-1} \end{bmatrix} \begin{bmatrix} \exp(\lambda_{1,t+1|t}) e_{t+1|t}^{y} \\ \exp(\lambda_{2,t+1|t}) e_{t+1|t}^{\pi} \\ \exp(\lambda_{1,t|t}) e_{t|t}^{y} \\ \exp(\lambda_{2,t|t}) e_{t|t}^{\pi} \\ \exp(\lambda_{1,t-1}) e_{t-1}^{y} \\ \exp(\lambda_{2,t-1}) e_{t-1}^{\pi} \end{bmatrix}
$$

Back

$\boldsymbol{B}_{*,2}$ and $\boldsymbol{B}_{*,3}$ represent the second and third power of matrix $\boldsymbol{B}_*$, respectively:

$$\underset{Nm\times Nm}{B_*} = \begin{bmatrix} \underset{N\times Np}{\beta} & 0_{N\times N(m-p)} \\ I_{N(m-1)} & 0_{N(m-1)\times N} \end{bmatrix} \tag{4}$$

where $m = \max(H+1, p)$.

Back

Annual averages y-o-y to quarterly q-o-q forecasts

For real GDP and HICP inflation, we observe:

$$X^A_{t,\text{OBS}} = \left[\frac{\frac{1}{4}\left(Y_t^{(1)} + Y_t^{(2)} + Y_t^{(3)} + Y_t^{(4)}\right)}{\frac{1}{4}\left(Y_{t-1}^{(1)} + Y_{t-1}^{(2)} + Y_{t-1}^{(3)} + Y_{t-1}^{(4)}\right)} - 1 \right] \cdot 100 \tag{5}$$

After calculations:

$$\log\left(\frac{X^A_{t,\text{OBS}}}{100} + 1\right) = \frac{1}{4}\Bigg[\log\left(\frac{Y_t^{(4)}}{Y_t^{(3)}}\right) + 2\log\left(\frac{Y_t^{(3)}}{Y_t^{(2)}}\right) + 3\log\left(\frac{Y_t^{(2)}}{Y_t^{(1)}}\right) + 4\log\left(\frac{Y_t^{(1)}}{Y_{t-1}^{(4)}}\right) + 3\log\left(\frac{Y_{t-1}^{(4)}}{Y_{t-1}^{(3)}}\right) + 2\log\left(\frac{Y_{t-1}^{(3)}}{Y_{t-1}^{(2)}}\right) + \log\left(\frac{Y_{t-1}^{(2)}}{Y_{t-1}^{(1)}}\right)\Bigg] \tag{6}$$

Quarterly y-o-y to quarterly q-o-q forecasts

For real GDP and HICP inflation we observe:

$$X^{Q}_{t,\mathrm{OBS}} = \left(\frac{Y^{(1)}_{t}}{Y^{(1)}_{t-1}} - 1 \right) \cdot 100 \tag{7}$$

After calculations:

$$\log\left(\frac{X^{Q}_{t,\mathrm{OBS}}}{100} + 1 \right) = \log\left(\frac{Y^{(1)}_{t}}{Y^{(1)}_{t-1}} \right) + \log\left(\frac{Y^{(4)}_{t-1}}{Y^{(3)}_{t-1}} \right) + \log\left(\frac{Y^{(3)}_{t-1}}{Y^{(2)}_{t-1}} \right) + \log\left(\frac{Y^{(2)}_{t-1}}{Y^{(1)}_{t-1}} \right) \tag{8}$$

Modeling Volatility Dynamics via AR(1) Process

We set the law of motion of stochastic volatility to follow AR(1) process

$$\lambda_t = \rho\lambda_{t-1} + u_t, \qquad u_t \sim \mathcal{N}(0, \sigma_u^2) \tag{9}$$

To simplify, we assume agents form expectations based on the unconditional path of volatility, that is,

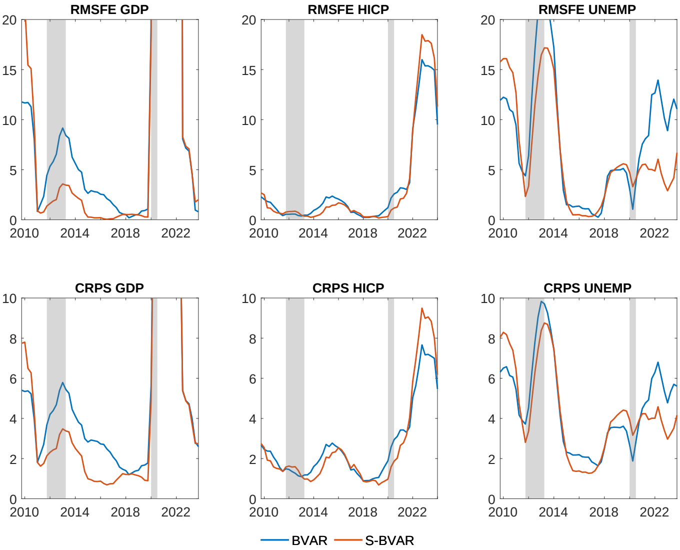
$$\lambda_{t+j|t} = \rho^j \lambda_{t-1} \qquad \forall j = 0, ..., h \tag{10}$$

implying that respondents do not assume any conditionality about future uncertainty

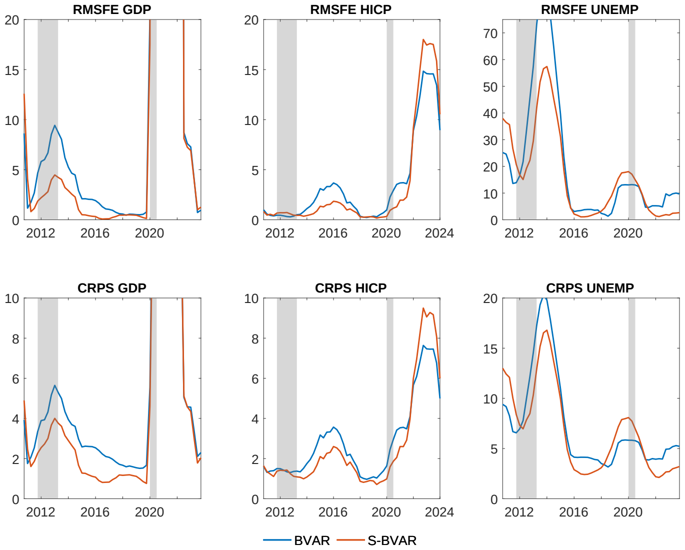
$$u_{t+j|t} = 0 \qquad \forall j = 0, ..., h \tag{11}$$

Back

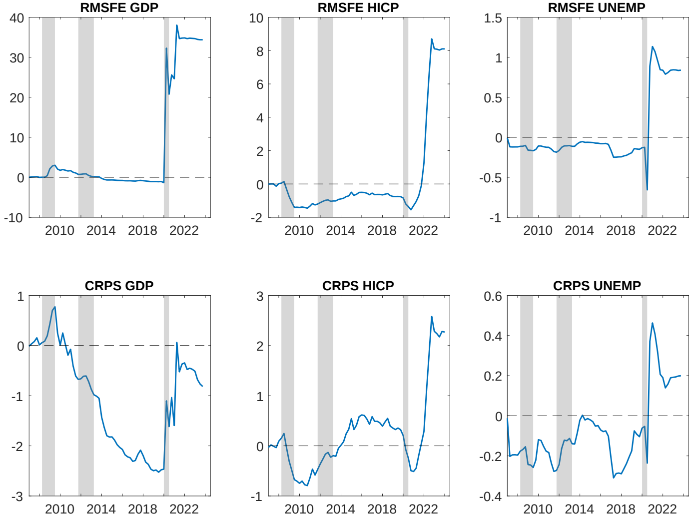
Absolute Rolling Scores at h=4



Absolute Rolling Scores at h=8



Forecast performance at one-quarter-ahead



Average relative scores: S-BVAR only HICP/BVAR

Horizon	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
					GDP				
RMSFE	1.0177	1.0049	1.0095	1.0059	1.0247	1.0304	1.0281	1.0514	1.1152
CRPS	1.0268	1.0366	1.0357	1.017	1.0673	1.0839	1.0563	1.0863	1.1819
					HICP				
RMSFE	1.2858	1.1176	1.1048	**0.993**	1.0752	1.1837	1.115	1.008	1.1512
CRPS	1.1942	1.1069	1.0865	1.0103	1.0839	1.1269	1.0582	**0.9906**	1.0856
					Unemployment				
RMSFE	**0.9849**	1.0252	1.0163	1.0081	1.0078	1.0189	1.0308	1.0456	1.0587
CRPS	1.0024	1.0326	1.0324	1.0291	1.0287	1.0411	1.0521	1.0626	1.077

Back

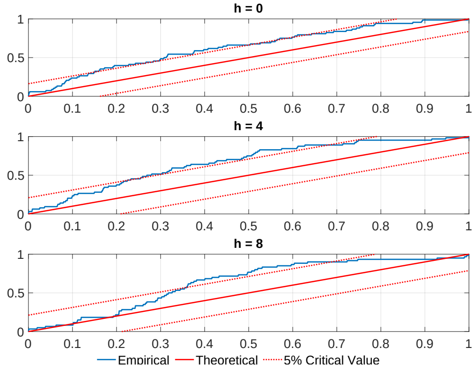
Average relative scores: S-BVAR only GDP/BVAR

Horizon	h=0	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
					GDP				
RMSFE	1.0469	1.0091	1.0179	**0.9913**	1.0171	1.023	1.0031	1.0265	1.0931
CRPS	**0.9966**	1.0021	**0.9732**	**0.9082**	**0.9786**	**0.9951**	**0.9363**	**0.9583**	1.0903
					HICP				
RMSFE	1.0193	1.0752	1.1089	1.0434	1.0926	1.1987	1.1513	1.0193	1.142
CRPS	1.0296	1.1087	1.1206	1.0709	1.1198	1.1786	1.1344	1.0544	1.1132
					Unemployment				
RMSFE	**0.947**	**0.9328**	**0.9119**	**0.8961**	**0.8989**	**0.8901**	**0.8857**	**0.8794**	**0.8844**
CRPS	**0.9636**	**0.9608**	**0.9441**	**0.9352**	**0.9405**	**0.9364**	**0.931**	**0.9205**	**0.9253**

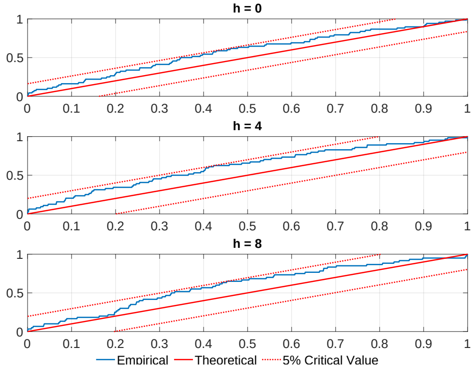
Back

Forecast calibration at selected horizons: **Real GDP**

(a) Baseline

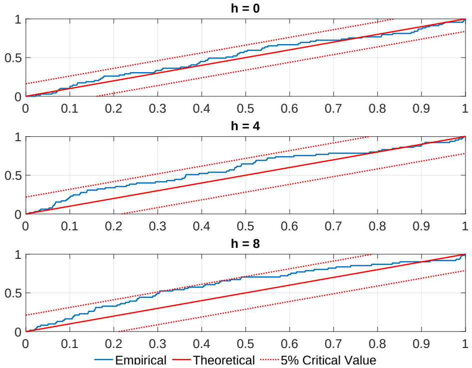


(b) S-BVAR

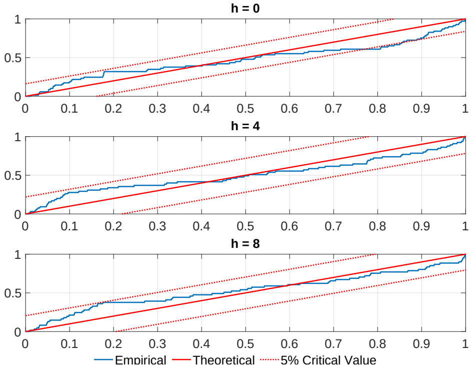


Forecast calibration at selected horizons: **HICP inflation**

(a) Baseline

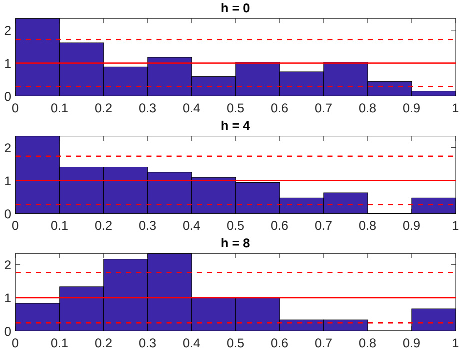


(b) S-BVAR

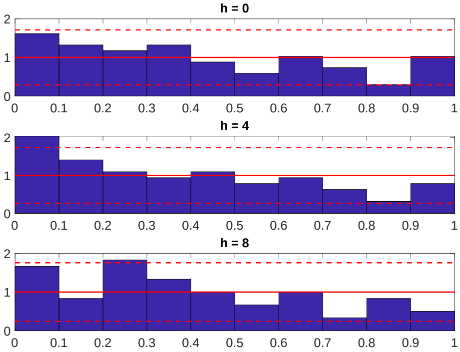


Forecast calibration at selected horizons: **Real GDP**

(a) Baseline

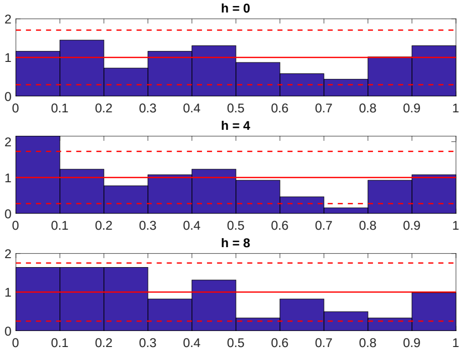


(b) S-BVAR

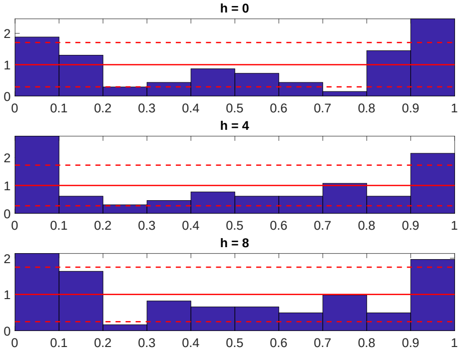


Forecast calibration at selected horizons: **HICP inflation**

(a) Baseline

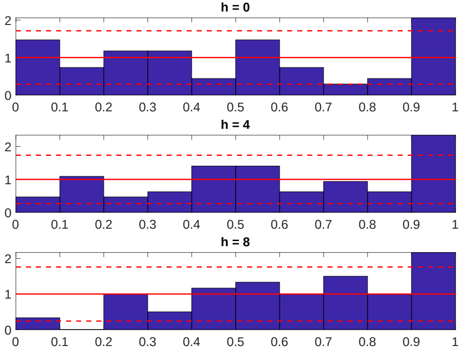


(b) S-BVAR

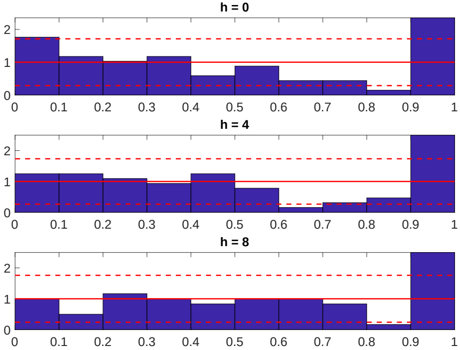


Forecast calibration at selected horizons: **unemployment**

(a) Baseline

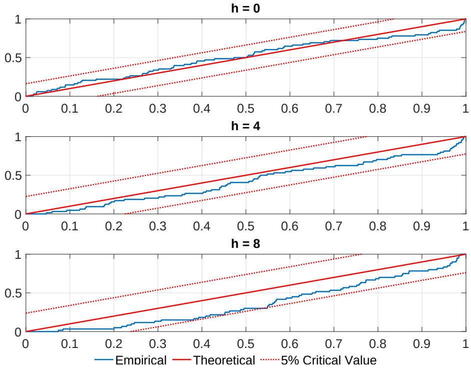


(b) S-BVAR



Forecast calibration at selected horizons: **Unemployment**

(a) Baseline



(b) S-BVAR