Combining Bayesian VARs with survey density forecasts: does it pay off?

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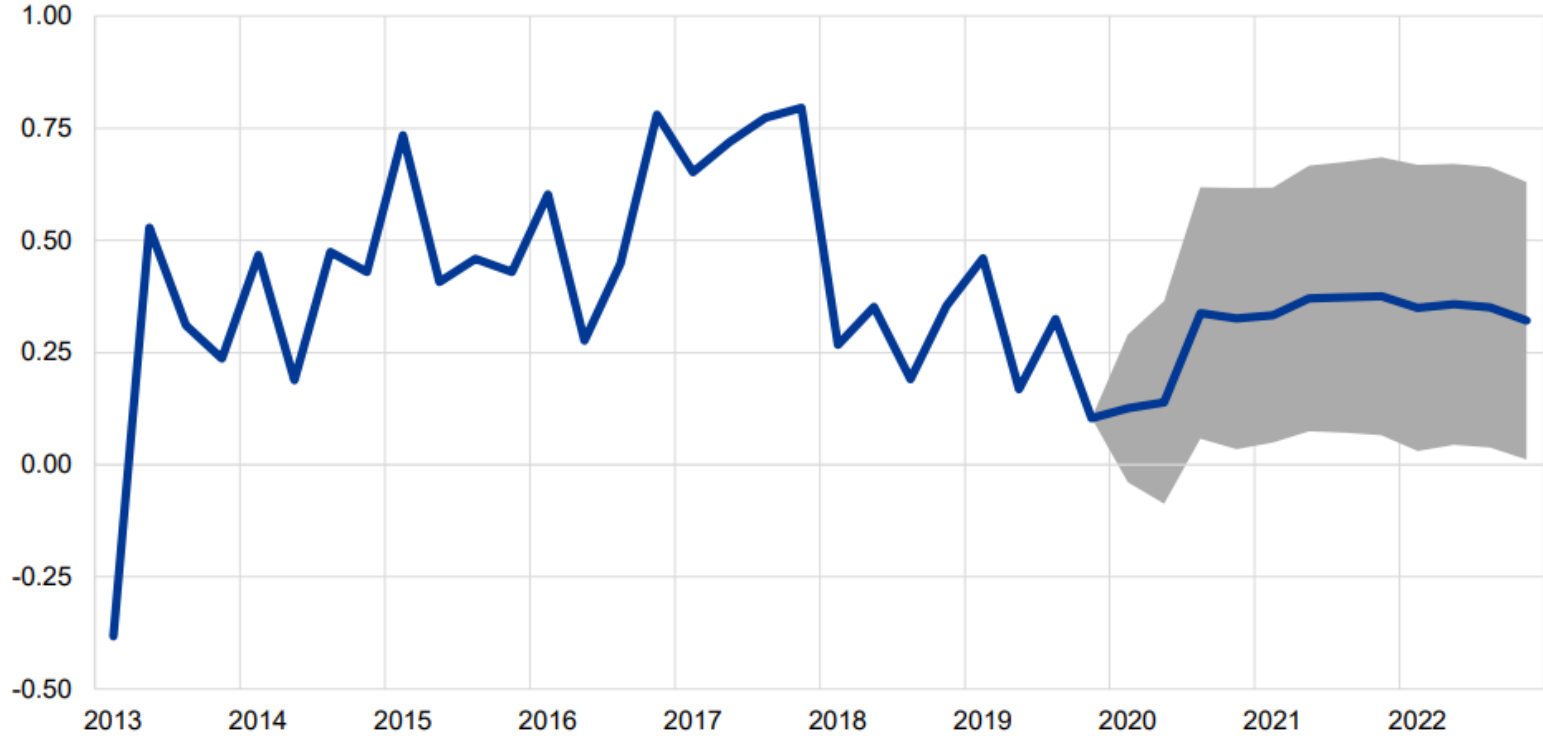
Euro area real GDP

(quarter-on-quarter percentage changes, seasonally and working day-adjusted quarterly data)



Notes: The ranges shown around the projections are based on the differences between actual outcomes and previous projections carried out over a number of years. The width of the ranges is twice the average absolute value of these differences. The method used for calculating the ranges, involving a correction for exceptional events, is documented in "New procedure for constructing Eurosystem and ECB staff projection ranges", ECB, December 2009, available on the ECB's website.

Source: Eurosystem staff macroeconomic projections for the euro area, March 2020.

Summary

- **Bayesian VARs** a standard tool for computing density forecasts. Moreover, model **uncertainty** and **absence of forward-looking information** are issues.
- We estimate in **real-time** a wide range of model specifications on European data, then **optimally combine** the forecast densities.
- We incorporate forward-looking survey information:
  - **Tilt first** each individual model, then perform optimal pooling ("ex-ante");
  - **Tilt directly the combined density** obtained from optimal pooling ("ex-post").
  - **Include** the SPF as additional prediction.

1. **Optimally combining several models** improves overall point and density performance, as well as forecast calibration.
2. **Including survey forecasts** on the target's **mean** helps, while on the variance hinders, overall performance.
3. Ex-ante performs well $\longrightarrow$ scope for **improving** ex-ante models and then combine.

BVARs, combinations and SPF

- **BVAR model** types: Minnesota priors with SV; democratic priors with SV; (Survey) Local Mean with SV; TVP-SV; UCSV. Different data set compositions: 3 or 19 variables, aggregated euro area or by country. 13 models and it can be extended to other specifications.
- **EU SPF**.
- **Optimal linear predictive pool**.
- Combining survey and model information: "ex-ante" and "ex-post" **tilting**.
- Target variables: y-o-y growth rate of euro area HICP inflation and GDP, evaluated at 1- and 2-year ahead horizon.
- Real-time recursive estimation, with forecasts evaluated from 2000:Q1 to 2019:Q4.

Combination performance - GDP

	Optimal Pool: *abs. scores*	SPF	Opt. Pool w/SPF	μ tilted ex-ante	μ tilted ex-post	μ & σ tilted ex-ante	μ & σ tilted ex-post
4-q							
CRPS	0.808	**0.994**	**0.997**	**0.935**	**0.932**	**0.966**	**0.971**
LPS	-1.922	-0.627	**0.030**	**0.302**	**0.026**	-0.406	-0.485
PITS	0.042	0.000	0.016	**0.624**	**0.279**	0.000	0.000
8-q							
CRPS	0.994	1.091	1.001	1.080	1.033	1.102	1.099
LPS	-1.973	-1.112	-0.094	-0.042	-0.095	-1.243	-1.303
PITS	0.020	0.000	0.011	**0.099**	0.004	0.000	0.000

Table: Relative accuracy scores with respect to optimal pooling (i.e. first column); p-values of Berkowitz uniformity test (in absolute terms).

Combination performance - HICP

	Optimal Pool: *abs. scores*	SPF	Opt. Pool w/SPF	μ tilted ex-ante	μ tilted ex-post	μ & σ tilted ex-ante	μ & σ tilted ex-post
4-q							
CRPS	0.503	**0.932**	**0.991**	**0.917**	**0.937**	**0.943**	**0.944**
LPS	-1.306	-0.024	**0.003**	**0.117**	**0.056**	-0.007	-0.082
PITs	**0.839**	0.002	**0.704**	**0.218**	**0.156**	0.000	0.000
8-q							
CRPS	0.567	**0.949**	1.020	**0.922**	**0.941**	**0.964**	**0.963**
LPS	-1.429	-0.040	-0.001	**0.082**	**0.032**	-0.263	-0.284
PITs	**0.552**	0.000	**0.961**	**0.368**	**0.232**	0.000	0.000

Table: Relative accuracy scores with respect to optimal pooling (i.e. first column); p-values of Berkowitz uniformity test (in absolute terms).

Combination performance - Bivariate

	Optimal Pool: *abs. scores*	SPF	Optimal Pool with SPF	μ-tilted ex-ante	μ-tilted ex-post	μ and σ-tilted ex-ante	μ and σ-tilted ex-post
4-q							
ES	1.015	**0.995**	**0.987**	**0.961**	**0.954**	**0.983**	**0.984**
LPS	-3.355	-0.416	**0.144**	**0.433**	**0.220**	-0.106	-0.352
PITs y|h	**0.538**	0.000	**0.907**	**0.690**	**0.650**	0.000	0.000
PITs h|y	0.026	0.013	0.078	**0.219**	**0.168**	0.002	0.001
8-q							
ES	1.254	1.054	**0.989**	1.024	1.016	1.069	1.068
LPS	-3.766	-0.501	**0.061**	**0.233**	-0.017	-0.782	-0.874
PITs y|h	**0.214**	0.000	**0.623**	**0.721**	**0.185**	0.000	0.000
PITs h|y	0.075	0.002	**0.156**	**0.707**	**0.225**	0.000	0.000