New avenues to incorporate inflation expectations into forecasting models - state of work at the ECB[1]

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[1] The views expressed in this paper are of the author only and do not necessarily reflect those of the European Central Bank.

Motivation

Inflation expectations are usually closely monitored at central banks as they are believed to be an important determinant of current inflation (see e.g. latest ECB's Strategy Review).

Models used to forecast inflation often do not include measures of expectations.

Do they contain additional information beyond what can be captured in other inflation predictors and macro models?

Questions

- How can one incorporate information on *observed* inflation expectations in *model-based* forecasts?
- Does it help to incorporate such information in a model?
- Which measures of expectations help (most)?
- How robust are the results across models and economic areas?
- What happens after COVID-19?

Mainly drawing from two papers:

1. Bańbura, Leiva-León and Menz (2021) “Do inflation expectations improve model-based inflation forecasts?”
2. Bańbura, Brenna, Paredes and Ravazzolo (2021) “Combining Bayesian VARs with survey density forecasts: does it pay off?”

Focus on time series (reduced form) models, the euro area (and largest member states); starting in 2000s; most results based on the pre-pandemic period.

How to incorporate survey results in a model

A “stylised” literature review

Expectations serve:

- as boundary values
  [Faust and Wright, 2013], [Clark and Doh, 2014], [Chan et al., 2018], [Hasenzagl et al., 2018], [Jarociński and Lenza, 2018], [Bańbura and Bobeica, 2022]
- as explanatory variables
  [Stockhammar and Österholm, 2018], [Moretti et al., 2019], [Álvarez and Correa-López, 2020], [Kulikov and Reigl, 2019]
- to tilt or constrain the model forecasts
  [Krüger et al., 2017], [Ganics and Odendahl, 2021], [Tallman and Zaman, 2020], [Bańbura et al., 2021], [Galvao et al., 2021], [Bobeica and Hartwig, 2022]
- to inform the model parameters
  [Wright, 2013], [Frey and Mokinski, 2016]

Most papers find improvements when including expectation info, with few exceptions [Cecchetti et al., 2017, Forbes et al., 2019]

Modelling approaches, paper 1

1. ADL models with time-varying trend inflation
[Bańbura and Bobeica, 2022]
boundary

2. ADL models with time-varying trend inflation and time-varying coefficients
[Chan et al., 2018]
boundary

3. Bayesian VARs with democratic priors
[Wright, 2013, Clark, 2011]
priors

4. Bayesian VARs with time-varying trends
[Bańbura and van Vlodrop, 2018]
boundary

5. Phillips curves with constant coefficients
explanatory variables

6. Bayesian VARs with Minnesota priors
explanatory variables

Modelling approaches, paper 2

Bayesian VARs in different implementations

With Minnesota priors, democratic priors, time-varying trends, time-varying parameters.

1. Including SPF distributions in a model combination (an optimal pool)
2. Tilting model distributions to the SPF mean (and variance)
   a. ex ante - tilting individual model forecasts before combining
   a. ex post - tilting the combined forecasts

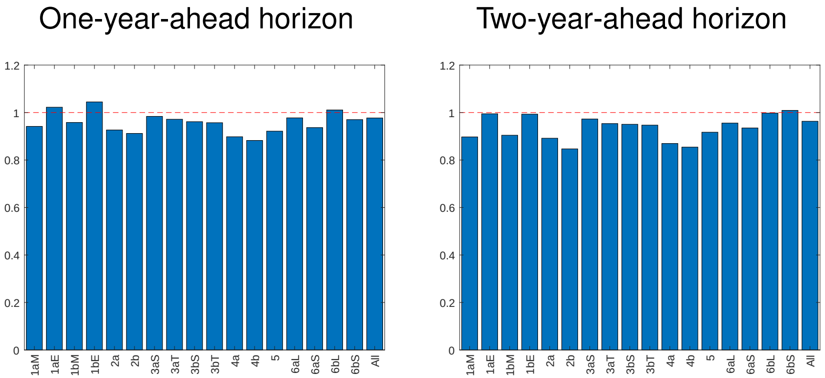
Scope of the analysis

- Real-time out-of-sample forecast evaluation, matching information available to survey respondents
- Point and density forecasts
- Medium-term horizons (one and two years ahead)
- Different measures of expectations (source and horizon)

  Survey of Professional Forecasters (SPF), Consensus Economics, Expectations of firms and households from European Commission survey, Inflation-linked swap rates
- Euro area and several member states

Adding expectations from the SPF, euro area

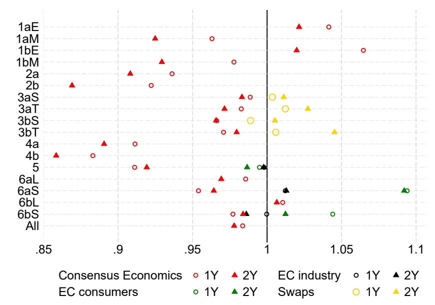
Relative RMSFE, Headline HICP



Note: The figure shows the RMSFE of the model version incorporating expectations divided by the RMSFE of the version not incorporating such information. The RMSFE is computed over 2001Q4-2019Q4 for one-year-ahead horizon and over 2002Q4-2019Q4 for two-year-ahead horizon. The numbers denote the model classes: 1: ADL models with time-varying trend inflation, 2: ADL models with time-varying trend inflation, time-varying coefficients and stochastic volatility, 3: Bayesian VARs with democratic priors, 4: Bayesian VARs with time-varying trends, 5: Phillips curves with constant coefficients, 6: Bayesian VARs with Minnesota priors. ’a’ and ’b’ refer to univariate and multivariate models, respectively.

Adding other types of expectations, euro area

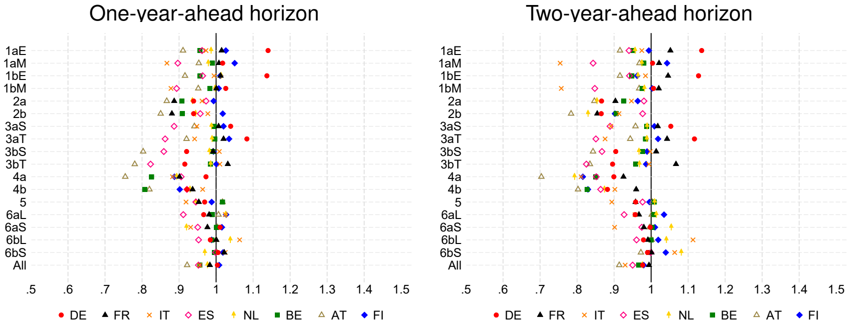
Relative RMSFE, Headline HICP



Note: The figure shows the RMSFE of the model version incorporating expectations divided by the RMSFE of the version not incorporating such information. The RMSFE is computed over 2001Q4-2019Q4 for one-year-ahead horizon and over 2002Q4-2019Q4 for two-year-ahead horizon, with the exception of inflation linked swaps for which the respective evaluation samples are 2006Q1-2019Q4 and 2007Q1-2019Q4. The numbers denote the model classes: 1: ADL models with time-varying trend inflation, 2: ADL models with time-varying trend inflation, time-varying coefficients and stochastic volatility, 3: Bayesian VARs with democratic priors, 4: Bayesian VARs with time-varying trends, 5: Phillips curves with constant coefficients, 6: Bayesian VARs with Minnesota priors. 'a' and 'b' refer to univariate and multivariate models, respectively.

Adding expectations from Consensus, EA countries

Relative RMSFE, Headline HICP



Note: The figure shows the RMSFE of the model version incorporating expectations divided by the RMSFE of the version not incorporating such information. The RMSFE is computed over 2005Q4-2019Q4 for one-year-ahead horizon and over 2006Q4-2019Q4 for two-year-ahead horizon. The numbers denote the model classes: 1: ADL models with time-varying trend inflation, 2: ADL models with time-varying trend inflation, time-varying coefficients and stochastic volatility, 3: Bayesian VARs with democratic priors, 4: Bayesian VARs with time-varying trends, 5: Phillips curves with constant coefficients, 6: Bayesian VARs with Minnesota priors. 'a' and 'b' refer to univariate and multivariate models, respectively.

Combining BVAR forecasts and SPF expectations

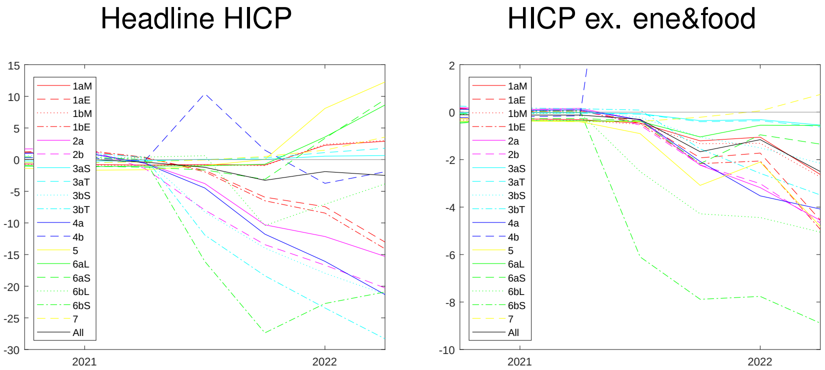
Headline HICP

	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

Note: CRPS and LPS: relative accuracy scores with respect to optimal pooling (i.e. first column); PITs: p-values of Berkowitz uniformity test (in absolute terms).

Adding exp. from the SPF, euro area, COVID-19

Difference of cumulative sum of squared forecast errors



Note: The figure shows the cumulative sum of squared forecast errors of the model version incorporating expectations minus the CSSFE of the version not incorporating such information. The sums are computed over 2020Q4-2022Q2. The numbers denote the model classes: 1: ADL models with time-varying trend inflation, 2: ADL models with time-varying trend inflation, time-varying coefficients and stochastic volatility, 3: Bayesian VARs with democratic priors, 4: Bayesian VARs with time-varying trends, 5: Phillips curves with constant coefficients, 6: Bayesian VARs with Minnesota priors. 'a' and 'b' refer to univariate and multivariate models, respectively.

Summary and conclusion

- Incorporating information from *mean* expectations embedded in *professional forecasts* helps across models/methods/countries. The gains are modest.
- The expectations of *firms and households* and those derived from *financial market prices* (inflation-linked swap rates) *do not* improve forecast accuracy.
- Models perform somewhat worse than the SPF in terms of *point forecast* but the SPF tends to be *overconfident*.
- It is usually better to "correct" the model forecasts (using the SPF mean) *before combining* them.
- SPF seems useful for improving model forecasts also after 2019; also in terms of variance?

The results indicate that models augmented by inflation expectations of professional forecasters should be included in inflation forecaster's toolkit as those measures of expectations appear to contain information that is difficult to "replicate" by models.

Ongoing work

- Role of surveys during the pandemic and the high inflation period

  Controlling for model modifications in order to deal with atypical observations, as in e.g. [Stock and Watson, 2016, Carriero et al., 2022, Bobeica and Hartwig, 2022]

  How to derive future paths for survey expectations?

  Are they behind the curve? (as in the 70 and 80s, see [Mertens, 2016])

- Role of surveys in predicting tails of inflation

  ESCB Expert Group on Macro at Risk

- New ways to incorporate off model (e.g. survey) information

  Parametric tilting (to a skewed-t distribution) [Montes-Galdón et al., 2022];

  see also tilting to SPF histograms [Clark et al., 2022]

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