Do inflation expectations improve model-based inflation forecasts?[1]

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[1] The views expressed in this paper are of the authors only and do not necessarily reflect those of the European Central Bank, the Banco de España or the Deutsche Bundesbank.

Motivation

Inflation expectations are usually closely monitored at central banks as they are believed to be an important determinant of current inflation.

ESCB Expert Group on Inflation Expectations [Baumann et al., 2021]

- Which measures of expectations are available and relevant?
- What have been the developments? Are there signs of de-anchoring?
- Does it help to incorporate information on *observed* inflation expectations in *model-based* forecasts?
  - Which measures of expectations help (most)?
  - How robust are the results across models and economic areas?

Work also linked to the ECB's strategy review.

Motivation

Does it help to incorporate information on *observed* inflation expectations in *model-based* forecasts?

- Models used to forecast inflation often do not include measures of expectations.
- Available measures are only imperfect proxies.
- Do they contain additional information beyond what is captured in other inflation predictors?
- Papers typically focus on specific measure/model/country or do not undertake out-of-sample forecasts.

Scope of the analysis

- A wide range of *time series models* (and ways to incorporate the expectations)
- Euro area and several member states
- Different measures of expectations (source and horizon)

  Survey of Professional Forecasters, Consensus Economics, Expectations of firms and households from European Commission survey, Inflation-linked swap rates
- 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)
- Headline HICP and core HICP (excluding energy and food)

Main findings

Incorporating information from expectations embedded in *professional forecasts* helps in most of the cases but the gains are modest.

- The average forecast accuracy of model version incorporating expectations is usually higher compared to the version without expectations.
- Relative performance of both versions *changes over time* and the gains from incorporating expectations are *significant* in some periods.
- Models perform somewhat worse than the SPF (especially in the recent years) but many of them better than (typically hard to beat) model benchmarks.
- The expectations of *firms and households* and those derived from *financial market prices* (inflation-linked swap rates) *do not* improve forecast accuracy.
- For the countries: improvements less “uniform”; it is more difficult to improve the forecasts for HICP excluding energy and food; models sometimes beat the expectations.

“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]

Some papers do not find important role for expectations
[Cecchetti et al., 2017], [Forbes et al., 2019]

Modelling approaches

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, details

1. ADL models with time-varying trend inflation

$$\pi_t - \bar{\pi}_t = \alpha(\pi_{t-1} - \bar{\pi}_{t-1}) + \beta y_t + \nu_t\,, \quad \nu_t \sim N\left(0, \sigma^2\right),$$

Trend given by the long-term inflation expectations: $\bar{\pi}_t = \pi_t^{Exp}$; in no expectations version by average or by EWMA of past inflation rates; [Bańbura and Bobeica, 2022]

2. ADL models with time-varying trend inflation and time-varying coefficients

$$\begin{aligned}(\pi_t - \bar{\pi}_t) &= \alpha_t(\pi_{t-1} - \bar{\pi}_{t-1}) + \beta_t y_t + \nu_t, \quad \nu_t \sim N\left(0, \sigma^2_{\nu,t}\right), \\ \bar{\pi}_t &= \bar{\pi}_{t-1} + e_t, \quad e_t \sim N\left(0, \sigma^2_{e,t}\right).\end{aligned}$$

Trend linked to the long-term inflation expectations

$$\pi_t^{Exp} = a_t + b_t \bar{\pi}_t + u_t, \quad u_t \sim N\left(0, \sigma^2_{u,t}\right).$$

Random walk in no expectations version; [Chan et al., 2018]

Modelling approaches, details

3. Bayesian VARs with democratic priors

$$y_t - \mu = \sum_{i=1}^{p} B_i (y_{t-i} - \mu) + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t),$$

The mean of the prior for μ given by the the long-term expectations; loose in no expectations version; [Wright, 2013, Clark, 2011]

4. Bayesian VARs with time-varying trends

$$\begin{aligned} y_t - \mu_t &= \sum_{i=1}^{p} B_i (y_{t-i} - \mu_{t-i}) + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t), \\ \mu_t &= \mu_{t-1} + \eta_t, \quad \eta_t \sim N(0, V_t). \end{aligned}$$

Trend linked to the long-term expectations

$$y_t^{Exp} = \mu_t + g_t, \quad g_t \sim N(0, G_t).$$

Random walk in no expectations version; [Bańbura and van Vlodrop, 2018]

Modelling approaches, details

5. Phillips curves with constant coefficients

$$\pi_t = c + \alpha\pi_{t-1} + \beta y_t + \gamma\pi_t^{Exp} + \nu_t\,, \quad \nu_t \sim N\left(0, \sigma^2\right),$$

Hybrid PC including one-year-ahead inflation expectations; backward looking PC in no expectations version.

6. Bayesian VARs with Minnesota priors

$$y_t = c + \sum_{i=1}^{p} B_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, H_t\right),$$

One-year-ahead or long-term inflation expectations included as endogenous variables; not included in no expectations version.

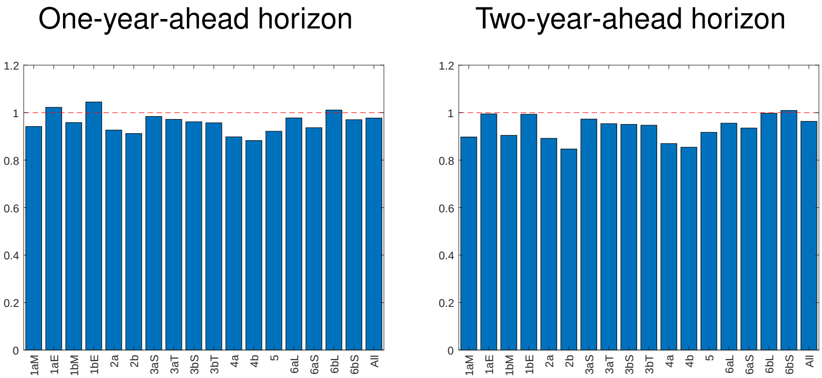
Models 2-4 and 6 with stochastic volatility. Models 1-4 and 6 in a univariate and multivariate version.

Details of the forecast evaluation

- Quarterly real-time data vintages for 2001-2019 (linked to SPF deadline to respond dates, shorter evaluation period for some countries)
- Main results use the SPF as the measure of expectations for the euro area and Consensus Economics forecasts for the countries
- Evaluation for one-year-ahead or two-year-ahead horizon
- Evaluation in terms of RMSFE, CRPS (for density forecasts) and fluctuation test of Giacomini and Rossi (2010)
- Comparison to the SPF and to model benchmarks (random walk and unobserved component stochastic volatility (UCSV) model [Stock and Watson, 2007])

Adding expectations from the SPF, euro area

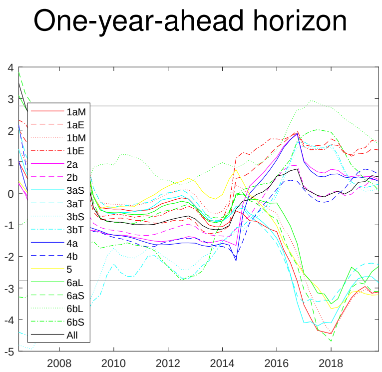
Relative RMSFE, Headline HICP

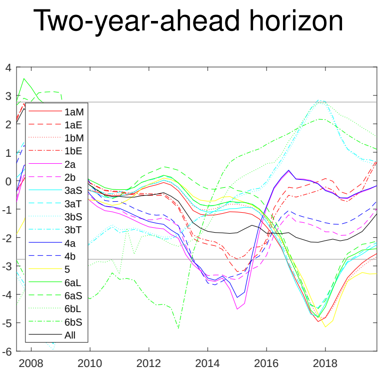


Note: The figure shows the RMSFE of the model version incorporating expectations divided by the RMSFE of the version not incorporating such information. The RMSFE is computed over 2001Q4-2019Q4 for one-year-ahead horizon and over 2002Q4-2019Q4 for two-year-ahead horizon. The numbers denote the model 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 expectations from the SPF, euro area

Fluctuation test, Headline HICP

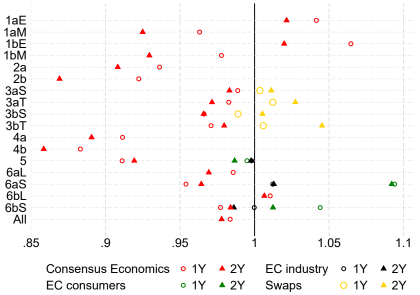




Note: The figure shows the Giacomini and Rossi (2010) fluctuation test statistics for a rolling window of 20 quarters. Grey lines show the critical values for the 90 % confidence interval. The null of equal forecasting performance is rejected when the test statistic is outside the interval. The values of test statistics below the interval mean that the model that incorporates expectations was performing significantly better than the model that does not (and vice versa for test statistics values above the interval). 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.

Adding other types of expectations, euro area

Relative RMSFE, Headline HICP



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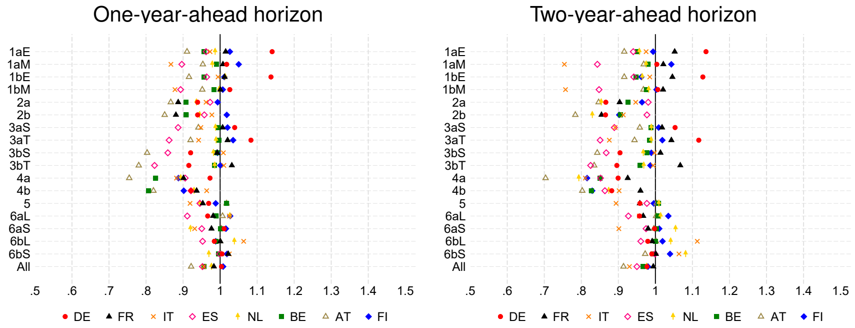
Adding expectations from Consensus, EA countries

Relative RMSFE, Headline HICP



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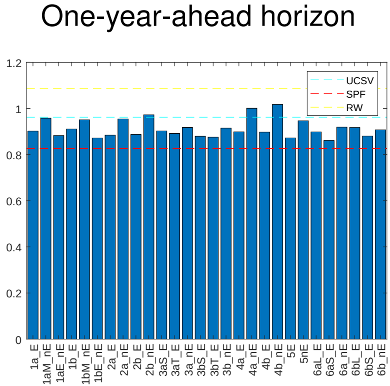
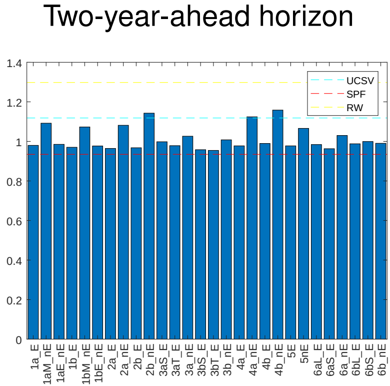
Performance compared to the SPF, euro area

Absolute RMSFE, Headline HICP





Note: The figure shows the (absolute) RMSFE of all the models. 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.

Conclusion

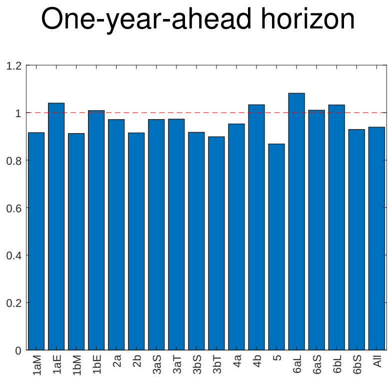
- The results indicate that models augmented by inflation expectations of professional forecasters should be included in inflation forecaster's toolkit.

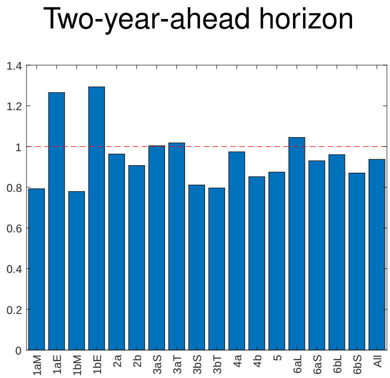
- Those measures of expectations appear to contain information that is difficult to "replicate" by the models.

ADDITIONAL SLIDES

Adding expectations from the SPF, euro area

Relative RMSFE, HICP ex. energy and food





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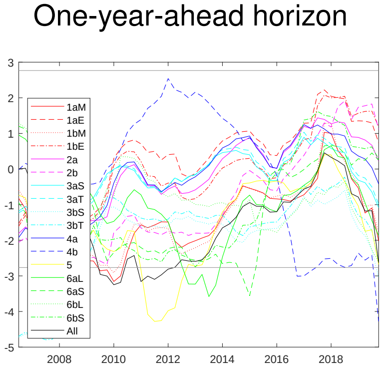
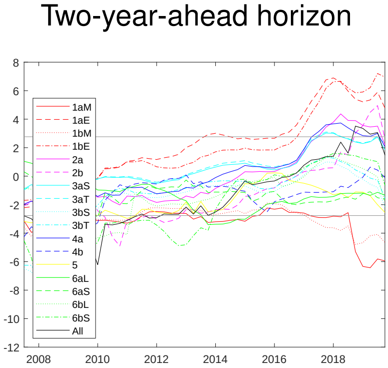
Adding expectations from the SPF, euro area

Fluctuation test, HICP ex. energy and food





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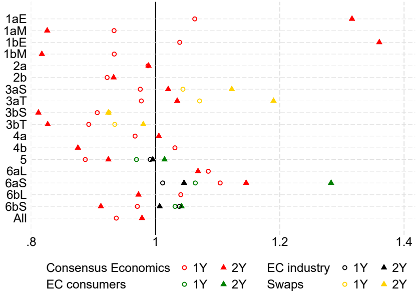
Adding other types of expectations, euro area

Relative RMSFE, HICP ex. energy and food



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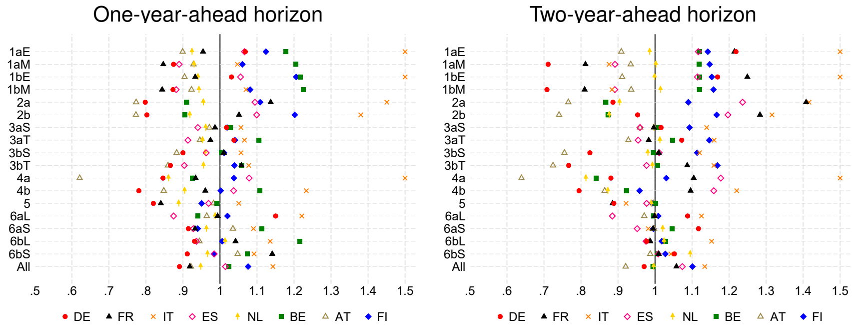
Adding expectations from Consensus, EA countries

Relative RMSFE, HICP ex.energy and food,



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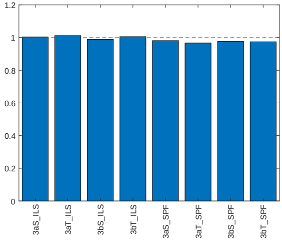
Adding expectations from inflation swaps

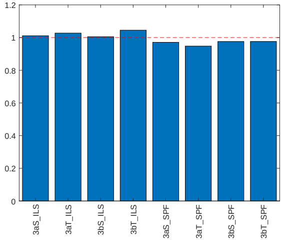
Headline HICP

One-year-ahead horizon

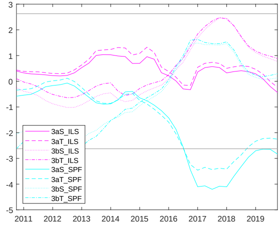
Two-year-ahead horizon

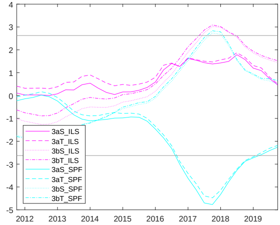
Relative RMSFE





Fluctuation test





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