

Density forecasts of inflation: a quantile regression forest approach

Michele Lenza (ECB and CEPR)
Ines Moutachaker (INSEE)
Joan Paredes (ECB)

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Density Forecasting

- Adequate policy response requires to assess the temporary/persistent nature of past, current (and future, to a certain extent) “facts” for inflation dynamics
- The future is uncertain: economic policy is based on an analysis of the likelihood of different events (risk analysis)

⇒ **Accurate density forecasts are a fundamental input for monetary policy**

Non-Linearity

- The Eurosystem analysis of inflation dynamics is heavily skewed toward linear models (Darracq Pariès et al. 2021)
- Yet, non-linearities are often argued to play an important role for inflation dynamics
 - Expanding literature on macroeconomics@risk underscores the importance of considering non-linearity in the dynamics of key policy-relevant variables, particularly for the sake of “risk assessment”
 - Adrian et al. (2019), Carriero et al. (2016), Chavleishvili and Manganelli (2019), López-Salido and Loria (2020), Adams et al. (2021), Korobilis et al. (2021), Goulet Coulombe et al. (2022), Kiley (2022), Amburgey and McCracken (2023a), Amburgey and McCracken (2023b), Botelho et al. (2023), Boyarchenko et al. (2023), Chavleishvili et al. (2023) and Chavleishvili and Kremer (2023)

Aim of this paper

- Design and evaluate the accuracy of a new model for euro area density inflation forecasting
- No commitment to one type of non-linearity, more general than existing models and able to handle large information set monitored in a central bank
- Assess the role of non-linearities for euro area (headline and core) inflation dynamics, by controlling for "overfitting" (out-of-sample accuracy criterion)

⇒ **Quantile regression forests (a variant of Random Forests) as a way to operationalize non-parametric models**

Related literature

Inflation forecasting

Large literature, see Faust and Wright (2013) and my forthcoming survey with M. Banbura and M. Lenza. To be singled out: Medeiros et al. (2021), Random Forest for point US inflation forecast

Non-linearity in inflation dynamics, besides @risk

See, for example, Akerlof et al., 1996; Costain et al., 2022; Fahr and Smets, 2010; Benigno and Ricci, 2011; Linde and Trabandt, 2019; Del Negro et al. 2020; Forbes et al., 2021; Goulet-Coulombe et al., 2022

Ensemble methods for prediction

See, for example, Athey et al., 2019; Avramov, 2002; Bai and Ng, 2009; Cremers, 2002; Faust et al., 2013; Fernandez et al., 2001; Inoue and Kilian, 2008; Jin et al., 2014; Ng, 2013; Rapach and Strauss, 2010; Sala-I-Martin et al., 2004; Varian, 2014; Wager and Athey, 2018; Wright, 2009; Giannone et al., 2021; Medeiros et al., 2021; Clark et al. 2022a; Clark et al. 2022b

Outline of the rest of the talk

- Empirical strategy
- Comparison with state-of-the-art linear models
- Comparison with institutional (BMPE) judgemental forecasts
- Examples of model policy use in real-time (2022Q4-2024Q1)

General modelling strategy

- Define our measure of prices as p_t . Assume we have data until time (i.e. month) t . $h = (3, 6, 9, 12)$ months:

$$\pi_t^h = (1200/h) \times [p_t/p_{t-h} - 1]$$

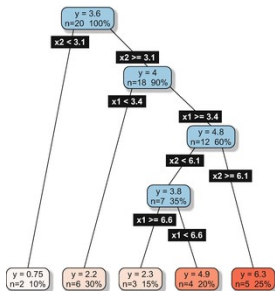
- Estimate $\pi_t = m(\pi_{t-h} \dots \pi_{t-h-p}; x_{t-h} \dots x_{t-h-k}) + \varepsilon_t$
- Project forward: $\hat{\pi}_{t+h} = m(\pi_t \dots \pi_{t-p}; x_t \dots x_{t-k})$

Main ingredients

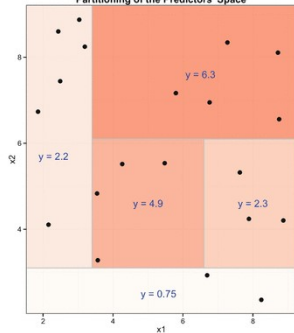
- Direct density forecast
- $m(\cdot)$ quantile regression forecasts (variant of the random forest)

Non-linearity: Regression trees

Example of a Regression Tree



Partitioning of the Predictors' Space



Non-linearity: Regression trees

- Regression trees allow very general relationships between predictors and the target variable
- However, regression trees are normally bad forecasting models, high variance, overfitting
 - One could "prune" them (akin to shrinkage), reducing ex ante their ability to (over-)fit
 - Normally, not the path taken in the literature

Variance reduction is rather achieved by combination of several trees: random forests

The idea of Random Forests - Breiman 2001

- 1 **Bootstrap** observations (and keep the "out-of bag" observations)
- 2 Grow **many** trees
- 3 In each tree, use only a (randomly chosen) **sub-set of predictors** at each node
- 4 **Combine** the predictions of the trees at the end

Does this make sense?

- Combination reduces variance of the forecasts
- Variance reduction maximized when the predictions are not correlated
 - Bootstrap to ensure "diversity" in the trees
 - The randomization step further de-correlates the trees
- Density forecasts: rather than taking averages of the target variable in the last nodes, compute sample quantiles ⇒ **Quantile Regression Forest** (Meinshausen, 2006)
- One issue with regression trees/random forests: they do not extrapolate. How long can it take to adapt to unprecedented developments? Is "conservativeness" good or bad?

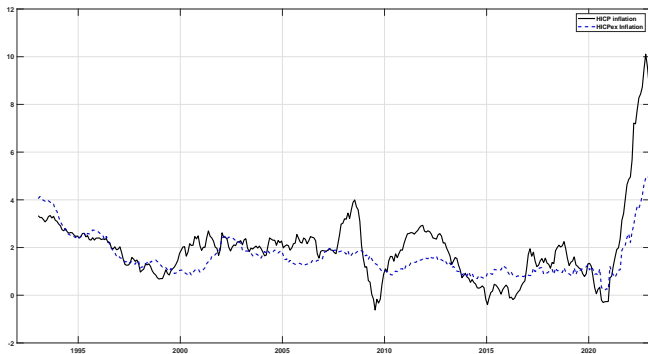
Hyperparameters

The specification choices for Random Forests are just a few. In general, we take the default choices in the literature (but further tuning is possible)

- **Depth of trees**
 - Control overfitting
 - We experimented with several configurations (varying number of splits, number of observations in the last node) - no impact on results
- **Number of variables randomly drawn for each split**
 - We use the default value for regression trees (a third of the variables), but also experimented with other values, small differences in results
- **Number of trees**
 - 500 trees, selected by assessing "stabilization" of out-of-bag error in the first training sample

Data 1: Targets

Figure: Headline and Core Inflation - year-on-year



Note: Headline inflation: black solid line; Core inflation: blue dashed line.

Data 2: Predictors

- We consider sixty predictors, routinely monitored at the ECB (de Bondt et al. 2018), plus two inflation lags
- Logic for the choosing the predictors: Phillips Curve.
- Four broad groups of variables: inflation expectations, (domestic and global) cost pressures, real activity and financial variables
- No real-time database (but many variables are timely released and un-revised), stationarized, de-seasonalized (according to out-of-sample logic)

Benchmark models

- Combination of 500 5-variate B-VARs (randomly drawn regressors) - VARCOMB
 - Ensemble of linear models to isolate as much as possible the linear/non-linear dimension
 - One difference in how the forecasts are produced (iterative/direct method)
- Comparison with institutional forecasts (SPF and BMPE)
 - Due to the comparison with the BMPE (which are not seasonally adjusted), we will always compute forecast accuracy statistics and produce charts for the year-on-year rates
 - SPF and BMPE are "real-time" judgemental forecasts, while we use revised data
 - SPF and BMPE quarterly frequency; we adapt to this frequency for QRF and VARCOMB, also aligning as much as possible the data availability

Out-of-sample accuracy

- Full sample: January 1992 - December 2022
- About twenty years of out-of-sample evaluation (first estimation sample until end 2001)
- Update by one of observation and re-estimate the model (recursive scheme)
- Forecast horizon: 3, 6, 9 and 12 months ahead; 20 years of out-of-sample evaluation
- CRPS for density forecasts. RMSE for point forecasts

Out-of-sample accuracy - summary

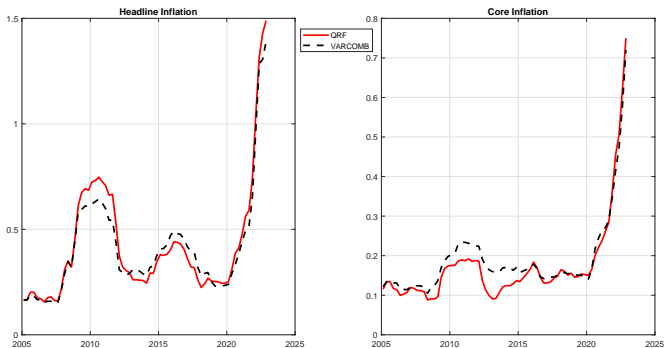
- The QRF is competitive with the linear benchmark
 - Slightly better for core inflation (by a small margin);
 - On par for headline inflation at short horizons and worse for long horizons
- Also competitive with institutional forecasts, especially at short horizons

⇒ **QRF more a complement than a substitute for traditional techniques**

Focus on some results

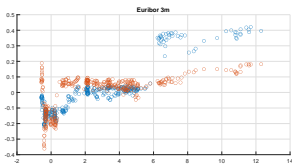
- Performance over time: similar (on average) but different (over time)
- Opening the black-box: contributions of different predictors. Non-linearities in inflation dynamics
- Judgement and non-linearity

Comparison with linear model, $h=6$



Note: Red solid line: QRF; Black dashed line: VARCOMB. The value on the vertical axis at each point refers to the average CRPS over the current quarter and the previous eleven quarters.

Non-linearities: Shapley Values - Top Contributors

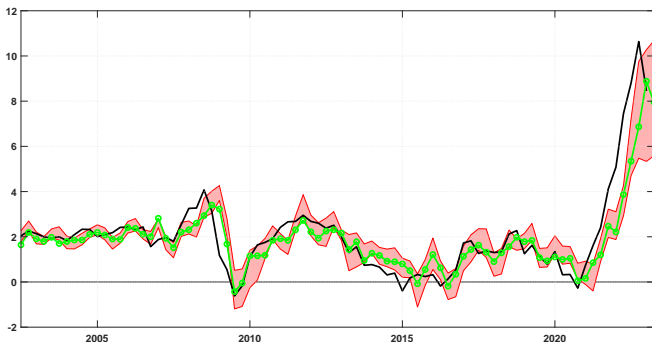


Note: Vertical axis: in-sample Shapley values for the variable indicated in the title for headline inflation (red) and core inflation (blue). Horizontal axis: value of the variable indicated in the title

Non-linearity in inflation dynamics

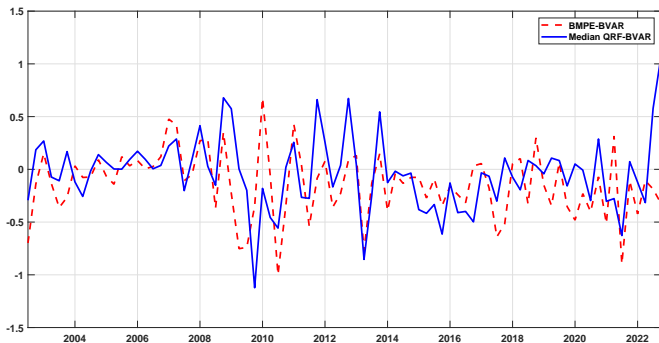
- Summing up the outcomes of the forecasting comparison and the analysis of the Shapley values, mild non-linearity, more evident for core
- Difference between core and headline: energy and food components
- These components, which are the most volatile of headline inflation, are driven mostly by commodity prices
- Direct effects of commodity prices have largely a linear impact on inflation

Headline Inflation, density forecasts of QRF and BMPE point forecast, $h=6$



Note: Black solid line: year-on-year growth rate of HICP; Red area: 16th-84th quantiles QRF density forecasts; Green line with circles: BMPE projections.

Distance from non-linearity: gaps of BMPE and QRF versus VARCOMB



Note: Solid blue line: six months ahead (median) QRF forecast of headline inflation minus corresponding VARCOMB forecast; Dashed red line: six months ahead BMPE forecast of headline inflation minus corresponding VARCOMB forecast.

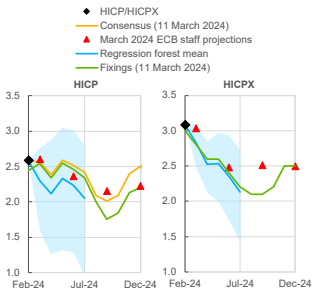
Conclusion

- The quantile regression forest (QRF) is a welcome addition to the Eurosystem toolbox to forecast inflation
- Complement rather than substitute the currently available tools
- Non-linearity in inflation dynamics: perhaps, mostly for core inflation
- QRF quite similar to BMPE/SPF, both in dynamics and accuracy - judgement partly adds "non-linearity"?

Example of policy use

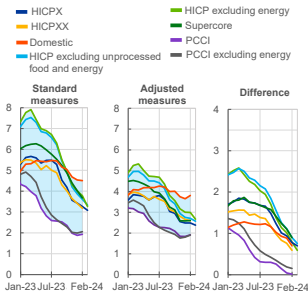
Short-term forecasts and measures of underlying inflation

Short-term forecasts for HICP and HICPX (annual percentage changes)



Sources: Eurostat, March 2024 ECB staff short-term inflation outlook, Consensus Economics, Bloomberg and ECB calculations. Notes: The cut-off date for the latest mechanical update and regression forest is 11 March 2024, and for fixings is 11 March 2024. Consensus Economics data were collected on 11 March. The quantile regression forest estimates are from Lenza, Moutachaker and Paredes (2023). The HICP fixings are observed market prices, whereas the HICPX fixings are estimated based on the model in Grenlund, Jørgensen and Schupp (2024). Latest actual observation: February 2024 (flash).

Measures of underlying inflation (annual percentage changes)



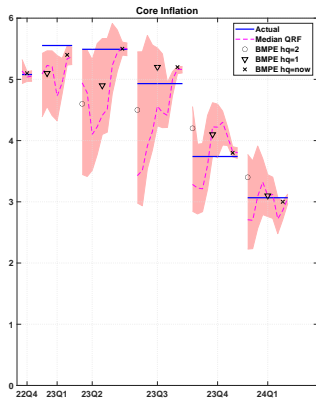
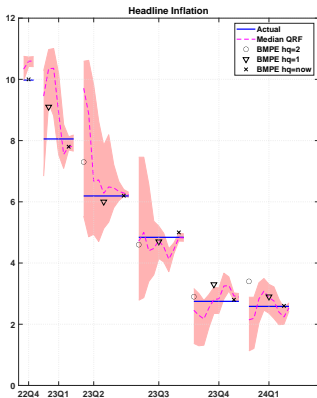
Sources: Eurostat and ECB calculations. Notes: PCCI refers to the Persistent and Common Component of Inflation. The "adjusted" measures abstract from energy and supply-bottleneck shocks using a large SVAR, see Barbu, Bobeica and Martínez-Hernández (2023). "What drives core inflation? The role of supply shocks", Working Paper Series, No 2875, ECB. Latest observations: February 2024 (flash) for HICPX, HICP excluding energy and HICP excluding unprocessed food and energy, and January 2024 for the rest.

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Note: Extracted from speech of ECB Executive Board Member Philip Lane, 15 March 2024, www.ecb.europa.eu.

Real-Time assessment, 2022Q4-2024Q1



THANK YOU!

BACKGROUND SLIDES

What we find - comparison with state-of-the-art linear models

- The quantile regression forest (QRF) is a good forecasting model, especially at short horizons and for core inflation
- Overall, similar accuracy with state-of-the-art linear models on full sample. Different accuracy in sub-samples, diversity in the toolbox

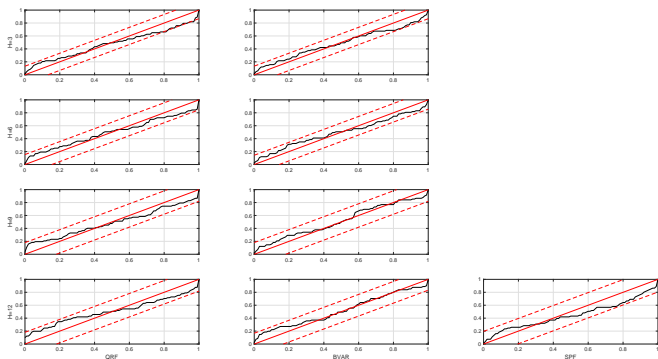
⇒ **Complementarity of the approaches. Non-linearity maybe more relevant in specific episodes and for core inflation.**

What we find - comparison with judgemental institutional and survey forecasts

- QRF is good in terms of relative accuracy, despite not being able to incorporate future info using judgement
- Quite strong collinearity with (judgemental) Eurosystem forecasts!

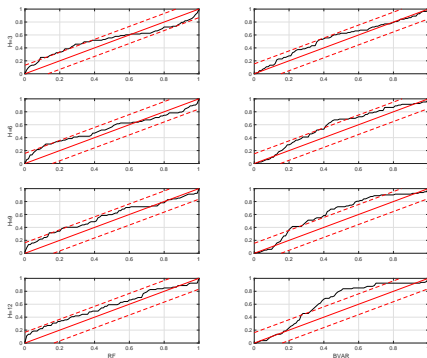
⇒ **Judgement may be adding mild non-linearity to the Eurosystem forecasts.**

Calibration Headline Inflation - Rossi and Sekhposyan (2019)'s test of uniformity of PITs



Note: Red lines: 1% critical values of the Kolmogorov-Smirnov test of PIT uniformity (dashed) and 45% degree line; Black line: Cumulative distribution function (CDF) of the PITs.

Calibration Core Inflation - Rossi and Sekhposyan (2019)'s test of uniformity of PITs



Note: Red lines: 1% critical values, Kolmogorov-Smirnov test of PIT uniformity (dashed) and 45% degree line; Black line: Cumulative distribution function (CDF) of the PITs.

Comparison with linear model - CRPS - full sample

Horizon	QRF	BVAR
Panel a: Headline Inflation		
h=3	0.29	0.28
h=6	0.50	0.49
h=9	0.74	0.67
h=12	0.93	0.88
Panel b: Core Inflation		
h=3	0.14	0.14
h=6	0.23	0.24
h=9	0.31	0.32
h=12	0.37	0.39

Note: CRPS for QRF (second column) and VARCOMB (third column)

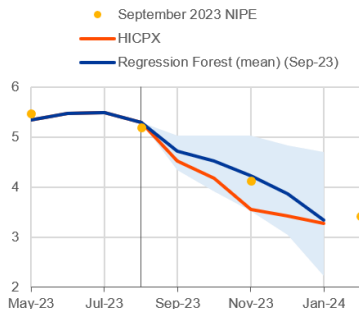
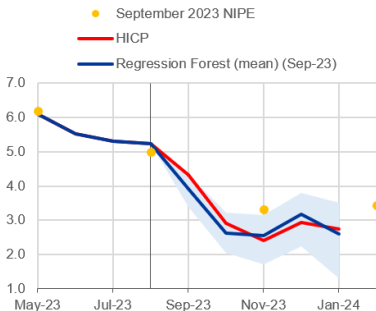
Functional forms

- Most of the top contributors seem to be in a linear relationship with inflation
- Euribor: systematic monetary policy?
- Unemployment and wages: linear Phillips Curve-type correlations?
- Inflation expectations: non-linear relationship! Steeper change in slope for core inflation

Comparison with Eurosystem - point forecast

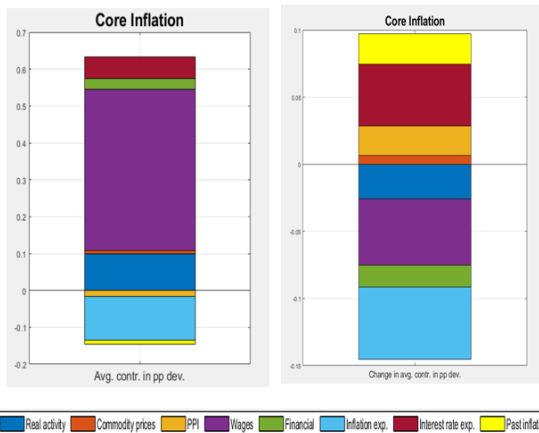
- QRF median forecasts are competitive with (B)MPE up to two quarters ahead. Then the (B)MPE is more accurate
- Strong collinearity! Does it say something on judgement?

Example of policy use: Forecast and Risks



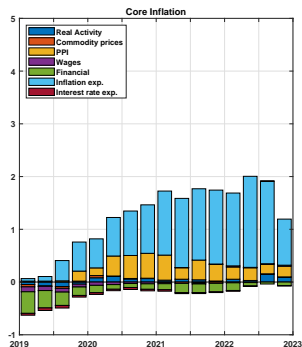
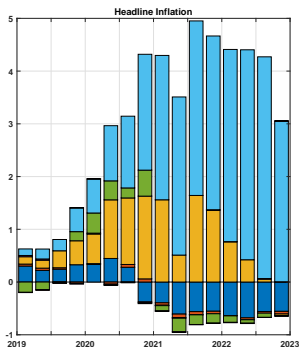
Note: Red solid line: year-on-year growth rate of the HICP; blue area: 5th to 95th quantiles of the QRF density forecasts with a horizon of six months ahead; yellow circles: quarterly frequency Eurosystem staff inflation projections.

Example of policy use: Forecast interpret-ability



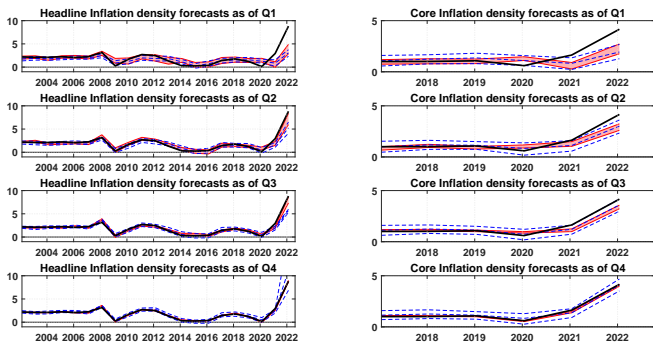
Note: Shapley values for core inflation. Av. contr. of specific group of variables for the 1 to 6 month ahead forecast in deviation from QRF mean. LHS: Abs. contr. RHS: Change in contr. compared to a previous forecast.

Shapley Values - Recent contributions $h=6$



Note: Shapley values associated with different groups of predictors, sample 2019 - 2022, horizon of six months ahead. Left panel: Headline inflation; Right panel: Core inflation.

SPF - density forecast of QRF and SPF for current year



Note: Red Area: 16th to 84th quantile of the QRF, current year for headline inflation (left panels) and core inflation (right panels); Dashed Lines: 16th to 84th quantile of the SPF, current year for headline inflation (left panels) and core inflation (right panels).