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Macro-at-Risk in the euro area
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Abstract

This paper introduces reduced-form macroeconometric tools, emphasising quantile regression models, to identify key risk drivers for the euro area economy and assess risks around the baseline ECB/Eurosystem staff macroeconomic projections for the euro area inflation and growth. The analysis uses a large number of risk factors, going beyond the usual financial factors, employing a sequential selection approach with robustness checks. To support the analysis a MATLAB toolbox (M@RX) was developed, incorporating several quantile regression-based model classes with a novel parametric tilting methodology and a copula approach for transforming predictive densities across frequencies. This paper contributes to the literature on the treatment of the COVID-era data in quantile regression models. Results indicate that the predictive content of risk factors is horizon, time and objective-dependent. For example, labour market indicators are particularly relevant for assessing upside inflation risks, but to a time-varying extent and with limited predictive power for downside risks. Conversely, uncertainty, money and credit indicators perform better for downside inflation risks. As regards risks to growth, the results confirm the established role of financial conditions, while also highlighting the relevance of monetary indicators, particularly for downside risks. Combined risk factor frameworks – with several different risk indicators – tend to systematically outperform single-factor specifications for density forecasting, due to complementarities across risk indicator groups. An empirical application highlights the policy relevance of these tools, as they provide timely signals and accurately track the direction of realised outcomes. Given the time-varying and state-dependent nature of their predictive performance, a regular performance assessment of the specifications is recommended to maintain reliability.

Keywords: Macro-at-Risk, tail risks, quantile regression, forecasting, density forecasts.

JEL codes: C22, C53, E27, E37

Executive summary

This paper develops and applies a comprehensive Macro-at-Risk (MaR) framework to assess the risks surrounding euro area real gross domestic product (GDP) growth and Harmonised Index of Consumer Prices (HICP) inflation projections. Motivated by the heightened uncertainty characterising the post-pandemic environment, the analysis seeks to identify key macro-financial risk drivers and to provide density-based risk assessments that complement the baseline ECB/Eurosystem staff projections.

The empirical strategy relies on a large, data-rich environment with a real-time dataset of about 350 quarterly indicators spanning financial conditions, money and credit aggregates and labour market variables, as well as a broad set of domestic and global nominal and real factors. Using a purpose-built MATLAB toolbox, reduced-form quantile regression models are employed to characterise the conditional distribution of growth and inflation across various forecast horizons. Particular attention is also given to the treatment of the COVID period, whose exceptional dynamics and influence on quantile regression-based estimates are explicitly examined. To address the high dimensionality of the dataset, the paper adopts a constrained sequential selection approach and evaluates predictive performance using a broad set of out-of-sample density forecast metrics.

Three main results emerge. First, the predictive content of individual risk drivers is strongly horizon, time and objective-dependent. For inflation, labour market indicators are particularly informative for upside risks, especially at medium-term horizons, while uncertainty, money and credit variables are more relevant for downside risks. For growth, financial conditions but also monetary indicators play a central role in explaining downside tail risks, with labour market variables gaining importance at longer horizons. Second, models that combine risk drivers drawn from multiple, distinct indicator groups consistently outperform single-factor specifications in terms of density forecast accuracy across all horizons and evaluation metrics, with the performance gains stemming from exploiting complementarities across indicators rather than expanding the number of regressors. Third, the state-dependent nature of indicator relevance underscores the importance of regular model reassessment to ensure robust and reliable risk analysis, particularly in policy-oriented applications.

The paper further demonstrates how MaR tools can be integrated into the ECB/Eurosystem projection process. The model-based quarter-on-quarter predictive densities are aggregated into calendar-year distributions using a purpose-built copula-based approach and subsequently re-centred on staff point forecasts using a parametric tilting approach, thereby ensuring consistency between baseline projections and empirically derived risk assessments. An empirical application shows that the resulting combined densities provide timely and policy-relevant signals, accurately tracking subsequent realisations, most notably the persistent upside risks to inflation identified in late 2022.

Overall, the findings support the use of MaR frameworks as a valuable complement to baseline-focused projection exercises. While the reduced-form nature of the

models limits structural interpretation, their ability to quantify time-varying and asymmetric risks around baseline forecasts makes them a useful operational tool for monetary policy analysis, particularly in environments characterised by elevated uncertainty and non-linear dynamics.

1 Introduction

The effective conduct of monetary policy at central banks is crucially dependent on the ability of its staff to comprehensively characterise and assess a wide range of macroeconomic risk factors in a timely fashion. In the current environment of high uncertainty, there is a growing need for innovative model-based approaches to risk assessment, capable of quantifying the impact of past and present macroeconomic developments on the entire distribution of future macroeconomic outcomes. Spurred by the influential work of Adrian et al. (2019), this methodological approach has been developed by both central banks and academia under the label of “Macro-at-Risk”, and has formed the core of novel macroeconometric toolkits deployed within international macro-financial institutions to support financial stability analyses and macroprudential policy.

This paper presents the methodology and outlines the main results of a large-scale project undertaken by a group of experts from the European System of Central Banks (ESCB), with the focus on identifying and modelling macroeconomic tail risks to euro area GDP growth and HICP inflation. The following two overarching goals have guided the analyses: i) to explore and detect potential key risk drivers for the euro area economy; and ii) to provide a set of reduced-form macroeconometric tools and metrics for assessing risks around the baseline ECB/Eurosystem projections.

To these ends, the work of the ESCB experts has focused on building a comprehensive empirical framework that relies on combining multiple predictive accuracy metrics. To consolidate these analyses and to ensure the validity of the findings, a broad set of robustness checks is employed, including predictive performance comparisons against standard benchmarks and across time periods, models and estimators.

Among many advancements and innovations reported in this paper, the following three contributions stand out as especially salient. First, this work considers a large number of potential risk factors (~350 indicators partitioned into nine distinct groups of risk indicators), going far beyond the handful of financial risk indicators usually employed in the literature. As automated (e.g. machine learning) data reduction and model selection procedures have not been fully developed for the class of econometric models employed in this paper, this study relies instead on a constrained sequential selection method (i.e. imposing restrictions on the number and type of variables that can enter competing specifications) to tackle the large number of available risk indicators. Despite its conceptual limitations, the primary advantage of this selection approach is its practical feasibility, as the estimation of all potential specifications would be computationally prohibitive. A set of robustness checks performed across the entire selection procedure should ease concerns about statistical selection bias.

Second, the analyses reported in this paper inspired and implemented a number of original econometric contributions. Among these, the development of a copula approach for transforming high-frequency predictive densities into lower-frequency densities (e.g. from quarter-on-quarter to annual average growth rates) stands out as especially innovative. In addition, the paper introduces a parametric tilting approach, which under certain constraints enables the shifting of the mode of distribution to a selected target value. Both methodological advances are extremely useful in the context of macroeconomic point projections for policy analyses and advice.

Finally, a practical outcome of this work is a purpose-built and extensible MATLAB toolbox (named “M@RX” for “Macro-@-Risk toolboX”), developed and tested by the ESCB experts. M@RX encompasses the latest econometric models and forecast evaluation methodologies for the fast estimation and comprehensive assessment of macroeconomic tail risks in a data-rich environment. As well as being used in the context of this study, M@RX was first made available to ESCB researchers and practitioners for their day-to-day analyses of macroeconomic tail risks before its release to the wider public.

As previously mentioned, the academic research on macroeconomic tail risks originates from the influential work of Adrian et al. (2019), which employs univariate quantile regression models for US GDP growth with a single risk factor.[1] This contribution gave rise to a broad literature examining a wide variety of alternative risk drivers, such as additional financial variables (e.g. Giglio et al., 2016; De Santis and van der Veken, 2020; Korobilis et al., 2021), macroeconomic indicators (Cook and Doh, 2019; Plagborg-Møller et al., 2020), macroprudential measures (Franta and Gambacorta, 2020) and global factors (González-Rivera et al., 2019; Leiva-Leon and Rodriguez-Moreno, 2021; Busetti et al., 2021a). In addition, follow-up papers also explore wider geographies (e.g. the euro area in Cohen et al., 2019 and Figueres and Jarociński, 2020), mixed-frequency data (Ghysels et al., 2018; Ferrara et al., 2022) and longer-term forecast horizons (Aikman et al., 2021).[2]

Most studies in this literature employ the quantile regression models of Koenker and Bassett (1978) to estimate relevant risk determinants for GDP growth and inflation, often combined with factor analysis to achieve data reduction in the presence of a large number of potential risk drivers.[3] However, Macro-at-Risk analyses can build on any econometric model that generates a predictive distribution for the variable of interest. Therefore, several alternative model-based approaches have been proposed in the literature, including BVAR with stochastic volatility (Carriero et al., 2023), expectile regressions (Busetti et al., 2021b), parametric Skew-t distributions (Delle Monache et al., 2024; Wolf, 2022), Markov regime-switching models (Caldara et al., 2021) and time-varying parameter mixed-frequency dynamic factor models (Eraslan and Schröder, 2022). The multivariate frameworks for macroeconomic tail-risk analyses have also been proposed in the literature. These include quantile VAR generalisations (Chavleishvili and Manganelli, 2024), non-parametric approaches to assess joint distributions of the variables of interest (Adrian et al., 2021), copulas

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1 From the policy perspective, the Growth-at-Risk approach is widely used for risk assessment on financial stability issues (IMF, 2017; IMF, 2022), country surveillance (Prasad et al., 2019) and macroprudential frameworks (Carney, 2020; Chavleishvili et al., 2021a, 2021b), and potentially for stress testing (Chavleishvilli and Manganelli, 2019).

2 Other policy-relevant “at-Risk” variables studied in the literature are unemployment rates (Kiley, 2022), industrial production (Chavleishvili and Manganelli, 2024) and core inflation (Busetti et al., 2021b).

3 Alternative approaches are provided by Koop and Koribilis (2014) and Cook and Doh (2019). Leiva-Leon and Rodriguez-Moreno (2021) propose a Markov-Switching three-pass regression filter (Guérin et al., 2020), which can additionally account for non-linearities.

based on SPF distributions (Odendahl, 2021) and methods that exploit the cross-sectional commonality (Brownlees and Souza, 2021).

Regarding the forecast horizons, most studies focus on assessing short-term macroeconomic tail risks (i.e. one to four quarters ahead; see Corden and Paustian, 2021, and Reichlin et al., 2020), while only a limited number of contributions examine longer-term horizons (8 to 12 quarters ahead; see Korobilis et al., 2021, and Sokol, 2021).

As regards the findings, several Growth-at-Risk studies point to asymmetric and horizon-dependent tail risks for GDP growth when financial risk factors are considered. For example, asset prices and credit aggregates are found to be particularly informative about risks to economic activity at shorter horizons, while sovereign spreads appear more informative for emerging market economies (IMF, 2017). Changes in monetary policy, credit and productivity tend to disproportionately affect lower GDP quantiles (Loria et al., 2019), with unexpected monetary policy tightening increasing the probability of very low growth in the short term (Franta and Libich, 2021).

In contrast to relatively homogeneous findings for Growth-at-Risk, the Inflation-at-Risk literature, which is so far less substantial, finds no clear consensus to support the presence of asymmetric tail risks for inflation (Tagliabracci, 2020; Sokol, 2021). A baseline Phillips curve specification shows a mixed picture regarding the detection of asymmetric responses for inflation (Berben, 2021; López-Salido and Loria, 2020). More sophisticated models, such as Bayesian quantile regression with time-varying parameters (Korobilis et al., 2021; Pfarrhofer, 2022), quantile regression on the residuals of a random walk process (Manzan and Zerom, 2013) and quantile autoregressive distributed lags models with mixed-frequency data (Ghysels et al., 2018) are reported to perform better in out-of-sample analyses. However, there is considerable heterogeneity across reported empirical findings (i.e. the way inflation quantiles react to business cycle movements, financial conditions and other global risk factors), depending on the included risk indicators, estimation samples and geographic coverage.[4]

The main caveat of the Macro-at-Risk approach à la Adrian et al. (2019) lies in the potential instabilities of model coefficients in short samples – a crucial issue for the euro area – especially when the focus is on extreme quantiles (Chernozhukov et al., 2017). Another important limitation with this approach pertains to the potential lack of monotonicity of estimated conditional quantiles – the so-called quantile crossing problem.[5] Finally, the baseline quantile regression approach might fail to account for the effects of extreme observations, such as during the COVID-19 pandemic period.

Against the backdrop of the recent literature, this study introduces a three-step framework combining distinct modelling approaches for the risk assessments of the

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4 For instance, in the euro area, the upper tail of the inflation distribution tends to be more sensitive to unemployment – in contrast to the median and lower tails – suggesting that high inflation risks arise from tight labour markets. In contrast, for the US the picture tends to be muted (López-Salido and Loria, 2020).

5 Statistical corrections, such as sorting quantile estimates (Chernozhukov et al., 2010), can overcome this shortcoming. Techniques to overcome the short sample size include Bayesian modelling (Kozumi and Kobayashi, 2011) or exploiting the cross-sectional dimension (Brownlees and Souza, 2021).

euro area economy. First, risks to euro area GDP growth, headline and core HICP inflation are evaluated for each individual risk driver in the dataset, mirroring the influential Adrian et al. (2019) paper. Second, the potential advantages of combining different risk indicators are assessed by evaluating specifications with up to five variables, each from a different group of risk indicators. Finally, aggregation of predictive densities from selected well-performing model specifications is employed for inferences on the risks to the ECB/Eurosystem staff point forecasts.

The empirical findings reported in this paper suggest that the information content of risk drivers tends to be time-varying, and their relevance is contingent on both the forecast horizon and the direction of risk (upside or downside). The main risk factors also differ across target variables, in our case real GDP growth and HICP inflation, although some commonality emerges. For instance, non-cost labour market variables, such as the unemployment rate, appear particularly informative for upside and downside risks to, respectively, inflation and growth. However, the explanatory power of these variables tends to diminish, especially in the post-pandemic period, when combined with other drivers. This decline in statistical significance suggests potential non-orthogonality between the information content of these labour market indicators and that of other drivers when considered jointly.

Results for euro area GDP growth are broadly consistent with the Growth-at-Risk literature: at short-term horizons, financial conditions (risk spread and Composite Indicator of Systemic Stress (CISS)), along with some domestic nominal variables, provide solid predictive accuracy. However, at medium-term horizons, external factors (though not commodity prices), together with uncertainty indicators, tend to outperform financial risks.

Inflation-at-Risk findings for the euro area, encompassing both headline and core HICP inflation, highlight the role of financial variables, including money and credit variables (e.g. bank loans to households), and domestic uncertainty indicators as particularly informative about risks to inflation at the short and medium-term horizons, respectively. Interestingly, these groups of indicators, together with labour market and other supply constraints indicators, also provide relevant information on future risks to inflation, irrespective of whether the recent high-inflation episode is excluded from the evaluation sample. Conversely, the saving ratio exhibits striking predictive power during that episode but loses its potency when the post-pandemic period is omitted from the evaluation sample. Energy commodity prices and, to a lesser extent, market-based inflation expectations, show limited value for Inflation-at-Risk analyses, notwithstanding the important role of energy commodity prices in driving inflation dynamics in the euro area.

The overall picture tends to favour combined risk factors over specifications with a single variable or combinations from a single risk category. At the broad level of density forecast accuracy, the results show a near-systematic superiority of models with combined risk factors over specifications including a single risk driver or a few variables from the same groups of risk indicators. Furthermore, while a comprehensive exploration of model selection procedures is beyond the scope of this analysis, the results underscore the importance of tailoring the selection process to the specific forecasting objective.

As an empirical application, a combined density derived from selected well-performing specifications was centred around the December 2022 – the then-latest available – ECB/Eurosystem staff projections. This analysis consistently indicated persistent upside risks to headline inflation, a finding that was subsequently validated by the forecast errors.

In terms of limitations and potential avenues for future research, an important caveat of the present analyses is the lack of structural interpretation of the results.[6] This limitation is inherent to the modelling approach and specific objectives of this study. While the focus is on predicting macroeconomic tail risks, a structural interpretation of the contribution of the main drivers of those risks would enhance our understanding of the underlying economic links between endogenous variables and risk drivers. Furthermore, although the class of models considered in this paper is designed to address certain forms of non-linearity, it is unlikely that more complex interactions and the effects of unexpectedly large shocks (such as pandemics or geopolitical events) can be correctly anticipated by the present framework. However, from an operational point of view, these models have been shown to provide valuable and policy-relevant information on risks, even at the medium-term horizons, and offer insights on the uncertainty surrounding the macroeconomic projections.

The remainder of the paper is organised as follows: Section 2 presents the data and key methodological choices of this study; Section 3 evaluates the relevance of individual and combined risk factors for euro area growth and Inflation-at-Risk; Section 4 illustrates how M@RX can be used in the context of ECB/Eurosystem projection exercises; and Section 5 concludes.

[6] See Montes-Galdón et al. (2024) for a discussion on the integration of non-linearities into structural models.

2 Data and empirical methodology

2.1 Dataset

An extensive dataset of around 350 variables, sampled at quarterly frequency, has been assembled for the euro area macroeconomic tail-risk analyses reported in this paper. Among these variables, the real GDP growth rate and the headline and core inflation rates are treated as target variables, with the remainder used as potential risk drivers. The selection of the variables in the dataset is based on the available literature, such as IMF (2017), Adrian et al. (2018), Prasad et al. (2019), Plagborg-Møller et al. (2020), Reichlin et al. (2020), Figueres and Jarociński (2020) and Ghysels et al. (2018) for Growth-at-Risk, and López-Salido and Loria (2020) and Korobilis et al. (2021) for Inflation-at-Risk.

The variables in the dataset are partitioned into nine groups of risk indicators, following specific Eurosystem policy needs and suggestions by Prasad et al. (2019). The grouping of the risk indicators is as follows:

1. Financial conditions (49 variables). This category comprises a number of aggregate financial conditions indices (FCIs), such as the CISS of Hollo et al. (2012) for the euro area, in line with Adrian et al. (2019), as well as variables measuring the price of risk, cost of funding and financial stress, such as various interest rates (Euribor, EONIA, sovereign), lending rates (corporates, household consumption, housing), spreads and stock market prices and volatility.

2. Money and credit variables (14 variables). This group includes the main monetary aggregates (M1 and M3) and several measures of credit volumes (for example, loans to non-financial corporations and to households).[7]

3. Labour market (five variables). This set contains both labour market cost and unemployment indicators, including the Non-Accelerating Inflation Rate of Unemployment (NAIRU).

4. Price and cost variables (15 variables). This classification includes all domestic prices and cost indicators not included in the previous groups, such as the GDP deflator, terms of trade or different producer price indices.

5. Survey-based and market-based expectations (11 variables). This category covers expectations of GDP growth or HICP inflation stemming from the ECB Survey of Professional Forecasters or from inflation-linked swap (ILS) rates.

6. Uncertainty/Volatility (14 variables). This group includes model-based or survey-based indicators of economic, political and financial uncertainty.

7. Other domestic factors (31 variables). These variables measure broad macroeconomic developments in the euro area and include Purchasing Managers' Indices (PMIs) (with various sub-categories, such as new export

[7] Many of these variables were taken from the selection provided by Korobilis et al. (2021).

orders, output and supplier delivery times), measures of slack (NAIRU gap, output gap), industrial production and indices for imports and exports, among other domestic variables.

8. Commodity prices (12 variables). This group contains multiple indices of global commodity prices, for both energy and non-energy commodities.

9. Other external factors (197 variables). This set includes extra-euro area indicators, notably the GDP, CPI, exchange rates, imports and exports of 18 key trading partners of the euro area. It also includes FCIs for a subset of countries, as well as aggregate indices of foreign demand and foreign prices.

In addition to these nine groups of risk indicators, the dataset is split into two blocks. The first block includes real-time vintages and projections for 97 variables, which are part of the ECB/Eurosystem staff projections exercises. Real-time vintages are available on a quarterly basis from the fourth quarter of 1998, so that for each quarter since 1998Q4 the dataset reflects the information available to a forecaster at that time, before any subsequent data revisions. All variables in this first block of the dataset are projected for up to (at least) eight quarters ahead and, where possible, backcast to 1980Q1.

The second block of the dataset contains the remaining variables that do not have real-time vintages (e.g. commodity prices, interest rates, PMI surveys). These are taken from a variety of sources, including the ECB Data Portal, the World Bank and the European Commission databases.

The latest available vintage corresponds to the December 2022 ECB/Eurosystem staff projections exercise, with projections up to 2025Q4. For convenience, all variables in the dataset are expressed in levels and their transformations are undertaken during the modelling process.[8]

2.2 Empirical methodology

2.2.1 Econometric framework

The econometric literature provides a number of methods for estimating and forecasting in the context of Macro-at-Risk analyses. This study relies on the standard Quantile Regression (QR) framework, in its frequentist and Bayesian

[8] A subset of 135 variables is employed in the actual empirical analyses reported in the paper, following a pre-selection procedure applied to external factors that was based on correlation with the endogenous variables and other tests. Details are available from the authors upon request. Table AI.1 in the Appendix details all the variables used in this study, with further information provided in Kulikov and Chahad (2024).

univariate versions. This choice reflects current practice in central banks and other financial institutions, where these tools are used to assess macroeconomic tail risks.[9]

The seminal paper of Koenker and Bassett (1978) introduced a simple approach for estimating conditional quantiles in the linear regression framework. It builds on the familiar linear regression model:

$$y_t = \boldsymbol{x}_t^{\mathrm{T}}\boldsymbol{\beta}_\tau + \varepsilon_t \quad \text{for all} \quad t = 1 \ldots T,$$

where $\boldsymbol{x}_t \in \mathbb{R}^{\boldsymbol{k}}$ are the regressors, $\boldsymbol{\beta} \in \mathbb{R}^{\boldsymbol{k}}$ is the vector of unknown parameters and $y_t \in \mathbb{R}$ is a scalar dependent variable. In contrast to the usual conditional mean framework, which minimises the sum of the squared residuals in this equation, the conditional QR model minimises the following criterion for each given conditional quantile hype-parameter 0< τ <1:

$$\boldsymbol{\beta}_\tau = \operatorname{argmin} \textstyle\sum_{t=1}^{T} \rho_\tau(y_t - \boldsymbol{x}^T\boldsymbol{\beta}),$$

where $\rho_\tau(\varepsilon) \coloneqq |\varepsilon| \cdot [\tau \cdot \mathbb{I}_{\varepsilon \geq 0} + (1-\tau) \cdot \mathbb{I}_{\varepsilon < 0}] = \varepsilon \cdot (\tau - \mathbb{I}_{\varepsilon < 0})$ is the "check function", and $\mathbb{I}_S$ denotes the indicator function on the set S. For any given 0< τ <1, this function assigns the weight τ to the non-negative residuals and (1 – τ) to the negative ones. The case τ = 0.5 corresponds to minimising the sum of absolute residuals, which yields the median regression. The parameter estimates in this model are usually restricted to a small set of vectors $\widehat{\boldsymbol{\beta}}_\tau$ for select values of τ in the unit interval.

The Bayesian QR model is based on the idea from Koenker and Machado (1999) that the likelihood-based inference with asymmetric Laplace densities is directly related to the minimisation problem above. In this case, the innovations ε_t in the QR model are assumed to be independent random variables distributed according to the asymmetric Laplace density:

$$f(\varepsilon; \tau, \sigma) = \frac{\tau(1-\tau)}{\sigma} \cdot e^{-\rho_\tau\left(\frac{\varepsilon}{\sigma}\right)},$$

where $\rho_\tau(\varepsilon)$ is the "check function" defined above, and $\sigma > 0$ can be either fixed or treated as an unknown parameter with a prior distribution; refer to Yu and Moyeed (2001) and Kozumi and Kobayashi (2011) for additional details on this approach.

Practical implementations of these and several other types of quantile regressions are incorporated into a MATLAB toolbox developed specifically for the purpose of this study (see Box 1).

[9] Quantile regressions may provide asymmetric predictive densities, which are expected to provide better information on the evolution of tail risks around a "central" forecast. The Bayesian QR approach may be more suited than its frequentist counterpart in the context of macroeconomic forecasting, as the former provides a natural regularisation of the estimation of the model parameters in a small-sample framework.

Box 1
Econometric toolbox for Macro-at-Risk analyses: M@RX

by Dmitry Kulikov

The MATLAB toolbox, developed jointly by experts within the ESCB for the purposes of this study and beyond, is named M@RX, an abbreviation of “Macro-@-Risk toolboX”.[10] A special-purpose macroeconomic (and partly real-time) database for the euro area economy (as detailed in Section 2.1) is integrated with M@RX, which provides quick and convenient access to the available statistical data series for macroeconomic risk assessments and forecasting. In addition, a robust framework for model evaluation, described later in this section, is incorporated into M@RX to facilitate the selection of well-performing models during regular Macro-at-Risk analyses.

M@RX is a multi-model MATLAB toolbox for assessing and forecasting risks in macroeconomic time series data using the latest econometric and forecasting methodologies available in the academic literature. Therefore, the toolbox is built to be highly configurable and extensible by its end users: all codes are provided in a non-encrypted format, allowing users to easily add new data and variables, as well as econometric and forecasting models. M@RX provides all the necessary infrastructure to deal with data, configuration options, error reporting and logging, and convenient storage of the final modelling results. The toolbox can be driven by either the text-based or Excel-based configuration files, which contain all necessary settings for steering the various M@RX components. In addition, a simplified and user-friendly graphical interface is under development for occasional users of M@RX who do not need to utilise all its advanced capabilities.

Data importing and processing can be done in M@RX using a variety of data sources, including various on-disk files or the special-purpose macroeconomic database specifically designed for the Macro-at-Risk analyses in this paper. The toolbox is also structured to accommodate additional data sources in the future; these can, for example, be online databases with well-defined data interfaces, such as the ECB Data Portal. Once data are imported, M@RX is capable of simultaneously running multiple models on multiple datasets in a single session using MATLAB parallel computing facilities. This capability of M@RX is crucial for producing results in a timely manner, particularly in operational forecasting environments. Finally, all M@RX output is stored in a single hierarchical MATLAB structure for easy saving, subsequent retrieval and processing.

A comprehensive M@RX User’s Guide is available in Kulikov and Chahad (2024). Future versions of M@RX may incorporate additional models and improved data interfaces to provide access to various online databases.

2.2.2 Model selection and evaluation

The following three-step empirical methodology for the analysis of euro area macroeconomic tail risks has been developed and utilised throughout this paper:

1. The risks to euro area GDP growth, HICP and HICP excluding energy and food (HICPX) inflation rates stemming from individual risk drivers are assessed by evaluating their marginal contribution to the predictive performance vis-a-vis a simple AR(2) benchmark. Unlike similar approaches in Adrian et al. (2019) and Figueres and Jarociński (2020), this study considers up to three potential risk

[10] The toolbox is available on GitHub: https://github.com/MATRXc/MATRXv1.0

drivers drawn from the same group of risk indicators that extend beyond financial conditions.

2. A combination of up to five potential risk drivers, each stemming from a different group of risk indicators, is used in predictive performance analyses to better account for complementarities, if any, between the nine groups of risk indicators.

3. Finally, based on the preceding results, a small subset of well-performing specifications is selected for additional performance tests and the empirical application.

In line with the approach of Adrian et al. (2019), the predictive densities are constructed by calibrating the Skew-t distribution (Azzalini and Capitanio, 2003) to match estimated empirical conditional quantiles (specifically, the 10th, 25th, 75th and 90th quantiles). The predictive performance and calibration of these fitted Skew-t densities is evaluated using a battery of tests (see Table 2.1) and over three different forecast horizons, Q+1, Q+4 and Q+8, using the real-time out-of-sample direct forecasting approach. The realised values of the dependent variables are defined as those released five quarters after the end of the projection period.

Table 2.1
Out-of-sample criteria

	Test	Description
Statistical tests	Probability Integral Transform (PIT) tests	To evaluate the correct specification of the predictive distributions, following Rossi and Sekhposyan (2019)[1)]
Proper scores	Continuous Ranked Probability Score (CRPS)	To evaluate the overall density,[2)] following Gneiting and Raftery (2007)
	Quantile score	To evaluate a given quantile of interest, following Gneiting and Raftery (2007)[3)]
Other indicators	Concordance ratio	The concordance between the sign of the forecast error and the projected balance of risks

1) The Rossi and Sekhposyan (2019) PIT tests are used in the current analysis for both rolling-window and recursive-window estimates, although the test was set only for the rolling-window estimation scheme.
2) Whole density evaluations using the log score are also available.
3) Here, the labelling and formula of the quantile score follow Gneiting and Raftery (2007), but it can also be referred to as the tick loss function (Giacomini and Komunjer, 2005) or, more traditionally, as the asymmetric linear or lin-lin loss function (Koenker and Bassett, 1978; Christoffersen and Diebold, 1996). See Gneiting and Raftery (2007) for a discussion.

One of the main objectives of this paper is to assess macroeconomic tail risks in the context of the ECB/Eurosystem staff (Broad) Macroeconomic Projections Exercises (hereafter (B)MPE).[11] The point forecasts provided by the (B)MPE are assumed to reflect the most likely outcome amongst all potential macroeconomic scenarios.[12] Therefore, the baseline (B)MPE point forecast is taken as the mode of the predictive distributions derived from the estimated QR models. The approach employed here for combining the (B)MPE point forecasts with the estimated model-based distributions relies on an ex post re-centring of the empirical predictive densities using a parametric tilting approach by Montes-Galdon et al. (2022), described in Box 2.

[11] For more details, refer to European Central Bank (2016).

[12] See, for instance, Lambrias and Page (2019).

Table 2.2 provides a detailed overview of the step-by-step model selection and evaluation methodology adopted in this study.

Table 2.2

Overview of the model selection and evaluation methodology

Step	Dependent variables	Risk indicators	Forecast horizons	Out-of-sample evaluation period	Econometric models	Lag structure	Re-centring to (B)MPE baseline
1	Real GDP (qoq growth)	All available variables in the database One to three explanatory variables from the same group of risk indicators	Q+1 Q+4 Q+8				No tilting
2	HICP[2)] (qoq growth)	Selected variables from Step 1 One to five explanatory variables No combination of variables from the same group of risk indicators	Q+1 Q+4 Q+8	2013Q1:2022Q3[1)]	Bayesian QR	0 or 1 lag	Tilting
3	HICP excluding energy and food[4)] (qoq growth)	Selected specifications from Step 2 No combination of variables from the same group of risk indicators	Y+0[3)] Y+1 Y+2				Tilting

1) The period 2020Q1-2020Q3 was dropped for all GDP analyses, including score averages, assuming that the GDP dynamics over this period were triggered by exceptional events that are not meant to be captured or forecast.
2) The HICP series were seasonally adjusted using X12 methodology.
3) For the December projections, the horizons are Y+1, Y+2 and Y+3.
4) The HICP excluding energy and food series were seasonally adjusted using X12 methodology.

Box 2
A robust approach to tilting predictive densities towards ECB/Eurosystem point forecast

by Carlos Montes-Galdon and Joan Paredes

The proposed methodology aims to re-centre the model-based forecast distributions around the baseline ECB/Eurosystem staff (Broad) Macroeconomic Projection Exercise – hereafter (B)MPE – point forecast to ensure that the final forecast distribution properly reflects the risk assessments based on the estimated QR models. The objective of the re-centring exercise is twofold: (i) the mode of the final distribution should coincide with the (B)MPE point forecast, and (ii) the shape of the final distribution should be as close as possible to the original model-based M@RX distribution. Model-based information is thus combined with the (B)MPE judgement to derive predictive distributions around the (B)MPE baseline.

A new methodology is employed that modifies the original contribution by Robertson, Tallman and Whiteman (2005) by imposing a parametric form on the final density in the optimisation problem, i.e. Skew-t distribution (see Azzalini and Capitanio 2003). This distribution is a flexible parametric density that allows fat tails as well as asymmetries that can be set by the parameters defining the distribution. A variable Y has a Skew-t (ST) distribution, $Y \sim ST(\xi, \omega, \alpha, \nu)$ where ξ is a location parameter, ω the scale, α the slant parameter that determines the skewness of the distribution, and ν the degrees of freedom. Note that when the degrees of freedom are infinitely large ($\nu \to \infty$) and $\alpha = 0$, the distribution reduces to the Gaussian case. The ST distribution has a closed-form solution for different moments, specifically for the skewness, and, most importantly, for the mode. These moments are non-linear functions of the four parameters of the distribution.

The idea of the proposed methodology is to find the parameters of a Skew-t distribution that minimises the Kullback-Leibler divergence criteria with respect to the model-based predictive distribution, imposing additional moment restrictions: the mode and the skewness. Formally, this is akin to defining the parametric tilting problem in terms of parametric densities as follows,

$$\min_{\xi,\omega,\alpha,\nu} \sum_{i=1}^{k} P(x_i) \cdot \log\left(\frac{P(x_i)}{ST(x_i)}\right)$$

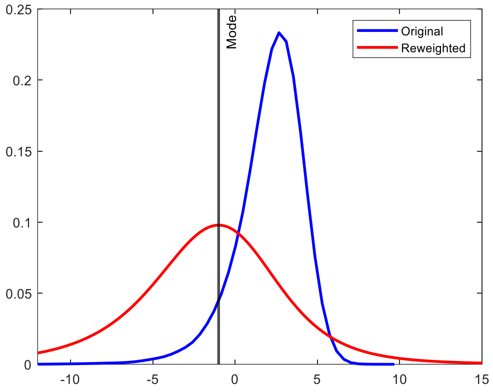
where x_i corresponds to the value of each draw in the model-based predictive density, $P(x_i)$. In this expression, $ST(x_i)$ denotes the desired tilted parametric density subject to restrictions on its moments, specifically the mode (m) and the skewness (γ):

$$m = \bar{m}\ ;\ \gamma = \bar{\gamma}$$

Choosing a parametric density, rather than directly finding the new weights, as in the original entropic tilting contribution (Robertson, Tallman and Whiteman, 2005), gives more control over the final shape of the density. Chart B2.1 shows an example of the parametric tilting approach. To derive the reweighted distribution, the mode of the original distribution is tilted from 3 to -1, which is further away to the left than the original one, while the original skewness of -1.55 was retained. In this case, the increase in the scale (or variance) of the final reweighted density is a natural consequence of the tilting, as it primarily reflects a disagreement on the location of the final distribution between the "underlying" model setting the target mode and the model generating the original predictive density. However, it is worth noting that, from a general point of view and beyond the tilting, sudden changes in the scale can also be attributed to empirical and econometric factors, reflecting an increase in uncertainty stemming from the data and the model of the underlying distribution. Monitoring the difference between the original and reweighted distribution is hence recommended to identify the source of changes in uncertainty.

Chart B2.1

Parametric tilting in an extreme scenario



Source: Authors' calculations.
Note: The chart depicts the predictive distribution before (blue line) and after (red line) the tilting imposing restrictions on both the mode and the skewness of the latter.

The dataset employed in this paper contains information up to the third quarter of 2022, which covers the COVID-19 pandemic period. The inclusion of the COVID-19 pandemic period in these data samples raises the question of the treatment of this exceptional event in this study. While several papers have addressed this issue for standard econometric models (e.g. Ng, 2021), no clear-cut recommendations from the literature are available in the context of QR models. Following some pre-existing examples, an ad hoc analysis was carried out specifically for the purpose of this study. The results, detailed in Box 3, indicate that dropping the observations in the first three quarters of 2020 is the most straightforward and effective approach to dealing with the exceptional COVID-19 period in the estimation sample in QR models.

Box 3
Assessing potential estimation issues with COVID-19 samples in QR models

by Mohammed Chahad and Florens Odendahl

The COVID-19 pandemic caused fluctuations in macroeconomic data series of unprecedented magnitude. For instance, euro area quarter-on-quarter real GDP growth dropped by 11.5% in 2020Q2 and rebounded by 12.4% in 2020Q3 (according to the dataset used in this paper).

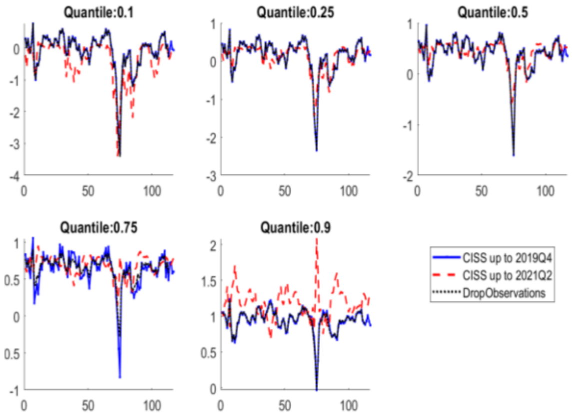
These pronounced swings have a strong impact on the parameter estimates of econometric models, including those explored in this study. To illustrate the problem, Chart B3.1 shows the results of in-sample predicted quantiles when estimating a QR model of the form: $y_t = c_q + \rho_{1,q}y_{t-1} + \rho_{2,q}y_{t-2} + \gamma_q CISS_t + e_t$, where y_t denotes the euro area quarter-on-quarter real GDP growth, and $CISS_t$ denotes the "Composite Indicator of Systemic Stress" for the euro area. The model is estimated once with a sample up to 2019Q4 (pre-COVID-19) and once with a sample up to 2021Q2 (post-COVID-19). As Chart B3.1 shows, the few observations in 2020 and 2021 have a substantial impact on the in-sample and, therefore, also on out-of-sample predictions. This feature is not desirable, since the observations associated with the onset of the pandemic dominate the parameter estimation.

The COVID-19 sample has a significantly smaller impact on estimation results when HICP inflation is the dependent variable in the specification above. However, the issue is neither unique to quantile regressions nor to the data used, as documented in Lenza and Primiceri, 2022 and Carriero et al., 2022, showing that parameter estimates of time-varying parameter models and models with stochastic volatility are also severely affected by the observations in 2020.

To address this issue, several approaches were evaluated to control for the effect of data outliers on parameter estimates: (i) dropping extreme COVID-19 period observations, (ii) the approach of Ng (2021), i.e. modelling the 2020 observations as non-standard economic shocks, for example a health shock, using, for instance, the number of infections or related hospitalisations as an explanatory variable, iii) assuming that the COVID-19 period data stem from standard economic shocks but entail a change in the transmission channel (TVP-BQR) or in their volatility (SV-BQR) or iv) a combination of the above.

After examining the results, based on quantile scores computed conditioning on a sample up to 2019Q4 and on a sample up to 2021Q2, the most straightforward approach to dealing with the 2020 observations for GDP, across the model classes and specifications considered in this paper, is to drop the 2020Q1-Q3 period from the in-sample estimation. The black dashed line in Chart B3.1 illustrates this finding, which is further corroborated by the out-of-sample density forecast evaluation reported in Table B3.1, in which values closer to one indicate a better performance of the methodology. The results reported in this paper are hence based on this approach.

Chart B3.1
Effect of COVID-19 observations on in-sample estimation for GDP growth



Source: Authors' calculations.
Notes: Real GDP qoq growth regressed on its first two AR terms and the CISS. In-sample fit with estimations up to 2019Q4 and 2021Q4. DropObservations refers to the option of removing observations for the period 2020Q1 to 2020Q3.

Table B3.1
Density forecast performance of different options to account for the COVID-19 data

	QS 10%	QS 25%	QS 50%	QS 75%	QS 90%	Average
Pre-COVID-19	1	1	1	1	1	1
No adjustment	1.23	1.13	1.11	1.08	1.38	1.19
Drop observations	1.03	1.01	1.01	1.00	1.05	1.02
Deaths	1.02	1.02	1.02	1.06	1.81	1.19
Cases	1.06	1.01	1.07	1.08	1.69	1.18
Deaths and cases	1.02	1.02	1.02	1.03	1.09	1.04
Google Mobility Index	1.12	1.06	1.07	1.03	1.14	1.08
Oxford Stringency Index	1.18	1.12	1.10	1.06	1.29	1.15
Hospitalisations	1.02	1.01	1.02	1.06	1.79	1.18
ICU admissions	1.02	1.02	1.02	1.07	1.83	1.19
Cases then hosp.	1.01	1.01	1.03	1.07	1.71	1.17

Source: Authors' calculations.
Notes: Estimations using Bayesian QR models and data until 2021Q4 except for pre-COVID-19. The figures reflect the quantile score computed at each specific quantile. All scores are rescaled based on the pre-COVID-19 score, with lower values indicating a better performance. The colours indicate scores ranking from the lowest (dark green) to the highest score (dark red) for each quantile. "Drop observations" indicates that the observations for the period 2020Q1 to 2020Q3 have been removed from both left-hand side and right-hand side variables.

3 Macro-at-Risk in the euro area

3.1 Individual risk drivers of Growth-at-Risk and Inflation-at-Risk

This section presents the results of the first stage of the three-step empirical methodology outlined in Section 2.2, which mimics the approach of Adrian et al. (2019) for Growth-at-Risk and Inflation-at-Risk analyses in the euro area. These analyses aim to enhance the understanding of key risk drivers of economic growth and inflation and their impact on density forecasts in univariate QR models. As the total number of possible combinations arising from the large number of available explanatory variables and diversity of lag structures is beyond the computational limits of this study, the estimated specifications were subject to restrictions designed to ensure adequate coverage of all risk drivers in the dataset. All potential risk drivers are therefore tested under the constraints on the combinations of lags and the number of additional covariates included in the estimated model specifications, as outlined in Table 2.2 above.[13]

3.1.1 Inflation-at-Risk

Headline HICP

Chart 3.1 shows the distributions of three test scores that are used to evaluate the empirical density forecasts: the CRPS for assessing the entire distribution, and the 10th and 90th quantile losses for evaluating the left and right tails, respectively. These scores are averaged over the entire out-of-sample period 2013Q1-2022Q3.[14] Each distribution corresponds to the set of risk drivers stemming from the nine groups of risk indicators described in Section 2.1.

A visual inspection of the chart suggests a trend of increasing predictive accuracy, relative to the AR(2) benchmark, for the estimated specifications as the projection horizon lengthens, highlighting the role of horizon-dependence in the predictive content of various risk drivers. This is evident from the widening distance between the best-performing specifications and the vertical benchmark line.[15] Additionally, the absolute predictive performance deteriorates significantly from the Q+1 to Q+4 horizons, as indicated by increasing values for all scores, but only marginally from Q+4 to Q+8. This pattern implies that QR models provide additional valuable insights into macroeconomic tail risks, even at relatively long forecasting horizons.

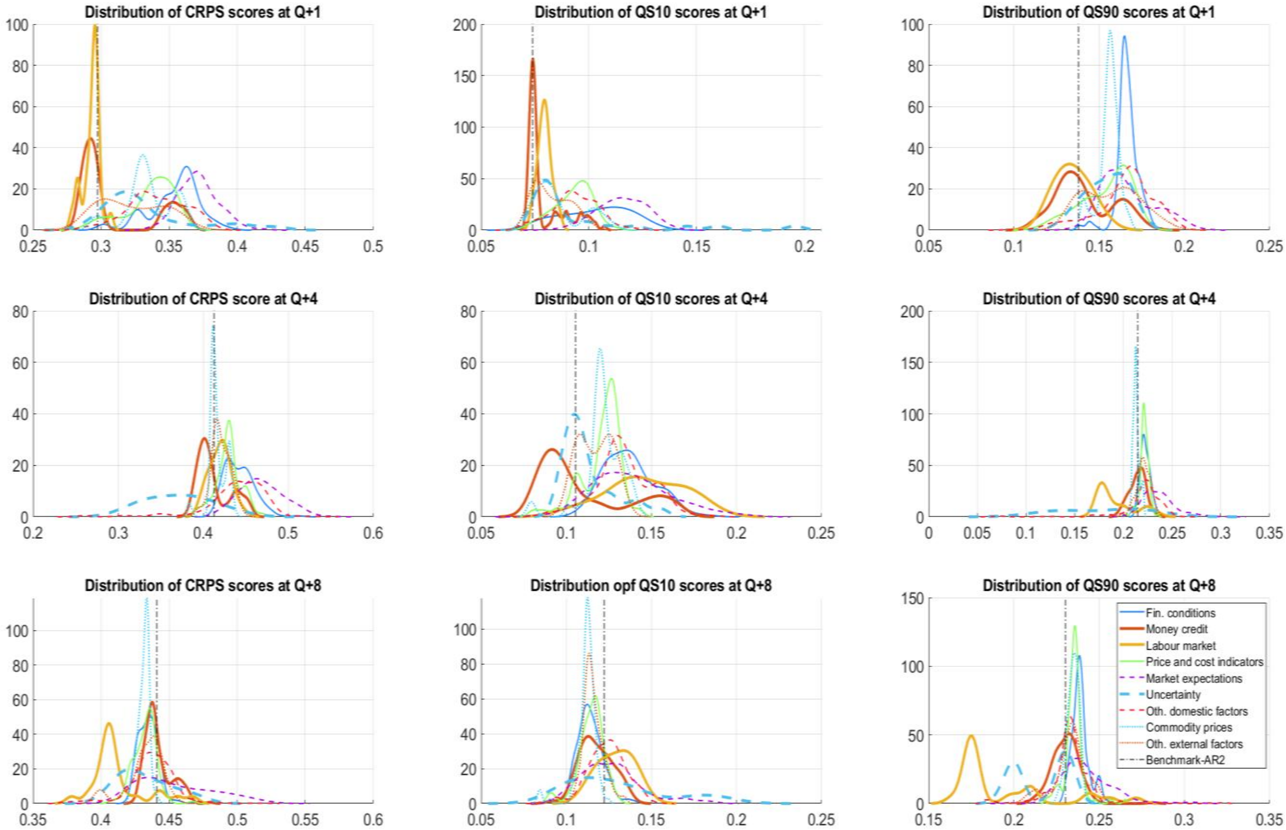
[13] Robustness analyses, not reported in this paper, but available from the authors upon request, indicate that these restrictions have a minor impact on the key empirical findings of this study.

[14] For one, four and eight-quarters ahead forecasts, hereinafter abbreviated as Q+1, Q+4 and Q+8, the out-of-sample periods start in 2013Q2, 2014Q1 and 2015Q1, respectively.

[15] For the Q+4 and Q+8 horizons, the marginal contribution of the additional factors tends to significantly increase compared with the Q+1 horizon, as the share of specifications outperforming the AR(2) benchmark appears much larger for the Q+4 and Q+8 than for the Q+1 horizons.

Chart 3.1

HICP inflation – Average score distributions from different individual risk drivers

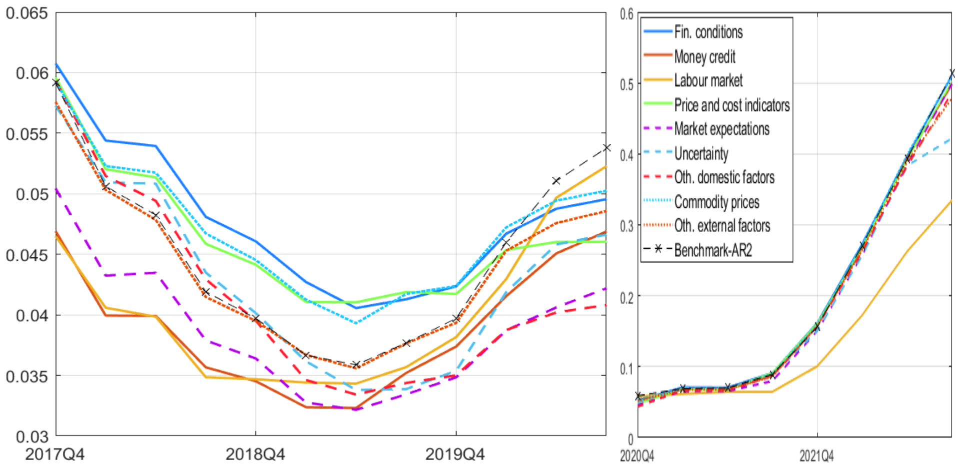


Source: Authors' calculations.
Notes: Kernel density estimations from histogram-based distributions. Low values stand for better forecasting performance.

The distribution of the scores highlights differences in the informational content of the risk drivers across the forecast horizon and also the direction (upside or downside) of risks to inflation. At the short forecasting horizons (Q+1), money and credit (the orange solid line), labour market (the yellow solid line) and uncertainty (the blue dashed lines) appear to be the best risk indicators for the HICP inflation rate and, interestingly, with respect to all considered scores. Uncertainty indicators emerge as relevant drivers for both the upper and lower tail risks to HICP inflation at the Q+4 and Q+8 horizons, while money and credit indicators appear to be informative about downside risks to inflation, possibly reflecting demand-driven adverse shocks also posing downside risks to growth (see Section 3.1.2). Labour market indicators are found to be particularly relevant for information on upper tail risks (i.e. QS90) to HICP inflation across all horizons, while their marginal contribution to lower tail risks (i.e. QS10) is relatively limited. Chart 3.2 shows that this performance gain from labour market indicators is mainly associated with the recent high-inflation period, while their predictive power over the period just before the COVID-19 pandemic is comparable to, or even lower than that of, other risk indicators. This time-dependent nature of predictive content is not unique to labour market variables. Similar patterns are found for other risk indicators, forecasting horizons and evaluation scores, suggesting that the relevance of any single set of variables for predicting inflation risk varies over time.

Chart 3.2

HICP inflation – Rolling-window QS90s at Q+8 horizon



Source: Authors' calculations.
Notes: The charts report the average QS90 over the current and the previous 11 quarters at each point. Rather than drawing the full distribution, the performance of each risk group is represented by the 10th percentile of the corresponding distribution. Low values stand for better forecasting performance.

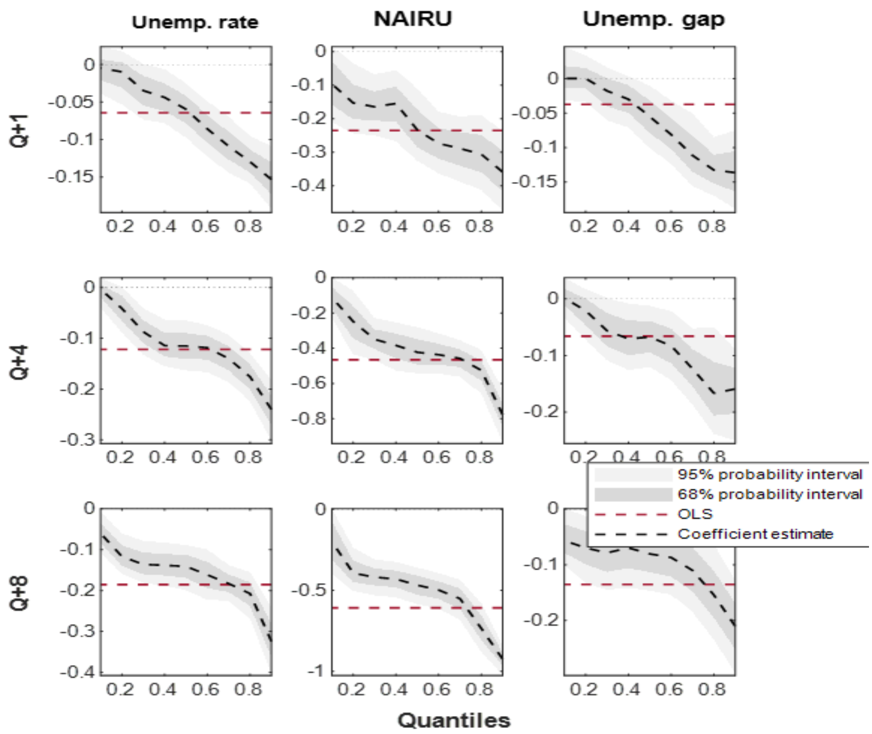
Among all labour market variables, both the unemployment rate and the NAIRU emerge as important for assessing upside risks to headline inflation, especially at the Q+8 horizon. This is in line with the findings of López-Salido and Loria (2020), and is also evident in the shape of the in-sample coefficient estimates across different quantiles and forecast horizons shown in Chart 3.3.[16] The measures of labour market tightness and/or slack (unemployment rate, NAIRU, unemployment gap) show pronounced asymmetries: while the mid-quantile estimates align closely with the Ordinary Least Squares (OLS) estimates, the coefficients for tail quantiles show notable disparities. In particular, the coefficients are larger in absolute values for the upper quantiles, indicating a greater sensitivity of upside HICP inflation risks to non-cost labour market variables.[17]

[16] To streamline the presentation of the results, the estimated specifications for these charts adopt a simplified approach, wherein no lag is incorporated in the explanatory variables.

[17] See Benigno and Eggertsson (2023) on a recent appraisal of non-linearity in the New-Keynesian Phillips curve.

Chart 3.3

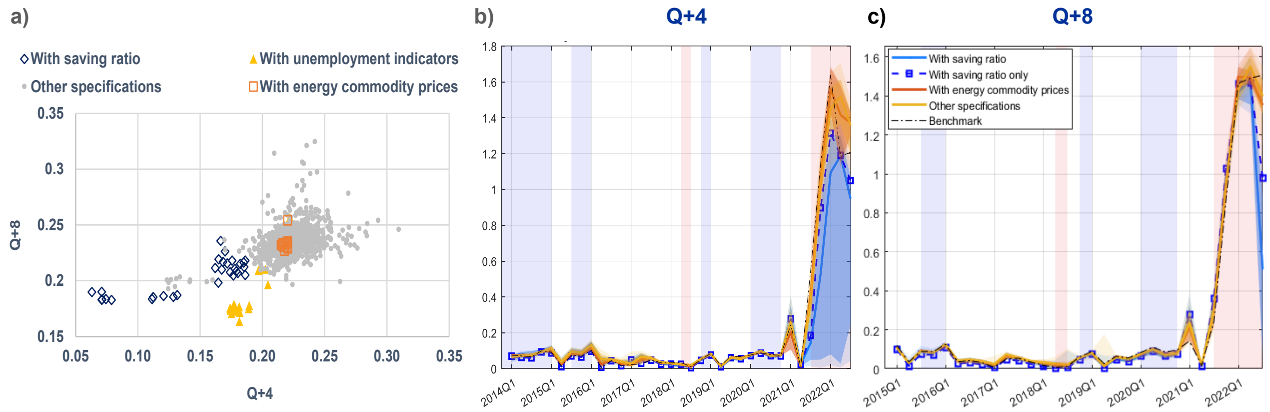
HICP inflation – estimated coefficients from bivariate Bayesian quantile regressions



Source: Authors' calculations.
Notes: Estimated coefficients across a set of quantiles at all considered projection horizons. The estimated specifications include the first AR terms and one explanatory variable with no lag.

Out-of-sample analyses further highlight the role of non-cost labour market variables as particularly relevant for assessing upside risks to headline inflation, especially at Q+8 (see panel a) of Chart 3.4). The saving ratio also shows a robust predictive power during the recent high-inflation period, particularly at the Q+4 horizon. Focusing on the dynamics of the 90th quantile score in panels b) and c) of Chart 3.4, the outstanding performance of specifications incorporating the saving ratio is primarily driven by their ability to anticipate significant upside risks to inflation in 2021-22. This time-dependent performance likely reflects the exceptional build-up of excess savings during the COVID-19 period, which the model identifies as a potential source of inflationary pressures driven by pent-up demand. However, the informational advantage of these specifications appears contingent upon combining the saving ratio with other variables, supporting the variable combination strategy further explored in Section 3.2.

Chart 3.4
HICP inflation – QS90 performance from groups of variables at the medium term and its dynamics over time



Source: Authors' calculations.
Note: Panel a) represents the average QS90 from different groups of variables at the Q+4 and Q+8 forecast horizons. Panels b) and c) depict the dynamics of QS90 over the out-of-sample range. Blue (resp. red) shaded area depicts low (resp. high) inflation periods defined as quarter-on-quarter inflation lower than 0.25% (resp. higher than 0.625%).

Chart 3.4 also illustrates the subpar performance of specifications incorporating energy commodity prices over the full out-of-sample period, including the recent high-inflation episode, even though the latter was mainly driven by the surge in energy prices (Chahad et al., 2022). The energy crisis that followed the war in Ukraine at the end of the first quarter of 2022 represents an unexpected shock to commodity prices that was not captured by the information set used for the estimation. Given the essentially backward-looking nature of the estimated QR models, these results can be attributed, at least in part, to the absence of the proper conditioning on commodity prices as discussed in Box 4, although the accuracy of the projected conditioning variables (such as commodity prices) is itself subject to questions.

Box 4
The relevance of some (B)MPE conditioning variables for headline HICP inflation

by Claudia Pacella, Paulo M. M. Rodrigues and Markus Roth

Variables from the ECB/Eurosystem staff projections database include standard assumptions as well as endogenous macroeconomic variables, which all can be used as conditioning variables in the Macro-at-Risk framework.

Bayesian QR is used to estimate a benchmark AR(2) model and investigate versions of this model which include one of the conditioning variables. The model considered is:

- $Q_\alpha(y_{t+h}|y_{t-1}, y_{t-2}, CondVar_{j,t+h}) = \beta_0(\alpha) + \beta_1(\alpha)y_{t-1} + \beta_2(\alpha)y_{t-2} + \beta_3(\alpha)CondVar_{j,t+h}$

where h is the forecasting horizon, α indicates the quantile order, $\beta_i(\alpha)$ are quantile-specific parameters, y_t is the variable of interest and $CondVar_{j,t}$ corresponds to the j-th ECB/Eurosystem staff projections conditioning variable, meaning that for $\beta_3(\alpha) = 0$ it boils down to the benchmark AR(2) model.

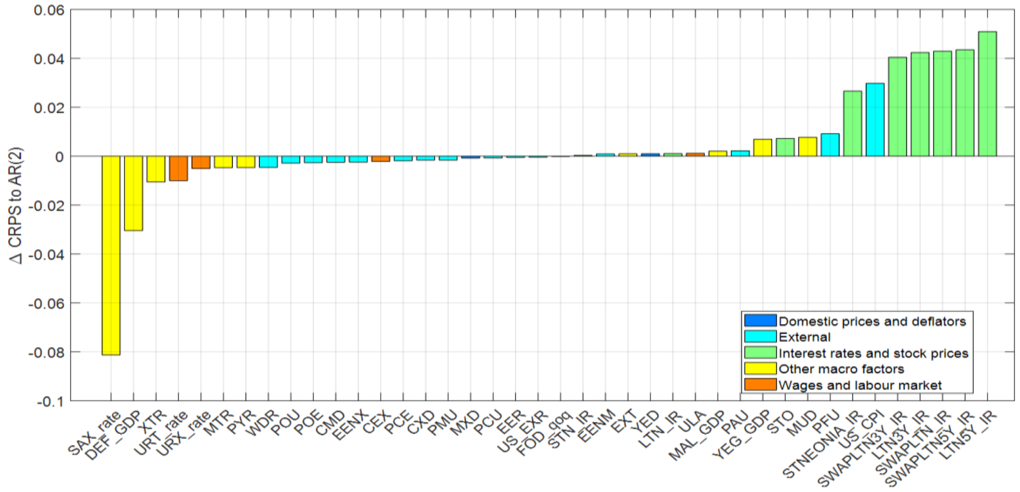
Chart B4.1 shows that conditioning on some ECB/Eurosystem staff macroeconomic projections (including profit margin, public debt and labour unit cost) or assumptions (mainly interest rates) will not necessarily improve the forecasting performance for HICP inflation. Similarly, some external factors have marginal positive impacts on performance. However, labour market variables and other macro factors (especially the saving rate and the public deficit) appear to be relevant predictors. The findings are broadly consistent across horizons.

Looking at metrics which focus on specific regions of the predictive density, wages and labour market variables matters more for the right (QS90) than for the left (QS10) tail.

Chart B4.1

Accuracy of models including conditioning variables – HICP inflation, four quarters ahead

(CRPS, difference with respect to the CRPS of a benchmark AR(2) model, average over sample 2014Q1-2022Q3; negative values denote better results)



Source: Authors' calculations.
Notes: The chart depicts the difference in the CRPS between the AR(2) benchmark and the benchmark augmented with some (B)MPE-based conditioning variables. Negative (positive) values mean that the conditioning improves (worsens) the density forecast accuracy. For the list of variables, see Appendix I.

Tilting the forecast density towards the ECB/Eurosystem projections changes the picture in terms of the relevant group of variables, without altering the overall assessment. For instance, the relevance of commodity prices is reduced after tilting, which seems consistent with the fact that the (B)MPE outlook is already conditioned on similar forward-looking assumptions.

Focusing on the post-pandemic period (2021Q1-2022Q3), the overall picture holds. Market-based energy commodity assumptions seem not to play a much stronger role than usual in this particular period. This could be explained by the absence of gas prices as a conditioning variable, but also by the inability of the markets to predict the surge in energy prices (see, for instance, Chahad et al., 2022). However, the price of metal, which to a certain extent proxies supply bottlenecks, and the saving ratio appear to significantly improve the forecasting accuracy in the medium term.[18]

HICP excluding energy and food

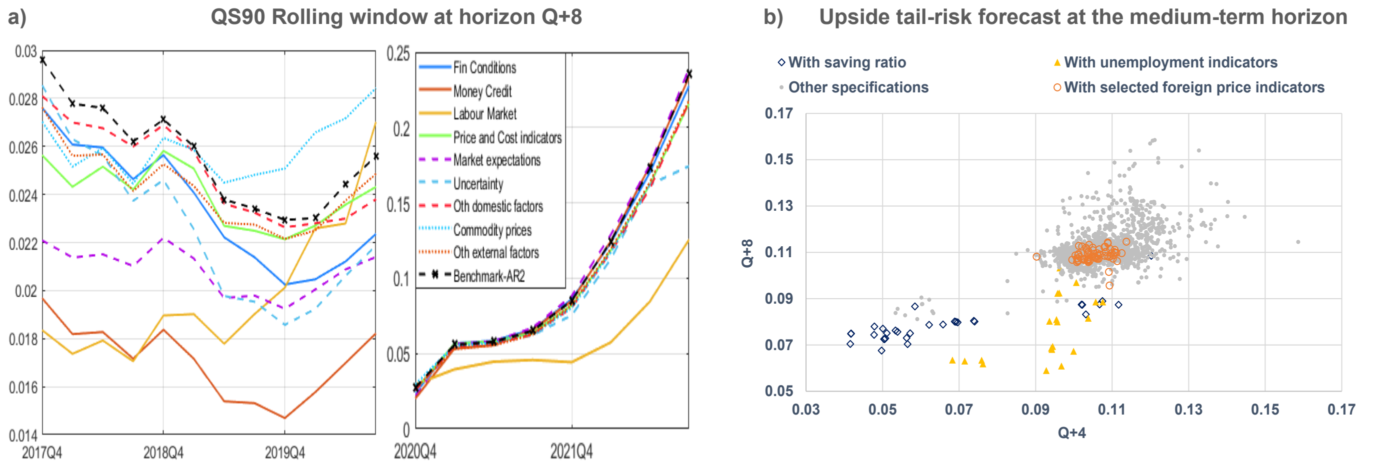
Turning to HICP excluding energy and food (HICPX) inflation, the forecasting performance improves relative to headline inflation, with significantly lower CRPS and quantile scores. This points to a sizeable contribution of volatile components to the deterioration of both point and density forecasts for headline HICP inflation.

18 All these results are available upon request.

In the same way as for headline inflation, labour market variables and, for the pre-COVID period, money and credit variables remain key predictors of upside risks at both Q+4 and Q+8 horizons for HICPX inflation, largely driven by the recent high-inflation period (see panel a) of Chart 3.5). However, labour market variables appear to be relatively more informative here, while commodity prices contribute less, often adding very little or even leading to a deterioration of the simple benchmark predictive power.

Chart 3.5

HICPX inflation – Upside risk drivers



Source: Authors' calculations.
Notes: The a) panels report the average QS90 over the current and the previous 11 quarters at each point. Rather than drawing the full distribution, the performance of each risk group is represented by the 10th percentile of the corresponding distribution. Panel b) reports the average QS90 from different groups of variables at the Q+4 and Q+8 forecast horizon. The selected foreign price indicators are mainly US and Chinese price indicators.

In terms of individual predictors and in the same way as for headline HICP, both the saving ratio and the unemployment indicators appear to be the most relevant upside risk drivers by far at both Q+4 and Q+8 horizons (see panel b) of Chart 3.5).[19] [20]

3.1.2 Growth-at-Risk

Turning to risks to euro area real GDP growth, the results in Chart 3.6 highlight the relevance of financial indicators, in particular money and credit variables, and to a lesser extent financial conditions. This broadly holds for all forecast horizons and all evaluation scores. Intriguingly, the importance of financial indicators is confirmed by these results even though the Global Financial Crisis of 2008 is excluded from the evaluation sample. The relevance of financial indicators echoes the findings of Adrian et al. (2019) for the United States and Figueres and Jarociński (2020) for the

[19] In the same way as for headline HICP inflation, the in-sample analyses reveal strong asymmetries across quantile estimates with labour market indicators. Other variables, such as house prices, demonstrate more pronounced asymmetric features for the HICPX than the HICP inflation quantiles. House prices also appear to be highly informative regarding HICPX upside risks across all examined forecast horizons.

[20] Regarding downside risks, the results point to a good performance by foreign and more generally trade-related variables in improving benchmark density forecast performance, particularly for the medium-term horizon.

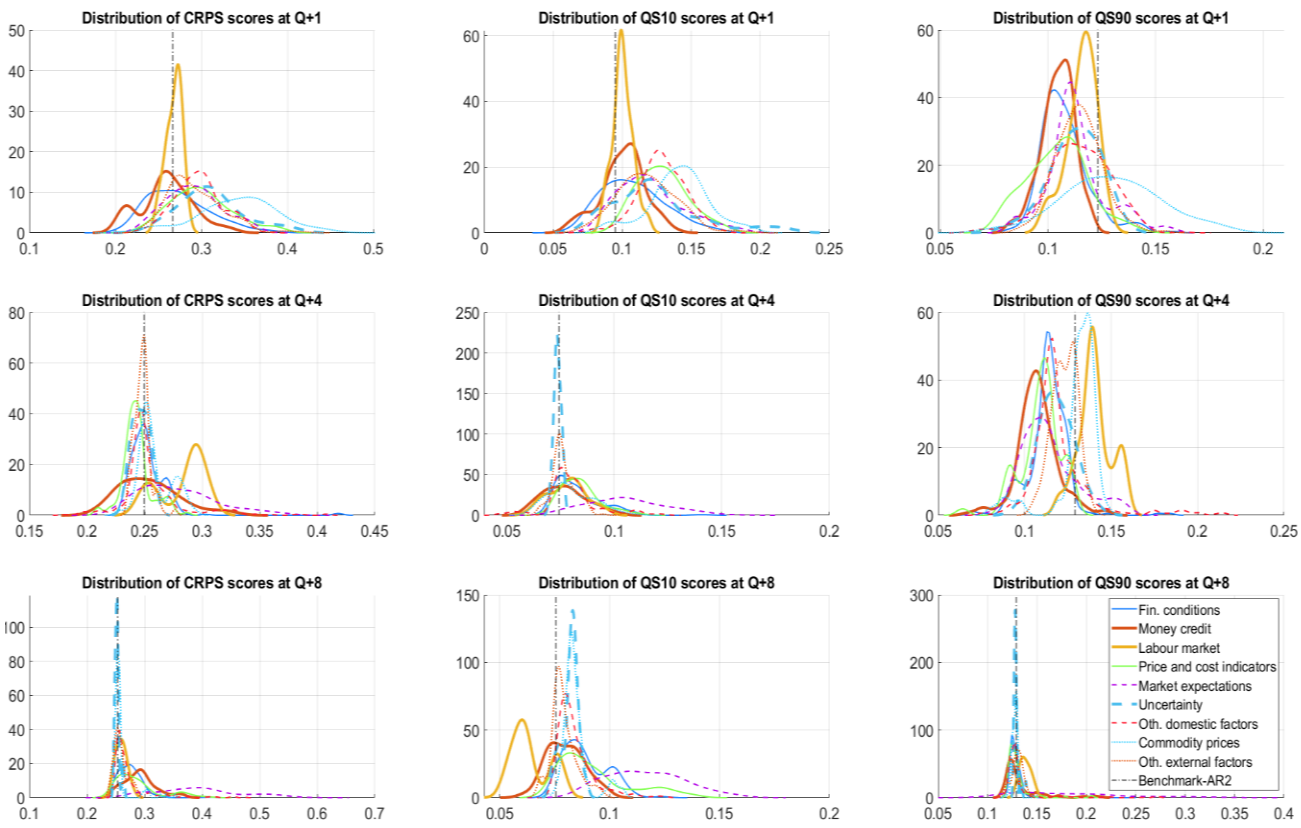
euro area, where both of these studies focus exclusively on the financial conditions in their Growth-at-Risk analyses.

The analyses also suggest that labour market variables are particularly relevant for providing information on downside risks to growth, especially at the Q+8 horizon. This finding mirrors their effectiveness in forecasting upside risks to inflation at the same horizon, as reported in Section 3.1.1, potentially highlighting the role of labour market supply shocks in shaping medium-term economic risks over the past decade.

In the same way as for inflation, the marginal contribution of external factors to GDP growth density forecasts appears generally limited compared with domestic factors. However, external variables seem to provide valuable predictive content for medium-term growth density forecasts. This stands in contrast to their performance for inflation, where they tend to be more relevant at shorter horizons. This divergence might be attributable to differing time lags associated with the transmission of external shocks to inflation and GDP.

Chart 3.6

Real GDP growth – Average score distributions from different risk drivers



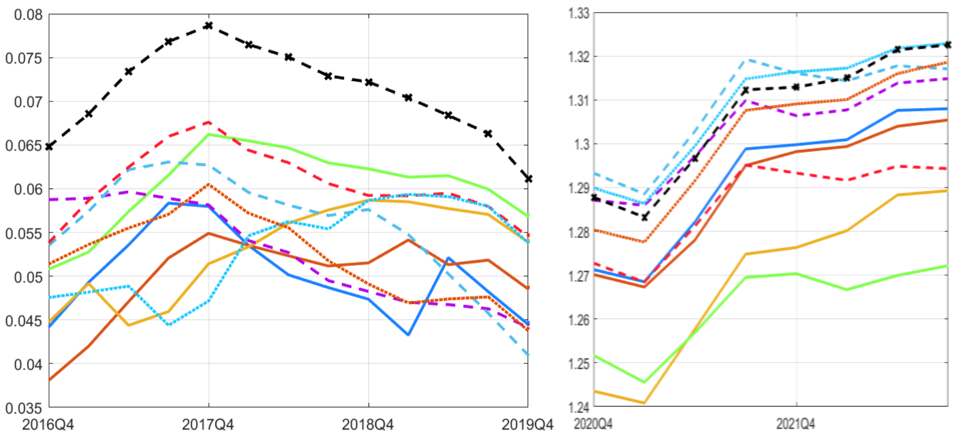
Source: Authors' calculations.
Notes: Average scores excluding 2020Q1-Q3 period. Kernel density estimations from histogram-based distributions. Low values stand for better forecast performance.

Focusing on the downside risks to growth, Chart 3.7 depicts the dynamics of the 10th quantile scores at the medium-term horizon. The results confirm the relevance of financial conditions at the Q+4 horizon – although their performance worsens gradually over the post-pandemic period – and show low forecast accuracy relative to other factors at the longer Q+8 horizon. Labour market (driven mainly by the NAIRU) and, to a lesser extent, money and credit variables (in particular bank loans to non-financial corporations (NFCs)) seem instead to be relevant at both horizons, and the deterioration of the predictive performance in the post-pandemic period seems relatively more limited.

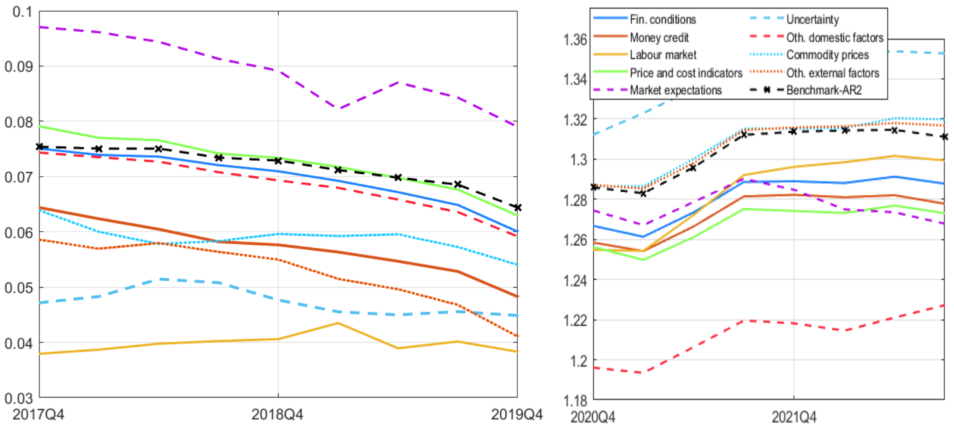
Chart 3.7

Real GDP growth – QS10 rolling window scores

At horizon Q+4



At horizon Q+8



Source: Authors' calculations.
Notes: The charts report the average QS10 over the current and the previous 11 quarters at each point. Rather than drawing the full distribution, the performance of each risk group is represented by the 10th percentile of the correspondent distribution. The average scores exclude the 2020Q1-Q3 period.

3.2 Combined risk drivers of Growth-at-Risk and Inflation-at-Risk

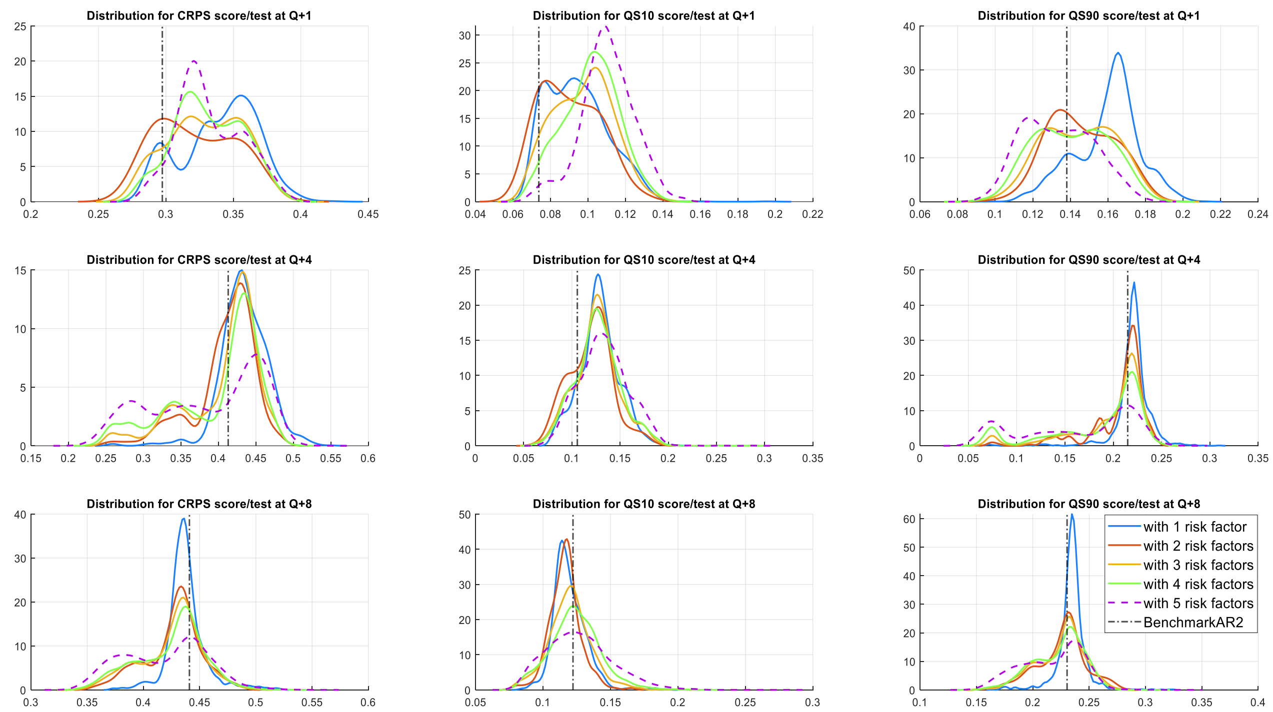
This section explores the relevance of combining risk drivers from different groups of risk indicators, which is the second step of the three-step empirical methodology outlined in Section 2.2.[21] To this end, the best-performing variables from the previous section are selected and new model specifications are constructed with up to five predictors, where each model includes at most one variable from each of the nine groups of risk indicators, compared with the single-risk-indicator specifications, which consider up to three variables from one group.

3.2.1 Individual versus combined risk drivers

The combination of various risk drivers appears to considerably improve the density forecasting performance for headline HICP inflation (Chart 3.8).[22]

Chart 3.8

HICP inflation – Density forecast performance of single vs combined risk factors



Source: Authors' calculations.
Notes: Kernel density estimations from histogram-based distributions. Low values stand for better forecast performance. While specifications "with 1 risk factor" might include up to three variables from the same group, all other specifications include at most one variable from each of the nine groups of risk indicators.

While the combined risk drivers framework generally tends to outperform the single-risk-indicator specifications, the benefits of combining different risk drivers appear particularly pronounced at the medium-term horizons (Q+4 and Q+8), relative to the short-term horizon (Q+1). Interestingly, the density forecast improvement primarily stems from combining variables from different groups of risk indicators, rather than simply adding more explanatory variables. Specifications with exactly two variables,

21 This methodology also calls for an evaluation of whether combining predictors from across different groups of risk indicators improves density forecast accuracy compared with the more standard univariate specifications.

22 Within the combined risk driver framework, both Philips curve-based and unconstraint specifications were initially considered. The results show that the unconstraint specifications tend to outperform the Philips curve ones in terms of density forecast and at all forecast horizons and evaluation scores. Only results stemming from the unconstraint framework are reported in this paper.

each from a distinct group of risk indicators (orange line), tend to systematically outperform those with up to three variables, but from the same group of risk indicators (blue line).

3.2.2 Best combinations of risk drivers

In this section, the best combinations of risk drivers are obtained by pooling up to five variables from different groups and identifying the combination of risk indicators that provides the best density forecasting performance. In practice, the predictive performance is evaluated by comparing the score distribution of each candidate combination with those of all other specifications.[23]

3.2.2.1 Inflation-at-Risk

Headline HICP

The analyses show that combining financial conditions and money and credit risk factors with commodity prices or other domestic factors leads to significant improvements in short-term density forecasts of headline HICP. For the medium term, uncertainty indicators emerge as particularly relevant, as nearly all of the selected best combinations incorporate an uncertainty variable (see Table 3.1).

Table 3.1

HICP inflation – Frequency of risk factors in selected best combinations

	Horizon Q+1			Horizon Q+4			Horizon Q+8		
	CRPS	QS10	QS90	CRPS	QS10	QS90	CRPS	QS10	QS90
Financial conditions	81.8%	50.0%	44.4%	23.1%	32.4%	30.9%	71.4%	0.0%	34.4%
Money and credit	36.4%	100.0%	22.2%	38.5%	40.5%	23.5%	0.0%	0.0%	31.3%
Labour market	9.1%	0.0%	23.8%	32.7%	24.3%	36.8%	28.6%	0.0%	31.3%
Price and cost indicators	27.3%	0.0%	46.0%	30.8%	43.2%	19.1%	28.6%	100.0%	6.3%
Market expectations	0.0%	0.0%	25.4%	32.7%	37.8%	55.9%	14.3%	0.0%	18.8%
Uncertainty	9.1%	0.0%	42.9%	100.0%	100.0%	50.0%	100.0%	100.0%	59.4%
Oth. domestic factors	63.6%	50.0%	73.0%	19.2%	10.8%	85.3%	42.9%	0.0%	96.9%
Commodity prices	54.5%	50.0%	39.7%	34.6%	54.1%	25.0%	0.0%	100.0%	25.0%
Oth. external factors	9.1%	0.0%	4.8%	28.8%	13.5%	11.8%	42.9%	0.0%	21.9%

Source: Authors' calculations.
Notes: The table shows the frequency of each risk factor in selected combinations. The latter refers to combinations of risk factors that show significant density forecast improvement compared with all remaining specifications. Density forecast evaluation is conducted through the CRPS, QS10 and QS90, assessed for each forecast horizon (Q+1, Q+4 and Q+8).

At first, the prominence of the financial factors contrasts with the limited role they played in the single-risk-indicator analysis of Section 3.1.1. Conversely, labour market variables – previously highly informative, especially at longer horizons – lose their role once combined with other predictors. This pattern suggests that financial factors provide information not captured by other groups, whereas the signal from labour market variables may be absorbed by domestic price and cost indicators, at

[23] To be more specific, for a combination to be selected, it needs to show higher density accuracy than the remaining set of specifications at each percentile of the best 75% specifications of each group.

least over the sample period under consideration. Consequently, financial conditions and money and credit variables consistently enhance the predictive performance when combined with risk drivers from other groups.

Furthermore, Table 3.1 corroborates the relevance of other domestic factors, especially for upside risks to inflation, as suggested in Section 3.1.1. This finding is largely driven by the role of the household saving ratio during the post-pandemic surge in inflation, but is also robust when excluding this episode. Before 2021, labour market indicators and external variables were relatively more relevant for signalling upside and downside inflation risks, respectively.[24] Interestingly, inflation expectation variables, at least those examined in this analysis (ILS and SPF inflation expectations at a one-to-two-year horizon), provide a minimal marginal contribution, even when combined with other variables.

HICP excluding energy and food

As regards HICPX, the picture is broadly similar to that of headline inflation. By most metrics, financial conditions combined with commodity prices and other external factors and other (mainly non-nominal) domestic variables represent the best combination for achieving high density forecast accuracy. However, the results for HICPX emphasise further the important role of domestic price and costs factors alongside domestic uncertainty indicators, which remain relevant even at short horizons (See Table AII.1 in the Appendix).

3.2.2.2 Growth-at-Risk

Turning to GDP growth, the evaluation of all of the density forecasts suggests that financial and monetary variables are consistently relevant for predictive accuracy, particularly at the Q+1 and Q+4 horizons. At the short-term horizon, the combination of financial conditions with some price and cost variables leads to a good predictive accuracy of GDP growth, while at Q+4, money and credit factors provide information beyond financial conditions (see Table 3.2). At the Q+8 horizon, the picture is more mixed: the best combinations include some external factors (though not commodity prices) together with domestic price and uncertainty indicators.

Focusing on downside risks to growth, non-commodity external factors, together with financial conditions, are particularly relevant at the Q+1 and Q+4 horizons. At the Q+8 horizon, labour market factors become especially informative, notably when combined with money and credit variables and/or some external factors. Most of these patterns are robust to the exclusion of the 2021-22 period from the evaluation sample.[25]

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[24] These results are available upon request.

[25] These results are available from the authors on request.

Table 3.2

Real GDP growth – Frequency of risk factors in selected best combinations

	Horizon Q+1			Horizon Q+4			Horizon Q+8		
	CRPS	QS10	QS90	CRPS	QS10	QS90	CRPS	QS10	QS90
Financial conditions	81.8%	55.4%	70.0%	100.0%	91.2%	58.0%	55.2%	58.5%	29.6%
Money and credit	48.5%	43.1%	55.0%	81.8%	55.9%	60.0%	48.3%	56.6%	48.1%
Labour market	0.0%	3.1%	2.5%	0.0%	23.5%	0.0%	6.9%	66.0%	0.0%
Price and cost indicators	66.7%	40.0%	57.5%	18.2%	17.6%	74.0%	58.6%	13.2%	40.7%
Market expectations	30.3%	43.1%	42.5%	0.0%	17.6%	30.0%	3.4%	11.3%	14.8%
Uncertainty	18.2%	30.8%	27.5%	54.5%	38.2%	30.0%	65.5%	47.2%	92.6%
Oth. domestic factors	42.4%	44.6%	55.0%	45.5%	32.4%	44.0%	24.1%	30.2%	63.0%
Commodity prices	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Oth. external factors	42.4%	69.2%	7.5%	45.5%	64.7%	36.0%	79.3%	58.5%	44.4%

Source: Authors' calculations.
Notes: The table shows the frequency of each risk factor in selected combinations. The latter refers to combinations of risk factors that show significant density forecast enhancement compared with all remaining specifications. Density forecast evaluation is conducted through the CRPS, QS10 and QS90, assessed for each forecast horizon of interest (Q+1, Q+4 and Q+8).

4 Macro-at-Risk models in the context of ECB/Eurosystem projections

This section focuses on the identification and aggregation of a parsimonious set of best-performing models to assess risks around the ECB/Eurosystem staff growth and inflation projections.

A multi-stage selection process is implemented to identify a small number of specifications exhibiting superior out-of-sample performance. The primary benchmark for comparison is the Stochastic Volatility-Bayesian Vector Autoregression (SV-BVAR) model by Clark et al. (2020), which has demonstrated strong density forecasting performance.

The selected specifications must comply with multiple criteria.

First, the specifications are required to outperform the SV-BVAR benchmark in terms of CRPS, and either the QS at the 10th percentile for real GDP growth or the QS at the 90th percentile for HICP inflation.[26]

Second, acknowledging that forecast accuracy can vary with the forecast horizon, selection is performed at horizons of Q+1 and Q+4 to capture the best-performing specifications in the short term, and at Q+4 and Q+8 for the medium term. For the sake of parsimony, the selected specifications were pooled, although their performance may be horizon-specific.

Third, the selection procedure also considers the ability to predict the sign of forecast errors, using the concordance ratio. This metric serves as an indicator of the accuracy of the balance of risk, which, in the context of the (B)MPE, aligns conceptually with skewness. The selection process mandates a minimum concordance ratio of 80% over the second half of the sample.

Fourth, assuming that the (B)MPE point forecast represents the most likely scenario, all density forecasts in this section are tilted using the methodology outlined in Section 2. This aligns with the approach of Clark et al. (2020), who utilise forecast errors within the SV-BVAR framework. The impact of tilting on the predictive performance of the selected specifications is further discussed in Box 5.

Finally, the predictive densities generated by the selected specifications are combined using the quantile aggregation method proposed by Busetti (2017). This approach involves a linear combination of quantiles, preserving the desirable characteristic that the combined density remains within the same (or a closely related) distributional family as the individual densities (Aastveit et al., 2019). Each

[26] The current approach aims to assign more weight on the upside (resp. downside) risks to inflation (resp. growth) through the 90th (10th) percentile score. An alternative weighting scheme, such as the quantile-weighted CRPS proposed by Gneiting and Ranjan (2011), could be employed in future analyses.

individual predictive distribution is weighted by the inverse of its mean CRPS, and the combined density is assumed to follow a Skew-t distribution.

Box 5
The impact of tilting predictive distributions

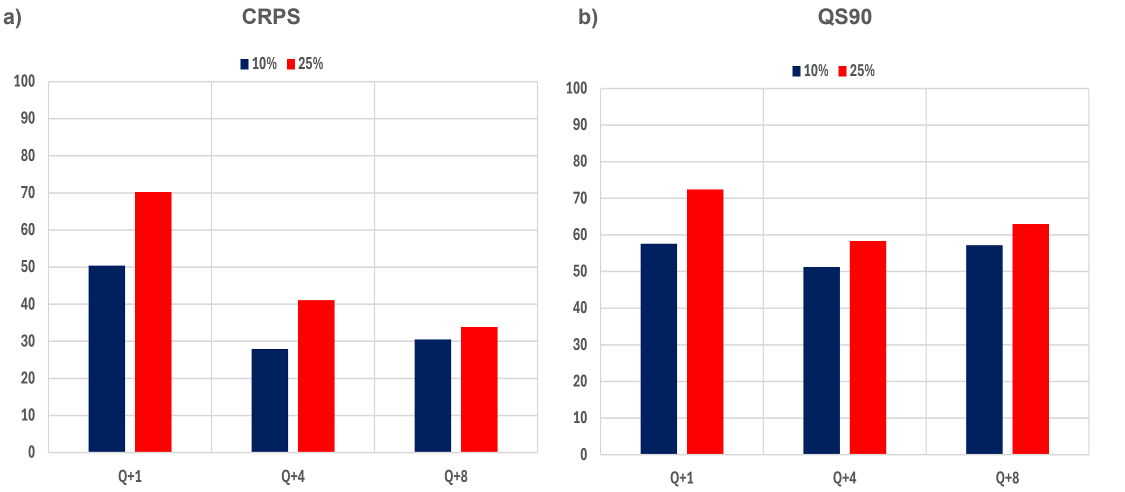
by Matteo Mogliani and Claudia Pacella

Most of the results in this section are based on predictive distributions tilted towards the ECB/Eurosystem macroeconomic projections mode, thereby aligning the models with the baseline forecast narrative (see Box 2).

While essential for aligning the output of the econometric models with the projections, tilting may unintentionally alter the distributional features of the former, with a potential impact on the results presented in this paper. This Box therefore examines its impact on (i) the selection of best-performing specifications and (ii) their predictive accuracy. For this purpose, more than 1,500 univariate forecasting specifications were reevaluated for headline HICP inflation at horizons Q+1, Q+4, and Q+8, with an out-of-sample spanning 2013Q1-2022Q3, comparing tilted with non-tilted densities.

As regards model selection, the ranking of the specifications was compared according to their average predictive performance over the out-of-sample period, evaluated through either the CRPS or the QS90. The relative frequency of the 10% and 25% best specifications that are common to the two subsets of results (non-tilted and tilted densities) was then computed. As shown in Chart B5.1, tilted and non-tilted densities share a large fraction of top specifications (50-70%) at Q+1, irrespective of the metric. However, for Q+4 and Q+8, the overlap is high for QS90 but lower for CRPS, likely reflecting the fact that the tilting approach is designed to reshape the predictive densities by targeting the mode, while leaving unaltered the asymmetry of the original distribution, which may result in a more pronounced impact on the central part of the distribution, rather than on the tails.

Chart B5.1: Relative frequency of 10% and 25% common best-performing specifications



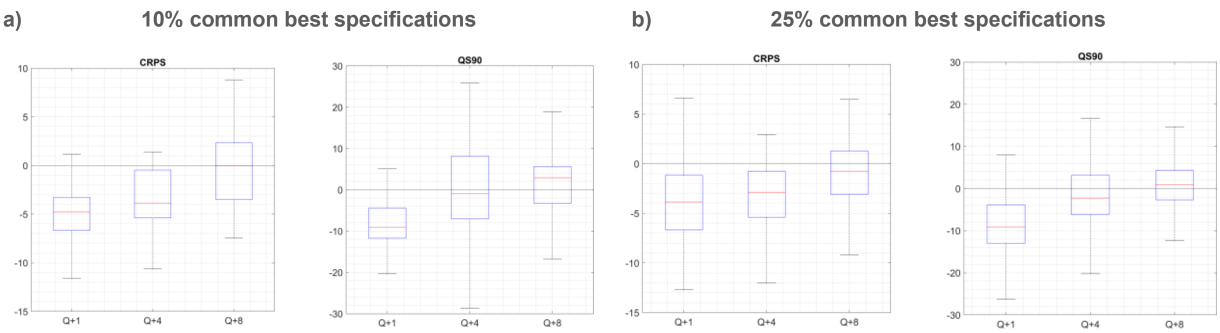
Source: Authors' calculations.
Note: CRPS and QS90 computed over the sample 2013Q1-2022Q3.

As for the impact of the tilting approach on predictive accuracy, the focus was put on the percentage gain/loss from the distribution tilting in terms of average CRPS and QS90 for each specification in the top 10% and 25% common best specifications. Chart B5.2 suggests that the tilted distributions show some predictive gains at Q+1: the median gain is around 5% for CRPS and 10% for QS90, and in both cases the inter-quantile range (IQR) of the relative gains does not include zero. For Q+4 and Q+8, the results deteriorate and seem to point instead to an overall equal predictive accuracy, except for the CRPS at Q+4, which still shows some median gains. These results may be attributed, at least in part, to the substantial forecast errors on HICP inflation in ECB/Eurosystem staff projections over 2022-2023 (post-COVID-19, war in Ukraine), and in particular over the medium-term horizons, which in turn are expected to adversely affect the performance of the tilted distributions.

Despite the caveats discussed above, the tilting approach appears sufficiently neutral on the selection of the best-performing specifications, and also tends to improve their predictive accuracy. As for the latter, evidence was found of the strongest gains being concentrated on short-term forecasts, which also suggests a high predictive content of the ECB/Eurosystem projections baseline at the shortest horizons.

Chart B5.2

Percentage gain/loss of the tilted distributions with respect to the non-tilted distributions



Source: Authors' calculations.
Notes: CRPS and QS90 computed over the sample 2013Q1-2022Q3. Negative values denote relative predictive gains for the tilted distributions.

4.1 Inflation-at-Risk

Eight density forecast specifications were identified as high performing for headline inflation. They are presented in Table AIII.1. Consistent with previous findings, the most relevant predictors across these specifications include non-energy commodity prices, the saving ratio and uncertainty indicators. They were subsequently combined using the aforementioned quantile aggregation approach.

Table 4.1 compares the performance of the combined density with that of the individual densities. The combined density performs better than nearly all the individual densities that enter the combination. This is particularly evident in the CRPS and the 90th percentile QS, where almost all the individual densities underperform the combined version at both the Q+1 and Q+4 horizons.

Table 4.1

HICP inflation – Predictive density scores – combined vs individual densities

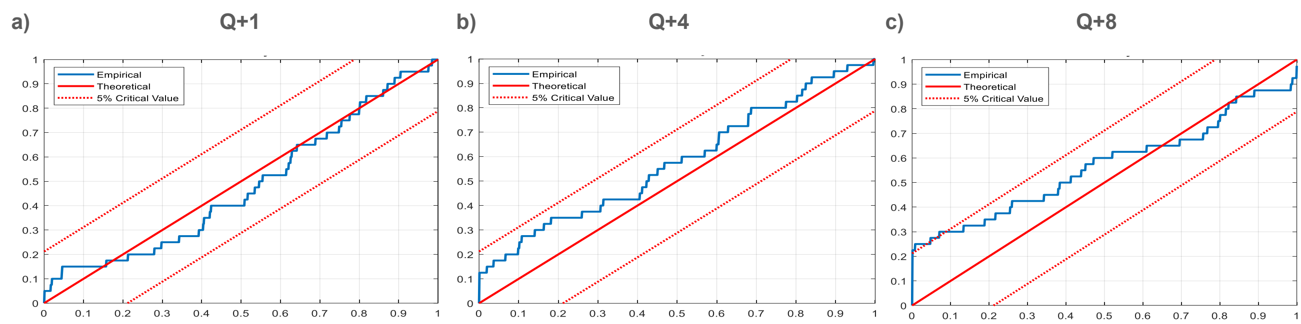
	CRPS			QS10			QS90		
	Q+1	Q+4	Q+8	Q+1	Q+4	Q+8	Q+1	Q+4	Q+8
Specification 1	1.04	1.01	1.29	**0.84**	**0.83**	1.10	1.23	1.21	1.30
Specification 2	1.59	1.31	**0.98**	1.18	1.06	0.65	1.67	1.53	**0.99**
Specification 3	1.35	1.47	**0.95**	1.49	1.50	1.04	1.47	1.59	1.03
Specification 4	1.07	**0.95**	**0.92**	1.18	1.47	**0.92**	1.46	1.79	1.01
Specification 5	1.84	1.13	1.06	0.89	**0.92**	**0.84**	1.21	**0.96**	**0.92**
Specification 6	1.06	1.26	1.81	1.70	1.24	1.05	2.01	1.04	1.08
Specification 7	**0.94**	1.37	1.53	**0.96**	1.39	2.26	1.16	1.59	1.33
Specification 8	1.00	1.00	1.00	0.81	1.11	1.81	1.32	2.48	1.27
Aggregated density	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Source: Authors' calculations.
Notes: The table shows the relative density forecast accuracy of the aggregated density versus the individual densities that enter the combination. A ratio smaller than one (highlighted in bold) indicates that the combined density underperforms the individual specification for a given horizon and accuracy measure (and vice versa for a ratio larger than one).

Linear combinations of individual densities often show greater dispersion than the constituent densities. Gneiting and Ranjan (2013) proved that combining individually well-calibrated densities necessarily leads to an uncalibrated and potentially less sharp combined density, due to the increased variance associated with the linear opinion pool. While density calibration was not explicitly included in the selection criteria for the individual specifications, all the considered densities turn out to be well calibrated at the Q+1 horizon according to the Rossi and Sekhposyan (2019) test, and six out of eight are well calibrated at the Q+4 horizon. Interestingly, the combined density is also found to be well calibrated across all horizons, including Q+1.[27] Chart 4.1 depicts the empirical Cumulative Distribution Function (CDF) of the PITs alongside the critical values for the 5% significance level p-test, indicating that the null hypothesis of correct specification cannot be rejected at any forecasting horizon.[28] This result likely reflects the fact that all aggregated specifications are tilted towards the same mode. This approach reduces the dispersion or disagreement surrounding the "point forecast", which is a key contributory factor in the increased dispersion observed in combined densities.

Chart 4.1

HICP inflation – Empirical cumulative density function of the combined density PIT



Source: Authors' calculations.
Notes: The charts show the empirical CDF of the combined density Probability Integral Transforms (blue line), the hypothetical CDF of the PITs under the null hypothesis of correct specification (the 45-degree red solid line) and the 5% critical values bands from Rossi and Sekhposyan (2019).

27 This also holds for all the forecast horizons – Q+1, Q+2, Q+3, and Q+8 – that were considered in this part of the exercise.

28 At the Q+8 horizon, the combined density seems to slightly underestimate extreme downside risks to inflation, but this stands close to the 5% critical value. Using the Cramér–von Mises critical values, the empirical density lies within the 95% confidence interval.

As regards the risk assessment, the ECB/Eurosystem macroeconomic projections framework primarily focuses on the dynamics observed over calendar years, particularly for medium-term and long-term horizons. This contrasts with the model-based assessments of this paper, which leverage predictive distributions obtained from econometric models specified at a quarterly frequency that directly generate multi-step-ahead forecasts of quarterly target variables. Consequently, a method is required to aggregate the information contained within the individual predictive densities for quarter-on-quarter growth rates into predictive densities for annual averages. Box 6 details an approach initially developed for this paper to address this aggregation challenge (see also Mogliani and Odendahl, 2025).

Box 6
From quarter-on-quarter to annual average predictive densities

by Matteo Mogliani and Florens Odendahl

The estimated quarterly models in the M@RX output provide predictive distributions of quarter-on-quarter (qoq) growth rates, while the assessment of risk is primarily focused on calendar-year growth rates. Moving from quarter-on-quarter to annual distributions is more challenging in the context of a direct multi-step-ahead forecasts approach. Assuming distributional independence between the marginal densities, i.e. no correlation between qoq forecasts at different horizons, one simple approach would consist in mimicking the computation for the annual average rates of point forecasts, i.e. drawing randomly a sequence of qoq rates from the marginals and computing the annual average rates, using, for instance, an exact or first-order approximation formula. However, as the assumption of serial independence is usually violated empirically, this approach would likely fail to provide an accurate estimate of the distribution for the annual rates. Draws from the joint predictive distribution of the qoq rates would help to attenuate this issue, but this approach is simply infeasible, as the joint distribution is unknown.

To overcome the above issues, a novel approach based on copulas has been developed to estimate a joint distribution of qoq rates, taking into account the serial correlation between qoq forecasts by drawing them from their joint distribution.[29] The implementation of the (Gaussian) copula approach for computing annual average predictive densities from marginal qoq predictive densities requires the following steps: 1) compute the sequence of realised PITs for the marginal predictive densities at each forecast horizon h=1,..,H, from a pseudo out-of-sample exercise over a training sample; 2) combine the marginal distributions into a joint distribution via a multivariate Gaussian copula through the rank correlation estimated on the realised PITs; and 3) obtain joint draws of qoq rates from the multivariate distribution constructed in 2). The joint distribution of qoq rates at all forecast horizons should reflect the serial dependence between forecasts, and can be used to compute annual levels (or other transformations, such as year-on-year growth rates) and average predictive distributions.

In order to evaluate the performance of the copula approach, a simple Monte Carlo (MC) experiment is performed. A stationary AR(4) process for qoq rates is simulated, with innovations drawn from one of the following distributions: i) Normal distribution; ii) Skew-Normal distribution; iii) Skew-t distribution. These distributions are calibrated to have zero mean and variance equal to 0.5,

[29] A copula is a multivariate cumulative distribution function (CDF) characterising the dependence structure between random variables. According to Sklar's Theorem, any multivariate joint distribution can be expressed mathematically in terms of univariate marginal distributions and a copula.

as well as, for cases ii) and iii), negative skewness (shape parameter α set at -4). For the Skew-t distribution, the degrees of freedom parameter ν is set at 4, which implies considerably heavier tails than the Normal distribution. The forecasting model is estimated either by OLS (for case i) or by QR, the latter with subsequent quantile matching using the Azzalini and Capitanio (2003) Skew-t distribution. Forecasts are computed using a direct forecast framework, up to 12 quarters ahead. T denotes the number of in-sample observations, while T_OOS denotes the out-of-sample (OOS) size used to compute the correlation of the empirical PITs for the copula approach. The in-sample size is held fixed at T across the exercise (rolling window). Three years of annual average predictive densities are computed from the 12 qoq predictive distributions, using copulas as well as the simple exact formula as a benchmark. Finally, these approaches are evaluated by computing the Kullback-Leibler (KL) divergence of the estimated densities with respect to the “true” predictive density (median across 60 MC iterations).

The results, reported in Table B6.1, suggest that the copula approach provides better results overall than the benchmark exact formula (lower values in the table indicate a better performance). The results also tend to improve when the number of OOS observations increases, as the estimates of the copula correlation parameter become more accurate. Additional simulation results (not reported) also suggest that the improvement with respect to the benchmark increases with the serial correlation between the marginal distributions of qoq rates. Also, information about the shape of the marginal distributions (such as positive or negative skewness) is not lost with the copula approach when computing annual average predictive distributions.

Table B6.1

Monte Carlo evaluation of the copula approach

(Kullback-Leibler divergence, median)

			Normal errors			Skew-N errors			Skew-t errors		
T	T_OOS	Approach	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
		QoQ -> AA	0.15	0.20	0.24	0.17	0.19	0.18	0.23	0.27	0.27
			(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
100	20	copula	0.09	0.15	0.19	0.07	0.15	0.12	0.10	0.16	0.15
			(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
	40	copula	0.06	0.07	0.07	0.06	0.09	0.09	0.08	0.11	0.12
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)

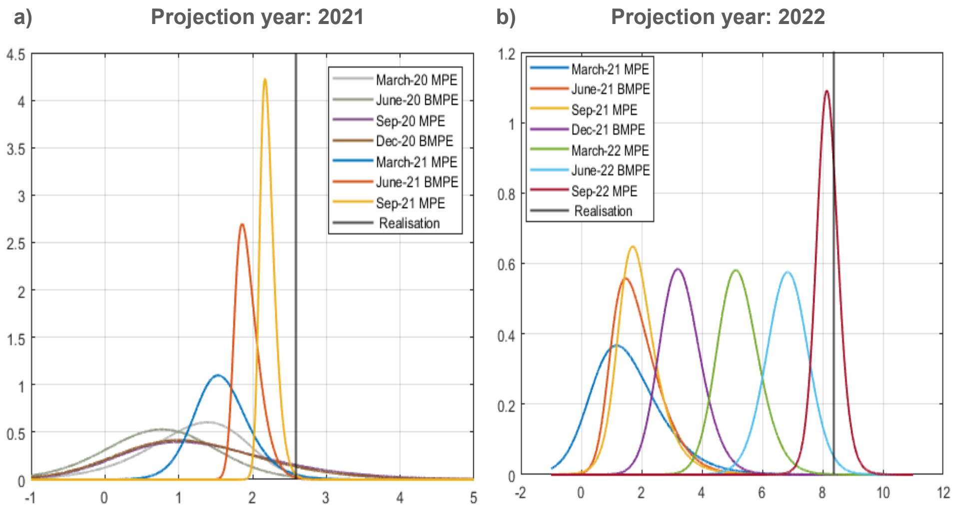
Source: Authors’ calculations.
Note: The table reports median Kullback-Leibler values over 100 MC simulations, and corresponding bootstrap standard errors in parentheses (based on 9,999 bootstrap replications). T denotes the number of in-sample observations, while T_OOS denotes the out-of-sample size. Lower values in the table indicate better results.

Chart 4.2 leverages the derived calendar-year distributions to illustrate how the aggregated densities would have assessed risks to inflation over the 2021-22 high-inflation period. For 2021, the models initially pointed to downside risks to euro area inflation in the March and June 2020 ECB/Eurosystem staff projections, reflecting the adverse impact of strong demand shocks at the beginning of the COVID-19 pandemic. However, the models also assessed significant uncertainty surrounding these forecasts, in such a way that the actual outcome fell within the range of plausible projections, despite the substantial baseline forecast error. Notably, from the third quarter of 2020 onwards, the combined models consistently projected upside risks to the baseline point forecasts, which indeed ultimately turned out to be significantly lower than the realised inflation rate.

A similar pattern emerges for 2022 HICP inflation. From the March 2021 projections until the September 2022 projections, the models persistently pointed to upside risks to the inflation projections for 2022, in line with the higher than anticipated outcome. However, following the upwards revision to the inflation projection in the September 2022 exercise, the risk assessment shifted towards a broadly balanced view. Interestingly, while the narrowing of forecast distributions for both 2021 and 2022 with the approaching year-end is an expected behaviour, the models consistently assessed the uncertainty surrounding the 2022 projections as considerably higher than for 2021 at the same forecast horizons. This likely reflects the heightened uncertainty arising from events such as the post-COVID-19 period.

Chart 4.2

HICP inflation – Dynamics over 2020-22 of the risk assessment to (B)MPE projections for 2021-22



Source: Authors' calculations.
Notes: The charts depict the combined predictive densities of the annual average HICP inflation. The mode of the distributions is tilted towards the (B)MPE point forecast.

To evaluate their performance more systematically, hit rates for the direction of forecast errors were computed over the 2017Q1-2022Q3 period. For headline inflation, the models correctly predicted the sign of errors between 60% and 75% of the time.[30] This accuracy is particularly noteworthy considering the heightened uncertainty that characterised the latter part of the evaluation period.[31]

This strong directional performance reflects the explicit use of the concordance ratio as a selection criterion. Relaxing this criterion would have led to significantly weaker concordance ratio test results. While a detailed exploration of model selection procedures is beyond the scope of this report, this feature hints at the importance of tailoring the model selection procedure to the specific forecasting objective.

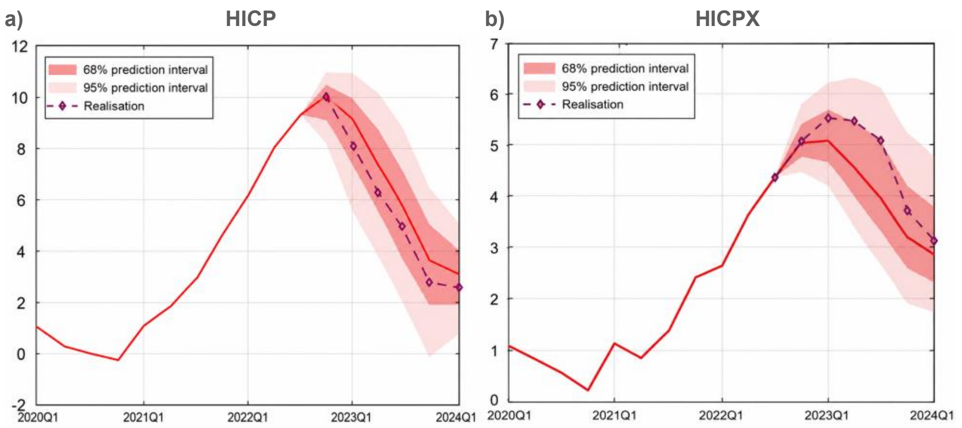
30 The fact that the out-of-sample range is shorter at the annual than the quarterly period is due to the need for an additional training out-of-sample in the former case, which shortens the available out-of-sample range.

31 For the less volatile HICPX, the six best-performing models (see Table AIII.2) show an even stronger ability to predict the sign of forecast errors. For instance, over the last 20 projection rounds, the aggregate density for HICPX correctly predicts the sign of the forecast errors in 85%, 79% and 60% at the Y1, Y2 and Y3 horizons respectively. At the quarterly level and over the entire evaluation sample, several specifications show a concordance ratio higher than 80%, even at the Q+8 horizon.

Chart 4.3 displays so-called fan charts for both HICP inflation (panel a) and HICPX inflation (panel b). These charts are constructed around the December 2022 ECB/Eurosystem baseline projections, which used the same information set as this paper. The charts are augmented with the actual outcomes observed at the time this study was finalised.

The realised inflation rate consistently falls within the 68% prediction interval for both inflation categories. Moreover, the balance of risks surrounding the December 2022 ECB/Eurosystem staff projections accurately reflects the subsequent outcomes. For 2022Q4 to 2024Q1, the balance of risks is tilted towards the downside for HICP inflation and towards the upside for HICPX inflation, aligning with the realised outcomes in each quarter. This example highlights that although stringent selection criteria limit the number of retained models, those that pass the filter provide powerful and reliable signals on the risks around point projections.

Chart 4.3
HICP and HICPX inflation – Combined density fan chart and realisations



Source: Authors' calculations.
Notes: The charts depict the predictive distribution around the December 2022 Eurosystem projections as it would have been derived by the combined model conditional on inflation available by 2022Q4 only. All distributions were tilted towards the December 2022 point forecast (red line). The inflation realisation is reported with the purple dashed line.

4.2 Growth-at-Risk

The selection process for GDP growth identified eight specifications, presented in Table AIII.3 of the Appendix, which were aggregated following the same approach as for inflation. Table 4.2 shows the performance of combined densities versus individual specifications, and, in the same way as for inflation, the aggregated density consistently outperforms the worst-performing individual specification in all categories and horizons. Furthermore, the aggregated density puts in a good predictive performance overall, improving over several individual specifications, especially in terms of CRPS and QS10 at medium-term horizons.

Table 4.2

Real GDP growth – Predictive density scores – combined vs individual densities

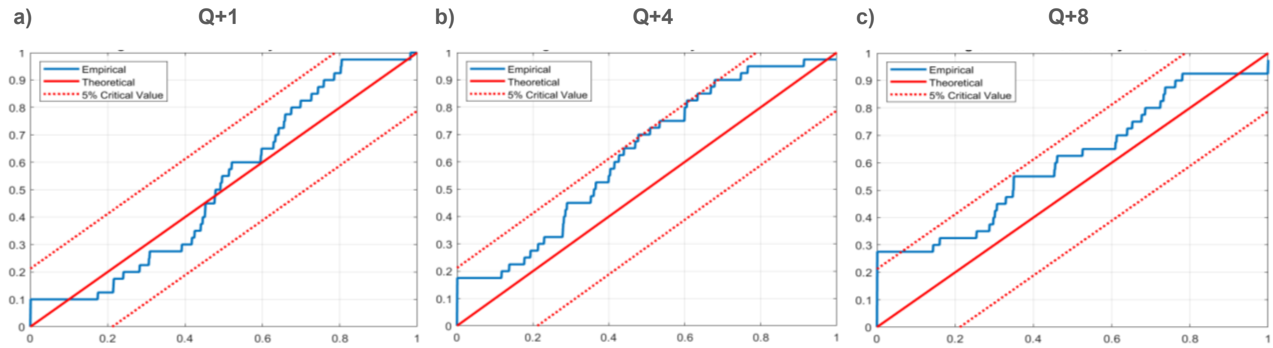
	CRPS			QS10			QS90		
	Q+1	Q+4	Q+8	Q+1	Q+4	Q+8	Q+1	Q+4	Q+8
Specification 1	1.10	1.42	1.17	1.20	1.14	**0.96**	**0.97**	1.27	1.00
Specification 2	1.74	1.25	1.03	1.87	1.36	**0.92**	1.61	**0.86**	**0.92**
Specification 3	1.47	**0.97**	1.07	**0.88**	1.14	1.18	1.37	**0.89**	1.01
Specification 4	2.16	1.04	1.25	1.75	1.25	1.78	**0.91**	**0.91**	**0.90**
Specification 5	**0.93**	1.18	1.09	**0.82**	1.05	1.20	1.15	1.09	1.08
Specification 6	1.21	1.20	1.17	**0.95**	1.35	1.03	1.35	1.45	1.20
Specification 7	1.23	1.07	1.30	**0.89**	1.17	1.10	1.11	2.43	1.22
Specification 8	1.18	2.22	1.16	1.03	1.70	**0.98**	2.40	5.58	3.86
Aggregated density	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Source: Authors' calculations.
Notes: The table shows the relative density forecast accuracy of the aggregated density versus the individual densities that enter the combination. A ratio smaller than one (highlighted in bold) indicates that the combined density underperforms the individual specification for a given horizon and accuracy measure (and vice versa for a ratio larger than one).

An analysis of density calibration reveals that the combined density shows good calibration across all forecast horizons, although the individual specifications were again well calibrated at the short-term horizon. However, at the Q+8 horizon, the combined density shows a slight tendency to underestimate extreme downside risks to growth. This is evident in panel c) of Chart 4.4, where the empirical CDF of the combined forecasts lies above the 45-degree line in the lower tail, indicating that more realisations fall within this region than predicted by the density. This feature can be observed to a lesser extent at the Q+4 horizon and potentially applies to the entire density spectrum. This pattern aligns with the generally optimistic nature of the (B)MPE projections, which have historically tended to over-predict growth outcomes.[32]

Chart 4.4

Real GDP growth – Empirical cumulative density function of the combined density PIT



Source: Authors' calculations.
Notes: The charts show the empirical CDF of the combined density Probability Integral Transforms (blue line), the hypothetical CDF of the PITs under the null hypothesis of correct specification (the 45 degree red solid line) and the 5% critical values bands from Rossi and Sekhposyan (2019).

Turning to the risks assessed by these models and focusing on the year 2022, Growth-at-Risk models are already accurately predicting in 2021 clear downside risks to the 2022 growth projections (see panel a) of Chart 4.5).[33] After the significant downward revisions initiated in the December 2021 ECB/Eurosystem staff projections, the asymmetry in the models' densities decreased, indicating a nearly

[32] Over the evaluation sample, roughly two-thirds of the (B)MPE projections for both the Q+4 and Q+8 horizons fell below the actual outcome.

[33] The risk assessment for 2021 growth is not discussed here, as it was directly affected by the COVID-19 period.

balanced risk around the projected growth in the March 2022 exercise. Furthermore, and following the additional significant downward revision to the 2022 growth projections in the following June round of the same year, which placed them below the actual outcome, the combined density continued to indicate some slight downside risk, before shifting in September 2022, transitioning to a clear indication of upside risks in line with the realised growth.

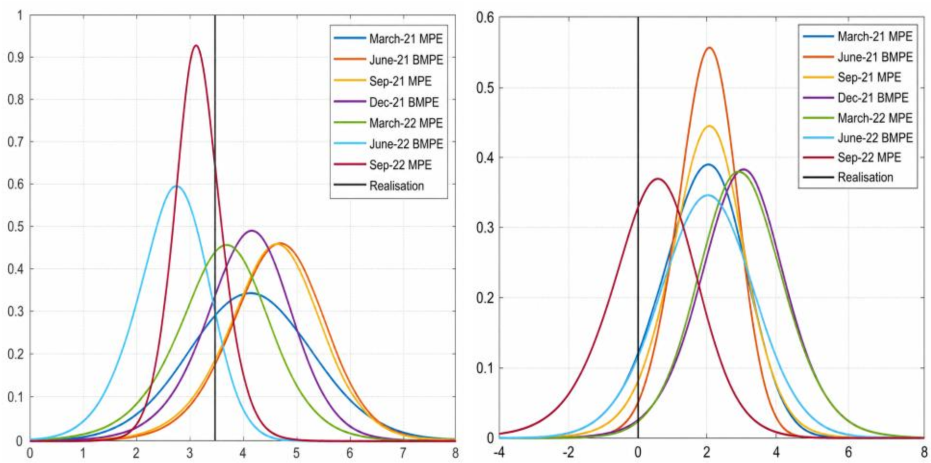
Turning to 2023, the combined models pointed to downside risks as early as the March 2021 round (panel b) of Chart 4.5). The balance of risks showed a clear downward tilt, and this downside assessment intensified significantly after the March 2022 round. This coincided with a noticeable increase in the uncertainty surrounding the projections with the start of the war in Ukraine, as evidenced by the more dispersed predictive distributions in the charts. This trend is noteworthy, considering that shorter projection horizons generally feature less dispersed distributions.

Overall, the combined models' ability to predict the direction of forecast errors for GDP growth aligns with their performance for headline inflation. The concordance ratio for GDP growth remains at around 52% at the one-year and three-year forecast horizons and reaches 78% at the two-year horizon.

Chart 4.5

Real GDP growth – Dynamics over 2021-22 of the risk assessment to (B)MPE projections for 2022-23

a) Projection year: 2022 | b) Projection year: 2023

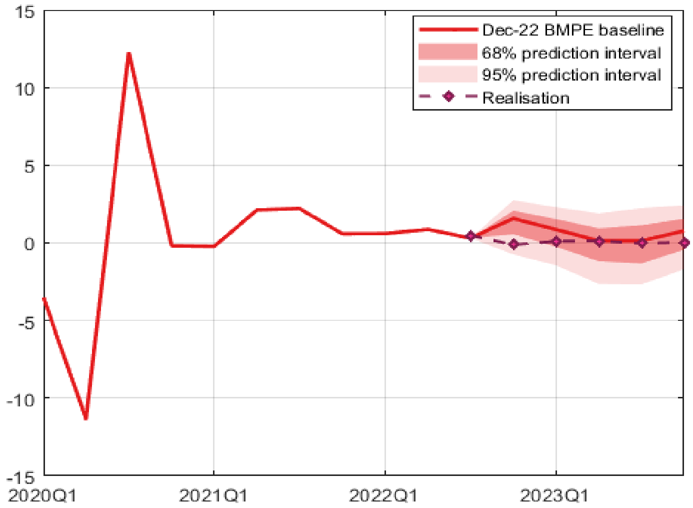


Source: Authors' calculations.
Notes: The charts depict the combined predictive densities of the annual average real GDP growth. The mode of the distributions is tilted towards the (B)MPE point forecast.

The fan charts produced for the December 2022 projections highlighted clear downside risks to the GDP growth projections over the subsequent five quarters (Chart 4.6). This assessment aligns with the realised outcomes, which were consistently lower than the baseline projections throughout the entire horizon, although the deviations were marginal in the second and third quarters of 2023.

Chart 4.6

Real GDP growth – Combined density fan chart and realisations



Source: Authors’ calculations.
Notes: The charts depict the predictive distribution around the December 2022 Eurosystem projections as it would have been derived by the combined model conditional on inflation available by 2022Q4 only. All distributions were tilted towards the December 2022 point forecast (red line). The outcome is reported with the purple dashed line.

5 Conclusion

This paper summarises the results of an extensive empirical analysis of the identification of the key risk drivers to the euro area economy, aiming, among other things, to provide a set of reduced-form macroeconometric tools and metrics for assessing macroeconomic risks around the baseline ECB/Eurosystem projections.

Around 350 potential risk indicators, going beyond the usual financial factors typically employed in the Macro-at-Risk literature, were considered and narrowed down to a small set of best-performing specifications through a sequential selection approach, in which the number and class of variables entering the competing specifications were restricted using a battery of robustness checks. Further, the analyses on empirical density forecasts benefited from a new parametric tilting methodology and a copula approach for transforming high-frequency predictive densities into lower-frequency densities. All these features were implemented in a purpose-built MATLAB toolbox (M@RX), which has been extensively tested in the context of this study.

The main results highlight that the informational content of risk factors is highly horizon, time and objective-dependent. For instance, labour market indicators are found to be particularly relevant in assessing risks to inflation, but mainly upside risks. Moreover, their predictive power tends to vary over time: they do provide notable gains in predictive performance during the recent high-inflation period, but their contribution in the years preceding the COVID-19 pandemic was comparable to, or even weaker than, that of other risk indicators. In contrast, for downside risks to inflation, labour market variables offer limited informational value, whereas uncertainty indicators, as well as money and credit indicators, perform more strongly. As for risks to growth, the results point to the broad and robust relevance of financial conditions, in line with established evidence in the empirical literature. Furthermore, they underscore the role of monetary indicators, which are particularly effective in predicting downside risks to growth.

While the analyses of individual risk factors provide useful insights into potential drivers of macroeconomic tail risks, for density forecast purposes the combined risk factors framework seems preferable. Across all forecast horizons and evaluation metrics, the combined risk factor framework systematically outperforms the standard single-factor specifications. The density forecast gains primarily stem from combining diverse variables from different groups of risk indicators, rather than simply adding more explanatory variables, underscoring the value of exploiting complementarities among the drivers of risk.

The empirical applications to euro area inflation and growth, which are documented in this paper, illustrate the relevance of such tools and methodologies for policy purposes. Their ability to provide timely signals, and to accurately track the direction of realised outcomes, makes them a valuable addition to the analytical toolkit used to assess risks surrounding institutional projections, such as those of central banks. However, due to the time-varying and state-dependent nature of their predictive performance, a regular assessment of the performance of the estimated specifications is highly recommended.

The results reported in this study provide a comprehensive empirical framework for assessing the main euro area macroeconomic tail risks, but they also highlight certain limitations that could serve as avenues for future research. One important caveat is the lack of a structural interpretation of the results, inherent to the modelling approach and specific objectives of this study. While careful attention was paid to the prediction of macroeconomic tail risks, a structural interpretation of the contribution of main drivers to these risks would undoubtedly enhance the understanding of the economic interplay between endogenous variables and macroeconomic risks. Therefore, while the models considered in this study do offer valuable information, even at medium-term horizons, on the uncertainty surrounding macroeconomic projections, they cannot provide a structural reading of this uncertainty. This is left to future research.

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Appendix

Appendix I. Data and empirical methodology

Table AI.1 List of explanatory variables

Variable	Description	Variable	Description	Variable	Description
Financial conditions		SERINP	Services, input prices index (survey)	MANSDT	Manufacturing, supplier delivery times (survey index)
TERMSPR	Term premium	SERPRC	Services, prices charged index (survey)	SERNEW	Services, new business (survey index)
GBYSPR	Government bond risk spread	COMINP	Composite index of input prices (survey)	MTR	Imports of goods and services
CPYSPR	Corporate bond yield spread	COMPRC	Composite index of prices charged (survey)	XTR	Exports of goods and services
B_SPR	Bank rate spread (average spread on the yield of bank bonds relative to German federal BuBill)	MUD	Profit margin indicator (GDP deflator at basic prices growth - ULA growth)	XTD_GOOD_SA	Exports of goods. Domestic currency (incl. conversion to current currency made using a fixed parity).
New_CISS	Composite Indicator of Systemic Stress, Euro Area	PPI_TOT	Producers Price Index, domestic sales, total industry excl. construction. Not seasonally nor working day adjusted	XTD_SERV_SA	Exports of srvices. Domestic currency (incl. conversion to current currency made using a fixed parity).
EUSTOXX_price	EURO STOXX price index	PPI_MAN	Producers Price Index, domestic sales, manufacturing. Not seasonally nor working day adjusted	MTD_GOOD_SA	Imports of goods. Domestic currency (incl. conversion to current currency made using a fixed parity).
VSTOXX	EURO STOXX volatility	IPI_TOT	Import Price Index (extra Euro Area). Total industry excl. construction. Not seasonally nor working day adjusted	MTD_SERV_SA	Imports of services. Domestic currency (incl. conversion to current currency made using a fixed parity).
EUSTOXX_MAT	Dow Jones EURO STOXX Basic Materials index. Equity Index	IPI_MAN	Import Price Index (extra euro area). Manufactured products. Not seasonally nor working day adjusted	EC_INDU	European Commission Survey Indicator for Industrial Confidence
EUSTOXX_FIN	Dow Jones EURO STOXX Financials index. Equity Index	HP	House prices	EC_SERV	European Commission Survey Indicator for Services Confidence
EUSTOXX_IND	Dow Jones EURO STOXX Industrials index. Equity Index			EC_RETA	European Commission Survey Indicator for Retail Trade Confidence
EUSTOXX_UT	Dow Jones EURO STOXX Utilities index. Equity Index	**Survey/Market Expectations**		EC_BUIL	European Commission Survey Indicator for Construction Activities Confidence
NIKKEI	Equity index, Nikkei 225	SPFHICP_0M	ECB Survey of Professional Forecasters (SPF) - HICP at the time when survey is done (nowcasting). Average of point forecasts	RET_SALES	Retail sales excluding repair of goods, volume
SP500	Equity index, Standard & Poor's 500	SPFHICP_1Y	ECB Survey of Professional Forecasters (SPF) - HICP at 1-year horizon from survey. Average of point forecasts	EC_ESI	European Commission Survey Economic Sentiment Indicator (ESI)
LR_NFC_SPR	NFC lending rates spread	SPFHICP_2Y	ECB Survey of Professional Forecasters (SPF) - HICP at 2-year horizon from survey. Average of point forecasts	CAPUTIL	Capacity utilisation in manufacturing
LR_HH_SPR	HH lending rates spread	SPFHICP_LT	ECB Survey of Professional Forecasters (SPF) - HICP at longer-term horizon from survey. Average of point forecasts		
BLS_NFC	Bank lending standards to non-financial corporations. Net percentage of respondents indicating a tightening of credit standards in the last 3 months	SPFRGDP_3M	ECB Survey of Professional Forecasters (SPF) - Real GDP growth at 3-month horizon from survey. Average of point forecasts	**Commodity prices**	
BLS_HH	Bank lending standards to households. Loans for house purchase. Net percentage of respondents indicating a tightening of credit standards in the last 3 months	SPFRGDP_9M	ECB Survey of Professional Forecasters (SPF) - Real GDP growth at 9-month horizon from survey. Average of point forecasts	ENERGY_WB	Energy Price Index (in USD)
FCIBME	Financial Conditions Index (FCI) based on BMEs weights	SPFRGDP_21M	ECB Survey of Professional Forecasters (SPF) - Real GDP growth at 21-month horizon from survey. Average of point forecasts	GAS_bcast	Gas prices - backcasted using the PCE variable in the BMPE dataset
FCIVAR	Financial Conditions Index (FCI) based on IRFs weights	SPFRGDP_LT	ECB Survey of Professional Forecasters (SPF) - Real GDP growth at longer-term horizon from survey. Average of point forecasts	POU	Oil price assumption (in USD)
FCIIPA	Financial Conditions Index (FCI) by DG-I	1y_ILS_2y	1-year ILS forward rate 1 year ahead	POE	Oil price assumption (in EUR, converted from POU)
FCIBBG	Bloomberg Financial Conditions Index (FCI)	1y_ILS_9y	1-year ILS forward rate 9 years ahead	NONEN_WB	Non-energy Price Index (in USD)
FCIGS	Goldman Sachs Financial Conditions Index (FCI)	5y_ILS_5y	5-year ILS forward rate 5 years ahead	PRECMETAL_WB	Precious Metals Price Index (in USD)
STN_IR	3-month EURIBOR			PCU	Non-energy commodity prices (in USD)
				PCE	Non-energy commodity prices (in EUR, converted from PCU)
Money and credit		**Uncertainty/Volatility**		PFU	Non-energy commodity prices: food (in USD)
M1	M1 vis-a-vis EA non-MFI excl. central gov.	EA_DIS	Forecast disagreement (consensus forecasts, GDP)	PMU	Non-enery commodity prices: metal (in USD)
M3	M3 vis-a-vis EA non-MFI excl. central gov.	EA_FINANCIAL	PC of conditional variance of equity prices, gov. yields and EUR/USD rate	PAU	Non-energy commodity prices: non-food agricultural (in USD)
LOANS_NFC	Bank loans to NFC	EA_GC_MEAN	Mean of available uncertainty measures (ECB indicators)	FOOD	DG-AGRI food price : total Food (in EUR)
LOANS_NFC_GDP	Bank loans to NFC to GDP ratio	EA_SURVEY_SD	Financial uncertainty based on Jurado et al. (2015)		
LOANS_HH	Bank loans to NFC, index of notional stocks	EA_SURVEYCVAR	Macroeconomic uncertainty based on Jurado et al. (2015)	**Other external factors**	
LOANS_HH_GDP	Bank loans to households	EA_PUI	Political uncertainty for EA, based on Baker et al. (2016)'s EPU	US_INFEXP1_HH	University of Michigan: Expected Inflation Rate, Next Year (%)
LOANS_NFPS	Bank loans to households to GDP ratio	EA_SURVEY_SD	Standard deviation of balance indicators (consensus forecast)	US10YGBY	US 10-year government bond yield
LOANS_NFPS_GDP	Bank loans to households, index of notional stocks	EA_SURVEYCVAR	Conditional variance (consensus forecast)	EME_SHAREPRICE	Emerging Markets: Share Price Index, US$
CREDIT_NFPS	Bank loans to non-financial private sector (NFC and households)			US_FHFA	FHFA House Price Index: Purchase Only, United States (SA)
CREDIT_NFPS_GDP	Bank loans to non-financial private sector (NFC and households) to GDP ratio	**Other domestic indicators**		US_SP_HOMEINDEX	S&P CoreLogic Case-Shiller Home Price Index: US National (NSA)
RES_LOANS	Credit private sector non financial (extended with weighted average of EA countries data)	YEG_GDP	Output gap (% of GDP)	ASIA5_LEADIND	Major 5 Asia: Total Leading Indicator (SA, Normalized)
CONS_LOANS	Credit private sector non financial to GDP ratio	PYR	Real gross disposable income	CN_INDVA	China: Index of Industrial Value Added
		INDPROD_SA	Industrial production, total excluding construction	CN_IFA	China: Investment in Fixed Assets (cumulative)
Labour market		CAR_REG	Car registrations	CN_IPEXCONS	Canada: Industrial Production ex. Construction (SA, 2015=100)
ULA	Unit labour costs (ULC), whole economy (compensation to employee per employee/productivity per head)	PMI_MAN	PMI manufacturing	US_PX	US competitors' prices
CEX	Compensation per employee	PMI_COMP	PMI composite	CPX	Euro area's competitors' export prices
URX_rate	Unemployment rate	SEROUT	Services, business activity index (survey)	US_CPIX	CPI-U: all items less food and energy (NSA)
URT_rate	NAIRU	MANOUT	Manufacturing output (survey index)	CXD	Competitors' prices on the export side (partners NA export deflator weighted by double export weights)
UR_gap_rate	NAIRU gap (unemployment minus NAIRU, computed as URX_rate - URT_rate)	CONOUT	Construction output index (survey)	CMD	Competitors' prices on the import side (partners NA export deflator weighted by import shares)
		MANNEW	Manufacturing, new orders (survey index)	US_PCE	PCE: chain price index (SA, 2012=100)
Price and cost indic		SAX_rate	Gross household saving ratio (% of disposable income)	CN_MMTR	China: merchandise imports (NSA, in USD)
YED	GDP deflator	DEF_GDP	Deficit (or surplus) as a percentage of GDP	US_PX	US competitors' prices
MXD	Imports of goods and services, deflator	MAL_GDP	Government debt (EDP) as a percentage of GDP	CPX	Euro area's competitors' export prices
EXT	Terms of trade	COMNEW	Composite index of new orders (survey)		
MANPRC	Manufacturing, prices charged index (survey)	MANCAP	Manufacturing, capacity utillisation (survey index)		
MANINP	Manufacturing input prices index (survey)	MANNEX	Manufacturing, new export orders (survey index)		

Appendix II. Macro-at-Risk in the euro area

Table AII.1: HICPX inflation – Frequency of risk factors in selected best combinations

	Horizon Q+1			Horizon Q+4			Horizon Q+8		
	CRPS	QS10	QS90	CRPS	QS10	QS90	CRPS	QS10	QS90
Financial conditions	64.6%	48.1%	42.7%	58.5%	56.0%	33.3%	56.7%	64.0%	46.8%
Money and credit	22.8%	21.2%	25.3%	19.5%	40.0%	23.6%	25.4%	30.0%	24.2%
Labour market	27.8%	34.6%	18.7%	12.2%	12.0%	31.9%	11.9%	12.0%	12.9%
Price and cost indicators	34.2%	23.1%	41.3%	43.9%	20.0%	52.8%	56.7%	34.0%	56.5%
Market expectations	0.0%	0.0%	21.3%	7.3%	8.0%	16.7%	3.0%	2.0%	6.5%
Uncertainty	59.5%	65.4%	65.3%	53.7%	44.0%	45.8%	49.3%	58.0%	46.8%
Oth. domestic factors	57.0%	40.4%	76.0%	63.4%	52.0%	79.2%	47.8%	42.0%	58.1%
Commodity prices	46.8%	65.4%	33.3%	17.1%	0.0%	30.6%	35.8%	30.0%	46.8%
Oth. external factors	3.8%	0.0%	14.7%	39.0%	64.0%	19.4%	32.8%	46.0%	21.0%

Source: Authors' calculations.
Notes: The table shows the frequency of each risk factor in selected combinations. The latter refers to combinations of risk factors that show significant density forecast enhancement compared with all remaining specifications. Density forecast evaluation is conducted through the CRPS, QS10 and QS90, assessed for each forecast horizon of interest (Q+1, Q+4 and Q+8).

Appendix III. Macro-at-Risk models in the policy application

Table AIII.1: HICP inflation – Selected high-performing specification

Endo variable		Explanatory Variables															
Endo name	Transfornation Endo	Lag Endog	Expl1	Expl2	Expl3	Expl4	Expl5	Transf_Expl1	Transf_Expl2	Transf_Expl3	Transf_Expl4	Transf_Expl5	Lag_Expl1	Lag_Expl2	Lag_Expl3	Lag_Expl4	Lag_Expl5
HIC_sa	qoq	[1;2]	NONEN_WB	1y_ILS_2y	SAX_rate	PPI_TOT	EA_SURVEY_SD	qoq	none	none	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	GPYSPR	SAX_rate	ULA			none	none	qoq			[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	NONEN_WB	M3	MANSDT	EA_SURVEYCAR		qoq	qoq	none	none		[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	MANSDT	ULA	EA_SURVEYCAR			none	qoq	none			[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	NONEN_WB	1y_ILS_2y	SAX_rate	ULA	EA_SURVEY_SD	qoq	none	none	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	POE	SPFHICP_2Y	LOANS_HH	SAX_Rate	EA_SURVEY_SD	qoq	none	qoq	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	NONEN_WB	TERMSPR	MANSDT	EA_SURVEYCVAR		qoq	none	none	none		[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HIC_sa	qoq	[1;2]	NONEN_WB	GBYSPR	MANSDT	EXT		qoq	none	none	none		[0;1]	[0;1]	[0;1]	[0;1]	[0;1]

Source: Authors' calculations.

Table AIII.2: HICPX inflation – Selected high-performing specification

Endo variable		Explanatory Variables															
Endo name	Transfornation Endo	Lag Endog	Expl1	Expl2	Expl3	Expl4	Expl5	Transf_Expl1	Transf_Expl2	Transf_Expl3	Transf_Expl4	Transf_Expl5	Lag_Expl1	Lag_Expl2	Lag_Expl3	Lag_Expl4	Lag_Expl5
HEF_sa	qoq	[1;2]	SPFHICP_2Y	CAPUTIL	M3	SAX_rate	ULA	none	none	qoq	none	qoq	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HEF_sa	qoq	[1;2]	GBYSPR	CAPUTIL	CEX	EA_SURVEYCVAR		none	none	qoq			[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HEF_sa	qoq	[1;2]	SPFHICP_2Y	UR_gap_rate	M1	CEX	EA_SURVEYCVAR	none	none	qoq	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HEF_sa	qoq	[1;2]	SPFHICP_2Y	UR_gap_rate	US_CPIX	CEX	EA_SURVEYCVAR	none	none	qoq	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HEF_sa	qoq	[1;2]	SPFHICP_2Y	CAPUTIL	NONEN_WB	SAX_rate	ULA	none	none	qoq	none	qoq	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
HEF_sa	qoq	[1;2]	NONEN_WB	CAPUTIL	LOANS_NFPS	ULA	EA_GC_MEAN	qoq	none	qoq	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]

Source: Authors' calculations.

Table AIII.3: GDP growth – Selected high-performing specification

Endo variable		Explanatory Variables															
Endo name	Transfornation Endo	Lag Endog	Expl1	Expl2	Expl3	Expl4	Expl5	Transf_Expl1	Transf_Expl2	Transf_Expl3	Transf_Expl4	Transf_Expl5	Lag_Expl1	Lag_Expl2	Lag_Expl3	Lag_Expl4	Lag_Expl5
YER	qoq	[1;2]	ASIAS_LEADIND	URT_rate	EA_SURVEYCVAR			diff	none	none	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	US_FHFA	GBYSPR	MTR	CEX	EA_SURVEY_SD	qoq	none	qoq	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	US_HFA	LOANS_NFC_GDP	CEX	EA_SURVEY_SD		qoq	none	qoq	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	SPFHICP_1Y	GBYSPR	M1	EA_SURVEYCVAR		none	none	qoq	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	US_HFA	GBYSPR	LOANS_NFC_GDP	EA_FINANCIAL		qoq	none	none	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	US_HFA	GBYSPR	MUD	HP		qoq	none	none	qoq	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	New_CISS	M1	MTR	URT_rate		none	qoq	qoq	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]
YER	qoq	[1;2]	US_HFA	SPFHICP_1Y	LOANS_NFC_GDP	MUD	EA_SURVEY_SD	qoq	none	none	none	none	[0;1]	[0;1]	[0;1]	[0;1]	[0;1]

Source: Authors' calculations.

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