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Elena Angelini, Matthieu Darracq Pariès, Thomas Haertel, Magdalena Lalik (editors)

The ESCB forecasting models: what are they and what are they good for?

Working Group on Forecasting (WGF) – Report by the Expert Group on the Model-based Assessment of Projections (EGMAP)

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Abstract

This report provides a comprehensive overview of the models and tools used for macroeconomic projections within the European System of Central Banks (ESCB). These include semi-structural models, dynamic stochastic general equilibrium (DSGE) models, time series models and specialised satellite models tailored to particular questions or country-specific aspects. Each type of model has its own strengths and weaknesses and can help answer different questions. The models should therefore be seen as complementary rather than mutually exclusive. Semi-structural models are commonly used to produce baseline projection exercises, since they offer the flexibility to combine expert judgement with empirical data and have enough complexity and structure to provide a good representation of the economy. DSGE models, valued for their internal consistency and strong theoretical foundations, are another core forecasting tool used by some central banks, particularly to analyse counterfactuals. Time series models tend to be better suited to forecasting the short term, while scenario analysis and special events may require satellite models, extensions of existing models or even the development of new models tailored to the question at hand. The report also addresses the challenges to macroeconomic projections posed by data quality, including revisions and missing data, and describes the methods implemented to mitigate their effects. The report identifies “quick wins” to improve the projection process by enhancing the transparency and comparability of results through standardised reporting frameworks and better measurement of the judgement integrated in forecasts. The findings highlight the fundamental role of macroeconomic models in underpinning the ESCB’s projection exercises and ensuring that the Governing Council’s assessments and deliberations rest on coherent, granular and credible analysis of both demand-side and supply-side dynamics.

JEL codes: C30, C53, C54, E52

Keywords: economic models, monetary policy, forecasting, macroeconometrics

Non-technical summary

This report provides a comprehensive overview of the models used within the European System of Central Banks (ESCB) for macroeconomic forecasting. It highlights the diversity of models used by national central banks (NCBs) and the European Central Bank (ECB), their different applications and the role they play in delivering coherent and credible economic projections.

Central banks use models as structured tools to understand the economy, predict future trends and assess the impact of policy measures. The ESCB relies on a variety of models, including semi-structural, dynamic stochastic general equilibrium (DSGE), time series and satellite models. The models serve different but complementary purposes in the forecasting process. Semi-structural models offer flexibility and are well suited to incorporating expert judgement and addressing country-specific features. DSGE models provide a strong theoretical foundation and are valuable for ensuring internal consistency and analysing the impact of structural shocks. Time series models, meanwhile, are better suited to forecasting the short term, while scenario analysis and special events may require specialised satellite models. Together, they support a more robust approach to macroeconomic forecasting.

The report finds that although models may be designed and applied differently across countries, shared practices ensure coherence across the ESCB. Short-term forecasting tools and supporting models play a vital role in refining and cross-checking the output of core models. These tools help to incorporate information from high-frequency data, sector-specific studies and expert knowledge.

Comparing the forecasting process across central banks reveals several challenges and opportunities for improvement. Data quality issues, such as revisions and missing observations, need to be addressed to enhance the accuracy and reliability of any projection process. The report emphasises the gains from harmonising practices across the ESCB, including standardising how assumptions are treated and how the contribution of expert judgement is reported. By creating common frameworks for reporting and integrating data, the ESCB can ensure greater transparency and comparability across central banks.

In summary, this report reviews the role of macroeconomic models in the ESCB's forecasting and policy analysis and offers practical recommendations for further improvement. By enhancing transparency and adaptability, the ESCB can continue to provide state-of-the-art economic projections that support effective monetary policy decision-making.

1 Introduction

Central banks have long relied on macroeconomic models for forecasting. In recent years, there have been several publications by the European System of Central Banks (ESCB) describing the models involved in its forecasting process. In particular, the 2020 European Central Bank (ECB) monetary policy strategy review included a dedicated work stream to examine the tools and practices contributing to the economic, monetary and financial analysis supporting monetary policy decisions. This resulted in a comprehensive overview of the Eurosystem's modelling portfolio, including its strengths and weaknesses, which is documented in Darracq Pariès et al. (2021). Further initiatives were subsequently launched within the ESCB Working Group on Forecasting, culminating in the creation of the Expert Group on the Model-Based Assessment of Projections (EGMAP). This is composed of the ESCB experts responsible for developing and maintaining the core models used in the macroeconomic projection exercises. The group's primary goal is to enhance the use of models in the projections, with a particular focus on developing model-based measures of the expert judgement embedded in baseline projections.

Quarterly macroeconomic projections are essential in guiding the ECB's monetary policy decisions. They form the cornerstone of the forward-looking monetary policy strategy designed to account for uncertainties in the transmission of monetary policy to the economy and to inflation. These projections combine model outputs and expert judgement, though distinguishing between the two is not always straightforward as judgement is frequently informed by model-based analysis. Expert judgement in forecasting is inherently model-specific because it can only be defined by reference to a baseline produced by a model with no judgemental adjustments (although few models are designed to be used this way). However, expert judgement measured within a given model is often informed by other models, making its measurement challenging. For instance, specialised satellite models may be better at capturing specific phenomena, such as credit supply effects, but fail to account for other macroeconomic links. If experts modify the core model's outcomes based on such specialised models, how should this adjustment be characterised? In the ECB projection exercises, this is still considered "expert judgement" even though it is based on the satellite model. Similarly, a satellite model might accurately forecast aggregate GDP but lack detailed information about GDP components. Experts may then adjust the component variables in the core model to align with the aggregate GDP forecast. Furthermore, the choice of method by which off-model information is incorporated into the core model can require additional layers of judgement.

Other factors also affect the interpretation and measurement of expert judgement. The quality of statistical data, for instance, can affect forecasts when revisions are not well understood. Determining how much these revisions should influence projections often requires expert judgement. In addition, models may undergo updates or improvements between projection exercises, explaining part of the change in the forecasts. However, the nature of these updates can vary. If a model is re-estimated purely to incorporate benchmark data revisions, the resulting changes –

driven by updated parameters – should not, in principle, be classified as expert judgement. By contrast, if certain parameters are adjusted based on other information (e.g. modifying the sensitivity of the model to oil prices), such changes should be considered expert judgement. This raises the question of how to clearly distinguish between mechanical model updates and judgement-based adjustments in forecasting practice.

To address these questions, one must first define the "judgement-free" baseline produced by the core model, which should serve as a benchmark to measure expert judgement. EGMAP began by distributing a questionnaire to catalogue existing ESCB models used in macroeconomic projections. This survey aimed to provide a clearer overview of the tools available to forecasters and their practical applications. Section 4 presents the findings of this survey, along with some specific illustrations of forecasting practices at national central banks (NCBs). In parallel, EGMAP is working to develop protocols to create model-based indicators to measure expert judgement. The aim is to improve transparency and consistency in how judgement is assessed and reported. The results of this ongoing work will be detailed in a forthcoming working paper.

This report presents the outcomes of the questionnaire as returned by 24 institutions, including the ECB and 23 NCBs in the European Union, of which 19 are in the euro area. The primary objective of the survey was to gather information on modelling practices within ESCB central banks, especially in constructing baseline projections. The survey also aimed to uncover insights into how expert judgement is embedded in projections and how this judgement interacts with model-based forecasts. This will help enhance the transparency and credibility of baseline projections across the ESCB. The stocktaking of modelling practices offers an opportunity to develop a more structured and harmonised framework to report key aspects of the baseline projections, such as the impact of assumptions, of the short-term forecast and of expert judgements.

Summary of the main findings

The survey results confirmed earlier findings documented in the literature (see e.g. Holm-Hadulla et al., 2021, Darracq Pariès et al., 2021 and Ciccarelli et al., 2024). In particular, the models used for forecasting vary significantly across the ESCB. They differ in type, size, assumptions and the extent to which they are backward-looking or forward-looking. In addition, expert judgement relies on a wide range of supporting and satellite models, as well as other tools. Despite differences across central banks, the findings highlight that the overall modelling approaches are quite similar.

Semi-structural models play a dominant role in producing the baseline projections, offering the flexibility to accommodate country-specific aspects and to incorporate expert judgement. All countries use additional models for short-term inflation projections and near-term economic forecasts (including nowcasting). These are integrated into the main macroeconomic models using comparable methods. While

projections may condition on different variables in the short term, the models operate similarly over the medium term, when projections become more model-driven.

The common assumptions provided by the ECB are central to all country models, though some specific assumptions may be tailored to individual needs. Overall, large models serve as a framework to marshal information and discipline the projection.

Structure of the report

The following sections will explore specific modelling practices, the frequency of projections, the integration of short-term forecasts and the use of cross-checking models. This will describe how NCBs construct and cross-validate their baseline projections. The report begins by explaining why central banks use models. It then explores the main models employed by NCBs and provides an overview of supporting tools, such as satellite models and cross-checking processes. Following the structure of the questionnaire, the report briefly describes how off-model information is integrated into the main macro models. It also examines the frequency at which different NCBs produce projections and how often their main models are re-estimated.

In later sections, the report summarises findings on the treatment of forecast assumptions and other exogenous variables, alongside issues related to data quality. It also describes how NCBs communicate the impact of assumptions, data and expert judgement to key stakeholders. The final sections present recommendations for “quick wins” and future work to enhance the harmonisation of model-based projections, with a focus on improving the reporting of expert judgement within baseline projections. In addition, the report provides examples of “projections in practice” through illustrative case studies, highlighting institutional practices from several NCBs and the ECB. Finally, the report concludes with recommendations for future harmonisation to enhance the consistency, comparability and transparency of ESCB macroeconomic projections.

2 Do we need models to forecast?

Before presenting the European System of Central Banks (ESCB) forecasting models, it is important to first consider why models are essential for ESCB forecasting. A recent European Central Bank (ECB) blog post by Ciccarelli et al. (2023) provides a plausible account in this respect.

Central banks must anticipate future economic conditions to make informed, forward-looking policy decisions. Economic models, though simplified representations of reality, are designed to help economists reason and process economic data in a structured manner. Models help policymakers understand the current state of the economy, its likely evolution, potential risks and the effects of policy actions. For central banks, these models are crucial in order to produce projections and evaluate economic risks and alternative scenarios[1].

In the context of the Eurosystem/ECB staff projections (see ECB, 2016), models play an additional role in ensuring consistency across countries and over time. The Eurosystem, including 20 national central banks (NCBs) and the ECB, follows a bottom-up approach to forecasting. This means that each country produces its own forecast using its own models, with results aggregated to form the euro area forecast. The Broad Macroeconomic Projection Exercise (BMPE), conducted in June and December, relies on both NCB and ECB models to produce country forecasts, with differences resolved through a peer review process. By contrast, during the Macroeconomic Projection Exercise (MPE), conducted in March and September, country forecasts are based only on ECB models. This requires models to ensure consistency not only across countries (for the peer review process), but also across different projection exercises. Therefore, in addition to the country-specific models, the ECB employs dedicated models of the euro area economy as a whole to cross-check the projections aggregated from country-specific models.

The internal coherence of the (B)MPE projections is also guaranteed by a shared set of common assumptions. These assumptions, which are produced by the ECB, are themselves model-based. In addition, a Narrow Inflation Projection Exercise (NIPE) is conducted each quarter by euro area NCBs, aggregating country-level results to inform the inflation forecast for the euro area as a whole. In practice, this means that over the NIPE horizon (usually one year ahead), inflation figures are imposed in all the main forecasting models.

Finally, models play a vital role in crafting a projection “narrative” by providing a structural interpretation of cyclical developments – the “story” behind the forecast. This narrative helps to explain the underlying dynamics and assumptions that shape the projections. Thus, models function not only as forecasting tools but also as a disciplining framework, facilitating structured discussions, providing a structural interpretation of baseline projections and measuring expert judgement.

1 See Ciccarelli et al. (2023).

In addition, central banks continuously update their models to handle new shocks (e.g. financial crises, pandemics) and policy regimes (e.g. inflation targeting). They also develop new modelling approaches, such as projection updates, to improve the consistency and transparency of baseline projections. To further support these efforts, the Working Group on Forecasting established the Expert Group on the Model-based Assessment of Projections to harmonise and improve practices across the ESCB. This initiative not only facilitates cross-checking of the final projections but also enhances their communication, following a complex process that integrates different models and datasets as well as expert judgement.

3 Questionnaire on ESCB macro models regularly used for baseline projections

This section introduces the design and findings of the questionnaire on the European System of Central Banks (ESCB) macro models used for baseline projections, as conducted by the Expert Group on the Model-based Assessment of Projections in the first half of 2024. The focus of the survey was threefold. First, it documented the models regularly used by national central banks (NCBs) by type and intended purpose, whether for short-term forecasting, medium-term to long-term projection, scenario analysis or policy assessment. Second, it examined how these models are integrated into the process of constructing baseline projections, shedding light on how forecast assumptions, model-based outputs and expert judgement are considered. Third, it identified how forecasting models are used in practices across NCBs, aiming to pinpoint areas where greater harmonisation could lead to efficiency improvements. The overarching goal was to identify “quick wins” – practical steps that could enhance the transparency of baseline projections.

The questionnaire

The questionnaire was structured into four main parts, each aimed at assessing different aspects of the modelling process.

Part 1: the ESCB operational modelling toolkit

This section aimed to understand the types of model used by NCBs, their design and their specific application. The key questions focused on:

- describing the main macro models used for baseline projections (e.g. type of model and size, semi-structural, dynamic stochastic general equilibrium (DSGE), time series);
- identifying additional models used to support or cross-check baseline projections;
- understanding the incorporation of short-term outlook and satellite model results into baseline projections;
- gathering insights on how often the projections are produced and how frequently the models are re-estimated.

Part 2: forecast assumptions and data preparation for baseline projections

This section focused on the assumptions and data preparation that feed into the models. The questions explored were as follows:

- Which forecast assumptions (e.g. foreign demand, fiscal variables, energy prices) are included in the models?
- How are forecast assumptions and other exogenous variables included in the models?
- How do NCBs handle historical data revisions, ragged edge problems and the overall quality of statistical data in their projections?

Part 3: information reported to support the forecast narrative

The aim of this part was to explore how NCBs communicate the role of judgement and assumptions in their baseline projections. Specifically, it focused on:

- how judgement is embedded in the forecasts and how additional information beyond the main model is used to motivate adjustments to projections;
- how NCBs break down revisions in projections (e.g. impact of assumptions, data and other residual factors) and whether they provide further granularity.

Part 4: additional information on analytical challenges related to model-based forecasts

The final part of the survey investigated the broader challenges of developing and implementing model-based forecasts, including:

- the benefits of introducing model-based forecasts for institutions that do not currently use them;
- technical hurdles and potential areas for future development and improvement of model-based forecasting practices.

High-level summary of survey results

The questionnaire on ESCB macro models regularly used for baseline projections gathered responses from 24 institutions, including 19 euro area NCBs, four non-euro area central banks and the European Central Bank (ECB). The survey findings show that semi-structural models are the most widely used, with 18 institutions relying on them to construct baseline projections, while four NCBs use DSGE models as their main tool. All respondents use models to support their baseline projections, and 16 of them cross-check their projections with additional models. To integrate short-term forecasts and satellite model results into the baseline, 14 institutions use residual adjustments (often referred to as “add-factoring”), and 13 opt for exogenising specific variables, reflecting varied strategies for incorporating off-model information.

Additionally, 17 respondents provide interim projections or mechanical updates outside of the regular Broad Macroeconomic Projection Exercise (BMPE) rounds. While all euro area institutions consistently incorporate ECB assumptions, the

treatment of fiscal and lending rate assumptions is less harmonised. The coverage of these assumptions varies across countries, and not all institutions include lending rate assumptions in their forecasts. Most institutions do not apply transformations to the assumptions or data, and they generally begin assessing the impact of these assumptions from the first period of their forecast. Key areas for improvement include standardising the reporting of key components behind forecast revisions, establishing common practices for setting "neutral" residuals (i.e. model-consistent residuals that can be considered free of expert judgement)[2], incorporating country-specific assumptions and developing a unified methodology for model-based forecast indicators. These steps, if standardised, would help to better identify and quantify the role of expert judgement embedded in baseline projections.

Before proceeding, it is important to note that the ESCB modelling toolkit is permanently evolving thanks to improvements, developments and re-estimations. Therefore, the survey results presented here should be viewed as reflecting the toolkit at a specific point in time, broadly corresponding to the June 2024 BMPE.

[2] In semi-structural models, the notion of "neutral" residuals corresponds to a model-consistent approach, i.e. free of expert judgement. In DSGE models, the "neutral" residuals are consistent with a zero-innovation assumption.

4 What are the ESCB models? Outcome of the questionnaire

The survey revealed that the macroeconomic models used by national central banks (NCBs) within the European System of Central Banks (ESCB) are diverse in their design. NCBs' modelling approaches are essentially influenced by national economic structures and data availability, which may also call for specific methodological approaches. Nevertheless, they share various key features. These models can generally be categorised based on their structure and function.

- **Model types:** The models include semi-structural, dynamic stochastic general equilibrium (DSGE) and time series models. DSGE models have a strong theoretical foundation, semi-structural models blend theory with a good fit of empirical data, while time series models rely solely on empirical data. Semi-structural models are more flexible than DSGE models, allowing for adjustments based on expert judgement and empirical observations. Time series models are flexible in fitting data patterns but lack theoretical rigor.
- **Model sizes:** The models vary in scale between small, medium and large. Smaller models often focus on specific sectors or short-term forecasting, while larger models may incorporate multiple economic sectors and longer-term projections.
- **Expectation formation:** Models incorporate different methods of expectation formation, including backward-looking (adaptive) and forward-looking (rational) expectations. The choice of expectation formation affects how the models handle future economic conditions and policy changes.
- **Structural components:** Most models are built around key economic blocks such as supply, demand, price, labour market and government sectors. These components help in capturing the dynamics of the economy and provide a comprehensive framework for forecasting.
- **Integration of expert judgement:** Models are designed to integrate off-model information and expert judgement to enhance the accuracy of forecasts. This approach ensures that the models can incorporate insights from economic experts and take limitations into account.

4.1 Main macro models for the baseline projections

The main macro models used by NCBs for baseline projections are rather elaborate and diverse, reflecting the specific economic contexts of each country. Below are the key features of these models.[3]

Country (code)	Model name	Short model description
Belgium (BE)	NONAME and BEMGIE	The NONAME model is a semi-structural model that can be run with model-consistent expectations. However, for the purpose of forecasting exercises, it is used in a purely backward-looking manner, with no expectations incorporated. Although Belgium has also developed BEMGIE, a DSGE model, NONAME remains the primary model currently in use.
Czech Republic (CZ)	g3+	Česká národní banka uses the g3+ model, a DSGE model for the domestic economy with a semi-structural foreign sector. This model is central to the Czech Republic's economic forecasting.
Germany (DE)	BbKM-DE	The BbKM-DE model is a large-scale, semi-structural, backward-looking and primarily used for medium-term projections.
Ireland (IE)	COSMO and EireMod	The COSMO semi-structural model and EireMod DSGE model are used for scenario analysis and the cross-checking of main forecasts. These models are designed to address Ireland's unique economic conditions and its vulnerability to external shocks.
Greece (EL)	semi-structural	The main model is a semi-structural model used for medium-term economic forecasting, combining empirical data with theoretical frameworks.
Spain (ES)	MTBE	Spain's main model is the MTBE model, a large-scale macroeconometric model for medium-term macroeconomic forecasting, predominantly demand-driven in the short run.
France (FR)	FR-BDF	The main macroeconomic model is the FR-BDF model, a large-scale, semi-structural macroeconomic model with backward-looking expectations based on Polynomial Adjustment Costs (PAC).
Croatia (HR)	PACMAN	Hrvatska narodna banka uses the PACMAN model, a semi-structural, entirely backward-looking model for baseline projections.
Italy (IT)	BdIQEM	BdIQEM is semi-structural, large-scale, and backward-looking, used for medium-term economic projections.
Cyprus (CY)	semi-structural	Cyprus employs a semi-structural model designed for small open economies, focusing on medium-term projections and integrating both forward-looking and backward-looking expectations.
Latvia (LV)	DSGE and semi-structural	Latvia's main model is a DSGE model used for scenario analysis and baseline projections. Latvia is also developing a semi-structural model for cross-checking the consistency of baseline projections.
Lithuania (LT)	STREAM	STREAM is used for baseline projections. It is backward-looking and of medium size.
Luxembourg (LU)	QLM	The Quarterly Luxembourg Model (QLM) is a medium-scale, backward-looking, semi-structural model based on the theoretical framework in the ECB's Area-Wide Model by Fagan et al. (2005). It is mostly used to analyse portfolios and compute basic model elasticities.
Malta (MT)	STREAM	Malta's STREAM model is a semi-structural, medium-scale, backward-looking model used to produce initial baseline projections, which are then refined using expert judgement.
Netherlands (NL)	DELFI	The DELFI model is a medium-scale, semi-structural, quarterly macroeconomic model with a strong emphasis on modelling the supply side of the economy. The model includes detailed modelling of demand components and the government sector along with a financial transmission mechanism.
Austria (AT)	Austrian Quarterly Model (AQM)	This model is small to medium-sized and semi-structural, combining neoclassical long-run behaviour with Keynesian short-run dynamics.
Poland (PL)	NECMOD	The NECMOD model is a semi-structural macroeconometric model, including long-term theoretical foundations and short-term empirical dynamics and focusing on detailed sectoral analysis.
Portugal (PT)	M	The M model, a medium-sized, semi-structural, backward-looking model for economic forecasting, is aligned with the basic theoretical framework of the ECB's Area-Wide Model. It comprises several interconnected blocks
Slovenia (SI)	Quaterly Macro Model	Slovenia follows a suite-of-models approach, with the Slovenian Quarterly Macroeconomic Model being a large-scale, semi-structural model used for scenario analysis, baseline projections and projection exercises (and belonging to the class of ECB-MC models).
Slovakia (SK)	semi-structural	Slovakia uses a medium-sized, backward-looking, semi-structural model that relies on error correction mechanisms and focuses on long-term relationships among key macroeconomic variables.
Finland (FI)	Aino 2	The Aino 2 model is a medium-scale to large-scale DSGE model that is key for the forecasting and policy analysis of Suomen Pankki – Finlands Bank.
Sweden (SE)	MAJA	MAJA is a medium-sized DSGE model used for economic analysis and forecasting. This medium-sized model includes forward-looking components, making it suitable for analysing the effects of various economic policies over time. Additionally, Sweden uses a BVAR (Bayesian vector autoregression) model for supplementary analysis, particularly for short-term forecasting and scenario analysis.
European Central Bank (ECB)	ECB-MC	The ECB Multi-County Model (ECB-MC) is a large-scale, semi-structural model used for deriving baseline projections for the largest euro area countries. This model includes various blocks such as demand, supply and financial sectors, and uses generalised adjustment costs.

[3] See annex for a list of corresponding academic references.

The main models also serve as an organising and harmonising tool, making sure that the resulting forecasts are internally coherent and provide a comprehensive narrative underlying and anchoring the numerical forecast for the main variables of interest.

4.2 Supporting and cross-checking models

NCBs additionally employ a variety of supporting models and cross-checking tools to enhance the robustness and reliability of their baseline projections. These models and tools provide additional layers of analysis and validation, ensuring that projections are comprehensive, consistent and accurate.

4.2.1 Supporting models

Supporting models typically address specific aspects of the economy such as potential output, labour market dynamics, current account balances and inflation forecasts. These models often focus on short-term or medium-term horizons and are used to refine and validate the output of the main macro models. In line with the Eurosystem's annual supply side review (ASSR)[4] and the European Central Bank's (ECB's) 2021 strategy review, particular emphasis is placed on supply side blocks, which embed structural drivers such as productivity, demographics, wage-setting institutions and trend unemployment into the forecasting process. The most common supporting models employed by NCBs to support the construction of baseline projections are listed below.

NIPE tools/inflation forecast models

Main application: Narrow Inflation Projection Exercise (NIPE) tools and models are primarily used to forecast inflation in the short term, typically focusing on key components of consumer prices such as the Harmonised Index of Consumer Prices (HICP). These models often disaggregate inflation into its subcomponents (e.g. energy, food, core inflation) to provide detailed forecasts.

Countries employing this model: All countries.

Short-term/nowcasting GDP models

Main application: These models are used for real-time or short-term forecasting of GDP and in some cases its components. Nowcasting models provide up-to-date estimates of economic activity based on high-frequency data such as industrial

[4] For more information on the ASSR and the emphasis on structural trends in the ECB's 2021 strategy review, see, for example, Holm-Hadulla et al. (2021).

production, retail sales and other timely indicators. They are crucial for understanding the current state of the economy and making near-term projections.

Countries employing this model: All countries.

Potential output models

Main application: Models for potential output estimate the economy's long-term productive capacity, typically through production function or semi-structural approaches complemented by filtering or unobserved components methods. These models combine information on capital accumulation, labour force participation, demographics, productivity trends and the non-accelerating inflation rate of unemployment, thereby helping to assess the output gap and to capture structural heterogeneity and demographic change in the medium-term projection framework.

Countries employing this model: 19 countries (BE, CZ, DE, IE, ES, FR, HR, IT, LV, LT, LU, MT, NL, AT, PT, RO, SI, SK, FI) and the ECB.

Labour market and wage models

Main application: Labour market and wage models are used to project employment, participation and wage dynamics. They take into account both more traditional factors, such as unemployment rates, productivity, inflation and sector-specific wage agreements, and other institutional factors (timing and intensity of wage negotiations, etc.) that characterise national labour markets. These models are important for understanding labour market dynamics and the transmission of wage pressures into broader inflationary trends.

Countries employing this model: Ten countries (BE, CZ, DE, IE, GR, IT, LV, NL, AT, SI) and the ECB.

House price models

Main application: House price models are employed to forecast changes in the housing market, often using factors such as economic activity, interest rates, construction costs, disposable income, investment projections, mortgage lending rates as well as sector-specific information gathered through surveys. These models help to assess the potential risks to financial stability and the broader economy from fluctuations in housing prices.

Countries employing this model: 15 countries (BE, CZ, DE, GR, ES, HR, IT, CY, LV, LU, MT, NL[5], SI, SK, FI) and the ECB.

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5 While De Nederlandsche Bank does not have separate satellite models for house prices or for lending rates and volumes, the DELFI 2.0 semi-structural model itself models a variety of real-financial linkages through both the housing market and the banking sector.

Lending rate and loan volume models

Main application: Models for lending rates are used to forecast the interest rates on loans, particularly for households and non-financial corporations. Loan volume models are used to project the amount of credit extended to households and businesses. Both model types are used to assess credit market conditions and are often informed with information from surveys among banks, firms and households.

Countries employing this model: Lending rates (nine countries: BE, DE, GR, ES, IT, CY, LV, SI, SK and the ECB); loan Volumes (11 countries: CZ, DE, ES, IT, LV, LU, MT, NL, SI, SK, FI and the ECB).

Public finance models

Main application: Public finance models are specialised tools used by NCBs to forecast and analyse the dynamics of fiscal variables. These models focus on key fiscal variables such as government revenue, public expenditures, debt and budget deficits. Public finance models incorporate detailed data on tax revenues, government investments, social benefits and debt servicing costs derived from planned fiscal interventions by national governments to assess the sustainability of public finances over time.

Countries employing this model: 15 countries (BE, CZ, DE, IE, ES, FR, IT, LV, LU, MT, NL, AT, RO, SI, FI) and the ECB.

4.2.2 Cross-checking models

In this section, we provide an overview of the cross-checking models used by various countries to validate their baseline projections. Most countries participating in the survey employ additional models to ensure the robustness of their macroeconomic forecasts. The application of these models varies across countries, with some opting for fully model-based forecasts, while others incorporate partial cross-checks through supplementary tools.

- Belgium (BE): Belgium cross-checks its projections through a consensus process involving the workhorse macro model, expert judgement and satellite models that are used to review and adjust projections, incorporating shocks and general equilibrium effects.
- Czech Republic (CZ): The Czech Republic compares short-term forecasts from tools with medium-term forecasts from the g3+ model. A revision decomposition process is used, focusing on variables like interest rates and inflation.
- France (FR): France uses a basic model elasticities (BME) tool to cross-check revisions to baseline projections. Inflation forecasts are benchmarked using various Phillips curves.

- Germany (DE): Germany uses a range of models for cross-checking, including price-Phillips curves, wage equations, structural vector autoregression (VAR) models and a three-region DSGE model. These models (except for wage equations) focus on GDP and the HICP, providing structural shock decompositions (except for Phillips curves).
- Ireland (IE): Ireland cross-checks its inflation forecasts using alternative time series models, including autoregressive distributed lag, autoregressive and VAR models. These models are used to produce alternative forecasts based on different assumed paths for variables. For labour market forecasts, error correction models are used to cross-check the results from the VAR models.
- Italy (IT): Italy uses a Bayesian vector autoregression (BVAR) model to cross-check housing market projections as part of its overall macroeconomic forecasting framework.
- Cyprus (CY): Cyprus uses the Cyprus Macroeconometric Model (CYMCM), a semi-structural macroeconometric model, to analyse and cross-check medium-term projections. This model is critical for assessing the impacts of fiscal and economic scenarios on the Cypriot economy.
- Latvia (LV): Latvia uses a semi-structural macro model for medium-term projections, based on the framework of Fagan et al. (2005). In addition, Latvia employs GDP nowcasting models, which include a variety of time series models such as bridge models, BVAR models and factor models for short-term GDP forecasting.
- Luxembourg (LU): Luxembourg cross-checks its projections by combining judgement with short-term forecast tools (bridge equations, time series models) and satellite models.
- Netherlands (NL): The Netherlands uses debt analysis from the Working Group on Public Finance to cross-check its fiscal forecasts. This analysis ensures that the fiscal projections are consistent and reliable by incorporating detailed evaluations of public finance data.
- Portugal (PT): Portugal cross-checks its short-term projections for GDP using factor models and its projections for inflation and wages using Phillips curves. Additionally, an unobserved components model is used for potential output and a BVAR model is in development for cross-checking macroeconomic projections.
- Romania (RO): Romania cross-checks its macroeconomic projections using a DSGE model (R.E.M. 2.0), which incorporates forward-looking expectations and focuses on medium-term projections. The model includes partial euroisation and is used to assess various aspects of the Romanian economy.
- Slovakia (SK): Slovakia uses a nowcasting toolbox (including dynamic factor (DF) and BVAR models) to cross-check GDP growth and Phillips curve models

for wages and inflation. The output gap is cross-checked using a mixed-frequency BVAR and DF model.

- Slovenia (SI): Slovenia employs an auxiliary, predominantly accounting and identity-based model to cross-check its projections. This model is used for bottom-up aggregation, logical controls and the construction of Broad Macroeconomic Projection Exercise reports. After the projection rounds are completed, the latest baseline is regularly cross-checked with mechanical updates using the nowcasting tool, which provides a weekly reassessment of the short-term forecasts.
- Finland (FI): Finland relies on BVAR models to cross-check macroeconomic outlooks, housing market projections and HICP components over the forecast horizon.
- European Central Bank (ECB): To cross-check euro area projections, the ECB employs two flagship models: ECB-BASE, a large semi-structural model, and NAWM II, a DSGE model. These models are instrumental in producing model-based indicators such as projection updates and conditional forecasts for the euro area. Notably, NAWM II is utilised for the structural interpretation of baseline projections.

4.3 Scenario simulation models

In this section, we provide a summary of models used for scenario and sensitivity analysis across NCBs. These simulations are especially valuable during periods of heightened uncertainty, when robust assessments of the risks surrounding the baseline are essential. The countries predominantly use their main macroeconomic projection models for scenario simulations. However, many have expanded their toolkits by incorporating additional models to improve the accuracy and scope of their simulations. Several countries, such as the Czech Republic, Germany, Ireland, Greece, Spain, Latvia, Portugal, Slovakia, Finland and Sweden, have either extended the structure of their existing DSGE models or developed new DSGE models to better capture structural dynamics and macro-financial linkages. Other NCBs, such as Ireland and the Netherlands, supplement their primary models with tools like global econometric models (e.g. the National Institute Global Econometric Model, NiGEM) to explore external shocks. This expansion reflects an effort to model various economic channels more accurately, accounting for complex interdependencies and shocks within the economy.

- Belgium (BE): No specific scenario models were mentioned.
- Czech Republic (CZ): Typically uses scenario simulations based on the baseline model but has extended or modified models for specific simulations, such as long-term rates and inflation target horizon shifts.
- Germany (DE): Uses the semi-structural BbKM-DE model and the three-region DSGE model for medium-term GDP and inflation scenario analysis.

- Ireland (IE): Uses a semi-structural model or DSGE model for scenario analysis, alongside the COSMO model and NiGEM for international shock analysis.
- Greece (GR): Employs DSGE models, VAR models and a semi-structural macro model for scenario simulations.
- Spain (ES): Uses the MTBE and JoSe models for scenario simulations.
- France (FR): Occasionally uses alternative versions of its main model (FR-BDF), such as versions with endogenous financial blocks and forward-looking expectations for scenario simulations.
- Croatia (HR): Uses the PACMAN semi-structural model for both baseline and alternative scenario projections.
- Italy (IT): Employs the BdIQEM semi-structural model for medium-term projections.
- Cyprus (CY): Uses the CYMCM macroeconomic model for scenario simulations.
- Latvia (LV): Uses a DSGE model, a computable general equilibrium model for fiscal sector analysis and EUROMOD for microsimulations and short-term fiscal scenarios.
- Lithuania (LT): Uses its main macroeconometric model for scenario simulations.
- Luxembourg (LU): Uses the Quarterly Luxembourg Model (QLM), a medium-sized, semi-structural model for scenario analysis.
- Malta (MT): Uses BMEs based on the STREAM macro model for scenario analysis.
- Netherlands (NL): Uses NiGEM to generate international scenarios and assess the impact of external shocks.
- Austria (AT): Uses the same model structure as described before for scenario analysis.
- Poland (PL): Uses the NECMOD model for scenario simulations around baseline projections.
- Portugal (PT): Uses the M model and PESSOA (DSGE model) for specific scenario simulations.
- Romania (RO): Uses its main macroeconometric model for scenario simulations.
- Slovakia (SK): Recently updated its forecasting model with blocks for household income and expenses, tax and social benefits, an aggregated balance sheet

and financial variables including house prices. It also uses the PreMISE and EAGLE DSGE models for scenario simulations.

- Slovenia (SI): Uses the Slovene Quarterly Macroeconomic Model (SiQM), a large semi-structural model based on ECB-BASE, for scenario simulations.
- Finland (FI): Primarily uses Aino 2 or Aino 3, a small-open economy DSGE model capturing macro-financial linkages and macroprudential policies.
- Sweden (SE): Uses the MAJA DSGE model for scenario simulations.
- European Central Bank (ECB): Uses multiple models, including ECB-MC, ECB-BASE, ECB-Basir and NAWM II, with additional topical and ad hoc tools for specific scenarios.

5 How models are used to develop baseline projections

One of the key outcomes from the questionnaire was that it provided a detailed account of how forecasters use their models during the regular projection process. While the first part of the survey highlighted diverse approaches to model development, the actual use of these models – despite structural differences – appears to be quite consistent across institutions. This section of the questionnaire focused on understanding how forecasters incorporate information from satellite models, integrate European Central Bank (ECB) assumptions and address data quality issues. Additionally, it documented the frequency of projection updates and model re-estimations.

Some information was not included in the questionnaire as it is well known to European System of Central Banks (ESCB) forecasters. However, it is important to mention it here in order to provide proper context for the exercise. Each forecasting round builds on the results of the previous projection, following an incremental process. Readers should note that the general approach to crafting baseline projections for each national central bank (NCB) and the ECB is similar. Starting with the previous baseline, three key steps are needed to initialise the next forecast. These are (i) incorporating new data and the short-term outlook, (ii) updating assumptions, (iii) and applying expert judgement when necessary.

5.1 Incorporation of short-term forecasts and supporting tools into baseline projections

In this section, we explore how NCBs integrate both short-term forecasts and information from satellite models into their baseline macroeconomic projections, highlighting common approaches and notable differences across countries.

To provide a detailed perspective, we distinguish between short-term forecasting models and other supporting models – both commonly referred to as satellite models – while highlighting the unique role of short-term tools in the projection process.

Short-term models, such as nowcasting tools, typically focus on key macroeconomic variables like Harmonised Index of Consumer Prices (HICP) inflation, GDP and sometimes labour market variables. These models rely on high-frequency data, which allows them to react to real-time developments. This means that short-term projections from satellite models can diverge from the main macroeconomic model's projections due to their more detailed and updated data inputs.

Medium-term models, by contrast, focus on longer-term trends and structural factors such as potential output, demographic trends and other variables that anchor the medium-term to long-term projections. In addition, projections from medium-term

models commonly reflect a theoretical coherence as opposed to purely data-driven dynamics. These models help assess the trajectory of the economy beyond immediate fluctuations, focusing on underlying factors rather than short-term volatility.

The main distinction between these two types of models is that short-term satellite models focus on real-time, high-frequency data, often leading to discrepancies with the main forecasting models. Conversely, medium-term satellite models that focus on long-term trends and theoretically derived behaviours align more closely with the main models' outputs over time.

Across most NCBs, satellite models are crucial in supporting the construction of baseline projections. There are two prevalent methods for integrating these satellite model results: (i) temporarily exogenising certain variables (making them externally determined for a period); and (ii) "add-factoring", where experts adjust the model's residuals (or innovations) to better reflect short-term conditions.

Countries that impose short-term projections by exogenising variables or assuming them as data: BE, CZ, DE, IE, ES, IT, CY, LT, AT, PT, RO, SI, SK, SE.

Countries that use add-factoring to adjust the model's residuals: CZ, DE, GR, FR, IT, LU, MT, NL, PL, PT, RO, SK, and the ECB.

Some countries (like CZ, DE, FR, HR, IT, PT, SK and FI[6]) use both methods, exogenising certain variables while also applying add-factoring for other adjustments.

5.2 Incorporation of forecast assumptions

Owing to the heterogeneity of the models employed in the forecasting exercises, the methods for incorporating specific forecast assumptions also vary across countries. In fact, each model has different conditioning assumptions. However, all euro area NCBs adopt shared assumptions as provided by the ECB. Below we group these assumptions into their main blocks.

Common forecast assumptions used in the Broad Macroeconomic Projection Exercise (BMPE) process: Commodity prices, exchange rates, world demand, competitors' prices, market expectations of euro area short-term and long-term interest rates.

Country/model-specific conditioning variables:

- Narrow Inflation Projection Exercise projections, i.e. near-term inflation projections (HICP and components);
- fiscal projections, including projections on government spending and tax rates;

[6] For instance, FI adopts both methods, but with a strong emphasis on the exogenising approach.

- labour market variables, i.e. employment, participation rates and sectoral trends;
- lending rate and loan volume projections;
- house prices;
- wage projections, including wage tracker models;
- demographic and labour market development, i.e. workforce and non-accelerating inflation rate of unemployment projections;
- potential output.

These assumptions usually constitute input into the models rather than being endogenously determined by the main macro model itself. The process of integrating forecasts and other external assumptions into the main macro models typically involves defining specific inputs from outside sources and either treating them as fully exogenous variables or adjusting the corresponding residuals, which allows for feedback loops. Survey responses indicate that the majority of countries make use of the exogenisation of variables (or groups of variables) to implement these assumptions, although other approaches are also present.

General approach to incorporating forecast assumptions

Exogenous variables: Common forecast assumptions like foreign demand, exchange rates, oil prices and interest rates are treated as exogenous variables. These assumptions are a fixed input into the models rather than being dynamically determined by the model itself.

Conditional forecasting algorithms: Some countries, mainly those relying on dynamic stochastic general equilibrium models, use conditional forecasting techniques to incorporate assumptions into their models.

Feedback mechanism: In some instances, the assumption variables also have feedback effects on themselves. This is often done for fiscal variables which are part of a conditional forecast algorithm that accounts for mutual feedback. For instance, Italy and Germany allow for such feedback loops where expert assumptions influence the projections iteratively.

Specialised inputs from experts: Several NCBs incorporate inputs from their internal experts using add-factoring, particularly when it comes to fiscal projections or specific domestic economic factors.

Special treatment: Certain assumptions, especially those relating to energy and food prices, are sometimes treated with a more specific approach. For instance, Latvia uses assumptions such as gas prices, oil prices and synthetic energy price indexes that are integrated into satellite models rather than the main model.

Starting date for incorporating forecast assumptions

Common practices for loading the first date of assumptions in macroeconomic models typically follow similar protocols across countries, but with some variations based on data availability, technical requirements and model design. The two most common practices are as follows.

- **Fixed starting quarter:** Many countries load assumptions from the first quarter of the forecast horizon (denoted as t+1, where t is the current quarter), ensuring that all external assumptions start affecting the projections from the same point. This approach is standard across several NCBs.
- **Same starting date for all assumptions:** Most NCBs apply the same starting date for all forecast assumptions, ensuring consistency in the treatment of variables across the different assumption blocks (e.g. fiscal, foreign demand).

5.3 Dealing with data quality: data revisions and missing data

The quality of statistical data is paramount to ensuring a reliable and coherent forecast process. The overall quality of European statistics is good, although smaller countries in particular often suffer from large data revisions. A common pain point faced by all countries is also the unavailability of some of the latest data points when producing a forecast. For instance, while national accounts data are usually published around 45 days after the end of the quarter, the more detailed sectoral breakdown only becomes available with a longer lag. This constitutes a ragged edge problem, whereby some missing information must be inferred based on the other indicators available. A specific example concerns disposable income and saving rate data, which, as part of the quarterly sector accounts, are not automatically updated when new data on private consumption and compensation to employees become available as part of the national account release. All NCBs have therefore developed tools and techniques to overcome these data issues. Some of the solutions are listed below.

- **Estimating missing data using external tools:** Some countries use an external tool to make a forecast for the missing quarter. This allows models to smooth the transition between historical data and projected data by estimating missing values for the most recent periods.
- **“Flipping” the model:** Some countries invert the model structure so that the missing observations are part of endogenous variables, while the rest of the model variables are given exogenously. The model is then simulated to create model-consistent values.
- **Splicing:** Several NCBs use a technique called splicing, whereby new data and assumptions are extended over the forecast horizon using the growth rates from the previous forecast. This ensures that assumptions about future trends

are smoothly integrated with existing data, minimising artificial breaks that could exert an unwanted impact on the forecast variables.

In summary, NCBs generally follow a structured approach where assumptions are loaded from the first quarter of the forecast horizon. They typically treat all assumption blocks in a consistent manner, though there are some variations in the application of techniques like flipping, splicing and other real-time adjustments as new data emerges.

5.4 Frequency of baseline projections

ESCB central banks follow a structured schedule for producing baseline macroeconomic projections, with variations in frequency and scope across countries.

All euro area countries participate in the BMPE rounds in June and December. These rounds represent the most comprehensive projections, incorporating the full range of macroeconomic variables, with detailed inputs from satellite models and cross-checking tools.

Beyond the BMPE rounds, many NCBs also produce interim projections to keep forecasts updated in line with new economic data or shocks. These interim projections generally occur twice a year, often in March and September, and are aligned with the ECB assumptions used for Macroeconomic Projection Exercise projections. The frequency and depth of interim projections vary.

Full interim projections: Some countries produce fully fledged interim projections that mirror the BMPE exercises. **Countries following this approach:** IE, GR, ES, FR, HR, IT, CY, LV, LT, MT, PT, SK and the ECB.

Mechanical updates: A more streamlined approach is employed by other NCBs, where only selected variables are updated mechanically[7] without a complete projection overhaul. **Countries employing this method:** BE, DE, AT, SI, FI.

Occasional or on-demand projections: Some NCBs only produce interim projections in response to significant economic shocks or changes in assumptions. These updates are not scheduled regularly but are triggered by external factors, such as economic crises or geopolitical events.

In some cases, countries do not produce formal interim projections but may rely on high-frequency updates or short-term tools (e.g. nowcasting models) to maintain a current view of economic conditions. In these instances, data are used for internal analysis or cross-checking but are not formalised into a published projection.

[7] Mechanical updates are sometimes affected by limited expert influence.

5.5 Frequency of model re-estimation

NCBs tend to re-estimate their main macro models at varying intervals depending on specific needs and circumstances. There are no strict rules for the frequency of re-estimation, and many NCBs re-estimate based on developments in the economy, model performance or when major revisions are required, such as changes in the reference year for national accounts. The typical intervals for re-estimation range from quarterly to every few years.

Frequent re-estimations (quarterly or annually): Some NCBs re-estimate their models regularly, either quarterly or annually, in response to the latest data or as part of a regular review process. This approach is followed by DE, HR, IT, LU, MT, PL and RO.

Ad hoc re-estimations: Several countries re-estimate their models on an as-needed basis, depending on model performance or new data. For example, BE, LV, AT, PT, SI and FI apply ad hoc re-estimation processes without fixed schedules.

Scheduled re-estimations (every two to three years): Many NCBs follow a scheduled cycle for re-estimation, typically every two to three years. This approach is followed by CZ, ES, CY, LT, NL SE and the ECB.

Longer intervals (more than four years): Some countries only re-estimate their models approximately every four to five years, or when significant structural changes occur. This is the case for GR, FR and SK, with smaller adjustments made more infrequently.

6 Reporting and incorporating judgement

As highlighted elsewhere in this report, a key objective of the Expert Group on the Model-based Assessment of Projections (EGMAP) is to develop tools and modelling approaches to better identify and measure the expert judgement embedded in baseline projections. By defining a protocol to report key aspects of the baseline projections, such as the impact of assumptions, the short-term forecast and expert judgement, this initiative seeks to enhance the transparency and credibility of Eurosystem/European Central Bank (ECB) staff projections. While many national central banks (NCBs) and the ECB already implement practices for identifying and reporting expert judgement, establishing a harmonised approach will further strengthen communication and ensure greater consistency across the Eurosystem. This section documents the current state of these practices, outlining the existing approaches and the challenges identified through the survey.

6.1 Main sources of judgement and incorporation approaches

The sources of judgement in baseline projections are typically various off-model inputs. Short-term models, often based on high-frequency data like industrial production, retail sales and other real-time economic indicators, play a vital role in ensuring timely updates. Narrow Inflation Project Exercise models, which focus on granular near-term inflation forecasts, are commonly used, providing detailed insights that are closely monitored by expert teams. Satellite models also offer specialised analysis in areas such as housing markets, public finances and labour market trends, supplying more granular sector-specific insights. Moreover, expert meetings are essential, with NCBs gathering valuable information from industry stakeholders, firms and specialised internal experts. Surveys, both general and focused (e.g. business sentiment, consumer confidence, lending standards), supplement the models with qualitative data. External data sources, such as international market developments, demographic changes and specialised sector reports, further enhance the understanding of current and anticipated economic conditions. These diverse inputs ensure that projections are comprehensive and adaptable to real-world developments not captured within the core models.

While there is no universally defined approach to “judgement”, the methods for incorporating off-model information into baseline projections are quite consistent across NCBs. These approaches are similar to those used for integrating short-term outlooks and satellite model insights. In the case of semi-structural models, two main techniques are employed: (i) residual adjustment or add-factoring, and (ii) (partial) exogenisation of certain variables. For dynamic stochastic general equilibrium models, judgement is often introduced as prior information on structural shocks or observations of key state variables.

6.2 Reporting judgement

When presenting baseline projections to key stakeholders, many NCBs include a breakdown that highlights the role of expert judgement embedded in the final forecast. Survey responses reveal diverse approaches to reporting this judgement. Some institutions routinely disclose the magnitude of judgemental adjustments, while others either refrain from reporting such measures or limit this information to internal use during the preparatory process.

Based on the survey responses, 11 countries (BE, CZ, GR, ES, FR, LV, AT, PT, SI, FI and the ECB) regularly report some form of judgement embedded in the baseline projections to their stakeholders.

Six countries (IE, HR, IT, NL, LV, LT) report judgement occasionally or only for selected variables or specific cases. For instance, some countries report judgement only on inflation components, labour market variables or during exceptional circumstances such as changes in fiscal policies or government measures.

Additionally, some countries (FR, IT) conduct post-mortem evaluations after final data become available to assess how judgement contributed to forecast errors.

The key considerations for measuring and reporting judgement across countries include the following.

- **Data revisions:** Several respondents highlight challenges in reporting judgement due to frequent and significant data revisions, which can affect the relevance or necessity of prior judgements.
- **Difficulty of distinguishing "judgement" from the overall forecasting process**, largely because no institution operates with a purely model-based forecast. In many cases, the judgement is inferred from the residual between the total revision and the impacts of assumptions and data (often referred to as "others").

The widespread use of the term "other" instead of "expert judgement" highlights a general reliance on this ambiguous categorisation to account for non-model-based inputs in the forecasting process. To an observer, the distinction may appear negligible or merely a matter of terminology. However, from a more rigorous modelling perspective, the difference is significant. The term "expert judgement" explicitly conveys that adjustments are informed by the expertise of skilled professionals, who base their decisions on knowledge of country-specific developments and insights from diverse sources. By contrast, "other" is a more ambiguous label that obscures the judgement component, making it less clear whether the changes are deliberate or incidental. This terminology is often used because, in practice, some baseline adjustments may stem from other factors, such as changes in model structure. Therefore, it is essential to develop clear, model-based indicators to differentiate these subtle nuances and further enhance the transparency of projections.

6.3 Breakdown of baseline revisions

Based on the survey responses, 18 countries have the capacity to produce a breakdown of baseline revisions into the impact of assumptions, data and other factors, which capture the residual and can be interpreted as (a broad form of) judgement. Among these NCBs, 13 countries regularly report this breakdown to their stakeholders, ensuring transparency regarding how the forecast evolves between exercises. These countries include BE, CZ, IE, ES, FR, LT, AT, PT, RO, SI, SK, FI and the ECB. This regular reporting includes detailed decomposition into key factors that shape the forecast revisions, which aids in explaining changes to policymakers and stakeholders.

Additionally, five countries (DE, HR, IT, LU and SK) use this breakdown as an internal cross-checking tool rather than for external reporting. In these cases, the breakdown helps ensure consistency in forecasting and supports internal discussions, especially when comparing forecast updates with previous iterations. This internal use highlights the role of the breakdown as a diagnostic tool, even if it is not yet fully formalised in external reporting frameworks for these countries.

The findings suggest that many countries are already equipped to provide a breakdown of forecast revisions into categories like data, assumptions and “other” (which can be interpreted as a proxy for expert judgement). This represents a significant opportunity for further harmonisation of reporting practices across countries. Establishing a standardised methodology, as proposed in a forthcoming paper by EGMAP, could streamline this process, ensuring consistency and transparency in how revisions are presented. This would enhance cross-country comparability and provide a clearer picture of how much of the forecast is influenced by specific inputs and expert judgement. Future work may then aim at distinguishing between different forms of “judgement” or, more precisely, of the sources of differences between the final projection numbers and the output of the standardised methodology.

7 “Quick wins” and areas for further development

The survey responses indicate significant diversity in the modelling toolkits used across national central banks, with their application in the forecasting process being fairly country-specific, reflecting the idiosyncratic economic characteristics of each economy. However, there are also shared practices and approaches that are largely consistent across countries, which present opportunities for further harmonisation. These areas of commonality could offer “quick wins” in the Broad Macroeconomic Projection Exercise process, potentially enhancing the credibility and transparency of baseline projections. The primary objective is to quantify, as much as possible, the extent to which baseline projections are influenced by three key factors: forecast assumptions, short-term outlook and expert judgement.

A structured and consistent framework for reporting the impact of assumptions, including both shared and country-specific elements, could help to streamline and harmonise modelling approaches across countries. In addition, the reporting of new data and short-term outlooks and their influence on medium-term projections could be developed further. The third component would involve measuring “expert judgement”, defined as deviations in the medium-term baseline projections from model-based forecasts, assuming consistent assumptions between the two.

Outlined below are the key steps and best practices that can be quickly implemented to improve the reporting and decomposition of baseline projections.

- **Common exogenous assumptions:** These include European Central Bank forecast assumptions such as commodity prices, exchange rates, world demand, competitors’ prices and euro area interest rates. These assumptions are already consistent across countries, making it relatively straightforward to harmonise their reporting.
- **Other exogenous variables (beyond the common forecast assumptions):** It is essential to identify the country-specific exogenous variables that influence forecast results, in addition to the common forecast assumptions. The reporting of the impact of these variables should be harmonised, where feasible, and reported under a unified category labelled “other assumptions” to ensure consistency and clarity in reporting across countries.
- **Standardised treatment:** A common starting date and methodology/transformation to incorporate these common assumptions into macroeconomic models could be proposed. This alignment could improve comparability and coherence in the forecasts.
- **Harmonised reporting framework:** A standardised framework for reporting the impact of assumptions and other exogenous variables could be developed. This framework should specify the methodology for incorporating these variables into

the models and ensure consistency in how their impacts are measured and reported.

- **Short-term outlook:** A common reporting framework for key variables such as GDP, the Harmonised Index of Consumer Prices and their components could be established. This should cover a harmonised reporting horizon but also consistent measurement of the impact that short-term outlooks exert on medium-term projections. This could be further enhanced by disentangling the nowcasts from the impact of the latest available data.

Areas for further development: model-based forecast indicators

- **Introduce model-based forecast indicators to cross-check baseline projections:** Develop a common protocol for producing ex post projection cross-checks, using for instance a projection update approach, whereby the previous forecast is updated using new data, assumptions and new short-term outlooks but keeps relevant model judgement elements unchanged with respect to the previous forecast exercise.
- **Establish a protocol/general guideline for creating "neutral" residuals in semi-structural models:** This approach would allow for the creation of a model-based forecast without incorporating the expert judgement embedded in the previous forecast round.
- **Develop new satellite tools to cross-check the baseline projections.**
- **Perform detailed fiscal block analysis:** Fiscal assumptions are crucial and often complex. Collecting more detailed information on the structure of fiscal components in main models, as well as on dedicated fiscal models, is essential. This analysis will help harmonise the treatment of fiscal assumptions across countries, improving consistency and comparability.

8 Projections in practice

This section provides an overview of how macroeconomic projections are conducted at selected national central banks (NCBs), focusing on the role of models in these processes. The boxes in this section highlight different approaches to forecasting, with examples from both large and small NCBs, as well as from institutions that use semi-structural models and those that rely on dynamic stochastic general equilibrium (DSGE) models. The selected cases include both euro area and non-euro area central banks, showcasing the diversity in practices.

Boxes 1 and 2 examine the projection processes at two of the largest euro area central banks: the Deutsche Bundesbank and the Banque de France. Both institutions use large semi-structural models as their core tools for macroeconomic forecasting. Boxes 3 and 4 shift the focus to smaller NCBs – the Banco de Portugal and Banka Slovenije – where semi-structural models are also central to their forecasting frameworks. Finally, Boxes 5 and 6 explore the practices of two central banks that use DSGE models as their core tools: Suomen Pankki – Finlands Bank and Česká národní banka. Notably, Česká národní banka operates outside the euro area and thus produces independent forecasts for its economy, rather than using the shared Eurosystem assumptions.

We conclude the overview with a description of how models are used during the projection exercises at the European Central Bank (ECB) (Box 7). Like many NCBs, the ECB relies on a large semi-structural model to develop its baseline projections and uses a set of satellite models to provide additional insights for the forecast. However, due to its unique institutional role, the ECB also employs a wide range of models to produce the common Eurosystem assumptions that all NCBs use in the Broad Macroeconomic Projection Exercise. Additionally, because the ECB follows a bottom-up approach – where the euro area aggregate is calculated from individual country forecasts – specific euro area models have been developed. These include both structural and semi-structural models, which are used to cross-check and validate the euro area projections.

The boxes offer a concise overview of the complex processes involved in macroeconomic forecasting, while emphasising the use of specific models. As discussed earlier in the report, the choice of models and tools varies across institutions to account for country-specific characteristics. Nevertheless, the cases also reveal a shared conceptual approach across NCBs. Key elements of this approach include the use of data and assumptions, short-term or nowcasting models to capture immediate economic developments, and core models for medium-term projections. Core models also help decompose the baseline forecasts, offering insights into underlying drivers and supporting the narrative of the projections.

It is important to note that the practices described in these boxes reflect the current state of forecasting as observed during the survey period. Forecasting models and processes are continually evolving to improve their accuracy and adapt to changing economic conditions. As such, this section serves as a “snapshot” of existing

approaches, while leaving room for future enhancements. For example, the Expert Group on the Model-based Assessment of Projections is working on a protocol for introducing model-based projection indicators, which could further refine the interpretation of projections. In this way, these boxes serve as a useful transition to the forthcoming document that will describe a harmonised approach for implementing the model-based projection updates at the ESCB.

Box 1

The Bundesbank's projection process underlying the Broad Macroeconomic Projection Exercise

Prepared by Thomas Haertel and Markus Kontny (both Deutsche Bundesbank)

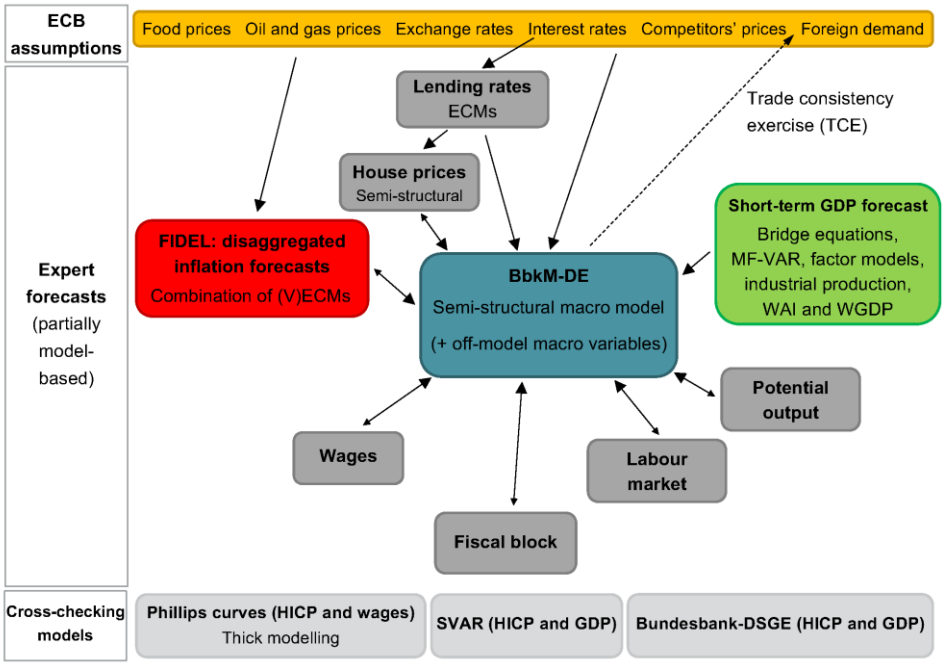
The Bundesbank's projection process underlying the Broad Macroeconomic Projection Exercise (BMPE) follows an iterative, bottom-up approach.[8] Chart A illustrates this procedure. Its bottom-up nature stems from the fact that the creation of the macroeconomic projection baseline includes several expert forecasts for different blocks of the economy. These parts comprise the real estate market in terms of house prices, the labour market and wages, potential output estimation and inflation as well as the fiscal sector. While the important financial market variables are part of the common assumptions of the Eurosystem (in the top row in Chart A), lending rate and loan volume forecasts are also provided by Bundesbank experts (in the monetary policy division).[9]

[8] See the table in Annex 10.2.1 for a list of references of Bundesbank models regularly used in the BMPE.

[9] Lending rates are also integrated into the projection process as shown in the chart. Loan volumes are forecast via a VAR model conditioned on the projected paths for some macro variables, such as real GDP and unemployment rate. However, in the forecasting process, there is no feedback from the projected credit volumes back to the other models. In the main macro model (see the next paragraph in the main text), credit market effects are captured via lending rates and bank lending survey credit standards, where the latter feature a model-endogenous feedback mechanism between the real and the financial sector.

Chart A

A bird's eye view of the Bundesbank projection process



Source: Deutsche Bundesbank.

The members of the Bundesbank forecasting team in charge of constructing the projection baseline ("coordinating forecasters") govern this process and interact with expert forecasters. For this purpose, the coordinating forecasters use the macro model (BbkM-DE), as it provides a common framework for bringing together expert forecasts and serves as a coordinating tool. This job involves handling a multitude of further variables, in particular core macro model variables (e.g. GDP, its subcomponents and deflators) not covered by the experts as well as off-model series that also serve as input for the experts. In some sense, the macro model delivers a consistency check of the set of expert forecasts. BbkM-DE has therefore been set up to reflect the experts' approaches, to the extent this is possible in a macro model setting. However, given the variety of models and tools used by experts, this is a challenging task and macro modellers have to compromise.

Experts' approaches range from typical single-equation to multidimensional time series models, while non-parametric procedures and specific tools such as sector-specific collective wage forecasts are also applied. For example, the latter make use of the comprehensive Bundesbank database of negotiated wages, while the potential output estimation accounts for cross-sectoral heterogeneity based on a sector-specific Solow growth decomposition. Furthermore, the inflation forecast builds on a disaggregated framework that models individual Harmonised Index of Consumer Prices (HICP) components separately to allow component-specific features to feed into the outlook. An error correction equation determined by a small semi-structural model of the housing market serves as a foundation for the house price projection. Last but not least, the Bundesbank's short-term GDP forecast is based on the outcome from a comprehensive model suite.

Given the amount of information used in the projection process, an iterative protocol is implemented that also provides sufficient feedback between the expert and the overall macro forecasts (indicated by the two-sided arrows in Chart A). Expert forecasts from satellite models and tools are incorporated sequentially into the macro model. Equation-specific residuals of BbkM-DE are used to condition on the respective expert forecast. This approach allows other model variables to react endogenously to changes in expert forecasts. The model is used to consolidate expert forecasts and to provide macro feedback to satellite models and experts. Its output helps the coordinating forecasters detect inconsistencies between individual projections and inform the experts, such that the overall projection converges towards a coherent picture over several iteration loops.

Cross-checking exercises are an integral part of the projection process, focusing mainly on the GDP and HICP outlook, but also on wage projections. The corresponding cross-checking models are a dynamic stochastic general equilibrium (DSGE) model and several structural vector autoregression (VAR) models. One way of cross-checking is to construct model-based structural decompositions of the baseline. These help uncover the implicit drivers of the economy's path over the projection horizon. The drivers' contributions can then be quantified and their relative importance illustrated. However, the decomposition is also used to evaluate the overall narrative of the projection through the lens of these models. Furthermore, the model-based forecasts from the cross-checking models can be confronted with the actual baseline. In addition, cross-checking also involves the use of single-equation models such as Phillips curves, for instance via a thick modelling approach. Furthermore, modified versions of BbkM-DE's wage equation serve as cross-checking tools for the projection of negotiated and effective wages.

The projection exercise is usually accompanied by further analyses, which help develop the conclusive narrative or assess potential risks to the baseline. One of the methods used in this context is to place and evaluate topic-related questions in the Bundesbank Online Panel, i.e. a survey among households (BOP-HH) and firms (BOP-F). In some cases, the corresponding results are incorporated into simulations with BbkM-DE.[10] BbkM-DE is regularly applied in the projection process for scenario and sensitivity analyses as a mandatory part of the Eurosystem-wide projection exercise but also for internal Bundesbank purposes.[11] Of course, other models from the forecasting toolbox also play an important role in analyses that complement the baseline projection.[12] Moreover, the uncovering of gaps in the toolbox due to new analytical questions raised can also lead to the development of new tools.[13]

To summarise, the Bundesbank's projection process underlying the BMPE is not a pure one-model-based forecast, simply run by pushing a button for one model. While BbkM-DE serves as a central coordinating tool, the projection process involves a lot of staff, information, tools and

10 See Deutsche Bundesbank (2021).

11 Some but not all of these analyses are published in the monthly report. The most recent examples were in the context of the COVID-19 pandemic and the war in Ukraine (see Deutsche Bundesbank, 2020a, 2020b, 2022b and 2022c)) and the US risk scenario (see Deutsche Bundesbank, 2024c). The basic model elasticities are also generated with BbkM-DE. Very recently, stochastic simulations with BbkM-DE were implemented to generate model-based density forecasts. However, BbkM-DE is also regularly used outside the projection process (see, for example, Deutsche Bundesbank, 2024a).

12 See, for example, Deutsche Bundesbank (2022a) for the estimated effects of selected government relief measures on consumer prices and the box entitled "Impact of permanently higher energy costs on German potential output".

13 An example is the Bundesbank's weekly activity index (WAI), which resulted from the need for higher-frequency monitoring methods during the COVID-19 pandemic.

coordination. The Bundesbank outlook for the German economy reflects the profound and comprehensive outcome of this process.

Box 2
The Banque de France's projection platform underlying the Broad Macroeconomic Projection Exercise and interim forecast exercises

Prepared by Pierre Aldama (Banque de France)

Macroeconomic projections at the Banque de France do not rely on a single macroeconomic model but rather on a suite of interacting models. Chart B illustrates the bank's macroeconomic projections platform underlying the Borad Macroeconomic Projection Exercise (BMPE). At the core of this forecasting platform is the bank's semi-structural quarterly macroeconomic model, FR-BDF (Lemoine et al., 2019). It is a large-scale semi-structural model with almost 590 endogenous variables and 470 exogenous variables.

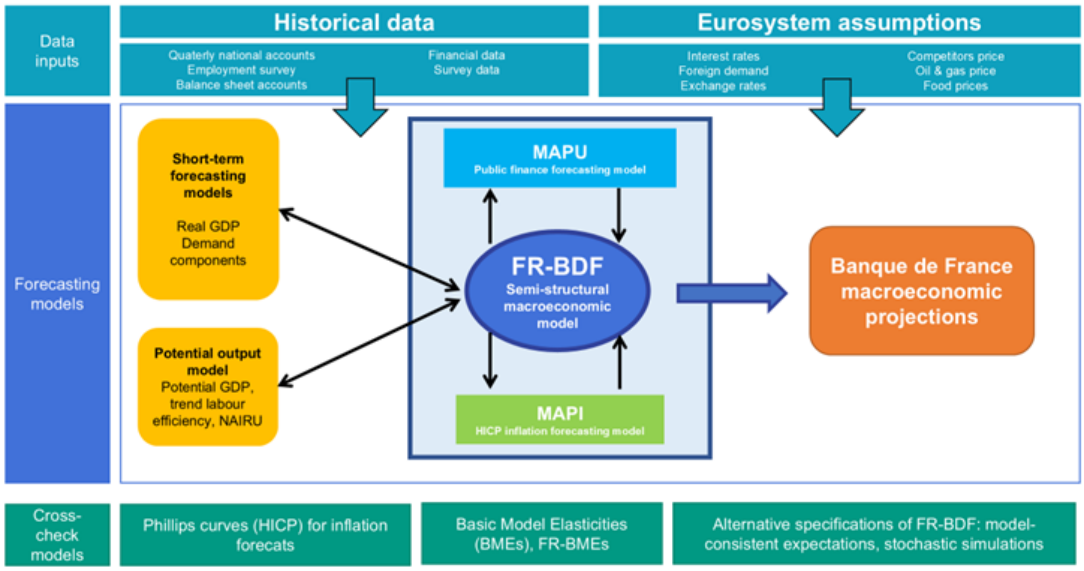
Three features of the FR-BDF model are particularly notable.

- First, agents' expectations play a central role in the model, shaped by the polynomial adjustment costs approach first introduced in the Federal Reserve System's FRB/US model. Agents' expectations can either be backward-looking, based on a small vector autoregression (VAR) model (E-SAT) or forward-looking, derived from the full macroeconomic model itself. In the context of forecasting, the Banque de France employs the VAR-based expectations version of FR-BDF, where agents form their expectations using the auxiliary VAR model E-SAT, conditional on information at time t or t-1. By contrast, the model-consistent expectations version assumes that agents know the future path of exogenous variables (or shocks) and form expectations accordingly, in line with the model. The latter version is primarily used for policy simulations or counterfactuals around the forecast.
- Second, FR-BDF has a rich financial block (Bove et al., 2020; Dees et al., 2022), with bank lending rates, bond rates and cost of equity playing a strong role.
- Third, the model features a detailed supply-side block, which accounts for potential output, further enhancing its analytical capabilities.

Macroeconomic forecasts produced by FR-BDF are frequently cross-checked using basic model elasticities (BMEs), and uncertainty around the forecasts can be evaluated using stochastic simulations of FR-BDF (Turunen et al., 2023).

Chart B

A bird's eye view of the Banque de France projection platform underlying the BMPE



Source: Banque de France.

Satellite and short-term models

FR-BDF interacts with two satellite models for public finance forecasts (MAPU) and inflation forecasts (MAPI). MAPU ("Maquette Agrégée des Finances Publiques") produces detailed forecasts of public finance variables using information from the annual budget bill and based on the FR-BDF macroeconomic projections. In contrast to FR-BDF, MAPU is modelled annually. Consistent with the Eurosystem forecasting framework, MAPI (Model for Analysis and Projection of Inflation; de Charsonville et al., 2017; Ulgazi and Vertier, 2022) produces detailed, disaggregated forecasts for Harmonised Index of Consumer Prices (HICP) components at different frequencies (monthly, quarterly) and different horizons in an integrated fashion. In the forecasting process, inflation forecasts are often cross-checked and benchmarked against reduced-form Phillips curve models.

These three models, FR-BDF, MAPU and MAPI, are at the core of the macroeconomic forecast and typically iterate several times during a forecast in order to converge. For example, when the inflation forecast is updated based on new external assumptions, the macroeconomic forecasters update their forecasts using FR-BDF by conditioning consumer price inflation (consumption deflator) on HICP inflation. Afterwards, the public finance division uses this as input to update its annual projection of public finance variables, which is then incorporated as exogenous variables into FR-BDF once converted from annual to quarterly frequency. This process is repeated until the three models converge.

The core macroeconomic model FR-BDF also interacts – though less directly – with two other types of model: a potential output model and a suite of short-term forecasting models. The potential output model produces projections for potential GDP, trend labour efficiency and equilibrium unemployment (non-accelerating inflation rate of unemployment, NAIRU). It employs a production function approach, unobserved component models and statistical filters. The

model uses inputs from the macroeconomic projections, such as unemployment rate, labour force and capital services. In return, FR-BDF integrates these variables as exogenous inputs into its macroeconomic projections, which can have substantial impacts on the forecasting horizon (see Aldama and Ouvrard, 2020).

For short-term forecasts, the Banque de France relies on a suite of models to produce GDP nowcasts, published monthly alongside its Monthly Business Survey (MBS). The first of these models is the Monthly Indicator of Business Activity (MIBA; Mogliani et al., 2017), which uses three bridge equations (one equation per month) and incorporates soft data from the MBS. A second model is a revised version of OPTIM ("Outil de Prévisions Trimestrielles à partir d'Indicateurs Trimestriels"; a previous version of the model is described in Barhoumi et al., 2008), a kind of augmented MIBA that includes additional soft and hard data on industrial production from the French National Institute of Statistics and Economic Studies.

Additionally, the Banque de France uses a re-estimated PRISME model (Thubin et al., 2016), a disaggregated model of added value in six sectors, which acts as a safeguard against aggregated models like MIBA and OPTIM. More recently, the Banque de France developed a mixed-frequency factor model (MF3PRF), which leverages a rich dataset of about 60 predictors, including hard and soft data, monetary and financial variables, prices, international variables and political uncertainty indicators.

Lastly, although not published, the Banque de France's short-term forecasting division also produces nowcasts for most GDP demand components, such as household consumption and investment, corporate investment, exports and imports. These forecasts, using both aggregated and disaggregated approaches, help condition the first quarter projections through residual adjustments by macroeconomic forecasters.

Banque de France interim projections

In March and September each year, the Banque de France publishes its interim projections based on the Eurosystem Macroeconomic Projection Exercise (MPE) assumptions. For several years, these projections were carried out in the same manner as BMPE exercises, which are described above.

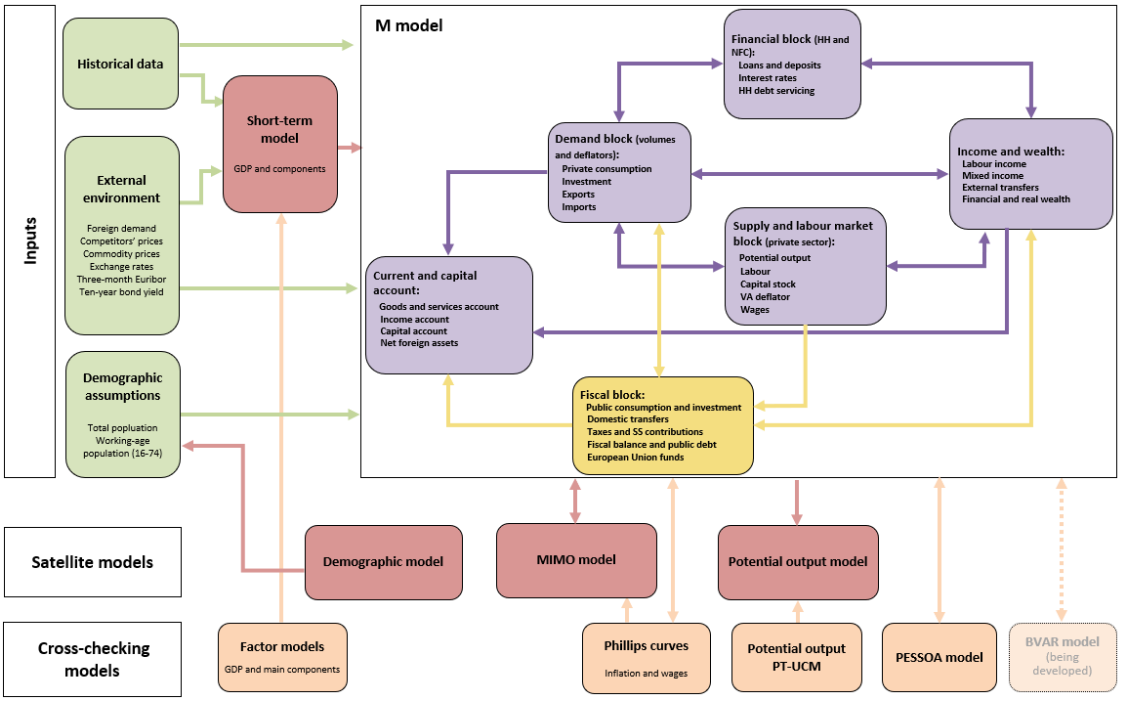
Since March 2024 the Banque de France has adopted a simplified forecasting platform for interim forecasts. These exercises are now conducted using the FR-BMEs model, a linearised version of FR-BDF focusing on a subset of macroeconomic variables (such as real GDP and its components, labour force, employment and unemployment rate, and main deflators). In essence, the approach updates the previous BMPE forecast by incorporating (i) new historical data (carry-over effects); (ii) shocks or revisions to technical and international assumptions (e.g. foreign demand, exchange rates, short-term and long-term interest rates, oil and gas prices); (iii) public finance shocks; and (iv) adjustments based on expert judgement for key macroeconomic variables. This streamlined method eliminates the interaction between FR-BMEs and the public finance model MAPU, as well as between the macroeconomic forecasts and the potential output model. However, inflation forecasts continue to be produced using MAPI, which interacts with FR-BMEs in a similar manner as FR-BDF. Short-term forecasts are also integrated into the macroeconomic forecast using add-ons (which are equivalent to residual adjustments). As a result, macroeconomic projections are largely simplified in this framework, but at the cost of being less detailed.

Box 3
The Banco de Portugal's projection approach – an overview

Prepared by Gabriela Castro and Ana Sequeira (both Banco de Portugal)

The projections at the Banco de Portugal rely on a set of models that are linked through the M model. Chart C illustrates the projection platform. The M model functions as the core model, centralising various inputs and generating the majority of the projection. It is a large-scale, semi-structural, backward-looking model, featuring behavioural equations with error correction mechanisms. The fundamental theoretical elements are standard and align with the European Central Bank's Area-Wide Model. The M model is composed of several interconnected blocks – demand, supply, income and wealth, financial, current account and fiscal – ensuring full consistency across them.[14] This model is used not only to produce baseline quarterly projections, but also to construct alternative scenarios and assess economic policies.

Chart C
The Banco de Portugal's projection platform



Source: Banco de Portugal.

[14] Although integrated into the M model, the fiscal block is managed by the experts from the fiscal unit, who are part of the Working Group on Public Finance (WGPF).

The M model is complemented by satellite models that add layers of detail and broader coverage to the projection. The short-term model covers the expenditure components of GDP in greater detail and is used to project the current and following quarters. This model consists of a set of bridge equations built on a large monthly dataset of conjunctural indicators, further extended with ARIMA models.[15] The demographic model – which incorporates the latest information available on vital statistics and migration flow, ensuring full consistency between flows and stocks – provides updated projections for the total population and the working-age population. In turn, the MIMO model is employed to forecast monthly HICP subcomponents over the entire projection horizon. It relies on a set of equations with error correction mechanisms for market-based prices, alongside simple rules, and public information for administered and quasi-administered prices. The potential output estimates are produced using a satellite model based on a Cobb-Douglas production function. This model takes on board a set of actual variables consistent with the M model projections and produces trend estimates based on filtering techniques.

The platform also incorporates cross-checking models to evaluate the robustness of the projections. The short-term projections are validated using factor models, while a set of Phillips curves is used to validate inflation and wage projections over the entire horizon. The potential output estimates are compared against the results of an unobserved components model specifically tailored to the Portuguese economy. Lastly, the macroeconomic projections are also assessed through the lens of a structural model for the Portuguese economy, known as the PESSOA model. This model helps to build a narrative around the projection and is also used for specific scenario analyses.

Operationally, the projection exercises follow a sequential, iterative and complementary process, ensuring a reliable and accurate outcome. Chart D illustrates the main steps of a typical forecasting round. The process starts from the previous baseline, with an update of the historical data, external assumptions and short-term outlook. The M model is simulated conditioned on this updated information and keeping the residuals from the previous round unchanged. The results – particularly the quarter-on-quarter rates of change and the revisions compared with the previous round – are then evaluated in the context of the current narrative. The residuals are adjusted to ensure consistency and validity. Following this, the inflation projection is generated using inputs from the M model (unit labour costs and import deflators). An iterative process then takes place, where both the M and the MIMO models are repeatedly run until their projections converge.[16] This step is crucial for ensuring full consistency within the projection. The final step involves running the potential output model. The resulting projection is then discussed with a broader team of experts, allowing for further refinement, which may lead to an additional forecasting round. The Banco de Portugal publishes these macroeconomic projections quarterly, in March, June (BMPE), October and December (BMPE).

Judgement plays a crucial role in each round, ensuring that the projections are both plausible and consistent with the narrative. Judgement is typically applied to short-term projections to address unexpected changes in observed data or include information not captured by the model (such as production halts in large firms). Additionally, it may be used to adjust revisions over the projection horizon or to incorporate insights from the cross-checking models. A breakdown

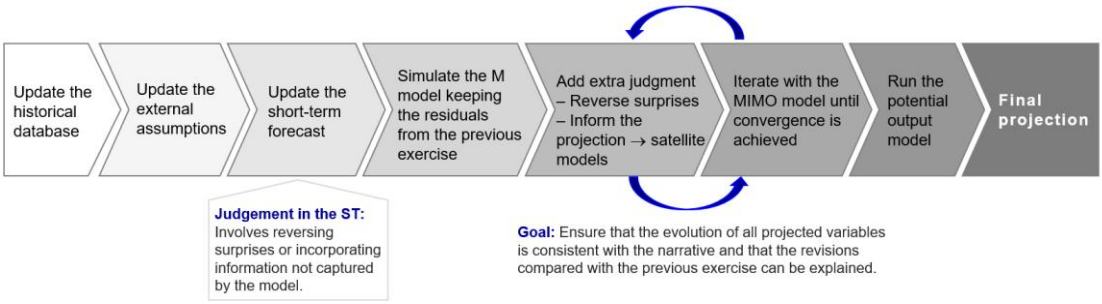
[15] This dataset includes both soft and hard data, with most indicators published by traditional sources (e.g. confidence indicators, trade data, retail sales). Additionally, it includes data from sectoral associations or firms, such as car sales, cement sales and ATM transactions.

[16] The forecast for headline inflation is loaded into the M model, and the path for private consumption deflator growth is adjusted accordingly.

of the projection revisions for GDP growth and inflation is often reported, at least internally. This breakdown typically includes the impact of (i) updates to external assumptions, (ii) statistical carry-over from revisions to historical data, (iii) updates to the short-term outlook, (iv) new fiscal measures (if applicable) and (v) remaining adjustments, which are usually attributed to judgement.

Chart D

The projection process – a roadmap



Source: Banco de Portugal.

Box 4

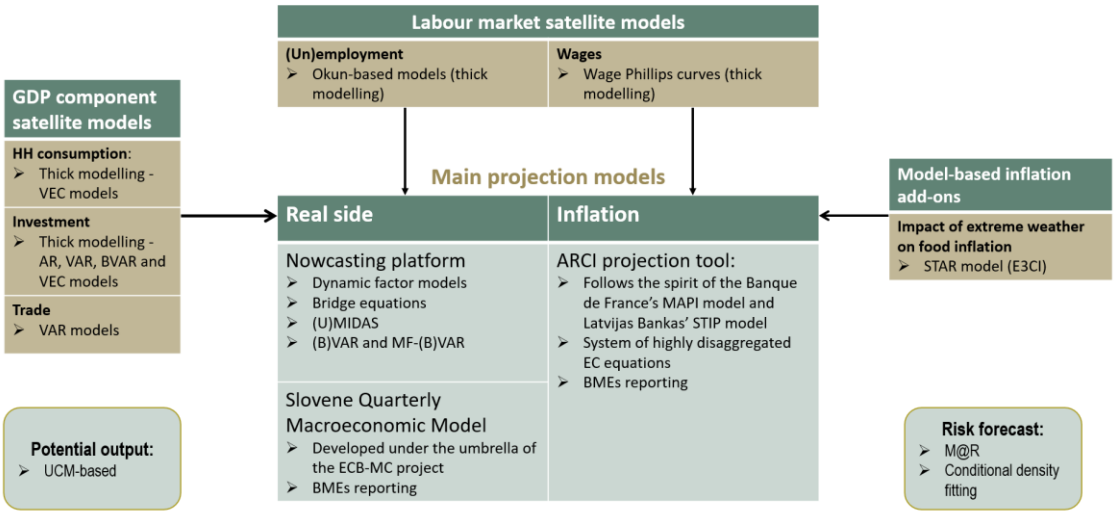
Projection process at Banka Slovenije

Prepared by Milan Damjanović (Banka Slovenije)

To strike a balance between prediction accuracy and credible storytelling, the projection process at Banka Slovenije relies on a suite-of-models approach (Chart E). The core of the projection infrastructure is tied to a three-part modelling apparatus consisting of a nowcasting GDP platform, a large semi-structural macroeconomic model (SiQM) and an inflation projection model (ARCI). The nowcasting platform integrates various short-term forecasting models, including dynamic factor models, bridge equation models, mixed data sampling regression models and mixed-frequency (Bayesian) vector autoregression (VAR) models (see Radovan, 2017 and Caka, 2020). The Slovene Quarterly Macroeconomic Model (SiQM; Damjanović, 2023) represents the country version of ECB-BASE (Angelini et al., 2019). The model generates the basic model elasticities associated with the Broad Macroeconomic Projection Exercise (BMPE) process, enables a technical breakdown of projections, and supports scenario analyses. The inflation projections are generated using the inflation projection tool ARCI, which belongs to the same class of models as the Banque de France's MAPI model (Ulgazi and Vertier, 2022) and Latvijas Bankas' STIP model (Bessonovs and Krasnopjorovs, 2020). These types of model relate to a system of error correction equations for highly disaggregated Harmonised Index of Consumer Prices components.

Chart E

A bird's eye view of Banka Slovenije's modelling infrastructure



Source: Banka Slovenije.

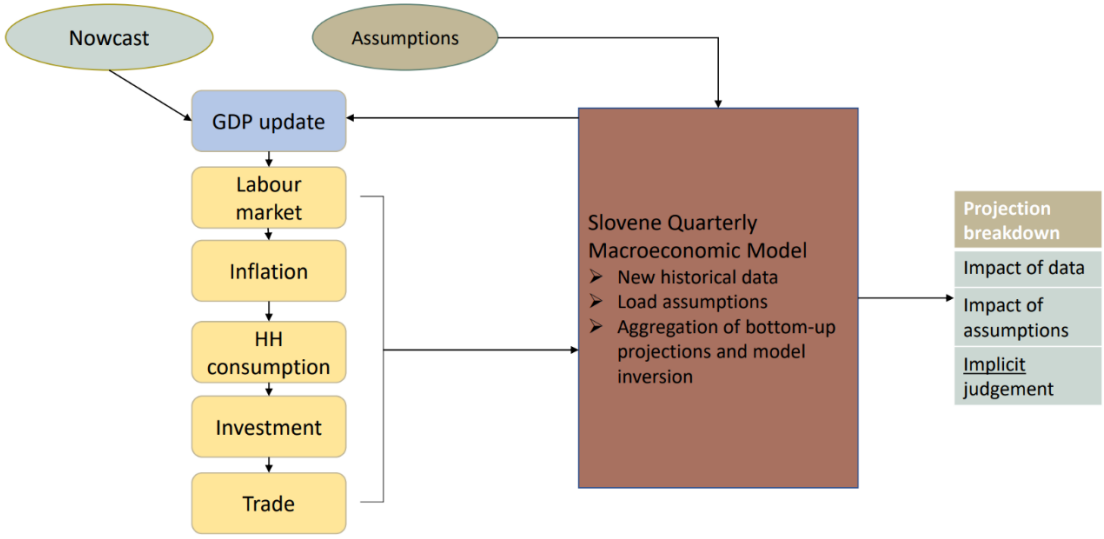
The core projection models interact with satellite models related to specific reporting variables within the BMPE process. For GDP expenditure components, the thick modelling approach is adopted, comprising various small-scale time series models (vector error correction (VEC), (B)VAR or autoregression (AR) models). Similarly, for the purpose of labour market projections, the thick modelling spans reduced-form single equations inspired by theoretical underpinnings, such as Okun's law for employment projections and wage Phillips curves used for projections of compensation per employee and labour costs. While the thick modelling framework yields benefits in terms of empirical fit and prediction power, the low dimensionality of the specific models included implies significant gaps in terms of building a forecast narrative from the perspective of specific transmission channels, theoretical coherence and general equilibrium projection assessment. In addition to the core and satellite models, the main projection infrastructure is complemented by an unobserved components model (Radovan, 2020) used for evaluating long-term structural trends, macro-at-risk models used for sensitivity analysis in line with Figueres and Jarocinski (2020) and ad hoc models used for informing judgement and closing specific analytical gaps. Such an ad hoc model was recently used to evaluate the effect of extreme weather events on food inflation in Slovenia (see Kovač, 2024).

The projection process at Banka Slovenije relies on a bottom-up iterative approach. The process is initiated with the production of the initial GDP profile, which updates the previous baseline with the nowcast estimate of GDP growth for two additional quarters and a medium-term evaluation of technical assumptions using the main macro model SiQM. The updated GDP profile is then incorporated into the sequential evaluation of satellite models. In particular, the revised GDP is used to update employment and unemployment projections via Okun's law equations, which are then used to produce new wage and cost-of-labour projections. The updated GDP and labour market projections are then embedded into the ARCI projection tool to produce a new inflation forecast. Finally, revised GDP, labour and inflation projections, alongside technical assumptions, enter satellite models related to GDP expenditure components. The bottom-up projections are in a

model-consistent way aggregated within an auxiliary aggregating model, comprised of observed and calibrated identities.

Chart F

The interplay of models within the bottom-up projection process



Source: Banka Slovenije.

The narrative surrounding the projections importantly relies on the technical breakdown of forecast revisions and the evaluation of risk scenarios. Upon convergence, final projections are read into the main macro model (SiQM), which is then used in several ways to support the construction of the narrative behind the projections. First, the revision of projections between respective BMPE rounds is communicated in terms of a technical breakdown of the impact of data, impact of assumptions and the model-implied judgement. It should be noted that the latter relates to the difference between the actual forecast and the model-based evaluation of the conditional (new data and technical assumptions) and therefore lacks an explicit and stand-alone interpretation. It can nevertheless offer guidance on the magnitude of the add-on beyond the model evaluation and helps identify potential gaps in the overall narrative. Second, the main macro model is a useful tool for evaluating risk scenarios, which in the presence of large shocks in recent years has provided an important augmentation of the baseline projection narrative. For example, practical cases for such model use can be found in the evaluation of the macroeconomic impact of the Russian invasion of Ukraine[17] and Slovenia's sustained inflation differential.[18] Finally, the main macroeconomic model has been used to derive counterfactual analysis related to normative policy questions[19] and to provide conditional densities surrounding specific variables of interest.

17 See Section 3 of Banka Slovenije (2022), "Review of macroeconomic developments with projections", December.

18 See Section 3 of Banka Slovenije (2023), "Review of macroeconomic developments with projections", June.

19 An example of such an exercise in times of heightened inflation risks was to find a wage growth path that would violate the monetary policy price stability objective (see Damjanović, 2023, p. 31).

Box 5
Using the Aino model and satellite models for forecasting at Suomen Pankki – Finlands Bank

Prepared by Mikko Sariola and Hannu Viertola (both Suomen Pankki – Finlands Bank)

Suomen Pankki – Finlands Bank employs a sophisticated approach to economic forecasting, utilising both its core Aino dynamic stochastic general equilibrium (DSGE) model and various satellite models. The Aino model (Kilponen et al., 2016) is central to the forecasting process, providing a comprehensive framework that integrates various aspects of the economy. This box outlines the use of the Aino model, the complementary satellite models and the procedures involved in generating accurate forecasts, which ensure a high level of consistency in the numbers and narrative.

The core Aino DSGE model

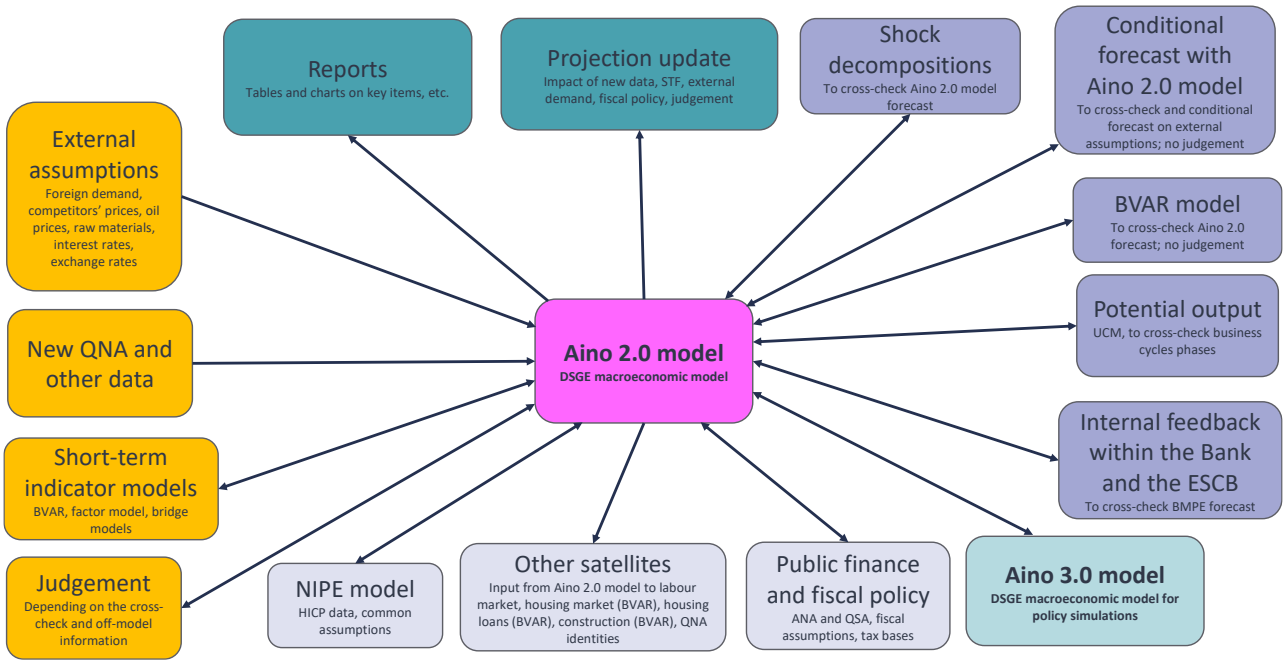
The Aino model, a New Keynesian, small open economy DSGE model, is a critical tool for Suomen Pankki – Finlands Bank. It is similar to models used by several other central banks, such as the Ramses model of Sveriges Riksbank and the New Area-Wide Model of the European Central Bank (ECB). Recently the Aino model was updated to use input data in log levels rather than data in detrended quarter-over-quarter growth rates, improving its forecast performance and enabling more accurate cyclical analysis. The model is periodically re-estimated using full-information Bayesian methods.

The model incorporates monopolistic competition, featuring intermediate goods production, importers and exporters. It accounts for nominal rigidities in the pricing of domestic intermediate goods, export and import goods, wages and lending rates. The banking sector is also characterised by monopolistic competition and an incomplete although relatively fast pass-through of short-term interest rates to bank lending rates. Banks are subject to binding capital requirements. Additionally, the model features adjustment costs for both physical investments and bank capital. It also includes various structural shocks, such as productivity shocks, mark-up shocks and monetary policy shocks. The rest of the world is assumed to be fully exogenous from the perspective of the domestic economy, including euro area monetary policy.

The forecasting process with the Aino model involves several steps. First, new quarterly national accounts data are incorporated into the previous forecast. Then, short-term forecasts for the current and next quarters are generated using indicator models and high-frequency data. New assumptions from the ECB that affect foreign variables are introduced, creating conditional forecasts. Expert judgement with off-model information is added to improve the forecast. Shock decompositions are used to analyse the driving factors of the forecast. They serve as an important tool to cross-check the forecast coherency and narrative and are used iteratively to fine-tune the forecast. This process is iterated with the public sector forecast platform in order to take account of the macro outlook in public finances and, in turn, its feedback to the Aino 2.0 economy. Finally, the forecasts are documented and presented.

Chart G

Suomen Pankki – Finlands Bank forecasting hub: the core Aino model and integrated elements



Source: Suomen Pankki – Finlands Bank.
Note: The Aino 2.0 DSGE model is at the core of the Suomen Pankki – Finlands Bank forecasting process and serves as a central hub for integrating various elements.

Projection update

To understand how and why a forecast has changed from the previous forecast, it is essential to examine the different components involved in the projection update process. These components are data, nowcasting, external assumptions and judgement, each playing a pivotal role in shaping the final forecast (Table A).

Table A

Example of disaggregation of the GDP projection update

COMPARISON WITH PREVIOUS FORECAST (June 2024 BMPE)

	2022	2023	2024	2025	2026
New data	0.0	-0.2	0.1	0.1	0.0
New short term (t+1, t+2)	0.0	0.0	-0.1	-0.2	0.0
New external assumptions	0.0	0.0	0.0	0.0	0.1
Judgement	0.0	0.0	0.0	0.0	0.0
GDP (Sep 2024 Suomen Pankki – Finlands Bank interim)	**1.3**	**-1.2**	**-0.5**	**1.1**	**1.8**
GDP (June 2024 BMPE)	1.3	-1.0	-0.5	1.2	1.7

Source: Suomen Pankki – Finlands Bank.
Notes: The table shows an example from the Suomen Pankki – Finlands Bank September 2024 interim forecast, illustrating how a GDP forecast changed from the previous forecast. In the upper section of the table: difference in GDP growth rate in percentage points. In the lower section of the table: growth rates in percent. External assumptions took effect from the fourth quarter of 2024.

The first component is new data, which involves the incorporation of new quarterly national accounts data, released after the previous forecast, into the existing forecast. This step ensures that the most recent and accurate information is used as the foundation for the forecast. Data updates provide real-time insights into economic trends and enable the model to adjust its predictions accordingly. By continuously integrating fresh data, the model remains responsive to the latest developments in the economy.

Nowcasting models are used to assess short-term economic conditions and generate forecasts for the current and next quarters. These models, including Bayesian vector autoregression (BVAR)[20] and factor-augmented vector autoregression (FAVAR) models, rely on high-frequency data to produce real-time predictions of quarter-on-quarter GDP growth. With these nowcasts, Suomen Pankki – Finlands Bank can capture immediate economic signals and refine its forecasts with greater accuracy.

Common external assumptions from the ECB also play a crucial role in the forecasting process. These assumptions encompass various foreign variables that influence the domestic economy. By incorporating these external factors, the model can create conditional forecasts that account for international influences. The breakdown of external assumptions' impacts on the real economy and on inflation are reported and analysed as soon as new assumptions become available. This step ensures that the forecasts are not solely based on domestic data but also consider the broader global economic context.

Finally, expert judgement is a vital component that adds a layer of refinement to the forecasts. Off-model information, such as sector-specific insights, internal discussions, peer review scrutiny and analysis using shock decompositions, are integrated into the model to enhance its accuracy (Chart H). This step allows for the incorporation of qualitative factors that may not be captured by the quantitative models alone. The iterative process of adding expert judgement and

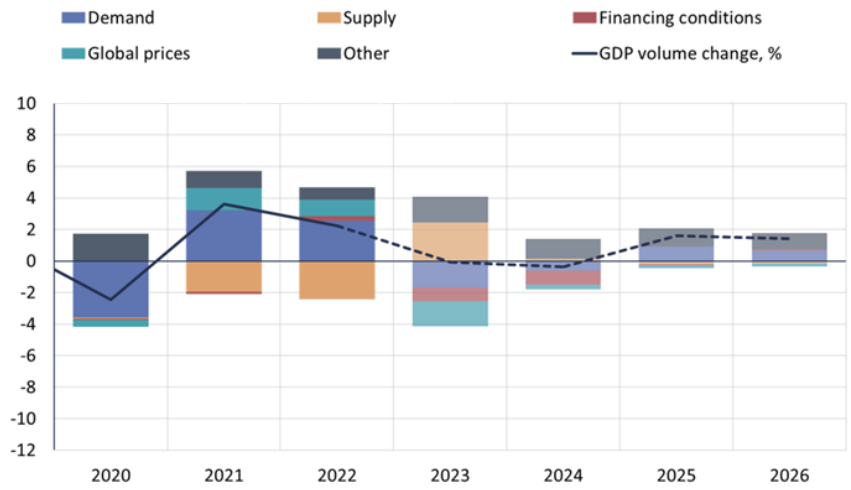
[20] See Itkonen and Juvonen (2017). The real-time model forecast can be accessed here.

off-model information continues until the forecasts are deemed to have reached a satisfactory level of consistency.

The final shock contributions produced with the Aino model incorporate the observed data, assumptions and judgement. They help to explain the economic developments and the narrative of the forecast, also in quantitative terms.

Chart H
Finnish GDP growth and the structural shocks driving growth through the lens of the Aino model (December 2023 BMPE)

(impact on annual GDP growth in percentage points)



Source: Suomen Pankki – Finlands Bank.
Notes: The chart shows GDP growth per capita at basic prices, broken down into shares that are explained by the different structural shocks used in the Suomen Pankki – Finlands Bank Aino 2.0 model. The shock contributions are formed in the following manner: demand includes domestic and foreign demand shocks; supply includes productivity and markup shocks; financing conditions include interest rates and exchange rates; global prices include energy and other commodity prices and export prices of Finland's competitors; other includes the model's trend rate of growth and random variation.

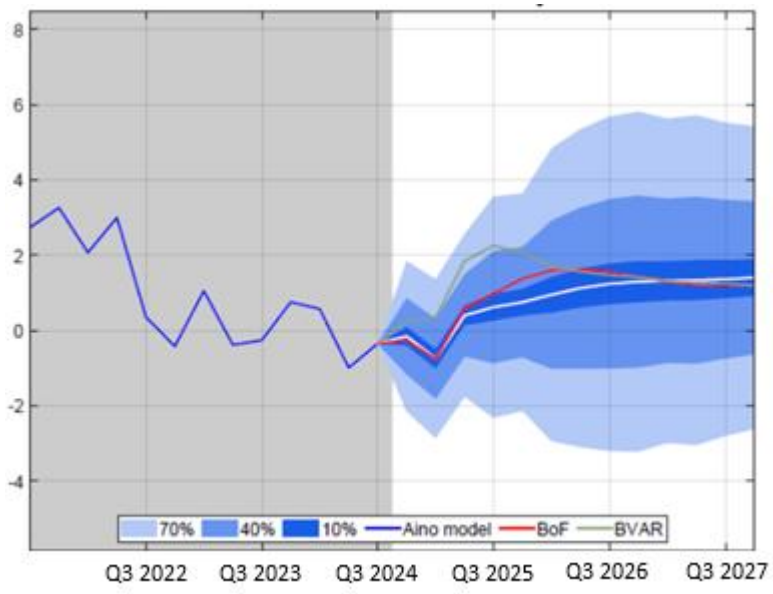
Conditional model forecasts

An essential aspect of the forecasting process at Suomen Pankki – Finlands Bank involves the creation of conditional model forecasts for all key macroeconomic variables. These forecasts are visualised using fan charts that display the range of potential outcomes, calculated based on forecast root mean squared errors. The fan charts serve as a visual tool to assess the uncertainty surrounding the forecasts, providing a clear depiction of the possible scenarios that could unfold (Chart I).

Chart I

Cross-check of the baseline forecast against conditional model forecasts

(year-on-year percentage change)



Source: Suomen Pankki – Finlands Bank.
Notes: The blue line and uncertainty bands represent a conditional DSGE model forecast of private consumption growth (y-o-y, percentage), produced with the Aino model. The red line is the baseline forecast, which includes expert judgement. The green line is a conditional BVARX forecast.

Conditional model forecasts are a useful tool for cross-checking the baseline forecasts. Unlike the main projections, these forecasts do not incorporate any expert judgement and are purely model-based. This contrasts with projection updates, which take into account how the changes in assumptions since the previous forecast affect the projections. The conditional forecast approach helps to highlight how external assumptions influence the forecast without the past cumulated judgement.

Satellite models and short-term assessment with nowcasting models

To enhance the robustness of the forecasts, the Aino model is complemented by various satellite models that provide additional insights into specific areas of the economy. These satellite models include models for inflation forecasts using the Harmonised Index of Consumer Prices and models for labour market variables such as unemployment and employment. The fiscal balance is projected by using the forecasting platform for fiscal variables based on sectoral tables of national accounts, taking into account discretionary fiscal policy measures and accounting for automatic stabilisers as well as changes in tax bases generated by the Aino model. Furthermore, the impact of discretionary fiscal policy on the macro economy is assessed using the Aino 2.0 model.

Other key satellite models include a shadow forecast that utilises a large BVARX model to cross-check the general macroeconomic outlook and a potential output model (Sariola, 2019**) as well.** The potential output model helps in forming a consistent view of the supply side of the economy and determining the phase of the business cycle as well as available slack in the economy in terms of the output gap and the unemployment gap. Other important satellite models

include a model for household loans (Nyholm and Silvo, 2022) and conditional BVAR forecasts for the housing sector.

In addition, the Suomen Pankki – Finlands Bank model toolkit also includes Aino 3.0, the latest vintage in the Aino DSGE model family that is used for scenario and policy analysis (Silvo and Verona, 2020**).** The Aino 3.0 model closely follows the structure of the Aino 2.0 model. It incorporates two-agent household heterogeneity, a housing market, a housing construction sector and long-term adjustable-rate mortgages into the Aino model framework. It aims to capture the most relevant macro-financial linkages in the Finnish economy and provides a rich laboratory for the analysis of various macroeconomic scenarios and policies.

Finally, Suomen Pankki – Finlands Bank also employs nowcasting models to assess short-term economic conditions. These models include BVAR, FAVAR and bridge models. For instance, the BVAR model, specified in log levels and incorporating over 40 variables, helps to make real-time predictions of GDP growth (Itkonen and Juvonen, 2017).

Conclusion

The Suomen Pankki – Finlands Bank forecasting process is thorough and multifaceted, involving the core Aino 2.0 DSGE model and a host of satellite models that enhance the overall accuracy, consistency and reliability of the forecasts. The structured procedures and the integration of various data inputs and expert judgements ensure that the forecasts are robust and reflective of the current economic conditions and off-model information. The use of fan charts and conditional model forecasts further bolsters the forecasting process, providing comprehensive cross-checks and a more nuanced view of the potential economic outcomes. Finally, internal discussions within Suomen Pankki – Finlands Bank and the European System of Central Banks complement the expert judgement and improve the accuracy and consistency of the forecasts.

Box 6
Forecast process at Česká národní banka[21]

Prepared by František Brázdik (Česká národní banka)

Monetary policy at Česká národní banka operates within an inflation-targeting framework, relying heavily on macroeconomic forecasts. Adjustments of the short-term interest rate are the primary monetary policy instrument used by the central bank. However, in certain periods the exchange rate **may be** also employed. The bank's board meets eight times a year to discuss and decide on monetary policy issues, ensuring the alignment of its strategies with bank objectives.

The Česká národní banka framework builds on the premise that decisions made by the bank's board today will most significantly affect inflation 12-18 months in the future. This forward-looking perspective is crucial for maintaining economic stability and achieving the inflation targets set by the bank. Thus, macroeconomic forecasts that incorporate an endogenous trajectory of interest rates are important for making informed policy decisions.

[21] The Česká národní banka monetary policy analytical and modelling framework recently underwent an external review (https://www.cnb.cz/en/monetary-policy/external-review-of-the-CNBs-monetary-policy-analytical-and-modelling-framework/).

The comprehensive ecosystem of tools and processes used to achieve these goals is known as the Forecasting and Policy Analysis System (FPAS).[22] This system is centred on a core forecasting model of the New Keynesian dynamic stochastic general equilibrium type, known as g3+23.[24]

In addition to the core model, a wide array of supplementary modelling tools is employed at the bank to refine forecasts and policy analyses further. These include sector-specific models that focus on the real economy, labour market dynamics and structural components of the foreign economy.

Chart J provides an overview of the FPAS. The FPAS process is initiated by setting conditioning assumptions for both foreign and domestic economies. These assumptions are processed using near-term forecasting tools that provide a detailed analysis of various economic sectors. The tools focus on key areas such as the real economy (supply and demand, trend cycle and fiscal issues), the labour market (unemployment, wage growth) and the structural foreign economy block (evaluating external demand, trade dynamics and international economic conditions).

Econometric and data-based methods are employed for the backcast, nowcast and near-term forecasts. These methods are crucial for assembling the majority of data inputs required by the core model and span multiple sectors of the economy to provide an aggregate view. They also utilise various assumptions for the foreign economy (foreign demand and policy stance, commodity prices), assumptions for fiscal developments and other assumptions such as the administered prices outlook.

This set of domestic and foreign trajectories is adopted to condition the medium-term forecast over various horizons. In this phase we also preserve the endogeneity of the policy rate trajectory, meaning for variables such as inflation and exchange rates the conditioning is only applied in the first forecast quarter to maintain the model's endogenous response. However, for variables like administered prices and the outlook for foreign variables, econometric methods and satellite models provide trajectories for the entire forecasting horizon.

The final step in the forecasting process is to integrate the projection into the staff forecast. This step involves feeding back the medium-term forecast into the near-term models and various satellite models to obtain forecasts for areas not directly covered by the core model. It also serves as a consistency check for the forecast story, where central trajectories are scrutinised from the perspective of different modelling approaches.

In addition to the baseline forecast scenario, Česká národní banka conducts regular forecasting exercises to develop additional scenarios that serve specific purposes. These include the following.

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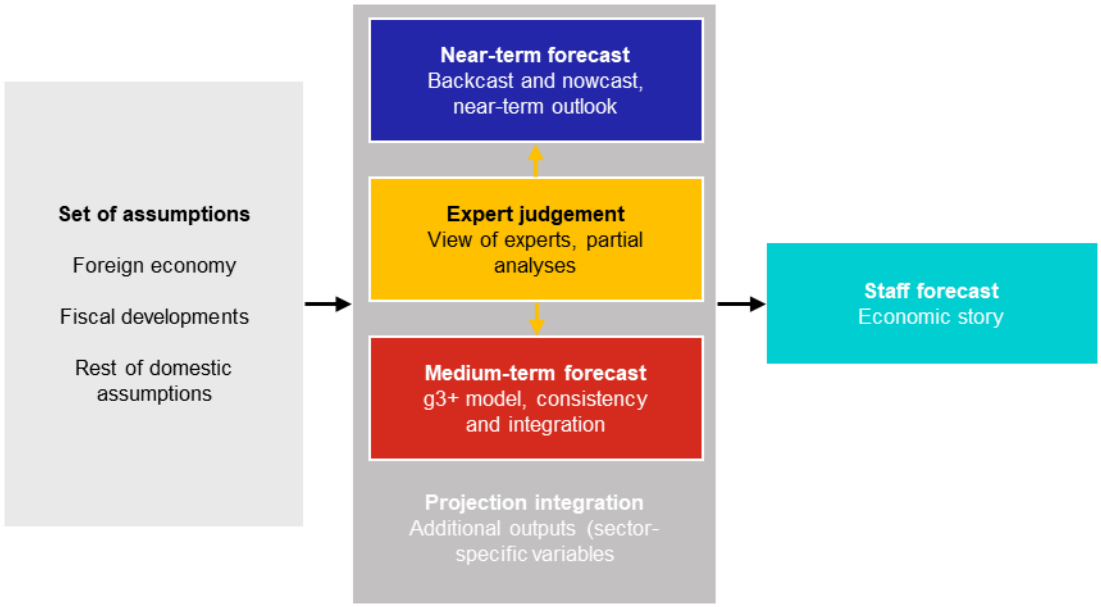
22 For a detailed description, see Česká národní banka (2024), "CNB's Forecasting and Policy Analyses System: Forecasting Tools", October.

23 "g3" signifies the third generation of models, and "+" indicates updates and enhancements that have been made to improve forecasting accuracy and adaptability to changing economic conditions.

24 See Andrle et al. (2009) and Brázdik et al. (2020).

- Alternative scenarios: These scenarios are based on different sets of conditioning assumptions (trajectories) and result in comprehensive forecasts, including integration steps. Examples include a slowdown in foreign demand, geopolitical events like Brexit, a halt in energy commodity supplies from Russia to the EU and a change in monetary policy strategy, such as the exchange rate commitment.
- Sensitivity scenarios: Designed to capture the sensitivity of the baseline scenario to specific macroeconomic aspects. Such scenarios may arise from assumptions differing from the baseline, such as a different setting of the near-term foreign exchange rate in the first quarter of the forecast or the evaluation of features not explicitly present in the model structure, such as uncertainty about changes in consumer spending behaviour.
- Monetary policy scenarios: These scenarios stem from the baseline scenario but involve additional assumptions regarding domestic monetary conditions, typically concerning the path of domestic nominal interest rates. The scenarios may include keeping interest rates fixed or simulating alternative monetary policy paths to assess their potential impact on the economy.

Chart J
Forecast flow at Česká národní banka



Source: Česká národní banka.

Analysis of interest rate trajectory changes

The standard method for presenting updated interest rate trajectories in the regular forecasting exercise involves comparing the current forecast with the previous one. With a particular focus on the domestic nominal interest rate path and by analysing the contribution of predefined pieces of information, we can determine the elements leading to changes in the projected interest rate trajectory. This comparison helps to identify the changes in economic conditions (data) and assumptions (outlooks, expert judgement) that influence the projected path of interest rates, as presented in Chart K.

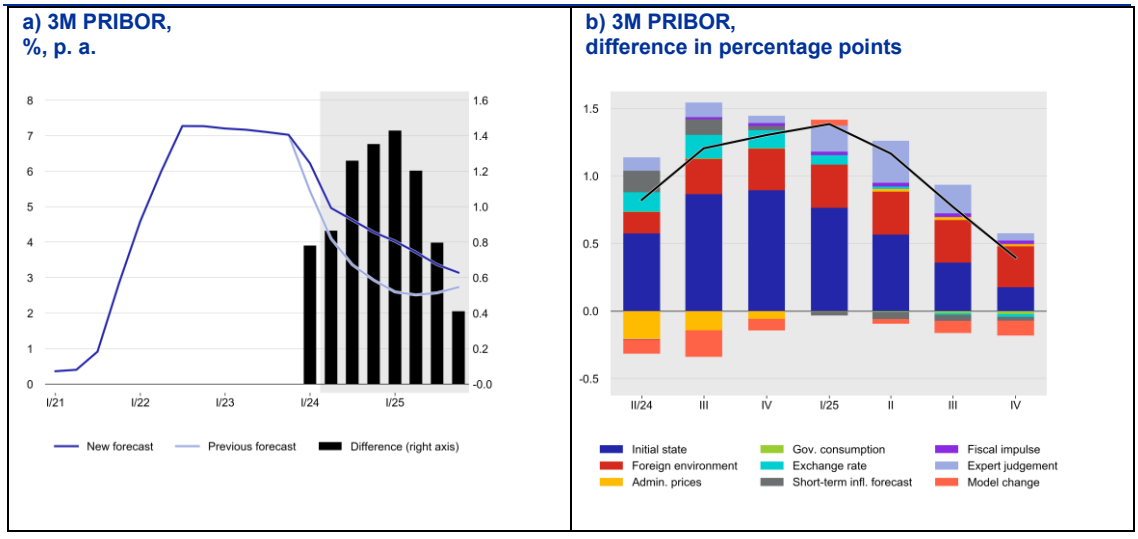
This comprehensive analysis is presented in the Česká národní banka monetary policy report, where the decomposition of changes provides valuable insights. The decomposition highlights the following.

- Impact of newly available data – initial state: New economic data can alter the outlook by providing updated information. For example, an unexpected increase in inflation data may prompt a reassessment of future interest rate hikes. This group also covers data revisions.
- Changes in external assumptions: These include shifts in foreign demand, commodity prices or international monetary policies. For instance, a change in the European Central Bank's policy stance could influence Česká národní banka's interest rate decisions due to trade and financial linkages.
- Short-term inflation forecast and exchange rates: These groups quantify the contribution of conditioning on the first quarter of inflation and exchange rates.
- Revisions to expert judgement: Expert assessments and judgements can be revised based on the latest economic conditions and trends, affecting policy projections. For example, a revision to expectations about domestic consumption or investment trends can lead to changes in interest rate forecasts.

The endogenous trajectory of the policy interest rate within the FPAS allows Česká národní banka to maintain a responsive and adaptive monetary policy framework. By regularly analysing and updating forecasts, Česká národní banka can navigate economic uncertainties and ensure that its monetary policy remains aligned with its inflation-targeting objectives. This approach not only provides transparency and accountability in monetary policy decisions but also enhances the bank's ability to respond proactively to changing economic conditions and transparently quantify the effect of changes.

Chart K

Policy rate trajectory change decomposition



Source: Česká národní banka.
Note: Spring 2024 MPR.

Box 7

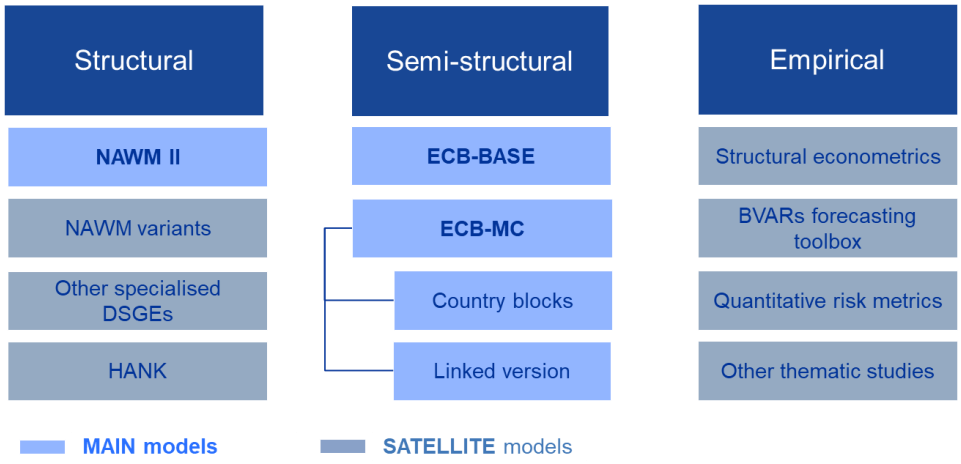
The use of models in the European Central Bank's projection process

Prepared by Magdalena Lalik and Máté Barnabás Tóth (both European Central Bank)

The European Central Bank (ECB) uses a wide range of macroeconomic models to combine country-specific and euro area-wide perspectives.[25] These models include both structural and semi-structural approaches, such as the ECB Multi-Country Model (ECB-MC), ECB-BASE and the New Area-Wide Model II (NAWM II), which play a central role in the projection process. The forecasting models and data are seamlessly integrated through the ECB's advanced projection platform, PERFORM. This platform allows for the efficient and consistent use of extensive data sources and a diverse suite of models, ensuring robust and reliable forecasts.

Figure A

The ECB's suite of models for forecasting and policy analysis



Source: Ciccarelli et al. (2024).

The ECB's approach to forecasting is largely shaped by its institutional framework. The Eurosystem forecasting process consists of two key projection exercises: the Broad Macroeconomic Projection Exercise (BMPE), conducted in June and December, and the Macroeconomic Projection Exercise (MPE), held in March and September. In the BMPE, projections are collaboratively produced by national central banks (NCBs) and ECB staff, each using their own models, with differences resolved through a thorough peer review process. The MPE, on the other hand, primarily reflects the consensus of ECB staff. The ECB adopts a bottom-up approach to forecasting, starting at the country level with semi-structural models tailored to individual economies. These forecasts are then aggregated to produce euro area-wide projections. For the five largest euro area countries, the ECB Multi-Country Model (ECB-MC) is used, while projections for smaller economies rely on the projection platform and specialised models integrated within the PERFORM system. To ensure consistency and reliability, the euro area-wide figures are

[25] For a comprehensive description of the models, please refer to Ciccarelli et al. (2024).

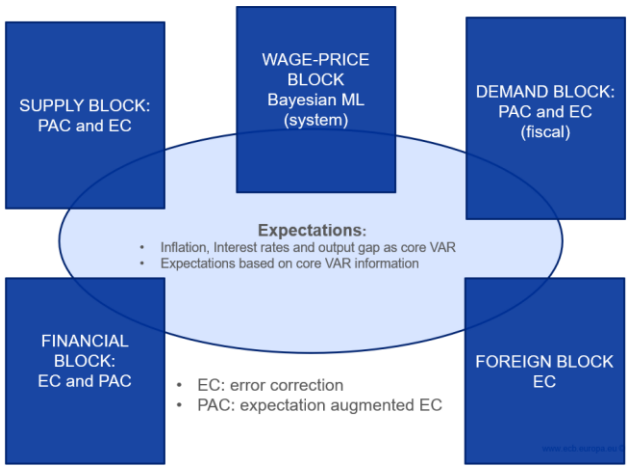
cross-checked using models specifically designed to capture the broader dynamics of the euro area economy.

Additionally, the ECB's modelling framework includes a range of tools specifically designed to generate technical assumptions, which are central to the Eurosystem's forecasting process. These assumptions, such as interest rates, exchange rates, foreign demand and commodity prices, serve as a common foundation, ensuring that all institutions, including NCBs and the ECB, use consistent key variables in their models.

The ECB Multi-Country Model[26]

The ECB Multi-Country Model (ECB-MC) is the main tool for multi-country analysis, offering both flexibility and detailed insights. The model focuses on the "big five" economies – Germany, France, Italy, Spain and the Netherlands – capturing their interactions and interdependencies. As illustrated in Figure B, the ECB-MC model for each of the big five economies is organised into five distinct blocks: supply, wage-price, demand, financial and foreign. Each block comprises behavioural equations, bridging equations and identities. The behavioural equations, grounded in theoretical underpinnings, are estimated to reflect the optimising behaviour of firms, households and financial markets. Agents' expectations are modelled by incorporating polynomial adjustment costs (as in Kozicki and Tinsley, 2002). The ECB-MC model builds on its euro area-level predecessor, the ECB-BASE model (see Angelini et al., 2019), which remains a key tool for policy and scenario analysis at the euro area level. Both the ECB-BASE and ECB-MC models employ methodologies similar to the FRB/US model developed by the Federal Reserve System, emphasising their suitability for forecasting. To enhance their accuracy, residuals are embedded within the models' equations, ensuring alignment with empirical data. This feature is critical for the forecasting process, as it enables expert judgement to refine model-driven outcomes, providing more precise and reliable projections.

Figure B
The ECB-MC main structure



Source: ECB.

[26] For a detailed description of the ECB-MC model, together with its application to the forecasting process, see Angelini et al. (2025).

Big five projection process using ECB-MC

The projection process is highly iterative and relies on collaboration between ECB and NCB experts. After setting external, financial and fiscal assumptions, ECB country-level projections for the five largest euro area economies are generated using ECB-MC. Together with the small country projections, these are aggregated to yield the euro area baseline. Expert judgement is incorporated through adjustments to model residuals informed by short-term forecasting tools, satellite models (typically time series tools), ad hoc analyses and iterative discussions among all stakeholders of the projection process. The results undergo multiple rounds of checks and validation, ensuring they are robust and reflect the most up-to-date assessment of the state of the economy.

The starting point in a forecast round is always the final iteration from the previous round. Correspondingly, the main focus of the projection exercises is on revisions to the previous baseline, apart from the case when a new year is added to the projection horizon. Revisions to the previous baseline in principle can occur for three different reasons: new incoming data, new conditioning assumptions and changes in expert judgement. In the current practice, the new data as well as revisions to historic data are taken on board by allowing for statistical carry-over effects, whereby the new data for the endogenous variables are "spliced" with the previous baseline (i.e. extended in terms of quarter-on-quarter growth rates). The endogenous variables are then exogenised, while the model residuals are endogenised and recomputed consistently (i.e. the model is "inverted" on the previous baseline). Once the new data and new residuals are integrated, the new assumptions are loaded. The resulting baseline, or "iteration zero", thus contains updated historical data and the simulated impact of new assumptions over the projection horizon. Furthermore, in the current setup of the infrastructure, iteration zero is generated mechanically, without any manual intervention from the country desks with respect to model residuals, and as such serves as a basis for evaluating the expert judgement.

After establishing the starting point as outlined above, the big five country desks iteratively apply expert judgement by adjusting model residuals and integrating relevant off-model information. They generally distinguish between two projection horizons: short-term and medium-term. While the technical approach remains consistent, these horizons draw on different sources of information to motivate judgement.

At the short end of the projection horizon, expert judgement is typically more data-driven due to the availability of high-frequency data for the previous and current quarters, as well as some forward-looking survey information for the next quarter. For quarterly real GDP growth, the most important activity indicator for the projections, the higher-frequency (typically monthly) data and survey information are summarised using a common set of mechanical time series tools (such as bridge equations and dynamic factor models estimated on respective country data). Although these estimates deliver key information over the short-term activity outlook, they are not mechanically and directly imposed on the baseline, but inform the judgement implemented by the country desk. For example, the country desk may deviate from the GDP growth profile implied by the short-term tools, given systematic forecast errors in the latter. Regarding GDP components over the short-term projection horizons, country desks rely on country-specific and component-specific tools to inform their judgement. Conversely, on the nominal side, the short-term – up to four quarters ahead – inflation forecast is pinned down by the Narrow Inflation Projection Exercise, which is typically imposed mechanically by inverting the ECB-MC model on a predefined Harmonised Index of Consumer Prices and components profile, provided by the NCBs subject to a peer review process by the Working Group on Forecasting.

Over the medium term, expert judgement introduced by the country desks is less data-driven and leverages more economic reasoning about relevant factors or policies not directly captured by the main model mechanisms or the conditioning assumptions. Examples of such off-model information include non-linearities in the monetary policy transmission mechanism, credit supply effects not captured by the financial assumptions, VAT changes or the introduction of CO_2 pricing schemes. Also, periods with extraordinary large shocks – such as the COVID-19 pandemic – and the temporary breakdown of established economic relationships (e.g. between output and employment) due to unprecedented policy interventions warrant the exercise of expert judgement.

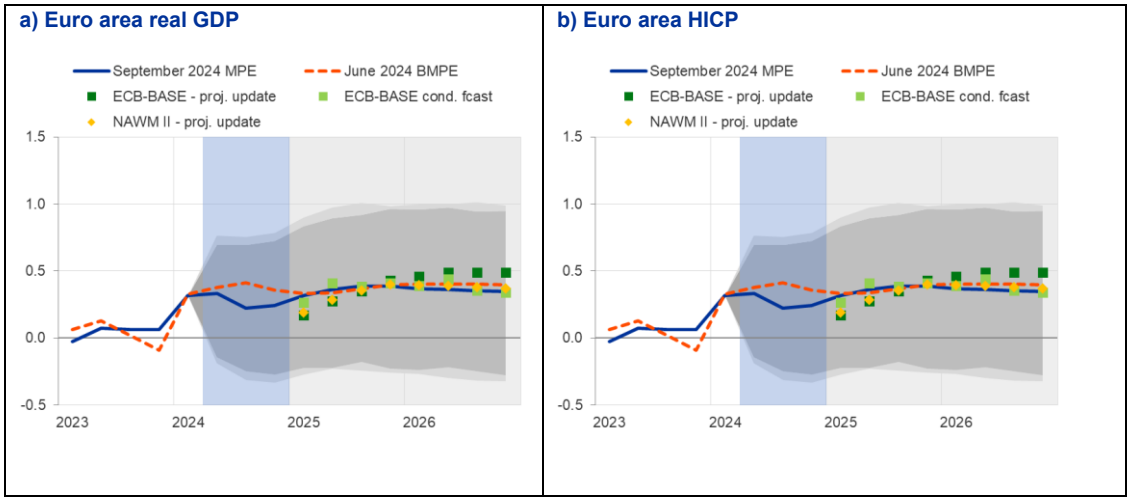
Cross-checking the baseline projections

Projections are cross-checked through projection updates and conditional forecasts to ensure their reliability. Projection updates refine previous forecasts by integrating new data, short-term outlooks and updated assumptions while preserving earlier expert judgement to assess incremental changes. By contrast, conditional forecasts provide a fresh perspective by interpreting new information independently of prior judgement, offering a purely model-based analysis. By comparing these approaches, the ECB can evaluate the influence of external inputs on the forecasts and continuously refine its baseline projections for greater precision and accuracy. An example of the cross-checking exercise for real GDP and HICP projections in the June 2024 BMPE is shown in Chart L. The exercise was undertaken with two flagship euro area models: ECB-BASE and NAWM II.

Chart L

Cross-check of the September **2024** MPE with ECB-BASE and NAWM II models

(lhs: quarter-on-quarter percentage change; rhs: year-on-year growth rates, in percent)



Source: ECB.

Satellite models and short-term assessment with nowcasting models

Satellite models complement this framework by focusing on specific variables over the short term, such as GDP and its components, trade consistency, sectoral developments and price developments. These specialised tools support the ECB's forecasting and policy analysis, addressing targeted needs like property market trends, fiscal projections, flow-of-funds analyses and financial sector dynamics.

The GDP nowcasting models (or short-term tools) have a prominent role in the projections as they summarise the information content of a rich set of monthly data flows relevant for near-term activity developments. The current set of nowcasting models rely on a system of bridge equations to predict industrial (excluding construction) and services value added, as well as some rule-of-thumb equations. It is typical at the beginning of a forecast iteration that national accounts data for the previous (t-1) and the ongoing quarter (t) are not yet available, while relevant monthly data and survey information for these quarters are readily accessible. Forward-looking survey information may also have some bearing on the following (t+1) quarter. As the projection round goes ahead, the t-1 national accounts data (at least the GDP flash estimate) are typically published and the monthly data and survey information for the ongoing quarter become more complete. Beyond the t+1 horizon, the data-driven nowcasting/short-term forecasting models have little useful information to rely on and are thus mainly driven by mean reversion.

Although they play an important role in assessing near-term activity developments, the output of the nowcasting models is not directly imposed on the baseline by inverting the model, but it is used to inform the judgement applied by the country experts.

9 Conclusion

This report provides an in-depth analysis of the macroeconomic modelling frameworks used by the European System of Central Banks (ESCB) for macroeconomic projections. It synthesises findings from a comprehensive survey conducted by the Expert Group on the Model-based Assessment of Projections (EGMAP), with contributions from national central banks (NCBs) and the European Central Bank (ECB).

The ESCB forecasting models, while diverse in structure and application, form the backbone of the ESCB's efforts to deliver consistent and credible macroeconomic projections over time. The findings underscore that while the modelling approaches vary across NCBs, they share common principles and practices that ensure coherence and coordination within the ESCB.

The survey highlights the central role of semi-structural models in producing baseline projections. These models offer the flexibility to integrate empirical data with expert judgement, making them particularly effective at capturing country-specific dynamics. However, they are not the only models used to form baseline projections.

Semi-structural models typically serve as the backbone, providing a solid framework, but they cannot capture all economic dynamics, particularly over shorter time horizons. To address this, NCBs have developed a range of satellite models that are more specialised. These satellite models play a crucial role in refining projections. While the diversity of models enhances forecast quality, it also adds a layer of complexity, as inputs from various sources must ultimately converge into a single baseline projection.

Traditionally, the infrastructure for integrating these inputs has been built around the main semi-structural models. Methods for combining diverse sources into one forecast are therefore relatively consistent across NCBs. Although the main models are not perfect and require adjustments – often through the incorporation of "expert judgement" – the techniques for these adjustments are broadly similar across institutions.

Experts typically incorporate their judgements either by adjusting model residuals or by imposing specific variables through the exogenisation of certain parts of the main model. These common practices present an opportunity to develop model-based indicators that can be applied universally to measure the extent of expert judgement incorporated into forecasts.

The report also identifies data quality and assumptions as challenging areas. Data revisions, missing data and inconsistencies in some assumptions highlight the need for robust methods to integrate accurate and timely information into projections.

The survey, conducted as a stock-taking exercise of models and forecasting practices applied in the June 2024 Broad Macroeconomic Projection Exercise,

identified several “quick wins”. These include creating harmonised frameworks for reporting the impact of new data, short-term outlooks and forecast assumptions, introducing model-based forecast indicators and refining fiscal block analysis.

Focusing on these areas can strengthen the Eurosystem’s modelling capabilities, resulting in more accurate forecasts and more effective policy analyses in a rapidly evolving economic environment. It will also improve the transparency of baseline projections, demonstrating that they are grounded in robust frameworks supported by models often published in academic research. Additionally, identifying the extent of expert judgement applied to these models – particularly over the medium-term horizon – would enhance the credibility and understanding of the forecasts.

Finally, the illustrative examples of projections in practice offer valuable insights into the forecasting methods employed by the ESCB. They demonstrate the high-quality models, robust toolkits, meticulous expert assessments and effective cooperation both within the NCBs and across the Eurosystem through peer review processes. While the boxes provide a snapshot of current practices, these practices are continuously evolving as the ESCB strives to further enhance its tools and methodologies. A notable example of this commitment to improvement is the establishment of EGMAP. This group focuses on developing modelling approaches to cross-check and validate baseline projections, ensuring a consistent and coherent measurement of expert judgement embedded in these forecasts.

In conclusion, the report highlights the significant progress made by the ESCB in refining its modelling toolkit while acknowledging the need for continued innovation and collaboration. By addressing existing challenges and seizing opportunities for improvement, the ESCB can further strengthen its capacity to produce reliable and actionable macroeconomic projections, thereby supporting informed and effective monetary policy decisions.

10 Annex: List of models

10.1 References for main projection models used in the European System of Central Banks

Country	Main model	References
Belgium	NONAME	Jeanfils, P. and Burggraeve, K. (2008), "NONAME: A new quarterly model for Belgium", *Economic Modelling*, Vol. 25, No 1, pp. 118-127.
Czech Republic	g3+	Brázdik, F., Hlédik, T., Humplová, Z., Martonosi, I., Musil, K., Ryšánek, J., Šestořád, T., Tonner, J., Tvrz, S. and Žáček, J. (2020), "The g3+ Model: An Upgrade of the Czech National Bank's Core Forecasting Framework", *Working Paper Series*, No 7, Česká národní banka, December.
Germany	BbkM-DE	Haertel, T., Hamburg, B. and Kusin, V. (2022), "The macroeconometric model of the Bundesbank revisited", *Technical Paper Series*, No 01, Deutsche Bundesbank.
Ireland	EireMod	Clancy, D. and Merola, R. (2016), "Eire Mod: A DSGE Model for Ireland", *The Economic and Social Review*, Vol. 47, No 1, pp. 1-31.
	COSMO	Bergin, A., Conroy, N., Rodriguez, A.G., Holland, D., McInerney, N., Morgenroth, E.L. and Smith, D. (2017), "COSMO: A new COre Structural MOdel for Ireland", *ESRI Working Papers*, No 553, Economic & Social Research Institute, February.
Spain	MTB	Arencibia Pareja, A., Hurtado, S., de Luis López, M. and Ortega, E. (2017), "New Version of the Quarterly Model of Banco de España (MTBE)", *Occasional Papers*, No 1709, Banco de España.
France	FR-BDF	Lemoine, M., Turunen, H., Chahad, M., Lepetit, A., Zhutova, A., Aldama, P., Clerc, P. and Laffargue, J.P. (2019), "The FR-BDF Model and an Assessment of Monetary Policy Transmission in France", *Working Papers*, No 736, Banque de France, October.
Croatia	PACMAN	Nadoveza Jelić, O. and Ravnik, R. (2021), "Introducing Policy Analysis Croatian MAcroecoNometric Model (PACMAN)", *Surveys*, No S-41, Hrvatska narodna banka, February.
Italy	BdIQEM	Bulligan, G., Busetti, F., Caivano, M., Cova, P., Fantino, D., Locarno, A. and Rodano, L. (2017), "The Bank of Italy econometric model: an update of the main equations and model elasticities", *Temi di Discussione*, No 1130, Banca d'Italia, July.
Latvia	Latvia's DSGE	Bušs, G. and Grüning, P. (2023), "Fiscal DSGE model for Latvia", *Baltic Journal of Economics*, Vol. 23, No 1, pp. 1-44.

Luxembourg	QLM	Quarterly Luxembourg Model (QLM) based on “old” multi-country model described in European Central Bank Working Papers 42, 149, 456, 646, 654 and 660.
Malta	STREAM	Grech, O. and Rapa, N. (2016), “STREAM: A Structural Macro-Econometric Model of the Maltese Economy”, *Working Papers*, No 01, Central Bank of Malta, February.
Netherlands	DELFI	Berben, R.P., Kearney, I. and Vermeulen, R. (2018), “DELFI 2.0, DNB’s Macroeconomic Policy Model of the Netherlands”, *Occasional Studies*, Vol. 16, No 5, De Nederlandsche Bank, September.
Austria	AQM	Leibrecht, M. and Schneider, M. (2006), “AQM-06: The macroeconomic model of the OeNB”, *Working Papers*, No 132, Oesterreichische Nationalbank, September.
Poland	NECMOD	Budnik, K., Greszta, M., Hulej, M., Kolasa, M., Murawski, K., Rot, M., Rybaczyk, B. and Tarnicka, M. (2009), “The New Macroeconometric Model of the Polish Economy (NECMOD)”, *Working Papers*, No. 62, Narodowy Bank Polski.
Portugal	M model	Castro, G. and Duarte, C. (2023), “The M Model: a macroeconomic model for the Portuguese economy”, *Economic Studies*, Vol. IX, No 2, Banco de Portugal, April.
Slovakia	NBS Main forecasting model	Reľovský, B. and Široká, J. (2009), “A structural model of the Slovak economy”, *Biatec*, Vol. 17, No 7, Národná banka Slovenska, pp. 9-14.
Finland	Aino 2	Kilponen, J., Orjasniemi, S., Ripatti, A. and Verona, F. (2016), “The Aino 2.0 model”, *Research Discussion Papers*, No 16, Suomen Pankki – Finlands Bank, May.
Sweden	MAJA	Corbo, V. and Strid, I. (2020), “MAJA: A two-region DSGE model for Sweden and its main trading partners”, *Working Paper Series*, No 391, Sveriges Riksbank, July.
ECB	ECB-MC	Angelini, E., Bokan, N., Ciccarelli, M., Lalik, M. and Zimic, S. (2025), “The ECB-Multi Country Model: A semi-structural model for forecasting and policy analysis for the largest euro area countries”, Working Paper Series, No 3119, ECB, September

10.2 List of all models used in the forecasting process by selected NCBs

This section provides a detailed list of models used by selected national central banks (NCBs).

The models are grouped into four categories, corresponding to the questionnaire structure.

Categories: a) main models, b) satellite models, c) cross-checking models, d) simulation models

Model types: structural, semi-structural, time series (TS), non-parametric

Model sizes: small (S), medium (M), large (L)

Horizon: short-term (S), medium-term (M), long-term (L)

10.2.1 Germany

Category	Model	Type	Size	Horizon	Target var.	Expect. format.	Jurisd.	Model-based forecasts	Details	References
a)	BbKM-DE	Semi-structural	L	M	Overall economy	Backward-looking (adaptive)	DE	-	-	Haertel et al. (2022)
b)	Short-term GDP	TS	S	S (two quarters)	GDP (+subcomponents)	-	DE	Yes (augmented with expert judgement when incorporated into baseline projection)	Model suite comprising BEM, factor model, MF-VAR, model for industrial production, WAI, WGDP	Deutsche Bundesbank (2018b, 2023)
b)	FIDEL: disaggregated inflation forecasts: short-term inflation (NIPE) / medium-term inflation	TS	S	S (11 months) / M (as cross-check)	HICP (subcomponents)	-	DE	Yes (augmented with expert judgement when incorporated into baseline projection)	Disaggregated approach for (>20) HICP subcomponents (suite of mainly individual ECMs)	NIPE models are currently under substantial revision (related description will be published in a forthcoming monthly report)
b)	Housing market	Semi-structural	S	M	House prices	-	DE	Yes (augmented with expert judgement when incorporated into baseline projection)	-	Deutsche Bundesbank (2017) and Kajuth (2021)
b)	Lending rates	TS	S	M	Long-term bank interest rate on loans to NFCs and on HH mortgage loans	-	DE	Yes (serves as input into baseline construction)	ECM (interest rate pass-through)	Expert Group on Financial Assumptions (EGFA) (2013), "Status report on country-specific lending rate modelling".
b)	Potential output	Non-parametric	S	L	Potential output and its components (TFP, capital, labour), including NAIRU	-	DE	Yes (augmented with expert judgement)	Disaggregated approach accounting for cross-sectoral heterogeneity, based on sector-specific Solow growth decomposition	Deutsche Bundesbank (2012)
b)	Wages	Wage tracker		M	Negotiated wages	-	DE	--	Disaggregated approach using industry-specific agreements as collected in the Bundesbank's negotiated pay rates database	Radowski (2024) Deutsche Bundesbank (2024b)
b)	Loan volumes	TS	S	M	Loans to NFCs, housing loans to HH	-	DE	Yes	Bayesian VAR (in levels)	Based on Giannone et al. (2015)

c)	Price Phillips curves	TS	S	M	HICP, HICP excluding energy and food	-	DE	Yes (as cross-check)	Thick modelling approach	Deutsche Bundesbank (2016)
c)	BbKM-DE price block	Semi-structural	L	M	HICP, HICP excluding energy and food	Backward-looking (adaptive)	DE	Yes (as cross-check for the inflation forecast)	Use neutral residuals in all behavioural equations of the price block, conditioned on the baseline projection for the rest of the macroeconomy	Haertel et al. (2022)
c)	Wage equations	TS	S	M	Negotiated and effective wages	-	DE	-	Modified versions of the wage equation in BbkM-DE; cross-check focuses on drivers of wage forecast	Deutsche Bundesbank (2018a)
c)	Structural VAR	TS	S	M	GDP, HICP excluding energy	-	DE	-	Cross-check focuses on structural shock decomposition of GDP and HICPX baseline	-
c)	Three-region DSGE	Structural	M	M	GDP, HICP	Forward-looking	DE, euro area and rest of world	-	Cross-check focuses on structural shock decomposition of GDP and HICP baseline	Hoffmann et al. (2021)
d)	BbKM-DE	Semi-structural	L	M	Overall economy	Backward-looking (adaptive)	DE	-	-	Haertel et al. (2022)
d)	Three-region DSGE	Structural	M	M	GDP, HICP	Forward-looking	DE, euro area and rest of world	-	-	Hoffmann et al. (2021)
d)	NiGEM	Semi-structural	L	M	All major economies	Forward-looking	World	-	-	Hantzsche et al. (2018)

10.2.2 Italy

Category	Model	Type	Size	Horizon	Target var.	Expect. format.	Jurisd.	Model-based forecasts	Details	References
a)	BdIQEM	Semi-structural	L	M	Overall economy	Backward-looking	IT	-	-	Bulligan et al. (2017)

b)	Short-term GDP	TS	S/L	S (current quarter)	GDP (+subcomponents)	-	IT	Yes (augmented with expert judgement)	Models for GDP: bridge models, BMA, DFM Models for industrial production: BVAR model, dynamic OLS model Other models: €-coin and ITA-coin	BMA: Bencivelli et al. (2016); DFM: Banbura and Runstler (2007); Angelini et al. (2010); BVAR: Aprigliano (2020); €-coin / ITA-coin: Altissimo et al. (2010); Aprigliano and Bencivelli (2013)
b)	NIPE	TS	S	S (four quarters)	HICP (subcomponents)	-	IT	Yes (augmented with expert judgement)	Highly disaggregated approach for HICP subcomponents	-
b)	Lending rates	TS	S	M	Bank interest rates	-	IT	Yes (augmented with expert judgement)	ARDL, thick modelling	Albertazzi et al. (2014), Bottero et al. (2023)
b)	Loan volumes	TS	S	M	Bank loans	-	IT	Yes (augmented with expert judgement)	ARDL, Bayesian VAR	Albertazzi et al. (2014), Conti et al. (2018)
b)	Potential output	Non-parametric	S	L	Potential output	-	IT	Yes (augmented with expert judgement)	Model averaging of four semi-structural approaches over BMPE horizon; long-term dynamics based on long-term anchors and production function	Bassanetti et al. (2010)
b)	Fiscal variables	TS, reduced-form	M	M	General government accounts	-	IT	Yes (augmented with expert judgement)	See Note 1	--
b)	Wages	Wage tracker	-	M	Actual wages	-	IT	Yes (augmented with macro model forecasts for economic activity and inflation)	Disaggregated approach using self-collected data on collective contract agreements (sector-specific) and soft information on possible developments, as collected by the Banca d'Italia. Cross-check with Phillips curve	-
c)	Housing market	TS	S	M	House prices	-	IT	Yes (augmented with expert judgement)	BVAR	Emiliozzi et al. (2018)
d)	BdIQEM	Semi-structural	L	M	Overall economy	Backward-looking	IT	-	-	Bulligan et al. (2017)

10.2.3 Netherlands

Category	Model	Type	Size	Horizon	Target var.	Expect. format.	Jurisd.	Model-based forecasts	Details	References
a)	DELFI 2.0	Semi-structural	M[27]	M	Overall economy	Backward-looking (adaptive)	NL	In development	-	DELFI (dnb.nl)
b)	Short-term GDP	Dynamic factor	S	S (two quarters)	GDP	-	NL	Yes	-	DFROG (dnb.nl)
b)	NIPE	TS	S	S -12 months for core; 36 months for energy and food	HICP – headline; food; energy; services; NEIG; administered prices; indirect tax contributions	-	NL	Yes (augmented with expert judgement)	Model averaging of two models: (1) suite of individual linear regressions for eight HICP subcomponents (these use the ECB DG Agri, exchange rate and energy price assumptions together with own wage assumptions); (2) SARIMA forecasts using ~ 230 HICP disaggregated prices (excluding energy prices)	-
b)	Potential output	TS and semi-structural	S	L	Potential output	-	NL	Yes	We use two models: (1) medium-term CES model of output distilled from the DELFI supply-side model; (2) UCM model (ten years)	-
b)	Wages	Wage tracker		M	Negotiated wages	-	NL	-	-	-
c)	WGPF DF (disaggregated framework for the analysis of structural fiscal developments)	Excel spreadsheet	S	M	Tax revenues	-	NL	Yes (as cross-check)	The tool gives a disaggregated breakdown of the fiscal forecasts based on a harmonised estimate of the CAB. This analysis can highlight inconsistencies in the initial forecast relative to the DF tool's structural estimates.	-

[27] Approximately 600 equations.

d)	NiGEM	Semi-structural	L	M	All major economies	Forward-looking	World		We use NiGEM with DELFI. For example, see the DNB autumn projections 2023.	NiGEM macroeconomic model (niesr.ac.uk)

10.2.4 Portugal

Category	Model	Type	Size	Horizon	Target var.	Expect. format.	Jurisd.	Model-based forecasts	Details	References
a)	M	Semi-structural	Large	Medium-term	Overall economy	Backward-looking	PT	-	-	Castro and Duarte (2023)
b)	Short-term model	TS	Small	Two quarters	GDP and subcomponents	-	PT	-	ARIMA and BRIDGE models	-
b)	NIPE*	TS	Small	Short-term and medium-term	HICP and subcomponents	-	PT	-	Disaggregated approach for HICP subcomponents (ECMs for market-based prices and simple rules and public information for administered and quasi-administered prices)	Félix et al. (2007)
b)	Potential output: PT-UCM	Semi-structural unobserved components model	Small	Long-term	Potential output	-	PT	-	Used to compute NAWRU. Cross-check results from the Cobb-Douglas approach	Duarte et al. (2020)
b)	Potential output: production function	Semi-structural	Small	Long-term	Potential output	-	PT	-	Cobb-Douglas production function using the NAWRU computed in the PT-UCM	Braz et al. (2019)
b)	Demographic model	Parametric model with Markovian structure	Large	Long-term	Population by age, gender and education level	-	PT	Yes (augmented with expert judgement when incorporated into baseline projection)	This satellite model is based on transition matrices. Demographic transitions are driven by three main assumptions: fertility, mortality and net migration. Estimates of educational attainment by age and gender are based on transitions between schooling levels	Antunes et al. (2023)

c)	Factor models	TS	Small	Two quarters	GDP and main components	-	PT	Yes (as cross-check)	-	Dias et al. (2018)
c)	Phillips curves	TS	Small	Medium-term	Private sector wages and HICP excluding energy and food	-	PT	Yes (as cross-check)	-	Serra (2018)
c)	PESSOA	DSGE	Large	Long-term	Overall economy	Forward-looking	PT	-	Structural shock decomposition of baseline GDP and HICP	Júlio and Maria (2017)

10.2.5 Slovakia

Category	Model	Type	Size	Horizon	Target var.	Expect. format.	Jurisd.	Model-based forecasts	Details	References
a)	NBS main forecasting model	Semi-structural model utilising the error correction mechanism	M	Entire forecast horizon	Entire economy	Backward-looking	SK	Yes	The core structure of the model is standard and follows the tradition of Fagan et al. (2001). Tool for running official projections starting in March 2025. Model includes a complete fiscal, financial block and is also used for scenario simulations (MP impact, fiscal consolidation, etc.), including scenarios in BMPE questionnaire	Reľovský and Široká (2009); new documentation in progress
b)	Model for short-term forecasting of GDP	Model with simple equations for short-term forecast of GDP and its components	S	Three quarters ahead	GDP components	Backward-looking	SK	-	Used for baseline description, the short-term forecast is often corrected with expert judgement	NBS AK29 (in Slovak only)
b)	NIPE tools	Simple equations for short-term forecasting of NEIG, services, food and fuel prices	S	NIPE horizon	HICP components	Backward-looking	SK	-	For energy excluding fuels forecasting, we use simplified formulas of the regulatory body that sets energy administered prices. Bottom-up approach for HICP projection	-
b)	Labour market model, DFM models	Short-term prediction of labour market indicators	S	Three quarters ahead	Employment, unemployment, wages	Backward-looking	SK	Yes	Cross-check of the official employment and unemployment forecast	NBS AK44, NBS AK33 (in Slovak only)

b)	Univariate ECM models for interest rates	ECM	S	Entire forecast horizon	Interest rates (NFC, households)	Backward-looking	SK	Yes	Four models - loans to NFCs (long-term, short-term) and loans to households (long-term, short-term)	-
b)	House price and loan BVAR	BVAR models	S	Entire forecast horizon	House prices and loans (NFC, HH)	Backward-looking	SK	-	Three models in total – one specifically for house prices, one specifically for loans and the last one combining both targets	Giannone et al. (2015)
b)	Unobserved components model	UCM	S	Current position of the economy	Output gap	Backward-looking	SK	-	Model that combines a multivariate filter approach with a Cobb-Douglas production function. This combination allows potential output estimates to incorporate more economic structure than the traditional production function approach. The model decomposes observed variables into trend and cyclical components. To do so, it relies on several reduced-form relationships across the cyclical components, such as a wage and a price Phillips curve and an Okun's law-type relationship, while it also assumes common trends for a few variables and allows for hysteresis effects	Tóth (2021)

c)	Nowcasting toolbox for GDP and its components	DFM, bridge models, OLS equations	S	Two quarters ahead	GDP components	Backward-looking	SK	Yes	GDP nowcasting toolbox consists of seven models – three bridge models, two DF models and two semi-machine-learning approaches based on OLS equations. Addit ionally, we use independent models for consumption, exports and imports	NBS AK74 (in Slovak only)
c)	Phillips curve models for wages	Phillips curves	S	Entire forecast horizon	Wages	Backward-looking	SK	Yes	Cross-check of the official wage forecast	-
c)	Okun's law models for employment	Okun's law	S	Entire forecast horizon	Employment	Backward-looking	SK	Yes	Cross-check of the official employment forecast	-
c)	Phillips curve models for HICP inflation	Phillips curves	S	Entire forecast horizon	HICP	Forward-looking	SK	Yes	Cross-check of the official HICP forecast	-
c)	Mixed-frequency BVAR + dynamic factor model for output gap	Mixed frequency BVAR + DF model		Entire forecast horizon	Output gap	Backward-looking		Yes	Used for cross-checking the output gap estimation	Ostapenko (2022)
Other	PreMISE	DSGE model	M	Entire forecast horizon	Entire economy	Forward-looking	SK	-	Used for assessing uncertainty around the baseline prediction and risks to price stability and recession	Výškrabka et al. (2019)
Other	EAGLE	DSGE model	M	Entire forecast horizon	Entire economy	Forward-looking	SK	-	Used e.g. for fiscal simulations (impact of gov. investments or euro funds). Extension not yet published	Senaj and Výškrabka (2011)

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Co-leads of the expert group

Matthieu Darracq Pariès
European Central Bank
Email: matthieu.darracq_paries@ecb.europa.eu

Thomas Haertel
Deutsche Bundesbank
Email: thomas.haertel@bundesbank.de

Coordinators

Magdalena Lalik
European Central Bank
Email: magdalena.lalik@ecb.europa.eu

Elena Angelini
European Central Bank
Email: elena.angelini@ecb.europa.eu

Contributors

Pierre Aldama
Banque de France

František Brázdik
Česká národní banka

Guido Bulligan
Banca d'Italia

Gabriela Castro
Banco de Portugal

Milan Damjanović
Banka Slovenije

Davide Fantino
Banca d'Italia

Martin Feješ
Národná banka Slovenska

Pablo Garcia Sanchez
Banque centrale du Luxembourg

Kacper Grejcz
Narodowy Bank Polski

Paolo Guarda
Banque centrale du Luxembourg

Katarzyna Hertel
Narodowy Bank Polski

Darius Imbrasas
Lietuvos bankas

Íde Kearney
De Nederlandsche Bank

Markus Kontny
Deutsche Bundesbank

Bob Krebs
Banque centrale du Luxembourg

Laura Mociūnaitė
Lietuvos bankas

Ieva Opmane
Latvijas Banka

Abigail Marie Rapa
Central Bank of Malta

Maria Christine Saliba
Central Bank of Malta

Mikko Sariola
Suomen Pankki – Finlands Bank

Ana Sequeira
Banco de Portugal

Yiqiao Sun
European Central Bank

Máté Barnabás Tóth
European Central Bank

Grigor Stoevsky
European Central Bank

Wouter Van der Veken
Nationale Bank van België/Banque Nationale de Belgique

Rubén Veiga Duarte
Banco de España

Hannu Viertola
Suomen Pankki – Finlands Bank

Ernestas Virbickas
Lietuvos bankas

Klaus Vondra
Oesterreichische Nationalbank

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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