

Bank of England

Decompositions, forecasts and scenarios from an estimated DSGE model for the UK economy

**Daniel Albuquerque, Jenny Chan, Derrick Kanngiesser,
David Latto, Simon Lloyd, Sumer Singh and Jan Žáček**



Plan for today

1. Introduction

2. The model

3. Data, calibration and estimation

4. Impulse Response Functions (IRFs)

5. Policy applications

5a. Forecast performance

5b. Structural decompositions

5c. Scenario analysis

6. Key areas for future development

Q&A



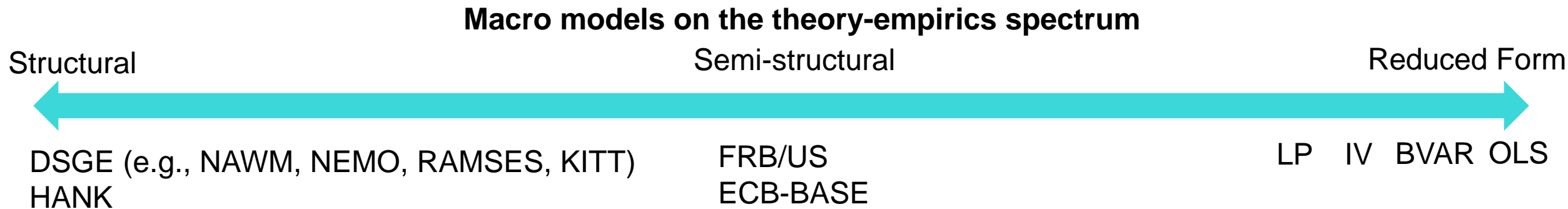
1. Introduction

DSGE modelling for central bank policymaking

We have updated and re-estimated the Bank of England's core DSGE model

- DSGE models are important in central bank toolkits because they provide structural interpretations of the macroeconomy
- Large shocks in recent past, particularly to energy prices, have posed challenges in using these models for policymaking
- A key enhancement of our updated model is the introduction of an energy sector in the style of Chan et al. (2024), where energy is consumed by households and used as an input to production

This model is one input into policymaking, amongst many others, but it allows for a variety of useful policy applications



Key policy use cases (non-exhaustive):

- Credible **unconditional and conditional density forecasts** of key macroeconomic variables
- **Decompositions of historical data and projections into structural drivers**
- **Counterfactual scenarios** for the macroeconomy

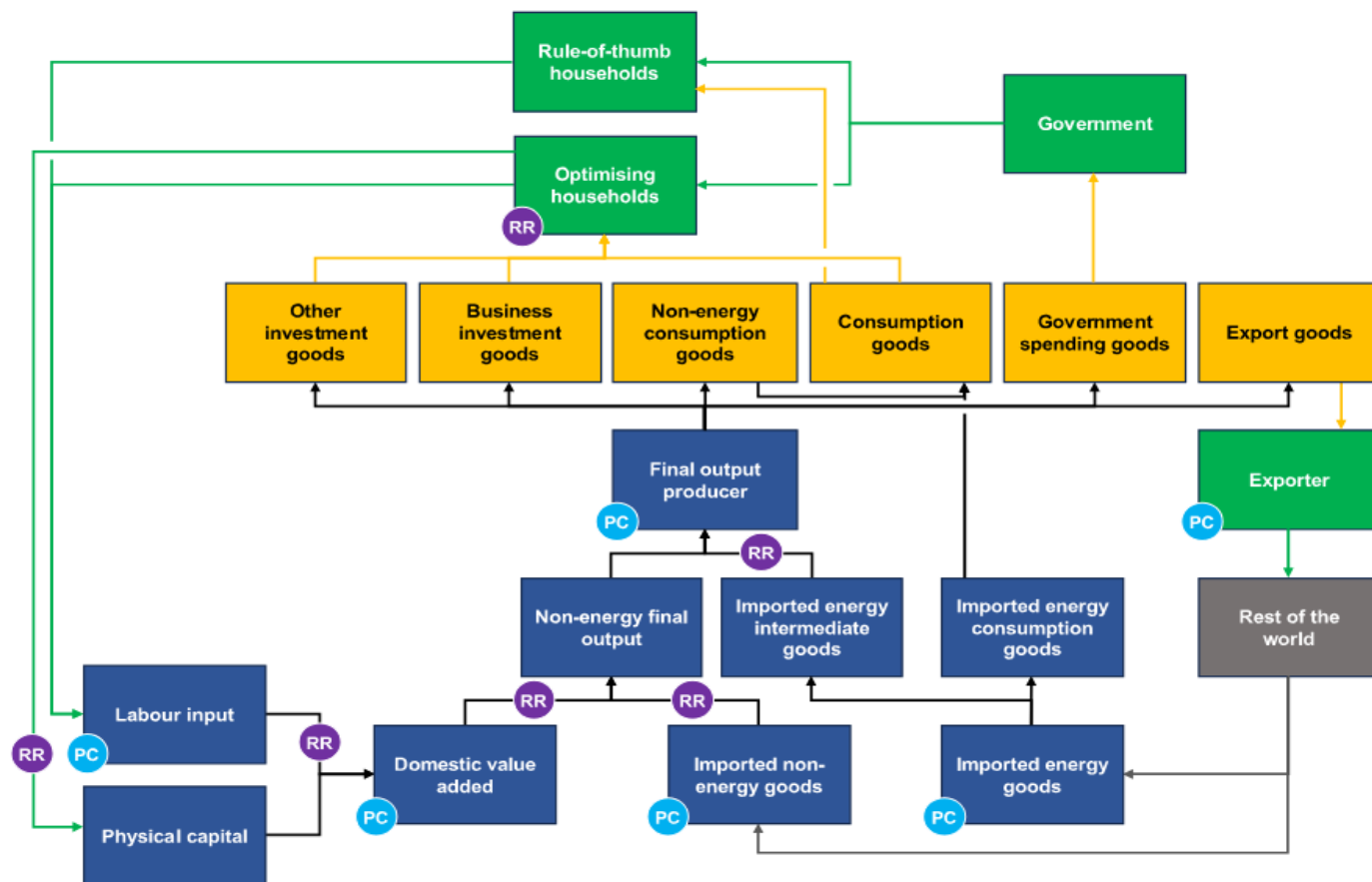


2. The model

Structure and key features

The model has a standard New Keynesian structure, alongside adaptations that capture important features of the UK economy

Figure 1: OVERALL STRUCTURE OF THE MODEL



Notes: "RR" and "PC" denote real rigidities and Phillips Curves that capture nominal rigidities, respectively.

Key characteristics of the model

1. Household heterogeneity

- Optimising and Rule of Thumb households

2. Real rigidities

- Adjustment costs that slow down the response of real variables to shocks

3. Small Open Economy (SOE)

- Phillips Curves for exported and imported goods, which are inputs into domestic consumption and production

4. Energy

- Model has been updated with energy as a component of household consumption baskets, as well as an input into production

Key characteristics of the model

1. Household heterogeneity

- Optimising and Rule of Thumb households

2. Real rigidities

- Adjustment costs that slow down the response of real variables to shocks

3. Small Open Economy (SOE)

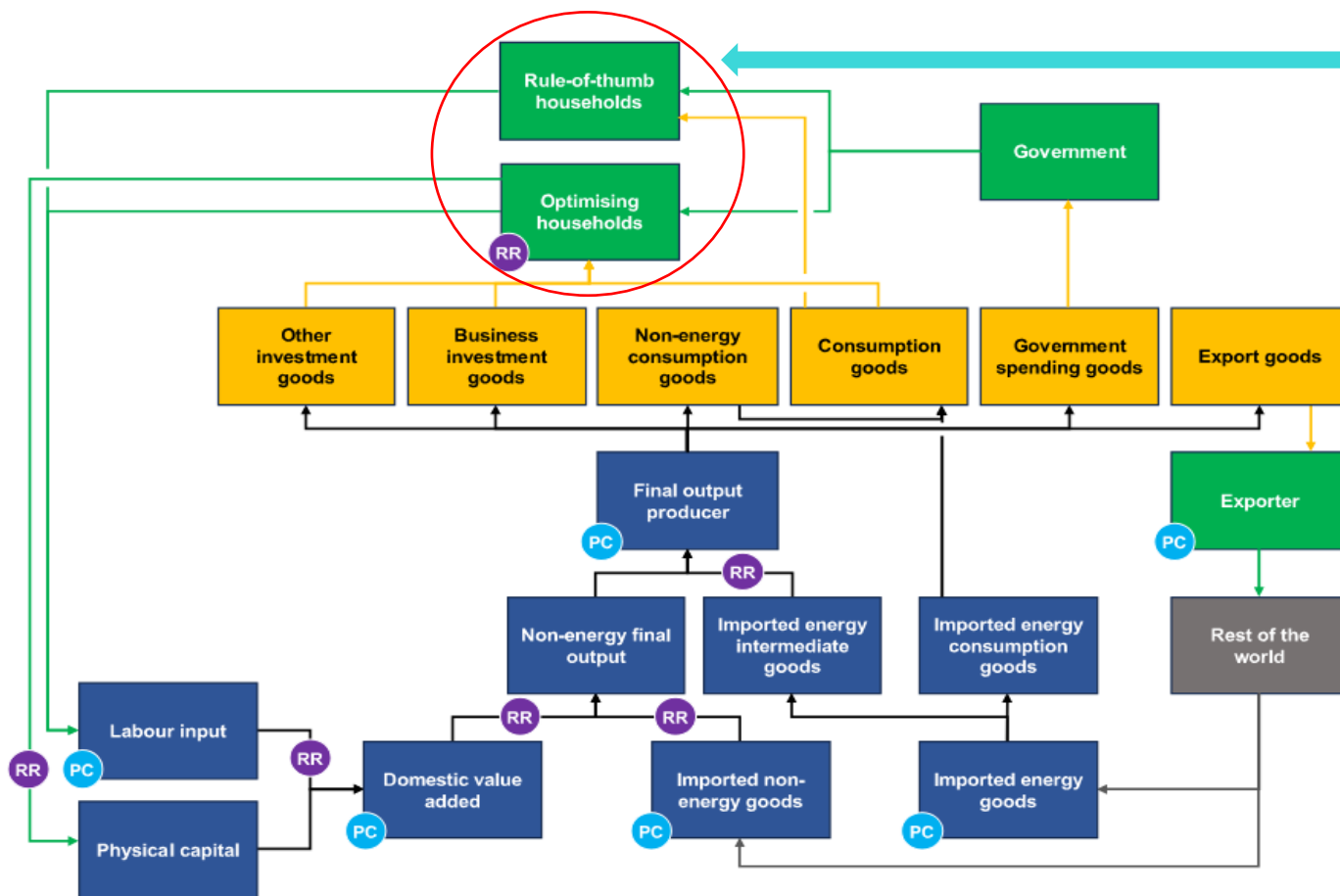
- Phillips Curves for exported and imported goods, which are inputs into domestic consumption and production

4. Energy

- Model has been updated with energy as a component of household consumption baskets, as well as an input into production

Two types of households: Optimising and Hand-to-Mouth

Figure 1: OVERALL STRUCTURE OF THE MODEL



Realistic transmission of shocks and marginal propensities to consume

Tractability through Two Agent New Keynesian (TANK) model structure

Optimising households have access to complete asset markets and can smooth consumption over time

Rule-of-Thumb or Hand-to-mouth households consume all their disposable income in each period

Notes: “RR” and “PC” denote real rigidities and Phillips Curves that capture nominal rigidities, respectively.

Key characteristics of the model

1. Household heterogeneity

- Optimising and Rule of Thumb households

2. Real rigidities

- Adjustment costs that slow down the response of real variables to shocks

3. Small Open Economy (SOE)

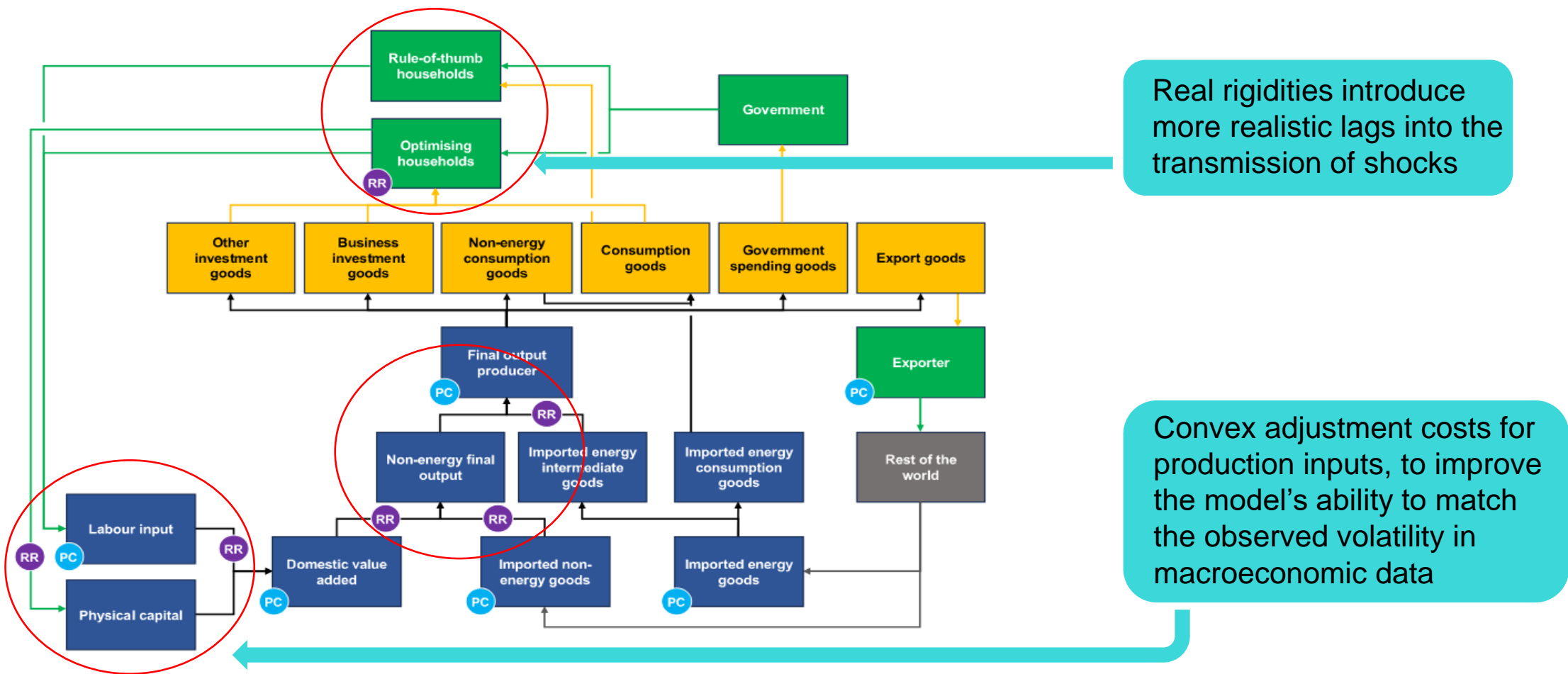
- Phillips Curves for exported and imported goods, which are inputs into domestic consumption and production

4. Energy

- Model has been updated with energy as a component of household consumption baskets, as well as an input into production

Real rigidities feature in household behaviour, and production within the economy

Figure 1: OVERALL STRUCTURE OF THE MODEL



Notes: "RR" and "PC" denote real rigidities and Phillips Curves that capture nominal rigidities, respectively.

Key characteristics of the model

1. Household heterogeneity

- Optimising and Rule of Thumb households

2. Real rigidities

- Adjustment costs that slow down the response of real variables to shocks

3. Small Open Economy (SOE)

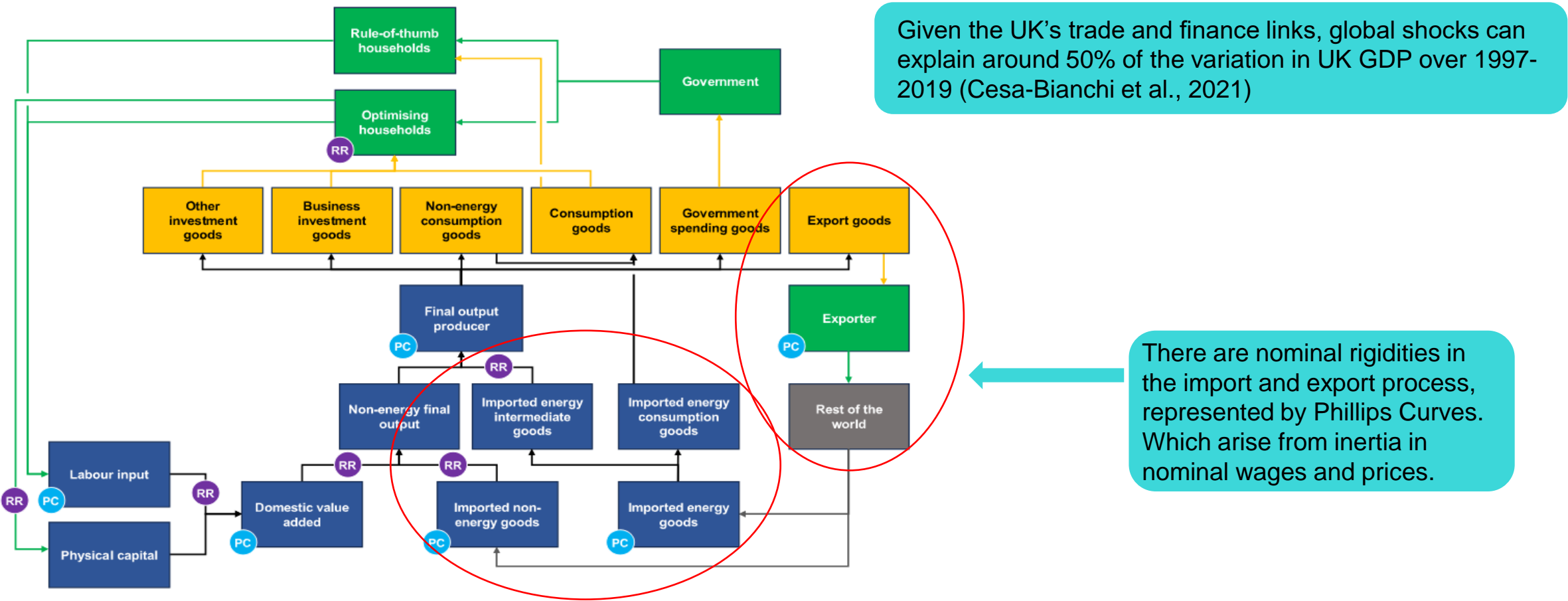
- Phillips Curves for exported and imported goods, which are inputs into domestic consumption and production

4. Energy

- Model has been updated with energy as a component of household consumption baskets, as well as an input into production

UK imports are a key input into domestic consumption and production in the model

Figure 1: OVERALL STRUCTURE OF THE MODEL



Notes: “RR” and “PC” denote real rigidities and Phillips Curves that capture nominal rigidities, respectively.

Key characteristics of the model

1. Household heterogeneity

- Optimising and Rule of Thumb households

2. Real rigidities

- Adjustment costs that slow down the response of real variables to shocks

3. Small Open Economy (SOE)

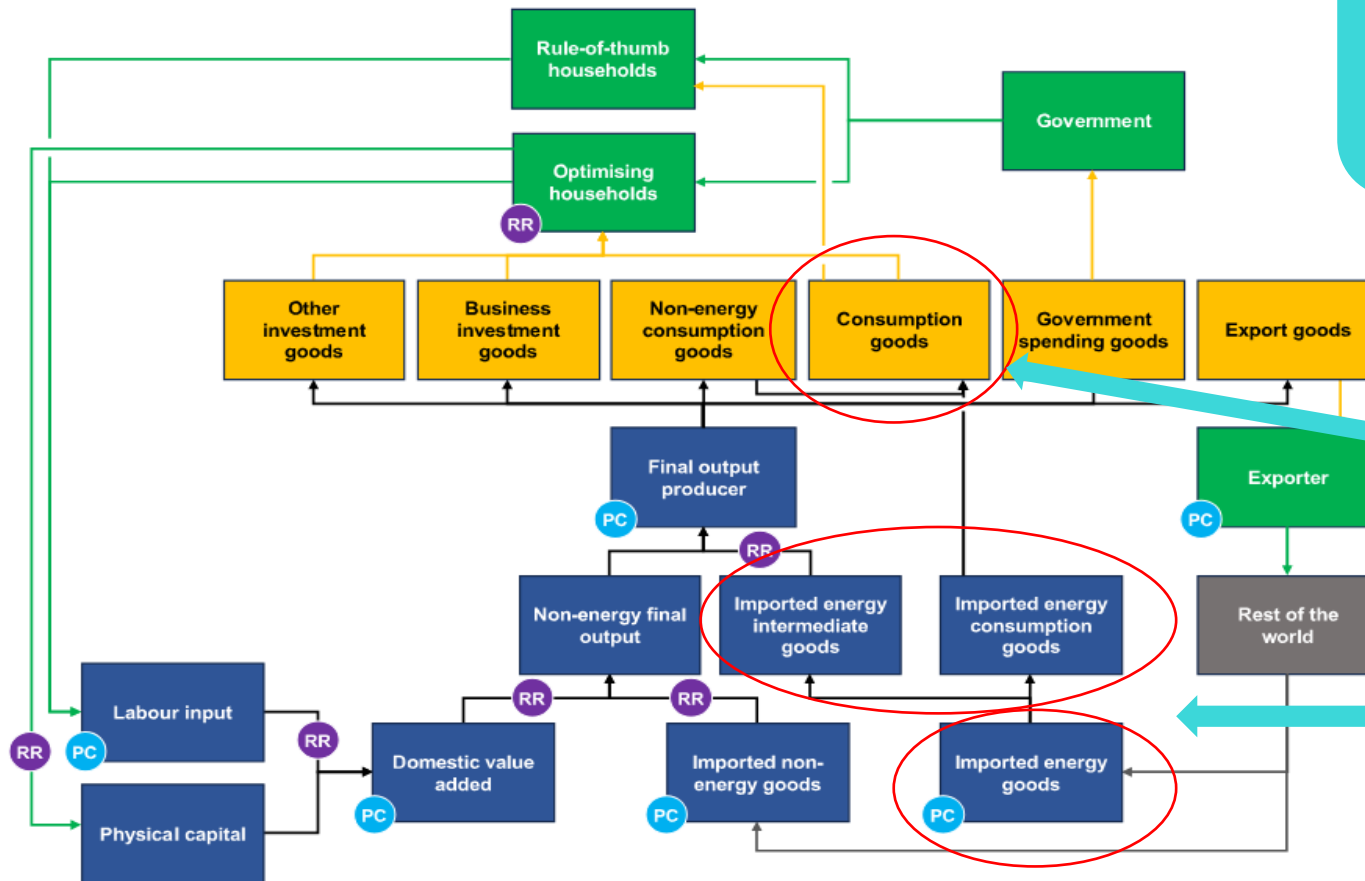
- Phillips Curves for exported and imported goods, which are inputs into domestic consumption and production

4. Energy

- Model has been updated with energy as a component of household consumption baskets, as well as an input into production

Energy now features as an input into consumption and production

Figure 1: OVERALL STRUCTURE OF THE MODEL



Driven by large shocks to oil and gas prices, energy directly contributed up to around 4pp to UK CPI inflation in 2022 and 2023 – around 1/3rd of the overshoot versus 2%

Model now captures various channels through which energy prices can affect demand and supply in general equilibrium

Constant Elasticity of Substitution (CES) for consumption and production

Imported energy consumption is complementary to non-energy goods consumption

Imported energy is also complementary to domestic labour and capital as a factor of production

Notes: “RR” and “PC” denote real rigidities and Phillips Curves that capture nominal rigidities, respectively.



3. Data, calibration and estimation

Detrending the data, calibration and estimation approach

The model is estimated using data as deviations from steady state. Creates need to transform raw and non-stationary data into detrended model observables.

We do this in three steps:

1. The non-stationary data (e.g., GDP, its components, and price levels) are converted into growth rates by taking log differences.
2. Where necessary, we use variable-specific time-varying trends to account for structural breaks in trends.
3. Finally, for GDP, expenditure and labour market variables, we use a data filtering approach to allow for the extreme outturns in the Covid-19 period. We simulate data during this period using a Kalman filter and effectively 'dummy out' the deviations from the actual data.

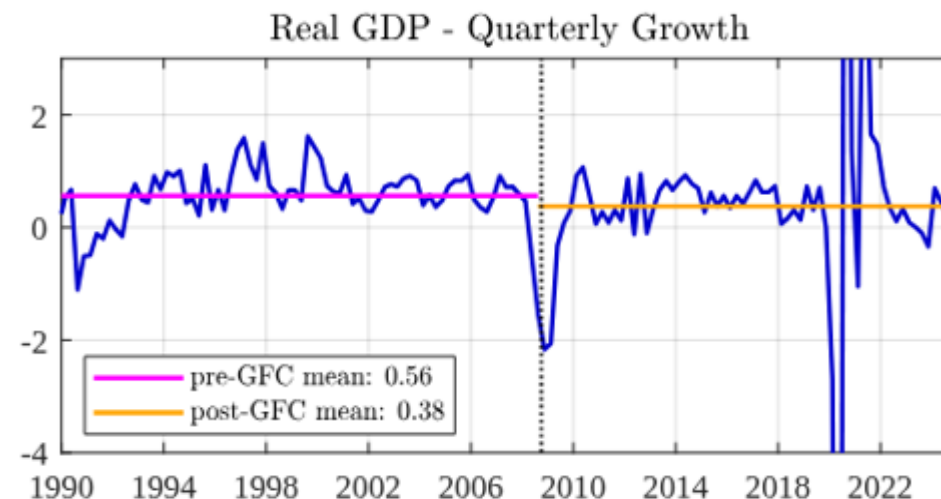
Taking Real GDP as an example, we start with the untransformed and non-stationary level series

Figure 3: TRANSFORMATION OF GDP



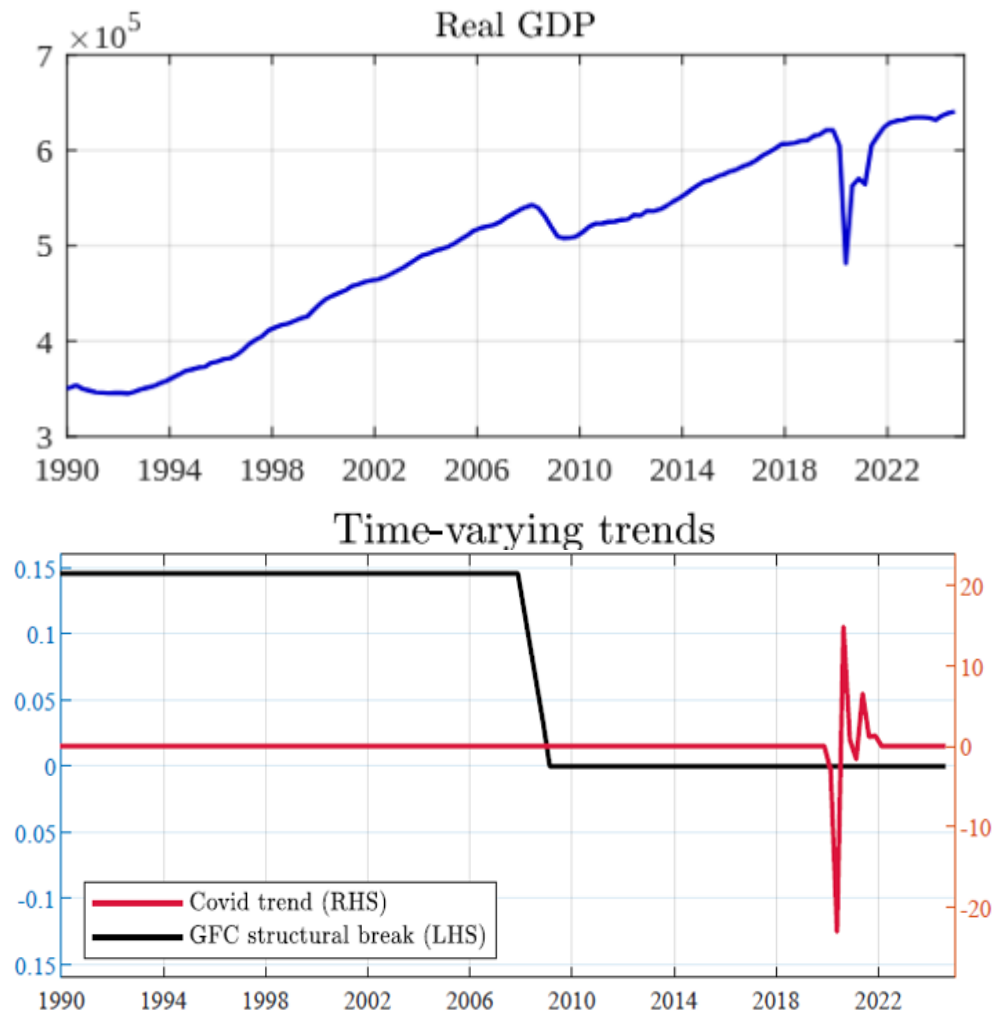
Then we convert to quarterly growth rates by taking log differences

Figure 3: TRANSFORMATION OF GDP



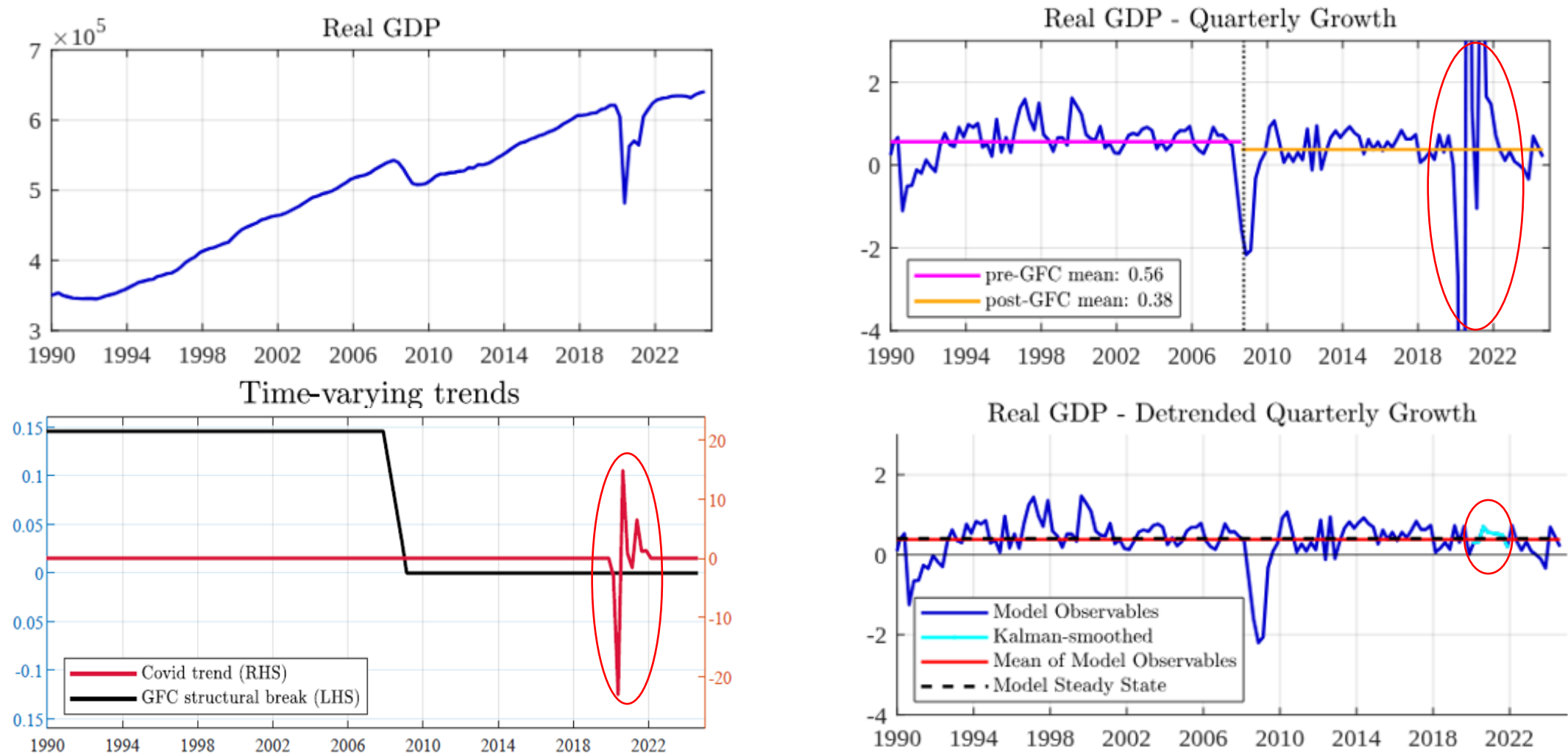
And include a time varying trend to account for a structural break around the Global Financial Crisis (GFC)

Figure 3: TRANSFORMATION OF GDP



We abstract from extreme pandemic outturns by simulating counterfactual data using a Kalman filter, and ‘dummy out’ the deviations from actual outturns

Figure 3: TRANSFORMATION OF GDP



The model's parameters are set using a combination of calibration and Bayesian estimation

- There are **6 broad groupings of parameters**: (i) energy, (ii) households, (iii) firms, (iv) monetary policy, (v) the world and (vi) steady-state ratios/growth
- We **estimate** parameters where we can, especially where we do not have strong priors (e.g., Calvo-pricing and real adjustment costs)
 - The estimation is based on **quarterly data from 1987 to 2023**, largely covering the UK's transition to an inflation targeting regime
 - Data used in estimation have been through at least two iterations of annual ONS Blue Book National Accounts revisions
- We **calibrate** parameters that are poorly identified in the data, or where we have strong priors, including based on the academic literature/microdata evidence (e.g., expenditure shares)



4. Impulse Response Functions (IRFs)

Monetary policy and global energy price shocks

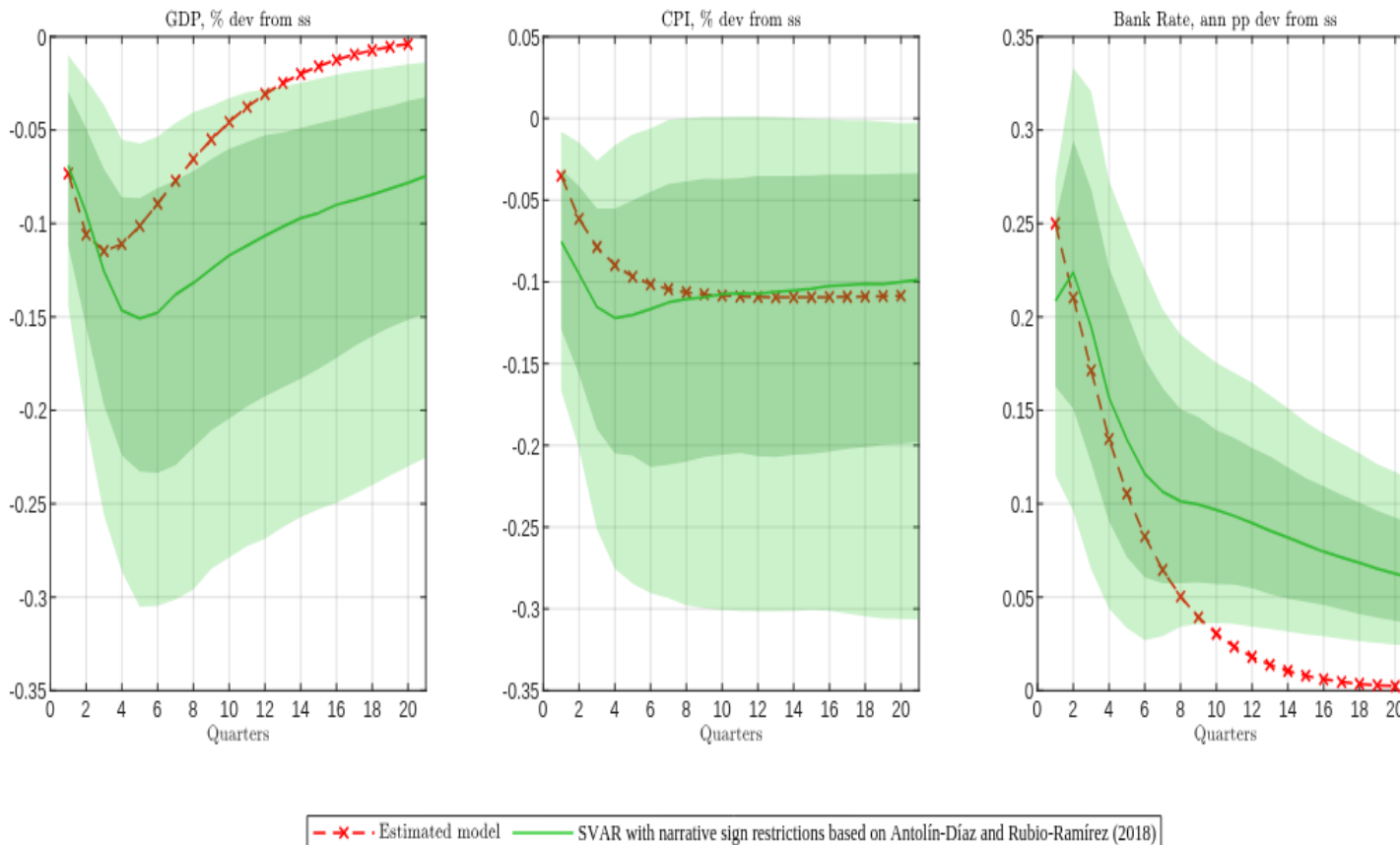
The model matches key moments in the data and provides IRFs that are broadly in line with empirical cross-checks

In particular:

1. **IRFs for monetary policy shocks** are broadly in line with empirical cross-checks from an internal SVAR model based off the academic literature on policy shock identification
2. **IRFs for global energy price shocks** are broadly in line with empirical cross-checks from Local Projections (LPs) on oil news shocks

Monetary policy shock IRFs are broadly in line with impulse responses from a cross-check SVAR model with narrative sign restrictions

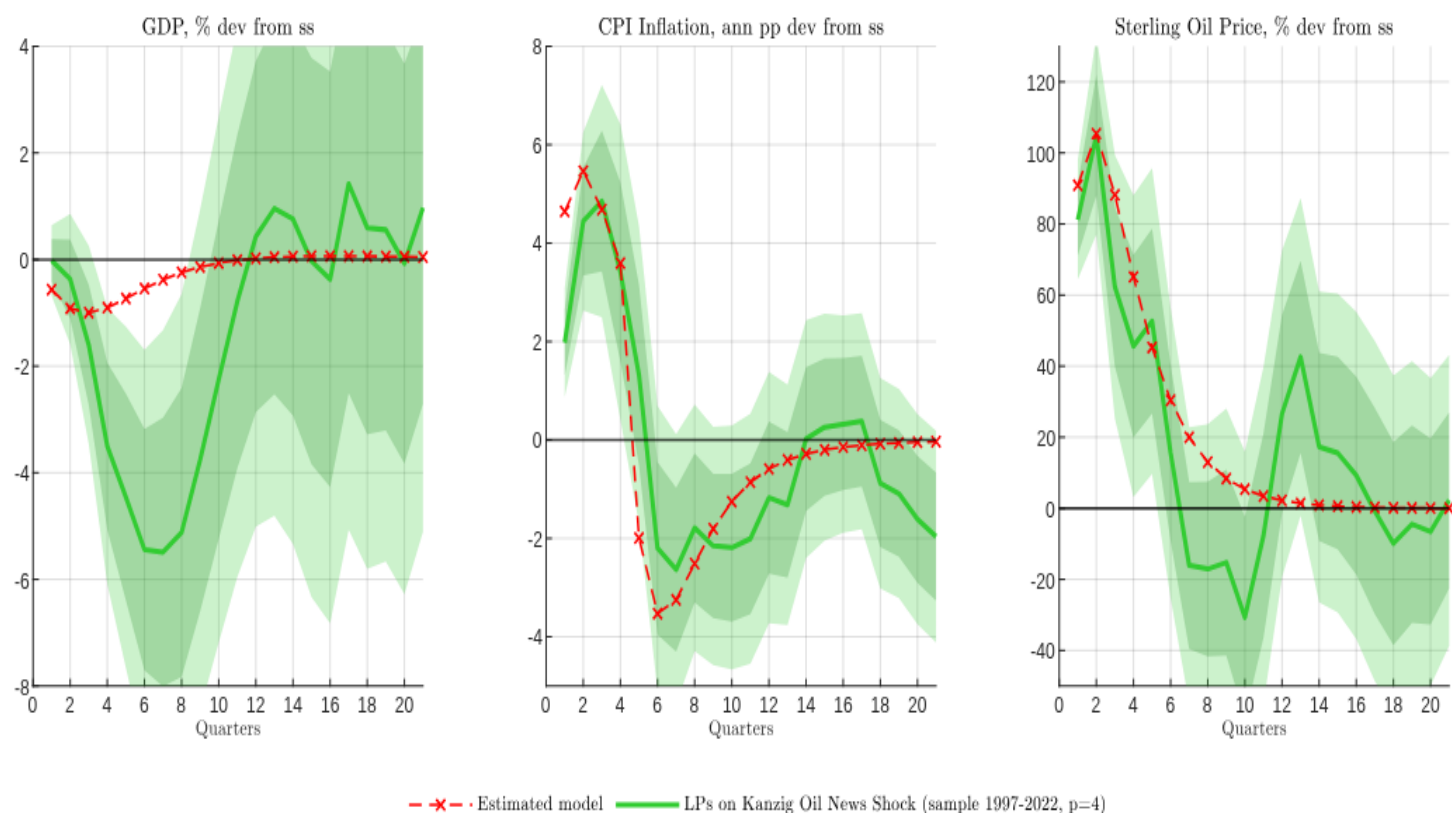
Figure 5: IMPULSE RESPONSES TO A MONETARY POLICY SHOCK



- We benchmark against a SVAR with narrative sign restrictions based on Antolin-Díaz and Rubio-Ramírez (2018)
- A contemporaneous monetary policy tightening shock to Bank Rate of 25bps leads to falls in GDP and CPI
- CPI responses are similar for the estimated model and the SVAR; Bank Rate and GDP responses are more persistent in the latter

IRFs for global energy price shocks in the model are broadly in line with a Local Projections (LPs) empirical cross-check

Figure 6: IMPULSE RESPONSES TO A GLOBAL ENERGY-PRICE SHOCK



- LPs estimated using an oil news shock series by Kanzig (2021). Results here are normalised to match 4pp peak inflation impact observed in 2022 (middle chart).
- Model IRFs scaled to deliver the same associated peak in energy prices (RHS).
- Estimated model performs well in matching the magnitude and dynamics of CPI inflation response in the LPs. GDP response in estimated model is weaker than LPs, although they are more closely aligned in the initial quarters.



5. Policy applications

Forecast performance, structural decompositions and scenario analysis

The model has useful policy applications

- For instance, it can produce credible unconditional and conditional density forecasts of key macroeconomic variables
- But its real strength is the ability to provide structural interpretations of macroeconomic dynamics and conduct counterfactual scenario analysis



5a. Forecast performance

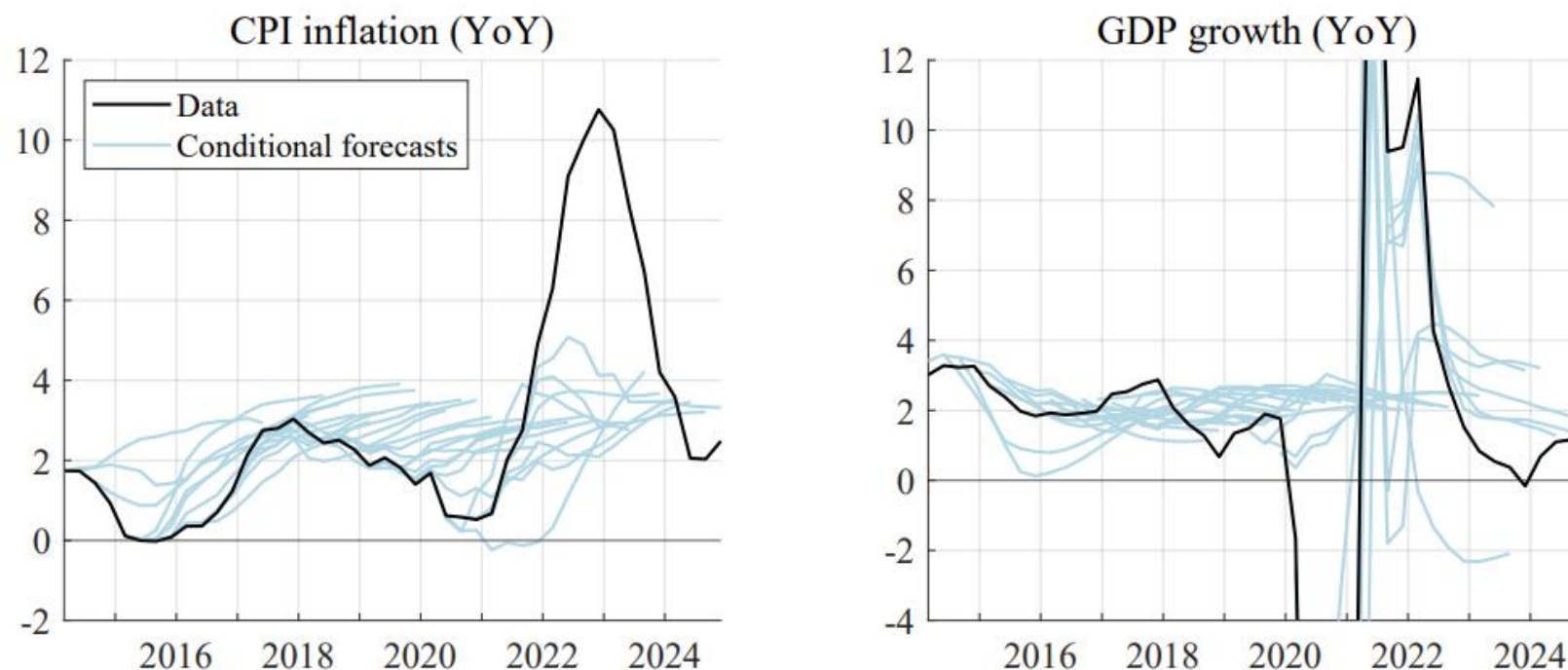
Model conditional forecast accuracy, and counterfactual model forecasts

Training DSGE models with extra off-model information typically improves forecast performance

- We incorporate the same near-term outlook and set of conditioning variables as the Bank of England's Monetary Policy Report projections
- **Conditioning variables:** the overnight-indexed swap (OIS) forward curve for Bank Rate, a path for the nominal effective exchange rate, the outlook for energy prices and government spending, world interest rates, world GDP, world trade, world export price deflator, and world CPI outlook
- Based on high-frequency forecasting techniques (Moreira, 2025), we also constrain the short-term outlook using nowcasts and nearcasts
- **Short term outlook constraints:** real GDP and its expenditure components, hours worked, average aggregate wage, and export and import price deflators for the first quarter. Alongside the CPI outlook for two-quarters ahead.

The model performs reasonably well at forecasting inflation and GDP growth during ‘standard times’

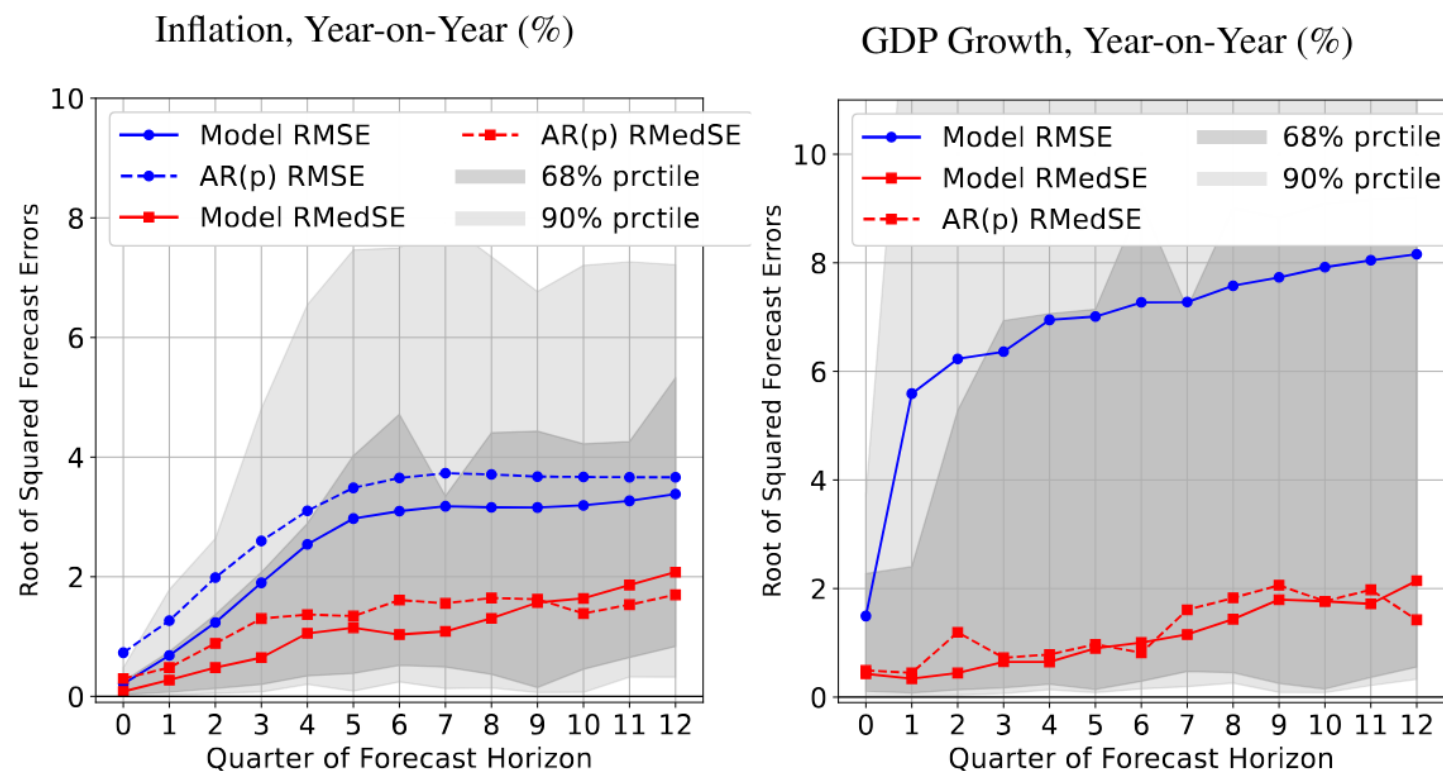
Figure 10: OUTTURNS VERSUS MODEL CONDITIONAL FORECASTS



Notes: This figure shows the model's 13 quarters ahead conditional forecasts (light blue lines) for year-on-year (%) inflation and real GDP growth from 2014Q1 to 2024Q4 relative to data outturns (black lines) over this period. The forecasts are based on data vintages available as of the projection start date, and conditional on multiple domestic and global variables over the whole forecast horizon.

Over 2014-24, the model's conditional inflation and GDP growth forecasts are reasonably accurate across a 3-year horizon

Figure 11: CONDITIONAL FORECAST ACCURACY



Notes: This figure contains the root-mean squared error (RMSE, blue lines) with corresponding 68% and 90% confidence intervals (grey swathes), and the root median square error (RMedSE, red lines) at forecast horizons $h = 0, \dots, 13$ for year-on-year (%) inflation and GDP growth from the estimated DSGE model and an AR(p) model. RMSE from AR(p) omitted from right-hand figure as it goes beyond the y-axis scale.

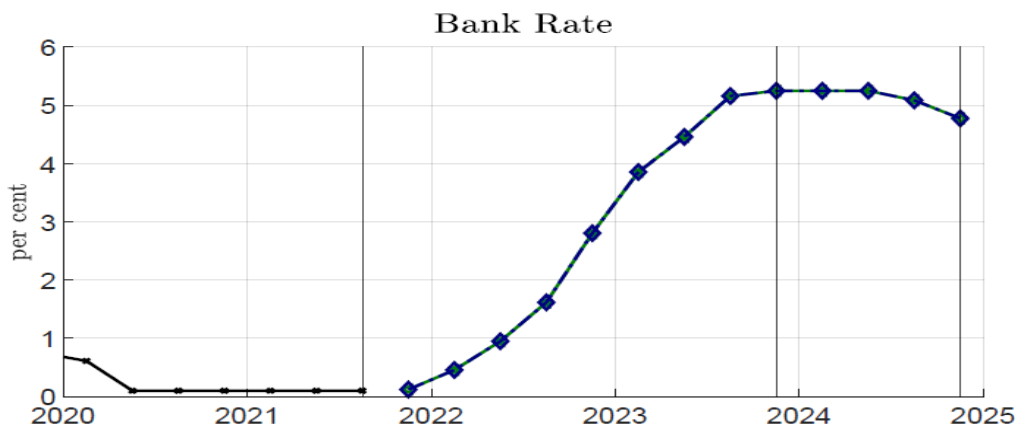
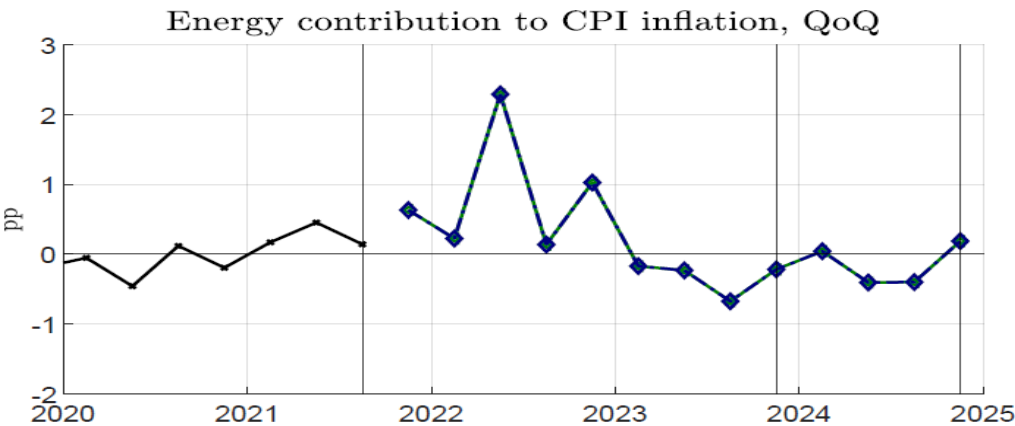
Delving further into the model's 2022-24 forecast errors

- News to conditioning paths is unforecastable from a conditional forecast perspective. This can play an important role in contributing to forecast errors.
- To further explore the model's forecasting ability, we produce counterfactual forecasts for CPI inflation and GDP growth based on data available as of 2021, but conditional on **realised** values of key forecast conditioning paths as of November 2024
- This exercise aims to answer the question: *“Had we known ex-ante how key conditioning paths actually turned out, what would the model have predicted for CPI inflation and GDP growth ahead of the energy crisis in 2022?”*

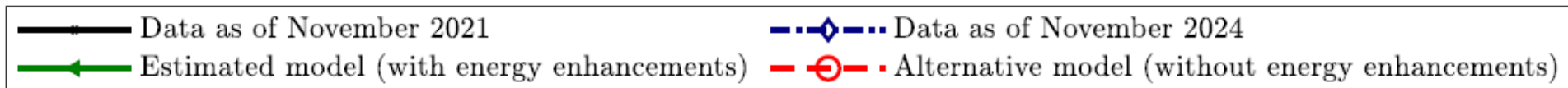
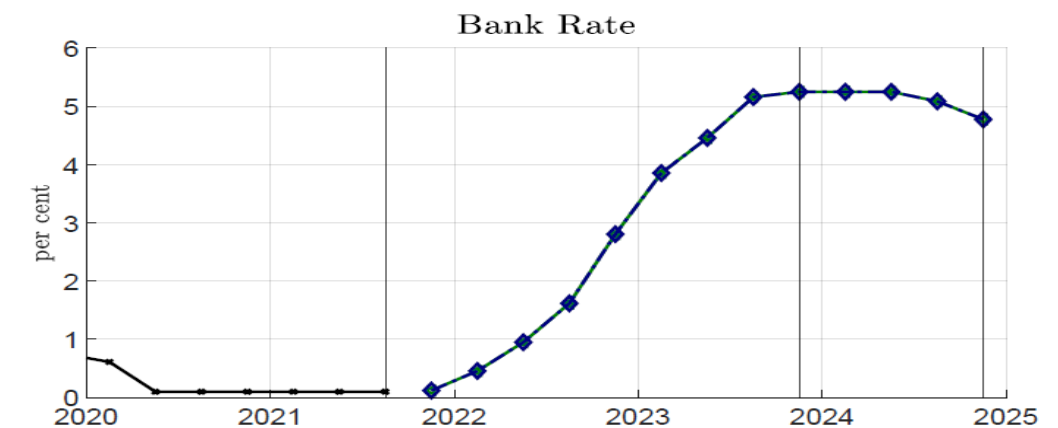
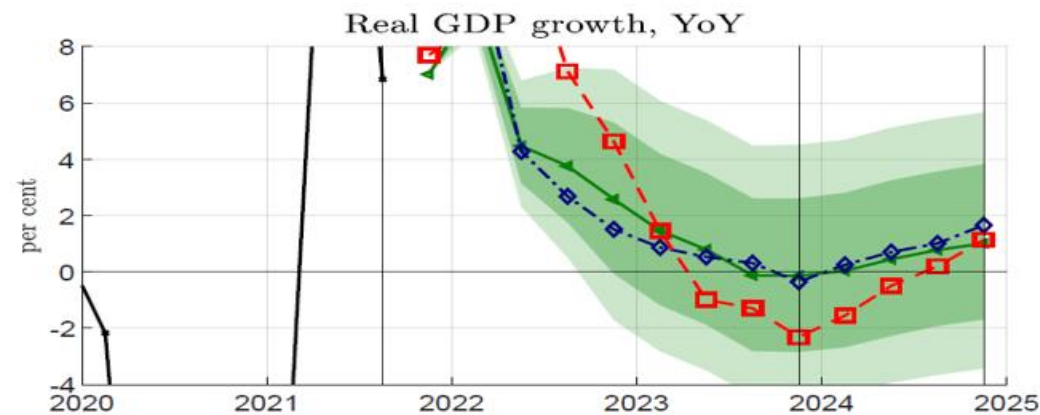
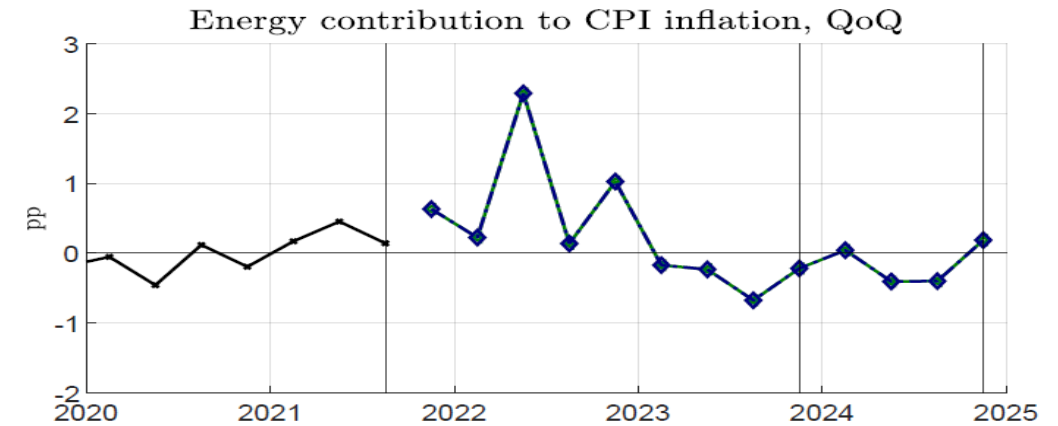
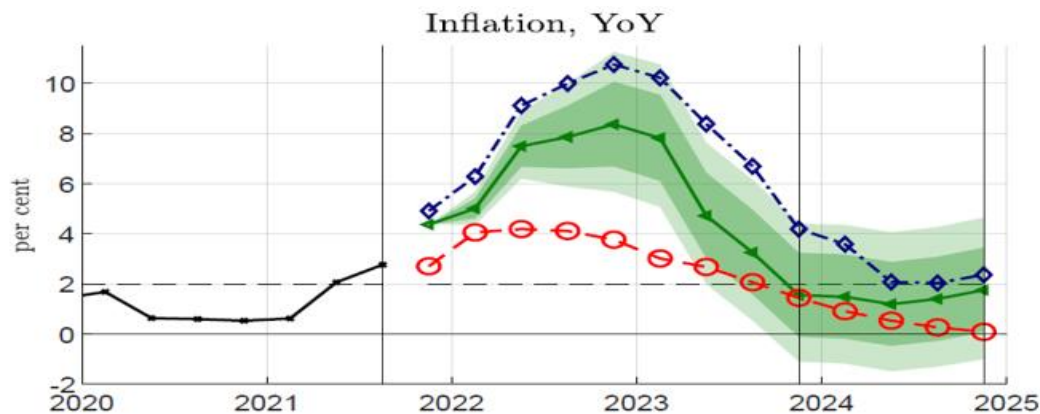
Exploring the role of unforecastable news to conditioning paths in generating forecast errors

Standing in November 2021, we condition the model on actual values of conditioning paths, based on data as of November 2024

Internally, we have compared this to (a) the model's out of sample forecast errors over the same period and (b) an earlier version of the model that omitted the energy sector



The model's counterfactual forecasts (green lines and swathes) are close to observed inflation and GDP growth outturns (blue lines). An earlier version of the model without an energy sector delivers downwards-biased projections by comparison (red lines).





5b. Structural decompositions

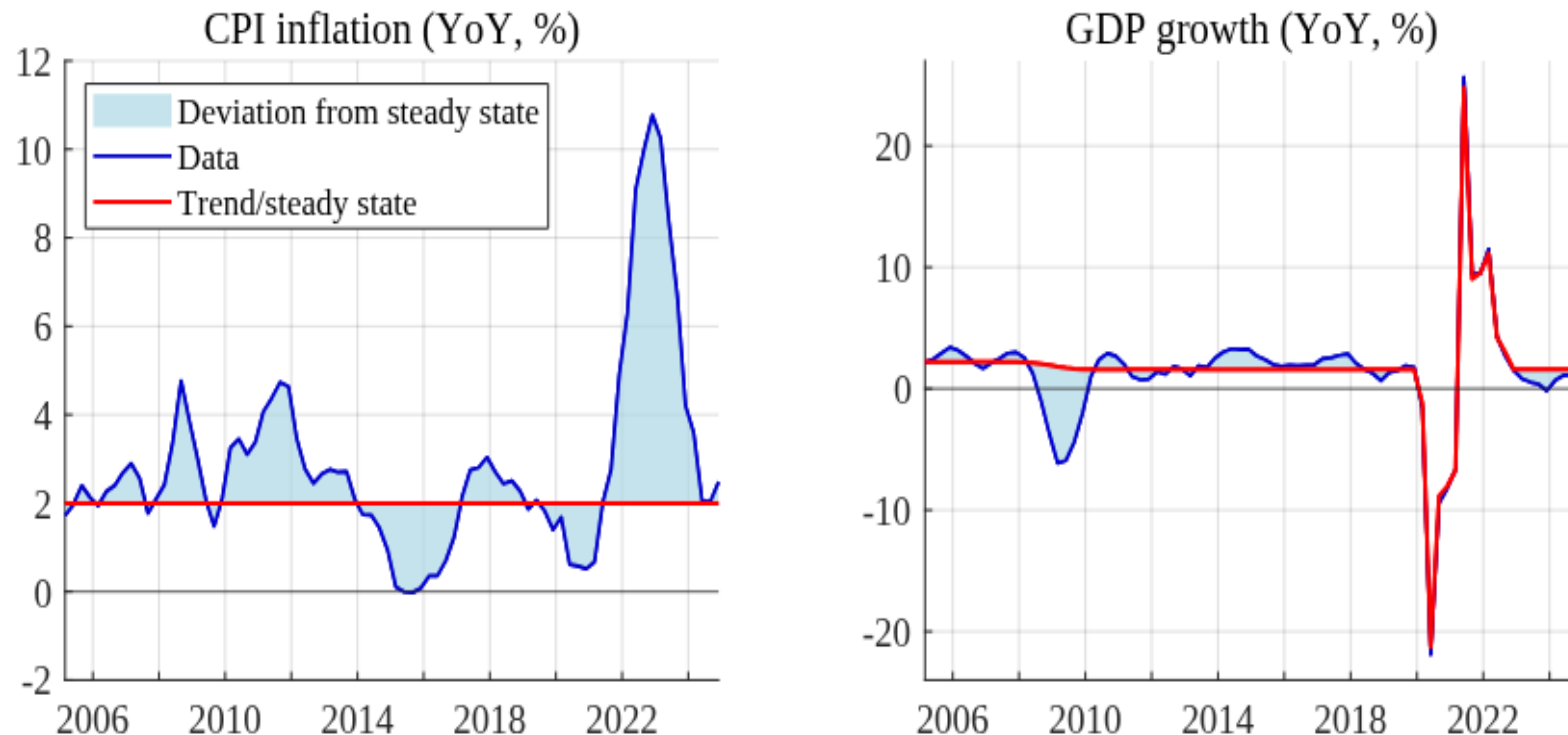
Using model-based shock decompositions to understand macroeconomic dynamics

Historical shock decompositions in a DSGE model

- In a DSGE model, shocks fully and jointly account for the deviation of all variables from their steady state or trend. This allows for model-based shock decompositions of key macroeconomic variables of interest to policymakers.
- These decompositions are useful for policymaking, as they allow us to interrogate the drivers of macroeconomic dynamics and provide insights relevant for contemporaneous or future policy setting
- Moreover, if the model decompositions provide sensible interpretations that align with the narrative based on real-time data, this provides further re-assurance regarding the quality of the model itself

The model decomposes deviations of a variable from its steady state or trend value (shaded blue), rather than the data itself

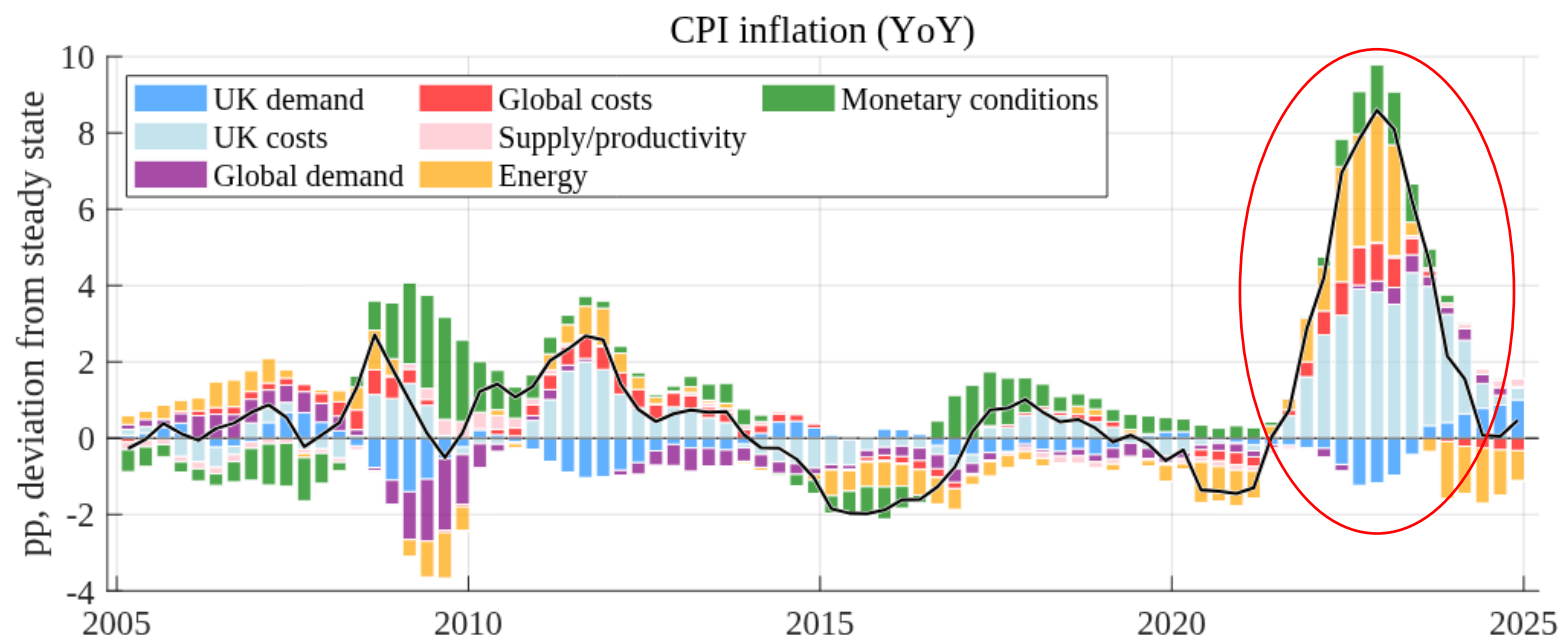
Figure 7: DATA TRANSFORMATION INTO DEVIATIONS FROM STEADY STATE



Notes: This figure shows the transformation of observed CPI inflation and GDP growth into deviations from its target and steady state, respectively. To retrieve deviations from the steady states, data inputs are adjusted for (1) off-model trends, which capture structural breaks, transition periods and extraordinary events; and (2) the steady states, which account for long-term dynamics.

Our model's CPI inflation decomposition highlights the role of energy and cost shocks in the inflation spike over 2022 and 2023

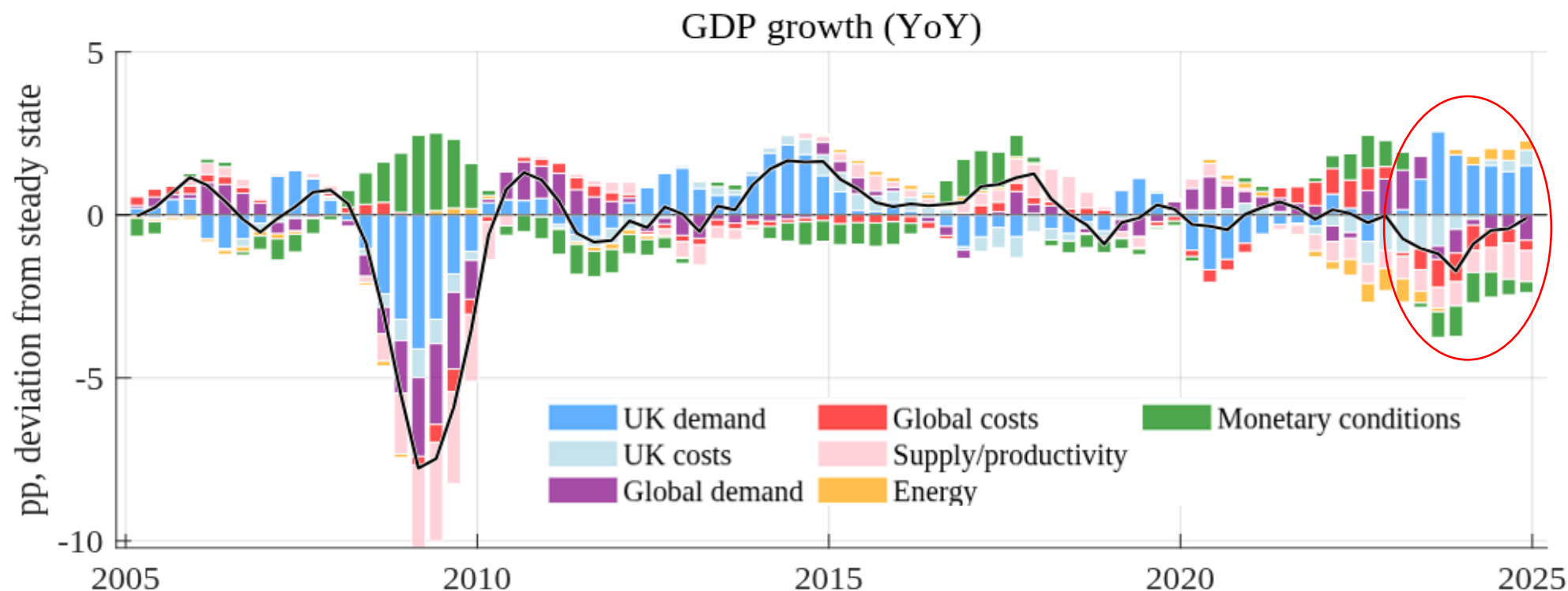
Figure 8: HISTORICAL SHOCK DECOMPOSITION OF MODEL VARIABLES



Notes: This figure shows the historical shock decomposition of year-on-year CPI inflation, as a model observable, in percentage point deviation from its steady state. The bars represent the contributions of model shocks grouped into aggregate categories.

Conversely, the GDP growth decomposition highlights the role played by UK demand and supply conditions in driving GDP growth over the same period

Figure 8: HISTORICAL SHOCK DECOMPOSITION OF MODEL VARIABLES



Notes: This figure shows the historical shock decomposition of year-on-year GDP growth, as a model observable, in percentage point deviation from its steady state. The bars represent the contributions of model shocks grouped into aggregate categories.



5c. Scenario analysis

Types of counterfactual scenarios, and using the model for scenario analysis in practice

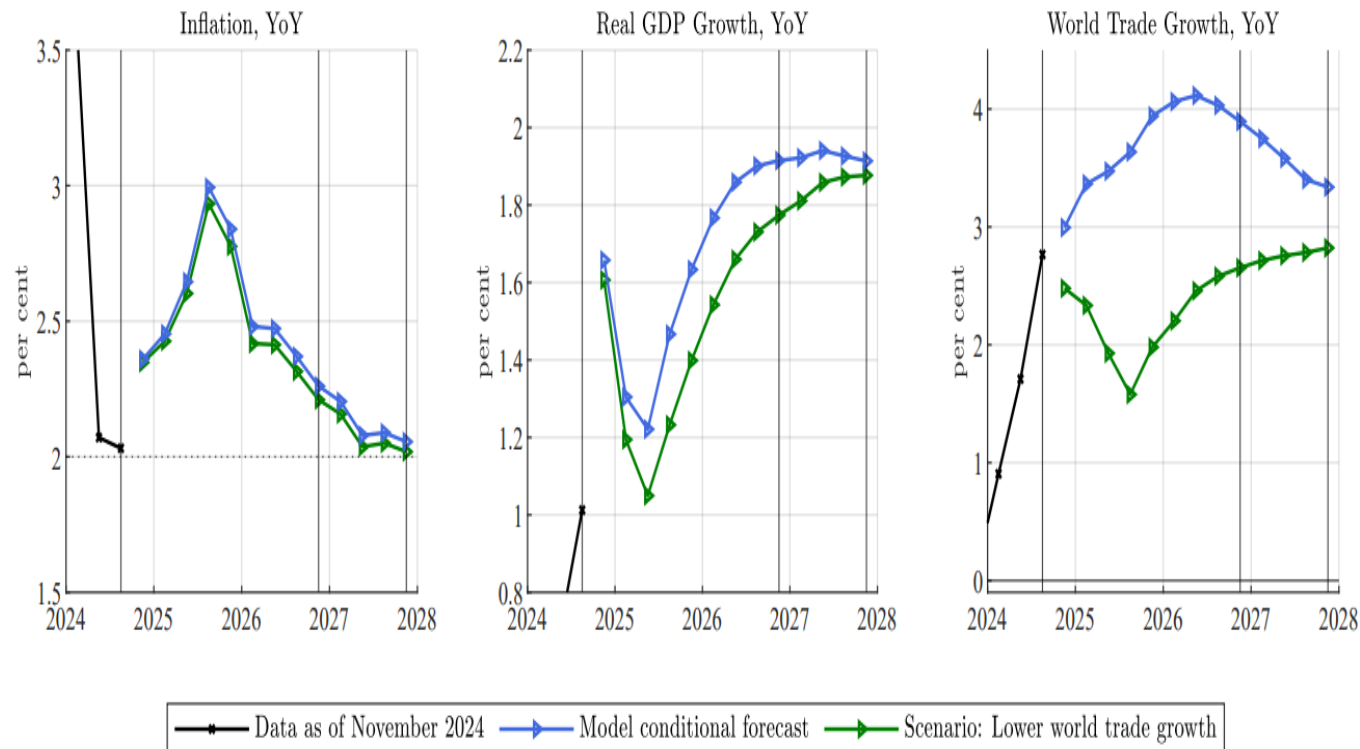
Internally-consistent scenarios with endogenous monetary policy responses

- A key benefit of our highly structural and flexible DSGE model is that it enables counterfactual scenario analysis which is not subject to the Lucas Critique
- As noted by Lombardelli (2025), scenarios and various policy simulations are a useful tool to help policymakers understand risks and uncertainties around their central projection and infer policy implications
- We can use the model to generate a variety of counterfactual scenarios to inform policymaking

Scenarios can be based on different conditioning paths, or can reflect specific economic events, represented by a single shock or combination of shocks

Scenarios can be based on different conditioning paths, or can reflect specific economic events, represented by a single shock or combination of shocks

Figure 13: ALTERNATE SHOCKS AND CONDITIONING PATHS SCENARIO - LOWER WORLD TRADE GROWTH



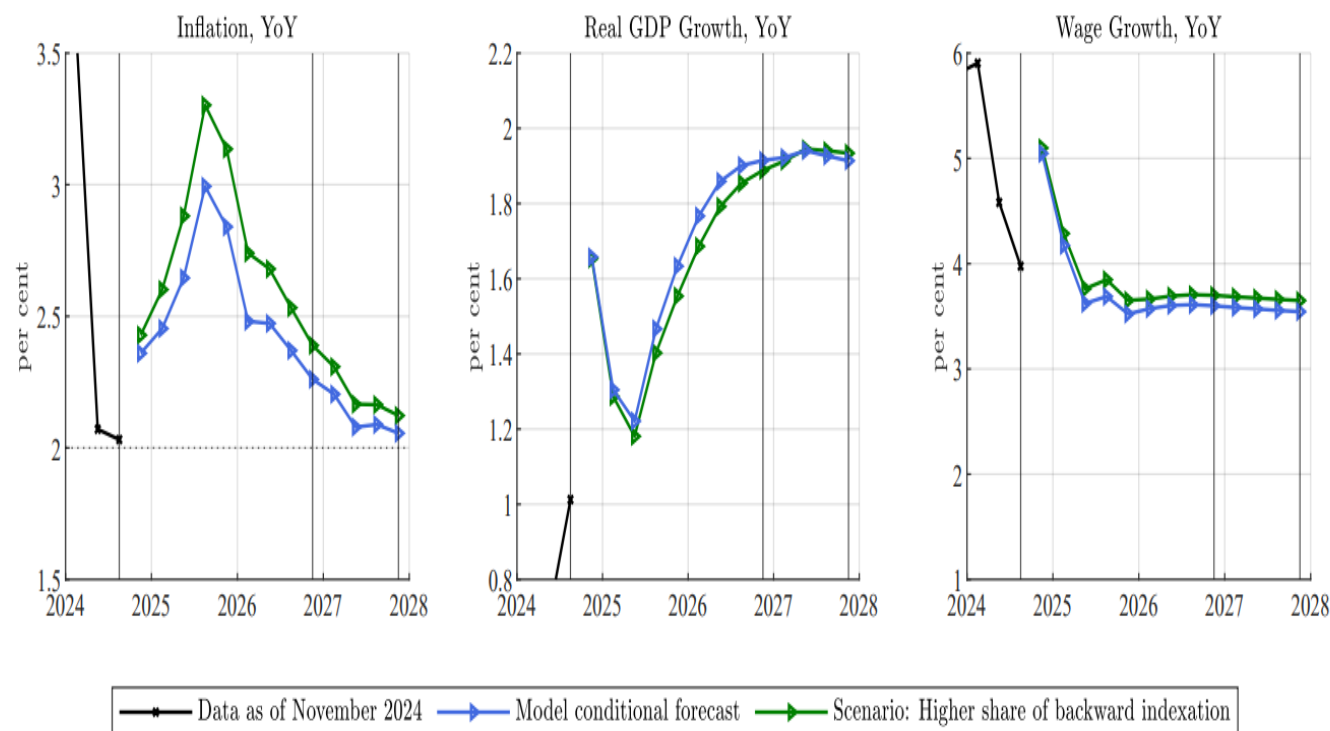
- A hypothetical example is where (standing in November 2024) a world trade shock is assumed to reduce world trade growth by around 1pp throughout 2025
- The model's alternative scenario projections (green lines) have weaker GDP growth and inflation, relative to its conditional forecasts (blue lines)
- This is because, within the model, this scenario dampens UK investment and demand

We can also produce scenarios where key structural features of the economy may differ. By using alternative assumptions about economic processes, parameters, or even the model's structure.

- This allows for an analysis of how the economy could evolve if it were subjected to the same constellation of shocks as in a central projection, but under different structural conditions

We can also produce scenarios where key structural features of the economy may differ. By using alternative assumptions about economic processes, parameters, or even the model's structure.

Figure 14: STRUCTURAL SCENARIO - HIGHER BACKWARDS INDEXATION IN PRICE AND WAGE SETTING



- Another hypothetical example is where (again, standing in November 2024) price and wage setting behaviour is assumed to be structural different
- The degree of backward indexation for price and wages is increased, such that a larger share of firms and households in the model index their prices and wages to previously observed values
- The model's alternative projections in this scenario (green lines) have higher inflation and wage growth compared to the model's conditional forecast (blue lines). As well as lower GDP growth.

In practice, we have used the model to construct scenarios with a combination of alternative shocks and structural parameters

Such as the two scenarios described in the Bank of England's *May 2025 Monetary Policy Report*.

1. Weaker demand scenario

- Explored the risk that a heightened degree of uncertainty in the UK, driven by both domestic and global developments, might have dragged on UK activity more than already incorporated into the baseline forecast

2. Higher persistence scenario

- Explored the risk that households' and businesses' inflation expectations were more sensitive to recent price rises than normal
- This could generate more persistence in price and wage setting, and so the impact of the renewed cost push shock in mid-2025 could have more lasting effects on inflation than in the baseline



6. Key areas for future development

Bounded rationality, fiscal policy, labour market, and non-linearities

This is an important first step in our monetary policy transformation, but there's much more to do

- The updated model has many useful policy applications, and we plan to further develop it to capture other important macroeconomic channels that are relevant for policymaking
- Areas for future development include, but are not restricted to:
 1. Introducing bounded rationality and cognitive discounting in the model
 2. Account for a wider array of fiscal tools, such as distortionary taxes
 3. Richer labour market set up, with search and matching frictions between employment and unemployment
 4. Non-linear version of the model to better capture and interpret extreme events and macroeconomic uncertainty



Q&A

