

# Forecasting Macroeconomic Risks in the UK

David Aikman<sup>1</sup> Rhys Bidder<sup>2</sup> Simon Lloyd<sup>3</sup> Giulia Mantoan<sup>3</sup>  
Simone Maso<sup>4</sup> Aditya Mori<sup>5</sup> Matthew Tong<sup>3</sup>

<sup>1</sup>National Institute for Economic and Social Research

<sup>2</sup>King's College London

<sup>3</sup>Bank of England

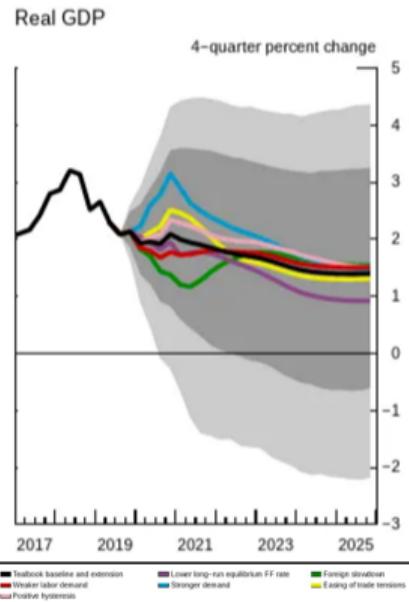
<sup>4</sup>University College London

<sup>5</sup>University of Oxford

December 2025

# Risks Matter for Policy

## Scenarios: Fed Tealbook, Dec 2019



## Fans: BoE MPR, Nov 2022



⇒ Important to have tools to quantify risks, as well as metrics to evaluate them

# This Paper

- #1. **Build statistical tools for quantifying macro risks in the UK**
- #2. **Reveal drivers of risks to UK inflation and GDP growth**
- #3. **Compare our estimates (in pseudo real time) to Bank of England Fan Charts**

# This Paper

## #1. Build statistical tools for quantifying macro risks in the UK

- Quantile regressions to estimate inflation- and growth-at-risk
  - ↪ Account for UK-specific features, in particular exposure to global factors
- *One of many possible approaches:* dynamic skew-*t*, QVARs, GARCH ...

## #2. Reveal drivers of risks to UK inflation and GDP growth

## #3. Compare our estimates (in pseudo real time) to Bank of England Fan Charts

# This Paper

## #1. Build statistical tools for quantifying macro risks in the UK

- Quantile regressions to estimate inflation- and growth-at-risk
  - ↪ Account for UK-specific features, in particular exposure to global factors
- *One of many possible approaches:* dynamic skew-*t*, QVARs, GARCH ...

## #2. Reveal drivers of risks to UK inflation and GDP growth

- New insights about macroeconomic factors impacting tail risks to UK inflation
  - ↪  $\pi^e$ ,  $\pi^{oil}$  and slack contribute to infl. persistence risks (i.e., right tail)
- Although similar to US, term structure of UK growth-at-risk has global foundations
  - ↪ Tighter fin. conditions weigh on left tail in near term; global credit growth in medium term

## #3. Compare our estimates (in pseudo real time) to Bank of England Fan Charts

# This Paper

## #1. Build statistical tools for quantifying macro risks in the UK

- Quantile regressions to estimate inflation- and growth-at-risk
  - ↪ Account for UK-specific features, in particular exposure to global factors
- *One of many possible approaches*: dynamic skew-*t*, QVARs, GARCH ...

## #2. Reveal drivers of risks to UK inflation and GDP growth

- New insights about macroeconomic factors impacting tail risks to UK inflation
  - ↪  $\pi^e$ ,  $\pi^{oil}$  and slack contribute to infl. persistence risks (i.e., right tail)
- Although similar to US, term structure of UK growth-at-risk has global foundations
  - ↪ Tighter fin. conditions weigh on left tail in near term; global credit growth in medium term

## #3. Compare our estimates (in pseudo real time) to Bank of England Fan Charts

- Calibration and sharpness: how 'reasonable'? Relative accuracy: is one better than another?
  - ↪ Inflation fans relatively well calibrated, less so for GDP growth
  - ↪ Quantile regressions outperform fans in some dimensions, especially in tails

# Uses in Practice

## #1. Data-driven signal about balance of macro risks

- Can highlight *key, policy-relevant, drivers* of uncertainty and skew in outlook
- Clearer foundations than fan charts, which blurred past forecast errors and ‘judgement’
- *Albeit imperfect*: only as good as past data

# Uses in Practice

## #1. Data-driven signal about balance of macro risks

- Can highlight *key, policy-relevant, drivers* of uncertainty and skew in outlook
- Clearer foundations than fan charts, which blurred past forecast errors and ‘judgement’
- *Albeit imperfect*: only as good as past data

## #2. Define set of density-forecast evaluation metrics to evaluate tools

- Clarify dimensions in which fan charts had “weak conceptual foundations”
- Guide to future development of macro risk-assessment tools

[Bernanke 24]

# Uses in Practice

## #1. Data-driven signal about balance of macro risks

- Can highlight *key, policy-relevant, drivers* of uncertainty and skew in outlook
- Clearer foundations than fan charts, which blurred past forecast errors and ‘judgement’
- *Albeit imperfect*: only as good as past data

## #2. Define set of density-forecast evaluation metrics to evaluate tools

- Clarify dimensions in which fan charts had “weak conceptual foundations” [Bernanke 24]
- Guide to future development of macro risk-assessment tools

## #3. Support scenario development and synthesis

- Act as reference for ‘scenario synthesis’
- Gauge degree of scenario ‘completeness’ [Adrian et al. 25]

# At-Risk Estimates

# Quantile-Regression Setup

$$Q_{y_{t+h}}(\tau | \mathbf{x}_t) = \alpha^h(\tau) + \mathbf{x}'_t \boldsymbol{\beta}^h(\tau)$$

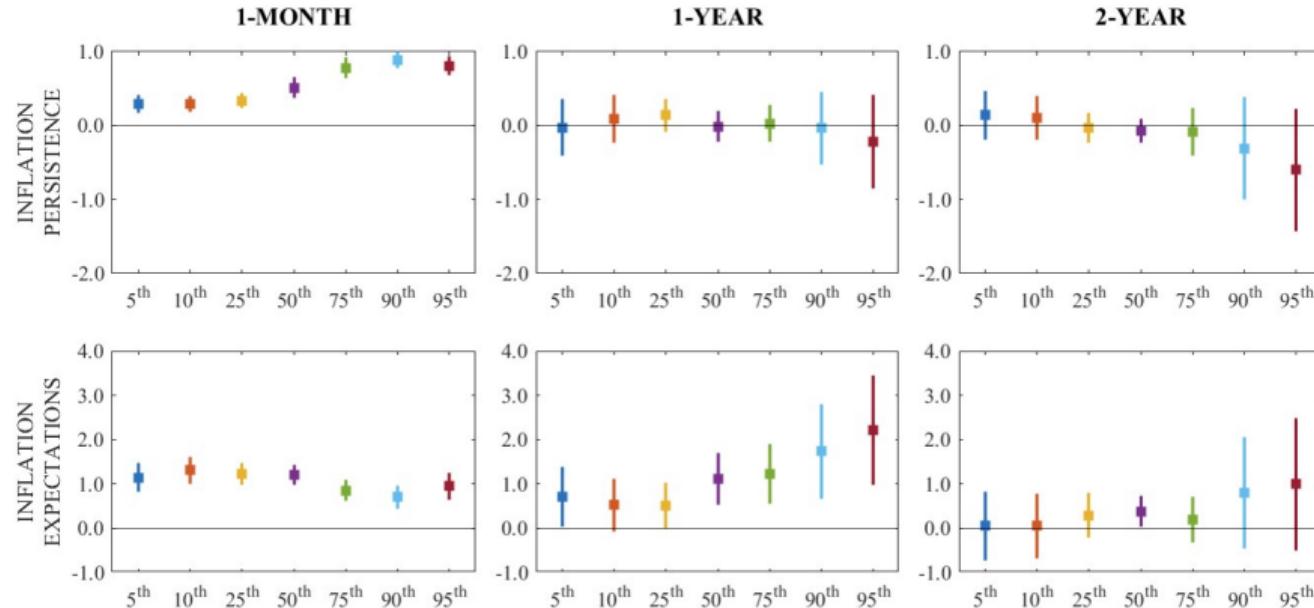
- ▶  $Q$ : conditional quantile function
- ▶  $\tau \in (0, 1)$ : quantiles
- ▶  $y_t$ : dependent variable
  - Annual UK CPI inflation (monthly):  $\pi_t = \ln P_t - \ln P_{t-12}$
  - Year-on-year UK real GDP growth (quarterly):  $\Delta^4 y_t = \ln GDP_t - \ln GDP_{t-4}$
- ▶  $\mathbf{x}_t$ : 'risk factors', with quantile- and horizon-specific coefficients  $\boldsymbol{\beta}^h(\tau)$
- ▶ Full Samples: 1990:01-2024:12 (inflation); 1980Q1-2024Q4 (GDP growth)
- ▶ Out-of-sample, expanding window, analysis from 2004:01-2025:01 (2004Q1-2025Q1)

# Preferred Specifications

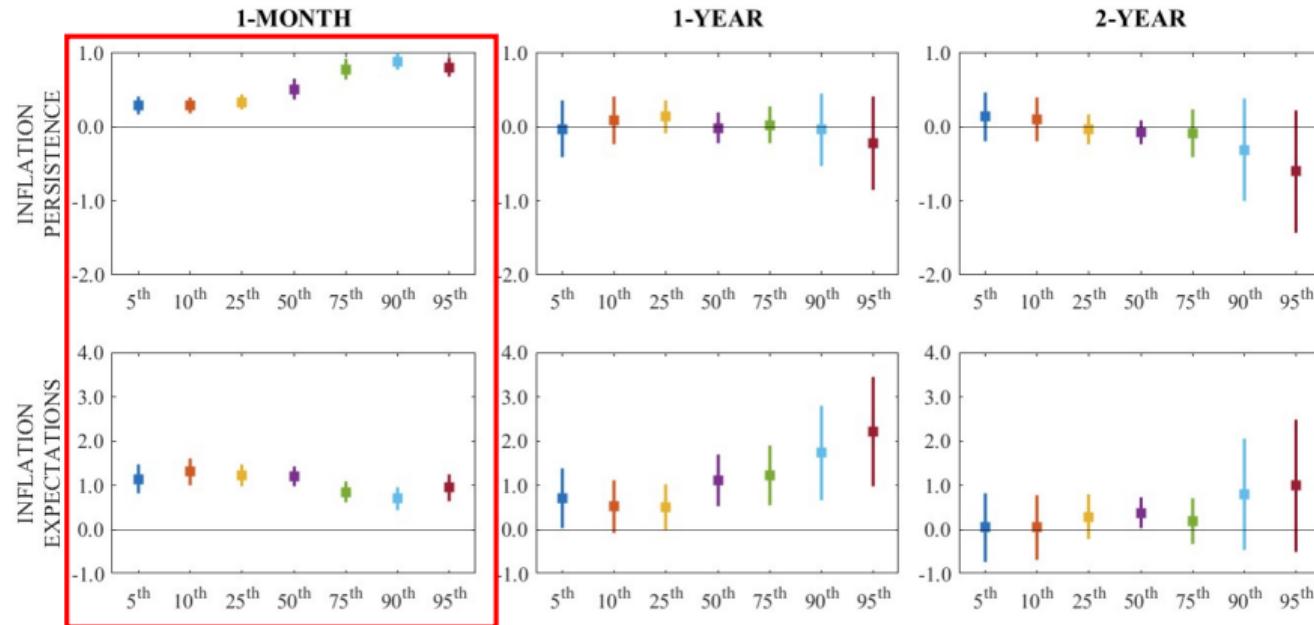
Search over range of specifications, minimising CRPS at forecast-relevant horizons

| Inflation (1990:01-2024:12)  | GDP Growth |
|--|------------|
| I. PERSISTENCE:  |            |
| Avg. CPI inflation in previous year, $\bar{\pi}_{t-11,t}$                  |            |
| II. EXPECTATIONS:  |            |
| CPI infl. exp. for next calendar year, $\pi_{t,1}^e$                       |            |
| III. ECONOMIC TIGHTNESS:   |            |
| 1y chg. in vacancy-unemp. ratio, $\Delta^{12}\left(\frac{v_t}{u_t}\right)$ |            |
| IV. FINANCIAL CONDITIONS:  |            |
| UK Excess Bond Premia, $ebp_t$   |            |
| V. EXTERNAL CONDITIONS:  |            |
| Global y-o-y oil price infl., $\pi_t^{oil}$                                |            |
| COVID-19 DUMMY: 2020:04-2020:09  |            |

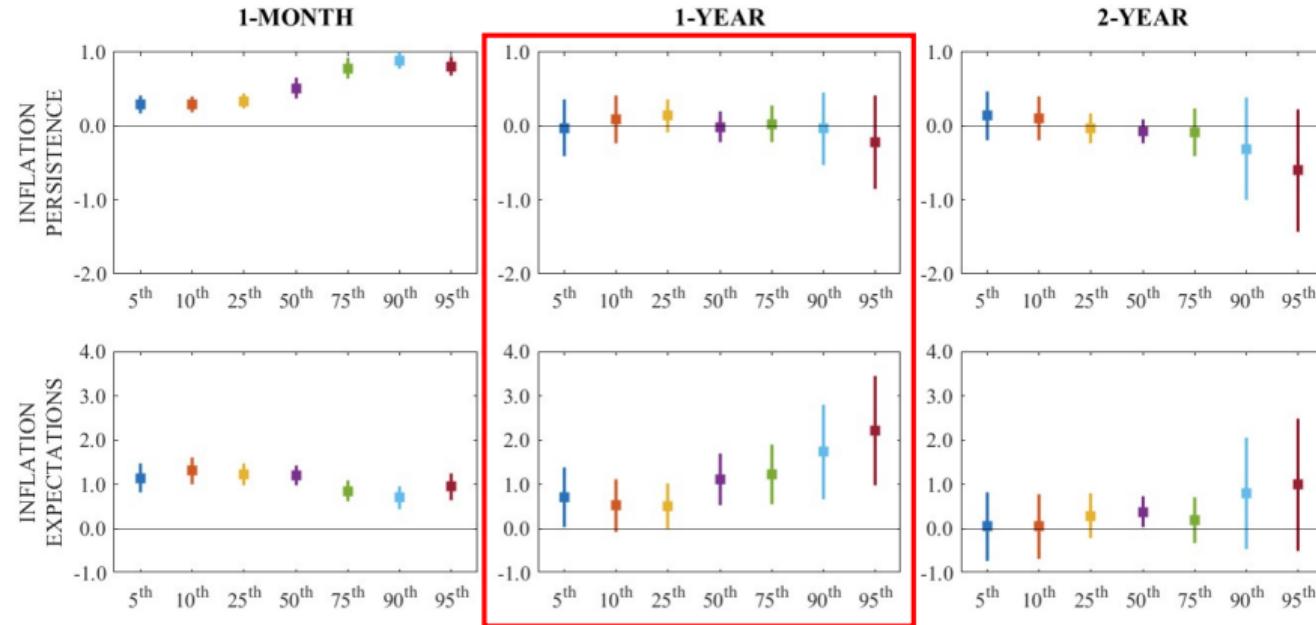
# Inflation Persistence and Inflation Expectations



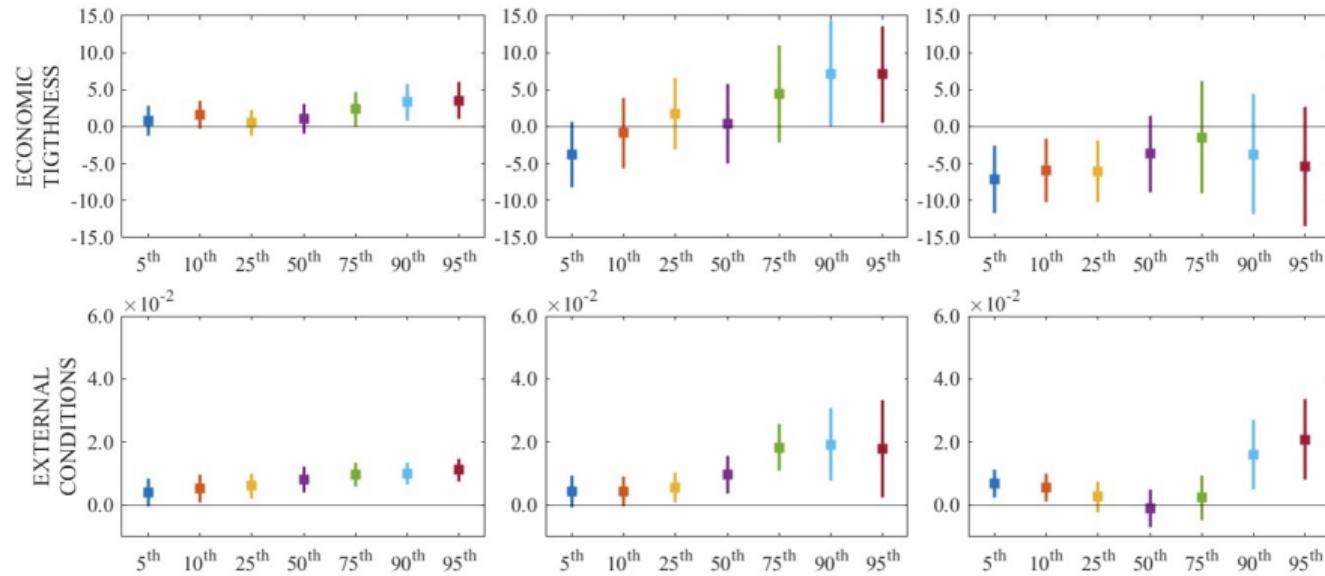
# Inflation Persistence and Inflation Expectations



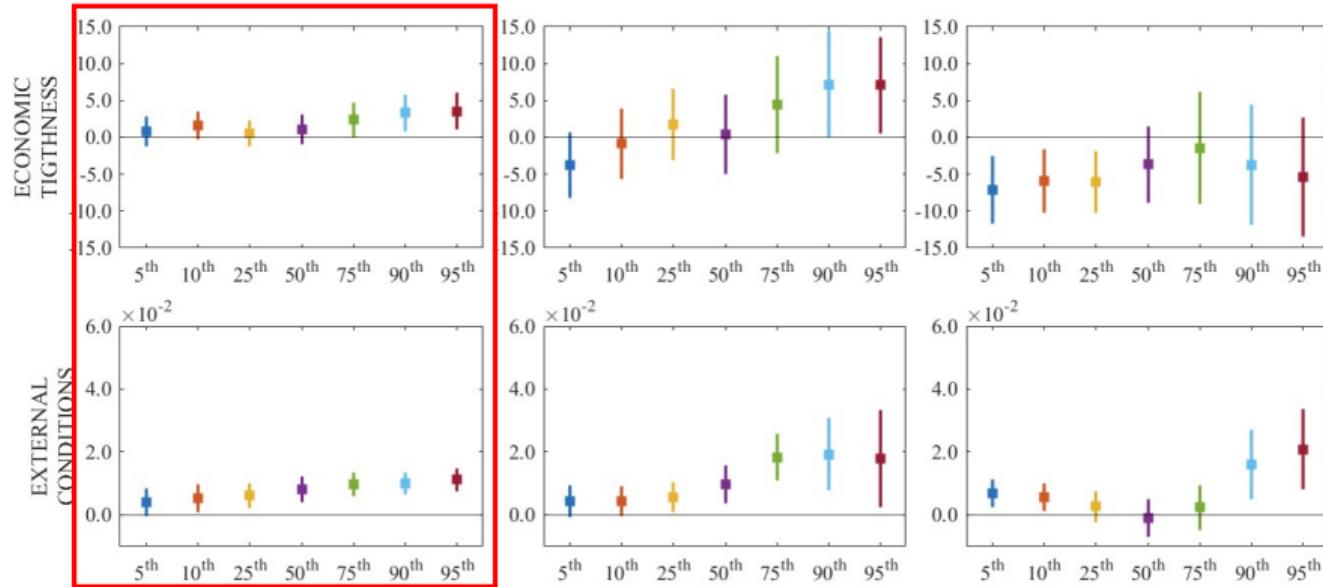
# Inflation Persistence and Inflation Expectations



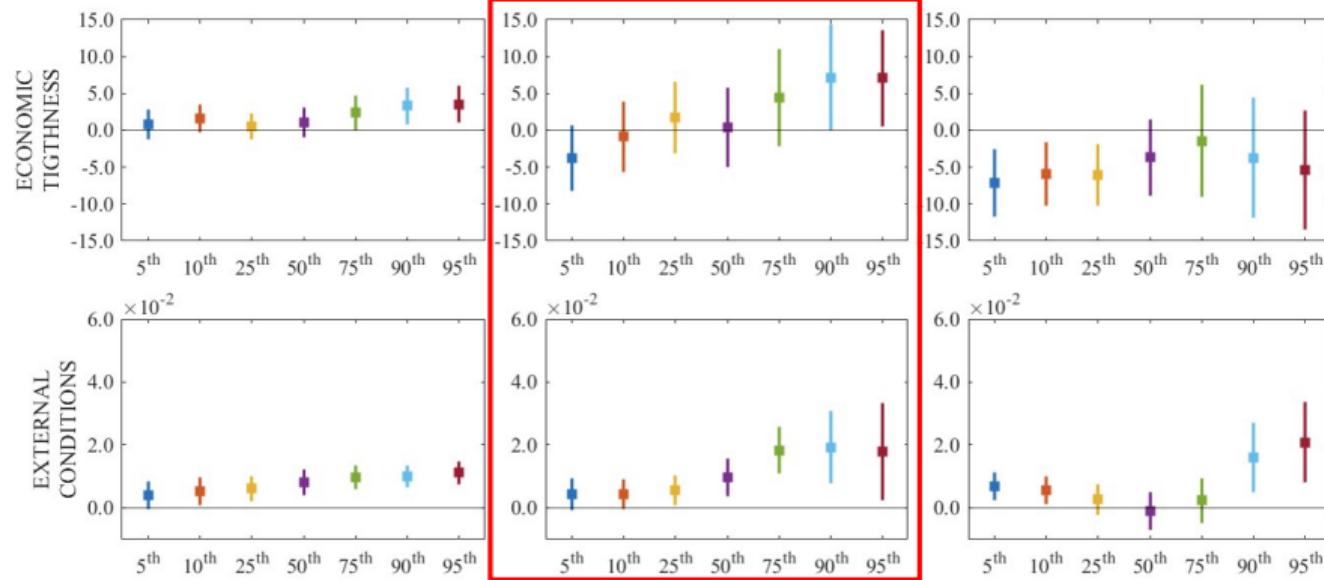
# Economic Tightness and External Conditions



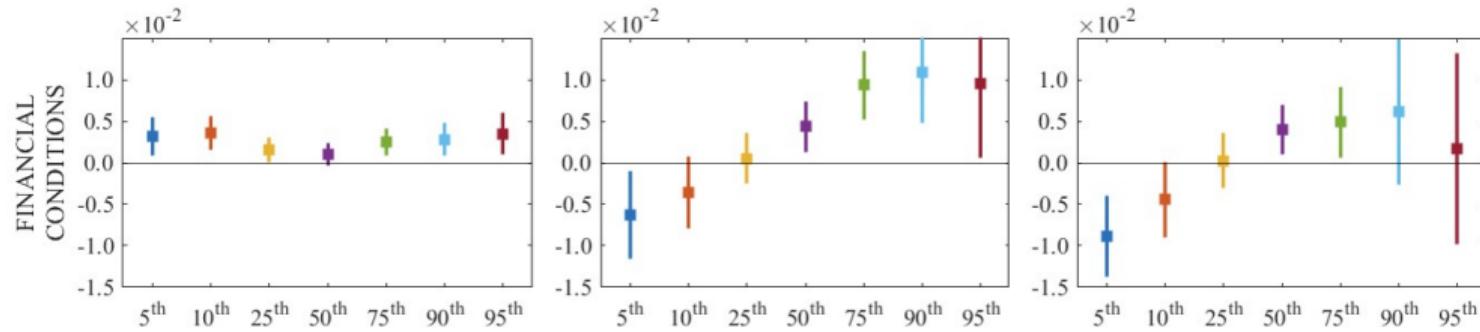
# Economic Tightness and External Conditions



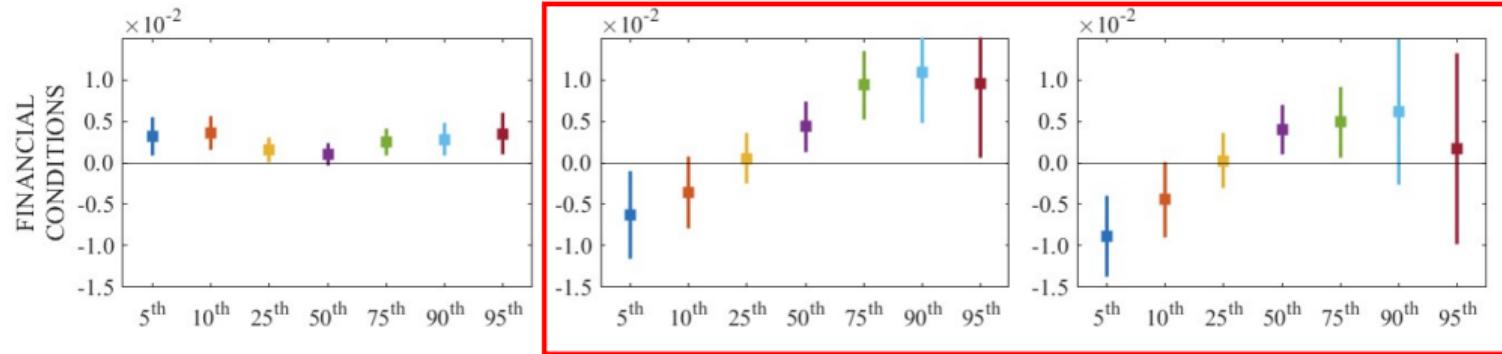
# Economic Tightness and External Conditions



# Financial Conditions

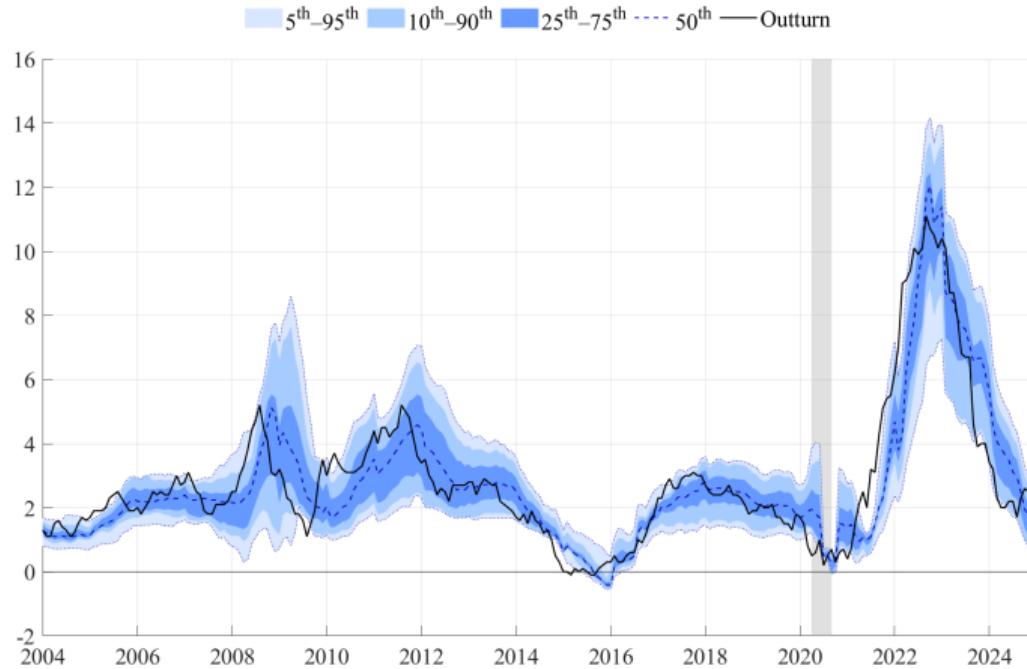


# Financial Conditions



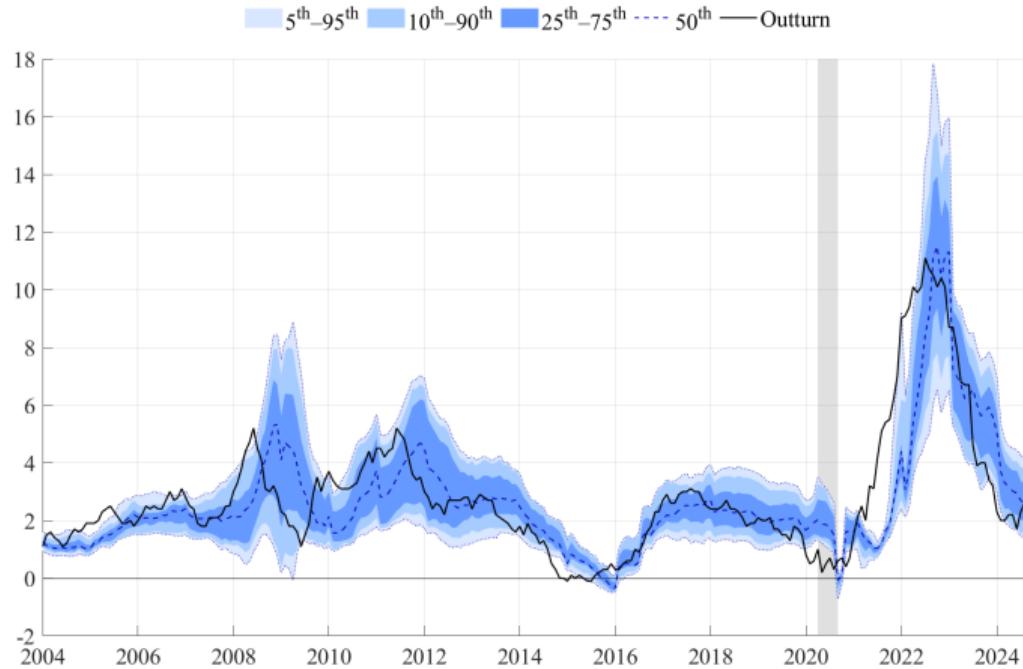
# Out-of-Sample Quantile Forecasts for Annual CPI Inflation

1-month-ahead



# Out-of-Sample Quantile Forecasts for Annual CPI Inflation

1-quarter-ahead



# New Evidence on Macro Risks in UK

## Inflation

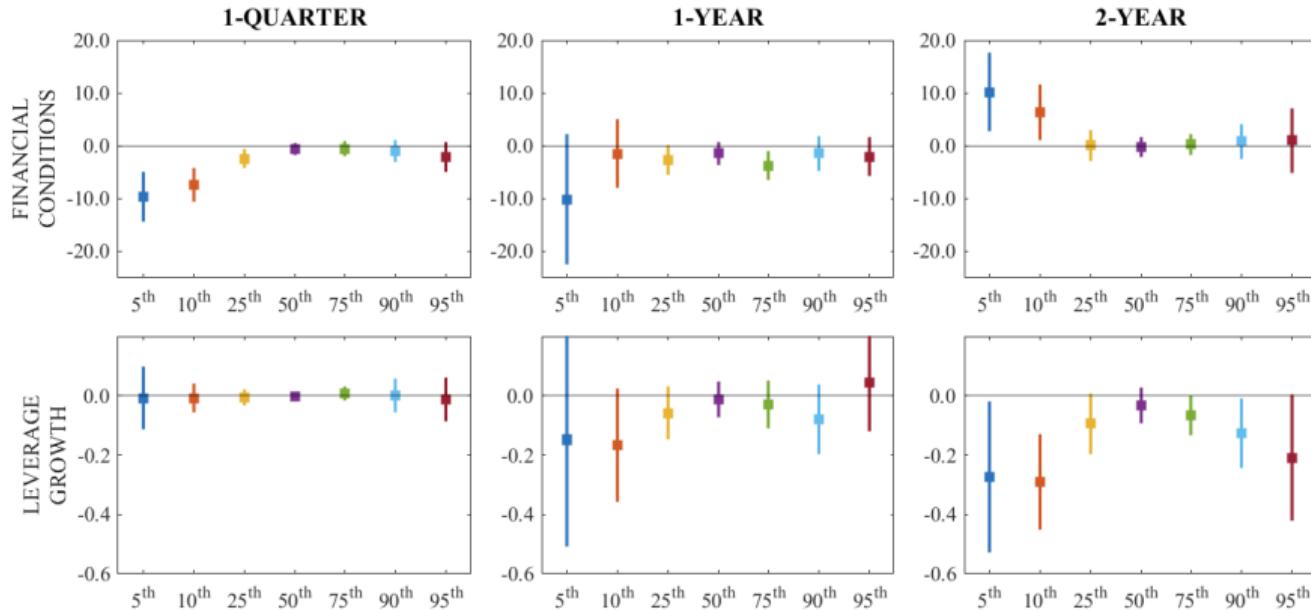
- ▶  $\pi^e$ ,  $\pi^{oil}$  and slack have outsized effect on right tail, driving persistence risks
- ▶ Tighter fin. conditions increase uncertainty and eventually tilt risks to the downside
- ▶ Forecasts and realisations closely aligned
  - At 1-month horizon, 10<sup>th</sup> – 90<sup>th</sup> forecasts bands almost always contain the realisation
  - 1-quarter horizon more challenging, but forecasts (esp. for right tail) detect the variation in risk

# Preferred Specifications

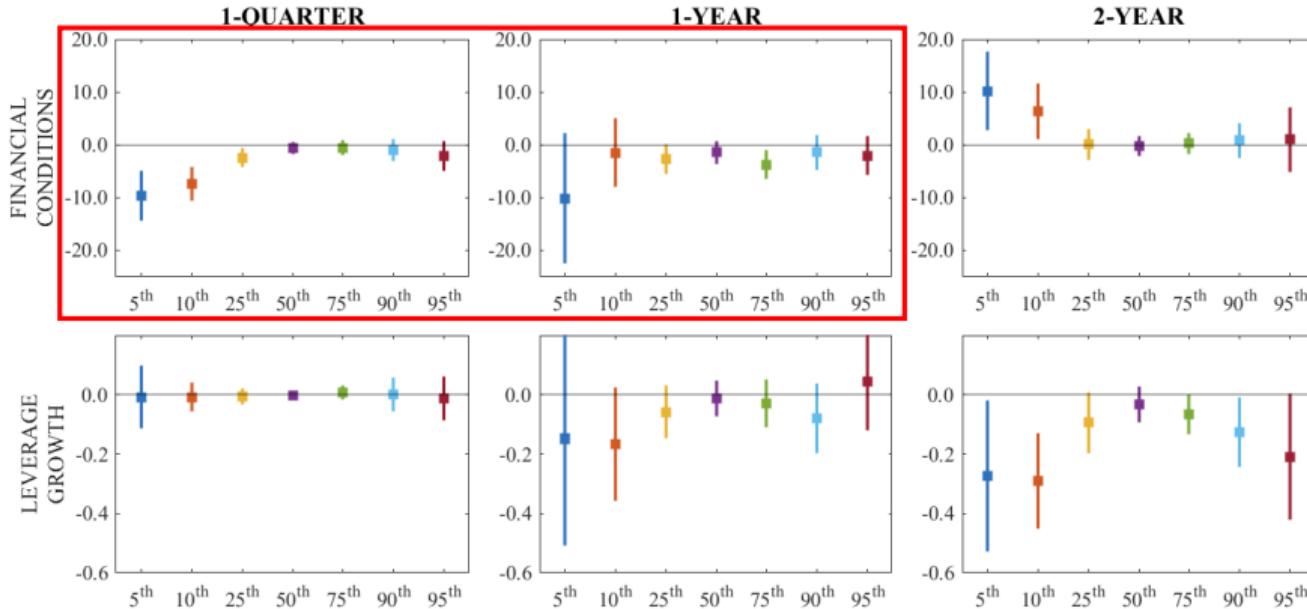
Search over range of specifications, minimising CRPS at forecast-relevant horizons

| Inflation (1990:01-2024:12)  | GDP Growth   |
|--|--|
| <b>I. PERSISTENCE:</b><br>Avg. CPI inflation in previous year, $\bar{\pi}_{t-11,t}$                | <b>I. ECONOMIC ACTIVITY:</b><br>y-o-y monthly GDP gr., $\ln y_{t+1}^{m=1,2} - \ln y_{t+1-4}^{m=1,2,3}$ |
| <b>II. EXPECTATIONS:</b><br>CPI infl. exp. for next calendar year, $\pi_{t,1}^e$                   | <b>II. FINANCIAL CONDITIONS:</b><br>CISS index, $ciss_t$   |
| <b>III. ECONOMIC TIGHTNESS:</b><br>1y chg. in vacancy-unemp. ratio, $\Delta^{12}(\frac{v_t}{u_t})$ | <b>III. LEVERAGE GROWTH:</b><br>3y chg. in global credit-to-GDP, $cred_t^{WORLD}$                      |
| <b>IV. FINANCIAL CONDITIONS:</b><br>UK Excess Bond Premia, $ebpt$                                  | <b>IV. PRICE INDICATOR:</b><br>y-o-y import fuel deflator, $\pi_t^{fuel}$                              |
| <b>V. EXTERNAL CONDITIONS:</b><br>Global y-o-y oil price infl., $\pi_t^{oil}$                      |  |
| COVID-19 DUMMY: 2020:04-2020:09  | COVID-19 DUMMY: 2020Q2-2022Q2  |

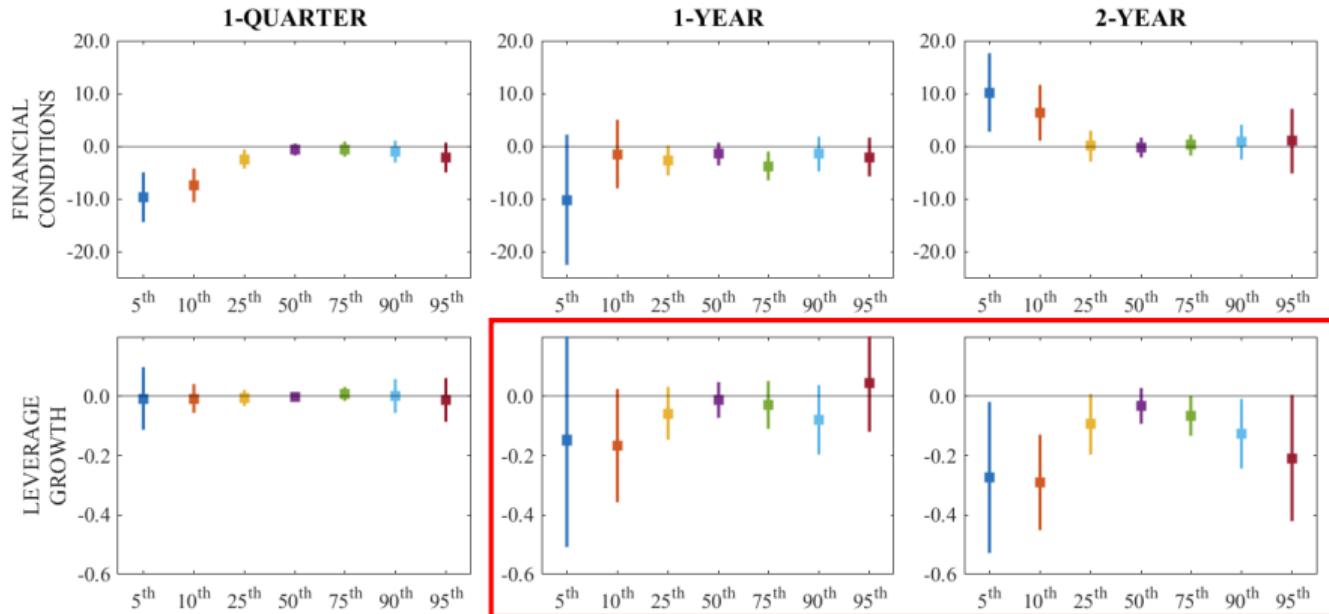
# Financial Conditions and Leverage Growth



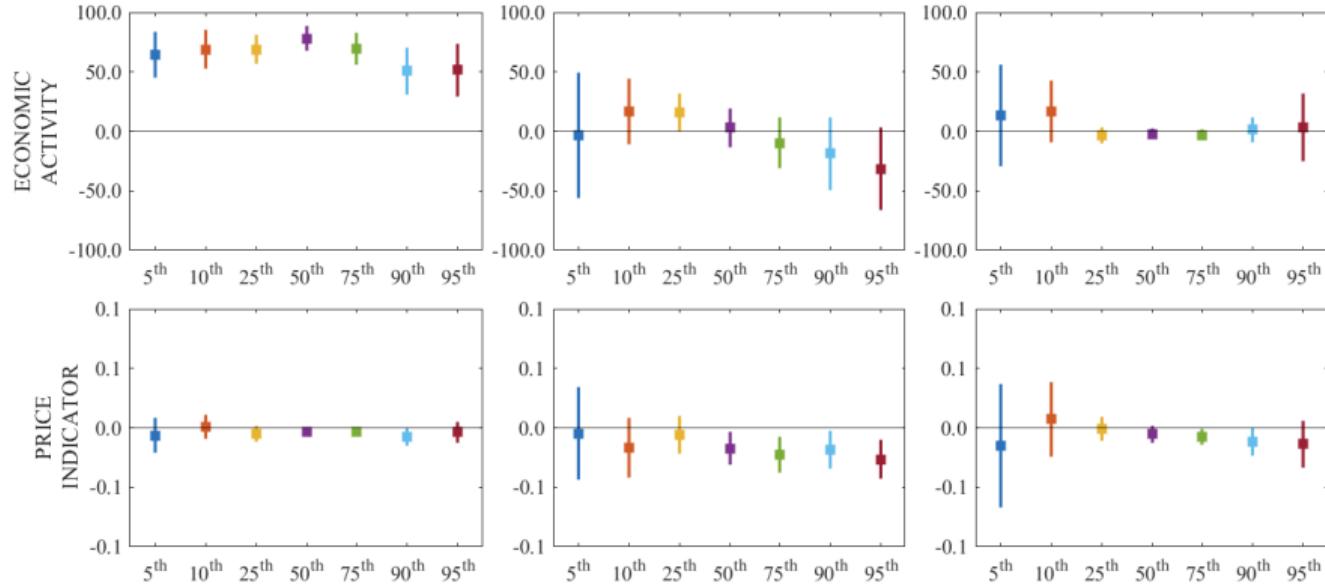
# Financial Conditions and Leverage Growth



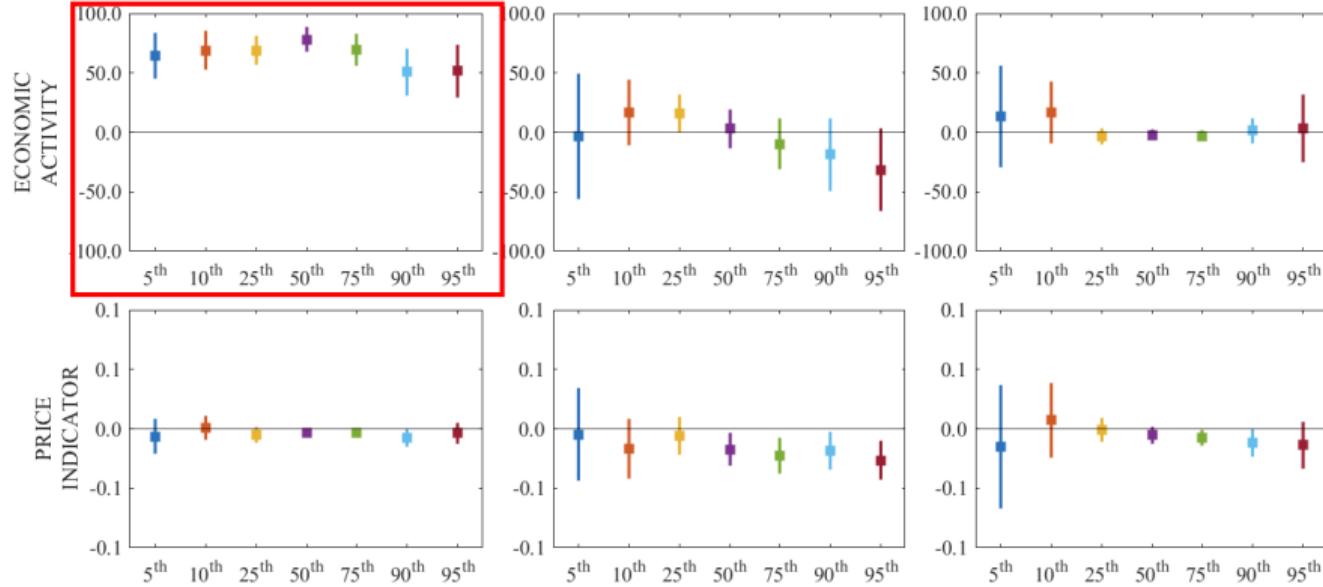
# Financial Conditions and Leverage Growth



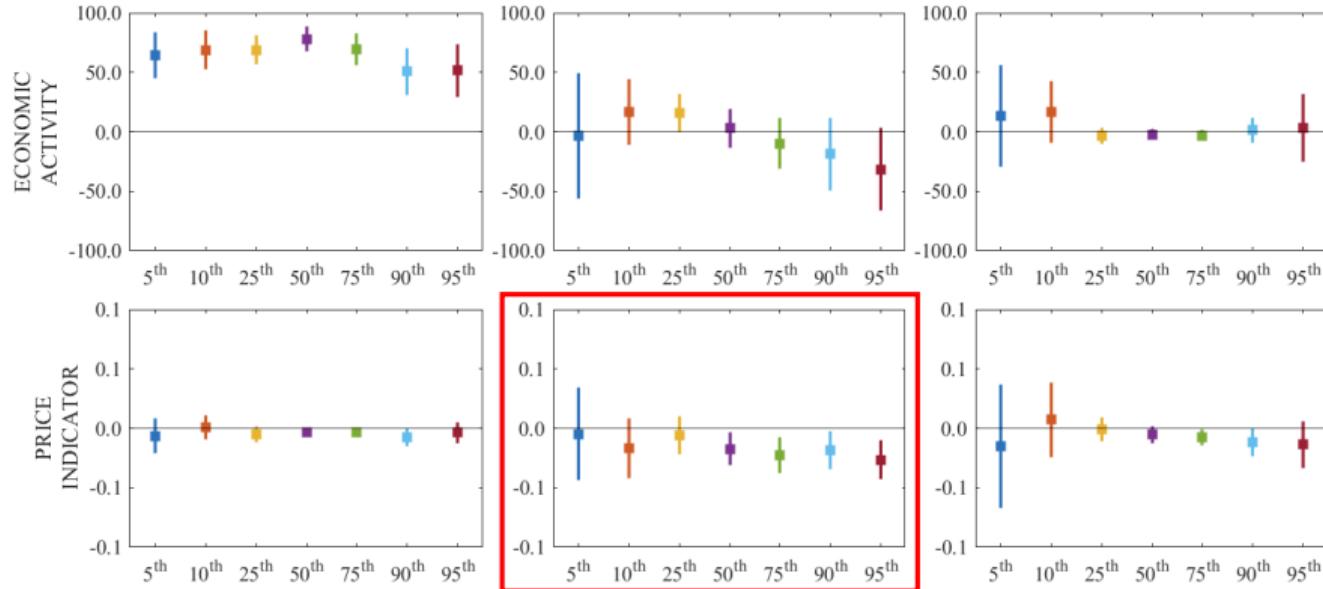
# Economic Activity and Price Indicator



# Economic Activity and Price Indicator

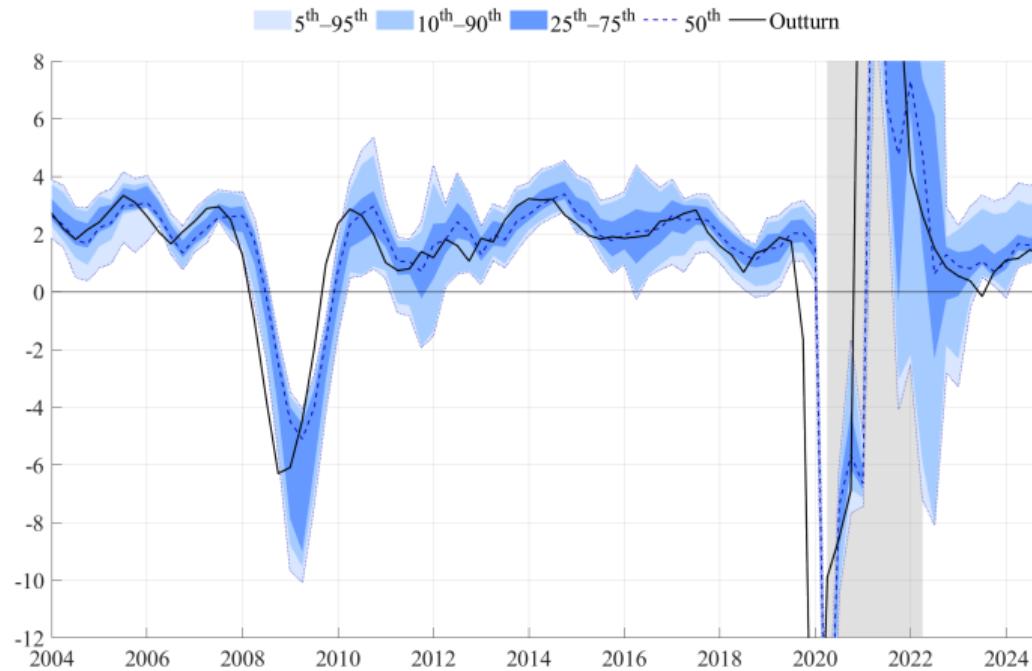


# Economic Activity and Price Indicator



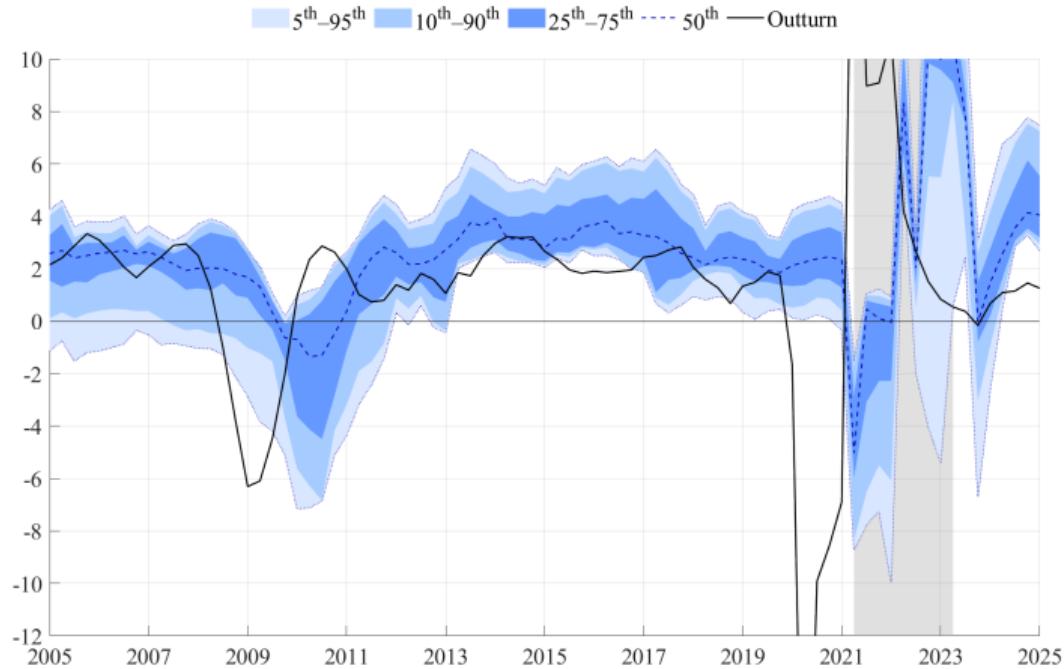
# Out-of-Sample Quantile Forecasts for GDP Growth

1-quarter-ahead



# Out-of-Sample Quantile Forecasts for GDP Growth

1-year-ahead



# New Evidence on Macro Risks in UK

## Inflation

- ▶  $\pi^e$ ,  $\pi^{oil}$  and slack have outsized effect on right tail, driving persistence risks
- ▶ Tighter fin. conditions increase uncertainty and eventually tilt risks to the downside
- ▶ Forecasts and realisations closely aligned
  - At 1-month horizon, 10<sup>th</sup> – 90<sup>th</sup> forecasts bands almost always contain the realisation
  - 1-quarter horizon more challenging, but forecasts (esp. for right tail) detect the variation in risk

## GDP Growth

- ▶ Tighter financial conditions increase near-term downside risks [Adrian et al. 22]
- ▶ Reflecting UK's position as open econ., global credit impacts med-term left tail [Lloyd et al. 24]
- ▶ Short-term accuracy and ability to capture downside risk

# Forecast Evaluation and Comparison with Fan Charts

# Fan Charts

The Bank of England fan charts are constructed as two-piece (or split) normal distributions:

$$f(y|\mu, \sigma, \gamma) = A \exp \left[ -\frac{1}{2\pi\sigma^2} \left( (y - \mu)^2 + \gamma \left( \frac{y - \mu}{|y - \mu|} \right) + (y - \mu)^2 \right) \right]$$

Calibration: Past forecast errors + judgement



# Predictive Distributions from Quantile Regressions

Use out-of-sample quantile forecasts  $\hat{Q}_{y_{t+h}}(\tau|x_t)$  to construct densities via 2 approaches:

#1 **Parametric:** Skew-t, with four moments:

[Azzalini & Capitanio 03]

$$f(\mathbf{y}; \mu, \sigma, \gamma, \kappa) = \frac{2}{\sigma} t\left(\frac{\mathbf{y} - \mu}{\sigma}; \kappa\right) T\left(\gamma\left(\frac{\mathbf{y} - \mu}{\sigma}\right) \sqrt{\frac{\kappa + 1}{\kappa + \left(\frac{\mathbf{y} - \mu}{\sigma}\right)^2}}; \kappa + 1\right)$$

# Predictive Distributions from Quantile Regressions

Use out-of-sample quantile forecasts  $\hat{Q}_{y_{t+h}}(\tau|x_t)$  to construct densities via 2 approaches:

#1 **Parametric:** Skew-t, with four moments:

[Azzalini & Capitanio 03]

$$f(\mathbf{y}; \mu, \sigma, \gamma, \kappa) = \frac{2}{\sigma} t\left(\frac{\mathbf{y} - \mu}{\sigma}; \kappa\right) T\left(\gamma\left(\frac{\mathbf{y} - \mu}{\sigma}\right) \sqrt{\frac{\kappa + 1}{\kappa + \left(\frac{\mathbf{y} - \mu}{\sigma}\right)^2}}; \kappa + 1\right)$$

#2 **Semi-parametric:**

[Mitchell et al. 24]

$$\hat{F}(y_{t+h} | x_t) = \tau_j + \frac{\tau_{j+1} - \tau_j}{x_t^\top \hat{\beta}_{\tau_{j+1}} - x_t^\top \hat{\beta}_{\tau_j}} \left( y_{t+h} - x_t^\top \hat{\beta}_{\tau_j} \right)$$

# Predictive Distributions from Quantile Regressions

Use out-of-sample quantile forecasts  $\hat{Q}_{y_{t+h}}(\tau|x_t)$  to construct densities via 2 approaches:

#1 **Parametric:** Skew-t, with four moments:

[Azzalini & Capitanio 03]

$$f(\mathbf{y}; \mu, \sigma, \gamma, \kappa) = \frac{2}{\sigma} t\left(\frac{\mathbf{y} - \mu}{\sigma}; \kappa\right) T\left(\gamma\left(\frac{\mathbf{y} - \mu}{\sigma}\right) \sqrt{\frac{\kappa + 1}{\kappa + \left(\frac{\mathbf{y} - \mu}{\sigma}\right)^2}}; \kappa + 1\right)$$

#2 **Semi-parametric:**

[Mitchell et al. 24]

$$\hat{F}(y_{t+h} | x_t) = \tau_j + \frac{\tau_{j+1} - \tau_j}{x_t^\top \hat{\beta}_{\tau_{j+1}} - x_t^\top \hat{\beta}_{\tau_j}} \left( y_{t+h} - x_t^\top \hat{\beta}_{\tau_j} \right)$$

**For today:** Since skew-t forecasts more accurate than semiparametric, focus on former

# Fan Charts & Quantile Regression: How Can We Judge Them?

## Probabilistic Calibration

If model predicts 70% chance of event and that event happens  $\sim 70\%$  of time, forecast distribution matches reality

→ valuable for policymakers, since well-calibrated forecasts accurately capture likelihoods

# Fan Charts & Quantile Regression: How Can We Judge Them?

## Probabilistic Calibration

If model predicts 70% chance of event and that event happens  $\sim 70\%$  of time, forecast distribution matches reality

→ valuable for policymakers, since well-calibrated forecasts accurately capture likelihoods

Statistically, it means testing if the PITs of density forecast are uniform:

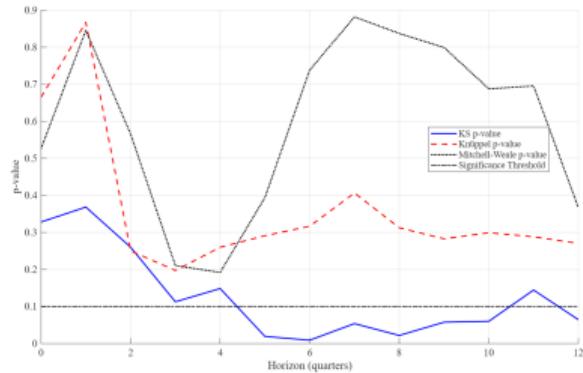
$$z_{t,t+h} = \int_{-\infty}^{y_{t+h}} f_t(y_{t+h}) \, dy = F_t(y_{t+h})$$

Tests we apply account for nature of macro time series:

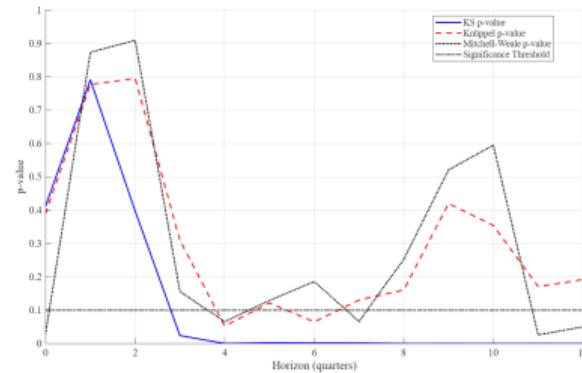
- Rossi and Sekhposyan (19): Time-series dependence
- Knüppel (15): Focus on moments
- Mitchell & Weale (23): Censoring of fans
- Galvão et al. (25): Joint test across forecast horizons

# Inflation Fans and Quantile Regressions Both Well-Calibrated

Fan Charts



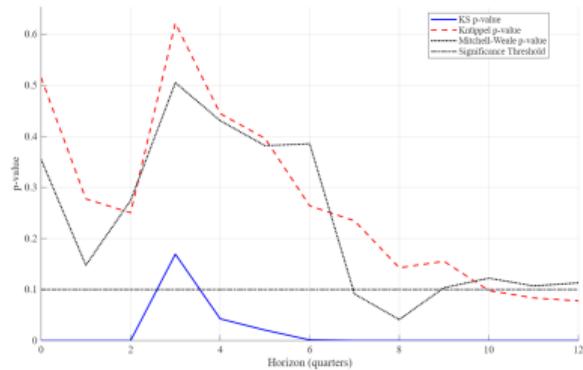
Inflation-at-risk



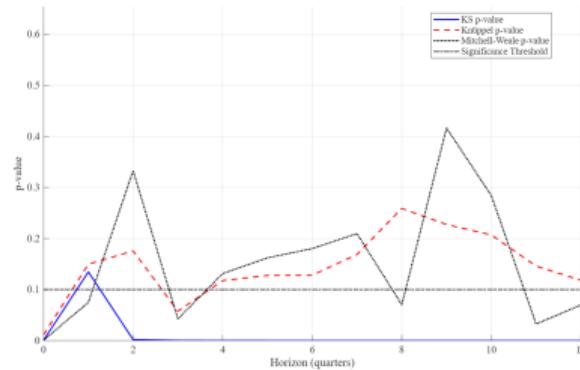
| Galvão et al. ('25) | Sup test | Decr w | Incre w | Sup test | Decr w | Incre w |
|---------------------|----------|--------|---------|----------|--------|---------|
| Joint at 5%         | ✓        | ✓      | ✓       | ✓        | ✓      | ✓       |

# Near-Term GDP Fans Calibrated, (So Far) Mixed for Quantile Regs.

## Fan Charts



## GDP-at-risk



Galvão et al. ('25)

Sup test

Decr w

Incre w

Sup test

Decr w

Incre w

Joint at 5%

✗

✓

✗

✗

✗

✗

# Fan Charts & Quantile Regression: How Can We Judge Them?

## Sharpness

Sharpness measures the concentration of the forecast density to distinguish between two calibrated forecasts.

# Fan Charts & Quantile Regression: How Can We Judge Them?

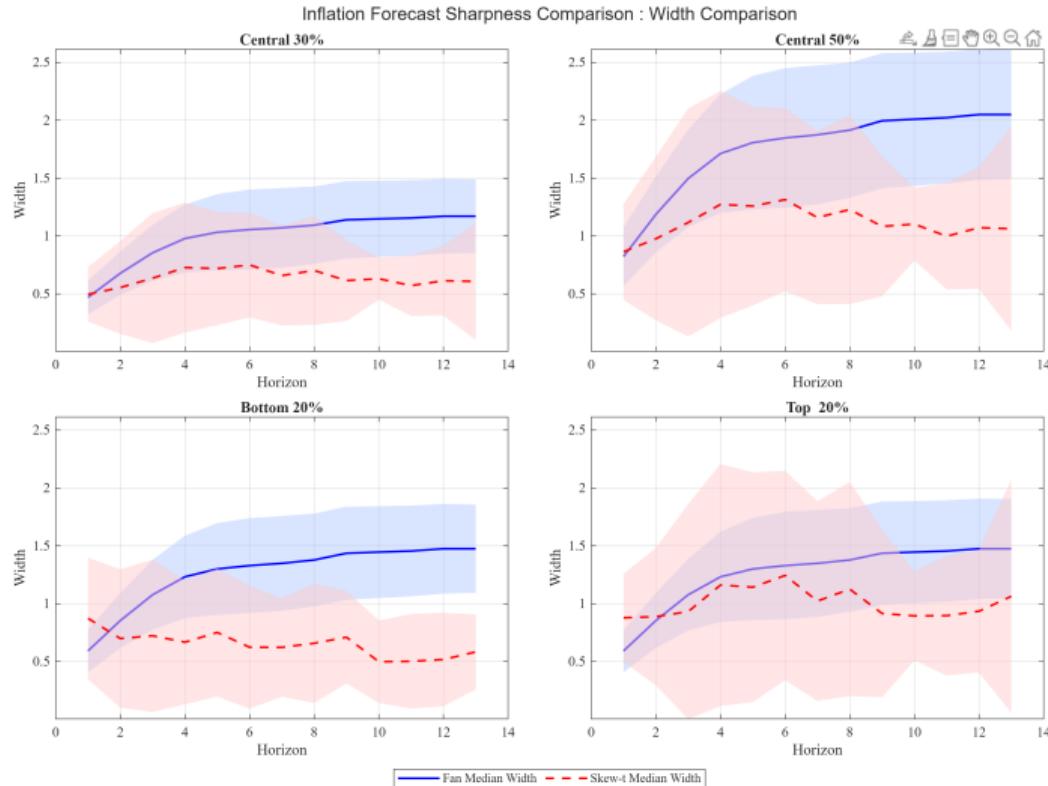
## Sharpness

Sharpness measures the concentration of the forecast density to distinguish between two calibrated forecasts.

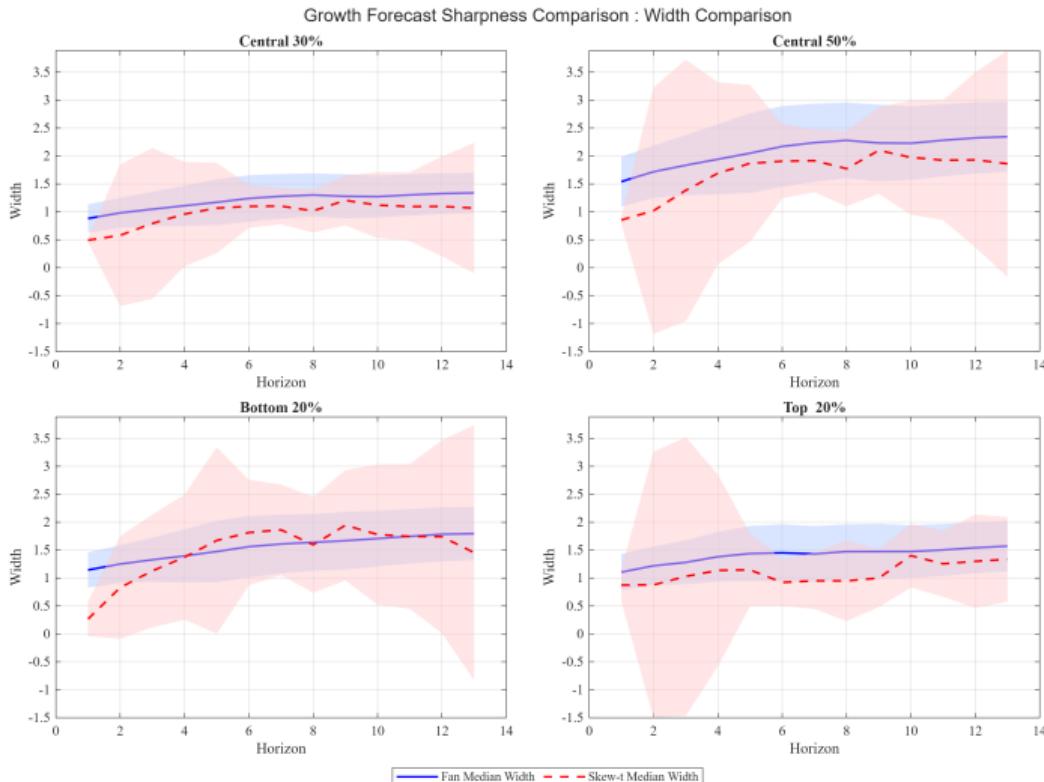
How can we measure this?

- ▶ Comparing widths of the predictive density in a given interval (implemented here)
- ▶ Proper scoring rules (e.g. CRPS)

# Sharpness: Inflation



# Sharpness: GDP Growth



# Relative Accuracy: Weighted Likelihood Ratio

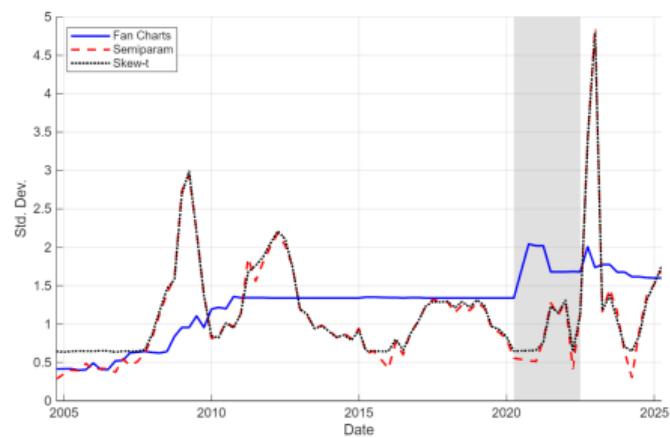
$$d_{t,t+h} \equiv w(\cdot) \left[ \log \left( \hat{f}_t^{Fan}(\mathbf{y}_{t+h}) \right) - \log \left( \hat{f}_t^{QR}(\mathbf{y}_{t+h}) \right) \right] \begin{cases} > 0 \text{ if Fan} \succ \text{QR} \\ < 0 \text{ if Fan} \prec \text{QR} \end{cases}$$

| Horizon | Inflation |               |               |           | GDP           |               |               |               |
|---------|-----------|---------------|---------------|-----------|---------------|---------------|---------------|---------------|
|         | Centre    | Tails         | Right Tail    | Left Tail | Centre        | Tails         | Right Tail    | Left Tail     |
| 0       | 2.922     | 2.471         | 2.912         | 3.679     | <b>-1.649</b> | 0.552         | <b>-4.947</b> | 0.351         |
| 1       | 4.137     | 1.257         | 2.405         | 3.449     | 0.843         | 0.0300        | 0.344         | 0.615         |
| 4       | 2.748     | 1.844         | 2.230         | 2.453     | 1.805         | <b>-1.032</b> | 1.933         | <b>-0.189</b> |
| 8       | 2.537     | 0.243         | 1.507         | 2.805     | <b>-1.013</b> | <b>-1.285</b> | <b>-0.907</b> | <b>-1.526</b> |
| 12      | 1.784     | <b>-0.573</b> | <b>-0.100</b> | 1.728     | 1.131         | <b>-1.200</b> | 1.313         | <b>-0.120</b> |

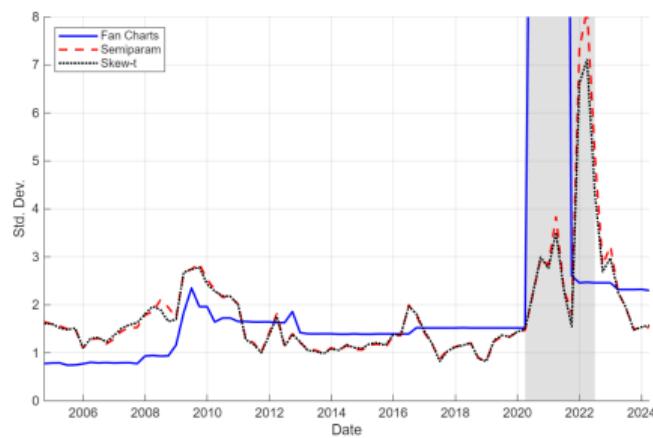
- For inflation, fan chart more accurate across distribution. Almost expected.
- For GDP, quantile regressions more accurate in tails

# But Quantile Regs. Capture Better Narrative Around Higher Moments

## Inflation



## GDP Growth



# Conclusions

In this paper we:

- ▶ **Build statistical toolkit to assess risks around UK inflation and GDP growth that:**
  - ↪ provide accurate forecasts
  - ↪ identify drivers of risks
  - ↪ inform narrative around balance of risks for policymakers
- ▶ **Provide a framework for density-forecast evaluation:**
  - ↪ allow us to elicit the best forecast according to their past performance

Still refining today's model specifications, but also exploring further work:

- ▶ Exploring other tools for forecast-density estimation
- ▶ Analysing benefits from forecast-density combination across models

# Forecasting Macroeconomic Risks in the UK

David Aikman<sup>1</sup> Rhys Bidder<sup>2</sup> Simon Lloyd<sup>3</sup> Giulia Mantoan<sup>3</sup>  
Simone Maso<sup>4</sup> Aditya Mori<sup>5</sup> Matthew Tong<sup>3</sup>

<sup>1</sup>National Institute for Economic and Social Research

<sup>2</sup>King's College London

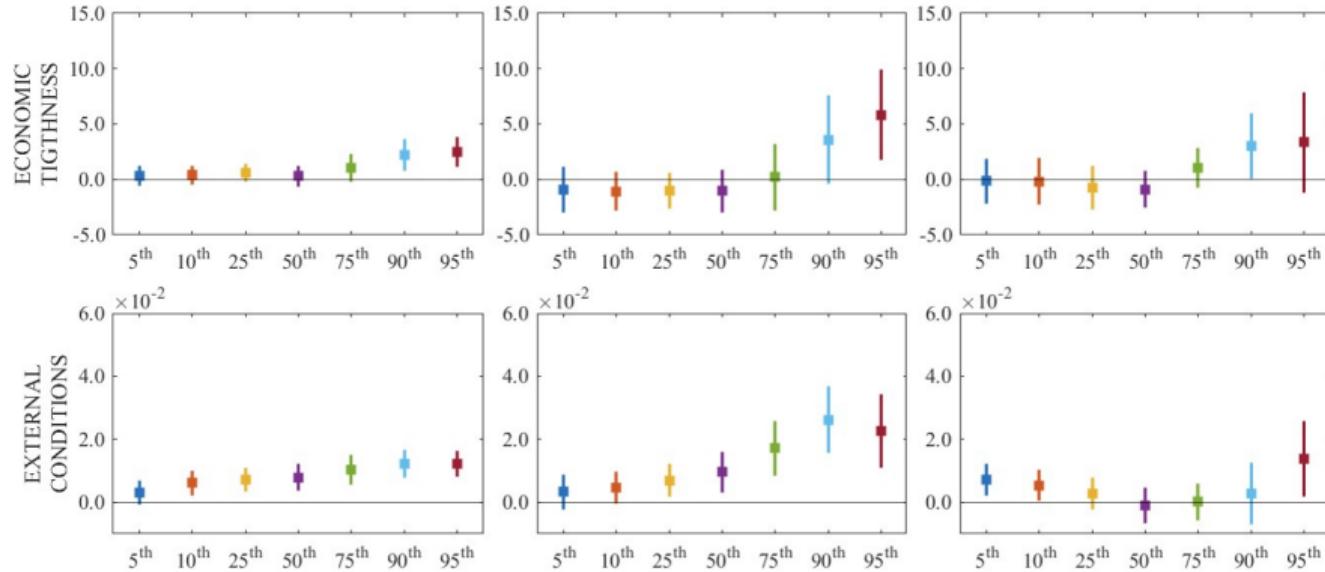
<sup>3</sup>Bank of England

<sup>4</sup>University College London

<sup>5</sup>University of Oxford

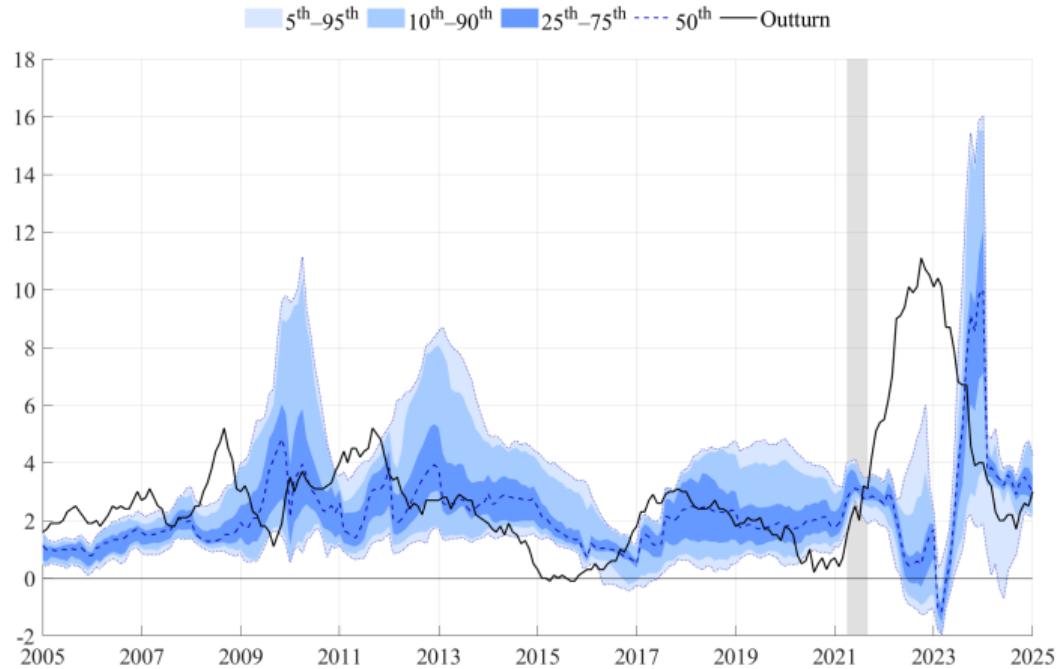
December 2025

# Economic Tightness and External Conditions (V/U)



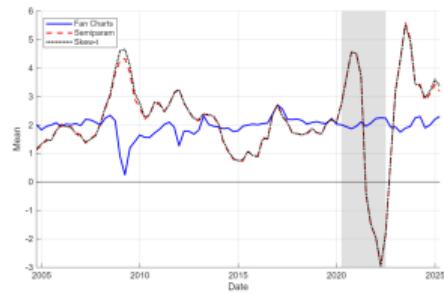
# Out-of-Sample Quantile Forecasts for Annual CPI Inflation

1-year-ahead

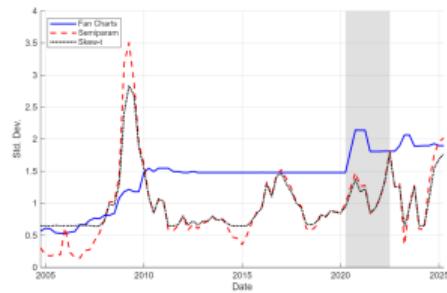


# Moment Comparison: 2-Years-ahead

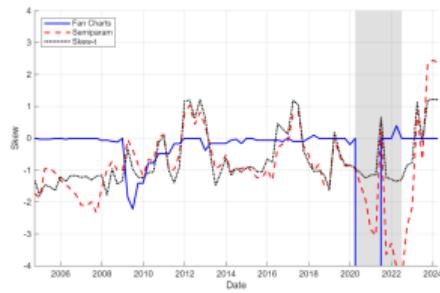
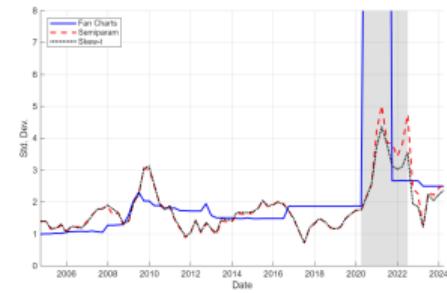
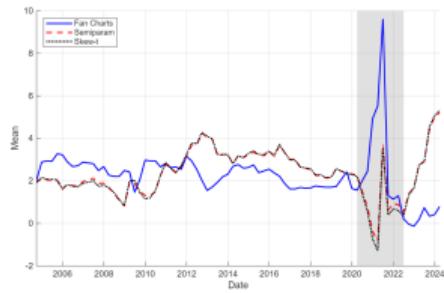
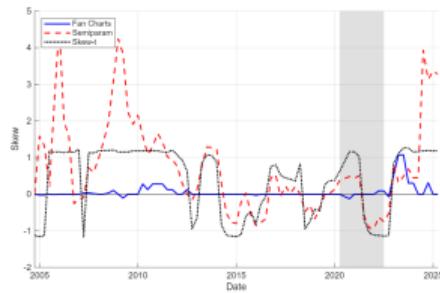
Mean



Std. Dev.

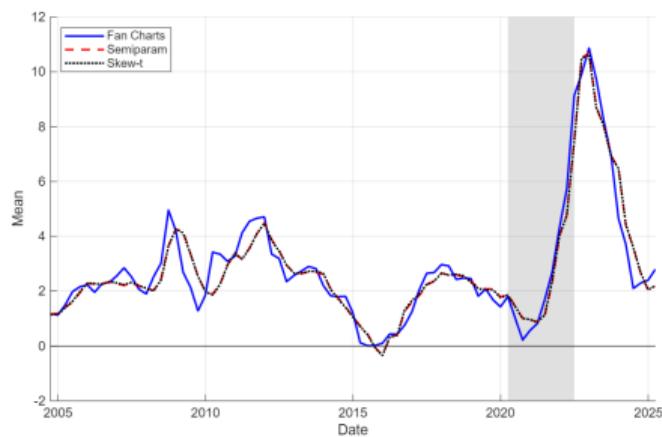


Skew



# Moment Comparison: Mean

Inflation

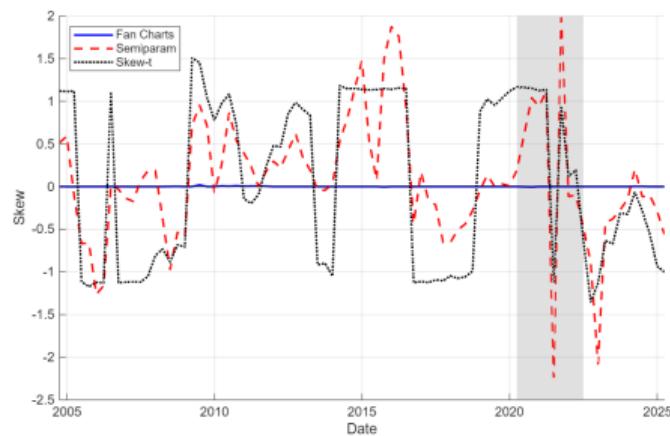


GDP Growth



# Moment Comparison: Skewness

Inflation



GDP Growth

