Topics in Economic Forecasting: Methods and Applications

Research Topics Seminar in Statistics & Data Science

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Economic forecasting: questions and methods

1. **Research applications.** Growth, credit, inflation, and uncertainty in estimated factors.

2. **An inflation case study.** Build international factors and forecast the whole distribution.

3. **Forecast evaluation.** Where do international factors help, and what explains the gains?

Questions from my research

Research area	Question
Daily growth at risk	Can daily indicators help us anticipate weak GDP growth?
Credit and energy prices	Which conditions predict adverse outcomes?
Factor uncertainty	How accurately can we estimate common economic signals?
Inflation factors	Does international information improve domestic inflation forecasts?
FARS software	How can we estimate distributions and explore stress scenarios in R?

Journals publishing this research

SCImago Journal Rank (SJR), 2025









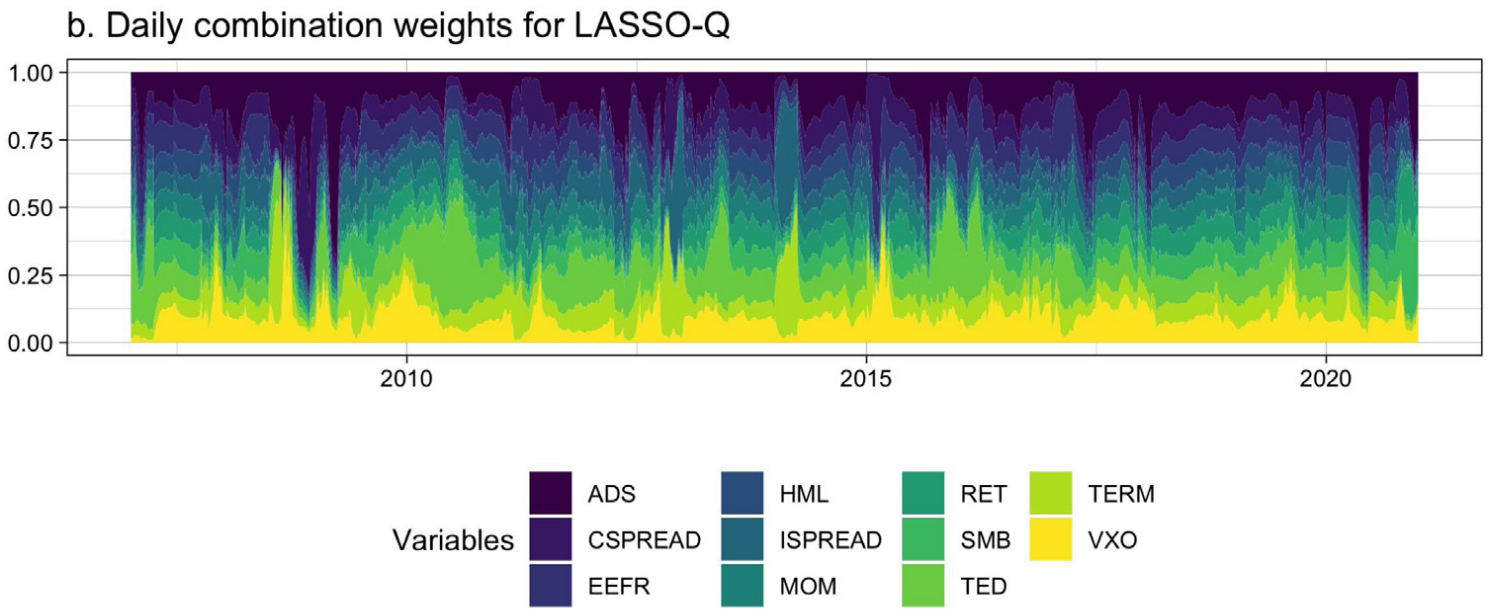


Daily growth at risk

International Journal of Forecasting

Research question

Can daily information improve forecasts of weak quarterly GDP growth?



- Combine daily real and financial indicators using regularised quantile models.
- Predictor importance changes across crises: financial indicators matter around the financial crisis, real activity during Covid-19.

Credit and energy-inflation risks

Vulnerable funding

Journal of Banking and Finance

Tighter US financial conditions predict weaker credit-growth tails abroad. The relationship differs across countries.

Geopolitical risk and energy inflation

Applied Economics Letters

Country geopolitical risk is associated with higher upside energy-inflation risk. Its relationship with the median is much weaker.

A shared statistical idea

A predictor can matter for extreme outcomes even when its relationship with the centre of the distribution is weak.

The empirical distribution of sequential LS factors in Multi-level Dynamic Factor Models

Research question

How reliable are estimates of common global and group-specific signals?

- **Method:** Monte Carlo simulations with known factors, estimated using sequential least squares.
- **Finding:** approximations developed for principal-component factors also describe these estimates well in the simulations.
- Accounting for correlated errors and uncertainty in the estimated loadings improves uncertainty measurement.

An inflation forecasting research worked example

Research question

Does inflation in other countries help us forecast the risks surrounding domestic inflation?

1. Motivation: inflation, international links, and vulnerability.
2. Methods: common factors and quantile regression.
3. Evidence: forecasts for Germany, results across countries, and what explains the gains.

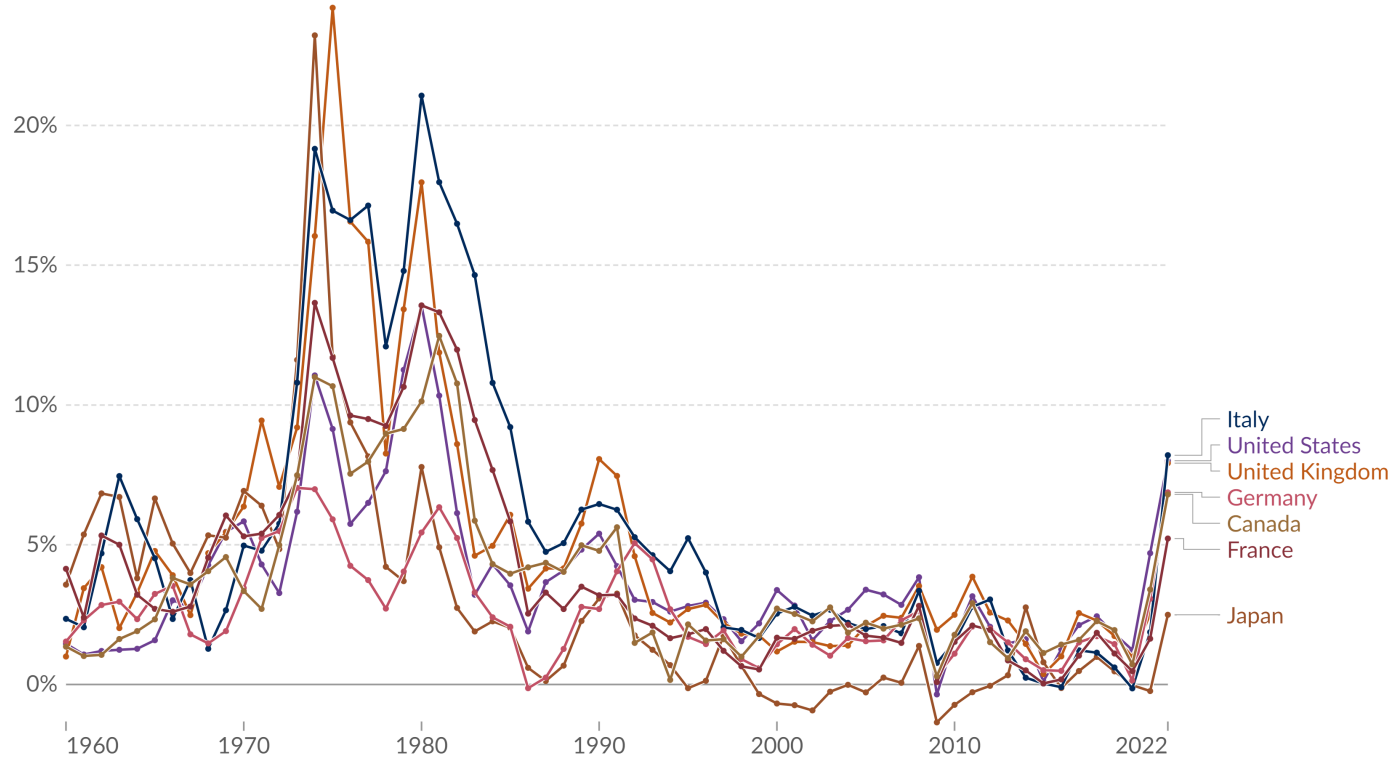
Why study inflation?

- Inflation affects households' purchasing power and firms' costs.
- Inflation forecasts inform monetary policy, investment, and saving decisions.
- Very high inflation and deflation create different economic risks.

Forecasting question: what might happen next, and how uncertain is that prediction?

Why international?

G7 annual CPI inflation, 1960–2022



- Inflation often moves together across countries, while the size of the changes differs.
- Global and group-specific signals may add information to domestic inflation history.

Why vulnerability?

An average forecast leaves important questions unanswered.

Part of the distribution	**Question**
Median	What is a typical outcome?
Upper tail	How high could inflation become?
Lower tail	Is very low inflation or deflation a concern?

Quantile regression allows the same predictor to have different relationships with each part of the distribution.

The data

- **115 countries**, with monthly CPI data from 1999 to 2022.
- Inflation: the month-to-month price change expressed at an annual rate.
- Countries belong to both a **geographical region** and a **development group**.

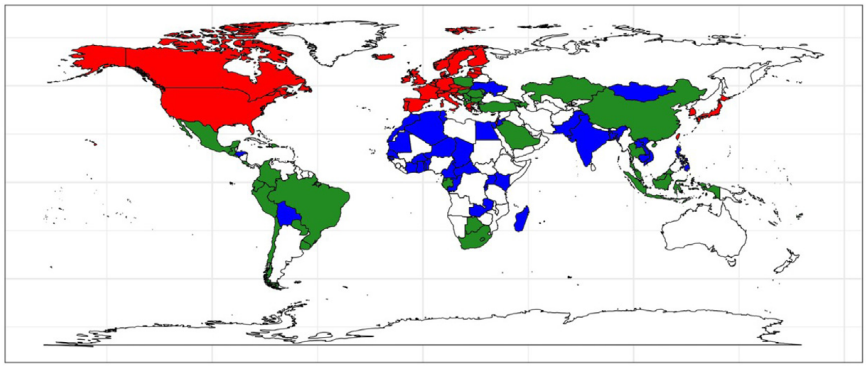
Example: Germany

Its inflation can share movements with the world, with its region, and with other advanced economies.

The countries and their overlapping groups

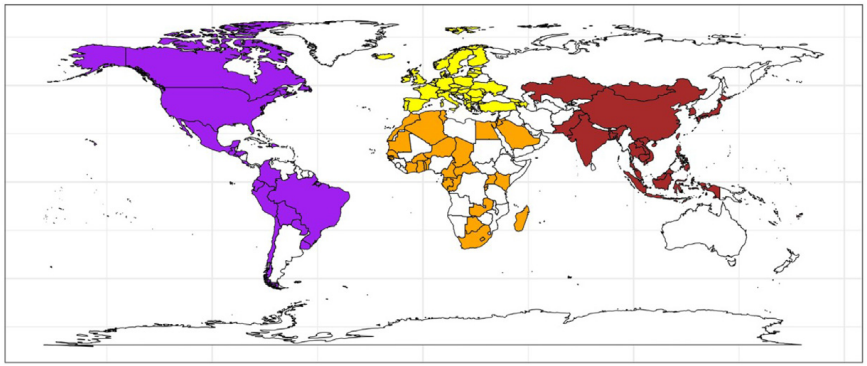
115 countries, 1999–2022

Development groups



- Advanced economies (35)
- Middle/high-income emerging and developing economies (42)
- Low-income emerging and developing economies (38)

Geographical regions



- Africa and the Middle East
- America
- Asia and Oceania
- Europe

Each country belongs to **one region and one development group**.
White countries are outside the sample.

Building the MLDFM: global and group signals

Multi-Level Dynamic Factor Model

A **factor** summarises common movements across several inflation series.

$$y_{it} = \underbrace{\lambda_i^g F_t}_{\text{global}} + \underbrace{\lambda_i^r F_{r(i),t}}_{\text{own region}} + \underbrace{\lambda_i^d F_{d(i),t}}_{\text{own development group}} + \varepsilon_{it}.$$

- **Eight factors in total:** one global, four regional, and three development factors.
- Each country loads on **three factors**; loadings on other groups are set to zero.
- The loadings λ_i measure each country's response; ε_{it} is its remaining country-specific component.

Germany

Global signal + European signal + advanced-economy signal + country-specific component.

Extracting International Factors: Multi-Level DFM

We represent the complex structure of common factors in monthly inflations by fitting

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \\ Y_{3t} \\ Y_{4t} \\ Y_{5t} \\ Y_{6t} \\ Y_{7t} \\ Y_{8t} \\ Y_{9t} \\ Y_{10t} \\ Y_{11t} \\ Y_{12t} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} & 0 & 0 & 0 & \lambda_{16} & 0 & 0 \\ \lambda_{21} & \lambda_{22} & 0 & 0 & 0 & 0 & \lambda_{27} & 0 \\ \lambda_{31} & \lambda_{32} & 0 & 0 & 0 & 0 & 0 & \lambda_{38} \\ \lambda_{41} & 0 & \lambda_{43} & 0 & 0 & \lambda_{46} & 0 & 0 \\ \lambda_{51} & 0 & \lambda_{53} & 0 & 0 & 0 & \lambda_{57} & 0 \\ \lambda_{61} & 0 & \lambda_{63} & 0 & 0 & 0 & 0 & \lambda_{68} \\ \lambda_{71} & 0 & 0 & \lambda_{74} & 0 & \lambda_{76} & 0 & 0 \\ \lambda_{81} & 0 & 0 & \lambda_{84} & 0 & 0 & \lambda_{87} & 0 \\ \lambda_{91} & 0 & 0 & \lambda_{94} & 0 & 0 & 0 & \lambda_{98} \\ \lambda_{10,1} & 0 & 0 & 0 & \lambda_{10,5} & \lambda_{10,6} & 0 & 0 \\ \lambda_{11,1} & 0 & 0 & 0 & \lambda_{11,5} & 0 & \lambda_{11,7} & 0 \\ \lambda_{12,1} & 0 & 0 & 0 & \lambda_{12,5} & 0 & 0 & \lambda_{12,8} \end{bmatrix} \begin{bmatrix} F_{gt} \\ F_{AFt} \\ F_{Amt} \\ F_{Ast} \\ F_{Eut} \\ F_{Adt} \\ F_{Mit} \\ F_{Lit} \end{bmatrix} + \varepsilon_t.$$

- Global factor, F_{gt}, which loads in all inflations in the system;
- Regional block, F_{Aft}, F_{Amt}, F_{Ast}, and F_{Eut}, which loads in inflations in Africa, America, Asia and Europe, respectively;
- Development block, F_{Adt}, F_{Mit}, and F_{Lit}, which loads in inflations of ADV, MHI-EMD and LI-EMD economies, respectively.

Estimating the MLDFM

Sequential least squares

1. **Prepare the panel.** Transform monthly CPI into inflation, remove seasonality, and treat extreme outliers.

2. **Initialise the factors.** Use canonical correlations and principal components to obtain starting common signals.

3. **Alternate least-squares updates.** Estimate loadings given factors, then factors given loadings. Preserve the group restrictions and repeat until the fit stabilises.

4. **Respect the forecast date.** Re-estimate factors and loadings within each rolling estimation window.

The estimated global, regional, and development signals become predictors of domestic inflation quantiles.

Forecasting domestic inflation quantiles

For a given country, fit a simple predictive relationship:

$$q_\tau(y_{t+1} \mid y_t, \widehat{F}_t) = \alpha_\tau + \phi_\tau y_t + \beta_\tau' \widehat{F}_t.$$

y_t: current inflation. $\widehat{F}_t$: estimated international factors.

- At $\tau = 0.50$, forecast the median. At $\tau = 0.95$, forecast an upper-tail outcome.
- Coefficients can change across quantiles.
- Fit a smooth distribution to these quantiles to describe the range of possible inflation outcomes.

A fair forecasting comparison

Benchmark

Predict next month's inflation using domestic inflation history.

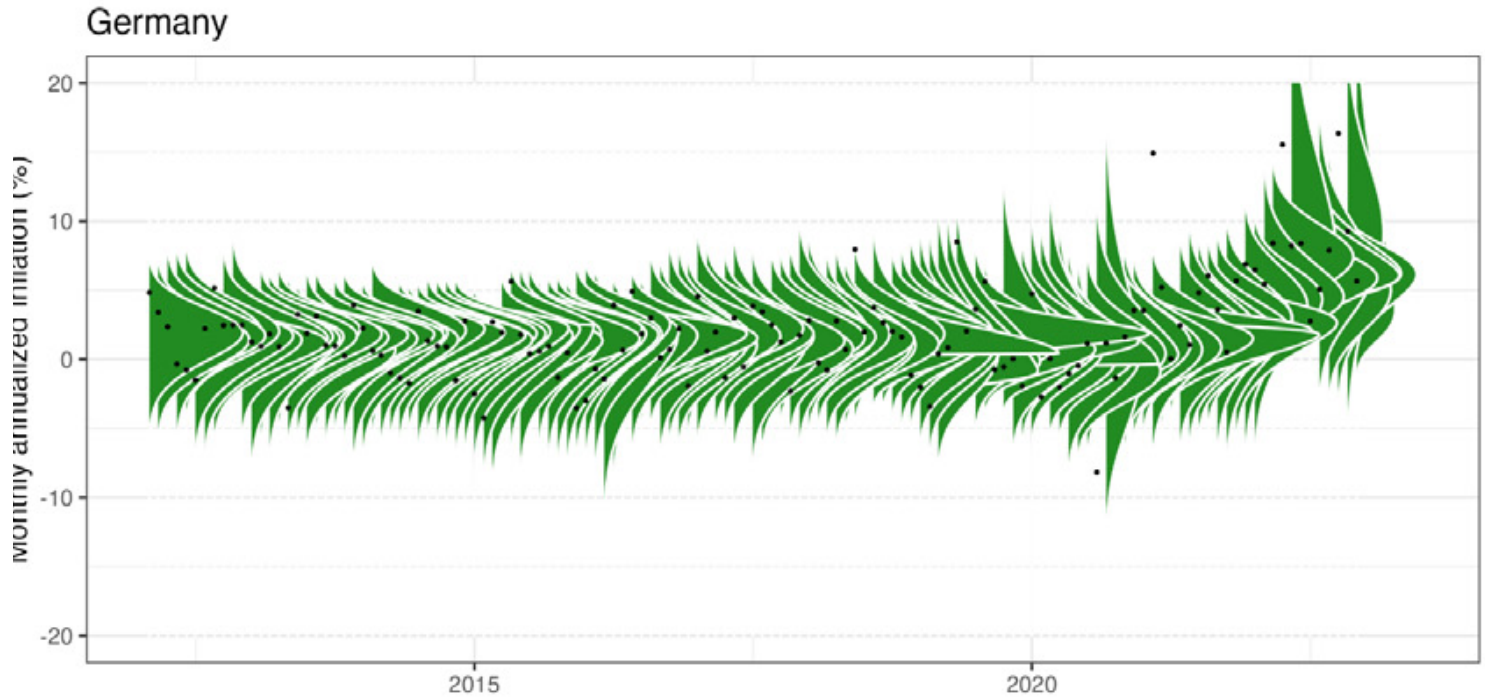
Extension

Add the estimated international factors.

1. Estimate both models using past observations.
2. Predict the next month, then move the estimation window forward.
3. Compare forecast losses over the same future months.

In the paper, the evaluation period is **2012–2022**. Factors and regressions are re-estimated in each window.

Example: Germany's inflation forecasts



- Each green shape is a one-month-ahead forecast distribution. Dots show observed inflation.
- The location and spread change over time. Compare the forecasts around 2015 and 2022.

Discussion: what information would a single point forecast leave out?

A basic result: gains differ across tails

Countries with significant forecast improvements (%)

	Lower-tail score	Upper-tail score
All countries	19.1	42.6
Europe	25.6	71.8

The comparison uses domestic-only forecasts as the benchmark and a 10% significance level.

Interpretation: international factors help more often for upside inflation risk, especially in Europe.

What explains the gains?

Measure the gain for each country and year:

$$D_{iy} = \text{annual average}\left(L_{it}^{\text{domestic}} - L_{it}^{\text{factors}}\right).$$

A positive D_{iy} means that international factors reduce forecast loss.

Relate gains to country characteristics x_{iy}:

$$D_{iy} = \alpha_i + \gamma_y + x_{iy}'\delta + u_{iy}.$$

- Annual data for **38 countries, 2012–2022**, where explanatory data are available.
- Country effects α_i control for persistent differences; year effects γ_y capture common yearly shocks.
- Fit the panel regression separately for each forecast score, with panel-corrected standard errors.

What explains the gains? Main findings

Increase in	Associated forecast gain
Inflation	Larger gains across all forecast scores.
Trade openness	Larger gains in the upper tail.
GDP growth	Larger gains in the upper tail; smaller gains in the lower tail.
GDP per capita growth and unemployment	Larger gains in the lower tail.
Central bank independence	Smaller gains for the density scores.
Geopolitical risk	Larger gains at the median.

These are conditional associations; the regression does not establish causal effects.

Factor Augmented Regression Scenarios in R

- Estimate global and group-specific factors, with uncertainty measures.
- Fit quantile regressions and conditional densities.
- Explore how risk measures change under stressed factors.

The package connects factor estimation with density forecasting and scenario analysis.

Ongoing projects

1. **Nowcasting CO_2**

   With Andrey Ramos (Banco de España).

2. **Nickell bias in panel quantile models**

   With Vladimir Rodríguez-Caballero, Helena Veiga, and Andrey Ramos.

3. **Poverty estimation in Ecuador**

   With the World Bank.