Inflation Forecasting in Small Open Economies: Incorporating Short Predictors to Compare Global and Domestic Drivers

Zhoulihua Zhang

Co-authors: Dr Sharada Davidson, Dr Ping Wu

University of Strathclyde

Supported by ESRC grant ES/Y001699/1

2026/05/19

Background

- Inflation in small open economies is shaped by both **global shocks** and **domestic conditions**, and the relative importance of these drivers can change across episodes such as the global financial crisis, supply-chain disruptions, and the post-pandemic recovery.
- Existing studies show that **global inflation** and **global macro-financial conditions** help explain cross-country inflation comovements and can improve domestic inflation forecasts (Duncan and Martínez-García, 2015; Gillitzer and McCarthy, 2019).
- At the same time, **domestic macroeconomic and financial indicators** remain important for capturing country-specific inflation dynamics, particularly at short horizons (Stock and Watson, 2002a,b; Joseph et al., 2024).
- A practical challenge is that many newly relevant indicators have **short histories**, so they are often excluded from standard forecasting models based on long and balanced predictor panels, even though they may contain timely information (Koop et al., 2024).

Research question

- This paper asks whether retaining **short predictors** improves inflation forecast performance in small open economies.
- It also examines how the predictive content of global and domestic drivers compares across countries.
- To address this, we group predictors into three broad blocks, retain short series using a **factor-based missing-data approach**, and compare forecasting performance across five representative small open economies: **the UK, Canada, Norway, Mexico, and Malaysia**.

Main question: Do short predictors improve forecast performance, and which global and domestic drivers matter most for forecasting inflation across countries?

Data overview

- Monthly data from **1990M1 to 2023M12**.
- Target variable: **headline CPI inflation** (YoY).
- Five economies: **UK, Canada, Norway, Mexico, Malaysia**.
- Predictors are grouped into three blocks:
  - Global inflation (GI)
  - Global economic conditions (GEC)
  - Domestic indicators (D)

How predictors are grouped

Global inflation (GI)

- Advanced Western (16 variables, 0 short)
- Advanced Asia (4 variables, 1 short)
- Emerging Europe (12 variables, 4 short)
- Emerging Latin America (5 variables, 2 short)
- Middle East and Africa (5 variables, 1 short)
- Emerging Asia (6 variables, 2 short)

Global economic conditions (GEC)

- Energy and weather supply (7 variables, 2 short)
- Non-energy supply (9 variables, 1 short)
- Global demand (7 variables, 2 short)
- Global financial conditions (6 variables, 1 short)

Domestic indicators (D)

- Macroeconomic conditions
- Financial indicators

Fill in missing: Tall-Project algorithm (Cahan et al., 2023)

This method fills missing values in big panel data using factor model.

How does TP work?

1. Choose a "Tall Block":
   - Find units with complete data for all periods (no missing).
   - Estimate common factors from this block.
2. Estimate factor loadings:
   - For units with missing data, estimate loadings by regression using observed values.
3. Impute missing values:
   - Use factors and loadings to fill missing observations.

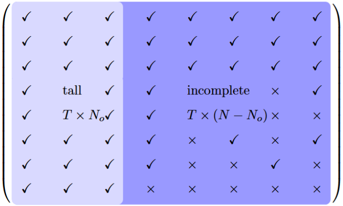

Figure 1: The Tall-Incomplete Representation of the Data

A Factor-Augmented Regression for Inflation Forecasting

Benchmark: AR(p)-SV

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, e^{h_t}), \tag{1}$$

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \varepsilon_t^h, \quad \varepsilon_t^h \sim \mathcal{N}(0, \sigma_h^2), \tag{2}$$

where $|\phi_h| < 1$. y_t depends linearly on its p lagged values, and the number of lags p is set to 2.

We then extend the model by including global and domestic factors. The extended model can be expressed as:

$$y_t = \mathbf{x}_t' \boldsymbol{\beta} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, e^{h_t}), \tag{3}$$

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \varepsilon_t^h, \quad \varepsilon_t^h \sim \mathcal{N}(0, \sigma_h^2), \tag{4}$$

where $\mathbf{x}_t = (1, y_{t-1}, \cdots, y_{t-p}, \mathbf{z}_t')$, $\boldsymbol{\beta} = (\beta_0, \beta_1, \cdots, \beta_p, \gamma')'$, $\boldsymbol{\gamma'} = (\boldsymbol{\gamma_1}, \cdots, \boldsymbol{\gamma_j})$.
$\mathbf{z_t'} = (\mathbf{z_{1t}}, \cdots, \mathbf{z_{jt}})$ are factors, extracting from different global and domestic indicators blocks.

Forecast design and evaluation

Forecast design

- Pseudo-real-time forecasting starts in 2005m1, Forecast horizons: $h = 1, 3, 6, 12$.
- We use a change-length rolling window to handle missing.

$$\text{Window size} = \left\lfloor \frac{\mathit{Total}}{\mathit{Observed}} \times 120 \right\rfloor$$

  Total: total entries in the window; *Observed*: non-missing entries.
- Within each window, predictors are standardised, missing values are imputed using the **Tall-Project** algorithm, and factors are then extracted for forecasting.

Evaluation

- Point forecasts: Root Mean Square Forecast Error

$$\text{RMSFE} = \sqrt{\frac{1}{P}\sum_{p=1}^{P}\left(y_{T+p} - \hat{y}_{T+p|T+p-h}\right)^2}$$

- Density forecasts: Continuous Ranked Probability Score

$$\text{CRPS}(F, y) = \int_{-\infty}^{\infty} \left(F(z) - \mathbf{1}\{y \le z\}\right)^2 dz$$

Lower RMSFE and CRPS indicate better forecast performance.

Which drivers matter for inflation forecasting?

	GI		GEC		D	
Ctry	**All**	**Best outperforming**	**All**	**Best outperforming**	**All**	**Best outperforming**
UK	0.96/0.99	**AW** 0.86/0.92	0.98/0.97	**SNE** 0.96/0.94	0.93/0.90	**Macro** 0.93/0.90
CAN	1.07/1.16	None	1.04/1.07	**GD** 0.98/0.92	0.93/1.01	**Macro** 0.96/1.05
NOR	1.01/1.12	**ELA** 0.98/0.96	1.03/1.04	**SE** 0.99/0.97	1.00/1.02	None
MEX	1.02/1.09	None	1.04/1.16	**SE** 0.99/0.97	1.06/1.23	None
MAL	0.99/1.00	**AA** 0.99/1.03	1.00/0.96	**SE** 0.99/0.97	1.00/1.00	**Fin** 0.99/0.97

Notes: The table reports relative RMSFE at the 1- / 6-month horizons. Values below 1 indicate improvement over the AR(2)-SV benchmark. CRPS gives very similar conclusions, so I only report RMSFE results.

- **GEC delivers the most systematic gains** across countries.
- **GI is more uneven**, with the clearest gains in the UK.
- **Domestic predictors help selectively**, especially in the UK, at short horizons in Canada, and through financial indicators in Malaysia.

The Importance of Jointly Capturing Different Drivers

Country	Model	Forecast horizon h			
		1	3	6	12
	All-in pooling	0.86	0.84	0.86	0.99
UK	GI+GEC+D	0.88	0.87	0.90	1.01
	GI Advanced Western+GEC Non-energy Supply+D Macro	0.82	0.81	0.86	1.04
	All-in pooling	1.00	1.04	1.08	1.21
Canada	GI+GEC+D	1.04	1.07	1.10	1.22
	GEC Demand+D Macro	0.96	1.00	1.05	1.26
	All-in pooling	1.03	1.05	1.12	1.20
Norway	GI+GEC+D	1.03	1.10	1.20	1.23
	GI Emerging Latin America+GEC Energy Supply	0.97	0.94	0.94	0.97
	All-in pooling	1.12	1.26	1.33	1.37
Mexico	GI+GEC+D	1.11	1.27	1.35	1.36
	GEC Energy Supply	0.99	0.98	0.97	1.02
	All-in pooling	0.98	1.00	1.06	1.22
Malaysia	GI+GEC+D	0.98	0.98	1.02	1.15
	GI Advanced Asia+GEC Energy Supply+D Fin	0.98	0.98	1.00	1.13

Notes: Entries report RMSFE ratios relative to the benchmark in the same country and forecast horizon. Values below 1 indicate an improvement over the benchmark.

- Jointly incorporating several global and domestic drivers reflects differences in the dominant inflation drivers across countries.
- The strongest performance comes from selectively combining only the most informative drivers, rather than pooling all available information.
- This suggests that broader combinations may dilute strong predictive signals, while parsimonious specifications better preserve the key channels driving inflation.

Do short predictors improve forecast performance?

Table 1: Contribution of short predictors across forecast horizons

Country	Best model	1	3	6	12
UK	GI AW + GEC SNE + D Macro	0.94	0.93	0.96	0.99
Canada	GEC Demand + D Macro	1.00	1.00	1.01	1.00
Norway	GI ELA + GEC SE	0.97	0.95	0.94	0.97
Mexico	GEC Energy Supply	0.98	0.96	0.96	1.00
Malaysia	GI AA + GEC SE + D Fin	0.98	0.96	0.96	1.00

Note: The table reports the relative RMSFE ratio between the model with and without short predictors, at forecast horizons $h = 1, 3, 6, 12$. Values below 1 indicate that short predictors improve forecast performance, while values above 1 indicate that short predictors have no effect.

- Forecast performance generally improves when short predictors are included.
- The gains from short predictors are strong in the UK, Norway, Mexico, and Malaysia, especially at medium horizons.
- Canada is the main exception, where the incremental value of short predictors is limited.

Conclusions

- Short predictors play an important role in inflation forecasting performance. Their inclusion substantially improves forecasting performance.
- Global supply and demand side information, exhibit broadly consistent predictive power across countries.
- The global inflation factor reflects the common movement in international prices and the transmission of global cost shocks across borders. Its predictive relevance is more uneven.
- Domestic indicators add value in some cases but their contribution is country-specific.
- Combining information by jointly considering global and domestic drivers is useful: parsimonious specifications centred on the most informative drivers perform better than simply pooling all information together.

Thanks!

References I

Cahan, E., Bai, J., and Ng, S. (2023). Factor-based imputation of missing values and covariances in panel data of large dimensions. *Journal of Econometrics*, 233(1):113–131.

Duncan, R. and Martínez-García, E. (2015). Forecasting local inflation with global inflation: When economic theory meets the facts. *Available at SSRN 2589712*.

Gillitzer, C. and McCarthy, M. (2019). Does global inflation help forecast inflation in industrialized countries? *Journal of Applied Econometrics*, 34(5):850–857.

Joseph, A., Potjagailo, G., Chakraborty, C., and Kapetanios, G. (2024). Forecasting uk inflation bottom up. *International Journal of Forecasting*, 40(4):1521–1538.

Koop, G., McIntyre, S., Mitchell, J., Poon, A., and Wu, P. (2024). Incorporating short data into large mixed-frequency vector autoregressions for regional nowcasting. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 187(2):477–495.

Stock, J. H. and Watson, M. W. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American statistical association*, 97(460):1167–1179.

Stock, J. H. and Watson, M. W. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2):147–162.