

International Vulnerability of Inflation

Ignacio Garrón

Universidad Carlos III de Madrid (UC3M)

joint with

Vladimir Rodríguez-Caballero (ITAM) Esther Ruiz (UC3M)

Internal seminar
Getafe, Madrid



Why study Inflation?

- Low and stable inflation → economic growth and employment
- Very low or very high inflation → macroeconomic challenges.
- Inflation forecasts have implications for policy makers, central banks, and business decisions.
- Recent geopolitical events → Inflation forecasts recently moved to the forefront of the policy debate.

Debate on the performance of inflation models using domestic drivers

- Forecasting ability of Phillips curve-based models → Dotsey, Fujita, and Stark, Int. J. Central Banking 2018).
- Using disaggregate items and novel machine learning tools to improve forecastability → Joseph et al. (IJF 2024).
- Inflationary impact of gasoline prices → Kilian and Zhou (Energy Economics 2024).

Why International?

Draghi (2015 Speech to the Economic Club of NY):

Over the last decade there has been a growing interest in the concept of global inflation. This is the notion that in a globalized world inflation is becoming less responsive to domestic economic conditions and is instead increasingly determined by global factors.

- Increasing role of **global economic activity** on domestic inflation.
- Important to understand the sources of international movements in inflation and the way how the domestic inflation in a given country reacts to various global and specific factors.
- **Ignoring international inflation may overrate domestic inflation and mislead macroeconomic policies.**

Why International?

Consensus on Global Inflation

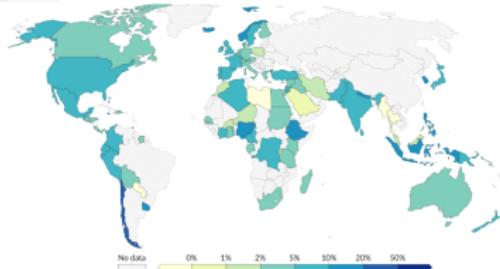
- Medeiros et al. (WP 2024)
- Ha et al. (J. Intern. Money and Finance 2023)
- Mumtaz and Musso (JBES 2021)
- Kamber and Wong (J. Inter. Economics 2020)
- Ahmad and Staveley-O'Carroll (J. Inter. Money and Finance 2017)
- Kabukcuoglu and Marínez-García (J. Econom. Dyn. Control 2018)
- Eickmeier and Pijnenburg (OBES 2013)

Inflation over time

Inflation of consumer prices, 1970

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.

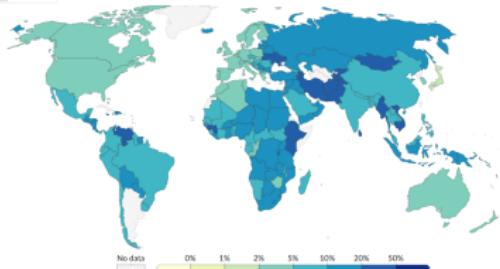
[Table](#) [Map](#) [Chart](#)



Inflation of consumer prices, 1980

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.

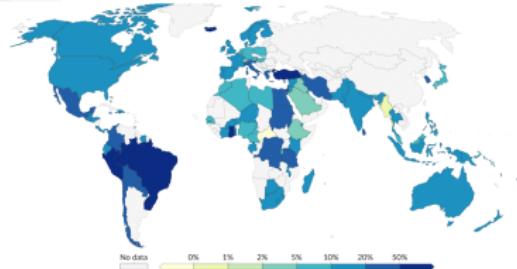
[Table](#) [Map](#) [Chart](#)



Inflation of consumer prices, 1980

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.

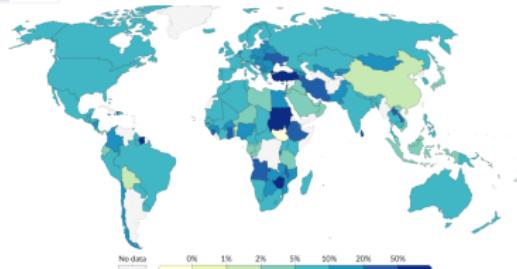
[Table](#) [Map](#) [Chart](#)



Inflation of consumer prices, 2008

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.

[Table](#) [Map](#) [Chart](#)



Discussion on commonality and heterogeneity

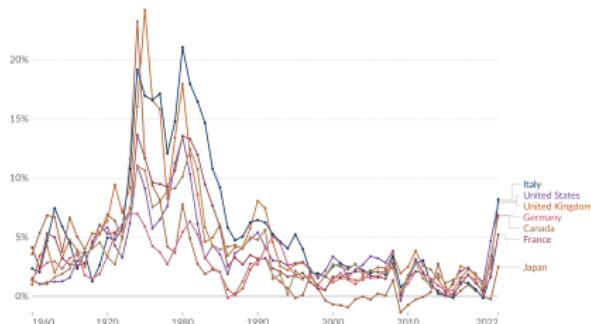
Sources of international movements

By groups of nations working together

The Group of Seven (G7)

Inflation of consumer prices, 1960 to 2022

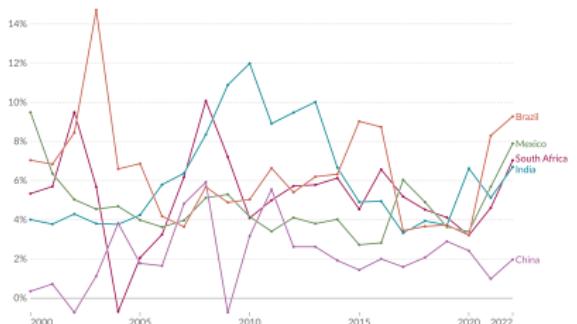
Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.



The Group of Five (G5)

Inflation of consumer prices, 2000 to 2022

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.



Discussion on commonality and heterogeneity

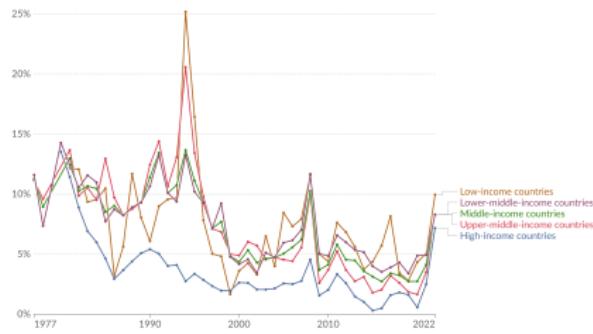
Sources of international movements

By income level or geographical regions

Income

Inflation of consumer prices, 1977 to 2022

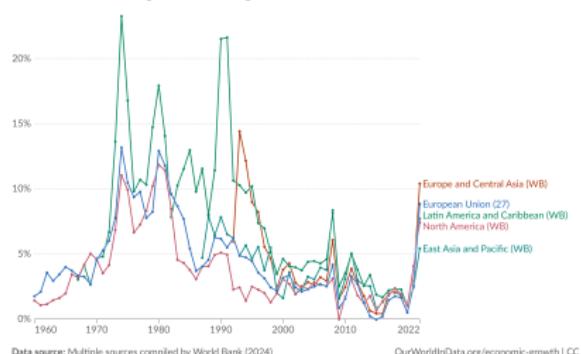
Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.



Regions

Inflation of consumer prices, 1960 to 2022

Annual changes in the cost to the average consumer of acquiring a set basket of goods and services. This measure is used to track changes in the cost of living over time.



Why Vulnerability?

- Relevant for policy-makers and central banks to assess the risk of having either very low or very high inflation (Kilian and Manganelli, J. Inter. Money Credit and Banking 2008).

Growing literature on measuring risk to inflation.

Using quantile regressions:

- **with domestic macroeconomic indicators:** Manzan and Zerom (IJF 2013), Adams et al. (IJF 2021), Korobilis et al. (WP 2021), Tabliabracchi (WP 2020).
- **with global factors:**

Zheng et al. (Energy Economics 2023) use global energy connectedness index,

Banerjee et al. (J. of Intern. Money and Finance 2024) uses as regressor oil prices.

Paper Contributions:

- ① Understanding the sources of international movements in the distribution of prices.
- ② Measuring the predictive accuracy of international factors (global and specific to regions and/or economic development level) for inflation densities.

Methodology:

- Factor augmented quantile regressions: Estimate the density of inflation in a given country as a function of international common factors.
- Multi-level DFM: Considering global common factor and block factors defined by geographical regions and economic development level.

Methodology to estimate Inflation densities

Factor-Augmented Quantile Regression and Multi-level DFM

Let y_{it} be the inflation observed in country i at time t , for $i = 1, \dots, N$, and $t = 1, \dots, T$.

The one-step-ahead τ -quantile of the conditional distribution of y_{it} is obtained by estimating the following FA-QR model

$$q_\tau(y_{it+1}|y_{it}, F_t) = \mu(\tau, i) + \phi(\tau, i)y_{it} + \sum_{k=1}^r \beta_k(\tau, i)F_{kt},$$

- The model has $(r + 2) \times 1$ vector of parameters.
- $F_t = (F_{1t}, \dots, F_{rt})'$ is the $r \times 1$ vector of underlying unobserved international factors at time t .
- The underlying factors are replaced by estimated factors, \hat{F}_t , which are extracted from the ML-DFM.

Predictive accuracy

- In-sample predictive accuracy can be evaluated via a quantile R^1 based on the loss function, which is the natural analogue of the R^2 coefficient in a regression model.
- The Information Criteria for FA-QR proposed by Ando & Tsay (2011).

Methodology to estimate Inflation densities

Factor-Augmented Quantile Regression and Multi-level DFM

For each country i , forecast horizon h , and quantile τ^* , fit a factor-augmented quantile regression:

$$q_\tau(y_{it+1}|y_{it}, F_t) = \mu(\tau, i) + \phi(\tau, i)y_{it} + \sum_{k=1}^r \beta_k(\tau, i)F_{kt},$$

After estimating the FA-QR models, the inflation densities in each country are estimated using the Skewed-t distribution of Azzalini and Capitanio (JRSS-B, 2003), obtaining $\tilde{k}(y_{it+h})$.

Compute

- 1 Probability of high inflation (Prob $(y_{it+h} \geq \pi^*)$)

$$\text{IaR}_{i,t+h}(\pi^*) = \int_{\pi^*}^{\infty} \tilde{k}(y_{i,t+h}) dy_{i,t+h}$$

- 2 Probability of low inflation (Prob $(y_{it+h} \leq \pi^*)$)

$$\text{DaR}_{i,t+h}(\pi^*) = \int_{-\infty}^{\pi^*} \tilde{k}(y_{i,t+h}) dy_{i,t+h}$$

Tabliabracchi (2020) proposes measuring DaR and IaR with $\pi = 0$ and 2 , respectively.

Why Multi-Level Factor Models?

Multi-level Factor models

The cornerstone of these models is to decompose the common factor structure into different levels, with factors associated to the full cross-section, i.e. pervasive, and factors that impact on and explain only a specific sub-group of variables, the non-pervasive factors.

PC does not take full advantage of the block structure of the system of inflation series. Consequently, PC factors are not able to separately identify specific factors for different blocks of variables and, they are not optimal;

Possible methodologies:

- ① Considering zero restrictions in the associated loadings matrix, as discussed in Breitung and Eickmeier (2016) [Adv.Econ.], Choi et.al (2018) [JAE], Rodríguez-Caballero and Caporin (2019) [J.Int.Fin.Mark.Ins], Han (2021) [JBES].
- ② Considering a hierarchical approach as discussed Kose, Otrok, and Whiteman (2003) [AER], and Moench, Ng, and Potter (2013) [RES].
- ③ Under a state space model setup as in Delle Chiaie, Ferrara and Giannone (2022) [JAE].
- ④ Under a long-memory setup as in Ergemen and Rodríguez-Caballero (2022) [IJF]

Data Set

- Monthly observations of headline CPI from January 1999 (introduction of the Euro and pegging of European currencies) to December 2022 ($T=288$).
- Data from the novel Global Database on Inflation by Ha et al. (2023a).
- We consider for a set of $N = 115$ countries.

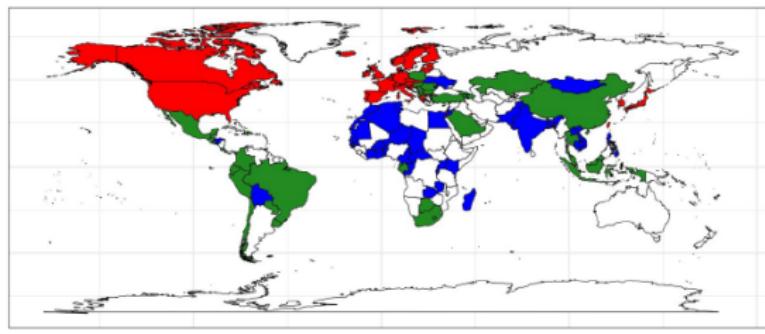
CPI prices are transformed to annualized month-on-month (mom) inflation.

Each series is sequentially cleaned

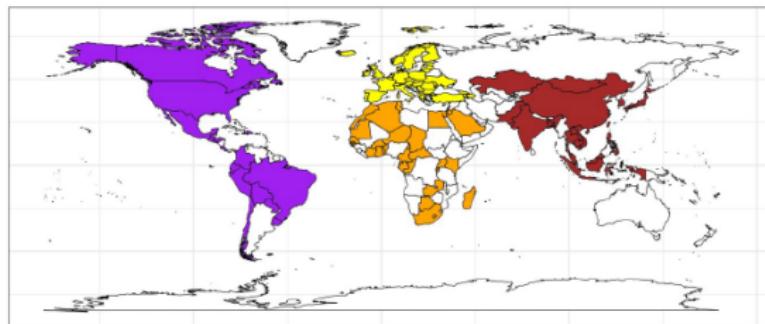
- Seasonal components: KF; Harvey (2006)
- Outliers: $10 \times$ inter-quartile range as in McCracken and Ng (2016)

Data Set (Blocks)

The 115 countries are divided into overlapping blocks according to two different criteria.
→ Economic development level (3 blocks) → Geographic area (4 blocks)



Countries (115): from 1999 to 2022 Red: Advanced Economies (35) Green: EMDEs (42) Blue: Low income EMDEs (38)



Countries (115): from 1999 to 2022 Orange: Africa (33) Purple: America (21) Dark Red: Asia & Oceania (22) Yellow: Europe (39)

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.

Extracting International Factors: Multi-Level DFM

Africa advanced: $Y_{1t} = \lambda_{11} F_{gt} + \lambda_{12} F_{AFt} + \lambda_{16} F_{Adt} + \varepsilon_t$

Africa MHI-EMD: $Y_{2t} = \lambda_{21} F_{gt} + \lambda_{22} F_{AFt} + \lambda_{27} F_{Mt} + \varepsilon_t$

Africa LI-EMD: $Y_{3t} = \lambda_{31} F_{gt} + \lambda_{32} F_{AFt} + \lambda_{38} F_{Lt} + \varepsilon_t$

America advanced: $Y_{4t} = \lambda_{41} F_{gt} + \lambda_{43} F_{Amt} + \lambda_{46} F_{Adt} + \varepsilon_t$

America MHI-EMD: $Y_{5t} = \lambda_{51} F_{gt} + \lambda_{53} F_{Amt} + \lambda_{57} F_{Mt} + \varepsilon_t$

America LI-EMD: $Y_{6t} = \lambda_{61} F_{gt} + \lambda_{63} F_{Amt} + \lambda_{68} F_{Lt} + \varepsilon_t$

Asia and Oceania advanced: $Y_{7t} = \lambda_{71} F_{gt} + \lambda_{72} F_{Ast} + \lambda_{76} F_{Adt} + \varepsilon_t$

Asia and Oceania MHI-EMD: $Y_{8t} = \lambda_{81} F_{gt} + \lambda_{82} F_{Ast} + \lambda_{87} F_{Mt} + \varepsilon_t$

Asia and Oceania LI-EMD: $Y_{9t} = \lambda_{91} F_{gt} + \lambda_{92} F_{Ast} + \lambda_{98} F_{Lt} + \varepsilon_t$

Europa advanced: $Y_{10t} = \lambda_{10,1} F_{gt} + \lambda_{10,2} F_{Eut} + \lambda_{10,6} F_{Adt} + \varepsilon_t$

Europa MHI-EMD: $Y_{11t} = \lambda_{11,1} F_{gt} + \lambda_{11,2} F_{Eut} + \lambda_{11,7} F_{Mt} + \varepsilon_t$

Europa LI-EMD: $Y_{12t} = \lambda_{12,1} F_{gt} + \lambda_{12,2} F_{Eut} + \lambda_{12,8} F_{Lt} + \varepsilon_t.$

Extracting International Factors: Multi-Level DFM

Identification:

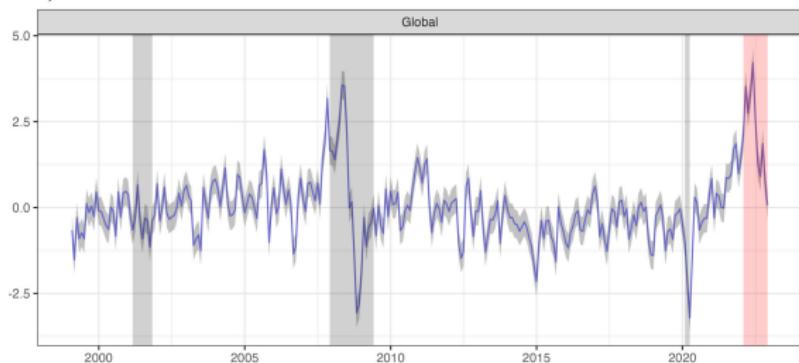
- Within each block (regional or development): $(F'F)/T = I$ and $\Lambda'\Lambda$ is diagonal with distinct entries. Needed to allow sequential estimation of the factors within each block; see Choi et al. (JAE, 2018) and Lin and Shin (Manuscript, 2023).
- Regional factors are orthogonal with respect to the development level factors.
- All block factors are orthogonal with the global factor.

Estimation:

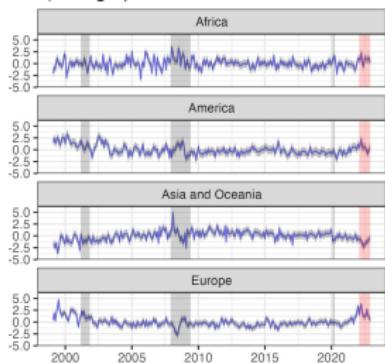
- First, initial estimates of the factors are obtained using canonical correlations and PC. Second, a sequential Least Squares (LS) procedure is implemented to estimate the loadings and factors; Breitung and Eickmeier (2016) and Rodríguez-Caballero and Caporin (J. Inter. Financial Markets, Institutions and Money, 2019)
- Confidence bands for factors and loadings are obtained based on the asymptotic distribution of Bai (2003).

Extracting International Factors: Multi-Level DFM

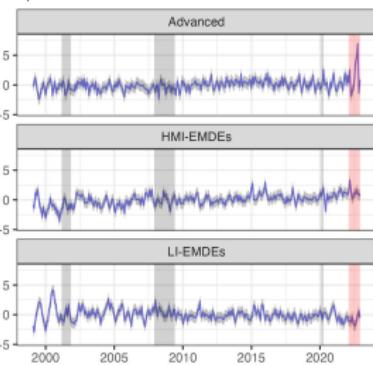
a) Global factor



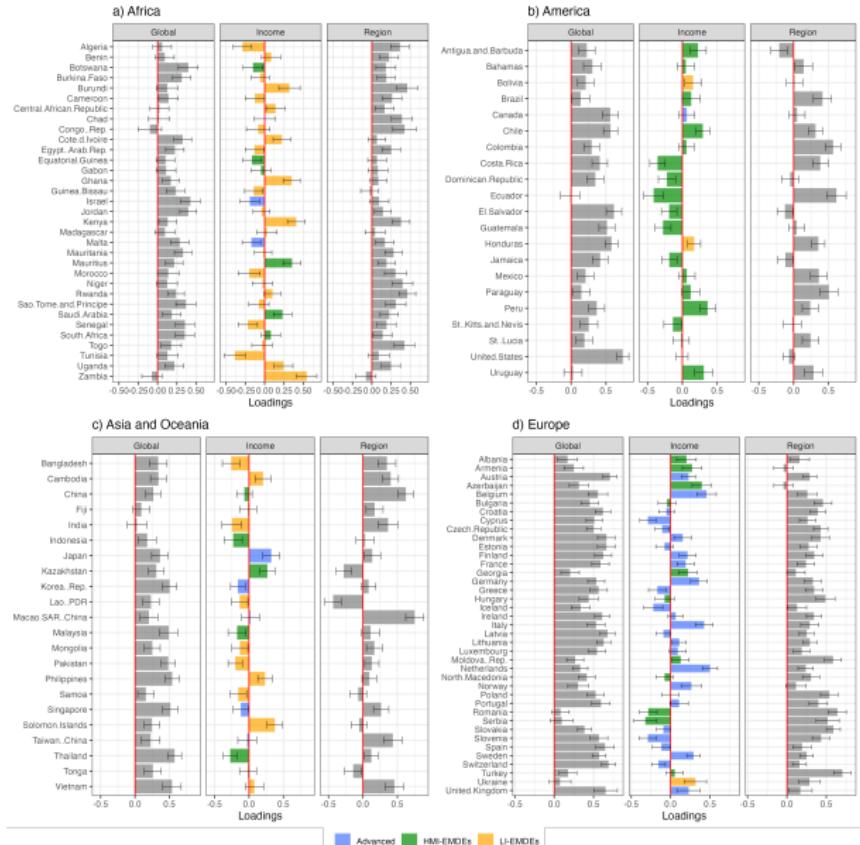
b) Geographical factors



c) Income factors



Extracting International Factors: Multi-Level DFM



Blue: Advanced Green: HHI-EMDEs Orange: LI-EMDEs

Inflation Densities: Estimation Results (some selected countries)

	Brazil			Mexico			China		
	0.05	0.50	0.95	0.05	0.50	0.95	0.05	0.50	0.95
μ	-1.667 (0.00)	2.191 (0.00)	6.980 (0.00)	-1.535 (0.00)	2.908 (0.00)	7.898 (0.00)	-5.854 (0.00)	1.715 (0.00)	10.383 (0.00)
ϕ	0.504 (0.00)	0.612 (0.00)	0.837 (0.00)	0.242 (0.03)	0.359 (0.00)	0.360 (0.00)	0.108 (0.38)	0.083 (0.50)	0.156 (0.38)
β_1	0.382 (0.11)	0.038 (0.90)	0.102 (0.82)	0.859 (0.00)	0.196 (0.43)	-0.144 (0.61)	0.597 (0.20)	0.936 (0.03)	0.366 (0.63)
β_2									
β_3	-0.057 (0.84)	0.000 (1.00)	-0.198 (0.54)	1.330 (0.00)	0.445 (0.13)	0.185 (0.00)			
β_4							0.688 (0.21)	0.105 (0.86)	0.370 (0.71)
β_5									
β_6									
β_7	0.312 (0.14)	0.245 (0.42)	0.573 (0.17)	0.366 (0.13)	0.012 (0.97)	-0.592 (0.08)	0.687 (0.06)	0.304 (0.56)	-0.795 (0.29)
β_8									
R^1	0.23	0.20	0.36	0.13	0.13	0.21	0.06	0.02	0.01
AIC	1662.0	1579.4	1787.0	1656.7	1489.6	1721.5	1895.7	1745.3	2028.8
AIC-AR	1660.6	1532.6	1584.8	1705.0	1461.1	1784.3	1915.0	1731.7	2026.7

Estimated parameters for $h = 1$. p-values in parenthesis. In bold, estimates significant at the 10% level.

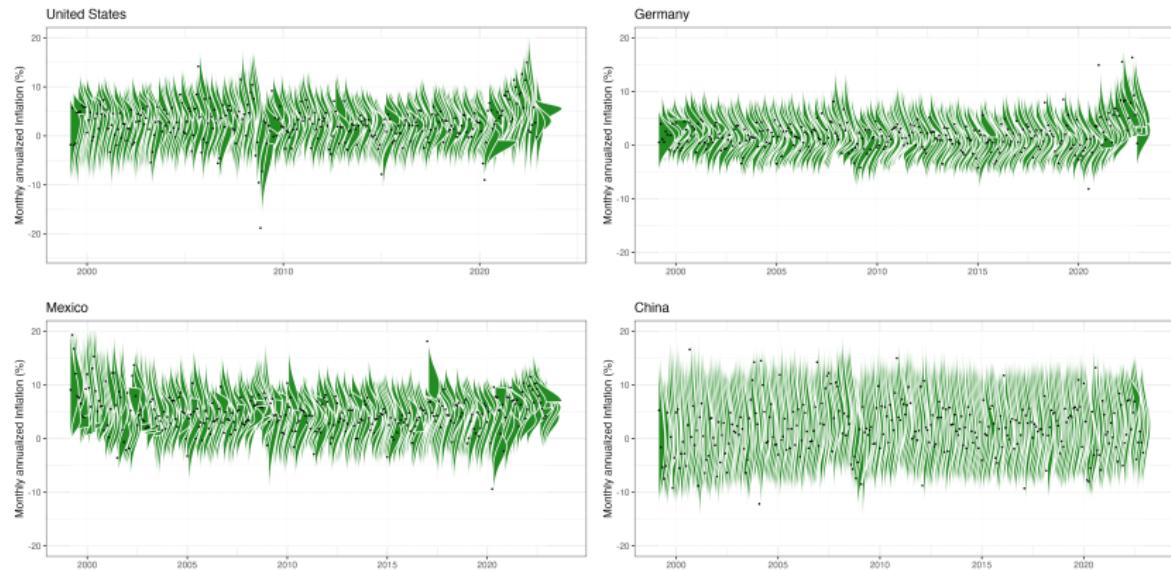
Inflation Densities: Estimation Results (some selected countries)

Tests of joint significance of the parameters of the FA-QR models associated to international factors. In blue rejection of the null when p -value is smaller than 0.10.



Inflation Densities: Estimation Results (some selected countries)

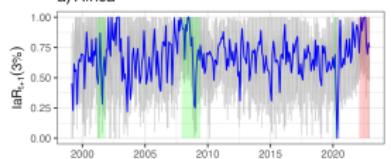
Predicted domestic inflation densities in the US, Germany, Mexico, and China obtained using the FA-QR model.
The bullets represent the observed inflation.



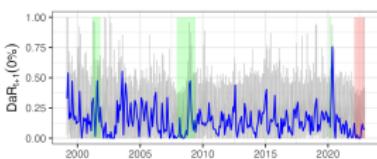
Inflation Densities: Estimation Results (some selected countries)

Estimates of $laR_{it+1}(3)$ (left) and $DaR_{it+1}(0)$ (right), for all economies in Africa (first row), America (second row), Asia (third row), and Europe (fourth row).

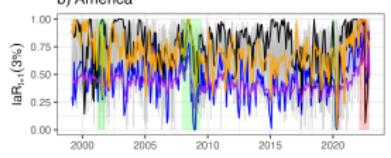
a) Africa



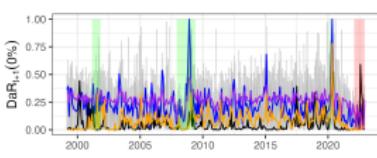
Note: South Africa (blue), other countries (gray area).



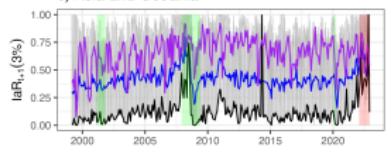
b) America



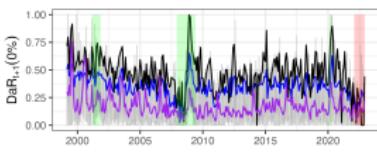
Note: United States (blue), Brazil (black), Canada (purple),
Mexico (orange), other countries (gray area).



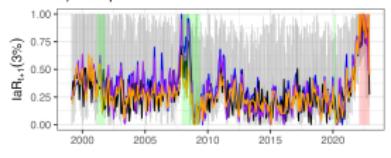
c) Asia and Oceania



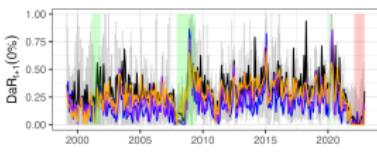
Note: China (blue), Japan (black), India (purple),
other countries (gray area).



d) Europe



Note: United Kingdom (blue), France (black), Italy (purple),
Germany (orange), other countries (gray area).



Out-of-sample forecasts

We use scoring rules specified in terms of the full density function. Particularly, the Continuous Ranked Probability Score (CRPS) proposed by Gneiting and Ranjan (2011).

$$CRPS(i) = \frac{1}{J} \sum_{j=1}^J \omega(\tau_j) QS(i, \tau_j), \quad (1)$$

where the Quantile Score is defined as

$$QS(i, \tau) = \frac{1}{P} \sum_{t=R}^P (1(y_{it+1} \leq \hat{q}_\tau(y_{it+1})) - \tau)(\hat{q}_\tau(y_{it+1}) - y_{it+1}); \quad (2)$$

with $J = 5$, $\tau_1 = 0.05, \dots, \tau_5 = 0.95$, and $\omega(\tau)$ is one of the following weighting schemes:

- left tail $\omega(\tau) = (\tau - 1)^2$;
- right tail $\omega(\tau) = \tau^2$; and
- equal tail $\omega(\tau) = 1$

Out-of-sample forecasts

- Estimation period from February 1999 to December 2011 ($R = 155$ observations) and an out-of-sample period from January 2012 to December 2022 ($P = 132$ observations).
- Using a rolling-window scheme, we compute the scoring function $QS(i, \tau)$ for $i = 1, \dots, 115$ and $\tau = 0.05, 0.25, 0.5, 0.75$ and 0.95 , and the $CRPS(i)$ statistic, for each of the three weighting schemes.
- The benchmark is the AR-QR model.

Out-of-sample forecasts

FA-QR model generates smaller losses when forecasting the quantiles of the density of domestic inflation in UK, France, and Italy, and South Africa.

	QS(0.05)	QS(0.50)	QS(0.95)	CRPS-E	CRPS-L	CRPS-R
US	0.95	1.03	0.94	1.00	1.00	1.00
Canada	1.10	1.03	0.94	1.00	1.03	0.97
Japan	1.11	1.00	0.97	1.01	1.04	0.99
UK	0.95	0.80***(**)	0.59***(**)	0.79***	0.85***	0.73***
France	1.13	0.84***	0.65**	0.84**	0.94	0.76***
Germany	1.00	0.93**(*)	1.00	0.95*	0.97	0.95
Italy	1.27	0.88**(*)	0.81***	0.91*	1.02	0.84***
India	1.08	0.99	1.05	1.01	1.03	1.01
Brazil	1.06	1.01	1.08	1.04	1.04	1.05
China	1.05	1.01	1.05	1.01	1.01	1.01
South Africa	0.87*	0.92**(**)	0.96	0.91**	0.89**	0.92**
Mexico	0.99	1.01	0.93*	0.99	0.98	0.99

Table: Ratios of forecast losses obtained with the FA-QR and AR-QR models. The ratios marked with stars are those for which the loss of forecasts obtained with the FA-QR model are significantly smaller than those of the AR-QR model according to the DM test of equal predictive accuracy. * 10%, ** 5%, and *** 1% significance levels. The ratios significant according to the AM tests are marked in parenthesis.

Out-of-sample forecasts

International factors are relevant for 41.70% of the total number of countries. This percentage increases to 71.80% among European countries and to 68.60% among advanced economies.

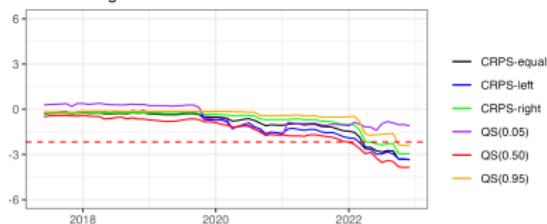
	QS(0.05)	QS(0.50)	QS(0.95)	CRPS-E	CRPS-L	CRPS-R
% total	12.20	40.90	31.30	34.80	19.10	41.70
% total in Africa	12.10	24.20	21.20	21.20	12.10	24.20
% total in America	14.30	28.60	33.30	33.30	19.00	28.60
% total in Asia	13.60	22.70	22.70	22.70	18.20	27.30
% total in Europe	10.30	71.80	43.60	53.80	25.60	71.80
% total in ADV	8.60	68.60	48.60	48.60	17.10	68.60
% total in HMI	19.00	35.70	21.40	38.10	31.00	35.70
% total in LI	7.90	21.10	26.30	18.40	7.90	23.70

Table: Ratios of forecast losses obtained with the FA-QR and AR-QR models. The table reports the percentage of countries with significant DM tests.

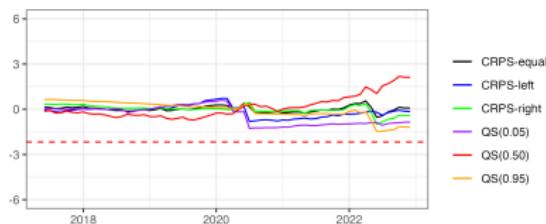
Out-of-sample forecasts

Giacomini and Rossi (2010)'s Fluctuation test to detect **Pockets of Probability**:

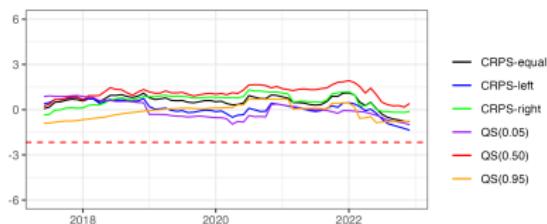
United Kingdom



United States



Mexico



France

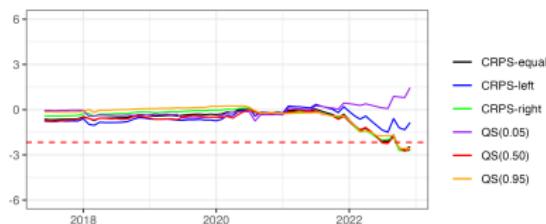


Figure: Fluctuation test for equal predictive ability of the FA-QR model with respect to the benchmark AR-QR model

Conclusions and ongoing Work

Conclusions:

- We show that the influence of international factors is relevant to understand the distribution of domestic inflation in a large proportion of countries.
- These factors can be global (with weights for most countries), regional, factors common to economies in a given region, or associated to the level of economic development.
- We show that the relevance of international factors is stronger in advanced than in low-income economies.
- We find strong out-of-sample power of the international factors.