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Global Inflation, Regional Factors

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Abstract:
This paper shows that global inflation dynamics have a sizable regional component. Using a balanced panel of 61 countries that starts in 1970, we document that while the global factor, defined as the dominant principal component, explains a large portion of inflation variation in advanced economies, a model with only one principal component is less successful for developing countries. By contrast, a hierarchical dynamic factor model, which includes a global (unconstrained) factor and regional (restricted) factors, performs substantially better for emerging market and developing economies. The regional factors are linked to commodity prices and help improve the accuracy of inflation forecasts at the country level. Employing an unsupervised machine-learning technique, we show that the estimated clusters of countries, grouped according to similarities in inflation dynamics, exhibit a strong regional pattern. Our findings suggest that policymakers in developing countries should pay close attention to inflation dynamics in their neighboring countries.

JEL Classifications: E3, E5, F4, F6
Keywords: Clustering, developing countries, globalization, inflation, regional factors

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1 Introduction

Is inflation typically a global phenomenon? The 2021–2022 inflation surge took place simultaneously in many advanced and developing economies. This episode of high international comovement of inflation is not unique. For instance, high inflation comovement occurred during the oil price shocks of the 1970s and 1980s. Many influential studies in the literature agree that, at least from the perspective of highly developed economies, inflation is global. For instance, using data from a sample of 22 Organisation for Economic Co-operation and Development (OECD) economies, Ciccarelli and Mojon (2010) document that a single common component can explain, on average, as much as 70 percent of inflation variation. Auer, Pedemonte, and Schoenle (2024) confirm this finding for advanced economies but report that the global factor explains a substantially smaller share of inflation variance in developing countries. More generally, recent studies find that both real and financial outcomes of interest tend to move in cycles that are common across countries. This is true across business cycles (Kose, Otrok, and Whiteman 2003, 2008), interest rate cycles (Forbes, Ha, and Kose 2024), and financial cycles (Miranda-Agrippino and Rey 2022). This comovement has been rationalized with models of trade and monetary policy spillovers, which are transmitted via production chains and risk premiums (e.g., di Giovanni et al. 2022, 2023).

Our paper shows that for emerging market and developing economies (EMDEs), inflation comoves strongly within geographical regions. We introduce a novel concept of *regional inflation factors* and show that they can explain a sizable portion of inflation variation in developing countries. The model that includes the regional factors as well as the global factor characterizes international inflation dynamics much better than the model with the global factor alone.

We use inflation data from a balanced panel of 61 economies that covers the 1970–2023 period. Our sample includes 25 advanced economies (AEs) and 36 EMDEs located in Africa, Asia, and Latin America. The longer time frame enables us to examine changes in the roles of the regional factors as well as the global factor between the relatively more volatile early period and—with the exception of post-pandemic inflation—the relatively calm Great Moderation period. Our study focuses on headline inflation because, for many countries in our sample, the core inflation series starts at a much later date.

Following the literature, our starting point is a global inflation factor estimated as a dominant component using principal component analysis (PCA). This global factor explains, on average, 51.7 percent of inflation variation in advanced economies but, depending on the geographical region, only 10.3 to 18.9 percent in our sample's developing countries. That is, using a larger and more heterogeneous sample of countries than that in the literature results in an estimated global factor that has somewhat less explanatory power for advanced economies and relatively little for

EMDEs.[1]

Next, we extend the PCA model to include a larger number of components. Our preferred specification includes five common components, based on the Bai and Ng (2002) information criteria, among other considerations. With these additional components, the average share of explained inflation variation increases to 38.6 to 54.5 percent in EMDE regions and 64.4 percent in advanced economies. The marginal improvement is particularly noticeable for EMDEs. However, we do not observe an "EMDE" component, as the share of explained variation rises gradually.

Most importantly, we observe a clear tendency for the higher-order principal components to have regional interpretation. For instance, in the three-component PCA, the dominant component corresponds to advanced economies, the second component loads mostly on Latin American economies, and the third component represents Asian and African countries. In the five-component model, the first two components retain their interpretation, while the third component represents Asian economies and the fifth component African economies. The fourth component has high loading coefficients for the African and Asian groups.

Building on these results, we propose a hierarchical dynamic factor model (H-DFM) in the spirit of Kose, Otrok, and Whiteman (2003). This model includes (1) a global factor that drives inflation in all countries in the sample and (2) non-overlapping "regional" factors.[2] We group EMDEs into the Africa, Asia, and Latin America regions. To avoid using groups that comprise only two or three countries, which would be the case for North America and Oceania, we treat all advanced economies as one group. This procedure yields a model with five factors, one global and four regional, and hence can be interpreted as putting structure (constraints) on the five-component PCA model discussed earlier to enhance the factors' interpretation.

The key finding of our paper is that, in EMDEs, the regional factors explain a sizable share of inflation variance, a share typically exceeding the portion explained by the global factor. In Asia, the regional factor explains 27.8 percent of inflation variation, while the global factor explains only 8.9 percent. In Latin America, the corresponding estimates are 22.5 percent and 16.2 percent, respectively. In Africa, the difference is smaller: 15.4 versus 14.2 percent. By contrast, in advanced economies, the regional factor explains relatively little inflation variation (5.6 percent), while much of the variation is absorbed by the global factor (51.6 percent). We note, however, that the global factor is likely disproportionately influenced by advanced economies, and the hierarchical structure of our model ensures that the common variation is allocated to the global factor. Overall, the H-

[1] For comparison, the Auer, Pedemonte, and Schoenle (2024) sample includes 10 EMDEs for the period as long as ours and an additional six EMDEs starting in 1980. For the period starting in 2000, their EMDE sample adds 18 countries, 12 of which, however, are members of the European Union. Many of these countries, located in Central and Eastern Europe, have recently been reclassified as advanced economies.

[2] The model is estimated using the expectation-maximization algorithm, as in Bańbura, Giannone, and Reichlin (2011) and Bańbura and Modugno (2014), among others.

DFM model retains the high explanatory power of the five-component PCA model, with increased interpretability.

When we examine the stability of our baseline estimates over the sample period, we find that for the full sample of countries, the average shares of variance explained by the the global and regional factors remain virtually unchanged from the earlier half of the sample period to the later half. This stability, however, masks significant heterogeneity across country groups. In advanced economies, the inflation variance explained by the regional factor nearly doubles, although it remains substantially smaller than the variance explained by the global factor. The latter changes minimally over the sample period. In all the regions of the EMDE sample, however, the share of the global factor increased, while the shares of the regional factors declined somewhat. This may indicate that EMDEs in the sample, as a group, have been on a convergence path with their developed peers.

While our baseline analysis focuses on actual inflation, we find that the contributions of the global factor to *cyclical* inflation is similar to this factor's contributions to actual inflation. However, the results for the regional factors are more nuanced. In some countries (for example, India and Nepal), the regional factor explains a relatively large share of actual inflation variance but a low share of cyclical inflation variance. In other countries (for example, Cameroon and Niger), it is vice versa.

To confirm the importance of regional factors without imposing an a priori regional structure on the model, we turn to clustering analysis. We apply K-means clustering, an unsupervised machine-learning algorithm, to allocate the 61 countries in our sample to arbitrary clusters based on the similarity of their inflation dynamics. Overall, the resulting clusters support the allocation based on the regional groups used in the H-DFM analysis. Specifically, when the algorithm's outcome is evaluated against the target labels associated with the geographical regions, the accuracy score is about 75 percent, with the precision and recall rates of the classifier substantially higher than in the case of random assignment based on group sizes. Thus, the regional inflation comovement also broadly holds in model-agnostic frameworks.

What drives this regional inflation comovement? We find that, in general, each region's factor is positively and significantly correlated with the prices of that region's import commodities and negatively and significantly correlated with the prices of its export commodities, with two exceptions: (1) The advanced-country factor is uncorrelated with the prices of the region's export commodities, and (2) the Latin America factor is uncorrelated with the prices of its import commodities. We also find that the global, advanced-economy, and Latin America factors are positively correlated with regional interest rates and negatively correlated with regional exchange rates.

Finally, we conduct two exercises that shed light on the predictive power of inflation components. First, we estimate global and regional inflation persistence (see Fuhrer 2010). We confirm that the global factor is highly persistent (a persistence coefficient, ρ, of 0.97) but find substantial heterogeneity in the persistence of the regional factors. While the advanced-economy and Latin America factors are also highly persistent ($\rho > 0.94$), the Asia and Africa factors are much less so (0.54 and 0.62, respectively). We also find heterogeneity in the persistence of the idiosyncratic inflation component, ranging down from $\rho = 0.66$ to a statistical zero (with one negative outlier).

Second, we investigate whether the regional as well as global factors improve inflation forecasts. We compare pseudo out-of-sample forecasts over the 2010–2023 period of the benchmark autoregressive model with the model augmented with (1) the global factor only and (2) both the global and regional factors. We evaluate the forecasts using root mean squared errors and the Diebold and Mariano (1995) tests. We find that including global and regional factors improves the one-quarter-ahead forecasts for all regions relative to the benchmark, and in most cases, including the regional factor improves the forecasts over those of the model with the global factor only. The results are similar but somewhat weaker at longer forecasting horizons such as four and eight quarters.

Our paper aligns closely with the literature examining the common sources of inflation variation. Early analyses focus on small samples of mostly advanced economies and employ simple dimensionality reduction techniques such as PCA (e.g., Hakkio 2009, Monacelli and Sala 2009, Ciccarelli and Mojon 2010).[3] Mumtaz and Surico (2012) compare the properties of global and country-specific inflation using dynamic factor models with a variety of restrictions applied to a small sample of advanced economies. More recent papers extend their coverage to larger samples, including EMDEs, and estimate dynamic factors, often imposing additional structural restrictions (e.g., Ha, Kose, and Ohnsorge 2019, 2023). Our main contribution to this literature is in showing the benefits of regional factors.[4] We also provide new evidence from a broad balanced panel of both advanced and developing economies.

Our paper also relates to the literature on the factors of cyclical inflation. For example, Stock and Watson (2007) study a trend-cycle decomposition applied to US inflation. Forbes (2019) combines PCA with a trend-cycle decomposition for a panel of countries. We contribute to this literature by estimating the dynamic factor model with regional factors for the cyclical inflation component.

More broadly, the related literature seeks to understand what drives the international comovement of macroeconomic indicators. Kose, Otrok, and Whiteman (2008), Mumtaz, Simonelli, and

[3] Monacelli and Sala (2009) leverage disaggregated CPI data but for only four OECD countries. Most other papers in this strand of literature focus on aggregate CPI inflation for a larger number of countries.

[4] Mumtaz, Simonelli, and Surico (2011) is one of the few studies that includes regional factors, but it has a smaller sample of 36 countries that is dominated by advanced economies. While their paper uses annual data ending in 2007, it makes a substantial historical contribution, as the estimated factors date back as far as the 1860s. Our paper also relates to Moench and Ng (2011), who use a H-DFM model to study regional housing-price factors in the United States.

Surico (2011), Kose, Otrok, and Prasad (2012), and others estimate factor models that include measures of economic activity as well as inflation. Wang and Wen (2007) and Bianchi and Civelli (2015), among others, examine this comovement from a Phillips curve perspective. Kamber and Wong (2020) and Ha et al. (2024) estimate a factor-augmented vector autoregression (FAVAR). Auer, Levchenko, and Sauré (2019) and Cascaldi-Garcia et al. (2024), among others, study sectoral factors of inflation using disaggregated inflation data, while Alvarez-Blaser et al. (2025) extend this line of research to granular firm-level data. Our contribution to this broad literature, again, highlights the regional dimension in the international transmission of shocks and business-cycle comovement.

The paper proceeds as follows. Section 2 briefly describes the data. In Section 3, we study the global inflation factor estimated as the first principal component, document the share of inflation variance that it explains, and extend the PCA model to include a larger number of components. Section 4 presents our main results from the H-DFM model. It documents how the inflation variation explained by the regional factors changed over time and examines cyclical inflation. Section 5 presents the K-means analysis, showing that the unsupervised algorithm produces strongly regional clusters. Section 6 correlates the global and regional factors with commodity prices, interest rates, and exchange rates. Section 7 examines the persistence and forecasting power of the inflation factors. Section 8 concludes.

2 Data

We use data from the Global Database of Inflation constructed by the World Bank's Prospects Group (Ha, Kose, and Ohnsorge 2023). This database covers as many as 209 countries over the 1970–2023 period at various frequencies and starting dates. For our analysis, we extract a balanced sample for the entire period that comprises 61 countries. Our preferred inflation measure is based on quarterly log differences in the total consumer price index (CPI).[5] The underlying CPI data are sourced from the OECD, the International Monetary Fund's (IMF) *International Financial Statistics*, and, in one case in our final balanced panel, national sources.[6]

We construct our country-group indicators as follows. First, we collect a regional classification from the World Bank.[7] Next, we combine Europe and North America into the advanced-economy group, to which we add Australia, Israel, Japan, Korea, Malta, New Zealand, and Singapore, coun-

[5] Appendix Table A.1 reports moments and percentiles of the distribution of four-quarter log differences in the total CPI by country.

[6] The database also provides other measures of inflation. However, their coverage is limited. For instance, data on quarterly core CPI inflation for the entire period are available for only 18 OECD countries.

[7] This classification comprises seven regions: Europe and Central Asia (19 countries in our sample), Latin America and the Caribbean (14 countries), Sub-Saharan Africa (10), East Asia and Pacific (8), Middle East and North Africa (4), South Asia (4), and North America (2).

tries the IMF classifies as advanced.[8] To ensure that each regional group includes a sufficient number of countries for our analysis, we further combine countries in East Asia and the Pacific and South Asia into the Asia region, and countries in Sub-Saharan Africa and the Middle East and North Africa into the Africa region. Overall, our sample is separated into 28 advanced economies, 14 Latin American countries, 12 African countries, and 7 Asian countries.

3 Global Inflation

We revisit evidence concerning the global inflation factor's role in international inflation dynamics to fix benchmarks for our sample of countries and estimation period. We then extend this model to allow for a larger number of unrestricted inflation factors. This approach helps us understand whether a single global factor sufficiently explains the common variation of inflation. It also provides new insight into the regional dimension of inflation variation.

3.1 Global Factor as a Dominant Principal Component

Following Ciccarelli and Mojon (2010), among others, we define the global inflation factor as the dominant principal component. That is, we estimate the following relationship:

$$\pi_{i,t} = \lambda_i f_t + \varepsilon_{i,t}, \tag{1}$$

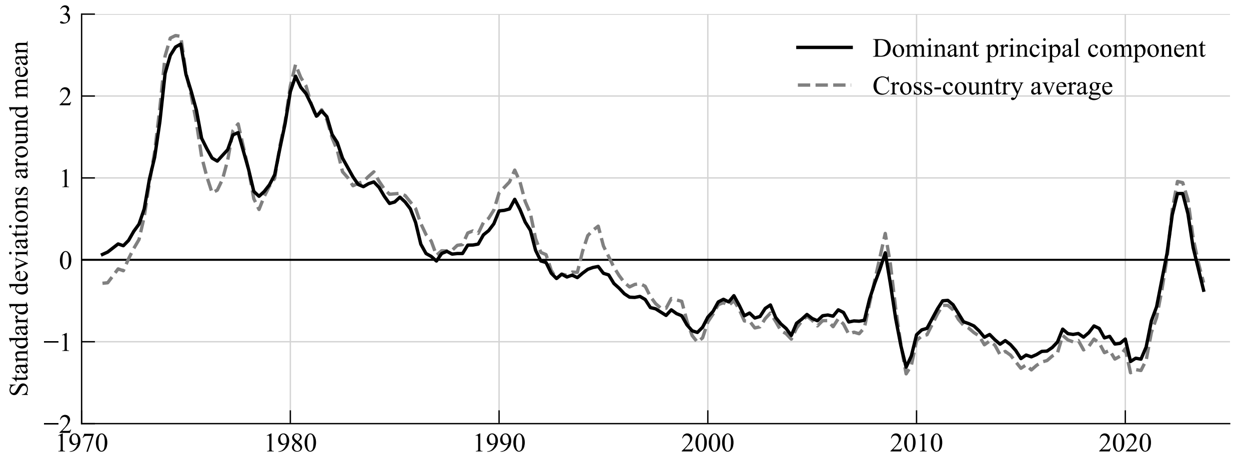
where $\pi_{i,t}$ is a measure of inflation in country i and quarter t, f_t is a global factor, λ_i is the factor's loading on country i's inflation, and $\varepsilon_{i,t}$ is an idiosyncratic component that represents country-specific inflation not captured by the global factor.

Figure 1 shows the estimates of this factor, $\hat{f}_t$, along with the unweighted average inflation across countries, each normalized to have a zero mean and unit variance. While our sample is substantially richer than the sample of 22 OECD countries in Ciccarelli and Mojon (2010) and includes a large fraction of developing countries, we still find that the simple unweighted average of inflation rates across all countries in the sample is very close to the estimated static factor, as demonstrated in the paper.[9]

[8] This procedure allocates Cyprus, Malta, and Türkiye to the Advanced Economies group, whereas the IMF classifies these countries in the Emerging and Developing Countries group. Our choice, however, fits our analysis better, mainly for two reasons. First, we emphasize the importance of regional linkages; most Advanced Economies in our sample are located in Europe. Second, given our sample, they would not be a good fit for any other regional group: The Asia sample is dominated by countries in South and Southeast Asia, while the Africa sample comprises countries mostly in Sub-Saharan Africa. Note that this classification choice does not materially affect our results.

[9] Moreover, when we apply the PCA model to the sample of advanced economies, the estimated global factor looks very similar to the one obtained from the full sample (Appendix Figure A.1). This is because the AE loadings are materially larger than the EMDE loadings.

Figure 1: Global Inflation



Source: The results presented in all tables and figures are based on the authors' calculations using data described in Section 2.
Note: The black solid line shows estimates of the global inflation factor, $\hat{f}_t$, from Equation (1) for a sample of 61 countries during the 1970–2023 period at a quarterly frequency. Inflation, $\pi_{i,t}$, is measured as a log difference in the total CPI. The dashed gray line shows the unweighted country average of $\pi_{i,t}$, normalized to have a zero mean and unit variance.

However, we find that the comovement of country-level inflation with the global factor differs drastically between advanced economies and EMDEs. Appendix Figure A.2 shows the inflation contribution of the global factor, $\hat{\lambda}_i \hat{f}_t$, for select advanced economies (that is, G7 plus Spain). In all these countries, the common components track country-level inflation closely over the entire period, with persistent deviations observed only in Germany before the unification. By contrast, the inflation component driven by the global factor behaves quite differently from actual inflation in EMDEs (Appendix Figure A.3). This result leads to an important conclusion: The first principal component—commonly referred to as the "global inflation" factor—is instead an advanced-economy factor, which has little explanatory power for inflation in many developing countries.

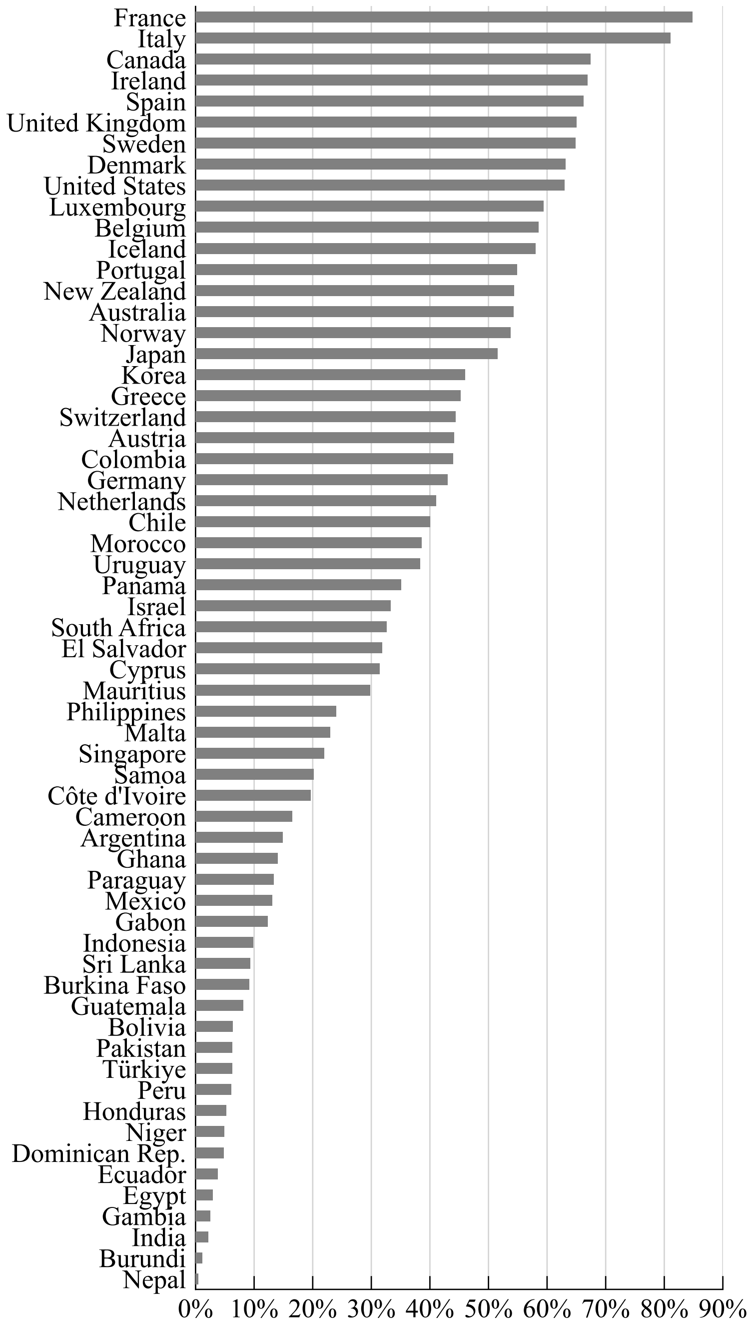
We formalize these results further by decomposing inflation variance into common and idiosyncratic components. Equation (1) implies that the share of inflation variance in country i explained by the global factor, denoted by ς_i, can be computed as follows:

$$\varsigma_i = \lambda_i^2 \frac{\mathbb{V} f_t}{\mathbb{V} \pi_{i,t}}, \tag{2}$$

where $\mathbb{V}$ is the variance operator.

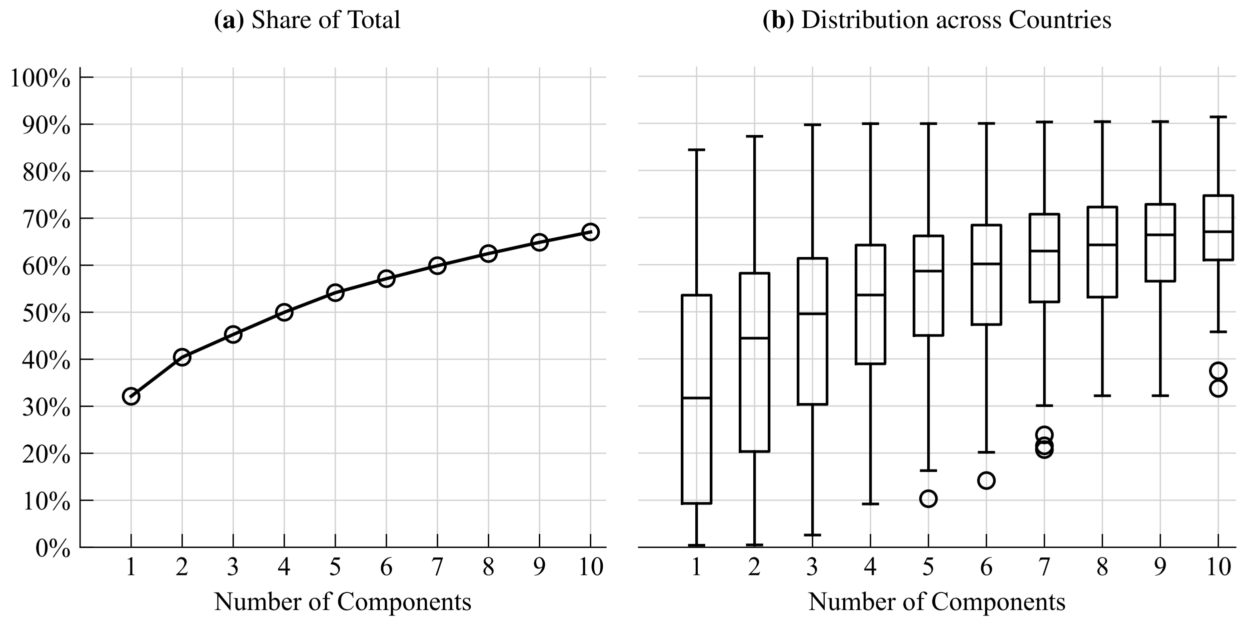
Figure 2 shows the share of inflation variance explained by the global factor by country. These shares are large for small open developed economies. However, for a vast majority of EMDEs in the sample, the global factor explains little variation in inflation; in over half of the EMDEs, it explains less than 10 percent.

Figure 2: Share of Inflation Variance Explained by the Global Factor



Note: The shares are computed using Equation (2).

Figure 3: Inflation Variance Explained by Principal Components



Note: Panel (a) shows the share of inflation variance explained by the principal components. Panel (b) shows the distribution across countries of the share of explained variance. Each box extends from the first quartile to the third quartile of the distribution, with the horizontal line inside the box representing the median. The whiskers extend from the boxes' top and bottom edges to the farthest data point lying within 1.5 times the inter-quartile range. The circles show the data points located beyond the end of the whiskers.

3.2 Regional Interpretation of Principal Components

Reducing inflation variation observed in the data to just one or two principal components is limiting. We therefore extend the PCA model to explain a larger portion of inflation variation in the data.

First, we determine how many principal components to include in our analysis. Figure 3 shows the share of inflation variance explained by principal components (Panel a) and the distribution of explained variance across countries (Panel b). The first principal component (the global factor) explains just over 30 percent of the variation in the data, with a significant heterogeneity across countries. Indeed, the 25th percentile of the distribution is below 10 percent. Adding the second component increases the median from 32 percent to 45 percent and also more than doubles the first quartile. Moreover, adding more components further reduces the mass in the left tail of the distribution. Based on these and other checks, we select a model with five principal components, which minimizes the Bai and Ng (2002) information criteria (see Appendix Table A.2).

Next, we show that these additional factors have a regional interpretation. Table 1 reports the share of inflation variance explained by the five-factor PCA model for advanced economies and for EMDEs by geographical group. This model explains a substantial amount of inflation variation in each group, with mean shares varying from 38.6 percent to 64.4 percent (Column 1). When we

Table 1: Percentage of Variance Explained by Group

	Total		Factor 1		Factor 2		Factor 3		Factor 4		Factor 5	
	Mean	Top 5	Mean	Top 5	Mean	Top 5	Mean	Top 5	Mean	Top 5	Mean	Top 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Advanced Economies	64.4	78.7	51.7	73.3	4.8	12.8	3.5	11.8	2.6	9.2	1.8	7.6
Africa	38.6	53.0	15.4	27.4	4.2	8.9	1.8	3.6	5.0	10.0	12.3	25.3
Asia	41.5	50.0	10.3	13.9	1.4	2.0	11.7	15.7	15.3	21.3	2.8	3.9
Latin America	54.5	66.3	18.9	37.9	22.5	33.6	6.8	13.9	3.5	8.1	2.8	6.4

Note: This table shows the share of inflation variance explained by the PCA model with five factors. Odd-numbered columns report the mean across all countries in the group, while even-numbered columns report the average of the top-five shares in the group. Columns (1) and (2) report the variance explained by the entire model, whereas Columns (3) through (12) report it separately for each factor.

focus on the top five countries with the most variance explained in each group, the shares are even larger, varying from 50.0 percent to 78.7 percent (Column 2).[10]

Columns (3) through (12) of Table 1 show the contributions of each factor separately. The first (global) factor explains more than half of the inflation variation in advanced economies but less than one-fifth, on average, in any other group. The second principal component can be interpreted as a Latin America factor, while the fifth component's marginal contribution peaks for the Africa group. There is no clear Asia factor, however, with both the third and fourth factors making substantial contributions to inflation in this group.[11]

Appendix Figure A.5 examines heterogeneity within each group. In advanced economies (Panel a), the first principal component accounts for the largest contribution in all countries except Türkiye and Singapore. In the Latin America group (Panel b), the second component makes the largest marginal contribution in most countries. One notable exception in this group is Honduras, for which the third factor plays the dominant role. In four countries in this group, the first factor is dominant. There is some heterogeneity in the Asia and Africa groups (Panels c and d, respectively), but, overall, countries with a larger share of explained variance tend to have a larger contribution of the regional component corresponding to those countries.

4 Regional Factors

In the preceding analysis, principal components have a suggestive regional interpretation. However, each component loads on every country in the sample. To crystallize the significance of regional factors, we estimate a factor model that imposes identifying restrictions on the regional factors such that each regional factor loads only on the countries in that region, not on any other country. We also allow for persistence in the factors, which may be important for the regional as

[10] Top five here refers to the countries for which a given factor explains the most variation. That is, the top five countries vary across the columns.

[11] Appendix Figure A.4 plots these factors over time.

well as the global factors.

Specifically, we estimate a hierarchical dynamic factor model (H-DFM) in which inflation in country i depends on the global factor, f_t^{G}, and a regional group factor, $f_t^{r(i)}$, corresponding to country i. This model is characterized as follows:

$$\pi_{i,t} = \lambda_i f_t^{\mathrm{G}} + \mu_i f_t^{\mathrm{r}(i)} + \varepsilon_{i,t}, \tag{3a}$$

$$f_t^{\mathrm{G}} = \rho_1 f_{t-1}^{\mathrm{G}} + \ldots + \rho_p f_{t-p}^{\mathrm{G}} + \eta_t, \tag{3b}$$

$$f_t^{r} = \varphi_{r,1} f_{t-1}^{r} + \ldots + \varphi_{r,q} f_{t-q}^{r} + \nu_t, \tag{3c}$$

$$\varepsilon_{i,t} = \kappa_{i,1}\varepsilon_{i,t-1} + \ldots + \kappa_{i,z}\varepsilon_{i,t-z} + \omega_{i,t}, \tag{3d}$$

where $r \in \{\text{Advanced Economy}, \text{ Africa}, \text{ Asia}, \text{ Latin America}\}$ denotes a regional group, and $\mathrm{r}(i)$ is a selection function that maps country i to the region r to which it belongs. This model is estimated using the expectation-maximization (EM) algorithm, along the lines of Bańbura, Giannone, and Reichlin (2011) and Bańbura and Modugno (2014).

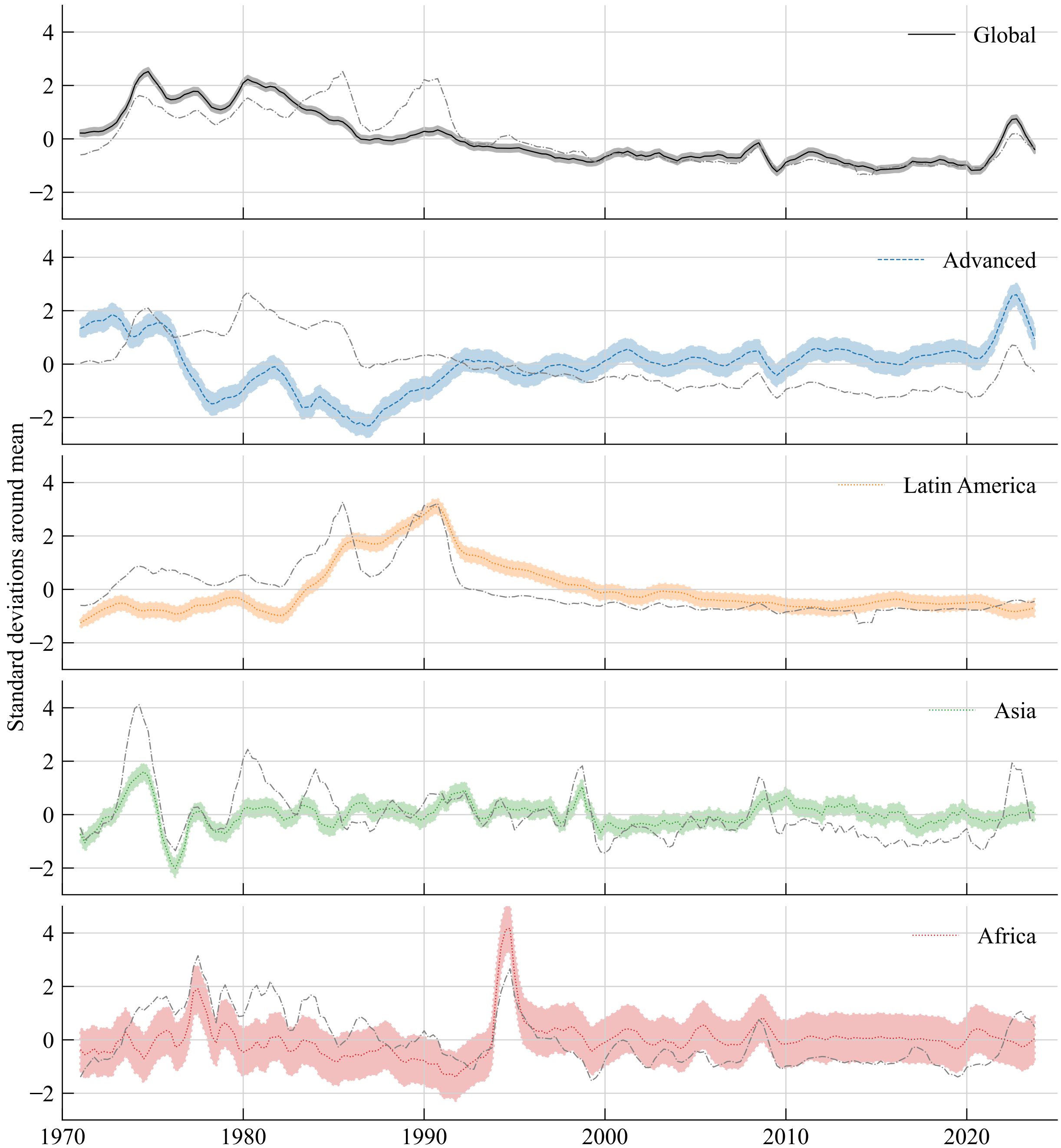
4.1 Baseline Estimates

Figure 4 plots the estimated global inflation factor (black solid line in the top panel) and regional inflation factors (colored broken lines in the lower four panels), together with their 95 percent confidence bands, and compares them with the group average inflation (gray dash-dotted lines). The global factor estimated using Equations (3) looks broadly similar to the first principal component obtained from Equation (1). The advanced-economy factor appears to correlate strongly with the global factor, starting in the early 1990s. Before then, the relation between the two is more nuanced. For example, in the mid-1980s, both the global and advanced-economy factors were declining. By contrast, in the late 1980s, the global factor was steady while the advanced-economy factor was rising.

The peaks in the regional factors correspond to known inflation episodes in the regions. For instance, the peak in the Latin America factor in the late 1980s and early 1990s corresponds to a period of hyperinflation and debt crises in the region. The late-1990s peak in the Asia factor corresponds to the East Asian financial crisis. And the largest peak in the Africa factor corresponds to the CFA franc devaluation that occurred on January 12, 1994, when, overnight, the currency was devalued by 50 percent relative to the French franc.

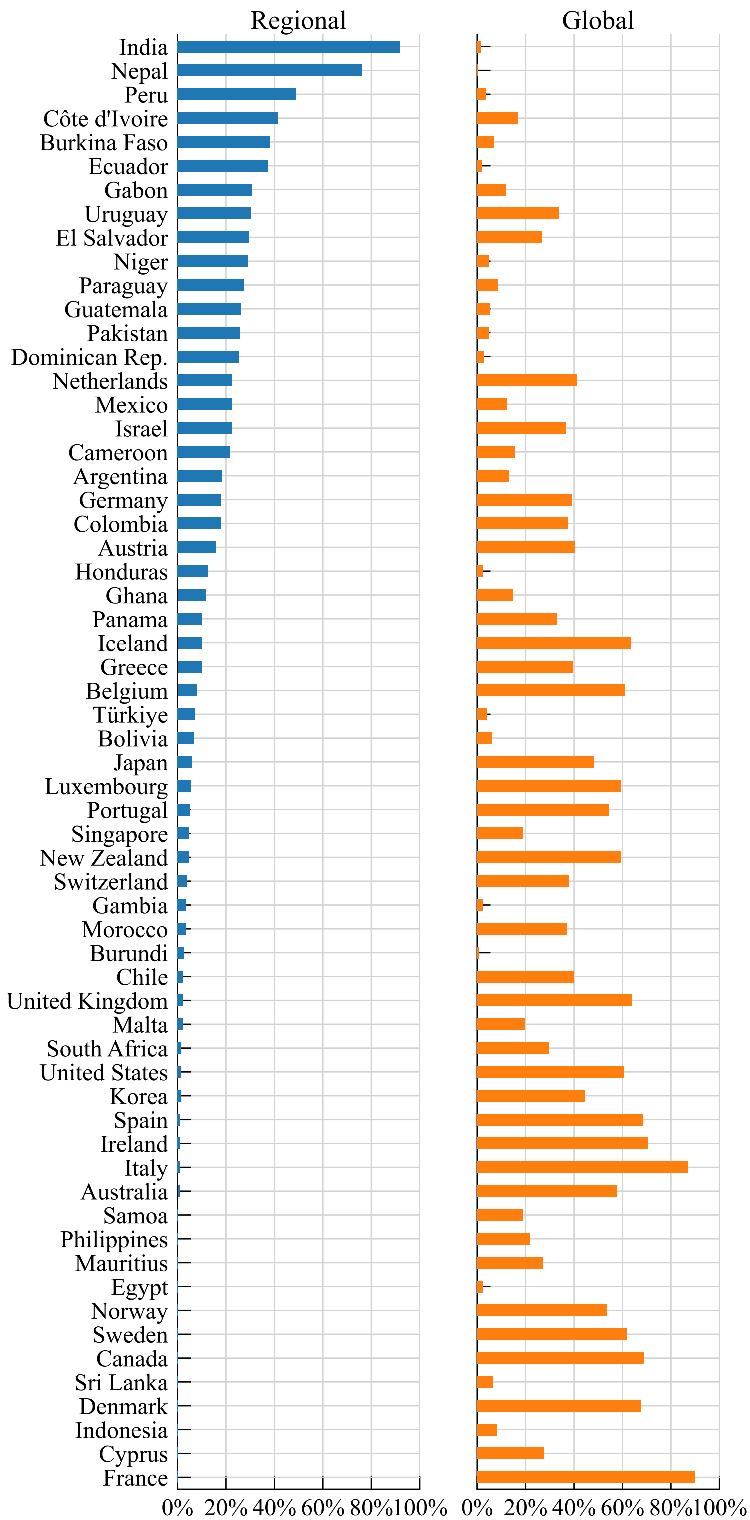
We also find that both the global and regional factors contribute materially to the average inflation within regions. For instance, during the post-pandemic period, the average inflation rate increased for all groups. Yet, while both the global and regional factors contributed to this increase for advanced economies and, to lesser degree, for Asian economies, the inflation increase in Latin America and Africa was entirely due to global forces.

Figure 4: Global and Regional Inflation Factors



Note: This figure shows estimates of the global inflation factor $\hat{f}_t^{\mathrm{G}}$ (solid line in the top panel) and of the regional factors $\hat{f}_t^{r}$ (colored broken lines in the lower four panels), from Equations (3), together with their 95 percent confidence bands. These estimates are smoothed to represent year-over-year inflation, while the model is estimated using quarterly CPI log differences. The gray dash-dotted line shows cross-country year-over-year inflation rates, which, like the factors, are scaled to have a zero mean and unit variance. The factors are oriented in the direction of the averages. The estimation sample includes 61 countries during the 1970–2023 period at a quarterly frequency.

Figure 5: Share of Inflation Variance Explained by Regional and Global Factors



Note: This figure shows the share of inflation variance explained by the respective regional factor (left panel) and the global factor (right panel) estimated using the model from Equations (3).

Table 2: Share of Inflation Variance Explained by Factors (in Percentages)

	Regional Factors			Global Factor		
	Full Sample (1)	1970–1997 (2)	1998–2023 (3)	Full Sample (4)	1970–1997 (5)	1998–2023 (6)
All Countries	13.9	15.8	15.7	31.2	24.1	27.8
Advanced Economies	5.6	7.7	15.4	51.6	43.2	45.9
Africa	15.4	17.2	9.0	14.2	6.6	13.1
Asia	27.8	29.1	24.5	8.9	8.0	12.3
Latin America	22.5	24.0	17.6	16.2	9.0	12.1

Note: This table shows the average share of inflation variance explained by regional and global factors across countries within a given group.

Figure 5 shows the variance decomposition obtained using the H-DFM model by country. The left panel depicts the share of inflation variance explained by the respective regional factor, while the right panel shows the variance share explained by the global factor. Columns (1) and (4) of Table 2 aggregate these estimates by region. Two main results emerge. First, the regional factor explains a sizable share of inflation variance in many EMDEs.[12] Second, the explanatory power of the regional factor in advanced economies is almost entirely absorbed by the global factor. Thus, we conclude that while the global inflation factor alone may sufficiently explain inflation variation in advanced economies, regional factors are needed to model inflation in the rest of the world.

4.2 Time Breaks

We conduct our baseline analysis using a relatively long period, during which trend inflation declined in many countries. This could be a challenge for principal-component and dynamic-factor models, because they estimate time-invariant factor loadings. We explore the sensitivity of our results to this assumption by reestimating our baseline H-DFM for two subsamples: 1970 through 1997 and 1998 through 2023. We choose this time break for the following reasons. In the early 1990s, the Reserve Bank of New Zealand pioneered formal inflation targeting, which advanced economies, including Canada and the United Kingdom, adopted shortly thereafter. While the timing and implementation details of inflation targeting varied across other advanced economies, it is widely believed that in many of them, inflation behaved as if the target were adopted in the early 1990s. Moreover, the 1997 Asian Financial Crisis, which quickly spread to other parts of the world, resulted in the sharp depreciation of many EMDE currencies, leading to inflation measured in local currency prices. Hence, in both development groups, inflation was relatively high and volatile during the 1970–1997 period, while, with the exception of 2021 through 2023, inflation was relatively low during the latter period. Conveniently, the two subsamples have nearly equal lengths.

[12] We do not find material differences between commodity exporters and importers (Appendix Figure A.6 and Table A.3).

Table 2 shows how the share of inflation variance explained by the regional and global factors changed between the two periods. For all countries, the average shares of inflation variance explained by the regional and global factors changed little: The variance share associated with the regional factors is 15.8 percent for the earlier sample and 15.7 percent for the later sample (Columns 2 and 3, respectively). The share of the global factor increased slightly from 24.1 percent to 27.8 percent (Columns 5 and 6).[13]

Examining the changes for each country group separately, we find that the share of the global factor in developing countries' inflation increased by one-third to one-half, depending on the group, but in advanced economies, the role of the global factor remained almost unchanged. The share of the regional factors doubled in advanced economies and declined somewhat in developing countries. These results point to weak convergence of inflation dynamics across the groups.[14]

4.3 Cyclical Inflation

While our baseline analysis focuses on actual inflation, the cross-country comovement of cyclical inflation could differ drastically from that of actual inflation. To highlight the cyclical inflation component, we apply the Baxter and King (1999) band-pass filter to inflation series at the country level.

Figure 6 shows our estimates of the global factor using PCA (Panel a) and H-DFM as well as our regional factors (Panel b), applied to the cyclical inflation component. Overall, the global factor extracted from actual inflation appears to correlate with the global factor for cyclical inflation. The regional factors for cyclical inflation also appear to correlate with their counterparts based on actual inflation but substantially less so.

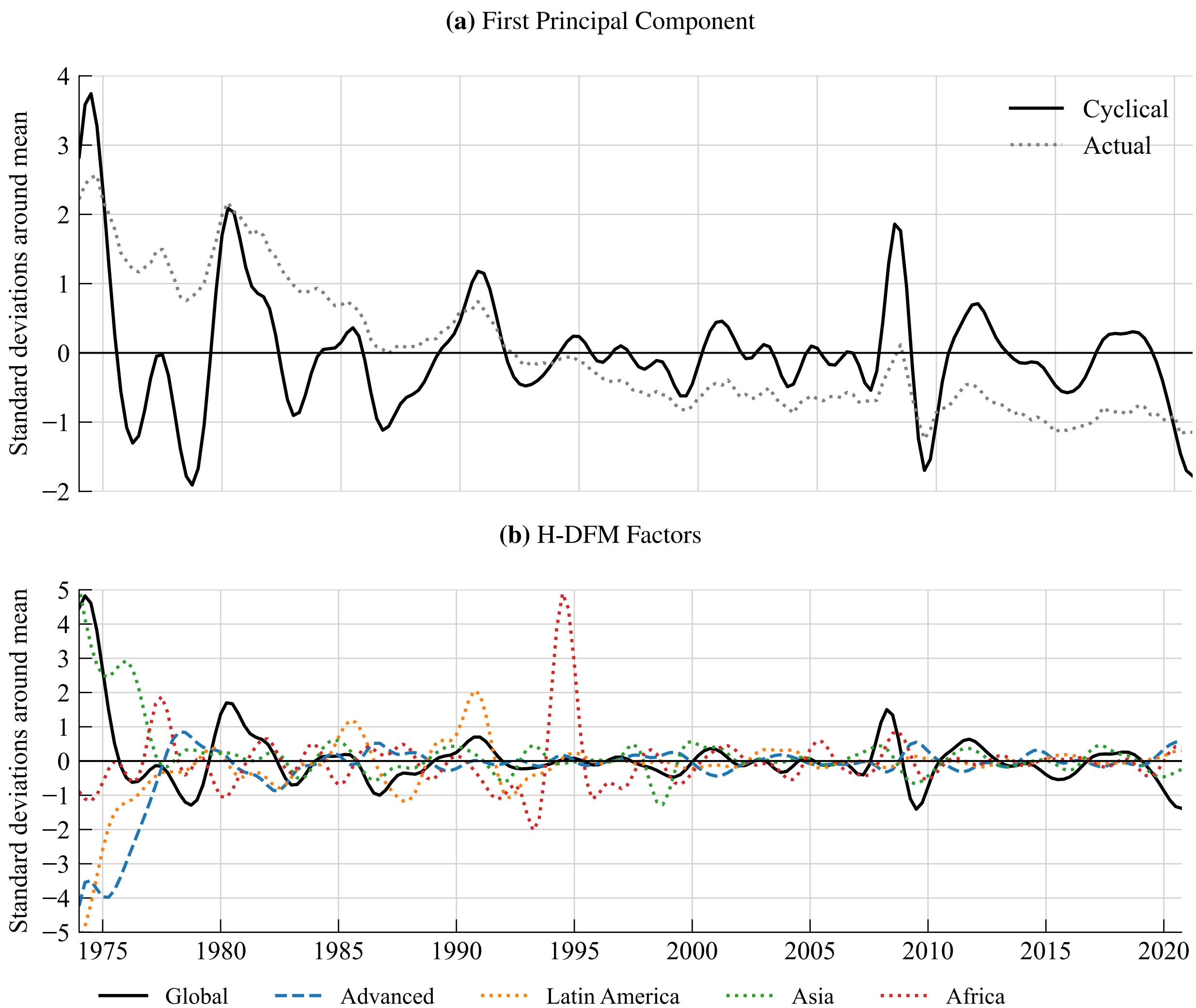
Figure 7 illustrates this finding by showing the scatterplots of the shares of actual inflation variance (horizontal axes) vis-à-vis the shares of cyclical inflation variance (vertical axes) for the regional factors (Panel a) and the global factor (Panel b). For the regional factors' shares, the correlation is positive but weak. For the global factor's shares, the slope of the relation is larger, but the fit is loose. We conclude that the reasons that inflation comoves across countries is due to comovement of trends as well as of cyclical components and that the trend and cyclical comovement each differ across country groups.

Examining the variance decomposition of the cyclical component country by country (Appendix Figure A.8), we confirm our finding that the global component explains a relatively large portion of inflation variance for advanced economies and a relatively small portion for EMDEs.

[13]Note that the factors and all parameters are estimated separately for each sample period. Hence, the variance decomposition obtained from the full sample does not necessarily fall between the corresponding estimates in subperiods.

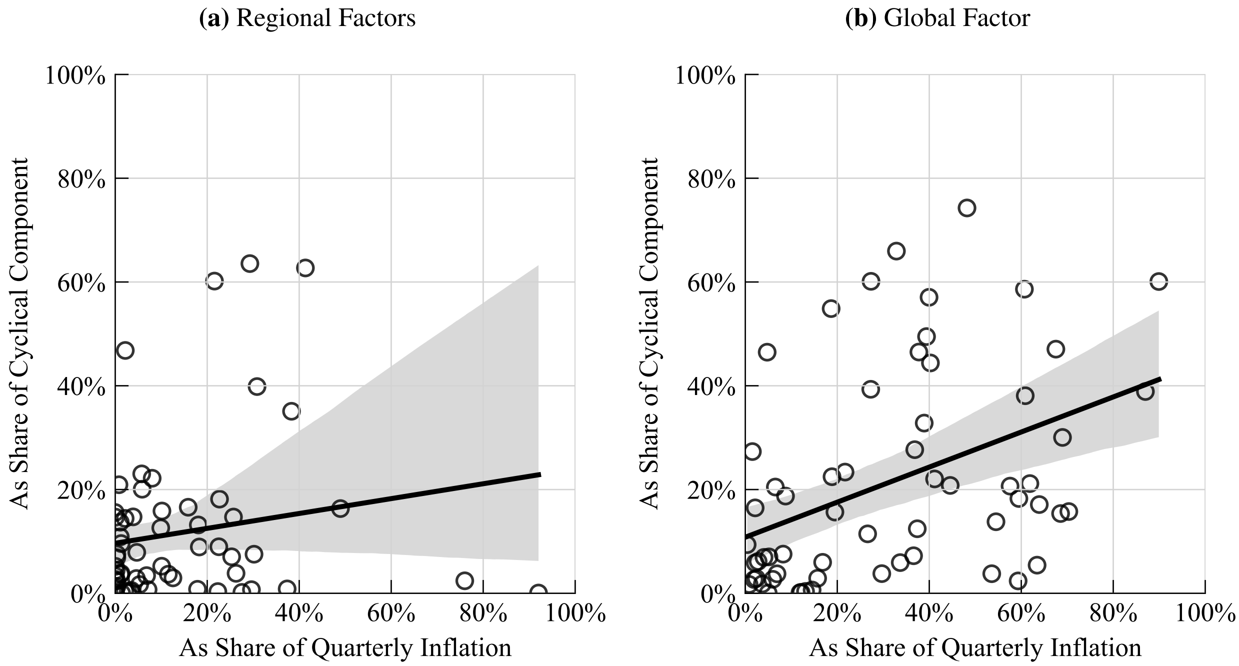
[14]We note that despite the apparent stability of the variance decomposition on average, there is significant heterogeneity across countries (see Appendix Figure A.7).

Figure 6: Global and Regional Factors of Cyclical Inflation



Note: Panel (a) shows the first principal component of cyclical inflation (black solid line) and of actual inflation (gray dashed line). Panel (b) shows the global and regional factors of cyclical inflation. The cyclical inflation component is extracted using the Baxter and King (1999) band-pass filter, which removes fluctuations at frequencies shorter than six quarters and longer than 32 quarters, truncating 12 quarters on each side.

Figure 7: Explained Variance of Actual versus Cyclical Inflation



Note: This figure depicts the shares of variance of actual inflation (horizontal axes) against that of cyclical inflation (vertical axes) explained by the regional factors (Panel a) and by the global factor (Panel b). Each circle represents a country. The solid lines show linear fit, and the shaded areas represent 95 percent confidence bands.

However, for the regional factors, the results are more nuanced. For instance, for advanced economies, the regional component plays a much larger role in the dynamics of cyclical inflation than in the dynamics of actual inflation (that is, cyclical plus trend). As for developing countries, Niger, Côte d'Ivoire, and Cameroon, for instance, the variance shares for cyclical inflation are about 60 percent, substantially larger than those for actual inflation. By contrast, the large actual inflation variance shares for India and Nepal appear to be due to trend comovement, not cyclical comovement.

4.4 Sensitivity Analysis

We conduct several sensitivity checks for our baseline H-DFM model. First, we examine the model in which all regional factors are combined in the same EMDE group while the advanced-economy group remains intact. We find that this model explains substantially less inflation variance than the baseline model, especially for the Asia and Africa groups (Appendix Figure A.9). This is because, as we show in the PCA analysis, the second principal component loads disproportionately on the Latin America group.

Second, international inflation data are subject to episodes of hyperinflation. Latin America is particularly prone to such episodes during the sample period, with quarterly rates reaching triple digits. While we would like to preserve the episodes of high inflation, as they may be important for regional factors, we do not want these outliers to drive our results numerically. To show that this is not the case, we winsorize quarterly log differences at 0.25 and -0.025. This means that quarterly inflation at an annual rate above 100 percent and below -10 percent is capped at these values. We winsorize 234 observations (1.8 percent of the total): 106 observations from above and 128 from below. Appendix Figure A.10 shows that the estimated factors are almost indistinguishable from the baseline. The only visible difference is in the Latin America factor's peak in the early 1990s, which dropped somewhat. However, the presence of outliers does not materially affect the estimates of the Latin America factor or other factors during normal times.

Third, we assess the stability of loadings due to the imposed hierarchical structure of the model. We do so by conducting the following exercise. For each region r, we estimate a DFM model with one global factor:

$$\pi_{i,t} = \delta_i f_t^{G_{\mathrm{r}(i)}} + \varepsilon_{i,t},$$

where $f_t^{G_{\mathrm{r}(i)}}$ is the global factor for the regional subsample corresponding to country i. Combined with Equation (3a), we obtain the following restriction:

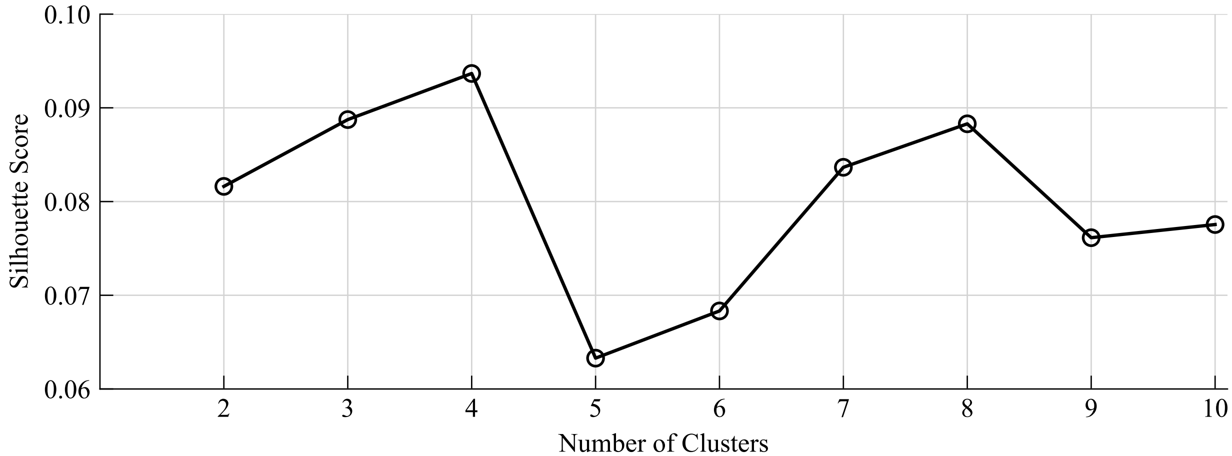
$$\delta_i f_t^{G_{\mathrm{r}(i)}} = \lambda_i f_t^{\mathrm{G}} + \mu_i f_t^{\mathrm{r}(i)}.$$

That is, the projections obtained from the DFM with one global factor estimated separately for each regional subsample should strongly comove with the projections from the baseline H-DFM. Indeed, we estimate high correlation between the two projections: The median correlation coefficient is 0.876, and for 47 of 61 countries, it is greater than 0.7 (Appendix Figure A.11). This evidence suggests that, on balance, the factor loadings are stable, and the restrictions imposed by H-DFM are consistent with a nonhierarchical DFM that encompasses it.

Next, we analyze the effect of controlling for energy prices. We conduct two exercises. In one, we use quarterly log differences in the West Texas Intermediate (WTI) spot oil price as an exogenous factor added to the baseline model. In the other, we consider a model with two global factors: The first global factor loads only on inflation, as in the baseline, while the second global factor also loads on oil-price changes. Overall, these oil factors have limited impact on the estimates of regional factors (Appendix Figure A.12). This is likely because inflation factors are quite persistent, whereas oil-price changes are significantly less so.

Finally, in our baseline specification, the autoregressive order of the global and regional factors is set at $p = q = 1$. Appendix Figure A.13 shows estimated factors that allow for more persistence by setting $p = q = 4$. While the resulting factors are predictably smoother, the autoregressive order overall has a relatively minor effect on the estimated factors' dynamics.

Figure 8: Silhouette Plot of the *K*-means Classifier



Note: This figure shows the silhouette score for clustering done with varying numbers of clusters. A higher silhouette score indicates a more successful clustering result.

5 Regional Inflation Clustering

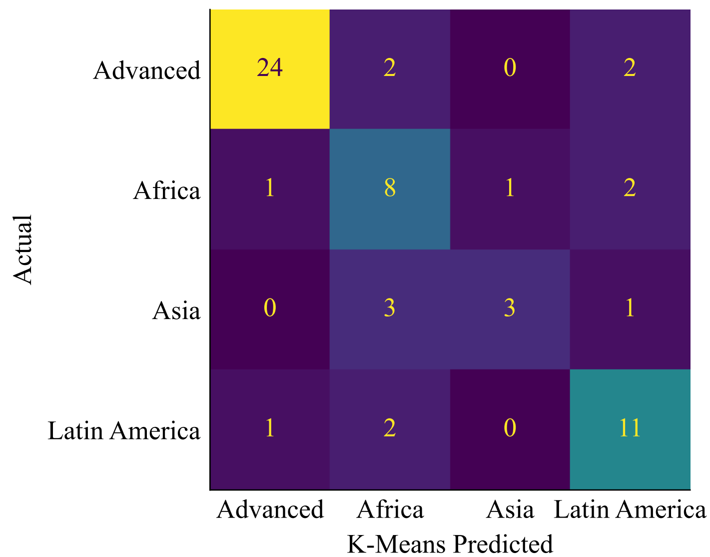
To provide further rationale for our grouping choices, we turn to K-means clustering. This unsupervised machine-learning algorithm organizes data into distinct groups based on the similarity of multiple characteristics. In our case, we cluster countries into a given number of groups based on the similarity of their quarterly inflation time-series over our full sample period. As we change the number of clusters we instruct the algorithm to use, we assess the algorithm's performance based on the silhouette score, described later. For the most successful result, we then compare the groups that the algorithm assigned with the groups we had previously defined: advanced economies, Africa, Asia, and Latin America.

Key to this analysis is that the K-means clustering algorithm is unsupervised. In other words, the clusters are chosen with no input from the researcher. The algorithm starts by choosing K cluster centers and assigning surrounding countries to the closest cluster based on the distance of inflation across all time periods.[15] The centers are then recalculated based on these initial clusters, and then surrounding countries are reassigned. This continues until the clusters are stable.

The success of each country's assignment is assessed based on both the average distance a_i to other countries within the same cluster and the average distance b_i to the nearest cluster to which it does not belong. Ideally, a country should be close, in terms of inflation similarity across time, to other countries in its cluster and far from countries outside its cluster. These two metrics are

[15] The initial cluster seeding is based on a greedy variant of the "k-means++" algorithm (Arthur and Vassilvitskii 2007). The results are qualitatively similar to the ones obtained using random initialization with 10,000 repetitions.

Figure 9: Confusion Matrix of the *K*-means Classifier



Note: The confusion matrix shows the number of countries that are classified according to the label along the horizontal axis while being in the region labeled along the vertical axis. The diagonal elements correspond to the countries that are correctly classified, while off-diagonal elements indicate misclassification.

combined into a silhouette score:

$$\text{Silhouette Score}_i = \frac{b_i - a_i}{\max\left(a_i,\, b_i\right)}.$$

A higher silhouette score indicates a more successful assignment. We then average silhouette scores across countries for an overall silhouette score. Figure 8 shows the silhouette score obtained for various numbers of clusters. According to this metric, the most successful clustering algorithm uses four clusters, the same number of regional groups we selected in Section 4.1.

Naturally, the next question is how well these algorithmically assigned optimal clusters align with our regional groups. To assess the overall performance, we compute the accuracy score, defined as the proportion of countries classified correctly (that is, the sum of true positives and true negatives over the total), where we assign each cluster to a regional group based on the majority of countries in that cluster. The accuracy score is 75.4 percent, which indicates that, while misclassifications are common, the algorithm is moderately successful overall.

To help assess the clustering performance with respect to each region, Figure 9 depicts the confusion matrix. The diagonal elements show the number of countries classified correctly for each group, while the off-diagonal elements break down the misclassified cases. The algorithm is quite successful for the advanced economies, with 24 of 28 countries in this group classified correctly, and for Latin America, with 11 of 14 correct classifications.[16] Relatively more confusion

[16] Appendix Figure A.14 shows normalized confusion matrices, while Table A.4 itemizes all the misclassified cases.

Table 3: Precision and Recall Rates of K-means Clusters (in Percentages)

	Advanced Economy (1)	Africa (2)	Asia (3)	Latin America (4)
Precision	92.3	53.3	75.0	68.8
Recall	85.7	66.7	42.9	78.6
F_1-score	88.9	59.3	54.5	73.3

Note: This table reports the precision and recall rates of the clusters chosen by the K-means algorithm using four clusters. Precision is defined as the ratio of true positives to selected elements (that is, the sum of true positives and false positives). Recall is defined as the ratio of true positives to relevant elements (that is, the sum of true positives and false negatives). The F_1-score is the harmonic mean of precision and recall.

occurs between the Africa and Asia groups.

To formalize the performance metrics, we compute the precision and recall of each cluster, where precision is the ratio of true positives to selected elements (that is, the sum of true positives and false positives), and recall is the ratio of true positives to relevant elements (that is, the sum of true positives and false negatives). In other words, precision indicates the proportion of countries assigned to a cluster that should actually belong to that cluster, whereas recall indicates the proportion of countries in a region that are assigned correctly to their cluster.[17]

Table 3 shows precision and recall for each cluster. Precision ranges from 68.8 to 92.3 percent, while recall ranges from 42.9 to 85.7 percent.[18] The Africa group has higher recall than precision, while the Asia group has a relatively high precision and lower recall.[19] Thus, the four regional factors not only capture a large proportion of the variance in the data, as demonstrated in Section 4.1, but also map relatively closely to the clusters that would be chosen by an unsupervised machine-learning algorithm such as K-means.

6 Understanding Regional Inflation

To better understand the economic meaning of the global and regional factors, we correlate them to macroeconomic variables: commodity prices, interest rates, and exchange rates. We start by describing the analysis with commodity prices before turning to interest rates and exchange rates.

To assess a degree of misclassification, Appendix Table A.5 shows the relative distances to all clusters. In many misclassified cases, the distances to the true clusters (that is, geographic regions) appear to be similar to the distances to the countries' own cluster centers, suggesting that misclassification is marginal.

[17] The Type II error rate is one minus recall. The Type I error rate relates to precision but is calculated as the ratio between false positives and true negatives.

[18] The table also reports the F_1-score, which is the harmonic mean of precision and recall and shows the balance between the two. The F_1-score is a special case of F_β-score that attributes equal importance to precision and recall.

[19] We note that the interpretation of these performance metrics is sensitive to the relative sizes of each group in the case of imbalanced clusters. Appendix Figure A.15 shows the precision–recall curves for each group and compares them to the case of random classifiers that account for group imbalances. Appendix Figure A.16 examines the area under the receiver operating characteristic (ROC) curve. In all cases, the K-means classifier performs noticeably better than the random classifier.

6.1 Commodity Prices

Theoretically, an increase in prices of imported commodities leads to inflation via its direct impact on the consumption basket, while an increase in prices of exported commodities results in exchange rate appreciation and, therefore, deflation (e.g., Chen and Rogoff 2003, Stein 2025). To test these hypotheses vis-à-vis regional inflation factors, we construct import and export commodity price indexes for each region. We use the prices of 37 commodities at a monthly frequency starting in January 1992, obtained from the IMF Primary Commodity Prices data set. We map these commodities to the relevant Harmonized System (HS) industry codes and calculate the annual imports and exports of these commodities for each region at the region-HS-year level using data from the United Nations Commodity Trade Statistics Database (UN Comtrade). We then calculate the export and import shares of commodity h for region r in year y:

$$\text{Export Share}_{r,h,y} = \frac{\max\left\{0,\ NX_{r,h,y}\right\}}{\sum_h \max\left\{0,\ NX_{r,h,y}\right\}}, \tag{4a}$$

$$\text{Import Share}_{r,h,y} = \frac{\max\left\{0,\ -NX_{r,h,y}\right\}}{\sum_h \max\left\{0,\ -NX_{r,h,y}\right\}}, \tag{4b}$$

where NX denotes net exports. Note that these formulae set export (import) shares to zero if a region imports (exports) a given commodity more than it exports (imports) it. Assuming equal shares for every quarter in a given year, we calculate commodity export and import price indexes for each region r in quarter q as follows:

$$\text{Commodity Export Price Index}_{r,q} = \sum_h \left(\text{Export Share}_{r,h,q} \times p_{h,q}\right), \tag{5a}$$

$$\text{Commodity Import Price Index}_{r,q} = \sum_h \left(\text{Import Share}_{r,h,q} \times p_{h,q}\right), \tag{5b}$$

where p denotes the log commodity price. Quarterly prices are calculated as the mean of the three monthly prices in a quarter. These indexes embed regional differences in trade exposure to different commodities over time. For example, in all years except one, Africa, as a region, imports rice. Latin America exports copper, and it also tends to export beef and soybeans. Advanced economies, on balance, import crude oil, whereas Latin America exports it.

Table 4 shows how each of the regional factors relates to its respective commodity import and export price indexes. As theory holds, we estimate a positive and significant coefficient on the commodity import price index and a negative and significant coefficient on the export price index for Asia and Africa. For advanced economies, both coefficients are positive, but only the commodity import price index is statistically significant. The lack of negative correlation with the commodity export price index is likely caused by advanced economies' consumption of goods that they export.

Table 4: Correlation of Regional Inflation Factors with Commodity Prices

	Advanced (1)	Latin America (2)	Asia (3)	Africa (4)
Regional Import Commodity Price Index	0.604***	−0.041	0.573***	1.037**
	(0.178)	(0.136)	(0.180)	(0.460)
Regional Export Commodity Price Index	0.008	−0.445***	−0.351**	−0.725*
	(0.124)	(0.105)	(0.141)	(0.379)
R^2	0.343	0.649	0.054	0.255
N	128	128	128	128

Note: This table shows the estimates of a regression of each regional factor on that region's commodity import price index and commodity export price index, as defined in the text. Newey–West standard errors are in parentheses and are calculated using four lags, selected using the Andrews rule (see Stock and Watson 2015).

For example, wheat is not only a commodity with the highest export share for advanced economies but also an important component of their consumption. Thus, when the price of wheat rises, the cost of the consumption basket increases. In fact, the advanced-economy factor is positively and significantly correlated with the prices of all commodities considered, except for animal hides and lamb (see Appendix Figure A.17). Additionally, because advanced economies tend to have their imports denominated in their own currency (see Boz et al. 2022, Gopinath, Itskhoki, and Rigobon 2010), the mechanism through which an increase in prices of exported commodities prompts deflation is impeded. Conversely, the Latin America factor is statistically negatively correlated with its commodity export price index, and the regression R^2 is large. However, it is not statistically correlated with its commodity import price index.

6.2 Interest Rates and Exchange Rates

Next, we analyze how the regional factors comove with interest rates and exchange rates. Following the literature (e.g., Auer, Pedemonte, and Schoenle 2024), we examine the correlation of the global factor with the federal funds rate and the US nominal effective exchange rate (NEER).[20] Additionally, for each region, we choose a "representative" interest rate and exchange rate based on two considerations: first, the country with the most variation explained by that regional factor and, second, data availability. For exchange rates, we choose a candidate currency that is currently floating. For advanced economies, we use the NEER in Germany as well as the Euro Overnight Index Average (EONIA). For Latin America, we use the Bank of Mexico's Average Cost of Funds

[20] Specifically, we use the *narrow* nominal effective exchange rate index from the Bank for International Settlements (BIS). We favor this measure over the broad effective exchange rate indexes because it is available for a longer period: The narrow exchange rate indexes start in 1964, while the broad ones start in 1994. The broad indexes, however, include a larger number of countries. The bilateral exchange rates, used in the cases where NEER data are not available, are also obtained from the BIS.

Table 5: Correlation of Inflation Factors with Interest Rates and Exchange Rates

	Global (1)	Global (2)	Advanced (3)	Latin America (4)	Asia (5)	Africa (6)
Panel A: Interest Rates						
Federal Funds Rate	0.192***	0.160***	−0.152***	−0.079***	0.014	−0.020
	(0.017)	(0.022)	(0.055)	(0.026)	(0.023)	(0.019)
EONIA		0.049	0.108*			
		(0.032)	(0.057)			
Mexico CPP Rate				0.016**		
				(0.007)		
India Bank Rate					0.026	
					(0.043)	
South Africa Discount Rate						−0.046***
						(0.017)
Capital Account Openness			0.356	−3.261**	−0.005	7.767**
			(1.263)	(1.254)	(1.328)	(3.159)
R^2	0.561	0.570	0.180	0.584	0.009	0.176
N	215	215	215	194	215	215
Panel B: Exchange Rates						
USA NEER	0.032***	−0.015	−0.048***	−0.037***	−0.014**	−0.008
	(0.006)	(0.011)	(0.015)	(0.011)	(0.006)	(0.007)
Germany NEER		−0.102***	−0.175***			
		(0.025)	(0.028)			
Mexico NEER				−0.015***		
				(0.004)		
Indian Rupee vs USD					1.204	
					(2.270)	
South African Rand vs USD						0.002
						(0.160)
Capital Account Openness			4.824***	−3.877***	−0.072	6.237**
			(0.821)	(0.628)	(0.795)	(3.054)
R^2	0.131	0.387	0.482	0.593	0.019	0.127
N	215	215	215	215	215	215

Note: This table shows the estimates of regressions of the global and regional factors on select interest rates and exchange rates. Nominal effective exchange rates (NEERs) correspond to the narrow NEER indexes from the BIS. Bilateral exchange rates are also from the BIS. All exchange rates are defined so that an upward move indicates an appreciation. Interest rates are obtained from the OECD's "immediate interest rates, call money, interbank rate" series. The capital account openness measure is the standardized measure from Chinn and Ito (2006), averaged across all countries in a given region for which data are available from 1970 onward. Newey–West standard errors are in parentheses and are calculated using four lags, selected using the Andrews rule (see Stock and Watson 2015).

(Costo Porcentual Promedio, or CPP) rate, an overnight rate calculated as commercial banks' average cost of term deposits, and the Mexican NEER. For Asia, we use the Reserve Bank of India's bank rate, also known as the policy repo rate, and the bilateral Indian rupee exchange rate against the US dollar. For Africa, we use the South African Reserve Bank's discount rate and the South African exchange rate against the US dollar.[21] We define all exchange rates so that an upward move indicates an appreciation. Interest rates are measured by the "immediate interest rates, call money, interbank rate" series from the OECD. For regressions of the regional factors, we also include capital account openness of each region, defined as the standardized Chinn and Ito (2006) measure averaged across all countries in a given region for which data are available since 1970.[22] Independent monetary policy requires a floating exchange rate or capital controls, a set of choices referred to as the monetary trilemma.

Theoretically, the correlation of interest rates with regional inflation factors could be positive, due to central bank responsiveness to inflation, or negative due to inflation responsiveness to the central bank's policy actions. Separately, an exchange rate appreciation should lead to deflation in open economies, as imported goods become less expensive; however, exchange rates also appreciate with surprise increases in interest rates.

Results for interest rates are shown in Panel A of Table 5. As in Auer, Pedemonte, and Schoenle (2024), the global factor is positively correlated with both the federal funds rate and the exchange rate. Moreover, we find that the advanced-economy and Latin America factors are also positively correlated with their regional interest rate. It is likely that high inflation in these regions prompts the central banks to raise policy rates faster than inflation responds to these policy changes. On the other hand, the Africa factor is negatively correlated with the regional interest rate, and there is no correlation for Asia.

Panel B of Table 5 shows the correlations for exchange rates. As in Auer, Pedemonte, and Schoenle (2024), the global factor is positively correlated with the US exchange rate. However, when we also control for the German exchange rate, the coefficients on both the US and German exchange rates become negative. Similarly, the advanced-economy and Latin America factors are negatively correlated with their relevant exchange rates. The Asia and Africa factors are uncorrelated with their regional exchange rates but are negatively correlated with the US exchange rate. We note that many African countries in our sample have adopted a currency peg against the euro—or, before the euro's creation, the French franc.

[21] Note that while the Asia factor explains 92.0 percent of inflation variation in India—the most across the Asian countries in our sample—neither Mexico nor South Africa is the "regional leader" according to this metric. The Latin America factor still explains a sizable share of variation in Mexico's inflation (22.5 percent). However, the Africa factor explains only 1.4 percent of South Africa's inflation. Unfortunately, we could not pick another representative country for Africa due to extremely limited data on that region's interest rates.

[22] Since the Chinn and Ito (2006) measure ends in 2021, we extrapolate it for 2022 and 2023.

7 Predictive Power of Inflation Components

7.1 Common and Idiosyncratic Inflation Persistence

The literature argues that the global inflation factor is persistent and can capture the nonstationarity of the inflation process, whereas idiosyncratic, country-specific inflation is mean-reverting (Ciccarelli and Mojon 2010). Here, we examine the persistence of regional inflation factors and reassess the evidence on global and country-specific inflation using the model that includes regional factors.

This analysis enhances our understanding of inflation persistence, especially in developing countries. If the regional factor is persistent, developing countries' central banks need to pay closer attention to the inflation dynamics in their neighboring countries, as inflationary shocks originating there could spill over into the domestic economy. However, if the regional factor is highly volatile, the estimates of idiosyncratic inflation persistence obtained from the models that do not account for the regional factor may be biased downward. This could give rise to the illusion that country-specific shocks tend to be transitory.

To estimate the persistence of inflation components, we follow a standard procedure used in the literature but incorporate the regional factor. We estimate an autoregressive process of the residuals obtained from the DFM specification in Equation (3a):

$$\hat{\varepsilon}_{i,t} = \pi_{i,t} - \hat{\lambda}_i \hat{f}_t^{\mathrm{G}} - \hat{\mu}_i \hat{f}_t^{\mathrm{r}(i)} \tag{6a}$$

$$\hat{\varepsilon}_{i,t} = \rho_i(L)\hat{\varepsilon}_{i,t} + \eta_{i,t}, \tag{6b}$$

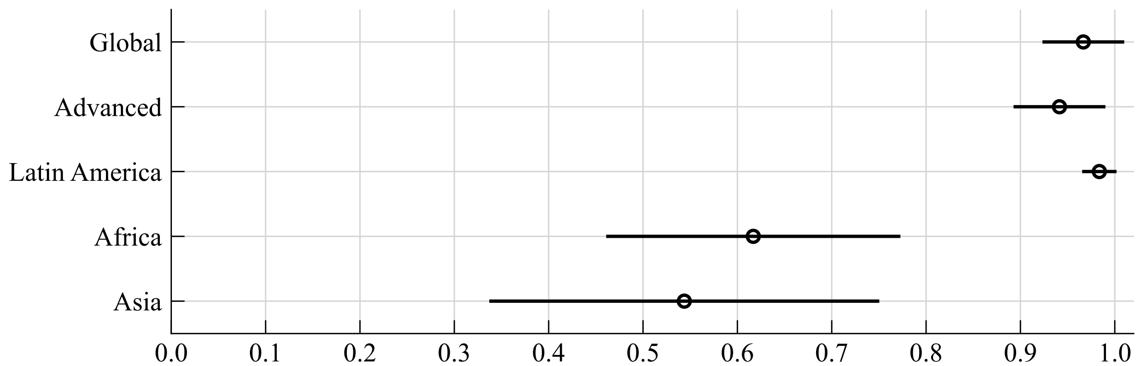
where ρ_i is a lag polynomial of order k. Similarly, we estimate the autoregressive processes for the global factor, $\hat{f}_t^{\mathrm{G}}$, and each regional factor, $\hat{f}_t^{r}$. To be consistent across the specifications, we set the number of lags as $k = 4$ and measure persistence with the sum of autoregressive coefficients (SARC); see Fuhrer (2010).[23]

Figure 10 shows our estimates of inflation persistence for the global and regional factors (black circles) along with two-standard-error bands. These estimates confirm that the global factor is highly persistent, with a SARC of 0.967. Similarly to Ciccarelli and Mojon (2010), we cannot reject the unit root in the global inflation process. The persistence of the global factor did not change, on balance, during the 2010s and early 2020s, a period not covered by the earlier study. The advanced-economy factor is almost as persistent, with a SARC of 0.941. This is hardly surprising since the advanced-economy factor is broadly comparable to the global factor.

The regional factors, however, exhibit significant heterogeneity in persistence. The Latin

[23]The Akaike, Bayesian, and other information criteria tend to select fewer lags, but allowing for four lags is prudent when working with quarterly data. Appendix Figure A.18 shows that the autoregressive coefficients estimated using AR(1) processes are generally similar, though the Asia factor is somewhat less persistent.

Figure 10: Persistence of Inflation Factors



Note: This figure shows global and regional factors' persistence, measured by the sum of autoregressive coefficients (SARC) estimated using an AR(4) specification, together with two-standard-error bands.

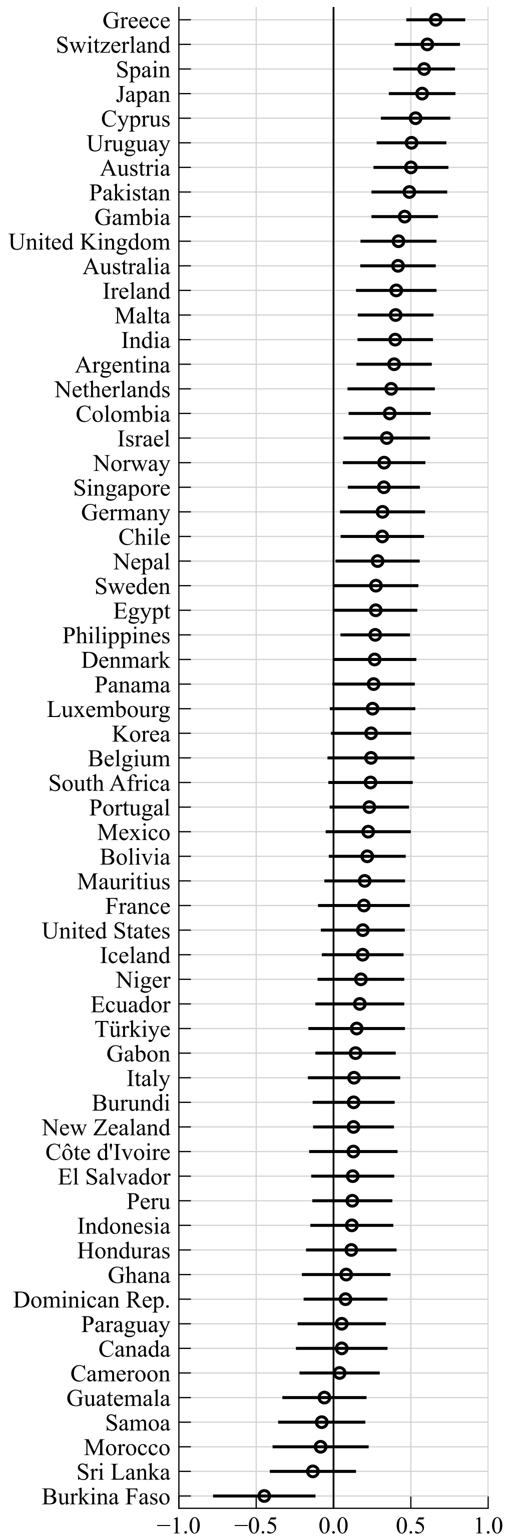
America factor appears to be as persistent as the global and advanced-economy factors (SARC = 0.984). Yet, the Africa and Asia factors are much less so (0.617 and 0.544, respectively). While the confidence bands of these two factors are rather wide, we can still reject the null hypotheses of zero (completely idiosyncratic regional inflation) or one (nonstationary regional inflation). These results imply that while the central banks in African and Asian countries would still benefit from monitoring regional developments, these benefits may be substantially smaller than those for their Latin American counterparts.

Next, we turn to the idiosyncratic component. Figure 11 shows the SARC of country-specific inflation. The idiosyncratic inflation persistence varies from 0.661 in Greece to essentially zero, with one outlier (Burkina Faso) having statistically negative persistence. These estimates imply that more than 80 percent of idiosyncratic inflationary shocks are resolved within a year and more than 95 percent within two years. Hence, the inflation persistence found in country-level data is largely due to the global and regional common components, as opposed to the country-specific sources. We note, however, that for countries large enough to materially affect the economic conditions in the region (or globally), the persistence of the idiosyncratic component may be less indicative of the role that country-specific conditions play in that country's inflation dynamics. For example, inflationary shocks that originate in the United States may affect global inflation and therefore not fully appear in the idiosyncratic component.

7.2 Implications for Forecasting

Accounting for the global and regional factors could improve inflation forecasting. For example, Ciccarelli and Mojon (2010) show that including the global inflation factor in a variety of forecasting models reduces the inflation forecast error for a sample of OECD economies. Similarly, we examine whether regional inflation factors can be useful for forecasting, and using a more diverse

Figure 11: Persistence of Country-specific Components



Note: This figure shows the persistence of country-specific inflation, measured by the sum of autoregressive coefficients estimated using an AR(4) specification, together with two-standard-error bands.

Table 6: Median RMSE Relative to Benchmark (2010:Q1–2023:Q4)

	One Quarter Ahead		Four Quarters Ahead		Eight Quarters Ahead	
	Global	Both	Global	Both	Global	Both
	(1)	(2)	(3)	(4)	(5)	(6)
Advanced Economies	0.960	0.964	1.019	1.009	1.033	1.032
Africa	0.963	0.946	0.973	0.997	1.004	0.986
Asia	0.977	0.976	0.985	0.975	1.007	0.990
Latin America	1.034	0.986	0.971	0.996	0.949	0.938

Note: This table shows the RMSE from the forecasting models that include the global factor (odd-numbered columns) and both the global and regional factors (even-numbered columns) relative to the RMSEs obtained from the univariate autoregressive forecasting models.

sample of countries, we revisit the evidence concerning the global factor.

Following the literature, we use an AR(p) model as a benchmark against which we compare alternative specifications. In this model, an h-step-ahead forecast can be obtained as follows:

$$\pi_{i,t+h} = c_i^h + \rho_i^h(L)\pi_{i,t} + \varepsilon_{i,t+h}^h, \tag{7}$$

where $\rho_i^h(L)$ is a lag polynomial of order p.

This model can be augmented with the lags of estimated global and regional factors as follows:

$$\pi_{i,t+h} = c_i^h + \rho_i^h(L)\pi_{i,t} + \varphi_i^h(L)\hat{f}_t^{\mathrm{G}} + \psi_i^h(L)\hat{f}_t^{\mathrm{r}(i)} + \varepsilon_{i,t+h}^h, \tag{8}$$

where $\hat{f}_t^{\mathrm{G}}$ is the estimated global inflation factor, $\hat{f}_t^{\mathrm{r}(i)}$ is the estimated regional inflation factor that corresponds to the region of country i, and $\varphi_i^h(L)$, $\psi_i^h(L)$ are lag polynomials of orders q and s, respectively.

To evaluate the relative contribution of the factors to the reduction in forecast error, we estimate three specifications: (1) the benchmark univariate AR(p) process described in Equation (7), (2) the benchmark augmented with the global factor, and (3) the full model that includes the autoregressive part, the global factor, and the regional factor; see Equation (8). We set the orders of lag polynomials to $p = q = s = 4$.[24] To evaluate the models, we compute root mean squared errors (RMSEs) of the pseudo out-of-sample forecasts with respect to inflation series, taking estimated inflation factors as given. Our forecast period is from 2010:Q1 through 2023:Q4. That is, for each quarter of this period, we reestimate our forecasting model for the sample ending in that quarter and make forecasts for the following quarter, four quarters, and eight quarters.

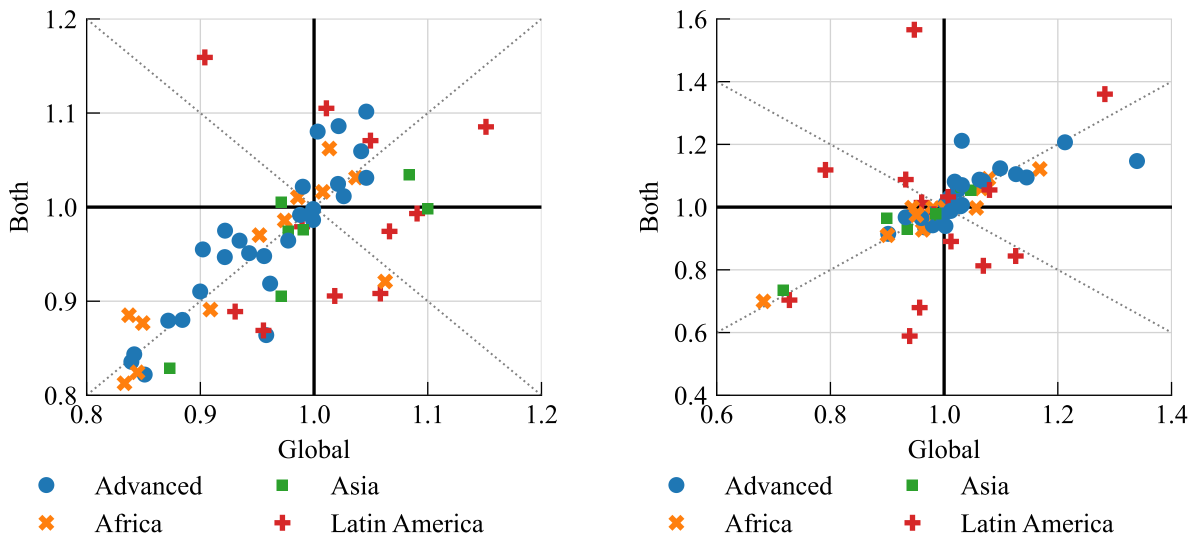
Table 6 shows the median RMSE across countries in the group relative to the benchmark AR(4) model.[25] We report the relative RMSE of inflation forecasts one quarter ahead (Columns 1 and 2),

[24] See Footnote 23.

[25] For each country, we compute the relative RMSE as the ratio of the augmented model's RMSE to the benchmark

Figure 12: RMSE Variation across Countries and Regions

(a) One-quarter-ahead Forecasts **(b)** Four-quarter-ahead Forecasts



Note: This figure shows RMSEs relative to the benchmark univariate autoregression. Numbers less than one indicate performance improvement. The relative RMSEs of the benchmark model augmented with the global factor are shown on the horizontal axis, while those of the model with both the global and regional factors are on the vertical axis. Panel (a) removes five outliers for visibility: They represent RMSEs for Austria, Bolivia, Chile, Guatemala, and Israel. The dotted gray lines are 45 degree lines.

four quarters ahead (Columns 3 and 4), and eight quarters ahead (Columns 5 and 6). The global factor improves next-quarter forecasts by 3.7 percent in Africa, 2.3 percent in Asia, and 4.0 percent in advanced economies. Taken together, the global and regional factors improve inflation forecasts in all groups relative to the benchmark. At longer horizons, we find some variation in the relative performances of the global factor. However, when used together, the global and regional factors reduce RMSEs of the benchmark model in all developing regions.

We note that there is considerable heterogeneity in the RMSEs across countries. Figure 12 shows the scatterplots of the relative RMSEs of the model with the global factor (horizontal axis) and the model with the regional factor as well as global factor (vertical axis).[26] If the global factor improves the RMSE relative to the benchmark model but the regional factor, added on top of the global factor, does not, we would see the points clustered along the 45 degree line in the lower left quadrant. However, if the regional factor improves the RMSE further, we would see a cluster of points in the octant formed by that 45 degree line and the right (vertical) border of the lower left

model's RMSE. We then report the median of these ratios across the countries in each group. Numbers less than one indicate that inflation factors improve the performance of the benchmark model.

[26]In the appendix, we tabulate the RMSEs shown in this chart by country and model (see Table A.6). We also show the time-series of the inflation forecasts from the model with both global and regional factors for select advanced and developing economies (Figures A.19 and A.20, respectively).

Table 7: Diebold–Mariano Tests: Percent of Countries with $p < 0.1$

	One Quarter Ahead			Four Quarters Ahead		
	Global vs Benchmark (1)	Both vs Benchmark (2)	Both vs Global (3)	Global vs Benchmark (4)	Both vs Benchmark (5)	Both vs Global (6)
All Countries	31.1	32.8	24.6	19.7	19.7	18.0
Advanced Economies	42.9	32.1	14.3	10.7	7.1	10.7
Africa	41.7	41.7	8.3	16.7	16.7	16.7
Asia	14.3	28.6	42.9	42.9	42.9	14.3
Latin America	7.1	28.6	50.0	28.6	35.7	35.7

Note: This table aggregates the results of the one-sided Diebold–Mariano pairwise tests for each country. For the "A vs B" column, the null hypothesis is that Model B performs at least as well as Model A. The table entries report the fraction of countries for which the p-value of the test is less than 0.1, meaning that Model A statistically outperforms Model B.

quadrant.

Panel (a) of Figure 12 focuses on one-quarter-ahead forecasts. It shows that for the advanced economies where the global factor improves inflation forecasts, the points are indeed clustered along the 45 degree line. Hence, the advanced-economy factor does not add much information to the global factor. This result is intuitive because the global factor is most influenced by large advanced economies such as the United States. Yet, for a handful of Latin American economies and a few African and Asian economies, the regional factor does improve the RMSE even when the global factor is accounted for, and in some cases, incorporating the global factor does not make the forecast more accurate than the benchmark forecast.

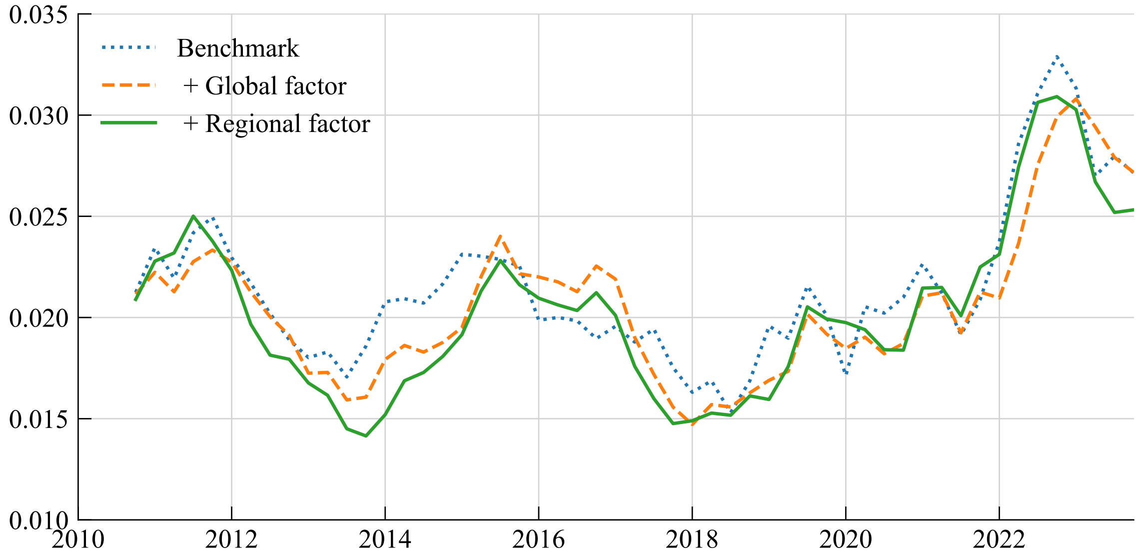
The result that the global and regional factors can improve inflation forecasts weakens at longer horizons. Panel (b) of Figure 12 shows that for four-quarter forecasts, fewer points lie in the lower left quadrant, and there is also a visible cluster around the (1, 1) point. This cluster indicates that the three models perform equally well or equally poorly. It confirms the known result that inflation is difficult to forecast even over a relatively short horizon.

To distinguish between the models' forecasting performances statistically, we employ the Diebold and Mariano (1995) test conducted separately for each country. Table 7 shows the fraction of countries for which adding the global and regional factors results in a statistically significant improvement in the forecast's accuracy.[27] The first three columns report the tests for one-quarter-ahead forecasts; the last three columns report for four-quarter-ahead forecasts. For the former, the global inflation factor model significantly outperforms the benchmark in about one-third of the sample (Column 1), whereas the model that adds the regional factor outperforms the model with the global factor in about one-quarter of the sample (Column 3). The global factor is relatively more important for inflation forecasts in advanced economies and in Africa, whereas the regional

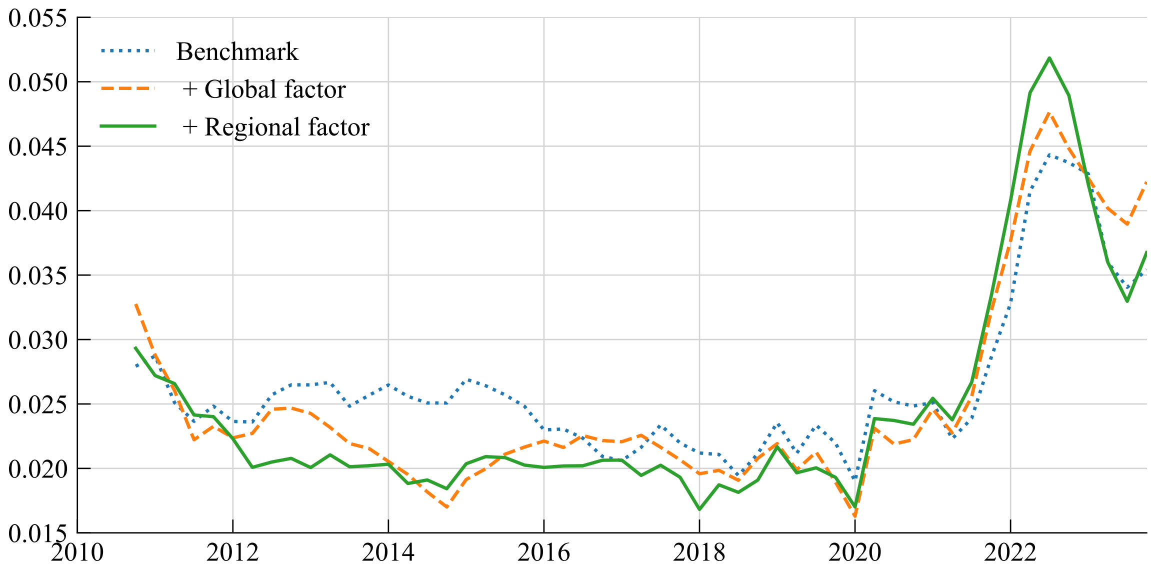
[27] Appendix Table A.7 reports the test results separately for each country.

Figure 13: Median Absolute Forecast Error

(a) One-quarter-ahead Forecasts



(b) Four-quarter-ahead Forecasts



Note: This figure shows the median (across countries) absolute forecast error. The benchmark forecasting model (dotted blue line) is the AR(4) process for the quarterly inflation rates. The orange dashed line shows forecast errors of the benchmark model augmented with the global factor. The green solid line shows forecast errors for the benchmark model augmented with both the global and regional factors.

factor is relatively more important in Asia and Latin America.[28] For the longer horizon (Columns 4 through 6), the shares of significant differences decline somewhat. One notable difference is an increase in the proportions of countries in Asia and Latin America where the global factor matters: from 14.3 to 42.9 percent in Asia and from 7.1 to 28.6 percent in Latin America. This could be explained by the time it takes inflation to spill over from advanced economies into developing economies in these regions. Notably, in Latin America, the "regional" model still statistically outperforms the "global-only" model in more than one-third of the countries. Yet, in Asia, this fraction drops to less than 15 percent (that is, just one of the seven countries in this group).

Figure 13 illustrates variation in the models' forecasting performance across time by showing the median absolute forecast error over the forecasting horizon.[29] The model with both the global and regional factors, on balance, outperforms the alternative during the pre-pandemic period. As inflation surged globally during the COVID-19 episode, the "global-only" model appears to perform best at one-quarter horizons, whereas at four quarters, neither enhanced model outperforms the benchmark. However, as inflation declines, the "regional" model appears to perform well, which could be due to the differences in disinflationary policies across countries and regions.

8 Conclusion

In this paper, we show that regional factors play an important role in international inflation comovement. We estimate that the global inflation factor explains a sizable share of inflation variation in advanced economies but a small share in emerging-market and developing countries. By contrast, a model enhanced by regional factors performs well with both groups. We validate these results by showing that an agnostic classifier based on an unsupervised machine-learning technique identifies inflation clusters that closely resemble geographical clusters. These regional factors relate, in general, to the commodity exports and imports of respective regional groups. The advanced-economy and Latin America factors are also correlated to regional interest rates and exchange rates.

Our estimates of explained variance are stable over time on average (that is, across all countries in the sample). However, the role of the global factor in developing countries has increased, while that of the regional factors has decreased somewhat, indicating the likely convergence, or synchronization, of inflation between the two groups.

Despite recent progress in understanding global inflation comovement, important challenges remain. One such challenge is the lack of data for larger samples of countries with long time-series and for a variety of inflation measures. With more countries in the sample, researchers could

[28]Note that the cases in which the benchmark model statistically outperforms the enhanced models are rare. Thus, the null hypothesis corresponds mainly to the case in which the two models' forecasts are statistically indistinguishable.

[29]We focus on the median absolute error because the distribution of inflation across countries is subject to outliers.

consider narrower regions, and having more countries per region could improve the measurement of estimated regional factors. Another important challenge involves gaining a better understanding of what drives these regional factors. Are they salient, for example, due to lower trade costs, policy synchronization, cultural similarities, or historical linkages between the countries in a region? We hope that future research addresses these challenges.

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Appendix

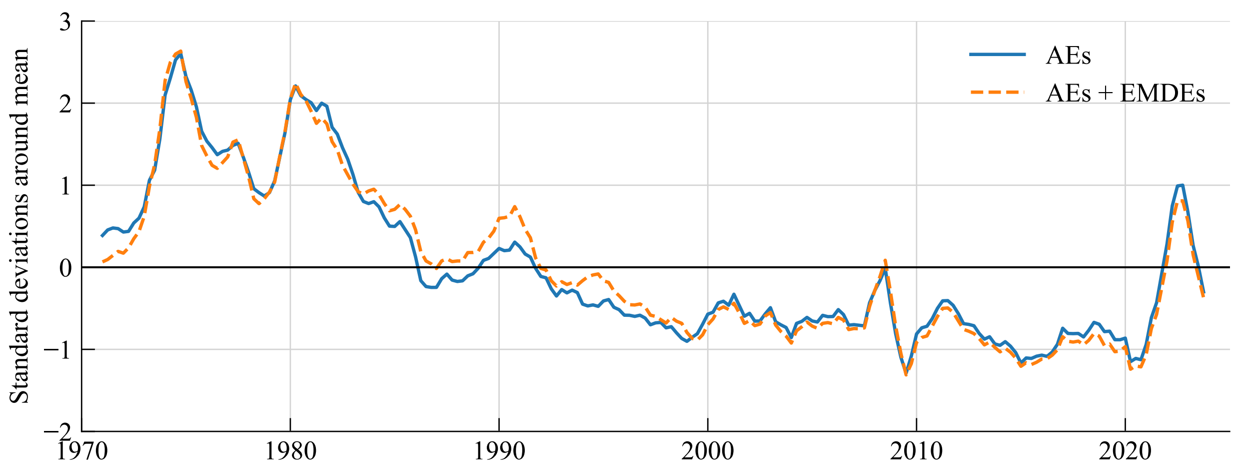
A Additional Results

Table A.1: Inflation by Country: Descriptive Statistics

	Count	Mean	SD	Min	25%	50%	75%	Max
Argentina	212	56.1	82.2	−124.2	8.4	30.4	81.6	495.1
Australia	212	4.9	3.7	−0.4	2.0	3.4	7.5	16.3
Austria	212	3.3	2.2	0.0	1.7	2.6	4.1	10.1
Burundi	212	9.9	8.1	−7.5	4.7	8.1	14.0	35.8
Belgium	212	3.6	2.9	−1.2	1.5	2.6	5.1	14.8
Burkina Faso	212	4.1	6.9	−16.4	−0.3	2.4	6.7	35.8
Bolivia	212	28.7	76.3	−0.1	3.4	6.4	15.0	530.7
Canada	212	3.9	3.0	−0.9	1.6	2.7	5.1	12.0
Switzerland	212	2.2	2.5	−1.4	0.5	1.3	3.4	10.2
Chile	212	22.5	40.1	−3.1	3.3	8.0	20.6	208.5
Côte d'Ivoire	212	5.2	6.0	−3.0	1.4	3.5	7.4	30.0
Cameroon	212	5.5	6.0	−5.5	1.7	3.4	8.8	38.6
Colombia	212	13.3	8.4	1.5	5.1	13.1	21.2	33.0
Cyprus	212	3.8	3.4	−2.8	1.9	3.4	4.9	16.3
Germany	212	2.7	2.0	−0.9	1.3	2.0	4.0	8.2
Denmark	212	4.1	3.6	0.1	1.7	2.4	6.0	15.1
Dominican Rep.	212	10.8	11.5	−1.5	4.2	6.9	11.6	59.0
Ecuador	212	16.7	16.5	−1.2	3.4	11.5	25.6	71.7
Egypt	212	10.7	6.2	1.6	5.7	10.1	13.9	31.7
Spain	212	6.1	5.4	−1.1	2.4	4.3	8.7	24.1
France	212	3.9	3.7	−0.4	1.4	2.1	5.8	14.0
Gabon	212	4.5	7.7	−18.5	0.7	3.2	7.1	36.8
United Kingdom	212	5.1	4.8	0.3	2.0	2.9	7.4	23.6
Ghana	212	24.0	19.2	1.2	10.8	17.2	29.3	90.1
Gambia	212	8.7	7.5	−2.0	4.6	6.8	10.6	52.4
Greece	212	8.4	7.5	−2.4	2.6	5.2	14.2	28.5
Guatemala	212	8.5	7.5	−2.2	4.3	7.1	10.5	44.8
Honduras	212	8.6	6.2	1.4	4.5	7.0	9.9	33.4
Indonesia	212	9.4	8.5	−0.6	4.6	7.4	10.0	57.9
India	212	7.3	4.7	−11.7	4.9	6.8	9.4	26.9
Ireland	212	5.0	5.2	−6.3	1.6	3.2	7.8	20.8
Iceland	212	13.5	14.8	0.2	2.7	6.0	20.8	67.0
Israel	212	21.3	34.4	−2.5	1.7	8.0	19.3	172.7
Italy	212	5.7	5.4	−0.5	1.9	4.1	8.5	22.1
Japan	212	2.3	3.9	−2.3	−0.1	0.9	3.1	21.1
Korea	212	6.0	6.0	0.0	2.2	3.8	7.0	27.8
Sri Lanka	212	9.5	7.3	−0.9	5.0	8.4	12.4	52.7
Luxembourg	212	3.4	2.6	−1.2	1.7	2.7	4.2	10.6
Morocco	212	4.4	3.9	−0.5	1.4	3.0	7.0	17.8
Mexico	212	17.5	20.2	2.2	4.3	8.4	21.9	102.0
Malta	212	3.1	3.2	−3.2	1.1	2.5	4.1	15.7
Mauritius	212	7.3	6.3	−1.2	3.7	6.0	9.2	38.0
Niger	212	4.0	7.7	−10.9	−0.7	2.9	6.7	36.7
Netherlands	212	3.2	2.6	−1.2	1.5	2.4	4.1	11.6
Norway	212	4.4	3.2	−1.4	2.0	3.2	6.4	13.7
Nepal	212	7.5	4.6	−4.4	4.1	7.8	9.8	19.7
New Zealand	212	5.5	5.0	−0.5	1.6	3.3	9.0	17.3
Pakistan	212	9.0	5.6	1.6	5.3	8.1	10.7	31.8
Panama	212	2.8	3.2	−2.2	0.7	1.6	3.9	16.0
Peru	212	40.0	82.1	−1.0	3.1	7.4	47.2	455.5
Philippines	212	8.3	7.7	−0.9	3.5	6.1	9.9	47.6
Portugal	212	8.0	7.7	−1.5	2.1	4.1	12.5	38.0
Paraguay	212	10.8	7.8	1.0	4.6	8.8	15.3	35.2
Singapore	212	2.7	4.2	−2.8	0.5	1.7	3.7	28.8
El Salvador	212	7.8	7.2	−1.9	1.8	5.4	12.8	28.2
Sweden	212	4.3	3.8	−1.4	1.1	2.8	7.5	13.8
Türkiye	212	30.1	20.4	4.3	10.2	25.7	49.0	80.0
Uruguay	212	27.3	22.3	3.4	7.7	17.6	46.7	82.7
United States	212	3.9	2.8	−1.6	2.1	3.1	4.7	13.5
Samoa	212	6.5	7.0	−6.7	1.6	5.2	9.8	31.6
South Africa	212	8.3	4.1	−1.8	5.1	7.5	11.7	17.6

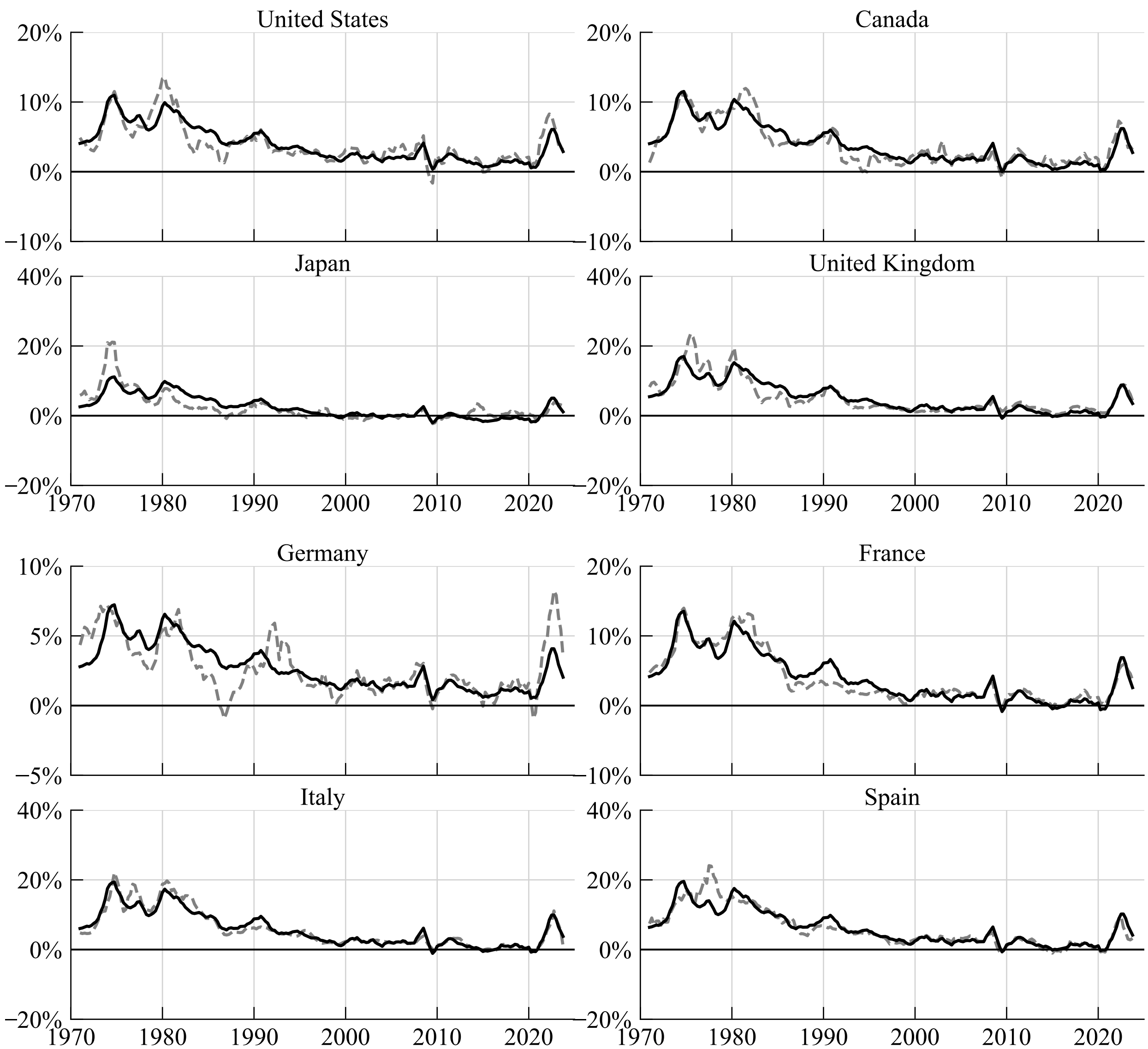
Note: This table shows statistics of the four-quarter log differences ($\times$ 100) in the total CPI by country. The sample period is 1970 through 2023.

Figure A.1: Global Inflation Factor: Sample Composition



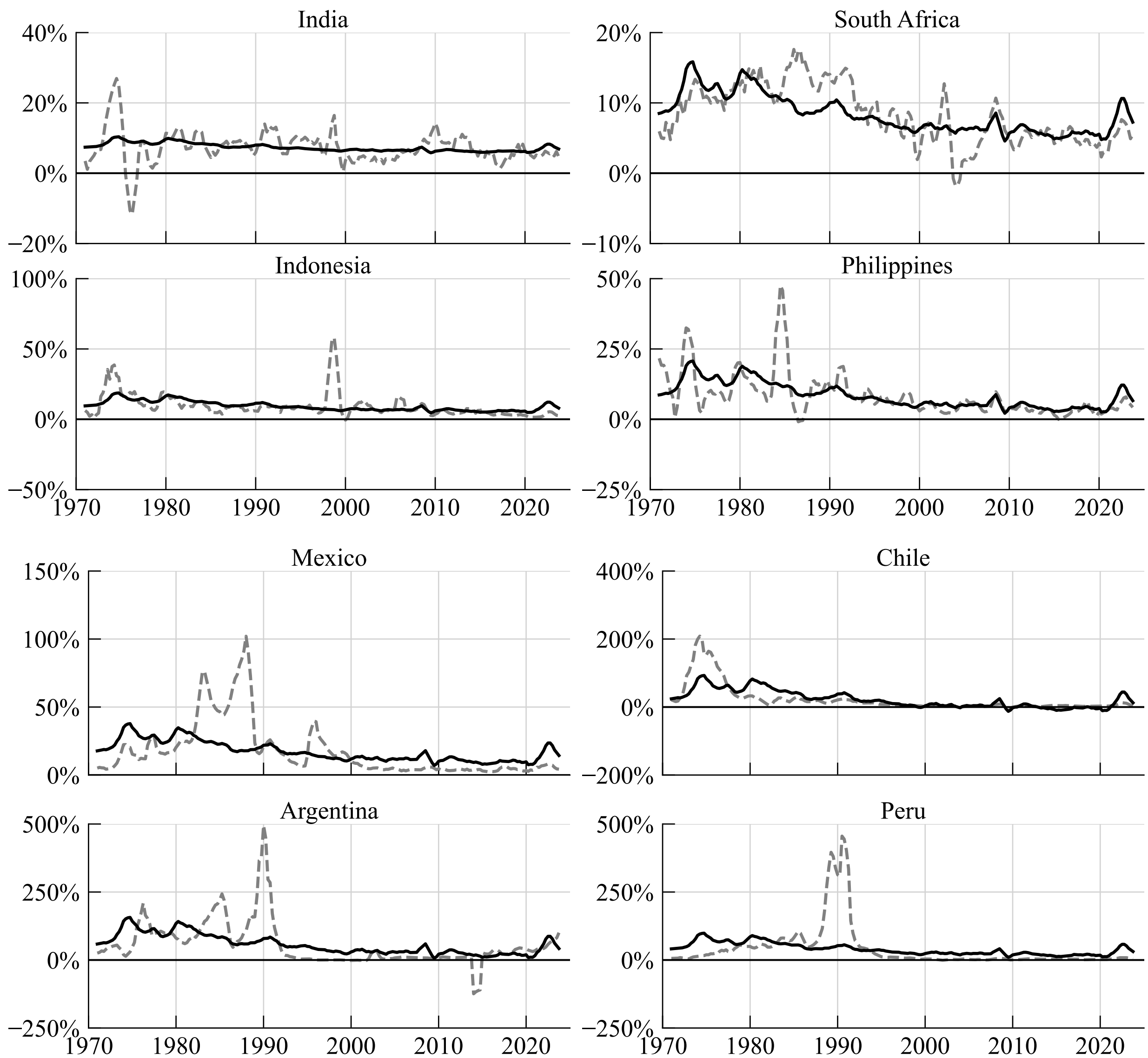
Note: This figure replicates Figure 1 using the sample of advanced economies (blue solid line). The orange dashed line shows the global factor estimated in the full sample.

Figure A.2: Global Inflation Component: Select Advanced Economies



Note: The gray dashed lines show annualized inflation, $\pi_{i,t}$, for select countries i, measured as a four-quarter log difference in the total CPI. The black solid lines show the contribution of the global inflation factor, $\hat{\lambda}_i \hat{f}_t$, in Equation (1).

Figure A.3: Global Inflation Component: Select Emerging-market and Developing Economies



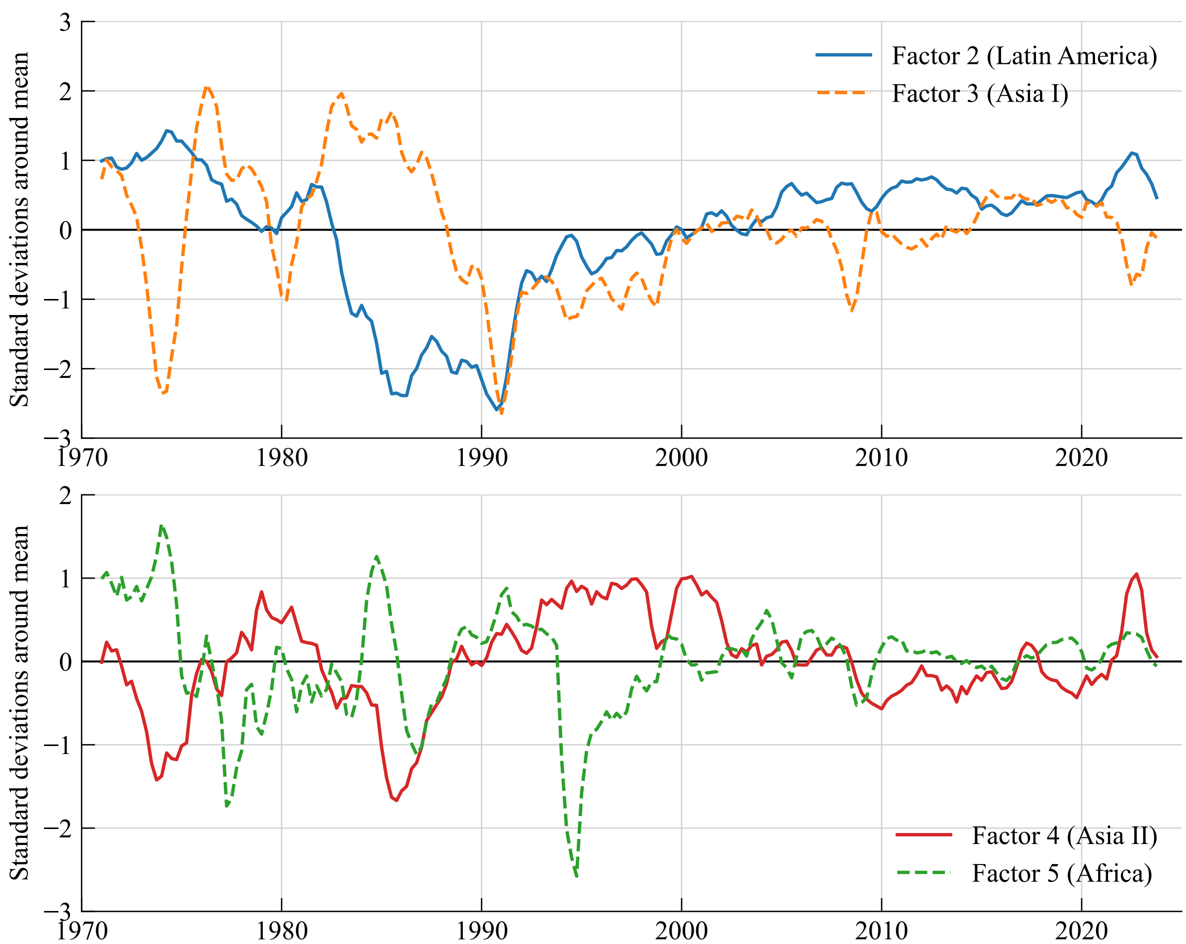
Note: The gray dashed lines show annualized inflation, $\pi_{i,t}$, for select countries, i, measured as a four-quarter log difference in the total CPI. The black solid lines show the contribution of the global inflation factor, $\hat{\lambda}_i \hat{f}_t$, in Equation (1).

Table A.2: PCA Information Criteria

N	IC_{p1} (1)	IC_{p2} (2)	IC_{p3} (3)
0	9.482	9.482	9.482
1	9.175	9.181	9.161
2	9.126	9.136	9.098
3	9.123	9.138	9.081
4	9.114	9.135	9.058
5	9.108	9.134	9.039
6	9.122	9.153	9.039
7	9.137	9.173	9.040
8	9.151	9.193	9.040
9	9.167	9.214	9.042
10	9.183	9.236	9.045

Note: This table shows the Bai and Ng (2002) information criteria for the PCA model. The optimal number of factors is highlighted.

Figure A.4: Principal Components from the Model with Five Factors



Note: The figure shows the second through fifth factors from the PCA model with five principal components. The first factor is the global factor in Figure 1.

Figure A.5: Cumulative Share of Inflation Variance Explained by Factors

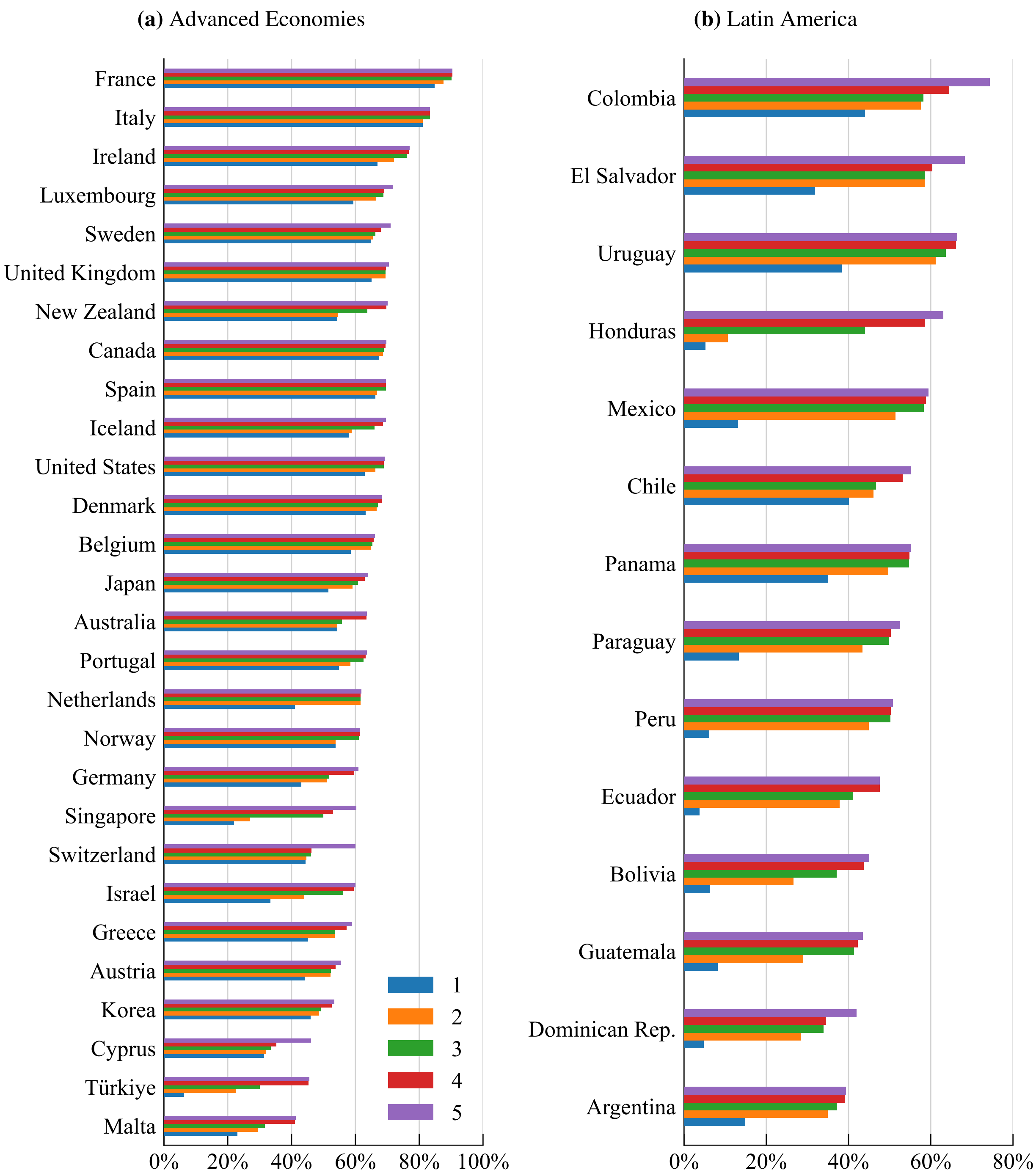
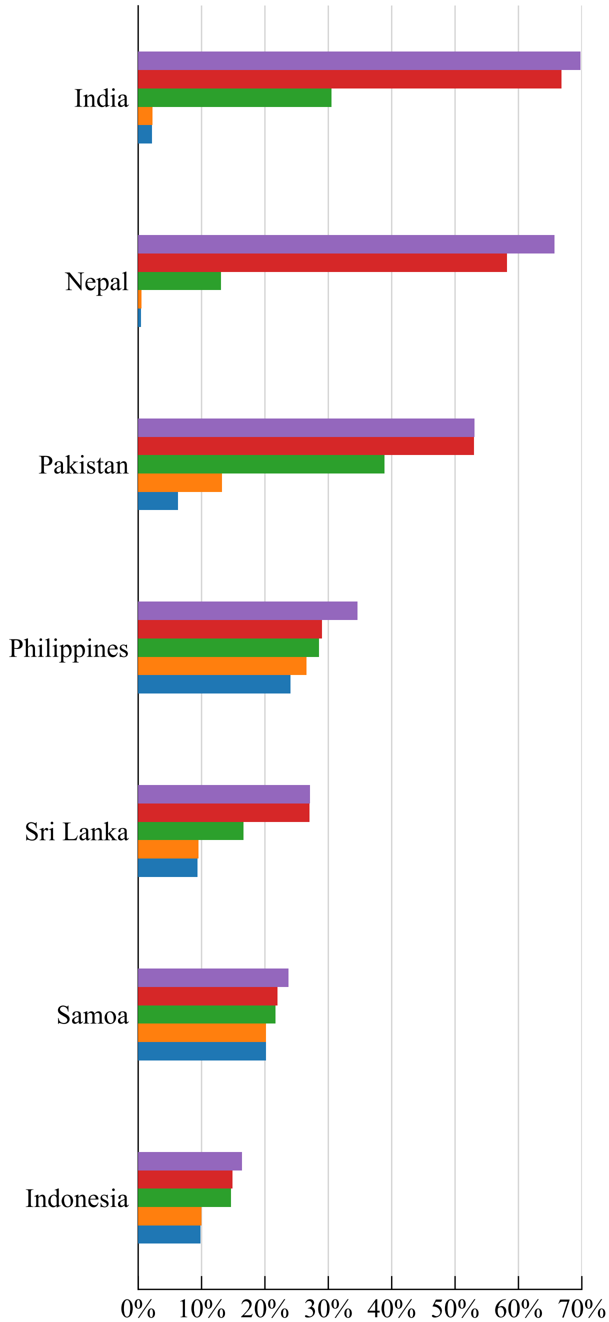
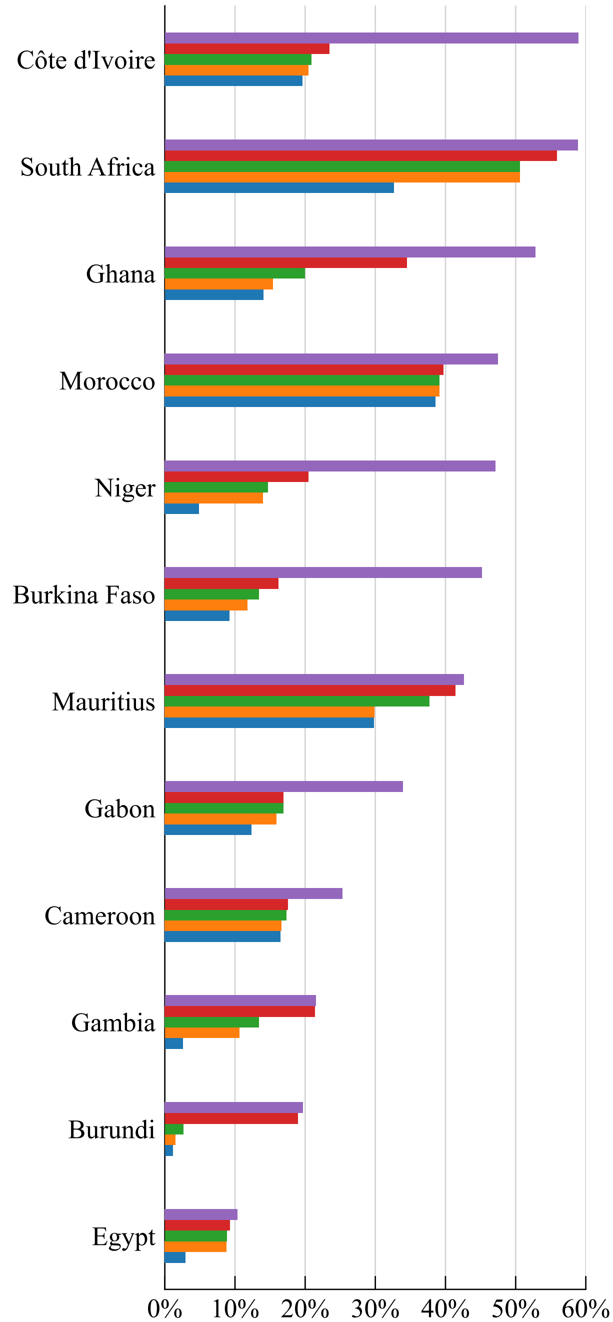


Figure A.5: Share of Inflation Variance Explained by the Number of Factors and Country Group (cont.)

(c) Asia

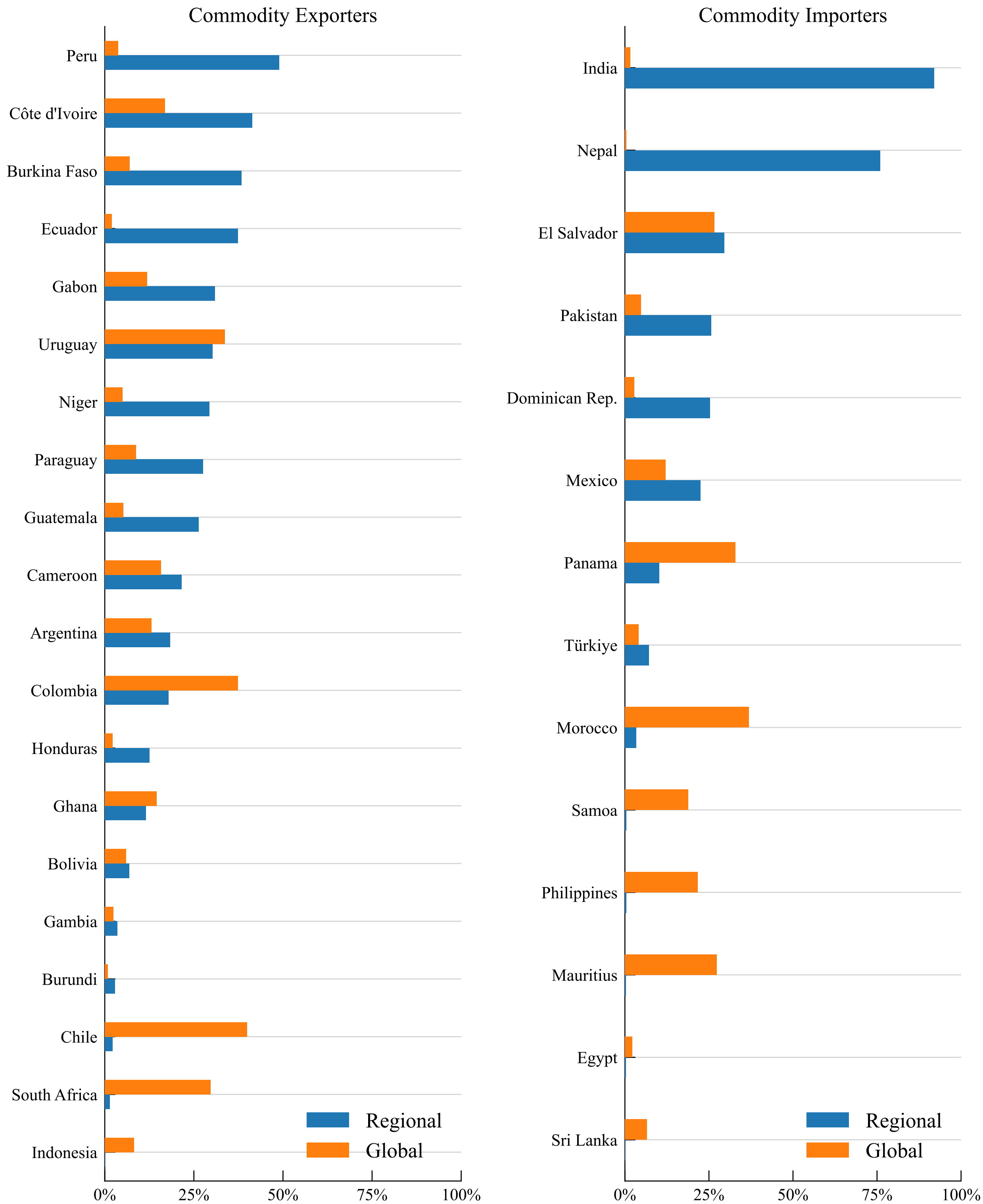


(d) Africa



Note: This figure shows the cumulative share of inflation variance explained by the first five principal components. Note that the marginal contribution represents the importance of each factor in the five-factor model.

Figure A.6: Share of Inflation Variance Explained in EMDEs: The Role of Commodities



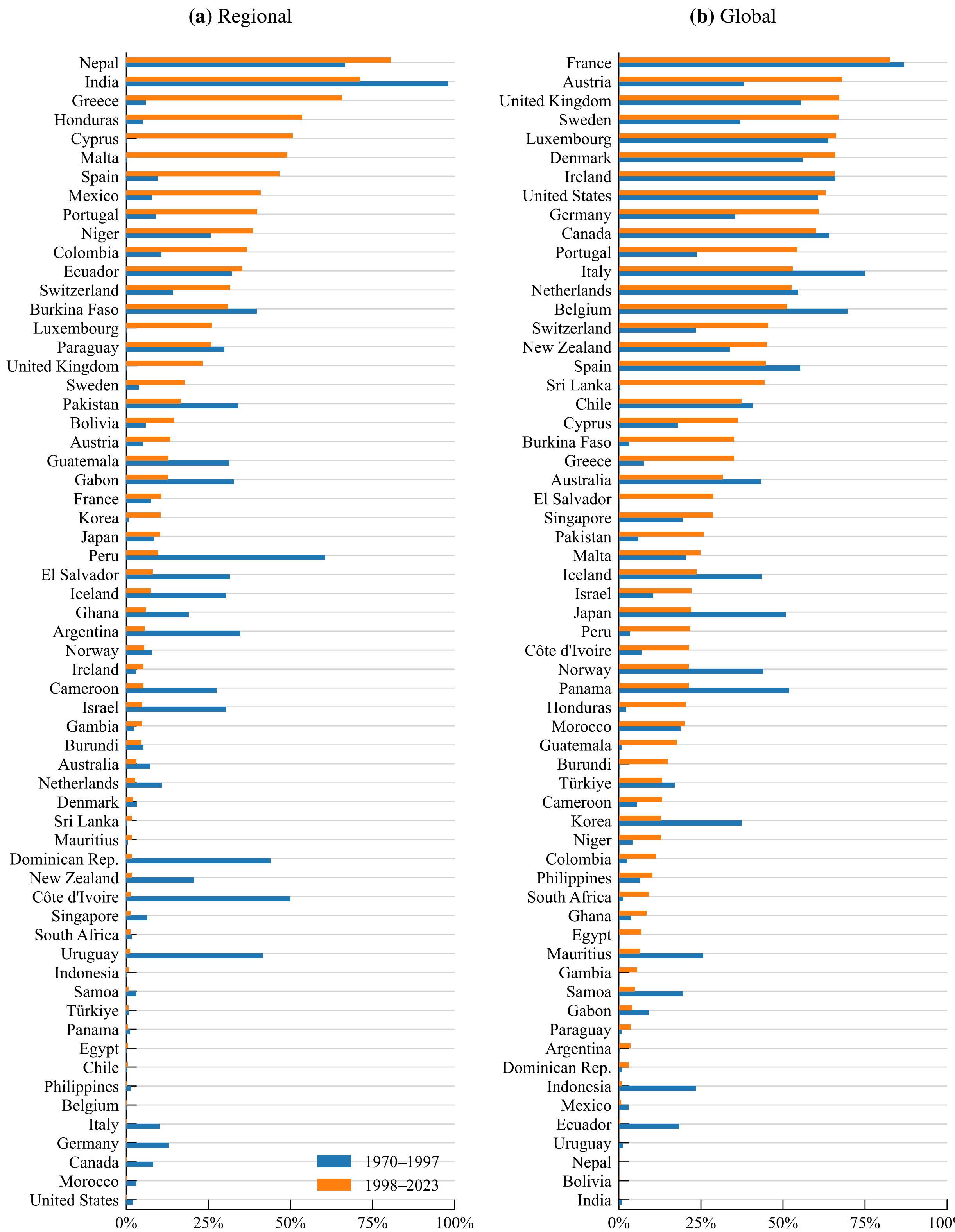
Note: We use the classification of commodity exporters and importers from the 2022 World Bank Global Economic Prospects report. The classification is based on World Bank data for the 2017–2019 period and available for 34 EMDEs in the sample.

Table A.3: Average Share of Explained Inflation Variance: Split by Commodity Status

	Regional (1)	Global (2)
Commodity Exporters	20.4	13.2
Commodity Importers	21.0	14.2
Both Groups	20.6	13.6

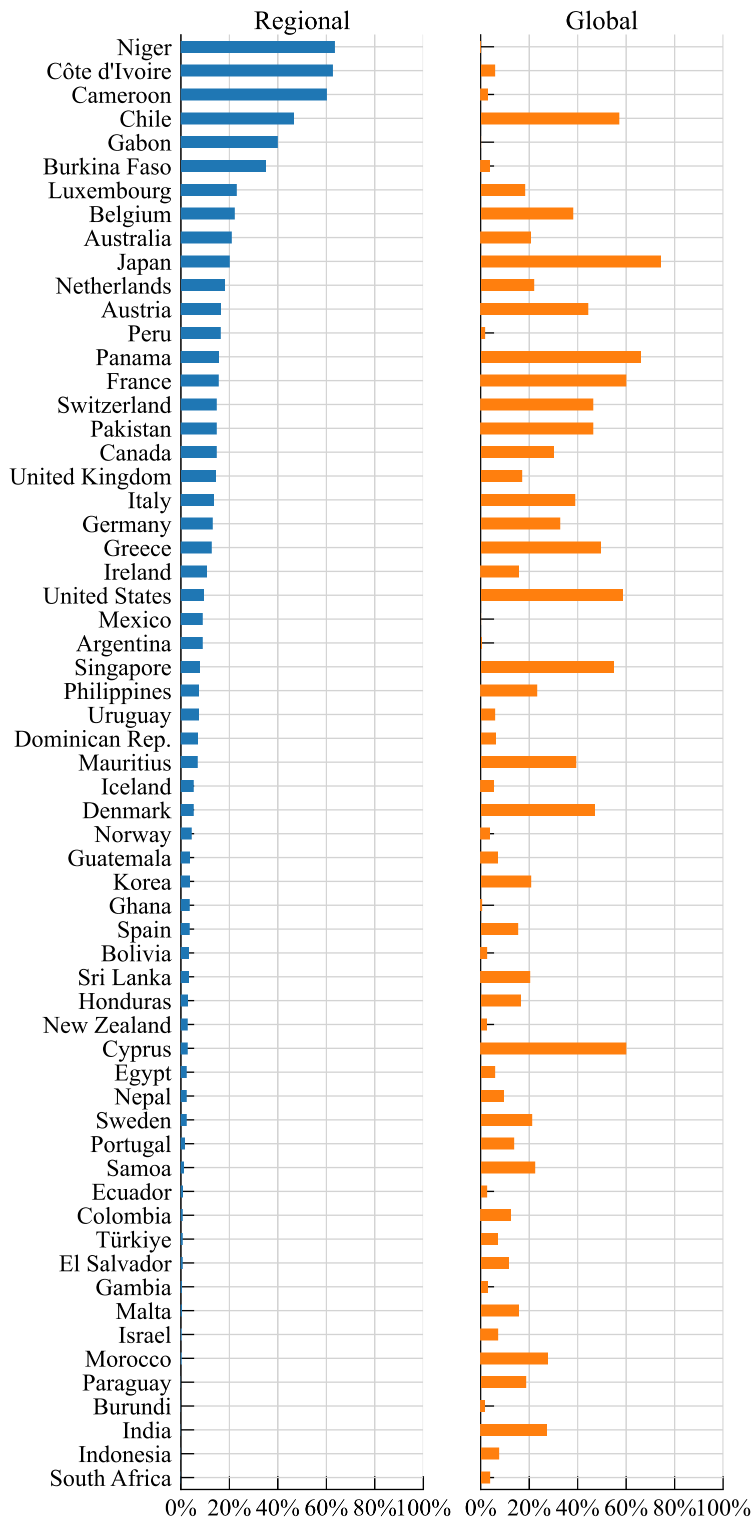
Note: See note to Figure A.6.

Figure A.7: Changes in Share of Explained Inflation Variance by Factor



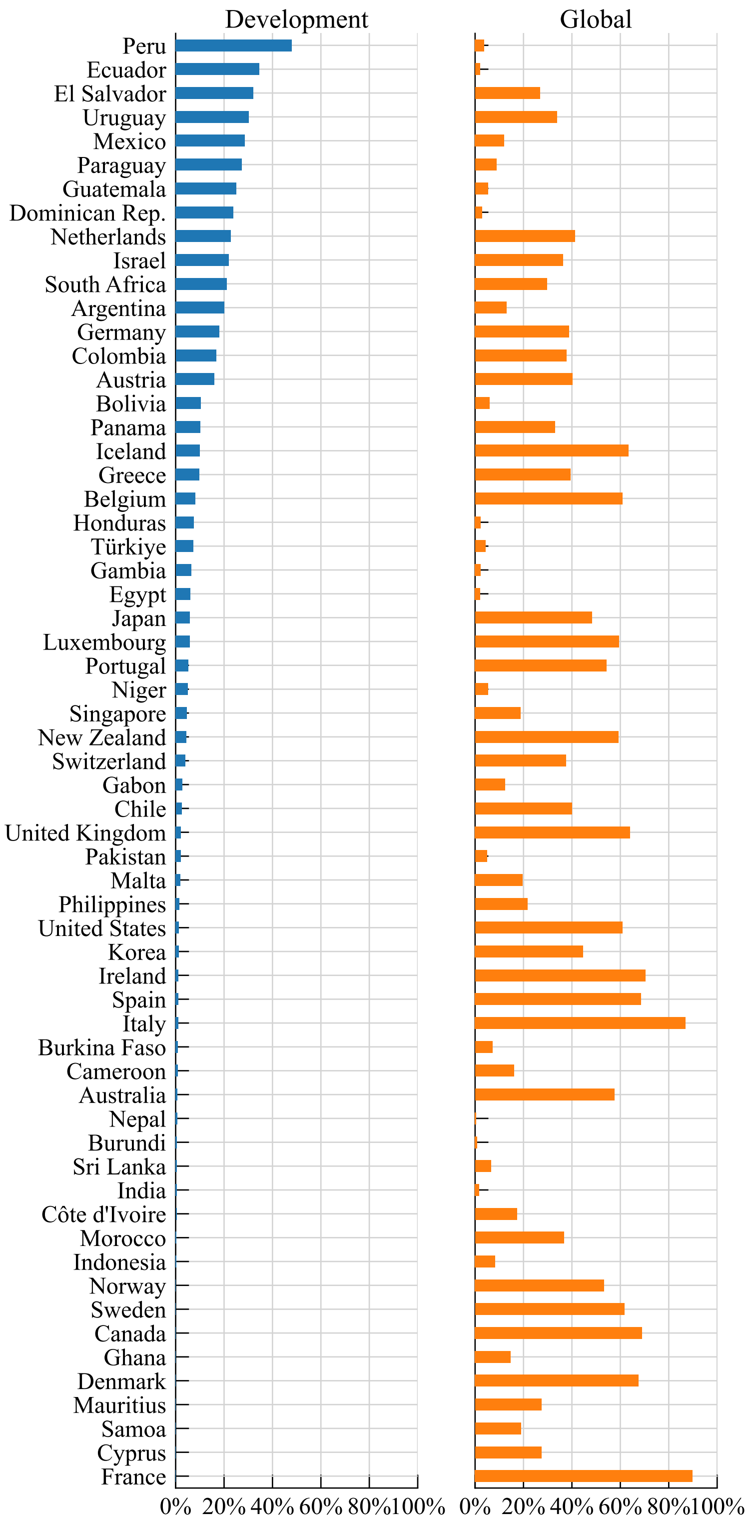
Note: The figure shows changes in the share of variance explained by the regional factor (left panel) and the global factor (right panel).

Figure A.8: Share of Explained Cyclical Inflation Variance by Factor



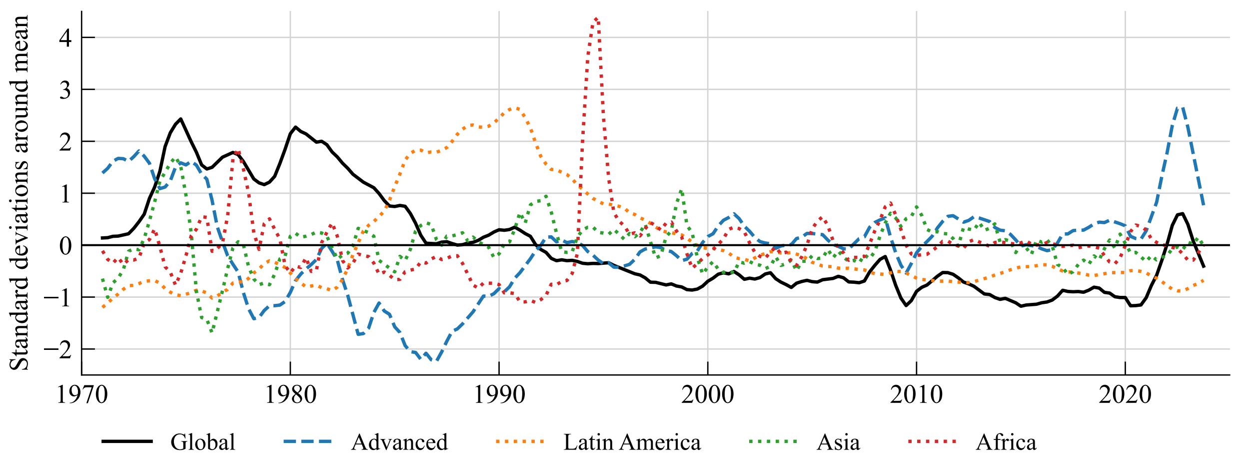
Note: This figure shows the share of cyclical inflation variance explained by the regional factor (left panel) and the global factor (right panel) estimated using Equations (3).

Figure A.9: Share of Explained Inflation Variance: Development Factor



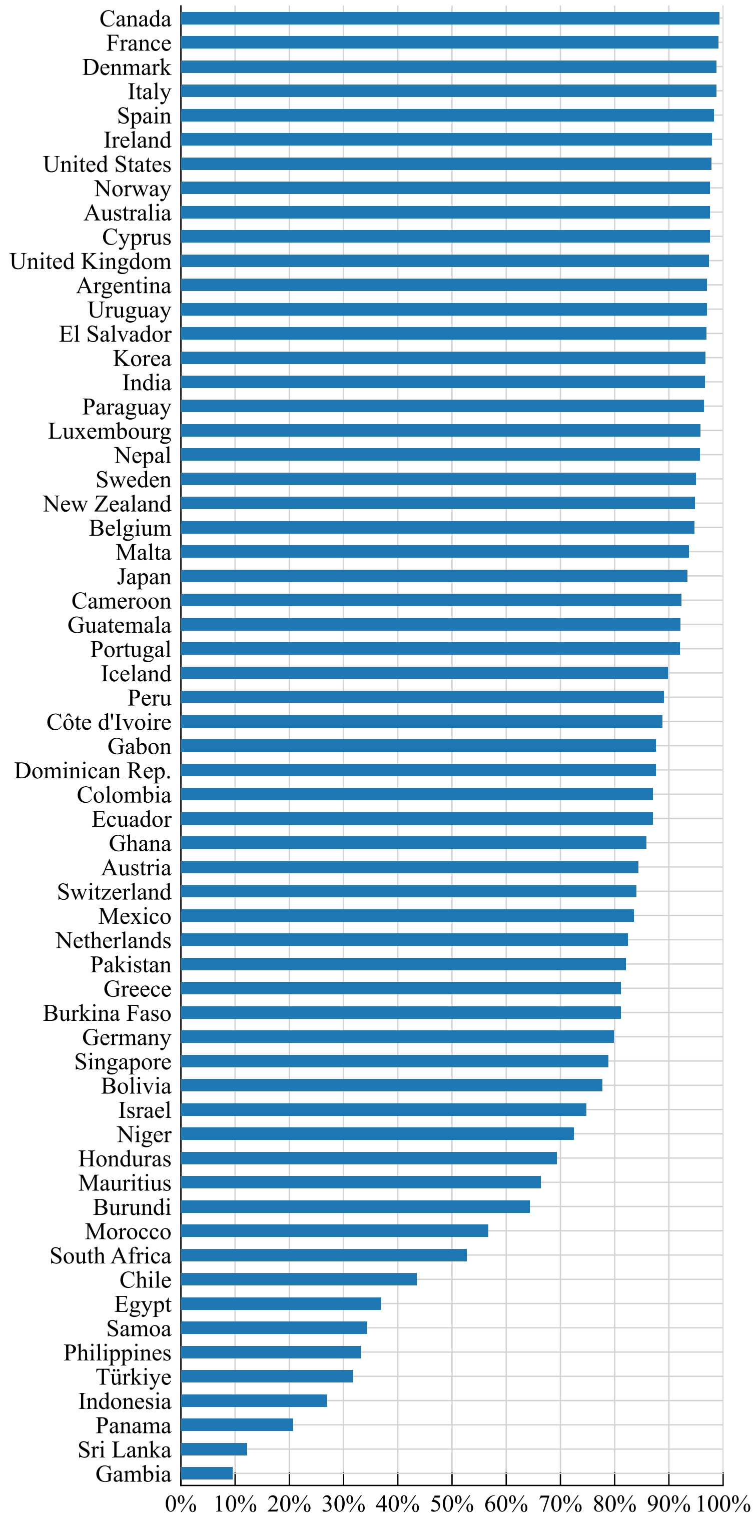
Note: This figure shows the share of inflation variance explained by the development factor (left panel) and the global factor (right panel). The development factor combines Africa, Asia, and Latin America into the EMDE group while preserving the advanced-economies group, as in the baseline model.

Figure A.10: Inflation Factors with Winsorized Data



Note: This figure replicates our baseline H-DFM estimation using data that winsorizes inflation at 25 percent from above (106 observations) and −2.5 percent from below (128 observations).

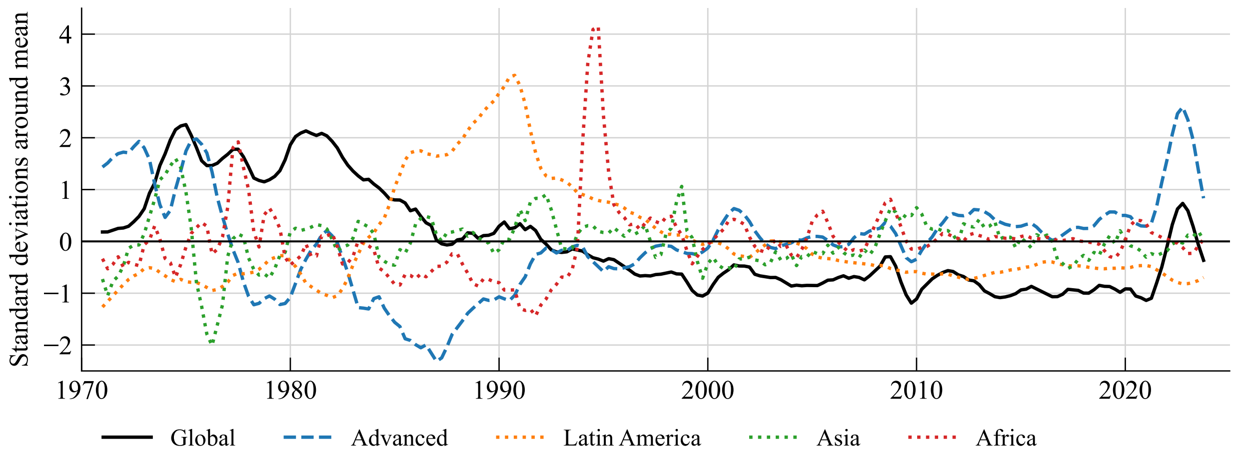
Figure A.11: Correlation of Inflation Projections: Baseline vs. Subsamples



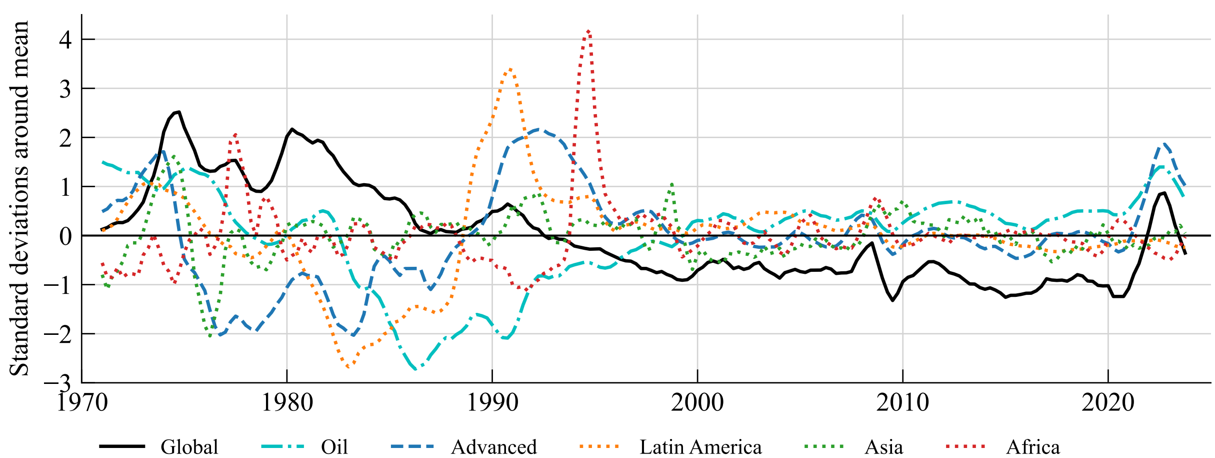
Note: This figure shows the correlation of the inflation projections on the global and regional factors in the baseline H-DFM with the projections on one "global" factor estimated separately for each region.

Figure A.12: H-DFM Model Augmented with an Oil Factor

(a) Exogenous Oil Factor

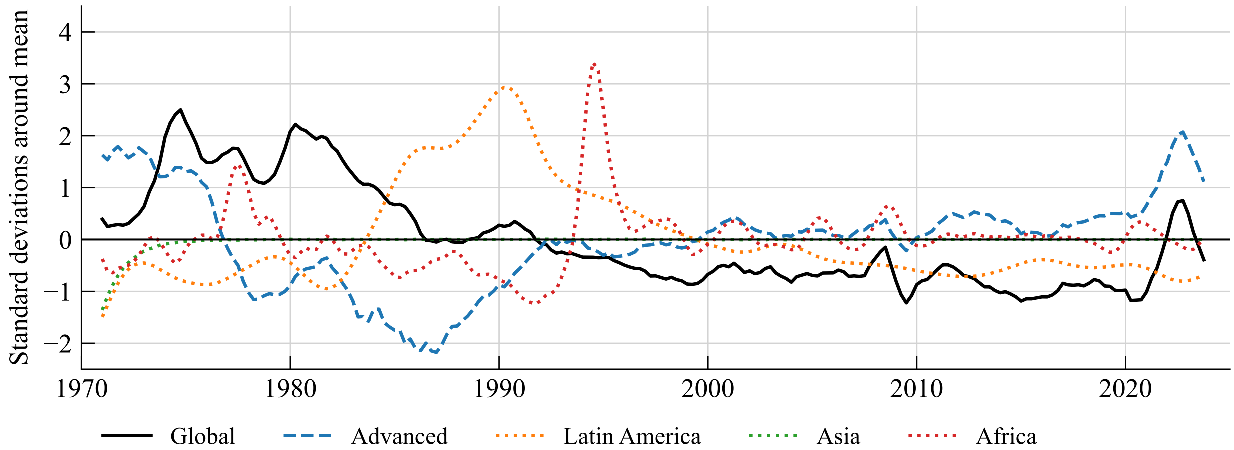


(b) Endogenous Oil Factor



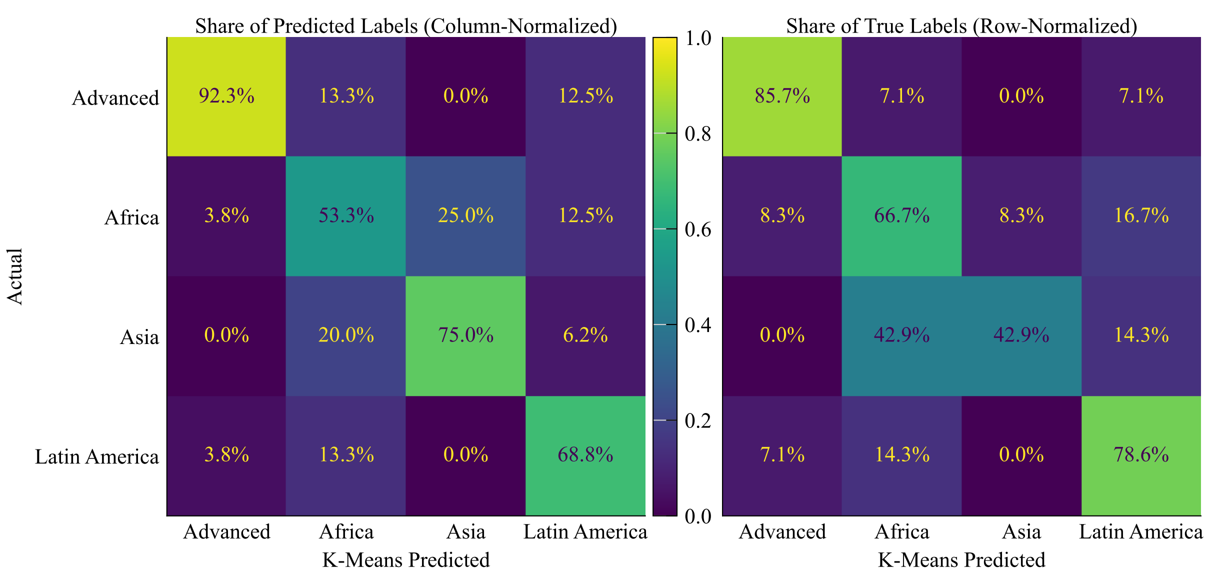
Note: Panel (a) shows estimates of the baseline model augmented with an exogenous oil factor represented by the quarterly log difference in West Texas Intermediate (WTI) spot oil prices. Panel (b) adds oil as a second global factor. In this model, the first global factor (labeled “Global”) loads on country-specific inflation only, while the second global factor (labeled “Oil”) also loads on the log difference in the oil price.

Figure A.13: H-DFM Model with AR(4) Factors



Note: This figure shows factors from the H-DFM model that allows for relatively more persistence.

Figure A.14: Confusion Matrix of the *K*-means Classifier



Note: The left chart shows the confusion matrix normalized by the sum of column elements. The diagonal elements correspond to the classifier's precision for each group. The right panel shows the confusion matrix normalized by the sum of row elements. The diagonal elements correspond to recall.

Table A.4: Regional Clusters

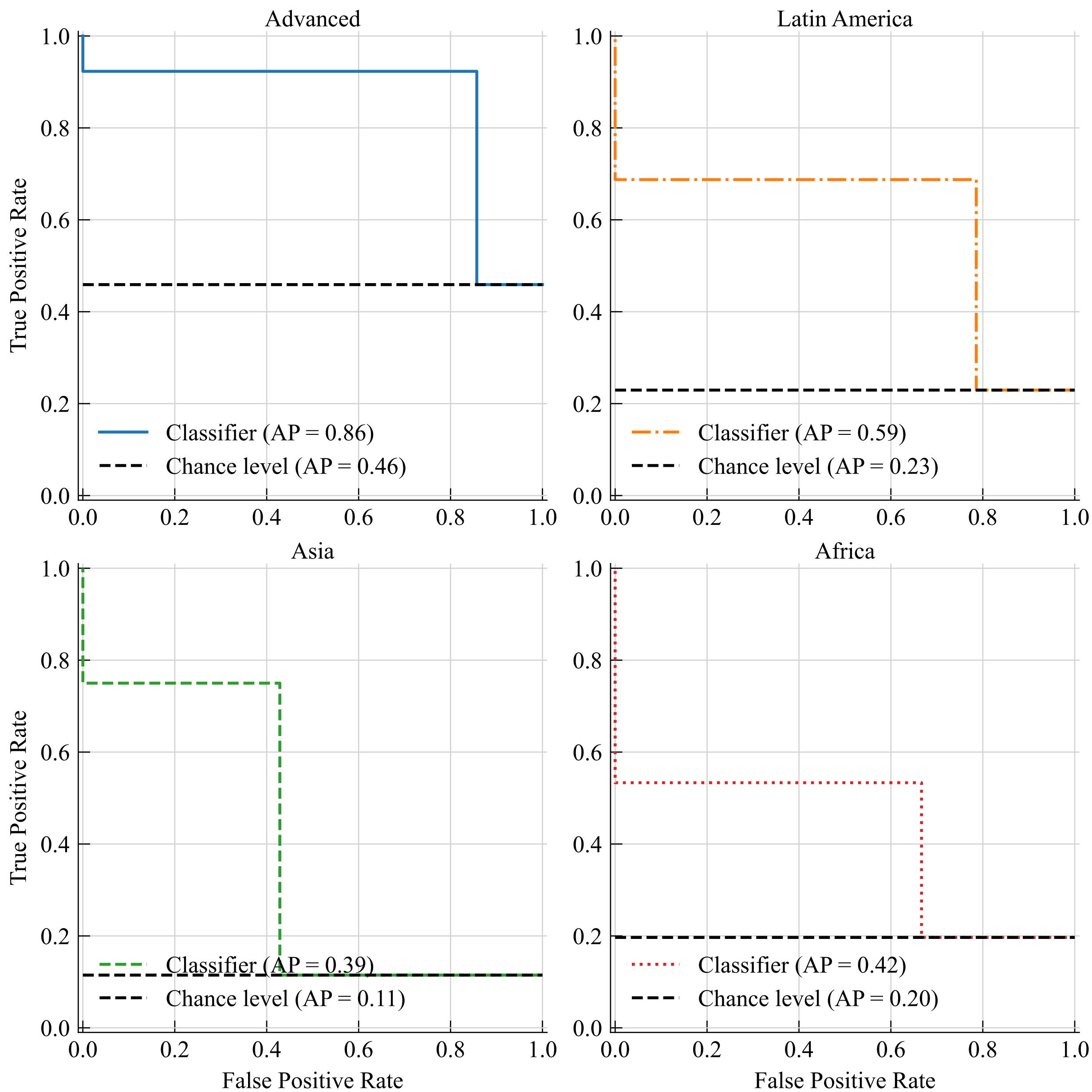
	K-Means (1)	Actual (2)
Australia	Advanced	Advanced
Austria	Advanced	Advanced
Belgium	Advanced	Advanced
Canada	Advanced	Advanced
Switzerland	Advanced	Advanced
Cyprus	Advanced	Advanced
Germany	Advanced	Advanced
Denmark	Advanced	Advanced
Spain	Advanced	Advanced
France	Advanced	Advanced
United Kingdom	Advanced	Advanced
Greece	Advanced	Advanced
Ireland	Advanced	Advanced
Iceland	Advanced	Advanced
Italy	Advanced	Advanced
Japan	Advanced	Advanced
Luxembourg	Advanced	Advanced
Malta	Advanced	Advanced
Netherlands	Advanced	Advanced
Norway	Advanced	Advanced
New Zealand	Advanced	Advanced
Portugal	Advanced	Advanced
Sweden	Advanced	Advanced
United States	Advanced	Advanced
Morocco	Advanced	Africa
Chile	Advanced	Latin America
Korea	Africa	Advanced
Singapore	Africa	Advanced
Burundi	Africa	Africa
Burkina Faso	Africa	Africa
Côte d'Ivoire	Africa	Africa
Cameroon	Africa	Africa
Egypt	Africa	Africa
Gabon	Africa	Africa
Ghana	Africa	Africa
Mauritius	Africa	Africa
Indonesia	Africa	Asia
Sri Lanka	Africa	Asia
Samoa	Africa	Asia
Honduras	Africa	Latin America
Panama	Africa	Latin America
Niger	Asia	Africa
India	Asia	Asia
Nepal	Asia	Asia
Pakistan	Asia	Asia
Israel	Latin America	Advanced
Türkiye	Latin America	Advanced
Gambia	Latin America	Africa
South Africa	Latin America	Africa
Philippines	Latin America	Asia
Argentina	Latin America	Latin America
Bolivia	Latin America	Latin America
Colombia	Latin America	Latin America
Dominican Rep.	Latin America	Latin America
Ecuador	Latin America	Latin America
Guatemala	Latin America	Latin America
Mexico	Latin America	Latin America
Peru	Latin America	Latin America
Paraguay	Latin America	Latin America
El Salvador	Latin America	Latin America
Uruguay	Latin America	Latin America

Table A.5: Excess Distance to Cluster Centers (in Percentages)

	Advanced (1)	Africa (2)	Asia (3)	Latin America (4)
Argentina	23.4	23.0	51.0	*
Australia	*	21.3	54.9	17.7
Austria	*	19.8	53.2	35.5
Burundi	20.8	*	32.9	18.2
Belgium	*	21.7	70.7	36.2
Burkina Faso	23.2	*	21.9	30.8
Bolivia	34.5	19.6	56.2	*
Canada	*	37.0	87.6	44.8
Switzerland	*	38.8	79.7	36.4
Chile	*	8.3	52.4	15.6
Côte d'Ivoire	24.6	*	60.2	28.5
Cameroon	17.2	*	41.1	18.6
Colombia	24.4	26.0	88.6	*
Cyprus	*	17.5	32.8	22.0
Germany	*	11.6	50.2	27.5
Denmark	*	45.2	108.1	50.4
Dominican Rep.	27.2	16.0	46.3	*
Ecuador	33.3	24.8	58.8	*
Egypt	15.2	*	16.5	8.6
Spain	*	55.5	100.0	54.9
France	*	97.1	191.2	106.8
Gabon	19.8	*	29.5	23.3
United Kingdom	*	51.1	121.3	66.4
Ghana	26.1	*	63.1	15.4
Gambia	18.9	7.4	22.4	*
Greece	*	25.6	75.2	11.4
Guatemala	36.2	13.3	49.6	*
Honduras	31.0	*	36.2	9.3
Indonesia	23.0	*	41.3	10.9
India	118.7	93.1	*	103.6
Ireland	*	47.4	107.8	60.8
Iceland	*	26.6	78.8	18.7
Israel	12.7	25.7	74.5	*
Italy	*	49.9	130.8	41.4
Japan	*	17.1	47.9	28.5
Korea	4.9	*	67.3	17.2
Sri Lanka	22.2	*	43.4	20.0
Luxembourg	*	54.8	104.0	69.7
Morocco	*	9.5	49.8	7.4
Mexico	44.4	36.7	84.5	*
Malta	*	6.1	27.3	23.3
Mauritius	24.5	*	56.5	16.6
Niger	41.4	24.8	*	50.8
Netherlands	*	29.0	54.7	44.6
Norway	*	26.8	73.3	23.9
Nepal	108.9	89.3	*	94.5
New Zealand	*	31.6	74.2	25.2
Pakistan	49.8	31.7	*	53.6
Panama	11.3	*	36.7	35.7
Peru	55.2	38.5	82.4	*
Philippines	16.6	10.4	50.8	*
Portugal	*	40.1	108.4	24.2
Paraguay	42.7	26.3	83.1	*
Singapore	19.8	*	24.4	26.5
El Salvador	33.0	32.1	75.9	*
Sweden	*	54.5	117.7	45.6
Türkiye	22.6	15.4	46.3	*
Uruguay	39.1	48.6	93.0	*
United States	*	24.3	66.2	39.2
Samoa	14.9	*	31.7	11.7
South Africa	18.0	24.3	52.9	*

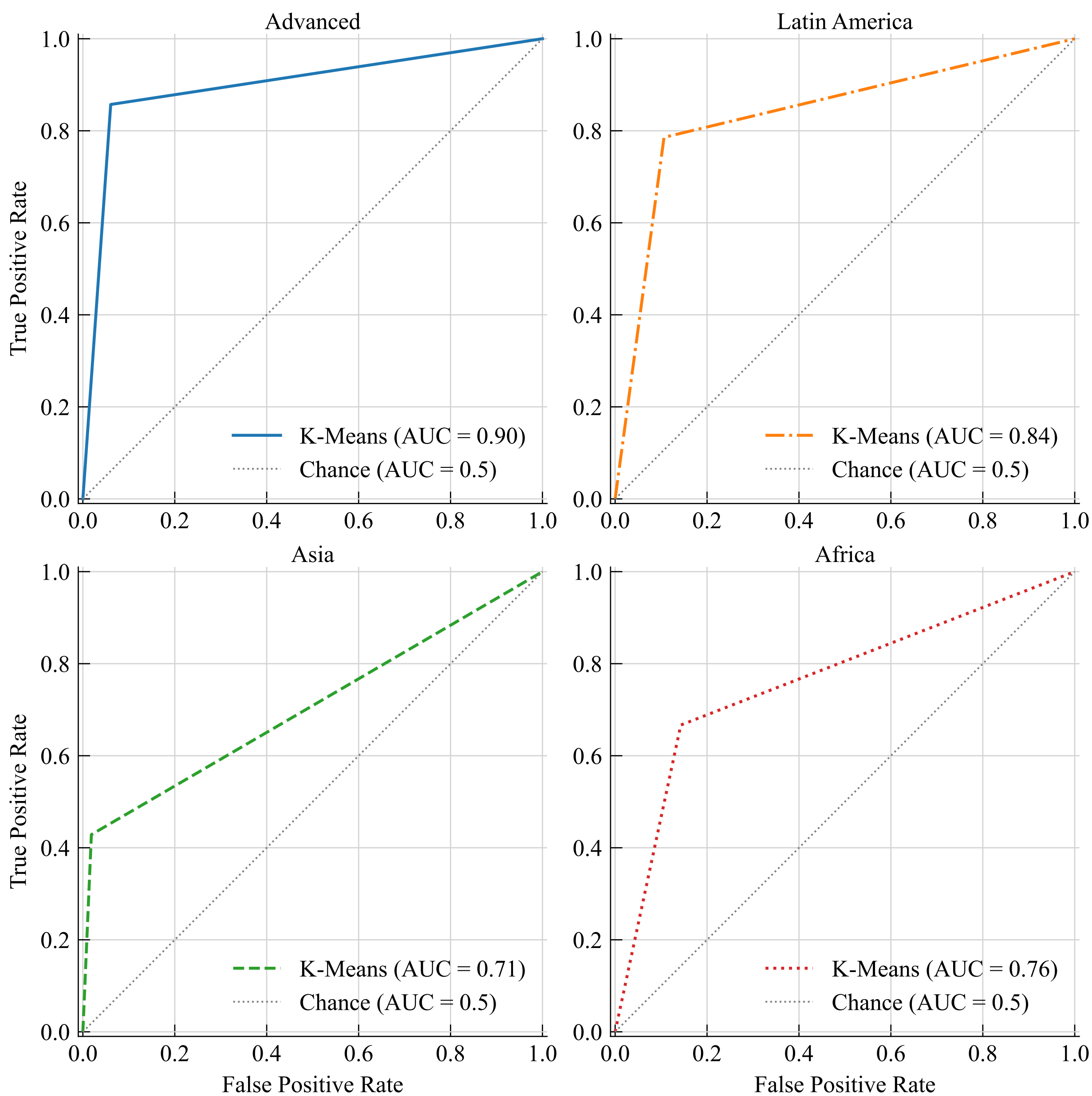
Note: The table shows excess distances to neighboring countries' cluster centers relative to a country's own cluster centers, in percentages. For example, Argentina is 23.4 percent farther from the advanced-economies cluster center than from its own (Latin America) cluster center. The stars indicate a country's own clusters. The misclassified cases are highlighted.

Figure A.15: Precision–Recall Curve



Note: This figure shows the precision–recall curve (PRC) of the K-means classifier, along with the average precision (AP), in comparison with the random classifier. The closer the PRC is to the top-right corner, the better the classifier.

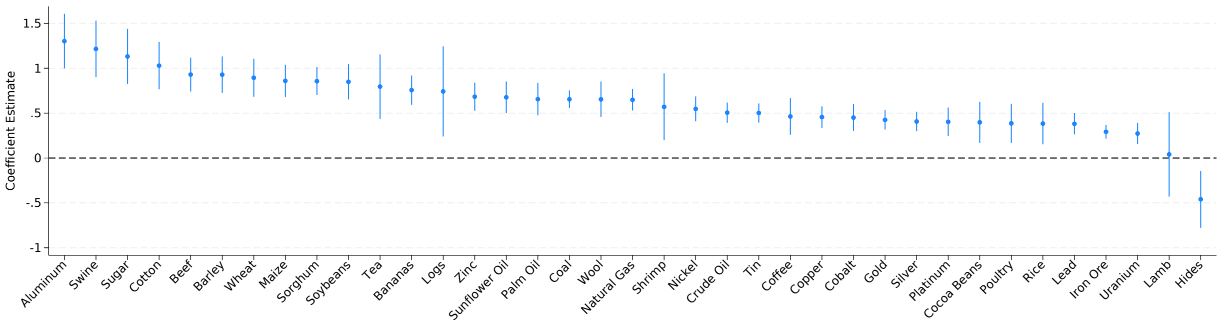
Figure A.16: Receiver Operating Characteristic (ROC) Curve



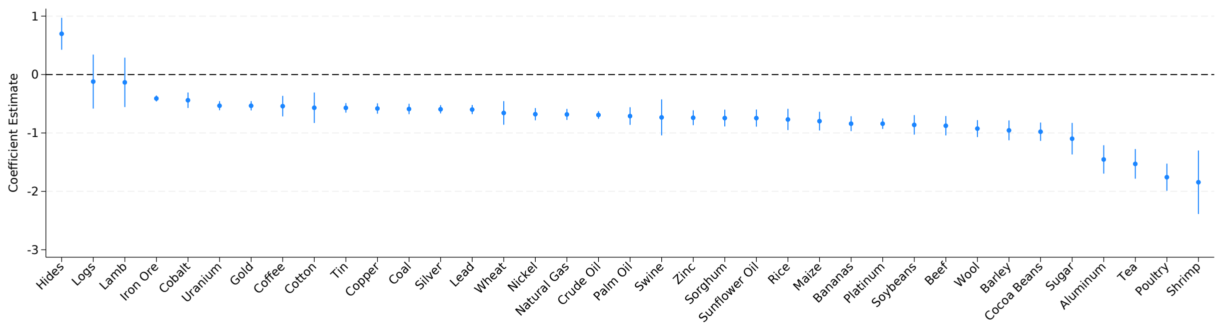
Note: This figure shows the receiver operating characteristic (ROC) curve for the K-means classifier along with the ROC curve for the random classifier. The closer the ROC curve is to the top-left corner, the better the classifier. The area under the curve (AUC) summarizes the classifier's performance.

Figure A.17: Correlation of Regional Factors with Individual Commodities

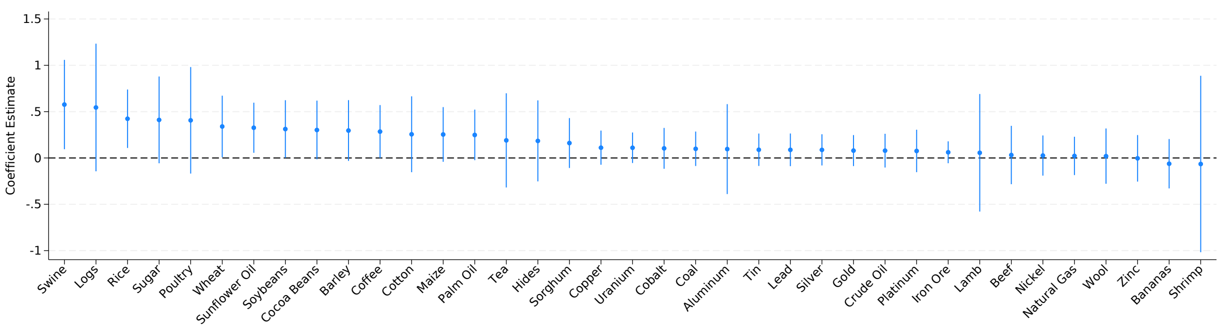
(a) Advanced Economies



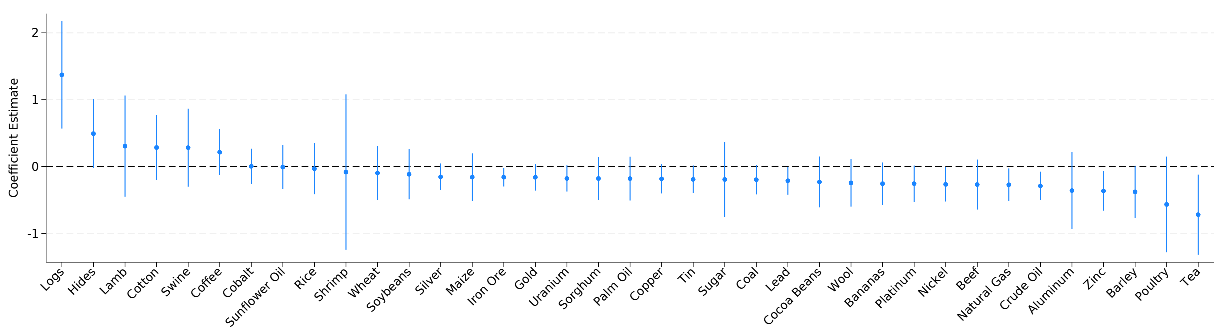
(b) Latin America



(c) Asia

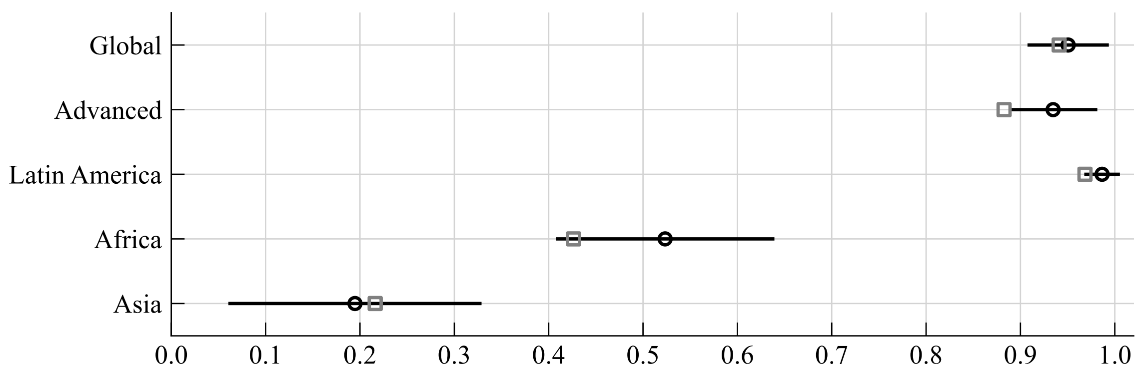


(d) Africa



Note: These plots report the coefficient estimates from univariate regressions of the various regional factors on the log prices of each commodity. The blue lines denote 90 percent confidence intervals.

Figure A.18: Persistence of Inflation Factors: AR(1) Process



Note: The black circles show global and regional factors' persistence, measured by the autoregressive coefficient of an estimated AR(1) process, together with two-standard-error bands. The gray squares show the corresponding estimates obtained from the H-DFM model.

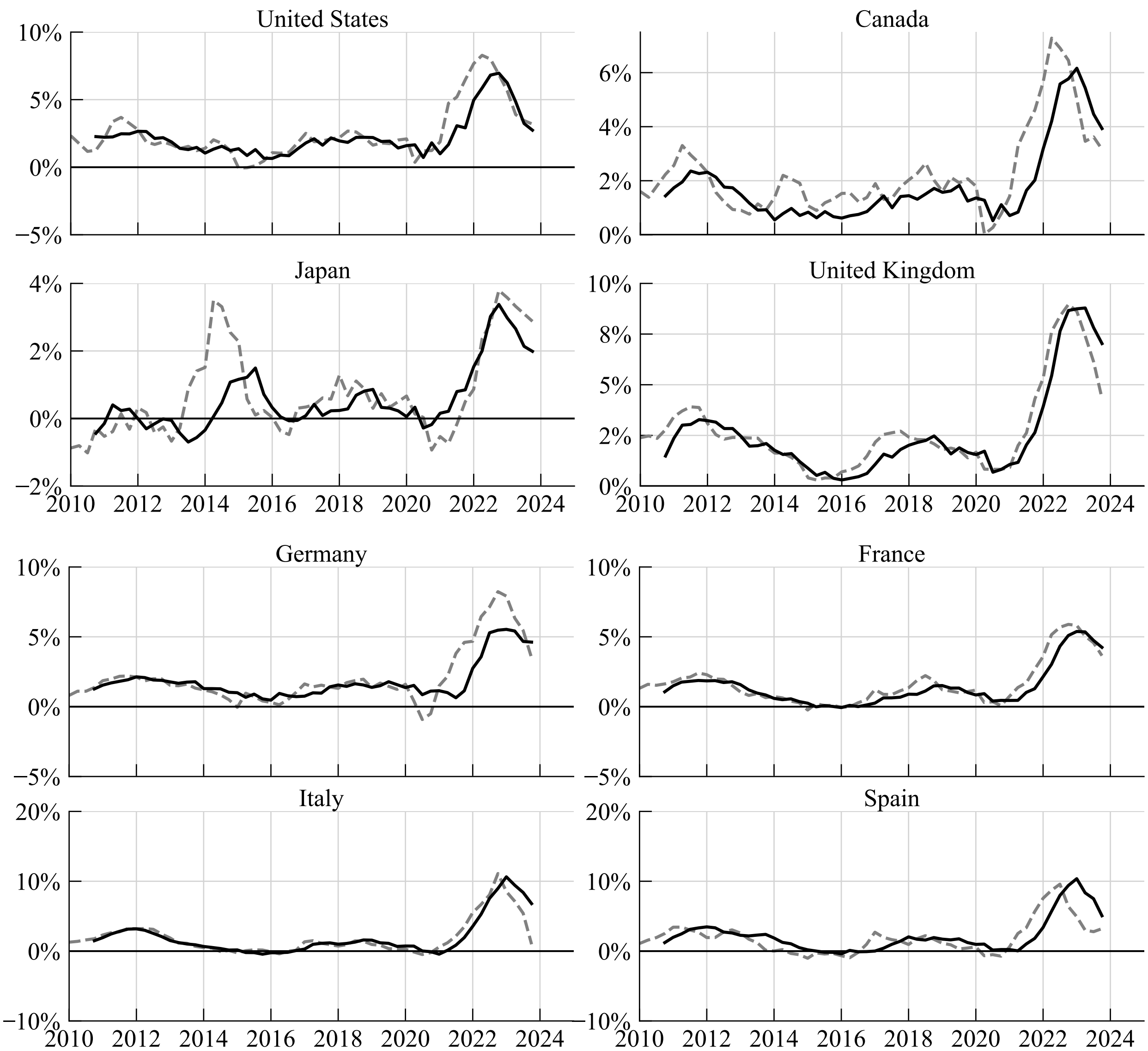
Table A.6: RMSE Relative to Benchmark (2010:Q1–2023:Q4)

	One Step Ahead		Four Steps Ahead		Eight Steps Ahead	
	Global	Both	Global	Both	Global	Both
Guatemala	0.971	0.709	0.939	0.589	0.867	0.576
Austria	0.867	0.732	1.029	1.003	1.061	1.035
Cameroon	0.833	0.813	0.962	0.928	0.965	0.936
Denmark	0.851	0.822	0.980	0.942	1.002	0.982
Ghana	0.845	0.824	0.682	0.699	0.885	0.903
Samoa	0.873	0.829	0.985	0.979	0.971	0.982
Cyprus	0.839	0.836	1.019	1.004	0.975	0.966
Ireland	0.842	0.844	0.902	0.915	1.069	1.033
Netherlands	0.958	0.864	0.997	0.974	1.036	1.014
Paraguay	0.955	0.869	1.012	0.891	0.717	0.546
Mauritius	0.849	0.877	0.900	0.910	0.817	0.871
Australia	0.872	0.879	1.069	1.076	0.997	1.023
Italy	0.884	0.880	0.960	0.965	1.032	1.022
Burkina Faso	0.837	0.885	1.056	0.997	0.993	0.990
Colombia	0.931	0.889	0.982	0.977	1.038	1.037
Morocco	0.909	0.891	1.001	0.998	1.045	1.045
Philippines	0.971	0.905	0.717	0.734	0.622	0.681
El Salvador	1.018	0.906	1.080	1.055	0.974	0.904
Dominican Rep.	1.058	0.908	0.957	0.680	1.040	0.887
Malta	0.900	0.910	1.010	1.031	1.067	1.098
Germany	0.961	0.919	0.983	0.958	1.006	1.019
Niger	1.063	0.921	1.168	1.122	1.192	1.114
Belgium	0.921	0.947	0.977	0.977	1.020	0.998
France	0.956	0.948	0.993	0.973	1.064	1.019
Switzerland	0.943	0.951	0.966	0.935	0.957	0.948
United Kingdom	0.902	0.955	1.099	1.124	1.081	1.044
Spain	0.934	0.964	1.024	1.055	0.996	1.058
United States	0.977	0.964	1.012	0.988	1.009	0.996
South Africa	0.952	0.970	0.951	0.974	0.985	0.982
Honduras	1.066	0.974	1.126	0.844	1.106	0.785
Pakistan	0.977	0.974	0.935	0.930	1.008	0.989
Sweden	0.922	0.975	0.932	0.967	1.047	1.075
Sri Lanka	0.991	0.976	0.992	0.975	1.007	0.991
Argentina	0.989	0.979	0.960	1.015	0.982	1.086
Burundi	0.974	0.986	0.981	0.997	0.984	0.969
Korea	0.999	0.986	1.339	1.147	0.900	0.822
New Zealand	0.988	0.992	1.126	1.105	1.124	1.173
Ecuador	1.091	0.993	1.069	0.813	0.886	0.628
Luxembourg	0.999	0.998	1.019	1.081	1.031	1.002
India	1.100	0.998	1.029	1.064	1.086	1.077
Indonesia	0.971	1.005	0.899	0.965	0.951	0.990
Gabon	0.986	1.010	1.078	1.090	1.050	1.141
Greece	1.026	1.012	1.002	0.940	1.014	1.003
Côte d'Ivoire	1.008	1.016	1.065	1.059	1.014	0.941
Singapore	0.990	1.022	1.062	1.088	1.048	1.058
Canada	1.021	1.025	1.031	1.007	1.069	1.072
Japan	1.046	1.031	1.003	1.011	1.029	1.031
Egypt	1.037	1.031	0.965	0.978	1.021	1.024
Nepal	1.084	1.034	1.047	1.054	1.035	1.057
Norway	1.041	1.059	1.069	1.082	1.070	1.143
Gambia	1.013	1.062	0.944	0.998	1.157	1.160
Panama	1.050	1.071	1.007	1.032	0.986	1.013
Portugal	1.003	1.080	1.145	1.095	1.069	1.082
Mexico	1.151	1.085	0.728	0.704	0.742	0.791
Türkiye	1.022	1.086	1.031	1.070	1.085	1.116
Iceland	1.046	1.102	1.213	1.207	1.034	1.099
Uruguay	1.011	1.105	0.948	1.566	0.924	1.656
Peru	0.904	1.159	0.791	1.119	0.680	1.011
Bolivia	1.245	1.527	0.932	1.088	0.846	0.972
Chile	1.576	1.559	1.283	1.360	1.167	1.278
Israel	0.972	1.636	1.031	1.211	0.925	1.307

Table A.7: Diebold–Mariano Tests: p-values

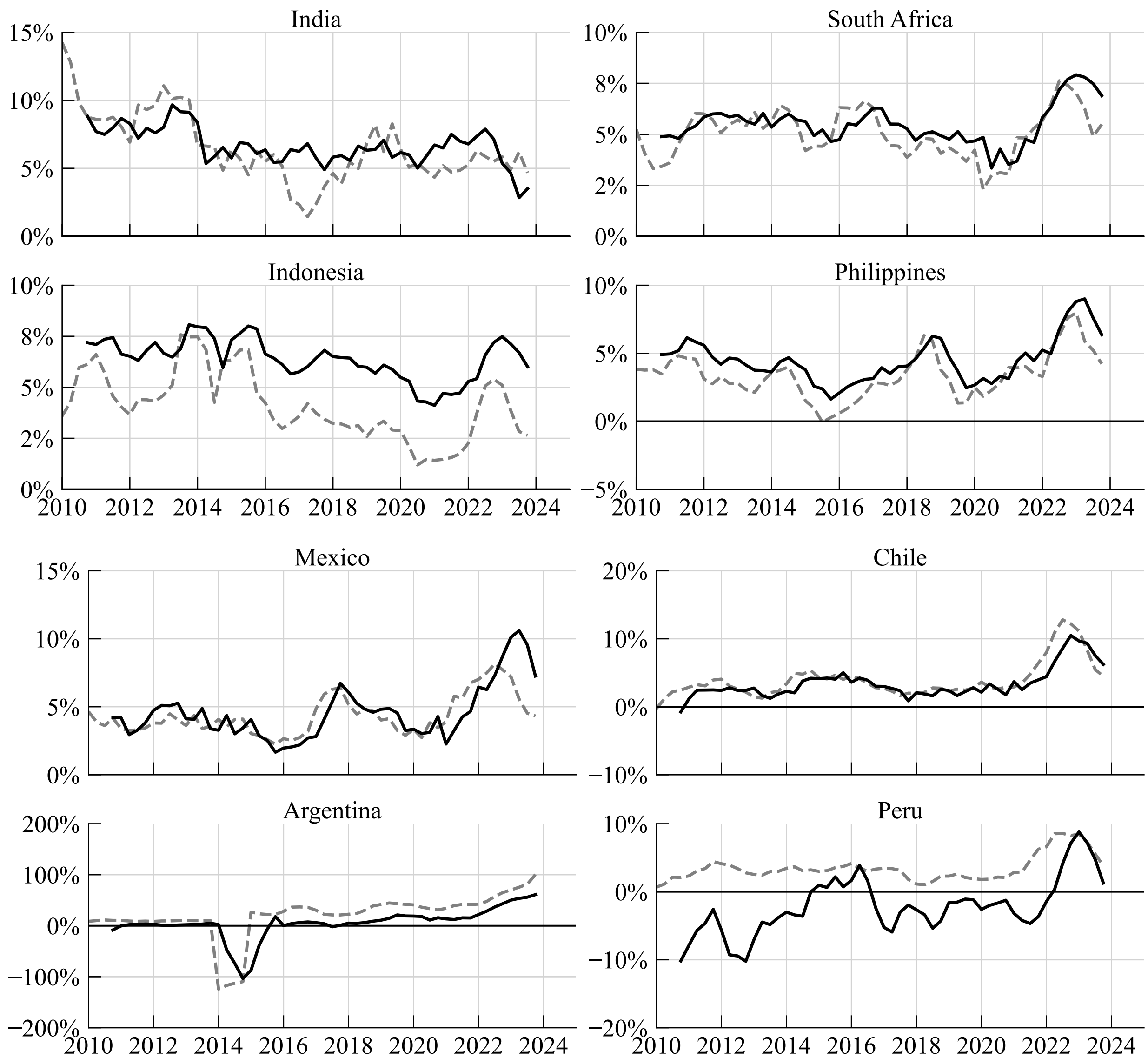
	One Quarter Ahead			Four Quarters Ahead		
	Global vs Benchmark (1)	Both vs Benchmark (2)	Both vs Global (3)	Global vs Benchmark (4)	Both vs Benchmark (5)	Both vs Global (6)
Argentina	0.292	0.260	0.316	0.172	0.584	0.916
Australia	0.002	0.001	0.721	0.992	0.977	0.607
Austria	0.012	0.006	0.011	0.793	0.532	0.108
Burundi	0.155	0.341	0.762	0.149	0.424	0.858
Belgium	0.027	0.037	0.819	0.277	0.228	0.492
Burkina Faso	0.019	0.067	0.898	0.696	0.488	0.016
Bolivia	0.978	1.000	1.000	0.314	0.684	0.978
Canada	0.727	0.715	0.581	0.830	0.567	0.120
Switzerland	0.028	0.187	0.577	0.074	0.051	0.149
Chile	0.999	0.999	0.330	0.987	0.993	0.910
Côte d'Ivoire	0.573	0.599	0.581	0.839	0.821	0.417
Cameroon	0.016	0.006	0.272	0.337	0.209	0.168
Colombia	0.183	0.122	0.170	0.325	0.389	0.460
Cyprus	0.022	0.027	0.453	0.704	0.534	0.261
Germany	0.121	0.084	0.095	0.257	0.120	0.107
Denmark	0.024	0.006	0.096	0.315	0.121	0.124
Dominican Rep.	0.877	0.066	0.001	0.009	0.000	0.000
Ecuador	0.937	0.456	0.003	0.731	0.010	0.000
Egypt	0.788	0.758	0.218	0.175	0.215	0.854
Spain	0.051	0.216	0.886	0.909	0.989	0.982
France	0.139	0.104	0.320	0.349	0.147	0.128
Gabon	0.437	0.543	0.764	0.733	0.764	0.907
United Kingdom	0.184	0.372	0.728	0.815	0.819	0.766
Ghana	0.016	0.008	0.184	0.000	0.000	0.797
Gambia	0.581	0.780	0.977	0.329	0.495	0.950
Greece	0.967	0.555	0.436	0.536	0.123	0.105
Guatemala	0.261	0.000	0.001	0.016	0.000	0.000
Honduras	0.765	0.377	0.029	1.000	0.000	0.000
Indonesia	0.242	0.538	0.820	0.000	0.173	0.958
India	0.891	0.492	0.028	0.728	0.799	0.749
Ireland	0.046	0.095	0.513	0.036	0.095	0.695
Iceland	0.655	0.751	0.748	0.844	0.891	0.477
Israel	0.405	0.994	0.997	0.590	0.977	0.915
Italy	0.036	0.041	0.450	0.317	0.355	0.620
Japan	0.792	0.676	0.312	0.524	0.562	0.598
Korea	0.496	0.439	0.359	0.980	0.891	0.059
Sri Lanka	0.233	0.241	0.316	0.300	0.059	0.037
Luxembourg	0.476	0.490	0.494	0.701	0.967	0.874
Morocco	0.027	0.012	0.211	0.510	0.486	0.330
Mexico	0.909	0.780	0.002	0.000	0.000	0.272
Malta	0.085	0.107	0.671	0.560	0.673	0.931
Mauritius	0.002	0.015	0.989	0.003	0.005	0.980
Niger	0.789	0.157	0.009	0.866	0.807	0.017
Netherlands	0.081	0.008	0.015	0.450	0.207	0.072
Norway	0.811	0.890	0.914	0.790	0.844	0.699
Nepal	0.848	0.719	0.164	0.832	0.853	0.580
New Zealand	0.415	0.457	0.551	0.951	0.872	0.292
Pakistan	0.401	0.386	0.424	0.047	0.053	0.413
Panama	0.811	0.858	0.911	0.606	0.757	0.726
Peru	0.050	0.936	0.978	0.000	0.763	0.950
Philippines	0.277	0.029	0.020	0.000	0.000	0.976
Portugal	0.520	0.905	0.831	0.984	0.943	0.095
Paraguay	0.144	0.040	0.051	0.549	0.101	0.004
Singapore	0.458	0.577	0.814	0.909	0.908	0.860
El Salvador	0.603	0.083	0.036	0.868	0.740	0.345
Sweden	0.058	0.346	0.972	0.086	0.277	0.842
Türkiye	0.830	0.880	0.878	0.924	0.871	0.778
Uruguay	0.577	0.808	0.843	0.166	0.998	1.000
United States	0.200	0.115	0.247	0.714	0.376	0.159
Samoa	0.020	0.010	0.095	0.408	0.372	0.412
South Africa	0.125	0.245	0.930	0.195	0.315	0.972

Figure A.19: Pseudo Out-of-sample Inflation Forecasts with Global and Regional Factors: Select Advanced Economies



Note: The gray dashed lines show annualized inflation, $\pi_{i,t}$, for select countries, i, measured as a four-quarter log difference in the total CPI. The black solid lines show the inflation forecasts from the AR(4) model estimated using quarterly log differences in the total CPI and augmented with four lags of the global inflation factor and of the regional inflation factor. The forecasts are annualized using four-quarter moving sums.

Figure A.20: Pseudo Out-of-sample Inflation Forecasts with Global and Regional Factors: Select Emerging-market and Developing Economies



Note: The gray dashed lines show annualized inflation, $\pi_{i,t}$, for select countries, i, measured as a four-quarter log difference in the total CPI. The black solid lines show the inflation forecasts from the AR(4) model estimated using quarterly log differences in the total CPI and augmented with four lags of the global inflation factor and of the regional inflation factor. The forecasts are annualized using four-quarter moving sums.