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Inflation shocks: quantile unit root inference for panel data with cross-correlations☆

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ABSTRACT

The growing empirical literature documents evidence on persistence of shocks to inflation; however, little is known about the nature of inflation shocks with asymmetric persistence and cross-correlations. By introducing panel quantile unit root approach with common shocks for a sample of 75 countries from January-1980 to December-2022, this study provides new insights on the persistence of inflation shocks. The panel quantile unit root analysis sheds light on that (i) inflation appears to exhibit significant cross-correlations across countries at all quantiles, and persistence of inflation shocks shifts notably between low and high quantiles, reflecting asymmetric persistence in inflation dynamics, (ii) inflation rates tend to be mean reverting during low to moderate inflation periods, but more persistent in high inflation period, (iii) inflation becomes persistent at higher thresholds in countries with a history of inflationary episodes. These findings reveal the importance of considering asymmetric persistence and cross-correlations for analyzing inflation shocks.

1. Introduction

Investigating the persistence of inflation shock is an important research area in macroeconomic analysis, which carries insightful policy implications. While lower persistence indicates that shocks dissipate quickly and are less costly to address, high persistence often necessitates comprehensive policy actions. From the point of empirical modelling, early approaches relied on conventional univariate unit root tests to determine whether inflation shocks are stationary (temporary) or nonstationary (persistent), with varying results across countries and time periods (Evans and Wachtel, 1993; Hassler and Wolters, 1995).

One caveat to conventional unit root analysis is the low power, possibly arising from univariate perspective. To overcome this issue,

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panel unit root approaches are suggested since they have increasing power by combining information from both cross-section and time dimensions. One important advancement in the panel unit root literature is the consideration of cross-correlations (co-movement or cross-section dependency) across individuals in a panel.[1] Another caveat to conventional (time series and panel) unit root analysis is the strict assumption on the constant speed of adjustment process over the whole period; and quantile unit root approaches have gained their importance to account for asymmetric analyzes of persistence with respect to different magnitudes of (negative and positive) shocks under non-normal distributions.[2]

To analyze the nature of shocks to inflation, even though more recent studies conduct either quantile unit root approaches to capture asymmetric persistence or panel unit root methods to account for cross-correlations, no study to date has accounted for asymmetric persistence and cross-correlations together. This gap in the empirical literature may provide room for jointly addressing these characteristics of inflation to gain new insights into better understanding the nature of inflation shocks.

This study investigates the nature of shocks to inflation with a focus on simultaneously accounting for asymmetric persistence and cross-correlations by employing a recently developed panel quantile unit root approach. A snapshot of our comprehensive results, from a sample of 75 countries from January-1980 to December-2022, indicates that (i) inflation appears to exhibit significant cross-correlations across countries at all quantiles, and persistence of inflation shocks shifts notably between low and high quantiles, reflecting asymmetric adjustment process in inflation dynamics, (ii) inflation rates tend to be mean-reverting during low to moderate inflation periods, but are more persistent in high-inflation periods, (iii) inflation becomes persistent at higher thresholds in countries with a history of inflationary episodes.

This paper contributes to the literature by examining persistence under joint presence of distributional heterogeneity and cross-sectional dependence. To clarify our contribution within the context of econometric modelling, the quantile unit root tests without common factors (among others, Koenker and Xiao, 2004; Li and Park, 2018) attribute all dependence to idiosyncratic components. The factor-based panel unit root tests without quantiles (see Bai and Ng, 2004; Pesaran, 2007), in contrast, focus on mean dynamics allowing cross-correlations and therefore mask asymmetric persistence across tails of distribution.[3] The panel unit root tests with non-linear dynamics (for instance Lee et al. 2016; Nazlioglu et al., 2023) model regime changes over time but do not characterize heterogeneity in persistence across conditional distribution. Thus, existing approaches address cross-correlations and asymmetric behavior in isolation. The panel quantile unit root framework explicitly allows persistence to vary across quantiles while simultaneously controlling for common factors. It further controls structural changes in the degree of persistence, being a less sensitive to outliers and extreme values. Thus, it enables better understanding complex dynamics of inflation, which may not be adequately addressed by assuming constant unit root dynamics or ignoring cross-correlations.

We also contribute to the literature by examining a large sample of 75 countries with different economic backgrounds. We categorize these countries into high-income, upper-middle-income, and lower-middle-income groups to conduct a detailed analysis across different income categories. Finally, we present a simple and intuitive approach to identify threshold levels for persistence within the quantile framework. It allows to pinpoint the specific inflation rates for countries where inflation becomes persistent and thus better understand the dynamics of inflation persistence.

In the remainder of this paper, Section 2 presents a literature review; Section 3 introduces the methodology; Section 4 describes the data; Section 5 presents the empirical findings; and Section 6 is devoted to the discussion and concluding remarks.

2. Literature review

2.1. Sources of inflation asymmetry and cross-correlations

Inflation dynamics often display asymmetric behavior and cross-correlations across economies due to a combination of microeconomic frictions, institutional arrangements, and the transmission of common shocks. These features arise naturally even in the absence of explicit nonlinear policy rules or country-specific structural breaks.[4]

A key source of inflation asymmetry stems from price-setting frictions as outlined by Ball and Mankiw (1994) and Nakamura and Steinsson (2008). When firms face costs of adjusting prices, they tend to respond differently to positive and negative shocks. In an environment with positive trend inflation, upward price adjustments occur more frequently than downward adjustments, as firms seek to avoid eroding real margins. This asymmetry is reinforced when cost shocks are persistent or when firms anticipate future inflation,

[1] Several studies note that a panel estimator can be biased without correcting for the effects of cross-correlations (among others, Pesaran, 2006; Bai, 2009). The same issue can arise in unit root tests, and a test ignoring cross-correlations can produce biased results (Bai and Ng, 2004; Pesaran, 2007), which can lead to greater or fewer rejections of a true null hypothesis (Nazlioglu et al., 2023). As global factors are pronounced sources of inflation, ignoring co-movement may lead to overestimating the importance of domestic factors (Ciccarelli and Mojon, 2010) and may further pose challenges for policymakers in responding to inflation shocks. We refer to Ha et al. (2019a) and Ha et al. (2019b) for the comprehensive reviews of the literature on inflation co-movement.

[2] Inflation often deviates from the normal distribution and displays skewed and leptokurtic patterns (Charemza et al., 2005); thus, it may exhibit asymmetric behavior in different (low and high) inflation regimes. Structural breaks, policy changes, and varying economic conditions can lead to non-normal distributions, asymmetry, and non-linearity in inflation (Kumar and Okimoto, 2007).

[3] The panel unit root tests, ignoring cross-correlations, tend to exhibit not only size distortions see, Gengenbach et al., 2006), but also lack of power unless dependencies are modeled properly (see, Banerjee and Carrion-i-Silvestre, 2015).

[4] See Akdoğan (2015) and Aslanidis et al. (2024) for discussions on how inflation-targeting central banks react asymmetrically to deviations from their target in the process of extended period of low inflation.

Table 1
Panel statistics.

	Full Panel (N = 75)			High income (N = 34)			Upper-middle income (N = 20)			Lower-middle income (N = 21)		
	Statistic		p-val.	Statistic		p-val.	Statistic		p-val.	Statistic		p-val.
IPS	−25.363	***	0.000	−14.547	***	0.000	−14.229	***	0.000	−15.579	***	0.000
PANIC	17.313	***	0.000	6.336	***	0.000	20.642	***	0.000	20.792	***	0.000
CIPS	−4.133	***	0.000	−4.069	***	0.000	−4.464	***	0.000	−4.366	***	0.000
IPS(τ)												
0.1	−132.55	***	0.000	−23.030	***	0.000	−11.267	***	0.000	−446.110	***	0.000
0.2	−12.246	***	0.000	−6.392	***	0.000	−18.898	***	0.000	−15.214	***	0.000
0.3	−10.496	***	0.000	−5.694	***	0.000	−20.018	***	0.000	−8.662	***	0.000
0.4	−6.154	***	0.000	−4.461	***	0.000	−8.753	***	0.000	−6.302	***	0.000
0.5	−3.552	***	0.000	−2.730	***	0.000	−4.838	***	0.000	−3.600	***	0.000
0.6	−1.269	**	0.022	−1.056		0.503	−1.490	***	0.008	−1.400	**	0.041
0.7	1.031		1.000	0.198		1.000	1.492		1.000	1.965		1.000
0.8	3.814		1.000	1.609		1.000	4.580		1.000	6.758		1.000
0.9	8.403		1.000	4.300		1.000	5.744		1.000	18.171		1.000
CIPS(τ)												
0.1	−5.122	***	0.000	−4.717	***	0.000	−5.228	***	0.000	−5.698	***	0.000
0.2	−5.356	***	0.000	−5.018	***	0.000	−5.421	***	0.000	−5.863	***	0.000
0.3	−5.194	***	0.000	−4.788	***	0.000	−5.499	***	0.000	−5.563	***	0.000
0.4	−4.589	***	0.000	−4.064	***	0.000	−4.862	***	0.000	−5.197	***	0.000
0.5	−3.501	***	0.000	−3.006	***	0.000	−3.928	***	0.000	−3.894	***	0.000
0.6	−2.142	***	0.000	−1.839	***	0.000	−2.501	***	0.000	−2.281	***	0.000
0.7	−0.954		0.995	−1.067		0.954	−1.034		0.975	−0.679		1.000
0.8	−0.110		1.000	−0.259		1.000	−0.127		1.000	0.162		1.000
0.9	0.479		1.000	0.237		1.000	0.410		1.000	0.962		1.000
CD tests												
CD	51.120	***	0.000	51.956	***	0.000	7.404	***	0.000	10.840	***	0.000
CD(τ)												
τ = 0.1	107.525	***	0.000	73.896	***	0.000	30.734	***	0.000	25.297	***	0.000
τ = 0.2	78.126	***	0.000	62.803	***	0.000	18.409	***	0.000	18.402	***	0.000
τ = 0.3	62.722	***	0.000	56.641	***	0.000	12.734	***	0.000	14.175	***	0.000
τ = 0.4	54.300	***	0.000	53.905	***	0.000	8.702	***	0.000	11.797	***	0.000
τ = 0.5	48.825	***	0.000	52.213	***	0.000	6.324	***	0.000	9.946	***	0.000
τ = 0.6	46.904	***	0.000	52.017	***	0.000	4.467	***	0.000	9.239	***	0.000
τ = 0.7	47.030	***	0.000	52.280	***	0.000	4.107	***	0.000	9.330	***	0.000
τ = 0.8	50.045	***	0.000	53.197	***	0.000	6.087	***	0.000	9.684	***	0.000
τ = 0.9	58.106	***	0.000	55.379	***	0.000	10.613	***	0.000	10.811	***	0.000

Notes: IPS is the panel unit root test of Im et al. (2003) and PANIC is the panel unit root test of Bai and Ng (2004). The optimal number of factors for PANIC test is selected by the IC_2 panel information criterion of Bai and Ng (2002) by setting maximum number of factors to 5. *CIPS* and *CIPS*(τ) are based on the truncated individual CADF and CADF (τ). p-values for *IPS* and *PANIC* are based on the asymptotic standard normal distribution. p-values for *CIPS* and *CIPS*(τ) are based on the simulated statistics with 10,000 Monte Carlo replications (see Pesaran, 2007; Yang et al. 2022). CD (cross-section dependency) test of Pesaran (2021) are based on the residuals from the OLS estimation of y_{it} on $(1, y_{it-1}, \Delta y_{it})'$. CD ($\tau$), the quantile counterpart of CD test, are based on the residuals from the quantile regression estimation of y_{it} on $(1, y_{it-1}, \Delta y_{it})'$. p-values for CD and CD (τ) are based on the standard normal distribution. ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10%, respectively. p-value < 0.01 (1%), p-value < 0.05 (5%), and p-value < 0.1 (10%).

leading to a stronger pass-through of positive shocks relative to negative ones.

Labor market rigidities provide an additional mechanism generating asymmetric inflation dynamics. As outlined by Akerlof et al. (1996) and Smith (2000), nominal wages typically adjust upward more easily than downward due to contractual arrangements, institutional constraints, and coordination problems among workers and firms. As a result, inflationary pressures induced by wage increases tend to persist, while disinflationary forces originating from labor markets are muted. This asymmetry is further amplified when expectations adjust slowly, causing wage growth to remain elevated even after inflation begins to decelerate.

Asymmetric inflation responses also emerge from monetary policy transmission. Central banks often exhibit nonlinear responses to inflation deviations, either implicitly or explicitly, due to concerns about credibility, financial stability, or the zero lower bound. Such asymmetries imply stronger policy reactions to inflationary pressures than to disinflationary ones (Poole, 1988), generating uneven persistence across different inflation regimes. These policy-induced nonlinearities interact with private-sector expectations, further reinforcing asymmetric inflation dynamics. Guerra et al. (2025) argue that inflation expectations tend to become unanchored when inflation deviates further above its target, making disinflationary action more necessary. In such environments, the role of expectations and policy communication play a central role in shaping inflation persistence. In this context, Tetlow (2024) suggests that prompt and credible interventions can limit the persistence of expectations, thereby lowering the cost of disinflation. Consistent with the communication channel, favorable media coverage of monetary policy strengthens the transmission of policy signals to the public, shaping expectations and enhancing the effectiveness of disinflationary actions (see, Doan et al., 2024).

Cross-correlations in inflation arise primarily from exposure to common shocks, interconnected economic structures, and (internationally) coordinated monetary and fiscal policies. Global supply chains, integrated financial markets, and synchronized policy responses transmit shocks across economies, inducing correlated inflation movements. Cost shocks originating in energy, commodities, or intermediate inputs propagate through production networks, affecting prices in multiple economies simultaneously. The degree of pass-through and persistence of these shocks may vary across countries, but their common origin generates cross-sectional dependence in inflation rates.

Financial linkages also contribute to inflation co-movements by synchronizing credit conditions and aggregate demand. Changes in global financial conditions influence borrowing costs, investment, and consumption across economies, leading to correlated inflation responses. When financial cycles are aligned, inflation dynamics tend to co-move even in economies with otherwise distinct structural characteristics. Besides, trade policy uncertainty weakens both domestic and foreign investment by raising the cost of irreversible investment and inducing firms to adopt a wait-and-see behavior, thereby amplifying synchronized demand fluctuations across economies (Akyuz et al., 2024). Importantly, asymmetry and cross-correlations are mutually reinforcing. Common shocks may generate heterogeneous inflation responses across economies depending on institutional rigidities, while asymmetric adjustment mechanisms can amplify or dampen the transmission of global shocks. Consequently, inflation dynamics exhibit both regime dependence and cross-sectional dependence, underscoring the need for analytical frameworks that allow for nonlinear behavior and common factors simultaneously.

2.2. Empirical literature

Empirical research on inflation persistence has developed alongside growing recognition of asymmetric dynamics and cross-sectional dependence in inflation processes. Early studies predominantly rely on linear unit root tests, most notably the Augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1979). Beginning with the seminal contribution of Nelson and Plosser (1982), a large body of work—including Evans and Lewis (1995), Crowder and Hoffman (1996), and Crowder and Wohar (1999)—finds that inflation exhibits non-stationary behavior. Nonetheless, Rose (1988) in contrast to these studies uncovers the stationarity of inflation shocks in US.

Linear unit root tests suffer from low power when data generation process is characterized by nonlinear adjustment, and threshold-type behavior substantially weakens the ability of linear tests to detect mean reversion (see Balke and Fomby, 1997). Motivated by this insight, several studies adopt nonlinear unit root frameworks, particularly smooth transition autoregressive models to capture regime-dependent inflation dynamics (Kapetanios et al., 2003; Cuestas and Harrison, 2010; Arize and Malindretos, 2012; Osman, 2021). These studies provide evidence that inflation persistence varies across regimes, consistent with asymmetric adjustment mechanisms emphasized in theoretical models. More recently, quantile autoregression–based unit root tests, introduced by Koenker and Xiao (2004), offer a distributional perspective on inflation persistence by allowing persistence to differ across conditional quantiles. Empirical findings from this literature reveal pronounced asymmetries, by documenting stationary process in lower quantiles and unit root or near-unit-root behavior in upper quantiles. For example, inflation persistence declines in the Euro Area following the establishment of the EMU (Beechey and Österholm, 2009), while evidence from Turkey (Çiçek and Akar, 2013), MENA countries (Bolat et al., 2017), Brazil (Gaglianone et al., 2018), and the United States (Manzan and Zerom, 2015; Wolters and Tillmann, 2015) indicates that inflation dynamics differ markedly between low- and high-inflation regimes.

A growing literature documents co-movements of inflation rates across countries by means of factor model approaches (see inter alia, Ha et al., 2019a; Ha et al., 2019b; Nazlioglu et al., 2025). Increasing co-movement of inflation emerges an importance of accounting for cross-correlations to examine persistence of inflation shocks within the panel data framework. Consistent with this view, the literature using panel unit root framework evolves from early approaches assuming cross-sectional independence (Culver and Papell, 1997; Lee and Wu, 2001; Lee and Chang, 2007) toward approaches accounting for common factors. For instance, Ho (2009) demonstrates that inflation appears non-stationary (stationary) in OECD countries when cross-sectional dependence is (not) ignored. Basher and Westerlund (2008), Romero-Ávila and Usabiaga (2009), and Hurlin (2010), similarly highlight the crucial role of cross-sectional dependence in shaping persistence properties.

The literature documents that inflation exhibits asymmetric persistence across regimes and cross-correlations across economies. The existing studies address these features separately and this gap in the literature motivates empirical frameworks jointly accounting for distributional heterogeneity and cross-correlations.

3. Methodology

3.1. Panel unit root test with cross-correlations

We utilize the panel unit root framework when testing the stationarity of inflation rates. The literature on panel unit root testing emphasizes the importance of accounting for cross-sectional heterogeneity and correlations within a panel framework. The panel unit root tests, ignoring cross-correlations, tend to exhibit not only size distortions, but also lack of power unless dependencies are modeled properly (see among others Bai and Ng, 2004; Pesaran, 2006). To capture cross-correlations, we employ a heterogeneous panel data model within a factor model suggested by Pesaran (2007), defined as:

$$y_{it} = \alpha_i + \rho_i y_{it-1} + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \lambda_i z_t + e_{it} \tag{2}$$

where y_{it} is the inflation rate; $i = 1, \cdots, N$ is the cross-section dimension; $t = 1, \cdots, T$ represents the time dimension; α_i denotes fixed effects; z_t is the unobserved common factor, which captures cross-sectional dependence arising from cross-correlations; λ_i shows the factor loadings; and e_{it} defines an idiosyncratic error.[5]

The unobserved common factor z_t is estimated with the cross-sectional averages of observed data given by $\bar{y}_{t-1}$ and $\Delta\bar{y}_t$ for large N where $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$ and $\Delta\bar{y}_t = N^{-1}\sum_{i=1}^{N}\Delta y_{it} = \bar{y}_t - \bar{y}_{t-1}$. The cross-sectionally augmented Dickey-Fuller (CADF) regression model is defined as

$$y_{it} = \alpha_i + \rho_i y_{it-1} + a_i\bar{y}_{t-1} + b_i\Delta\bar{y}_t + e_{it}. \tag{3}$$

Note that e_{it} is not serially correlated, the CADF regression is extended by including the lagged first differences of both y_{it} and $\bar{y}_t$ to correct for a serial correlation in common and idiosyncratic components, given by

$$y_{it} = \alpha_i + \rho_i y_{it-1} + a_i\bar{y}_{t-1} + \sum_{j=0}^{p} b_{ij}\Delta\bar{y}_{t-j} + \sum_{j=1}^{p} c_{ij}\Delta y_{it-j} + e_{it} \tag{4}$$

The null hypothesis of a unit root is defined as $H_0 : \rho_i = 1$ for all i, against the alternative hypothesis, given by $H_1 : \rho_i < 1 \text{ for } i = 1, \cdots, N_1$ and $\rho_i = 1 \text{ for } i = N_1 + 1, \cdots, N$ where $\frac{N_1}{N} \to \delta$ with $0 < \delta \leq 1$ as $N \to \infty$. The alternative hypothesis hence accommodates variation in ρ_i across cross-sections and allows for the presence of a unit root in certain cross-sections. The null hypothesis is tested by the t-ratio of ρ_i, referred to as CADF statistic. The panel statistic, denoted as CIPS, is then calculated as the average of individual statistics, with

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{5}$$

Note that $CADF_i$ statistics are asymptotically similar but are asymptotically correlated due to the common factor. Since this correlation causes CIPS statistic to have a non-standard distribution, Pesaran (2007) suggests obtaining panel statistic based on the truncated version of $CADF_i$.

3.2. Quantile panel unit root test with cross-correlations

Yang et al. (2022) introduce a quantile unit root inference for panel data with cross correlations, which can serve as a quantile counterpart of CADF and CIPS statistics. The quantile regression version of equation (4) can be written as

$$Qy_{it}(\tau|\Im_{t-1}) = \alpha_i + \rho_i y_{it-1} + a_i\bar{y}_{t-1} + \sum_{j=0}^{p} b_{ij}\Delta\bar{y}_{t-j} + \sum_{j=1}^{p} c_{ij}\Delta y_{it-j} + F^{-1}e_i(\tau) \tag{6}$$

where Qy_{it} denotes the τ th conditional quantile of y_{it} and $\Im_{t-1}$ is the information contained in $\{z_1, \cdots, z_t; e_{11}, \cdots, e_{1,t-1}; \cdots; e_{N1}, \cdots, e_{N,t-1}\}$. The null hypothesis of a unit root in this setup is expressed as $H_0 : \rho_i(\tau) = 1$ for all i and τ against the alternative of stationarity, defined as $H_1 : \rho_i(\tau) < 1 \text{ for } i = 1, \cdots, N_1$ and $\rho_i(\tau) = 1 \text{ for } i = N_1 + 1, \cdots, N$ for a given τ. The panel quantile statistic, denoted as $CIPS(\tau)$, is the average of individual t-ratio statistics, denoted as $CADF_i(\tau)$, is expressed as

$$CIPS(\tau) = \frac{1}{N}\sum_{i=1}^{N} CADF_i(\tau) \tag{7}$$

$$CADF_i(\tau) = \frac{\widehat{f}_{e_i}\left(F_{e_i}^{-1}(\tau)\right)}{\sqrt{\tau(1-\tau)}}\left(Y_{i,-1}' P_X Y_{i,-1}\right)^{1/2}(\widehat{\rho}_i(\tau) - 1) \tag{8}$$

where $Y_{i,-1}$ is the vector of lagged dependent variables (y_{it-1}), P_x is the projection matrix on the space orthogonal to $x = \left(1, \bar{y}_{t-1}, \Delta\bar{y}_{t-j}, \Delta y_{t-j}\right)$ and $\widehat{f}_{e_i}\left(F_{e_i}^{-1}(\tau)\right)$ is a consistent estimator of $f_{e_i}\left(F_{e_i}^{-1}(\tau)\right)$. Yang et al. (2022) demonstrate that the $CADF_i(\tau)$ statistics are not independent because of the common factor and propose using the truncated version of $CADF_i(\tau)$ to construct panel statistic.

[5] In estimating unobserved common factors, two approaches are the workhorse of industry, namely the principal components analysis (PCA) by Bai and Ng (2004) and the cross-sectional averages (CA) approach by Pesaran (2006, 2007). Notably, CA method is more straightforward to implement within a quantile regression framework, as demonstrated by Yang et al. (2022), enabling the derivation of more robust results. PCA provides consistent estimates of the factor space as $N, T \to \infty$ simultaneously (Bai and Ng, 2004), and CA method shares the same asymptotic properties but demonstrates better performance in small to medium-sized panels (Westerlund and Urbain, 2015; Reese and Westerlund, 2016).

3.3. Notes to implementation of tests

First, to clarify the implementation of tests, we estimate the common factor as the cross-sectional averages and employ it in all quantile estimations. Thus, in conjunction with Yang et al. (2022), the common factor is not estimated separately for each quantile.

Second, we employ uniform lag structure to obtain the panel unit root statistic, given by $\hat{p} = [4(T/100)]^{1/4}$, which follows from Bai and Ng (2004), Pesaran (2007), and Yang et al. (2022).

Third, the truncated version of individual statistics is obtained as described in Pesaran (2007). Specifically, let the truncated statistic $CADF_i^* = CADF_i$ if $-K_1 < CADF_i < K_2$; $CADF_i^* = -K_1$ if $CADF_i \le -K_1$; and $CADF_i^* = K_2$ if $CADF_i \ge K_2$; with $K_1 = 6.19$ and $K_2 = 2.16$ for the model with an intercept (Pesaran 2007, p.35). The truncated $CADF_i(\tau)$ is obtained with the same way (Yang et al., 2022, p. 2).

Fourth, we follow Koenker and Xiao (2004, p. 780) to consistently estimate the quantile density function $f_{e_i}\left(F_{e_i}^{-1}(\tau)\right)$. It thus is estimated with $\overline{x}'(\hat{\rho}_i(\tau)(t+h_n) - \hat{\rho}_i(\tau)(t-h_n))$ where h_n is bandwidth that is defined as in Bofinger (1975). The 90 percent confidence intervals for $\hat{\rho}_i(\tau)$ is obtained with bootstrap sampling by setting the number of iterations to 10,000.

Finally, to obtain the empirical distribution of $CIPS(\tau)$, we follow the simulation procedure in Yang et al. (2022, p.2), including four steps: (i) We generate $y_{it} = \rho_i y_{it-1} + \lambda_i z_t + e_{it}$, with $\rho_i = 1\forall i$, $\lambda_i = 1\forall i$, z_t $i.i.d.N(0,1)$, e_{it} $i.i.d.N(0,1)$. (ii) We run quantile regression of y_{it} on $x_{it} = \left(1, y_{it-1}, \overline{y}_{t-1}, \Delta\overline{y}_t\right)$ for a given τ and obtain the truncated $CADF_i(\tau)$. (iii) We compute $CIPS$ and $CIPS(\tau)$ using the truncated individual statistics. (iv) We repeat steps (i)-(iii) with 10,000 replications to collect the simulated statistics for T = 500 and N = 75 to be consistent with our data. For the ease of presenting results succinctly and simplifying inferences, we use the empirical p-values, given by $\frac{1}{B}\sum_{b=1}^{B}\mathbb{I}\left(s_b^* < s\right)$, where $\mathbb{I}$ is the indicator function, B is the number of replications, s_b^* denotes the simulated statistic.[6]

4. Data

We employ monthly consumer price index (CPI) for 75 countries from January 1980 to December 2022. The CPI data were transformed into an annualized inflation rate, effectively beginning from January 1981. We collect the CPI data from the Global Database of Inflation by Ha et al. (2023). While the database provides a comprehensive set of inflation data for up to 186 countries over the period of January 1970- December 2023, differences in data availability across countries prevent the construction of a balanced panel over the full sample period. To construct a balanced panel for factor-based panel analysis, we exclude countries with insufficient time coverage. Thus, our panel consists of 75 countries over January 1980 to December 2022.[7] We thus select an optimal period that maximizes both coverage and continuity. In addition to conducting estimations for the full panel, including 75 countries, we employ sub-panels by categorizing the countries into high-income, upper-middle-income, and lower-middle-income groups to conduct a detailed analysis across different income categories.

Table A1 in the appendix provides descriptive statistics on annualized inflation for each country. The five countries with the lowest average annual inflation rate are Japan, Switzerland, Singapore, Taiwan, and Germany, while the five countries with the highest average annual inflation are Bolivia, Brazil, Peru, Slovenia, and Turkey, respectively. The coefficient of variation ranges from 0.424 in Botswana to 5.813 in Bolivia. The Jarque and Bera (1987) test rejects the null hypothesis of normality for 73 out of 75 countries, further highlighting the importance of employing the quantile unit root framework.

5. Empirical results

5.1. Importance and evaluation of common global factor

Our initial step involves testing the significance of cross-correlations through the cross-sectional dependence (CD) statistic proposed by Pesaran (2021), which tests the null hypothesis of zero cross-correlations (cross-sectional independence), $H_0 : cov\left(\varepsilon_{it}\varepsilon_{jt}\right) = 0\forall t$ and $\forall i \ne j$, against the alternative hypothesis of non-zero cross-correlations (cross-sectional dependence), $H_1 : cov\left(\varepsilon_{it}\varepsilon_{jt}\right) \ne 0$ for some t and some $i \ne j$. The CD statistic, presented at the bottom of Table 1, demonstrates that the null hypothesis is rejected at 1% significance level for the full and sub-panels. To further examine the significance of cross-correlations at various quantiles, we employ the quantile version of the CD test, denoted as $CD\ (\tau)$, by following Payne et al. (2025). The $CD\ (\tau)$ statistics, shown at the bottom of Table 1, further confirm that the null hypothesis is rejected at each quantile for all panels. These results, therefore, underscore the importance of conducting quantile unit root testing within a panel data framework by adopting a common factor approach to consider asymmetric persistence and cross-correlations.

To highlight the importance of common factor, it would be insightful to investigate whether the estimated common factor represents the global inflation dynamics. In that respect, we plot the estimated common factors (cross-section averages) for the full and

[6] The replication code is available upon request from corresponding author.

[7] Note that the number of countries reduces to 55 over January 1980 – December 2023.

sub-panels in Fig. 1A.[8] At the first glance, the estimated common factors from each panel are in tandem, with almost overlapping lines. This close alignment signals the importance of global inflationary forces affecting countries.

The dynamics of estimated global factors appear to be consistent with the global inflation dynamics. Major inflationary and disinflationary episodes—notably the early 1980 s disinflation, the late-1980 s inflationary pressures, the sharp decline during the global financial crisis, and the recent post-pandemic inflation surge—are clearly synchronized across groups, shedding a light on dominance of common shocks. At the same time, differences in amplitude reveal heterogeneity in inflation transmission, with lower and upper-middle income economies exhibiting more pronounced fluctuations than high income countries, particularly during periods of global shocks.

These observations overall reveal that inflation dynamics tend to be driven by global factors, but country characteristics can still play a role to shape inflation dynamics in response to common shocks. To assess to what extend factor structure explains variation of inflation rates, we plot the variance explained by the estimated common factor in Fig. 1B. Note that a higher share of common factor in the explained variance implies a higher degree of inflation co-movement. The results indicate that global factor accounts for a substantial portion of inflation fluctuations, explaining about 42% of variance in the full panel. The importance of global factor is strongest in high-income economies, where it exceeds 60%, reflecting a high degree of inflation co-movement driven by common shocks. In contrast, the contribution of global factor declines to 39% and 28% and for upper-middle and lower-middle income economies, respectively. This finding suggests that country-specific shocks and domestic policy factors play a relatively larger role in shaping inflation dynamics in these economies.

Given that common global shocks appear to drive co-movement of inflation rates, as captured by the estimated common factor, it is informative to examine the relationship between this factor and key global variables. In reference to the empirical literature on inflation co-movement (inter alia, Ha et al., 2019a; Ha et al., 2019b; Nazlioglu et al., 2025; and references therein), we employ industrial production index, interest rate, money supply, exchange rate, and commodity prices.[9] We regress the estimated common factor on each of observables and report R-square in Fig. 1C to evaluate the correlation between estimated factor and observed variables.

The estimated common inflation factor is strongly correlated with global macro-financial conditions rather than commodity-specific shocks. Across all panels, a large share of variation in the factor is explained by variation in interest rates, industrial production, and exchange rate, highlighting the central role of global monetary and real activity forces in shaping inflation. The explanatory power of these variables is particularly pronounced for high- and upper-middle-income economies, consistent with stronger financial integration and more synchronized policy cycles. In comparison to these global macro-financial variables, correlations with commodity prices—especially oil and food—are relatively weaker. Thus, global inflation dynamics appear to be primarily driven by demand and financial factors, with heterogeneous transmission across income groups.

5.2. *Inflation persistence*

Table 1 represents the results from panel unit root tests. In addition to CIPS test of Pesaran (2007), we employ IPS test of Im et al. (2003) and PANIC test of Bai and Ng (2004) for the sake of a comprehensive and robust analysis. Given that inflation dynamics can be characterized by heterogeneous country-specific behavior, common global shocks, and varying degrees of cross-sectional dependence, relying on a single panel unit root test may lead to incomplete or misleading conclusions regarding inflation persistence. Employing IPS, CIPS, and PANIC panel unit root tests allows for a comprehensive and robust assessment of persistence by addressing different sources of heterogeneity and cross-sectional dependence. IPS test accommodates heterogeneity in autoregressive dynamics across cross-sectional units but assumes cross-sectional independence, making it informative as a baseline benchmark. CIPS test relaxes this assumption by explicitly controlling for common factors through cross-sectional averages, thereby providing robustness to weak and moderate cross-sectional dependence. PANIC approach further decomposes panel data into common and idiosyncratic components, enabling separate inference on whether non-stationarity originates from pervasive common shocks or unit-specific dynamics. Using these complementary tests jointly ensures that conclusions regarding inflation persistence are not driven by restrictive assumptions about cross-sectional dependence or homogeneity and allows for a clearer interpretation of the underlying sources of inflation dynamics.

IPS, PANIC, and CIPS statistics reject the null hypothesis of a unit root in favor of the alternative hypothesis of stationarity at 1% significance level for all panels. This result suggests that inflation does not exhibit persistence for either full panel or income-based subpanels. The mean-based panel unit root tests together indicate that inflation shocks, arising from whether global or country-specific factors, do not generate permanent effects on inflation levels. Instead, inflation rates tend to revert to its long-run levels despite heterogeneity across countries and exposure to common shocks.

Nonetheless, it is important to note that while the mean-based panel unit root approach provides a general information about inflation persistence, and it does not account for potential asymmetries in inflation behavior. To gain a more comprehensive understanding of persistence dynamics of inflation, we concentrate on the panel quantile unit root analysis. The CIPS(τ) statistic rejects the null hypothesis of a unit root at 1% significance level from 10 to 60 percent quantiles for all panels. These results suggest that inflation

[8] Note that Fig. 1 plots the common factor from the standardized data, which is used as natural interpretation of normalized global inflation index (with zero mean and unit variance), wherein negative (positive) values represent below (above) average inflation for the whole sample (Parker, 2018).

[9] See notes to Fig. 1C for definition and data source of observed variables.

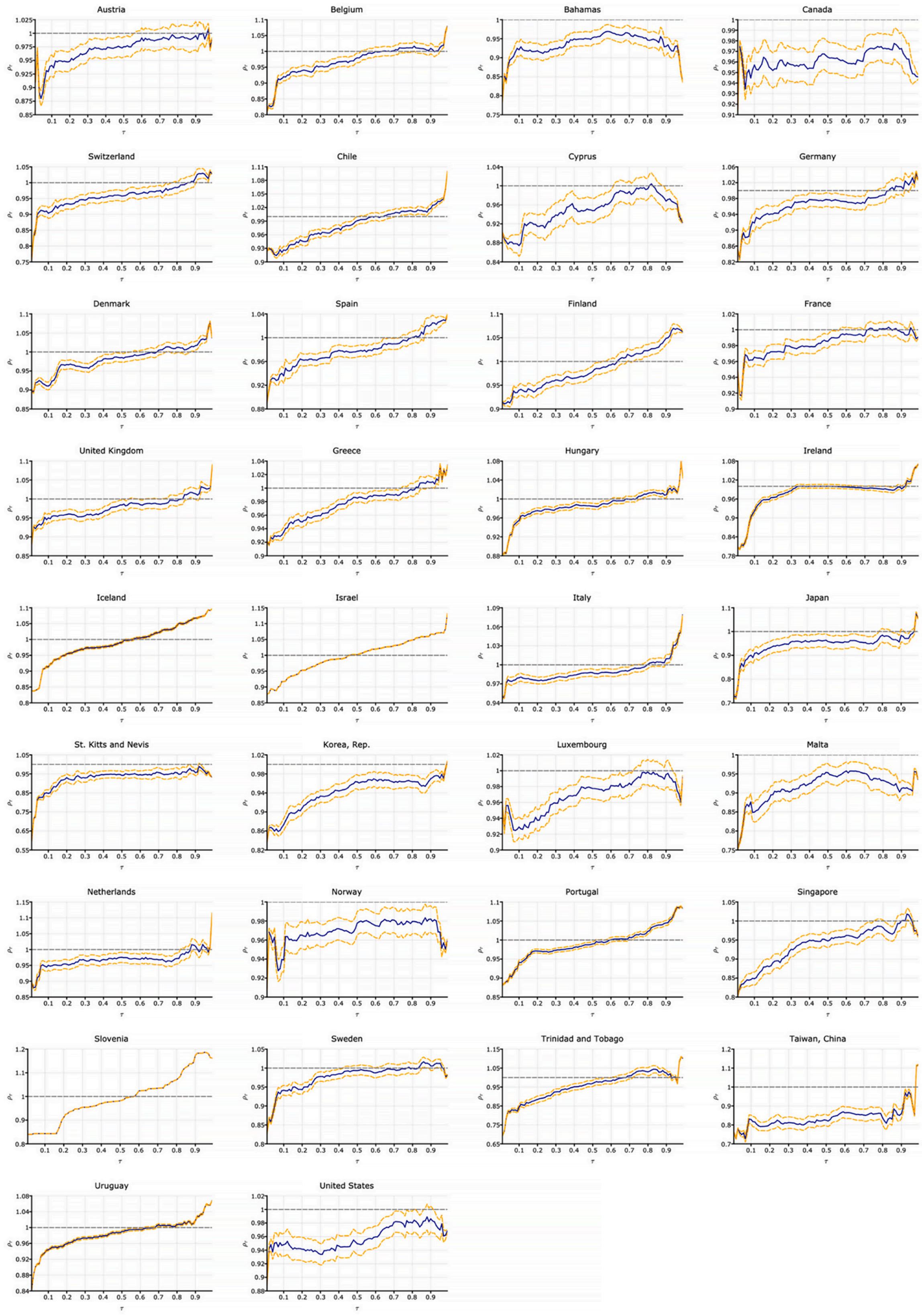

Fig. 2. Degree of persistence in high income countries.

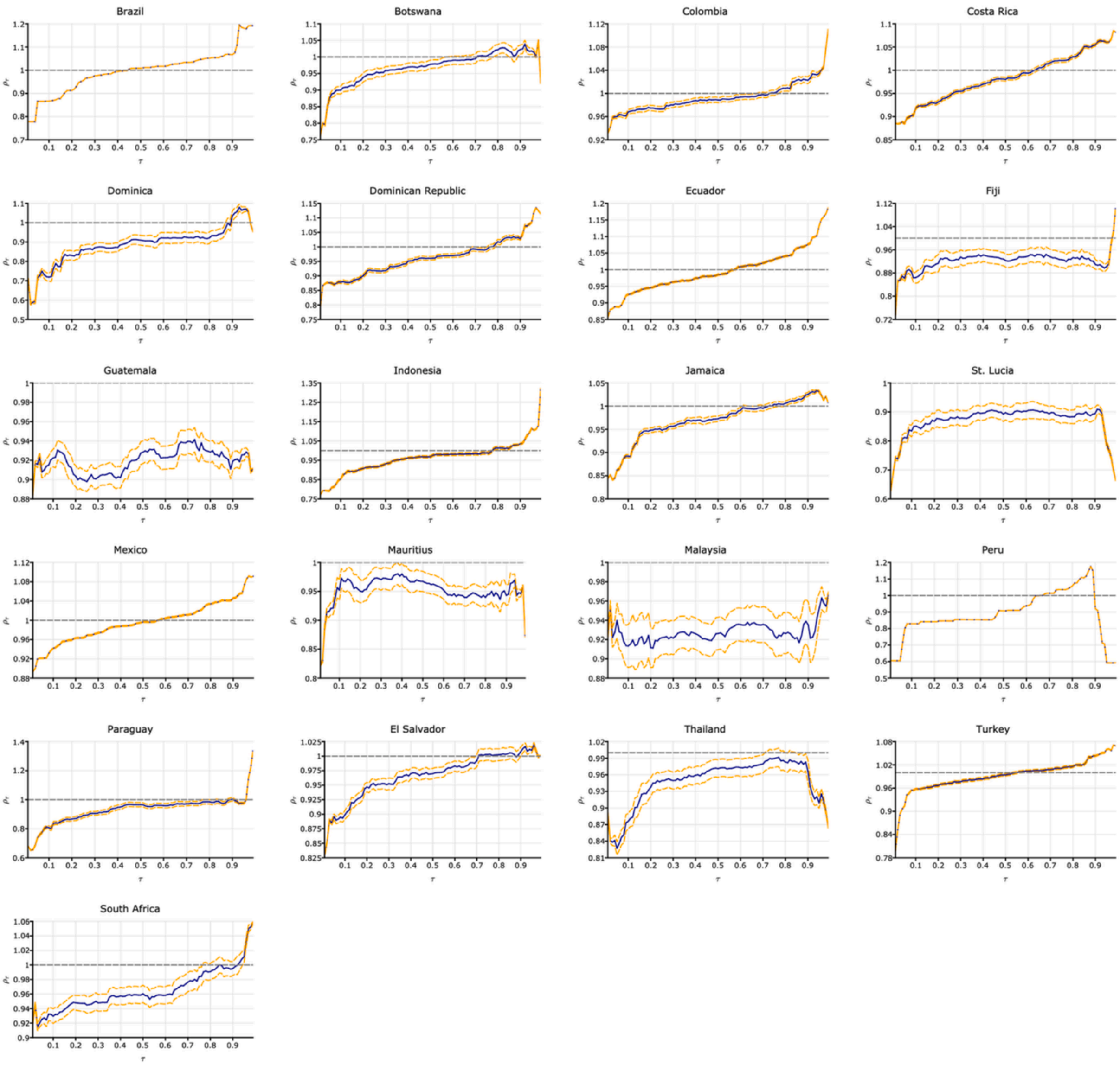

Fig. 3. Degree of persistence in upper-middle income countries.

exhibits asymmetric persistence; and this asymmetry seems robust to common shocks. Thus, the findings unveil the importance of employing quantile autoregressive unit root tests, as inflation behavior varies significantly across quantiles.

To assess whether similar pattern from the quantile autoregressive model with common factor emerges, we carry out unit root analysis based on the quantile autoregressive model without common factor. To this end, we estimate equation (6) without common factor terms ($\overline{y}_{t-1}$ and $\Delta\overline{y}_t$) and construct the panel quantile unit root statistic, denoted as IPS(τ), as the average of individual quantile unit root statistic which is equivalent to that of Koenker and Xiao (2004). The same result from CIPS(τ) statistic, with an exception, is provided by means of IPS(τ) statistic. The exception is uncovered for the high-income panel wherein IPS(τ), as opposite to CIPS(τ), cannot reject null hypothesis at the quantile 0.6.

The rejection of the null hypothesis does not necessarily mean that inflation exhibits a stationary process in all countries because the alternative hypothesis allows some cross-sections to still contain a unit root. Investigating country-specific results may deepen our insights on how positive and negative shocks can affect unit root dynamics. The individual results are reported in Appendix Table A2 for the full-panel and in Appendix Table A3 for the sub-panels.

For the full panel, CADF test rejects the null hypothesis of a unit root in 60 out of 75 cross-sections, providing limited evidence for inflation persistence. On the other hand, CADF(τ) statistics uncover an asymmetric persistence, by providing evidence on persistent/temporary inflation shocks at higher/lower quantiles. In particular, CADF(τ) test rejects the unit root null hypothesis for 73 countries

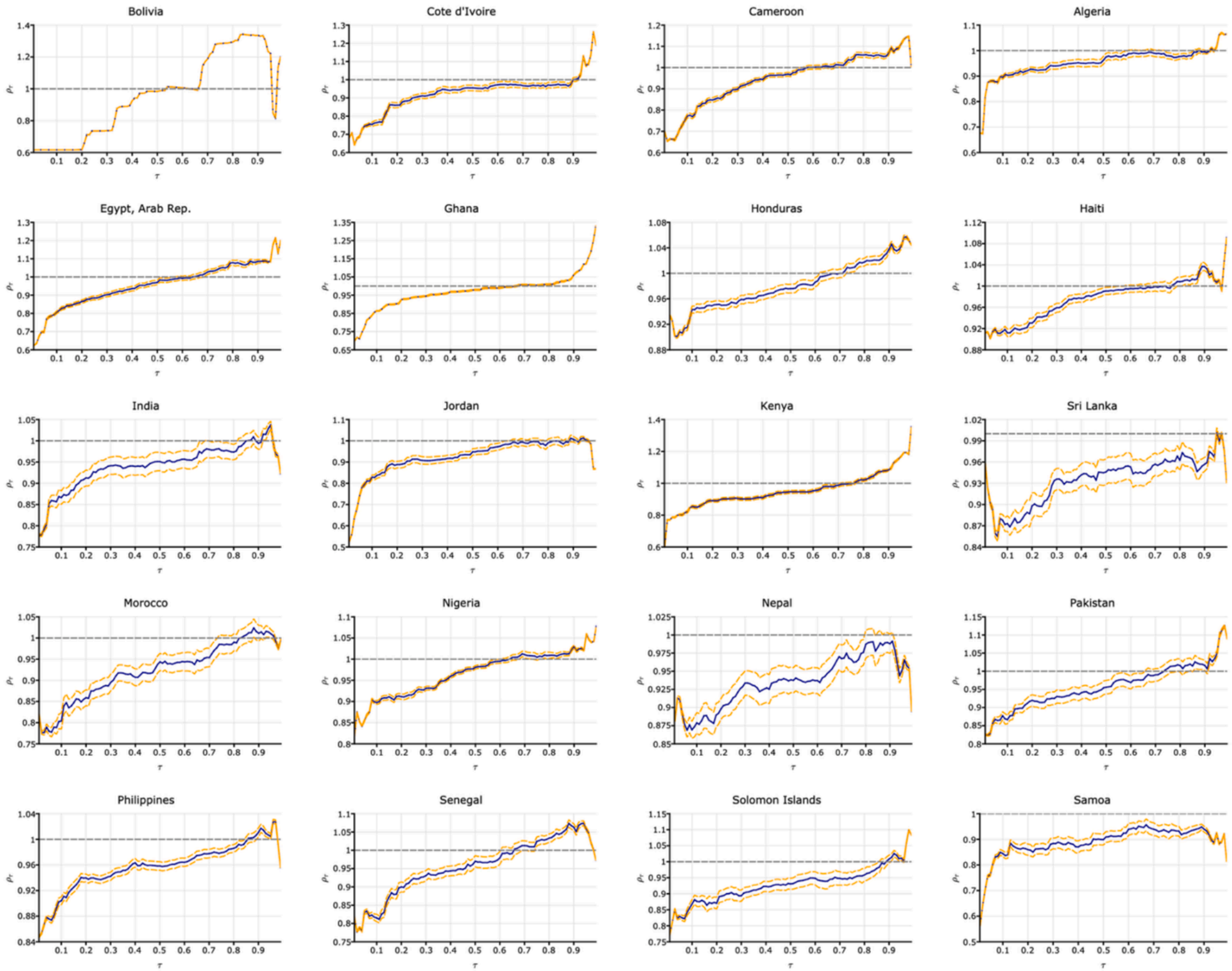

Fig. 4. Degree of persistence in lower-middle income countries.

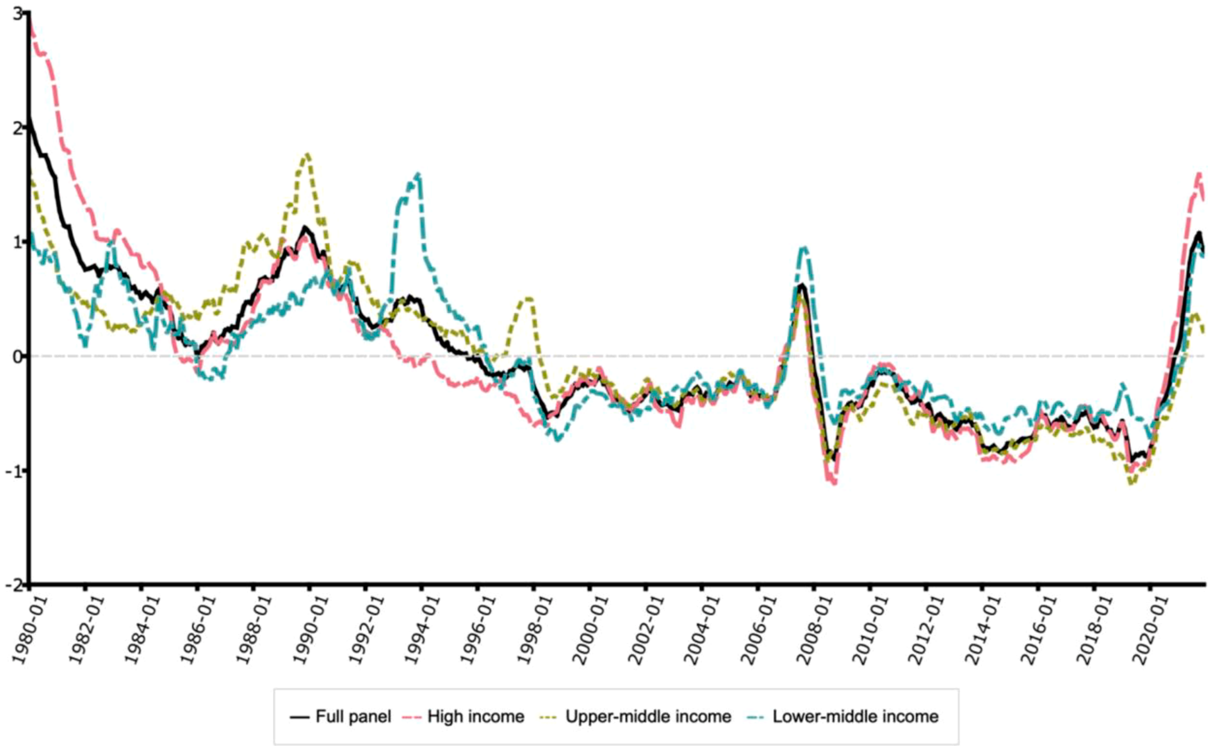

Fig. 1A. Estimated common factors.

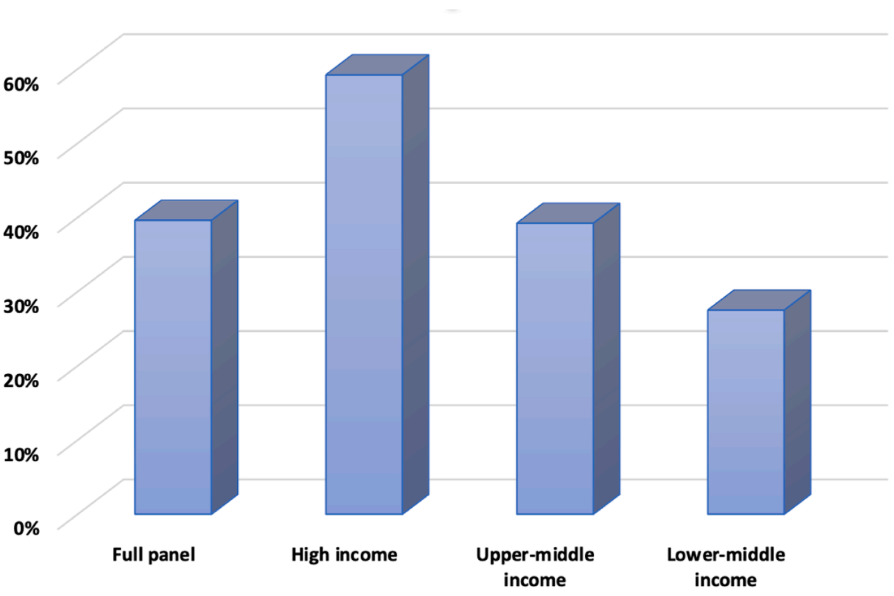

Fig. 1B. Explained variance by common factor, Notes: The sample size N = 75 for full panel, N = 34 for high income, N = 20 for upper-middle income, and N = 20 for lower-middle income. The estimated common factor denotes the cross-sectional averages of N countries for each year (see Pesaran, 2007). The explained variance represents the percentage contribution of the estimated common factor to the variance of inflation as an average for N countries. The estimations were based on the demeaned and standardized inflation data.

at the 10 percent quantile, 67 countries at the median (50 percent quantile), and 9 countries at the 90 percent quantile.

For the panel of high-income countries, while the null hypothesis of a unit root is rejected for 26 countries with *CADF* statistics, it is rejected for 33 countries at the 10 percent quantile, 29 countries at the 50 percent quantile, and only 4 countries at the 90 percent quantile with *CADF(τ)* statistics. Moreover, it seems important shifts in individual country outcomes due to variations in the common

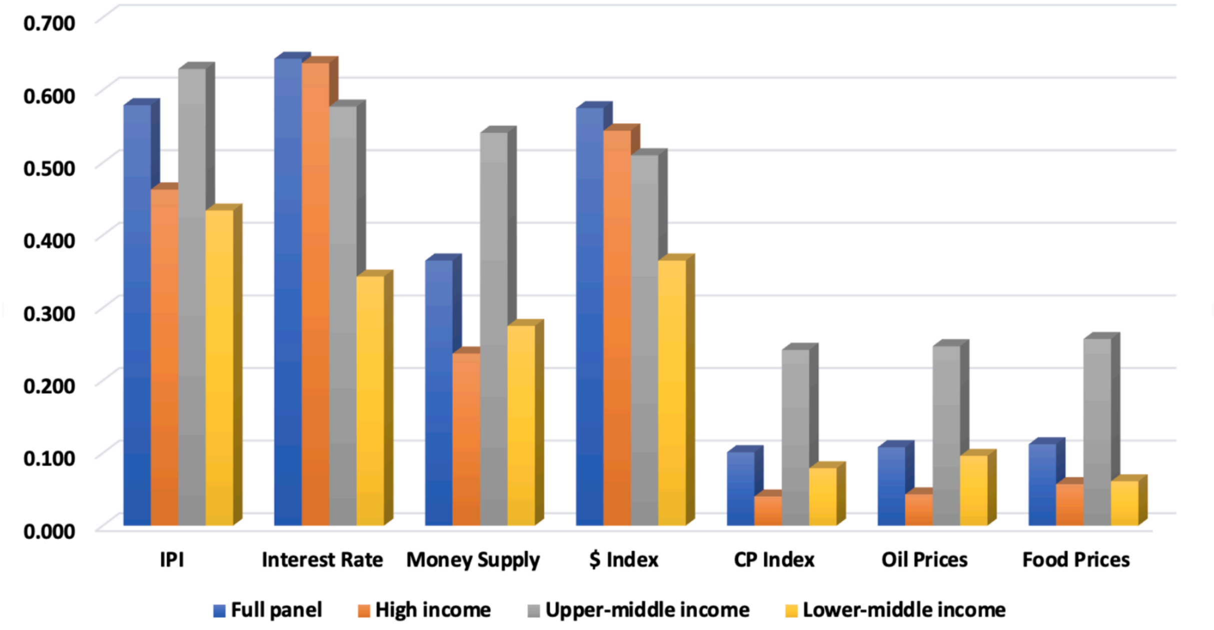

Fig. 1C. Evaluating factors and observables.
Notes: The values show R^2 from regressing the estimated common factor on each observable. Variable; definition; time period; and data. Source: IPI: Industrial production index for OECD (2015=100); 1980-2022; OECD. Interest Rate: Federal funds effective rate, percent, not seasonally adjusted; 1980-2022; FRED. Money Supply: M3 Monetary Aggregate Index for OECD (2015=100), Calendar and seasonally adjusted; OECD. $ Index: Nominal effective exchange rate for USA, Index (2010=100), Weighted Index; IMF. CP index: All commodity price index (2010=100); 1980-2022; World Bank Pink Sheet. Oil prices: Crude oil, average, ($/bbl), nominal USD; 1980-2022; World Bank Pink Sheet. Food Prices: Food price index (2010=100); 1980-2022; World Bank Pink Sheet

factor influencing each panel.[10]

For the upper- middle income countries, while the null hypothesis of a unit root is rejected for 17 countries with *CADF* statistics, it is rejected for 20 countries at the 10 percent quantile, 19 countries at the 50 percent quantile, and 5 countries at the 90 percent quantile with *CADF(τ)* statistics. Although the results do not indicate pronounced shifts as observed in the high-income group, there are notable changes in the statistical significance levels that impact the robustness of the findings.[11]

For the lower-middle income countries, while the null hypothesis of a unit root is rejected for 19 countries with *CADF* statistics, it is rejected for all 20 countries at the 10 percent quantile, 18 countries at the 50 percent quantile, and the null hypothesis of unit root cannot be rejected for any countries at the 90 percent quantile with *CADF(τ)* statistics. The results show only minimal changes compared to the full panel, with shifts far less pronounced than those observed in both high- and upper-middle-income groups.[12]

5.3. *Degree of persistence and conditional thresholds*

Since ρ_i in equation (6) measures the degree of persistence at a given quantile (τ), it can further be interpreted as regime-switching process of asymmetric persistence of negative and positive shocks with different magnitudes from low to high quantiles. To more clearly visualize the regime switching process of the degre of persistence across the entire conditional distribution, Figs. 2-4 plots $\widehat{\rho}_i$ along with 90 percent confidence interval from bootstrap sampling with 10,000 iterations over the conditional distribution with $\tau = 0.01, 0.02, \cdots, 0.99$. Note that $\widehat{\rho}_i$ equal to one indicates unit root behavior; $\widehat{\rho}_i$ above one signals local explosiveness; and $\widehat{\rho}_i$ distinctly

[10] For example, CADF statistics reject the null hypothesis of unit root for Denmark for the full panel, yet the null of unit root cannot be rejected in panel consisting only high-income countries. Conversely, while the null hypothesis of a unit root is not rejected for Chile, the UK, Hungary, Israel, and Sweden in the full panel results, it is rejected in the high-income country group, highlighting the role of income-group characteristics in shaping these results.

[11] For instance, while the null hypothesis of a unit root in the 90th percentile quantile was initially rejected for Guatemala at 5%, it is rejected at 1% within the upper-middle income group. For Mexico, CADF statistic indicates rejection of the null hypothesis at 5%, but in the upper-middle-income panel, the significance level shifts to 10%. Similarly, for Paraguay and South Africa, CADF statistics reject the null hypothesis of unit root at 1%, however the significance shifts to 10% in the upper-middle income panel results. In the case of El Salvador, CADF statistics initially reject the unit root hypothesis at the 1% l, yet the null hypothesis cannot be rejected in the upper-middle-income panel.

[12] For Haiti, Nigeria and Bolivia, CADF significance changes from 10% to 5%, 5% to 1%, 1% to 5%, respectively. For Algeria, CADF statistics reject the unit root hypothesis in the full panel, yet fail to reject it in the lower-middle income panel.

Table 2
Conditional threshold levels for shifting to persistent inflation process.

High income					Upper-middle income					Lower-middle income				
Country	τ^*	Lower Bound	Threshold	Upper Bound	Country	τ^*	Lower Bound	Threshold	Upper Bound	Country	τ^*	Lower Bound	Threshold	Upper Bound
Austria	0.94	6.23	6.33	6.43	Brazil	0.45	7.29	7.30	7.31	Bolivia	0.54	7.40	7.41	7.42
Belgium	0.64	2.78	2.82	2.86	Botswana	0.71	10.51	10.66	10.80	Cote d'Ivoire	0.90	9.15	9.24	9.34
Bahamas	–	–	–	–	Colombia	0.73	21.72	21.81	21.91	Cameroon	0.58	3.07	3.09	3.12
Canada	–	–	–	–	Costa Rica	0.63	10.41	10.47	10.53	Algeria	0.88	19.41	19.59	19.77
Switzerland	0.86	3.88	3.95	4.02	Dominica	0.90	6.32	6.48	6.63	Egypt	0.64	12.93	13.10	13.26
Chile	0.60	7.69	7.75	7.82	Dominican R.	0.77	12.26	12.36	12.46	Ghana	0.67	24.07	24.17	24.26
Cyprus	0.81	5.20	5.32	5.44	Ecuador	0.58	22.62	22.69	22.75	Honduras	0.72	10.28	10.35	10.42
Germany	0.84	3.47	3.54	3.60	Fiji	0.98	11.94	11.98	12.03	Haiti	0.74	17.60	17.75	17.91
Denmark	0.70	3.03	3.07	3.10	Guatemala	–	–	–	–	India	0.86	11.39	11.58	11.77
Spain	0.80	7.20	7.27	7.33	Indonesia	0.78	10.49	10.57	10.64	Jordan	0.89	9.69	9.82	9.96
Finland	0.64	3.10	3.13	3.17	Jamaica	0.73	16.07	16.16	16.26	Kenya	0.77	14.66	14.80	14.94
France	0.72	2.80	2.83	2.85	St. Lucia	–	–	–	–	Sri Lanka	0.95	22.04	22.17	22.30
UK	0.84	5.74	5.82	5.90	Mexico	0.57	9.64	9.65	9.66	Morocco	0.83	7.28	7.42	7.55
Greece	0.82	18.13	18.29	18.45	Mauritius	–	–	–	–	Nigeria	0.64	16.48	16.58	16.68
Hungary	0.72	10.94	11.01	11.08	Malaysia	–	–	–	–	Nepal	–	–	–	–
Ireland	0.35	1.65	1.66	1.67	Peru	0.66	12.30	12.30	12.30	Pakistan	0.74	11.16	11.35	11.53
Iceland	0.57	5.48	5.50	5.51	Paraguay	0.89	23.97	24.27	24.57	Philippines	0.86	12.13	12.21	12.30
Israel	0.47	3.75	3.76	3.77	El Salvador	0.71	11.62	11.74	11.85	Senegal	0.66	3.24	3.29	3.33
Italy	0.80	7.14	7.18	7.22	Thailand	–	–	–	–	Solomon Is.	0.89	16.43	16.62	16.82
Japan	0.97	4.56	4.61	4.67	Turkey	0.55	36.46	36.57	36.68	Samoa	–	–	–	–
St. Kitts & Nevis	–	–	–	–	South Africa	0.93	16.64	16.81	16.98					
South Korea	0.99	23.48	23.53	23.57										
Luxembourg	–	–	–	–										
Malta	–	–	–	–										
Netherlands	0.88	3.92	3.99	4.05										
Norway	–	–	–	–										
Portugal	0.60	4.41	4.44	4.46										
Singapore	0.90	5.42	5.51	5.60										
Slovenia	0.58	9.28	9.28	9.28										
Sweden	0.77	5.56	5.63	5.71										
Trinidad & Tobago	0.69	8.71	8.85	8.99										
Taiwan	0.98	11.20	11.25	11.30										
Uruguay	0.68	35.08	35.20	35.32										
United States	–	–	–	–										

Notes: τ^* is the conditional quantile wherein a shock to inflation rate is significantly persistent (i.e., $\widehat{\rho}_i(\tau) \geq 1$). The conditional threshold is given by $Q_{\tau_i^*}(\pi_{it}|\pi_{it-1}) = \widehat{\alpha}_i(\tau_i^*) + \widehat{\rho}_i(\tau_i^*)\pi_{it-1}(\tau_i^*)$ where π is the inflation rate. Lower and upper bounds denote the 90 percent bootstrap confidence intervals with 10,000 iterations.

below one implies a mean reversion. The estimated degree of persistence can further provide the conditional threshold levels for inflation.

To estimate the conditional threshold, we first determine the conditional quantile $\left(\tau_i^*\right)$ wherein a shock to inflation rate is significantly persistent (i.e., $\widehat{\rho}_i(\tau) \geq 1$). Then, we get the conditional threshold value of inflation rate by $Q_{\tau_i^*}(\pi_{it}|\pi_{it-1}) = \widehat{\alpha}_i\left(\tau_i^*\right) + \widehat{\rho}_i\left(\tau_i^*\right)\pi_{it-1}\left(\tau_i^*\right)$ where π is the inflation rate. The conditional threshold can give us the inflation's threshold rate at which inflation becomes persistent given that lagged inflation is also high. Thus, it can provide a robust conditional threshold accounting for inflation dynamics under high inflation environments. Inflation rates above this threshold indicate persistence, meaning that shocks to inflation are not mean-reverting and can have long-term impacts. Table 2 reports the conditional quantile $\left(\tau_i^*\right)$ and threshold levels for each country.

An overall observation from Table 2 and Figs. 2-4 is that inflation threshold levels display significant variation across income groups which reflect different economic structures and inflationary dynamics. High income countries generally exhibit lower thresholds, typically around 3–12% range, with an average threshold of 7.83%. The average even drops further to 5.60% when South Korea (23.53%), Greece (18.29%) and Uruguay (35.20%) are excluded. These relatively moderate levels are likely due to stable monetary frameworks and lower inflation tolerance of high-income countries. Compared to other income groups, high income countries tend to exhibit higher quantile levels, typically above the 0.9 percentile, before inflation becomes persistent. This suggests that persistent inflation in these economies is rare and arises only in the tails of the distribution.

Upper-middle income countries display a broader range of threshold levels, with Dominica having the lowest (6.48%) and Turkey the highest (36.57%). In terms of quantile levels, upper middle-income countries fall between high and lower middle-income countries and thresholds range broadly between 0.45 for Brazil to 0.98 for Fiji. This reflects the structural volatility and varying degrees of inflation tolerance for upper middle-income countries. This variation reflects the diverse structural dynamics and economic complexities of emerging and developing economies. In addition, it is worth noting that the lowest threshold (6.48%) for Dominica is still higher than those of 17 high income countries. Many of these countries face the difficulty of maintaining monetary policy credibility with volatile exchange rates and external shocks. Another challenge for upper-middle income countries is the trade-off between controlling inflation and promoting economic growth. Lastly, historical inflationary periods in these countries might have led to greater tolerance of inflation, resulting in higher threshold levels compared to high income countries.

Lower-middle income countries also display a broader range of threshold levels compared to high income countries. For instance, while Cameroon has the lowest threshold at 3.09%, Ghana has the highest at 24.17%. The average threshold of lower-middle income countries is 12.81%. These countries often deal with vulnerabilities such as weak institutions, limited access to capital markets, trade imbalances, inefficiencies in the agricultural sector or geopolitical instability. While lower threshold levels might be attributed to developed country characteristics, it may not be the case for Senegal (3.29%) and Cameroon (3.09%). One possible explanation could be that these countries face more immediate pressures to maintain price stability to prevent political instability or social unrest. Additionally, global commodity price fluctuations affect less diversified economies such as Senegal and Cameroon. In contrast to high income countries, lower-middle income countries often see inflation persistence at lower quantiles.

These threshold points highlight the level where inflation begins to generate self-reinforcing momentum. Apart from country-specific structural dynamics of inflation, one can argue that this dynamic is rooted in price adjustment delays and expectations stickiness. Alvarez et al. (2006) suggest that implicit or explicit contracts, marginal costs, coordination failure contribute to price stickiness and the time lag of a price reaction after a shock by the median firm lies between 1 to 3 months. Moreover, Mankiw et al. (2003) explore the heterogeneity in expectations setting behavior among agents and they point out that the sticky-information model explains the evolution of both the central tendency and dispersion of inflation expectations over time. These threshold levels can be interpreted as an indicator to better understand the inflationary pressures that may result in sustained inflation beyond certain levels.

5.4. Robustness analysis

The empirical evidence on asymmetric persistence in inflation appears to hold for the full-panel and sub-panels. We should at this point note that the sub-panels are classified with respect to income level of countries, which raises a question of whether this finding remains robust under different samples. In that respect, we conduct a battery of robustness analysis.

First, we classify countries based on monetary policy frameworks by grouping countries as inflation-targeting and non-inflation targeting and based on exchange rate regimes as floating and non-floating.[13] The results from these sub-panels are reported in Table A4. The mean-based IPS, PANIC, and CIPS statistics reject the null hypothesis of a unit root in favor of the alternative hypothesis of stationarity at 1% for all panels. The quantile-based IPS(τ) and CIPS(τ) statistics reject the null hypothesis of a unit root at 1% from 10 to 50 percent quantiles for the "inflation targeting" and "floating" sub-panels, and from 10 to 60 percent quantiles for the "non-inflation targeting" and "non-floating" sub-panels. These results are in consistent with those from the sub-panels based on income level classification.

Second, we evaluate the sensitivity of results to the exclusion of hyperinflation (1980–2000) and stabilization (2001–2022) episodes in countries such as Brazil, Bolivia, Peru, and Turkey. We further winsorize extreme inflation periods by employing the sub-samples for high-inflation (1980–1994) and dis-inflation (1995–2020) episodes, in conjunction with the dynamics of estimated

[13] The classifications are based on the Annual Report on Exchange Arrangements and Exchange Restrictions 2023 (AREAER) published by the International Monetary Fund (IMF, 2024).

common factors in Fig. 1A.[14] The results from these sub-samples for the full panel are reported in Table A5.[15] The mean-based IPS, CIPS, and PANIC tests uniformly reject the null hypothesis of a unit root at 1% across all sub-samples, indicating that inflation does not follow a permanent stochastic trend even during episodes of hyperinflation or stabilization. The quantile-based IPS(τ) and CIPS(τ) tests reveal pronounced asymmetry in persistence. The inflation shocks are temporary at lower and median quantiles but are persistent at upper quantiles. The evidence of non-stationarity at upper quantiles tend to strength substantially during hyperinflation episodes wherein extreme inflation observations can lead to persistence of shocks.

6. Discussion and conclusion

The empirical results reveal that inflation rates appear to exhibit significant cross-correlations across countries, and inflation shocks in majority of 75 countries tend to be temporary during low to moderate inflation periods, but more persistent in high inflation period. These findings reveal the importance of considering asymmetric persistence and cross-correlations for analyzing inflation shocks. Only for a few countries, namely Bahamas, Fiji, Guatemala, S. Korea, St. Lucia, Malaysia, Malta, Peru and Taiwan, inflation shocks are temporary irrespective of negative or positive shocks.

The asymmetric persistence suggests that price stability can be maintained under normal economic conditions but can become more vulnerable to positive inflation shocks. Since inflation does not react uniformly across different economic conditions, policymakers thereby may consider asymmetric behavior of inflation shocks by means of more refined and effective policy implications. This may involve implementing tail-based forecasting models to predict high inflation risks and inflationary spikes. A recent literature on inflation-at-risk sheds light more on persistent inflation in higher quantiles is shaped by a combination of domestic demand conditions, commodity price shocks, expectation dynamics, and price pass-through, particularly in open or vulnerable economies (see inter alia, Lopez-Salido and Loria, 2024; Banerjee et al., 2024; Canepa, 2024; Nazlioglu et al., 2025).

The stationarity of inflation at lower quantiles means that countries can successfully manage inflation shocks during stable periods. However, non-stationarity at higher quantiles indicates that shocks can expose vulnerabilities. Even though the results show that moderate inflation levels appear manageable for many countries, this finding does not necessarily imply ignoring strategic frameworks to mitigate risks posed by high and volatile inflation periods. Therefore, policies may not only address normal economic conditions but also focus on building flexible frameworks adjusting swiftly to inflationary pressures. Enhancing coordination between policy (monetary and fiscal) authorities may create a comprehensive strategy in responding to inflation surges while supporting sustainable economic growth (Laurens and De la Piedra, 1998).

The country-specific conditional inflation thresholds, which can be considered as regime switching of temporary to persistent inflation shocks, reveals substantial heterogeneity across income groups and economic structures. High-income economies generally exhibit relatively low threshold levels, indicating that even moderate inflation rates can trigger persistent dynamics, consistent with strong nominal rigidities and well-anchored expectations that amplify deviations from low-inflation environments. In contrast, emerging and developing economies display markedly higher thresholds, reflecting that short-lived inflation spikes may not necessarily generate persistent inflation, allowing for policy flexibility in the face of transitory shocks. Countries with histories of high or volatile inflation—such as Turkey, Uruguay, and several Latin American and African economies—exhibit especially elevated thresholds, suggesting that inflation persistence emerges after inflation surpasses substantially higher levels. These cross-country differences highlight that inflation persistence is state-dependent and shaped by institutional credibility, historical inflation experiences, and structural rigidities. This may call attention to importance of credibility-enhancing policies, effective communication, and timely stabilization efforts.

Declarations:

Data and material: Available upon request from corresponding author.

CRediT authorship contribution statement

Saban Nazlioglu: Writing – original draft, Investigation, Software, Methodology, Writing – review & editing. **Dogukan Tarakci:** Writing – original draft, Investigation, Data curation. **Cagin Karul:** Visualization, Software, Methodology, Formal analysis. **Lokman Salih Erdem:** Writing – review & editing, Writing – original draft, Investigation.

[14] We further diagnose the residual tail plot of the estimated common factor from the quantile regression estimation of y_{it} on $(1, y_{it-1})$ at the median quantile. While the residuals have more volatile structure for the 1980–1994 period, they exhibit less volatility for the 1995–2020 period. Thus, our sub-samples are further consistent with the extreme observations in the residuals. The residual tail plots are not reported here to save space, that are available upon request from corresponding author.

[15] The results for the sub-panels are not reported here to save space, that are available upon request from corresponding author.

Appendix A

Table A1
Descriptive Statistics.

Country	Mean	Median	Max.	Min.	SD	CV	JB	p-val.
Austria	2.554	2.132	11.047	−0.279	1.682	0.659	803.25	0.000
Belgium	2.762	2.208	12.268	−1.681	2.280	0.826	314.61	0.000
Bahamas	3.024	2.401	13.067	−1.422	2.324	0.769	277.48	0.000
Bolivia	332.012	6.267	23447.034	−1.265	1930.103	5.813	132832.7	0.000
Brazil	316.671	7.958	6821.312	1.645	872.949	2.757	11651.5	0.115
Botswana	8.551	8.460	18.780	0.885	3.629	0.424	4.324	0.000
Canada	3.012	2.195	12.896	−0.950	2.527	0.839	760.75	0.000
Switzerland	1.538	0.950	7.482	−1.444	1.908	1.240	101.06	0.000
Chile	9.041	4.771	36.527	−3.381	8.394	0.928	115.24	0.000
Cote d'Ivoire	3.994	2.868	33.234	−3.855	5.092	1.275	3771.48	0.000
Cameroon	4.615	2.596	47.263	−6.061	6.916	1.499	4118.54	0.000
Colombia	13.009	8.368	32.367	1.489	9.560	0.735	55.550	0.000
Costa Rica	13.706	10.903	108.772	−1.204	15.303	1.117	5572.89	0.000
Cyprus	3.004	2.942	12.014	−2.974	2.766	0.921	22.77	0.000
Germany	2.105	1.705	8.821	−1.041	1.674	0.795	242.11	0.000
Dominica	2.488	1.783	19.505	−3.008	2.914	1.171	1038.33	0.000
Denmark	2.886	2.220	12.888	−0.101	2.521	0.873	605.25	0.000
Dominican Rep.	12.791	6.581	82.497	−1.569	16.215	1.268	771.04	0.000
Algeria	8.710	5.751	40.281	−5.171	8.523	0.979	328.20	0.000
Ecuador	22.114	13.222	107.875	−1.601	23.998	1.085	169.00	0.000
Egypt	11.524	10.836	35.111	−2.878	6.860	0.595	55.88	0.000
Spain	4.343	3.525	16.103	−1.369	3.763	0.866	131.47	0.000
Finland	2.899	1.933	13.438	−1.551	2.807	0.968	175.39	0.000
Fiji	4.056	3.598	14.739	−3.525	3.122	0.770	25.81	0.000
France	2.736	1.941	14.313	−0.725	2.940	1.075	999.41	0.000
United Kingdom	3.367	2.448	13.045	0.200	2.500	0.743	353.40	0.000
Ghana	26.171	17.352	174.144	0.390	26.777	1.023	2134.09	0.000
Greece	7.846	4.148	26.818	−2.853	7.934	1.011	56.09	0.000
Guatemala	9.172	6.920	61.643	−4.301	9.642	1.051	2671.08	0.000
Honduras	9.525	7.324	40.197	1.840	7.624	0.800	588.53	0.000
Haiti	12.676	10.739	56.422	−15.604	10.489	0.827	138.31	0.000
Hungary	9.828	6.601	38.577	−1.479	8.656	0.881	139.64	0.000
Indonesia	8.743	6.973	82.416	−1.165	10.048	1.149	20804.8	0.000
India	7.657	7.262	19.672	0.000	3.304	0.431	21.13	0.000
Ireland	3.467	2.571	23.208	−6.562	4.421	1.275	1202.74	0.000
Iceland	11.683	4.502	102.174	0.000	17.130	1.466	1800.15	0.000
Israel	32.040	4.254	480.319	−2.839	80.979	2.527	4998.58	0.000
Italy	4.216	2.697	19.301	−0.583	4.248	1.008	435.28	0.000
Jamaica	14.406	9.196	107.905	1.685	14.928	1.036	5283.95	0.000
Jordan	4.335	3.238	37.501	−4.540	5.706	1.316	2954.21	0.000
Japan	0.811	0.500	7.397	−2.559	1.442	1.778	87.73	0.000
Kenya	11.436	9.186	61.542	−3.662	9.370	0.819	1653.45	0.000
St. Kitts & Nevis	2.585	2.266	14.941	−4.008	2.875	1.112	116.49	0.000
South Korea	4.039	3.268	28.764	−0.426	3.649	0.904	4675.60	0.000
St. Lucia	2.808	2.591	20.341	−4.236	3.423	1.219	587.04	0.000
Sri Lanka	10.416	8.906	72.535	−2.284	8.825	0.847	9212.10	0.000
Luxembourg	2.691	2.217	10.758	−1.419	2.247	0.835	279.30	0.000
Morocco	3.585	2.406	15.527	−1.668	3.521	0.982	185.19	0.000
Mexico	23.486	6.941	179.732	2.131	33.889	1.443	949.34	0.000
Malta	2.316	2.053	13.464	−3.367	2.300	0.993	779.47	0.000
Mauritius	6.026	5.631	19.892	−1.604	4.019	0.667	49.52	0.000
Malaysia	2.728	2.616	10.579	−2.890	2.012	0.738	241.75	0.000
Nigeria	19.026	13.153	89.567	−4.930	16.873	0.887	459.52	0.000
Netherlands	2.330	2.085	14.532	−1.297	1.879	0.807	2586.80	0.000
Norway	3.561	2.526	15.242	−1.832	2.910	0.817	420.04	0.000
Nepal	7.950	8.123	23.312	−0.114	4.381	0.551	87.25	0.000
Pakistan	8.338	8.218	27.258	1.324	4.396	0.527	253.1	0.000
Peru	315.412	4.603	12377.813	−1.114	1285.726	4.076	34076.7	0.000
Philippines	7.636	5.541	63.818	−0.997	8.746	1.145	7518.37	0.000
Portugal	6.337	3.183	32.197	−1.665	7.278	1.148	296.05	0.000
Paraguay	11.574	8.779	43.106	0.477	9.204	0.795	181.84	0.000
Senegal	3.606	1.601	42.918	−7.769	6.671	1.850	2561.12	0.000
Singapore	1.871	1.415	11.170	−2.506	2.214	1.183	202.23	0.000
Solomon Isl.	8.241	8.233	25.021	−5.404	5.462	0.663	2.683	0.261

(continued on next page)

Table A1 (*continued*)

Country	Mean	Median	Max.	Min.	SD	CV	JB	p-val.
El Salvador	7.922	4.874	33.295	−2.254	8.389	1.059	132.77	0.000
Slovenia	86.456	7.227	3465.396	−1.232	339.252	3.924	64827.9	0.000
Sweden	3.231	1.969	13.609	−1.872	3.398	1.052	107.98	0.000
Thailand	3.220	2.945	15.763	−4.426	2.852	0.886	167.77	0.000
Trinidad & Tobago	6.699	5.944	16.796	0.277	4.108	0.613	31.52	0.000
Turkey	38.217	31.478	125.891	3.986	29.858	0.781	41.13	0.000
Taiwan	1.928	1.445	22.711	−2.340	2.983	1.547	10782.7	0.000
Uruguay	28.509	9.635	133.663	3.376	29.831	1.046	159.56	0.000
United States	3.083	2.758	11.825	−2.097	2.005	0.650	428.26	0.000
Samoa	5.715	4.426	29.548	−7.390	6.681	1.169	64.29	0.000
South Africa	8.393	6.937	20.942	−1.999	4.746	0.565	22.81	0.000

Notes: Med.: median, Max.: maximum value, Min.: minimum value, SD: standard deviation, and CV: coefficient of variation (SD/mean), JB is the Jarque and Bera (1987)'s statistic for the null hypothesis of normality, and p-val. is the probability of JB statistic.

Table A2
Individual results from full panel.

Country	CADF		p-val.	CADF (0.1)		p-val.	CADF (0.5)		p-val.	CADF (0.9)		p-val.
Austria	−2.389		0.249	−3.137	**	0.034	−2.319	**	0.031	−0.183		0.493
Belgium	−2.616		0.175	−5.743	***	0.000	−2.018	*	0.074	0.670		0.802
Bahamas	−5.242	***	0.000	−3.144	**	0.029	−4.255	***	0.000	−2.431	**	0.012
Bolivia	−4.276	***	0.002	−6.190	***	0.000	−4.576	***	0.000	2.610		1.000
Brazil	−5.146	***	0.000	−6.190	***	0.000	4.992		1.000	2.610		1.000
Botswana	−3.736	**	0.013	−6.190	***	0.000	−2.443	*	0.060	1.078		0.923
Canada	−4.452	***	0.001	−2.467		0.127	−3.878	***	0.001	−1.222		0.152
Switzerland	−4.033	***	0.006	−6.190	***	0.000	−4.246	***	0.000	0.947		0.871
Chile	−2.500		0.210	−6.190	***	0.000	−1.259		0.328	1.652		0.968
Cote d'Ivoire	−4.864	***	0.000	−6.190	***	0.000	−3.576	***	0.004	0.029		0.751
Cameroon	−5.191	***	0.000	−6.190	***	0.000	−3.639	***	0.002	2.413		0.998
Colombia	−2.003		0.410	−3.336	**	0.011	−3.150	***	0.006	2.423		0.996
Costa Rica	−5.357	***	0.000	−6.190	***	0.000	−5.003	***	0.000	2.610		1.000
Cyprus	−3.642	**	0.017	−3.187	**	0.018	−2.586	*	0.059	−1.020		0.218
Germany	−2.591		0.182	−3.465	**	0.011	−2.435	**	0.023	0.472		0.736
Dominica	−5.798	***	0.000	−5.739	***	0.000	−4.813	***	0.000	0.575		0.858
Denmark	−2.962	*	0.089	−6.190	***	0.000	−2.146	**	0.043	1.260		0.929
Dominican Rep.	−5.459	***	0.000	−6.190	***	0.000	−5.913	***	0.000	1.628		0.984
Algeria	−3.402	**	0.033	−5.824	***	0.000	−2.779	**	0.045	−0.250		0.549
Ecuador	−2.709		0.148	−6.190	***	0.000	−3.496	***	0.004	2.610		1.000
Egypt	−4.067	***	0.005	−5.038	***	0.000	−2.092		0.128	2.610		0.999
Spain	−3.141	*	0.062	−4.610	***	0.000	−3.980	***	0.000	1.231		0.916
Finland	−2.319		0.274	−4.683	***	0.000	−2.912	**	0.010	2.610		1.000
Fiji	−4.370	***	0.001	−3.846	***	0.002	−4.725	***	0.000	−2.818	**	0.010
France	−3.629	**	0.017	−5.231	***	0.000	−3.050	***	0.004	−0.382		0.425
United Kingdom	−2.675		0.157	−4.391	***	0.000	−2.111	**	0.045	0.923		0.863
Ghana	−6.190	***	0.000	−6.190	***	0.000	−5.313	***	0.000	2.610		1.000
Greece	−4.451	***	0.001	−6.190	***	0.000	−3.073	**	0.011	0.755		0.838
Guatemala	−6.190	***	0.000	−4.046	***	0.000	−6.190	***	0.000	−4.452	**	0.000
Honduras	−4.110	***	0.004	−6.113	***	0.000	−3.954	***	0.001	2.610		1.000
Haiti	−2.996	*	0.083	−4.284	***	0.000	−1.409		0.333	1.438		0.973
Hungary	−2.769		0.134	−4.259	***	0.001	−3.204	**	0.010	0.699		0.881
Indonesia	−6.190	***	0.000	−6.190	***	0.000	−6.190	***	0.000	2.536		0.999
India	−4.758	***	0.000	−5.911	***	0.000	−3.344	***	0.008	−0.234		0.508
Ireland	−4.207	***	0.003	−4.130	***	0.000	−0.001		0.707	−0.724		0.287
Iceland	−3.455	**	0.028	−6.190	***	0.000	−2.802	**	0.017	2.610		1.000
Israel	−0.617		0.902	−6.190	***	0.000	1.112		0.936	2.610		1.000
Italy	−2.213		0.317	−4.072	***	0.002	−4.362	***	0.000	1.311		0.938
Jamaica	−5.201	***	0.000	−6.190	***	0.000	−4.735	***	0.000	2.610		0.998
Jordan	−4.804	***	0.000	−6.190	***	0.000	−4.254	***	0.000	0.210		0.770
Japan	−3.363	**	0.036	−3.752	***	0.006	−2.331	**	0.033	−0.728		0.290
Kenya	−4.052	***	0.005	−6.190	***	0.000	−6.190	***	0.000	2.610		1.000
St. Kitts & Nevis	−4.434	***	0.001	−5.158	***	0.000	−4.784	***	0.000	−1.223		0.193
South Korea	−6.190	***	0.000	−6.190	***	0.000	−3.561	***	0.002	−1.991	**	0.039
St. Lucia	−6.190	***	0.000	−4.527	***	0.000	−5.280	***	0.000	−2.205	**	0.048
Sri Lanka	−4.326	***	0.002	−6.020	***	0.000	−3.488	***	0.009	−1.490		0.195
Luxembourg	−3.303	**	0.041	−4.641	***	0.000	−2.741	**	0.014	−0.273		0.504
Morocco	−4.962	***	0.000	−6.190	***	0.000	−4.021	***	0.002	0.401		0.732
Mexico	−3.492	**	0.026	−6.190	***	0.000	−2.273	*	0.053	2.610		1.000
Malta	−4.906	***	0.000	−4.263	***	0.001	−2.879	**	0.022	−3.553	***	0.001

(continued on next page)

Table A2 (*continued*)

Country	CADF		p-val.	CADF (0.1)		p-val.	CADF (0.5)		p-val.	CADF (0.9)		p-val.
Austria	−2.389		0.249	−3.137	**	0.034	−2.319	**	0.031	−0.183		0.493
Mauritius	−4.095	***	0.005	−1.670		0.317	−2.508	*	0.058	−1.229		0.224
Malaysia	−5.311	***	0.000	−2.602	*	0.082	−6.190	***	0.000	−1.870	*	0.053
Nigeria	−3.762	**	0.012	−6.190	***	0.000	−3.700	***	0.003	1.777		0.992
Netherlands	−2.727		0.144	−2.511	*	0.089	−2.774	***	0.008	0.383		0.721
Norway	−4.034	***	0.006	−3.457	**	0.012	−3.061	***	0.007	−1.202		0.151
Nepal	−5.139	***	0.000	−5.207	***	0.000	−4.572	***	0.000	−0.463		0.498
Pakistan	−3.404	**	0.032	−6.059	***	0.000	−3.120	**	0.020	0.605		0.849
Peru	−5.937	***	0.000	−6.190	***	0.000	−6.190	***	0.000	−1.752	*	0.069
Philippines	−6.190	***	0.000	−6.190	***	0.000	−6.190	***	0.000	1.034		0.907
Portugal	−1.245		0.740	−6.190	***	0.000	−2.300	*	0.056	2.610		1.000
Paraguay	−4.910	***	0.000	−6.190	***	0.000	−2.320	*	0.084	0.098		0.718
Senegal	−3.968	***	0.007	−6.113	***	0.000	−2.411	*	0.080	1.944		0.994
Singapore	−5.619	***	0.000	−6.190	***	0.000	−4.747	***	0.000	0.016		0.571
Solomon Isl.	−4.892	***	0.000	−3.878	***	0.002	−4.482	***	0.000	0.241		0.789
El Salvador	−3.863	***	0.009	−6.190	***	0.000	−4.150	***	0.001	0.531		0.797
Slovenia	−4.848	***	0.000	−6.190	***	0.000	−6.190	***	0.000	2.610		1.000
Sweden	−2.676		0.157	−2.896	**	0.044	−0.804		0.414	0.438		0.728
Thailand	−5.337	***	0.000	−5.553	***	0.000	−2.684	**	0.025	−1.283		0.171
Trinidad & Tobago	−4.073	***	0.005	−6.190	***	0.000	−2.363	*	0.095	0.819		0.899
Turkey	−2.231		0.311	−5.362	***	0.000	−1.782		0.179	2.610		1.000
Taiwan	−6.190	***	0.000	−3.908	***	0.002	−6.190	***	0.000	−3.103	***	0.002
Uruguay	−2.973	*	0.087	−5.944	***	0.000	−2.571	**	0.037	2.219		0.994
United States	−5.109	***	0.000	−3.254	**	0.027	−5.399	***	0.000	−0.755		0.280
Samoa	−5.457	***	0.000	−3.799	***	0.002	−4.781	***	0.000	−1.474		0.210
South Africa	−4.056	***	0.005	−5.027	***	0.000	−5.060	***	0.000	−0.314		0.455

Notes: *CADF* and *CADF*(τ) statistics are the truncated statistics. The tests are implemented using the lags (p) with the integer value of $[4(T/100)]^{1/4}$. p-values are based on the simulated statistics with 10,000 Monte Carlo replications (see Pesaran, 2007; Yang et al. 2022). ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10%, respectively. p-value < 0.01 (1%), p-value < 0.05 (5%), and p-value < 0.1 (10%).

Table A3

Individual results from sub-panels.

	CADF		p-val.	CADF (0.1)		p-val.	CADF (0.5)		p-val.	CADF (0.9)		p-val.
Panel A: High Income Countries												
Austria	−2.606		0.178	−3.137	**	0.033	−2.319	**	0.032	−0.183		0.493
Belgium	−2.877		0.107	−5.743	***	0.000	−2.018	*	0.074	0.670		0.801
Bahamas	−5.496	***	0.000	−3.144	**	0.028	−4.255	***	0.000	−2.431	**	0.012
Canada	−4.651	***	0.000	−2.467		0.128	−3.878	***	0.001	−1.222		0.145
Switzerland	−5.513	***	0.000	−6.190	***	0.000	−4.246	***	0.000	0.947		0.868
Chile	−4.975	***	0.000	−6.190	***	0.000	−1.259		0.333	1.652		0.971
Cyprus	−3.783	**	0.011	−3.187	**	0.017	−2.586	*	0.054	−1.020		0.219
Germany	−2.695		0.152	−3.465	**	0.010	−2.435	**	0.028	0.472		0.734
Denmark	−2.489		0.213	−6.190	***	0.000	−2.146	**	0.046	1.260		0.925
Spain	−3.009	*	0.080	−4.610	***	0.000	−3.980	***	0.001	1.231		0.923
Finland	−2.609		0.177	−4.683	***	0.000	−2.912	**	0.010	2.610		1.000
France	−3.814	**	0.011	−5.231	***	0.000	−3.050	***	0.004	−0.382		0.408
United Kingdom	−4.212	***	0.003	−4.391	***	0.001	−2.111	**	0.044	0.923		0.858
Greece	−5.014	***	0.000	−6.190	***	0.000	−3.073	**	0.012	0.755		0.832
Hungary	−3.066	*	0.072	−4.259	***	0.000	−3.204	***	0.007	0.699		0.877
Ireland	−4.008	***	0.007	−4.130	***	0.001	−0.001		0.698	−0.724		0.291
Iceland	−3.421	**	0.031	−6.190	***	0.000	−2.802	**	0.018	2.610		1.000
Israel	−2.979	*	0.086	−6.190	***	0.000	1.112		0.935	2.610		1.000
Italy	−2.469		0.220	−4.072	***	0.002	−4.362	***	0.000	1.311		0.930
Japan	−4.508	***	0.001	−3.752	***	0.005	−2.331	**	0.036	−0.728		0.297
St. Kitts & Nevis	−4.400	***	0.001	−5.158	***	0.000	−4.784	***	0.000	−1.223		0.194
South Korea	−6.190	***	0.000	−6.190	***	0.000	−3.561	***	0.002	−1.991	**	0.034
Luxembourg	−3.445	**	0.029	−4.641	***	0.000	−2.741	**	0.016	−0.273		0.496
Malta	−4.841	***	0.000	−4.263	***	0.001	−2.879	**	0.028	−3.553	***	0.001
Netherlands	−2.719		0.146	−2.511	*	0.092	−2.774	**	0.012	0.383		0.716
Norway	−3.877	***	0.009	−3.457	**	0.011	−3.061	***	0.008	−1.202		0.151
Portugal	−2.275		0.293	−6.190	***	0.000	−2.300	*	0.055	2.610		1.000
Singapore	−5.726	***	0.000	−6.190	***	0.000	−4.747	***	0.000	0.016		0.574
Slovenia	−3.565	**	0.021	−6.190	***	0.000	−6.190	***	0.000	2.610		1.000
Sweden	−4.356	***	0.001	−2.896	**	0.042	−0.804		0.419	0.438		0.731
Trinidad & Tobago	−4.777	***	0.000	−6.190	***	0.000	−2.363		0.100	0.819		0.895
Taiwan, China	−6.190	***	0.000	−3.908	***	0.002	−6.190	***	0.000	−3.103	***	0.003

(*continued on next page*)

Table A3 (*continued*)

	CADF		p-val.	CADF (0.1)		p-val.	CADF (0.5)		p-val.	CADF (0.9)		p-val.
Panel A: High Income Countries												
Austria	−2.606		0.178	−3.137	**	0.033	−2.319	**	0.032	−0.183		0.493
Uruguay	−6.190	***	0.000	−5.944	***	0.000	−2.571	**	0.037	2.219		0.993
United States	−5.586	***	0.000	−3.254	**	0.029	−5.399	***	0.000	−0.755		0.284
Panel B: Upper-middle Income Countries												
Brazil	−5.463	***	0.000	−6.190	***	0.000	2.610		1.000	2.610		1.000
Botswana	−3.808	**	0.011	−6.190	***	0.000	−2.443	*	0.055	1.078		0.924
Colombia	−2.801		0.125	−3.336	**	0.010	−3.150	***	0.006	2.423		0.996
Costa Rica	−5.313	***	0.000	−6.190	***	0.000	−5.003	***	0.000	2.610		1.000
Dominica	−5.717	***	0.000	−5.739	***	0.000	−4.813	***	0.000	0.575		0.857
Dominican Rep.	−5.435	***	0.000	−6.190	***	0.000	−5.913	***	0.000	1.628		0.983
Ecuador	−2.801		0.125	−6.190	***	0.000	−3.496	***	0.005	2.610		1.000
Fiji	−4.449	***	0.001	−3.846	***	0.002	−4.725	***	0.000	−2.818	**	0.013
Guatemala	−5.213	***	0.000	−4.046	***	0.001	−6.190	***	0.000	−4.452	***	0.000
Indonesia	−6.190	***	0.000	−6.190	***	0.000	−6.190	***	0.000	2.536		0.999
Jamaica	−6.190	***	0.000	−6.190	***	0.000	−4.735	***	0.000	2.610		0.999
St. Lucia	−6.190	***	0.000	−4.527	***	0.000	−5.280	***	0.000	−2.205	**	0.047
Mexico	−3.013	*	0.079	−6.190	***	0.000	−2.273	*	0.055	2.610		1.000
Mauritius	−4.265	***	0.002	−1.670		0.319	−2.508	*	0.057	−1.229		0.216
Malaysia	−5.488	***	0.000	−2.602	*	0.082	−6.190	***	0.000	−1.870	*	0.056
Peru	−5.168	***	0.000	−6.190	***	0.000	−6.190	***	0.000	−1.752	*	0.070
Paraguay	−2.941	*	0.093	−6.190	***	0.000	−2.320	*	0.088	0.098		0.722
El Salvador	−2.046		0.391	−6.190	***	0.000	−4.150	***	0.000	0.531		0.790
Thailand	−5.619	***	0.000	−5.553	***	0.000	−2.684	**	0.026	−1.283		0.169
Turkey	−2.433		0.232	−5.362	***	0.000	−1.782		0.182	2.610		1.000
South Africa	−3.206	*	0.052	−5.027	***	0.000	−5.060	***	0.000	−0.314		0.441
	CADF		p-val.	CADF (0.1)		p-val.	CADF (0.5)		p-val.	CADF (0.9)		p-val.
Panel C: Lower-middle Income Countries												
Bolivia	−3.453	**	0.028	−6.190	***	0.000	−4.576	***	0.000	2.610		1.000
Cote d'Ivoire	−5.021	***	0.000	−6.190	***	0.000	−3.576	***	0.004	0.029		0.756
Cameroon	−5.367	***	0.000	−6.190	***	0.000	−3.639	***	0.002	2.413		0.998
Algeria	−2.421		0.236	−5.824	***	0.000	−2.779	**	0.042	−0.250		0.556
Egypt.	−4.006	***	0.007	−5.038	***	0.000	−2.092		0.125	2.610		0.999
Ghana	−6.190	***	0.000	−6.190	***	0.000	−5.313	***	0.000	2.610		1.000
Honduras	−3.961	***	0.007	−6.113	***	0.000	−3.954	***	0.001	2.610		1.000
Haiti	−3.464	**	0.028	−4.284	***	0.000	−1.409		0.328	1.438		0.975
India	−4.476	***	0.001	−5.911	***	0.000	−3.344	***	0.009	−0.234		0.507
Jordan	−4.739	***	0.000	−6.190	***	0.000	−4.254	***	0.001	0.210		0.760
Kenya	−4.168	***	0.004	−6.190	***	0.000	−6.190	***	0.000	2.610		1.000
Sri Lanka	−4.359	***	0.001	−6.020	***	0.000	−3.488	***	0.009	−1.490		0.195
Morocco	−4.118	***	0.004	−6.190	***	0.000	−4.021	***	0.001	0.401		0.736
Nigeria	−3.887	***	0.009	−6.190	***	0.000	−3.700	***	0.002	1.777		0.992
Nepal	−4.733	***	0.000	−5.207	***	0.000	−4.572	***	0.000	−0.463		0.500
Pakistan	−3.592	**	0.019	−6.059	***	0.000	−3.120	**	0.017	0.605		0.849
Philippines	−5.417	***	0.000	−6.190	***	0.000	−6.190	***	0.000	1.034		0.911
Senegal	−3.905	***	0.009	−6.113	***	0.000	−2.411	*	0.080	1.944		0.995
Solomon Islands	−4.566	***	0.000	−3.878	***	0.002	−4.482	***	0.000	0.241		0.785
Samoa	−5.485	***	0.000	−3.799	***	0.003	−4.781	***	0.000	−1.474		0.206

Notes: *CADF* and *CADF*(τ) statistics are the truncated statistics. The tests are implemented using the lags (p) with the integer value of $[4(T/100)]^{1/4}$. p-values are based on the simulated statistics with 10,000 Monte Carlo replications (see Pesaran, 2007; Yang et al. 2022). ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10%, respectively. p-value < 0.01 (1%), p-value < 0.05 (5%), and p-value < 0.1 (10%).

Table A4
Results from sub-panels with monetary policy frameworks.

	Inflation Targeting (N = 30)			Non-Inflation Targeting (N = 45)			Floating (N = 41)			Non-Floating (N = 34)		
Panel Tests	Statistic		p-val.	Statistic		p-val.	Statistic		p-val.	Statistic		p-val.
IPS	−15.635	***	0.000	−19.772	***	0.000	−16.255	***	0.000	−19.928	***	0.000
PANIC	18.792	***	0.000	9.535	***	0.000	7.067	***	0.000	23.935	***	0.000
CIPS	−4.369	***	0.000	−3.967	***	0.000	−4.015	***	0.000	−4.362	***	0.000
IPS(τ)												
0.1	−11.009	***	0.000	−213.590	***	0.000	−22.682	***	0.000	−265.055	***	0.000
0.2	−15.846	***	0.000	−9.846	***	0.000	−12.648	***	0.000	−11.762	***	0.000
0.3	−16.242	***	0.000	−6.665	***	0.000	−12.787	***	0.000	−7.734	***	0.000
0.4	−7.521	***	0.000	−5.242	***	0.000	−6.455	***	0.000	−5.791	***	0.000

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Table A4 (*continued*)

Panel Tests	Inflation Targeting (N = 30) Statistic		p-val.	Non-Inflation Targeting (N = 45) Statistic		p-val.	Floating (N = 41) Statistic		p-val.	Non-Floating (N = 34) Statistic		p-val.
0.5	−3.755	***	0.000	−3.417	***	0.000	−3.381	***	0.000	−3.758	***	0.000
0.6	−0.878		0.877	−1.530	***	0.000	−0.978		0.721	−1.620	***	0.000
0.7	1.885		1.000	0.462		1.000	1.137		1.000	0.904		1.000
0.8	4.521		1.000	3.343		1.000	3.307		1.000	4.426		1.000
0.9	6.893		1.000	9.410		1.000	5.920		1.000	11.398		1.000
CIPS(τ)												
0.1	−5.343	***	0.000	−4.857	***	0.000	−4.750	***	0.000	−5.358	***	0.000
0.2	−5.289	***	0.000	−5.075	***	0.000	−5.011	***	0.000	−5.381	***	0.000
0.3	−5.090	***	0.000	−4.952	***	0.000	−4.898	***	0.000	−5.379	***	0.000
0.4	−4.694	***	0.000	−4.440	***	0.000	−4.466	***	0.000	−5.028	***	0.000
0.5	−3.493	***	0.000	−3.438	***	0.000	−3.187	***	0.000	−3.953	***	0.000
0.6	−2.113	***	0.000	−2.097	***	0.000	−1.991	***	0.000	−2.256	***	0.000
0.7	−0.914		0.998	−1.106		0.917	−1.016		0.982	−0.812		1.000
0.8	0.181		1.000	−0.091		1.000	−0.181		1.000	0.218		1.000
0.9	0.803		1.000	0.409		1.000	0.417		1.000	0.827		1.000

Notes: See Table 1.

Table A5
Panel results from sub-samples with inflation episodes.

Panel Tests	*Hyperinflation episode* 1980:01–2000:12 Statistic		p-val.	*Stabilization episode* 2001:01–2022:12 Statistic		p-val.	*High inflation episode* 1980:01–1994:12 Statistic		p-val.	*Dis-inflation episode* 1995:01–2020:12 Statistic		p-val.
IPS	−15.360	***	0.000	−11.520	***	0.000	−10.060	***	0.000	–22.342	***	0.000
PANIC	8.856	***	0.000	22.445	***	0.000	4.718	***	0.000	11.520	***	0.000
CIPS	−3.163	***	0.000	−2.834	***	0.000	−2.541	***	0.000	−3.647	***	0.000
IPS(τ)												
0.1	–22.26	***	0.000	−2.916	***	0.000	−16.88	***	0.000	−3.822	***	0.000
0.2	−6.711	***	0.000	−2.945	***	0.000	−4.492	***	0.000	−4.120	***	0.000
0.3	−5.483	***	0.000	−2.877	***	0.000	−3.156	***	0.000	−4.044	***	0.000
0.4	−3.642	***	0.000	−2.406	***	0.000	−2.668	***	0.000	−3.489	***	0.000
0.5	−2.417	***	0.000	−1.986	***	0.000	−1.920	***	0.000	−3.027	***	0.000
0.6	−1.363	***	0.001	−1.458	***	0.001	−1.186	*	0.074	−2.320	***	0.000
0.7	0.040		1.000	−1.008		0.480	−0.418		1.000	−1.657	***	0.000
0.8	1.568		1.000	−0.527		1.000	0.260		1.000	−0.950		0.410
0.9	2.183		1.000	−0.141		1.000	1.112		1.000	−0.258		1.000
CIPS(τ)												
0.1	−3.821	***	0.000	−2.234	***	0.000	−3.005	***	0.000	−2.870	***	0.000
0.2	−4.091	***	0.000	−2.490	***	0.000	−2.922	***	0.000	−3.270	***	0.000
0.3	−3.902	***	0.000	−2.540	***	0.000	−2.789	***	0.000	−3.286	***	0.000
0.4	−3.322	***	0.000	−2.566	***	0.000	−2.433	***	0.000	−3.189	***	0.000
0.5	−2.402	***	0.000	−2.351	***	0.000	−1.906	***	0.000	−2.943	***	0.000
0.6	−1.693	**	0.016	−2.111	***	0.000	−1.391		0.431	−2.544	***	0.000
0.7	−0.943		0.996	−1.745	***	0.002	−1.013		0.983	−2.183	***	0.000
0.8	−0.244		1.000	−1.379		0.119	−0.594		1.000	−1.673	***	0.000
0.9	0.140		1.000	−0.980		0.526	−0.302		1.000	−1.113		0.186

Notes: See Table 1.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.najef.2026.102592.

Data availability

Data will be made available on request.

References

Akdoğan, K. (2015). Asymmetric behaviour of inflation around the target in inflation-targeting countries. *Scottish Journal of Political Economy, 62*(5), 486–504.

Akerlof, G. A., Dickens, W. T., Perry, G. L., Gordon, R. J., & Mankiw, N. G. (1996). The macroeconomics of low inflation. *Brookings Papers on Economic activity, 1996*(1), 1–76.
Akyuz, M., Gorus, M. S., & Gunes, C. (2024). Trade uncertainty and investments in an emerging country: A Fourier VAR approach. *Journal of Asian Business and Economic Studies, 31*(2), 99–110.
Alvarez, L. J., Dhyne, E., Hoeberichts, M., Kwapil, C., Le Bihan, H., Lünnemann, P., & Vilmunen, J. (2006). Sticky prices in the euro area: A summary of new micro-evidence. *Journal of the European Economic Association, 4*(2–3), 575–584.
Arize, A. C., & Malindretos, J. (2012). Nonstationarity and nonlinearity in inflation rate: Some further evidence. *International Review of Economics & Finance, 24*, 224–234.
Aslanidis, N., Koursaros, D., & Otto, G. (2024). Asymmetry in inflation persistence under inflation targeting. *The Quarterly Review of Economics and Finance, 101922*.
Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica, 70*(1), 191–221.
Bai, J., & Ng, S. (2004). A PANIC attack on unit roots and cointegration. *Econometrica, 72*(4), 1127–1177.
Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica, 77*(4), 1229–1279.
Balke, N. S., & Fomby, T. B. (1997). Threshold cointegration. *International Economic Review, 38*(3), 627–645.
Ball, L., & Mankiw, N. G. (1994). Asymmetric price adjustment and economic fluctuations. *The Economic Journal, 104*(423), 247–261.
Banerjee, A., & Carrion-i-Silvestre, J. L. (2015). Cointegration in Panel Data with Structural Breaks and Cross-Section Dependence. *Journal of Applied Econometrics, 30*, 1–23.
Banerjee, R., Contreras, J., Mehrotra, A., & Zampolli, F. (2024). Inflation at risk in advanced and emerging market economies. *Journal of International Money and Finance, 142*, Article 103025.
Basher, S. A., & Westerlund, J. (2008). Is there really a unit root in the inflation rate? more evidence from panel data models. *Applied Economics Letters, 15*(3), 161–164.
Beechey, M., & Österholm, P. (2009). Time-varying inflation persistence in the Euro area. *Economic Modelling, 26*(2), 532–535.
Bofinger, E. (1975). Optimal condensation of distributions and optimal spacing of order statistics. *Journal of the American Statistical Association, 70*(349), 151–154.
Bolat, S., Tiwari, A. K., & Kyophilavong, P. (2017). Testing the inflation rates in MENA countries: Evidence from quantile regression approach and seasonal unit root test. *Research in International Business and Finance, 42*, 1089–1095.
Canepa, A. (2024). Inflation dynamics and persistence: The importance of the uncertainty channel. *The North American Journal of Economics and Finance, 72*, Article 102135.
Charemza, W. W., Hristova, D., & Burridge, P. (2005). Is inflation stationary? *Applied Economics, 37*(8), 901–903.
Ciccarelli, M., & Mojon, B. (2010). Global inflation. *The Review of Economics and Statistics, 92*(3), 524–535.
Crowder, W. J., & Hoffman, D. L. (1996). The long-run relationship between nominal interest rates and inflation: The Fisher equation revisited. *Journal of Money, Credit and Banking, 28*(1), 102–118.
Crowder, W. J., & Wohar, M. E. (1999). Are Tax Effects Important in the Long-Run Fisher Relationship? evidence from the Municipal Bond Market. *The Journal of Finance, 54*(1), 307–317.
Cuestas, J. C., & Harrison, B. (2010). Inflation persistence and nonlinearities in Central and eastern European countries. *Economics Letters, 106*(2), 81–83.
Culver, S. E., & Papell, D. H. (1997). Is there a unit root in the inflation rate? evidence from sequential break and panel data models. *Journal of Applied Econometrics, 12*(4), 435–444.
Çiçek, S., & Akar, C. (2013). The asymmetry of inflation adjustment in Turkey. *Economic Modelling, 31*, 104–118.
Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366a), 427–431.
Doan, T. N., Do, D. P., & Luong, D. V. (2024). Monetary stance and favorableness of the monetary policy in the media: The case of Vietnam. *Journal of Asian Business and Economic Studies, 31*(2), 111–123.
Evans, M. D., & Lewis, K. K. (1995). Do expected shifts in inflation affect estimates of the long-run Fisher relation? *The Journal of Finance, 50*(1), 225–253.
Evans, M., & Wachtel, P. (1993). Inflation regimes and the sources of inflation uncertainty. *Journal of Money, Credit and Banking, 25*(3), 475–511.
Gaglianone, W. P., de Carvalho Guillén, O. T., & Figueiredo, F. M. R. (2018). Estimating inflation persistence by quantile autoregression with quantile-specific unit roots. *Economic Modelling, 73*, 407–430.
Gengenbach, C., Palm, F., & Urbain, J. (2006). Cointegration Testing in Panels with Common Factors. *Oxford Bulletin of Economics and Statistics, 68*, 683–719.
Guerra, R., Kamin, S. B., Kearns, J., Upper, C., & Vakil, A. (2025). Latin America's nonlinear monetary response to pandemic inflation. *International Finance, 28*(1), 2–22.
Ha, J., Kose, M.A., Ohnsorge, F. L. 2019a. Global inflation synchronization. World Bank Policy Research Working Paper Series, 8768, World Bank.
Ha, J., Kose, M. A., & Ohnsorge, F. L. (2019b). *Inflation in emerging and developing economies: Evolution, drivers and policies*. Washington DC: World Bank.
Ha, J., Kose, M. A., & Ohnsorge, F. (2023). One-stop source: A global database of inflation. *Journal of International Money and Finance, 137*, Article 102896.
Hassler, U., & Wolters, J. (1995). Long memory in inflation rates: International evidence. *Journal of Business & Economic Statistics, 13*(1), 37–45.
Ho, T. W. (2009). The inflation rates may accelerate after all: Panel evidence from 19 OECD economies. *Empirical Economics, 36*(1), 55–64.
Hurlin, C. (2010). What would Nelson and Plosser find had they used panel unit root tests? *Applied Economics, 42*(12), 1515–1531.
Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*(1), 53–74.
International Monetary Fund. (2024). *Annual Report on Exchange Arrangements and Exchange Restrictions 2023*. Washington, DC: IMF.
Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review/Revue Internationale de Statistique*, 163–172.
Kapetanios, G., Shin, Y., & Snell, A. (2003). Testing for a unit root in the nonlinear STAR framework. *Journal of Econometrics, 112*(2), 359–379.
Koenker, R., & Xiao, Z. (2004). Unit root quantile autoregression inference. *Journal of the American statistical association, 99*(467), 775–787.
Kumar, M. S., & Okimoto, T. (2007). Dynamics of persistence in international inflation rates. *Journal of Money, Credit and Banking, 39*(6), 1457–1479.
Laurens, B., & De la Piedra, E. (1998). Coordination of monetary and fiscal policies. *IMF Working Paper.*
Lee, C. C., & Chang, C. P. (2007). Mean reversion of inflation rates in 19 OECD countries: Evidence from panel Lm unit root tests with structural breaks. *Economics Bulletin, 3*(23), 1–15.
Lee, H. Y., & Wu, J. L. (2001). Mean reversion of inflation rates: Evidence from 13 OECD countries. *Journal of Macroeconomics, 23*(3), 477–487.
Lee, C., Wu, J. L., & Yang, L. (2016). A simple panel unit-root test with smooth breaks in the presence of a multifactor error structure. *Oxford Bulletin of Economics and Statistics, 78*(3), 365–393.
Li, H., & Park, S. Y. (2018). Testing for a unit root in a nonlinear quantile autoregression framework. *Econometric Reviews, 37*(8), 867–892.
Lopez-Salido, D., & Loria, F. (2024). Inflation at risk. *Journal of Monetary Economics, 145*, Article 103570.
Mankiw, N. G., Reis, R., & Wolfers, J. (2003). Disagreement about inflation expectations. *NBER macroeconomics annual, 18*, 209–248.
Manzan, S., & Zerom, D. (2015). Asymmetric quantile persistence and predictability: The case of US inflation. *Oxford Bulletin of Economics and Statistics, 77*(2), 297–318.
Nakamura, E., & Steinsson, J. (2008). Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics, 123*(4), 1415–1464.
Nazlioglu, S., Lee, J., Tieslau, M., Karul, C., & You, Y. (2023). Smooth structural changes and common factors in nonstationary panel data: An analysis of healthcare expenditures. *Econometric Reviews, 42*(1), 78–97.
Nazlioglu, S., Gurel, S. P., Gunes, S., Akin, T., Karul, C., & Kar, M. (2025). Inflation co-movement: New insights from quantile factor model. *Empirical Economics*, 1–34.
Nelson, C. R., & Plosser, C. R. (1982). Trends and random walks in macroecnomic time series: Some evidence and implications. *Journal of Monetary Economics, 10*(2), 139–162.
Osman, M. (2021). Persistence, mean reversion, and non-linearities in inflation rates in the GCC countries: An eclectic approach. *Applied Economics, 53*(8), 913–923.
Parker, M. (2018). How global is "global inflation"? *Journal of Macroeconomics, 58*, 174–197.

Payne, J. E., Nazlioglu, S., Karul, C., & Smyth, R. (2025). Stochastic convergence of renewable energy intensity across US States: Evidence from a panel unit root test with asymmetries and common factors. *Applied Economics, 57*(58), 9883–9904.
Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multi-factor error structure. *Econometrica, 74*(4), 967–1012.
Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*, 265–312.
Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics, 60*(1), 13–50.
Poole, W. (1988). Monetary policy lessons of recent inflation and disinflation. *Journal of Economic Perspectives, 2*(3), 73–100.
Reese, S., & Westerlund, J. (2016). Panicca: Panic on cross-section averages. *Journal of Applied Econometrics, 31*(6), 961–981.
Rose, A. K. (1988). Is the real interest rate stable? *The Journal of Finance, 43*(5), 1095–1112.
Romero-Ávila, D., & Usabiaga, C. (2009). The hypothesis of a unit root in OECD inflation revisited. *Journal of Economics and Business, 61*(2), 153–161.
Smith, J. C. (2000). Nominal wage rigidity in the United Kingdom. *The Economic Journal, 110*(462), 176–195.
Tetlow, R. J. (2024). How large is the output cost of disinflation? *International Finance, 27*(3), 231–252.
Wolters, M. H., & Tillmann, P. (2015). The changing dynamics of US inflation persistence: A quantile regression approach. *Studies in Nonlinear Dynamics & Econometrics, 19*(2), 161–182.
Westerlund, J., & Urbain, J. P. (2015). Cross-sectional averages versus principal components. *Journal of Econometrics, 185*(2), 372–377.
Yang, J., Wei, J., & Cai, B. (2022). Quantile unit root inference for panel data with common shocks. *Economics Letters, 219*, Article 110809.