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Modeling the Trend, Persistence, and Volatility of Inflation in Pacific Alliance Countries: An Empirical Application Using a Model with Inflation Bands*

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Abstract

This paper estimates and analyzes the dynamics of trend inflation, as well as the persistence and volatility of the inflation gap, in the Pacific Alliance countries (Chile, Colombia, Mexico, and Peru). The econometric approach employs methodologies proposed by Stock and Watson (2007) and Chan et al. (2013), including the AR-Trend-Bound model, which incorporates the implications of inflation targeting in estimating the unobserved components of inflation. The results show that this model effectively attributes most of the permanent component to trend inflation. Additionally, all four countries exhibit a declining trend inflation during the 1990s, stabilization in the first two decades of the century, and a growing trend inflation following the onset of the COVID-19 pandemic. The low levels of inflation gap persistence before the pandemic reflect the effectiveness of central banks in keeping inflation close to its trend level. Lastly, the volatility of the inflation gap captures the Great Moderation of inflation, with pandemic-era increases in volatility reaching levels comparable to those observed in the 1990s.

Keywords: Inflation, Trend Inflation, Inflation Gap Persistence, Inflation Gap Volatility, Inflation Targets, Pacific Alliance.
JEL Classification: C32, E32, E51.

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1. Introduction

Macroeconomic literature suggests that trend inflation, along with the persistence and volatility of the inflation gap, varies over time. In Latin America, research by Ramos-Francia and Torres (2008), Capistrán and Ramos-Francia (2009), Ysusi (2011), Humala and Rodriguez (2012), and De Oliveira and Petrassi (2014) highlights a decline in trend inflation and inflation gap persistence since the late 1990s. This improvement is closely linked to the adoption of inflation targeting (IT) (Hyvonen, 2004; Vega and Winkelried, 2005; Mishkin and Schmidt-Hebbel, 2007), which anchors inflation expectations by providing a clear target range (Mishkin and Savastano, 2001; Hammond, 2011). A stable trend inflation underpins a predictable economic environment, while analyzing the persistence and volatility of the inflation gap provides critical insights for understanding and managing inflation-related risks.

This paper estimates and analyzes trend inflation, as well as the persistence and volatility of the inflation gap, for Chile, Colombia, Mexico, and Peru—the members of the Pacific Alliance (PA), a political, trade, and economic regional integration initiative. Most theoretical and empirical research models trend inflation as a random walk in state-space frameworks, both univariate (Stock and Watson, 2007) and multivariate (Cogley and Sargent, 2005; Garnier et al., 2015). The random walk specification assumes no systematic pattern over time, implying that trend inflation changes randomly across periods. However, evidence suggests that IT adoption by central banks contributes to maintaining trend inflation near the inflation target.

This study applies five univariate Bayesian state-space models, following the methodologies of Stock and Watson (2007) and Chan et al. (2013). The primary model, referred to as the AR-Trend-Bound model, constrains trend inflation within bands consistent with each country's inflation target range. Inflation gap persistence is estimated using a first-order autoregressive process, bounded between zero and one, to allow for a gradual reduction in the inflation gap over time. Volatility is modeled as the variability of disturbances in the inflation gap. Studies also employ AR-Trend, Trend-SV, Trend, and Trend-Bound models, which differ in their estimation methods.

Estimating trend inflation, as well as the persistence and volatility of the inflation gap, yields valuable information on inflation dynamics in Latin America. These three indicators, often regarded as unobserved components of inflation, provide essential information for central banks to implement effective monetary policies. They also enhance certainty for households and businesses in their spending and investment decisions. This analysis is particularly relevant for Latin America, which faced high inflation and significant economic instability during the 1970s, 1980s, and part of the 1990s, with far-reaching social and economic consequences.

Central banks aim to maintain price stability by closely monitoring trend inflation and ensuring that inflation aligns with the target over the medium term. IT supports this objective by enabling market participants to anchor their inflation expectations. Consequently, the level and variability of trend inflation serve as measures of the degree to which inflation expectations remain anchored (Garnier et al., 2015). Under IT, changes in trend inflation are expected to remain near zero when expectations are anchored but increase when they become unanchored.

The inflation gap, defined as the difference between actual inflation and its trend, represents the transitory component of inflation. According to Morley et al. (2013), central banks use discretionary monetary policy tools, such as changes in the reference interbank interest rate, to manage this gap and stabilize the economy. However, certain transitory factors can persist over multiple periods, leading to changes in inflation gap persistence.

Although central banks can implement measures to address inflation gap volatility, many factors influencing it, such as global or supply-side shocks, lie beyond their control. When such disruptions do not influence inflation expectations and their impacts are transitory, central banks can maintain their monetary policy stance. In this context, central bank credibility, reputation, and effective communication are crucial for preventing increases in inflation uncertainty (Hammond, 2011; Bordo and Siklos, 2015).

The main findings are as follows. First, the AR-Trend-Bound model effectively identifies and estimates the permanent component of trend inflation. Second, trend inflation in all PA countries declined during the 1990s, stabilized within the target range during the first two decades of the century, and increased during the COVID-19 pandemic. Third, inflation gap persistence reflects prolonged changes in the transitory component of inflation, remaining mostly low since the beginning of the century. Fourth, inflation gap volatility responds to abrupt short-term inflationary pressures. Lastly, the robustness analysis confirms the reliability of the AR-Trend-Bound model's estimates and conclusions.

The structure of this paper is as follows. Section 2 reviews the relevant literature. Section 3 introduces the five models used in the analysis. Section 4, following Chan et al. (2013), examines the properties of the models, focusing on trend inflation specifications. Prior predictive analysis evaluates whether the models replicate observed moments and persistence and assesses their parsimony. Section 5 presents and analyzes the empirical results, including estimates of trend, persistence, and volatility, alongside a brief discussion of inefficiency factors. Section 6 discusses robustness exercises, and Section 7 concludes.

2. Literature Review

The empirical literature on estimating the unobserved components of inflation encompasses a wide range of approaches. Cogley and Sbordone (2008) estimate U.S. trend inflation and inflation gap persistence from 1960 to 2003 using Bayesian methods and Markov Chain Monte Carlo (MCMC) algorithms to model the Neo-Keynesian Phillips curve. Their findings show that trend inflation fluctuates in response to changes in monetary policy, rising in the 1970s and falling in the later sample period. They also demonstrate that inflation gap persistence depends largely on changes in trend inflation.

Baxa et al. (2015) adopt a similar methodology but extend the analysis to inflation volatility, examining Central European countries from 1995 to 2012. Their results indicate that effective monetary policy is essential for reducing inflation gap persistence and volatility, and that inflation targets alone are insufficient. They also find that trend inflation remains stable when persistence and volatility decline. For PA countries, Ramos-Francia and Torres (2008) use moment methods and the Neo-Keynesian Phillips curve to analyze inflation dynamics in Mexico between 1992 and 2007, finding that inflation gap persistence plays a key role, even as more firms set prices based on expectations. Other studies also employ the Neo-Keynesian Phillips curve to analyze unobserved inflation components (Cogley and Sargent, 2005; Benati, 2008; Davig and Doh, 2014; Koop and Korobilis, 2012; Mavroeidis et al., 2014; Gemma et al., 2017).

Unobserved inflation components can also be estimated from survey data on inflation expectations (Clark, 2011; Kozicki and Tinsley, 2012; Faust and Wright, 2013; Wright, 2013; Clark and Doh, 2014; Mertens, 2016; Nason and Smith, 2020). Clark and Davig (2008) estimate U.S. trend inflation from 1982 to 2008, finding a closer relationship with long-term rather than short-term expectations. They also show that improved Fed policy communication stabilizes trend inflation and reduces inflation gap persistence. Chan et al. (2018) estimate trend inflation via Bayesian econometrics and MCMC algorithm, using long-term U.S. inflation expectations surveys conducted between 1980 and 2016, concluding that accounting for expectations enhances the precision of trend inflation estimates.

An alternative approach involves using state-space models to estimate the three unobserved components of inflation as time-varying variables, with volatility modeled as a function of either trend inflation or the inflation gap. Stock and Watson (2007) employ an unobserved components model with stochastic volatility (SV) to analyze U.S. inflation, decomposing it into stochastic trend inflation and a transitory, serially uncorrelated inflation gap. Their results show increased trend inflation variance during the 1970s and 1980s, followed by declines in later decades, while inflation gap variance remains relatively stable.

Chan et al. (2013) extend this line of research by developing an inflation model incorporating bands for trend inflation and inflation gap persistence. Applied to U.S. data, their model successfully captures the behavior of trend inflation, as well as the persistence and volatility of the inflation gap. Their findings reveal stable trend inflation, with a gradual increase during the 1970s and 1980s. Inflation gap persistence reflects that inflation is largely driven by the cyclical component, while inflation gap volatility illustrates the Great Moderation and the impact of the Global Financial Crisis (GFC).

The concept of core inflation also provides a framework for analyzing trend inflation. Bryan and Cecchetti (1994) define core inflation as the permanent inflation component over a medium-term horizon, excluding high and transitory price fluctuations. While common measures exclude food and energy prices, other researchers propose more sophisticated methods (Cutler, 2001; Rangasamy, 2009; Crone et al., 2013; Shiratsuka, 2015; Gamber and Smith, 2019). Clark (2001) estimates U.S. core inflation by grouping goods and services in the Consumer Price Index (CPI) into 36 categories for 1967–1997 and excluding the eight most volatile ones. Detmeister (2012) builds on Clark's approach by identifying 200 categories for 1978–2009 and excluding the sixty most volatile ones. Stock and Watson (2016) model U.S. core inflation for 1995–2015 using a weighted sum of inflation from major industries, with weights varying over time based on their persistence, volatility, and co-movement.

For PA countries, studies on trend and core inflation mirror approaches used in developed economies (Cordova et al., 2008; Ysusi, 2011; Carlomagno et al., 2021). Lahura and Vega (2011) apply a wavelet-function methodology and multiresolution analysis to estimate core inflation in Peru. Their approach captures medium- and long-term inflation movements and proves useful for short-term forecasts. Humala and Rodriguez (2012) estimate a measure called pure inflation in Peru using a dynamic factor decomposition model that isolates the effects of idiosyncratic relative price changes. They find that pure inflation strongly correlates with alternative measures of core inflation, as both describe historical trend inflation behavior. Acosta (2018) estimates core inflation in Mexico by grouping CPI goods into ten clusters based on their volatility levels, concluding that inflation estimated from the five least volatile clusters closely resembles trend inflation.

Studies show reduced inflation gap persistence following IT adoption. Capistrán and Ramos-Francia (2009) analyze the mean and persistence of inflation in PA countries from 1980 to 2007, finding that both exhibit frequent changes over time. They also conclude that inflation gap persistence decreases when changes in mean inflation are accounted for. De Oliveira and Petrassi (2014) examine inflation gap persistence in industrialized and emerging countries, finding that it decreased in Peru and Chile but slightly increased in Colombia between 2001 and 2011. Chiquiar et al. (2010) test for changes in the persistence of Mexican inflation and identify a transition from a non-stationary to a stationary process between late 2000 and early 2001, aligning with IT adoption. Roache (2014) demonstrates that improved monetary policy implementation in IT countries, which better anchored inflation expectations, has reduced inflation gap persistence. Additional references include Cecchetti and Debelle (2006), Pincheira (2008), and Belaire-Franch (2019).

Research on inflation volatility in PA countries highlights the Great Moderation of inflation, characterized by a reduction in volatility during the 1990s and early 2000s (Singh, 2006; Castillo et al., 2012, 2016; Ha et al., 2019). Broto (2011) applies an autoregressive conditional heteroskedasticity model to examine inflation volatility in the region, concluding that IT adoption has reduced both inflation levels and volatility. Ferreira and Aparecida Palma (2016) use a model with time-varying parameters and stochastic volatility to analyze the effects of inflation uncertainty in Colombia, Mexico, and other Latin American countries from 1996 to 2015. They identify high volatility at the start of the period, followed by reductions after IT implementation. Their findings also emphasize that IT regimes have been implemented consistently even in the face of external shocks, notably the GFC.

None of the above empirical studies on PA countries incorporates models that account for the specific characteristics of IT in estimating trend inflation, as well as inflation gap persistence and volatility. Moreover, these studies do not jointly estimate the three unobserved components. This research is the first to address these aspects in PA countries.

3. Methodology

3.1. *Modeling Trend, Persistence, and Volatility*

Following Chan et al. (2013), inflation, denoted by π_t, is decomposed as follows:

$$\pi_t = \tau_t + c_t, \tag{1}$$

where τ_t represents trend inflation and c_t is the inflation gap. The inflation gap and the three unobserved components are modeled as follows:

$$(\pi_t - \tau_t) = \rho_t(\pi_{t-1} - \tau_{t-1}) + \epsilon_t \exp\left(\frac{h_t}{2}\right), \tag{2}$$

$$\tau_t = \tau_{t-1} + \epsilon_t^{\tau}, \tag{3}$$

$$\rho_t = \rho_{t-1} + \epsilon_t^{\rho}, \tag{4}$$

$$h_t = h_{t-1} + \epsilon_t^{h}, \tag{5}$$

where ρ_t represents inflation gap persistence, h_t reflects the volatility of the inflation gap, and $\epsilon_t \sim \mathcal{N}(0,1)$, $\epsilon_t^h \sim \mathcal{N}(0,\sigma_h^2)$. Shocks to trend inflation follow $\epsilon_t^{\tau} \sim \mathcal{TN}(a - \tau_{t-1}, b - \tau_{t-1}; 0, \sigma_\tau^2)$, where a and b define the trend bands, and $\mathcal{TN}(a, b; \mu, \sigma^2)$ is a truncated Gaussian distribution between a and b with mean μ and variance σ^2. The conditional expectation of trend inflation one period ahead is influenced by the trend bands and satisfies:

$$E_t[\tau_{t+1}] = \tau_t + \sigma_\tau \left[\frac{\phi\left(\frac{a-\tau_t}{\sigma_\tau}\right) - \phi\left(\frac{b-\tau_t}{\sigma_\tau}\right)}{\Phi\left(\frac{b-\tau_t}{\sigma_\tau}\right) - \Phi\left(\frac{a-\tau_t}{\sigma_\tau}\right)} \right], \text{ if } a \le \tau_t \le b, \tag{6}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density and the cumulative density functions of the standard Gaussian distribution, respectively.

Shocks to inflation gap persistence follow $\epsilon_t^{\rho} \sim \mathcal{TN}(a_\rho - \rho_{t-1}, b_\rho - \rho_{t-1}; 0, \sigma_\rho^2)$, where the persistence bands are $a_\rho = 0$ and $b_\rho = 1$. Consequently, persistence is bounded ($0 < \rho_t < 1$), ensuring that the inflation gap converges to zero in the long term. The conditional expectation of persistence one period ahead is given by:

$$E_t[\rho_{t+1}] = \rho_t + \sigma_\rho \left[\frac{\phi\left(\frac{a_\rho-\rho_t}{\sigma_\rho}\right) - \phi\left(\frac{b_\rho-\rho_t}{\sigma_\rho}\right)}{\Phi\left(\frac{b_\rho-\rho_t}{\sigma_\rho}\right) - \Phi\left(\frac{a_\rho-\rho_t}{\sigma_\rho}\right)} \right], \text{ if } a_\rho \le \rho_t \le b_\rho. \tag{7}$$

The model described by equations (1) - (7) is referred to as the AR-Trend-Bound model. In this specification, trend, persistence, and expectations are influenced by the inflation bands. This approach aligns with the monetary policy frameworks of PA central banks, which take measures when inflation or inflation expectations deviate from target. The estimation algorithm is detailed in Section 5.1.

3.2. Other Models

The AR-Trend-Bound model is compared with four other models: (i) the AR-Trend model, which is identical to the AR-Trend-Bound model but excludes bands (i.e. $a = b = a_\rho = b_\rho = 0$), with $\epsilon_t^\tau \sim \mathcal{N}(0, \sigma_\tau^2)$ and $\epsilon_t^\rho \sim \mathcal{N}(0, \sigma_\rho^2)$; (ii) the Trend-SV model, a variation of the model proposed by Stock and Watson (2007), where $\pi_t = \tau_t + \epsilon_t \exp\left(\frac{h_t}{2}\right)$, with $\rho_t = 0$ and $\epsilon_t^\tau \sim \mathcal{N}(0, \exp(g_t))$, thereby incorporating SV components into the variance of trend inflation, characterized by $g_t = g_{t-1} + \epsilon_t^g$ and $\epsilon_t^g \sim \mathcal{N}(0, \sigma_g^2)$; (iii) the Trend model, which removes both bands and the autoregressive component from the AR-Trend-Bound model ($a = b = 0$ and $\rho_t = 0$); and (iv) the Trend-Bound model, which is similar to the AR-Trend-Bound model but excludes the autoregressive component ($\rho_t = 0$).

4. Properties of Trend Inflation Models

4.1. Data

PA countries play a significant role in Latin America, accounting for 35% of the population, 36% of GDP, and 47% of the region's imports. According to Spillan and Virzi (2017), these countries share similar economic structures[1] and exhibit significant trade openness. From a monetary policy perspective, PA countries initially adopted implicit IT schemes between 1991 and 1995, later transitioning to explicit IT schemes.

Following Faust and Wright (2013) and Garnier et al. (2015) each country's monthly CPI is seasonally adjusted using the X-12 filter developed by the U.S. Census Bureau. This adjustment removes seasonal patterns from price data. The annualized monthly inflation rate is calculated as $\pi_t = 1200 \times \left[\frac{IPC_t - IPC_{t-1}}{IPC_{t-1}}\right]$. Unlike annual inflation, seasonally adjusted monthly inflation is not affected by annual base effects, allowing for a clearer view of contemporaneous inflationary pressures. The sample begins in the year each PA country adopted implicit IT and extends through October 2022. Figure 1 illustrates the monthly annualized (blue) and annual (red) inflation rates for each PA country. At the start of the analysis period, inflation rates exceeded 20% in Colombia and Mexico and 10% in Chile and Peru. By the late 1990s, inflation had declined significantly, stabilizing at low levels in the early 21st century—first in Chile and Peru, followed by Mexico and Colombia. However, inflation spiked in 2021 and 2022 following the COVID-19 pandemic, driven primarily by rising fuel prices and supply chain disruptions. These levels represent the highest inflation rates in the past two decades for PA countries.

Table 1 summarizes the years of implicit and explicit IT and the evolution of targets, based on central bank announcements and Vega and Winkelried (2005). Chile was the first PA country to adopt implicit IT and the second globally after New Zealand (Broto, 2011). Colombia followed in 1995, Mexico in the wake of its 1994 financial crisis, and Peru shortly after launching structural reforms in 1994. By 1999, all PA countries had transitioned to explicit IT, except for Peru, which did three years later. The Table shows that initial target ranges were high, reflecting elevated inflation rates, with implicit targets near 20%. Over time, these ranges were gradually reduced, stabilizing in the mid-2000s at levels consistent with long-term monetary policy objectives.

[1] In this research, economic structure refers to the fundamental variables that shape the economies of PA countries, including: (i) dependence on extractive industries such as mining and hydrocarbons, which drive growth but heighten vulnerability to global market changes; (ii) underdeveloped financial systems characterized by low savings rates and limited access to credit; (iii) governance challenges, including political instability, regulatory inefficiencies, and unstable tax revenues resulting from economic dependence on natural resources; and (iv) consumer and investment confidence, which drives spending, attracts investment, and sustains capital inflows.

Figure 1: *Annualized Inflation (blue,* $\pi_t = 1200 \times \left[\frac{IPC_t - IPC_{t-1}}{IPC_{t-1}}\right]$*) and Annual Inflation Rates (red,* $\pi_t = 100 \times \left[\frac{IPC_t - IPC_{t-12}}{IPC_{t-12}}\right]$*).*

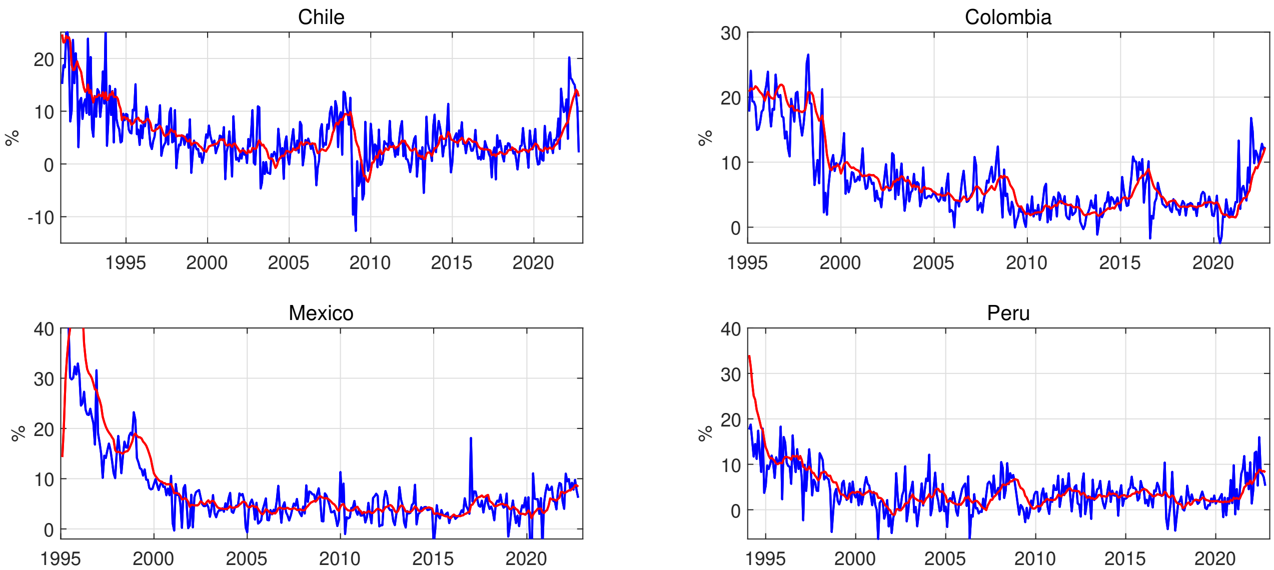


Table 1: *Implicit Inflation Targeting (IIT) and Explicit Inflation Targeting (EIT) for each Country*

Country	IIT Regime Introduction Date	EIT Regime Introduction Date	Inflation Targets		
Chile	1991	1999	1991: 15% - 20%	1995: 8%	1999: 4.3%
			1992: 13% - 16%	1996: 6.5%	2002 - 2018: 3% ± 1%
			1993: 10% - 12%	1997: 5.5%	
			1994: 9% - 11%	1998: 4.5%	
Colombia	1995	1999	1992 - 1993: 22%	1999: 15%	2006: 4% - 5%
			1994: 19%	2000: 10%	2007 - 2008: 3.5% - 4.5%
			1995: 18%	2001: 8%	2009: 4.5% - 5.5%
			1996: 17%	2002: 6%	2010 - 2018: 3% ± 1%
			1997: 18%	2003 - 2004: 5% - 6%	
			1998: 16%	2005: 4.5% - 5.5%	
Mexico	1995	1999	1995: 19%	1998: 12%	2001: 6.5%
			1996: 10%	1999: 13%	2002: 4.5%
			1997: 15%	2000: 10%	2003 - 2018: 3% ± 1%
Peru	1994	2002	1994: 15% - 20%	1998: 7.5% - 9%	2002 - 2006: 2.5% ± 1%
			1995: 9% - 11%	1999: 5% - 6%	2007 - 2018: 2% ± 1%
			1996: 9.5% - 11.5%	2000: 3.5% - 4%	
			1997: 8% - 10%	2001: 2.5% - 3.5%	

Source: Bank of Mexico, Bank of the Republic of Colombia, Central Bank of Chile, Central Reserve Bank of Peru, Galindo and Ros (2005), Gomez et al. (2002), Mishkin and Savastano (2001), Vega and Winkelried (2005).

4.2. Priors

In the AR-Trend-Bound model, the unobserved components of inflation, as defined in equations (3), (4), and (5), are initialized as follows: $\tau_1 \sim \mathcal{TN}(a, b; \tau_0, \omega_\tau^2)$, $\rho_1 \sim \mathcal{TN}(a_\rho, b_\rho; \rho_0, \omega_\rho^2)$, and $h_1 \sim \mathcal{N}(h_0, \omega_h^2)$, where τ_0, ω_τ^2, ρ_0, ω_ρ^2, h_0, and ω_h^2 are known constants. Due to differing initial inflation rates, country-specific hyperparameters are used. Initial trend mean priors are set as follows: $\tau_0 = 4$ for Chile, $\tau_0 = 5$ for Colombia and Mexico, and $\tau_0 = 4$ for Peru. Robustness checks (detailed in Section 6) assess the stability of these results. Hyperparameters for persistence and volatility are $\rho_0 = h_0 = 0$, with variances $\omega_\tau^2 = \omega_h^2 = 10$ and $\omega_\rho^2 = 1$, allowing for relatively non-informative priors.

The remaining parameters are defined as $\theta = (\sigma_h^2, \sigma_\rho^2, \sigma_\tau^2)'$, with priors given by $p(\theta) = p(\sigma_h^2)p(\sigma_\rho^2)p(\sigma_\tau^2)$. These follow an Inverse-Gamma distribution: $\sigma_\tau^2 \sim \mathcal{IG}(\underline{\mathrm{v}}_\tau, \underline{\mathrm{S}}_\tau^2)$, $\sigma_\rho^2 \sim \mathcal{IG}(\underline{\mathrm{v}}_\rho, \underline{\mathrm{S}}_\rho^2)$, and $\sigma_h^2 \sim \mathcal{IG}(\underline{\mathrm{v}}_h, \underline{\mathrm{S}}_h^2)$, with hyperparameters $\underline{\mathrm{v}}_\tau = \underline{\mathrm{v}}_\rho = \underline{\mathrm{v}}_h = 10$, $\underline{\mathrm{S}}_\tau^2 = 0.18$, $\underline{\mathrm{S}}_\rho^2 = 0.009$, and $\underline{\mathrm{S}}_h^2 = 0.45$. For further details, see Section 3.2 of Chan et al. (2013).

4.3. *Results of Prior Predictive Analysis*

4.3.1 *Properties of Trend Inflation Under Different Specifications*

This section examines the properties of trend inflation specifications through simulations, comparing the AR-Trend-Bound, Trend, and Trend-SV models. The simulation sequence for the predictive density of future trends τ_{T+k} , with $k = 20$,[2] is as follows: (i) set parameters $\sigma_\tau = 0.141$, $\sigma_h = 0.224$, and $g_\tau = -3$; (ii) specify two trend bands for the AR-Trend-Bound model to test for biases in trend estimates: AR-Trend-Bound-1 ($a = 1$, $b = 4.5$) and AR-Trend-Bound-2 ($a = 0$, $b = 5$); (iii) set $m = 1$ and $M = 4$ for the total number of trend specifications; (iv) set $\tau_T = m$ as the initial value; (v) set $j = 1$ and $J = 10,000$ as the total number of simulations; (vi) generate $\tau_{T+1}, \tau_{T+2}, \ldots, \tau_{T+k}$ for each model, and additionally $g_{T+1}, g_{T+2}, \ldots, g_{T+k}$ for the Trend-SV model using equation (3) and the modeling errors described in Sections 3.1 and 3.2; (vii) if $j < J$, set $j + 1$ and return to step (vi); otherwise, proceed to the next step; (viii) if $m < M$, set $j + 1$ and return to step (iv); otherwise, terminate the process. For additional details, see Chan et al. (2013).

Figure 2 presents predictive density distributions for the AR-Trend-Bound-1 (blue), AR-Trend-Bound-2 (red), Trend (orange), and Trend-SV (purple) models. The Trend-SV model shows significant dispersion, including extreme values caused by its stochastic volatility component. For example, with $\tau_T = 3$, the Trend-SV model produces trend values ranging from 0 to 6, deviating significantly from the medium-term trend. This pattern persists across other scenarios.

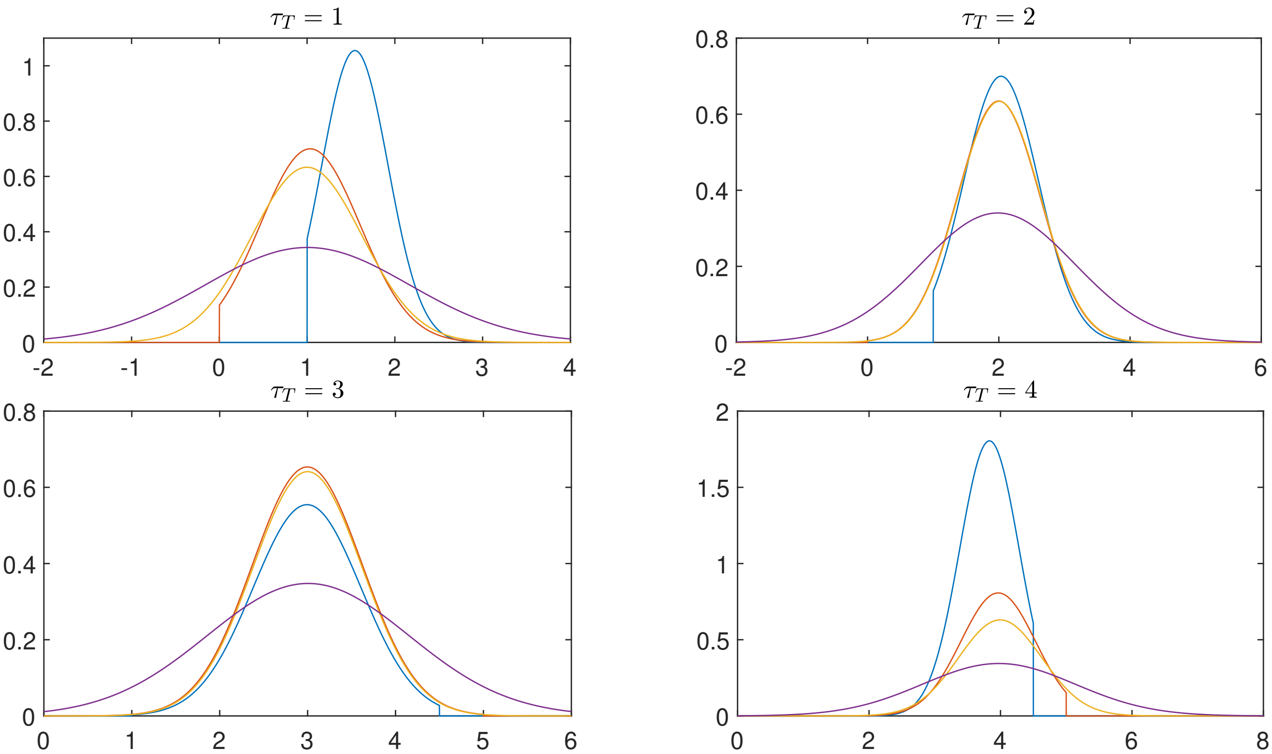
The AR-Trend-Bound-1 model exhibits a right bias and truncation at the lower bound ($\tau_T = 1$) due to its narrow bands, whereas the AR-Trend-Bound-2 model, with wider bands, centers its probability density around the true value without bias. Although the AR-Trend-Bound-2 model shows greater concentration than the trend model, the bands still ensure that trend inflation remains above the lower bound. At $\tau_T = 4$, the upper bound in the AR-Trend-Bound-2 model introduces a left bias and truncation. In this case, the AR-Trend-Bound-2 model centers the density around $\tau_T = 4$, with higher concentration than the trend model, keeping trend inflation below the upper bound. Finally, the Trend model remains unbiased with high variance but lacks the constraints necessary to influence the dynamics of the trend.

The results indicate that trend inflation simulations using the AR-Trend-Bound model are both accurate and unbiased when appropriate bands are selected to avoid truncation issues. Additionally, this model demonstrates greater efficiency compared to the other models analyzed in terms of trend inflation simulation.

The trend bands in the bounded models are aligned with the inflation target ranges of the PA countries. To address the bias issues discussed in this section, the AR-Trend-Bound model incorporates information derived from the AR-Trend model results when specifying the bands. The country-specific bands are as follows: Chile

[2]We define $k = 20$ to generate simulations of the predictive density of medium-term trend inflation. These simulations are particularly relevant as they enable the amplification of errors over the medium term, making the results both representative and practically useful for: (i) capturing key properties of trend inflation, such as mean, variance, skewness, and truncation, under different specifications; (ii) comparing the variance between models with and without stochastic volatility; and (iii) analyzing the mean, truncation, and skewness between models with and without bands.

Figure 2: *Predictive Densities for τ_{t+k} under the AR-Trend-Bound-1 (blue, with bounds $a = 1$ and $b = 4.5$), AR-Trend-Bound-2 (red, with bounds $a = 0$ and $b = 5$), Trend (orange) and Trend-SV (purple); $k = 20$.*



$a = 1$ and $b = 10$, Colombia $a = 1$ and $b = 10$, Mexico $a = 1$ and $b = 9$, and Peru $a = 0$ and $b = 8$.

4.3.2 Prior Predictive Analysis for Data Features of Interest

Following Geweke (2010), a prior predictive analysis is conducted for two main purposes. First, to establish whether the model can replicate the moments and persistence observed in the data. Models that fail to capture these behaviors are deemed inadequate and discarded. The prior cumulative distribution functions (CDFs) of the features assess a model's ability to replicate the statistical properties observed in the data. Second, the analysis evaluates the parsimony of the model, focusing on its capacity to generate datasets similar to the observed one. The Bayes Factor (BF) provides additional insights into model parsimony, facilitating comparisons between models that generate similar moments and persistence levels but differ in complexity.

We begin by analyzing the prior CDFs of features. Each model j for country i is denoted as M_{ij}, and each feature of interest k, such as quantiles, variances, and autocorrelations, is defined as z_{kj}. For each M_{ij}, the sequence is: (i) obtain the prior parameters for M_{ij}; (ii) simulate the unobservable components using the state equations of M_{ij}; (iii) use the initial inflation value for country i; (iv) generate a dataset using the measurement equation of M_{ij}; (v) calculate the features of interest z_{kj}; (vi) repeat the process 10,000 times, drawing new prior parameters and state equations. The prior CDFs for z_{kj} are constructed using the draws $z_{kj}^{(1)}, z_{kj}^{(2)}, \ldots, z_{kj}^{(10{,}000)}$ for each M_{ij}.

Table 2 presents the prior CDFs of the features, calculated under each model for each country, showing the likelihood that a feature, given the prior and the model, is less than the observed value. This is expressed as $F_{kj}(z_{kj}^0 \mid M_{ij}) = P(z_{kj} \leq z_{kj}^0 \mid M_{ij})$. Each row represents a feature of interest, with the final row showing the estimated moving average (MA) coefficient in an integrated MA(1) process, which serves as the maximum likelihood estimate for ψ in the equation $y_t = u_t + \psi u_{t-1}$, where $u_t \sim \mathcal{N}(0, \sigma^2)$. Models with values near 0 or 1 are deemed inadequate for replicating the observed data features.

Table 2: *Prior CDFs of Features*

Feature	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound
	Chile					Colombia				
16%-tile	0.824	0.852	0.328	0.775	0.365	0.867	0.943	0.552	0.821	0.577
Median	0.675	0.921	0.510	0.691	0.497	0.701	0.964	0.670	0.724	0.653
84%-tile	0.532	0.881	0.781	0.511	0.732	0.575	0.912	0.868	0.538	0.823
Variance	0.245	0.745	0.752	0.352	0.706	0.271	0.769	0.774	0.379	0.730
Fraction of $y_t < 0$	0.147	0.178	0.666	0.235	0.627	0.055	0.109	0.501	0.194	0.469
Fraction of $y_t > 10$	0.522	0.875	0.785	0.501	0.732	0.594	0.927	0.873	0.560	0.828
Lag 1 autocorrelation	0.263	0.687	0.958	0.559	0.596	0.368	0.834	0.989	0.660	0.804
Lag 4 autocorrelation	0.230	0.612	0.938	0.259	0.802	0.332	0.768	0.977	0.389	0.898
MA coefficient	0.313	0.783	0.971	0.496	0.323	0.452	0.923	0.997	0.598	0.428
	Mexico					Peru				
16%-tile	0.860	0.944	0.481	0.816	0.507	0.796	0.784	0.271	0.733	0.313
Median	0.710	0.968	0.658	0.701	0.624	0.655	0.888	0.459	0.656	0.452
84%-tile	0.568	0.913	0.861	0.521	0.792	0.507	0.870	0.746	0.502	0.687
Variance	0.397	0.842	0.849	0.413	0.791	0.218	0.725	0.719	0.343	0.658
Fraction of $y_t < 0$	0.064	0.114	0.555	0.202	0.511	0.200	0.220	0.727	0.269	0.684
Fraction of $y_t > 10$	0.561	0.909	0.845	0.522	0.773	0.486	0.853	0.770	0.473	0.705
Lag 1 autocorrelation	0.411	0.861	0.992	0.689	0.761	0.237	0.655	0.949	0.541	0.512
Lag 4 autocorrelation	0.399	0.808	0.985	0.434	0.871	0.220	0.608	0.932	0.266	0.777
MA coefficient	0.523	0.954	0.999	0.606	0.408	0.288	0.753	0.960	0.480	0.283

The AR-Trend-Bound model demonstrates robust performance, with values close to 0.5 for percentiles, variance, and autocorrelations at different lags, while avoiding extreme values in other categories. The AR-Trend model also performs well but shows limitations in replicating the mean inflation and the proportion of instances where inflation falls below zero. Conversely, the Trend-Bound model effectively replicates both the mean inflation and these proportions but underperforms in autocorrelations and the MA coefficient. The Trend model shows weaknesses in replicating both mean and variance, while the Trend-SV model exhibits extreme values, reducing its ability to capture the data's key characteristics.

Therefore, models incorporating bounds on trend inflation and autoregressive components achieve greater accuracy at values closer to 0.5, reflecting moderate flexibility and relatively non-informative priors. However, excessive flexibility may lead to unrealistic behavior. The BF provides further evidence, offering a qualitative assessment of model performance.

Table 3 compares each model against the Trend-SV model using log BFs. Column 2 shows the log prior densities evaluated at observed values for the Trend-SV model, while columns 3 through 6 display the log BFs favoring each model relative to the Trend-SV model.

The sequence for estimating BFs is as follows: (i) approximate the joint prior distribution of the features $p(z \mid M_j) = p(z_1, \ldots, z_q \mid M_j)$ using simulated data combined with a Gaussian kernel, as outlined in Geweke (2010); (ii) evaluate the prior distribution at the observed value $p(z = z_0 \mid M_j)$; (iii) calculate the BF between models M_j and M_k as the ratio of $p(z = z_0 \mid M_j)$ to $p(z = z_0 \mid M_k)$.

The features are grouped into three categories: "Quantiles" (16th percentile, median, and 84th percentile), "Spread and Drift" (variance, the proportion of $y_t < 0$, and the proportion of $y_t > 10$), and "Dynamics" (first and fourth lag autocorrelations and the MA coefficient). The final row, labeled "All", aggregates all nine features of interest.

Table 3: *Log Bayes Factors in Favor of Each Model Over the Trend-SV*

Feature	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound
	Chile					Colombia				
Quantile	-15.141	6.329	8.289	-411.422	8.180	-14.626	3.540	5.650	-347.215	6.788
Spread and drift	-14.821	0.613	2.771	$-\infty$	2.812	-17.848	5.107	7.657	$-\infty$	8.574
Dynamics	-0.140	0.495	-2.385	-0.141	-1.121	1.806	-2.028	-6.294	-2.396	-4.394
All	-29.424	6.307	5.357	$-\infty$	10.497	-30.428	0.779	3.139	$-\infty$	12.485
	Mexico					Peru				
Quantile	-13.636	3.910	4.893	-365.473	6.496	-15.905	8.687	10.359	-373.654	8.777
Spread and drift	-13.650	0.749	1.863	$-\infty$	5.182	-16.478	5.084	6.404	$-\infty$	6.619
Dynamics	2.740	-3.249	-8.094	-3.955	-4.796	-0.093	0.812	-2.000	-0.256	-1.050
All	-24.017	-3.249	-6.533	$-\infty$	7.467	-31.747	12.873	11.675	$-\infty$	14.923

The second column displays the log prior densities evaluated at the observed values for the Trend-SV model.

Table 3 provides compelling evidence for the AR-Trend-Bound model across all countries. For all nine features, the BF comparing the AR-Trend-Bound model to the Trend-SV model is approximately 3.6×10^4, 2.6×10^5, 1.7×10^3, and 3.0×10^6 for Chile, Colombia, Mexico, and Peru, respectively. This highlights the superiority of the AR-Trend-Bound model over the widely accepted Trend-SV benchmark.

The BF also demonstrates that the AR-Trend-Bound model outperforms the Trend-Bound model, with values of approximately 1.8×10^2, 1.1×10^4, 1.2×10^6, and 2.6×10^1 for Chile, Colombia, Mexico, and Peru, respectively. These results suggest that while bounding trend inflation improves model performance, incorporating autoregressive components provides additional benefits.

In contrast, the AR-Trend model—incorporating a time-varying autoregressive lag into the Trend model—shows poor performance, as evidenced by the results in Table 3. This underperformance arises because, under relatively non-informative priors, the AR-Trend model frequently generates explosive series.

The AR-Trend-Bound model demonstrates strong performance across most features of interest. In Colombia, Mexico, and Peru, it achieves the highest log BFs in the "Quantiles" and "Spread and Drift" categories. In Chile, it attains the highest BF in "Spread and Drift", while its "Quantiles" performance is comparable to that of the Trend-Bound model. Although the AR-Trend-Bound model faces challenges in the "Dynamics" category, it does not rank as the least effective model. Its overall performance underscores its suitability for explaining observed inflation dynamics in these countries.

5. Empirical Results

This section presents empirical results for the five models described in Section 3, using the priors outlined in Section 4.2 and the annualized monthly inflation rate defined in Section 4.1. All results are based on 50,000 draws from the MCMC algorithm, following a burn-in period of 5,000 iterations.

5.1. Posteriors

The conditional posterior distributions of the unobserved components and parameters are estimated using an MCMC algorithm, where $\pi = (\pi_t, \ldots, \pi_T)'$, $\tau = (\tau_t, \ldots, \tau_T)'$, $\rho = (\rho_t, \ldots, \rho_T)'$, and $h = (h_t, \ldots, h_T)'$. The sequence for estimating the AR-Trend-Bound model is as follows: (i) propose initial values from the priors in Section 4.2; (ii) set $j = 1$ and $J = 50,000$ as the total number of estimations; (iii) estimate the posterior distribution $p(\tau \mid \pi, h, \rho, \theta)$, where the inequality constraints in equation (6) result in a non-standard conditional distribution. This necessitates the algorithm developed by Chan and Strachan (2012) for approximating $p(\tau \mid \pi, h, \rho, \theta)$ using an Independence Chain Metropolis-Hastings approach based on candidate estimates generated by the Chan and Jeliazkov (2009) algorithm. These estimates undergo an Acceptance-Rejection process within the Metropolis-Hastings framework; (iv) estimate $p(h \mid \pi, \tau, \rho, \theta)$ using the posterior distribution algorithm for trend inflation; (v) estimate $p(\rho \mid \pi, h, \tau, \theta)$ using the posterior distribution algorithm for trend inflation; (vi) estimate $p(\sigma_h^2, \sigma_\rho^2, \sigma_\tau^2 \mid \pi, \tau, h, \rho, \theta) = p(\sigma_h^2 \mid \pi, h, \rho, \theta)p(\sigma_\rho^2 \mid \pi, h, \rho, \theta)p(\sigma_\tau^2 \mid \pi, h, \rho, \theta)$, where the posterior distributions $p(\sigma_\tau^2 \mid \pi, h, \rho, \theta)$ and $p(\sigma_\rho^2 \mid \pi, h, \rho, \theta)$ follow non-standard densities, using the Metropolis-Hastings algorithm with a proposed Inverse Gamma density, while $p(\sigma_h^2 \mid \pi, h, \rho, \theta)$ has a standard density and is an Inverse Gamma distribution; (vii) if $j < J$, set $j + 1$ and return to step (iii); otherwise, proceed to the next step; and (viii) discard the first 5,000 iterations to reduce the influence of initial values. Details of the implementation and modifications for other models are provided in Appendix A of Chan et al. (2013).

5.2. *Results for Trend, Persistence, and Volatility*

This section presents the estimated unobserved components of inflation, beginning with an individual analysis of each component followed by an assessment of inefficiency factors for each parameter. Finally, the most efficient model for representing the unobserved components of inflation is identified.

5.2.1 *Trend*

Trend inflation serves as a critical indicator of core inflation and is influenced by structural factors such as inflation targets (Ireland, 2007; Garnier et al., 2015), economic structure (Cogley et al., 2010), inflation expectations (Chan et al., 2018), and demographic changes in the working-age population (Juselius and Takats, 2018). Trend inflation is defined as the level toward which inflation converges once transitory shocks—such as demand or supply shocks and idiosyncratic price changes—dissipate (Behera and Patra, 2022).

Figure 3 displays the posterior median of trend inflation for the five models: AR-Trend-Bound (blue), AR-Trend (red), Trend-SV (green), Trend (purple), and Trend-Bound (black), alongside the explicit inflation target range (gray area). The Trend and Trend-SV models exhibit highly volatile trends, closely mirroring inflation and showing abrupt shifts over short periods—behavior inconsistent with the trend concept described in Section 3.1. The inclusion of trend bands in the Trend-Bound model mitigates this volatility, constraining dynamics to more plausible levels.

Comparing the Trend-Bound model to models incorporating an autoregressive component in the inflation gap (AR-Trend and AR-Trend-Bound), the latter models produce a more stable trend aligned with the definition of trend inflation. The inclusion of inflation gap persistence ensures that inflation converges to a stable trend, reflecting the anchoring of long-term expectations. These findings suggest that, since IT adoption, permanent factors have played a minor role in observed inflation increases.

Figure 4 illustrates the posterior median (blue line) and credibility intervals (dotted blue lines) for trend inflation in the AR-Trend-Bound model, along with the explicit inflation target range (gray area) for each country. Trend inflation shows a gradual decline, stabilizing below the high levels observed in the late 1990s. By 2002, trend inflation in Chile, Mexico, and Peru stabilized at annual averages of 3.1%, 4.9%, and 2.7%, respectively. In Colombia, trend inflation declined further that year, reaching an annual average of 6.2%. Notably, trend inflation in Chile, Mexico, Peru, and Colombia were very close to their inflation targets of 3%, 4.5%, 2.5%, and 6%, respectively. Between 2002 and 2004, trend inflation remained mostly within target ranges, indicating stability during this period.

Figure 3: *Posterior Mean of τ_t under the AR-Trend-Bound (blue), AR-Trend (red), Trend-SV (green), Trend (purple), Trend-Bound (black) Models and Explicit Target Range for Inflation (shaded grey bands).*

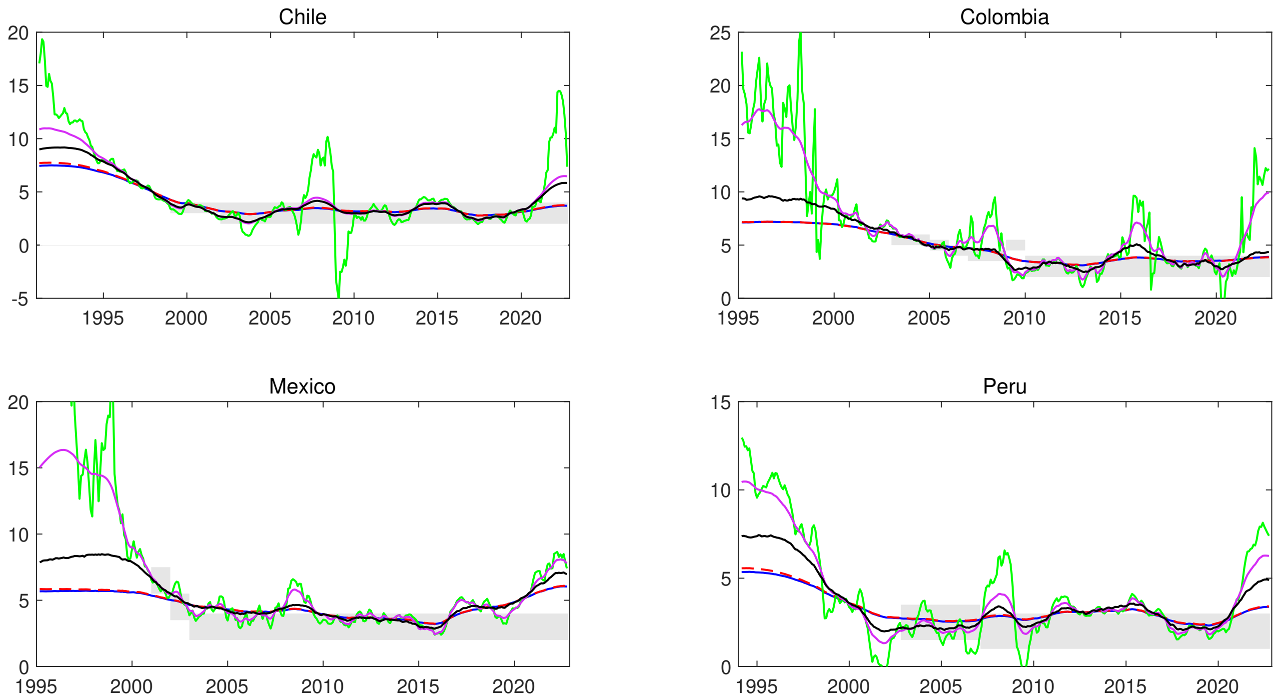
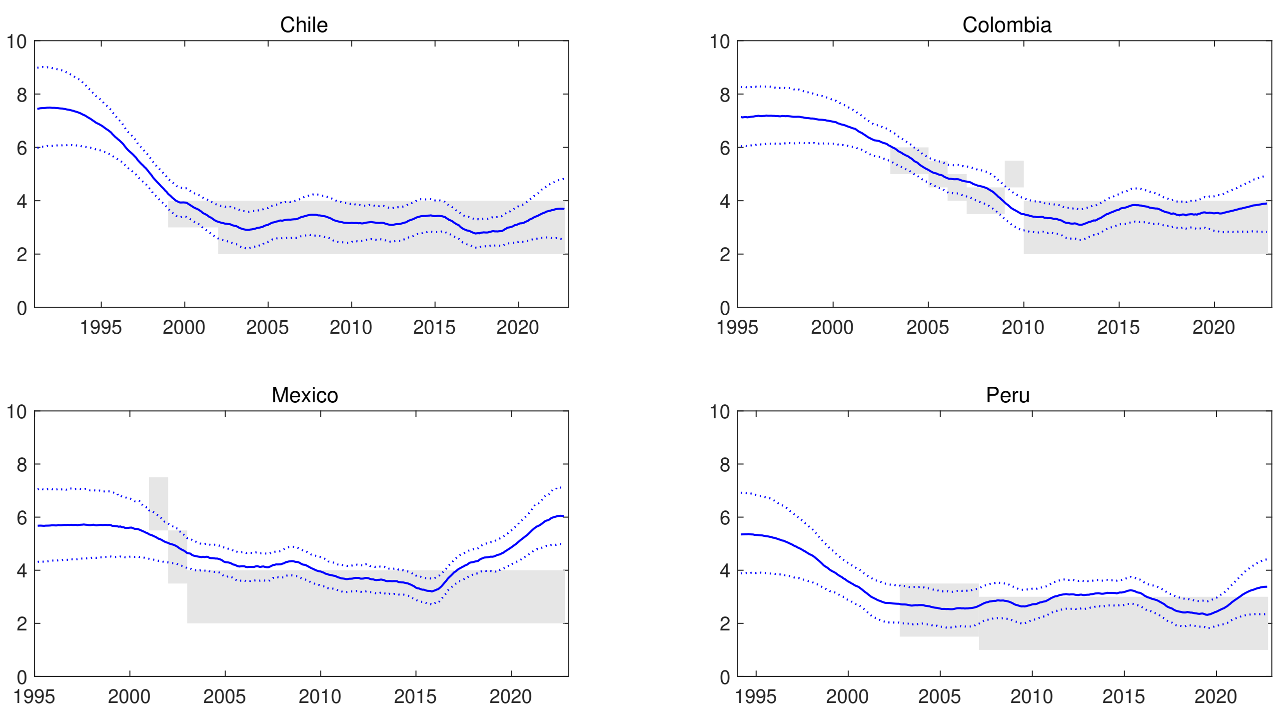


Figure 4: *Posterior Mean (blue line), 16th and 84th percentiles (blue dotted line) of τ_t under the AR-Trend-Bound Model and Explicit Target Range for Inflation (shaded grey bands).*



The disinflation process in PA countries is attributed to both global and domestic factors (Laban and Larrain, 1994; Calvo and Mendoza, 1999; Rosende and Tapia, 2015). Globally, disinflation stemmed from an increased global supply of goods, driven by the participation of China, India, and Russia in international trade, and capital inflows to Latin America. Domestically, central bank independence, price stabilization mandates, high reference interest rates, and improved fiscal discipline played key roles.

From 2001 to 2005, Colombia's trend inflation decreased by an average of 0.4 percentage points (p.p.) annually, consistent with adjustments to its inflation target range. However, rising oil prices between 2006 and 2008 slowed this decline to 0.2 p.p. per year. By 2007, Colombia's trend inflation exceeded its target range for the first time since 2002, reaching 4.6%.

Between 2005 and 2008, trend inflation increased in Chile, Mexico, and Peru, driven by a sharp rise in commodity prices that significantly impacted the region's economic structure.[3] In Peru, corporate financial indicators improved, with companies experiencing increased liquidity that facilitated collections and payments, reduced financial constraints, and attracted foreign investment (Banco Central de Reserva del Peru, 2006; Pereda, 2012). Households saw rising incomes, expanded employment opportunities, and enhanced consumer confidence (Asencios and Castellares, 2021). The government boosted tax revenues and royalties, mitigated fiscal risks, and gained better access to financing (Ocampo, 2017; Jimenez and Montoro, 2018). In Chile, trend inflation rose from 3.0% to 3.5% between September 2004 and February 2008, while in Peru, it increased from 2.5% to 2.9% between February 2005 and June 2008. Despite an average rise of 0.5 p.p. in both countries, trend inflation remained within their target ranges. In Mexico, trend inflation rose from 4.1% to 4.4% between January 2006 and July 2008, exceeding the upper limit of the inflation target range by 0.4 p.p.

From the second half of 2008, trend inflation in the PA countries stabilized, coinciding with the beginning of corrections in commodity prices. This adjustment occurred within the context of a recession in the U.S. and European economies triggered by the GFC. Subsequently, the rapid recovery of the Chinese economy in 2010 and 2011 drove a rebound in commodity prices. However, this increase was transitory and did not significantly impact the region's economic structure or trend inflation.

Since the onset of the COVID-19 pandemic, findings indicate a notable rise in trend inflation across PA countries, driven by challenges such as supply chain disruptions, elevated oil prices due to production caps, and escalating fertilizer costs linked to the Ukraine-Russia conflict. From August 2020 to October 2022, trend inflation in the region increased by an average of 0.7 p.p. The pandemic, which began in February 2020, triggered a shift from constrained economic activities to a sudden surge in expenditure, placing additional strain on production chains and amplifying external inflationary pressures. PA countries faced heightened inflation due to these factors, compounded by rising prices of tradable goods and increased production, transportation, and distribution costs. Notably, even as oil prices briefly turned negative in April 2020, subsequent OPEC production cuts from May pushed oil prices higher through 2020 and 2021.

Economic structural transformations persisted into 2022. A resurgence of COVID-19 cases in China led to mobility restrictions and continued supply chain disruptions. Meanwhile, the ongoing Ukraine-Russia conflict, which began in February 2022, drove up international energy, fertilizer, and food prices. These inflationary pressures were further exacerbated by a historic peak in oil prices in June 2022, also driven by OPEC production cuts. Post-lockdown, companies engaged in continued cost restructuring, while surging global demand resulted in significant shifts in economic structures, affecting trend inflation, relative prices, and inflation expectations.

The analysis reveals a rise in trend inflation of 0.5 p.p. in Chile and 0.4 p.p. in Colombia from March 2020 to October 2023, with both remaining within their target ranges. In contrast, Mexico and Peru saw trend

[3] For example, the price of copper increased from USD 1.40 to USD 3.80 per pound between January 2005 and July 2008, with Chile, Peru, and Mexico ranking among the top ten copper exporters worldwide.

inflation exceed their targets by 2.0 p.p. and 0.4 p.p., respectively. Notably, Mexico's trend inflation has been above target since April 2017. Mexico also experienced periods of inflation expectations exceeding the target range, notably from January 2016 to February 2017, in January and April 2018, and from January to June 2019.

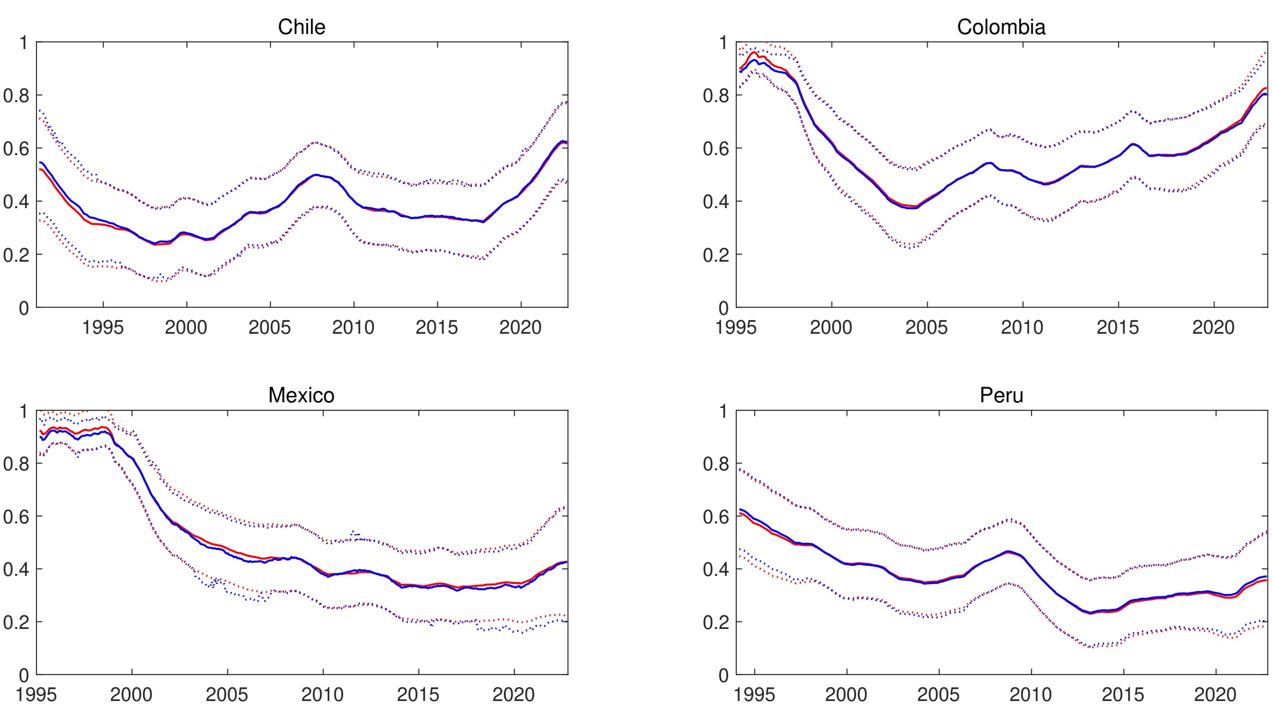
5.2.2 Persistence

Inflation gap persistence measures the extent to which transitory shocks deviate inflation from its trend over an extended period (Roache, 2014). Higher persistence indicates that such shocks have a more pronounced and prolonged impact on the inflation gap, complicating central banks' efforts to stabilize inflation. This necessitates more intensive monetary policy interventions, increasing trade-offs with the output gap.

Figure 5 illustrates the median estimates (solid lines) and credibility intervals at the 16th and 84th percentiles (dotted lines) of inflation gap persistence for the AR-Trend (red) and AR-Trend-Bound (blue) models. The results from both models are generally consistent, with differences primarily observed in the early years of the sample. The AR-Trend-Bound model shows persistence levels below one across all percentiles, reflecting the influence of trend and persistence bands. These findings support the medium-term reduction of the inflation gap, as discussed in Section 3.1.

The AR-Trend-Bound model results indicate that inflation gap persistence decreased in the early years of the sample across all four PA countries, from 0.55 to 0.25 in Chile, 0.90 to 0.53 in Colombia, 0.90 to 0.43 in Mexico, and 0.62 to 0.34 in Peru. This reduction coincides with the implementation of monetary policies aimed at mitigating inflation inertia.

Figure 5: *Posterior Mean (line), 16th and 84th percentiles (dotted line) of ρ_t under the AR-Trend-Bound (blue) and AR-Trend (red) Models.*



From 1997 to 1998, most countries experienced a more modest decline in persistence amid natural disasters and regulatory pressures. In Colombia, inflationary inertia in agricultural products stemmed from the

"Guatemalan moth" plague and the 1998 El Niño phenomenon (ENP). Peru faced similar ENP-related challenges, although the effects were partly offset by declining non-tradable food and fuel prices. Conversely, Mexico recorded higher persistence due to wage indexation practices and two 15% minimum wage hikes in 1998, alongside government-regulated price increases for products such as tortillas and gasoline.

From 2005 to 2007, persistence rose in all four countries, though to varying degrees. Chile saw an increase from 0.34 to 0.50, Colombia from 0.54 to 0.63, and Peru from 0.35 to 0.45, driven by inflationary pressures arising from the economic dynamism of their trade partners and high food and fuel prices. Mexico's persistence rose more moderately, from 0.43 to 0.46, amid inflationary pressures from the aforementioned prices and disinflationary effects from reduced U.S. economic activity.

From mid-2008, inflation gap persistence decreased across the PA countries, reflecting a decline in inflationary pressures due to correcting commodity prices, the GFC, and recessions in major trading partners. Chile experienced the largest drop in persistence, driven by a marked reduction in demand-driven inflationary pressures.

In the wake of the COVID-19 pandemic, persistence began to rise again. In Mexico and Peru, this trend started in early 2020, while in Chile and Colombia, it emerged several months earlier. Country-specific factors in 2019 played a role: in Chile, inflationary inertia arose from social protests, while in Colombia, adverse climatic conditions, including the ENP and prolonged droughts, contributed to rising persistence.

From June 2020 to October 2022, inflation gap persistence increased further, driven by sustained inflationary pressures from transitory factors. During this period, inflation gap persistence rose by 0.16 in Chile and 0.15 in Colombia, while Mexico and Peru saw smaller increases of 0.10 and 0.07, respectively. External shocks, such as rising oil and fertilizer prices, supply chain disruptions, and currency depreciation, were common challenges across the PA countries. However, the domestic rebound in demand, coupled with currency depreciation and output gaps, was more pronounced in Chile and Colombia, resulting in greater persistence compared to Mexico and Peru.

5.2.3 Volatility

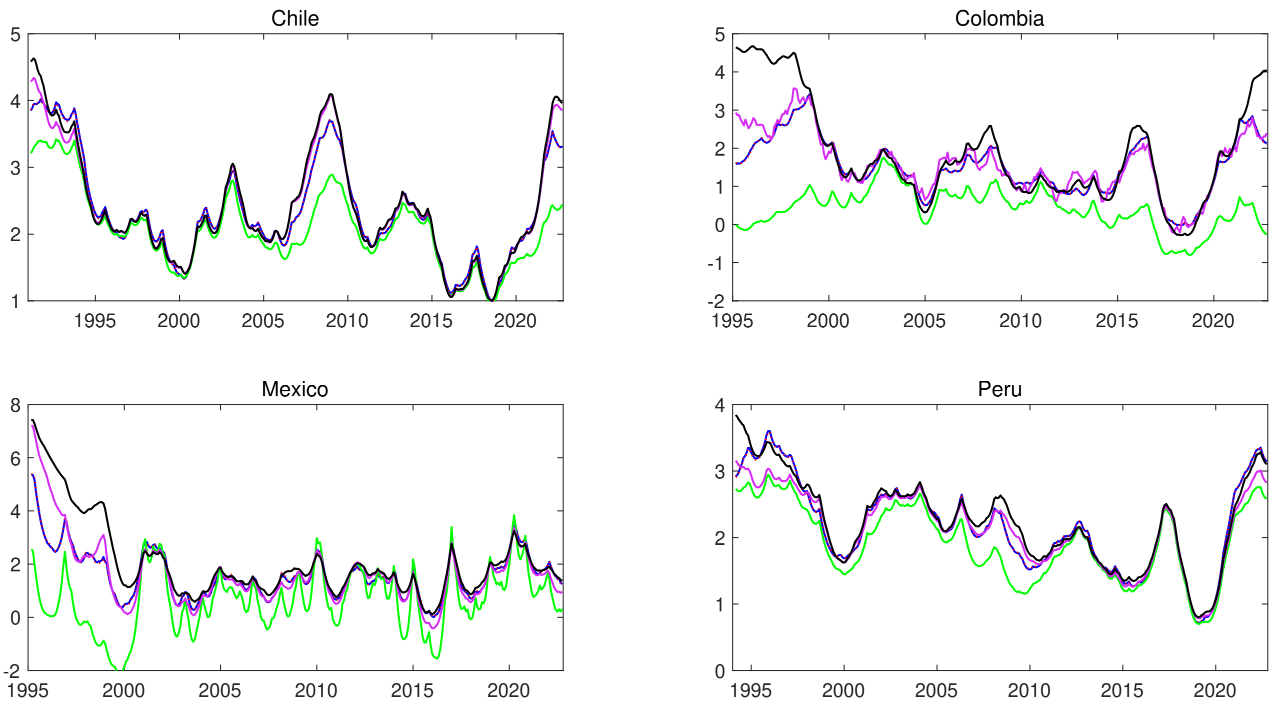
Volatility measures fluctuations in the inflation gap over time, where price instability increases inflation uncertainty (Rother, 2004). Elevated volatility undermines the precision of inflation forecasts (Hall and Jaaskela, 2011), adversely affecting the purchasing power of households and businesses. Additionally, volatility introduces instability in the value of financial assets and liabilities, raising risk premiums (David, 2008).

Changes in volatility are primarily driven by supply shocks, such as unexpected shortages, or demand shocks without corresponding supply adjustments. Global factors, including input price fluctuations affecting production costs, shifts in economic uncertainty, and IT adoption, can also influence volatility (Carriero et al., 2022; Arsić et al., 2022; Arespa and Gonzalez-Alegre, 2022).

Figure 6 presents the median posterior estimates of inflation gap volatility for five models: AR-Trend-Bound (blue), AR-Trend (red), Trend-SV (green), Trend (purple), and Trend-Bound (black). The Trend-SV model shows the lowest levels of volatility, as its specification attributes most inflation variability to trend volatility. In contrast, the Trend and Trend-Bound models exhibit the highest levels of volatility, as they do not account for inflation gap persistence, treating it as a stochastic process.

Volatility estimates for the AR-Trend and AR-Trend-Bound models fall between those of the Trend-SV model (lowest) and the Trend and Trend-Bound models (highest). This outcome stems from their specifications, where the volatility of the disturbances in the inflation gap's autoregressive process is modeled as described in equation (2). These specifications ensure trend inflation and inflation gap persistence exhibit relatively stable behavior over time, facilitating the identification of structural economic changes in trend inflation while isolating short-term variations in persistence.

Figure 6: *Posterior Mean of h_t under the AR-Trend-Bound (blue), AR-Trend (red), Trend-SV (green), Trend (purple) and Trend-Bound (black) Models.*



Given the importance of inflation bands in estimating trend inflation and inflation gap persistence, the dynamics of volatility under the AR-Trend-Bound model are examined separately. Figure 7 displays the median (blue line) and credibility intervals (dotted blue line) at the 16th and 84th percentiles of the posterior distribution of inflation gap volatility in the AR-Trend-Bound model. The results align with Latin American literature on the Great Moderation of inflation in PA countries, which documents reduced volatility in the inflation gap since the adoption of implicit IT, with exceptions during the GFC and the COVID-19 pandemic. In Mexico, the Great Moderation was disrupted briefly in 1998 due to an unexpected exchange rate depreciation caused by the Asian and Russian financial crises, alongside volatile fruit and vegetable prices driven by rainfall cycles and floods. In Colombia, volatility increased in response to supply-side pressures from transport strikes during the same period.

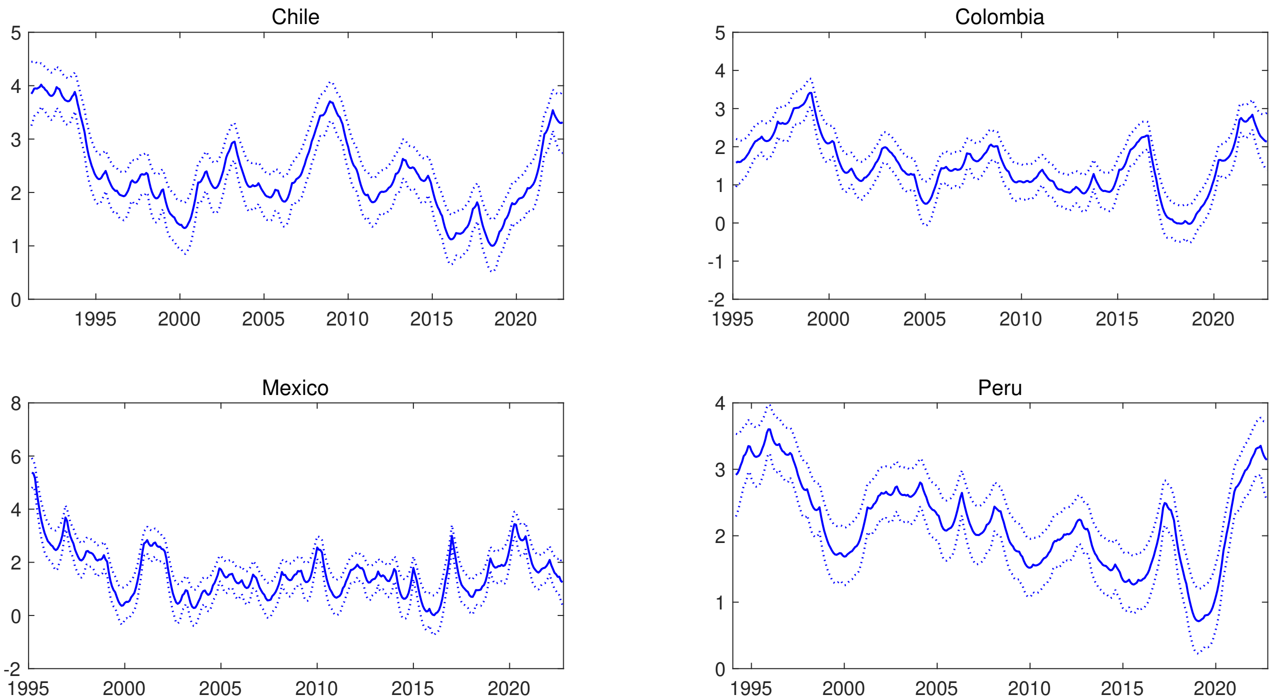
Between 2002 and 2003, inflation gap volatility rose temporarily in PA countries due to fluctuations in fuel and food prices, with negative inflation rates observed in Chile and Peru. As these prices normalized, inflation returned to target ranges.

The GFC disrupted the Great Moderation, leading to heightened risk and uncertainty, which caused a sharp decline in international metal, oil, and food prices. However, expansionary monetary and fiscal policies prevented deflation. Volatility peaked in PA countries in late 2009, driven by China's economic recovery and the global surge in commodity prices. Chile recorded the highest volatility during this period, with inflation plunging from 9.9% in October 2009 to -2.3% in November, reflecting demand-side deflationary pressures.

After the GFC, inflation gap volatility in PA countries returned to Great Moderation levels, remaining stable until the COVID-19 pandemic. Notable exceptions include Colombia, where volatility spiked temporarily in 2016 due to currency depreciation and transport strikes, and Peru, where sudden drops in the prices of electricity and food items (e.g., sugar, meat, potatoes) caused inflation to decline sharply from 3.2% in August

2017 to 0.4% in March 2018, crossing from above to below the target range within six months.

Figure 7: *Posterior Mean (blue line),* $16th$ *and* $84th$ *percentiles (blue dotted line) of* h_t *under the AR-Trend-Bound Model.*



The COVID-19 pandemic marked another interruption of the Great Moderation. Inflation gap volatility reached its highest levels since 1995 across all four PA countries, reflecting heightened uncertainty in a context of abrupt shifts, including rising fuel and service prices, increased international freight costs, and inflationary pressures arising from sudden demand changes.

5.2.4 Inefficiency Factors

The efficiency of the MCMC method is assessed using the inefficiency factor, defined as $1 + 2\sum_{l=1}^{L}\phi_l$, where ϕ_l is the sample autocorrelation at lag l, and L should be large enough for autocorrelation to decrease. Ideally, the inefficiency factor equals 1, indicating that posterior simulations are uncorrelated. For example, an inefficiency factor of 5 implies that 500 posterior simulations are required to obtain the equivalent information of 10 independent simulations. Therefore, more efficient models yield less autocorrelated estimates.

Table 4 reports the inefficiency factors for the unobserved components and parameters estimated across the five models. Since each component has T inefficiency factors—one for each month over the sample period—and 45,000 simulations are considered, the 25th, 50th, and 75th percentiles are presented for brevity. For parameters that remain constant over time, a single inefficiency factor is provided.

In general, the AR-Trend and AR-Trend-Bound models exhibit the lowest inefficiency factors across all parameters. In contrast, the Trend-Bound model demonstrates the highest inefficiency factors for trend inflation and its variance across the four countries, as well as for inflation gap volatility in Mexico and Peru. The Trend-SV model has the second-highest inefficiency factors for trend inflation in most countries, while the Trend model shows the highest inefficiency factors for volatility and variances in Colombia. Unlike the

Table 4: *Ineffienciency Factors of Selected Parameters*

Parameter	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound	Trend-SV	Trend	Trend-Bound	AR-Trend	AR-Trend Bound
	Chile					Colombia				
$\tau_{(25\%)}$	4.9	1.6	21.6	1.3	9.0	10.2	27.3	1097.8	1.7	6.7
$\tau_{(50\%)}$	11.9	3.0	30.9	2.3	11.8	26.9	144.3	1258.1	3.4	8.4
$\tau_{(75\%)}$	27.7	8.9	42.5	4.5	17.0	69.0	625.3	1387.1	5.9	9.8
$\rho_{(25\%)}$	-	-	-	1.5	19.4	-	-	-	2.0	12.5
$\rho_{(50\%)}$	-	-	-	2.5	35.7	-	-	-	2.9	19.4
$\rho_{(75\%)}$	-	-	-	3.5	82.8	-	-	-	6.3	31.0
$h_{(25\%)}$	14.8	2.7	4.6	2.5	3.3	95.8	368.3	34.7	4.7	4.6
$h_{(50\%)}$	24.1	3.6	6.2	3.3	4.2	178.4	821.6	64.4	6.7	6.5
$h_{(75\%)}$	49.3	4.8	8.6	4.4	5.6	300.3	1257.9	105.0	10.5	8.4
σ^2_τ	-	84.1	250.7	56.8	107.9	-	1138.2	1383.2	46.1	36.6
σ^2_ρ	-	-	-	49.0	49.5	-	-	-	23.9	130.4
σ^2_h	177.7	33.0	23.4	46.1	30.1	633.5	705.9	23.4	55.9	68.5
σ^2_g	335.6	-	-	-	-	707.8	-	-	-	-
	Mexico					Peru				
$\tau_{(25\%)}$	8.0	2.4	867.1	5.9	21.6	3.7	1.7	340.1	2.2	8.4
$\tau_{(50\%)}$	20.5	3.4	1058.9	9.3	37.1	8.1	3.2	430.7	3.5	10.5
$\tau_{(75\%)}$	54.4	5.3	1246.5	13.3	81.5	18.6	7.5	526.4	6.5	14.5
$\rho_{(25\%)}$	-	-	-	6.6	56.4	-	-	-	1.8	8.0
$\rho_{(50\%)}$	-	-	-	8.0	104.5	-	-	-	2.9	10.3
$\rho_{(75\%)}$	-	-	-	10.9	205.8	-	-	-	4.8	13.9
$h_{(25\%)}$	29.9	10.9	44.3	28.0	19.8	7.8	2.2	12.7	2.5	2.7
$h_{(50\%)}$	68.9	13.1	86.4	38.6	25.5	13.1	2.9	20.3	3.4	3.4
$h_{(75\%)}$	150.7	16.2	169.9	57.6	33.1	25.7	4.6	29.0	4.3	4.4
σ^2_τ	-	43.0	855.5	38.5	96.4	-	80.5	1267.5	66.9	71.1
σ^2_ρ	-	-	-	37.8	152.8	-	-	-	28.7	51.6
σ^2_h	155.1	42.6	480.8	139.3	119.7	104.1	34.3	36.7	29.2	33.3
σ^2_g	776.6	-	-	-	-	464.9	-	-	-	-

AR-Trend model, the AR-Trend-Bound model incorporates the specific features of IT regimes to estimate trend inflation, persistence, and volatility (Section 3.1). These results indicate that the AR-Trend-Bound model is the most efficient for modeling the unobserved components of inflation in PA countries.

6. Robustness Analysis

The robustness analysis evaluates the stability of results obtained with the AR-Trend-Bound model by modifying initial assumptions and identifying potential sources of bias. To this end, alternative estimates are generated by varying the hyperparameters of priors related to trend inflation and inflation gap persistence.

Figure 8 illustrates the median results of the posterior distribution under different initial hyperparameters for trend inflation expectations at $t = 0$, where $\tau_0 = 0$ (blue), $\tau_0 = 3$ (orange), $\tau_0 = 4$ (yellow), $\tau_0 = 5$ (purple), and $\tau_0 = 6$ (green). The findings indicate that trend, persistence, and volatility estimates remain largely unaffected by changes in these hyperparameters, provided they align with the disinflation process observed in the 1990s. Notably, using priors that fail to account for the high inflation levels at the sample's start introduces biases. For example, when $\tau_0 = 0$, trend inflation shows an upward trajectory during the early sample years, inconsistent with the documented disinflation of the 1990s.

In contrast, estimates based on the other priors exhibit minor differences, which diminish over time. At $t = 0$, the average discrepancy between trend inflation estimates for $\tau_0 = 3$ and $\tau_0 = 6$ is 0.6 p.p. However, extending the analysis period to January 2001–October 2022 reduces this difference to 0.2 p.p., reflecting the influence of the high inflation rates of the early 1990s.

Figure 8: *Posterior Mean of τ_t, ρ_t and h_t under the AR-Trend-Bound Model with $\tau_0 = 0$ (blue), $\tau_0 = 3$ (orange), $\tau_0 = 4$ (yellow), $\tau_0 = 5$ (purple) and $\tau_0 = 6$ (green).*

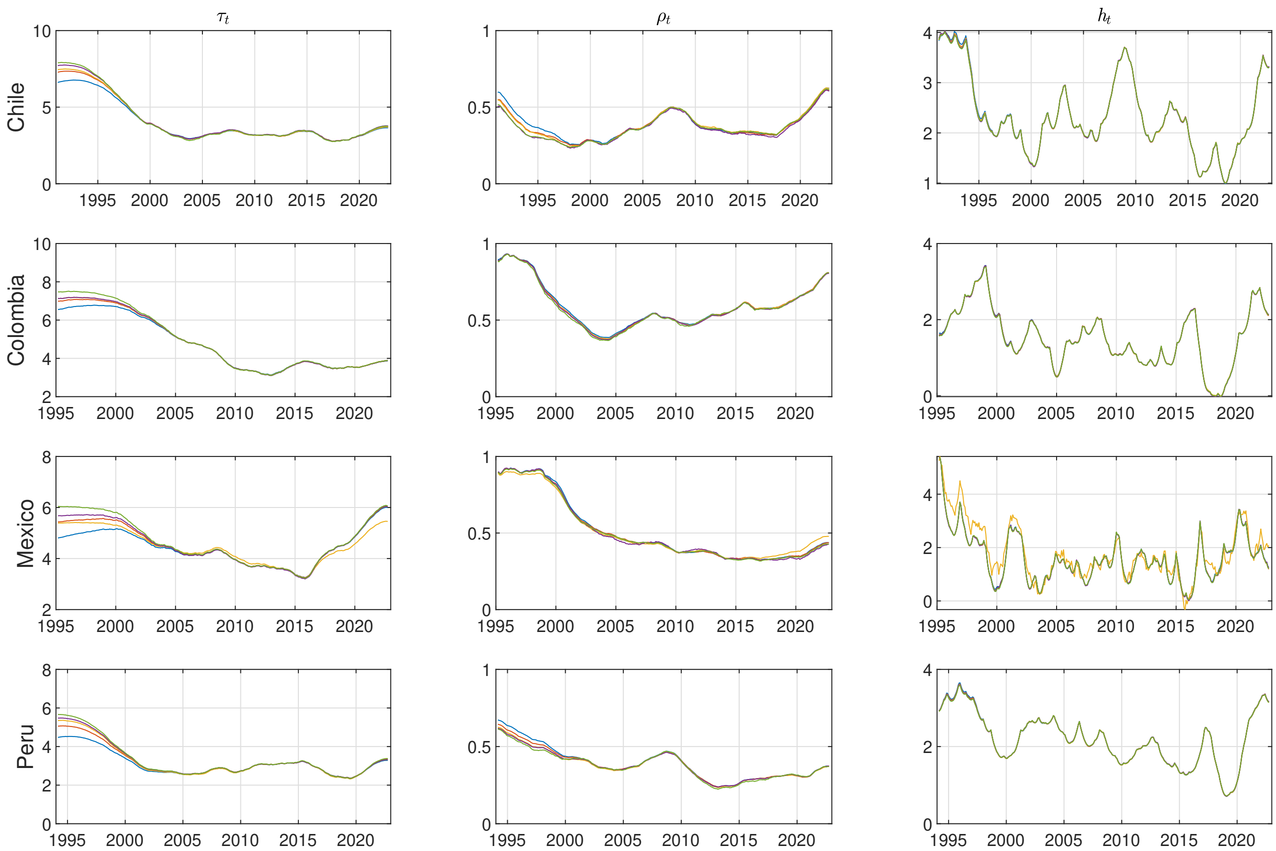
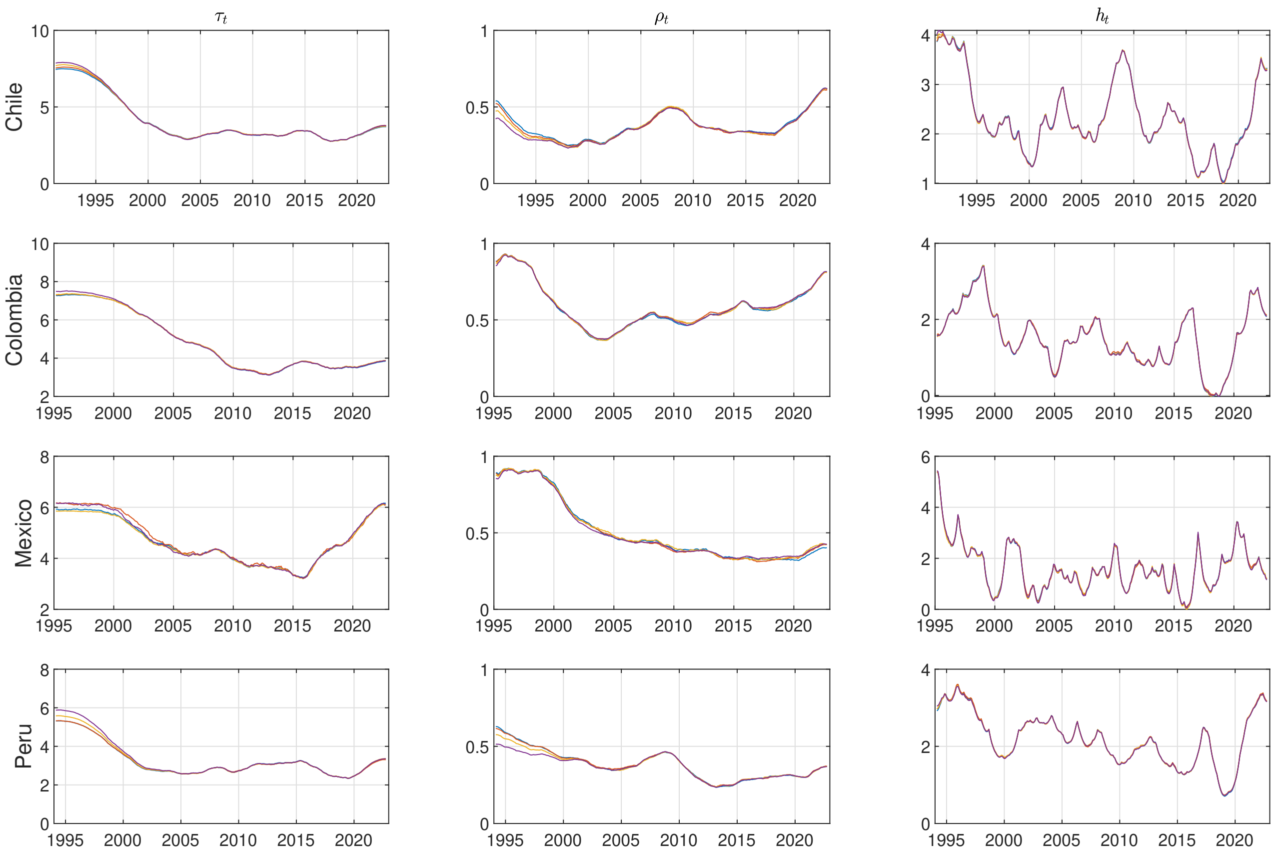


Figure 9 displays results obtained with varying hyperparameters for the variance of inflation gap persistence, denoted as $\omega_\rho^2 = 1$ (blue), $\omega_\rho^2 = 2$ (orange), $\omega_\rho^2 = 5$ (yellow), and $\omega_\rho^2 = 10$ (purple). As ω_ρ^2 increases, the prior variance for the first estimated value rises, rendering the initial distribution less informative. This shift reduces the influence of the prior, placing greater weight on the data in estimating the posterior distribution.

The results indicate that the estimations for trend, persistence, and volatility are robust to changes in the hyperparameters for inflation gap persistence. However, slight deviations occur in the estimation of persistence during the sample's initial months. In Chile and Peru, for instance, the discrepancy in persistence estimates between $\omega_\rho^2 = 1$ and $\omega_\rho^2 = 10$ is 0.1 p.p. in 1991 and 1994, respectively. These differences dissipate within three years. In contrast, for Colombia and Mexico, the discrepancies across hyperparameter values are negligible.

Figure 9: *Posterior Mean of τ_t, ρ_t and h_t under the AR-Trend-Bound Model with $\omega_\rho^2 = 1$ (blue), $\omega_\rho^2 = 2$ (orange), $\omega_\rho^2 = 5$ (yellow) and $\omega_\rho^2 = 10$ (purple).*



7. Conclusions

This study estimates and analyzes trend inflation, as well as the persistence and volatility of the inflation gap, in PA countries, employing methodologies proposed by Stock and Watson (2007) and Chan et al. (2013). This framework incorporates IT features into the estimation of unobserved components of inflation.

The AR-Trend-Bound model emerges as the most suitable for capturing unobserved components of inflation. Its prior CDF effectively replicates inflation features across all four countries, while the BFs underscore its parsimony across features. The results for each unobservable component align with historical inflation patterns, central bank reports, and the economic literature. Moreover, the model exhibits low inefficiency factors across parameters. The robustness analysis further supports these findings, demonstrating stable dynamics in trend inflation, persistence, volatility, and inefficiency factors under alternative specifications.

This study underscores the importance of jointly estimating trend inflation, along with inflation gap persistence and volatility, for a thorough understanding of inflation dynamics. The results emphasize the importance of accurately specifying the inflation gap within the methodological framework, as highlighted by Cogley et al. (2010) and Chan et al. (2013). Estimating persistent inflation gaps is crucial to capturing the behavior of trend inflation. Additionally, accounting for inflation gap volatility enhances the characterization of trend inflation and inflation gap persistence by avoiding excessive fluctuations.

The results reveal a gradual decline in trend inflation during the 1990s, stabilizing within target ranges by

2004. This trend reflects the influence of global economic factors (Calvo and Mendoza, 1999; Rosende and Tapia, 2015) and country-specific institutional developments (Ireland, 2007; Garnier et al., 2015). Between 2005 and 2008, trend inflation increased in most PA countries during a period of structural shifts driven by high commodity prices, consistent with findings by Cogley et al. (2010) for developed economies. Following the onset of the COVID-19 pandemic, trend inflation rose across all four countries, exceeding target ranges in Mexico and Peru by 2.0 p.p. and 0.4 p.p., respectively. These increases occurred amid regional structural adjustments driven by supply chain disruptions, elevated oil and fertilizer prices due to prolonged OPEC restrictions, and the Ukraine-Russia conflict.

Inflation gap persistence declined across all PA countries in the initial years of the sample, coinciding with the implementation of monetary policies targeting inflation inertia (Roache, 2014). From 2005 until the GFC, persistence increased alongside elevated food and fuel prices but subsequently declined from mid-2008 amid reduced inflationary pressures, including recessions in PA countries' primary trading partners. During the COVID-19 pandemic, persistence was notably higher in Colombia and Chile than in Mexico and Peru, reflecting differences in initial conditions as of 2019, such as social unrest in Chile and adverse climatic events in Colombia.

Volatility in the inflation gap diminished across most PA countries during the 1990s and early 2000s, reflecting the Great Moderation in inflation (Singh, 2006; Castillo et al., 2012, 2016; Ha et al., 2019). This reduced volatility reflects the effectiveness of IT central banks, consistent with findings by Arsić et al. (2022) for emerging economies in Europe and Central Asia. However, volatility increased during the GFC and the first two years of the COVID-19 pandemic, interrupting the Great Moderation due to fluctuations in international food, oil, and mineral prices, echoing the conclusions of Carriero et al. (2022) for developed countries.

Future research could explore alternative approaches for estimating the three unobserved components based on the Neo-Keynesian Phillips curve, as proposed by Baxa et al. (2015), and further integrate IT features into the models. Including additional variables, such as inflation expectations, could also enhance the estimation of unobserved components, as suggested by Chan et al. (2018), while linking these results to improved central bank communication strategies, as discussed by Clark and Davig (2008). Additionally, comparisons between trend inflation and alternative measures of core inflation could employ methodologies proposed by Lahura and Vega (2011), Humala and Rodriguez (2012), and Stock and Watson (2016). Finally, investigating the implications of reductions in the economically active population due to the COVID-19 pandemic on trend inflation, as per Juselius and Takats (2018), offers a promising avenue for further research.

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