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A composite approach to nonlinear inflation dynamics in BRICS countries and Türkiye

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Abstract

This study introduces a novel composite approach to nonlinear inflation dynamics in identifying historical inflation patterns and forecasting future regime shifts. Assuming inflation's responsiveness to its determinants varies across inflation regimes and that inflation shock magnitude shapes the dynamics, we endogenously identify distinct inflation regimes and analyze nonlinear behaviors within such regimes for the BRICS countries (Brazil, Russia, India, China, and South Africa) and Türkiye. In the first stage of our analysis, we employ a Hidden Markov Regime Switching Model combined with Monte Carlo simulations to establish high- and low-inflation thresholds. In the second stage, we utilize an ordered probit model to identify nonlinear probabilistic relationships between inflation regimes and key drivers of inflation such as unit labor costs, exchange rates, and global inflation. Our method achieves over 90% accuracy in predicting inflation regimes based on historical data. It also shows particularly strong out-of-sample performance in the post-pandemic period, outperforming the forecasts of international financial institutions. Even without prior knowledge of exogenous variables, the method anticipates regime shifts in five of the six countries analyzed for 2022 and 2023. Our approach offers researchers and central bankers a robust alternative analytical framework for managing high- and low-inflation environments where traditional linear or equilibrium-based models fall short.

Keywords: high inflation, regime switching model, probit model, early warning

JEL Codes: E31, E37, E12, C24, C51

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Non-technical summary

Focus

The study investigates the nonlinear inflation dynamics in emerging economies, with a particular focus on the BRICS countries (Brazil, Russia, India, China, and South Africa) and Türkiye. We explore how the relationship between inflation and its underlying determinants evolves across different inflation regimes and in response to varying shock magnitudes. Specifically, we analyze the structural behavior of both high- and low-inflation environments, assessing how regime-dependent and magnitude-driven nonlinearities affect inflation forecasting and detection of regime transitions in these economies.

Contribution

The study introduces a novel composite framework that integrates shock magnitude and regime-based nonlinearities. Using a Hidden Markov Regime Switching Model (HMM) with Monte Carlo simulations, we endogenously identify inflation regimes for each country from the 1990s to 2024. We also develop a probit model that incorporates magnitude-related nonlinearities to predict inflation regimes accurately. The framework enhances theoretical understanding of inflation dynamics in emerging markets and can serve as an early-warning tool for monetary authorities facing inflationary risks in uncertain environments.

Findings

Our composite model achieves over 90% in-sample forecasting accuracy and demonstrates robust out-of-sample predictions for post-pandemic inflation dynamics in the BRICS countries and Türkiye. The results indicate that inflation exhibits an asymmetric response to large shocks. Pricing behavior varies across inflation regimes, with cautious adjustments prevailing in low-inflation regimes, and aggressive, synchronized price increases characterizing high-inflation regimes. The framework accurately detects regime shifts such as the post-2020 surge in inflation without relying on exogenous inputs, thereby underscoring its practical utility for monetary policy in emerging economies.

1. Introduction

The post-pandemic period revealed that many central banks significantly underestimated the magnitude and persistence of high inflation. Traditional forecasting models failed to anticipate the surge in inflation (Bernanke, 2024), and despite its persistent nature, many prominent central bankers initially characterized high inflation as a transient phenomenon (Ihrig & Waller, 2024). Forecasting failures are not exclusive to high-inflation periods, similar problems have arisen during persistent low-inflation episodes. A substantial body of literature attempts to explain this phenomenon of “missing inflation.” While inaccurate low-inflation forecasts might dent the credibility of central banks slightly, failure to anticipate persistent high-inflation episodes can severely erode trust in monetary policy (Coleman & Nautz, 2022).

Recent questioning of the lasting quality of recent inflation declines highlights an emerging concern among economists about a resurgence of inflation driven by trade tensions and gaps in current forecasting models. A study of “sellers’ inflation” provides a possible explanation for institutional failures in accurately forecasting high inflation, attributing it to a strong nonlinear relationship between inflation and exchange rates (Yusifzada, Cömert, & Parmaksiz, 2024). The authors conclude that most episodes of high inflation can be anticipated by observing sharp currency depreciations. Taylor (2000) and subsequent studies take a different tack, attributing low-inflation episodes to the reduced pricing power of firms caused by shifts in expectations. In considering this view, it is prudent to acknowledge that the determinants of inflation at a given time influence inflation expectations during the same period (Nasir, Huynh, & Vo, 2020). Consequently, a form of nonlinearity exists wherein these determinants not only influence inflation expectations but also impact their pass-through to actual inflation, often leading to forecast errors by economists.

Similar to these studies, our approach to understanding high- and low-inflation environments is grounded in two types of nonlinearities, which, we argue,

are the main reason linear forecasting models may fall short. The first type of nonlinearity relates to shock magnitude. It refers to the disproportionately large effect of determinants on inflation when they surpass a certain threshold. In other words, the response of inflation to an economic disturbance is not simply proportional to the size of the shock. Relatively small shocks can have modest, short-lived impacts on prices, while large shocks can trigger disproportionately hefty and persistent inflationary responses. Such dynamics are partially discussed in the literature on sellers' inflation, as well as in mainstream research that models nonlinear inflation dynamics such as Frankel, Parsley, & Wei (2012), Caselli & Roitman (2019), and Ögünç & Özel (2025).

The second type, regime nonlinearity, relates to the underlying inflation process and behaves quite differently across regimes. In a low-inflation regime, for example, firms tend to adjust prices cautiously, and price or wage shocks typically dissipate quickly. In contrast, price-setting in a high-inflation regime becomes aggressive and synchronized, with even moderate shocks triggering broad and persistent price increases. This form of nonlinearity has been partially explored in mainstream literature following Taylor (2000), as well as in the sellers' inflation literature, including the seminal works by Lerner (1958), Baer (1967), and their successors. In parallel, several strands of empirical research within the mainstream literature identify regime-dependent nonlinearities within the traditional Phillips curve framework. Notable contributions to this body of work include Busetti, Caivano, & Monache (2021), Cristini & Ferri (2021), Smith, Timmermann, & Wright (2024), and Benigno & Eggertsson (2024).

Considering that emerging economies often face larger external shocks than advanced economies, as well as more volatile expectations and structural changes that can push the economy into a different inflation regime, the nonlinear dynamics driving inflation are significantly more pronounced in these economies. Consequently, many widely used forecasting models, particularly mean-reverting or equilibrium-converging linear models, including Dynamic Stochastic General

Equilibrium (DSGE) models and Quarterly Projection Models (QPM),¹ have proven inadequate in capturing the frequent episodes of high and low inflation characteristic of emerging economies.

Aware of this, the Central Bank of Türkiye (Öğünç & Özel, 2025) and the Central Bank of Brazil (Marodin & Portugal, 2018) have leveraged the magnitude-based nonlinearity between inflation and exchange rates to better understand inflationary behavior. Regime-triggered nonlinearity, however, remains overlooked.

In response to these limitations, this research introduces a novel composite approach to explore nonlinear inflation dynamics to better understand historical inflation patterns and forecast future regime shifts. Building on the notions that inflation's responsiveness to its determinants varies across inflation regimes and that shock magnitude shapes these dynamics, we first endogenously identify distinct inflation regimes and then analyze nonlinear behaviors within these regimes for the BRICS countries and Türkiye. In the literature, different inflation regimes (e.g. high and low) are generally identified based on a threshold inflation level beyond which economic growth declines. Rather than using this traditional regime identification, we focus here on the structural price formation mechanisms within high- and low-inflation regimes as they can diverge significantly from those observed in normal inflation environments. To operationalize this, we employ a Hidden Markov Regime Switching Model (HMM) for each country in a sample covering the period from the 1990s to 2024. This approach allows for the endogenous identification of high- and low-inflation regimes. The HMM ensures that the structure of price-setting (specifically, markups and elasticities) aligns with the theoretical foundations of regime nonlinearity.

¹ The Banco Central do Brasil (2025), the Central Bank of Russia (2025), the Reserve Bank of India (2025), and the South African Reserve Bank (2025) apply these models widely in their policymaking processes.

Once the thresholds for high- and low-inflation regimes are established, we ask whether nonlinearities are strong enough to explain and predict inflation regimes in the BRICS and Türkiye. Here, we apply a probit model to analyze and predict inflation regimes, accounting for both types of nonlinearities. This framework ensures that the responsiveness of inflation to its determinants varies across inflation regimes and with shock magnitude. The probit model used in this composite approach can also serve as an early-warning tool for future inflation regime switches.

This research makes two primary contributions to the literature and central banking practices. First, it proposes a new composite methodology for defining high and low inflation regimes that is well grounded in economic theory.² The approach offers a robust foundation for understanding inflation dynamics, particularly in emerging markets. The second contribution is the development of the nonlinear probit model that incorporates the two identified types of nonlinearities. The model demonstrates over 90% accuracy in in-sample forecasting and provides robust out-of-sample predictions for post-pandemic inflation dynamics.

For example, when trained using data up to 2021 and incorporating auto-ARIMA-based conditions on inflation determinants for the following year, the model successfully forecasts high- and low-inflation probabilities for Russia, China, and Türkiye. While the model accurately predicts the forthcoming regime for India, it comes close to failure in 2023. The model also shows a minor misprediction in Brazil, failing to detect the low inflation that occurred in 2023 (inflation reached 3.76%, nearly our threshold of 3.83%). Conversely, in South Africa, the ARIMA model's misprediction of a significant exchange-rate depreciation of up to 20% (an important

² Kinlaw, Kritzman, Metcalfe, & Turkington (2023) also use the HMM to determine inflation regimes, but as a statistical tool rather than a theoretical framework. They benefit from the dynamics of inflation persistence in the HMM in determining states, but do not include a structural inflation equation. We take inspiration from their work, but note that determination of regimes in our case is rooted in the structural relationship between inflation and its determinants.

factor in determining inflation regimes) led the probit model to signal a high probability of low inflation that did not materialize in the post-pandemic period. Once the magnitude of the depreciation became available in the later training sample, the regime predictions in the model were corrected accurately.

The paper proceeds as follows. The next section develops a structural theoretical framework for our empirical investigation. The third section introduces the data. In the fourth section, we identify endogenously determined regime-switching inflation thresholds using a Hidden Markov Regime Switching model aided by Monte Carlo simulations. Leveraging these endogenously derived thresholds within an ordered probit model, we examine the implications of the different magnitudes of the shock across the same inflation regimes in the fifth section. The sixth section discusses out-of-sample predictions of our composite method and its policy implications. The final section concludes.

2. A structural theoretical framework

“High inflation” is often defined in the literature as the level of inflation that impedes economic growth.³ Low inflation is characterized as inflation near zero, particularly in advanced economies, as seen in the work of Akerlof, Dickens, Perry, Gordon, & Mankiw (1996). This binary framework does not fully account for the unique inflation dynamics of emerging economies, where inflation tends to be higher and more volatile than in advanced economies. Arias, Erceg, & Trabandt, (2016) and Andersson, Corbo, & Löf (2015) offer an alternative definition of inflation regimes based on deviations from central bank target rates. This approach also fails

³ In earlier research, Bruno and Easterly (1998) note that a 40% inflation rate leads to substantial output losses. However, as presented in Table A.1 in the Appendix, different research studies find varying high-inflation threshold values for different countries. Consequently, consensus on the definition of a high-inflation level remains elusive.

to capture the structural price-setting dynamics affected by low- and high-inflation environments in emerging economies.

We define high inflation as the level at which inflation expectations become distorted,⁴ and thereby make buyers more likely to accept price hikes. When faced with cost shocks in such an environment, firms “can safely increase prices since they have a mutual expectation that all market players will do the same” (Weber & Wasner, 2023, p. 190). This phenomenon is often referred to as profit-led inflation (Lerner, 1958; Nikiforos, Grothe, & Weber, 2024). Firms believe consumers with distorted price perceptions are more amenable to higher prices. In such an environment, firms can protect their profit margins and even increase them (Franzoni, Giannetti, & Tubaldi, 2023; Weber & Wasner, 2023). This is only possible as long as consumers accept higher prices.

Originated by the early work of Lerner (1958) and Baer (1967), this conceptual framework is supported by a growing body of literature, particularly from the seller’s perspective. It has gained prominence in advanced economies in the wake of the supply shortages that arose during the Covid pandemic. Several strands of mainstream empirical literature also provide evidence of similar regime-dependent nonlinearities in inflation behavior, particularly within a Phillips curve framework. For example, Buseti, Caivano, & Monache (2021) observe a higher influence of domestic and foreign output gap in the right tail of the conditional inflation distribution; Cristini & Ferri (2021) find that import prices have a more pronounced impact during boom periods; Smith, Timmermann, & Wright (2024) and

⁴ This idea originated from Robert A. Blecker’s feedback on our previous research on high inflation, where we followed the conventional literature defining high inflation as harmful to growth. We took seriously his question “What if we define high inflation as a level that distorts inflation expectations?” and, thanks to his further guidance, explored how distorted expectations impact inflation dynamics. This ultimately led us to formulate our framework for defining inflation regimes based on nonlinearities.

Benigno & Eggertsson (2024) document a steeper Phillips curve in tight labor market conditions.

In line with this understanding of high inflation, we define low inflation as a level at which inflation falls below a specific threshold, thereby eroding the willingness of consumers to accept price increases and limiting the pricing power of firms. The expectation-driven reduction in pricing power in low-inflation environments is well-documented, particularly in the theoretical literature following Taylor (2000). The empirical studies of nonlinear Phillips curves such as Gagnon and Collins (2019) further demonstrate that the Phillips curve flattens when inflation is low, suggesting weaker inflationary pressure in such regimes.

While we visualize high and low inflation through the lens of sellers' pricing behavior as outlined in the sellers' inflation literature initiated by Lerner (1958), we also emphasize the crucial role of consumer acceptance of price changes needed to provide the fertile ground for inflation to take root. In this regard, we build our theoretical foundation on the sellers' inflation literature (a similar equation can be obtained from the mainstream literature, which treats markup as endogenous) and the following structural inflation equation:⁵

$$\pi = \Phi_1(\omega_{-1} - [\omega_{f0} - \Phi_5(\Delta shk_{t-1} - \pi_{-1})]) + \Phi_2(\Delta ULC) + \Phi_4\Delta(1 + UMC_{wl}), \quad (1)$$

where π is inflation, Φ_1 , Φ_2 , and Φ_4 are the price adjustment parameters of firms with respect to the discrepancy between the previous period's actual real wage (ω_{-1}) and the firms' desired real wage rate (ω_f), Unit Labor Cost (ULC), and Unit Material Cost (UMC). The term $\Phi_1(\omega_{-1} - [\omega_{f0} - \Phi_5(\Delta shk_{t-1} - \pi_{-1})])$ explains endogenous markup dynamics, which differ from mainstream inflation equations and constitute an essential part of nonlinearity.

⁵ The derivation of Equation 1 is provided in Section A.1 of the Appendix.

Within this framework, sellers gain additional pricing power if consumers tolerate higher price increases due to distorted inflation expectations in a high-inflation environment. This leads to an increase in their price adjustment parameter, Φ , as well as potential benefits from larger profit margins. In a low-inflation environment, sellers' pricing power becomes constrained – even in the face of rising costs – as emphasized by Taylor (2000). This framework allows us to distinguish among inflation regimes.

Nonlinear price-setting behavior is observed not only between inflation regimes but also within them, particularly when sellers face exceptionally large or small cost shocks. This means that even within a given regime, large cost shocks can lead to disproportionately higher inflation. This occurs through both an increase in the price adjustment parameter (Φ) and through the higher markup channel. These are partially explored in the sellers' inflation literature, as well as in the mainstream literature that estimates nonlinear inflation equations such as Frankel, Parsley, and Wei (2012), Caselli and Roitman (2019), Ögünç & Özel (2025), and asymmetric pass-through literature such as Pham, Nguyen, Nasir, & Huynh (2023), Deluna, Loanzon, & Tatlonghari (2021), Modenesi, Luporini, & Pimentel (2017).

When both magnitude and regime nonlinearities are activated, sellers gain near-complete pricing power, while consumers, influenced by distorted expectations, accept higher prices with less reluctance. In this environment, the inflation equation can be expressed as:

$$\begin{aligned} \pi = & \Phi_{1,R,M_{shk}}(\omega_{-1} - [\omega_{f0} - \Phi_{5,R,M_{shk}}(\Delta shk_{t-1} - \pi_{-1})]) \\ & + \Phi_{2,R,M_{ULC}}(\Delta ULC) + \Phi_{4,R,M_{UMC}}\Delta(1 + UMC_{wl}) , \end{aligned} \quad (2)$$

where the parameters are sensitive to the R-inflation regime in the previous period and the M-magnitude of the shock.

3. Data

Before estimating the structural inflation equation (Equation 2), we address a few data-related challenges. The first pertains to markup dynamics not observable for BRICS and Türkiye over an extended period. Similar to many empirical studies, we proxy markup using the constant term of a reduced-form econometric model. Unlike mainstream approaches, however, we allow markup to be an endogenous function of cost shocks and can vary significantly under various inflation regimes due to cost shocks (the regime nonlinearity discussed earlier). Thus, markup is neither constant nor time-varying for each period, but varies by regime.

As we need wage, labor, and GDP data to estimate the Unit Labor Cost (ULC) for each country, our second challenge arises from the lack of accessible average wage data over a long horizon for most of our analyzed countries (wage data for South Africa and China are available). To address this problem, we take minimum-wage data as a proxy. Such data are available for the entire analysis period for all countries. For Brazil, the central bank provides monthly observations. For South Africa, the central bank provides quarterly observations. For India, the Ministry of Labor provides yearly observations. For Türkiye, data are based on minimum wage adjustments recorded quarterly. For China and Russia, data are provided by national statistical committees on an annual basis. Annual observations are converted into quarterly data using the Chow-Lin methodology, with nominal GDP as the reference variable.

Labor data are obtained from the World Bank as annual observations and converted into quarterly observations using the same Chow-Lin methodology, with nominal GDP as the reference variable for all analyzed countries.⁶

⁶ Since the estimation of ULC requires dividing the product of these series by GDP, it eliminates any potential noise or volatility introduced by the Chow-Lin-based transformation. Consequently, the final ratio of real wage to productivity is not sensitive to the transformation methodology.

To complete the ULC estimation, we obtain nominal GDP data for all analyzed countries as quarterly observations. The sources of this data include central banks for Brazil and South Africa, the OECD for India, the national statistical committee for China, and the International Financial Statistics (IFS) for Russia and Türkiye. Use of multiple data sources helps maximize the data coverage across all countries.

Table 1. Coverage of the data

Country	CPI	Minimum Wage	Labor	GDP	FX
Brazil	1980-2024	1990-2024	1990-2023	1990-2024	1957-2024
Russia	1992-2024	1995-2024	1994-2023	1994-2024	1992-2024
India	1957-2024	1996-2024	1996-2023	1996-2024	1957-2024
China	1986-2024	1998-2024*	1992-2023	1992-2024	1957-2024
South Africa	1957-2024	1970-2024**	1990-2023	1960-2024	1957-2024
Türkiye	1955-2024	1974-2024	1998-2023	1998-2024	1957-2024

* Income from Wages and Salaries Nationwide, Accumulated (yuan)

** Remuneration per worker in non-agricultural: Total seasonally adjusted

Note: Real Unit Labor Cost is estimated as follows:

$$ULC = \frac{\text{Real Minimum Wage}}{\text{Real Productivity}} = \frac{\text{Minimum Wage}}{\text{GDP Deflator}} * \left(\frac{\frac{\text{GDP}}{\text{Labor}}}{\text{GDP Deflator}} \right)^{-1} = \frac{\text{Minimum Wage} * \text{Labor}}{\text{GDP}}$$

Data on Consumer Price Index (CPI) and exchange rates (national currency per US dollar) are obtained from IFS for all countries as quarterly observations. The data coverage is presented in Table 1. Due to the challenge of obtaining imported inflation data for all analyzed countries over the entire estimation period, we complete the UMC calculation using global inflation as a proxy for imported inflation. Global inflation is calculated as the median of quarterly annual changes in CPI across all 197 available countries from the IFS, with data available from 1956 onward.

Once the data are collected, observations are transformed into quarterly annual changes (except for the global inflation variable, which is already expressed in quarterly annual changes due to our estimation methodology). The choice of quarterly annual changes over quarter-on-quarter changes is driven by the research

methodology rather than a purely statistical approach. Since the focus is on identifying low- and high-inflation periods, quarter-on-quarter changes may lead to inconclusive results if quarterly changes are small, but quarterly annual changes are significantly high or low.

4. Endogenously determined inflation regimes

Recalling our theoretical framework for high and low inflation, we empirically test the varying markup (constant term) and varying price adjustment parameters, Φ , with respect to regimes. We expect a higher constant term and elasticities when inflation is high and a lower constant term and elasticities when inflation is low compared to a moderate level. In this regard, we need a model that endogenously identifies representative inflation levels where inflation environments differ significantly. Thus, all model parameters, including mean, standard deviation, constant terms, and elasticities, should be endogenous.

To our knowledge, this type of environment has not been previously modeled in inflation studies. Kinlaw, Kritzman, Metcalfe, & Turkington (2023) utilize a Hidden Markov Model to analyze different inflation regimes and leverage its regime-based mean and standard deviation outputs to determine inflation regimes. Unlike their statistical inflation-focused analysis, however, we seek to validate structural changes in price adjustment parameters – the key outcomes of environment switches.

Inspired by Kinlaw, Kritzman, Metcalfe, & Turkington (2023) regarding the use of HMM to detect regimes endogenously, we estimate the structural inflation equation across different regimes. The Hidden Markov Regime Switching Model is employed to determine low- and high-inflation thresholds for each country based on the relationship between inflation and its key determinants:

$$\mu_{k,t} = \beta_{k0} + \beta_{k1} * ulc_{t-1} + \beta_{k2} * fx_{t-1} + \beta_{k3} * global\ inflation_{t-1} , \quad (3)$$

where k represents states, and $\mu_{k,t}$ is state-specific inflation mean. β_{k0} could be considered as a proxy for markup, as in Friedrich & Selcuk (2022), β_{k1} , β_{k2} , and β_{k3} represent price adjustment parameters of sellers in different inflation regimes.

We estimate HMM for three states to identify high-, moderate-, and low-inflation regimes. The results are presented in Table 2.⁷

HMM estimation here presents three major challenges. The first arises in countries that have historically experienced inflation exceeding 100%. In such cases, even increasing the number of states in HMM does not yield stable and acceptable results compared to countries that have not experienced such extreme inflation episodes. To mitigate instability from episodes of hyperinflation or near-hyperinflation, we assume that any high-inflation threshold detected by the model will always be below 100%. Periods of inflation above this threshold are directly classified as high inflation. However, simply starting the model from the period after inflation drops below 100% is also unreliable due to reference-period effects.

To address this issue, we utilize the Bai-Perron multiple breakpoints test for countries that have experienced episodes with inflation exceeding 100%. We then select the starting period after the first breakpoint following the final instance of inflation exceeding 100%. With this resampling approach, we obtain stable results for Brazil, Russia, and Türkiye.

⁷ The magnitude or signs of the HMM coefficients may not clearly reflect the relationship between inflation and its determinants. This is because they do not account for baseline effects or the magnitude nonlinearity that drives the regime switch. These coefficients merely describe the environment in which sellers respond to cost factors, capturing only the regime nonlinearity discussed in Section 2. Therefore, the coefficients presented in this table should not be mistaken for the overall impact of inflation determinants. To fully understand these effects, we develop a comprehensive view using probit coefficients in Section 5.

Table 2. 3-state Hidden Markov Regime Switching Model

Brazil								
Bai-Perron multiple breakpoints test		1999Q1	1 st breakpoint after inflation exceeds 100%					
Sample coverage:		1999Q2-2024Q1	Median Inflation:		6.06	Mean Inflation:		6.32
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	5.52	0.13	0.14	0.91	0.90	9.99	9.092	> High
State 2	6.92	0.01	0.05	-0.17	0.71	6.66	5.949	
State 3	3.67	-0.05	0.02	0.31	0.97	4.80	3.833	<Low
Russia								
Bai-Perron multiple breakpoints test		1999Q4	1 st breakpoint after inflation exceeds 100%					
Sample coverage:		2000Q1-2024Q1	Median Inflation:		9.04	Mean Inflation:		9.94
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	4.43	0.09	0.19	2.52	2.048	15.313	13.265	> High
State 2	4.36	0.04	0.09	1.24	1.313	9.746	8.433	
State 3	2.18	0.00	0.07	1.11	1.412	6.696	5.284	<Low
India								
No period with inflation exceeding 100%								
Sample coverage:		1997Q3-2024Q1	Median Inflation:		5.51	Mean Inflation:		6.33
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	8.58	0.10	0.14	0.19	1.583	9.465	7.882	> High
State 2	4.19	-0.02	0.14	0.36	1.040	6.108	5.068	
State 3	2.99	-0.08	-0.10	0.46	0.864	4.540	3.676	<Low
China								
No period with inflation exceeding 100%								
Sample coverage:		1999Q2-2024Q1	Median Inflation:		1.83	Mean Inflation:		1.97
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	2.70	-0.51	-0.12	0.03	0.706	2.963	2.257	> High
State 2	2.12	-0.33	-0.02	-0.07	0.777	1.939	1.162	
State 3	1.53	-0.30	0.05	-0.18	0.698	0.939	0.241	<Low
South Africa								
No period with inflation exceeding 100%								
Sample coverage:		1991Q2-2024Q1	Median Inflation:		5.89	Mean Inflation:		6.35
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	3.09	-0.02	0.09	1.25	1.313	9.266	7.953	> High
State 2	3.16	0.07	0.04	0.62	0.961	6.283	5.322	
State 3	1.05	0.06	0.10	0.75	1.049	5.166	4.117	<Low
Türkiye								
Bai-Perron multiple breakpoints test		2002Q2	1 st breakpoint after inflation exceeds 100%					
Sample coverage:		2002Q3-2024Q1	Median Inflation:		9.51	Mean Inflation:		16.72
3-state HMM	Intercept	ULC (t-1)	FX (t-1)	Global inflation (t-1)	SD	State Mean	Threshold	Regime
State 1	0.14	0.24	0.46	5.35	3.252	26.276	23.024	> High
State 2	-0.49	-0.09	0.41	2.90	1.67	16.177	14.507	
State 3	7.53	-0.12	0.08	0.28	1.772	9.76	7.988	<Low
Note: Bold numbers indicate theoretically expected results								

The second issue with HMM estimation is its sensitivity of outcomes to newly added data. This problem stems from the endogenous selection of priors in

the HMM methodology. Following Robert & Casella (2004), we mitigate this sensitivity using Monte Carlo (MC) simulations (500 iterations to ensure robustness of results).

Beyond technical issues, the primary outcome of the MC-based HMM is the identification of states. Since we do not impose prior definitions of high or low inflation (which we aim to determine endogenously), we name the states based on empirical characteristics following the approach of Kinlaw, Kritzman, Metcalfe, & Turkington (2023). Specifically, we define *high inflation* as the state with the highest mean, and *low inflation* as the state with the lowest mean. While identifying high inflation is straightforward, classifying State 3 as low inflation is less trivial. Although the state has the lowest mean, the mean remains close to what is generally perceived as normal inflation.⁸

Consequently, we define the regime states as high, moderate, and low, with *high inflation* is associated with State 1, *low inflation* is associated with inflation levels below State 3 (below normal levels), and *moderate inflation* encompasses all inflation levels falling between the high and low thresholds. In this regard, the lower bound of high inflation is set as the mean of state 1 minus one standard deviation,⁹ while the upper bound of low inflation is set as the mean of state 3 (normal state) minus its standard deviation.

Finally, we verify that the identified thresholds align with our theoretical framework and historical inflation dynamics. Examining intercept terms and elasticities, we find that HMM results are generally consistent with theoretical expect-

⁸ To resolve this issue, we initially attempted to increase the number of states, but the means of the first and last states remained nearly unchanged. This likely reflects the fact that emerging economies have rarely experienced prolonged low-inflation periods, making it difficult for the empirical model to detect such a regime.

⁹ The selection of 1.5 or higher standard deviations intersects with the second state's corridor, potentially causing ambiguity in regime classification.

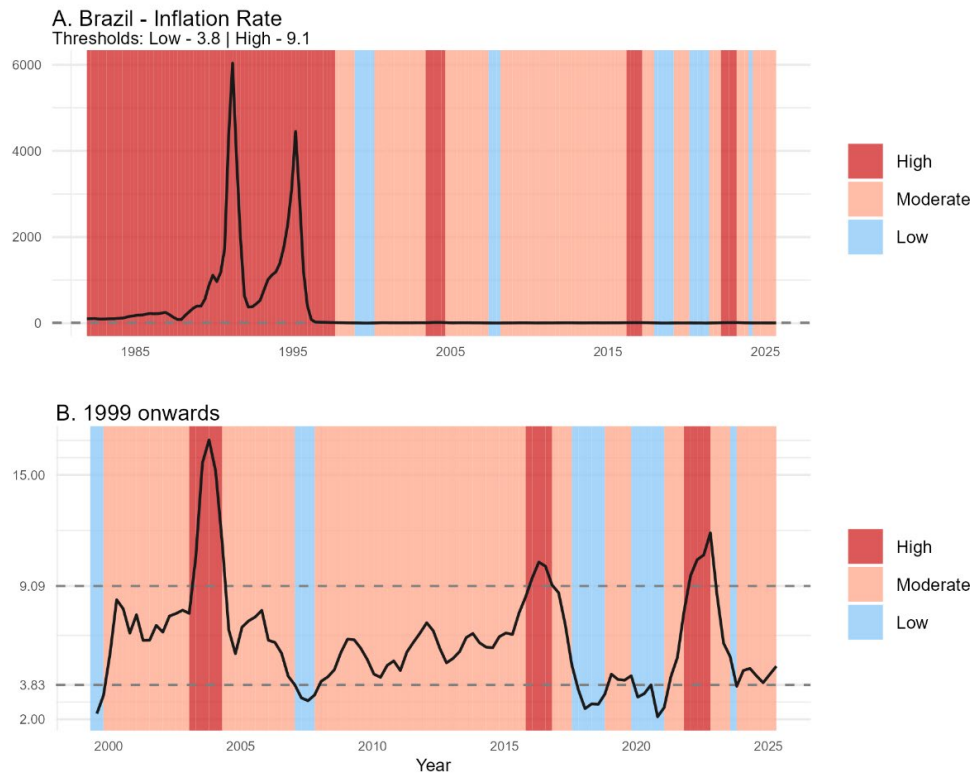
tations. In most cases, intercepts and elasticities are higher in high-inflation regimes and lower in low-inflation regimes. While inflation formation varies across countries (making full validation impossible in all cases), the results for Russia align perfectly with theoretical predictions, and all countries except China exhibit strong consistency with the theory. In China, only the intercepts and global inflation conform to expectations, likely due to unique price-setting mechanisms such as price controls and subsidies.

We plot inflation dynamics according to the regimes obtained from the HMM. As shown in Figure 1,¹⁰ the inflation regimes derived from the HMM results closely align with observed inflation dynamics. However, the regime outcomes for Türkiye and China differ significantly from those of the other analyzed countries. In China, inflation remains consistently low, resulting in the lowest inflation regime thresholds. In contrast, Türkiye's overall high-inflation dynamics, even in stable periods, lead to the highest low-inflation threshold among the analyzed economies. It is nearly as high as the high-inflation thresholds of the other countries.

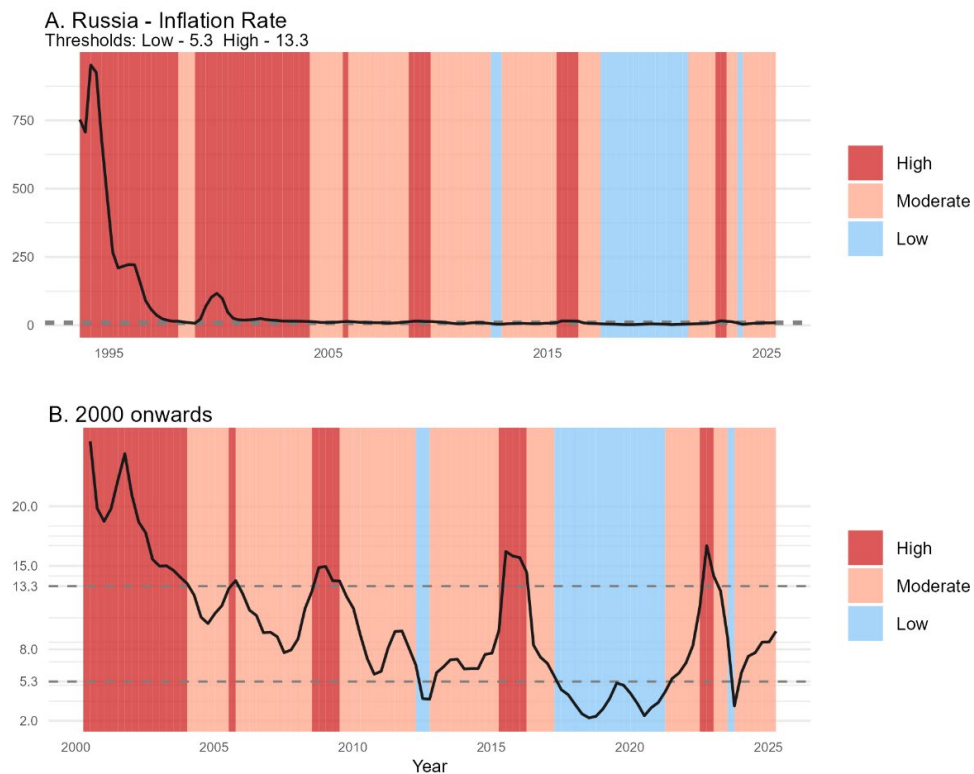
¹⁰ Figure A presents the full available inflation sample, while Figure B displays the subset of data that can be modeled using the HMM limited by the availability of Unit Labor Cost (ULC) components.

Figure 1. Inflation dynamics across regimes.

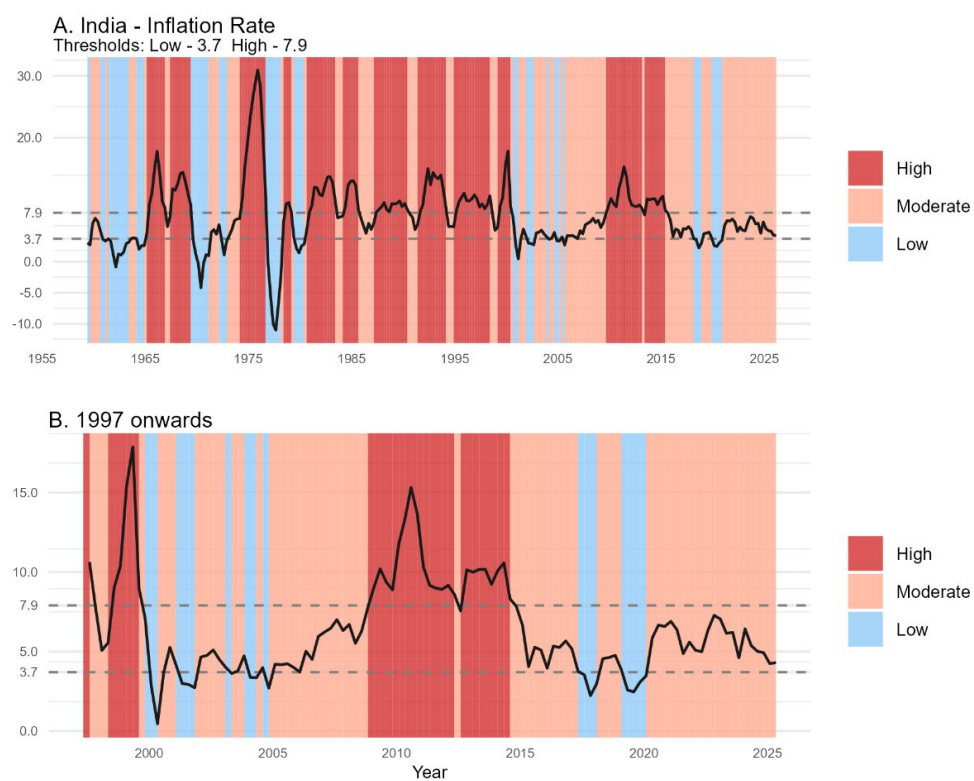
1. Brazil



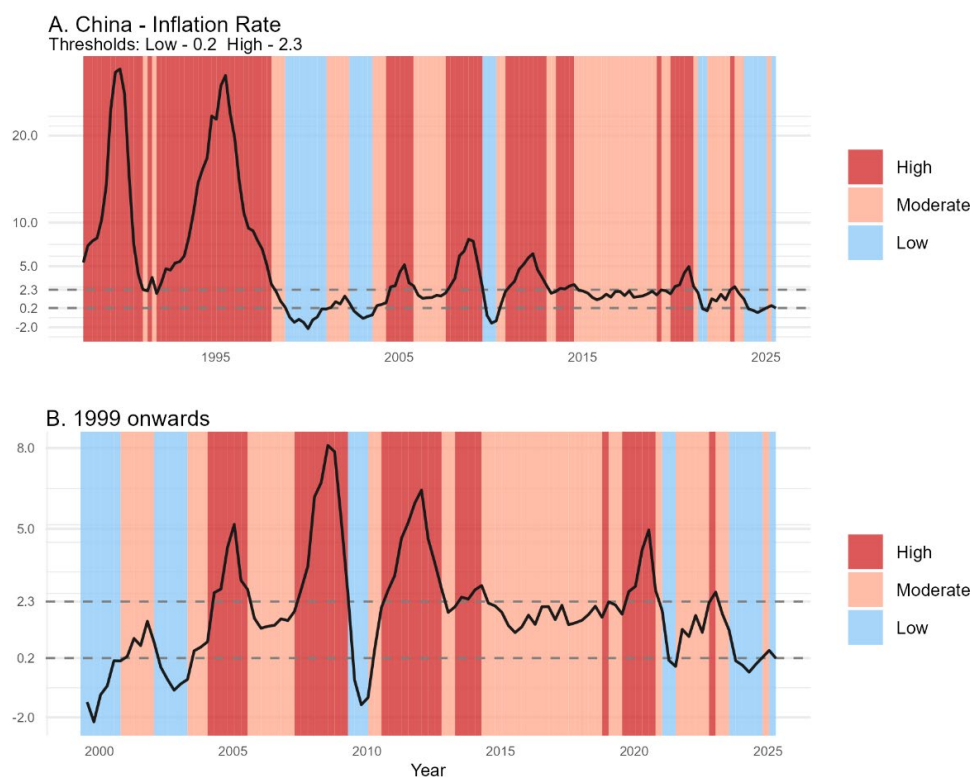
2. Russia



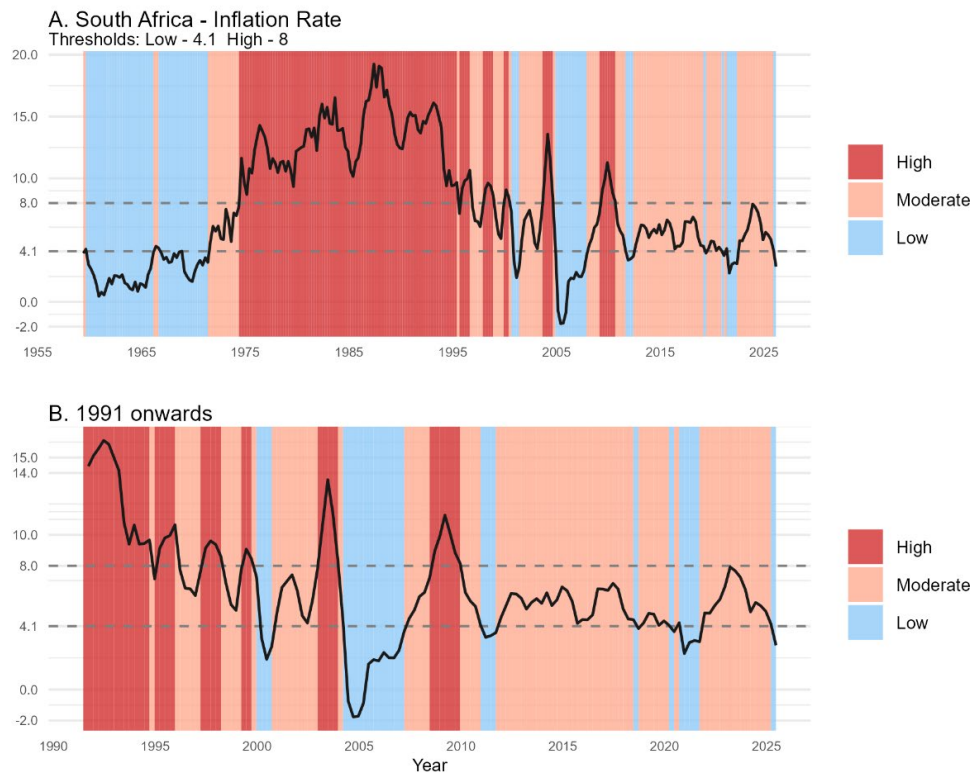
3. India



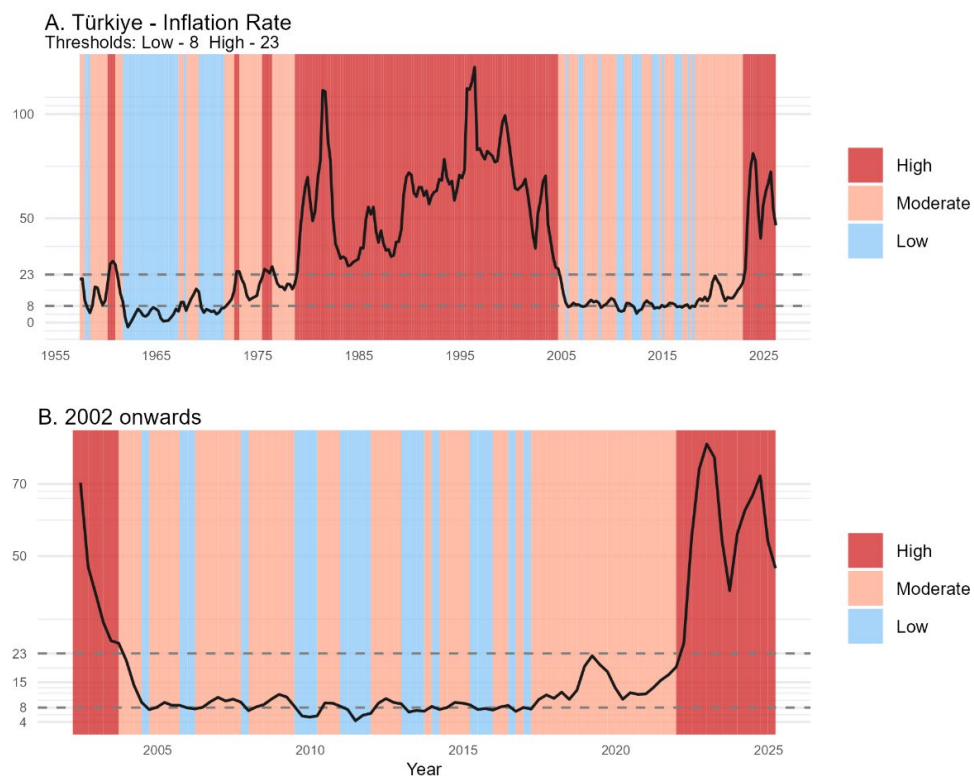
4. China



5. South Africa



6. Türkiye



Source: Authors' calculations.

Overall, when inflation shifts to higher regimes, sellers gain significant pricing power by taking advantage of the disrupted price perceptions of consumers. The HMM results validate this type of nonlinearity as evidenced by significantly higher coefficients in regimes with higher inflation means. Although the HMM does not perfectly identify low-inflation regimes in an economically intuitive way, the strong validation of this regime nonlinearity reassures us that coefficients in lower regimes would be much smaller as they consistently decrease in parallel with lower inflation means. Thus, we can use the HMM outcomes as an input for defining high-and low-inflation regimes.

5. Combining inflation regimes and shock magnitude

As the thresholds define three states – low, moderate, and high inflation – we construct an ordered probit model, where the dependent variable (inflation) takes the following values: 0 if it is below the low threshold, 0.5 if it is within the moderate range, and 1 if it is above the high threshold.¹¹

Next, we introduce the magnitude nonlinearity between inflation and its determinants to account for the empirically observed higher elasticity of inflation in response to large shocks. To capture this nonlinearity, we classify shocks: small shocks are those below the first quartile (Q1), while large shocks are those above the third quartile (Q3).

¹¹ Assigning different values for low, moderate, and high inflation in the probit model does not affect the results.

Furthermore, to account for regime-based nonlinearity, where high and low inflation regimes change the structure of price setting, we include the inflation regime as a determinant of elasticity. This recognizes that in high inflation regimes, the pass-through of shocks to inflation tends to be stronger.

Thus, we propose using the textbook version of the ordered probit model as outlined in Wooldridge (2010), but with the following nonlinear structure:

$$\begin{cases} P(y_t = 0|X_{t-1}, \dots, X_{t-n}) = \Phi(\tau_1 - \sum_{j=1}^n X_{t-j}(\beta_j + \beta_{j,1}M_{t-j} + \beta_{j,2}R_{t-1})) \\ P(y_t = 0.5|X_{t-1}, \dots, X_{t-n}) = \Phi(\tau_2 - \sum_{j=1}^n X_{t-j}(\beta_j + \beta_{j,1}M_{t-j} + \beta_{j,2}R_{t-1})) \\ \quad - \Phi(\tau_1 - \sum_{j=1}^n X_{t-j}(\beta_j + \beta_{j,1}M_{t-j} + \beta_{j,2}R_{t-1})) \\ P(y_t = 1|X_{t-1}, \dots, X_{t-n}) = 1 - \Phi(\tau_2 - \sum_{j=1}^n X_{t-j}(\beta_j + \beta_{j,1}M_{t-j} + \beta_{j,2}R_{t-1})), \end{cases} \quad (4)$$

where y_t is the ordinal outcome variable at time t , taking the value of 1 for high inflation, 0.5 for moderate inflation, and 0 otherwise; X_{t-j} is a vector of explanatory variables at lag j (up to n , determined by the Akaike information criterion); β_j , $\beta_{j,1}$, and $\beta_{j,2}$ represent the vector of coefficients for the explanatory variables and interaction terms; τ_1 and τ_2 are thresholds; and Φ is the cumulative distribution function of the standard normal distribution. Furthermore, M_{t-j} represents an interaction dummy for shocks magnitude, and R_{t-1} represent the inflation regime interaction term, which are assigned as follows:

$$M_{t-j} = \begin{cases} 1, & \text{if } X_{t-j} > Q3(X_{t-j}) \\ 0, & \text{if } X_{t-j} < Q1(X_{t-j}) \\ 0.5, & \text{otherwise} \end{cases} \quad R_{t-1} = \begin{cases} 1, & \text{if } y_{t-1} = 1 \\ 0, & \text{if } y_{t-1} = 0 \\ 0.5, & \text{otherwise} \end{cases} \quad (5)$$

After obtaining the regime-related probabilities, P , we generate the Inflation Score (IS) as a weighted average of these probabilities, calculated as follows:

$$IS = 0 * P_{low} + 0.5 * P_{moderate} + 1 * P_{high} \quad (6)$$

The IS score identifies inflation as below:

$$IS = \begin{cases} \textit{High}, & \textit{if } IS > 75\% \\ \textit{Low}, & \textit{if } IS < 25\% \\ \textit{Moderate}, & \textit{otherwise} \end{cases} \quad (7)$$

One important point to note is that inflation is transformed into ordered values, and the determinants that generated extreme cases, such as inflation exceeding 100%, are based on their original values. This means that the model attempts to fit such large shocks into the outcome of 1. Even when controlled for with magnitude interaction terms, these outliers statistically worsen the model's performance. However, each of these extreme cases carries significant information about inflation regimes. Therefore, similar to Yusifzade, Cömert, & Parmaksiz (2024), rather than removing the outliers, we replace them with the boundary values of the Tukey inner fence to improve the model's statistical performance.

According to Table 3 panel A, all determinants significantly impact inflation dynamics in Brazil, either at specific lags or when nonlinear interactions are considered. The ULC and FX coefficients clearly validate both types of nonlinearities in Brazil. The magnitude nonlinearity is also present in the impact of global inflation, but there is no statistical evidence supporting the regime nonlinearity in Brazil. However, when we average the lagged coefficients for each determinant (as displayed in Table A.2. in the Appendix), regardless of their statistical significance, we observe a higher average global inflation coefficient during high-inflation regimes (0.54), as well as under large shock conditions (0.5), compared to low-inflation periods (-0.93). In the probit framework, these coefficients reflect the change in the latent variable's z-score per unit increase in the determinant. Consequently, positive and larger coefficients in high-inflation and large-shock scenarios indicate an increased probability of transitioning to a high-inflation state, with the effect peaking under high-inflation regimes. These results highlight that inflation in Brazil is primarily driven by the endogenous fertile ground effect of ULC, FX, and global inflation shocks.

Table 3. Probit results for Brazil and Türkiye

A. Brazil			B. Türkiye		
Sample coverage 1992Q2-2024Q1			Sample coverage 2001Q1-2024Q1		
Number of Observations 128			Number of Observations 93		
Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
ULC (t-1)	-0.702**	(0.23)	ULC (t-1)	0.515*	(0.24)
M*ULC (t-1)	0.441*	(0.2)	M*ULC (t-1)	-0.212	(0.14)
R*ULC (t-1)	1.045**	(0.36)	R*ULC (t-1)	-0.973.	(0.51)
ULC (t-2)	-0.652*	(0.29)	ULC (t-2)	-0.248	(0.21)
M*ULC (t-2)	0.127	(0.2)	M*ULC (t-2)	0.119	(0.13)
R*ULC (t-2)	0.497.	(0.29)	R*ULC (t-2)	0.515	(0.38)
ULC (t-3)	0.175	(0.2)	ULC (t-3)	-0.136	(0.18)
M*ULC (t-3)	0.219	(0.19)	M*ULC (t-3)	0.286	(0.19)
R*ULC (t-3)	-0.388.	(0.22)	R*ULC (t-3)	-0.123	(0.2)
FX (t-1)	-0.29**	(0.11)	FX (t-1)	0.046	(0.08)
M*FX (t-1)	0.131*	(0.07)	M*FX (t-1)	-0.078	(0.07)
R*FX (t-1)	0.579**	(0.2)	R*FX (t-1)	0.131	(0.14)
FX (t-2)	0.36**	(0.13)	FX (t-2)	0.012	(0.11)
M*FX (t-2)	-0.136*	(0.07)	M*FX (t-2)	0.181*	(0.09)
R*FX (t-2)	-0.598*	(0.23)	R*FX (t-2)	-0.157	(0.17)
FX (t-3)	-0.168*	(0.08)	FX (t-3)	-0.226.	(0.13)
M*FX (t-3)	0.02	(0.06)	M*FX (t-3)	0.007	(0.08)
R*FX (t-3)	0.299**	(0.11)	R*FX (t-3)	0.506*	(0.24)
Global inflation (t-1)	-1.938	(1.48)	Global inflation (t-1)	0.932	(1.52)
M*Global inflation (t-1)	1.698*	(0.81)	M*Global inflation (t-1)	0.508	(0.64)
R*Global inflation (t-1)	-0.361	(2)	R*Global inflation (t-1)	1.987	(3.08)
Global inflation (t-2)	-3.51	(2.44)	Global inflation (t-2)	0.589	(2.52)
M*Global inflation (t-2)	-0.411	(0.71)	M*Global inflation (t-2)	-1.136	(0.97)
R*Global inflation (t-2)	6.7	(4.47)	R*Global inflation (t-2)	-2.141	(4.69)
Global inflation (t-3)	2.67	(1.76)	Global inflation (t-3)	-0.738	(1.41)
M*Global inflation (t-3)	0.221	(0.5)	M*Global inflation (t-3)	0.454	(0.59)
R*Global inflation (t-3)	-4.73.	(2.87)	R*Global inflation (t-3)	0.341	(2.3)
Threshold			Threshold		
0 0.5	-6.285**	(2.4)	0 0.5	2.392	(2.57)
0.5 1	1.913	(1.99)	0.5 1	11.384*	(5.42)
*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1			*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1		
M-Magnitude Dummy			M-Magnitude Dummy		
R-Inflation Regime Dummy			R-Inflation Regime Dummy		

As shown in Table 3.B, only the ULC and FX coefficients are significant in the case of Türkiye. However, unlike in Brazil, only FX validates both types of nonlinearities. This suggests that inflation regimes in Türkiye are mainly triggered by local currency depreciation. For example, the average FX coefficient across lags is 0.16 when the inflation regime is high – 4.4 times¹² greater than when the regime is not high, but a large depreciation has occurred. Moreover, when neither of these conditions is present, the average FX coefficient is almost zero (-0.06). In other

¹² This value does not indicate that the pass-through effect is 4.4 times higher when the inflation regime is high, as probit model coefficients cannot be interpreted in the same way as linear model coefficients. Rather, this comparison is made solely to validate the existence of nonlinearities.

words, large shocks may significantly contribute to the persistence of high inflation. However, once a high-inflation regime in Türkiye has become established, even relatively small disturbances can be enough to sustain it, making its persistence hard to break.

Table 4. Probit results for China and South Africa

A. China			B. South Africa		
2000Q2-2024Q1			1992Q2-2024Q1		
Sample coverage			Sample coverage		
Number of Observations	96		Number of Observations	128	
Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
ULC (t-1)	-7.784*	(3.93)	ULC (t-1)	-0.326	(0.38)
M*ULC (t-1)	5.715*	(2.89)	M*ULC (t-1)	0.446	(0.39)
R*ULC (t-1)	7.395.	(4.26)	R*ULC (t-1)	1.203.	(0.69)
ULC (t-2)	10.481*	(5.09)	ULC (t-2)	-0.304	(0.4)
M*ULC (t-2)	-4.698*	(2.32)	M*ULC (t-2)	0.045	(0.34)
R*ULC (t-2)	-12.419.	(6.59)	R*ULC (t-2)	-0.605	(0.65)
ULC (t-3)	-3.563	(2.53)	ULC (t-3)	-0.756.	(0.39)
M*ULC (t-3)	-0.294	(0.89)	M*ULC (t-3)	-0.326	(0.44)
R*ULC (t-3)	4.289	(4.1)	R*ULC (t-3)	2.417**	(0.88)
ULC (t-4)	-0.729	(1.71)	ULC (t-4)	0.523	(0.42)
M*ULC (t-4)	2.729.	(1.59)	M*ULC (t-4)	-0.879*	(0.43)
R*ULC (t-4)	1.939	(2.89)	R*ULC (t-4)	-1.09.	(0.66)
FX (t-1)	-2.482	(1.64)	FX (t-1)	-0.202	(0.12)
M*FX (t-1)	5.252*	(2.34)	M*FX (t-1)	0.207*	(0.1)
R*FX (t-1)	0.459	(1.95)	R*FX (t-1)	0.186	(0.18)
FX (t-2)	2.875	(2.25)	FX (t-2)	0.128	(0.15)
M*FX (t-2)	-3.626*	(1.6)	M*FX (t-2)	-0.104	(0.08)
R*FX (t-2)	-7.003.	(4.09)	R*FX (t-2)	0.081	(0.23)
FX (t-3)	-3.746.	(2.12)	FX (t-3)	-0.121	(0.14)
M*FX (t-3)	1.089	(1.15)	M*FX (t-3)	0.063	(0.08)
R*FX (t-3)	11.94*	(5.59)	R*FX (t-3)	0.156	(0.21)
FX (t-4)	-2.549.	(1.5)	FX (t-4)	0.173.	(0.1)
M*FX (t-4)	-0.079	(0.69)	M*FX (t-4)	-0.04	(0.1)
R*FX (t-4)	0.432	(1.51)	R*FX (t-4)	-0.066	(0.16)
Global inflation (t-1)	-16.914.	(8.77)	Global inflation (t-1)	2.408	(2.64)
M*Global inflation (t-1)	6.047*	(2.97)	M*Global inflation (t-1)	0.33	(0.61)
R*Global inflation (t-1)	19.797.	(11.04)	R*Global inflation (t-1)	-2.694	(3.02)
Global inflation (t-2)	19.512.	(11.32)	Global inflation (t-2)	-3.391	(3.93)
M*Global inflation (t-2)	-5.573.	(3.16)	M*Global inflation (t-2)	-2.682**	(0.99)
R*Global inflation (t-2)	-32.019.	(16.86)	R*Global inflation (t-2)	15.851*	(7.2)
Global inflation (t-3)	-6.415	(5.45)	Global inflation (t-3)	-4.694.	(2.84)
M*Global inflation (t-3)	0.521	(1.59)	M*Global inflation (t-3)	1.918*	(0.87)
R*Global inflation (t-3)	13.172	(8.17)	R*Global inflation (t-3)	-3.731	(6.17)
Global inflation (t-4)	-10.692*	(5.22)	Global inflation (t-4)	6.012*	(2.52)
M*Global inflation (t-4)	4.856.	(2.56)	M*Global inflation (t-4)	-0.53	(0.64)
R*Global inflation (t-4)	8.912.	(5.06)	R*Global inflation (t-4)	-6.736.	(4.09)
Threshold			Threshold		
0 0.5	-24.487*	(10.67)	0 0.5	1.496	(2.34)
0.5 1	-6.103	(3.9)	0.5 1	12.134***	(4.33)
*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1			*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1		
M-Magnitude Dummy			M-Magnitude Dummy		
R-Inflation Regime Dummy			R-Inflation Regime Dummy		

In Table 4.A, all determinants show significant impacts on inflation in China. However, due to the lag structure, the results are not as clearly observable

as in Brazil or Türkiye. To analyze nonlinearities, we use the average of lagged coefficients for each determinant. The results indicate the presence of magnitude nonlinearity between inflation and ULC, meaning that inflation's response to ULC increases relatively faster as shock magnitude rises. More importantly, both types of nonlinearities are observed in the effects of FX and global inflation. In addition to a notable difference between baseline and magnitude-interacted coefficients, when the inflation regime is high, the FX coefficient is 2.2 times larger, and the global inflation coefficient is 1.7 times larger compared to non-high inflation regimes. Once again, it should be noted that these coefficients only highlight the higher probability of observing high inflation, rather than pass-through elasticities.

For South Africa, as shown in Table 4.B, the magnitude nonlinearity is present in FX, while the regime nonlinearity is observed in ULC and global inflation. Although not statistically significant, the average determinant coefficients also suggest the presence of regime nonlinearity between inflation and FX. In other words, when the inflation regime is high, the average FX coefficient is 2.9 times higher than when the regime is not high, increasing the probability of high inflation occurrence.

For Russia, as observed in Table 5.A, only the regime nonlinearity exists between inflation and ULC and FX. However, when the average of coefficients is considered regardless of significance levels, both types of nonlinearities are observed in ULC, while regime nonlinearity is present in global inflation dynamics. For India, both types of nonlinearities are significantly validated for FX and global inflation. Regarding ULC, only the coefficient related to shock magnitude is significant.

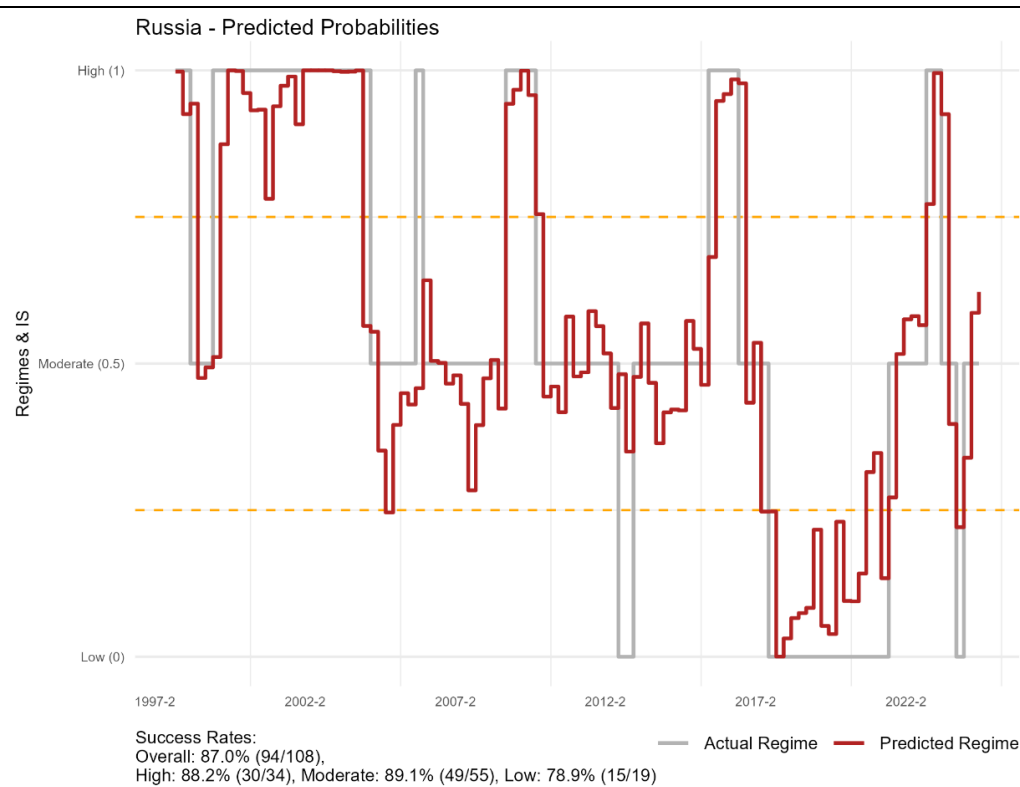
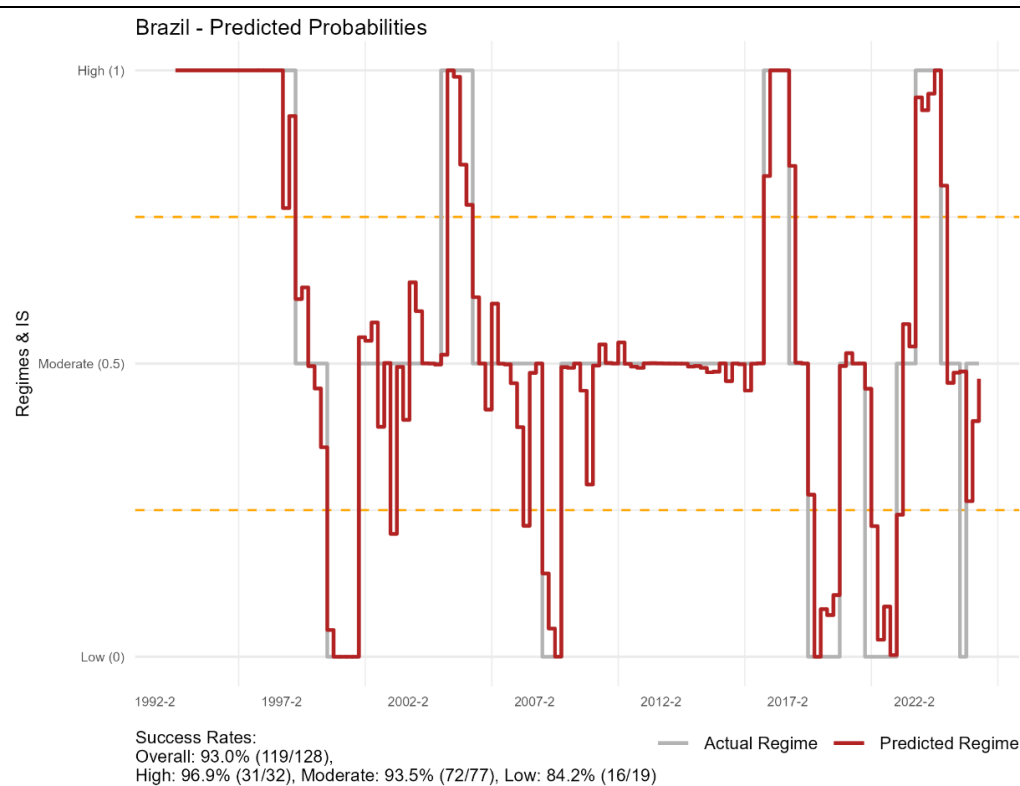
Overall, the results highlight the critical role of both types of nonlinearities in inflation dynamics across the analyzed countries. More importantly, these dynamics are also evident in China, where HMM-based coefficients were insufficient to validate nonlinearity. The findings reinforce FX as the universal determinant consistently driving nonlinearity across all countries, with ULC the second most influential factor. These results align with Yusifzada, Cömert, & Parmaksiz (2024), who argue that high inflation is often driven by exchange rate fluctuations.

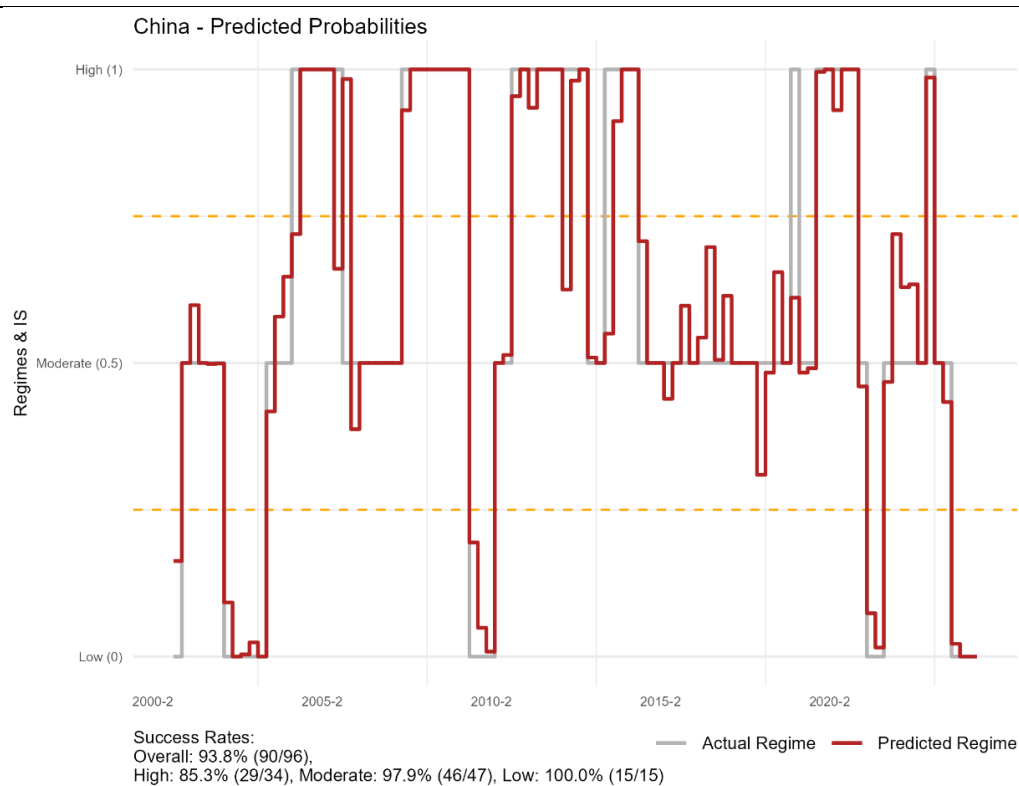
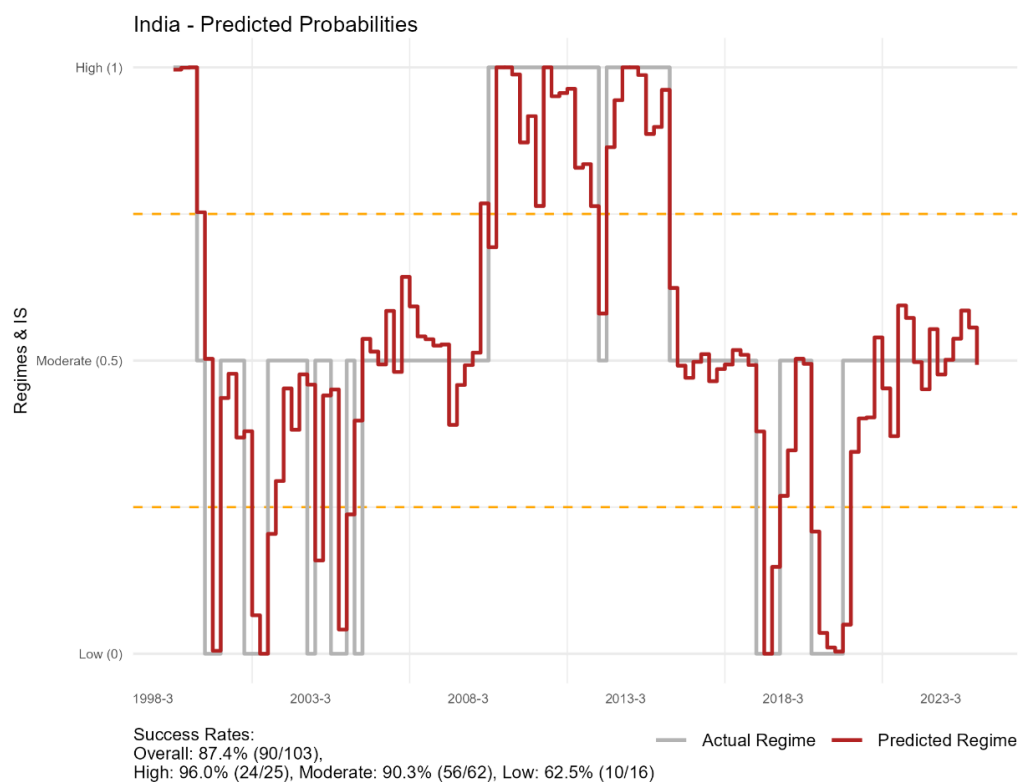
Table 5. Probit results for Russia and India

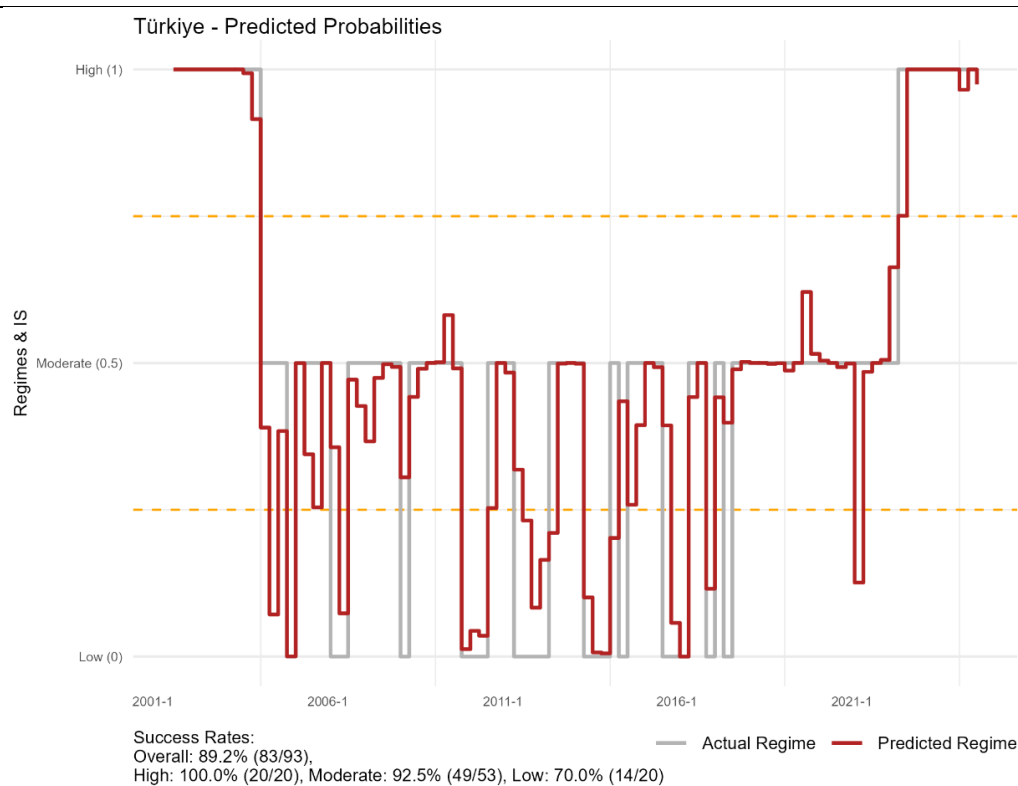
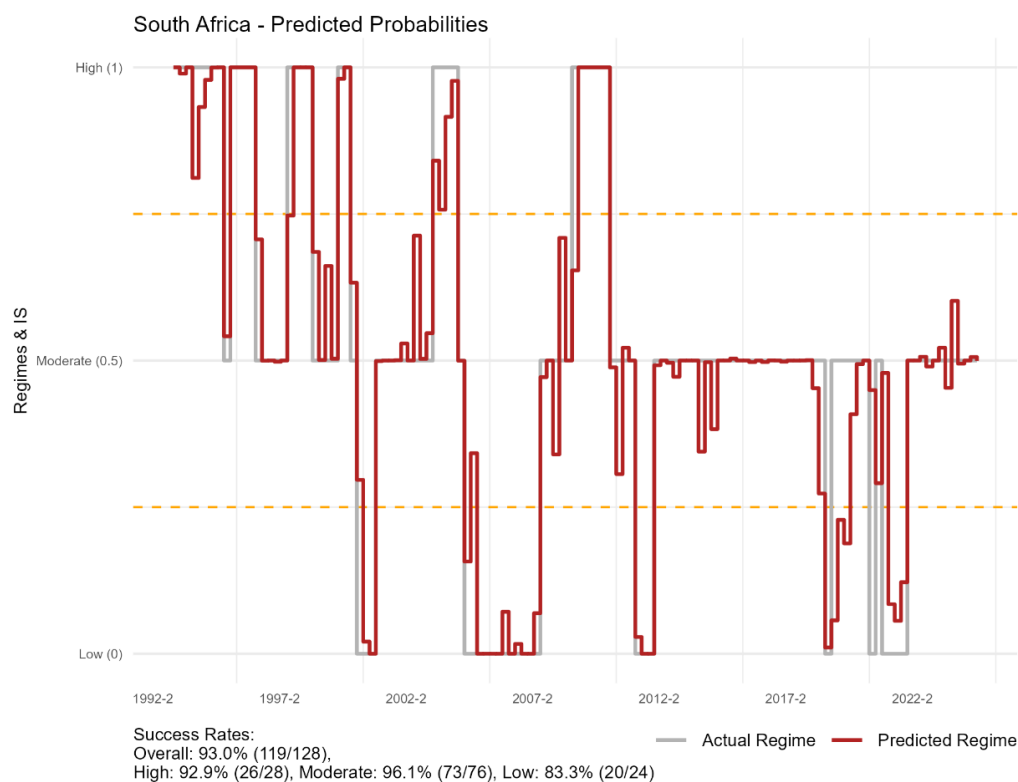
A. Russia			B. India		
Sample coverage		1997Q2-2024Q1	Sample coverage		1998Q3-2024Q1
Number of Observations		108	Number of Observations		103
Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
ULC (t-1)	-0.055	(0.05)	ULC (t-1)	-0.073	(0.11)
M*ULC (t-1)	0.014	(0.04)	M*ULC (t-1)	0.187*	(0.08)
R*ULC (t-1)	0.025	(0.05)	R*ULC (t-1)	-0.198	(0.15)
ULC (t-2)	-0.059	(0.05)	ULC (t-2)	0.087	(0.09)
M*ULC (t-2)	0.027	(0.04)	M*ULC (t-2)	-0.02	(0.07)
R*ULC (t-2)	0.131*	(0.06)	R*ULC (t-2)	-0.017	(0.13)
FX (t-1)	0.165**	(0.06)	FX (t-1)	0.166	(0.14)
M*FX (t-1)	-0.04	(0.05)	M*FX (t-1)	-0.107	(0.11)
R*FX (t-1)	-0.096	(0.08)	R*FX (t-1)	-0.134	(0.18)
FX (t-2)	-0.118.	(0.06)	FX (t-2)	-0.355*	(0.16)
M*FX (t-2)	-0.003	(0.06)	M*FX (t-2)	0.248*	(0.12)
R*FX (t-2)	0.199*	(0.08)	R*FX (t-2)	0.396*	(0.2)
Global inflation (t-1)	0.933	(1.05)	Global inflation (t-1)	-3.004*	(1.23)
M*Global inflation (t-1)	-0.217	(0.32)	M*Global inflation (t-1)	1.31**	(0.44)
R*Global inflation (t-1)	0.408	(1.3)	R*Global inflation (t-1)	2.562.	(1.49)
Global inflation (t-2)	-0.358	(0.94)	Global inflation (t-2)	1.864	(1.15)
M*Global inflation (t-2)	-0.446	(0.34)	M*Global inflation (t-2)	-0.783.	(0.41)
R*Global inflation (t-2)	0.581	(1.3)	R*Global inflation (t-2)	-1.275	(1.45)
Threshold			Threshold		
0 0.5	1.166	(1.22)	0 0.5	-1.629	(1.18)
0.5 1	4.651***	(1.38)	0.5 1	2.831*	(1.25)
*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1			*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.1		
M-Magnitude Dummy			M-Magnitude Dummy		
R-Inflation Regime Dummy			R-Inflation Regime Dummy		

Thus, the theoretical framework is empirically validated. The probit model demonstrates strong predictive accuracy, correctly identifying inflation regimes in an average of 90% of cases across the analyzed countries (Figure 2).

Figure 2. Probit model prediction accuracy.







Source: Authors' calculations.

Note: The figures display actual inflation regimes as a gray line and predicted regime probabilities as a red line. The X-axis represents time, while the Y-axis shows regimes and the IS score for predicted probabilities. Orange dashed lines indicate the cutoff points, set at 0.75 and 0.25, between regimes. Success rates are calculated based on the overlap between the IS scores (red line) and actual regimes (gray line) within the designated regime bands. Success rates are reported as the proportion of correctly predicted regimes (first value in parentheses) relative to the total number of regimes (second value in parentheses).

6. Out-of-sample performance and policy implications

This research highlights the importance of accounting for regime- and magnitude-dependent nonlinearities in inflation dynamics, particularly in emerging economies where inflation can be volatile and driven by sudden shocks. The framework developed in this paper provides a useful tool for central banks in anticipating inflation regime switches, and thus implementation of informed and timely policy responses. The model outperforms traditional linear models that may fail to fully capture the complexities of inflation dynamics in emerging markets.

Since our framework empirically validates both types of nonlinearities and successfully predicts historical regime shifts, a key remaining question – and one of this study’s primary motivations – is whether the model (trained only through 2021 without any knowledge of the exogenous shocks of 2022) can accurately predict out-of-sample inflation regime switches.

To address this, we perform a rolling out-of-sample forecast for each country, predicting inflation regimes one year ahead. The model is trained using available data up to the forecast period. The training and forecast datasets are iteratively shifted forward by one quarter. Since the model does not observe ULC, FX, or global inflation dynamics during the forecasting period, we rely on a simple auto-ARIMA model to forecast these determinants over the forecast horizon.

For instance, we initially train the model on data up to Q4 2021. ARIMA forecasts are then generated for 2022, and these forecasts are subsequently used in the probit model to predict the likelihood of regime switches. It is important to note

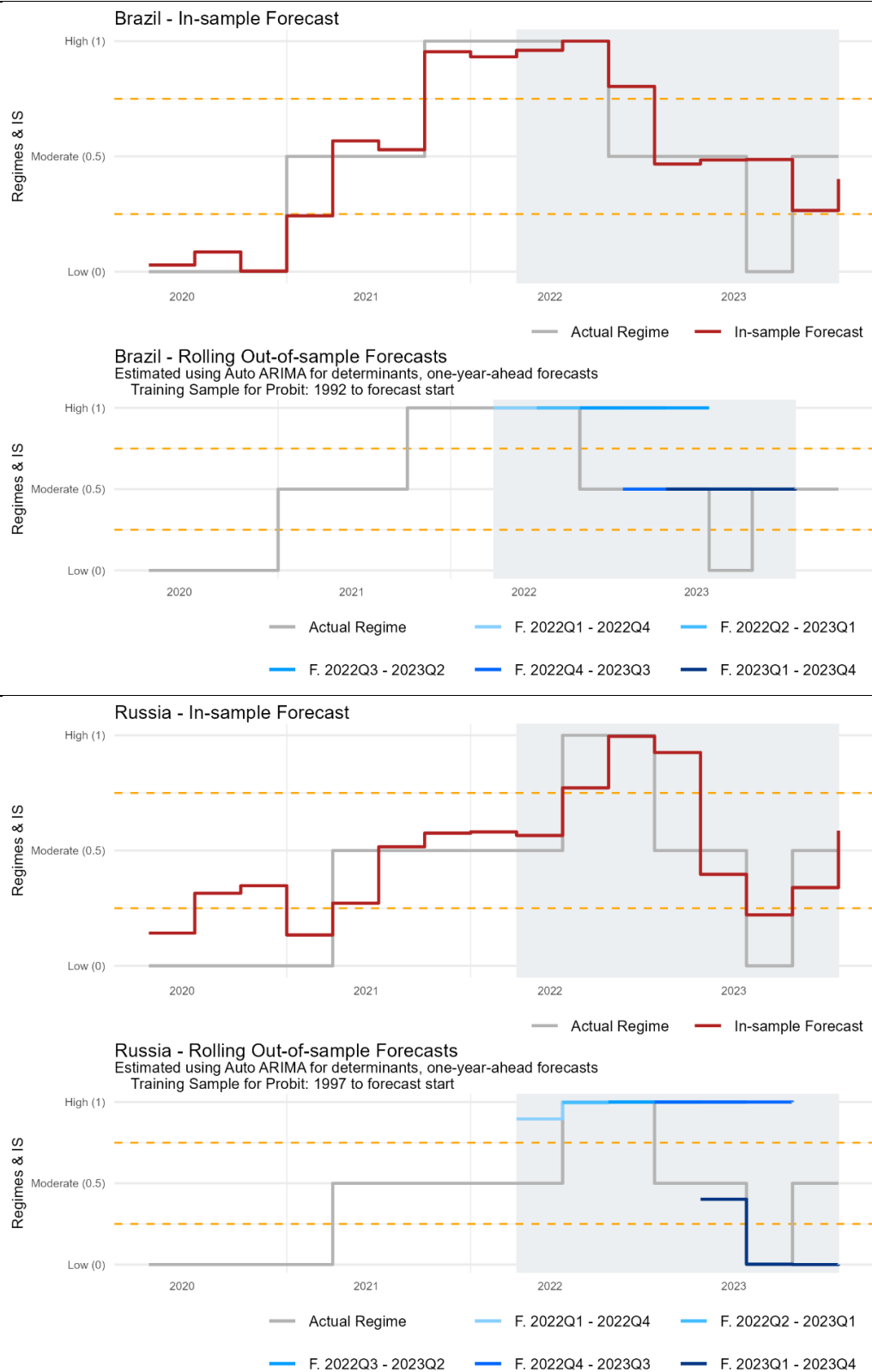
that ARIMA models cannot predict unexpected shocks in the determinants. Regime switches primarily depend on the delayed impacts of inflation determinants observed in the latest quarters available for training, rather than on the ARIMA forecasts themselves.

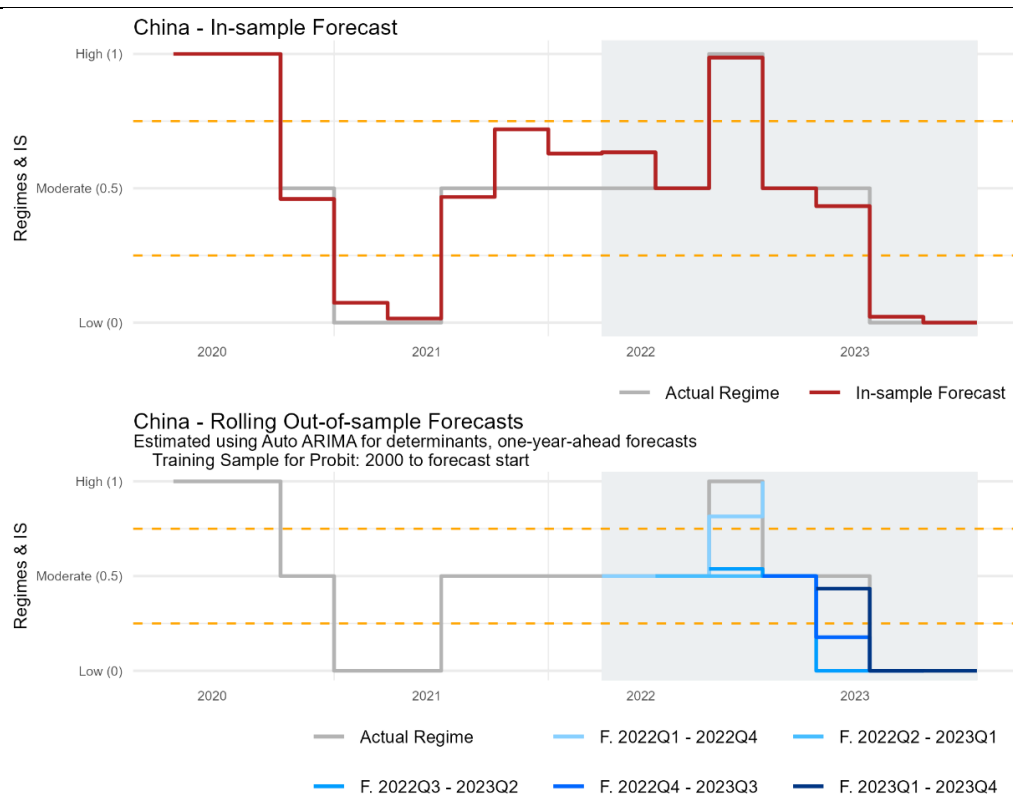
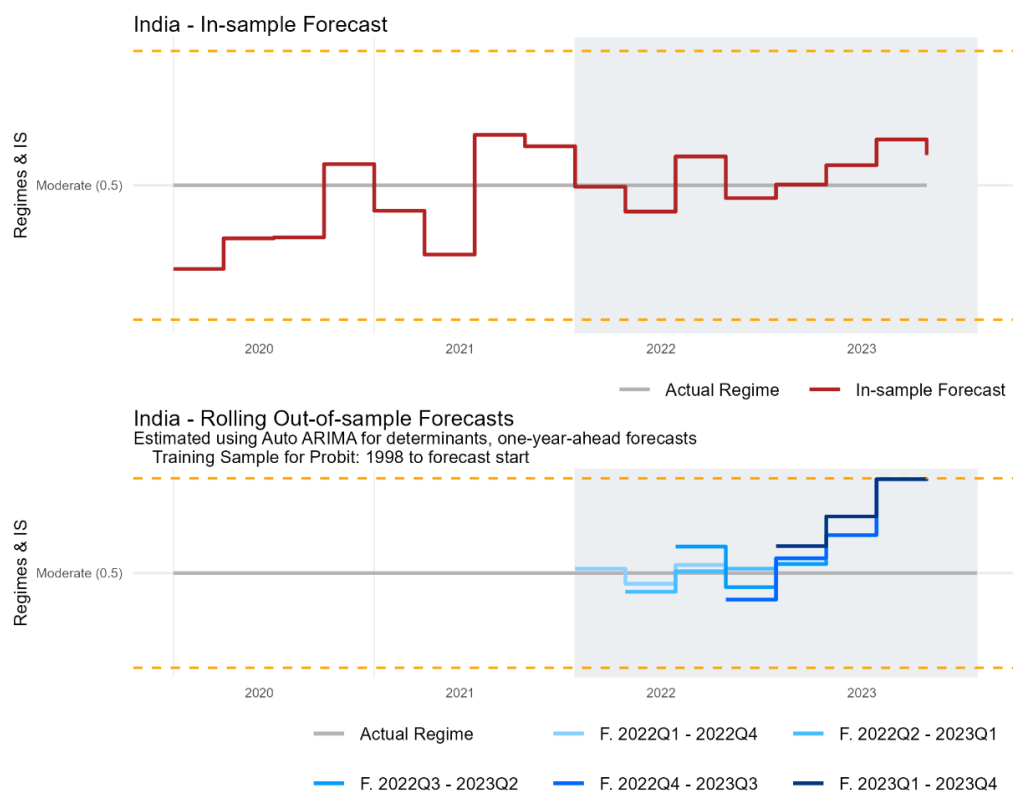
Following the generation of rolling out-of-sample predictions, we compare them with actual regimes and in-sample predictions, where full determinant information is available. To assess the accuracy of our model, we also compare its predictions with the IMF World Economic Outlook forecasts. The results are presented in Figure 3.

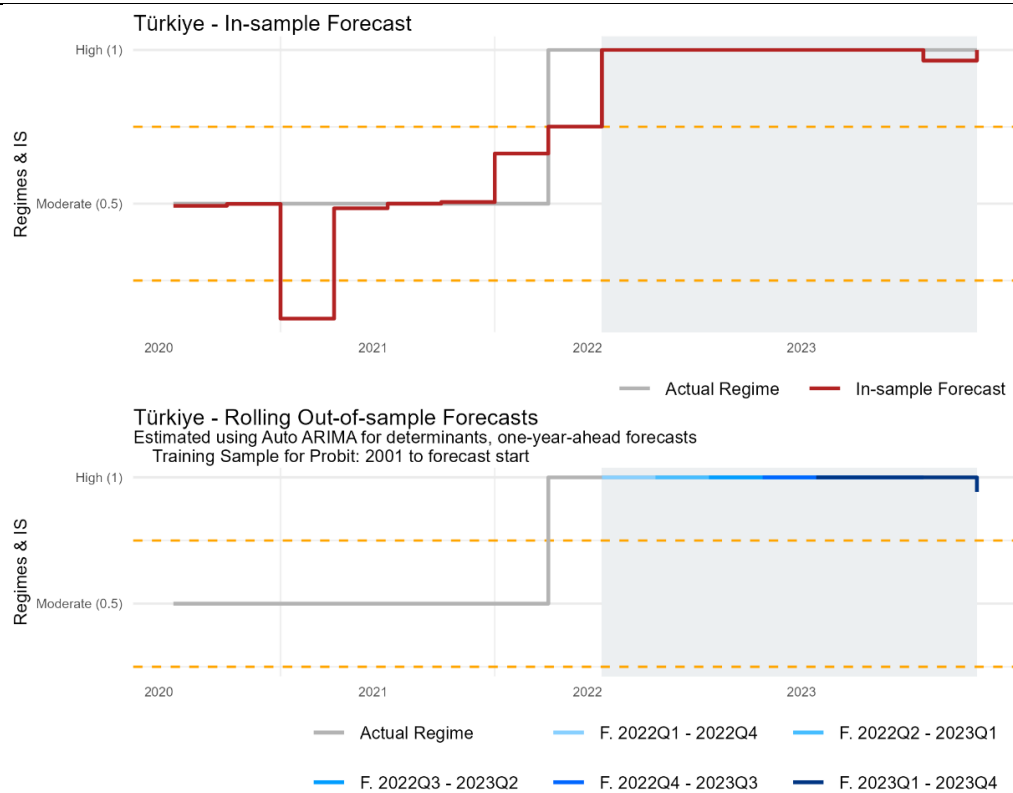
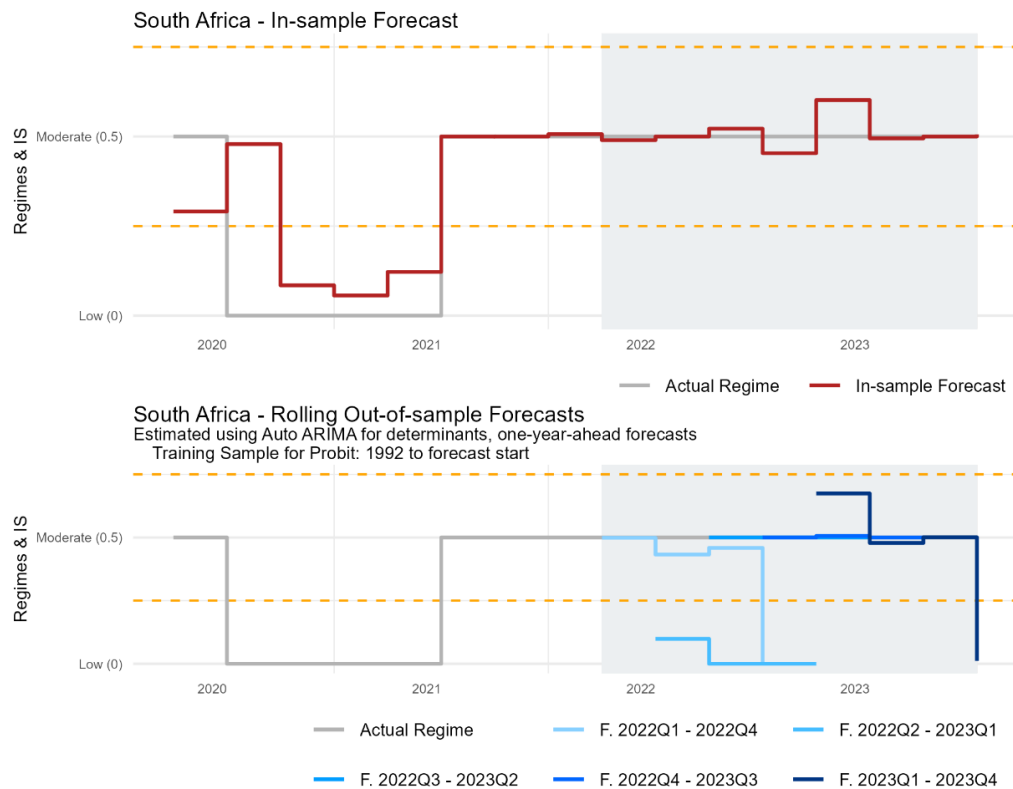
- **Brazil:** The model accurately predicts the persistence of high inflation in 2022 and predicts a transition to moderate inflation in 2023 as new data signal a forthcoming moderation. The model fails to detect low inflation in 2023 (annual inflation fell to 3.76%, and just below our threshold of 3.83%). The IMF forecast for Brazil's annual average inflation in 2022 was 5.3% (moderate inflation) according to its October 2021 outlook (International Monetary Fund, 2021).
- **Russia:** Due to determinant dynamics in the last two quarters of 2021, the model successfully predicts a regime switch to high inflation in 2022. After training with 2022 data, the model accurately anticipates a potential shift from moderate to low in 2023. The IMF forecast for Russian inflation in 2022 was 4.8% (low inflation) in its October 2021 outlook.
- **India:** Since no regime switch occurred in India, the model does not predict a switch. However, the IS score suggests a possibility of near-high inflation in 2023, a scenario that never materialized.
- **China:** As with Russia, the model correctly predicts a shift from moderate to high inflation in 2022 and from moderate to low in 2023. The IMF's 2022 inflation forecast for China, published in its October 2021 report, was 1.8% (moderate inflation).

- **South Africa:** Initial regime predictions in South Africa are less accurate due to mispredictions of FX depreciation dynamics in the ARIMA model. In 2021, the South African rand appreciated, which led ARIMA to underestimate the likelihood of significant depreciations (reaching 20%) in subsequent quarters. Since FX is the most influential determinant of regime switches, this misprediction affected the accuracy of the probit model. However, as the rolling sample extended and the model observed the actual depreciation of the rand, its regime predictions corrected themselves. The IMF forecast for inflation in South Africa in 2022 was 4.5%, which was closer to the actual inflation outcome.
- **Türkiye:** The model's predictions are entirely accurate. The IMF forecast for Türkiye was 15.4% (moderate inflation) for 2022.

Figure 3. Rolling out-of-sample prediction accuracy.







Source: Authors' calculations.

Note: In the plot, the blue lines with five shades represent the rolling forecasting periods. The first forecasting period starts in 2022Q1 and ends in 2022Q4, with each subsequent period shifting forward by one quarter until the final forecasting window, and eventually covering 2021Q1 to 2023Q4.

Our framework yields two important policy recommendations. First, the theoretical framework, supported by empirical evidence, underscores the significance of nonlinearities in inflation dynamics in emerging economies, particularly emphasizing the role of exchange rate fluctuations. When the inflation environment changes or shock magnitudes increase, passthrough effects no longer behave as they do in normal inflation periods. Therefore, policymakers should account for the potential deviations of traditional linear models that often underestimate inflationary impacts in extreme conditions.

Second, the nonlinear probit model demonstrates the possibility of accurately forecasting inflation regime shifts for five of the six analyzed countries for 2022 and 2023 without prior knowledge of exogenous variables. This implies that timely adoption of a composite model similar to the one proposed here could capture nonlinearities in inflation dynamics useful to central banks in proactively preparing for high inflation episodes in Brazil, Russia, China, and Türkiye in early 2022, as well as in anticipating low inflation in Russia and China in 2023.

Thus, our presented framework could be applied as an early-warning system for inflationary risks, making it particularly valuable for central banks facing inflationary environments driven by elevated uncertainty. By relying on this composite model, policymakers can obtain more reliable predictions regarding inflation behavior. The ability of the model to predict high- and low-inflation regimes with high accuracy allows policymakers to formulate monetary policy proactively in response to exogenous shocks by adjusting interest rates or employing other monetary instruments.

Like many empirical models, our model comes with significant limitations. The first, of course, is the volatility of regime switches. When regimes switch frequently as in Türkiye during tranquil periods or in India in the early 2000s, the

model's success decreases significantly. This highlights the role of threshold-setting. As the gap between thresholds narrows, the frequency of regime switches rises, degrading the model's statistical performance.

The second limitation is the model's reliance on assumptions about inflation determinants, which are estimated using a simple ARIMA model. While it performs well in the absence of extreme events such as the depreciation in South Africa in 2022, and quickly adjusts its predictions when new data is incorporated, the inability to accurately forecast key determinants reduces the model's overall predictive power.

Aside from the methodological limitations, this approach may also face data-related constraints, due particularly to the delayed releases of GDP and labor statistics. Labor data, notably, are only published on an annual basis, which poses a significant challenge for estimating Unit Labor Cost (ULC). This limitation necessitates statistical adjustments to interpolate the labor series into quarterly observations, potentially affecting the accuracy and reliability of the estimates.

7. Conclusion

This study describes a novel composite method for understanding nonlinear inflation dynamics, a topic highly relevant to emerging economies. The proposed method sheds light on historical inflation patterns and forecasts future regime shifts and inflation. Our method explains the historical inflation trends, successfully detects different inflation regimes for the BRICS countries and Türkiye, as well as achieves over 90% prediction accuracy, substantially outperforming standard linear benchmarks. Importantly, its strong performance was maintained out-of-sample – even in the post-pandemic period when many traditional models struggled to anticipate sharp movements in inflation.

Two types of nonlinearity proved essential in capturing these dynamics. First, our method allows the effect of shocks on inflation to depend on the shock's

magnitude. This means that the inflation response to an economic disturbance is not simply proportional to the size of the shock. Relatively small shocks may have modest, short-lived impacts on prices, while sufficiently large shocks can trigger disproportionately large and persistent inflationary responses. In other words, the coefficients of inflation determinants are larger for the big disturbances. Second, our methodology incorporates regime-dependent nonlinearities in pricing behavior. The underlying inflation process behaves quite differently across distinct regimes. In a low-inflation regime, firms may adjust prices cautiously, and both price and wage shocks tend to dissipate quickly. In a high-inflation regime, price-setting becomes aggressive and synchronized, with even moderate shocks leading to broad, persisting price increases. By explicitly considering these regime-specific behaviors, our framework captures how inflation and its drivers change as the economy shifts to a different inflation regime.

An important strength of the proposed approach is its ability to identify inflationary regimes endogenously. We find clear empirical validation for this feature. For instance, the model independently detected a transition to a high-inflation regime during the post-2020 surge, without a need for exogenous information about the supply chain disruptions or commodity price spikes that contributed to that surge. This endogenous identification is in line with economic narratives of inflation driven by pricing dynamics rather than solely by aggregate demand. In particular, it resonates with the concept of “sellers’ inflation,” in which widespread cost shocks provide firms with an opportunity to raise prices broadly as consumers initially accept higher prices, and thus diminishing demand elasticity and reinforcing the elevated-inflation environment. The first part of our composite method, employing a Hidden Markov Regime Switching-Model with Monte Carlo Simulations, without any direct input about such micro-level behavior, successfully picked up the macro-level regime change. This indicated that such behavioral shifts leave traces in the inflation data. These findings carry significant policy implications, especially for central banks in emerging economies. We suggest that policymakers in emerging economies may need to move beyond simple linear models – often borrowed from

advanced economy contexts – and instead employ country-specific composite methods that allow for nonlinear dynamics and regime shifts.

More specifically, many standard inflation models used in advanced economies assume a stable linear relationship (for example, a Phillips curve with fixed parameters) that reflects decades of low, stable inflation. Emerging economies, in contrast, frequently face larger external shocks, more volatile expectations, and structural changes that can drive the economy into a different inflation regime. Beyond capturing regime changes in inflation dynamics, it is also essential to consider nonlinearities within the same regimes, especially for developing countries, in which especially large and repetitive exchange rate shocks could increase the sensitivity of inflation to input prices. Our composite approach simultaneously captures both types of nonlinearities – and capturing such nonlinearities is not merely a technical improvement, but a practical necessity. Importantly, a composite nonlinear framework tailored to an economy’s unique characteristics can improve forecast accuracy and provide early warning of inflationary regime shifts, thereby providing the central bank with a window in which to respond proactively.

Sudden, massive shocks, of course, still pose challenges for the model. As with any method, abrupt and unprecedented events such as a sharp exchange-rate depreciation or a steep commodity price spike can initially reduce predictive performance. Such events can push the economy into a new inflation regime so rapidly that any model will briefly be caught off guard. Our framework is no exception. Immediate predictions were less accurate when confronted with out-of-sample shocks of great magnitude. Nonetheless, our framework quickly adapted once new data from the shock period was incorporated. In our case, after a few observations reflecting the post-shock reality became available, the model’s regime-detection mechanism was adjusted, and forecast performance was restored. This adaptive behavior indicates that while large shocks can cause short-term distortions in accuracy, our composite framework can learn from the new conditions and maintain its usefulness as more information becomes available.

As our composite approach validates both magnitude- and regime-related nonlinearities in price-setting behavior, we can consider integrating the findings into more structural and large-scale models. Future research, for example, might consider whether such nonlinear integration might enhance traditional structural models and benefit central bankers. Moreover, on the path to such integration, exploring the critical determinants of regime switches and transition probabilities may highlight the usefulness of more advanced regime-determining models beyond the HMM used in this study.

In summary, this paper demonstrated the critical importance of modeling inflation using flexible, nonlinear frameworks grounded in economic theory, while accounting for structural differences across country groups that reflect the actual complexities of economic behavior. By capturing how the magnitude of shocks and endogenous regime shifts generate disproportionate inflationary effects, the proposed framework achieves high predictive accuracy and provides deeper insights into the mechanisms driving inflationary dynamics. Policymakers in developing countries, particularly in an era of heightened global economic uncertainty, may find it valuable to consider such approaches.

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Appendix

Table A.1. High-inflation threshold literature review

Authors	Countries	Variables	Methodology	Threshold findings
Bruno and Easterly (1998)	127 countries	CPI, per capita growth	Descriptive analysis	40%
Khan and Senhadji (2000)	140 countries	GDP, CPI, investment, population, initial income, trade	Likelihood ratio (LR)	Developed economies 1-3% Developing economies 7-11%
David, Pedro, and Paula (2005)	138 countries	GDP, CPI, investment, population, trade, openness	Fixed effects	Industrialized economies 2.6% and 12.6% Non-industrialized economies 19.2%
Pollin and Zhu (2006)	80 countries	GDP, CPI, investment, government spending, fiscal deficit, educational level, life expectancy, trade, natural disasters, war impacts	Pooled ordinary least squares (OLS) between effects, fixed effects, and random effects	15-18%
Huang et al. (2010)	71 countries	GDP, CPI, private credit, bank assets, liquid liabilities, schooling, black market premium, government expenditure, openness	Instrumental-variable threshold regression	7.31-7.96%
Omay and Kan (2010)	6 industrialized countries	GDP, CPI, investment, openness	Panel Smooth Transition Regression (PSTR)	2.52%
Yilmazkuday (2011)	84 countries	GDP, CPI, initial secondary enrollment rate, M3, government size, openness	Rolling-window two-stage least squares regressions	8%
Kremer, Brick, and Nautz (2013)	124 countries	GDP, CPI, investment, population, initial income, openness	Dynamic Panel Threshold Model (DPTM)	Industrialized economies 2% Non-industrialized economies 17%
Vinayagathan (2013)	32 Asian Countries	GDP, CPI, investment, population, initial income, trade, openness	Dynamic Panel Threshold Model (DPTM)	5.43%
Muzaffar and Junankar (2014)	14 Asian developing countries	GDP, CPI, household consumption, financial deepening, government expenditure, trade openness, agriculture's share of GDP, Oil and commodity price	SGMM	13%
Thanh (2015)	ASEAN countries	GDP, CPI, employment, investment, government spending, trade	Panel Smooth Transition Regression (PSTR)	7.84%
Ibarra and R.Trupkin (2016)	138 countries	GDP per capita, CPI	Panel Smooth Transition Regression (PSTR)	Good institutional emerging economies 7-8% Regular institutional emerging economies 12-15% Bad institutional emerging economies 19%
Kelikume (2018)	41 African countries	GDP, CPI, investment, population, initial income, trade, openness	Dynamic Panel Threshold Model (DPTM)	11.10%
Ehigiamusoe, Lean, and Lee (2019)	16 West African countries	GDP, CPI, private credit, liquid liabilities, government expenditure, openness, human capital	ARDL	5.62%
Ibrahim, Aluko and Vo (2022)	36 sub-Saharan African countries	GDP, CPI, financial deepening, investment, population, openness, human capital	Threshold regression model	6.76-7.65%
Azam and Khan (2022)	16 developing and 11 developed economies	GDP per capita, CPI, investment, household consumption, government expenditure, real exports, population growth rate	FGLS	Developed economies 5.28% Developing economies 12.23%

A1. Theoretical formation of inflation

According to the sellers' inflation literature, a firm, in the pursuit of profitability, determines the price (p) of its product by applying a markup to its direct cost (Kalecki, 1971; Weintraub, 1978), as shown below:

$$p = (1 + k) \frac{wl}{y}, \quad (1)$$

where k is the average markup, w is average nominal wage, l is labor, and y is real output. Taking the logarithm of both sides and then differentiating with respect to time, as in Charles, Bastian, & Marie (2021) and Lavoie (2022), we obtain the following expression for inflation:

$$\pi = \Delta(1 + k) + \Delta w + \Delta l - \Delta y, \quad (2)$$

where Δ identifies growth. Inflation arises from growth in markup, wages, and labor productivity ($\Delta y - \Delta l$). In an open economy structure, following Matamoros (2023) and Lavoie (2022), Equation 1 can be rewritten as below, respectively:

$$p = (1 + k) \left(\frac{wl}{y} + p_{im} fx \frac{im}{y} \right) \quad (3)$$

$$p = (1 + k) \left(\frac{wl}{y} \right) (1 + j), \quad (3')$$

where j is the ratio of imported material cost in production to unit labor cost, which is affected by raw material prices (p_{im}), exchange rates (fx), and changes in the amount of imported materials in production ($\frac{im}{y}$) (Lavoie, 2022; Bastian & Setterfield, 2020). Explicitly, the inflation equation becomes:

$$\pi = \Delta(1 + k) + \Delta w + \Delta l - \Delta y + \Delta(1 + j) \quad (4)$$

$$\pi = \Delta(1 + k) + (\Delta w + \Delta l - \Delta y) + \Delta \left(1 + \frac{p_{im} fx im}{wl} \right), \quad (4')$$

where $(\Delta w + \Delta l - \Delta y)$ represents Unit Labor Cost (ULC) and $\left(\frac{p_{im} fx im}{wl} \right)$ is Unit Material Cost (UMC) per unit labor cost (UMC_{wl}). While Equation 4' is almost identical to the mainstream inflation equations of Batini, Jackson, and Nickell

(2005), Holmberg (2006), and Rumler (2007), the price-setting power of sellers is the essential separation point that helps us understand both types of nonlinearities. In this regard, sellers' inflation can be identified in a manner similar to that proposed by such authors as Lavoie (2022), Bastian & Setterfield (2020), Charles, Bastian, & Marie (2021), i.e.:

$$\pi = \Phi_1(\omega_{-1} - \omega_f) + \Phi_2\Delta w - \Phi_3(\Delta y - \Delta l) + \Phi_4\Delta(1 + UMC_{wl}) , \quad (5)$$

where Φ_1 , Φ_2 , Φ_3 , and Φ_4 are the price adjustment parameters of firms with respect to the discrepancy between the previous period's actual real wage (ω_{-1}) and the firms' desired real wage rate (ω_f), labor cost, productivity, and material cost. When $\Phi_{2,3,4} = 1$, implying that firms pass all costs along to consumers, Equation 5 became equal to Equation 4', while $\Phi_1(\omega_{-1} - \omega_f)$ identifies an increase in the markup.

Even though markups can be taken as fixed in a tranquil period, they become endogenous with respect to cost factors (Blecker, 2011). When there is a common cost shock to production, firms need to increase prices to keep profit margins intact (i.e. nominal markup) by more than the costs (Blair, 1974; Weiss, 1966). Firms thus need to reduce their real wage target, making it an increasing function of real cost factors. For instance, Lavoie (2022), Bastian & Setterfield (2020), and Blecker (2011) model this endogeneity through real exchange rate depreciation, the most important UMC factor. However, we can simply replace shocks from exchange rates with any exogenous shock. Similar to the impact of depreciation on production costs, other factors such as imported input prices or even minimum wage policies can create the same effect. In this regard, similar to these authors, the target real wage can be defined in linear form as:

$$\omega_f = \omega_{f0} - \Phi_5(\Delta shk_{t-1} - \pi_{-1}) , \quad (6)$$

where shk identifies exogenous cost shocks.

Replacing the real wage target of firms (Equation 6) in Equation 5, and simplifying the equation by assuming same price adjustment parameter for ULC components, we obtain the sellers' inflation equation:

$$\pi = \Phi_1(\omega_{-1} - [\omega_{f0} - \Phi_5(\Delta shk_{t-1} - \pi_{-1})]) + \Phi_2(\Delta ULC) + \Phi_4\Delta(1 + UMC_{wl}). \quad (7)$$

Table A.2. Average of the lagged coefficients for each determinant

	Brazil	Russia	India	China	South Africa	Türkiye
ULC	-0.393	-0.057	0.007	-0.399	-0.216	0.044
M*ULC	0.262	0.021	0.084	0.863	-0.179	0.064
R*ULC	0.385	0.078	-0.107	0.301	0.481	-0.194
FX	-0.033	0.024	-0.095	-1.475	-0.006	-0.056
M*FX	0.005	-0.022	0.071	0.659	0.031	0.037
R*FX	0.093	0.052	0.131	1.457	0.089	0.160
Global inflation	-0.926	0.288	-0.570	-3.627	0.084	0.261
M*Global inflation	0.503	-0.332	0.263	1.463	-0.241	-0.058
R*Global inflation	0.536	0.494	0.644	2.466	0.673	0.062

Note: Bold numbers indicate theoretically expected results

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