POLITICAL ECONOMY RESEARCH INSTITUTE

PERI

University of Massachusetts Amherst

POLITICAL ECONOMY RESEARCH INSTITUTE

Is "High Inflation" Always and Everywhere an Exchange Rate Phenomenon?

Tural Yusifzada, Hasan Comert, and Kagan Parmaksiz

October 2024

WORKINGPAPER SERIES

Number 609

Is "High Inflation" Always and Everywhere an Exchange Rate Phenomenon?

Tural Yusifzada[1], Hasan Comert[2], Kagan Parmaksiz[3]

Abstract

After decades of stable and low levels of inflation throughout the world, the recent global upsurge in inflation has once again triggered extensive debate among economists about the underlying reasons for the rising trend in inflation. This study aims to contribute to this ongoing discussion by exploring a potential channel that could be fundamental to our understanding of the high inflation levels common across a large number of countries.

Drawing upon a rich historical dataset spanning from 1961 to 2023 and employing a random effects panel probit model, our research reveals that the nominal exchange rate depreciation emerges as a strong predictor of "high inflation" episodes across different economies and time periods. Notably, this predictive capability extends to countries with varying income levels, with high-income, upper-middle-income, and lower-middle-income nations exhibiting success rates of 70%, 77%, and 63%, respectively, in forecasting "high inflation" based solely on exchange rate depreciation. Furthermore, food and energy prices also emerge as other important contributors to inflation.

These findings have important implications for recognizing exchange rate depreciation as a vital early warning signal for high inflation not only facilitates more timely and effective policy interventions but also emphasizes the critical role of historical exchange rate dynamics and supply-side factors in comprehending the complexities of "high inflation."

Keywords: high inflation, exchange rate, panel probit model, early warning model

JEL Codes: E31, E37, E12, C25

[1] Research, Central Bank of the Republic of Azerbaijan, tural_yusifzada@cbar.az
[2] Economics, Trinity College, hasan.comert@trincoll.edu
[3] Economics, Middle East Technical University, kaganp@metu.edu.tr

Introduction

After decades of stable and low levels of inflation and output volatility that was labelled as the period of 'great moderation,' the first decades of the new millennium brought back old memories of global turmoil and the world has been once again grappling with an unexpected resurgence of high inflation challenging central banks in maintaining price stability. Traditional forecasting models failing to predict the high levels of inflation (Bernanke, 2024), and contrary to its persistent nature, most reputable central bankers arguing it to be a temporary phenomenon (Ihrig & Waller, 2024), resulted in loss of credibility of monetary policy (Coleman & Nautz, 2022) and naturally raised the following questions; what are the causes of this inflation, and what lies behind the lack of predicting and understanding it?

In the literature, numerous studies have been conducted to understand the determinants of inflation. Mainstream explanation of inflation relies on the traditional Phillips curve framework with a heavy emphasis on expectations. Different variants of the models based on this structure have emerged to be the fundamental tools used by modern central banks both in understanding and dealing with inflation and these models carry a great weight in inflation literature as well. Although the structure of these models allows for both demand and supply side factors to generate persistent and high levels of inflation, most applied work using these models focuses on the demand side as both the cause and the potential cure of inflation following a traditional approach.

A less well-known and used strand of research following Lerner (1958) and generally building on Kalecki's (1971) and Weintraub's (1978) work focus solely on supply-side or sellers' inflation using wage-cost markup models as fundamental price dynamics. Unlike the mainstream view that inflation is driven by excess demand, post-Keynesians attribute it to supply-side factors (Lavoie, 2022). While higher economic activity may coincide with wage or price inflation, persistent price increases stem from conflicts over income distribution rather than resource scarcity. Consequently, these models, working from a completely different output pricing mechanism than the mainstream approach, view inflation as a result of distributional conflict, market power, and productivity dynamics over time. Therefore, inflation is often linked to supply-side factors resulting from changes in economic structures (Olivera, 1964; Canavese, 1982).

Even though the literature on inflation is ample and extensive, most research on mainstream monetary economics of the last couple of decades focuses on optimal monetary policy over the business cycle, taking low and stable levels of inflation as a given. Considering that most research is motivated by pressing macroeconomic problems, it is natural that the topic of high inflation is much less investigated during this period. Our study is an attempt to contribute to the literature in the following ways.

First, in contrast with the literature that focuses on the dynamics of inflation regardless of its level, our study focuses on the potential causes of "high inflation," which refers to the level of inflation beyond which economic growth is adversely affected. Although the causes of "high inflation" are likely to be among the broader determinants of inflation, the reverse is not necessarily true; that is, not all factors driving inflation have the capacity to push it to a "high" level. As the key factors driving a significant surge in inflation are still under investigation and remain underexplored in most inflation studies, we seek to answer this question.

Second, alongside its distributional impacts, high inflation levels harm real economic dynamics, particularly growth. The cost and challenges of dealing with high inflation increase non-linearly from a policy perspective and the recovery from a sudden loss of credibility is likely to be extremely costly. As such, early prediction of "high inflation" episodes has become a major focus for policymakers and we believe our study is an important step in this direction.

To comprehensively address these questions, we delve into the historical context of "high inflation," analyzing the period from 1961 to 2023 to identify significant episodes. Defining "high inflation" based on a literature review considering diverse economic characteristics, we set threshold levels exceeding 10% for middle-income countries and 5.5% for high-income countries. These benchmarks guide our investigation into the determinants of "high inflation," focusing on 21 high-income, 23 upper-middle-income, and 7 lower-middle-income countries.

From a theoretical perspective, our study is mostly within the second strand of literature we briefly laid out above, which corroborates the notion that supply factors significantly impact inflation. To provide a foundation and motivation for our empirical work, we start by writing out an inflation equation, which has some inspiration from mainstream studies such as Batini, Jackson, and Nickell (2005), Holmberg (2006), and Rumler (2007), but fundamentally is a heterodox one. We set our inflation equation apart from mainstream models by incorporating endogenous wages and bargaining power, which are functions of exchange rate depreciation, following the theoretical framework of Bastian & Setterfield (2020), Charles, Bastian, & Marie (2021), and Lavoie (2022).

Additionally, the inclusion of markup as a function of supply-side shocks, as suggested by Blecker (2011) and Lavoie (2022), further differentiates our inflation equation from the mainstream approach.

While examining inflation as a function of markup, unit labor, and material costs, we underscore the importance of the exchange rate on all three, especially in significant depreciation episodes. This framework allows for a nonlinear relationship between the exchange rate and inflation, a subject that is not theoretically explored in the majority of existing mainstream literature.[4]

We begin by visually exploring the relationship between variables using scatter diagrams, particularly observing the nonlinear relationship of exchange rates with inflation. Even though our theoretical inflation equation provides the potential transmission mechanisms from exchange rate to price level, the cross-country availability of empirical measures about these variables is almost non-existent. Consequently, for empirical analysis, we utilize a reduced-form inflation equation. Furthermore, our decision to practically define "high inflation" as a threshold value above which output growth is negatively affected naturally makes our variable of interest a binary one. Thus, our empirical analysis of the proposed relationship becomes a binary one that analyzes the contribution of a set of covariates on the likelihood of observing our binary variable, "high inflation." To proceed, we employ the random effects panel probit model to predict the probability of a "high inflation" episode in an attempt to uncover the primary determinants of "high inflation" episodes, which we believe has not been previously done in the literature.[5]

Our main finding can be summarized as follows: exchange rate depreciations emerge as the main determinant of "high inflation" episodes as exchange rate depreciation predicts nearly all instances of high inflation in upper-middle-income countries and a majority in high and lower-middle-income countries, which brings us to the answer to our paper's title to complement the famous

[4] Exceptions of well-developed studies on nonlinear exchange rate pass-through, such as those by Frankel, Parsley, and Wei (2012), Caselli and Roitman (2019), Cheikh & Zaied (2020) exist.

[5] The probit models have primarily been used to predict crises (Antunes, 2018) and recession (Filippopoulou, Galariotis, & Spyrou, 2020) probabilities in the economics literature. By introducing "high inflation" as a type of crisis, we introduce the probit model to determinants of inflation studies. While the probit model has been used in several inflation-related research, such as predicting inflation and deflation (Silvia & Iqbal, 2015), to the best of our knowledge, its use in identifying the determinants of inflation represents a novel approach.

statement by Friedman (1963) with ours; "High inflation is frequently, and in almost everywhere, an exchange rate phenomenon."[6]

The plan of the paper is as follows: we begin by identifying the “high inflation” threshold in Section 1.1. Having established the benchmark for “high inflation,” we analyze the literature, focusing on major factors contributing to inflation in Section 1.2. In Section 2, we present our data and descriptive statistics. Section 3 outlines the panel probit model, and Sections 4 and 5, respectively, provide the results and discussions. The research concludes with a section summarizing the findings and implications.

1. Literature review

1.1. What is the “high” level of inflation?

In general, “high inflation” is defined as the inflation level beyond which harms economic growth in the literature. However, the relationship between inflation and economic growth is a dynamic and complex process. For instance, inflationary pressures can arise as an unintended consequence of increased aggregate demand, which may not significantly harm economic growth (Pollin & Zhu, 2006). Thus, such inflation levels are not identified as “high.” On the other hand, inflation and economic growth can be negatively related in certain situations, such as when inflation is caused by monopolistic pricing, exchange rate fluctuations, or supply disruptions of goods and services (Pollin & Zhu, 2006). It's important to note that in this study, we follow this literature that defines high inflation as a level that diminishes growth.

In earlier research, Bruno and Easterly (1998) noted that a 40 percent inflation rate leads to substantial output losses. However, what constitutes “low” and “high inflation” varies globally due to structural disparities in determinants (Thanh 2015). Several studies have explored the differences in inflation thresholds between developed and developing economies. In-depth analyses that distinguished between industrialized and non-industrialized economies revealed diverse threshold levels. Khan and Senhadji (2000) found that developed countries experience

[6] Following Rowthorn (1977), there is a significant body of literature that uses a similar statement, mostly highlighting that inflation is a conflict phenomenon, such as Rosenberg & Weisskopf (1981), Dutt (1992), Vera (2010), Hein (2024). However, while the exchange rate can also be seen as a conflict between the local and external sectors, as discussed in Hein (2024), we focus directly on the transmission of exchange rate movements to inflation formation rather than the factors determining exchange rates. Consequently, we refer to the exchange rate phenomenon rather than the conflict phenomenon.

significant output losses when inflation rates reach 1% to 3%, whereas developing countries can tolerate higher inflation rates of 7% to 11%.

Ibarra and R. Trupkin (2016) revealed three distinct threshold categories in a study focused on emerging economies. Inflation rates between 1% and 5% stimulate growth, while rates between 5% and 9% have no significant negative impact on output. However, countries with "regular" institutions experience harmful growth effects at inflation rates above 12% to 15%, and rates above 19% are detrimental to countries with "bad" institutions. On the other hand, "good" institutional emerging economies exhibit a 7% to 8% inflation threshold for stimulating growth. For example, ASEAN countries' growth experienced significant negative impacts after surpassing a 7.84% inflation threshold (Thanh 2015).

Table 1.1. "High Inflation" Threshold Literature Review: The Panel Analyzes

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%
Vinayagathasan (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%

Table 1.1. (continued)

Authors	Countries	Variables	Methodology	Threshold findings
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%
Aydın, Esen, and Bayrak (2016)	Azerbaijan, Kyrgyzstan, Kazakhstan, Uzbekistan, Turkmenistan	GDP, CPI, investment, population, initial income, trade, openness	Dynamic Panel Threshold Model (DPTM)	7.97%
Ndoricimpa (2017)	African countries	GDP, CPI, investment, population, initial income, trade, openness, government spending, political instability	Panel threshold model	Low-income countries 9% Middle-income countries 6.5%
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%
Farahani, Ghabel, and Mohammadpour (2021)	8 developing Islamic countries	GDP, CPI, financial development, physical capital, labor force, trade openness	Panel Smooth Transition Regression (PSTR)	11.88%
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%

As presented in Table 1.1, given the variation in "high inflation" threshold values across different research studies, a consensus about what defines a "high inflation" level remains elusive; hence, we chose to identify the "high inflation" threshold as the median value that emerged from 19 well-considered "high inflation" thresholds from the literature, presented in Table 1.1. which give threshold values of 10% for middle-income countries and 5.5% for high-income countries.[7] Furthermore, for a robustness check, we account for "high inflation" thresholds as the median value ± 0.5 standard deviations (approximately 0.5*4.5%) of the literature thresholds.

[7] However, it's important to acknowledge that while panel analyses offer valuable insights, these generalized threshold values might not perfectly fit every country within each income group, as evidenced by the findings outlined in Table A.1 in Appendix. Nonetheless, this limitation does not undermine the core objective of our study, which is to establish a global understanding of what qualifies as "high inflation."

1.2.Theoretical framework of determinants of inflation

Considering that this study seeks to identify the determinants of “high inflation,” it inherently suggests nonlinearity, as not all factors influencing inflation have the potential to push it to a “high” level. While the non-linear empirical relationship between inflation and exchange rates is well-documented in global studies, it often lacks a solid theoretical framework. Therefore, although we will also proceed with a non-linear reduced-form inflation equation due to empirical constraints, we must first determine whether theoretical non-linear transmission channels from the determinants to inflation exist in order to justify the “high inflation” phenomenon. Otherwise, like many previous mainstream studies, the empirical results may fail to align with the theoretical understanding of inflation dynamics.

In this regard, given the limited explanatory power of mainstream models in capturing these non-linearities we analyze inflation from the perspective of heterodox sellers' inflation approaches. According to Post Keynesian 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:

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

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:

$$\pi = \Delta(1+k) + \Delta w + \Delta l - \Delta y \tag{2}$$

, 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), Equations 1 can rewritten as below, respectively:

$$p = (1+k)(\frac{wl}{y} + p_{im}\, fx\, \frac{im}{y}) \tag{3}$$

$$p = (1+k)(\frac{wl}{y})(1+j) \tag{3'}$$

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)[8]. Explicitly, the inflation equations became as follows:

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

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

where $(\Delta w + \Delta l - \Delta y)$ represents Unit Labor Cost (ULC) and ($\frac{p_{im}\, fx\; im}{wl}$) is Unit Material Cost (UMC) per unit labor cost (UMC_{wl}). While Equation 4' is almost identical to the mainstream inflation equations such as Batini, Jackson, and Nickell (2005), Holmberg (2006), and Rumler (2007), there are structural differences in the markup and wage formation. In the Post Keynesian literature, both are formed through conflicting claims between firms and the labor force and market power (Hein, 2024) rather than an equilibrium process.

Thus, in its simple form, sellers' inflation can be identified as in Lavoie (2022), Bastian & Setterfield (2020), Charles, Bastian, & Marie (2021), and other authors as follows: [9]

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

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 to consumers, Equation 5 became equal to Equation 4', while $\Phi_1\left(\omega_{-1} - \omega_f\right)$ identifies a growth in the markup.

Moreover, according to Blecker (2011) and Lavoie (2022), firms' real wage targets are a function of their target markup. In this framework, when there is a common shock to production from UMC components, firms increase prices (i.e., the nominal markup) by more than the costs (Blair, 1974; Weiss, 1966). Besides, firms encountering a scarcity of inputs due to a bottleneck on the supply side may adopt a more assertive approach to increasing prices. This strategy not only safeguards

[8] We are very grateful to T. Sabri Öncü for his invaluable insight in identifying a derivation issue in the previous version.

[9] Considering that labor bargaining power and wage targets depend on unemployment (Blanchard & Katz, 1997; Ball & Moffitt, 2001; Lavoie, 2022), replacing the term $\Omega_1(\omega_w - \omega_{-1})$ with unemployment results in a wage equation defined by Blanchard & Katz (1997) and Ball & Moffitt (2001). However, unemployment is not the only determinant of wage targets and bargaining power. Thus, we follow the structure presented in Equation 5.

profit margins but could potentially lead to their expansion (Franzoni, Giannetti, & Tubaldi, 2023; Weber & Wasner, 2023). Thus, according to Blecker (2011) and Lavoie (2022), when faced with UMC shocks, especially in terms of exchange rate shocks, firms decide to reduce the real wage target to increase markups or at least keep it intact. This adjustment is important because if prices do not adjust, an increase in UMC will lead to a decrease in markup (Bastian & Setterfield, 2020), which can be seen in Equation 5. In this framework, the real wage target of firms can be identified as in Blecker (2011) below:

$$\omega_f = \frac{1}{1+k_f} \tag{6}$$

where k_f is the target profit markup rate, which is an increasing function of real exchange rate depreciation ($\Delta fx_{-1} - \pi_{-1}$). The target real wage can also be defined in linear form as in Lavoie (2022), Bastian & Setterfield (2020), and Blecker (2011) below:[10]

$$\omega_f = \omega_{f0} - \Phi_5(\Delta fx_{-1} - \pi_{-1}) \tag{6'}$$

Replacing firms' real wage target (Equation 6') in Equation 5, we obtain the sellers' inflation equation as below:

$$\pi = \Phi_1\big(\omega_{-1} - [\omega_{f0} - \Phi_5(\Delta fx_{-1} - \pi_{-1})]\big) + \Phi_2\Delta w - \Phi_3(\Delta y - \Delta l) + \Phi_4\Delta(1 + UMC_{wl}) \tag{7}$$

On the other hand, wage dynamics are also endogenous, as defined in most of the referenced Post Keynesian literature as follows:

$$\Delta w = \Omega_1(\omega_w - \omega_{-1}) + \Omega_2\pi_{-1} + \Omega_3(\Delta y - \Delta l) \tag{8}$$

where Ω_1 is a parameter that indicates to what extent labor unions react to a discrepancy between the previous period's actual real wage (ω_{-1}) and the desired real wage rate of labor (ω_w), Ω_2 is wage indexation bargaining power with respect to the previous period's inflation and Ω_3 denotes the wage adjustment parameter for labor productivity (Lavoie, 2022).

However, when inflation rates exceed some specific threshold (where it turns out to be "systematically high"), according to Simonsen (as cited in Charles, Bastian, & Marie (2021)),

[10] One point should be noted: in response to UMC shocks, firms do not necessarily need to squeeze nominal wages but can instead increase inflation targets, which also decreases real wage targets (Matamoros, 2023).

agents often adopt the exchange rate as one of the main references for wage indexation, because expectations became unanchored (Arias & Kirchner, 2019). In this case, the influence of exchange rates on inflation expectations increases significantly (Cortes & Paiva, 2017; Bems, Caselli, Grigoli, Gruss, & Lian, 2018). Therefore, while nominal wages indexation considers wage target relative to actual wage and current inflation, exchange rate depreciation became an additional component of wage determination as suggested by Bastian & Setterfield (2020) and Charles, Bastian, & Marie (2021) as below:

$$\Delta w = \Omega_1(\omega_w - \omega_{-1}) + \Omega_2\pi_{-1} + \Omega_3(\Delta y - \Delta l) + \Omega_4\Delta fx_{-1} \tag{9}$$

Moreover, according to Charles, Bastian, & Marie (2021), high-inflation memory-having countries tend to index faster than countries without such experience. When continuous real wage erosions become greater, labor will try to compensate for the loss through harder bargains (Lavoie, 2022). In this framework, the wage adjustment parameter to depreciation becomes an endogenous function of the “admissible distance (ε) between the target and the actual real wage” (Lavoie, 2022, p. 607):

$$\Omega_4 = \mathrm{f}_{\Omega}[\omega_w - (\omega_{-1} + \varepsilon)] \tag{10}$$

But how does this occur? Let’s transform Equation 4’ to obtain real wages as follows:

$$\Delta w - \pi = -\Delta(1 + k) + (\Delta y - \Delta l) - \Delta(1 + UMC_{wl}) \tag{4’’}$$

Real wages are negatively affected by markup and UMC (Bastian & Setterfield, 2020) and positively affected by productivity. Thus, when a “dramatic supply-side shock” occurs or the exchange rate significantly depreciates, UMC rises and decreases the real wages, activating Equation 10 (Lavoie, 2022). In other words, when currency depreciation exceeds certain thresholds, it leads to larger impacts on inflation (Frankel, Parsley, and Wei, 2012; Caselli and Roitman, 2019).

By placing Equation 10 into 9 and 9 into 7, we obtain the final inflation equation as below:

$$\pi = \Phi_1\big(\omega_{-1} - [\omega_{f0} - \Phi_5(\Delta fx_{-1} - \pi_{-1})]\big) + \Phi_2\{\Omega_1(\omega_w - \omega_{-1}) + \Omega_2\pi_{-1} + \Omega_3(\Delta y - \Delta l) + \mathrm{f}_{\Omega}[\omega_w - (\omega_{-1} + \varepsilon)]\Delta fx_{-1}\} - \Phi_3(\Delta y - \Delta l) + \Phi_4\Delta(1 + \frac{p_{im}\, fx\, im}{wl}) \tag{11}$$

Now, the exchange rate has become not only part of UMC but also directly affects i) wage indexation, ii) the power of indexation, and iii) the markup when inflation is "high." While this formulation may explain Latin American economies' propensity to experience high inflation rates (Charles, Bastian, & Marie, 2021), it clarifies how the non-linear relation between inflation and exchange rates emerges. Moreover, since depreciation is not only a component of UMC, it might also explain why Montes-Rojas & Toledo (2022) found a 2.5 times higher pass-through from the exchange rate compared to imported commodities. On the other hand, when inflation reaches high levels, the pass-through from exchange rate movements to domestic prices further increases significantly (Cheikh & Zaied, 2020). This can be explained through markup and ULC dynamics, as shown in Equations 6' and 10, respectively.

1.3. Reduced form Inflation Equation

Our structural inflation equation is given by Equation 11, however estimating Equation 11 to analyze the determinants of "high inflation" across all analyzed countries is challenging due to two key issues. First is the fact that dynamically changing bargaining powers and wage targets make ULC difficult to estimate. Second has to with data availability as country-level markup dynamics and import costs are not available for all analyzed countries. To address these challenges, we use proxies of our variables in the structural equation to construct a reduced-form inflation equation as follows:

$$\pi_t = \mathrm{f}\left(\Delta GDP_t, \Delta fx_t, \Delta p_t^{energy}, \Delta p_t^{food}\right) \tag{12}$$

where inflation is a function[11] of growth, depreciation, and commodity inflation. In Equation 12, ΔGDP_t is real economic growth, Δp_t^{energy} and Δp_t^{food} are energy and food commodity inflation, respectively. While ΔGDP_t and Δfx_t can represent markup and ULC dynamics, Δfx_t, p_t^{energy} and Δp_t^{food} represents UMC.

Starting with demand, we focus on output, following the approach of many Central Banks (Brázdik, et al., 2020) because, within the Keynesian framework, output cycles serve as a direct proxy for demand (Serrano, 2019). Besides the unavailability of related data, our decision to use

[11] The reduced form does not assume that inflation is a linear function of its determinants, as is often assumed in traditional studies. Considering the indexation and markup dynamics triggered by significant depreciation or dramatic supply shocks, a non-linear relationship between inflation and its determinants is expected.

output rather than estimate unit labor cost is also based on the endogeneity between markup, wage indexation, and exchange rate depreciation, which, if ignored, would result in countercyclicality, contrary to the expected procyclical nature of marginal costs (Mazumder, 2010).[12] Thirdly, according to Lavoie (2022), while the real wage target of labor is a function of the discrepancy between actual and "normal" economic growth, firms' real wage target depends on capacity utilization and rate of return. Moreover, labor bargaining power is also a function of unemployment (Blanchard & Katz, 1997; Ball & Moffitt, 2001; Lavoie, 2022). Therefore, using real output as a proxy for ULC simplifies the complex dynamics observed in endogenously determined labor market variables. Consequently, we use real GDP growth[13] as a proxy for demand growth. Furthermore, growth and depreciation dynamics also reflect markup dynamics, which can serve as a proxy for real wage dynamics given in Equation 6'.

Furthermore, considering the difficulties of estimating all imported input prices, empirical models often utilize oil and oil-excluded commodity indices as p_{im} in the inflation equation for commodity importer economies. In commodity-exporting countries, energy and raw food commodities are not considered as imported intermediate goods but rather as components of local input costs.[14] In this framework, Forbes, Gagnon, & Collins (2021) and Jasova, Moessner, & Takats (2020) found highly significant results for oil and nonfuel commodity impact on inflation through real marginal cost. However, among many commodity prices, oil and food commodity prices are found to be the most significant in determining inflation (Abbas & Lan, 2020), with impacts varying with country characteristics. For instance, economies characterized by larger proportions of food prices within their Consumer Price Index (CPI) baskets and higher reliance on fuel tend to be more vulnerable

[12] While most recent mainstream literature ignores this endogenous relation, Holmberg (2006) highlights the possibility of a higher degree covariation between "true" real marginal cost and inflation, explaining their insignificant marginal cost and inflation relationship result. Moreover, Neiss and Nelson (2005) highlight the lack of wage-adjustment equations in their analysis.

[13] Since we follow the heterodox sellers' inflation approach, rather than using the well-known and widely utilized output gap as a proxy for demand, we directly use GDP growth, which is demand-determined. Nonetheless, to ensure the robustness of the estimates, we will re-evaluate the empirical model using the output gap obtained from the HP filter.

[14] At the end, the reduced form inflation equation will not differ between commodity exporters and importers.

to sustained inflationary impacts resulting from fluctuations in commodity prices (Gelos & Ustyugova, 2012). Therefore, we utilize Δp_t^{energy} and Δp_t^{food} as a proxy to Δp_{im}.

For the final[15] and most crucial variable, exchange rates, we follow Gopinath et al. (2020) and the dominant currency paradigm.[16] Instead of using the nominal effective exchange rate (NEER), commonly employed in empirical inflation equations, we use the local currency value relative to the US dollar.

2. Data and Descriptive Statistics

2.1. Data preparation

The data used in this research span from the first quarter of 1961 to the first quarter of 2023 and are collected quarterly. The datasets encompass cumulative price levels, real GDP, and exchange rates against the USD, all retrieved from the International Financial Statistics (IFS). For Mexico, Türkiye, and South Africa, GDP growth data between the 1961-1992 period is obtained from the FRED.[17] To ensure consistency, all variables are converted into annual percentage changes.

Energy and food commodity indices data are sourced from the World Bank and are denominated in nominal US dollars, with a base year of 2010 and an index value of 100. These monthly indices are transformed into quarterly observations by calculating the averages.

Due to data availability constraints, the analysis focuses on 51 countries with complete datasets for the three variables in the IFS database. Among these, 21 nations are categorized as high-income, 23 as upper-middle-income, and 7 as lower-middle-income, according to the World

[15] Although it's acknowledged that expectations also determine inflation, the absence of a universal variable for identifying expectations across countries has prevented their inclusion in our analysis as a determinant of "high inflation." To navigate the challenge, we adopt a perspective proposed by Nasir, Huynh, and Vo (2020b), suggesting that the determinants of inflation at a given time also shape inflation expectations at that same time. Consequently, we don't explicitly differentiate between the impact of determinants on expectations and the subsequent influence of expectations on inflation. Instead, we assume that the impacts of all independent variables accumulate in inflation both directly and indirectly through expectations.

[16] The Dominant Currency Paradigm suggests that firms typically invoice in a dominant currency, such as the US dollar, and therefore, the US dollar exchange rate, not the bilateral exchange rate, drives global trade prices. For instance, according to Chen, Chung, and Novy (2022), pass-through for imports is low at 24.2% when estimated based on the bilateral exchange rate between exporting and importing countries. However, when the study allows the unit values of currency transactions to depend on the exchange rate between sterling and the vehicle currency, the pass-through is much larger at 59.2% for the UK. Thus, using the bilateral exchange rate underestimates pass-through because it does not adequately measure the invoice-relevant exchange rate variation.

[17] These are Composite Leading Indicators: Reference Series (GDP), calendar and seasonally adjusted for selected countries.

Bank's income group classification (selected countries are displayed in Table A.2 in the Appendix).

For several reasons, we preferred the yearly growth rate form the same quarter of last year over quarter-on-quarter growth when managing the data. Firstly, varying seasonal patterns across the analyzed countries make it challenging to uniformly apply well-known de-seasonalization methods such as TRAMO/SEATS and X-13/11. These methods require country-specific adjustments to account for calendar events, as using them without adjustment consideration could distort the inherent characteristics of the data. Secondly, the preference for using annual changes instead of quarterly changes is based on the existing literature's emphasis on identifying "high inflation," which typically focuses on annual changes. Using quarterly changes might make it harder to distinguish "high inflation" threshold values.

Before starting our analysis, it should be noted that each income group's dataset is substantially impacted by outliers specific to individual countries. To mitigate the influence of these outliers, we implement Tukey's fences method (Figure 2.1.1). This method relies on the concept of the interquartile range (IQR), which spans from the 25th percentile (Q1) to the 75th percentile (Q3) of the dataset. Outliers are identified as values that fall below Q1 minus 1.5 times the IQR (lower fence) or above Q3 plus 1.5 times the IQR (upper fence) (Dastjerdy, Saeidi, & Heidarzadeh, 2023).

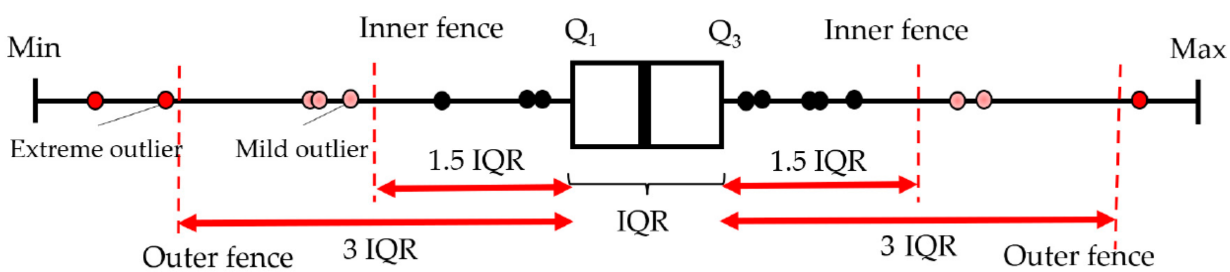


Figure 2.1.1 Outlier Detection

Source: Dastjerdy, Saeidi, and Heidarzadeh (2023).

Generally, the standard practice involves removing outliers once detected in the samples. However, this approach does not align with our dataset and research objectives, where we are seeking answers regarding the determinants of "high inflation," which is, in essence, an outlier itself. Moreover, implementing this methodology would lead to the exclusion of pivotal years marked by significant energy shocks, such as 1973, 1979, 2000, and 2021-2022, as illustrated in

Figure 2.1.2, along with their associated well-known "high inflation" episodes. Instead of outright removal, we replace these outliers with the border inner fence values. This decision allows us to retain the most critical years in our analysis while mitigating the estimation errors associated with outliers.

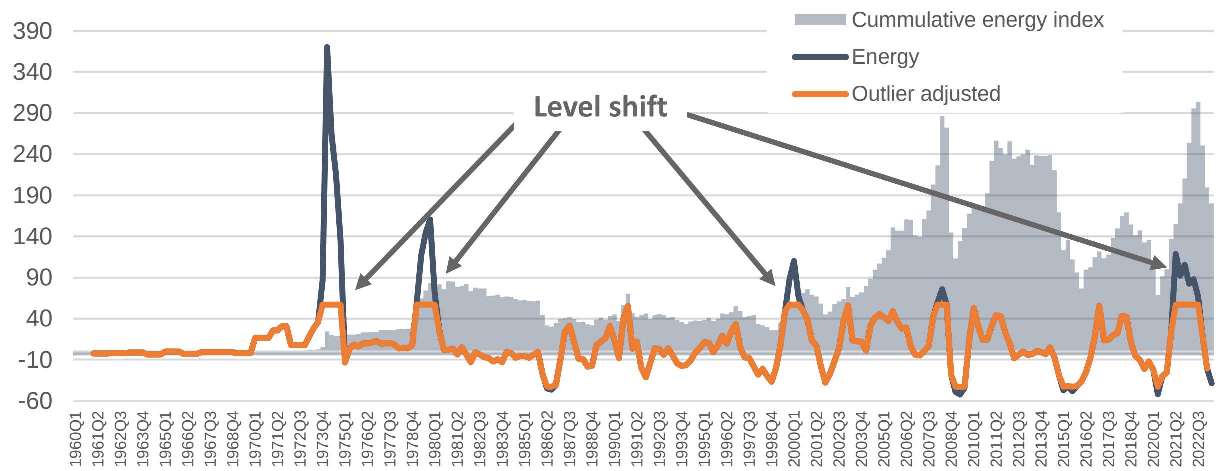
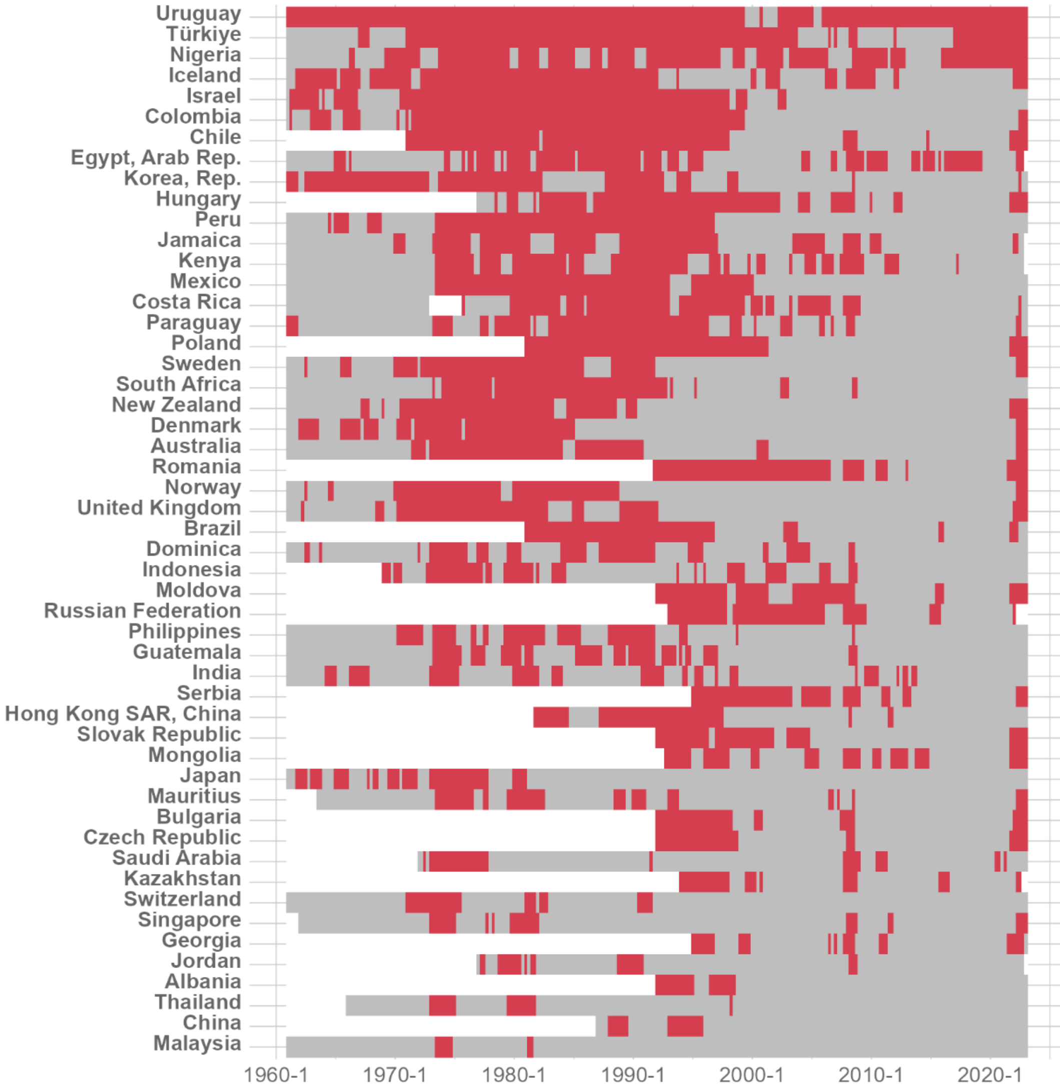


Figure 2.1.2 Outlier Detection for Energy Commodity Inflation

Source: Authors' calculation.

2.2.Descriptive Statistics

After determining the "high inflation" thresholds as the values of 10% for middle-income countries and 5.5% for high-income countries denoting "high inflation" levels, to validate the reasonability of these threshold values in explaining the majority of "high inflation" cycles throughout history, we turn to Figure 2.2.1. From the figure, it becomes evident that these "high inflation" threshold values effectively identify prominent periods such as the 1970s to 1990s, the global financial crisis in 2008-2009, and the recent years of 2021-2023 for most countries. However, it's important to acknowledge that, as previously discussed in Section 1, these threshold values might not universally represent all countries. Instances like those observed in Uruguay, China, and Malaysia demonstrate differing inflation dynamics compared to their counterparts within the same income group. While these countries might exert minimal distortion on the global commodity prices and inflation analysis, they could potentially contribute to strengthening the relationship between inflation and internal factors such as exchange rates and demand. Hence, these countries are not excluded from the analysis.



The red area highlights “high inflation” episodes, whereas the gray area is non-high episodes.

Figure 2.2.1 “High Inflation” Episodes

Source: Authors’ calculation.

After scrutinizing the reasonability of threshold values in the analyzed countries, we revisit our central question: What determines inflation and at what level do these factors transform inflation into “high inflation”? According to Figure 2.2.2.A, the inflation sensitivity to the exchange rate is notably high across all countries compared to other determinants. Moreover, it further increases during large depreciations, causing inflation to exceed its high threshold level, thereby highlighting the non-linearity discussed in the previous section.[18] Inflation’s response to demand and food

[18] For additional non-linearity-based relations, please refer to Figure A.1 in the Appendix.

commodities is positive but very low. On the other hand, the relationship between inflation and energy commodity inflation is almost horizontal, likely due to administered commodity prices.[19]

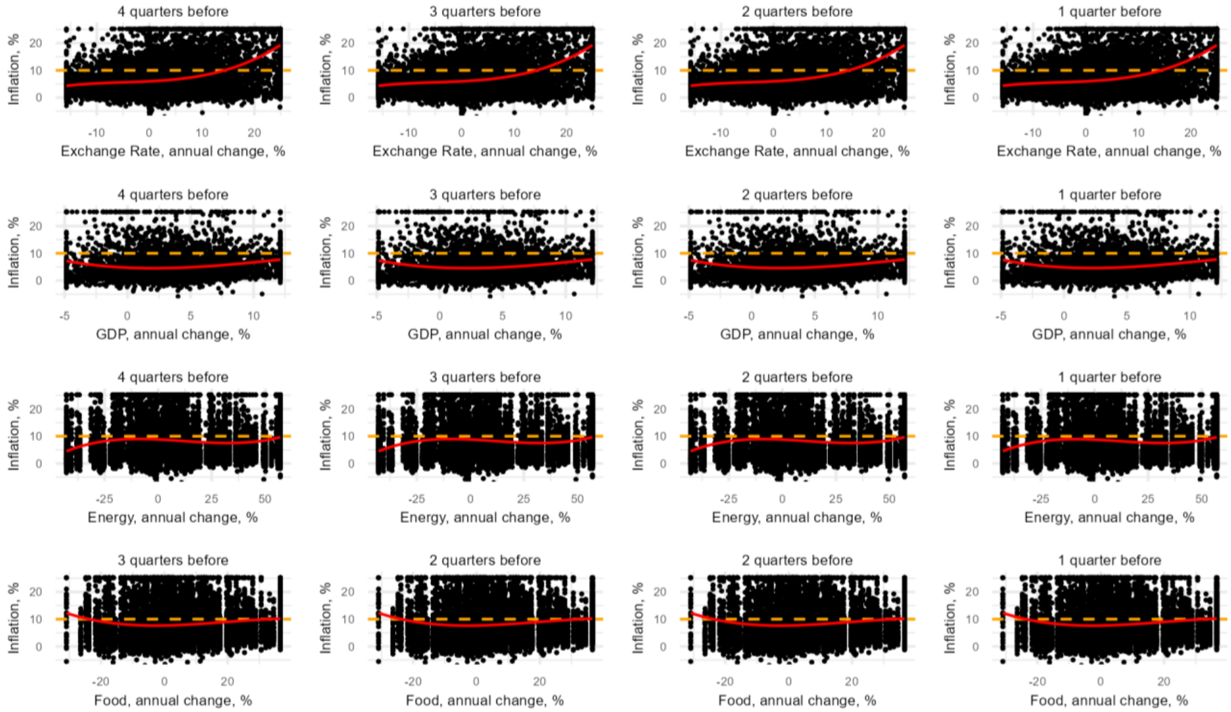
Moreover, scatter plots reveal several possible structural differences between country groups. For example, in upper-middle-income countries, the sensitivity of inflation to depreciation is significantly higher compared to high-income countries. This finding provides evidence for our theoretical discussion that wage indexation and markup responses to depreciation may be more pronounced in countries experiencing frequent significant depreciations. On the other hand, while the relationship between demand and inflation is positive in upper-middle-income countries, high growth has historically not been closely associated with "high inflation." In lower-middle-income countries, although the co-movement with depreciation is less pronounced than in other groups, depreciation alongside food commodity inflation is more closely related to "high inflation." In contrast to other income groups, the elasticity of inflation to growth is mostly negative in lower-middle-income countries.

Following an examination of historical patterns between inflation and its determinants, the next phase of our analysis will focus on exploring the determinants of "high inflation" using an empirical model.

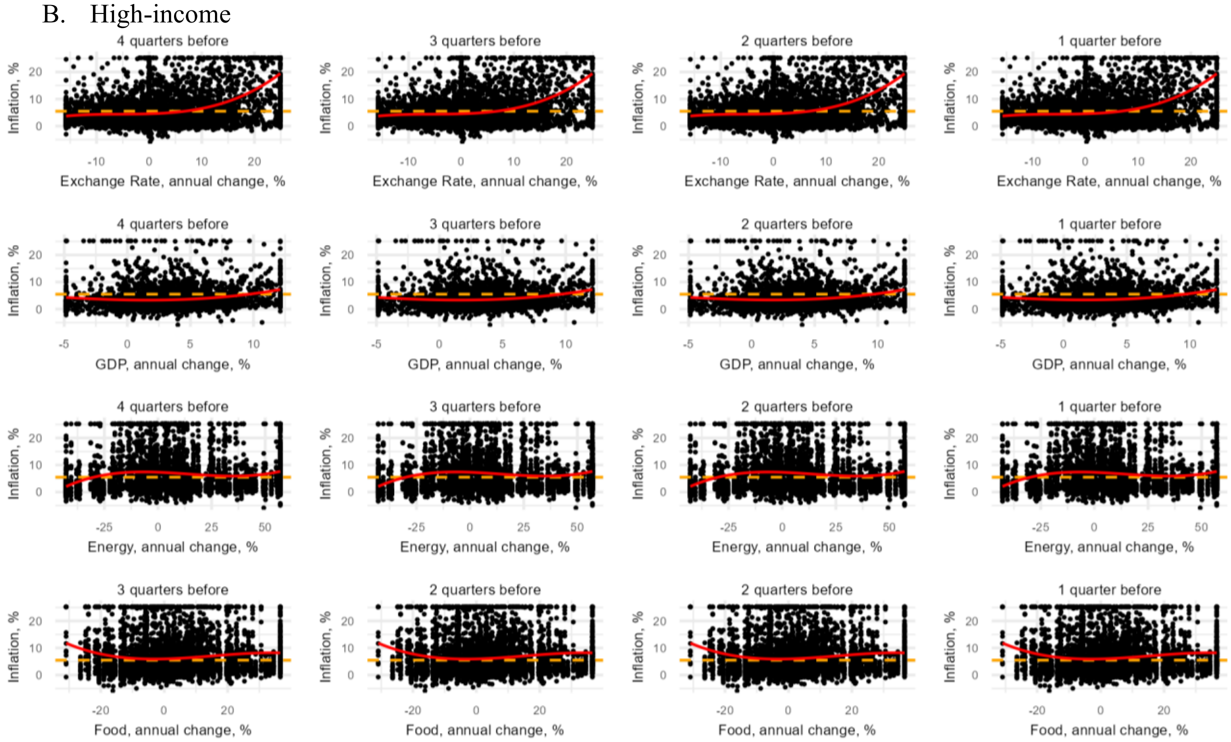
---

[19] As noted by the Mohanty & Klau (2001), in many nations, commodity prices, especially oil prices, are regulated, and adjustments to prices occur gradually. However, economies with pricing policies may experience inflationary pressures at different times and different magnitude due to the liberalization of administered prices at different times and varying levels of subsidies (Dua & Gaur, 2010). Consequently, in countries with price regulations, domestic commodity prices might not synchronize with sudden shifts in international commodity prices (Dua & Gaur, 2010), leading to a lower correlation between inflation and commodity prices in panel analyses.

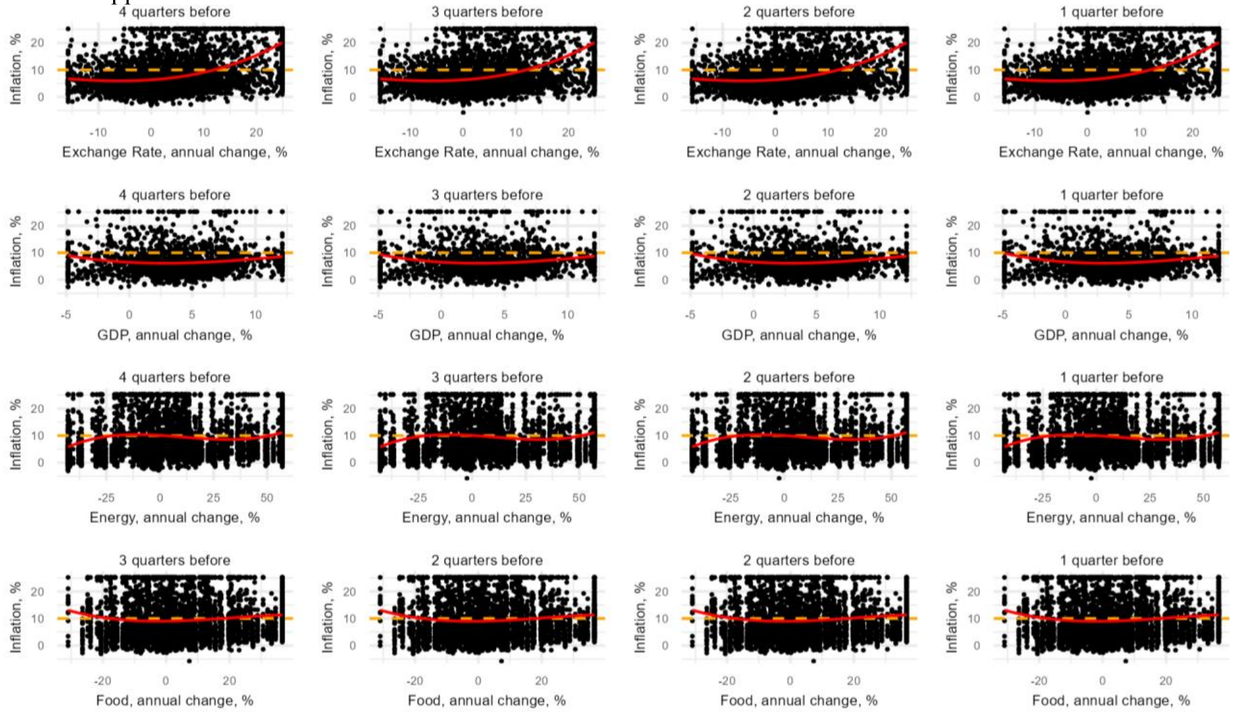
A. All Analyzed Countries



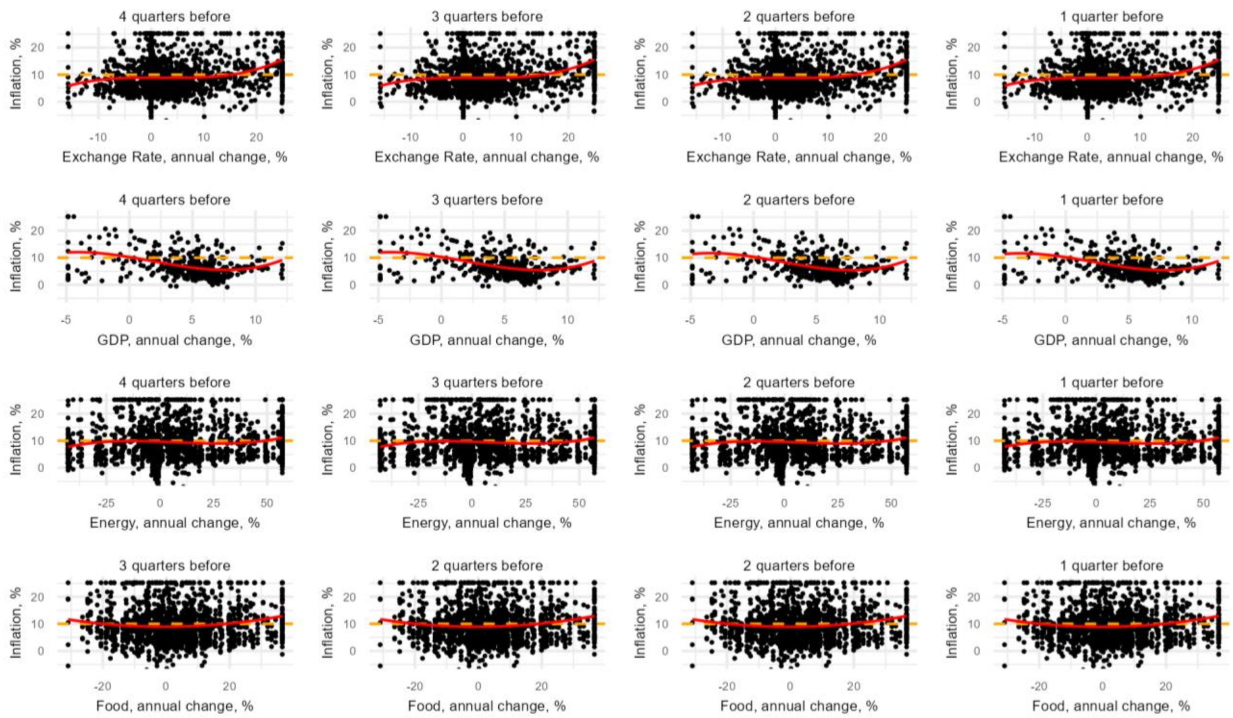
B. High-income



C. Upper-middle-income



D. Lower-middle-income



The red line is a degree-3 polynomial regression line between inflation and its determinants, and the orange dashed line indicates the "high inflation" threshold level.

Figure 2.2.2. Determinants of inflation

Source: Authors' calculation.

Note: The y-axis in each graph displays inflation values, while the x-axis shows associated determinants. Plots display 51 countries' (21 High income, 23 Upper middle income, and 7 Lower middle-income) observations. The subplot titles are labeled as: "n quarter(s) before" if inflation at time t is related to determinants at time t-n.

3. Panel Probit Model

Central to our investigation is to unravel the intricate web of factors contributing to "high inflation." What sets our study apart is its categorization of inflation into two discrete tiers: "high inflation" and "non-high inflation" levels. In this context, the panel probit model is well-suited for our research, which involves binary outcomes. By categorizing inflation levels as either "high" or "non-high," the model helps identify the determinants of "high inflation." While there is a popular alternative called the Signal approach, Boonman, Jacobs, Kuper, and Romero (2019) have consistently found that the binary choice model performs better than the Signal approach, both in-sample and out-of-sample.

However, another important focus is selecting true effects in panel probit models. Since we have 21, 23, and 7 countries in high-, upper-, and middle-income groups, respectively, and each country has its unique dynamics, we should be aware of the individual-specific effects to eliminate inefficient estimates (Amini, Delgado, Henderson, & Parmeter, 2012). In this regard, the model allows for individual-specific intercepts to vary randomly across entities while assuming a common relationship between the variables of interest, which is the random effects model. Moreover, panel probit random effects models are designed to strike a balance between fixed effects (which are more flexible but can be less efficient (Bollen & Brand, 2010)) and pooled models (which are more efficient (Shor, Bafumi, Keele, & Park, 2007) but less flexible). However, if there is a correlation between the unobserved individual effect and the conditioning regressors, employing a random effects model without accounting for the endogeneity of the conditioning regressors will result in estimates of the conditional mean that are both biased and inconsistent (Amini, Delgado, Henderson, & Parmeter, 2012). To confirm the compatibility of our data with random effects, we employ the Hausman test, as depicted in Table 3.1. According to the test, the absence of rejection regarding the exogeneity of the unobserved individual effect provides statistical backing for adopting a random effects model (Amini, Delgado, Henderson, & Parmeter, 2012).

Table 3.1. Hausman Test Results for Unobserved Variable Endogeneity

A. High income		B. Upper-middle-income		C. Lower-middle-income	
Chi-squared Statistic:	5.3117	Chi-squared Statistic:	4.9099	Chi-squared Statistic:	0.76032
p-value:	0.7238	p-value:	0.8421	p-value:	0.6838
Alternative hypothesis: one model is inconsistent					

Since we cannot reject the null hypothesis, we can benefit from the random effect models' efficiency (Amini, Delgado, Henderson, & Parmeter, 2012). The panel probit model with random effects equations can be represented as follows. For each individual i in the panel and time t, the probability of observing "high inflation" is modeled as:[20]

$$P(y_{it} = 1 | X_{it}, X_{it-1}, \dots, X_{it-n}, \alpha_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \alpha_i) \tag{13}$$

, where y_{it} is the binary outcome variable for individual i at time t, taking the value of 1 for "high inflation" and 0 otherwise; X_{it-n} is a vector of explanatory variables for individual i at different lags; n identifies lags; β_n represents the vector of coefficients for the explanatory variables; α_i is the individual-specific effect that captures unobservable heterogeneity across different countries; Φ is the cumulative distribution function of the standard normal distribution, which transforms the linear combination of $X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \alpha_i$ into a probability value between 0 and 1.

The random effects assumption introduces an additional layer to the model, accounting for the unobservable individual-specific effects (Greene, 2004):

$$\alpha_i = \eta + \mu_i \tag{14}$$

, where η is the common intercept capturing the average effect across all individuals; μ_i is the unobservable individual-specific effect for individual i, assumed to be normally distributed with mean 0 and constant variance σ_μ^2.

Incorporating the random effects into the panel probit model Equation 13 yields:

$$P(y_{it} = 1 | X_{it}, X_{it-1}, \dots, X_{it-n}, \eta, \mu_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \eta + \mu_i) \tag{15}$$

[20] This is the general formulation of the probit model. However, in this research, we utilize several methodologies to select appropriate lagged values for the determinants. For instance, the lags used in the paper range from 1 to 4 for high- and upper-middle-income economies, and only 2 for lower-middle-income countries.

The random effects panel probit model accounts for both the observable variables X_{it} and the unobservable individual-specific effects μ_i allowing for a more nuanced understanding of the determinants behind “high inflation” while considering the inherent heterogeneity present within the panel data.

In the lag selection, we did not select lagged values of the dependent variable because, in a panel probit model, it is generally not recommended. Including lagged values of the dependent variable in the model can introduce endogeneity (Guevara & Navarro, 2015) and potentially violate the assumptions of the probit model. This is because the lagged dependent variable is likely to be correlated with the current dependent and independent variables, leading to biased parameter estimates (Carro, 2007).

Instead of using lagged dependent variables, it's generally better to focus on lagged values of independent variables that are theoretically relevant to the model. These lagged independent variables can capture any potential dynamic effects in the relationship we are trying to model while avoiding the endogeneity issues associated with lagged dependent variables.

Literature generally refers to three main criteria for selecting optimal lags: the Akaike Information Criterion (AIC), the Bayesian Information Criterion, and MacFadden’s pseudo-R-squared (Hsu, 2016). The AIC criterion, while a valuable tool for model selection, carries the potential risk of overfitting, particularly when it consistently favors models with an increasing number of lags (Medel, 2014). The AIC, designed to find models that fit data well, often favors complexity by being less strict in penalizing the likelihood as parameters increase.

On the other hand, the Bayesian Information Criterion (BIC) serves as an alternative criterion for model selection that accounts for the complexity of the model in a stricter manner. By placing a heavier penalty on the number of parameters, the BIC encourages a parsimonious approach, favoring simpler models that effectively capture the essential patterns within the data. Unlike AIC, BIC's emphasis on model simplicity aligns more closely with the principle of Occam's razor, which posits that simpler explanations should be favored when competing hypotheses exist (Lazar, 2010). This propensity of BIC to discourage overly complex models can act as a safeguard against overfitting (Medel, 2014), ultimately contributing to the selection of models that are more likely to generalize well to new data. However, while decreasing complexity, BIC may fail to fit the model perfectly for actual data.

Additionally, MacFadden's pseudo-R-squared, a metric commonly employed in panel probit models, measures how well the model explains the variation in the binary outcomes compared to a null model (Hsu, 2016). While they provide insights into the proportion of variance captured by the model, pseudo-R-squared measures should not be solely relied upon as the sole criterion for model selection. Instead, they should be considered alongside other criteria, such as AIC and BIC, to arrive at a comprehensive and well-rounded understanding of a model's goodness of fit and its predictive capacity (Hsu, 2016).

Another method that ensures the robustness of lag selection is hold-out validation. The process of hold-out lag selection offers a strategic approach to addressing potential pitfalls associated with excessive lag inclusion. This technique involves designating a specific period, generally 20% of data (Montesinos López, 2022), distinct from the estimation sample, to evaluate the model's performance. In our case, we employed hold-out cross-validation by focusing on the period from 2011 to 2023, a span chosen independently from the estimation sample covering 1961 to 2010. By isolating this later timeframe, we aim to gauge how well the selected lag structure generalizes to new and unseen data, effectively simulating real-world conditions. This method allows us to mitigate the risks of overfitting by evaluating the model's ability to make accurate predictions beyond the range of data used for estimation (Montesinos López, 2022).

Taking into account the advantages and disadvantages of the four different lag selection criteria, it becomes evident that there is no universally optimal criterion that fits all scenarios. Each criterion offers its own unique benefits: AIC and MacFadden’s pseudo-R-squared help identify the best-fitting model, BIC aids in reducing model complexity and overfitting, and hold-out validation RMSE enhances model accuracy for unseen data. Rather than relying on a single criterion and making strong assumptions, we adopt a comprehensive approach that considers all four criteria’s results.

To navigate this multi-criterion decision-making process, we rank the values obtained from AIC, BIC, pseudo-R-squared, and RMSE. Specifically, for pseudo-R-squared, we opt for higher values indicating better fit, while for the other criteria, we seek lower values to minimize complexity and increase accuracy. By evaluating the ranks across all four criteria, we identify the optimal lags that provide the best intersection of results from these different perspectives. In this regard, the optimal lags are 1 to 4 for both high- and upper-middle-income countries and 2 for lower-middle-income countries (detailed criterion results and rankings are presented in Table A.3 in the Appendix).

3.1.Endogeneity Check

As our primary focus is on incorporating lagged independent variables rather than lagged dependent ones due to concerns about endogeneity, we must ensure the consistency of our model selection. Endogeneity arises when certain explanatory variables within an econometric model are correlated with the error term (Guevara C. A., 2015). This issue leads to estimators of the parameters being inconsistent (Wooldridge, 2012). To check for endogeneity in independent variables, we introduce instrument variables (IV) for possible endogenous variables (GDP, exchange rate, and food commodity prices). As IV, following Holmberg (2006), Rumler (2007), and Jasova, Moessner, & Takats (2020), we utilize the lags of possible endogenous independent variables that are not included in the main probit model.

In this regard, lags from 5 to 8 are utilized, and the validity of IVs is checked by the Sargan test, similar to Jasova, Moessner, & Takats (2020). The Sargan test results, as depicted in Table 3.2, display that the p-values are almost 1, which ensures the validity of IVs (Grace, 2021). Following Grace (2021) and Wooldridge (2012), after validation of IVs, we estimate our possible endogenous independent variables in relation to other independent variables used in the main probit model and independent variable-specific IVs (which are their 5-8 lags). Moreover, we obtain fitted values of independent variables and replace them in the main probit model instead of raw variables. Finally, we utilize the Hausman test to analyze the consistency of original and IV-based random effect panel probit models. As shown in Table 3.2, the p-values are higher than 0.05, ensuring that there exists no consistency difference between models, highlighting the non-existence of endogeneity. Therefore, we can say that the model has no endogeneity.

Table 3.2. Test Results for Observed Variable Endogeneity

A. High-income		**B. Upper-middle-income**		**C. Lower-middle-income**	
A. Sargan test results					
Test Statistic:	38.51996	Test Statistic:	29.55237	Test Statistic:	5.095537
p-value:	0.99	p-value:	0.99	p-value:	0.99
B. Hausman test results					
Chi-squared Statistic:	2.829	Chi-squared Statistic:	4.4359	Chi-squared Statistic:	0.090165
p-value:	0.5868	p-value:	0.3502	p-value:	0.764
Alternative hypothesis of Hausman test: one model is inconsistent					

4. Results

Once we have established the appropriate model and addressed outliers in the data, we proceed with the estimation using a random effects panel probit model for each income group. The estimation results are presented in Table 4.1. It's important to note that due to the missing real GDP data for lower-middle-income countries between 1961 and 1982, our estimations start in 1982 for these countries. The dataset encompasses 2695 observations for high-income countries, 2122 for upper-middle-income countries, and 425 for lower-middle-income countries. The random effects panel probit model is employed to derive the estimations, utilizing the Maximum Likelihood method with Newton-Raphson maximization.

Table 4.1. Estimation results

A. High-income
Number of Countries: 21
Total Observations: 2695
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-1.59135***	(0.06751)
GDP (t-1)	0.002953	(0.01443)
GDP (t-2)	0.010527	(0.01693)
GDP (t-3)	0.026561	(0.01665)
GDP (t-4)	0.061343***	(0.01395)
FX (t-1)	0.041497***	(0.00700)
FX (t-2)	0.004436	(0.01005)
FX (t-3)	0.000111	(0.01008)
FX (t-4)	0.030245***	(0.00708)
Energy (t-1)	0.008221***	(0.00234)
Energy (t-2)	-0.00148	(0.00336)
Energy (t-3)	0.0041	(0.00342)
Energy (t-4)	-0.00278	(0.00239)
Food (t-1)	0.015601**	(0.00488)
Food (t-2)	0.00097	(0.00715)
Food (t-3)	-0.0022	(0.00716)
Food (t-4)	0.012007*	(0.00491)
sigma	1.207666***	(0.09019)

B. Upper-middle-income
Number of Countries: 23
Total Observations: 2122
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-2.2124***	(0.11661)
GDP (t-1)	0.0125	(0.01697)
GDP (t-2)	-0.0042	(0.02085)
GDP (t-3)	0.0201	(0.02041)
GDP (t-4)	0.0908***	(0.01700)
FX (t-1)	0.0632***	(0.00797)
FX (t-2)	0.0174	(0.01159)
FX (t-3)	-0.0016	(0.01183)
FX (t-4)	0.0461***	(0.00823)
Energy (t-1)	0.0109***	(0.00302)
Energy (t-2)	0.0024	(0.00433)
Energy (t-3)	0.0015	(0.00434)
Energy (t-4)	-0.0032	(0.00302)
Food (t-1)	0.0158**	(0.00605)
Food (t-2)	0.0068	(0.00890)
Food (t-3)	-0.0086	(0.00902)
Food (t-4)	0.0223***	(0.00624)
sigma	1.2087***	(0.19457)

C. Lower-middle-income
Number of Countries: 7
Total Observations: 425
Period: 1982Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-0.84191***	(0.17822)
GDP (t-2)	-0.06646*	(0.02728)
FX (t-2)	0.069744***	(0.01177)
Energy (t-2)	0.005812	(0.00379)
Food (t-2)	0.028705***	(0.00778)
sigma	1.194372***	(0.20544)

*** if p-value < 0.001, ** if p-value < 0.01, * if p-value < 0.05, . if p-value < 0.1

According to model results, both intercept term and sigma values are significant at a 99.9% confidence interval, and all significant independent variables coefficients' signs are positive[21] except for demand in lower-middle-income countries. GDP growth shocks at time t significantly imply the emergence of "high inflation" in high- and upper-middle-income countries within 4 quarters, while the coefficient for lower-middle-income doesn't align with the expected theoretical relationship between demand and inflation. This observation could stem from data quality issues

[21] Positive coefficients indicate that an increase in the independent variable is associated with a higher probability of "high inflation" occurrence.

within lower-middle-income countries' datasets or indicate that demand factors do not typically contribute to "high inflation" episodes in these countries. For instance, higher growth in these countries, where an excess labor force exists, may be associated with overall economic stability, which in turn may be linked to stable, non-high inflation.

As anticipated, exchange rates have a significant impact on all income groups. Exchange rate depreciation serves as a clear indicator of a potential "high inflation" episode after 1 to 4 quarters across both high and upper-middle-income economies and after 2 quarters for lower-middle-income countries. The findings related to high and upper-middle-income countries, especially the impact of 4^{th} lag, align with the conclusions drawn from the research conducted by Colavecchio and Rubene (2019) and Forbes (2016), which emphasize the gradual and delayed transmission mechanisms associated with exchange rate movements.

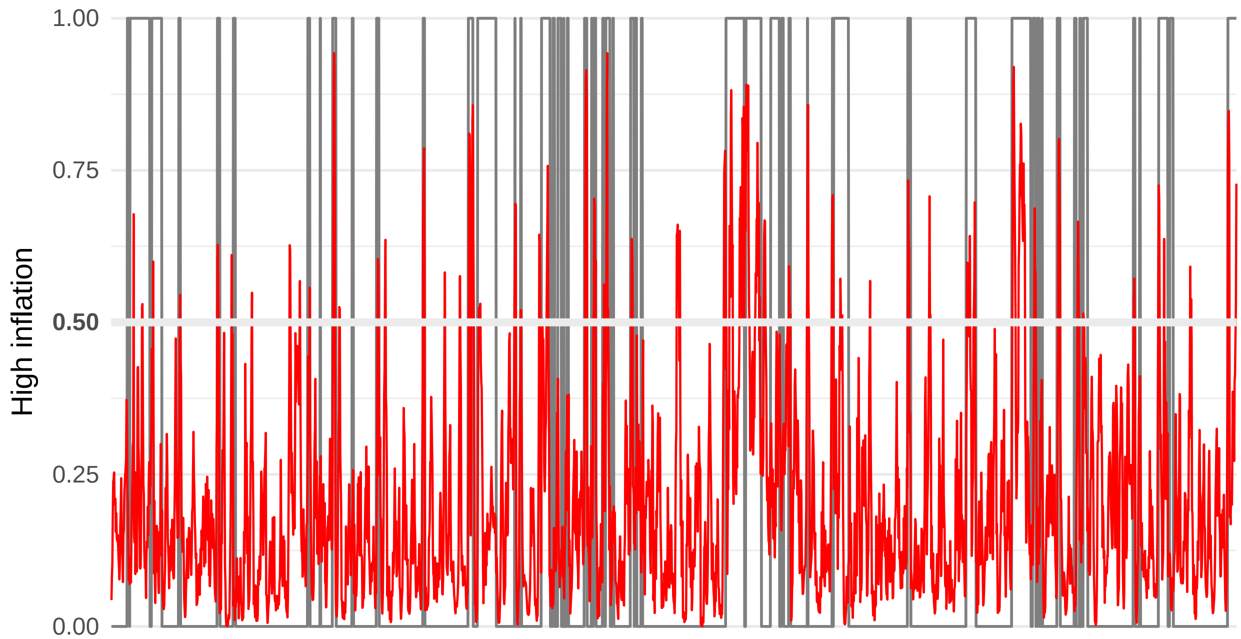
Furthermore, the heightened inflation levels in energy and food commodities also indicate potential "high inflation." However, in the context of lower-middle-income countries, the results reveal that energy inflation does not significantly impact "high inflation" episodes. This may be because 5 of the 7 lower-middle-income countries analyzed are oil exporters. However, when we run a panel probit for only the 2 lower-middle-income oil-importing countries, the coefficient remains insignificant (for model results, please refer to Table A.4. in the Appendix). Therefore, one reason for the insignificant coefficient may be related to the data sample for lower-middle-income economies, which started after 1982 and therefore cannot capture the impacts of the two major oil shocks. On the other hand, when oil prices rise sharply, all countries, regardless of income or oil exporter status, face "high inflation" (Figure A.1. in the Appendix).

To assess the model's accuracy in correctly predicting "high inflation" episodes, we employ the following evaluation metrics similar to Filippopoulou, Galariotis, and Spyrou (2020):

$$Predicted\ probability^* = \begin{cases} 1, \text{ if } predicted\ probability > 0.5 \\ 0, \text{ otherwise} \end{cases} \tag{16}$$

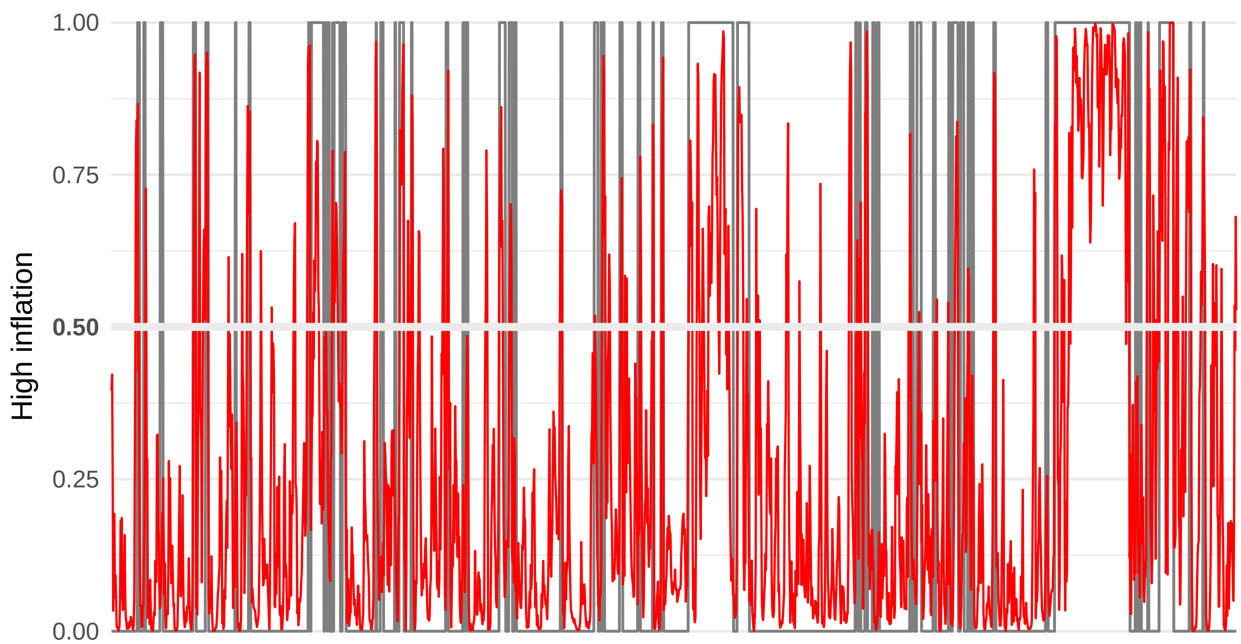
$$Model\ Evaluation \rightarrow \begin{cases} Success, \text{ if } actual\ value = predicted\ probability^* \\ Failure, \text{ otherwise} \end{cases} \tag{17}$$

A. "High Inflation" Probability Within the High-Income Group



Overall success: 82% | True "high inflation" signals: 47% | False "high inflation" signals: 2%

B. "High Inflation" Probability Within the Upper Middle-Income Group



Overall success: 84% | True "high inflation" signals: 78% | False "high inflation" signals: 5%

C. "High Inflation" Probability Within the Lower Middle-Income Group

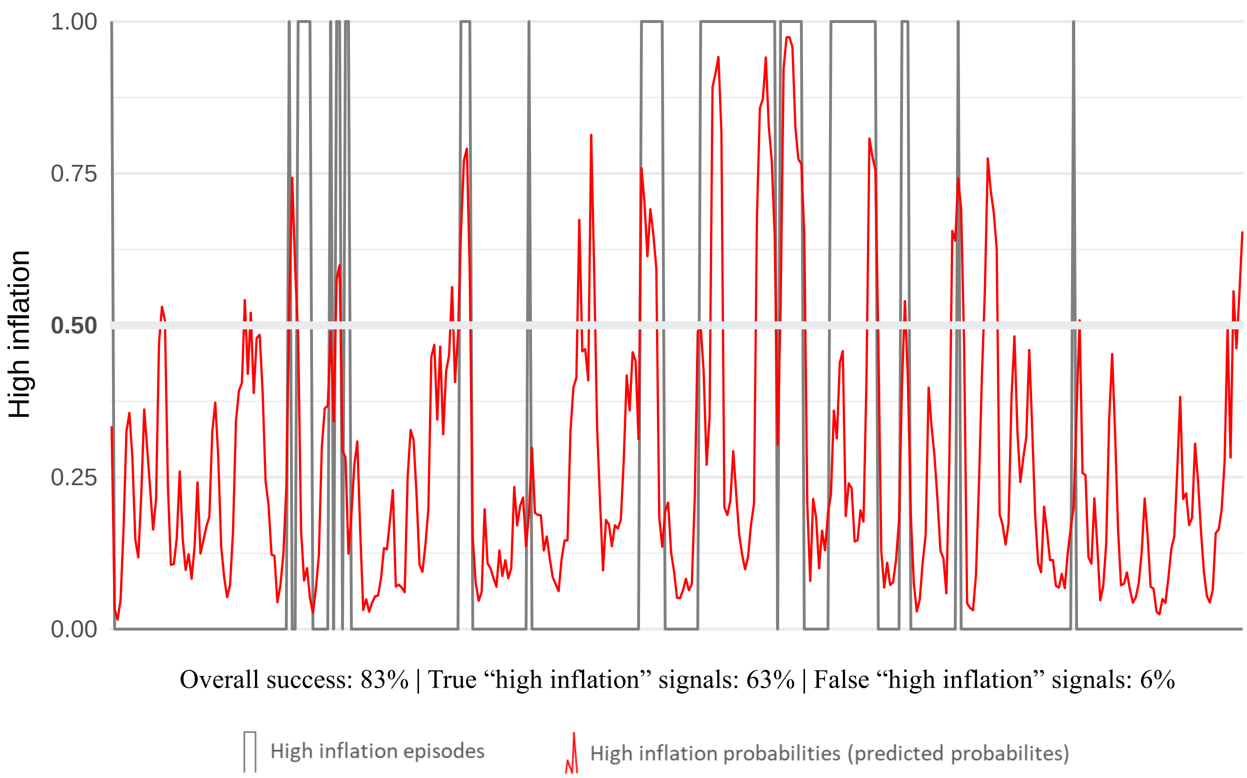


Figure 4.1. Actual "High Inflation" Episodes vs. Predicted Probabilities

Source: Authors' calculation

Note: The plots display each country and its associated years on the x-axis in ascending order. Since gray lines indicate actual high inflation episodes, where the probability is 1, and red lines represent estimated high inflation probabilities by the model, it is expected to observe that red lines and gray lines overlap. Moreover, when red lines exceed the 0.5 threshold, indicating a probability of high inflation occurrence higher than 50%, the model is considered successful for this episode.

Based on the model results and evaluation criteria, the model demonstrates an 82% success rate in accurately predicting instances of high and non-high inflation in high-income countries. Furthermore, this success rate improves to 84% for upper-middle-income countries and remains at 83% for lower-middle-income countries, as illustrated in Figure 4.1. Moreover, the model is successful in predicting "high inflation" episodes with success rates of 47%, 78%, and 63% in high, upper-middle, and lower-middle-income countries, respectively. The model also displays low, 2%, 5%, and 6% false "high inflation" predictions, respectively. Although still considerably[22]

[22] Although the model's success rate for high-income countries is 47%, which seem lower than for other income groups, it is still robust given that our model estimates frequent "high inflation" episodes, unlike the probit models used in studies such as Antunes (2018) and Filippopoulou, Galariotis, & Spyrou (2020), which focus on fewer crises.

high, the lower success rate in high-income economies compared to others may become clearer upon further investigation of the key drivers of "high inflation."

4.1.The Most Important "High-Inflation" Determinant

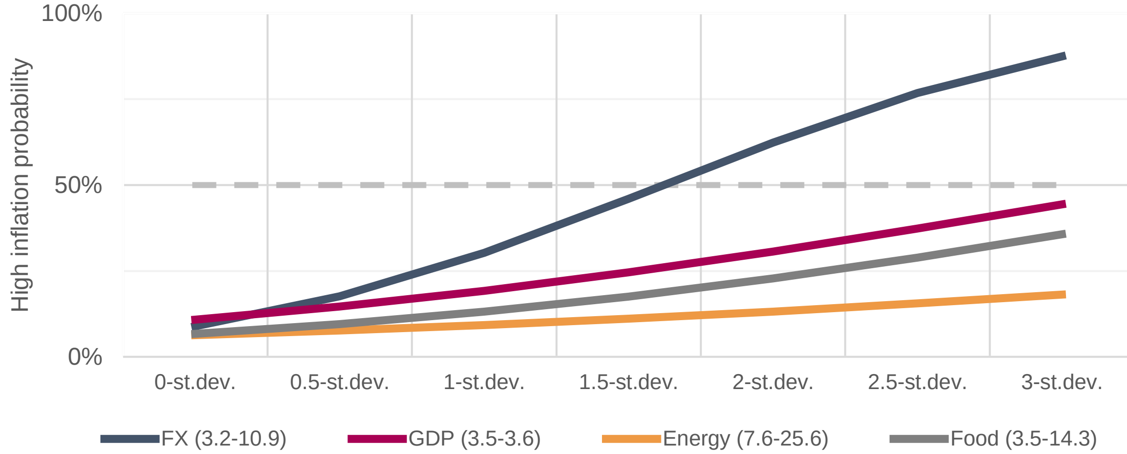
Moving forward, we computed the "high inflation" probabilities in response to deviations of inflation determinants from the mean. In this regard, we evaluated deviations ranging from 0 to 3 standard deviations from the mean, with intervals of 0.5 points. Figure 4.2 reveals that exchange rate deviations from the mean serve as the powerful explanatory variable for occurrences of "high inflation." Exchange rate shocks of approximately 25% (approximately 2 positive standard deviations) act as a strong indicator, forecasting "high inflation" in the subsequent quarters with a probability exceeding 70% in high and ~80% in middle-income countries. When depreciation surpasses 35%, the likelihood of "high inflation" sharply rises to 97% in upper-middle-income countries, 90% in high-income countries, and 95% in lower-middle-income countries. These findings again provide evidence that exchange rates are the primary determinant of "high inflation."

On the other hand, a growth magnitude of up to 3 standard deviations does not necessarily imply a high probability of "high inflation" occurring. Although the associated probability is 44% for high-income, it is low in upper- and lower-middle-income economies (only 30% and ~0%, respectively), which aligns with descriptive statistics.

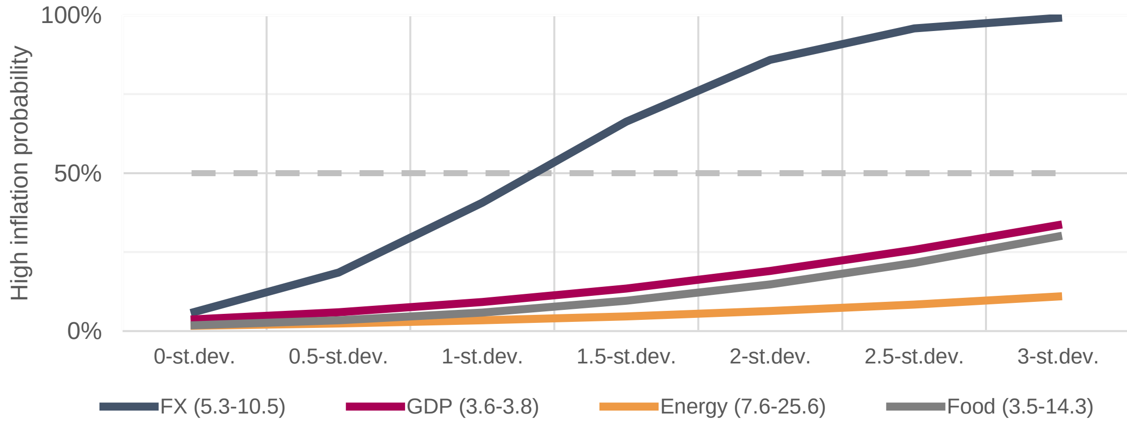
Moreover, food commodity inflation plays a crucial role in predicting inflation, particularly in lower-middle-income countries, where a deviation of more than 1.75 positive standard deviations in food commodity inflation (around 30%) in 2 quarters before forecasts "high inflation" with more than 50% probability. A similar high probability of signaling "high inflation" is observed in high- and upper-middle-income countries when food commodity prices rise by more than 3 standard deviations.

On the other hand, energy price shocks predict "high inflation," with a 30% probability in lower-middle-income economies when energy inflation rises more than 50%. However, the impact is not significantly pronounced in other income groups, aligning with descriptive statistics and the findings of Tiwari, Cunado, Hatemi-J, & Gupta (2019), Kilian and Zhou (2022), and Ye et al. (2023); moreover, it aligns with Gelos and Ustyugova (2012), who suggest that greater dependence on fuel and a large proportion of food in the consumption basket make economies more susceptible to commodity shocks.

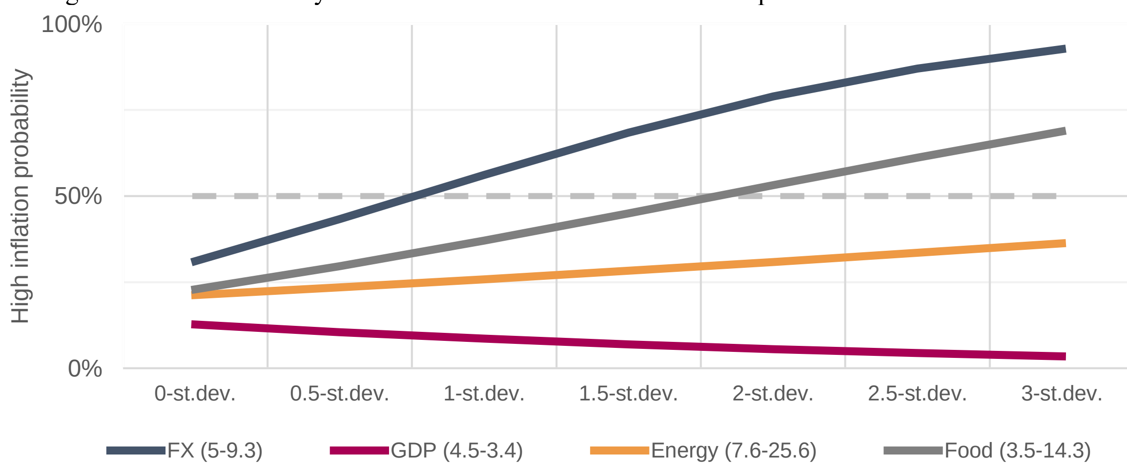
A. “High Inflation” Probability Within the High-Income Group



B. “High Inflation” Probability Within the Upper-Middle-Income Group



C. “High Inflation” Probability Within the Lower-Middle-Income Group



Parenthesis in each legend displays mean and standard deviations, respectively.

D. Thresholds Resulting In "High Inflation" (When Probability > 50%)

Determinants, annual change, %	High-income	Upper-middle	Lower-middle
Growth	15.7*	18.6*	-12.7
Exchange rate	20.9	17.7	12.1
Energy	197.5*	189.8*	144.9*
Food	60.3	60.9	29.3

*There are few observations that exceed these threshold levels

Figure 4.2. "High Inflation" Probabilities in Response to Shocks to Determinants

Source: Authors' calculation.

One point to note is that since this analysis is based on panel estimations, the varying responses of countries' inflations to the same energy shocks may diminish the significance of energy in high inflation formation. These differing responses may stem from factors such as administered energy prices, lagged impacts, balance of payment mechanisms, firms' price adjustment parameters for UMC shocks, and more. However, it is an inevitable truth that huge oil shocks (for instance, more than a 200% increase in energy inflation) will result in "high inflation," even when considering shelter policies.[23]

On the other hand, it's not just the short-run effects but rather the medium- and long-term impacts of energy that may have a more significant influence on inflation, as suggested by Tiwari, Cunado, Hatemi-J, & Gupta (2019). Therefore, further detailed studies focusing on the relationship between inflation and energy inflation while controlling for shelter mechanisms and considering the mid and long-run relationship may reveal the true impact of energy on inflation.

Returning to our earlier investigation of why our model for high-income economies displays relatively weaker success in predicting "high inflation" compared to middle-income countries, we can now link this to the significance of exchange rates, as highlighted in the literature review and reflected in the probit model (Figure 4.2), as a key determinant of "high inflation." Since pass-

[23] Nevertheless, these findings do not necessarily imply that energy inflation of less than 200% would not result in "high inflation."

through is high in middle-income economies[24] and depreciation is the primary determinant of "high inflation," the model succeeds in predicting "high inflation" in such economies. On the other hand, being a reserve currency or having less volatile and lower magnitude depreciation leads to lower pass-through (Yusifzada, 2024) and, consequently, relatively weaker success in predicting "high inflation" in high-income countries. Furthermore, although low, the high volatility of exchange rates in middle-income economies also increases false "high inflation" signals compared to high-income economies.

5. Discussion

The robustness check of the model with varying "high inflation" thresholds (Table A.5 in the Appendix) and utilizing the output gap as a proxy for demand (Table A.6 in the Appendix) supports that the main model results are robust. Additionally, we revisit the descriptive statistics to further justify the complex model's results in terms of threshold values for determinants based on historical observations (Figure A.3).

5.1. Sole depreciation-based Panel Probit Model

In the previous sections, we demonstrated the significant influence of exchange rate fluctuations on "high inflation" episodes in all analyzed countries. This finding is also supported by the literature: although no previous study has explicitly verified that exchange rate depreciations are the primary cause of "high inflation," exchange rate dynamics are commonly blamed in most discussions of high and hyperinflation. For instance, there is significant focus on exchange rate dynamics when analyzing German hyperinflation in Robinson (1938), Latin America's chronic inflation in the 1950s-1970s in Pazos (as cited in Bastian & Setterfield (2020)) and Dijkstra (1997), the high inflation in Türkiye in the 1970s in Kibritçioğlu (2001) and the recent high inflation period in Yilmazkuday (2022), and the high inflation in Hungary in the 1990s in Surányi & Vincze (1998).

[24] Considering three factors: (i) emerging economies frequently experience higher exchange rate depreciation (Yusifzada, 2024), (ii) currency depreciation beyond certain thresholds leads to larger impacts on inflation (Frankel, Parsley, and Wei, 2012; Caselli and Roitman, 2019), and (iii) as inflation reaches high levels, the pass-through from exchange rate movements to domestic prices increases significantly (Cheikh & Zaied, 2020), we can conclude that exchange rate pass-through to inflation is higher in emerging economies compared to advanced ones. This is also evident in previous studies such as Ha, Kose, Ohnsorge, & Yilmazkuday (2019) and in the scatter plots presented in the descriptive statistics section.

Furthermore, even the historical data clearly shows that the magnitude of depreciation is closely linked to the magnitude of inflation that exceeds the high threshold. According to Figure A.4 in the Appendix, while large exchange rate depreciations resulted in very high inflation in Brazil a year later, significant depreciations against the USD led to high inflation in all analyzed Latin American economies and Türkiye. On the other hand, moderate depreciations are associated with relatively lower "high inflation" in Hungary and Kazakhstan compared to the others.

While the literature overall tends to blame exchange rates, the case studies also strengthen our research findings that large exchange rate depreciations are the major factor behind "high inflation." First, the exchange rate depreciates, and then economies witness "high inflation" over time. Based on this, we go a step further and examine a stronger hypothesis: Can exchange rate depreciation alone account for the occurrence of "high inflation" across the globe without considering other determinants? In simpler terms, could most "high inflation" cases be attributed solely to exchange rate movements?

To test this hypothesis, we will re-estimate the random effect panel probit model, but this time with only one independent variable: the exchange rate and its corresponding lags. While the lags for each income group will remain the same as in the complete model discussed in section 3, both variables in this model (inflation and exchange rate) will cover the entire analysis period from 1961Q1 to 2023Q1. This extended timeframe allows us to delve into the dynamics of the 1970s and 1980s, particularly in lower-middle-income economies, which can provide valuable insights for our investigation.

Table 5.1. Estimation results of the Random Effects Panel Probit Model only depend on the Exchange Rate

A. High income
Number of Countries: 21
Total Observations: 4956
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-0.34572***	(0.03747)
FX (t-1)	0.029292***	(0.00419)
FX (t-2)	-0.00254	(0.00630)
FX (t-3)	-9.8E-05	(0.00629)
FX (t-4)	0.01394***	(0.00417)
sigma	0.443641***	(0.04177)

B. Upper middle income
Number of Countries: 23
Total Observations: 4816
Period: 1961Q1 - 2023Q1

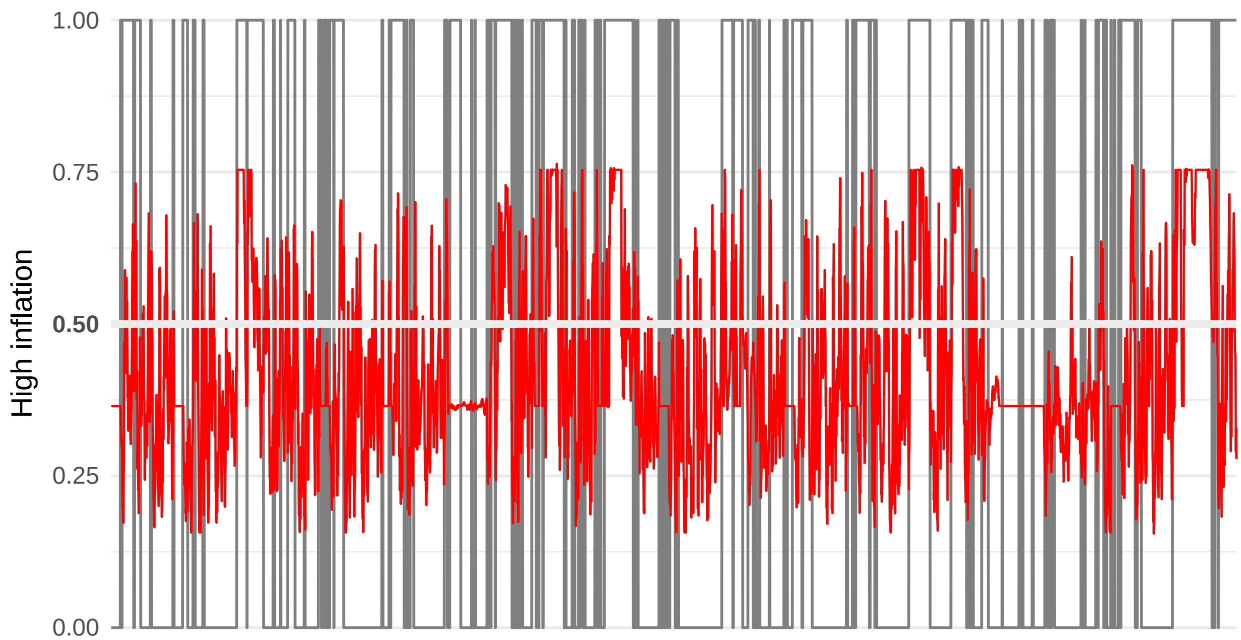
	Coefficient	Std. error
Intercept	-0.76808***	(0.05013)
FX (t-1)	0.04258***	(0.00438)
FX (t-2)	-0.00088	(0.00656)
FX (t-3)	-0.00074	(0.00660)
FX (t-4)	0.026552***	(0.00443)
sigma	0.392614***	(0.04159)

C. Lower middle income
Number of Countries: 7
Total Observations: 1593
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-0.27757***	(0.04281)
FX (t-2)	0.034405***	(0.00377)
sigma	0.493956***	(0.04518)

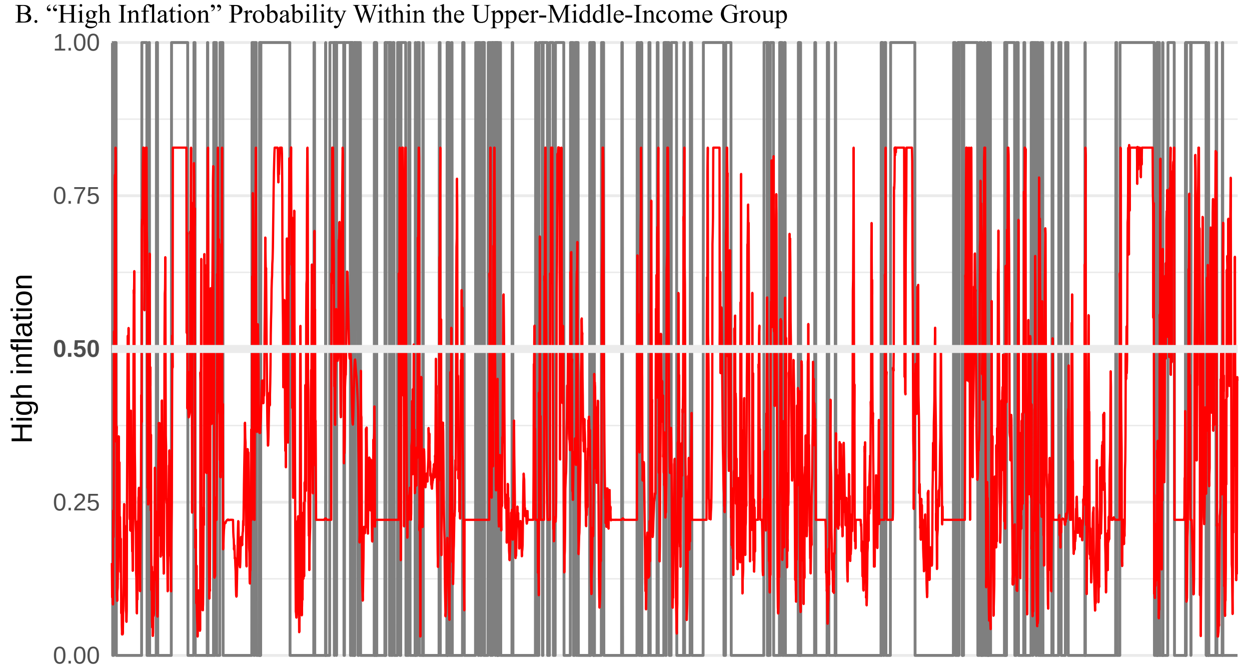
*** if p-value < 0.001, ** if p-value < 0.01, * if p-value < 0.05, . if p-value < 0.1

A. “High Inflation” Probability Within the High-Income Group



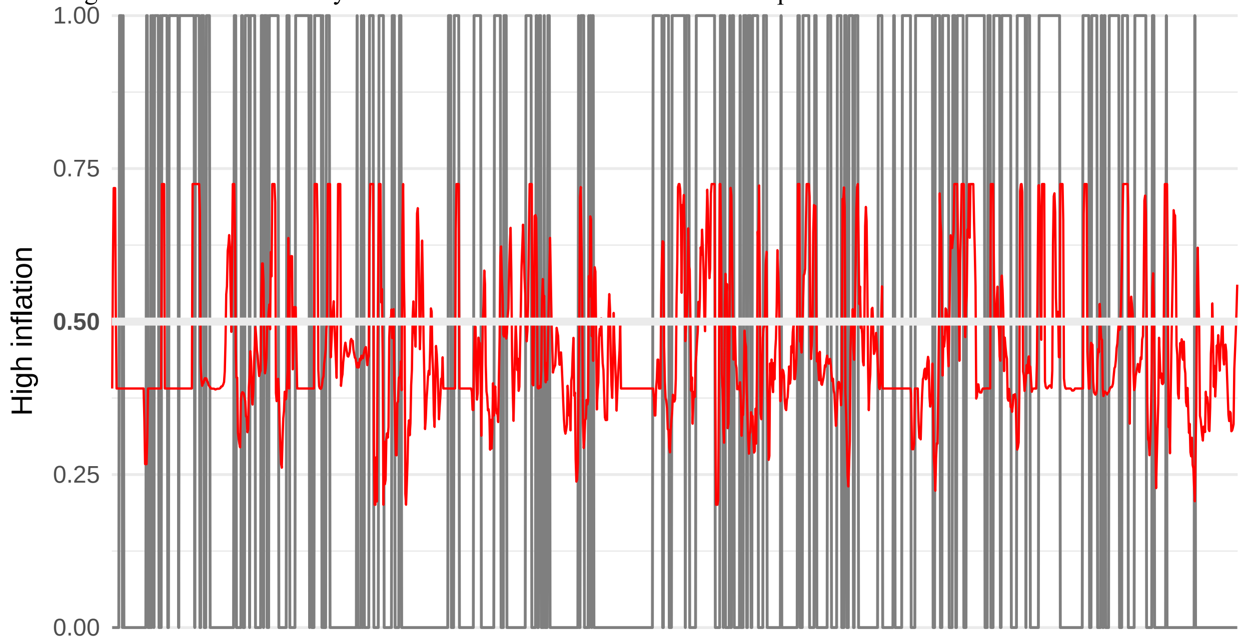
Overall success: 70% | True “high inflation” signals: 54% | False “high inflation” signals: 12%

B. “High Inflation” Probability Within the Upper-Middle-Income Group



Overall success: 77% | True “high inflation” signals: 68% | False “high inflation” signals: 8%

C. “High Inflation” Probability Within the Lower-Middle-Income Group



Overall success: 63% | True “high inflation” signals: 61% | False “high inflation” signals: 12%

High inflation episodes High inflation probabilities (predicted probabilites)

Figure 5.1. Predicted Probabilities That Only Depend on the Exchange Rate

Source: Authors’ calculation.

According to the results of Table 5.1, the exchange rate retains its significance for the same lags, similar to the complete model. As illustrated in Figure 5.1, the sole depreciation of the exchange rate is often sufficient to identify “high inflation” episodes. In high-income countries, the exchange rate alone achieves a 70% success rate in predicting whether inflation will be high or not, compared to the 82% success rate of the complete model. In upper-middle-income countries, the corresponding figures are 77% and 84%, while for lower-middle-income countries, they are 63% and 83%. These results strongly indicate that exchange rate depreciation is a primary driver of “high inflation.” These findings confirm that “high inflation” is frequently and almost universally an exchange rate phenomenon.

5.2.Policy Implications

Since exchange rate depreciations are found to be the most important determinant of “high inflation,” central banks should focus on managing depreciations to prevent the economy from experiencing “high inflation.” In this regard, direct exchange rate interventions or indirect supportive capital inflow operations should be the primary tools of monetary policy rather than demand-oriented policies in the case of “high inflation.” Given that demand is not identified as a major determinant of “high inflation,” traditional monetary policy may be ineffective in controlling large supply-based inflationary shocks (Benlialper & Cömert, 2016).

However, Benlialper and Cömert (2016) and Benlialper, Cömert, & Öcal (2017) show that the Central Bank of Türkiye (CBRT) and many other developing countries are already aware of the importance of exchange rates in achieving their target inflation rates. For instance, Benlialper’s and Cömert’s (2016) analysis displays that CBRT’s policy rate reacts approximately four times more strongly to a one standard deviation depreciation shock compared to an appreciation of the local currency. Furthermore, Benlialper, Cömert, & Öcal (2017) found that even inflation targeter 12 developing countries’ central banks significantly respond to exchange rate depreciations that exceed the 2.24% threshold, while a response to appreciations or smaller depreciations is insignificant. However, similar asymmetric responses are not observed in developed economies (Benlialper, Cömert, & Öcal, 2017).

The significant monetary policy response observed in emerging economies is likely related to the need to anchor inflation expectations. This anchoring could be a key driver of wage indexation to depreciation, which is one of the main causes of non-linear depreciation's impact on inflation. Since inflation expectations are unanchored in emerging economies (Kose, Matsuoka, Panizza, & Vorisek, 2019), central banks may focus on keeping inflation as close as possible to their target in the short term to build credibility (Benlialper, Cömert, & Öcal, 2017). “This requires an intense use of the direct exchange rate channel” (Benlialper, Cömert, & Öcal, 2017, p. 8), especially given its role as a main determinant of “high inflation.”

However, policies aimed at avoiding “high inflation” through exchange rate management may have structural limits. Firstly, the central bank's ability to influence the exchange rate through policy rates is closely linked to both country-specific and global risk premiums, which are beyond the control of monetary authorities (Cömert 2019). Additionally, direct exchange rate market operations are constrained by the central bank’s reserves and its ability to act independently. Therefore, it may be more advisable for the central bank to focus primarily on alleviating internal pressures on the currency value by employing macroprudential tools, managing depreciation expectations, and especially addressing speculative capital flows, which can cause significant fluctuations in exchange rates and drive “high inflation.” Developing a full-scale exchange rate policy, however, is beyond the scope of this paper.

Conclusion

This study analyzes the determinants of “high inflation.” From the outset, it identifies the value of “high inflation.” To accomplish this, the study reviewed the literature concerning 19 well-estimated “high inflation” thresholds, ultimately identifying threshold as the median value derived from the literature’s threshold values: 10% for middle-income countries and 5.5% for high-income countries. However, the methodology used in the paper remains effective even with higher (e.g., 40%) or lower thresholds (3.25 for high and 7.75 for middle-income).

Having set the benchmark for “high inflation,” we delved into the theoretical literature, focusing on key factors contributing to inflation. Once we have gained an understanding of the determinants of inflation and their underlying mechanisms, our attention turns to investigating whether these factors indeed instigate “high inflation” within the context of the 51 countries under analysis. We explore whether these factors equally contribute or if some are more impactful. To achieve this objective, we initiate our investigation with random effects panel probit model due to its adeptness in managing binary response variables. This choice allowed us to categorize inflation levels into discrete outcomes of “high” and “non-high,” enabling a focused investigation into the determinants of “high inflation.”

According to model results, exchange rate depreciation consistently and significantly signals potential “high inflation” in all income groups. For instance, depreciation levels exceeding 35% are associated with more than 95% probability of “high inflation” in middle-income countries and 90% in high-income countries. While other determinants, such as demand, food commodity prices, and energy price shocks, demonstrate significance in specific income groups, their predictive power is less consistent and universal. For instance, demand plays a role in driving “high inflation” in high-income countries, as an approximately 3 standard deviations increase in GDP growth forecasts “high inflation” with a 44% probability. Notably, food commodity inflation proves influential in lower-middle-income nations, with deviations exceeding 1.75 positive standard deviations, signaling “high inflation” with a 50% probability. Similarly, energy price shocks exhibit a 30% probability of predicting “high inflation” in lower-middle-income economies when energy inflation rises by more than 50%. However, these impacts are less pronounced in other income groups, highlighting the structural differences discussed earlier.

Since exchange rates have consistently emerged as a universal driver of “high inflation” in both descriptive and econometric analyses, we took one step further to examine whether exchange rate depreciation alone globally drives “high inflation.” Employing the random effects panel probit model with sole exchange rate as an independent variable shows that exchange rate depreciation is a dominant predictor of “high inflation.” In high-income, upper-middle, and lower-middle-income countries, exchange rate movements achieve success rates of 70%, 77%, and 63%, respectively, in predicting “high inflation,” indicating its primary role as a driver.

Finally, we conclude that:

1. Solely, exchange rate depreciation itself explains almost all high-inflation cases in upper-middle-income countries and most high-inflation cases in high and lower-middle-income countries.
2. As an early warning indicator of “high inflation,” ~25% of depreciation alerts “high inflation” with the probability of more than 80% in middle-income and 70% in high-income countries.

In conclusion, our research shed important light on the determinants of “high inflation,” across various countries belonging to different income groups. Acknowledging the significance of exchange rate depreciation as a crucial leading factor generating “high inflation” not only enables more prompt and efficient policy responses but also adds substantial value to the current body of research, reinforcing the crucial role played by historical exchange rate trends and supply-side factors in our understanding of the dynamics of “high inflation.”

References

Abbas, S. K., & Lan, H. (2020). Commodity price pass-through and inflation regimes. *Energy Economics, Vol. 92*.

Alsabban, S. O., & Alnuwaiser, S. N. (2021). Estimating Optimal Inflation Rate in Saudi Arabia: Using Dynamic Threshold Regression Model. *International Journal of Economics and Finance, Vol. 13, No. 3*, 40-49.

Amini, S., Delgado, M. S., Henderson, D. J., & Parmeter, C. F. (2012). Fixed Vs Random: The Hausman Test Four Decades Later. *Essays in Honor of Jerry Hausman (Advances in Econometrics, Vol. 29)*, 479-513.

Antunes, A. B. (2018). Forecasting banking crises with dynamic panel probit models. *International Journal of Forecasting*, 249-275.

Arias, A., & Kirchner, M. (2019). Shifting Inflation Expectations and Monetary. *Central Bank of Chile Working Paper 829*, 1-53.

Asaduzzaman, M. (2021). Relationship between threshold level of inflation and economic growth in Bangladesh: A multivariate quadratic regression analysis. *Social Science Research Network Electronic Journal*.

Aydın, C., Esen, Ö., & Bayrak, M. (2016). Inflation and Economic Growth: A Dynamic Panel Threshold Analysis for Turkish Republics in Transition Process. *Procedia - Social and Behavioral Sciences, Vol. 229*, 196-205.

Azam, M., & Khan, S. (2022). Threshold effects in the relationship between inflation and economic growth: Further empirical evidence from the developed and developing world. *International Journal of Finance & Economics, Vol. 27, Issue 4*, 4224-4243.

Ball, L., & Moffitt, R. (2001). Productivity Growth and the Phillips Curve. *NBER, Working Paper 8421*, 1-52.

Bastian, E. F., & Setterfield, M. (2020). Nominal exchange rate shocks and inflation in an open economy: towards a structuralist inflation targeting agenda. *Cambridge Journal of Economics, 44 (6)*, 1271-1299.

Batini, N., Jackson, B., & Nickell, S. (2005). An open-economy new Keynesian Phillips curve for the U.K. *Journal of Monetary Economics, Vol. 52*, 1061-1071.

Bawa, S., & Abdullahi, I. S. (2012). Threshold effect of inflation on economic growth in Nigeria. *CBN Journal of Applied Statistics, Vol. 3, No. 1*, 43-63.

Behera, J., & Mishra, A. K. (2017). The recent inflation crisis and long-run economic growth in India: An empirical survey of threshold level of inflation. *South Asian Journal of Macroeconomics, and FinancePublic, Vol. 6, Issue 1*, 105-132.

Bems, R., Caselli, F., Grigoli, F., Gruss, B., & Lian, W. (2018). Expectations' Anchoring and Inflation Persistence. *IMF Working Paper WP/18/280*, 1-31.

Benlialper, A., & Cömert, H. (2016). Implicit asymmetric exchange rate peg under inflation targeting regimes: the case of Turkey. *Cambridge Journal of Economics, 40 (6)*, 1553-1580.

Benlialper, A., Cömert, H., & Öcal, N. (2017). Asymmetric exchange rate policy in inflation targeting. *Institute for International Political Economy Berlin, Working Paper, No. 86/2017*, 1-30.

Bernanke, B. (2024). Forecasting for monetary policy making and communication at the Bank of England: a review. *Bank of England Independent Evaluation Office*.

Blair, J. M. (1974). Market Power and Inflation: A Short-Run Target. *Journal of Economic Issues, Vol. 8 (2)*, 453-478.

Blanchard, O., & Katz, L. F. (1997). What We Know and Do Not Know About the Natural Rate of Unemployment. *Journal of Economic Perspective, Vol. 11 (1)*, 51-72.

Blecker, R. A. (2011). Open economy models of distribution and growth. In E. Hein, & E. S. (eds.), *A Modern Guide to Keynesian Macroeconomics and Economic Policies* (pp. 215–239). Cheltenham, UK: Edward Elgar.

Bollen, K. A., & Brand, J. E. (2010). A General Panel Model with Random and Fixed Effects: A Structural Equations Approach. *Social Forces, Vol. 89, Issue 1*, 1-34.

Boonman, T. M., Jacobs, J. P., Kuper, G. H., & Romero, A. (2019). Early Warning Systems for Currency Crises with Real-Time Data. *Open Economies Review, Vol. 30*, 813-835.

Brázdik, F., Hlédik, T., Humplová, Z., Martonosi, I., Musil, K., Ryšánek, J., . . . Žáček, J. (2020). The g3+ Model: An Upgrade of the Czech National Bank's Core Forecasting Framework. *Czech National Bank, Working Paper Series 7/2020*, 1-64.

Bruno, M., & Easterly, W. (1998). Inflation crises and long-run growth. *Journal of Monetary Economics, Vol. 41, Issue 1*, 3-26.

Canavese, A. J. (1982). The Structuralist Explanation in the Theory of Inflation. *World Development, 10(7)*, 523-529.

Carro, J. M. (2007). Estimating dynamic panel data discrete choice models with fixed effects. *Journal of Econometrics, Vol. 140, Issue 2*, 503-528.

Caselli, F. G., & Roitman, A. (2019). Nonlinear exchange-rate pass-through in emerging markets. *International Finance, Vol. 22, Issue 3*, 279-306.

Charles, S., Bastian, E. F., & Marie, J. (2021). Inflation Regimes and Hyperinflation. A Post-Keynesian / Structuralist typology. *hal-03363240*, 1-48.

Cheikh, N. B., & Zaied, Y. B. (2020). Revisiting the pass-through of exchange rate in the transition economies: New evidence from new EU member states. *Journal of International Money and Finance, Vol. 100*, 1-16.

Chen, N., Chung, W., & Novy, D. (2022). Vehicle Currency Pricing and Exchange Rate Pass-Through. *Journal of the European Economic Association, Vol. 20, Issue 1*, 312-351.

Choudhary, M. A., Hanif, M. N., & Iqbal, J. (2014). On smoothing macroeconomic time series using the modified HP filter. *Applied Economics, Vol. 46, Issue 19*, 2205-2214.

Colavecchio, R., & Rubene, I. (2019). Non-Linear Exchange Rate Pass-Through to Euro Area Inflation: a Local Projection Approach. *Banque centrale du Luxembourg, Working Paper 138*, 1-35.

Coleman, W., & Nautz, D. (2022). Inflation Expectations, Inflation Target Credibility, and the COVID-19 Pandemic: Evidence from Germany. *Journal of Money, Credit and Banking, 55 (7)*, 1937-1953.

Cortes, G. S., & Paiva, C. A. (2017). Deconstructing credibility: The breaking of monetary policy rules in Brazil. *Journal of International Money and Finance, Vol. 74*, 31-52.

Cömert, H. (2019). From trilemma to dilemma: monetary policy after the Bretton Woods world. In *Finance, Growth and Inequality* (pp. 210-234). Edward Elgar Publishing

Dammak, T. B., & Helali, K. (2017). Threshold Effects on the Relationship Between Inflation Rate and Economic Growth in Tunisia. *International Economic Journal, Vol. 31, Issue 2*.

Dastjerdy, B., Saeidi, A., & Heidarzadeh, S. (2023). Review of Applicable Outlier Detection Methods to Treat Geomechanical Data. *Geotechnics, Vol. 3*, 375-396.

David, D., Pedro, G.-P., & Paula, H. -e. (2005). *Threshold effects in the relationship between inflation and growth: a new panel-data approach.* Germany: University Library of Munich.

Dijkstra, A. G. (1997). Fighting Inflation in Latin America. *Development and Change, 28(3)*, 531-557.

Dua, P., & Gaur, U. (2010). Determination of inflation in an open economy Phillips curve framework: the case of developed and developing Asian countries. *Macroeconomics and Finance in Emerging Market, Vol. 3, No. 1*, 33-51.

Dutt, A. K. (1992). Conflict inflation, distribution, cyclical accumulation and crises. *European Journal of Political Economy*, 579-597.

Ehigiamusoe, K. U., Lean, H. H., & Lee, C.-C. (2019). Moderating effect of inflation on the finance–growth nexus: insights from West African countries. *Empirical Economics, Vol. 57*, 399-422.

Farahani, M. H., Ghabel, S. N., & Mohammadpour, R. (2021). The Effect of Inflation Threshold on Financial Development and Economic Growth: A Case Study of D-8 Countries. *Iranian Economic Review, Vol. 25, Issue 3*, 465-475.

Filippopoulou, C., Galariotis, E., & Spyrou, S. (2020). An early warning system for predicting systemic banking crises in the Eurozone: A logit regression approach. *Journal of Economic Behavior & Organization, Vol. 172*, 344-363.

Forbes, K. (2016). Much Ado about Something Important: How do Exchange Rate Movements Affect Inflation? *The Manchester School, Vol. 84, Issue S1*, 15-41.

Forbes, K. J., Gagnon, J. E., & Collins, C. G. (2021). Low Inflation Bends the Phillips Curve around the World: Extended Results. *Peterson Institute for International Economics, Working Paper 21-15*, 1-23.

Frankel, J., Parsley, D., & Wei, S.-J. (2012). Slow Pass-through Around the World: A New Import for Developing Countries? *Open Economies Review, Vol. 23*, 213-251.

Franzoni, F. A., Giannetti, M., & Tubaldi, R. (2023). Supply Chain Shortages, Large Firms' Market Power, and Inflation. *Swiss Finance Institute Research Paper No. 23-105*.

Friedman, M. (1963). *Inflation: causes and consequences.* Bombay: Asia Publishing House.

Frimpong, J. M., & Oteng-Abayie, E. F. (2010). When is Inflation Harmful? Estimating the Threshold Effect for Ghana. *American Journal of Economics and Business Administration, Vol. 2, Issue 3*, 232-239.

Gelos, G., & Ustyugova, Y. (2012). Inflation Responses to Commodity Price Shocks – How and Why Do Countries Differ? . *IMF Working Paper, WP/12/225*, 1-32.

Gopinath, G., Boz, E., Casas, C., Díez, F. J., Gourinchas, P.-O., & Plagborg-Møller, M. (2020). Dominant Currency Paradigm. *American Economic Review, Vol. 110, No. 3*, 677-719.

Grace, J. B. (2021). Instrumental variable methods in structural equation models. *Methods in Ecology and Evolution, Vol. 12, Issue 7*, 1148-1157.

Greene, W. (2004). Convenient estimators for the panel probit model: Further results. *Empirical Economics, Vol 29*, 21-47.

Guevara, C. A. (2015). Critical assessment of five methods to correct for endogeneity in discrete-choice models. *Transportation Research Part A: Policy and Practice, Vol. 82*, 240-254.

Guevara, C. A., & Navarro, P. (2015). *Detection of weak instruments when correcting for endogeneity in binary logit models.* Windsor, UK: In Proceedings 14th International Conference on Travel Behaviour Research (IATBR).

Ha, J., Kose, M. A., Ohnsorge, F., & Yilmazkuday, H. (2019). Sources of Inflation: Global and Domestic Drivers. In J. Ha, M. A. Kose, & F. Ohnsorge, *Inflation in Emerging and Developing Economies Evolution, Drivers, and Policies* (pp. 143-205). Washington DC: World Bank Group.

Hein, E. (2024). Inflation is always and everywhere ... a conflict phenomenon: Post-Keynesian inflation theory and energy price driven conflict inflation, distribution, demand and employment. *European Journal of Economics and Economic Policies, Vol. 21, No. 2*, 202-231.

Holmberg, K. (2006). Derivation and Estimation of a New Keynesian Phillips Curve in a Small Open Economy. *Sveriges Riksbank Working Paper Series, No. 197*, 1-27.

Hsu, T. (2016). *U.S. recession forecasting using probit models with asset index predictor variables.* Baltimore: The University of Maryland Baltimore County.

Huang, H.-C., Lin, S.-C., Kim, D.-H., & Yeh, C.-C. (2010). Inflation and the finance–growth nexus. *Economic Modelling, Vol. 27, Issue 1*, 229-236.

Ibarra, R., & R.Trupkin, D. (2016). Reexamining the relationship between inflation and growth: Do institutions matter in developing countries? *Economic Modelling, Vol. 52, Part B*, 332-351.

Ibrahim, M., Aluko, O. A., & Vo, X. V. (2022). The role of inflation in financial development–economic growth link in sub-Saharan Africa. *Cogent Economics & Finance, Vol. 10, Issue 1*.

Ihrig, J., & Waller, C. (2024). *The Federal Reserve's responses to the post-Covid period of high inflation.* FEDS Notes.

Jasova, M., Moessner, R., & Takats, E. (2020). Domestic and global output gaps as inflation drivers: What does the Phillips curve tell? *Economic Modelling, Vol. 87*, 238-253.

Jiranyakul, K. (2017). Estimating the threshold level of inflation in Thailand. *Journal of Economics Bibliography, Vol. 4, Issue 2*, 150-155.

Kalecki, M. (1971). Class Struggle And The Distribution Of National Income. *Kyklos, Vol. 24, Issue 1*, 1-9.

Kelikume, I. (2018). An Estimation of Inflation Threshold for Africa. *International Journal of Management, Economics and Social Sciences, Vol. 7, Issue 4*, 283-300.

Khan, M. S., & Senhadji, A. S. (2000). Threshold Efects in the Relationship Between Inflation and Growth. *IMF Working Paper/00/110*, 1-32.

Kibritçioğlu, A. (2001). Causes of Inflation in Turkey: A Literature Survey with Special Reference to Theories of Inflation. *UIUC Working Paper No. 01-0115*, 1-35.

Kilian, L., & Zhou, X. (2022). The Impact of Rising Oil Prices on U.S. Inflation and Inflation Expectations in 2020-23. *Energy Economics, Vol. 113*.

Kose, M. A., Matsuoka, H., Panizza, U., & Vorisek, D. (2019). Inflation Expectations: Review and Evidence. *World Bank Policy Research Working Paper No. 8785*, 1-63.

Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: new evidence from a dynamic panel threshold analysis. *Empirical Economics, Vol. 44*, 861-878.

Lavoie, M. (2022). *Post-Keynesian Economics New Foundations.* Cheltenham, UK: Edward Elgar.

Lazar, N. (2010). Ockham's Razor. *WIREs Computational Statistics, Vol. 2*, 243-246.

Lerner, A. (1958). Inflationary depression and the regulation of administered prices. In *The Relationship Of Prices To Economic Stability And Growth: Compendium of Papers Submitted by Panelists Appearing before the Joint Economic Committee* (pp. 257-268). Washington, D.C.: Government Printing Office.

Matamoros, G. (2023). Are Firm Markups Boosting Inflation? A Post-Keynesian Institutionalist Approach to Markup Inflation in Select Industrialized Countries. *Review of Political Economy*, 1-23.

Mazumder, S. (2010). The new Keynesian Phillips curve and the cyclicality of marginal cost. *Journal of Macroeconomics, Vol. 32*, 747-765.

Medel, C. (2014). Probabilidad Clásica de Sobreajuste con Criterios de Información: Estimaciones con Series Macroeconómicas Chilenas. *Central Bank of Chile, Working Papers Central Bank of Chile 735*.

Mohanty, M. S., & Klau, M. (2001). What determines inflation in emerging market economies? *BIS Papers No 8*, 1-39.

Montesinos López, O. M. (2022). Overfitting, Model Tuning, and Evaluation of Prediction Performance. In O. M. Montesinos López, *Multivariate Statistical Machine Learning Methods for Genomic Prediction.* Springer, Cham.

Montes-Rojas, G., & Toledo, F. (2022). External Shocks and Inflationary Pressures in Argentina: APost-Keynesian-Structuralist Empirical Approach. *Review Of Political Economy, Vol. 34, No. 4*, 789-806.

Muzaffar, A. T., & Junankar, P. (. (2014). Inflation–growth relationship in selected Asian developing countries: evidence from panel data. *Journal of the Asia Pacific Economy, Vol. 19, Issue 4*, 604-628.

Nasir, M. A., Huynh, T. L., & Vo, X. V. (2020b). Exchange rate pass-through & management of inflation expectations in a small open inflation targeting economy. *International Review of Economics & Finance, Vol. 69*, 178-188.

Ndoricimpa, A. (2017). Threshold effects of inflation on economic growth in Africa: Evidence from a dynamic panel threshold regression approach. *African Development Bank Group, Working Paper, No. 249*.

Neiss, K. S., & Nelson, E. (2005). Inflation Dynamics, Marginal Cost, and the Output Gap: Evidence from Three Countries. *Journal of Money, Credit and Banking, Vol. 37, No. 6*, 1019-1045.

Olivera, J. H. (1964). On Structural Inflation and Latin-American 'Structuralism'. *Oxford Economic Papers, 16(3)*, 321-332.

Omay, T., & Kan, E. Ö. (2010). Re-examining the threshold effects in the inflation–growth nexus with cross-sectionally dependent non-linear panel: Evidence from six industrialized economies. *Economic Modelling, Vol. 27, Issue 5*, 996-1005.

Pollin, R., & Zhu, A. (2006). Inflation and economic growth: a cross-country nonlinear analysis. *Journal of Post Keynesian Economics, Vol. 28, Issue 4*, 593-614.

Robinson, J. (1938). The Economics of Inflation. *The Economic Journal, Vol. 48 (191)*, 507-513.

Rosenberg, S., & Weisskopf, T. E. (1981). A Conflict Theory Approach to Inflation in the Postwar U.S. Economy. *The American Economic Review, Vol. 71 (2)*, 42-47.

Rowthorn, R. E. (1977). Conflict, inflation and money. *Cambridge Journal of Economics, Volume 1 (3)*, 215-239.

Rumler, F. (2007). Estimates of the Open Economy New Keynesian Phillips Curve for Euro Area Countries. *Open Econ Rev, Vol. 18*, 427-451.

Serrano, F. (2019). Mind The Gaps: The Conflict Augmented Phillips Curve And The Sraffian Supermultiplier. *IE-UFRJ Discussion Paper, TD 011*, 1-36.

Shor, B., Bafumi, J., Keele, L., & Park, D. (2007). A Bayesian Multilevel Modeling Approach to Time-Series Cross-Sectional Data. *Political Analysis, Vol. 15, No. 2*, 165-181.

Silvia, J., & Iqbal, A. (2015). An Ordered Probit Approach to Predicting the Probability of Inflation/Deflation. *Business Economic, Vol. 50*, 12-19.

Surányi, G., & Vincze, J. (1998). Inflation in Hungary, 1990-97. In *Moderate inflation: The experience of transition economies* (pp. 150-171).

Tarawalie, A. B., & Kamara, F. (2022). Inflation and Growth Nexus: An Estimate of the Threshold Level of Inflation in Sierra Leone. *Applied Economics and Finance, Vol. 9, No. 2*.

Thanh, S. D. (2015). Threshold effects of inflation on growth in the ASEAN-5 countries: A Panel Smooth Transition Regression approach. *Journal of Economics, Finance and Administrative Science, Vol. 20, Issue 38*, 41-48.

Tiwari, A. K., Cunado, J., Hatemi-J, A., & Gupta, R. (2019). Oil price-inflation pass-through in the United States over 1871 to2018: A wavelet coherency analysis. *Structural Change and Economic Dynamics, Vol. 50*, 51-55.

Vera, L. (2010). Conflict inflation: an open economy approach. *Journal of Economic Studies, Vol. 37 (6)*, 597-615.

Vinayagathasan, T. (2013). Inflation and economic growth: A dynamic panel threshold analysis for Asian economies. *Journal of Asian Economics, Vol. 26*, 31-41.

Weber, I. M., & Wasner, E. (2023). Sellers' Inflation, Profits and Conflict: Why can Large Firms Hike Prices in an Emergency? *Review of Keynesian Economics, 11(2)*, 183–213.

Weintraub, S. (1978). The Missing Theory of Money Wages. *Journal of Post Keynesian Economics, 1 (2)*, 59-78.

Weiss, L. W. (1966). Business Pricing Policies and Inflation Reconsidered. *Journal of Political Economy*, 177-187.

Wooldridge, J. M. (2012). Instrumental Variables Estimation and Two Stage Least Squares. In J. M. Wooldridge, *Introductory Econometrics* (pp. 512-554). Mason, Ohio: South-Western Cengage Learning.

Yabu, N., & Kessy, N. J. (2015). Appropriate Threshold Level of Inflation for Economic Growth: Evidence from the Three Founding EAC Countries. *Applied Economics and Finance, Vol. 2, No. 3*.

Ye, M., Mohammed, K. S., Tiwari, S., Raza, S. A., & Chen, L. (2023). The effect of the global supply chain and oil prices on the inflation rates in advanced economies and emerging markets. *Geological Journal*.

Yilmazkuday, H. (2011). Thresholds in the finance-growth nexus: A cross-country analysis. *The World Bank Economic Review, Vol 25, Issue 2*, 278-295.

Yilmazkuday, H. (2022). Drivers of Turkish inflation. *The Quarterly Review of Economics and Finance, Vol. 84*, 315-323.

Yusifzada, T. (2024). Structural Inflation Dynamics In Developing Countries. In T. Yusifzada, *Essays on inflation dynamics [Ph.D. - Doctoral Program]* (pp. 13-40). Ankara: Middle East Technical University.

Appendix

Table A.1 "High Inflation" Threshold Literature Review: Country-Specific Analyses

Authors	Countries	Variables	Methodology	Threshold findings
Frimpong and Oteng-Abayie (2010)	Ghana	GDP, CPI, labor force, trade, money supply	Threshold regression model	11%
Bawa and Abdullahi Ismaila (2012)	Nigeria	GDP, CPI, investment, population, openness, financial deepening	Threshold regression model	13%
Yabu and Kessy (2015)	Kenya, Tanzania, and Uganda	GDP, CPI, FDI, investment, population, credit, openness	Quadratic regression model	Kenya 6.77% Tanzania 8.8% Uganda 8.41%
Dammak and Helali (2017)	Tunisia	GDP, CPI, M2, REER, export, import	Two-regime structural equation in threshold autoregression (TAR) model	3.48%
Jiranyakul (2017)	Thailand	GDP, CPI, investment, population	Conditional least square (CLS)	3%
Behera and Mishra (2017)	India	GDP, CPI, exchange rate, interest rate	Conditional least square (CLS)	4%
Asaduzzaman (2021)	Bangladesh	GDP, CPI, FDI, M2, trade openness, government spending, savings	Quadratic regression model	8%
Alsabban and Alnuwaiser (2021)	Saudi Arabia	GDP, CPI, investment, M3, trade	Threshold regression model	3%
Tarawalie and Kamara (2022)	Sierra Leone	GDP, CPI, investment, exchange rate, trade, openness	Quadratic regression model	10.30%

Table A.2. Analyzed countries

High-income countries		Upper middle-income countries		Lower middle-income countries	
AUS	Australia	ALB	Albania	EGY	Egypt, Arab Rep.
CHE	Switzerland	BGR	Bulgaria	IDN	Indonesia
CHL	Chile	BRA	Brazil	IND	India
CZE	Czech Republic	CHN	China	KEN	Kenya
DNK	Denmark	COL	Colombia	MNG	Mongolia
GBR	United Kingdom	CRI	Costa Rica	NGA	Nigeria
HKG	Hong Kong SAR, China	DMA	Dominica	PHL	Philippines
HUN	Hungary	GEO	Georgia		
ISL	Iceland	GTM	Guatemala		
ISR	Israel	JAM	Jamaica		
JPN	Japan	JOR	Jordan		
KOR	Korea, Rep.	KAZ	Kazakhstan		
NOR	Norway	MDA	Moldova		
NZL	New Zealand	MEX	Mexico		
POL	Poland	MUS	Mauritius		
ROU	Romania	MYS	Malaysia		
SAU	Saudi Arabia	PER	Peru		
SGP	Singapore	PRY	Paraguay		
SVK	Slovak Republic	RUS	Russian Federation		
SWE	Sweden	SRB	Serbia		
URY	Uruguay	THA	Thailand		
		TUR	Türkiye		
		ZAF	South Africa		

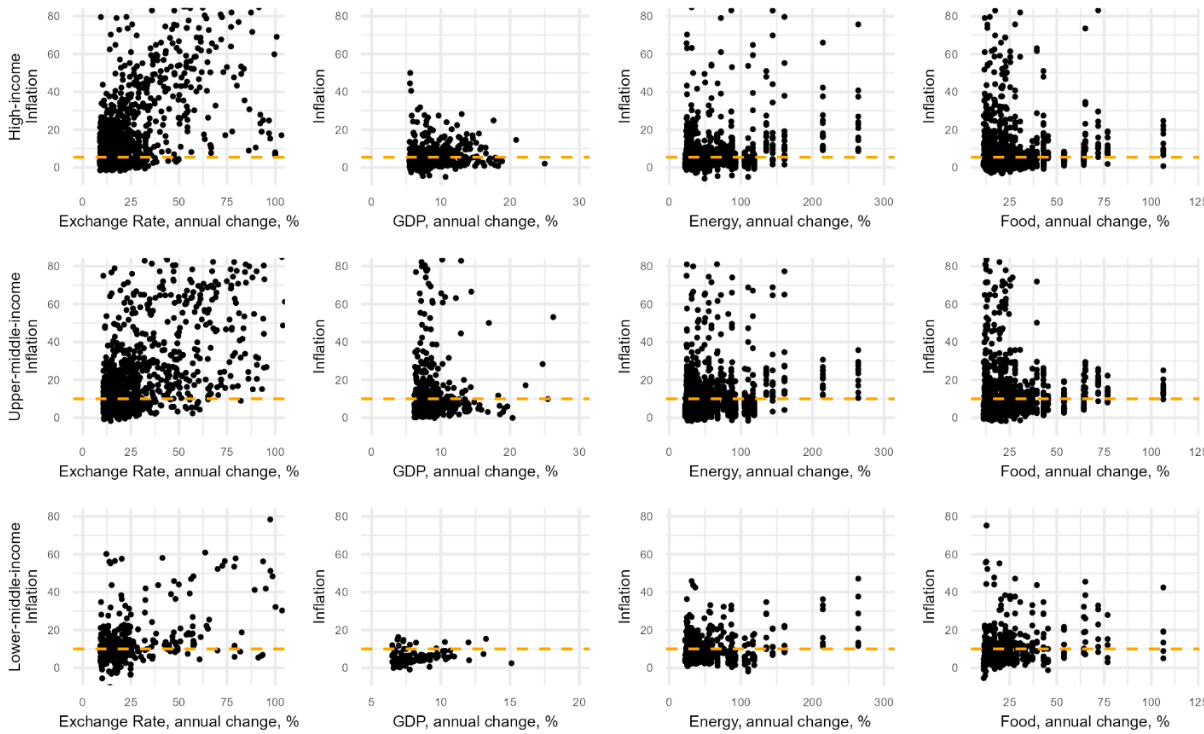
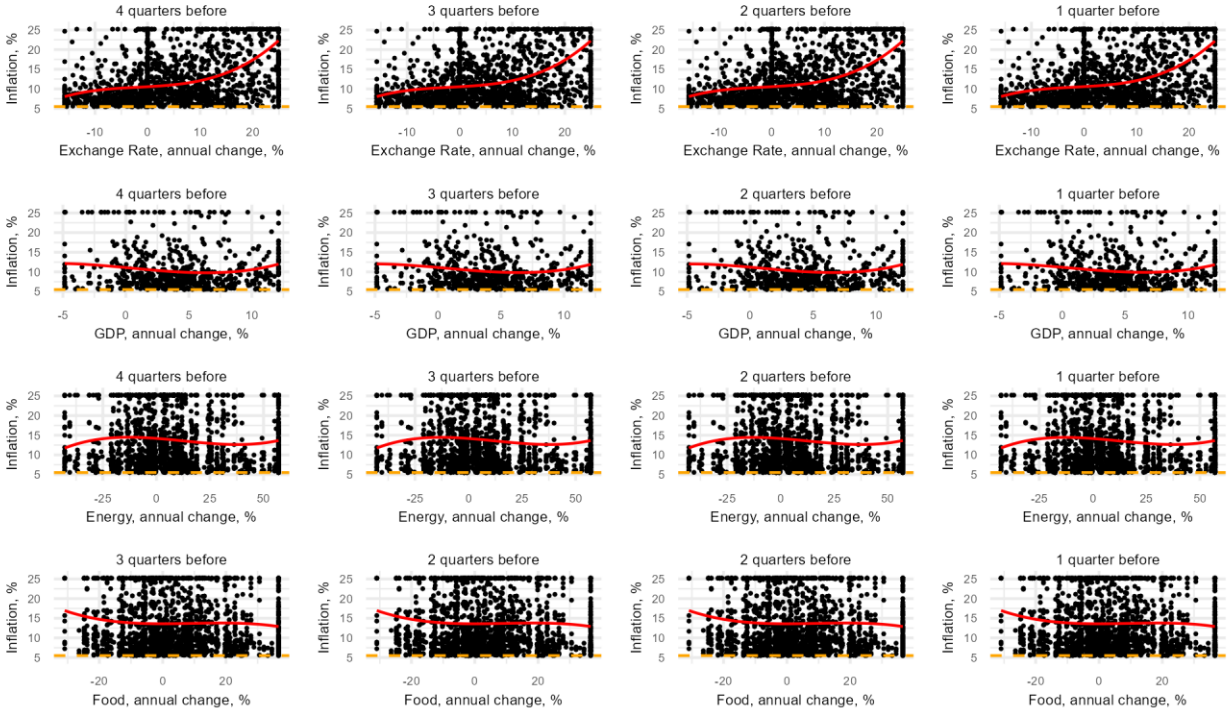


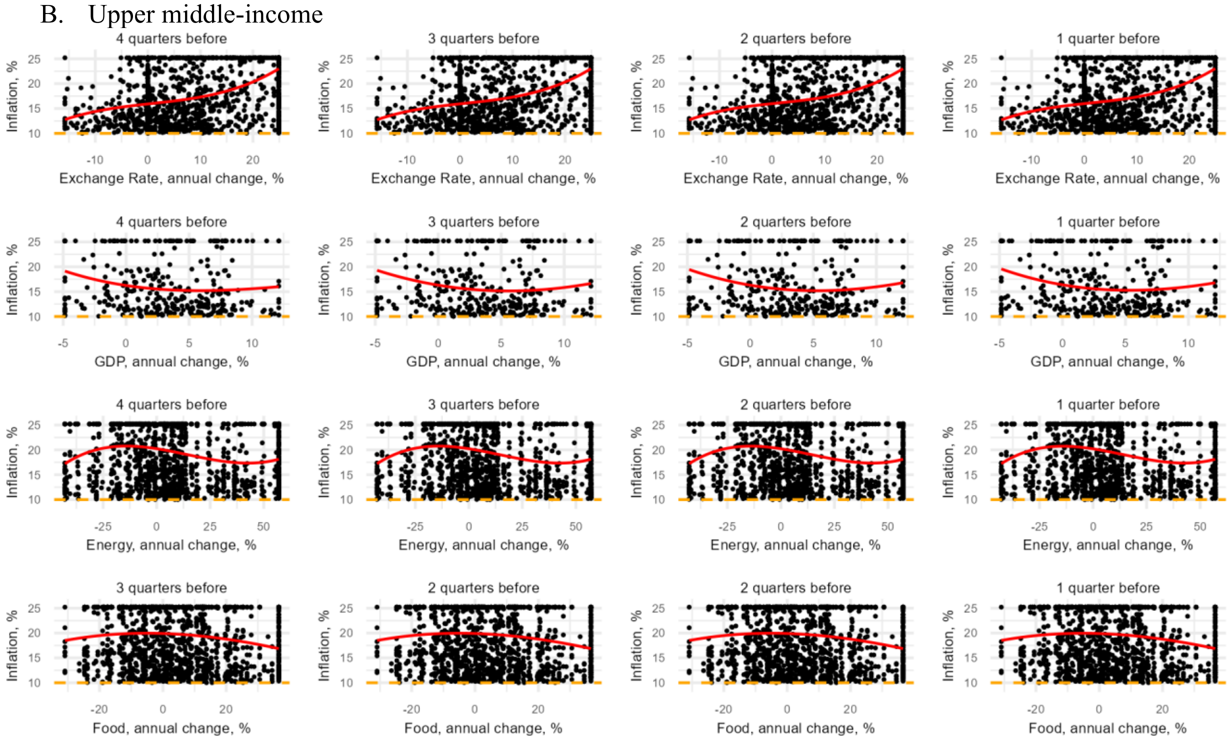
Figure A.1. Inflation Associated with Determinants Beyond The 75th Percentile

Source: Authors' calculation.

A. High-income



B. Upper middle-income



C. Lower middle-income

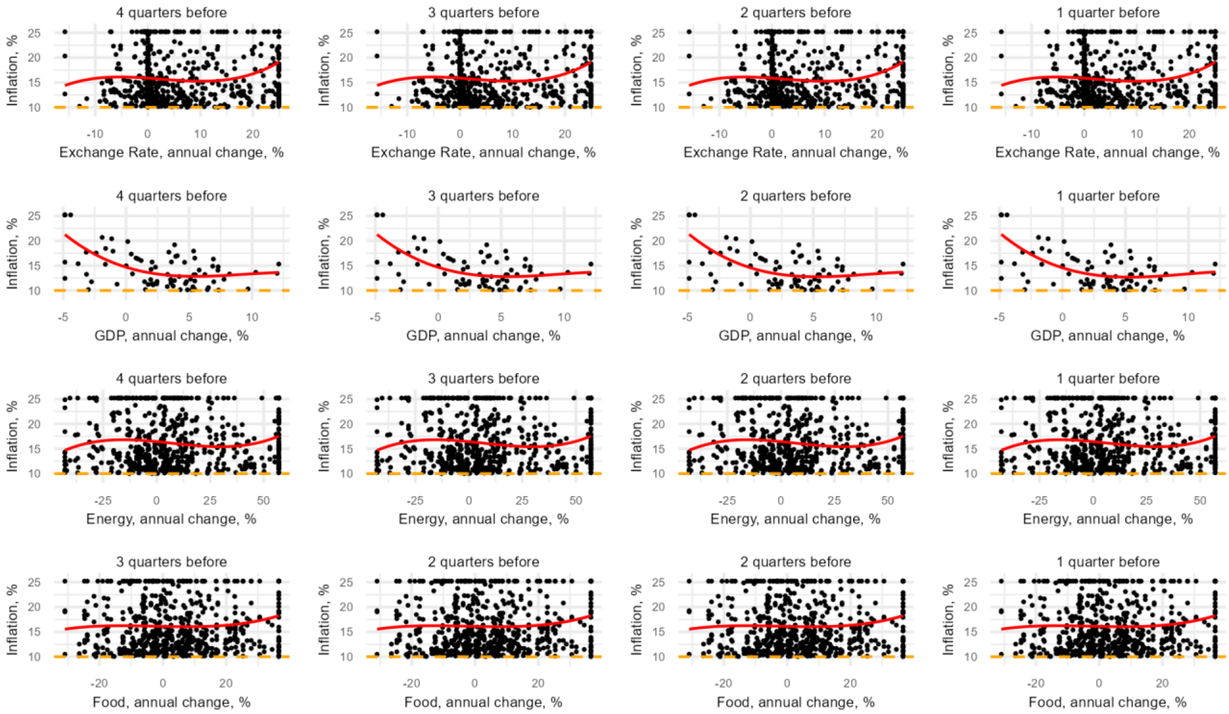


Figure A.2. Determinants of Beyond-High Inflation

Source: Authors' calculation.

Table A.3. Lag Selection

Group	Lag Combination	AIC	AIC rank	BIC	BIC rank	Pseudo R2	Pseudo R2 rank	RMSE	RMSE rank	Total rank
High income	(1 - 1)	1384.60	13	1419.54	1	0.47	14	0.98	9	15
High income	(1 - 2)	1382.66	12	1440.88	3	0.47	12	0.72	2	1
High income	(2 - 2)	1390.23	15	1425.17	2	0.47	15	0.71	1	10
High income	(1 - 3)	1375.91	11	1457.42	6	0.48	11	0.84	4	7
High income	(2 - 3)	1387.52	14	1445.74	4	0.47	13	0.83	3	13
High income	**(1 - 4)**	**1360.41**	**8**	**1465.22**	**7**	**0.49**	**8**	**0.90**	**6**	**1**
High income	(2 - 4)	1375.85	10	1457.36	5	0.48	10	0.90	5	3
High income	(1 - 5)	1345.49	7	1473.58	10	0.50	7	0.97	8	7
High income	(2 - 5)	1363.77	9	1468.58	8	0.49	9	0.96	7	10
High income	(1 - 6)	1334.13	4	1485.51	11	0.50	4	1.03	11	3
High income	(2 - 6)	1343.11	6	1471.21	9	0.50	6	1.02	10	5
High income	(1 - 7)	1328.84	3	1503.51	14	0.51	3	1.07	13	10
High income	(2 - 7)	1337.07	5	1488.45	12	0.50	5	1.05	12	13
High income	(1 - 8)	1312.02	1	1509.98	15	0.52	1	1.15	15	7
High income	(2 - 8)	1324.89	2	1499.57	13	0.51	2	1.13	14	5
Upper middle income	(1 - 1)	665.24	12	697.69	1	0.56	14	1.07	3	5
Upper middle income	(1 - 2)	650.86	10	704.95	3	0.58	11	1.18	5	3
Upper middle income	(2 - 2)	672.05	14	704.51	2	0.56	15	1.02	1	9
Upper middle income	(1 - 3)	649.64	9	725.37	4	0.58	9	1.25	6	2
Upper middle income	(2 - 3)	672.11	15	726.20	5	0.56	13	1.05	2	12
Upper middle income	**(1 - 4)**	**639.74**	**5**	**737.10**	**6**	**0.59**	**8**	**1.42**	**8**	**1**
Upper middle income	(2 - 4)	666.87	13	742.60	7	0.57	12	1.14	4	13
Upper middle income	(1 - 5)	637.24	4	756.24	8	0.60	6	1.71	15	10
Upper middle income	(2 - 5)	662.56	11	759.93	9	0.58	10	1.42	10	15
Upper middle income	(1 - 6)	627.51	2	768.15	11	0.61	3	1.53	13	3
Upper middle income	(2 - 6)	645.40	8	764.40	10	0.60	7	1.42	9	11
Upper middle income	(1 - 7)	629.09	3	791.36	13	0.62	2	1.52	12	5
Upper middle income	(2 - 7)	640.99	6	781.62	12	0.60	5	1.39	7	5
Upper middle income	(1 - 8)	626.83	1	810.74	15	0.62	1	1.59	14	8
Upper middle income	(2 - 8)	641.94	7	804.21	14	0.61	4	1.43	11	13
Lower middle income	(1 - 1)	135.67	9	159.15	2	0.67	15	0.97	1	3
Lower middle income	(1 - 2)	136.76	11	175.89	4	0.68	13	1.13	3	4
Lower middle income	**(2 - 2)**	**132.71**	**2**	**156.19**	**1**	**0.67**	**14**	**1.02**	**2**	**1**
Lower middle income	(1 - 3)	138.29	13	193.08	5	0.70	10	1.26	6	10
Lower middle income	(2 - 3)	134.98	6	174.11	3	0.69	12	1.13	4	2
Lower middle income	(1 - 4)	141.22	15	211.66	8	0.72	9	1.35	7	15
Lower middle income	(2 - 4)	138.73	14	193.52	6	0.70	11	1.19	5	13
Lower middle income	(1 - 5)	135.47	8	221.57	9	0.75	6	1.79	10	8
Lower middle income	(2 - 5)	136.66	10	207.10	7	0.73	8	1.46	8	8
Lower middle income	(1 - 6)	134.87	5	236.62	11	0.78	4	2.19	12	6
Lower middle income	(2 - 6)	137.16	12	223.26	10	0.75	7	1.61	9	14
Lower middle income	(1 - 7)	133.98	3	251.38	13	0.80	2	2.70	13	4
Lower middle income	(2 - 7)	135.45	7	237.20	12	0.77	5	2.06	11	11
Lower middle income	(1 - 8)	127.51	1	260.57	15	0.84	1	4.37	15	6
Lower middle income	(2 - 8)	134.21	4	251.62	14	0.80	3	2.84	14	11

Table A.4. Estimation results for oil importers

A. High income

Number of Countries: 8
Total Observations: 1073
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-1.765832***	(0.108654)
GDP (t-1)	0.033498	(0.022798)
GDP (t-2)	0.009402	(0.02778)
GDP (t-3)	0.028777	(0.027019)
GDP (t-4)	0.072527**	(0.022237)
FX (t-1)	0.053148***	(0.012578)
FX (t-2)	-0.007166	(0.017836)
FX (t-3)	-0.003067	(0.017753)
FX (t-4)	0.025733*	(0.012349)
Energy (t-1)	0.00463*	(0.00376)
Energy (t-2)	-0.00272	(0.005302)
Energy (t-3)	0.002112	(0.005405)
Energy (t-4)	-0.004925	(0.003868)
Food (t-1)	0.009536	(0.007709)
Food (t-2)	0.00157	(0.01136)
Food (t-3)	-0.004543	(0.011392)
Food (t-4)	0.010883	(0.007743)
sigma	1.198076***	(0.162698)

B. Upper middle-income

Number of Countries: 10
Total Observations: 1079
Period: 1961Q1 - 2023Q1

	Coefficient	Std. error
Intercept	-2.177032***	(0.153889)
GDP (t-1)	0.010131	(0.023546)
GDP (t-2)	-0.050129.	(0.029167)
GDP (t-3)	0.029229	(0.029243)
GDP (t-4)	0.055958*	(0.023791)
FX (t-1)	0.051885***	(0.011322)
FX (t-2)	0.029265.	(0.017041)
FX (t-3)	-0.006198	(0.017762)
FX (t-4)	0.045531***	(0.012321)
Energy (t-1)	0.008421*	(0.004233)
Energy (t-2)	0.0062	(0.00616)
Energy (t-3)	0.004897	(0.006269)
Energy (t-4)	-0.005154	(0.004288)
Food (t-1)	0.027394**	(0.008463)
Food (t-2)	0.003419	(0.012246)
Food (t-3)	-0.007773	(0.012769)
Food (t-4)	0.018323*	(0.008749)
sigma	0.789101***	(0.093982)

C. Lower middle-income

Number of Countries: 2
Total Observations: 122
Period: 2005Q2 - 2023Q1

	Coefficient	Std. error
Intercept	-2.059***	(0.5184)
GDP (t-2)	0.06228	(0.06722)
FX (t-2)	0.1017***	(0.02643)
Energy (t-2)	0.006606	(0.008549)
Food (t-2)	0.008121	(0.01586)
sigma	0	(0.1662)

*** if p-value < 0.001, ** if p-value < 0.01, * if p-value < 0.05, . if p-value < 0.1

Robustness Check of "High Inflation" Thresholds

To assess the robustness of the results, we revisit the selection of the "high inflation" threshold. This time, we estimate the panel probit model with the same specifications, defining the "high inflation" threshold as the median value ± 0.5 standard deviations (~0.5*4.5%) of literature thresholds for robustness checks. In this framework, the threshold values are 3.25 and 7.75 for high-income countries and 7.75 and 12.25 for middle-income countries. We compare the models using model evaluation criteria to assess the differences in estimation based on the threshold.

Table A.5. Robustness checks for "high inflation" threshold

Model	Model Evaluation / Share of Successful Predictions		
	High income	Upper middle-income	Lower-middle income
Baseline threshold-based model	82%	84%	83%
Threshold + 0.5*std.-based model	88%	89%	91%
Threshold - 0.5*std.-based model	71%	79%	65%

According to Table A.5, increasing the inflation threshold from 5.5 to 7.75 in high-income and 10 to 12.25 in middle-income increases the model's success by approximately 6 percentage points.

This result ensures that even if one defines higher threshold values, such as 40%, as in Bruno and Easterly (1998), our panel probit methodology with selected determinants will be more successful in determining high inflation episodes. Moreover, the model successfully determines high inflation even if thresholds decrease to 3.25 and 7.75.

Robustness Check of Demand

In the realm of mainstream inflation analysis, it is commonly perceived that the GDP gap holds more utility as a variable than GDP growth. Thus, in order to test the robustness of our Panel Probit model within the framework of economic theory, we have employed the Hodrick-Prescott (HP) filter to estimate the GDP gaps for all 54 countries under examination. The HP filter, which employs a unique lambda value of 1600, provides an estimation of potential GDP deviations from actual GDP levels. Given the diverse developmental stages of the countries in our sample, it is reasonable to question whether the lambda value of 1600 is universally applicable.

Considering the variations in development levels and economic characteristics among the countries in our study, the choice of a single lambda value may not be optimal for all economies (Choudhary, Hanif, & Iqbal, 2014). Moreover, the process of identifying optimal lambda values for each analyzed country is beyond the scope of our current research objectives. That was why we opted to initiate our analysis with GDP growth, a directly observable variable that offers greater reliability than GDP gap estimates obtained through the HP filter with a fixed lambda value.

Nonetheless, in order to assess the robustness of our model and its findings, we have undertaken an additional analysis. We have re-estimated the Random Effects Panel Probit model using the GDP gaps derived from the HP filter while maintaining the same model specifications and properties. This parallel investigation serves to provide insights into how different representations of the GDP-inflation relationship might influence the outcomes of our analysis.

As depicted in Table A.6, the determinant variables maintain their significance within the gap-based probit model. However, the Log-Likelihood and McFadden’s Pseudo R-squared values in the gap-based model are relatively lower than those in the growth-based main model. The AIC and BIC values are consistently higher in the gap-based model, although the RMSE in high- and lower-middle-income countries is lower.

Table A.6. Estimation results for Panel Probit model with the output gap

A. High income

Number of Countries: 21
Total Observations: 2695
Period: 1961Q1 - 2023Q1
Log-Likelihood: -991.1549 (-961.3031)

	Coefficient	Std. error
Intercept	-0.93879***	(0.0485094)
Output Gap (t-1)	2.352177**	(0.7655713)
Output Gap (t-2)	2.893381***	(0.7629669)
Output Gap (t-3)	2.756927***	(0.7619755)
Output Gap (t-4)	2.616643***	(0.7614824)
FX (t-1)	0.039073***	(0.0069352)
FX (t-2)	0.003012	(0.0099092)
FX (t-3)	0.001268	(0.009944)
FX (t-4)	0.027122***	(0.0069961)
Energy (t-1)	0.00744**	(0.0022773)
Energy (t-2)	-0.00097	(0.0032743)
Energy (t-3)	0.004258	(0.0033427)
Energy (t-4)	-0.00179	(0.0023334)
Food (t-1)	0.014963**	(0.0047874)
Food (t-2)	-0.00039	(0.0069962)
Food (t-3)	-0.00138	(0.0070321)
Food (t-4)	0.011647*	(0.0048435)
sigma	0.903677***	(0.078866)

AIC Values: 2018.31 (1958.606)
BIC Values: 2123.414 (2063.711)
McFadden's Pseudo R-squared Values:
0.2557513 (0.2781667)
In sample RMSE Values:
1.064621 (1.333512)

B. Upper middle-income

Number of Countries: 23
Total Observations: 1838
Period: 1992Q1 - 2023Q1
Log-Likelihood: -498.1026 (-497.5455)

	Coefficient	Std. error
Intercept	-2.32254***	(0.1200895)
Output Gap (t-1)	3.531557**	(1.1350552)
Output Gap (t-2)	3.397884**	(1.1103388)
Output Gap (t-3)	3.393532**	(1.1061713)
Output Gap (t-4)	3.737287***	(1.1120243)
FX (t-1)	0.051773***	(0.0084263)
FX (t-2)	0.020082	(0.0122121)
FX (t-3)	0.000715	(0.0124926)
FX (t-4)	0.032856***	(0.0088537)
Energy (t-1)	0.008728**	(0.0033048)
Energy (t-2)	0.003228	(0.0047272)
Energy (t-3)	0.001958	(0.0047246)
Energy (t-4)	-0.0026	(0.0032494)
Food (t-1)	0.022815***	(0.0068759)
Food (t-2)	0.00229	(0.010222)
Food (t-3)	-0.00861	(0.0105932)
Food (t-4)	0.023609**	(0.0072072)
sigma	1.004872***	(0.1055362)

AIC Values: 1032.205 (1031.091)
BIC Values: 1130.064 (1128.95)
McFadden's Pseudo R-squared Values:
0.3541801 (0.3549024)
In sample RMSE Values:
1.949596 (1.543866)

C. Lower middle-income

Number of Countries: 7
Total Observations: 425
Period: 1982Q1 - 2023Q1
Log-Likelihood: -136.825 (-133.8477)

	Coefficient	Std. error
Intercept	-1.15687***	(0.128836)
Output Gap (t-2)	-0.05652	(1.660466)
FX (t-2)	0.077508***	(0.011386)
Energy (t-2)	0.003669	(0.003706)
Food (t-2)	0.029693***	(0.00774)
sigma	1.252692***	(0.196936)

AIC Values: 285.6501 (279.6954)
BIC Values: 309.3383 (303.3836)
McFadden's Pseudo R-squared Values:
0.3028885 (0.3180576)
In sample RMSE Values:
1.107831 (1.117177)

*** if p-value < 0.001, ** if p-value < 0.01, * if p-value < 0.05, . if p-value < 0.1
(…) brackets display growth-based probit results

When selecting the optimal model, we prioritize higher log-likelihood and McFadden's Pseudo R-squared values, along with lower AIC and BIC values. In this context, the Panel Probit model, incorporating GDP growth, stands out as the more robust choice. This preference may be linked to the application of a singular lambda value (1600) for all countries in the HP filter-based estimation of the GDP gap. This approach might not accurately capture the nuanced economic characteristics of each country, potentially leading to less reliable output gap estimates. Hence, it is conceivable that if optimal lambda values were identified, well-estimated GDP gap measures were available, or targeted utilization rates were estimated, the inclusion of the gap variable could enhance the robustness of this research's findings.

A Further Descriptive Investigation of the Relevance of the Determinants' Thresholds

After determining the thresholds for determinants that generate "high inflation," as shown in Figure 4.2.D, we examine historical inflation dynamics over the following two quarters when "high inflation" determinants exceed their threshold values.

As seen from Figure A.3.B-D, when determinants exceed their threshold values, inflation historically surpasses its "high" threshold level.[25] This historical analysis confirms that the thresholds for determinants obtained from the model are consistent with historical dynamics. The only exception is growth. As shown in Figure A.3.A, growth has historically created "high inflation" in high-income economies when it exceeded its threshold. However, in middle-income countries, median inflation remained below the 10% "high inflation" threshold even when faced with high growth shocks.

This result is likely linked to the fact that, as noted in Figure 4.2.D and clearly observed in Figure A.3.A, there are few instances of growth and commodity crises that exceed the model's threshold values. In contrast, there have been frequent high exchange rate depreciations throughout history, resulting in "high" and "beyond high" inflation. This phenomenon is logical, as there may be natural real limits on the magnitude of growth or commodity prices, but exchange rates can depreciate without bound due to balance of payments issues, expectations, and other factors. As highlighted by the model, these unbounded depreciations have become a major source of "high inflation," while demand alone may not create "high inflation." On the other side, as Lavoie (2022) notes, only extraordinary or "dramatic supply-side shocks" can trigger markup and wage equations that result in "high inflation."

[25] This can be read from plots by comparing the median of boxplot with orange dashed lines which highlights 5.5% in high-income economies and 10% inflation in middle-income ones.

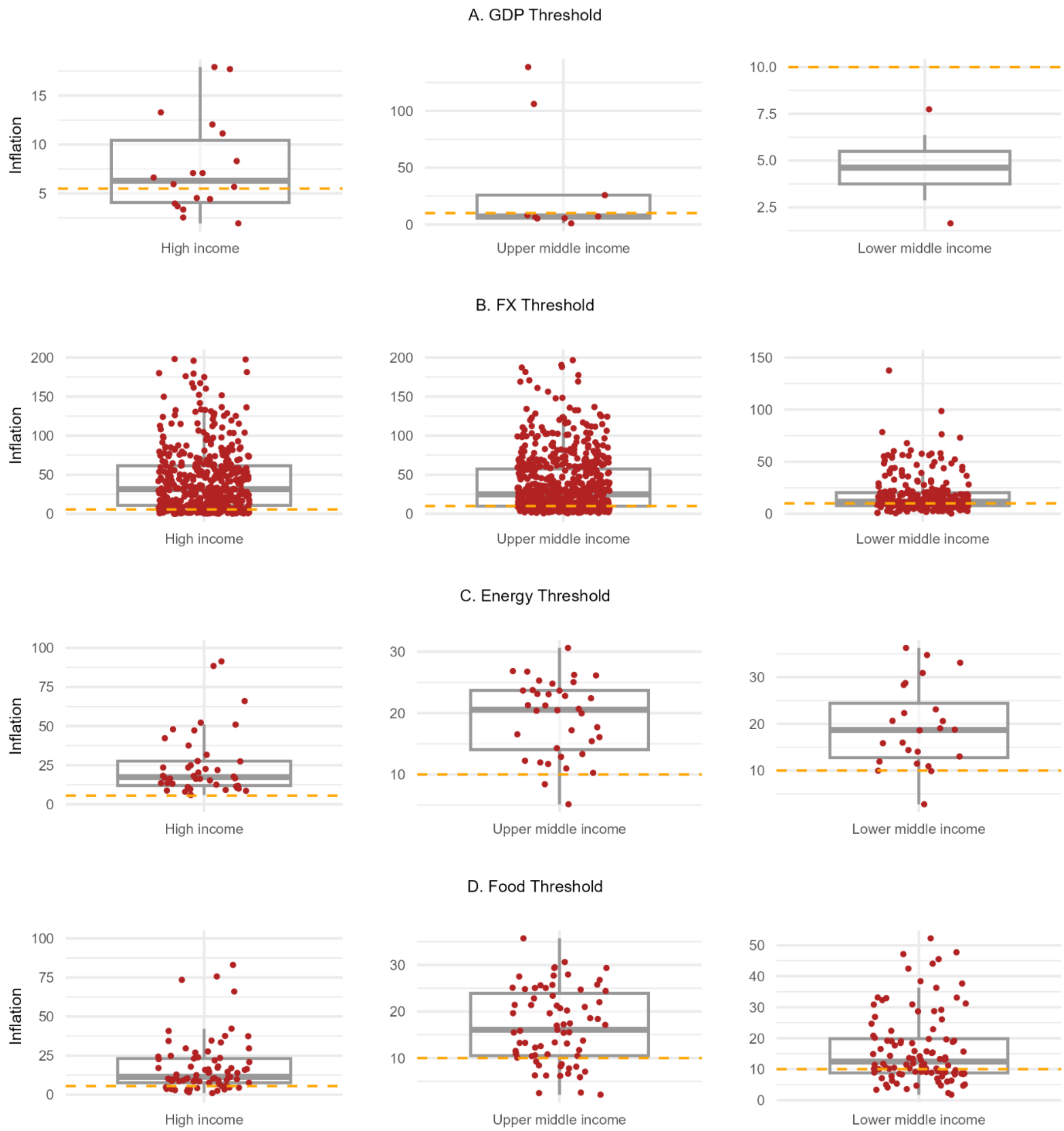


Figure A.3. Inflation Dynamics after Determinants Exceed their Threshold Values

Source: Authors' calculation.

Note: Red dots represent historical inflation two quarters after the determinant exceeded its threshold value, as shown in Figure 4.2.D. Orange dashed lines highlight the "high inflation" threshold level.

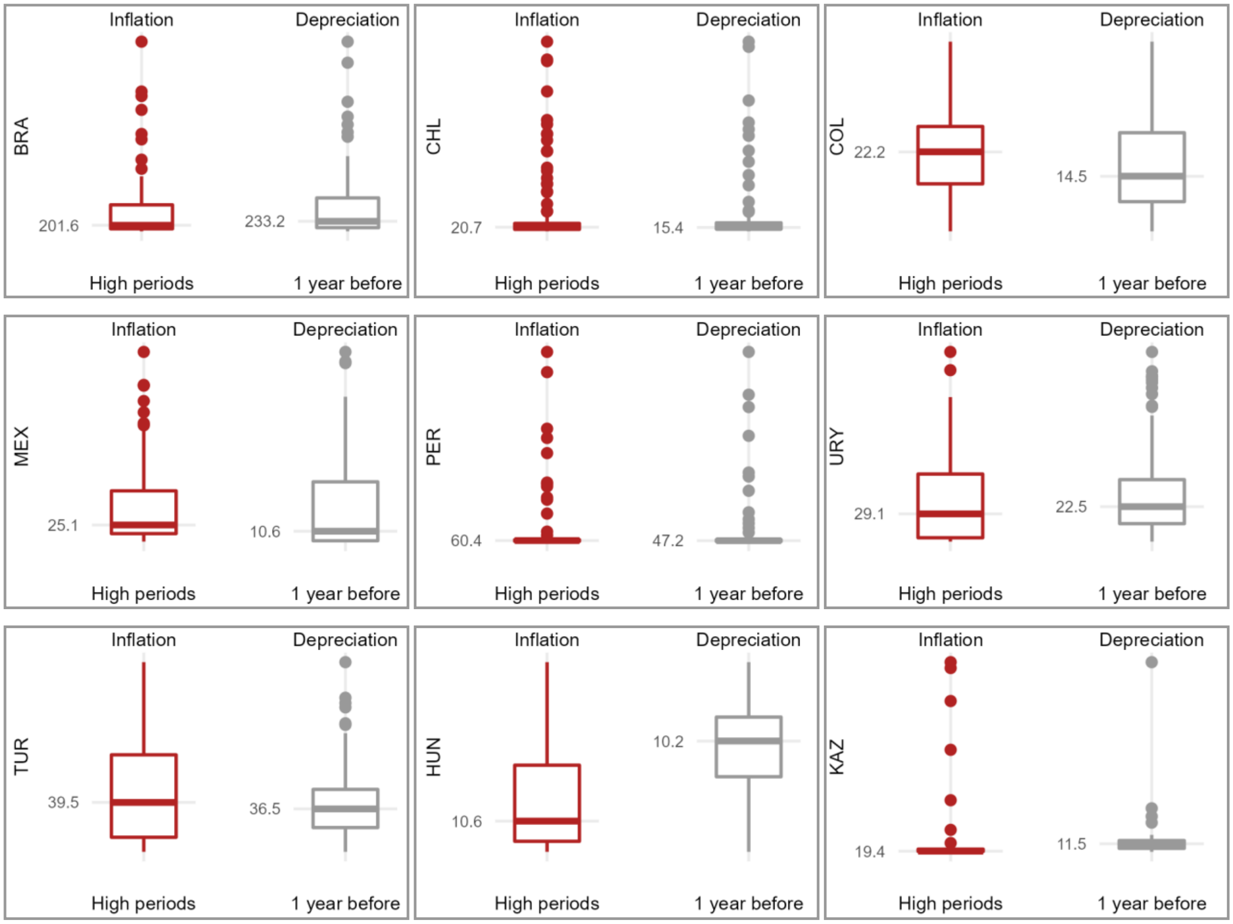


Figure A.4. Exchange Rate and Inflation dynamics in selected countries

Source: Authors' calculation.

Note: High periods identify the distributions of high inflation, while the 1 year before plots show exchange rate depreciations against the USD one year prior to high inflation episodes. The plots focus on median values.