Is “High Inflation” Always and Everywhere an Exchange Rate Phenomenon?

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

First Draft
24 September 2023
Please do not circulate

Abstract

The recent upsurge in inflation following the COVID-19 pandemic has prompted extensive investigation by economists to uncover its underlying determinants. This study aims to contribute to this ongoing discussion by exploring a fundamental question: What variables predominantly explain “high inflation”?

Drawing upon a rich historical dataset spanning from 1961 to 2023 and employing a random effects panel probit model, our research reveals that exchange rate depreciation emerges as a pivotal predictor of “high inflation,” challenging established perspectives. 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 67%, respectively, in forecasting “high inflation” based solely on exchange rate depreciation. Furthermore, energy and food prices also emerge as other important contributors to inflation, while the demand side does not look as important as the supply side factors.

Furthermore, exchange rate depreciation serves as a valuable early warning indicator for “high inflation,” with approximately 25% of depreciation signals accurately anticipating “high inflation” in the subsequent two quarters, boasting a probability exceeding 75% across all analyzed countries.

These findings have important implications for policymakers and economists. Recognizing exchange rate depreciation as a vital early warning signal for high inflation not only facilitates more timely and effective policy interventions but also contributes significantly to the existing literature, further emphasizing 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] Economics, Trinity College, hasan.comert@trincoll.edu
[2] Economics, Middle East Technical University, turalyusifzada@metu.edu.tr
[3] Research, Central Bank of the Republic of Azerbaijan, tural_yusifzada@cbar.az

Introduction

In the wake of the global COVID-19 crisis, economists worldwide turned their attention to the specter of "high inflation," recognizing the potentially destabilizing effects it could have on various aspects of the economy. The threat of "high inflation" loomed large, with concerns ranging from its impact on eroding savings and diminishing investor confidence to exacerbating income inequality (Ha, Ivanova, Ohnsorge, & Unsal, 2019). These concerns underscored the urgent need for policymakers to take swift and decisive action, even if it meant risking economic slowdown and a potential loss of credibility. In light of this pressing issue, this study seeks to make a valuable contribution to the ongoing discussion by addressing a fundamental question: What variables predominantly explain "high inflation"?

To address this question comprehensively, our study embarks on an exploration of the historical context of "high inflation." We focus our analysis on the period spanning from 1961 to 2023, a timeframe that allows us to identify significant episodes of "high inflation." In defining what qualifies as "high," we meticulously reviewed the existing literature, considering the diverse economic landscapes of different countries. This rigorous examination led us to establish specific threshold levels, defining "high inflation" as exceeding 10% for middle-income countries and 5.5% for high-income countries. These thresholds serve as crucial benchmarks for our investigation into the determinants of "high inflation" across various income groups, enabling us to shed light on the primary drivers behind this economic phenomenon.

Our analysis of the determinants of “high inflation” encompasses a wide range of factors, including energy prices, global food prices, exchange rates, and demand-related aspects. Our study spans 23 high-income, 23 upper-middle-income, and 8 lower-middle-income countries over the aforementioned period. To examine the relationships between variables visually, we employ descriptive methods such as box plots and scatter diagrams and find that exchange rate, along with commodity prices, has a noticeable co-movement with inflation. For analyzing these co-movements in more detail with rigorous econometric analysis, given our binary choice framework for assessing whether inflation is "high" or not, we employ the random effects panel probit model. This model is well-suited for binary response variables, making it the optimal choice for analyzing the determinants of “high inflation.” Our evidence suggests that the model effectively predicts “high inflation” in high-income (with a success rate of 83%), upper-middle-income (86%), and lower-middle-income (84%) countries. Most notably, exchange rate depreciation emerges as the preeminent and highly significant predictor of “high inflation” (70% in high-income, 77% in upper-middle-income, and 67% in lower-middle-income countries), underscoring its central role.

Our study corroborates the widely accepted notion that exchange rates exert a significant impact on inflation that is analyzed in wide Exchange-Rate Pass-Through (ERPT) literature. For instance, Kassi et al. (2019) illustrate that a 1% depreciation of a currency against its trading partners results in a 0.9% increase in inflation in emerging Asian countries. Similarly, Chen, Chung, and Novy (2022) estimate a 0.24% inflation effect for the UK under similar conditions. Although there are many similar literature findings for both emerging and developed economies that are discussed in Section 1, there is no conclusive evidence that exchange is the primary determinant of “high inflation.” Thus, our study differs from previous ERPT and inflation determinants studies by contributions that can be summarized in three main aspects:

1. Exchange rate fluctuations are the primary determinant of “high inflation.”
2. 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.
3. As an early warning indicator of “high inflation,” ~25% of depreciation alerts “high inflation” in the following 2 quarters with the probability of more than 75% in all analyzed countries.

With these findings, we can confidently amend Friedman’s famous, albeit dethroned, statement that “Inflation is always and everywhere a monetary phenomenon” to “High inflation is frequently, and in almost everywhere, an exchange rate phenomenon.”

In conclusion, our research provides a comprehensive understanding of “high inflation” across income, further emphasizing the critical role of historical exchange rate dynamics and supply-side factors in comprehending the complexities of “high inflation.” This insight holds crucial implications for policymakers and economists, emphasizing the importance of monitoring exchange rates as an early warning signal for potential high inflationary pressures.

From the outset, we embarked on identifying the “high inflation” threshold in Section 1.1. Having established the benchmark for “high inflation,” we proceeded to analyze the literature, focusing on major factors that contribute 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 dedicated section summarizing the findings and implications.

1. Literature review

1.1. What is the "high" level of inflation?

The concept of "high inflation" thresholds, beyond which rising inflation rates may hinder economic growth, has gained significant attention in global studies. 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 be significantly harmful to economic growth (Pollin & Zhu, 2006). Thus, such inflation levels will not be identified as "high." On the other hand, the supply-focused perspective suggests that 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). As "high inflation" determination is based on identifying the inflation level that harms real growth, according to the supply-focused perspective, "high inflation" would primarily be associated with non-demand factors.

In earlier research, Bruno and Easterly (1998) pointed out 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 significant output losses when inflation rates reach 1% to 3%, whereas developing countries can tolerate higher inflation rates of 7% to 11%.

In a study focused on emerging economies, Ibarra and R. Trupkin (2016) revealed three distinct threshold categories. 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

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%
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%

Table 1.1. (continued)

Authors	Countries	Variables	Methodology	Threshold findings
Ehigiamusoe, Lean, and Lee (2019)	16 West African countries	GDP, CPI, private credit, liquid liabilities, government expenditure, openness, human capital	ARDL	5.62%
Ekinci, Tüzün, and Ceylan (2020)	24 inflation-targeting countries	GDP, CPI, investment, population, initial income, trade, openness	Dynamic Panel Threshold Model (DPTM)	4.18%
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%

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).

Given the variation in “high inflation” threshold values across different research studies (as presented in Table 1.1), a consensus about what defines a “high inflation” level remains elusive. In light of this, several potential definitions of “high inflation” can be considered. The first approach involves calculating the median of well-established literature findings for threshold values within each income group. Another option is to decompose inflation into its cyclical and trend components and define “high inflation” as the deviation of inflation from its underlying trend, similar to the analysis of credit bubbles. It’s important to note that, aside from cyclic threshold values, persistent trends in inflation can also lead to welfare loss and reduced output (Ascari, Phaneuf, & R.Sims, 2018). Consequently, not only sudden spikes in inflation but also prolonged periods of “high inflation” can significantly impact the real economy.

Given the extensive existing literature on this topic and the well-established methodologies for such a determination, there is no necessity to generate a new estimate of “high inflation.” Instead, our approach involved an in-depth review of existing literature that defines “high inflation” through various methods. By aggregating and analyzing a comprehensive set of 20 well-considered “high inflation” thresholds from the literature (as presented in Table 1.1), we were able to identify the median value that emerged from these threshold values. Through this rigorous methodology, we established unique threshold values of 10% for middle-income countries and 5.5% for high-income countries.

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 evident from the findings outlined in Table 1.2. 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."

Table 1.2. "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%
Ezako (2023)	Burundi	GDP, CPI, household consumption, investment, exchange rate	Conditional least square (CLS)	13%

1.2. What may constitute "high inflation"?

In the context of determining "high inflation" and its impact on real economic growth, according to the supply-focused viewpoint, the identification of "high inflation" is often linked to factors beyond just changes in demand (Pollin & Zhu, 2006). Consequently, our initial focus centers on supply-related variables and exchange rates. On the other hand, to acknowledge the influence of demand-oriented theories on inflation, we incorporate the demand factor into our analysis. Although it's acknowledged that monopolistic pricing and expectations can also contribute to "high inflation," the absence of a universal variable for identifying such pricing and expectations across countries has prevented their inclusion in our analysis as a determinant of "high inflation."

To navigate the challenge related to expectations, 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 recognize that the impacts of all independent variables accumulate in inflation both directly and indirectly through expectations.

1.2.1. Demand

According to the extensive body of mainstream literature, prices exhibit sensitivity to fluctuations in demand. When the GDP experiences higher growth (indicating heightened demand) than its potential, manufacturers require an increased supply of production commodities, labor, or capital. In this scenario, the augmented demand for commodities tends to exert pressure on commodity prices, while the surge in labor demand leads to rising wages. Consequently, the escalation in manufacturing costs contributes to inflationary pressures, as highlighted by Machlup (1960). However, it's worth considering that in emerging countries, the labor force dynamics differ from those of advanced economies. In these contexts, where labor force restrictions are not as prevalent, excessive demand relative to the economy's potential might stimulate supply by reducing unemployment levels without substantial wage hikes (Braga & Serrano, 2023). As a result, the inflationary pressures stemming from demand-based factors might not be as evident in such economies.

1.2.2. Energy prices

One of the most recent article written by Kilian and Zhou (Kilian & Zhou, 2022) show that oil prices" hike from 72$ to 100$ (~40% growth) causes 3 p.p. higher inflation (0.47 p.p. for core inflation) in the US. Moreover, Ye et al. (2023) have observed that a $10 escalation in oil prices corresponds to a temporary increase in inflation rates ranging from 0.1% to 0.6% across both advanced economies and emerging markets. Turan and Özer (2022) lend further credence to this observation, underscoring the pronounced influence of oil price fluctuations on both long-term inflation rates in countries like Czechia, Hungary, and Poland, as well as short-term inflation rates in all five Central and Eastern European nations.

Consistent findings emerge from the work of Coulibaly (2021) and Abbas and Lan (2020), which underscore the pivotal role played by energy commodities in driving the inflationary process within advanced and emerging economies. These studies highlight that the pass-through effect of energy commodities on inflation surpasses that of other commodity categories, underscoring the substantial impact of energy price fluctuations on the broader price levels.

1.2.3. Global Food Prices

Extensive research has explored the relationship between food prices and inflation, consistently highlighting a positive correlation between these two variables. Recent literature reviews underscore that global food prices wield substantial influence over the consumer price index, signifying that upticks in food prices frequently lead to heightened inflation levels (Coulibaly, 2021). Intriguingly, both in the short term and the long term, agricultural and food commodities demonstrate a more pronounced pass-through effect on inflation, similar to energy inflation, when compared to other commodity categories (Abbas & Lan, 2020). In recent years, disruptions in the global supply chain and food trade have introduced numerous challenges, resulting in a surge in worldwide food prices (Nasir, Nugroho, & Lakner, 2022). Consequently, the inflationary pressures caused by rising food prices have become even more pronounced.

Global studies indicate that economies characterized by larger proportions of food prices within their Consumer Price Index (CPI) baskets, higher reliance on fuel, and elevated pre-existing inflation levels tend to be more vulnerable to sustained inflationary impacts resulting from fluctuations in commodity prices (Gelos & Ustyugova, 2012).

1.2.4. Exchange Rate

While comprehending the mechanisms through which inflation is influenced by supply and demand factors seems relatively straightforward, it’s essential to acknowledge that the transmission of exchange rate impacts is intricate and warrants significant attention. Consequently, we will place greater emphasis on unraveling how fluctuations in the exchange rate can lead to inflation and how scholars have quantified and analyzed this impact within the existing literature.

1.2.4.1. Exchange rate impact transmission

The impact of exchange rate changes can be divided into two phases. In the first phase, the changes in exchange rates have an effect on import prices (Forbes, 2016). This effect is generally expected to happen relatively quickly and is mostly completed within a year. In the second phase, the changes in import prices gradually transmit to the overall price level and contribute to inflation. This second phase is considered to be a slow process (Colavecchio & Rubene, 2019), with various estimates indicating that it may take more than years for most of the adjustments to occur and even longer for the full impact to materialize (Forbes, 2016).

However, not all imported goods are affected by exchange rate fluctuation at the same magnitude. For instance, sectors that exhibit a strong correlation with changes in the value of the local currency are typically those related to food and energy, which are predominantly determined in international markets (Forbes, 2016). Thus, food and energy-importer countries are more vulnerable to exchange rate movements. Considering the considerable portion of food within the consumption basket of developing economies (Akcelik and Comert 2022), the effect of exchange rates on these economies is expected to be more pronounced in comparison to developed economies.

Besides imported goods or domestic products that have a high import share, Forbes' (2016) analysis of the UK revealed a non-traditional response of non-imported goods to exchange rate fluctuations. When the local currency appreciates, leading to lower import prices, firms that produce goods primarily for the domestic market but face competition from international counterparts may need to reduce their prices to remain competitive and retain market share. This means even if these goods have minimal import content or are produced and sold within the country, their prices can still be sensitive to changes in the exchange rate if they are tradeable and face competition from international goods. In other words, the impact of exchange rate movements on prices is not solely dependent on import intensity but is also influenced by the sector's tradability and level of international competitiveness. Therefore, as imports and traded goods constitute a larger portion of the consumption basket, fluctuations in the exchange rate that influence import prices and tradable goods would naturally have a greater impact on overall prices (Forbes, 2016).

In addition to competitiveness and the import channel, exchange rates can indirectly impact inflation through expectations, an aspect that is not extensively explored in the existing literature. However, it is widely recognized that inflation expectations are significantly influenced by both current inflation levels and past expectations of inflation. As a result, Nasir, Huynh, and Vo (2020b) argue that inflation expectations are shaped by the factors that determine inflation itself. Their N-ARDL (Nonlinear Autoregressive Distributed Lag) methodology, employed to estimate and investigate the relationship between inflation expectations and the real exchange rate, demonstrates the significant importance of the link between inflation expectations and inflation in the Czech Republic (Nasir, Huynh, & Vo, 2020b). Furthermore, another study reveals a noteworthy and negative impact of the real effective exchange rate, indicating that currency appreciation can exert a potent deflationary influence on inflation expectations even in advanced economies such as New Zealand and the UK (Nasir, Balsalobre-Lorente, & Huynh, 2020c).

More importantly, a growing discrepancy between inflation expectations and inflation projections because of exchange rate uncertainty is generally interpreted as a decline in credibility. In such instances, it is observed that the Exchange Rate Pass-Through (ERPT) tends to rise when this disparity exceeds a specific threshold level (Gayaker, Ağaslan, Alkan, & Çiçek, 2021).

1.2.4.2. Quantified exchange rate impact on inflation

Numerous studies have already utilized various econometric models to analyze and measure the influence of exchange rates on inflation at an aggregate level. For instance, by using the ARDL model, Şen et al. (2020) investigate the potential long-run relationships between interest rates, inflation, and exchange rates in five emerging market economies known as the "Fragile Five." The results indicate that exchange rates and actual inflation rates tend to move together in the long run in all sample countries, suggesting that the depreciation of their currencies results in inflation through higher prices of imported goods. However, the pass-through is not only limited to import prices. According to Anh et al.'s (2021) structural vector autoregressive model, the producer price index is affected more than the consumer price index, where exchange rate shocks have an immediate effect within one quarter on producer prices in all founding members of the Association of Southeast Asian Nations (ASEAN).

To explore exchange rate impact further, Nimoh, Addai-Asante, and Obeng's (2017) study focused specifically on the relationship between exchange rate policy, particularly devaluation, and inflation in Ghana. They employed the Auto Regressive Distributed Lag (ARDL) method to analyze the effects of devaluation on inflation in both the short run and long run within the Ghanaian economy. The findings revealed that devaluations of the cedi, both in the short run and long run, have led to inflationary pressures. The estimated coefficient for the long-run nominal exchange rate suggests that a 1% devaluation of the cedi results in a 0.4052% increase in the general price level. Additionally, both short-run and long-run depreciation of the cedi have contributed to inflationary effects.

Furthermore, Kassi et al. (2019) conducted a study using the NARDL approach and dynamic panel techniques. Their research covered the period from 1995Q1 to 2016Q4 for emerging and developing Asian countries. The study found a significant and complete ERPT for the long run in response to nominal effective exchange rate (NEER) appreciation. On average, a 1% NEER appreciation led to a 0.90% increase in consumer prices, while a 1% NEER depreciation resulted in a -0.50% decrease in consumer prices for the entire region.

In a separate study by Pham et al. (2023), the NARDL model was employed to investigate the impact of a positive shock, specifically a 1% appreciation in the Real Effective Exchange Rate (REER) instead of NEER, on inflation in Malaysia and Thailand. The findings indicated that such an appreciation in the domestic currency relative to other currencies had a dampening effect on inflation in both countries, leading to a reduction in inflation.

Besides emerging markets-focused studies, the results of the developed economies studies also indicate significant evidence of Exchange Rate Pass-Through (ERPT) in the analyzed countries. For instance, Nasir and Vo (2020) employed a TVSVAR (Time-Varying Structural VAR) model to analyze the data spanning from 1976 to 2017 for the UK, New Zealand, and Canada. Their analysis shows that in the UK, prior to the adoption of inflation targeting by the Bank of England (BoE), a positive shock to the REER, which implies currency appreciation, had a positive effect on inflation. However, after the adoption of inflation targeting and the independence of the BoE, positive exchange rate shocks led to a significant drop in inflation. According to rough estimates provided by the Bank of England, the pass-through from exchange rate movements to UK import prices is typically estimated to be between 60% and 90%. The import intensity of the consumer price index (CPI) is roughly 30%. Combining these factors results in an overall pass-through coefficient of approximately 20% to 30%. In other words, a 17% appreciation of the sterling since the spring of 2013 would lead to a reduction in the level of the CPI by about 3% to 5% (Forbes, 2016).

On the other hand, Nasir and Vo (2020) suggest that in response to a positive shock to the Real Effective Exchange Rate, inflation in New Zealand decreased. In the earliest period analyzed, inflation quickly recovered after an exchange rate shock. However, in later periods, and particularly in recent times, the exchange rate shock had a more pronounced and persistent impact. This suggests that in New Zealand, ERPT has been increasing over time. In contrast to the UK and New Zealand, a positive shock to the REER in Canada led to an increase in inflation throughout all the periods analyzed. This implies that currency appreciation in Canada exerted upward pressure on inflation.

Another intriguing issue concerning the impact of exchange rates on inflation is nonlinearity. Frankel, Parsley, and Wei (2012) employ Error Correction Models (ECM) to study how exchange rate fluctuations affect prices in developing countries. Their study's key contribution is identifying a threshold effect for large exchange rate depreciations, where the impact on prices becomes proportionately larger for depreciation above 25%. Similarly, Caselli and Roitman (2019) analyze how exchange rate fluctuations affect prices in a panel of 27 emerging markets from 1990 to 2013. Their study finds evidence of a threshold leading to nonlinearities when the exchange rate experiences a large depreciation of more than 24%. Such high depreciations in exchange rates are referred to as a “currency crash,” as defined by Frankel and Rose (1996) as a nominal depreciation of the currency of at least 25 percent in a year.

Similar to emerging economies, Colavecchio and Rubene's (2019) nonlinear Local projections model shows that significant changes in exchange rates have a greater effect on the pass-through of those changes to import and consumer prices in the euro area. However, this impact is observed only within the first year. After one year, nearly 49% of large exchange rate movements (the threshold value is equal to one standard deviation of the first difference of the exchange rate series) affect import prices, while small movements have minimal impact and lack statistical significance beyond one year. The incomplete pass-through to import prices indicates that import prices respond more when the euro area experiences substantial exchange rate shocks, aligning with the menu costs theory. As for consumer prices, large exchange rate changes result in a cumulative effect on headline inflation of 7% after one year, while small changes have limited influence. In conclusion, the magnitude of exchange rate movements significantly influences the extent of exchange rate pass-through into import and consumer prices in the euro area.

However, the selection of the appropriate exchange rate type is crucial in order to obtain accurate and meaningful analysis results. For instance, Gopinath et al. (2020) have recently highlighted the inadequacy of using bilateral exchange rates in pass-through regressions. 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 relevant exchange rate variation.

Lastly, the study by Cheikh and Zaied (2020) highlights the importance of considering the inflation level as it may also impact the magnitude of the ERPT. Their research focuses on the exchange rate pass-through in ten new EU member states from 1996 to 2015 by proposing a nonlinear panel smooth transition regression (PSTR) approach. The results suggest that if CPI inflation is below 4.5%, a 1% increase in the rate of exchange rate depreciation leads to a 0.57% increase in import-price inflation. However, if CPI inflation is above 4.5%, the effect of exchange rate depreciation on import-price inflation becomes greater, approaching a unity elasticity. Thus, the level of inflation matters.

Once we have gained a comprehensive understanding of the primary determinants of inflation and the mechanisms through which they exert their influence, our analysis can shift towards investigating whether these determinants are indeed responsible for triggering episodes of “high inflation.” Furthermore, we can delve into whether their impact on driving inflation to "high" levels carries equal weight or if certain determinants hold a special significance in such instances.

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 on a quarterly basis. The datasets encompass cumulative price levels, real GDP, and exchange rates against the USD, all retrieved from the International Financial Statistics (IFS) with quarterly observations. To ensure consistency, all variables are converted into annual percentage changes. Additionally, the real GDP data is subjected to a Hodrick–Prescott (HP) filter to discern trend and gap components, where a lambda value of 1600 is utilized.

Due to data availability constraints, the analysis focuses on 54 countries with complete datasets for the three variables in the IFS database. Among these, 23 nations are categorized as High Income, 23 as Upper Middle-Income, and 8 as Lower Middle-Income, according to the World Bank’s income group classification.

Energy and food commodity indices data are sourced from the World Bank, 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.

In the management of the data, we deliberately opted for annual changes over quarterly ones for several reasons. Firstly, the presence of varying seasonal patterns across the analyzed countries makes it challenging to uniformly apply well-known deseasonalization methods such as TRAMO/SEATS and X-13/11. These methods require country-specific adjustments to account for calendar events, as applying them without consideration could distort the inherent characteristics of the data. Secondly, the preference for annual changes over quarterly changes is guided by the existing literature's focus on identifying "high inflation" and exchange rate depreciation. Since both of these aspects concentrate on annual changes, employing quarterly changes could complicate the distinction of threshold values.

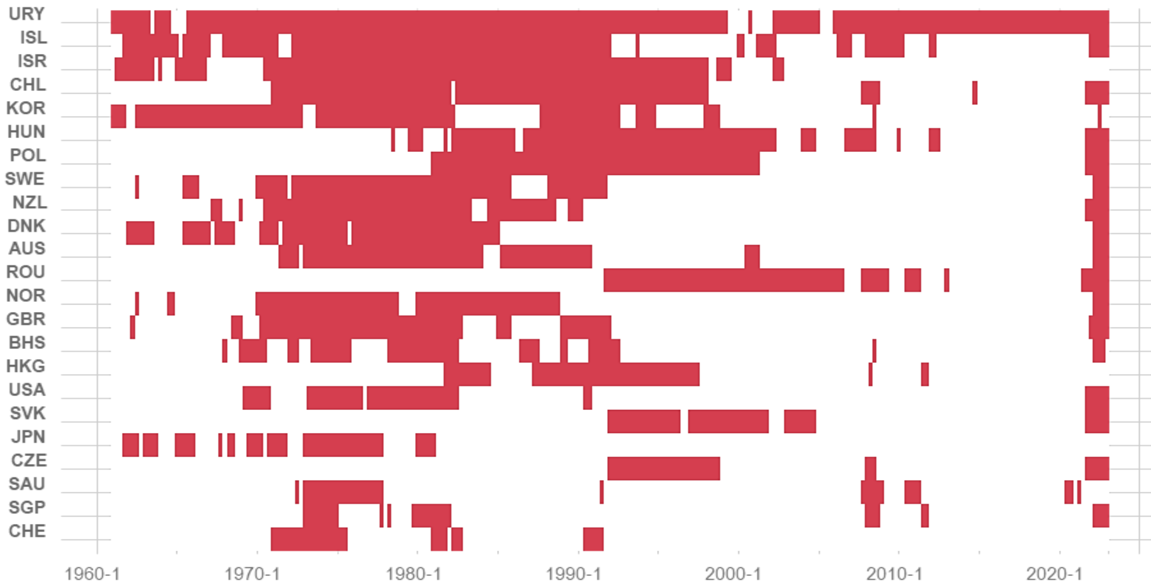
2.2. Descriptive Statistics

After thoroughly reviewing the well-estimated "high inflation" threshold values in the literature, we have determined that the values of 10% for middle-income countries and 5.5% for high-income countries denote "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.

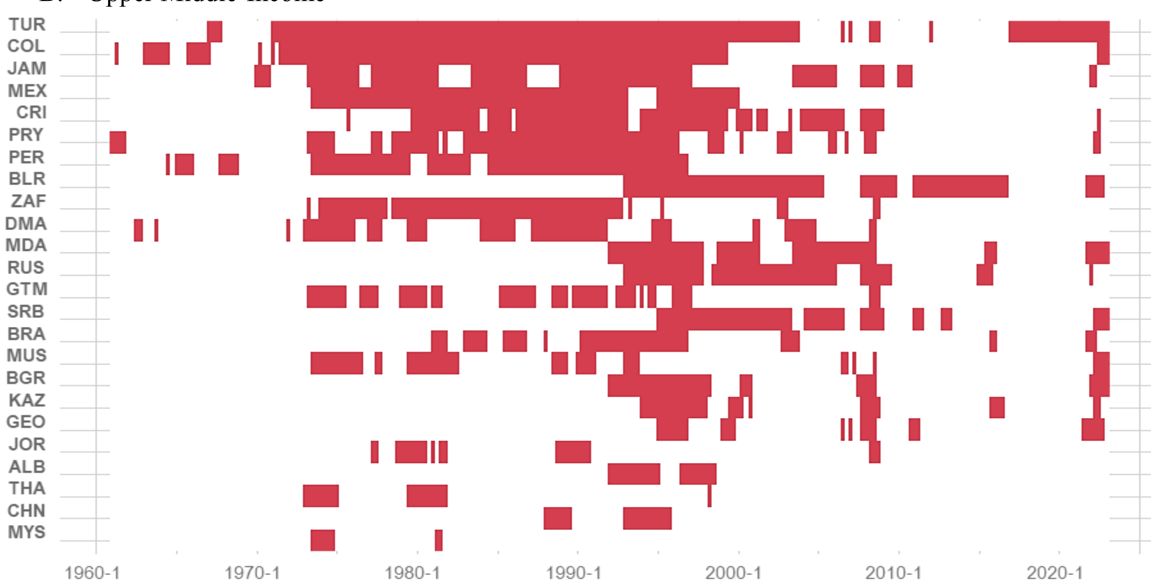
From the figure, it becomes evident that these "high inflation" threshold values effectively identify prominent periods such as the 1970s to 1990s, the global financial crisis in 2008-2009, and the recent years of 2021-2023 for a majority of countries. It's important to acknowledge, however, that, as 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 analysis between global commodity prices and inflation, 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.

Figure 2.2.1 “high inflation” episodes

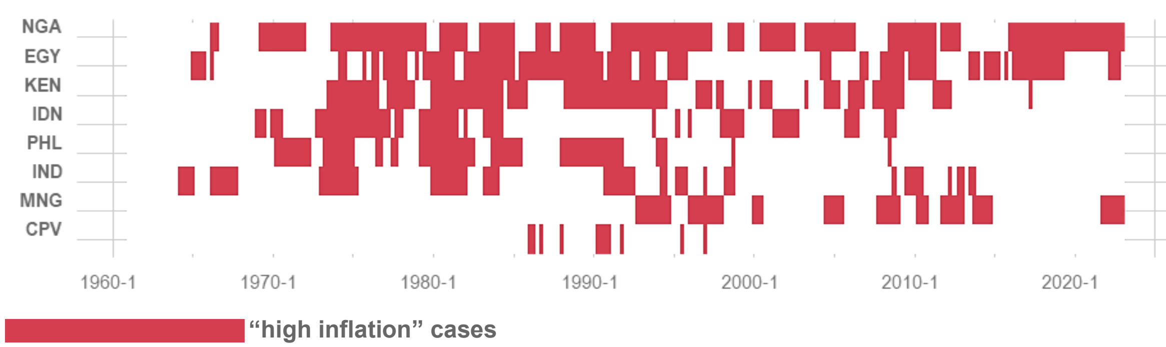
A. High Income



B. Upper Middle-Income



C. Lower Middle-Income



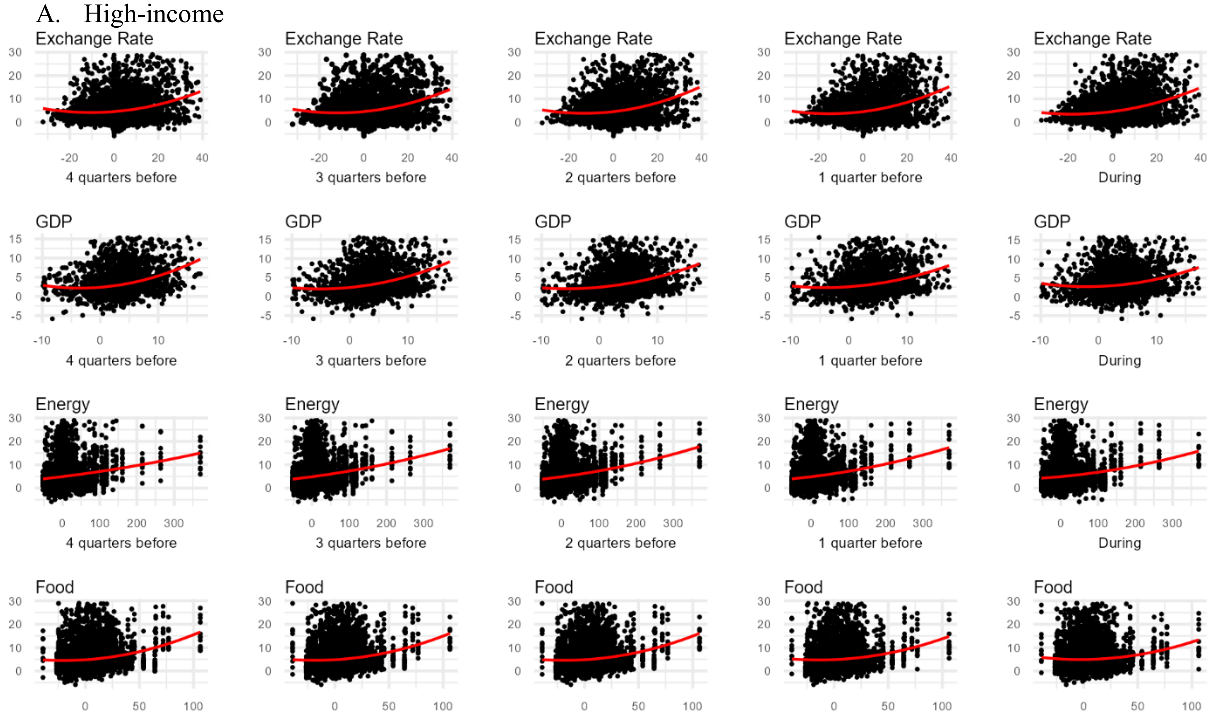
Source: Authors’ calculation.

Before starting our analysis, it should be noted that each income group's dataset is substantially impacted by outliers that are specific to individual countries. To mitigate the influence of these outliers, we implement Tukey's fences method. 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). These outlier values are then excluded from subsequent plots, except for commodity indices.

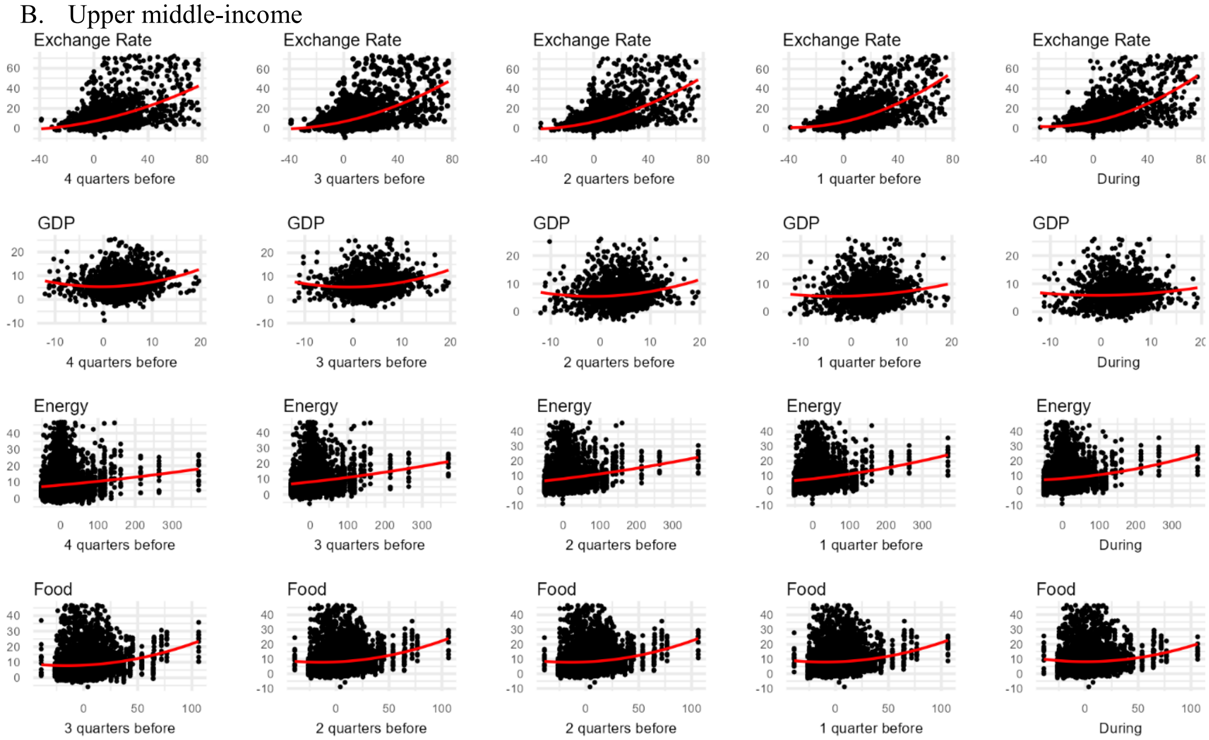
According to Figure 2.2.2, the elasticity of inflation to the exchange rate is notably high compared to other determinants. Conversely, although there is a well-demonstrated relationship between inflation and GDP in high and upper-middle-income countries, inflation typically does not reach the elevated levels driven by other determinants. For example, in high-income economies, the upper fence represents approximately 15% of inflation concerning demand growth, while it is nearly twice as high for supply-side determinants and exchange rates. In the dimension of commodity prices, the relationship between inflation and commodity prices is positive and high, as expected.

Figure 2.2.2. Determinants of inflation

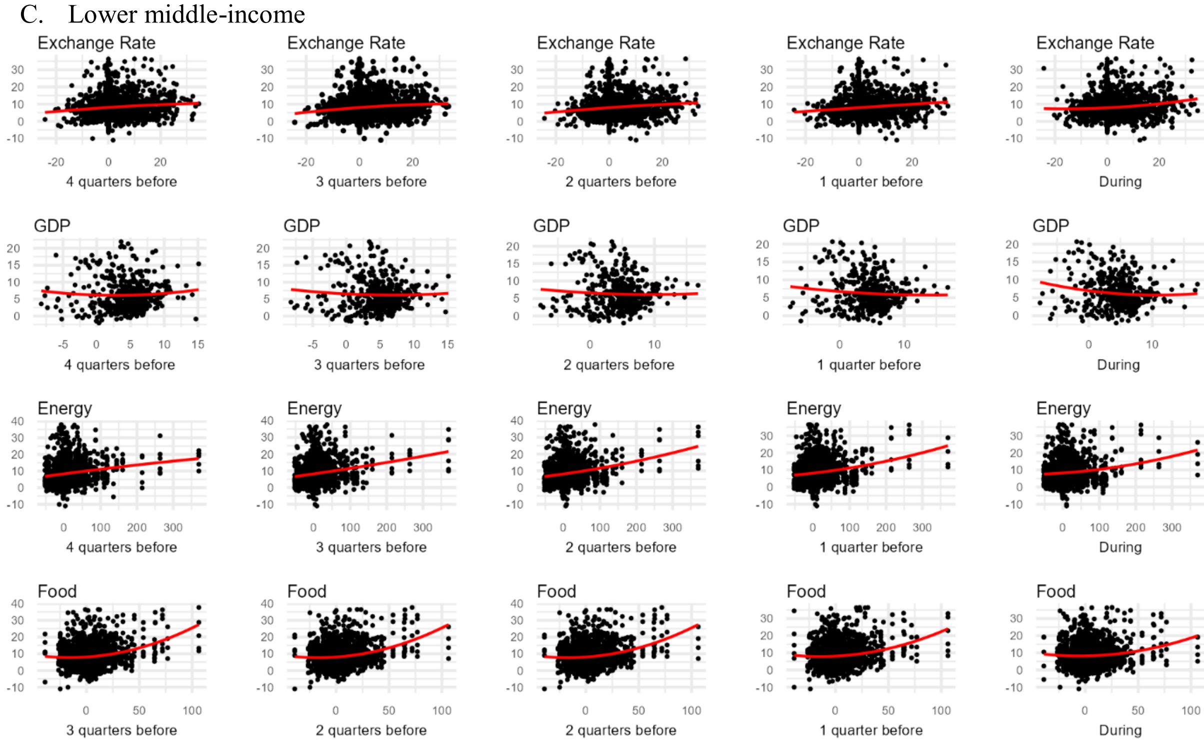
A. High-income



B. Upper middle-income



C. Lower middle-income



The red line is a quadratic (degree-2 polynomial) regression line between inflation and its determinants.

Source: Authors' calculation.

Note:

- The y-axis in each graph displays inflation values, while the x-axis shows associated determinants.
- Plots display 54 countries" (23 High income, 23 Upper middle income, and 8 Lower middle-income) observations.
- The x-axis is labeled as: "During" when inflation at time t is associated with its determinants at time t, "n quarter(s) before" if inflation at time t is related to determinants at time t-n.

Since we possess data encompassing all "high inflation" episodes and have gained an overall understanding of the relation between inflation and its determinants, our inquiry can now delve into pinpointing the triggers behind the initial spikes in inflation. Given that "high inflation" often endures for several quarters across most countries, it's plausible that the factors driving the first spike may differ from those influencing inflation's prolonged persistence. Thus, our initial focus is on addressing the following question: What are the specific determinants that lead to the initial surge in inflation, ultimately resulting in "high inflation" levels?

To answer this question, we shall scrutinize the well-established inflation determinants discussed in the first section, focusing on the periods during and preceding the "high inflation" cases. It's imperative to be meticulous in selecting the periods preceding these "high inflation" episodes. For instance, if "high inflation" is observed throughout the entirety of 2022, then the period "one quarter before" or t-1 should correspond to 2021Q4 rather than selecting 2022Q3 when analyzing the "high inflation" of 2022Q4. Since our focus is solely on the initial spikes, we concentrate on the entire year of 2022. Our objective is to identify which determinant led to an inflation spike surpassing the designated high threshold value.

Additionally, since we have a total of 23 countries in the high-income group, 23 in the upper-middle-income group, and 8 in the lower-middle-income group, we will conduct the same analyses for each individual country. In the next step, we group the results regarding income characteristics. The overall period for each inflation determinant can be articulated as follows:

During "high inflation": $\bigcup_{i=1}^{k} \Delta X_t$ (1)

1 quarter before the "high inflation" period:

$$\bigcup_{i=1}^{k} \Delta X_{\begin{cases} t-1, & if\ inflation\ is\ high\ at\ time\ t \\ t-1, & if\ inflation\ is\ high\ at\ time\ t,\ \ t+1,\ldots,\ \ t+m \end{cases}} \quad (2)$$

1-n quarters before the “high inflation” period:

$$\bigcup_{i=1}^{k} \Delta X_{\begin{cases} t-1:n, & if\ inflation\ is\ high\ at\ time\ t \\ t-1:n, & if\ inflation\ is\ high\ at\ time\ t,\ \ t+1,\ldots,\ \ t+m \end{cases}} \qquad (3)$$

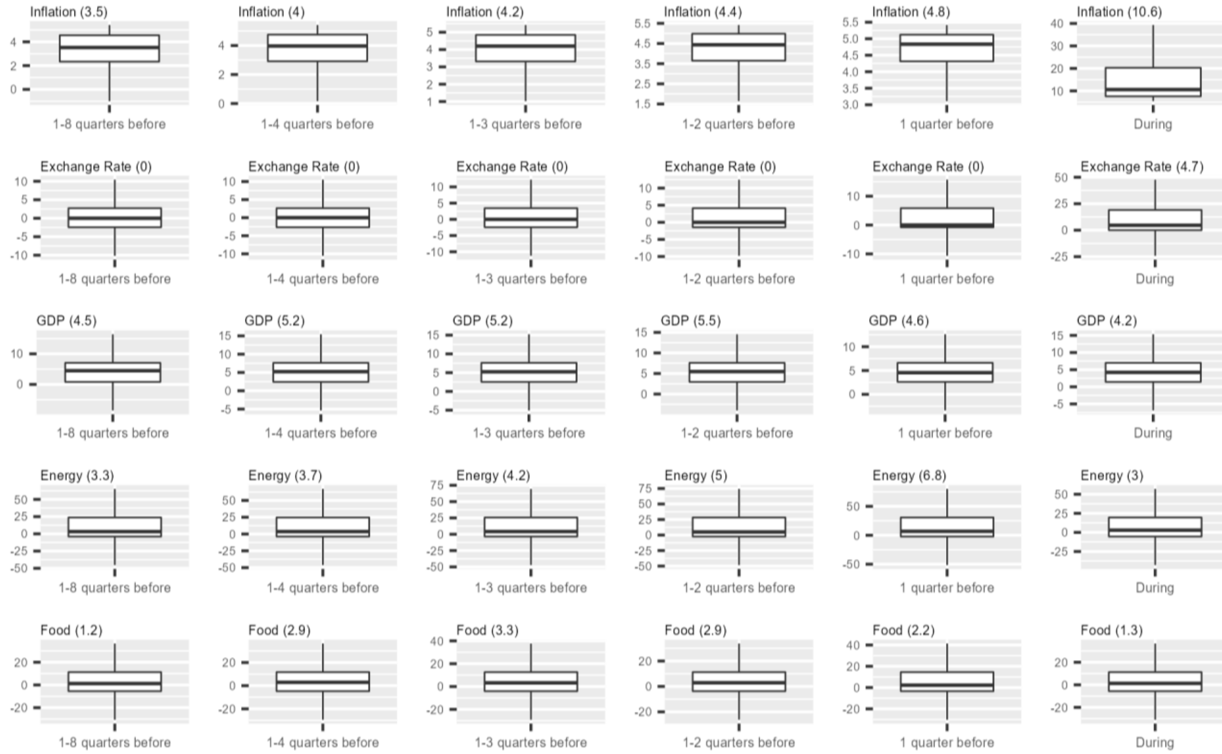
, where X is inflation determinants; Δ identifies annual percentage change, and $\bigcup_{i=1}^{k} \Delta X$ is inflation determinants” bundle for each income group that has k number of countries. It should be highlighted that the "1-n quarter(s) before" period does not intersect with any “high inflation” period for each country.

The core of these analyses revolves around the utilization of box plots, vividly depicted in Figure 2.2.3. Interpreting these box plots requires starting from the right and proceeding to the left. The far-right section showcases the specific inflation bundle pertaining to each group. Within this section, the brackets signify median values. The same column also unveils the inflation determinants during the “high inflation” period, presented in subsequent rows. These determinants encompass annual changes in exchange rates, GDP, energy inflation, and food inflation. Furthermore, the columns from right to left unveil inflation and its corresponding determinants during the preceding 1-n quarter(s) as defined in formulas (2) and (3) provided above. This meticulous arrangement allows us to clearly discern which determinants are potential triggers for the initial inflation spike that subsequently leads to the identification of “high inflation.”

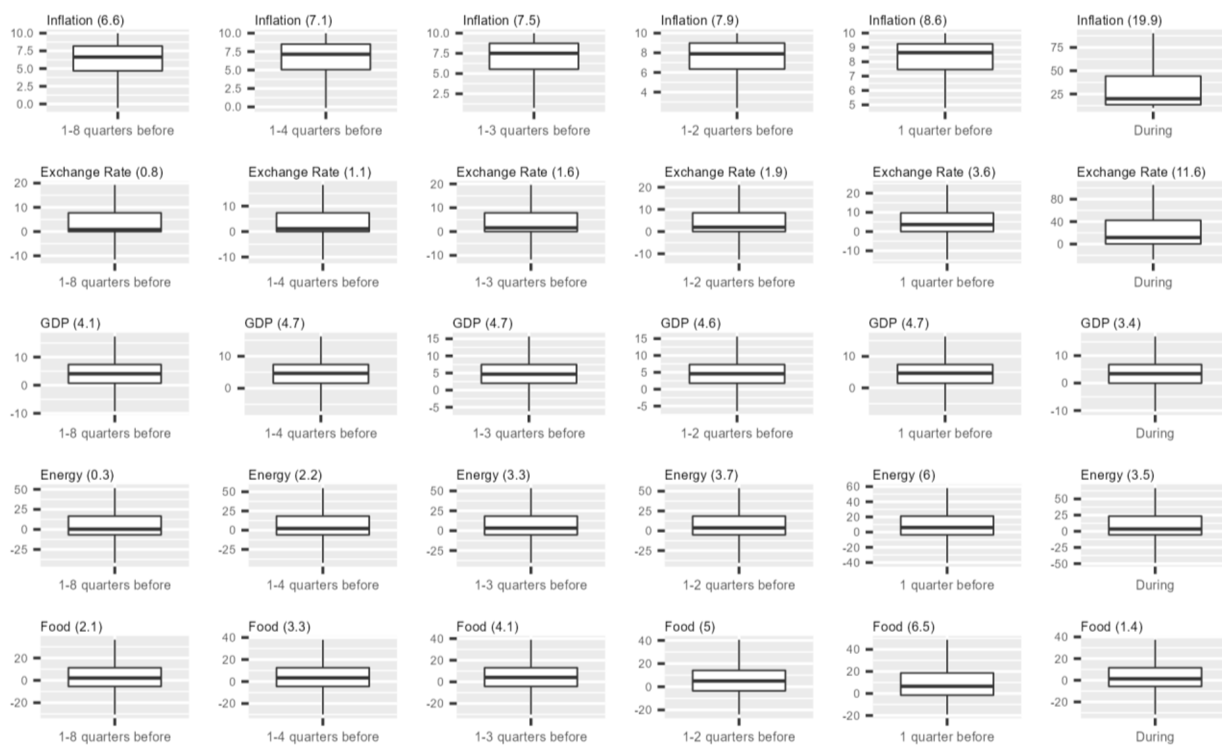
The analysis displays that “high inflation” tends to be consistently linked with exchange rate depreciation across various economies, as seen in Figure 2.2.3. This phenomenon is almost ubiquitous, indicating the significant influence of exchange rate movements on inflationary pressures. Furthermore, leading up to “high inflation” episodes, there's a discernible trend of exchange rate depreciation intensifying in middle-income countries, and even evident in high-income countries where the 75th quartile's increase is notable. Notably, the emergence of “high inflation” can be attributed to a combination of factors, including elevated energy and food inflation rates, as well as a pronounced increase in exchange rate depreciation observed in the preceding year. Concurrently, economic growth tends to diminish during periods of “high inflation,” highlighting the adverse effects that elevated price levels can have on overall economic activity.

Figure 2.2.3. Determinants of "first" "high inflation" occurrence

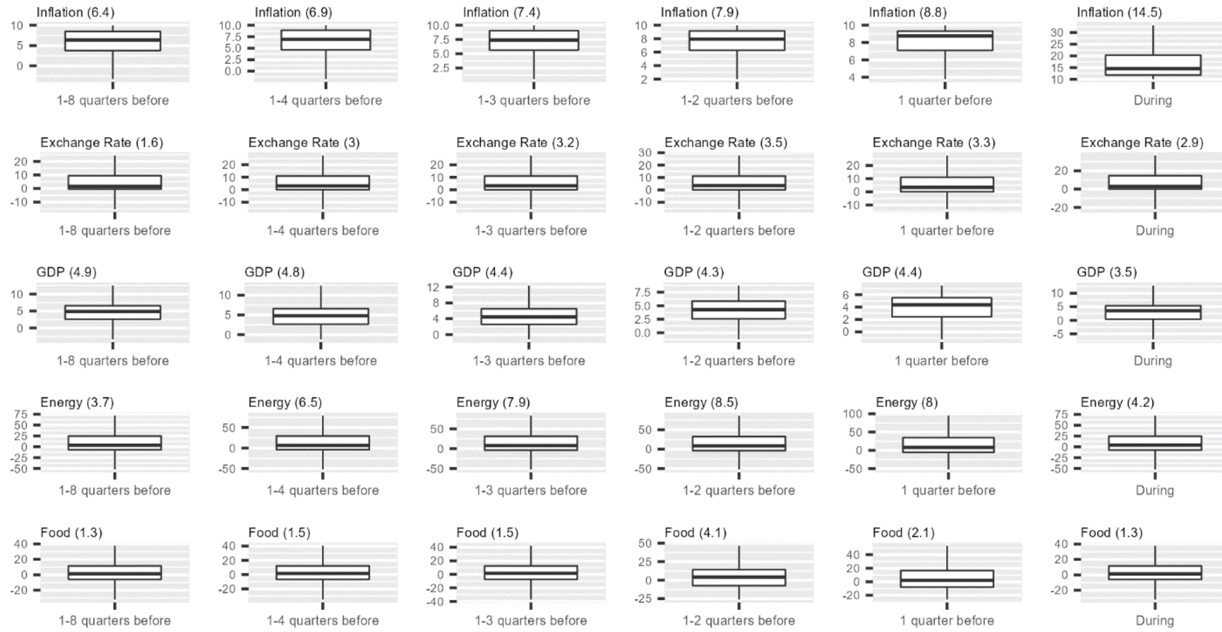
A. High-income



B. Upper middle-income



C. Lower middle-income



Source: Authors' calculation.
Note:

- Pharantesis in each subtitle displays median values.
- Plots display 54 countries" (23 High income, 23 Upper middle income, and 8 Lower middle-income) observations.
- The x-axis is labeled as: "During" for the "high inflation" period and "1-n quarter(s) before" for the distribution of variables in 1 to n quarters before the "high inflation" period.

Furthermore, upper-middle-income countries are more susceptible to experiencing higher median values of "high inflation" compared to other income groups. Similar characteristics are also evident in exchange rate depreciation. Moreover, other determinants show that, while upper-middle-income countries might be influenced by relatively higher food prices, lower-middle-income countries' "high inflation" episodes might be more strongly influenced by relatively high energy inflation compared to other income groups. Additionally, both high-income and upper-middle-income countries might be influenced by relatively robust growth in the previous year.

As depicted in Figure 2.2.3, exchange rate depreciation consistently demonstrates significantly higher levels throughout the entire "high inflation" period in comparison to the pre- "high inflation" period. It is essential to note that this observation does not necessarily imply a just-in-time exchange rate pass-through or simultaneous causality. Since the "during" period encompasses not just a single quarter but all consecutive "high inflation" quarters within a year, the standard lag-lead-related suggestions derived from this section of the box plot are not applicable. To delve deeper into this, consider Table 2.2.1, which illustrates that the median values during the period are higher than those from one quarter before, consistent with the trends in the box plots above. However, as indicated in the table, there is no evidence of a just-in-time pass-through or simultaneous causality whereby inflation directly leads to higher depreciation.

Table 2.2.1. “High inflation” box plot understanding

		1-quarter before	During				1-quarter after
		2021Q4	2022Q1	2022Q2	2022Q3	2022Q4	2023Q1
Actual values	Inflation	8	11	12	13	10	9
	Depreciation	5	7	9	7	4	4
Median	Inflation	8	11.5				9
	Depreciation	5	7				4

Instead, such findings emphasize the importance of exchange rate depreciation in prolonging periods of elevated inflation. In other words, a sustained depreciation may push inflation to levels beyond the high threshold, a phenomenon we refer to as “beyond high.” To address what contributes to inflation rising beyond the “high” level, we shift our focus from boxplots to standard lag impacts. This means that “high inflation” at time t is associated with determinants at time t, t-1, and t-n. Additionally, we now examine not only the initial spikes in “high inflation” but also later high cases. For example, if inflation remains high throughout 2022, one quarter before the period for 2022Q4 is 2022Q3 (as opposed to the 2021Q4 reference in the boxplot analysis). Therefore, the formulation for analyzing cases “beyond high” is as follows:

During “high inflation”: $\bigcup_{i=1}^{k} \Delta X_t$ (4)

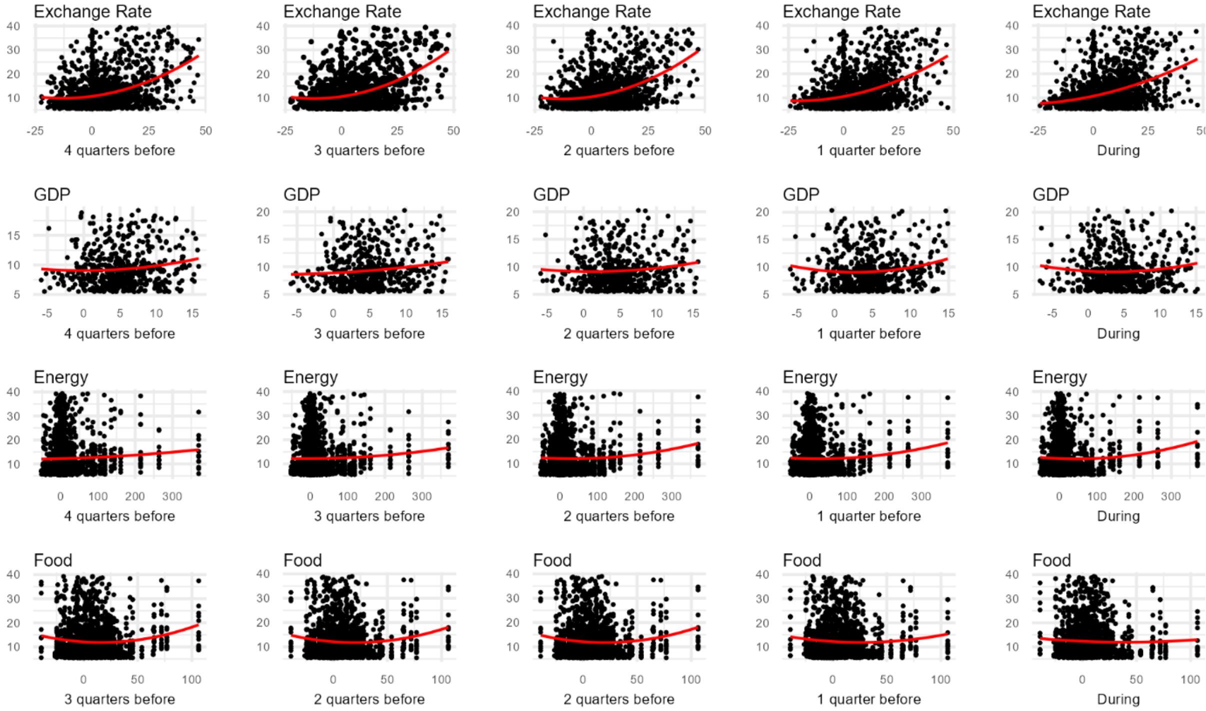
n quarter(s) before the “high inflation” period: $\bigcup_{i=1}^{k} \Delta X_{t-n}$ (5)

, where X is inflation determinants; Δ identifies annual percentage change and $\bigcup_{i=1}^{k} \Delta X$ is inflation determinants” bundle for each income group that has k number of countries. It should be highlighted that, unlike boxplots, the "n quarter(s) before" period may intersect with the “high inflation” period for each country.

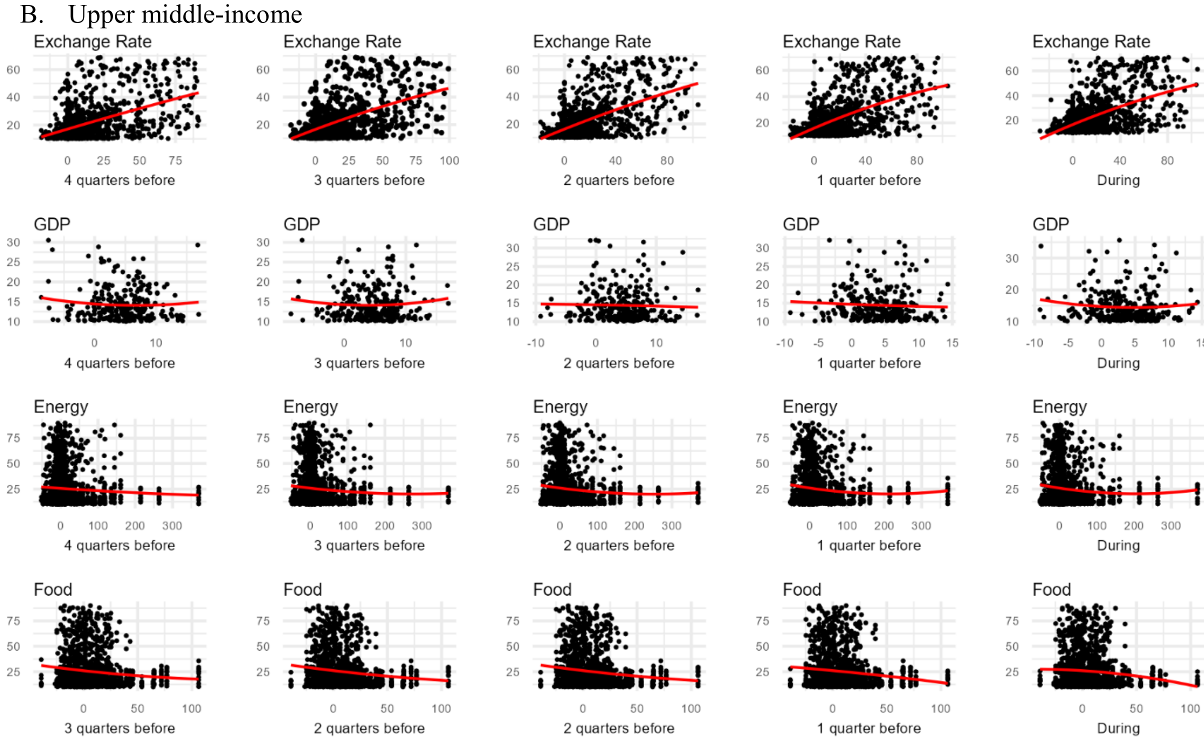
As in boxplot analysis, the bundle for each income group significantly suffers from country-specific outliers. Thus, outliers in the plots are excluded using Tukey's fences method, except for energy and food hikes.

Figure 2.2.4. Determinants of "beyond high inflation"

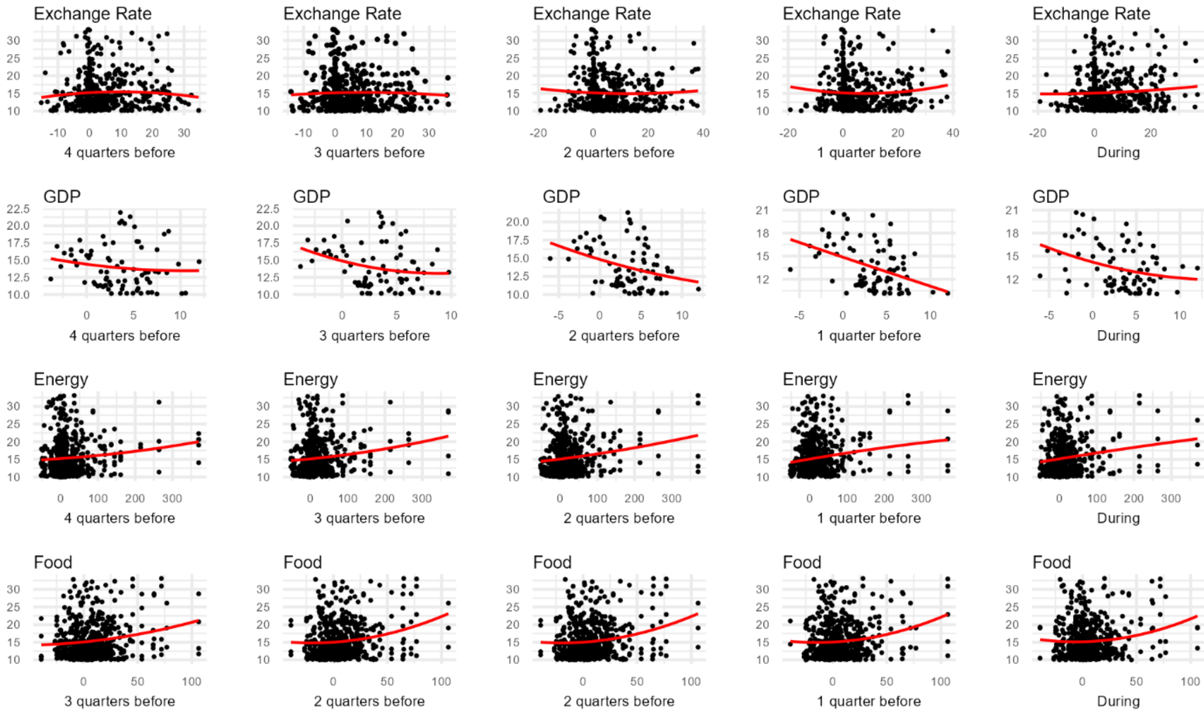
A. High-income



B. Upper middle-income



C. Lower middle-income



The red line is a quadratic (degree-2 polynomial) regression line between inflation and its determinants.

Source: Authors' calculation.

Note:

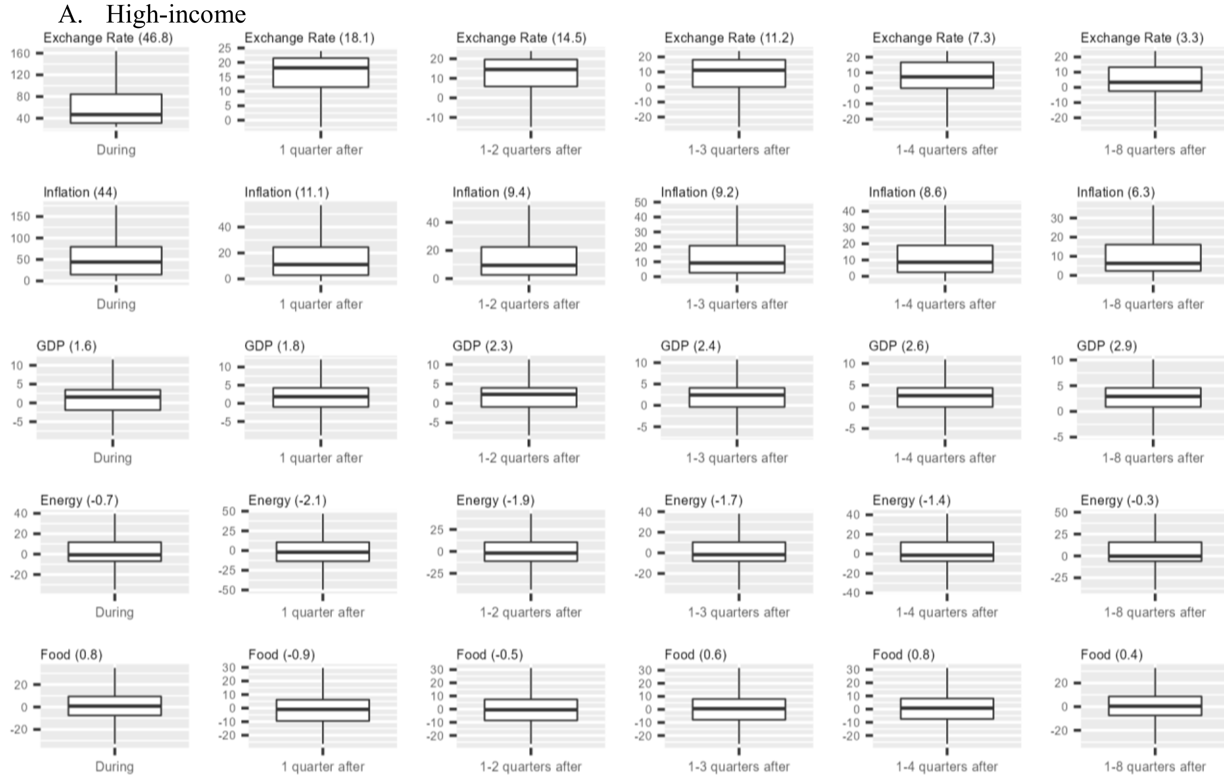
- The y-axis in each graph displays inflation values, while the x-axis shows associated determinants.
- Plots display 54 countries" (23 High income, 23 Upper middle income, and 8 Lower middle-income) observations.
- The x-axis is labeled as: "During" when "high inflation" at time t is associated with its determinants at time t, "n quarter(s) before" if "high inflation" at time t is related to determinants at time t-n.
- For large-scale graphs depicting the relationship between exchange rates and inflation, please refer to Figure A.2.1 in the Appendix, which shows that the relationship is more powerful at either a two-lag or one-lag interval.

According to Figure 2.2.4., "beyond high" inflation is frequently and, in most countries, an exchange rate phenomenon. More interestingly, the exchange rate impact elasticity is high, especially in upper-middle and high-income countries. These findings, with the boxplots above, strengthen our analysis in the sense that "high inflation" is mostly an exchange rate phenomenon, even in advanced economies. Moreover, energy and food inflation are fueling beyond the "high inflation" except for upper-middle-income countries. On the other hand, demand is not a part of "high inflation" stories, as pointed out in the supply-focused approach, except for high-income countries.

Observing a distinct pattern linking inflation to exchange rate depreciation across nearly all countries prompts us to delve deeper into the periods characterized by significant exchange rate depreciation. Given the scarcity of literature defining what is "high" exchange rate depreciation, we turn to Caselli and Roitman's (2019) threshold value of 24%.[4] This study, being one of the most recent and well-developed works in this domain, serves as a reference point for defining a "high" exchange rate depreciation threshold. The rationale underlying this analysis is to validate the robustness of our hypothesis, which posits that "high inflation" is primarily a result of exchange rate depreciation. By examining cases of high depreciation and verifying whether they consistently lead to "high inflation," we are essentially working in reverse to test the validity of our hypothesis. This approach adds an additional layer of confirmation to our findings and strengthens our understanding of the causal relationship between exchange rate movements and "high inflation."

Figure 2.2.5. Distribution of inflation determinants during and after high depreciation episodes

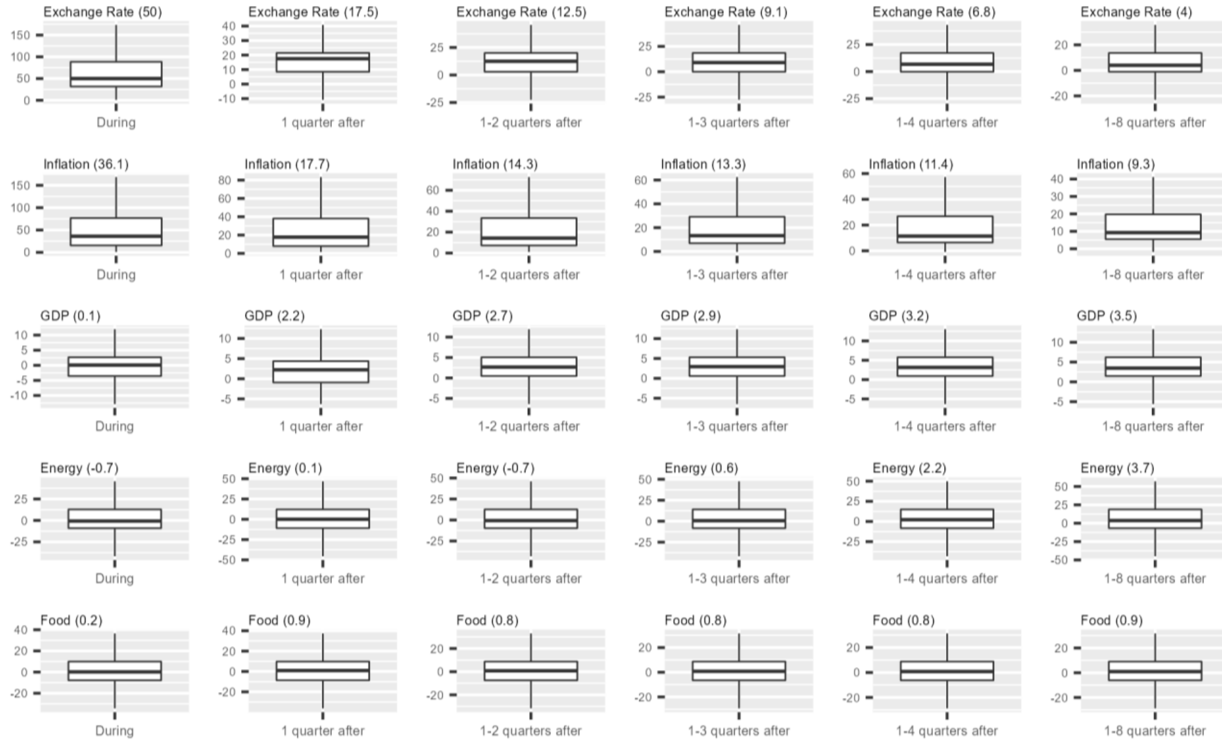
A. High-income



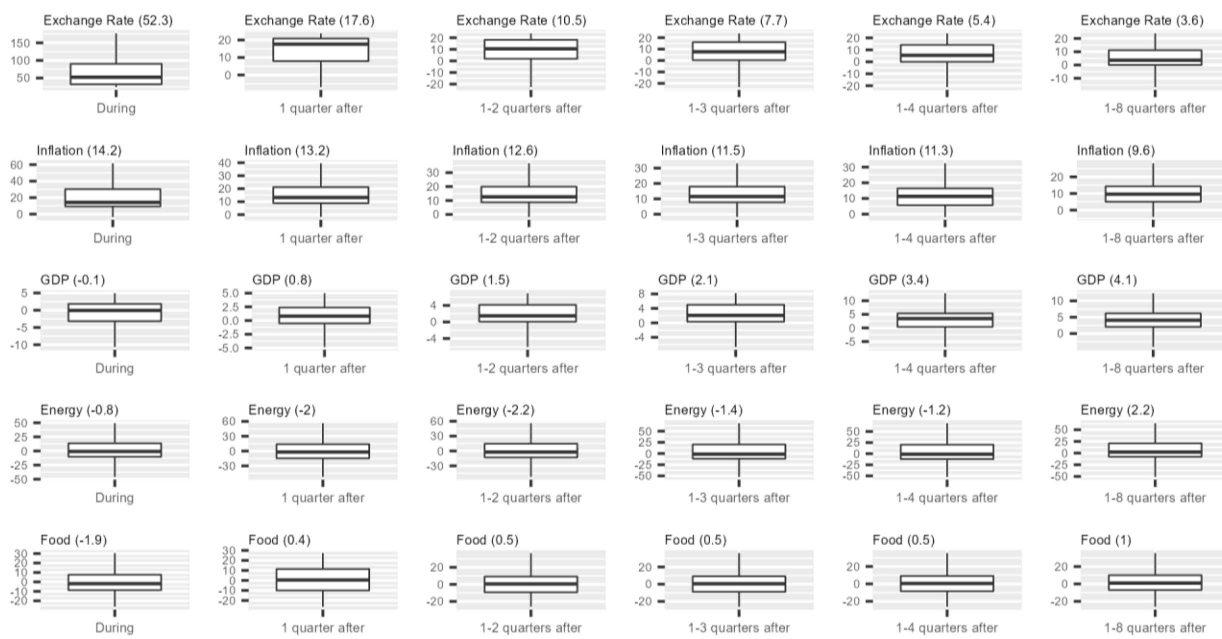
---

[4]In both cases of high inflation and depreciation, when using values of different yet similar magnitudes rather than relying on exact threshold values from the literature, it does not significantly impact the primary findings derived from the descriptive analyses.

B. Upper middle-income



C. Lower middle income



Source: Authors' calculation.

Note:

- Pharantesis in each subtitle displays median values.
- Plots display 54 countries" (23 High income, 23 Upper middle income, and 8 Lower middle-income) observations.

- The x-axis is labeled as: "During" for the high depreciation period and "1-n quarter(s) after" for the distribution of variables in 1 to n quarters after the high depreciation against USD.

As seen in Figure 2.2.5., high exchange rate depreciations consistently lead to “high inflation” levels, reinforcing the notion that this relationship holds true universally. While 47% high devaluation is associated with 44% inflation in high-income countries, the observed inflation median is 8 times higher than the “high inflation” threshold for such economies. In upper-middle-income countries, associated values are 50% depreciation and 36% inflation, which is 3.6 times higher than the group-specific inflation threshold. In lower-middle-income countries, the values are 52% depreciation and 14% inflation. A fascinating observation arises when considering the income level differences. Despite an increase in depreciation, there isn’t a corresponding parallel rise in inflation as income level decreases. However, the mystery unravels when analyzing later quarters. In these subsequent periods, the persistence of “high inflation” is more pronounced in upper-middle-income economies compared to high-income ones. This nuanced observation highlights that while depreciation is not the sole catalyst for the initial "high" spike in inflation, it does play a pivotal role in sustaining “high inflation” episodes. Of particular note is the extended impact of significant exchange rate shocks, with “high inflation” persisting for up to a year after substantial depreciation events, even when commodity prices later decline.

Thanks to descriptive analyzes, we conclude that:

- The elevated energy and food inflation and increasing exchange rate depreciation trend in the previous year clearly explain the emergence of “high inflation.”
- Exchange rate depreciation increases toward “high inflation” episodes in most economies.
- High exchange rate depreciations always and everywhere result in “high inflation.”
- Inflation remains high a year after the high depreciation shocks in almost all countries, even commodity prices decrease.
- High and beyond “high inflation” are frequently and, in most countries, an exchange rate phenomenon.

3. Panel Probit Model

In empirical research, the selection of an appropriate econometric model assumes paramount importance as it holds the key to unraveling complexities embedded within intricate datasets. In our pursuit to discern the underlying drivers of “high inflation”—a phenomenon of considerable economic significance—we conducted a meticulous evaluation of various econometric models to identify the one that aligns most effectively with the distinctive goals of our research.

Central to our investigation is the aspiration to unravel the intricate web of factors contributing to "high inflation." What sets our study apart is its deliberate categorization of inflation into two discrete tiers: "high inflation" and non-"high inflation" levels. Within this context, the panel probit model acknowledged for its adeptness in managing binary response variables, emerges as the apt choice to cater to the precise nature of our research objectives. By categorizing inflation levels into binary outcomes of "high" and "non-high," the panel probit model seamlessly aligns with our endeavor to discern the determinants underpinning "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 23, 23, and 8 countries in high-, upper-, and middle-income groups, respectively, and each country has its own unique dynamics, we should be aware of the individual-specific effects. 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 is the random effects model. This can be particularly useful when dealing with unbalanced panel data as it provides efficient estimates even when the unbalanced nature of the data remains.

Moreover, panel probit random effects models are designed to strike a balance between fixed effects (which are more flexible but can be less efficient) and pooled models (which are more efficient but less flexible). Random effects models allow for individual-specific effects to be modeled as a combination of fixed and random components, which balances the trade-off between efficiency and flexibility. Thus, Random effects models aim to provide more generalized estimates of the relationships between variables across all countries by capturing common effects while still accounting for individual differences. This allows for more generalizable insights compared to fixed effects models that only capture unit-specific effects.

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:

$$P(y_{it} = 1|X_{it}, X_{it-1}, \dots, X_{it-n}, \alpha_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \alpha_i) \quad (6)$$

, 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:

$$\alpha_i = \eta + \mu_i \quad (7)$$

, 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 (6) yields:

$$P(y_{it} = 1|X_{it}, X_{it-1}, \dots, X_{it-n}, \eta, \mu_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \eta + \mu_i) \quad (8)$$

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 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 variable, leading to biased and inconsistent parameter estimates.

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.

For selecting optimal lags, literature generally refers to three main criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion, and MacFadden's pseudo-R-squared. 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. The AIC, designed to find models that fit data well, often favors complexity by being less strict in penalizing the likelihood as parameters increase. This inclination can inadvertently steer the selection toward models that inadvertently capture noise in the data rather than the genuine underlying patterns. Overfitting becomes a concern when a model becomes too attuned to the noise within the training data, which can subsequently hinder its performance in generalizing to new and unseen data. Hence, a prudent approach to model selection is crucial to strike a balance between the goodness of fitting and preventing overfitting.

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, 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, serves as a measure of how well the model explains the variation in the binary outcomes compared to a null model. Although not without its limitations, this metric provides insights into the proportion of variation that the model captures and offers a benchmark for evaluating the explanatory power of different models. 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.

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, 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 2013 to 2023, a span chosen independently from the estimation sample covering 1961 to 2012. 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. However, relying solely on Root Mean Squared Error (RMSE) for lag selection in your probit model might not provide a complete understanding of model performance. Probit models are designed to predict probabilities, and RMSE on linear values does not fully capture their probabilistic nature. Other criteria like AIC, BIC, and pseudo-R-squared offer a more balanced approach, considering both model fit and complexity.

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, as in Table 3.1. (Detailed criterion results and rankings are presented in Table A.3 in the Appendix).

Table 3.1. Lag Selection

Group	Lag	AIC	AIC rank	BIC	BIC rank	Pseudo R2	Pseudo R2-rank	RMSE	RMSE -rank	**Total rank**
High income	**(2 - 6)**	1417.802	7	1546.701	6	0.481	7	1.099	8	**1**
High income	(1 - 7)	1395.446	2	1571.216	13	0.495	2	1.169	11	1
High income	(1 - 5)	1415.737	6	1544.636	5	0.482	6	1.180	12	3
High income	(2 - 5)	1443.898	9	1549.361	10	0.468	9	0.997	2	4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Upper middle-income*	(1 - 6)	696.968	2	837.606	11	0.566	3	1.640	9	1*
Upper middle-income	**(2 - 6)**	709.167	5	828.168	10	0.553	7	1.542	4	**2**
Upper middle-income	(1 - 7)	700.393	3	862.667	13	0.569	2	1.661	10	3
Upper middle-income	(2 - 7)	710.583	7	851.221	12	0.557	5	1.549	5	4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Lower middle-income	**(2 - 2)**	152.384	11	176.640	1	0.641	14	1.228	1	**1**
Lower middle-income	(2 - 3)	151.964	10	192.391	3	0.663	12	1.308	2	1
Lower middle-income	(2 - 4)	151.716	9	208.313	5	0.684	10	1.418	4	3
Lower middle-income	(2 - 5)	148.080	7	220.847	7	0.714	8	1.681	8	4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

* Optimization was unsuccessful for the whole time span of 1961-2023 for (1-6) lag combinations for upper-middle-income countries. Thus, the (2-6) lag combination is selected as best.

Based on the lag selection method applied, our analysis indicates that the impact of determinants on inflation starts with a delay of 2 quarters. Furthermore, our analysis reveals that the impacts of these determinants tend to persist for differing durations across different income groups. In high and upper-middle-income countries, the impact of determinants on inflation can last for up to 6 quarters. In contrast, the impact is more limited in lower-middle-income countries, where it lasts for only two quarters. This lag duration is theoretically sound and aligns with the price adjustment mechanisms discussed in the literature review section and descriptive statistics. Moreover, this finding is in line with previous research findings.

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 missing real GDP data for upper-middle-income countries between 1961-1992 and for lower-middle-income countries between 1961-1982, our estimations start from 1992 and 1982, respectively. The dataset encompasses 2804 observations for high-income countries, 1838 observations for upper-middle-income countries, and 484 observations for lower-middle-income countries. To derive these estimations, the random effects panel probit model is employed, utilizing the Maximum Likelihood method with Newton-Raphson maximization.

Table 4.1. Estimation results

A. High income

Number of Countries: 23
Total Observations: 2804
Period: 1961Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
6 iterations
Log-Likelihood: -961.4412
22 free parameters
Estimates:

	Coefficient	Std. error
Intercept	-1.6354***	(0.08069)
GDP (t-2)	0.03916**	(0.01420)
GDP (t-3)	0.01813	(0.01627)
GDP (t-4)	0.02888 .	(0.01640)
GDP (t-5)	0.01949	(0.01609)
GDP (t-6)	0.05789 ***	(0.01398)
FX (t-2)	0.05356***	(0.00741)
FX (t-3)	0.00092	(0.01049)
FX (t-4)	0.00197	(0.01060)
FX (t-5)	-0.0074	(0.01047)
FX (t-6)	0.04327***	(0.00737)
Energy (t-2)	0.00678**	(0.00252)
Energy (t-3)	0.00321	(0.00359)
Energy (t-4)	-0.0011	(0.00366)
Energy (t-5)	-0.0006	(0.00355)
Energy (t-6)	-0.0025	(0.00251)
Food (t-2)	0.02506***	(0.00508)
Food (t-3)	-0.0072	(0.00732)
Food (t-4)	0.00785	(0.00768)
Food (t-5)	-0.0107	(0.00752)
Food (t-6)	0.02220***	(0.00513)
sigma	0.81802***	(0.06665)

AIC Values: 1966.882
BIC Values: 2096.168
McFadden's Pseudo R-squared Values: 0.296655
In sample RMSE Values: 1.204597

B. Upper middle-income

Number of Countries: 23
Total Observations: 1838
Period: 1992Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
4 iterations
Log-Likelihood: -504.0573
22 free parameters
Estimates:

	Coefficient	Std. error
Intercept	-2.2403***	(0.12387)
GDP (t-2)	0.01139	(0.01830)
GDP (t-3)	-0.0020	(0.02099)
GDP (t-4)	0.05057*	(0.02090)
GDP (t-5)	-0.0004	(0.02072)
GDP (t-6)	0.05261**	(0.01778)
FX (t-2)	0.08338***	(0.00979)
FX (t-3)	-0.0091	(0.01324)
FX (t-4)	0.02187	(0.01340)
FX (t-5)	-0.0232 .	(0.01303)
FX (t-6)	0.05042***	(0.00909)
Energy (t-2)	0.01185***	(0.00359)
Energy (t-3)	0.00177	(0.00500)
Energy (t-4)	-0.0047	(0.00509)
Energy (t-5)	-0.0041	(0.00477)
Energy (t-6)	0.00154	(0.00337)
Food (t-2)	0.03102***	(0.00740)
Food (t-3)	-0.0174	(0.01099)
Food (t-4)	0.01909 .	(0.01114)
Food (t-5)	-0.0061	(0.01063)
Food (t-6)	0.01720*	(0.00729)
sigma	0.89933***	(0.08874)

AIC Values: 1023.131
BIC Values: 1164.483
McFadden's Pseudo R-squared Values: 0.3704353
In sample RMSE Values: 1.639812

C. Lower middle-income

Number of Countries: 8
Total Observations: 484
Period: 1982Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
5 iterations
Log-Likelihood: -136.2941
6 free parameters
Estimates:

	Coefficient	Std. error
Intercept	-0.8650***	(0.17673)
GDP (t-2)	-0.0645*	(0.02677)
FX (t-2)	0.07238***	(0.01203)
Energy (t-2)	0.00579	(0.00379)
Food (t-2)	0.0291***	(0.00776)
sigma	1.26266***	(0.19576)

AIC Values: 284.5881
BIC Values: 309.054
McFadden's Pseudo R-squared Values: 0.3441554
In sample RMSE Values: 1.108571

*** 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. GDP shocks at time t significantly imply the emergence of "high inflation" in high-income countries within 2 and 6 quarters and after 4 and 6 quarters for upper-middle-income countries. While the coefficient related to GDP shocks at a time "t" is significant for lower-middle-income countries, it is crucial to note that the sign of the coefficient doesn't align with the expected theoretical relationship between demand and inflation. This observation could stem from data quality issues within lower-middle-income countries' datasets or could be indicative of the fact that demand factors do not typically contribute to "high inflation" episodes in these countries.

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 within a span of 2 quarters across all income categories. Furthermore, it's noteworthy that the influence of exchange rate depreciation can extend over a more prolonged period, up to 6 quarters, in high and upper-middle-income countries. This temporal pattern is consistent with the insights gained from the analysis of "high inflation" persistence discussed in section 2. Additionally, these findings 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 levels of inflation in energy and food commodities also serve as indicators of potential "high inflation" within a 2-quarter timeframe for both high and upper-middle-income countries. Notably, similar to the impact of exchange rate depreciation, the influence of elevated food commodity prices can persist for up to 6 quarters. This observation underscores the potential implications for "high inflation" persistency, as discussed previously. In the context of lower-middle-income countries, the results reveal that energy inflation does not carry a significant impact on "high inflation" episodes. However, it is interesting to note that the inflation in food commodities at a lag of two quarters holds significance at a confidence interval of 99.9%. This finding highlights the potentially distinct role of food commodity prices in influencing "high inflation" within this specific income group, aligning with Akcelik and Comert's (2022) suggestion.

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):

$$\textit{Predicted Probability}^* = \begin{cases} \textit{1, if predicted probability} > 0.5 \\ \textit{0, otherwise} \end{cases} \tag{9}$$

$$\textit{Model Evaluation} \rightarrow \begin{cases} \textit{Success, if actual probability = predicted probability}^* \\ \textit{Failure, otherwise} \end{cases} \tag{10}$$

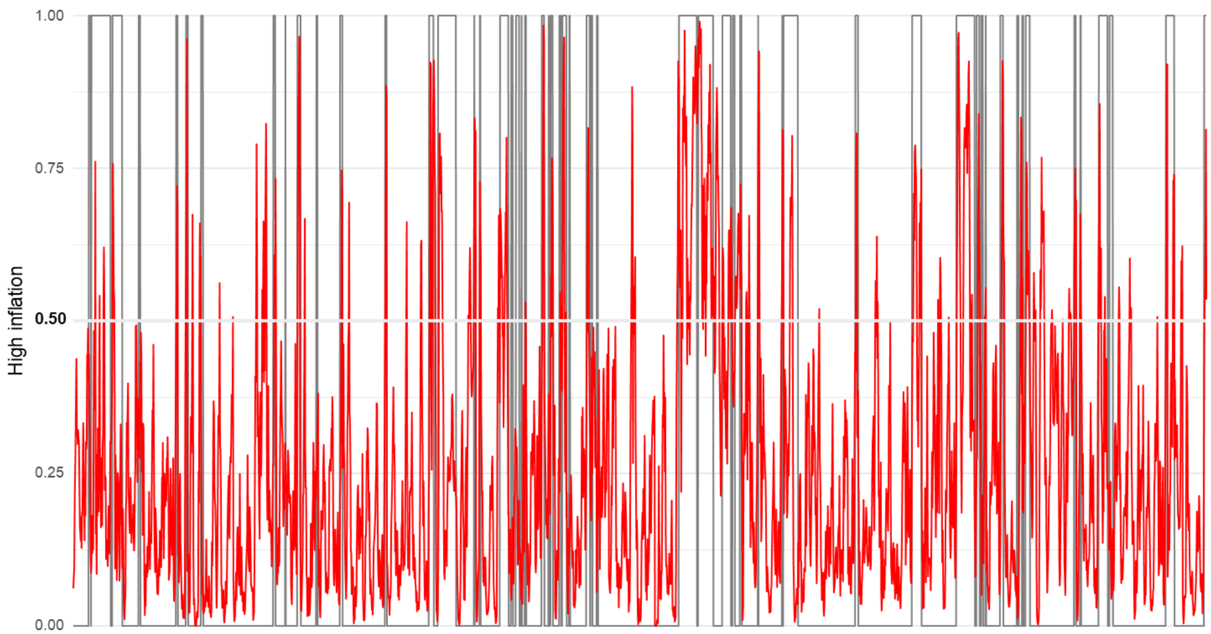
Based on the model results and evaluation criteria, the model demonstrates an 83% success rate in accurately predicting instances of high and non-"high inflation" in high-income countries.

Furthermore, this success rate improves to 86% for upper-middle-income countries and remains at 84% for lower-middle-income countries, as illustrated in Figure 4.1.[5]

Taking into account the favorable outcomes in predicting "high inflation" episodes within different income groups and the statistical significance of the model coefficients, we can draw the following conclusion: As a reliable early warning indicator, elevated levels of energy and food commodity inflation, along with exchange rate depreciation, serve as clear signals of the emergence of "high inflation" within a span of two quarters. These determinants exhibit consistent and robust relationships with "high inflation" episodes across varying income categories.

Figure 4.1. Actual "high inflation" episodes vs. predicted probabilities

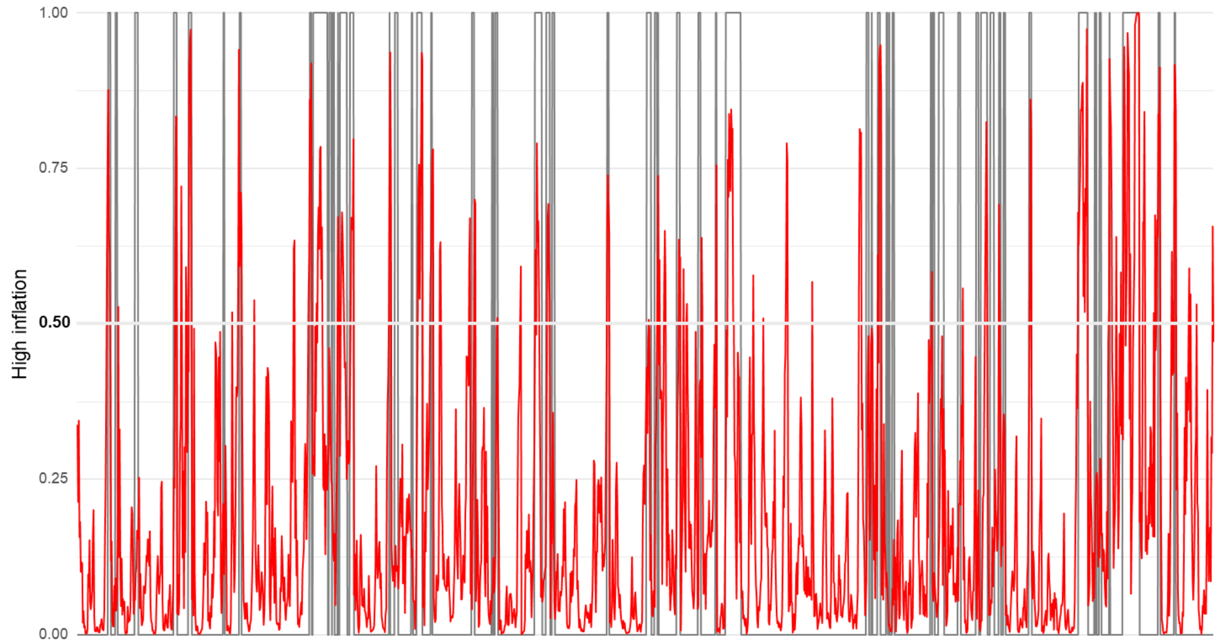
A. "high inflation" probability within High income group



Model Evaluation: 83% success

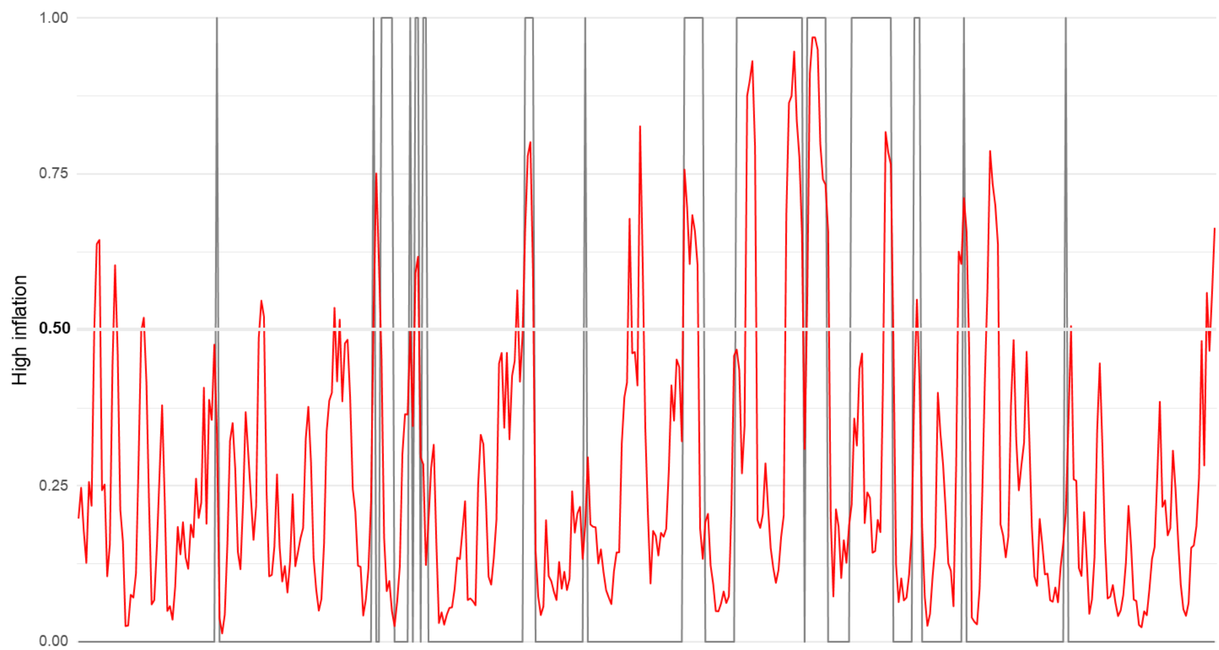
[5] In the depicted plots, each income group's countries are arranged in ascending order of year along the x-axis, while the y-axis represents the probability of "high inflation."

B. “high inflation” probability within the Upper middle-income group



Model Evaluation: 86% success

C. “high inflation” probability within the Lower middle-income group



Model Evaluation: 84% success

High inflation episodes   High inflation probabilities (predicted probabilites)

Source: Authors’ calculation

Taking a step forward, we computed the probabilities of “high inflation” in response to deviations of inflation determinants from the mean. In this regard, we evaluated deviations ranging from 0 to

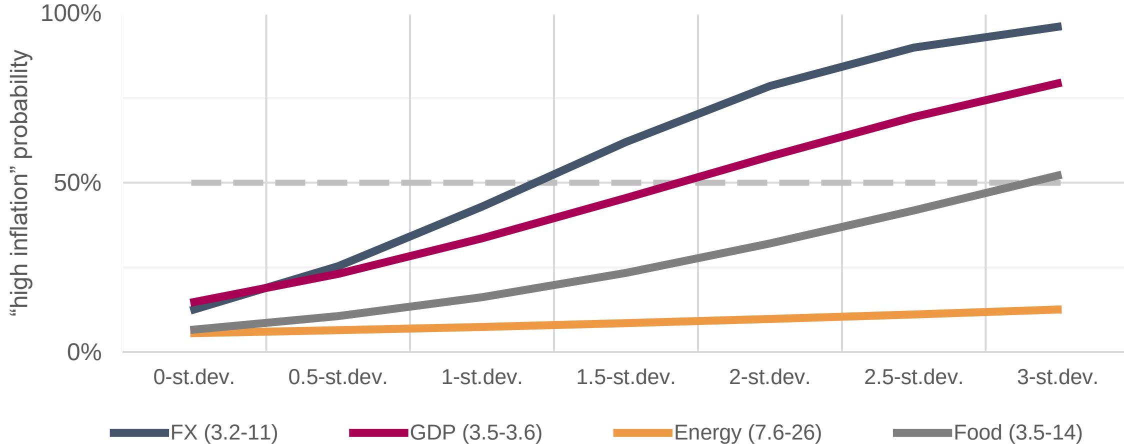
3 standard deviations from the mean, with intervals of 0.5 points. Figure 4.2 reveals that exchange rate deviations from the mean serve as the most explanatory variable for occurrences of "high inflation." To delve deeper, approximately more than a 1.25 positive standard deviation of the exchange rate (equivalent to around 18% depreciation) during the last 4 quarters signals a high possibility (over 50%) of "high inflation" in the following 2 quarters. Furthermore, roughly 25% depreciation (approximately 2 positive standard deviations) acts as a strong indicator, forecasting "high inflation" in the subsequent quarters with a probability exceeding 75% in all analyzed countries. When depreciation surpasses 35%, the likelihood of "high inflation" sharply rises to 99% in upper-middle-income, 96% in high-income, and 93% in lower-middle-income countries. These findings once again confirm that exchange rates are the primary determinant of "high inflation" in nearly every context.

On the other hand, other inflation determinants do not offer distinct patterns that can be universally regarded as global drivers of "high inflation." For instance, in high-income countries, demand serves as a driver of "high inflation," where a 1.75 positive standard deviation in GDP growth (approximately 10%) during the last 4 quarters predicts "high inflation" within two quarters with more than 50% probability. However, a growth magnitude of up to 3 standard deviations does not necessarily imply a high probability of "high inflation" occurring in upper- and lower-middle-income economies (only 30% and 3%, respectively).

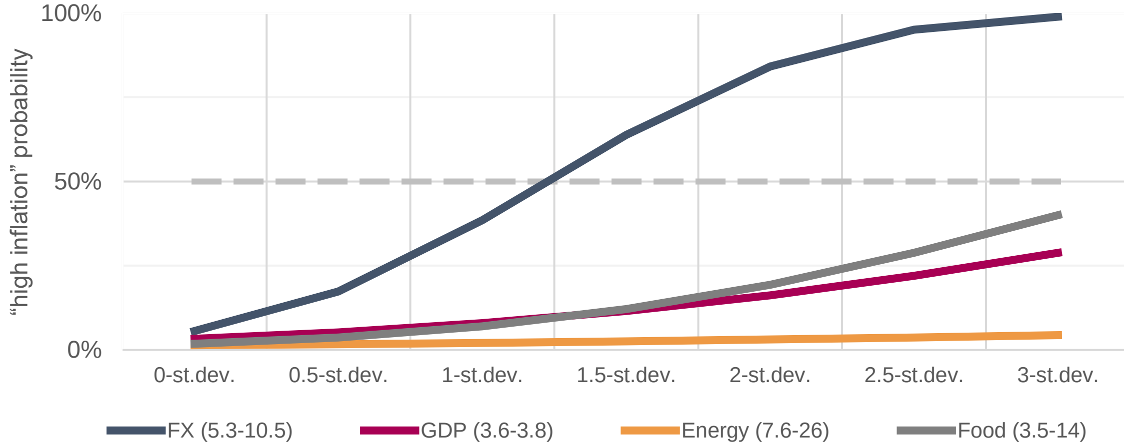
Moreover, food commodity inflation plays a crucial role in predicting inflation, particularly in lower-middle-income countries, where a deviation of more than 1.75 positive standard deviations in food commodity inflation (around 30%) during the last 4 quarters forecasts "high inflation" within two quarters 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 more than 3 standard deviations. On the other hand, energy price shocks predict "high inflation," with a 25% probability in lower-middle-income economies when energy inflation rises more than 40%. However, the impact is not significantly pronounced in other income groups, aligning with the findings of Kilian and Zhou (2022) and Ye et al. (2023) and also synchronizes 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.

Figure 4.2. "high inflation" probabilities in response to shocks to determinants

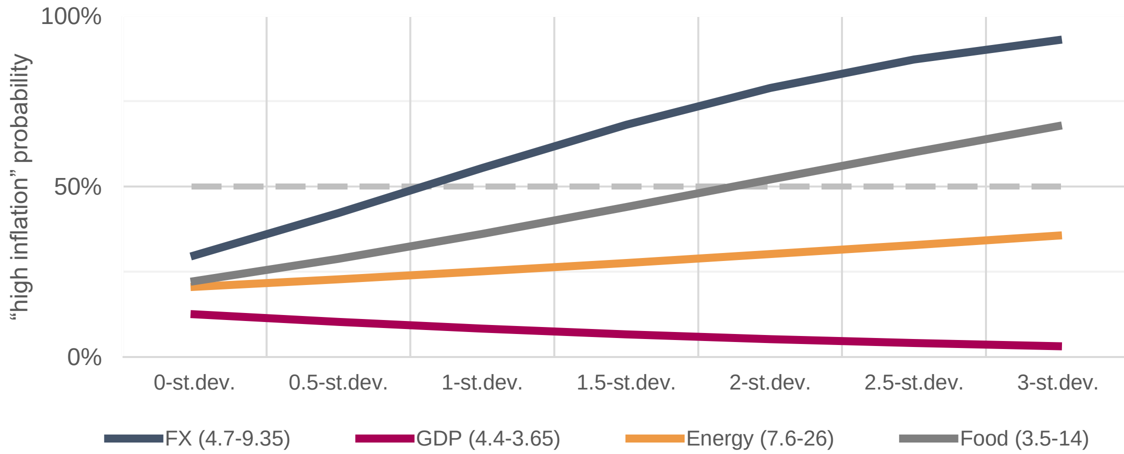
A. "high inflation" probability within High income group



B. "high inflation" probability within the Upper middle-income group



C. "high inflation" probability within the Lower middle-income group



Source: Authors' calculation

Note:

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

5. Discussion

In the realm of well-developed Phillips curve analysis, it is commonly perceived that the GDP gap holds more utility as a variable than GDP growth. However, the decision to opt for the GDP gap or GDP growth in modeling, particularly in the context of the Phillips curve for inflation analysis, hinges on a variety of factors, including the specific research objectives, the underlying economic theories being tested, and the availability of data. Each variable carries its own set of advantages and considerations.

The GDP gap represents the disparity between the actual GDP and the potential GDP, which signifies the level of output achievable when all resources are optimally utilized. This metric captures the cyclical fluctuations that the economy undergoes around its potential output. Within the framework of the Phillips curve, the GDP gap can be harnessed to account for the influence of the business cycle on inflation. By incorporating the GDP gap, it becomes feasible to isolate the short-term cyclical impacts from the long-term trends, thus facilitating a better understanding of inflation dynamics. This separation allows for an assessment of how much an economy is operating below or above its potential, which can offer valuable insights when evaluating inflationary pressures.

Indeed, estimating potential GDP is a complex endeavor that involves making assumptions about trend growth rates and potential output levels. This complexity can introduce a degree of uncertainty into the analysis, as accurately measuring the output gap becomes a challenge due to variations in the methodologies employed. While methodologies like the Hodrick-Prescott (HP) filter or the Kalman Filter are commonly used for detrending GDP data, the resulting gap estimates can differ significantly. Factors such as the choice of lambda value in the HP filter or initial conditions in the Kalman filter can lead to divergent outcomes in gap estimation. Thus, such unobserved variables may distort the true relationship between inflation and demand.

On the other hand, GDP growth represents the rate of change in the overall economic output of a country. It is a more straightforward measure that directly reflects economic activity. GDP growth encapsulates both cyclical and structural transformations within the economy, making it a comprehensive indicator of economic performance. This metric is easily obtainable from commonly available economic data sources. However, it's important to note that GDP growth amalgamates cyclical and structural changes, potentially blurring the distinction between short-term fluctuations and longer-term trends that are typical in the context of the Phillips curve.

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. As a result, we opted to initiate our analysis with GDP growth, a directly observable variable that offers greater reliability compared to 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 5.1, the GDP gap does not exhibit statistical significance in high-income countries when compared to the results obtained from the GDP growth-based model. However, the other determinant variables maintain their significance within the gap-based probit model. Interestingly, 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. Moreover, the AIC, BIC, and RMSE values are consistently higher in the gap-based model, with the exception of RMSE in high-income countries.

Table 5.1. Estimation results for Panel Probit model with GDP gap

A. High income

Number of Countries: 23
Total Observations: 2804
Period: 1961Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
7 iterations
Log-Likelihood: -1016.812
[**-961.4412**]
22 free parameters
Estimates:

	Coefficient	**Std. error**
Intercept	-0.9778***	(0.0511)
GDP (t-2)	0.00134	(0.01697)
GDP (t-3)	0.01206	(0.01773)
GDP (t-4)	0.01927	(0.01776)
GDP (t-5)	0.00911	(0.01744)
GDP (t-6)	0.02227	(0.01666)
FX (t-2)	0.04782***	(0.00713)
FX (t-3)	0.00029	(0.01015)
FX (t-4)	0.00139	(0.01026)
FX (t-5)	-0.0078	(0.01012)
FX (t-6)	0.038***	(0.00714)
Energy (t-2)	0.00659**	(0.00242)
Energy (t-3)	0.0029	(0.00342)
Energy (t-4)	-0.0004	(0.00349)
Energy (t-5)	-0.0000	(0.00339)
Energy (t-6)	-0.0015	(0.00242)
Food (t-2)	0.02291***	(0.00489)
Food (t-3)	-0.0059	(0.00707)
Food (t-4)	0.00611	(0.00740)
Food (t-5)	-0.0083	(0.00727)
Food (t-6)	0.01948***	(0.00498)
sigma	0.9081***	(0.08597)

AIC Values: 2077.624
[**1966.882**]
BIC Values: 2206.91
[**2096.168**]
McFadden's Pseudo R-squared Values:
0.2561485 [**0.296655**]
In sample RMSE Values: **1.065024**
[1.204597]

B. Upper middle-income

Number of Countries: 23
Total Observations: 1838
Period: 1992Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
10 iterations
Log-Likelihood: -515.834
[**-504.0573**]
22 free parameters
Estimates:

	Coefficient	**Std. error**
Intercept	-2.3145***	(0.13019)
GDP (t-2)	-0.0015	(0.02262)
GDP (t-3)	0.00645	(0.02384)
GDP (t-4)	0.05029*	(0.02380)
GDP (t-5)	-0.0056	(0.02327)
GDP (t-6)	0.04642*	(0.02203)
FX (t-2)	0.07434***	(0.00942)
FX (t-3)	-0.0084	(0.01289)
FX (t-4)	0.01861	(0.01303)
FX (t-5)	-0.0212 .	(0.01272)
FX (t-6)	0.04250***	(0.00886)
Energy (t-2)	0.01139**	(0.00352)
Energy (t-3)	0.00124	(0.00491)
Energy (t-4)	-0.0045	(0.00500)
Energy (t-5)	-0.0037	(0.00468)
Energy (t-6)	0.0019	(0.00331)
Food (t-2)	0.03108***	(0.00728)
Food (t-3)	-0.0170	(0.01085)
Food (t-4)	0.01824 .	(0.01100)
Food (t-5)	-0.0050	(0.01050)
Food (t-6)	0.01616*	(0.00719)
sigma	0.73547***	(0.08296)

AIC Values: 1075.668
[**1023.131**]
BIC Values: 1195.274
[**1164.483**]
McFadden's Pseudo R-squared Values:
0.3311903 [**0.3704353**]
In sample RMSE Values:
1.981838 [**1.639812**]

C. Lower middle-income

Number of Countries: 8
Total Observations: 484
Period: 1982Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
5 iterations
Log-Likelihood: -137.8647
[**-136.2941**]
6 free parameters
Estimates:

	Coefficient	**Std. error**
Intercept	-1.1392***	(0.12995)
GDP (t-2)	-0.0594	(0.03628)
FX (t-2)	0.07557***	(0.01193)
Energy (t-2)	0.00500	(0.00377)
Food (t-2)	0.02970***	(0.00770)
sigma	1.32983***	(0.19323)

AIC Values: 287.7294
[**284.5881**]
BIC Values: 312.1953
[**309.054**]
McFadden's Pseudo R-squared Values:
0.3365974 [**0.3441554**]
In sample RMSE Values: 1.109566
[**1.108571**]

*** 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 determining the preferred model based on the criterion of higher Log-Likelihood and McFadden's Pseudo R-squared values and lower AIC, BIC, and RMSE values, the Panel Probit model utilizing GDP growth emerges as the more robust choice. This trend could be attributed to the utilization of a single lambda value of 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 GDP gap estimates. Hence, it is conceivable that if optimal lambda values were identified or well-estimated GDP gap measures were available, the integration of the gap variable might enhance the robustness of this research's findings.

In the previous sections and even in the gap-based model, we demonstrated the significant influence of exchange rate fluctuations on “high inflation” episodes in all analyzed countries. However, can we go a step further and examine a stronger hypothesis: Is it possible that exchange rate depreciation alone can account for the occurrence of “high inflation” across the globe without the need to consider other determinants? In simpler terms, could the majority of “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 upper- and lower-middle-income economies, which can provide valuable insights for our investigation.

According to the results presented in Table 5.2, similar to the complete model, the exchange rate retains its significance for the same lags. 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 83% success rate of the complete model. In upper-middle-income countries, the corresponding figures are 77% and 86%, while for lower-middle-income countries, they are 67% and 84%. These results strongly indicate that exchange rate depreciation is a primary driver of “high inflation.” These findings align with the supply-focused approach discussed in section 1, further confirming that “high inflation” is frequently and almost universally an exchange rate phenomenon.”

Table 5.2. Estimation results of the Random Effects Panel Probit Model only depend on Exchange Rate

A. High income

Number of Countries: 23
Total Observations: 5454
Period: 1961Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
6 iterations
Log-Likelihood: -2696.188
7 free parameters
Estimates:

	Coefficient	Std. error
Intercept	-0.3248***	(0.02957)
FX (t-2)	0.03303***	(0.00428)
FX (t-3)	-0.0042	(0.00644)
FX (t-4)	0.00092	(0.00656)
FX (t-5)	-0.0076	(0.00644)
FX (t-6)	0.02105***	(0.00428)
sigma	0.57564***	(0.04723)

AIC Values: 5406.377
BIC Values: 5451.724
McFadden's Pseudo R-squared Values:
0.1565678
In sample RMSE Values: 0.7622262

B. Upper middle income

Number of Countries: 23
Total Observations: 4816
Period: 1961Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
4 iterations
Log-Likelihood: -2143.019
7 free parameters
Estimates:

	Coefficient	Std. error
Intercept	-0.9241***	(0.04099)
FX (t-2)	0.05069***	(0.00464)
FX (t-3)	-0.0049	(0.00683)
FX (t-4)	0.00377	(0.00690)
FX (t-5)	-0.0117 .	(0.00676)
FX (t-6)	0.03672***	(0.00460)
sigma	0.5018***	(0.07289)

AIC Values: 4300.039
BIC Values: 4344.64
McFadden's Pseudo R-squared Values:
0.2149138
In sample RMSE Values: 1.039929

C. Lower middle income

Number of Countries: 8
Total Observations: 1842
Period: 1961Q1 - 2023Q1

Maximum Likelihood estimation
Newton-Raphson maximization,
6 iterations
Log-Likelihood: -980.9964
3 free parameters
Estimate:

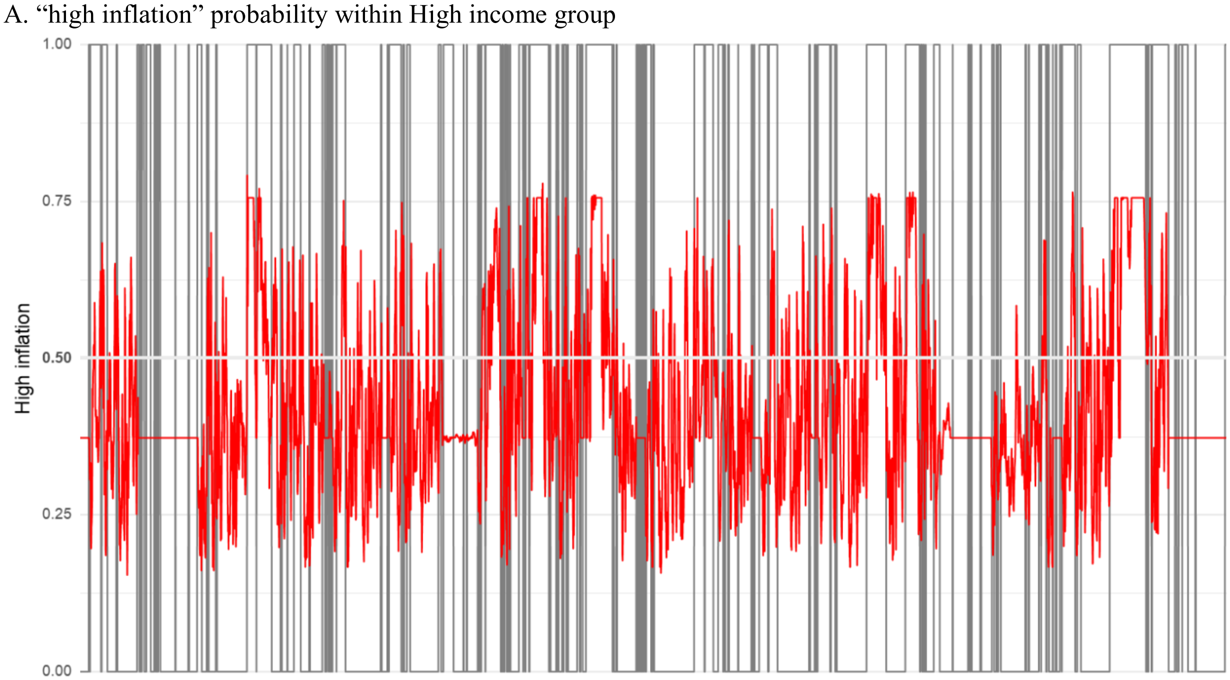
	Coefficient	Std. error
Intercept	-0.5329***	(0.05229)
FX (t-2)	0.03217***	(0.00386)
sigma	0.77342***	(0.09015)

AIC Values: 1967.993
BIC Values: 1984.281
McFadden's Pseudo R-squared Values:
0.1167229
In sample RMSE Values: 0.9135564

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

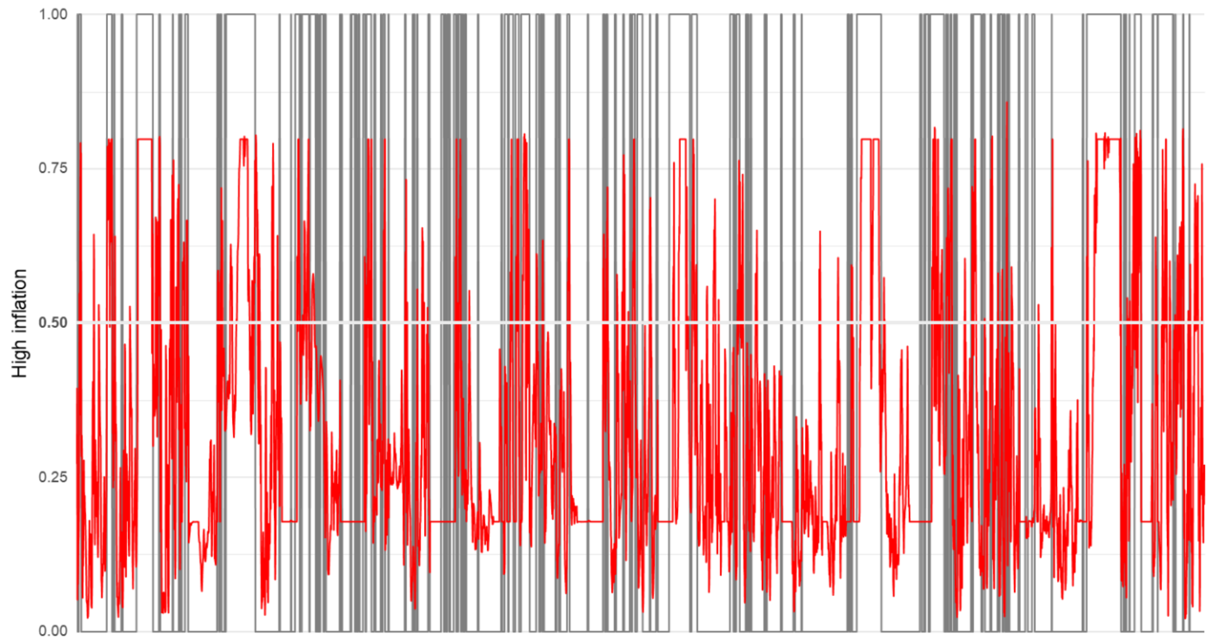
Figure 5.1. Predicted probabilities that only depend on the Exchange Rate

A. "high inflation" probability within High income group



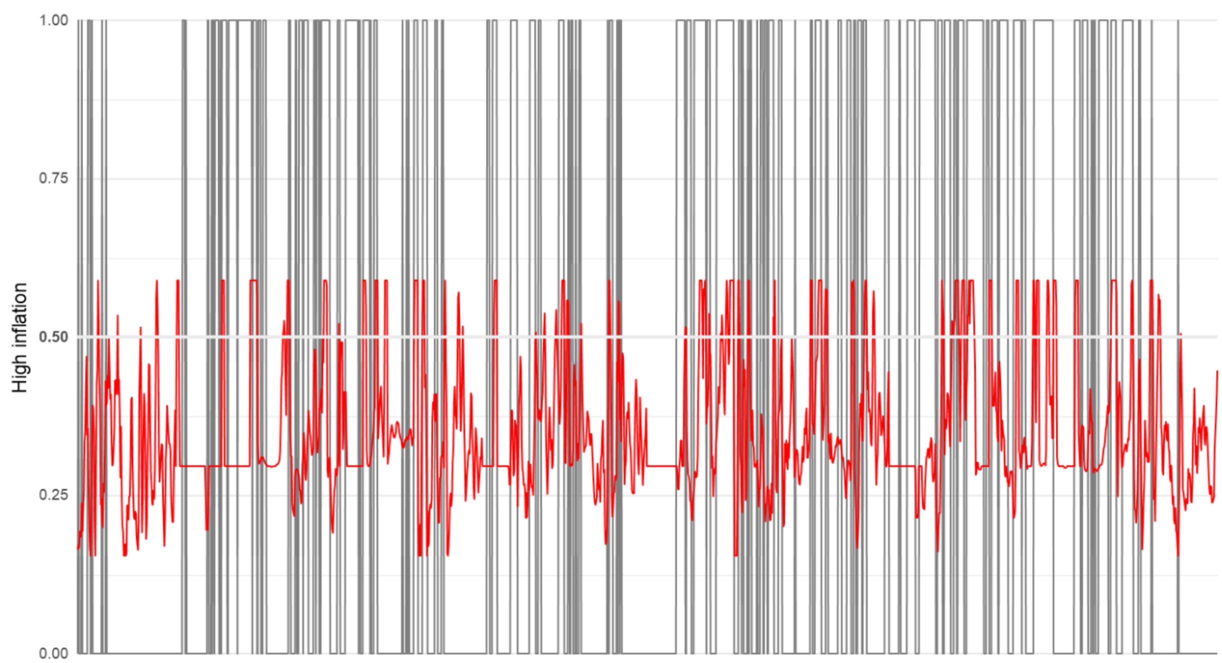
Model Evaluation: 70% success

B. “high inflation” probability within the Upper middle-income group



Model Evaluation: 77% success

C. “high inflation” probability within the Lower middle-income group



Model Evaluation: 67% success

High inflation episodes   High inflation probabilities (predicted probabilites)

Source: Authors’ calculation

Conclusion

This research delves deep into the complex interplay between inflation and exchange rates, replacing the assertion presented by Friedman in 1970 that 'inflation is always and everywhere a monetary phenomenon,' given the skepticism it has encountered from numerous scholars over time. This study takes a fresh perspective by reexamining Friedman's notion, investigating the multifaceted dynamics of "high inflation," and pinpointing its intricate underlying factors. From the outset, we embarked on identifying the threshold for what constitutes "high inflation." To accomplish this, the study reviewed the literature concerning 20 well-estimated "high inflation" thresholds, ultimately identifying "high inflation" as the median value derived from the literature's threshold values: 10% for middle-income countries and 5.5% for high-income countries.

Having established the benchmark for "high inflation," we proceeded to analyze the literature, focusing on major factors that contribute 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 54 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 descriptive analyses by answering two major questions: i) What are the specific determinants that lead to the initial surge in inflation, ultimately resulting in "high inflation" levels? ii) What determines the "beyond high" inflation?

According to descriptive statistics, we conclude that:

1. High and beyond "high inflation" is frequently and almost everywhere associated with exchange rate depreciation.
2. Elevated energy and food inflation and increasing exchange rate depreciation trend in the previous year clearly explain the emergence of "high inflation."

To prove our conclusions from descriptive statistics, through a meticulous evaluation of various econometric models, we identified the random effects panel probit model as the most suitable choice to address our research objectives, particularly 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, in all income groups, exchange rate depreciation consistently and significantly signals potential “high inflation” within 2 quarters, with a prolonged impact of up to 6 quarters in high and upper-middle-income countries. Elevated energy and food inflation also forecast “high inflation” within 2 quarters, lasting up to 6 quarters in high and upper-middle-income countries. Lower-middle-income countries see food inflation’s influence after 2 quarters. The model achieves a success rate of 83%, 86%, and 84% in predicting “high inflation” for high, upper-middle, and lower-middle-income countries, respectively.

Moreover, the panel probit model underscores the paramount importance of exchange rate depreciation in determining “high inflation,” with depreciation levels exceeding 35% correlating with a remarkable 99% likelihood of “high inflation” in upper-middle-income countries, 96% in high-income countries, and 93% in lower-middle-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,” as an approximately 10% increase in GDP growth forecasts “high inflation” with a probability exceeding 50%. 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 25% probability of predicting “high inflation” in lower-middle-income economies when energy inflation rises by more than 40%. However, these impacts are less pronounced in other income groups.

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 67%, respectively, in predicting “high inflation,” indicating its primary role as a driver.

Finally, according to model results, 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” in the following 2 quarters with the probability of more than 75% in all analyzed countries.

In conclusion, our research has unearthed a comprehensive understanding of “high inflation,” illuminating the interplay of various determinants and their roles across different income groups. The convergence of findings from descriptive statistics and model results solidifies the significance of exchange rate depreciation as a central driver of “high inflation” while also acknowledging the importance of energy and food inflation as key indicators. Appreciating the significance of exchange rate depreciation as a crucial precursor to elevated inflation not only enables more prompt and efficient policy responses but also adds substantial value to the current body of research, reinforcing the pivotal role played by historical exchange rate trends and supply-side factors in our understanding of the intricacies 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.

Anh, V. T., Quan, L. T., Phuc, N. V., Chi, H. M., & Duc, V. H. (2021). Exchange Rate Pass-Through in ASEAN Countries: An Application of the SVAR Model. *Emerging Markets Finance and Trade, Vol. 57, Issue 1*, 21-34.

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*.

Ascari, G., Phaneuf, L., & R.Sims, E. (2018). On the welfare and cyclical implications of moderate trend inflation. *Journal of Monetary Economics, Vol. 99*, 56-71.

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.

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.

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.

Braga, J., & Serrano, F. (2023). Post-Keynesian Economics: New Foundations by Marc Lavoie Chapter 8: Inflation Theory. *Review of Political Economy*.

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

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

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.

Coulibaly, S. (2021). COVID-19 policy responses, inflation and spillover effects in the West African Economic and Monetary Union. *African Development Review, Vol. 33, Issue S1*, S139–S151.

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*.

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.

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.

Ekinci, R., Tüzün, O., & Ceylan, F. (2020). The relationship between inflation and economic growth: Experiences of some inflation targeting countries. *Financial Studies, Vol. 24, Issue 1*, 6-20.

Ezako, J. T. (2023). Analyze of inflation and economic growth relationship in Burundi. *Cogent Economics & Finance, Vol. 11, Issue 1*.

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.

Frankel, e., 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.

Frankel, J. A., & Rose, A. K. (1996). Currency Crashes in Emerging Markets: Empirical Indicators. *NBER Working Paper Series 5437*.

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.

Gayaker, S., Ağaslan, E., Alkan, B., & Çiçek, S. (2021). The deterioration in credibility, destabilization of exchange rate and the rise in exchange rate pass-through in Turkey. *International Review of Economics & Finance, Vol. 76*, 571-587.

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.

Ha, J., Ivanova, A., Ohnsorge, F., & Unsal, F. D. (2019). Chapter 1. Inflation: Concepts, Evolution, and Correlates . In J. Ha, M. A. Kose, & F. Ohnsorge, *Inflation in Emerging Inflation in Emerging and Developing Economies Evolution, Drivers, and Policies* (pp. 5-92). World Bank.

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*.

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

Kassi, D. F., Sun, G., Ding, N., Rathnayake, D. N., & Assamoi, G. R. (2019). Asymmetry in exchange rate pass-through to consumer prices: Evidence from emerging and developing Asian countries. *Economic Analysis and Policy, Vol. 62*, 357-372.

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.

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*.

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

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

Machlup, F. (1960). Another View of Cost-Push and Demand-Pull Inflation. *The Review of Economics and Statistics, Vol. 42, No. 2*, 125-139.

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., & Vo, X. V. (2020). A quarter century of inflation targeting & structural change in exchange rate pass-through: Evidence from the first three movers. *Structural Change and Economic Dynamics, Vol. 54*, 42-61.

Nasir, M. A., Balsalobre-Lorente, D., & Huynh, T. L. (2020c). Anchoring inflation expectations in the face of oil shocks & in the proximity of ZLB: A tale of two targeters. *Energy Economics, Vol. 86*.

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.

Nasir, M. A., Nugroho, A. D., & Lakner, Z. (2022). Impact of the Russian–Ukrainian Conflict on Global Food Crops. *Foods, Vol. 11, Issue 19*.

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*.

Nimoh, S. A., Addai-Asante, J., & Obeng, D. K. (2017). Exchange Rate Policy and Inflation in Ghana. *American Scientific Research Journal for Engineering, Technology, and Sciences*, 1-16.

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.

Pham, T. A., Nguyen, T. T., Nasir, M. A., & Huynh, T. L. (2023). Exchange rate pass-through: A comparative analysis of inflation targeting & non-targeting ASEAN-5 countries. *The Quarterly Review of Economics and Finance, Vol. 87*, 158-167.

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.

Şen, H., Kaya, A., Kaptan, S., & Cömert, M. (2020). Interest rates, inflation, and exchange rates in fragile EMEs: A fresh look at the long-run interrelationships. *The Journal of International Trade & Economic Development; Vol. 29, Issue 3*, 289-318.

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.

Turan, T., & Özer, H. A. (2022). The impact of oil price shocks on inflation: Do asymmetries matter? *Acta Oeconomica ,Vol. 72, Issue 3*, 271-288.

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

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*.

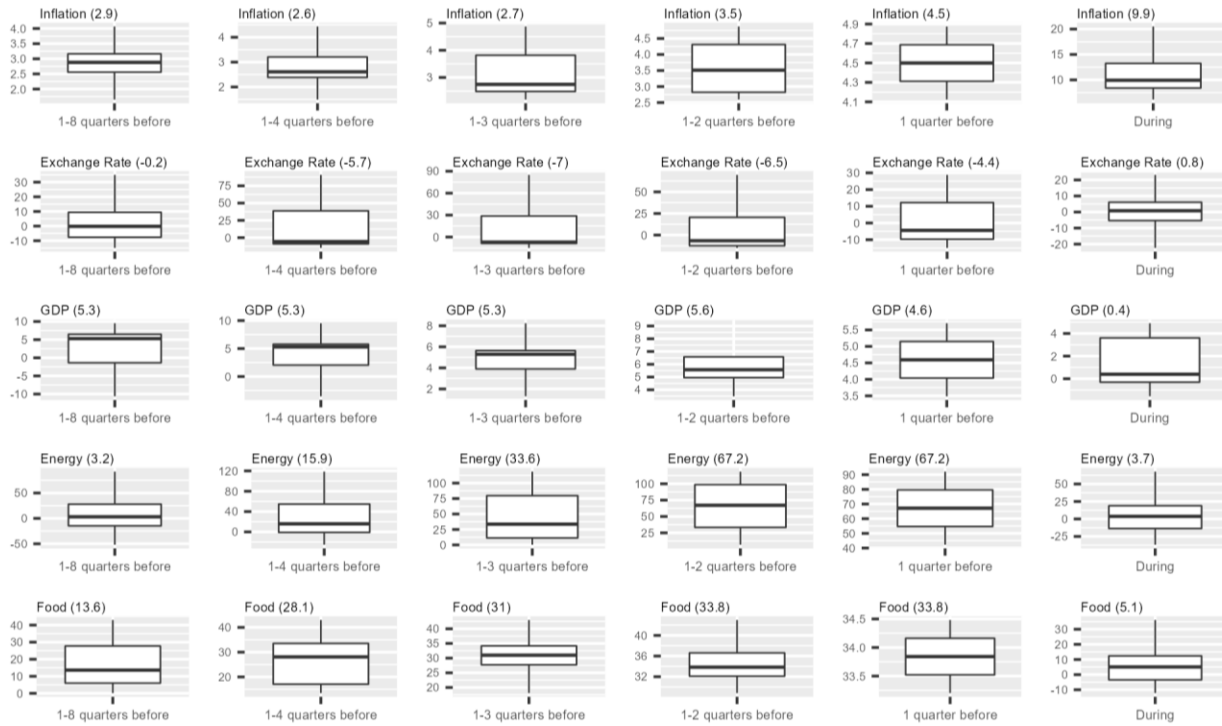
Yilmazkuday, H. (2011). Thresholds in the finance-growth nexus: A cross-country analysis. *The World Bank Economic Review, Vol 25, Issue 2*, 278-295.

Appendix

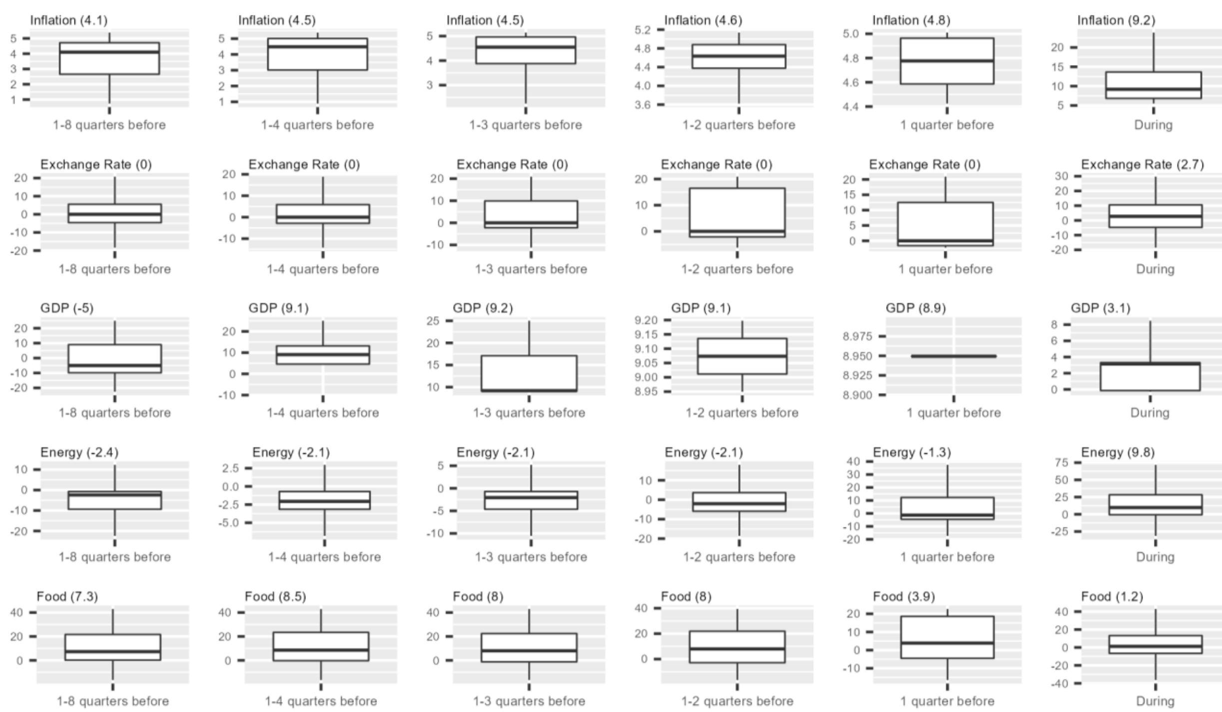
1. Case studies

Figure A.1.1. Case study: High-income countries

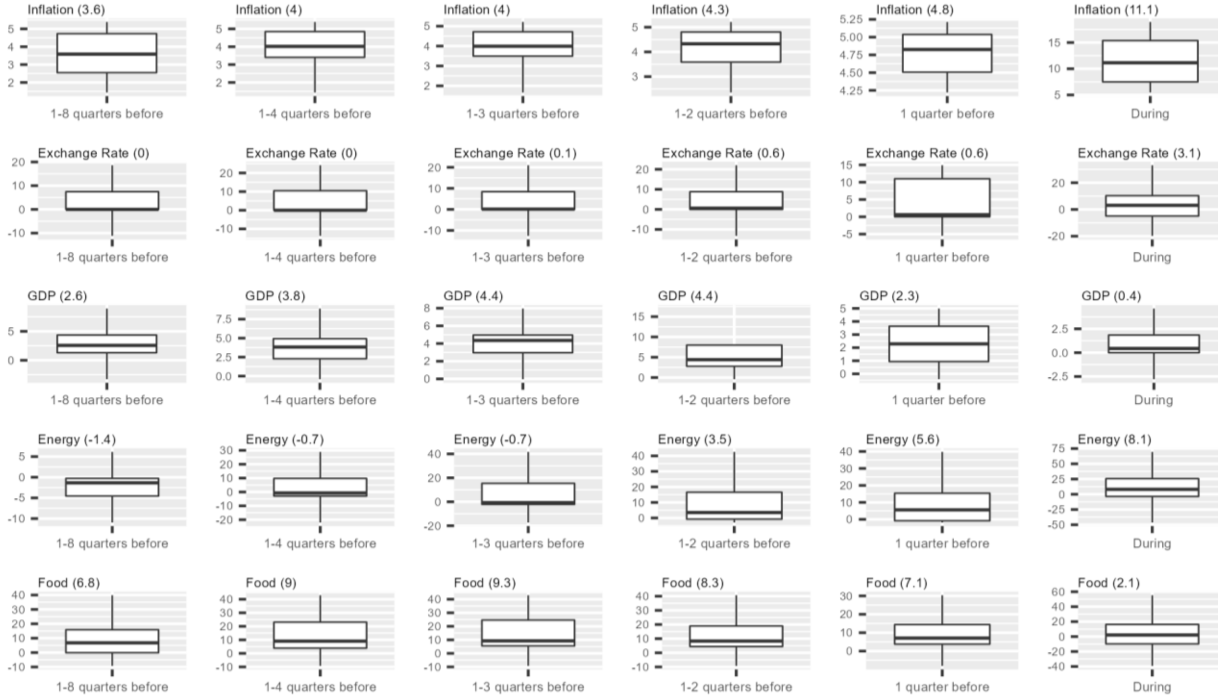
A. Czech Republic



B. Great Britain



C. New Zealand



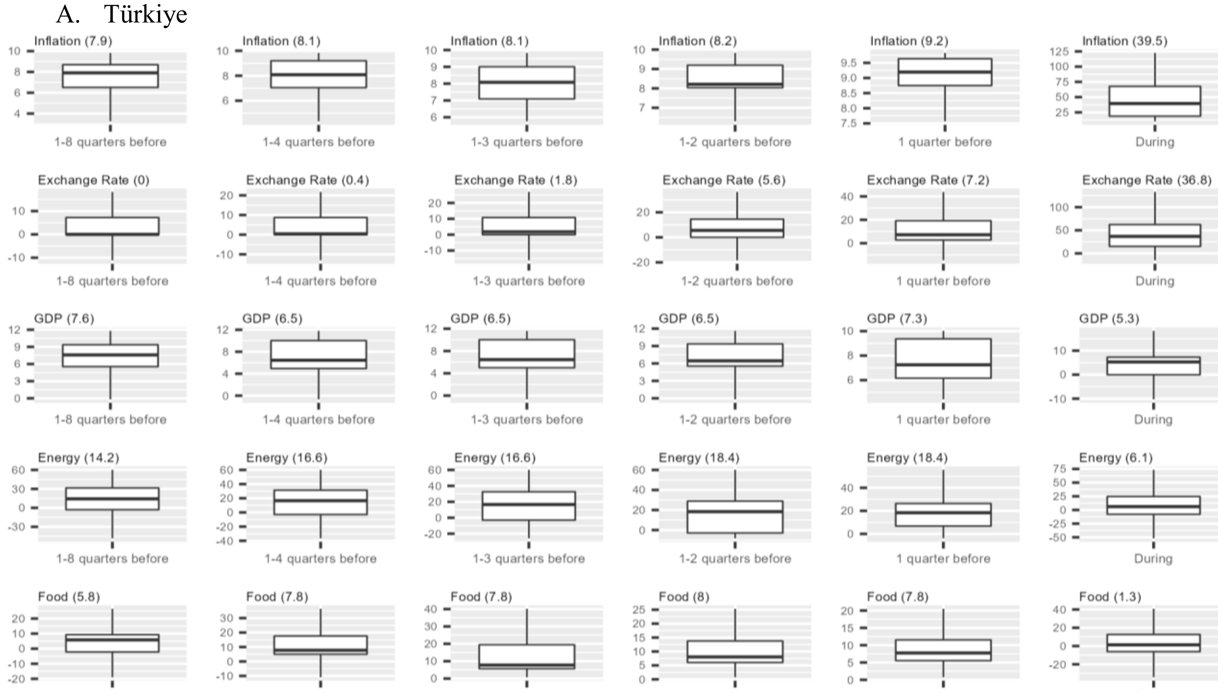
Source: Authors' calculation.

Note:

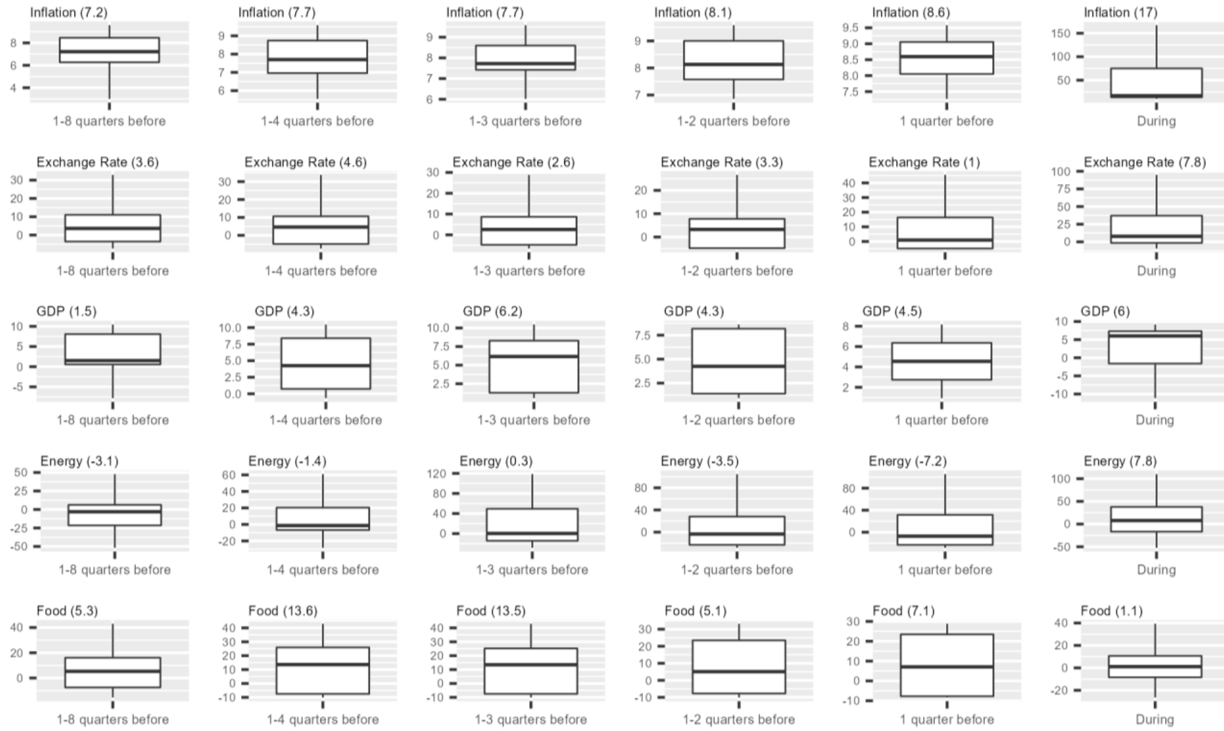
- The parenthesis in each subtitle displays median values.
- The x-axis is labeled as: "During" for the "high inflation" period and "1-n quarter(s) before" for the distribution of variables in 1 to n quarters before the "high inflation" period.

Figure A.1.2. Case study: Upper middle-income countries

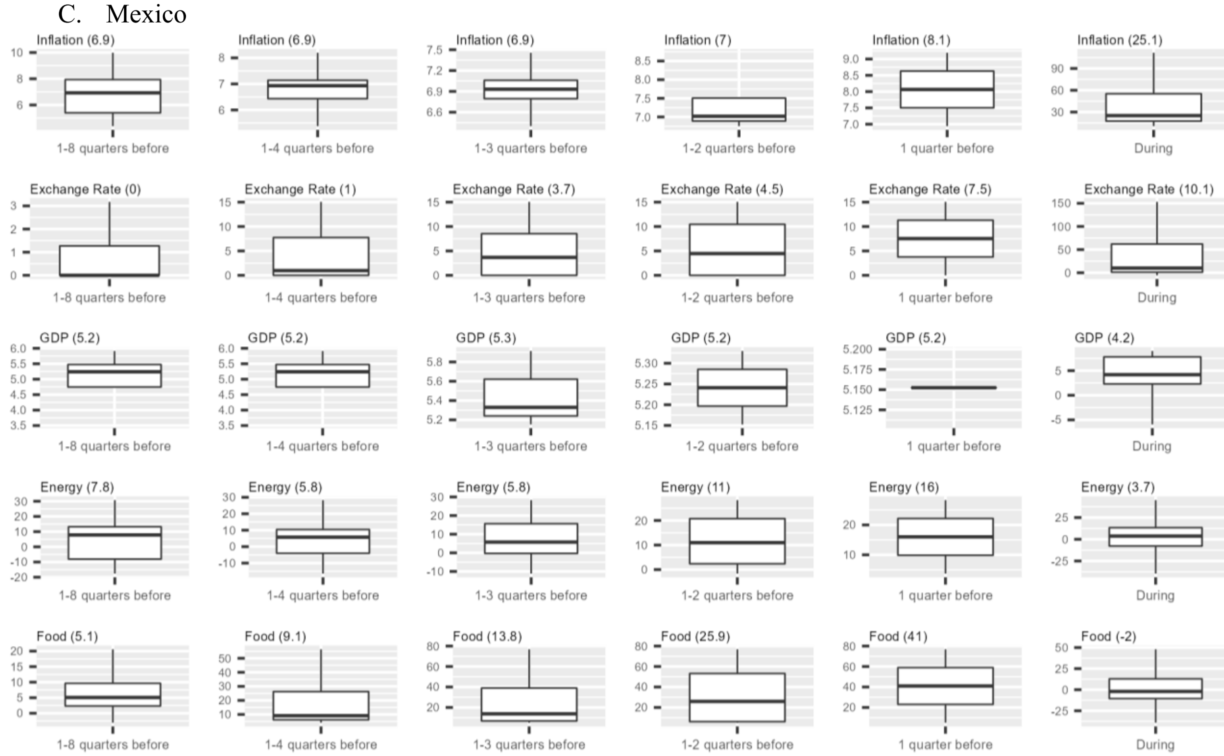
A. Türkiye



B. Russian Federation



C. Mexico



Source: Authors' calculation.

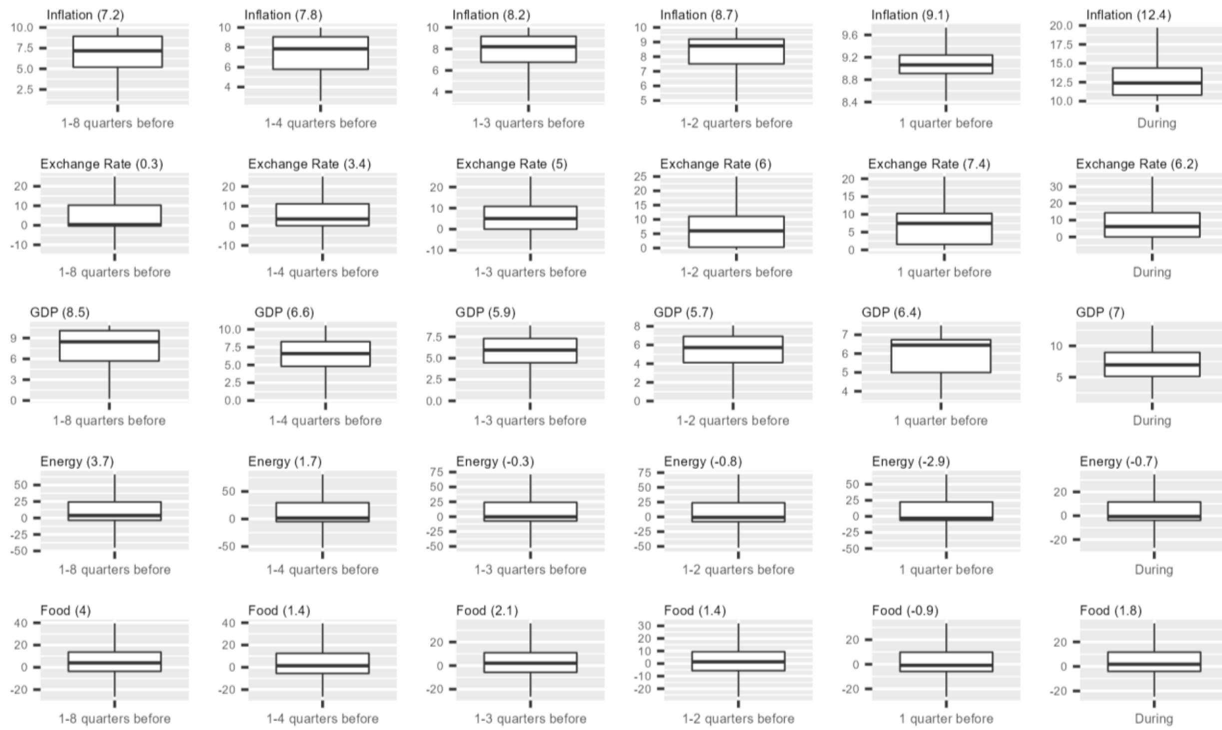
Note:

- Pharantesis in each subtitle displays median values.

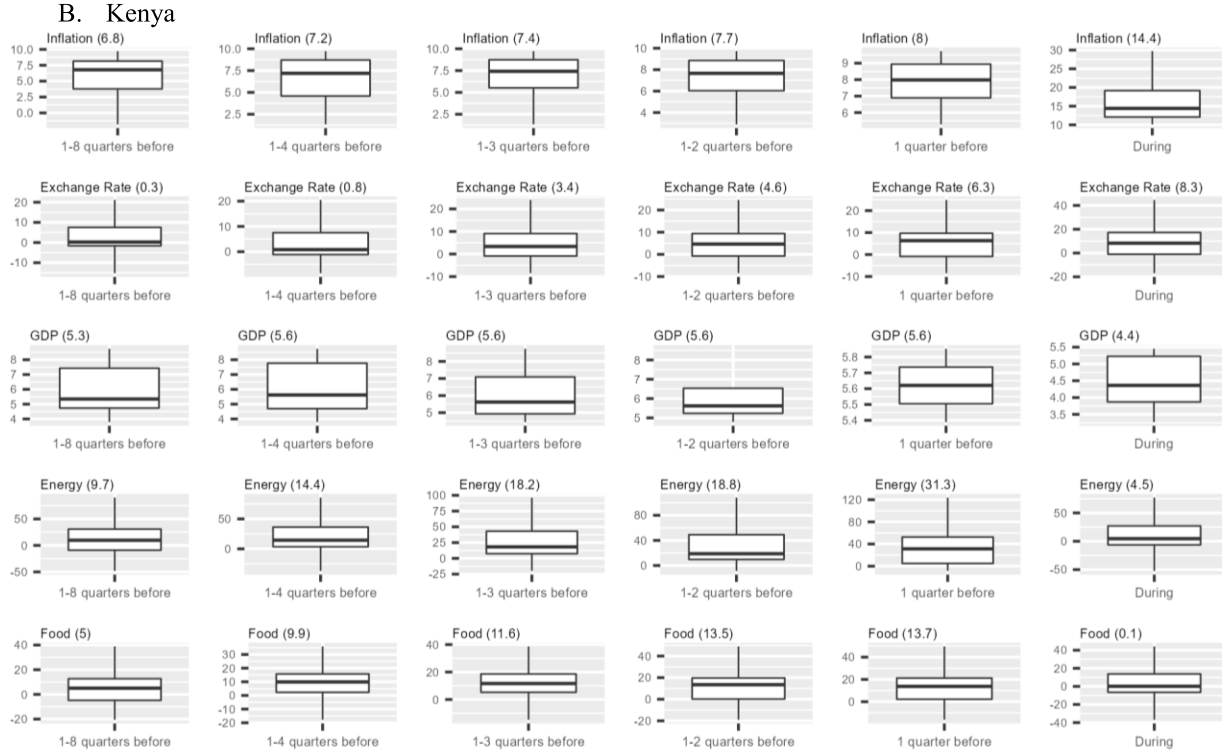
- The x-axis is labeled as: "During" for the "high inflation" period and "1-n quarter(s) before" for the distribution of variables in 1 to n quarters before the "high inflation" period.

Figure A.1.3. Case study: Lower middle-income countries

A. India



B. Kenya

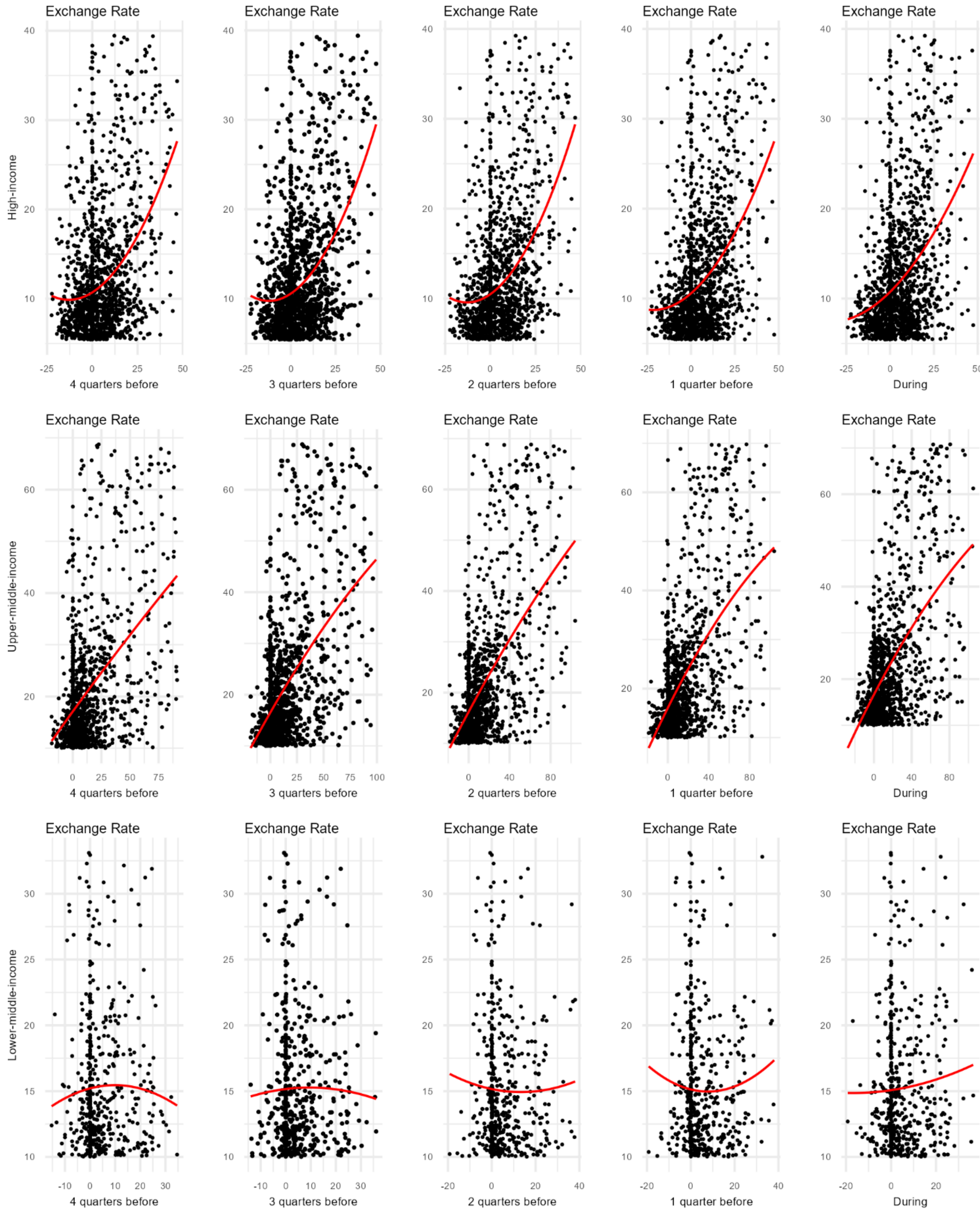


Source: Authors' calculation.
Note:

- Pharantesis in each subtitle displays median values.
- The x-axis is labeled as: "During" for the "high inflation" period and "1-n quarter(s) before" for the distribution of variables in 1 to n quarters before the "high inflation" period.

2. Beyond high inflation

Figure A.2. No simultaneous causation between exchange rate and inflation



The red line is a quadratic (degree-2 polynomial) regression line between inflation and its determinants.
Source: Authors' calculation.
Note:

- The y-axis in each graph displays inflation values, while the x-axis shows associated determinants.
- Plots display 54 countries" (23 High income, 23 Upper middle income, and 8 Lower middle-income) observations.
- The x-axis is labeled as: "During" when "high inflation" at time t is associated with its determinants at time t, "n quarter(s) before" if "high inflation" at time t is related to determinants at time t-n.

3. Lag selection

Table A.3. Lag Selection

Group	Lag	AIC	AIC rank	BIC	BIC rank	Pseudo R2	Pseudo R2 rank	RMSE	RMSE rank	Total	Total rank
High income	(1 - 1)	1487.228	14	1522.382	1	0.442	14	1.038	3	32	6
High income	(1 - 2)	1479.882	13	1538.472	4	0.448	13	1.061	5	35	13
High income	(2 - 2)	1488.480	15	1523.635	2	0.442	15	1.054	4	36	15
High income	(1 - 3)	1465.333	10	1547.359	8	0.457	10	1.087	7	35	13
High income	(2 - 3)	1478.256	12	1536.846	3	0.449	12	1.086	6	33	10
High income	(1 - 4)	1441.267	8	1546.730	7	0.469	8	1.125	9	32	6
High income	(2 - 4)	1465.932	11	1547.958	9	0.457	11	0.939	1	32	6
High income	(1 - 5)	1415.737	6	1544.636	5	0.482	6	1.180	12	29	3
High income	(2 - 5)	1443.898	9	1549.361	10	0.468	9	0.997	2	30	4
High income	(1 - 6)	1401.407	4	1553.742	11	0.490	4	1.232	15	34	12
High income	(2 - 6)	1417.802	7	1546.701	6	0.481	7	1.099	8	28	1
High income	(1 - 7)	1395.446	2	1571.216	13	0.495	2	1.169	11	28	1
High income	(2 - 7)	1407.751	5	1560.085	12	0.488	5	1.149	10	32	6
High income	(1 - 8)	1383.204	1	1582.411	15	0.503	1	1.217	14	31	5
High income	(2 - 8)	1397.170	3	1572.940	14	0.495	3	1.206	13	33	10
Upper middle income	(1 - 1)	750.613	14	783.067	1	0.503	14	1.633	7	36	12
Upper middle income	(1 - 2)	731.942	11	786.033	3	0.521	12	1.724	12	38	14
Upper middle income	(2 - 2)	753.475	15	785.930	2	0.501	15	1.177	1	33	11
Upper middle income	(1 - 3)	727.927	9	803.655	5	0.529	10	1.634	8	32	6
Upper middle income	(2 - 3)	749.200	13	803.291	4	0.510	13	1.194	2	32	6
Upper middle income	(1 - 4)	714.802	8	812.166	7	0.544	8	1.764	13	36	12
Upper middle income	(2 - 4)	735.692	12	811.420	6	0.524	11	1.541	3	32	6
Upper middle income	(1 - 5)	708.720	4	827.721	8	0.553	6	1.768	14	32	6
Upper middle income	(2 - 5)	730.521	10	827.886	9	0.533	9	1.670	11	39	15
Upper middle income	(1 - 6)	696.968	2	837.606	11	0.566	3	1.640	9	25	1
Upper middle income	(2 - 6)	709.167	5	828.168	10	0.553	7	1.542	4	26	2
Upper middle income	(1 - 7)	700.393	3	862.667	13	0.569	2	1.661	10	28	3
Upper middle income	(2 - 7)	710.583	7	851.221	12	0.557	5	1.549	5	29	4
Upper middle income	(1 - 8)	693.816	1	877.726	15	0.579	1	1.768	15	32	6
Upper middle income	(2 - 8)	709.434	6	871.709	14	0.563	4	1.602	6	30	5
Lower middle income	(1 - 1)	162.152	15	186.408	2	0.616	15	1.656	7	39	15
Lower middle income	(1 - 2)	156.475	14	196.902	4	0.651	13	1.355	3	34	10
Lower middle income	(2 - 2)	152.384	11	176.640	1	0.641	14	1.228	1	27	1
Lower middle income	(1 - 3)	155.995	13	212.592	6	0.673	11	1.473	5	35	12
Lower middle income	(2 - 3)	151.964	10	192.391	3	0.663	12	1.308	2	27	1
Lower middle income	(1 - 4)	154.939	12	227.706	8	0.696	9	1.606	6	35	12
Lower middle income	(2 - 4)	151.716	9	208.313	5	0.684	10	1.418	4	28	3
Lower middle income	(1 - 5)	148.676	8	237.614	10	0.733	7	2.014	10	35	12
Lower middle income	(2 - 5)	148.080	7	220.847	7	0.714	8	1.681	8	30	4
Lower middle income	(1 - 6)	145.753	4	250.861	11	0.761	4	2.536	12	31	7
Lower middle income	(2 - 6)	146.859	6	235.797	9	0.737	6	1.871	9	30	4
Lower middle income	(1 - 7)	143.937	3	265.216	14	0.786	3	3.228	14	34	10
Lower middle income	(2 - 7)	145.895	5	251.004	12	0.760	5	2.265	11	33	9
Lower middle income	(1 - 8)	135.846	1	273.295	15	0.827	1	5.715	15	32	8
Lower middle income	(2 - 8)	143.612	2	264.891	13	0.786	2	2.998	13	30	4