CENTRAL BANK OF MONTENEGRO

Working paper no. 36

OPTIMAL THRESHOLDS FOR INFLATION CRISIS PREDICTION IN MONTENEGRO

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Podgorica, 2025

PUBLISHED BY: *Central Bank of Montenegro*
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The views and opinions expressed in this working paper are those of the authors and do not necessarily reflect the official views and policies of the Central Bank of Montenegro.

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Abstract

This paper assesses the power of the Economic and Monetary Union (EMU) inflation rate and optimal thresholds in predicting the probability of an inflation crisis in Montenegro. The dataset consists of monthly observations spanning from January 2006 to October 2024, with forecasts projected for the period from November 2024 to October 2025. The standardized cumulative EMU inflation rate is important for the inflation rate in Montenegro. Contrary to assumptions, wages and unemployment are significant and decrease and increase the probability of inflation rate, respectively. Brent oil decreases the inflation crisis, while food prices increase the inflation crisis in Montenegro. The findings suggest the need for Montenegro to align policy measures with EMU trends while addressing structural issues like wage growth and unemployment to maintain economic stability.

Keywords: Inflation crisis, EMU and Montenegro, logit, forecasting

JEL classification: E31, G32, C58, G17

1. Introduction

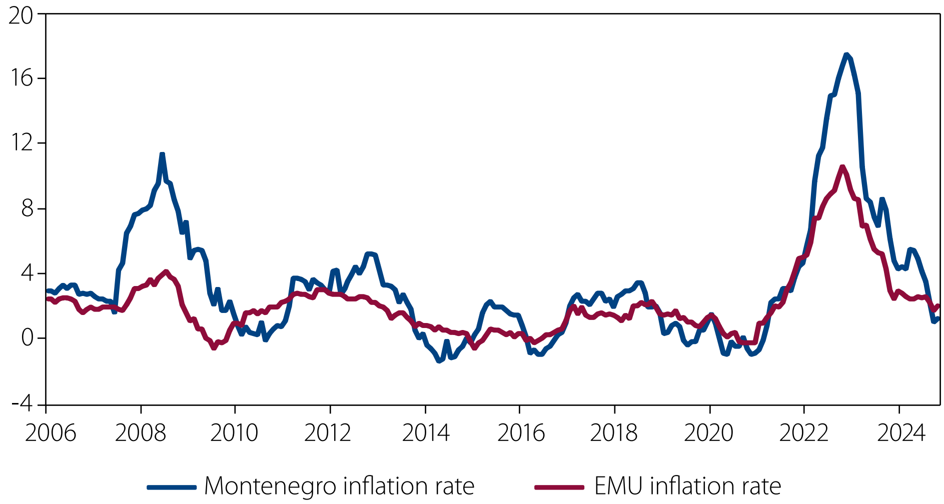
This paper aims to examine how the EMU inflation rate can predict the occurrence of inflation crises in Montenegro. The central research question focuses on whether standardized EMU inflation rate, such as the cumulative EMU inflation rate, is effective in forecasting Montenegro inflation crises. Addressing this question is crucial, as accurate predictions can help policymakers in vulnerable scenarios implement preemptive measures to avoid crises, thereby stabilizing the economy of Montenegro and ensuring long-term financial sustainability.

Inflation is a critical economic variable that can significantly impact macroeconomic stability, monetary policy effectiveness, and overall economic growth. Understanding the factors driving inflation dynamics is essential for policymakers, particularly in small, open economies like Montenegro. In recent years, the interplay between global inflationary trends and local inflation rates has gained increased attention, especially with the impact of regional monetary unions like the EMU. This paper aims to assess the power of the EMU's inflation rate as a predictor of the probability of inflation crises in Montenegro, with a specific focus on how standardized cumulative EMU inflation measures influence domestic inflation outcomes.

Montenegro, as a small open economy, is highly influenced by global economic trends and the economic conditions of its main trading partners, particularly those in the European Union (EU). As Montenegro aspires to EU membership, its economic policy and stability are closely aligned with EU norms, making it particularly susceptible to changes in EMU inflation dynamics. The EMU's monetary policy has wide-reaching effects on the economies of both member and non-member countries through trade links, capital flows, and price stability measures. Understanding how EMU inflation translates into inflationary pressures in Montenegro is vital for local policymakers seeking to maintain stable price levels and to design effective countercyclical policies.

Figure 1, which shows the inflation rates for the EMU and Montenegro, reveals both divergence and convergence in their trends over time. In the EMU, inflation experienced a sharp increase, up to 4.1%, from mid-2007 to mid-2008, followed by a notable decline. A similar pattern emerged in March 2022, when EMU inflation diverged significantly from Montenegrin inflation, rising rapidly until peaking at 10.1% around November 2022, before beginning to decline. In contrast, Montenegrin inflation shows a general co-movement with EU inflation, reflecting the interconnected nature of these economies, but with noticeable deviations at certain points. Despite these broad trends, a visual inspection of the graph suggests that identifying clear cycles and long-term trends is challenging, indicating the need for further quantitative analysis to better capture the nuances in these inflationary patterns.

Figure 1: EMU and Montenegro inflation cycles and trends (2006:1 – 2024:10)



Source: Author's calculations

A substantial body of literature has examined the relationship between global inflation trends and domestic inflation rates in small, open economies. The literature suggests that external factors, such as the inflation rates of major trading partners, can significantly influence local inflation. For instance, Mishkin (2008) highlights how global inflation trends impact emerging markets, emphasizing the role of monetary unions like the EMU in transmitting inflation through trade channels. Dreger and Reimers (2013) further emphasize the importance of considering external inflation pressures when evaluating inflation in EU candidate countries, as they often adjust their monetary policies in response to EMU-driven inflationary changes. Ivanovic (2023) concludes, using the ARDL model, that in the short term, an increase in inflation in the euro area of 1% leads to an increase in inflation in Montenegro by about 0.77%. Bojaj (2024) highlights, using Bayesian SVAR with connectedness networking, the impact and importance of the transmission volatility from the EMU to the Montenegrin inflation rate.

The influence of commodity prices, such as Brent oil, on inflation rates has also been a significant focus in previous research. Studies like those of Hamilton (2009) and Barsky and Kilian (2004) highlight the role of global oil prices in driving inflation in oil-importing countries. However, findings have been mixed, particularly in the context of small economies. While global oil price changes are often expected to correlate strongly with inflation, recent studies such as Baumeister and Kilian (2016) suggest that the link between oil prices and inflation can be weaker in countries with robust monetary policy frameworks or alternative energy sources.

The relationship between wages, unemployment, and inflation has been a core focus in macroeconomic theory, dating back to the Phillips Curve framework. According to Phillips (1958), lower unemployment is typically associated with higher inflation, as increased demand for labour leads to upward pressure on wages, which in turn increases prices. This has been supported by later studies, including Gali (2011), which demonstrate that wage dynamics and unemployment rates remain critical determinants of inflation, particularly in countries experiencing structural shifts in labour markets. However, this study finds that while wages reduce the probability of inflation crises in Montenegro, higher unemployment rates increase this probability, providing nuanced insights into the unique structure of the Montenegrin labour market and its inflationary pressures.

Despite the substantial literature on inflation dynamics, few studies have specifically analyzed the link between EMU inflation rates and inflation crises in non-EU economies like Montenegro. Most studies tend to focus on larger EU economies or on the impact of EMU policies on euro area the euro area member states, leaving a gap in the understanding of how EMU inflation affects EU candidate countries. This study contributes to the literature by providing a detailed analysis of how standardized cumulative EMU inflation measures impact the probability of inflation crises in Montenegro. It also explores why traditional drivers of inflation, such as Brent oil prices, may decrease inflation in this context, while local economic variables like wages and unemployment play a more significant role.

We construct a database for the first time that contains a binary variable on Montenegrin inflation. This database identifies periods of inflation crises, allowing us to apply predictive models that assess the relationship between EMU inflation and inflation crises in Montenegro. This novel dataset enables a more precise analysis of how external inflationary pressures influence Montenegro's economic stability.

The findings of this study have important implications for policymakers in Montenegro. By highlighting the predictive power of standardized EMU inflation measures, this research provides a framework for better-anticipating inflation crises and aligning local policies with broader European trends. Furthermore, the results emphasize the need to prioritize domestic economic conditions, such as labour market dynamics, in the design of anti-inflationary policies.

The remainder of the paper is organized as follows: Section 2 describes the data and methodology used to analyse the predictive power of EMU inflation rates. Section 3 presents the empirical results, focusing on the significance of the standardized cumulative EMU inflation rate, wages, and unemployment. Section 4 discusses the implications of these findings for inflation management in Montenegro and offers policy recommendations. Finally, Section 5 concludes the study and suggests avenues for future research.

2. Data and Methodology

Financial crises are characterized by extreme tail events, such as sudden collapses in credit markets or systemic shocks that disproportionately affect the financial system. The global and EMU economies experienced extreme market shocks, significant policy changes, or climate-related events leading to financial crises, such as a) the 2008 Financial Crisis in the United States and Europe, b) sovereign debt crises in Greece, Ireland, and Portugal, c) 1997-1998 Asian financial crisis and 2001-2002 Argentine economic crisis, d) Zimbabwe hyperinflation crisis (2000s) and Sierra Leone civil war (1991-2002), and e) hurricane Katrina (2005, United States) and drought in the Horn of Africa (2011).

Our objective is to assess the ability of the EMU inflation rate to predict inflation crises in Montenegro. We use a database that assigns a value of 1 if an inflation crisis exists (inflation rate ≥ 2%). Given our binary conception of a crisis, in that it either happens or it does not, using limited dependent-variable approaches such as logit or probit models is warranted. Probit models have been used in many previous empirical research projects involving discrete choice models (e.g., Eichengreen et al. 1996; Frankel and Rose 1996; Berg and Patillo 1999). The sole distinctive feature of our model was that, in both logit and probit models, the basic latent variable intended to produce the discrete event has a slightly different distribution. In logit models, it is more fat-tailed than in normal models.

In our dataset spanning more than one decade and encompassing an economy in transition, sharp fluctuations and outliers are prevalent. For example, the cumulative EMU inflation rate suddenly spikes in the lead-up to a crisis. The fatter tails of the logistic distribution allow the logit model to better accommodate such fluctuations without becoming overly sensitive, as probit models often do. Studies have demonstrated that logit models perform better in capturing such dynamics in financial instability contexts (Laeven and Valencia, 2020). The ability of the logit model to manage these outliers is particularly critical in financial cycle research, where sudden shifts in economic variables often signal crises (Cerutti, Claessens, and Laeven, 2017; Bojaj and Aharon, 2024). Adrian et al., 2019 highlight that when modelling crises where tail events are common, such as banking collapses or rapid spikes in inflation rates, the logit model's ability to handle these events robustly is essential for generating stable predictions. In financial contagion models, where systemic shocks can propagate across institutions and economies, the heavier-tailed logit model has been found to outperform the probit model, particularly in predicting events that occur infrequently but with severe consequences (Eichengreen and Gupta, 2023).

The logit probability model is based on the logistic equation. The logistic model has historically been used in determining the likelihood of achieving a certain outcome, in our case banking crisis. The logistic function has the form:

$$f(z) = \frac{1}{1+e^{-z}} \tag{1}$$

with $0 \leq f(z) \leq 1$, where z is a linear function of explanatory variables such as:

$$z = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \tag{2}$$

Then the logistic regression can take on the form:

$$g(x) = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\cdots+b_kx_k)}} \tag{3}$$

with $0 \leq g(x) \leq 1$. Therefore, the probability that the event will occur is:

$$p = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\cdots+b_kx_k)}} \tag{4}$$

and the probability that the event will not occur is:

$$1 - p = 1 - \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\cdots+b_kx_k)}} \tag{5}$$

Dividing these two expressions yields:

$$\frac{p}{1-p} = e^{(b_0+b_1x_1+b_2x_2+\cdots+b_kx_k)} \tag{6}$$

Finally, taking logs of both sides yields:

$$\ln\left(\frac{p}{1-p}\right) = ln\left(e^{(b_0+b_1x_1+b_2x_2+\cdots+b_kx_k)}\right) \tag{7}$$

Finally, the logit probability model is:

$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \tag{8}$$

The probit probability model is similar to the logit model described in Equations 1-8, but it incorporates a normal distribution rather than the logistic distribution. The cumulative normal distribution for a random variable $z \sim N(\mu, \sigma^2)$ is:

$$F(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi\sigma}} \cdot \exp\left((z-\mu)^2/2\sigma^2\right) \tag{9}$$

with

$$-\infty \leq z \leq \infty$$

$$0 \leq F(z) \leq 1$$

Our random variable z can also be a linear function, such as

$$z = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \tag{10}$$

The probability of the event y being observed is then computed from the inverse of the normal distribution. This is

$$Prob(y) = F^{-1}(z) \tag{11}$$

The focus of our interest in predicting stress or crises is on the tail of a distribution. Tail risk is the risk that future realizations lie in the tail of the distribution. Tail-risk realizations are relatively unlikely to occur but entail large losses such as stress events and crises. Stress or crisis realizations y_t are coded as binary variables. The 0 or 1 classification is based on pre-determined criteria: the falling short or superseding of a variable's threshold, the assumed extreme event; the occurrence of certain events such as defaults; and both events and the superseding of multiple thresholds happening together. Different thresholds produce different timings for tail-risk realizations (stress, crises). Events are often difficult to define precisely.

To explain why the logit model is often considered more appropriate than the probit model for certain datasets, especially those with outliers or extreme events such as in our case the inflation crisis, we can focus on the properties of their underlying distributions. Both models are used for binary outcomes, but they differ in how they model the probability of the dependent variable, the inflation crisis. The logit model uses the logistic distribution, while the probit model uses the standard normal distribution.

The logistic cumulative distribution function (CDF) is given by:

$$P(Y = 1 \mid \mathrm{X}) = \frac{1}{1+e^{-(\beta_0+\beta_0 X)}} \tag{12}$$

The probit CDF is:

$$P(Y = 1 \mid \mathrm{X}) = \Phi(\beta_0 + \beta_0 X) \tag{13}$$

where Φ is the cumulative distribution function of the standard normal distribution.

The logistic distribution has heavier tails than the normal distribution. This characteristic means that the logit model is more capable of accommodating outliers or extreme values in the dataset of inflation crises. The probability density function (PDF) of the logistic distribution is:

$$f(z) = \frac{e^{-z}}{(1+e^{-z})^2} \tag{14}$$

The tails of this distribution decay more slowly than those of the normal distribution:

$$f(z) \sim \frac{1}{z^2} \quad as \;\; z \to \infty \tag{15}$$

In contrast, the normal distribution's tails decay exponentially:

$$f(z) \sim \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \quad as \;\; z \to \infty \tag{16}$$

When dealing with datasets, such as inflation crises, that contain outliers or extreme observations, the logit model's heavier tails allow it to provide more stable estimates in the presence of these values. In other words, the logistic function can accommodate the probability of extreme outcomes better than the probit function.

Beyond its statistical robustness, the logit model offers a more intuitive interpretation in terms of odds ratios, which is a valuable feature when communicating findings to policymakers. In contexts where understanding the probability of a financial crisis is key, the log-odds representation provides a clear, actionable framework. Policymakers and central banks, who often rely on research such as this, benefit from the clarity provided by logit models, particularly when evaluating risk across a wide range of economic conditions (Reinhart and Rogoff, 2013).

The logit model, often used in binary classifications, relies on the assumption that the dependent variable is dichotomous, and it models the probability of an outcome occurring. While the model itself is robust and versatile, it does have limitations, particularly concerning skewness and bias in the data.

Skewness refers to the asymmetry in the distribution of the predictor variables. In the context of a logit model, if the independent variables are heavily skewed, it can lead to issues with the estimation of the coefficients. These issues arise because the logistic function transforms the linear combination of predictors into a probability. However, if the predictors themselves are not well-distributed, the estimated probabilities can become distorted. When predictors are heavily skewed, the logit model might produce biased estimates, leading to poor predictive performance. This outcome occurs because the logistic regression is sensitive to outliers and extreme values that can disproportionately influence the model. To mitigate the effects of skewness, transformations such as log transformations, square root transformations, or Box-Cox transformations can be applied to the predictors to make their distribution more symmetric (Busch et al. 2022). Additionally, the detection and treatment of outliers are crucial steps to ensure that extreme values do not unduly influence the model.

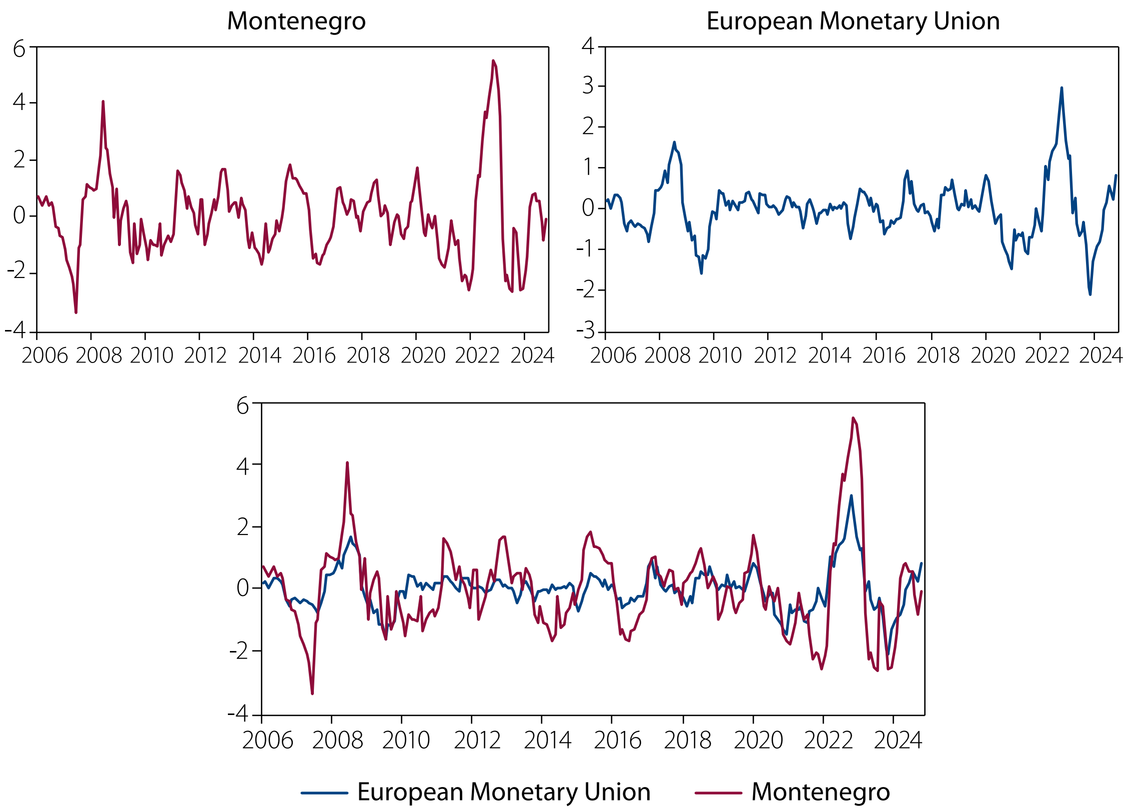
Despite these adjustments, there are inherent limitations when dealing with skewed data in logit models. Even after transformations, interpreting the coefficients of a logit model can become complex, especially when the original variables have been transformed to address skewness. In cases in which the data are very unbalanced (one outcome is much more common than the other), the logit model might become biased towards the majority class, leading to poor performance on the minority class. This issue is particularly problematic when the minority class is of greater interest in the analysis. Overfitting is a common issue when dealing with skewed data, especially if the model is complex or if there are many predictors. Regularization techniques such as L1 or L2 can be used to mitigate this issue, but the fundamental challenge remains (Yang et al. 2023). While the logit model is a powerful tool for binary classification, its effectiveness can be compromised by skewed data. Addressing skewness through transformations and careful pre-processing is essential, but these steps do not entirely eliminate the risk of biased estimates and misclassification. Understanding these limitations is crucial for applying the logit model correctly and interpreting its results in skewed data scenarios.

3. Results

3.1. Trend and cycle components

We construct trend and cycle components for selected EMU and Montenegro using the HP filter with lambda=1600. For each country, we analyze the inflation rate cycles and we date the peaks and the troughs. Do cycles exhibit different amplitudes?

Figure 2: EMU and Montenegro inflation cycles



Source: Author's calculations

The analysis using the Hodrick-Prescott (HP) filter on the EMU and Montenegro inflation rates in Figure 2 indicates that it effectively filters out fluctuations that correspond to cycles shorter than

2 years and longer than 8 years. This means that the HP filter functions similarly to a Band-Pass filter, isolating the typical business cycle frequencies that generally range from 2 to 8 years. These cycles are relevant for understanding medium-term economic dynamics, such as typical economic expansions and recessions.

However, the results also show that some short-term variations remain present in the filtered series, making it challenging to interpret the data with complete clarity. This residual short-term noise can obscure a clear view of the longer-term trends. Despite this, the HP filter allows us to identify key peaks (high points) and troughs (low points) in the inflation rates, which define the inflation cycles for both the EMU and Montenegro. These detected peaks and troughs can help in understanding the cyclical nature of inflation, even if the short-term fluctuations add complexity to the overall interpretation.

Table 1: EMU and Montenegro peaks and troughs of inflation cycles

Montenegro										
Peaks	08-M06	11-M03	12-M12	15-M05	17-M02	18-M07	20-M01	22-M11	23-M08	24-M05
Troughs	07-M06	09-M07	12-M03	14-M04	16-M06	17-M12	19-M01	21-M12	23-M07	23-M12
EMU										
Peaks	08-M07	10-M03	11-M03	15-M05	17-M02	18-M10	20-M01	22-M10	24-M07	
Troughs	07-M08	09-M07	11-M08	15-M01	16-M04	18-M02	20-M12	23-M11	24-M09	

Source: Author's calculations

The analysis of the peaks and troughs in the inflation cycles of Montenegro and the EMU reveals notable differences and similarities in their inflation dynamics. The detection of peaks (high points) and troughs (low points) in inflation cycles is not straightforward and requires advanced techniques. Traditional methods like the Bry and Boschan (1971) method have been widely used, but newer approaches like the BBQ (Business Cycle Dating) method offer alternative ways to date these cycles more precisely.

Peaks in inflation often coincide with economic crises or major disruptions, for example, 2008-M06/M07. This period corresponds to the Global Financial Crisis, which led to a significant spike in inflation due to financial instability and market volatility. The 2011-M03 peak aligns with the euro area Debt Crisis, where several EU countries faced severe debt issues, influencing inflationary pressures. Moreover, the 2022-M10/M11 peak is associated with the post-COVID-19 inflation surge, where disruptions in supply chains, energy shortages, and rising demand contributed to heightened inflation rates. However, some peaks do not have a direct link to a specific economic crisis, suggesting that other factors (like policy changes or commodity price shocks) may have driven inflation at those times.

Troughs, representing the low points in inflation cycles, are more challenging to correlate with specific recovery events. While they often indicate periods of subdued economic activity or deflationary pressures, identifying a direct cause can be complex. For example, 2015-M01 in the EMU corresponds to a period of deflation concerns in the euro area, but many other troughs are less easily associated with specific economic events.

The amplitude of inflation cycles, or the difference between peaks and troughs, appears to have increased in recent years, especially in Montenegro. This suggests that inflationary fluctuations have become more pronounced, which could be due to increased volatility in global markets, greater sensitivity to external shocks, or structural changes in these economies. This trend is particularly visible during the 2021-2022 post-pandemic period when both regions experienced significant inflationary pressure due to global supply chain disruptions and shifts in consumer demand.

Montenegro shows more pronounced peaks and troughs compared to the EMU, indicating that inflation in Montenegro may be more sensitive to external shocks and less cushioned by larger economic structures and policy frameworks that characterize the EMU. This could be due to Montenegro's smaller and more open economy, which makes it more vulnerable to external factors like global commodity price changes or regional financial disturbances.

Policymakers in Montenegro need to be particularly vigilant during periods of heightened global economic uncertainty, as their economy's sensitivity to external shocks makes it more prone to abrupt inflationary shifts. Regional coordination with EMU institutions could help Montenegro manage inflation more effectively, as alignment in monetary policies might provide more stability. Given the challenges in predicting troughs, maintaining a flexible monetary policy that can respond quickly to both inflationary and deflationary pressures is crucial. The increased amplitude of inflation cycles suggests a need for better monitoring of inflation drivers, such as commodity prices and global trade dynamics, to avoid being caught off-guard by sudden inflation spikes. Overall, these results highlight the complexity of managing inflation in smaller economies like Montenegro and underscore the need for tailored policy responses that account for their unique economic dynamics and sensitivity to global changes.

3.2. Correlation matrix

Do the inflation cycles co-move across EMU and Montenegro? We calculate the correlation matrix considering the pre-GFC (Great Financial Crisis) (2006:1-2008:1) and the post-GFC (2010:1-2024:10).

Table 2: Correlation matrix (Pre-GFC and Post-GFC)

	Pre GFC (2006M01-2008M01)		Post GFC (2010M01-2024M10)	
Probability	EMU inflation	MNE inflation	EMU inflation	MNE inflation
EMU inflation	1		1	
	-----		-----	
CG inflation	0.7577	1	0.7562	1
	0	-----	0	-----

Source: Author's calculations

The analysis of the correlation between inflation cycles in the European Monetary Union (EMU) and Montenegro, particularly during the pre-Global Financial Crisis (GFC) period (2006M01-2008M01), provides several key insights. During the pre-GFC period, the correlation between EMU inflation and Montenegro's inflation is 0.76 with a p-value of 0.00%, indicating a strong positive relationship. This suggests that inflation trends in the EMU had a significant influence on inflation in Montenegro before the financial crisis. The high correlation implies that any inflationary movements in the EMU during this time likely had a similar impact on Montenegro, which may be attributed to Montenegro's economic ties with the EMU, including trade relationships and monetary policy alignment.

The analysis notes that even after the GFC, the inflation cycles between EMU and Montenegro remain synchronized, with a continued positive correlation and very low p-values. This ongoing co-movement suggests that despite the economic disruptions caused by the GFC, the linkages between Montenegro and the EMU remained strong. It indicates that Montenegro's inflation trends continued to be influenced by broader European economic dynamics, including post-crisis monetary and fiscal policies. The synchronization of inflation cycles means that Montenegro's economic stability is closely tied to conditions in the EMU. As a smaller economy with significant ties to the EMU, Montenegro is more likely to be affected by the monetary and economic policies implemented at the EMU level. For example, if the European Central Bank (ECB) adopts a policy to curb inflation, it could also impact Montenegro's inflation levels through trade channels and investor expectations. During periods of economic turmoil, like the GFC, Montenegro might have been more exposed to the spillover effects of the EMU's economic challenges. However, during periods of economic stability and growth within the EMU, Montenegro likely benefited from positive economic trends as well.

3.3. Principal components

Policymakers in Montenegro need to closely monitor the economic developments within the EMU since these will directly influence domestic inflationary trends. This is especially important when formulating fiscal policies, as these should align with broader European trends to ensure stability. The EMU's understanding of the impact of its monetary policy on neighbouring economies like Montenegro can help in managing regional stability. The ECB's policies, while focused on the EMU, indirectly shape economic conditions in adjacent economies that are not EMU members but maintain close economic ties with it.

Table 3: Principal component analysis: Pre-GFC and Post-GFC

	Value	Difference	Proportion
Pre-GFC (2006:1-2008:1)			
PC1	1.75765	1.51530	0.87880
PC2	0.24235		0.12120
Post-GFC (2010:1-2021:12)			
PC1	1.52415	1.04829	0.76207
PC2	0.47585	---	0.23793
COVID-19 and Inflation era (2022:1-2024:10)			
PC1	1.87247	1.74493	0.93623
PC2	0.12753		0.06377

Source: Author's calculations

The Principal Component (PC) analysis results in Table 3 indicate how much of the variance in inflation rates between the EMU and Montenegro is captured by common underlying factors, both before and after the Global Financial Crisis (GFC). The first principal component, pre-GFC, accounts for 87.88% of the total variance in the data during the pre-GFC period. This means that a single underlying factor captures nearly 88% of the co-movements between the inflation rates of the EMU and Montenegro during this time. The second principal component (PC2) explains 12.12% of the variance, which suggests that while PC1 is dominant, there are still some other dynamics (12%) not captured by the primary factor. These might represent differences in inflation dynamics specific to Montenegro or unique external shocks that affected one region more than the other during the pre-GFC era.

The aftermath of the Global Financial Crisis (GFC) marked a significant shift in the relationship between EMU and Montenegro's inflation rates. Before the crisis, Montenegro's inflation closely mirrored trends in the EMU, suggesting that common factors largely influenced inflation dynamics in both regions. However, post-GFC analysis reveals that this connection has weakened, with the first principal component explaining only 76.20% of the variance in inflation rates, a noticeable decrease compared to the pre-GFC period. Concurrently, the second principal component's contribution rose to 23.79%, indicating that a larger portion of Montenegro's inflation variability now stems from factors independent of EMU trends.

This shift implies that Montenegro's inflation dynamics have become more complex and are increasingly driven by domestic factors or unique external shocks. Structural changes within Montenegro, such as labour market conditions, wage policies, and fiscal measures, appear to play a more prominent role in shaping inflation. As a result, for the period 2010:1-2021:12, policymakers could no longer rely solely on EMU inflation trends to predict and manage inflation crises effectively. For Montenegro, this means adopting a multi-faceted approach to inflation management. Policymakers need to balance monitoring EMU inflation with a closer examination of domestic economic indicators. Key focus areas should include addressing unemployment, promoting wage growth aligned with productivity, and enhancing the economy’s resilience to external shocks. Furthermore, flexibility in fiscal policy and strategic reforms will be crucial to mitigate inflation risks arising from local factors.

The COVID-19 and Inflation Era (2022:1-2024:10) reveals a significant shift in the relationship between EMU and Montenegro’s inflation dynamics. During this period, the first principal component (PC1) explains an overwhelming 93.62% of the variance, indicating a high degree of synchronization between the two regions’ inflation rates. In contrast, the second principal component (PC2) accounts for only 6.38%, suggesting that independent or domestic factors have had a much smaller influence on Montenegro's inflation during this time.

This resurgence in synchronization can be attributed to several global economic disruptions brought on by the COVID-19 pandemic and subsequent inflationary pressures. The pandemic caused significant disruptions to global supply chains, leading to shortages of goods and rising production costs that affected both the EMU and Montenegro similarly. Additionally, the rapid increase in energy prices, particularly in 2022, contributed to inflation spikes across Europe, including Montenegro, which relies heavily on energy imports. The European Central Bank’s (ECB) monetary tightening to combat inflation had direct spillover effects on Montenegro due to its use of the euro. Furthermore, Montenegro's close economic ties with the EMU, particularly in trade and tourism, intensified the alignment of inflation trends.

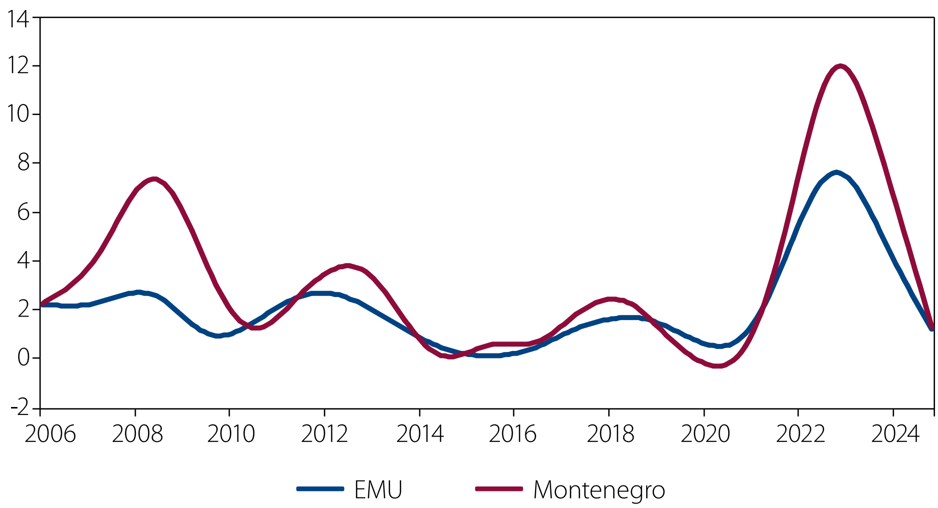
These factors underscore Montenegro's vulnerability to external shocks and highlight the limited scope for independent monetary policy due to euroization. As inflation in the EMU surged, Montenegro’s economy mirrored these trends, making it crucial for policymakers to remain vigilant to external inflationary forces. To address these challenges, Montenegro needs to focus on fiscal policy measures and structural reforms. Enhancing economic resilience through diversification, strengthening supply chains, and supporting labour market stability can help mitigate the impact of global inflationary shocks. In conclusion, the COVID-19 and Inflation Era highlights the importance of adapting policy strategies to a rapidly changing global environment to ensure Montenegro's economic stability and sustainability.

Both pre-and COVID-19 periods have a high proportion of variance explained by the first principal component, indicating that the inflation rates of the EMU and Montenegro are influenced by common factors across both time periods. The slight increase in the post-GFC period suggests a marginally stronger alignment of inflationary trends between the two regions, which could be due to greater economic interdependence or the influence of common shocks such as the COVID-19 pandemic or monetary policy responses in the EMU.

3.4. HP filter

The analysis using the HP filter, in Figure 3, allows us to observe the underlying trends in the inflation rates of EMU and Montenegro by separating out the cyclical components. This method is advantageous compared to simple linear trends because it allows the trend itself to have some volatility, providing a more nuanced view of long-term patterns. The trends extracted from the HP filter (using lambda = 1600) indicate that both the EMU and Montenegro inflation rates have similar long-term patterns, suggesting a degree of co-movement over time. This could imply that inflation in Montenegro is partly influenced by the broader inflationary environment in the EMU, which is consistent with Montenegro's strong economic ties to the European region.

Figure 3: Trend obtained using the HP filter with lambda = 1600



Source: Author's calculations

Interestingly, the trend component, even though it is intended to represent long-term movements, still exhibits some cyclical patterns. These cycles are not short-term fluctuations but rather "super-cycles" that are longer in duration compared to typical business cycles. This phenomenon is often observed in financial cycles, which can span over many years, reflecting deeper shifts in economic conditions, such as changes in monetary policy, structural reforms, or major global economic events. The presence of these super cycles within the trend suggests that there are longer-term dynamics at play beyond the immediate business cycle. These could be driven by factors like changes in monetary policy frameworks, global financial crises, or structural adjustments in the economy. For instance, the trend might capture the effects of the 2008 Global Financial Crisis, subsequent recovery phases, or the recent inflationary pressures following the COVID-19 pandemic and energy crises.

For policymakers, understanding these super cycles is crucial as they provide insights into the underlying resilience or vulnerabilities of an economy. While short-term cycles might require tactical adjustments (e.g., short-term interest rate changes), super-cycles often call for more strategic interventions like structural reforms or adjustments to long-term policy frameworks. Recognizing the nature of these cycles can help policymakers in Montenegro and the EMU to design more effective stabilization policies and anticipate the impact of external economic shock.

3.5. Frequency of inflation crisis

The inflation crisis, as seen in Table 4, appears to be highly frequent (59.73%) compared to the non-inflation crisis (40.27%). The rationale behind this is the fact that the high frequency of inflation crises in Montenegro, as indicated by our findings (59.73% for inflation crises compared to 40.27% for non-inflationary periods), can be attributed to several factors specific to Montenegro's economy and external environment during the period from January 2006 to October 2024: a) external economic shocks, b) euroization and monetary policy limitations, c) energy and food price volatility, d) tourism dependency and seasonal inflation, e) structural weaknesses and policy constraints, and f) post-COVID recovery and recent inflationary pressures.

Table 4: Frequency of inflation crises in Montenegro

Value	Count	Percent	Cumulative Count	Cumulative Percent
0	91	40.27	91	40.27
1	135	59.73	226	100
Total	226	100	216	100

Source: Author's calculations

In Table 5, we observe that for the EMU inflation rate, the mean (-3.29) is much higher than the median (driven by a strong asymmetry – more observation on the left tail of the distribution can prove the minimum value). As a consequence, the volatility is high. The heterogeneity of inflation dynamics in EMU implies a huge dispersion of the inflation growth rate in EMU. The negative mean (-3.2866) indicates that, on average, the growth rate of inflation is slightly declining over time. This could reflect a general deflationary pressure or periods of negative inflation in the EMU, likely due to economic conditions such as austerity measures or weak demand following financial crises (e.g., the euro area debt crisis or the effects of the COVID-19 pandemic).

Table 5: EMU inflation percentage change statistics

	INF_EMU_PERCED
Mean	-3.286692
Median	0.000000
Maximum	500.0000
Minimum	-600.0000
Std. Dev.	75.35850
Skewness	-1.574284
Kurtosis	32.79515
Jarque-Bera	8303.395
Probability	0.000000
Sum	-729.6457
Sum Sq. Dev.	1255038.
Observations	222

Source: Author's calculations

A median of zero suggests that half of the inflation growth rates are positive, and half are negative. This reflects a symmetric balance between periods of inflation and deflation over the analyzed period. Given that the median is higher than the mean, it indicates that the distribution might be skewed to the left, with some extreme negative values pulling the mean down. A high standard deviation shows significant volatility in the inflation growth rate. Large fluctuations in inflation growth could be driven by economic shocks, such as the 2008 global financial crisis, the European sovereign debt crisis, and more recently, the COVID-19 pandemic. These events might have caused sharp spikes and drops in inflation, reflecting instability within the EMU economy. The negative skewness indicates that the distribution is left-skewed, meaning that there are more extreme negative inflation growth values compared to positive ones. This could be due to sharp deflationary periods in EMU countries, potentially driven by economic contractions or monetary policy responses such as quantitative easing. A very high kurtosis value (well above the normal kurtosis of 3) indicates that the distribution has heavy tails and a sharp peak around the mean. This suggests the presence of extreme outliers—both very high and very low inflation growth rates—which could be associated with rare but significant economic events or policy shifts. The Jarque-Bera test indicates whether the distribution follows a normal distribution. With a high Jarque-Bera statistic (8303.395) and a probability value of 0.0000, we reject the null hypothesis of normality. This further reinforces the idea that inflation growth in the EMU is not normally distributed, likely due to the influence of extreme values and economic shocks.

3.6. Standardized and cumulative inflation growth

In the following analysis, let us consider two measures capturing inflation booms using inflation growth: (1) the EMU cumulative 2 months inflation growth; and (2) the EMU standardized cumulative 2 months inflation growth. We discuss and interpret the results obtained in Table 6 why the cumulative EMU inflation is a better indicator for an inflation boom. To minimize this asymmetry, cumulative EMU inflation is standardized: we remove the mean and divide by the standard error. Therefore, the standardized variable has zero mean and 1 variance, as seen in Table 6.

In this analysis, we compare two measures for capturing inflation booms in the EMU: cumulative 2 months inflation growth (INF_EMU_G2) and standardized cumulative 2 months inflation growth (SINF_EMU_G2). Here is a breakdown of why the cumulative inflation measure is a better indicator for an inflation boom, and how standardizing it helps address asymmetry. Cumulative inflation growth gives an immediate measure of how much inflation is increasing or decreasing over two months. Since inflation booms are typically defined by sustained or rapid price increases, the cumulative measure captures the total change in inflation over a short period, making it an effective tool for detecting these episodes.

Table 6: EMU standardized and non-standardized cumulative two months inflation growth

	INF_EMU_G2	SINF_EMU_G2
Mean	4.2542	0.0000
Median	3.5000	-0.1802
Maximum	20.7000	3.9291
Minimum	-0.9000	-1.2314
Std. Dev.	4.1856	1.0000
Skewness	1.9279	1.9279
Kurtosis	7.1002	7.1002
Jarque-Bera	296.9879	296.9879
Probability	0.0000	0.0000
Sum	957.2000	0.0000
Sum Sq. Dev.	3924.3385	224.0000
Observations	225.0000	225.0000

Source: Author's calculations

The mean for the cumulative inflation growth is positive (4.25%), which indicates that inflation growth, on average, is increasing. The maximum value (20.7%) further emphasizes that significant spikes in inflation growth are occurring, which are crucial in identifying inflation booms. Since the measure is in percentage points, it is directly interpretable without the need for further transformation. Policymakers and economists can easily relate to cumulative inflation growth because it reflects the raw change in inflation rates, which is a more intuitive measure for assessing inflationary risks.

While the cumulative inflation measure is useful, it comes with some drawbacks. The skewness of 1.93 and kurtosis of 7.10 indicate a distribution that is not symmetric and has a heavy tail. This asymmetry implies that inflation growth is not evenly distributed, with more extreme values (either high or low) being more frequent than a normal distribution would suggest. Such skewness can lead to misleading interpretations of the inflation boom frequency. The cumulative inflation growth has a wide range (from -0.90 to 20.7), making it harder to compare inflation across different time periods or countries. By standardizing this measure, we eliminate the impact of absolute scale differences, making the metric easier to compare across different datasets or regions.

Standardization transforms the series by removing the mean and dividing by the standard deviation. As a result, the new series has a mean of 0 and a standard deviation of 1, as seen in the table. This eliminates the skewness and kurtosis issues of the original cumulative series, making it easier to identify inflation booms that are outside of normal variation. The standardized measure allows us to focus on inflation booms that are significantly above or below average growth, which may be more useful for detecting abnormal inflationary trends. The maximum and minimum values of 3.93 and -1.23 suggest large deviations from typical inflation patterns, which might signal inflation booms or busts.

3.7. Logit regression

We try to make a good forecast of the inflation crisis at a 12-month horizon (2024M11-2025M10). To do this, we use logistic regression analysis. We regress the inflation crisis variable on both measures of inflation boom *inf_emu_g2* and *sinf_emu_g2*.

Table 7: Logistic regression of Montenegro inflation on EMU standardized and non-standardized inflation

Cumulative EMU inflation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
INF_EMU_G2	0.3452	0.0694	4.9743	0.0000
C	-0.9081	0.2581	-3.5184	0.0004
Standardized cumulative EMU inflation				
SINF_EMU_G2	1.4448	0.2905	4.9743	0.0000
C	0.5604	0.1759	3.1864	0.0014

Source: Author's calculations

In Table 7, we observe in the regression that the cumulative EMU inflation significantly explains the occurrence of the inflation crisis in Montenegro. This result is robust for standardized/non-standardized variables. The only difference is the value of the coefficient 1.44 for the standardized and 0.35 for the non-standardized. The first one makes more sense and is easier to interpret as the crisis variable is binary (0 or 1).

The coefficient of INF_EMU_G2 0.35 means that for each unit increase in EMU cumulative inflation growth (unstandardized), the odds of experiencing an inflation crisis in Montenegro increase by a factor of $e^{0.35}\approx 1.419$. In practical terms, a 1-unit increase in cumulative EMU inflation leads to a 1.42 of the odds of a crisis in Montenegro. In practical terms, if EMU inflation rises by one percentage point, the likelihood of a crisis in Montenegro increases by about 42%. Suppose EMU cumulative inflation growth increases from 2% to 3% (a 1-unit increase). This increase translates directly to a 42% higher chance of an inflation crisis in Montenegro.

The coefficient of the standardized cumulative EMU inflation growth (*SINF_EMU_G2*) is 1.44. Here, because the inflation variable has been standardized (mean = 0, standard deviation = 1), the interpretation of the coefficient becomes clearer. A 1 standard deviation increase in the EMU cumulative inflation growth increases the odds of an inflation crisis in Montenegro by a factor of $e^{1.44}\approx 4.221$. An increase by a factor of 4.22 means that the odds of experiencing an inflation crisis increase by 322%. This percentage increase is calculated as: (4.22%-1)*100%=322%.

This reflects a much stronger relationship between inflation growth and crisis since standardized values allow us to interpret changes in terms of relative scale (in standard deviation units). The fact that both the standardized and non-standardized models show statistical significance and robustness, it confirms that inflation growth in EMU, both in its raw form and as a deviation from the mean, plays a crucial role in predicting inflation crises in Montenegro.

Let us go through an example that demonstrates the relationship between standardized cumulative EMU inflation and inflation growth in Montenegro using hypothetical values. Assume that the cumulative two-month inflation growth in the EMU for a certain period is 15%. Let us also assume that for a different period, the cumulative two-month EMU inflation growth is 5%.

The distinction between cumulative and standardized EMU inflation growth is essential for understanding their respective roles in predicting inflation crises in Montenegro. These differences impact interpretability, scaling and comparability, and the magnitude of their impact on crisis prediction. Cumulative inflation growth offers a direct and intuitive measure in percentage points. Specifically, a 1-unit increase in cumulative EMU inflation growth corresponds to a 42% higher risk of a crisis in Montenegro. This straightforward approach helps policymakers understand the impact of inflationary changes in absolute terms. On the other hand, standardized inflation growth expresses changes relative to the typical variability (standard deviation) of inflation growth. A 1 standard deviation increase in standardized cumulative EMU inflation growth corresponds to a 322% higher risk of a crisis. This method allows for clearer interpretations when dealing with deviations from the average, offering a more context-aware measure of inflation risk. Cumulative inflation growth is particularly useful for analyzing changes in their raw form (e.g., percentage points), making it easier to interpret in practical policy terms. For instance, a 2% increase in cumulative inflation is directly relatable to observed economic changes. In contrast, standardized inflation growth is more appropriate for comparisons across different datasets, models, or time periods, as it accounts for variations in scale and dispersion. Standardization normalizes the data, ensuring that inflation growth is measured consistently, regardless of differences in magnitude or volatility across contexts. The standardized coefficient (1.44) is notably larger than the cumulative coefficient (0.35). This difference reflects the fact that changes measured relative to typical variability (standard deviations) have a more pronounced impact on predicting inflation crises. In other words, deviations from the average inflation rate tend to signal a higher risk of a crisis compared to smaller, absolute changes in cumulative inflation. In conclusion, both cumulative and standardized inflation growth provide valuable insights. Cumulative measures offer practical, straightforward interpretations, while standardized measures enable comparative and context-sensitive analyses. Together, they enhance the robustness of predicting inflation crises and inform more nuanced policy decisions.

3.8. Multivariate logit regression

The logit regression performed above does not include any other variable that may have predictive power for inflation crises in Montenegro. We now add: *fao_index* (FAO food price index), *brent_prices*, un (unemployment rate), wages (nominal wages in level, in euros), and GDP growth.

Table 8: Multivariate probit regression of inflation in Montenegro

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SINF_EMU_G2	2.5086	0.5164	4.8580	0.0000
BRENT_PRICES	-0.1016	0.0211	-4.8147	0.0000
FAO_INDEX	0.1784	0.0364	4.9065	0.0000
UN	0.2776	0.0799	3.4734	0.0005
WAGES	-0.0229	0.0036	-6.4298	0.0000
GDP	-0.1815	0.0689	-2.6347	0.0084
C	2.4988	2.2420	1.1146	0.2650

Source: Author's calculations

Variables in the multivariate model, in Table 8, the standardized cumulative 2-month EMU inflation, Brent prices, food prices, unemployment, wages, and GDP are significant. If wages, Brent prices, and GDP increase then the probability of an inflation crisis in Montenegro is lower. On the contrary, if unemployment, food prices, and standardized EMU inflation are higher, the probability of an inflation crisis in Montenegro increases.

The results of your logistic regression offer valuable insights for policy analysis, particularly in understanding the dynamics that contribute to or mitigate the likelihood of an inflation crisis. These findings can guide policymakers in formulating strategies that foster economic resilience and reduce systemic vulnerabilities. Here, we will explore the implications and underlying mechanisms of each significant indicator in detail, connecting them to potential policy interventions.

An increase in systemic inflation, particularly within the euro area (captured by the *SINF_EMU_G2* variable), significantly increases the probability of an inflation crisis in Montenegro. This relationship underscores the need for prudent monetary policy. When inflation becomes entrenched, it diminishes the purchasing power of consumers and destabilizes business planning due to rising input costs and unpredictable pricing. In response, central banks often tighten monetary policy by raising interest rates. While such measures aim to curb inflation, they also increase borrowing costs for businesses and households, potentially leading to loan defaults and credit squeezes. Policymakers must balance inflation control with financial stability by adopting gradual interest rate adjustments and communicating their policy trajectory clearly to avoid sudden shocks to the financial system.

An increase in systemic inflation in the euro area significantly raises the probability of a financial crisis in Montenegro. Given Montenegro's euroized economy (it uses the euro as its currency despite not being part of the euro area), it lacks independent monetary policy. As a result, Montenegro cannot directly control inflation through interest rate adjustments or money supply changes. The mechanism is straightforward. When inflation rises systemically across the euro area, it affects Montenegro through multiple channels. Prices of imports from the euro area countries increase, raising the cost of goods and services domestically. This reduces the purchasing power of Montenegrin households and businesses. Additionally, higher inflation in the euro area can lead the ECB to increase interest rates, which indirectly impacts Montenegro by making credit more expensive and reducing liquidity in the economy. This strain on borrowing costs increases the likelihood of defaults, weakens financial institutions, and heightens the risk of a financial crisis. A policy consideration is that Montenegro must rely on *fiscal policy tools* to mitigate inflationary pressures. This includes prudent public spending, targeted subsidies for essential goods, and enhancing competition to avoid price gouging. Strengthening the resilience of financial institutions to external shocks is also critical.

Interestingly, the inverse relationship between Brent oil prices and the likelihood of a financial crisis suggests that rising oil prices can be a sign of robust global economic activity. When demand for oil is strong, it typically signals that industrial production and trade are expanding. While Montenegro is a net oil importer, the relationship might reflect broader global economic trends where rising oil prices signal increased global demand and economic strength. Higher oil prices often correlate with stronger global economic activity, which boosts tourism and trade –

two pillars of Montenegro's economy. A growing global economy leads to increased tourist arrivals, higher foreign direct investment, and stronger export demand for services. This influx of foreign currency supports the Montenegrin economy and stabilizes its financial system, reducing the likelihood of an inflation crisis. For oil-exporting countries, higher revenues from oil sales can strengthen fiscal positions and support public investments, thereby stabilizing the economy. Policymakers in oil-importing countries, however, face the challenge of mitigating the adverse effects of rising fuel costs on consumers and businesses. This can be addressed through strategic energy reserves, investment in alternative energy sources, and targeted subsidies to shield vulnerable populations from energy price volatility. Despite the stabilizing effects of higher oil prices in a global growth context, Montenegro remains vulnerable to rising fuel costs domestically. Policies that diversify energy sources (e.g., investing in renewable energy) and improve energy efficiency can help mitigate the adverse effects of oil price volatility on consumers and businesses.

The positive relationship between the FAO Food Price Index and the probability of an inflation crisis highlights the destabilizing impact of rising food costs, particularly in economies where a significant portion of household income is spent on basic necessities. As a small country with a significant reliance on food imports, Montenegro is particularly sensitive to global food price fluctuations. Higher food prices not only contribute to inflation but can also trigger social unrest and political instability. The mechanism is clear: when global food prices rise, the cost of essential goods such as wheat, dairy, and meat increases domestically. This leads to higher living costs, reducing household purchasing power. In turn, lower consumption can weaken businesses, particularly small and medium-sized enterprises (SMEs), which form the backbone of Montenegro's economy. Rising food prices can also exacerbate social tensions, creating instability that may weaken investor confidence and the overall financial system. To mitigate these risks, Montenegro should develop strategic food reserves, encourage domestic agricultural production, and establish social safety nets like food assistance programs to support vulnerable populations during periods of high global food prices. Policymakers must ensure food security through diversified agricultural production, strategic grain reserves, and trade policies that prevent abrupt price shocks. Social safety nets, such as food assistance programs and direct cash transfers to low-income households, can also mitigate the socio-economic impacts of food price surges.

Unemployment (UN) emerges as another key factor that increases the likelihood of an inflation crisis. Given Montenegro's relatively small labour market and reliance on seasonal tourism, unemployment can rise sharply during economic downturns. When unemployment rates rise, household incomes decline, reducing consumer spending and weakening overall economic demand. This decline in spending can lead to reduced business revenues, job cuts, and a vicious cycle of economic contraction. Moreover, higher unemployment increases the risk of loan defaults, straining the banking sector. When unemployment increases, a significant portion of the workforce becomes idle. This reduction in labour supply leads to a decline in productive capacity. In sectors such as manufacturing, services, and agriculture, lower employment means fewer goods and services are being produced. When production falls while demand remains relatively stable (or declines less sharply), this creates supply-side constraints. In many cases, wages do not immediately adjust downward when unemployment rises due to contractual obligations, minimum wage laws, or collective bargaining agreements. This phenomenon is known as wage stickiness. Even if a significant number of people are unemployed, the wages of those still employed may remain unchanged or decline only marginally. Firms facing higher labour costs relative to their output may pass these costs onto consumers through higher prices, particularly if productivity declines. In Montenegro, where labour markets are small and specialized, structural unemployment (when workers' skills do not match available jobs) can persist. This structural rigidity means that even with high unemployment, there may be pressure to maintain or increase wages for skilled workers who remain in demand, leading to cost-push inflation. When unemployment rises and domestic production declines, Montenegro must rely more heavily on imports to meet demand for goods and services. Higher dependence on imports makes the economy vulnerable to global price fluctuations. If global prices for essential goods (e.g. food and energy) rise while unemployment remains high, Montenegro experiences imported inflation. This effect is compounded by the weakened domestic production capacity caused by unemployment. Higher costs for imports are passed on to consumers, driving up prices even further. Rising unemployment erodes consumer confidence and creates uncertainty about future economic prospects. Households that anticipate continued economic instability may choose to front-load spending on essential goods before prices rise further. This behavior, driven by expectations of future inflation, can lead to a temporary surge in demand for necessities, pushing prices higher despite overall economic weakness. In Montenegro, where household consumption is a key component of GDP, such shifts in spending patterns can exacerbate inflationary pressures. If consumers believe that unemployment will lead to persistent economic challenges, they may increase current spending to hedge against future price hikes, creating a self-fulfilling inflationary cycle. Higher unemployment often necessitates increased government spending on social benefits such as unemployment insurance, welfare programs, and economic stimulus measures. If this spending is financed through public borrowing, it can lead to rising government debt. In countries with limited fiscal capacity, such as Montenegro, higher debt levels can reduce investor confidence and lead to higher borrowing costs (interest rates). Rising interest rates can fuel inflation by increasing the cost of financing for businesses and households. Additionally, if the government resorts to tax increases to manage debt, these higher taxes can reduce disposable income while simultaneously increasing costs for businesses, contributing to inflationary pressures. For Montenegro, a country heavily reliant on sectors like tourism and services, increased unemployment in these areas can lead to fewer available services (e.g., fewer hotels and restaurants operating at full capacity). As supply decreases, prices for the available goods and services may rise due to scarcity. This supply-side inflation occurs despite overall economic weakness. To address unemployment, Montenegro should invest in *diversifying its economy* beyond tourism, such as developing *technology, agriculture*, and *renewable energy sectors*. Policies that promote job retraining and entrepreneurship can help stabilize employment rates and reduce vulnerability to external shocks.

Conversely, the finding that higher wages decrease the likelihood of an inflation crisis points to the stabilizing effect of rising incomes. Higher wages improve household incomes, boosting consumption and economic stability. When wages increase, households have more disposable income to spend, which supports businesses and fosters economic growth. Higher wages also reduce the risk of loan defaults, as people are better able to meet their financial obligations. This stabilizes the banking sector and reduces the likelihood of financial distress. Given Montenegro's reliance on tourism and services, wage growth can help sustain demand, particularly during the off-season. One of the most immediate effects of a wage increase is an improvement in household incomes and purchasing power. When wages rise by 26%, workers have more disposable income to spend on goods and services. Similarly, an increase in pensions of 7-8% supports the purchasing power of retirees, who often have a high propensity to consume. In Montenegro, where the economy relies heavily on domestic consumption and tourism, higher wages can lead to increased spending in sectors such as retail, hospitality, and services. This surge in demand can stimulate economic growth. As consumers spend more, businesses experience higher sales, which can lead to greater profitability and expansion. Businesses anticipating higher demand may invest in expanding operations, hiring more workers, or adopting new technologies, further stimulating economic activity. Increased demand for goods and services may lead to job creation, reducing unemployment and reinforcing the positive cycle of economic growth. This boost in economic activity can help counteract recessionary pressures and reduce the likelihood of an inflation crisis. By stimulating growth, wage increases support a healthier, more resilient economy that is better equipped to withstand external shocks. In Montenegro, the Europe Now 2 program's wage increases could encourage firms to modernize and become more competitive, fostering a more productive economy. When productivity rises in tandem with wages, businesses can absorb higher labour costs without passing them on to consumers through higher prices. This dynamic helps stabilize prices and mitigate inflationary pressures. One concern with wage increases is that they may lead to demand-pull inflation, where increased consumer spending pushes prices higher. However, this inflationary pressure can be offset if businesses respond by increasing the supply of goods and services. In Montenegro, if higher wages lead to increased demand, businesses may expand production to meet this demand. This expansion can prevent shortages and keep prices stable. Additionally, higher wages may attract more people into the labour market, increasing the workforce and enabling higher output. This increase in supply helps balance the rise in demand, reducing the risk of excessive inflation. Higher wages and pensions improve the ability of households to service their debts. In Montenegro, where many households may have loans or mortgages, rising incomes reduce the likelihood of loan defaults. Wage increases and pension adjustments can help reduce income inequality and improve social stability. Greater social stability supports investor confidence and economic growth, reducing the risk of financial crises driven by socio-economic instability. Policymakers should aim to foster wage growth through productivity-enhancing policies, collective bargaining mechanisms, and living wage initiatives. However, they must also ensure that wage growth is balanced with productivity to avoid inflationary pressures.

The negative relationship between GDP growth and the likelihood of an inflation crisis reinforces the importance of sustained economic expansion in maintaining financial stability. A growing economy reflects increased production, higher employment, and greater investor confidence. When GDP is expanding, governments benefit from higher tax revenues, which can be used to manage public debt and support financial institutions during periods of stress. When GDP grows, businesses thrive, employment rates improve, and government revenues increase. This creates a positive economic environment where households and firms are better able to meet their financial obligations. For Montenegro, GDP growth is often driven by tourism, infrastructure projects, and foreign investment. A growing economy supports confidence in the financial sector, reduces defaults, and stabilizes public debt levels. To sustain GDP growth, Montenegro should invest in infrastructure development, promote foreign direct investment (FDI), and support innovation and entrepreneurship. Diversifying the economy and enhancing the business environment through regulatory reforms can help maintain steady growth and reduce vulnerability to external shocks.

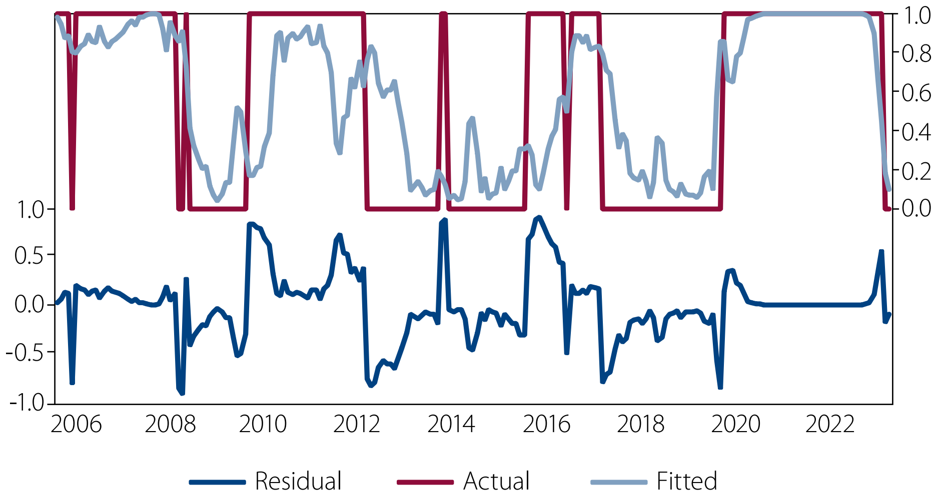
In summary, the results of this analysis provide a multifaceted view of the economic indicators that influence financial and inflation stability. Policymakers must adopt a balanced approach that addresses inflationary pressures while promoting economic growth, wage stability, and employment. Strategic interventions in energy and food markets, along with prudent fiscal policies, are essential to mitigating the risk of financial crises. By understanding these relationships, policymakers can craft informed, adaptive strategies that enhance resilience and protect against systemic shocks. This model provides useful insights for both short-term inflation management and long-term structural reforms aimed at stabilizing Montenegro's economy.

3.9. In-sample forecasting

Figure 4 shows that 2008, 2012, 2018, and the 2022 inflation crisis are pretty well captured and forecasted by the model, as can be seen by the flat line of residuals. Still, there remain some periods that the model cannot forecast accurately. For example, the model predicts that the inflation crisis of 2008 would start lowering in October 2008. The model can predict in advance the 2012 crisis. The model starts alarming February 2010, the 2012 crisis, therefore the model alarms a crisis ahead of time, up to 2 years.

The model's performance in predicting inflation crises over time demonstrates several notable strengths. The model successfully captures and forecasts the major inflation crises during these key years (2008, 2012, 2018, 2022). This is evident from the flat line of residuals, which indicates minimal deviation between the model's forecast and the actual inflation crisis occurrences during these periods. For example, in 2008 and 2022, the model accurately tracked the crisis dynamics, providing a good fit for the actual inflation trends. The model's success during these periods demonstrates its ability to forecast large economic shocks effectively, possibly driven by external global factors (e.g., the global financial crisis in 2008 and the COVID-19 aftermath in 2022). One of the key strengths of the model is its ability to predict crises ahead of time, particularly demonstrated with the 2012 inflation crisis, where the model started alarming as early as February 2010, providing an advanced warning of nearly two years. This capability could be invaluable for policymakers, enabling them to take preventive actions, such as tightening monetary policy, adjusting interest rates, or enacting fiscal measures to mitigate the potential crisis before it materializes.

Figure 4: In-sample forecasting for Montenegro inflation



Source: Author's calculations

3.10. Confusion matrix

Now, we examine the confusion matrix for a given threshold level, say 0.15. What is the True Positive Rate (TP) and the False Positive Rate (FP) associated with the 0.15 threshold? To present the relationship between crisis events (positive and negative) and detection outcomes (detects or misses), we create a matrix (or confusion table). Here's the structure that captures true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The cut-off (or threshold) in a binary classification model, like the logistic regression used here, is the probability value above which the model classifies an observation as positive (e.g., predicting an inflation crisis) and below which it classifies it as negative (e.g., no crisis). In this case, the cut-off values (0.05, 0.10, 0.15) represent different probability thresholds that determine whether the model predicts a crisis (1) or not (0).

Table 9: Inflation crisis detection matrix

	Crisis detected (True)	No crisis detected (False)
Cisis (Positive)	True Positive	False Negative
No crisis (Negative)	False Positive	True Negative

Source: Author's calculations

For TP, the model correctly detects a crisis (there was a crisis, and the model predicted it), while for FN, the model misses a crisis (there was a crisis, but the model did not predict it). For FP, the model falsely predicts a crisis (no crisis occurred, but the model predicted one), and for TN, the model correctly identifies no crisis (no crisis occurred, and the model correctly predicted no crisis). For example, a threshold of 0.15 means that if the probability of having a crisis is 15% or above, it predicts that Montenegro will have an inflation crisis. A cut-off of 0.15 means that if the model assigns a probability of 15% or higher for a crisis, it will predict that an inflation crisis is likely to occur. Lowering the cut-off (e.g. to 0.05) will increase the number of crises detected, but it will also increase the number of false positives, meaning more periods will be incorrectly predicted as crises.

In Table 9, for success cut-off=0.15, 74.77% of the cases (0 or 1) are well classified. Specificity 46.07% and sensitivity 95.20%. True positive is therefore 95.20% (4.80% of crises are missed). It means that the model detects correctly more than 9 crises out of 10, and more than 46% of the no-crisis periods. The model gives false alarms for positive crisis (1) 4.80% and 53.93% for no crisis (0). When you decrease the threshold, you expect to increase the true positive but also the false positive (missed detections/false alarms of no crisis (0)). For success cut-off=0.10, 67.76% of the cases (0 or 1) are well classified. Specificity 25.84% and sensitivity 97.60%. True positive is therefore 97.60% (2.40% of crises are missed). It means that the model detects correctly more than 97% of crises and more than 25% of the no-crisis periods. The model gives false alarms for positive crisis (1) 2.40% and 74.16% for no crisis (0). For success cut-off=0.05, 61.68% of the cases (0 or 1) are well classified. Specificity 7.872% and sensitivity 100.00%. True positive is therefore 100.00% (0.00% of crises are missed). It means that the model detects correctly 100% of crises and more than 7% of the no-crisis periods. The model gives false alarms for positive crisis (1) at 0.00% and 92.13% for no crisis (0).

Table 9: Confusion matrix for a cut-off of 0.15, 0.10, and 0.5

Success cut-off: C = 0.15	Dep=0	Dep=1	Total
% Correct	43.96	97.54	74.65
% Incorrect	56.04	2.46	25.35
Success cut-off: C = 0.10			
% Correct	28.57	99.18	69.01
% Incorrect	71.43	0.82	30.99
Success cut-off: C = 0.05			
% Correct	3.30	100.00	58.69
% Incorrect	96.70	0.00	41.31

Source: Author's calculations

The analysis of the confusion matrix at different threshold levels (0.05, 0.10, and 0.15) provides important insights into the trade-offs between the True Positive Rate (TP) (sensitivity) and False Positive Rate (FP) (specificity), which are essential for economic policy decisions.

At the 0.15 threshold, the model correctly identifies more than 97.54% of the inflation crises, missing only about 2.46%. However, the model generates false alarms for 56.04% of the no-crisis periods, indicating that while it is highly successful in detecting crises, it also predicts a crisis in a significant number of periods where no crisis occurs. Policymakers may choose this threshold if early detection of inflation crises is the priority, even at the cost of overreacting to some non-crisis periods. This could trigger proactive measures such as implementing inflation-targeting strategies earlier to prevent potential crises. At the 0.10 cut-off, the model becomes even more sensitive, capturing 99.18% of the inflation crises, but at the cost of false alarms in 71.43% of no-crisis periods. This threshold is highly accurate in catching crises but generates a lot of false positives. This threshold is useful in scenarios where missing a crisis could have severe consequences, such as periods of economic fragility. However, the high false positive rate could lead to policy fatigue, where policymakers react too frequently, causing unnecessary tightening of fiscal and monetary policies, and potentially stifling economic growth in non-crisis times. At 0.05, the model detects every single crisis (100% TPR), but 96.70% of the no-crisis periods are also predicted as crises. This extremely low threshold results in no missed crises, but it creates a high number of false alarms, leading to an overestimation of the probability of crises. This threshold may be used in highly risk-averse environments, where the priority is to avoid missing any potential inflation crisis. However, the overwhelming number of false alarms can lead to over-reactionary policies, such as constant monetary tightening, which could unnecessarily destabilize economic growth and reduce market confidence. In conclusion, policymakers should choose the threshold depending on the economic conditions and risk tolerance of the economy. For Montenegro, where inflation crises could severely impact macroeconomic stability, a balance between sensitivity and specificity is crucial to avoid both false crisis predictions and missed warnings of genuine crises.

3.11. The ROC and AUROC

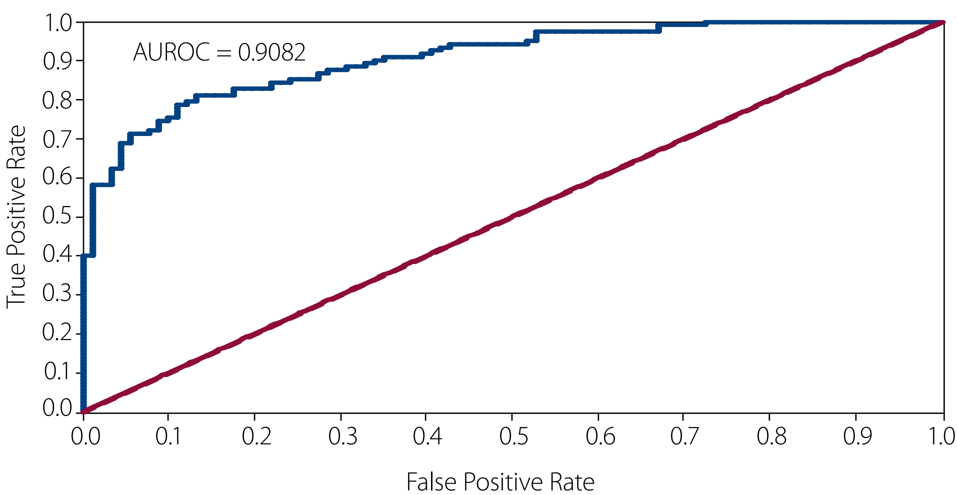
The Receiver Operating Characteristic (ROC) is a way to evaluate the predictive ability of the model. We produce the ROC curve as well as the AUROC. In Figure 5, the AUROC Value is 0.9082. This high Area Under the ROC Curve (AUROC) value suggests that the model has an excellent ability to distinguish between inflation crisis (1) and non-crisis (0) periods in Montenegro. A value close to 1 indicates high predictive power. For the true positive from 0.00 to 0.40, the curve stays vertical, so the false positive stays at 0.00. From 0.4 to 0.58 for the true positive on the y-axis, and from 0.00 to 0.01 for the false positive on the x-axis, the curve moves vertically. From 0.58 to 0.71 for the true positive on the y-axis, and from 0.03 to 0.05 for the false positive on the x-axis, the curve moves steeply. From 0.71 to 0.94 for the true positive on the y-axis, and from 0.05 to 0.43 for the false positive on the x-axis, the curve moves parallelly with the 45-degree line. From 0.94 till 1.00 for true positive on the y-axis, and from 0.43 till 1.00 for false positive on the x-axis, the curve moves slowly till the true positive and false positive meet with the 45-degree line.

The high AUROC score (0.9082) indicates that policymakers in Montenegro can rely on the model to accurately predict inflation crises with strong confidence. This allows for proactive interventions to mitigate the adverse impacts of such crises. The model is particularly strong in the initial range (TPR from 0 to 0.58) where the false positive rate remains at 0, indicating that the model can provide early warnings about inflation crises without triggering unnecessary false alarms. This feature is useful for policymakers to take preventative action while avoiding unnecessary economic disruptions based on false signals. As the model approaches higher thresholds (from TPR = 0.58 to TPR = 0.94), it begins to generate more false alarms (increasing FPR), which might lead to over-prediction of inflation crises.

Policymakers need to weigh this trade-off, where more aggressive predictions can be helpful in preparing for a crisis, but may also lead to economic policy overreactions. In the last segment (from 0.94 to 1.00), the curve flattens, indicating a significant increase in false positives. Policy actions based on this level of sensitivity might result in economic inefficiencies if too many non-crisis periods are mistakenly flagged as crises. Policymakers should consider using more conservative thresholds to minimize these false positives.

For policymakers, an optimal threshold around 0.58–0.70 (true positive range) could strike a balance between detecting inflation crises early and minimizing false alarms. During periods when the model forecasts inflation crises, the government could implement inflation-targeting measures, monitor EMU monetary policy, and prepare fiscal buffers to cushion the potential impact. In conclusion, the ROC curve analysis suggests that the model performs well in predicting inflation crises, particularly with minimal false positives in the early stages, allowing policymakers to prepare well in advance without unnecessarily disrupting the economy.

Figure 5: ROC and AUROC for Montenegro inflation



Source: Author's calculations

3.12. Optimal thresholds

Finally, we examine the optimal thresholds:

a. False-positive rate given true negative = Type 1 error

b. False-negative rate given true positive = Type 2 error

In predictive models, especially those related to crises (such as inflation crises), Type 1 and Type 2 errors occur when the model makes incorrect predictions. A Type 1 error occurs when the model predicts a crisis will happen, but in reality, no crisis occurs. Suppose a model predicts that an inflation crisis will occur in the country, but no crisis actually happens. This false alarm can lead to unnecessary policy actions, like raising interest rates or tightening fiscal policies, which might harm the economy. A Type 2 error occurs when the model predicts no crisis will happen, but in reality, a crisis occurs. Suppose a model predicts that an inflation crisis will not occur in Montenegro, but a crisis actually happens. This missed warning can prevent policymakers from taking necessary precautions, potentially leading to severe economic consequences. If false positives are very costly (e.g., implementing strict economic measures based on incorrect predictions), the threshold should be set to reduce Type 1 errors, even if it increases the risk of Type 2 errors. If missing a crisis is far more dangerous (e.g., failing to prevent an economic collapse), the threshold should be set to reduce Type 2 errors, even if it increases false positives.

For each probability threshold, we compute the following cost functions:

$$C1 = 0.5 * Type\ 2 + 0.5 * Type\ 1 \tag{16}$$

$$C2 = 0.7 * Type\ 2 + 0.3 * Type\ 1 \tag{17}$$

In this context, the cost functions C1 and C2 help determine the optimal thresholds for predicting an inflation crisis. These thresholds aim to balance the costs of different types of errors (Type 1 and Type 2) that could arise when classifying a country as either at risk or not at risk of an inflation crisis. Type 1 Error (false positive rate given true negative) occurs when the model incorrectly predicts a crisis for a country that is not actually at risk. For example, in Montenegro, a Type 1 error might mean labelling it as potentially in crisis when it is financially stable. A false positive could lead to unnecessary precautionary measures, public concern, or economic restrictions that aren't needed. Type 2 error (false negative rate given true positive) occurs when the model fails to predict an inflation crisis for Montenegro that is truly at risk. A Type 2 error might mean overlooking Montenegro which is on the brink of an inflation crisis. This type of error is often more costly because failing to identify an impending crisis can result in severe economic consequences for the country and its population. Each cost function represents a different approach to prioritizing the impact of these errors depending on the relative importance of correctly identifying a crisis versus avoiding false alarms.

In C1, both error types (Type 1 and Type 2) are weighted equally at 0.5. This implies that false positives and false negatives are seen as equally costly. C1 represents a balanced approach, suitable if the economic consequences of both errors are similar. It may be appropriate for economies where the resilience to both types of errors is generally stronger, meaning that both over-prediction (Type 1) and under-prediction (Type 2) can be managed with similar levels of caution. In C2, Type 2 errors are weighted more heavily at 0.7, while Type 1 errors are weighted at 0.3. This reflects the notion that false negatives (Type 2 errors) are more costly than false positives (Type 1 errors). This function places more emphasis on avoiding Type 2 errors, making it ideal for emerging and developing regions where a missed crisis prediction can have serious economic and social repercussions. In these economies, the ability to detect real crisis risks (Type 2) is often more critical than avoiding false alarms (Type 1), as failing to act on a true crisis can have far-reaching consequences, while a false positive may be less damaging.

For the purpose of the computation, we need a loop to find the optimal threshold and the output is Table 10 where we need to discuss the output.

Table 10: Optimal threshold for inflation in Montenegro

Threshold value	C1	C2
0.61	16.02	17.15

Source: Author's calculations

If we want to decrease the share of false positives, then the threshold should be higher (0.61). Also, to decrease the amount of false negatives, the threshold has to be higher (0.61). In the first case (50/50), the same weight is allocated to the Type 1 error as the Type 2 error. It means that sensitivity = specificity or, in other words, there is the same penalty for missing a crisis as a false alarm. The optimal cut-off is in this case 0.61. If the cost of false negatives increases (from 50% to 70%), it leads to the same cut-off point. The C1 cost function assigns equal importance to both Type 1 errors (false positives) and Type 2 errors (false negatives). In this scenario, missing a crisis (Type 2) is penalized equally as triggering a false alarm (Type 1). It reflects a balanced strategy where policymakers are equally concerned about falsely predicting a crisis and missing an actual crisis. The optimal threshold here is 0.61, which minimizes the overall cost by balancing both error types. A higher threshold means the model is more conservative in predicting a crisis, reducing the number of false positives (fewer false alarms), but accepting a higher risk of missing some crises. This strategy would be appropriate if policymakers are cautious about triggering unnecessary economic interventions based on false crisis alarms.

The C2 cost function gives more weight to Type 2 errors (false negatives) than Type 1 errors (false positives). In this case, missing a crisis (Type 2) is considered more costly than raising a false alarm (Type 1). This approach reflects a more aggressive crisis management strategy, where policymakers prefer to err on the side of caution and avoid missing any real crises, even at the expense of more false alarms. The optimal threshold for this function is 0.61.

A cut-off of C=0.61% means that the model classifies cases as a crisis (1) if the probability is 0.61 or higher, and as no crisis (0) if the probability is below 0.60. The optimal thresholds and percentages provided in the table are critical for understanding how predictive models can be used to anticipate an inflation crisis. The thresholds determine the probability cut-off at which policymakers decide to act. Each threshold corresponds to specific costs associated with Type 1 errors (false positives) and Type 2 errors (false negatives), which are reflected in the C1 and C2 cost functions. Let us explore these thresholds, percentages, and their implications for Montenegro in detail.

The analysis of the cost functions C1 (equal weighting of Type 1 and Type 2 errors) and C2 (higher weighting on Type 2 errors) reveals that the optimal threshold for Montenegro is 0.61 in both cases. This threshold represents the point at which the overall costs of misclassification are minimized, balancing the risks of false positives (Type 1 errors) and false negatives (Type 2 errors). Let us explore the implications of this finding for policy analysis, especially in the context of Montenegro's ambition to join the European Union (EU).

The C1 minimizes at 0.61, indicating that policymakers are equally concerned about false positives (predicting a crisis that does not occur) and false negatives (missing an actual crisis). This threshold ensures that both types of errors are kept in check, reflecting a stable and resilient economic strategy suitable for an economy like Montenegro, where financial stability and growth must be carefully balanced. The C2 also minimizes at 0.61, meaning that even when policymakers are more concerned about missing a crisis (false negatives), the same threshold applies. This highlights the need to be cautious about potential financial crises, especially in a developing economy where missing a crisis could have far-reaching social and economic consequences.

The fact that both cost functions result in a high threshold of 0.61 is significant for Montenegro's efforts to join the EU. The EU demands that candidate countries demonstrate that a threshold of 0.61 reflects a balanced approach to risk management, ensuring that Montenegro is neither too quick to impose unnecessary policy measures (avoiding false positives) nor too slow to react to real crises (avoiding false negatives). This balance is essential for demonstrating to the EU that Montenegro has the capacity for sound economic governance. The ability to adopt a high threshold shows that Montenegro can manage risks conservatively, a trait valued by EU institutions. It reflects a mature financial system that prioritizes long-term stability over-reactive measures. The threshold of 0.61 ensures that Montenegro is prepared to address potential crises proactively, minimizing the risk of systemic failures that could jeopardize its EU accession prospects.

To understand the significance of the optimal threshold of 0.61, let us compare it to a lower threshold of 0.15. At a threshold of 0.15, C1 = 31.45 and C2 = 19.85. These values are significantly higher compared to those at the optimal threshold of 0.61. This indicates that at 0.15, the model produces more misclassifications, increasing both false positives and false negatives. Predicting more crises that do not occur can lead to unnecessary policy actions, such as raising interest rates, reducing fiscal spending, or implementing restrictive measures. These actions could slow down economic growth and undermine public confidence. Missing actual crises can lead to severe economic consequences. In a developing country like Montenegro, failing to act on an impending crisis could result in financial instability, loss of investor confidence, and social disruption. A threshold of 0.15 would make the model too sensitive, causing frequent false alarms. Policymakers might lose credibility if they repeatedly implement crisis measures that turn out to be unnecessary. For Montenegro, adopting a lower threshold could signal a lack of confidence in its economic stability, which could be detrimental to its EU accession process. At 0.61, both C1 (16.02) and C2 (17.15) are minimized, indicating that the model strikes the best balance between avoiding false alarms and not missing real crises. A higher threshold reflects confidence in Montenegro's economic resilience and the capacity of its institutions to manage risks effectively.

The optimal threshold of 0.61 for Montenegro indicates a well-balanced and conservative approach to managing economic risks. This threshold minimizes the costs associated with both false positives and false negatives, providing a solid foundation for sound economic policy and financial stability. Adopting this threshold supports Montenegro's aspirations to join the EU by demonstrating that the country has the institutional capacity and economic resilience to handle potential crises. In contrast, a lower threshold (e.g. 0.15) would result in more misclassifications, undermining confidence in economic policies and potentially hindering EU integration. Policymakers should thus embrace the threshold of 0.61 as a strategic tool for balanced risk management, ensuring that Montenegro remains on a stable path toward economic growth and EU membership.

4. Implications

The study highlights that the standardized cumulative EMU inflation rate has a significant predictive power over Montenegro's inflation crises. This emphasizes the strong spillover effects from the EMU to Montenegro, a non-EU country that uses the euro. For policymakers in Montenegro, this underscores the importance of closely monitoring inflationary trends and monetary policy decisions within the EMU, as changes there can directly impact local inflation dynamics.

The research indicates that rising unemployment increases the probability of inflation crises in Montenegro, while higher wages are associated with a reduced likelihood of such crises. Policymakers should consider implementing measures that address structural unemployment, such as skills training and labour market reforms, to stabilize inflation. Meanwhile, supporting wage growth in alignment with productivity can help mitigate inflationary pressures without triggering a wage-price spiral.

Given the external nature of inflationary pressures on Montenegro's economy, as well as the limitations due to the euroization, the country lacks traditional monetary policy tools like adjusting interest rates. Therefore, Montenegro must rely more heavily on fiscal policy and structural reforms. Additionally, aligning domestic economic policies with broader European trends could provide a buffer against external shocks, helping maintain economic stability.

The analysis of inflation cycles suggests the presence of longer-duration "super-cycles" that extend beyond typical business cycles. Addressing these structural issues through reforms that enhance resilience, such as improving productivity and diversifying the economy, can provide long-term stability. Policymakers must also be prepared to implement strategic adjustments in response to these deeper economic shifts, as short-term measures alone might not suffice.

The study's evaluation of different threshold levels for predicting inflation crises (e.g., 0.15, 0.10, 0.05) shows the trade-offs between sensitivity (true positive rate) and false alarms. Policymakers should choose an optimal threshold of 0.61 that balances the risk of missing a potential crisis with the economic costs of frequent false alarms.

5. Conclusion

This study offers valuable insights into the dynamics of inflation crises in Montenegro, underscoring the importance of predictive modelling and the influence of broader EMU inflation trends. Through the use of advanced logit models, the research identifies an optimal probability threshold of 0.61 for predicting inflation crises. This threshold effectively balances the risk of false positives and false negatives, thereby providing policymakers with a reliable tool to anticipate and respond to potential economic disruptions.

One of the primary benefits of this study lies in its ability to enhance predictive accuracy. By recognizing the standardized cumulative EMU inflation rate as a key predictor of inflation crises, policymakers can now adopt a proactive approach to economic management. The threshold of 0.61 ensures that intervention measures are neither premature nor delayed, reducing the likelihood of unnecessary economic restrictions or missed opportunities for stabilizing the economy.

Furthermore, this study emphasizes the importance of aligning domestic policies with EMU inflation trends. Montenegro's euroized economy makes it particularly sensitive to inflationary pressures originating from the euro area. Monitoring these trends closely allows for more informed decision-making in monetary and fiscal policy, ultimately strengthening Montenegro's economic resilience.

The research also highlights the critical role of domestic economic indicators such as wages, unemployment, food prices, and GDP growth. Understanding these relationships enables policymakers to design targeted interventions. For instance, promoting wage growth in line with productivity supports household incomes, while reducing unemployment through diversification and job creation programs fosters long-term stability. Additionally, mitigating food price volatility through strategic reserves and agricultural investments can shield the population from sudden price shocks.

In the context of Montenegro's aspirations to join the European Union, this study reinforces the country's commitment to sound economic governance. The ability to predict and mitigate inflation crises demonstrates Montenegro's capacity to uphold financial stability, a key criterion for EU membership. Implementing evidence-based strategies not only addresses immediate economic challenges but also signals to the EU that Montenegro is prepared to meet the rigorous standards of the Union.

To translate these insights into practice, policymakers should establish real-time monitoring systems for EMU inflation trends and domestic indicators. These systems can trigger early warnings when the likelihood of an inflation crisis exceeds the threshold of 0.61, enabling timely and effective responses. Fiscal policies should remain flexible, with buffer funds in place to support vulnerable populations during inflationary periods. Investing in education, skill development, and sector diversification can help reduce unemployment and enhance economic resilience.

Furthermore, addressing energy and food price stability is essential. Investments in renewable energy projects can decrease dependence on volatile global oil markets, while strengthening domestic agricultural production can reduce reliance on food imports. Clear and transparent communication with the public is equally crucial. By ensuring that inflation management policies are well-communicated, policymakers can maintain public confidence and avoid unnecessary panic.

In conclusion, this study provides Montenegro with a comprehensive framework for managing inflation crises. By leveraging predictive accuracy, aligning with EMU trends, and implementing targeted domestic policies, Montenegro can foster a stable and resilient economy. These strategies not only safeguard the country's immediate economic interests but also support its long-term goal of EU integration, reinforcing its ability to navigate complex economic challenges with confidence and competence.

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