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Random Coefficient Modelling of the Global Effect of Exchange and Monetary Policy Rates on Inflation

—A Frequentist and Bayesian Generalized Additive Mixed Model Approach

Chioma Okoronkwo*, Geoffery Uzodinma Ugwuanyim, Hycinth Chukwudi Iwu, Harrison Obiora Amuji

Department of Statistic, Federal University of Technology, Owerri, Nigeria

Email: *chiomaookoronkwo@gmail.com, geoffrey.ugwuanyim@futo.edu.ng, hycinth.iwu@futo.edu.ng, harrison.amuji@futo.edu.ng

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Abstract

This research evaluates the effect of monetary policy rate and exchange rate on inflation across continents using both Frequentist and Bayesian Generalized Additive Mixed Models (GAMMs). Extending an earlier study that employed Frequentist and Bayesian Linear Mixed Model, continent-specific random slopes for exchange rate were incorporated to assess the variability in the rate at which changes in exchange rate influence inflation. Fixed effects captured the overall impact of the predictors, while random effects accounted for regional differences. Results consistently showed that the monetary policy rate significantly affects inflation, whereas the exchange rate does not. Strong evidence supported variation in baseline inflation across continents (random intercepts), but findings on random slope variability were mixed, suggesting modest and model-dependent heterogeneity. Bayesian models offered a slightly better fit and predictive accuracy. These findings underscore the central role of monetary policy in inflation control, while exchange rate effects remain context-dependent. These results highlight the importance of accounting for regional heterogeneity when modelling global inflation dynamics. Policymakers should tailor inflation strategies to regional contexts and prioritize robust monetary policy tools over exchange rate management. These findings are associational, not causal and future research should adopt a credible causal identification strategy to establish causal relationships.

Keywords

Inflation, Exchange Rate, Monetary Policy Rate, Frequentist Generalized

Additive Mixed-Model, Bayesian Generalized Additive Mixed-Model

1. Background of Study

Inflation control remains a central objective of macroeconomic policy worldwide, driving ongoing research into its primary determinants; the monetary policy rate and exchange rate. However, two significant challenges continue to hinder effective modelling and policy design in this domain. First, the empirical relationship between inflation and its monetary determinants remains highly inconsistent across regions, due to institutional, structural, and policy-specific factors. For instance, while monetary tightening often yields clear disinflationary effects in advanced economies, the same may not hold true in developing regions with weaker monetary transmission mechanisms. Again, the extent of exchange rate pass-through (ERPT), the degree to which exchange rate changes affect domestic prices, remains highly variable and poorly understood, particularly in global comparative contexts.

Recent data illustrate these disparities. Between 2014 and 2023, Sub-Saharan African economies experienced average annual inflation rates ranging from 5% to over 15%, with currency depreciation exceeding 30% in several cases [1]. In contrast, inflation rates in Organization for Economic Cooperation and Development (OECD) countries remained mostly below 3%, despite significant exchange rate fluctuations during global crises. These regional differences suggest that a uniform inflation model may fail to capture the precise, continent-specific dynamics at play. While there is broad theoretical consensus on the roles of monetary policy and exchange rate movements in influencing inflation, empirical evidence remains mixed. In a previous, yet-to-be-published study, both Frequentist Linear Mixed Model (LMM) using Restricted Maximum Likelihood (REML) and Bayesian Linear Mixed Model using Gibbs Sampling were employed to examine the global effects of monetary policy and exchange rates on inflation. That study identified a strong and statistically significant effect of the monetary policy rate across regions. In contrast, the effect of exchange rate fluctuations was largely insignificant, suggesting potential regional variability in exchange rate pass-through (ERPT), that is, the extent to which exchange rate changes are reflected in domestic price levels. To address these challenges, the current study introduces a more flexible model specification. Specifically, the exchange rate was modelled as a random coefficient that varies across continents, allowing the ERPT to differ by continent. This acknowledges structural and institutional differences that shape inflation dynamics in diverse macroeconomic environments.

Methodologically, a Linear Mixed Model (LMM) that includes a random slope for the exchange rate was employed. The residual diagnostics of the LMM indicated a violation of the homoscedasticity assumption. To address this, a square root transformation of the inflation variable was applied to stabilize the variance. However, subsequent diagnostics on the transformed LMM revealed violations of linearity, particularly in the relationship between the Monetary Policy Rate (MPR) and inflation, suggesting that a linear model could not fully capture this relationship. Consequently, a Generalized Additive Mixed Model (GAMM) was adopted, with a smooth term for MPR to capture its nonlinear effects. Both Frequentist and Bayesian frameworks are used: the Frequentist GAMM is estimated using REML, while the Bayesian GAMM is implemented via Gibbs Sampling [2]. This dual-framework approach enables robust estimation of both fixed and random effects, improving inference across a globally diverse dataset. This modelling approach is equally grounded in extensive empirical literature reviewed, which shows consistent regional differences in the effects of exchange rate on inflation. While the monetary policy rate is a robust predictor of inflation across most contexts, the exchange rate exhibits context-specific pass-through, stronger in regions such as Africa and South America, and weaker in North America and Europe. Moreover, many of the reviewed studies rely on traditional econometric models that do not account for hierarchical structures or allow for continent-specific slope variation. The present study builds on these insights by implementing a more flexible hierarchical model, combining Frequentist and Bayesian Generalized Additive Mixed Models (GAMMs), to better capture both global regularities and regional heterogeneities in inflation dynamics.

2. Literature Review

The relationship between exchange rates, monetary policy rates and inflation has been a cornerstone of macroeconomic theory. In the context of increasingly interconnected global markets, these variables have remained a central focus of macroeconomic research. Traditional theories such as Purchasing Power Parity (PPP) and the Taylor Rule propose that exchange rate fluctuations and policy interest rates should influence domestic inflation [3] [4], however, recent empirical results have painted a more precise picture.

A) Africa

Studies in Africa have consistently emphasised the importance of monetary policy instruments in controlling inflation, especially in economies prone to exchange rate shocks. For instance, Adusei (2019) [5], finds that in Ghana, the monetary policy rate significantly affects inflation, while the exchange rate only has short-term effects. Similarly [6], analysing South Africa, observes that inflation targeting effectively anchors expectations, with the monetary policy rate having a stronger influence on inflation than exchange rate fluctuations. Sulaiman *et al.* (2016) [7] carried out a comparative analysis between Nigeria and South Africa; the findings indicate that while monetary policy shocks significantly influence inflation, exchange rate fluctuations have a more pronounced effect in Nigeria due to its oil-dependent economy. More recent research by the International Monetary Fund on Sub-Saharan Africa found that exchange rate depreciations lead to sizable increases in domestic inflation, with the pass-through being higher than in other regions [8].

B) Asia

Asia's diverse economic structures lead to varying inflation dynamics. In emerging economies like India and Indonesia, Srinivasan *et al*. (2015) [9] highlight that while the monetary policy rate is the dominant inflation driver, the effect of the exchange rate varies based on trade exposure and capital flows. Chen and Shen (2020) [10] conducted an analysis of East Asian countries, revealing that while monetary policy rates are significant determinants of inflation, exchange rate pass-through varies depending on the country's trade openness and exchange rate regime. The recent financial instability in Taiwan Region, triggered by a sudden appreciation of its currency, underscores the potential for exchange rate fluctuations to impact inflation, particularly in economies with significant foreign exchange exposures [11].

C) Europe

In the Eurozone and broader Europe, inflation dynamics are largely a result of a coordinated monetary framework. Kiss and Vadas (2017) [12] analyze inflation determinants in Central and Eastern Europe, finding the monetary policy rate to be a stable inflation predictor, while exchange rate pass-through has declined since the 2008 crisis. A study of the Euro area by Bobeica *et al*. (2019) [13] reveals that the link between exchange rate and inflation has weakened which suggests that monetary policy plays a more dominant role in influencing inflation. Further research on the European Central Bank's policies indicates that conventional monetary policy measures are effective in controlling inflation, while exchange rate movements have a limited impact [14].

D) North America

In advanced economies such as the United States and Canada, empirical studies confirm the dominance of monetary policy in influencing inflation with exchange rate effects being secondary. Caldara and Herbst (2019) [15] demonstrate that interest rate shocks have clear, persistent effects on inflation, whereas exchange rate movements exhibit weaker and often insignificant pass-through in the United States. Similarly, Bank of Canada (2020) [16] reports low exchange rate pass-through under inflation targeting. The report from Federal Reserve's Covid-19 Response (2020) [17] highlights that the Federal Reserve's monetary policy measures during the COVID-19 pandemic, including interest rate cuts and quantitative easing were effective in stabilizing inflation expectations.

E) South America

South American economies, which are more vulnerable to external shocks, exhibit stronger exchange rate pass-through to inflation with monetary policy effectiveness varying. Carriere-Swallow *et al*. (2016) [18] show that in Chile and Brazil, exchange rate volatility significantly influences inflation in the short run. However, the monetary policy rate remains the main long-term anchor for inflation. Conversely, research on foreign exchange intervention in inflation-targeting Latin American countries shows that while monetary policy frameworks have improved, exchange rate interventions remain a key tool for controlling inflation

[19]. Similarly, further study on inflation dynamics during the COVID-19 pandemic indicates that exchange rate depreciation played a significant role in driving inflation in Latin America [20]. The relationship between exchange, monetary policy, and inflation rates exhibits notable regional variation, shaped by structural economic factors, policy frameworks, and external vulnerabilities. In Africa, empirical studies consistently emphasize the dominant role of monetary policy in inflation control, though exchange rate shocks remain relevant, especially in resource-dependent economies. In Ghana, the monetary policy rate significantly affects inflation, while the impact of the exchange rate is short-lived [5]. South Africa's inflation targeting regime strengthens the influence of interest rates over exchange rate movements [6]. Conversely, in Nigeria, a more pronounced exchange rate pass-through is observed due to its oil-exporting nature [7]. IMF (2024) [8] further highlights that Sub-Saharan Africa experiences a higher exchange rate pass-through to inflation than other global regions.

In Asia, the effects of exchange rates vary with economic openness and capital mobility. India and Indonesia exhibit inflation dynamics largely driven by monetary policy, though exchange rate effects depend on trade and financial integration [9]. In East Asia, monetary policy remains a key driver of inflation, but exchange rate pass-through differs across countries [10]. Taiwan region's recent experience with currency appreciation highlights the inflationary risks faced by economies with large foreign exchange exposures [11]. In Europe, coordinated monetary policy frameworks have reduced the influence of exchange rate fluctuations on inflation. In Central and Eastern Europe, the exchange rate pass-through has weakened since the global financial crisis, while the monetary policy rate continues to predict inflation reliably [12]. Similar patterns are observed in the Euro area, where the effectiveness of monetary policy has increased and exchange rate impacts have diminished [13] [14]. In North America, inflation is predominantly influenced by monetary policy, with minimal exchange rate pass-through. In the United States, interest rate shocks exhibit strong and persistent effects on inflation, whereas exchange rate movements are generally insignificant [15]. Canada's inflation-targeting regime further insulates domestic prices from exchange rate volatility [16]. During the COVID-19 crisis, U.S. monetary interventions helped stabilize inflation expectations despite currency fluctuations [17]. In South America, external vulnerability increases the prominence of exchange rate effects on inflation. In Chile and Brazil, short-run inflation is highly sensitive to exchange rate volatility, though the monetary policy rate serves as a long-term anchor [18]. Despite improved monetary frameworks, countries across Latin America continue to rely on foreign exchange interventions to manage inflation [19]. Recent evidence also points to exchange rate depreciation as a key inflation driver during the pandemic [20].

Collectively, the literature suggests that while monetary policy rates remain the primary tool for long-term inflation control, exchange rate effects are more pronounced in developing and externally vulnerable economies, underscoring the importance of country-specific macroeconomic contexts. Methodologically, the majority of the reviewed studies used traditional methods such as Vector Auto-Regressive method [6] [7] [13] [15], time series regressions [5] [12] [16] [18], fixed/random-effects panels [8]-[10] and case studies [11]. These methods often ignore hierarchical data structures. Even when heterogeneity is recognized, few studies explicitly estimate region-specific effects in a unified framework. The findings of the reviewed literature validate the modelling decision in this study to allow the exchange rate to vary across the continents while keeping the monetary policy rate fixed. It captures the heterogeneous role of exchange rates in shaping inflation dynamics across different economic contexts. It equally reinforces the methodological framework; Restricted Maximum Likelihood (REML)-based Frequentist GAMMs and Bayesian GAMMs through Gibbs Sampling, providing several improvements which includes:

1) Capturing regional heterogeneity in exchange rate effects by allowing random slopes across continents.

2) Maintaining parsimony by fixing the monetary policy rate globally, based on its consistently strong effect while capturing the non-linearity between MPR and inflation.

3) Validating findings across two approaches (Frequentist and Bayesian) for robust inference.

By extending the LMM approach used in the previous study, but enhancing it with a more flexible hierarchical model structure, this paper offers a richer and more globally sensitive understanding of how exchange and monetary policy rates interact with inflation.

3. Research Methodology

This section examines the data used in this study and provides a detailed breakdown of the methods of data analysis and statistical inference. The study combines Exploratory Data Analysis (EDA) with a novel application of Generalized Additive Mixed Models (GAMMs) under both Frequentist and Bayesian frameworks to investigate the impact of exchange rate and monetary policy rate on inflation across continents.

3.1. Data Sources

The data used in this paper are longitudinal data of three macroeconomic variables, inflation, exchange and monetary policy rates across five continents. The study covers a 10-year period from 2014 to 2023, to provide an insightful relationship between these variables. The data was sourced from Statista and Focus Economic data hubs and are measured in percentages.

3.2. Exploratory Data Analysis (EDA)

This paper will begin with summary statistics after presenting the data.

Summary Statistics

Summary statistics such as the mean, the standard deviation, skewness and kurtosis as well as the coefficient of variation (CV), among others will be calculated in order to describe the data. In particular, CV will be calculated in order to know which country's dependent and independent variables are most variable and uncertain. CV is calculated as [21]:

$$\mathrm{CV} = \frac{\text{Standard deviation}}{\text{Mean}} * 100\% \tag{1}$$

3.3. Method

To address the limitations of traditional linear models in capturing non-linearity and group-level heterogeneity, this study proposes a novel application of a Generalized Additive Mixed Model (GAMM) framework. Unlike conventional approaches that assume linearity and fixed relationships across groups, this study incorporates smooth functions and continent-specific random slopes to flexibly model the relationship between inflation, exchange rate, and monetary policy rate across five continents. The novelty lies in combining transformation techniques to address heteroscedasticity, non-linear smooth terms for monetary policy rate, and hierarchical random effects to capture both baseline differences and varying exchange rate sensitivities across regions. This approach provides insights that are not optimally captured by standard linear or mixed models, particularly in a global macroeconomic context.

3.4. Generalized Additive Mixed Model

The model specification and estimation procedures presented in this section are extensions of the analysis conducted in yet to be published research on the effect of exchange and monetary policy rates on inflation and apart from the fixed effects, only random intercepts were modelled. In this extended model, both random intercepts and random slopes are incorporated to account for the continent-level heterogeneity.

According to West *et al.* (2015) [22], the general formula of a Linear Mixed Model is expressed as:

$$\begin{aligned} Y_{ti} &= \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + \beta_3 * X_{ti}^{(3)} + \cdots + \beta_p * X_{ti}^{(p)} \\ &\quad + u_{1i} * Z_{ti}^{(1)} + \cdots + u_{qi} * Z_{ti}^{(q)} + \varepsilon_{ti} \\ t &= 1, \cdots, n_i \\ i &= 1, 2, \cdots, m \end{aligned} \tag{2}$$

where,

n_i = the number of observations for subject i

m = number of subjects

Y_{ti} = the t^{th} observation of the i^{th} subject

$$X_{ti}^{(1)} = 1 \quad \forall i$$

$X_{ti}^{(2)}, X_{ti}^{(3)}, \cdots, X_{ti}^{(p)}$ = the t^{th} observation value of subject i for the corresponding covariates $X^{(2)}, X^{(3)}, \cdots, X^{(p)}$ associated with the fixed effects.

$Z_{ti}^{(1)}, Z_{ti}^{(2)}, \cdots, Z_{ti}^{(q)}$ = the t^{th} observation value for subject i for the corresponding covariates $Z^{(1)}, Z^{(2)}, \cdots, Z^{(q)}$ associated with random effects; $q \le p$

$\beta_1, \beta_2, \cdots, \beta_p$ = fixed effects

$u_{1i}, u_{2i}, \cdots, u_{qi}$ = random effects specific to subject i

ε_{ti} = residual associated with the t^{th} observation on the i^{th} subject

The expression in (2) given the study data and considering a model with both a random intercept and random slope for exchange rate ($X_{ti}^{(2)}$) can be written as:

$$Y_{ti} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + \beta_3 * X_{ti}^{(3)} + u_{1i} * Z_{ti}^{(1)} + u_{2i} * Z_{ti}^{(2)} + \varepsilon_{ti} \tag{3}$$

$p = k + 1; k = 2$ (*i.e.*, exchange and monetary policy rates)

$q = 2$ (*i.e.*, the random intercept and random slope)

where;

$X_{ti}^{(1)} = 1 \quad \forall i$, $X_{ti}^{(2)}$ = exchange rate

$X_{ti}^{(3)}$ = monetary policy rate

β_1 = Global intercept

β_2 = Fixed effect of Exchange Rate

β_3 = Fixed effect of Monetary Policy Rate

u_{1i} = Continent-specific random intercept

u_{2i} = Continent-specific random slope for Exchange Rate

ε_{ti} = Residual error

In (3), $Z_{ti}^{(1)}$ represents the design matrix for the random effects; linking the random coefficients to the observed data. Specifically, $Z_{ti}^{(1)} = 1$ corresponds to the continent-specific random intercept (u_{1i}), while $Z_{ti}^{(2)} = X_{ti}^{(2)}$ corresponds to the continent-specific random slope on Exchange Rate (u_{2i}). In general, Z_i represents the design structure of random effects.

To address violations of homoscedasticity observed in the residuals of the extended LMM, a square root transformation was applied to Inflation Rate (the response variable) in order to stabilize variance and reduce heteroscedasticity [23] [24]. Y_{ti} becomes $\sqrt{Y_{ti}}$, then (3) can be described as:

$$\sqrt{Y_{ti}} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + \beta_3 * X_{ti}^{(3)} + u_{1i} * Z_{ti}^{(1)} + u_{2i} * Z_{ti}^{(2)} + \varepsilon_{ti} \tag{4}$$

Following the square root transformation of Inflation Rate to correct heteroscedasticity in the extended LMM, diagnostic checks using patterned residual plots of the transformed model revealed violation of the linearity assumption in the relationship between Exchange, Monetary Policy Rates and Inflation. Consequently, a Generalized Additive Mixed Model (GAMM) was employed to model non-linear effects while accounting for random effects (Wood, 2017) [2] which allows a flexible, non-linear relationships between Monetary Policy Rate and Inflation by incorporating smooth functions. Then (4) can be expressed as:

$$\sqrt{Y_{ti}} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + f\left(X_{ti}^{(3)}\right) + u_{1i} * Z_{ti}^{(1)} + u_{2i} * Z_{ti}^{(2)} + \varepsilon_{ti} \tag{5}$$

where,

$f\left(X_{ti}^{(3)}\right)$ = smooth term for Monetary Policy Rate (where non-linear effect is suspected)

In matrix notation the GAMM is described as:

$$\sqrt{Y_i} = X_i\beta + Z_i u_i + f_i + \varepsilon_i\,; \tag{6}$$

$i = 1, 2, \cdots, m$; ‘m’ = number of subjects (continents)

where:

$\sqrt{Y_i}$ = an $n_i \times 1$ vector of continuous responses represented as follows:

$$\sqrt{Y_i} = \begin{pmatrix} \sqrt{Y_{1i}} \\ \sqrt{Y_{2i}} \\ \vdots \\ \sqrt{Y_{n_i i}} \end{pmatrix} \tag{7}$$

n_i = the number of observations for subject i

X_i = an $n_i \times p$ fixed effects design matrix represented as follows:

$$X_i = \begin{pmatrix} X_{1i}^{(1)} & X_{1i}^{(2)} & \cdots & X_{1i}^{(p)} \\ X_{2i}^{(1)} & X_{2i}^{(2)} & \cdots & X_{2i}^{(p)} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n_i i}^{(1)} & X_{n_i i}^{(2)} & \cdots & X_{n_i i}^{(p)} \end{pmatrix} \tag{8}$$

Noting that $p = k + 1$ (where k is the number of covariates and $X_{ti}^{(1)} = 1$, $t = 1, 2, \cdots, n_i$), X_i can be written as:

$$X_i = \begin{pmatrix} 1 & X_{1i}^{(2)} & \cdots & X_{1i}^{(p)} \\ 1 & X_{2i}^{(2)} & \cdots & X_{2i}^{(p)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n_i i}^{(2)} & \cdots & X_{n_i i}^{(p)} \end{pmatrix} \tag{9}$$

β = a vector of p unknown regression coefficients or fixed effect parameters described as:

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix} \tag{10}$$

Z_i = $n_i \times q$ ($q \le p$) design matrix for the random effects represented as, where $Z_{ti}^{(1)} = 1 \quad \forall i$:

$$Z_i = \begin{pmatrix} 1 & Z_{1i}^{(2)} & \cdots & Z_{1i}^{(q)} \\ 1 & Z_{2i}^{(2)} & \cdots & Z_{2i}^{(q)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & Z_{n_i i}^{(2)} & \cdots & Z_{n_i i}^{(q)} \end{pmatrix} \tag{11}$$

u_i = $q \times 1$ vector of random effects represented as:

$$u_i = \begin{pmatrix} u_{1i} \\ u_{2i} \\ \vdots \\ u_{qi} \end{pmatrix} \tag{12}$$

f_i = $n_i \times 1$ vector for the smooth term (s) represented as:

$$f_i = \begin{pmatrix} f\left(X_{1i}\right) \\ f\left(X_{2i}\right) \\ \vdots \\ f\left(X_{n_i i}\right) \end{pmatrix} \tag{13}$$

To operationalize (13), the smooth term is represented using a basis expansion expressed as:

$$f\left(X_{n_i i}\right) = \sum_{k=1}^{d} b_k\left(X_{n_i i}\right)\gamma_k$$

where;

$b_k\left(X_{n_i i}\right)$ = pre specified basis functions

γ_k = unknown coefficients to be estimated

d = basis dimension

The choice of d balances flexibility against overfitting. Larger d allows for greater flexibility but may lead to overfitting unless penalized, while smaller d enforces smoother functions but risks under-fitting.

In practice, d is often guided by rules of thumb or empirical evaluation and the general guide for selecting basis dimension in this context is described in Table 1.

Table 1. Guide for choosing basis dimension (d).

Situation	Sample Size (n_i)	Recommended d
Simple, nearly linear relationship	<100	3 - 5
Mild curvature expected	100 - 500	6 - 10
Strong non-linearity, large data	>500	10 - 20+

ε_i = a vector of residuals represented as:

$$\varepsilon_i = \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \vdots \\ \varepsilon_{n_i i} \end{pmatrix} \tag{14}$$

From this study, equation (6) can be written in a matrix form as:

$$\begin{bmatrix} \sqrt{Y_{1i}} \\ \sqrt{Y_{2i}} \\ \vdots \\ \sqrt{Y_{10i}} \end{bmatrix} = \begin{bmatrix} 1 & X_{1i}^{(2)} \\ 1 & X_{2i}^{(2)} \\ \vdots & \vdots \\ 1 & X_{10i}^{(2)} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} 1 & Z_{1i}^{(2)} \\ 1 & Z_{2i}^{(2)} \\ \vdots & \vdots \\ 1 & Z_{10i}^{(2)} \end{bmatrix} \begin{bmatrix} u_{1i} \\ u_{2i} \end{bmatrix} + \begin{bmatrix} f\left(X_{1i}^{(3)}\right) \\ f\left(X_{2i}^{(3)}\right) \\ \vdots \\ f\left(X_{10i}^{(3)}\right) \end{bmatrix} + \begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \vdots \\ \varepsilon_{10i} \end{bmatrix}$$

That is, $\sqrt{Y_i} = X_i\beta + Z_i u_i + f_i + \varepsilon_i$

Note that $q = 2$ to accommodate:

- A random intercept representing baseline differences in inflation across continents.

- A random slope for exchange rate, allowing the effect of exchange rate on inflation to vary by continent.

Assumptions:

(a) $u_i \sim N(0, D)$

(b) $\varepsilon_i \sim N(0, R_i)$

where:

$$D = Var(u_i) = \begin{pmatrix} Var(u_{1i}) & cov(u_{1i}, u_{2i}) & cov(u_{1i}, u_{3i}) & \cdots & cov(u_{1i}, u_{qi}) \\ cov(u_{2i}, u_{1i}) & var(u_{2i}) & cov(u_{2i}, u_{3i}) & \cdots & cov(u_{2i}, u_{qi}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ cov(u_{qi}, u_{1i}) & cov(u_{qi}, u_{2i}) & cov(u_{qi}, u_{3i}) & \cdots & var(u_{qi}) \end{pmatrix} \quad (15)$$

And

$$R_i = Var(\varepsilon_i) = \begin{pmatrix} Var(\varepsilon_{1i}) & cov(\varepsilon_{1i}, \varepsilon_{2i}) & cov(\varepsilon_{1i}, \varepsilon_{3i}) & \cdots & cov(\varepsilon_{1i}, \varepsilon_{n_i i}) \\ cov(\varepsilon_{2i}, \varepsilon_{1i}) & var(\varepsilon_{2i}) & cov(\varepsilon_{2i}, \varepsilon_{3i}) & \cdots & cov(\varepsilon_{2i}, \varepsilon_{n_i i}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ cov(\varepsilon_{n_i i}, \varepsilon_{1i}) & cov(\varepsilon_{n_i i}, \varepsilon_{2i}) & cov(\varepsilon_{n_i i}, \varepsilon_{3i}) & \cdots & var(\varepsilon_{n_i i}) \end{pmatrix} \quad (16)$$

Assumptions (a) and (b) state that the error components are normal.

A Q-Q plot of residuals and random effects was used to assess the normality assumption of the GAMM. In this plot, residual quantiles are plotted against theoretical normal quantiles. A close alignment with a 45-degree reference line suggests that residuals are approximately normally distributed. Departures from this line may indicate issues such as skewness, outliers, or violations of model assumptions. Normality of residuals is crucial for valid inference in models assuming Gaussian errors [2] [25].

(c) Independence: An autocorrelation function (ACF) plot of the model residuals was used to evaluate the assumption of independence. The ACF plot displays the correlation of residuals across various lags. The absence of significant autocorrelation is indicated when all correlation values lie within the 95% confidence bounds. Deviations beyond these bounds suggest that residuals are temporally correlated, necessitating adjustments such as incorporating autoregressive correlation structures in the model.

The Durbin-Watson test is used to detect first-order serial correlation in model residuals particularly in grouped longitudinal data and the test statistic is given by (Durbin & Watson, 1950) [26]:

$$DW = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \quad (17)$$

where:

e_t = the residual at time, t

n = the total number of residuals

<u>**Hypothesis:**</u>

H_0: The errors are not autocorrelated (Errors are independent)

H_1: The errors are autocorrelated (Errors are not independent)

Decision rule:

- $DW \approx 2$: Indicates no autocorrelation
- $DW < 2$: Suggests positive autocorrelation
- $DW > 2$: Suggests negative autocorrelation.

If the test statistic has $p < 0.05$, then the null hypothesis of autocorrelation is rejected and if the test statistic has $p > 0.05$, then we do not reject the null hypothesis of autocorrelation

(d) Level 1 exogeneity, *i.e*, $E(e_{ti} \mid X_i) = 0$ and **Level 2 exogeneity,** *i.e.* $E(u_i \mid X_i) = 0$. Sophia & Skrondal, (2012) [27] say that with the assumption of normality of e and u, coupled with the above exogeneity conditions, e and u are independent.

(e) Homoscedasticity: A residual versus fitted values plot was used to assess homoscedasticity in the GAMM. The residuals should be randomly scattered around zero with consistent vertical spread across all levels of fitted values. A uniform spread supports the assumption of constant variance, whereas systematic patterns or increasing/decreasing spread indicate heteroscedasticity [2].

(f) Model Convergence and Fit: Convergence of the GAMM was assessed through convergence diagnostics provided by the estimation routine. The absence of warnings and stable estimates of smoothing parameters indicated successful convergence. Model fit was evaluated using observed vs. fitted plots and smooth term plots with confidence intervals. A close alignment between fitted and observed values suggests a good fit, while smooth term plots confirmed that non-linear relationships were adequately captured without overfitting [2].

This formulation goes beyond prior models by capturing latent non-linearity in monetary policy effects and accommodating heterogeneity in the exchange rate-inflation relationship through random slopes. It thus responds to the methodological gap in previous studies that modelled only fixed effects or assumed linearity across regions. The GAMM framework adopted here provides a richer, more flexible structure that aligns better with the underlying data complexities observed in macroeconomic trends.

3.5. Frequentist Approach

The Frequentist implementation of the proposed GAMM framework allows us to estimate fixed, smooth, and random components simultaneously using Restricted Maximum Likelihood (REML). This contrasts with simpler LMMs, enabling nuanced understanding of cross-regional variation and non-linear effects.

3.5.1. Estimation of Model Parameters

Generalized Additive Mixed Models (GAMMs) extend the linear mixed model framework by allowing for non-linear relationships between predictors and the response variable through the inclusion of smooth functions. As described by Wood (2017) [2], the response in a GAMM is expressed as:

$$g\left(E\left[Y_i\right]\right) = X_i\beta + Z_iu_i + \sum_j f_j\left(x_{ij}\right) \tag{18}$$

In this study, the model includes fixed effects, random intercept and a random slope for the Exchange Rate, allowing for group-specific variation in both the baseline inflation level and the effect of exchange rate changes, and smooth terms for Monetary Policy Rate, where non-linear effects are suspected. The random effects vector is described as follows:

$$u_i = \begin{bmatrix} u_{1i} \\ u_{2i} \end{bmatrix}$$

where,

$$D = \begin{bmatrix} \sigma^2_{u_{1i}} & \sigma_{u_{1i}u_{2i}} \\ \sigma_{u_{1i}u_{2i}} & \sigma^2_{u_{2i}} \end{bmatrix}$$

D is assumed to be an unstructured covariance matrix, hence;

$$Cov\left(u_{1i}, u_{2i}\right) = \sigma_{u_{1i}u_{2i}} \neq 0 .$$

The residuals $\varepsilon_i \sim N\left(0, \sigma^2 I_{n_i}\right)$, hence [2]:

$$R_i = \sigma^2 I_{n_i}$$

The marginal variance-covariance matrix for Y_i is described as:

$$Var\left(Y_i\right) = V_i = Z_iDZ_i' + R_i$$

Importantly, the variance components in D *i.e.* ($\sigma^2_{u_{1i}}, \sigma^2_{u_{2i}}, \sigma_{u_{1i}u_{2i}}$) and in R *i.e.* (σ^2) are not fixed but are estimated directly from the data during model fitting. This ensures that the model captures the true variability across the continents and within observations instead of imposing arbitrary assumptions.

Parameter estimation in GAMMs relies on penalized maximum likelihood, where smoothing parameters and random effects are estimated simultaneously. This is implemented using Restricted Maximum Likelihood (REML) to ensure unbiased estimation of variance and smoothing parameters, particularly effective for small sample sizes [2].

The estimator for the fixed effects β using either the REML is:

$$\hat{\beta} = \left(\sum_i X_i'\hat{V}_i^{-1}X_i\right)^{-1} \sum_i X_i'\hat{V}_i^{-1}y_i \tag{19}$$

where:

$$\hat{V}_i = Z_i\hat{D}Z_i' + \hat{R}_i \tag{20}$$

The variance of $\hat{\beta}$, $var\left(\hat{\beta}\right)$ is a $p \times p$ covariance matrix calculated using the formula:

$$var\left(\hat{\beta}\right) = \left(\sum_i X_i'\hat{V}_i^{-1}X_i\right)^{-1} \tag{21}$$

Compared to traditional linear mixed models with only random intercepts, the inclusion of both random slopes and smooth terms in GAMMs introduce additional complexity and flexibility, enabling the model to capture group-specific deviations and non-linear effects simultaneously. This results in a variance structure,

V_i that is both group-specific and non-exchangeable, reflecting realistic heterogeneity across continents [2].

The smooth effect of the monetary policy rate on inflation is estimated using basis function expansions, a common approach in GAMM [2] [28]. Specifically, the smooth function $f(.)$, representing a potentially nonlinear effect of a covariate X, is approximated as a linear combination of known basis functions described in the context of this study:

$$f\left(X_{n_i i}^{(3)}\right) = \sum_{k=1}^{d} \gamma_k b_k\left(X_{n_i i}^{(3)}\right) \tag{22}$$

where,

$b_k\left(X_{n_i i}^{(3)}\right)$ = known basic functions

γ_k = unknown basic coefficients to be estimated from the study data

d = the basic dimensions (number of basic functions used)

The coefficients $\gamma = \left(\gamma_1, \cdots, \gamma_K\right)^{\mathrm{T}}$ are estimated by minimizing a Penalized Least Squares (PLS) criterion of the form:

$$\mathrm{PLS} = \sum_{n_i i}\left(\sqrt{Y_{n_i i}} - \eta_{n_i i}\right)^2 + \lambda \int \left(f''\left(X_{n_i i}^{(3)}\right)\right)^2 \mathrm{d}x \tag{23}$$

where,

$\sqrt{Y_{n_i i}}$ = the square root-transformed response

$\eta_{n_i i} = X_{n_i i}\beta + Z_{n_i i}u_i + f\left(X_{n_i i}^{(3)}\right)$ is the linear predictor

λ = is the smoothing parameter, given by; $\lambda = \frac{\sigma_\varepsilon^2}{\sigma_u^2}$

$\left(f''\left(X_{n_i i}^{(3)}\right)\right)^2 \mathrm{d}x$ = the penalty term that ensures smoothness by penalizing excessive curvature

3.5.2. Model Fit and Predictive Performance

(a) Adjusted R^2: This is a refined version of the coefficient of determination (R^2) that accounts for the number of predictors in the model. It is especially useful when comparing models with a different number of explanatory variables. The formula is expressed as:

$$R_{adj}^2 = 1 - \frac{\left(1 - R^2\right)\left(n-1\right)}{n-p-1} \tag{24}$$

where,

n = number of observations

p = number of estimated parameters

R^2 = unadjusted coefficient of determination

A higher Adjusted R^2 indicates a better-fitting model after accounting for the number of predictors [29].

(b) K-Fold Cross Validation: K-fold cross-validation is a standard technique to assess the predictive performance of a model by splitting the data into mutually exclusive subsets or folds. The formula is given by:

$$\text{CV-MSE} = \frac{1}{K}\sum_{k=1}^{K} MSE_k \tag{25}$$

Where Mean Square Error for each fold MSE_k is given by:

$$MSE_k = \frac{1}{n_k}\sum_{i \in fold\ k}\left(y_i - \hat{y}_i\right)^2$$

Lower CV-MSE values indicate better model predictive performance [30].

3.6. Bayesian Approach

To strengthen inference and account for parameter uncertainty, a Bayesian version of the GAMM was also implemented through the Gibbs sampler. This Bayesian approach further enhances interpretability by providing credible intervals for all model components, while enabling posterior predictive checks and sensitivity diagnostics which is not feasible under Frequentist analysis alone.

3.6.1. Estimation of Model Parameters

The Bayesian formulation of the generalized additive mixed model (GAMM) applied to the square root-transformed outcome variable $y^* = \sqrt{y}$ expressed in (6).

Following the Bayesian approach recommended by Van der Merwe and Botha (1993) [2] [28] [29] [31], the joint posterior distribution is obtained through Bayes' Theorem:

$$P\left(\theta \mid y^*\right) \propto P\left(y^* \mid \theta\right) P\left(\theta\right)$$

Given $\theta = \left(\beta_i, \gamma, u, \sigma_\varepsilon^2, D\right)$ the joint likelihood is expressed as:

$$p\left(y^*, u \mid \beta_1, \beta_2, \gamma, \sigma_\varepsilon^2, D\right) = p\left(y^* \mid \beta_1, \beta_2, \gamma, u, \sigma_\varepsilon^2\right) * p\left(u \mid D\right) \tag{26}$$

where,

$$y^* \mid \beta_1, \beta_2, \gamma, u, \sigma_\varepsilon^2 \sim N\left(X\beta + B\gamma + Zu, \sigma_\varepsilon^2 I\right)$$

and

$$u \sim N\left(0, D\right)$$

The priors are assumed to be:

- $p\left(\beta\right) \propto 1$ (non-informative flat prior)
- $p\left(\gamma\right) \propto \exp\left(-\frac{1}{2}\gamma^{\mathrm{T}}\lambda S\gamma\right)$ with smoothing penalty matrix S and smoothing parameter λ
- $p\left(D\right) \propto \left|D\right|^{-\frac{v+q+1}{2}}$ (Inverse-Wishart prior on random effect covariance, weakly informative with small degrees of freedom, v)
- $p\left(\sigma_\varepsilon^2\right) \propto \sigma_\varepsilon^{-2}$ (non-informative Jeffrey's prior for residual variance)
- $p\left(\lambda\right) \propto 1$ (flat prior on smoothing parameter)

The posterior distribution is proportional to:

$$P\left(\beta, \gamma, u, D, \sigma_\varepsilon^2, \lambda \mid y^*\right) \propto N\left(y^* \mid X\beta + B\gamma + Zu, \sigma_\varepsilon^2 I\right) N\left(u \mid 0, D\right) p\left(\beta\right) * p\left(\gamma \mid \lambda\right) p\left(D\right) p\left(\sigma_\varepsilon^2\right) p\left(\lambda\right)$$

Using Gibbs Sampling, we iteratively sample from the full conditional posterior distributions of the parameters:

$$\sigma_\varepsilon^2 \mid y^*, \beta_1, \beta_2, \gamma, u$$
$$\sim IG\left[\frac{1}{2}n, \frac{1}{2}\left\{y^* - \sum_{i=1}^{2} X_i\beta_i - B\gamma - Zu\right\}'\left\{y^* - \sum_{i=1}^{2} X_i\beta_i - B\gamma - Zu\right\}\right] \tag{27}$$

$$D \mid u \sim \text{Inverse-Wishart}\left(v + G, \Lambda + \sum_{i=1}^{G} u_i u_i'\right) \tag{28}$$

where;

v = prior degrees of freedom, such that $v > q + 1$

G = number of continents

Λ = the prior scale matrix given as:

$$\Lambda = \begin{bmatrix} \sigma_{u_{1i}}^2 & \sigma_{u_{1i}u_{2i}} \\ \sigma_{u_{1i}u_{2i}} & \sigma_{u_{2i}}^2 \end{bmatrix}$$

$$u \mid y^*, \beta_1, \beta_2, \gamma, \sigma_\varepsilon^2, D \sim N\left(\tilde{u}, \tilde{V}_u\right) \tag{29}$$

where:

$$\tilde{V}_u = \left(\frac{1}{\sigma_\varepsilon^2} Z'Z + D^{-1}\right), \tilde{u} = \tilde{V}_u\left(\frac{1}{\sigma_\varepsilon^2} Z'\left(y^* - X\beta - B\gamma\right)\right)$$

$$\beta_i \mid y^*, \gamma, u, \sigma_\varepsilon^2 \sim N\left(\tilde{\beta}, \tilde{V}_\beta\right) \tag{30}$$

where:

$$\tilde{V}_\beta = \left(\frac{1}{\sigma_\varepsilon^2} X'X\right)^{-1}, \tilde{\beta} = \tilde{V}_\beta\left(\frac{1}{\sigma_\varepsilon^2} X'\left(y - B\gamma - Zu\right)\right)$$

$$u \mid y^*, \beta_1, \beta_2, \gamma, \sigma_\varepsilon^2, D \sim N\left(\tilde{\gamma}, \tilde{V}_\gamma\right) \tag{31}$$

with,

$$\tilde{V}_\gamma = \left(\frac{1}{\sigma_\varepsilon^2} B^{\mathrm{T}} B + \lambda S\right)^{-1}, \tilde{\gamma} = \tilde{V}_\gamma \frac{1}{\sigma_\varepsilon^2} B^{\mathrm{T}}\left(y^* - X\beta - Zu\right)$$

Given;

$$\lambda = \text{Gamma}\left(\alpha_\lambda, b_\lambda\right)$$

The Gibbs sampler iterates over these conditional distributions to draw samples from the posterior. After convergence, the posterior samples provide estimates, credible intervals, and inference for all model parameters including fixed effects, smooth terms, random effects, and variance components [2] [28] [29].

3.6.2. Analysis of Data

To ensure the validity and stability of the posterior distributions obtained from the Gibbs sampler, convergence diagnostics were performed following established guidelines in Bayesian inference [32].

(a) Gelman-Rubin Diagnostic: The Gelman–Rubin diagnostic evaluates the relationship between multiple chains by comparing within-chain and between-chain variances.

$$\hat{R} = \sqrt{\frac{\hat{V}}{W}} \tag{32}$$

where;

W = within chain variance

$\hat{V}$ = estimated target variance of the posterior

<u>**Decision Rule:**</u>

- If $\hat{R} \leq 1.1$ = Convergence is assumed
- If $\hat{R} > 1.1$ = Convergence is not assumed

(b) Effective Sample Size (ESS): The ESS measures the number of effectively independent draws from the posterior distribution, accounting for autocorrelation. It is estimated using the formula expressed as follows;

$$\text{ESS} = \frac{N}{1 + 2\sum_{k=1}^{\infty} \rho_k} \tag{33}$$

<u>**Decision Rule:**</u>

- ESS > 200 = A parameter is considered reliably estimated.
- ESS < 200 = More iterations may be necessary, or sampling may need to be improved as parameter estimate will be unreliable [32].

3.6.3. Model Fit and Predictive Performance

(a) Posterior Predictive Checks (PPC): PPC was used to evaluate model fit by comparing replicated data from the posterior to the observed data. If the Bayesian p-value is close to 0.5, the model fits well. On the other hand, if the Bayesian p-value is near 0 or 1 it suggests lack of fit [32].

(b) K-Fold Cross Validation: This was used to estimate predictive accuracy by partitioning data into training and validation sets. The formula is given as:

Let, the log predictive density be defined as;

$$lpd_k = \sum_{i \in fold_k} \log\left(\frac{1}{S}\sum_{s=1}^{S} p\left(y_i \mid \theta^{(s)}\right)\right)$$

Sum across all folds that is the Expected Log Pointwise Predictive Density (ELPD);

$$elpd_{K\text{-}fold} = \sum_{k=1}^{K} lpd_k \tag{34}$$

Higher $ELPD$ = better predictive performance and differences > 4 - 10 can be meaningful depending on data size [33].

(c) Bayesian R^2: This measures the proportion of variance explained by the model and defined by Gelman *et al.* (2019) [34] as:

$$R^2 = \frac{Var(\hat{y})}{Var(\hat{y}) + E\left[\sigma_\varepsilon^2\right]} \tag{35}$$

where,

$\hat{y} = X\beta + Sb + Zu$ the model's posterior mean

$Var(\hat{y})$ = the variance of fitted values across observations

σ_{ε}^{2} = the posterior samples of residual variance.

R^2 close to 1 suggests a better model fit that is the higher the R^2 the better the model.

3.7. Test of Hypotheses

The linear mixed regression model involves two fixed effects and two random effects variables; the random coefficient and the random slope for exchange rate. Hence our hypotheses are given by:

H_0: $\beta_i = 0$ (There is no statistically significant relationship between the fixed effects (exchange rate and monetary policy rate) and the response variable (inflation rate))

H_1: $\beta_i \neq 0$ (There is statistically significant relationship between the fixed effects and the response variable)

H_0: $u_{1i} = 0$ (There is no variation in baseline Inflation Rate across continents; that is, the intercept is the same for all continents)

H_1: $u_{1i} \neq 0$ (There is variation in baseline Inflation Rate across continents; that is, the intercept differs between continents.)

H_0: $u_{2i} = 0$ (There is no variation in the effect of Exchange Rate across continents, that is, the slope is the same for all continents)

H_1: $u_{2i} \neq 0$ (There is variation in the effect of Exchange Rate across continents, that is, the slope differs between continents)

In this study where a GAMM was adopted to estimate the parameters, the standard test statistic described by Wood (2017) [2] for a fixed effect β_i is given by:

$$t_{cal} = \frac{\hat{\beta}_i}{SE\left(\hat{\beta}_I\right)} \tag{36}$$

However, due to the hierarchical and smooth structure of GAMMs, which include both random effects and penalized smooth terms, the null distribution of the test statistic does not follow a standard t-distribution. This is particularly the case when random slopes or complex smooth functions are present. Thus, the degree of freedom associated with the null distribution of the test statistic cannot be approximated as $n - p$ rather an approximate degree of freedom is applied using the Satterthwaite approximation, which accounts for uncertainty in estimating random effects variances. The approximation is given as (Luke, 2017) [35]:

$$df = \frac{\left(Var\left(\hat{\beta}\right)\right)^2}{\sum\left(\frac{Var\left(\hat{\beta}_i\right)^2}{n_i}\right)} \tag{37}$$

where:

$Var\left(\hat{\beta}\right)$ = the estimated variance of $\hat{\beta}$

n_i = the number of observations associated with each variance component $\hat{\beta}_i$

$Var\left(\hat{\beta}_i\right)$ = the variance of the i^{th} component of the variance.

Decision rule:

- Do not reject H_0 at the $\alpha = 0.05$ level of significance *i.e.* p-value >0.05
- When the p value < 0.05 level of significance, reject H_0.

All analyses will be carried out using R software.

4. Results and Discussions

4.1. Data Presentation

Table 2 presents the dataset from five continents on Inflation Rate (IR), Exchange Rate (ER) and Monetary Policy Rate (MPR) for the period 2014-2023.

Table 2. Dataset from five continents on inflation rate (ir), exchange rate (er) and monetary policy rate (mpr) for the period 2014-2023.

	Africa			Asia			Europe			North America			South America		
Year	ER	MPR	IR	ER	MPR	IR	ER	MPR	IR	ER	MPR	IR	ER	MPR	IR
2014	50.50	9.25	7.33	47.14	7.72	5.38	4.19	2.93	3.04	32.73	2.50	3.95	752.42	11.53	12.98
2015	57.34	9.84	7.85	50.61	5.73	6.35	5.77	4.53	9.82	34.92	2.38	1.90	968.74	14.13	11.25
2016	76.87	11.26	10.12	47.13	5.55	4.20	6.30	2.85	3.24	37.99	3.00	1.98	922.56	12.38	15.30
2017	77.47	10.89	11.72	45.22	4.99	4.23	6.64	3.00	4.18	36.71	3.25	3.53	905.33	10.75	5.70
2018	81.49	10.05	7.67	47.89	8.99	5.58	6.50	3.75	3.66	37.27	3.56	3.33			
2019	81.55	9.00	5.95	46.01	5.58	5.78	5.70	2.85	2.56	38.55	2.81	2.80	1023.26	16.38	15.83
2020	89.40	7.04	5.50	47.73	6.25	4.55	6.72	1.22	0.90	41.05	1.31	2.75	1058.30	10.56	12.68
2021	97.50	7.08	7.47	52.41	6.55	6.75	6.43	1.85	3.70	44.18	2.13	4.93	1235.39	13.56	16.18
2022	103.89	12.04	14.65				8.29	7.20	9.90	43.46	6.56	8.25	1461.07	28.00	25.88
2023				66.75	15.46	15.80	8.52	6.75	7.42	43.31	7.19	5.00			

Source: Statista and Focus Economics data hub.

Summary Statistics

The descriptive statistics for exchange rate are provided in Table 3. The coefficient of variation indicates that Africa's exchange rate with CV = 31.70% is the most variable and uncertain while North America has the most stable exchange rate with CV = 9.92%.

Table 3. Summary statistics for exchange rate.

Description	Africa	Asia	Europe	North America	South America
Mean	79.56	50.10	6.51	39.01	1040.88
Standard Error	5.73	2.21	0.39	1.23	77.44
Median	81.51	47.73	6.47	38.27	996.0
Standard Deviation	25.22	6.63	1.24	3.87	219.0
Sample Variance	635.96	43.96	1.54	15.01	47971.1

Continued

Kurtosis	1.83	1.48	-0.65	-1.51	-0.82
Skewness	0.92	1.67	0.03	-0.04	0.63
Range	53.39	21.54	4.33	11.46	708.66
Minimum	50.50	45.22	4.19	32.73	752.42
Maximum	103.89	66.75	8.52	44.18	1461.07
Sum	716.01	450.88	65.06	390.15	8327.06
Count	9	9	10	10	8
Coefficient of Variation (%)	**31.70**	**13.23**	**19.05**	**9.92**	**21.04**

Similarly, **Table 4** shows the summary statistics for monetary policy rate. The result of the coefficient of variation reveals that North America's monetary policy rate with CV = 55.04% is the most variable and uncertain while Africa has the most stable monetary policy rate with CV = 18.00%.

Table 4. Summary statistics for monetary policy rate.

Description	Africa	Asia	Europe	North America	South America
Mean	9.61	7.42	3.69	3.47	14.66
Standard Error	0.58	1.09	0.62	0.60	2.02
Median	9.84	6.25	2.97	2.91	12.97
Standard Deviation	1.73	3.26	1.95	1.91	5.73
Sample Variance	3.00	10.63	3.82	3.63	32.79
Kurtosis	-1.40	1.18	-1.01	-0.65	0.76
Skewness	-0.26	1.57	0.66	0.95	1.47
Range	5.00	10.48	5.98	5.88	17.44
Minimum	7.04	4.99	1.22	1.31	10.56
Maximum	12.04	15.46	7.20	7.19	28.00
Sum	86.46	66.81	36.93	34.69	117.28
Count	9	9	10	10	8
Coefficient of Variation (%)	**18.00**	**43.94**	**52.85**	**55.04**	**39.09**

The summary statistics for inflation rate are displayed in **Table 5**. The result of the coefficient of variation suggests that Europe's inflation rate with CV = 64.05% is the most variable and uncertain while Africa has the most stable inflation rate with CV = 33.95%.

Table 5. Summary statistics for inflation rate.

Description	Africa	Asia	Europe	North America	South America
Mean	8.69	6.51	4.84	3.84	14.47
Standard Error	0.98	1.20	0.98	0.59	2.02
Median	7.67	5.58	3.68	3.43	14.14
Standard Deviation	2.95	3.60	3.10	1.88	5.71
Sample Variance	8.69	12.94	9.63	3.54	32.61
Kurtosis	-0.77	1.99	-1.27	0.27	-0.30
Skewness	0.79	1.83	0.61	1.08	0.52
Range	9.15	11.60	9.00	6.35	20.18
Minimum	5.50	4.20	0.90	1.90	5.70
Maximum	14.65	15.80	9.90	8.25	25.88
Sum	78.25	58.60	48.42	38.40	115.78
Count	9	9	10	10	8
Coefficient of Variation (%)	**33.95**	**55.30**	**64.05**	**48.96**	**39.46**

4.2. Generalized Additive Mixed Model—Frequentist Approach

This section presents the results of a GAMM used to investigate the impact of Exchange Rate and Monetary Policy Rate on Inflation, with random effects for continent-specific variations, particularly random slopes for Exchange Rate.

The fixed effects estimates are reported in Table 6. The intercept is statistically significant ($p = 0.002$), which suggests that the baseline level of inflation, that is, when covariates are zero, is approximately 2.5574.

Table 6. Fixed effects.

	Estimate	Std. Error	t value	Pr(>|t|)
X(Intercept)	2.557446	0.071666	35.686	0.002052
XExchangeRate	0.000101	0.000215	0.473	0.639
Xs(MonetaryPolicyRate)Fx1	−0.693255	0.112087	−6.185	

The estimate of p-value = 0.639 > 0.05 for exchange rate suggests that exchange rate has a positive but statistically insignificant effect on inflation across all continents.

The smooth term for Monetary Policy Rate (interpreted through the basis function coefficient) is significantly negative, which suggests that higher monetary policy rates are associated with lower inflation levels. However, the estimated smooth function reveals that this relationship is non-linear: the effect is strongly negative at lower levels of monetary policy rate, flattens out as the rate increases, and may even become slightly positive at higher levels.

The random effects estimates are presented in Table 7 showing that the random slope variance for Exchange Rate (0.0143) is higher than the random intercept variance (0.0020). This reveals that the effect of exchange rate on inflation varies more substantially across continents than baseline inflation levels do. The residual variance (0.5047) captures the variability in inflation not explained by the model and the estimate suggests that some variation remains unexplained.

Table 7. Random effects.

Groups	Name	Variance
Continent	(Intercept)	0.002046
	Exchange Rate	0.014336
Residual		0.504731

The continent-specific random slopes for Exchange Rate are summarized in **Table 8** which illustrate heterogeneity in its relationship with inflation. While Europe and South America show a positive relationship between exchange rate and inflation, Africa, Asia, and North America show a negative relationship. This result indicates that the impact of exchange rate changes on inflation is not uniform globally, which underscores the use of a mixed model approach with continent-specific random slopes.

Table 8. Random slope for exchange rate.

Continent	Random Slope Exchange Rate
Africa	−0.000103
Asia	−0.000199
Europe	0.000265
North America	−0.000273
South America	0.000134

Test of Assumptions for Generalized Additive Mixed Model (GAMM)

1. Test for Normality of Residuals

As observed from **Figure 1**, there is a close alignment with the 45-degree reference line which suggests that residuals are normally distributed.

2. Test for Homoscedasticity

The Homoscedasticity Plot in **Figure 2** indicates a uniform spread around zero which confirms the assumption of constant variance (homoscedasticity).

3. Test for Independence

As observed in **Figure 3**, at the various lags, the autocorrelation values lie within the 95% confidence bounds. The Durbin–Watson test results are given in **Table 9**, which suggests the absence of significant autocorrelation.

Table 9. Durbin-Watson test for autocorrelation.

Durbin-Watson	p-value
2.1084	0.6014

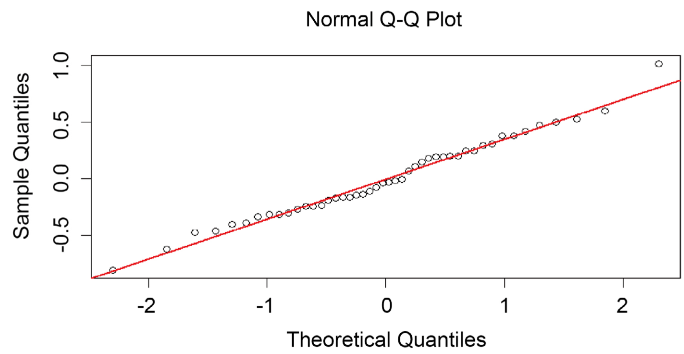

Figure 1. Normality plot.

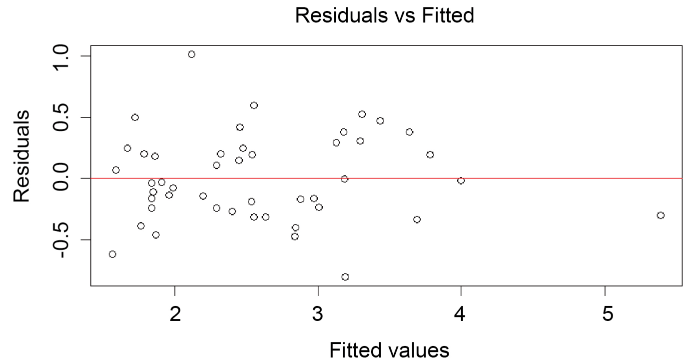

Figure 2. Homoscedasticity plot.

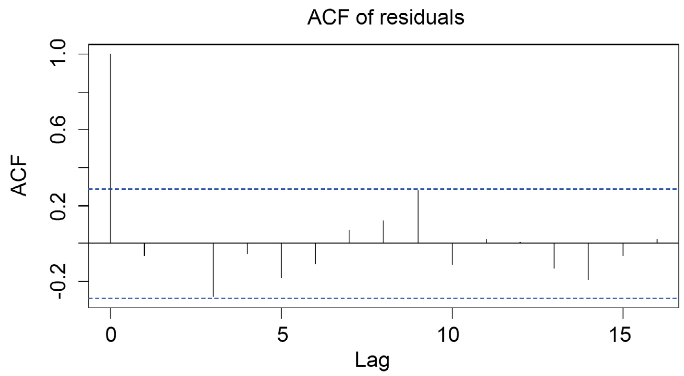

Figure 3. Autocorrelation plot.

In this analysis, the Durbin-Watson statistic is 2.1084, which is very close to 2. This indicates no evidence of autocorrelation in the model residuals. Again, the p-value = 0.6014 > 0.05 which confirms that we do not reject the null hypothesis and conclude that the residuals are not correlated that is, the assumption of independence is satisfied.

5. Normality of Random Effects

The Random Effect Normality Plot in Figure 4, reveals a close alignment with the 45-degree reference line which suggests that the random effects are normally distributed.

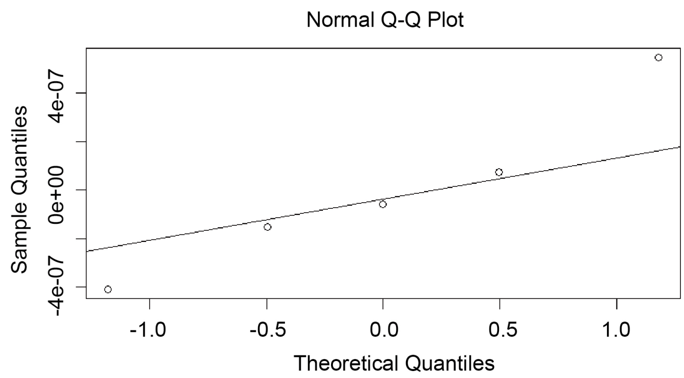

Figure 4. Random effect normality plot.

6. Model Convergence

The normal Q-Q Plot shown in **Figure 5** aligns with the reference line which suggests a good fit. A close alignment between fitted and observed values equally suggests a good fit, while the smooth term plots showing the residuals and linear predictors confirm that non-linear relationships were adequately captured without overfitting following the random scatter without any discernible pattern.

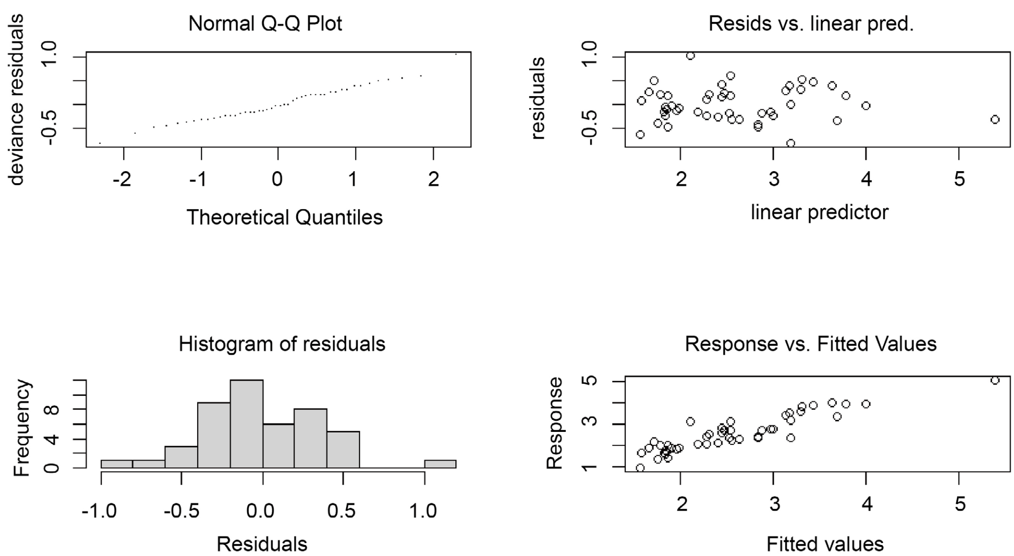

Figure 5. Model diagnostics plot.

The d-check is a diagnostic test used in GAMM to assess whether the basis dimension (d) specified for the smooth term is adequate to capture the underlying functional form without overfitting or underfitting. The adequacy of the smooth term basis dimension is assessed in **Table 10** which shows that the specified basis dimension for the monetary policy rate is sufficient and appropriate.

Table 10. d-check estimates.

	d'	edf	d-index	p-value
s (Monetary Policy Rate)	9.00	1.73	1.09	0.63

6.1. Model Fit and Predictive Performance

The model fit and predictive performance are reported in Table 11. An adjusted R-squared value of 0.817 means that approximately 81.7% of the variation in inflation is explained by the model, after accounting for the number of predictors. This result reflects a very good model fit which reinforces that the included fixed and random effects capture the majority of the variability in inflation across countries and continents.

Table 11. Model fit and predictive performance.

S/N	Description	Values
1	Adjusted R^2	0.817
2	5-fold Cross Validation RMSE	0.394

6.2. Generalized Additive Mixed Model—(Gibbs Sampling Posterior Results)

The posterior means of the fixed effects are shown in Table 12, with corresponding 95% confidence intervals in Table 13. The results suggest that exchange rate remains statistically insignificant, while the smooth term for monetary policy rate has a significant nonlinear effect on inflation. Closer inspection of the smooth function plot represented in Figure 6, Figure 7 show that while inflation decreases with monetary policy rate at lower levels, the relationship reverses at higher values, producing a curved non-linear pattern.

Table 12. Posterior mean of beta (fixed effects).

(Intercept)	**Exchange Rate**	**s (Monetary Policy Rate)**
1.276464	−0.003537	0.137321

Table 13. 95% confidence interval for beta.

	(Intercept)	**Exchange Rate**	**s (Monetary Policy Rate)**
0.025	−0.8558202	−0.025778	0.0734697
0.975	2.844331	0.023527	0.199757

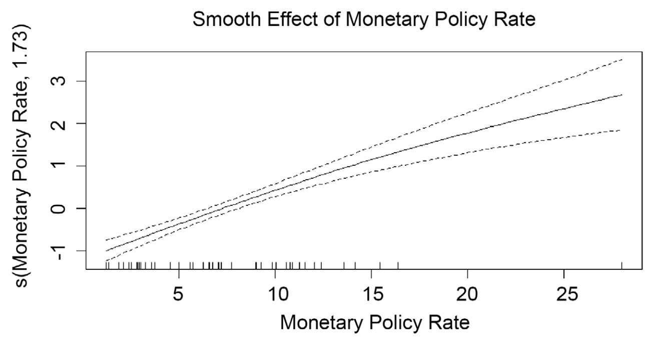

Figure 6. Smooth function plot—requentist.

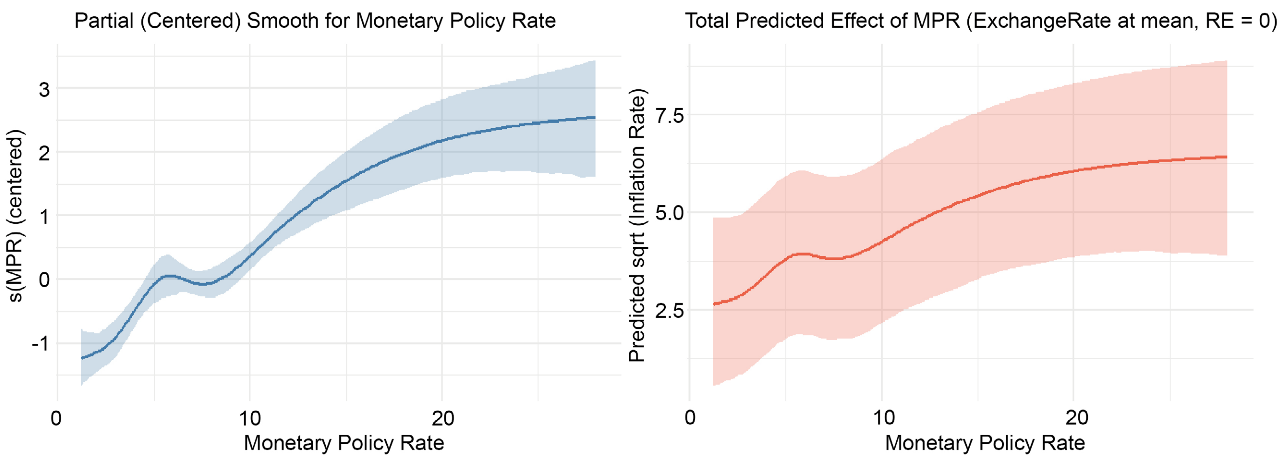

Figure 7. Smooth function plot—posterior samples.

Bayesian random effects are presented in **Table 14**, showing minimal variability in the random slope of exchange rate, moderate continent-level variation in baseline inflation, and substantial variation in the nonlinear monetary policy effect.

Table 14. Random effects (Bayesian).

	Mean	0.025	0.975
Residual variance	0.13292	0.07941	0.21724
Random slope variance	0.0012	0.0000	0.0046
Random intercept variance	0.4373	0.0025	2.3598
Smooth term Variance	0.55906	0.0025	3.24719

The continent-specific random slopes are reported in **Table 15**. All confidence intervals for continent-specific slopes cross zero which implies that although there is variation between the continents but the effect of exchange rate on inflation remains insignificant by continent.

Table 15. Random slopes estimates for exchange rate by continent.

Continent	Mean	0.025	0.975
Africa	0.005947	−0.020563	0.028555
Asia	0.005194	−0.021723	0.029331
Europe	0.051627	−0.027655	0.136475
North America	0.009022	−0.018036	0.034102
South America	0.003728	−0.0231697	0.025891

6.2.1. Test for Convergence

The Gelman-Rubin diagnostics are presented in **Table 16** summarising the PSRF for each model parameter specifically, Beta_mcmc, sigma2_e_mcmc, u_mcmc, and b_mcmc. A PSRF close to 1 suggests convergence across chains and most parameters show values near 1, indicating convergence. However, values above 1.1 for some parameters (e.g., Beta and u_mcmc) suggest that a few chains may not have fully converged, particularly those with point estimates of 1.24 - 1.29 and upper confidence bounds exceeding 1.5.

Table 16. Gelman-rubin diagnostic—potential scale reduction factors.

	Beta_mcmc		b_mcmc		u_mcmc		sigma2_e_mcmc	
	Point est.	Upper C.I.	Point est.	Upper C.I.	Point est.	Upper C.I.	Point est.	Upper C.I.
[1]	1.03	1.06	1.04	1.07	1.00	1.00	1	1
[2]	1.29	1.80	1.00	1.01	1.24	1.66		
[3]	1.00	1.00	1.00	1.00	1.19	1.50		
[4]			1.00	1.01	1.00	1.01		
[5]			1.00	1.00	1.17	1.45		
[6]			1.00	1.00	1.29	1.80		
[7]			1.00	1.00				
[8]			1.01	1.01				
[9]			1.01	1.01				
[10]			1.01	1.01				

The multivariate PSRF values for Beta_mcmc, b_mcmc, and u_mcmc are 1.24, 1.01, and 1.21 respectively. Again, values above 1.1 (especially Beta_mcmc and u_mcmc) raise concerns about convergence for these sets of parameters.

Effective sample sizes (ESS) are reported in **Table 17** which shows that most parameters have sufficiently large ESS (e.g., b_mcmc var6–var10 >10,000), suggesting reliable posterior estimates. However, low ESS values (e.g., Beta_mcmc var2 = 23.49, u_mcmc var6 = 21.03) indicate poor mixing in some chains.

Table 17. Effective sample size (ESS).

	Beta_mcmc	b_mcmc	u_mcmc	sigma2_e_mcmc
var1	436.3061	361.7016	30901.5232	14665.07
var2	23.4877	4464.735	53.2987	
var3	13128.3867	13049.3349	142.4296	
var4		7920.2423	5146.7192	
var5		4450.2851	208.7538	
var6		18044.1666	21.03698	
var7		22794.4737		
var8		36605.8001		
var9		11020.724		
var10		29546.6115		

Convergence is mostly achieved, but there are a few parameters (notably some random slopes and fixed effect terms) where PSRF and ESS suggest that results should be interpreted with caution.

6.2.2. Model Fit and Predictive Performance

From **Figure 8** the observed and predicted values align reasonably well. Posterior predictive check (PPC) values are presented in **Table 18**. PPC p-values which is greater than 0.05 suggest a strong model fit, indicating that the model replicates the observed data well.

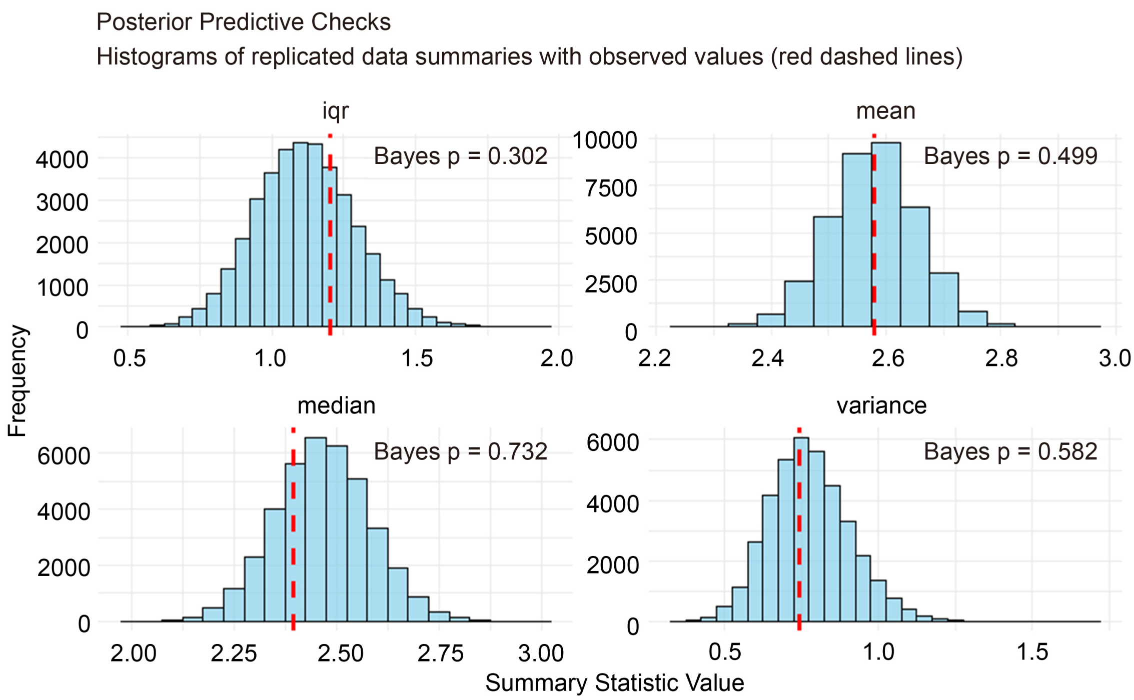

Figure 8. PPC plot.

Table 18. Posterior predictive check (PPC) values.

	Mean	Median	Variance	Iqr
Observed Value	2.5794	2.3953	0.7422	1.2037
p-value	0.4992	0.7315	0.5820	0.3020

The Bayesian R^2 values are given in **Table 19**. The posterior mean (0.828489) with a confidence interval that excludes zero indicates that the model explains approximately 83% of the variance in inflation which suggests strong explanatory power.

Table 19. Model fit.

	Mean	0.025	0.075
Bayesian R^2	0.828489	0.733646	0.896073

Predictive performance assessed through 5-fold Cross-Validation (CV) is reported in **Table 20**. The 5-fold CV Root Mean Square Error = 0.394 is relatively low, supporting good predictive performance. Generally, the model demonstrates strong fit and predictive power, with acceptable replication of data patterns.

Table 20. Predictive performance.

Description	Values
5-fold CV RMSE	0.3937

6.3. Model Comparison

The comparison between Frequentist and Bayesian GAMMs is summarized in **Table 21**;

1) The Bayesian GAMM offers slightly better predictive performance, as evidenced by lower RMSE value.

2) The Bayesian R^2 = 0.828 slightly exceeds the Frequentist adjusted R^2 = 0.817, which suggests slightly higher explanatory power.

3) The residual variance is considerably lower in the Bayesian model which indicates a tighter fit to the data.

4) While the Frequentist model detected greater random slope variability, the Bayesian estimate showed smaller variance and wider uncertainty intervals, which suggests weaker and less consistent evidence of slope variation across continents.

Table 21. Model comparison.

Metric	Frequentist GAMM	Bayesian GAMM (Gibbs Sampling)
Adjusted R^2 and Bayesian R^2	0.817	0.828 (95% CI: 0.734 - 0.896)
5-fold CV RMSE	0.394	0.3937
Residual Variance	0.5047	0.1329 (95% CI: 0.079 - 0.217)
Random Intercept Variance	0.0020	0.4373 (95% CI: 0.003 - 2.360)
Random Slope Variance (Exchange Rate)	0.0143	0.0012 (95% CI: 0.000 - 0.0046)

6.4. Discussion

To examine the impact of exchange rate and monetary policy rate on inflation, this study tested the significance of both fixed and random effects using Frequentist and Bayesian GAMMs. The hypotheses focused on whether (i) exchange and monetary policy rates (fixed effects) significantly influence inflation, (ii) baseline inflation levels vary across continents (random intercepts), and (iii) the effect of exchange rate varies by continent (random slopes).

The results from both approaches indicated that the monetary policy rate has a statistically significant effect on inflation, while the exchange rate did not exhibit a statistically significant effect on inflation. These findings align with long-standing macroeconomic theories, such as the Taylor Rule, and reinforce conclusions from prior empirical studies across regions, including those in Africa, Asia and North America which found the monetary policy rate to be a consistently strong determinant of inflation. In contrast, the weak or inconsistent effect of the exchange rate echoes evidence from Europe and Canada, where exchange rate pass-through has diminished over time or is actively mitigated by monetary policy frameworks.

By adopting a hierarchical modelling approach, this study was able to explore continent-specific differences in inflation dynamics, going beyond many existing studies that rely on traditional time-series or panel methods. The random intercept results showed strong evidence of variation in baseline inflation across continents, supporting the literature's emphasis on structural and institutional differences such as trade exposure, exchange rate regimes, and fiscal stability, as key determinants of regional inflation trends.

In the evidence for random slopes, the variation in the exchange rate's effect across continents was mixed. The Frequentist GAMM indicated moderate heterogeneity, suggesting that exchange rate influences may differ by continent, particularly in regions with external vulnerabilities like Latin America or Sub-Saharan Africa. In contrast, the Bayesian GAMM provided weaker evidence, with credible intervals including zero, suggesting that any heterogeneity is not statistically robust within that framework. This discrepancy mirrors findings from empirical literature where exchange rate pass-through is shown to be context-dependent, stronger in developing and commodity-exporting economies (e.g., Nigeria, Brazil) and weaker in advanced or inflation-targeting economies (e.g., US, Eurozone).

In terms of model performance, Bayesian GAMM slightly outperformed the Frequentist GAMM in terms of fit and prediction. This result underscores the literature advocating Bayesian hierarchical models for their ability to flexibly capture complex data structures and accommodate uncertainty in parameter estimates, especially in macroeconomic contexts with nested and cross-regional influences.

The hypothesis testing revealed that for the monetary policy rate (fixed effect), the null hypothesis was rejected under both approaches, confirming its robust influence on inflation. Conversely, for the exchange rate (fixed effect), the null hypothesis was not rejected, aligning with empirical studies that found weak or inconsistent global effects.

The result for the random intercepts shows that the null hypothesis was rejected, indicating significant differences in average inflation levels across continents. Similarly, for random slopes, the null hypothesis was rejected in the Frequentist model but weakly supported in the Bayesian model, indicating potential but inconclusive heterogeneity in the exchange rate's impact on inflation across continents.

These findings affirm the central role of monetary policy as a global anchor of inflation, while also highlighting the conditional and region-specific relevance of exchange rate effects. They further validate the study's methodological approach, which was deliberately chosen in light of existing literature:

1) Allowing random slopes for the exchange rate to capture regional heterogeneity.

2) Fixing the effect of the monetary policy rate globally, based on its documented consistent impact across diverse contexts.

3) Using both Frequentist (REML-based) and Bayesian (Gibbs Sampling) GAMMs to ensure robustness of inference and improved predictive performance.

By extending the traditional linear mixed model with a more flexible hierarchical structure, this study contributes a richer, more globally sensitive understanding of how exchange rates and monetary policy jointly shape inflation. It responds directly to gaps in the literature, where most prior studies failed to simultaneously capture global patterns and regional variations within a unified statistical framework.

6.5. Limitations

This study has some limitations:

1) The analysis is conducted at the continental level, which may mask important within-continent heterogeneity; future studies could extend this work by incorporating country-level data or refined regional groupings to provide a more detailed assessment of cross-country differences.

2) The findings are associational rather than causal, and the possibility of endogeneity cannot be ruled out. For example, central banks may adjust monetary policy in response to inflation trends which introduces potential reverse causality. In addition, unobserved confounding factors, feedback mechanisms or omitted variable bias may influence the observed relationships. There is a need for future research using causal identification strategies.

3) Furthermore, the study covers a short time span (2014-2023). While this period was selected to reflect recent structural and policy environments, it does not capture longer-term inflation dynamics across different monetary regimes. Extending the time horizon in future research would provide greater statistical power and allow for comparisons across distinct policy eras.

7. Conclusions

This study investigates the effects of exchange rate and monetary policy rate on inflation using both Frequentist and Bayesian Generalized Additive Mixed Models (GAMMs), accounting for fixed and random effects across continents. The findings consistently highlight the significant influence of the monetary policy rate on inflation aligning with macroeconomic theory and a broad base of empirical evidence, while the exchange rate effect is statistically insignificant. Strong evidence of continent-level differences in baseline inflation supports the inclusion of random intercepts, underscoring the importance of regional structural economic and institutional differences. However, the evidence for random slope variation in exchange rate effects was mixed, indicating only modest and model-dependent heterogeneity across continents.

Overall, the results underscore the dominant and stable role of monetary policy in inflation control, while exchange rate effects appear more context-specific and sensitive to continent-level vulnerabilities, such as trade exposure, commodity dependence, and exchange rate regimes.

Policymakers should prioritize effective monetary policy frameworks as a central tool for inflation management particularly in regions with strong institutional frameworks. In developing and externally exposed economies policymakers should recognize that exchange rate fluctuations may still pose short-run inflation risks, hence, selective foreign exchange interventions are recommended. Future research should employ hierarchical models like GAMMs to more accurately capture cross-regional differences and nonlinearities in macroeconomic relationships. Extending the time horizon of analysis could provide valuable insights into how different monetary regimes such as the post-Global Financial Crisis period, the 2014 oil price shock, and the post-COVID tightening cycle; have shaped long-run inflation dynamics. Compared to traditional time series or pooled panel regressions, this approach offers richer insights. Researchers and policy analysts should consider Bayesian frameworks when working with multi-level data and when uncertainty quantification is critical, as Bayesian GAMMs offer advantages in parameter estimation and model diagnostics.

It is pertinent to note that the findings of this study are associational rather than causal. Although the modelling approach accounts for complex data structures and regional heterogeneity, the analyses rely on the exogeneity assumption, which may be restrictive in practice. Unobserved confounding, feedback mechanisms, or omitted variable bias may still influence the observed patterns. As such, the results should be interpreted with caution and future studies are encouraged to incorporate explicit causal identification strategies, such as natural experiments, instrumental variables, or difference-in-differences designs, to more rigorously address potential endogeneity including reverse causality and to better assess the causal impact of exchange rate and monetary policy on inflation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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