Open Journal of Statistics, 2025, 15(6), 513-540
https://www.scirp.org/journal/ojs
ISSN Online: 2161-7198
ISSN Print: 2161-718X

Random Coefficient Modelling of the Global Effect of Exchange and Monetary Policy Rates on Inflation (2)

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

Department of Statistics, 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

How to cite this paper: Okoronkwo, C., Ugwuanyim, G.U., Iwu, H.C. and Amuji, H.O. (2025) Random Coefficient Modelling of the Global Effect of Exchange and Monetary Policy Rates on Inflation (2). *Open Journal of Statistics*, **15**, 513-540.
https://doi.org/10.4236/ojs.2025.156027

Received: November 14, 2025
Accepted: December 21, 2025
Published: December 24, 2025

Abstract

This study examined the relationship between the Monetary Policy Rate (MPR) and inflation across five continents from 2014 to 2023 using both Frequentist and Bayesian Linear Mixed Models (LMM). It extends the first part of this research which analyzed the relationship between exchange rate and MPR on inflation using the Generalized Additive Mixed Model under both the Frequentist and Bayesian frameworks. The Frequentist LMM revealed a positive and significant relationship between MPR and inflation, indicating that higher MPR is associated with increased inflation, though the effect varied minimally across continents. The Bayesian LMM produced a positive posterior mean for MPR, but its 95% credible interval included zero, reflecting uncertainty about the magnitude of the effect. Posterior predictive checks and convergence diagnostics confirmed model adequacy. The impact of monetary policy was stronger in Asia and North America but negligible in Africa, Europe and South America. Overall, the Bayesian LMM demonstrated superior flexibility, predictive accuracy and richer uncertainty representation.

Keywords

Monetary Policy Rate, Inflation, Rate, Random Slope, Frequentist Linear Mixed-Model, Bayesian Linear Mixed-Model

1. Background of Study

Inflation occurs when there is a sustained increase in the general price level of goods and services within an economy. During inflationary periods, the opportunity cost of holding money rises, leading to inefficiencies in the use of real resources in transactions. Inflation weakens the purchasing power of money and erodes the standard of living. Two critical determinants of inflation are the level of money supply and the stock of goods and services. When inflation persists, these factors become the primary targets of economic policies. An excess money supply may induce excess aggregate demand, resulting in higher inflation, while a shortage could trigger stagnation and impede economic growth [1]. Although fiscal policy plays a role in combating inflationary pressures, monetary policy remains the principal tool employed by central banks to ensure price stability. However, its effectiveness is contested, particularly in developing economies where inflationary challenges persist despite repeated policy interventions [1].

Medium-term price stability has long been regarded as the core goal of monetary policy. As Lowe (1997) [2] observed, high inflation distorts decision-making and slows economic growth, while monetary policy is the most effective instrument for influencing medium-term inflation outcomes. Similarly, Constancio (2015) [3] noted that inflation dynamics since the Great Recession have exhibited instability, producing systematic forecast errors. Friedman's classical dictum that inflation is always a monetary phenomenon, highlights the long-standing belief in the centrality of monetary policy, a view emphasised by Roberts (2004) [4], who argued that policy changes can substantially alter inflation dynamics. Yet, while economic theory suggests monetary policy should abate inflationary pressures, empirical evidence remains mixed.

The report from International Monetary Funds (IMF) indicates that globally inflation trends have fluctuated across decades. Following extremely high inflation in the 1980s and 1990s, rates stabilised between 3 - 5 percent in the early 2000s. A sharp increase occurred during the 2008 global financial crisis, but inflation remained relatively stable throughout the 2010s until the onset of the 2021 inflation crisis. Despite the economic impact of the Corona Virus (COVID-19) pandemic, global inflation initially fell to 3.26 percent in 2020, before rising to 4.66 percent in 2021 as supply chain disruptions took effect. The Russia-Ukraine war further aggravated inflationary pressures, alongside rising food and energy prices and post-pandemic fiscal instability. By 2024, global inflation reached 5.76 percent, its highest level since 1996 [5]. Regional variations in inflation trends are also notable. For instance, in Sub-Saharan Africa, the average annual inflation rate rose from 6.36 percent in 2014 to a peak of 17.57 percent in 2023. Much of this increase, particularly after 2020, has been attributed to the combined effects of the COVID-19 pandemic, geopolitical shocks and persistent currency depreciation.

Given these dynamics, monetary policy formulation becomes complex when influenced by multiple interacting variables. As Manmohan and Irfan (2019) [6] argue, policy credibility and expectations are critical: market participants must anticipate the direction of monetary policy in order to form rational expectations about inflation outcomes. The effectiveness of monetary policy, however, depends heavily on prevailing economic conditions. During crises, central banks may adopt more flexible measures, while in periods of expansion, tighter policies may be necessary to prevent overheating. Consequently, the debate over the effectiveness of monetary policy in controlling inflation remains unresolved [7].

This study contributes to the ongoing debate on the global effects of monetary policy by examining how monetary policy rates influence inflation across five continents from 2014 to 2023. The first part of this research examined the global effect of monetary policy rate and exchange rate on inflation using both Frequentist and Bayesian Generalised Additive Mixed Models (GAMMs), which incorporated continent-specific random slopes for exchange rate alone. The results indicated modest and model-dependent heterogeneity in the random slopes, while the GAMM approach effectively addressed linearity violations in the dataset. The findings further revealed that the exchange rate had no statistically significant impact on inflation, whereas the monetary policy rate emerged as a significant determinant, underscoring its crucial role in controlling inflation [8].

Building upon that earlier study, the present research departs methodologically by excluding the exchange rate and incorporating both random intercept and random slope components for the MPR. The analysis employs the Linear Mixed Model (LMM) framework for both Frequentist and Bayesian paradigms, with a square root transformation applied to the inflation data to correct for normality violations. Specifically, this study focuses on examining the relationship between the MPR and inflation rate across five continents from 2014 to 2023. This design enables a deeper assessment of heterogeneity in the relationship between MPR and inflation rate across continents, thereby providing new evidence on the global effectiveness of monetary policy in managing inflation.

2. Literature Review

Several researchers have widely assessed the relationship between monetary policy and inflation across different contexts, with a focus on instruments such as interest rates, money supply and credit channels. Loso *et al.* (2025) [7], using multiple linear regression, found that interest rates exhibit a negative relationship with inflation, suggesting that higher interest rates reduce inflationary pressures. In contrast, money supply and bank credit were positively associated with inflation which reveals that greater liquidity and credit availability fuel rising prices.

Kamugisha and Tibamwenda (2025) [9] employed Vector Autoregression (VAR) and Bayesian econometrics to analyse the interaction between monetary policy, inflation and economic growth. Their findings revealed that inflation is highly persistent, with past inflation serving as a strong predictor of future inflation. While interest rate adjustments were effective in moderating inflation, the broader impact of monetary policy on economic growth was limited as external economic conditions also played a critical role. Impulse Response Functions (IRFs) and Granger causality tests further indicated that inflation negatively affects GDP growth while the reverse relationship was statistically insignificant.

In Nigeria, Henry and Sabo (2020) [10] evaluated monetary policy management from 1985 to 2019 using the Autoregressive Distributed Lag (ARDL) approach. Their results showed that the monetary policy rate and exchange rate reduced inflation, whereas broad money supply exerted upward pressure. Similarly, Joel *et al*. (2024) [11], applying the ARDL framework, identified money supply, monetary policy rate and cash reserve ratio as the key instruments influencing inflation. Although the liquidity ratio was positively related to inflation, the effect was statistically insignificant. In South Africa, Lumengo (2017) [12] applied the Structural Vector Error Correction Model (SVECM) to evaluate the response of inflation to policy shocks during the inflation-targeting regime. The study showed that contractionary monetary policy was largely ineffective in reducing inflation but was successful in suppressing output, raising questions about policy trade-offs.

The broader Sub-Saharan African (SSA) context was analysed by Asiamah (2024) [13] using the system Generalised Method of Moments (GMM). Findings indicated that contractionary monetary policy reduces inflation, while expansionary policy has the opposite effect. Inflation, interest rates, potential growth and exchange rates were found to negatively and significantly affect inflation, whereas inflation squared, public debt and oil prices had a positive and significant influence. These results underscore the multifaceted impact of monetary policy on inflation dynamics in SSA.

Nguyen (2022) [14], analysing Vietnam from 1997 to 2020 using a VAR model, found that fiscal deficits, money supply, government expenditure and interest rates all positively influenced inflation, with government expenditure exerting the strongest effect. Trade openness, however, had a negligible negative impact on inflation. Ampudia *et al*. (2023) [15] explored the distributive effects of monetary policy across euro area countries. Their study highlighted heterogeneous responses, noting that high-income households, due to different consumption patterns experienced weaker inflationary effects from monetary policy adjustments compared to lower-income households. Subsequently, Ezeanyeji *et al*. (2021) [16] investigated the Nigerian context using Augmented Dickey-Fuller, Johansen's cointegration, and Error Correction Model (ECM) techniques. Their results indicated that monetary policy had no significant effect on inflation control in either the short run or the long run, raising doubts about the effectiveness of conventional policy tools in Nigeria.

Generally, these studies demonstrate that the effectiveness of monetary policy in controlling inflation varies widely across regions, instruments and socioeconomic settings. While much of the existing literature has focused on single-country analyses or specific regional contexts, there remains limited comparative evidence on how monetary policy rates influence inflation across different continents. This study addresses this gap by examining the global effects of monetary policy rates on inflation using data from five continents. By employing a Random Coefficient Linear Mixed Model within both Frequentist and Bayesian frameworks, the study applies random slopes for monetary policy rates alongside a random intercept. This approach enables an assessment of heterogeneity in the relationship between Monetary Policy Rate and Inflation across continents, providing new insights into the extent to which monetary policy effectiveness is shaped by regional differences.

3. Research Methodology

This section describes the data used in this study and provides a detailed breakdown of the methods of data analysis and statistical inference.

3.1. Data Sources

The data used in this paper are longitudinal data of two macroeconomic variables, the Inflation Rate defined as the annual percentage change in the Consumer Price Index (CPI) and the Monetary Policy Rate (MPR) which represents the benchmark interest rate set by a country's central bank. The study covers a 10-year period from 2014 to 2023, to provide insights into the dynamic relationship between these variables. The data was obtained from Statista and Focus Economic data hubs and all variables were 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, standard deviation, skewness, kurtosis and coefficient of variation (CV) were calculated to describe the data. The CV, in particular, was computed to identify which country's inflation and monetary policy rates are most variable and uncertain. CV is calculated [17] as:

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

3.3. Method

This study applies the Linear Mixed Model (LMM) using both the Frequentist and Bayesian frameworks to determine the global effect of monetary policy rate on inflation. In the previous study, a Generalised Additive Mixed Model (GAMM) was employed to explore potentially nonlinear relationships between the predictors and the response variable. For the current analysis, the LMM is preferred because linearity assumption is satisfied, providing a simpler and more interpretable framework for modelling linear relationships while accounting for continent-level random effects. In addition, LMMs are computationally more efficient, which is advantageous for a multi-continent panel dataset covering ten years and facilitate clearer policy-relevant interpretations of fixed and random effects.

Preliminary diagnostic tests revealed that the residuals of the original LMM violated the normality assumption. Consequently, the square root transformation of the inflation rate was applied to stabilize variance and approximate normality. The transformed LMM thus used $\sqrt{\text{Inflation Rate}}$ as the dependent variable. The model accounts for both within-continent and between-continent variations through the inclusion of a random intercept to capture baseline inflation differences among continents and a random slope for the MPR to allow its effect on inflation to vary by continent.

3.4. Linear Mixed Model

The general formula of the LMM is expressed as [18]:

$$\begin{gathered} Y_{ti} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + \beta_3 * X_{ti}^{(3)} + \cdots + \beta_p * X_{ti}^{(p)} \\ + u_{0i} * Z_{ti}^{(1)} + u_{1i} * Z_{ti}^{(2)} + \cdots + u_{qi} * Z_{ti}^{(q)} + \varepsilon_{ti} \\ t = 1, \cdots, n_i \\ i = 1, 2, \cdots, m \end{gathered} \tag{2}$$

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 of subject i for the corresponding covariates $Z^{(1)}, Z^{(2)}, \cdots, Z^{(q)}$ associated with the 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

Given the study data and the focus of the analysis, (2) can be simplified as:

$$\begin{gathered} Y_{ti} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + u_{0i} + u_{1i} * X_{ti}^{(2)} + \varepsilon_{ti} \\ p = k + 1; k = 1 \quad (\textit{i.e.}\ \text{MPR}) \\ q = 2 \quad (\text{random intercept and random slope}) \end{gathered} \tag{3}$$

where,

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

Y_{ti} = Inflation Rate

$X_{ti}^{(2)}$ = MPR

β_1 = Global intercept

β_2 = Fixed effect of MPR

u_{0i} = Continent-specific random intercept

u_{1i} = Continent-specific random slope for MPR

ε_{ti} = Residual error

Assumptions:

(a) $u_{ti} \sim N\left(0, \sigma_u^2\right)$

(b) $\varepsilon_{ti} \sim N\left(0, \sigma_\varepsilon^2\right)$

Assumptions (a) and (b) imply normality of error components.

A Q-Q plot of residuals was used to examine the normality assumption of the LMM. If the plots align closely with the 45-degree reference line, this suggests that the residuals are approximately normally distributed. Deviation from this line indicates issues such as skewness, outliers or violation of model assumptions. In addition, the histogram of residuals was inspected. A bell shaped distribution supports the assumption of normality whereas a different pattern may indicate violation [19] [20].

(c) Independence: To assess the assumption of independence, an autocorrelation function (ACF) plot of residuals was observed. The ACF plot shows the correlation of residuals at different lags. The absence of significant autocorrelation is indicated when all correlation values lie within the 95% confidence bounds. Deviation beyond these bounds suggest temporal dependence in the residuals, in which case model adjustments such as incorporating autoregressive correlation structures may be necessary.

Similarly, the Ljung-Box test was applied as a formal diagnostic for autocorrelation particularly suited for structured data. The test statistic is defined as:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \tag{4}$$

where:

Q = the test statistic

n = the sample size

h = the maximum lag being considered

$\hat{\rho}_k$ = the sample autocorrelations at lags 1 to h

Under the null hypothesis of no autocorrelation, the Ljung-Box test statistic in (4) follows a chi-squared distribution with $h-q$ degrees of freedom, where h is the number of lags being considered in the test and q is the number of parameters [21].

Decision rule:

If the test statistic has $p < 0.05$ level of significance, then the null hypothesis of no autocorrelation is rejected and if the test statistic has $p > 0.05$, then we do not reject the null hypothesis.

(d) Level 1 exogeneity, *i.e.*, $E(e_{ti} \mid X_i) = 0$ and **Level 2 exogeneity,** *i.e.* $E(u_i \mid X_i) = 0$. With the assumption of normality of e and u, coupled with the above exogeneity conditions, e and u are independent [22].

(e) Linearity: Condition (d) implies that Y is a linear function of the predictors, which is referred to as the mean structure [22]. The residual plot was used to assess linearity in the LMM. To evaluate the linearity assumption, a residual plot from the LMM displaying the observed values of the response variable against the predicted values was inspected. If the residual plot shows a random scatter around zero without a clear pattern, the linearity assumption is satisfied. In contrast, a systematic pattern such as curvature indicate violation of this assumption [19].

(f) Homoscedasticity: Homoscedasticity was assessed using the residuals versus fitted values plot. A consistent uniform spread of residuals across all fitted values supports the assumption of homoscedasticity, whereas systematic patterns or widening/narrowing spreads indicate heteroscedasticity [19]. To further validate this assessment, Levene's test was applied. The test statistic is given by:

$$W = \frac{N-g}{g-1} \times \frac{\sum_{j=1}^{g} n_j \left(\bar{z}_{j.} - z_{..}\right)^2}{\sum_{j=1}^{g} \sum_{i=1}^{n_j} \left(z_{ij} - \bar{z}_{j.}\right)^2} \tag{5}$$

where:

N = the total sample size

g = the number of groups

n_j = the sample size of the group

$\bar{z}_{j.}$ = the mean of the absolute deviations from the group mean for group j.

$\bar{z}_{..}$ = the overall mean of the absolute deviations.

z_{ij} = the i^{th} observation in the group j

Under the null hypothesis of constant variance (homoscedasticity), the Levene's test statistic in (5) follows an F-distribution with $g-1$ and $N-g$ degrees of freedom, where g is the number of groups being compared and N is the total number of observations across all groups.

Decision rule:

If the test statistic has $p < 0.05$, then the null hypothesis of homoscedasticity is rejected and if the test statistic has $p > 0.05$, then we do not reject the null hypothesis of homoscedasticity [21].

3.4.1. Test for Outliers and Influential Observations

The presence of outliers and influential observations was detected using the Cook's distance, defined as [23]:

$$D_i = \frac{\sum_{j=1}^{n} \left(\hat{Y}_{j(i)} - \hat{Y}_j\right)^2}{p \times \text{MSE}} \tag{6}$$

and MSE is given by:

$$\text{MSE} = \frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}{n} \tag{7}$$

where:

$\hat{Y}_{j(i)}$ = the predicted response value for observation j with observation i omitted.

$\hat{Y}_j$ = the predicted response value of observation j with all observations included.

p = the number of fixed effects in the model

MSE = the Mean Square Error of the model

n = total number of observations

Decision Rule:

- If $D_i > \frac{4}{n}$ = observation is considered to be influential
- If $D_i < \frac{4}{n}$ = observation is not considered to be influential

3.4.2. Sensitivity Analysis

After identifying influential observations, a robustness check was performed by re-estimating the model after excluding these observations. The results from the reduced dataset were then compared with those from the full sample. This comparison allowed the assessment of how the inclusion or exclusion of influential observations affected the model's fixed and random effect estimates, standard errors, and overall inference. Minimal changes in the estimates indicate that the model results are robust, while substantial changes suggest sensitivity to influential observations [24].

3.5. Estimation of Model Parameters

3.5.1. Frequentist Approach

The LMM extends the standard linear regression model by incorporating both fixed and random effects [18].

For this study, the response variable (Inflation Rate) was square root–transformed to correct for normality violation. The marginal distribution is therefore expressed as:

$$\sqrt{Y_{ti}} = \beta_1 * X_{ti}^{(1)} + \beta_2 * X_{ti}^{(2)} + u_{0i} + u_{1i} * X_{ti}^{(2)} + \varepsilon_{ti} \quad (8)$$

With mean and variance,

$$E\left(\sqrt{Y_{ti}}\right) = \beta_1 + \beta_2 X_{ti}^{(2)} \quad (9)$$

$$var\left(\sqrt{Y_{ti}}\right) = var_{u_{0i}} + 2X_{ti}^{(2)} cov_{u_{0i}u_{1i}} + \left(X_{ti}^{(2)}\right)^2 var_{u_{1i}} + var_{\varepsilon_{ti}} \quad (10)$$

The estimation of parameters is conducted using Restricted Maximum Likelihood (REML) Estimation method which produces unbiased estimates of covariance parameters by taking into account the loss of degrees of freedom that results from estimating the fixed effects [18].

The Generalised Least Squares (GLS) estimator of β is given by:

$$\hat{\beta} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n_i} \omega_{ij} X_{ti} \sqrt{Y_{ti}}}{\sum_{i=1}^{m}\sum_{j=1}^{n_i} \omega_{ij} X_{ti}^2} \quad (11)$$

where, $\omega_{ij} = var\left(\sqrt{Y_{ti}}\right)$

$$var\left(\hat{\beta}\right) = \left(\sum_{i=1}^{m}\sum_{j=1}^{n_i} \omega_{ij} X_{ti}^2\right)^{-1} \quad (12)$$

For this study, the random effects and residual variance are defined as:

$$var\left(u_{0i}\right) = \tau_{00},\ var\left(u_{1i}\right) = \tau_{11},\ cov\left(u_{0i}, u_{1i}\right) = \tau_{01},\ var\left(\varepsilon_{ti}\right) = \sigma^2$$

Thus (21) is written as:

$$var\left(\sqrt{Y_{ti}}\right)=\tau_{00}+2X_{ti}^{(2)}\tau_{01}+\left(X_{ti}^{(2)}\right)^2\tau_{11}+\sigma^2 \tag{13}$$

And,

$$cov\left(\sqrt{Y_{ti}},\sqrt{Y_{tj}}\right)=\tau_{00}+2X_{ti}^{(2)}\tau_{01}+\left(X_{ti}^{(2)}\right)^2\tau_{11} \tag{14}$$

Substituting the estimated variance components $\hat{\tau}_{00},\hat{\tau}_{01},\hat{\tau}_{11}$ and $\hat{\sigma}^2$ in (10) yields the final GLS estimates of $\hat{\beta}_1$ and $\hat{\beta}_2$.

3.5.2. Bayesian Approach

The Bayesian regression approach provides alternative framework by estimating the unknown model parameters through their posterior distributions rather than point estimates. The goal is to obtain the posterior distribution of the parameter's conditional on the observed data through Bayes' theorem:

$$P(\theta\mid data)=\frac{P(data\mid\theta)*P(\theta)}{\int P(data\mid\theta)*P(\theta)\mathrm{d}\theta} \tag{15}$$

where:

$P(\theta\mid data)$ = the posterior distribution of θ given data;

$P(\theta)$ = the prior distribution of θ;

$P(data\mid\theta)$ = the likelihood function [25].

In this study, the Bayesian LMM is expressed as (8), with the random components u and ε distributed as:

$$u_{0i},u_{1i}\sim N\left(0,\sigma_u^2\right),\varepsilon_{ti}\sim N\left(0,\sigma_\varepsilon^2\right)$$

The objective of the Bayesian techniques is to use Gibbs Sampling to estimate the posterior distribution of β_1, β_2, u_{0i}, u_{1i}, σ_u^2 and σ_ε^2. The joint distribution of the observed data and the parameters is defined as:

$$f\left(\sqrt{y_{ti}},u\mid\beta_1,\beta_2,\sigma_u^2,\sigma_\varepsilon^2\right)=f\left(\sqrt{y_{ti}}\mid\beta_1,\beta_2,u,\sigma_\varepsilon^2\right)f\left(u\mid\sigma_u^2\right) \tag{16}$$

Assuming normality, the conditional distribution of the response variable is given by:

$$\sqrt{y_{ti}}\mid\beta_1,\beta_2,u_{0i},u_{1i},\sigma_\varepsilon^2\sim N\left[\beta_1+\beta_2X_{ti}^{(2)}+u_{0i}+u_{1i}X_{ti}^{(2)},\sigma_\varepsilon^2\right]$$

gives rise to the full likelihood function from which posterior samples of the parameters can be obtained [26].

In the Bayesian treatment of (8), prior distributions will be assigned to all model parameters as follows:

$$\beta\sim N_p(0,100)$$

$$\sigma_\varepsilon^2\sim \text{Inverse-Gamma}(3,1)$$

$$\tau_u^2\sim \text{Wishart}(4,1)$$

These priors are weakly informative to ensure the posterior estimates are primarily data-driven while maintaining numerical stability and reproducibility.

Based on the specified model and priors, the Gibbs sampler cycles through the following full conditionals:

$$\sigma_\varepsilon^2 \mid \sqrt{y_{ti}}, \beta_1, \beta_2, u_{0i}, u_{1i}, \sigma_u^2 \sim IG\left[\frac{1}{2}n, \frac{1}{2}\sum\left(\sqrt{y_{ti}} - \beta_1 - \beta_2 X_{ti}^{(2)} - u_{0i} - u_{1i} X_{ti}^{(2)}\right)^2\right] \tag{17}$$

$$\sigma_u^2 \mid \sqrt{y_{ti}}, \beta_1, \beta_2, u_{0i}, u_{1i}, \sigma_\varepsilon^2 \sim IG\left(\frac{1}{2}q, \frac{1}{2}\sum u^2\right) \tag{18}$$

$$u \mid \sqrt{y_{ti}}, \beta_1, \beta_2, \sigma_\varepsilon^2, \sigma_u^2 \sim N\left(\frac{\sum_{i=1}^{n_i} z_i\left(\sqrt{y_{ti}} - \beta_0 - \beta_1 X_{ti}^{(2)}\right)}{\sigma_\varepsilon^2 + \sigma_u^2}, \left(\frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_u^2}\right)^{-1}\right) \tag{19}$$

where $z_i = \begin{bmatrix} 1 \\ X_{ti}^{(2)} \end{bmatrix}$

$$\beta_i \mid \sqrt{y_{ti}}, u, \sigma_\varepsilon^2, \sigma_u^2 \sim N\left(\frac{\sum X_{ti}^{(2)}\sqrt{y_{ti}}}{\sum\left(X_{ti}^{(2)}\right)^2}, \frac{\sigma_\varepsilon^2}{\sum\left(X_{ti}^{(2)}\right)^2}\right) \tag{20}$$

The inverse gamma distribution is defined by the density function:

$$f\left(\sigma^2\right) = \frac{b^a \mathrm{e}^{-b/a^2}}{\Gamma(a)\left(\sigma^2\right)^{a+1}} \tag{21}$$

The Gibbs sampler will be implemented in R using custom code. The sampling was conducted with 3 parallel chains each consisting of 100,000 iterations and a burn-in period of 10,000. Initial values for β and u_i were drawn from their respective priors. Posterior summaries, convergence diagnostics and Posterior Predictive Checks were subsequently performed based on the retained samples.

3.6. Test of Hypotheses

The linear mixed regression model involves two fixed effects and one random effect variables. Hence our hypotheses are given by;

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

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

$H_0 : u_i = 0$ (There is no correlation among observations within or between the continents).

$H_1 : u_i \neq 0$ (There is correlation among observations within or between the continents).

$$\text{Test Statistic} : T = \frac{\hat{\beta}_i}{SE\left(\hat{\beta}_I\right)} \tag{22}$$

Given a Linear Mixed Model (LMM), the null distribution of the t-statistic in (22) does not follow an exact t distribution. Therefore, the number of degrees of freedom for the null distribution of the test statistic is not equal to $n-p$. Instead, an approximate method is applied to estimate the degrees of freedom. The Satterthwaite approximation is applied in this study and the formula is expressed as follows;

Given an estimate of a parameter $\hat{\beta}$ with its standard error $SE\left(\hat{\beta}\right)$, the degrees of freedom for the t-statistic is [27]:

$$df=\frac{\left(Var\left(\hat{\beta}\right)\right)^{2}}{\sum\left(\frac{Var\left(\hat{\beta}_{i}\right)^{2}}{n_{i}}\right)} \tag{23}$$

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 if $t_{cal} > t_{tab}$.
- When the p value < 0.05 level of significance, reject H_0.

3.7. Test for Heterogeneity

The Intraclass Correlation Coefficient (ICC) will be used to quantify the proportion of total variance in the response variable that is attributable to the differences between groups which is one of the objectives of this work. It also measures the correlation or similarity among observations within the same group relative to the total variability across all groups.

The formula for ICC is defined as;

$$\text{ICC}=\frac{\sigma_{group}^{2}}{\sigma_{group}^{2}+\sigma_{error}^{2}} \tag{24}$$

where:

σ_{group}^2 = estimated variance component associated with the random grouping effect in the model.

σ_{error}^2 = residual variance component which represents the variability of the observations around the fitted values.

Decision rule:

- $\text{ICC} < 0.3$ suggests little similarity within groups.
- $0.3 < \text{ICC} < 0.5$ suggests moderate similarity within groups.
- $\text{ICC} > 0.5$ suggests strong similarity within groups [28].

3.8. Model Fit and Predictive Performance

3.8.1. Coefficient of Determination

In the context of linear mixed regression models, R^2 is used to measure the proportion of variance explained by the fixed effects in the model considering the hierarchical structure and potential correlations among observations within clusters or groups. It ranges from 0 to 1. It shows how good the regression model is in predicting the dependent variable (inflation rate) using the independent variable (monetary policy rate).

The coefficient of determination can be defined in terms of the Marginal R^2 and Conditional R^2 as follows;

$$R^2_{marginal} = \frac{Var\left(X\hat{\beta}\right)}{Var\left(Y\right)} \tag{25}$$

where:

$Var\left(X\hat{\beta}\right)$ = variance of the fitted values based on fixed effects $X\hat{\beta}$.

$Var\left(Y\right)$ = total variance of the response variable Y.

$$R^2_{conditional} = 1 - \frac{Var\left(Y - X\hat{\beta} - Z\hat{b}\right)}{Var\left(Y\right)} \tag{26}$$

where:

$Z\hat{b}$ = random effects

$Var\left(Y - X\hat{\beta} - Z\hat{b}\right)$ = residual variance after accounting for both fixed and random effects.

$Var\left(Y\right)$ = total variance of the response variable Y.

Decision rule:

- $R^2 < 0.3$ suggests weak influence.
- $0.3 < R^2 < 0.5$ suggests moderate influence.
- $R^2 > 0.5$ suggests strong influence [29].

3.8.2. Posterior Predictive Checks

In the Bayesian framework, the Posterior Predictive Checks were employed to examine the model fit to the study data through the Posterior Predictive Check p-value and the plot of observed and simulated data.

3.8.3. Test for Convergence

The test of convergence was employed to evaluate whether or not an iterative algorithm used in the analysis has converged to a stable solution. The methods employed to check convergence are as follows:

1) The Effective Sample Size was used to measure the amount of independent samples the correlated Markov Chain Monte Carlo (MCMC) effectively represents. A higher ESS indicates better sampling efficiency and more reliable estimates, additionally, the rule of thumb is as follows;

- $\text{ESS} > 100$ for each parameter is generally considered adequate.
- $\text{ESS} < 100$ suggests the need for longer runs or better tuning.
- $\text{ESS} < 10$ indicates serious autocorrelation and unreliable inference [30].

2) The Gelman-Rubin diagnostic was employed to evaluate whether the chains

are well-mixed and exploring the same posterior distribution. The rule of thumb states that convergence is typically assumed when $\hat{R} < 1.1$ [31].

3) The trace plot was further applied to reinforce the convergence of the Gibbs sampling iteration;

Decision rule:

- If the chains mix well and stabilize around a common value, we conclude that the analysis has converged to a stable solution.
- If the chains do not stabilize around a common value which suggests that the chains did not mix well, we conclude that the analysis did not converge to a stable solution [30].

3.8.4. K-Fold Cross Validation

The K-fold Root Mean Square Error (RMSE) was implemented, which is a performance metric used to evaluate the predictive accuracy of a model using K-fold cross-validation. It combines the concepts of cross-validation, where the data is split into K subsets and RMSE, which quantifies the average magnitude of prediction errors. It is defined as:

$$\text{RMSE}_{\text{k-fold}} = \sqrt{\frac{1}{N} \sum_{k=1}^{K} \sum_{i \in T_k} \left(y_i - \hat{y}_i^{(-k)} \right)^2} \tag{27}$$

where,

K = number of folds

T_k = indices of the test set in fold k

y_i = observed response for observation i, i.e. $y_i = \left(\sqrt{y_{ti}} \right)$

$\hat{y}_i^{(-k)}$ = predicted response for observation i, using the model trained on all data excluding fold k

N = total number of observations across all folds [32]

A smaller value of the RMSE indicates a better model.

All analyses will be carried out using R software.

4. Data Presentation, Results and Discussion

This section presents and discusses the results obtained from the analysis of the dataset used for this study, in line with the research objectives and methodology.

4.1. Data Presentation

Table 1 presents the dataset which comprises of the Inflation Rate (IR) and Monetary Policy Rate (MPR) across five continents from 2014 to 2023.

Table 1. Dataset from five continents on inflation rate (IR) and monetary policy rate (MPR) for the period 2014-2023.

Year	Africa		Asia		Europe		North America		South America	
	MPR	IR	MPR	IR	MPR	IR	MPR	IR	MPR	IR
2014	9.25	7.33	7.72	5.38	2.93	3.04	2.50	3.95	11.53	12.98
2015	9.84	7.85	5.73	6.35	4.53	9.82	2.38	1.90	14.13	11.25

Continued

2016	11.26	10.12	5.55	4.20	2.85	3.24	3.00	1.98	12.38	15.30
2017	10.89	11.72	4.99	4.23	3.00	4.18	3.25	3.53	10.75	5.70
2018	10.05	7.67	8.99	5.58	3.75	3.66	3.56	3.33	18.19	10.90
2019	9.00	5.95	5.58	5.78	2.85	2.56	2.81	2.80	16.38	15.83
2020	7.04	5.50	6.25	4.55	1.22	0.90	1.31	2.75	10.56	12.68
2021	7.08	7.47	6.55	6.75	1.85	3.70	2.13	4.93	13.56	16.18
2022	12.04	14.65	5.01	22.65	7.20	9.90	6.56	8.25	28.00	25.88
2023	13.71	20.55	15.46	15.80	6.75	7.42	7.19	5.00	33.25	39.35

Source: Statista and Focus Economics data hub.

4.1.1. Summary Statistics

To improve normality and stabilize variance, the inflation rate was square root transformed prior to modelling. However, descriptive statistics were computed using the original (untransformed) data.

Table 2. Summary statistics for monetary policy rate.

Description	Africa	Asia	Europe	North America	South America
Mean	10.02	7.18	3.69	3.47	16.87
Standard Error	0.66	1.00	0.62	0.60	2.45
Median	9.95	5.99	2.97	2.91	13.84
Mode			2.85		
Standard Deviation	2.09	3.17	1.95	1.91	7.74
Sample Variance	4.35	10.03	3.82	3.63	59.85
Kurtosis	-0.19	6.02	0.0014	0.79	1.25
Skewness	0.12	2.36	0.91	1.32	1.50
Range	6.67	10.48	5.98	5.88	22.69
Minimum	7.04	4.99	1.22	1.31	10.56
Maximum	13.71	15.46	7.2	7.19	33.25
Sum	100.17	71.82	36.93	34.69	168.72
Count	10	10	10	10	10
Coefficient of Variation (%)	**20.86**	**44.15**	**52.85**	**55.04**	**45.88**

The result of the coefficient of variation in Table 2 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 = 20.86%.

Table 3. Summary statistics for inflation rate.

Description	Africa	Asia	Europe	North America	South America
Mean	9.88	8.13	4.84	3.84	16.60
Standard Error	1.48	1.94	0.98	0.59	3.01
Median	7.76	5.68	3.68	3.43	14.14

Continued

Standard Deviation	4.67	6.13	3.10	1.88	9.51
Sample Variance	21.78	37.55	9.63	3.54	90.50
Kurtosis	2.20	3.21	−0.57	2.81	3.43
Skewness	1.55	1.99	0.85	1.51	1.75
Range	15.05	18.45	9.00	6.35	33.65
Minimum	5.50	4.20	0.90	1.90	5.70
Maximum	20.55	22.65	9.90	8.25	39.35
Sum	98.80	81.25	48.42	38.40	166.03
Count	10	10	10	10	10
Coefficient of Variation (%)	**47.27**	**75.40**	**64.05**	**48.96**	**57.29**

The result of the coefficient of variation in Table 3 suggests that Asia's inflation rate with CV = 75.40% is the most variable and uncertain while Africa has the most stable inflation rate with CV = 47.27%. The skewness and kurtosis values confirm that the response variable is non-normal which warrants further diagnostic evaluation.

4.1.2. Test of Outliers and Influential Observations

Using the conventional threshold of $4/n$, where $n = 50$, the maximum Cook's Distance = 0.778596 observed in Table 4 exceeds this cut-off. This suggests the presence of influential observations that may exert undue leverage on the model estimates. Most values, however, remain near zero.

Table 4. Summary of Cook's distance values.

Min	1st Quarter	Median	Mean	3rd Quarter	Max.
0.000025	0.001576	0.007322	0.048797	0.014719	0.778596

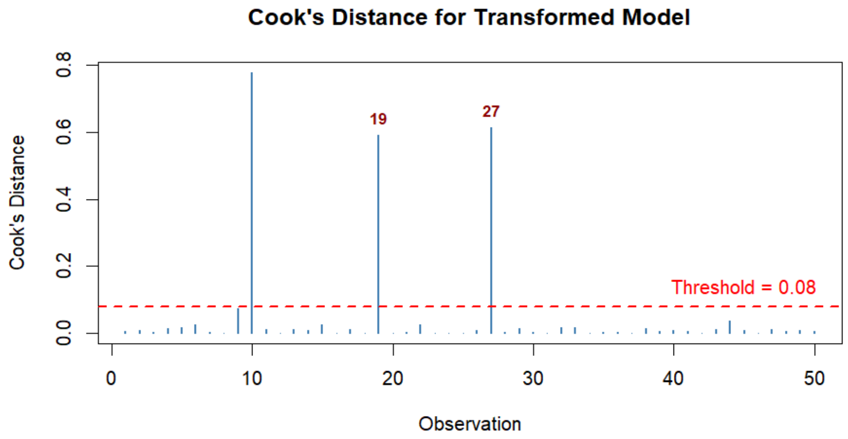

Figure 1. Cook's distance plot.

Figure 1 presents the Cook's Distance plot for the LMM. The red dashed reference line corresponds to the cut-off of 0.08. As shown, points 10, 19 and 27 surpass this line, with the maximum Cook's Distance value reaching approximately 0.778596 as indicated in Table 4, which indicates potential influence.

4.1.3. Sensitivity Analysis

To assess robustness, sensitivity analysis was conducted by removing influential observations. As shown in Table 5, the intercept slightly decreased from 1.5255 to 1.5119 and the slope for Monetary Policy Rate reduced marginally from 0.1535 to 0.1449. These small shifts suggest that the influential points do not drastically alter the model's conclusions. Hence, while some influence exists, the model's estimates remain robust and stable.

Table 5. Sensitivity analysis using Cook's distance.

Model	Intercept	Monetary Policy Rate
Original	1.525548	0.153518
After removing influential	1.511922	0.144861

4.2. Data Analysis: Frequentist Approach

4.2.1. Tests of Hypotheses

The results in Table 6 indicate that MPR has a positive and statistically significant impact on square root of Inflation Rate. A unit increase in MPR corresponds to an approximate 0.1535 units increase in the square root of Inflation Rate, holding other factors constant.

Table 6. Fixed effects.

	Estimate	Std.Error	df	t value	Pr (>|t|)
(Intercept)	1.52555	0.16441	2.54607	9.279	0.00499
Monetary Policy Rate	0.15352	0.01927	1.88155	7.966	0.01831

The random intercept value in Table 7 indicates that the average inflation rate varies moderately across continents. Similarly, the effect of Monetary Policy Rate (MPR) on inflation varies slightly across continents with a random slope value of 0.000622. Although the relationship between MPR and inflation is generally consistent, the small value suggests that there are minor differences in how strongly MPR affects inflation in different continents.

Table 7. Random effects.

Groups	Name	Variance	Std.Dev.
Continent	(Intercept)	0.0383031	0.19571
	Monetary Policy Rate	0.0006222	0.02494
Residual		0.2893678	0.53793

4.2.2. Tests of Assumptions

i) Linearity

As observed in Figure 2, linearity was assessed by examining the residual versus fitted plot. The plot reveals a random scatter around zero with no clear pattern, suggesting that the linearity assumption is satisfied.

ii) Normality

As observed in the residual diagnostic plots in Figure 2, the histogram of residuals and QQ plot suggests that residuals are approximately normally distributed, though mild skewness and deviations at the tails were observed. Given the indication of minor deviations from normality at the tails, no further transformation of the dependent variable was deemed necessary since the LMMs are generally robust to such deviations.

iii) Homoscedasticity

The residuals versus fitted plot in Figure 2 indicates no strong evidence of heteroscedasticity, with residuals largely centered around zero across the range of fitted values. This is reinforced by the result of the Levene's Test shown in Table 8 at $p = 0.8164 > 0.05$ which indicates constant variance across continents.

Table 8. Levene's test for homoscedasticity.

	Df	F value	Pr (>F)
Group	4	0.3876	0.8164
	45		

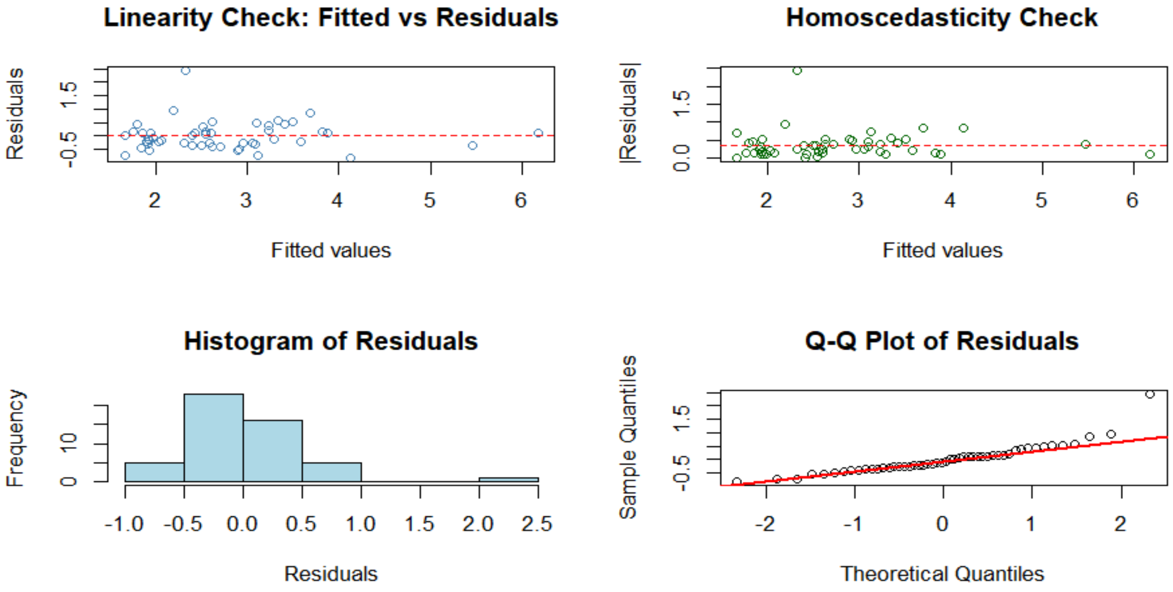

Figure 2. Model diagnostics plot.

iv) Test for independence (autocorrelation)

The Autocorrelation Function (ACF) plot observed in Figure 3 confirms absence of significant autocorrelation which supports independence of residuals. This compliments the Ljung-Box test shown in Table 9, revealing no significant autocorrelation in the residuals.

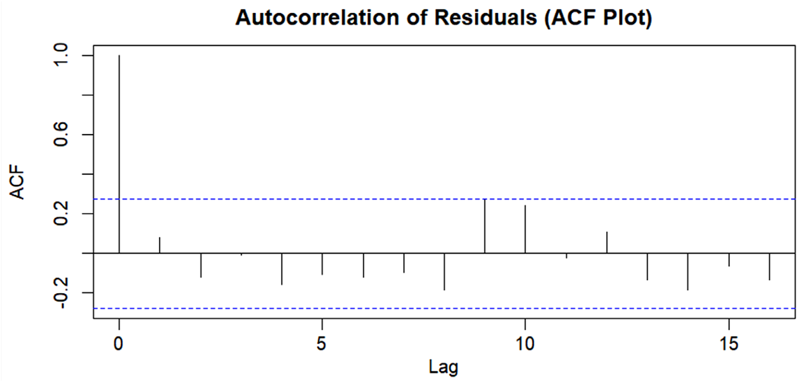

Figure 3. Autocorrelation function plot.

Table 9. Ljung-box test.

X^2	df	p-value
15.09	10	0.1288

4.2.3. Tests for Heterogeneity

A conditional Intraclass Correlation Coefficient (ICC) in **Table 10** indicates negligible between-continent variation.

Table 10. Intraclass correlation coefficient.

Conditional ICC	0.000344

To reinforce the result of the conditional ICC, the heterogeneity across continents was checked using the caterpillar plot in **Figure 4**. The random effects plot shows that both the continent-specific intercepts and the slopes for the Monetary Policy Rate are centered close to zero across all continents. These results indicate slight heterogeneity in the model suggesting that the relationship between monetary policy rate and inflation is largely consistent across continents.

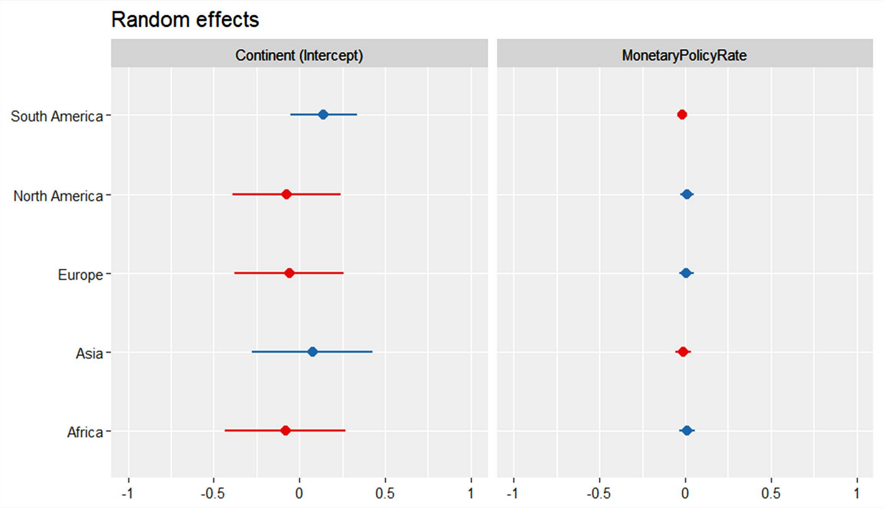

Figure 4. Random effects plot.

4.2.4. Model Fit and Predictive Performance

The results in Table 11 imply that 75% of the variance is explained by fixed effects alone and 77% is explained by both the fixed and random effects.

Table 11. Coefficient of determination.

Marginal R^2	Conditional R^2
0.749983	0.769467

4.3. Data Analysis: Bayesian Approach

As said in Section 3, the R software was used to perform an MCMC analysis of 100,000 trials with a 10,000 burn-in period and the number of chains of 3. This means that the first 10,000 iterations are discarded to allow the Markov chain to reach a stable distribution before collecting samples.

4.3.1. Parameter Estimates

As shown in Table 12, the posterior mean of MPR is positive, however, its 95% credible interval includes zero which suggests statistical uncertainty.

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

	Mean	X2.5	X97.5
Intercept	1.406	0.6788	2.111
Monetary Policy Rate	0.168	−0.2566	0.5924

The random intercept estimate in Table 13 suggests substantial variation in baseline inflation levels among continents and the credible interval does not include zero, which indicates that the variability is statistically meaningful in the Bayesian sense. Similarly, the random slope estimates of 0.2095 indicates moderate variability in how MPR influences inflation from one continent to another and the credible interval which excludes zero means that the differences across continents in the relationship between MPR and inflation are credible.

Table 13. Random effects.

Groups	Name	Estimate	0.025	0.975
Continent	τ_{00}	0.3749	0.09171	1.245
	τ_{11}	0.2095	0.06425	0.6287
σ^2		0.356	0.2334	0.5402

4.3.2. Effective Sample Size

The high Effective Sample Sizes (ESS) in Table 14 indicate efficient mixing and stable posterior estimates.

Table 14. Effective sample size.

(Intercept)	Monetary Policy Rate	σ^2	τ_{00}	τ_{11}
20520.56	245.20	190975.87	83791.87	11208.49

Table 15 shows the Gelman-Rubin diagnostics results which confirms full convergence across chains, given that $\hat{R} \approx 1.0$.

Table 15. Gelman-Rubin diagnostics.

Potential Scale Reduction Factor:						
	Fixed Effects		Random Effects		Residual Variance	
	Point est.	Upper C.I.	Point est.	Upper C.I.	Point est.	Upper C.I.
[1,]	1.00	1.00	1.00	1.00	1.00	1.00
[2,]	1.02	1.03	1.01	1.01		
[3,]			1.05	1.07		

Figure 5 presents the trace plot for all chains to further validate the convergence test results. As observed all chains mix well with the coloured lines overlapping densely without visible trends or drifts. The chains appear to have stationary behaviour with no persistent trends or divergences across iterations. Notably, for variance parameters the occasional spikes are normal but are not sustained, this does not indicate poor convergence. Random effect variances converged though with mild variability which is common in hierarchical models [32].

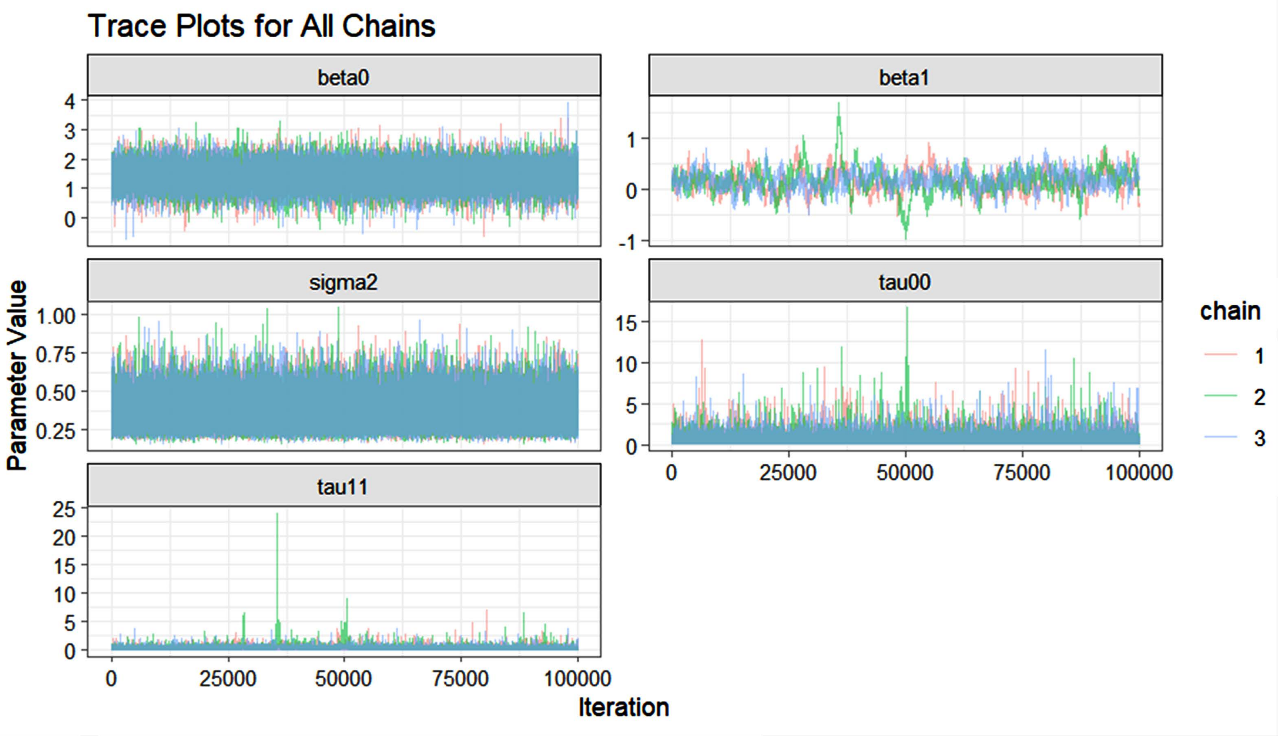

Figure 5. Trace plot.

4.3.3. Test for Heterogeneity

The posterior ICC shown in **Table 16** indicates that most of the variance in inflation is explained by between-continent variability.

Table 16. Intraclass correlation coefficient (ICC).

Posterior Mean (Conditional ICC)	X2.5	X97.5
0.9661	0.9195	0.9923

4.3.4. Model Fit and Predictive Performance

The results in **Table 17** indicate that the Bayesian model explains 64% of variance through fixed effects and 80% of variance is explained when random effects are included.

Table 17. Coefficient of determination.

Marginal R^2	Conditional R^2
0.6406	0.8021

The posterior predictive p-value in **Table 18** indicates excellent model fit.

Table 18. Posterior predictive checks.

Mean	p-value
2.7501	0.6145

As shown in **Figure 6**, the close clustering of points around the 45˚ diagonal confirms accurate predictions though mild underestimation of extreme inflation values is observed.

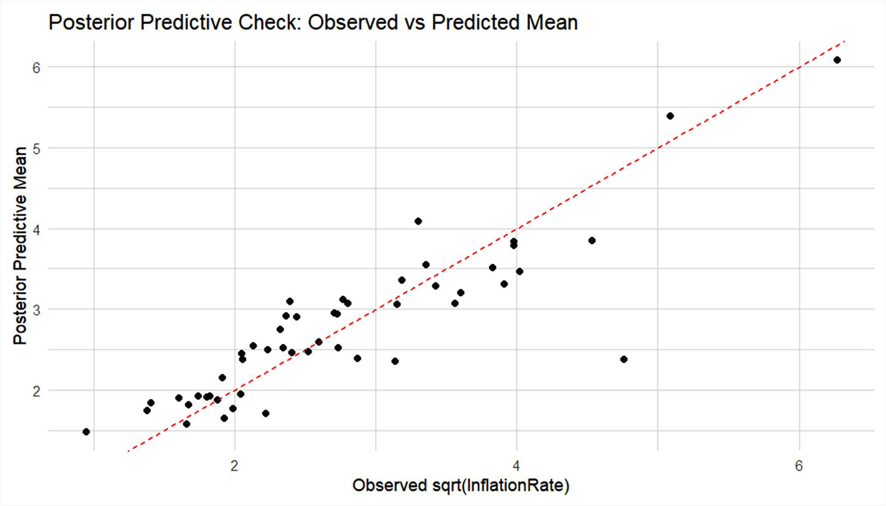

Figure 6. Posterior predictive checks plot.

4.4. Model Comparison

Table 19 compares the performance of the Frequentist and Bayesian LMM applied to evaluate the effect of MPR on the inflation rate across continents. Both approaches produced comparable fixed-effect estimates, with the intercept and MPR coefficients exhibiting similar magnitudes and positive direction. This indicates that higher MPR values are generally associated with an increase in inflation. Notable differences were observed in the estimated random effects. The Bayesian model yielded higher random intercept and random slope variances, which indicates that it captures greater heterogeneity in baseline inflation levels and the varying effects of MPR across continents.

A particularly striking contrast between the two frameworks emerges in the estimation of between-continent heterogeneity. The Frequentist model produced an extremely small conditional ICC which suggests negligible variation across continents, whereas the Bayesian analysis produced a posterior ICC that reveals substantial between-continent variability. This clear contradiction stems from fundamental differences in how both frameworks estimate variance components. The Frequentist LMM relies entirely on the observed data and with only five continent groups and relatively large within-continent variance, the REML estimator tends to shrink the group-level variance toward zero, a well-known issue in small-sample hierarchical models [33]. Conversely, the Bayesian approach incorporates prior distributions which, even when weakly informative, stabilise variance estimation and prevent near-zero solutions. Consequently, the Bayesian posterior attributes a greater share of the total variance to between-continent differences after integrating over the full uncertainty space. These opposing ICC values therefore reflect methodological differences rather than inconsistencies in model specification and highlight the sensitivity of heterogeneity detection to the estimation method applied.

Another important observation from the analysis is the positive relationship between the MPR and inflation, which may seem counterintuitive given the typical objective of raising the MPR to reduce inflation. This pattern is more plausibly interpreted as a reactive policy response rather than a causal effect. Particularly in emerging economies, central banks increase interest rates in response to already elevated inflation rather than proactively suppressing it. As a result, the positive relationship observed in both the Frequentist and Bayesian LMM likely reflects a policy reaction function, where inflationary pressures trigger rate hikes. In addition, structural factors such as supply shocks, exchange rate volatility and fiscal imbalances can weaken the immediate effect of monetary tightening which allows inflation to remain high despite higher MPR. Therefore, the positive coefficient does not indicate that increasing the MPR causes higher inflation; rather, it captures the macro-policy environment where policy rates are adjusted in response to prevailing inflationary conditions.

The contrast in ICC estimates, together with the positive relationship between MPR and inflation, highlights the interaction of within-continent variability and macro-policy dynamics. While the Frequentist model attributes most variation to within-continent fluctuations, the Bayesian framework recognizes substantial between-continent heterogeneity which reveals how different continents respond to monetary policy under diverse economic structures and inflationary pressures. Jointly, the ICC results and the counterintuitive MPR coefficient illustrate that observed inflation patterns are shaped not only by inherent heterogeneity across continents but also by the timing and responsiveness of monetary policy interventions.

In terms of model fit and predictive performance, the Frequentist model explained a larger proportion of variance due to fixed effects alone while the Bayesian model achieved a higher overall explanatory power when both fixed and random effects were considered. In addition, the Bayesian model demonstrated superior predictive accuracy, as indicated by a lower 5-fold cross-validated RMSE. These findings suggest that although the Frequentist model fits the fixed effects well, the Bayesian model provides a more comprehensive representation of data variability and better generalization to new data. In general, the Bayesian LMM is considered superior, as it offers enhanced flexibility in modelling hierarchical structures, richer uncertainty quantification and enhanced predictive performance.

Table 19. Comparative summary of the frequentist and Bayesian LMM.

Parameters	Category	Frequentist	Bayesian
Fixed Effects	(Intercept)	1.52555	1.406
	Monetary Policy Rate	0.15352	0.168
Random Effects	Random Intercept	0.038303	0.3749
	Random Slope	0.000622	0.2095
	Residual Variance	0.289368	0.356
Heterogeneity	Conditional ICC	0.000344	0.9661
Model Fit and Predictive Performance	Marginal R^2	0.74998	0.6406
	Conditional R^2	0.76947	0.8021
	5-fold Mean RMSE	0.539	0.5144

5. Conclusion, Limitation and Recommendation

5.1. Conclusion

This study assessed the relationship between the MPR and the inflation rate across five continents from 2014 to 2023 using both Frequentist and Bayesian Linear Mixed Models (LMM). The data were obtained from Statista and Focus Economics. To improve normality and stabilise variance, the inflation rate was square-root transformed prior to modelling, while descriptive statistics were computed using the untransformed data. The Frequentist model revealed a positive and statistically significant relationship between the MPR and the square root of the inflation rate. This implies that an increase in MPR is associated with a corresponding rise in the square root of inflation which indicates that monetary tightening may not immediately curb inflation uniformly across regions. The low conditional Intraclass Correlation Coefficient from the Frequentist model further reveals minimal between-continent heterogeneity in the relationship between MPR and inflation. Under the Bayesian LMM, the posterior mean of the MPR effect is positive, however, its 95% credible interval includes zero which suggests some posterior uncertainty about the precise magnitude of the effect. This contrasts with the findings of the previous study [8], which reported a positive and credible effect of MPR on inflation. The divergence in the results may be attributed to methodological differences between the two studies. While the earlier study excluded influential observations and applied the GAMM approach to correct for non-linearity, the present study retained all observations and applied a square-root transformation to improve normality and stabilize variance. By regularizing assumption violations through transformation rather than data exclusion, this study produced more robust and reliable inferences, offering a more comprehensive reflection of the intrinsic economic relationship. The Bayesian model also yielded larger posterior variances for continent-level random effects which reflects richer uncertainty quantification inherent in Bayesian hierarchical modelling. The Posterior Predictive Checks, convergence diagnostics and Cross-Validation support overall model adequacy. While monetary policy generally affects inflation positively, the strength of this impact varies across continents, being stronger in Asia and North America, and negligible in Africa, Europe and South America. These differences indicate structural and economic factors such as the depth and efficiency of the financial markets, the central bank credibility, the exchange rate regimes and the composition of national economies which influence the transmission of MPR. A comparison of model performance showed that both approaches produced similar fixed-effect estimates, but the Bayesian model captured greater heterogeneity across continents and demonstrated superior predictive performance. Summarily, the Bayesian LMM emerged as the better-performing model, offering enhanced flexibility, more comprehensive uncertainty representation and improved generalization. The findings generally indicate a broadly positive relationship between MPR and inflation, though the strength and certainty of this relationship differ depending on the inferential framework employed.

5.2. Limitations of the Study

Despite its comprehensive analytical framework, this study is not without limitations:

1) The study relied on secondary macroeconomic data from Statista and Focus Economics data hubs which may introduce measurement errors, reporting lags and definitional inconsistencies across continents.

2) The study utilized aggregated continental averages, which may obscure within-continent heterogeneity among individual countries.

3) Although weakly informative priors were employed in the Bayesian analysis, different prior specifications could yield slightly different posterior inferences.

4) The 10-year study period captures short to medium-term dynamics. Structural breaks or longer-term shifts outside this period are not addressed.

5.3. Recommendations

Based on the findings and limitations, the following recommendations are proposed for policymakers and future research:

1) Policymakers should exercise caution when using monetary tightening as an

immediate tool for inflation control, as results suggest that increases in MPR do not uniformly reduce inflation across regions. Coordinated fiscal and structural reforms should complement monetary measures to enhance transmission effectiveness and price stability.

2) Given the heterogeneity observed across continents, regional monetary authorities should tailor policy frameworks to local economic conditions considering factors such as financial market depth, policy credibility and economic structure rather than adopting a uniform global approach.

3) Enhanced transparency and harmonization in macroeconomic reporting are encouraged to improve cross-country comparability and model reliability.

4) Future studies should analyze country-level panel data to capture within-continent heterogeneity and identify nation-specific transmission channels of monetary policy

5) In Bayesian implementations, future research should incorporate systematic prior sensitivity analyses to evaluate how alternative priors influence posterior estimates in order to increase transparency and robustness.

6) Given observed uncertainty in the magnitude of effects across frameworks, policymakers should combine macroprudential tools with timely data monitoring to refine monetary responses and improve policy calibration.

Conflicts of Interest

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

References

[1] Gbadebo, A.D. and Mohammed, N. (2015) Monetary Policy and Inflation Control in Nigeria. *Journal of Economics and Sustainable Development*, **6**, 108-115.

[2] Lowe, P. (1997) The Link between the Cash Rate and Inflation. Reserve Bank of Australia Bulletin. https://www.rba.gov.au/publications/rdp/1995/pdf/rdp9504.pdf

[3] Vitor, C. (2015) Understanding Inflation Dynamics and Monetary Policy in a Low Inflation Environment. https://www.bis.org/review/r151110f.pdf

[4] Roberts, J.M. (2004) Monetary Policy and Inflation Dynamics. Finance and Economics Discussion Series, Division of Research & Statistics and Monetary Affairs. Federal Reserve Board.

[5] International Monetary Fund (2024) World Economic Outlook Update: January 2024. IMF.
https://www.imf.org/en/publications/weo/issues/2024/01/30/world-economic-outlook-update-january-2024

[6] Manmohan, A. and Irfan, A.S. (2019). Monetary Policy Effect on Inflation and Growth. Research and Information System for Developing Countries. Discussion Paper No. 239.

[7] Loso, J., Olyvia, R., Siddiqi, M. and Firayani, A.N. (2025) The Effect of Monetary Policy on Inflation: An Empirical Approach. *Nomico Journal*, **2**, 63-74.

[8] Okoronkwo, C., Ugwuanyim, G.U., Iwu, H.C. and Amuji, H.O. (2025) Random Coefficient Modelling of the Global Effect of Exchange and Monetary Policy Rates on Inflation. *Open Journal of Statistics*, **15**, 397-430.

https://doi.org/10.4236/ojs.2025.155022

[9] Kamugisha, N. and Tibamwenda, C. (2025) Evaluating the Impact of Monetary Policy on Inflation and Economic Growth Using Vector Autoregression and Bayesian Econometrics. *Metropolitan Journal of Academic Multidisciplinary Research*, **4**, 157-168.

[10] Henry, E.A. and Sabo, A.M. (2020) Impact of Monetary Policy on Inflation Rate in Nigeria: Vector Autoregressive Analysis. *Bullion*, **44**, 1-14. https://dc.cbn.gov.ng/bullion/vol44/iss4/6

[11] Joel, A.E., Masha, J.M., Balogun, A.E. and Ambrose, A.D. (2024) Effect of Monetary Policy Instruments on Inflation in Nigeria. *KASU Journal of Economics and Development Studies*, **10**, 95-113.

[12] Lumengo, B. (2017) Assessing the Effectiveness of the Monetary Policy Instrument during the Inflation Targeting Period in South Africa. *International Journal of Economics and Financial Issues*, **7**, 706-713.

[13] Asiamah, M. (2024) Evaluating the Impact of Monetary Policy on Inflation in Sub-Saharan Africa. *Asian Journal of Economic Modelling*, **12**, 262-280. https://doi.org/10.55493/5009.v12i4.5244

[14] Nguyen, T.T., Phan, T.D. and Tran, N.A. (2022) Impact of Fiscal and Monetary Policy on Inflation in Vietnam. *Investment Management and Financial Innovations*, **19**, 201-209. https://doi.org/10.21511/imfi.19(1).2022.15

[15] Ampudia, M., Ehrmann, M. and Strasser, G. (2023) The Effect of Monetary Policy on Inflation Heterogeneity along the Income Distribution. European Central Bank: Working Paper Series No. 2858.

[16] Ezeanyeji, C.I., Obi, C.O., Imoagwu, C.P. and Ejefobihi, U.F. (2021) Monetary Policy and Inflation Control: The Case of Nigeria. *European Journal of Management and Marketing Studies*, **6**, 1-23. https://doi.org/10.46827/ejmms.v6i2.1017

[17] Spiegel, M.R., Schiller, J. and Srinivasan, R.A. (2009) Schaum's Outline of Probability and Statistics. 4th Edition, McGraw-Hill.

[18] West, B.T., Welch, K.B. and Galecki, A.T. (2015) Linear Mixed Models: A Practical Guide Using Statistical Software. 2nd Edition, CRC Press.

[19] Wood, S.N. (2017) Generalised Additive Models: An Introduction with R. CRC Press.

[20] Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A. and Smith, G.M. (2009) Mixed Effects Models and Extensions in Ecology with R. Springer.

[21] Brown, H. and Gardner, R.W. (2018) Mixed-Effects Models for Complex Data. Chapman and Hall/CRC Press.

[22] Sophia, R.B. and Skrondal, A. (2012) Multilevel and Longitudinal Modelling Using Stata. 3rd Edition, Stata Press.

[23] James, G., Witten, D., Hastie, T. and Tibshirani, R. (2021) An Introduction to Statistical Learning with Applications in R. 2nd Edition, Springer.

[24] Zhang, X., Tao, X. and Jin, Y. (2023) Detecting Influential Subjects in Intensive Longitudinal Data using Mixed-Effects Regression. *BMC Medical Research Methodology*, **23**, Article No. 32.

[25] Donovan, T.M. and Mickey, R.M. (2019) Bayesian Statistics for Beginners: A Step-by-Step Approach. Oxford University Press.

[26] Van-der-Merwe, A.J. and Botha, T.J. (1993) Bayesian Estimation in Mixed Linear Models Using the Gibbs Sampler. *South African Statistics Journal*, **27**, 149-180.

[27] Little, R.C., Milliken, G.A., Stroup, W.W., Wolfinger, R.D. and Schabenberger, O. (2006) SAS for Mixed Models. 2nd Edition, SAS Institute.

[28] Fitzmaurice, G.M., Laird, N.M. and Ware, J.H. (2013) Applied Longitudinal Analysis. Wiley.

[29] Langford, I.H. and Solomon, R. (2009) Mixed-Effects Models for Complex Data. CRC Press.

[30] Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A. and Rubin, D.B. (2013) Bayesian Data Analysis. 3rd Edition, Chapman & Hall/CRC.

[31] Gelman, A. and Rubin, D.B. (1992) Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science*, **7**, 457-472. https://doi.org/10.1214/ss/1177011136

[32] Vehtari, A., Gelman, A. and Gabry, J. (2017) Practical Bayesian Model Evaluation Using Leave-One-Out Cross-Validation and WAIC. *Statistics and Computing*, **27**, 1413-1432. https://doi.org/10.1007/s11222-016-9696-4

[33] Hox, J. and McNeish, D. (2020) Small Samples in Multilevel Modeling. In: *Small Sample Size Solutions*, Routledge, 215-225. https://doi.org/10.4324/9780429273872-18