

THRESHOLD, MARGINAL AND INTERACTIVE EFFECTS AMONG ECONOMIC VARIABLES: AN INTEGRATED PANEL DATA FRAMEWORK¹

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ABSTRACT

This paper develops an integrated empirical workflow, referred to as the Interactive Panel Data Framework (IPDF), that systematically combines established panel data methods, such as interaction terms, threshold analysis, and marginal effect computation, within a unified estimation and inference strategy. Rather than proposing a new estimator, the IPDF provides a coherent analytical protocol for jointly evaluating regime-dependent, interaction-driven relationships in macro-panel setting. Using a balanced panel of emerging economies over the period 1980–2023, the study combines interaction terms, dynamic specifications, and nonlinear mechanisms within a unified empirical structure. Monte Carlo simulations and empirical estimations support the robustness of the proposed framework, while homogeneity tests and threshold analysis reveal substantial country-specific heterogeneity. The empirical results indicate statistically significant threshold and conditional marginal effects, showing that the impact of inflation and exchange rates on economic growth varies across regimes and economic conditions. Moreover, the identified interaction effects highlight the importance of jointly evaluating macroeconomic policy variables rather than analysing them in isolation. By integrating interaction effects, marginal responses, and threshold dynamics within a single panel data framework, this study contributes a coherent and policy-relevant empirical approach for analysing nonlinear and regime-dependent macroeconomic relationships in emerging economies.

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1. INTRODUCTION

In panel data analysis, the development of integrated and flexible analytical approaches aimed at explaining and modeling complex relationships among economic variables is of great importance for econometric research. Panel data models combine time series and cross-sectional data, enabling the modeling of both within-unit changes and between-unit differences. Owing to these characteristics, panel data models are widely used in many fields such as macroeconomic growth, monetary and fiscal policies, financial markets, investment, and trade relations.

Traditional Fixed Effects (FE) and Random Effects (RE) models provide a useful baseline for empirical analysis; however, they may face limitations when relationships among explanatory variables are conditional, interactive, or regime-dependent. For instance, the effects of monetary and fiscal policy instruments on economic growth and price stability may be only partially captured when such relationships are analysed exclusively through additive specifications. Accordingly, the literature has increasingly emphasised the use of extended and integrative modeling frameworks that allow interaction effects, marginal responses, and threshold mechanisms to be examined within a unified empirical setting.

This study develops an integrated empirical workflow, referred to as the Interactive Panel Data Framework (IPDF), that systematically combines established panel data methods - interaction terms, threshold analysis, and marginal effect computation - within a unified estimation and inference strategy. Rather than proposing a new estimator, the IPDF provides a coherent analytical protocol for jointly evaluating regime-dependent, interaction-driven relationships in macro-panel settings where standard linear specifications may be inadequate. The IPDF is designed as a coherent analytical framework that integrates established panel data methods for examining interaction, marginal, and threshold effects, rather than as a standalone estimator. The motivation for this framework stems from the complex structure of economic and financial systems, which often requires a more comprehensive examination of conditional interactions and nonlinear relationships that may not be adequately captured by purely linear and additive specifications. The Interactive Panel Data Framework (IPDF) provides a three-dimensional analytical structure that jointly considers the interaction structure among explanatory variables, the conditional marginal effects derived from these interactions, and threshold effects within panel data models. By bringing these three analytical dimensions together within a unified estimation structure, the framework facilitates a coherent and systematic interpretation of interaction-driven and regime-dependent relationships. Before proceeding further, it is

useful to review existing interaction-based approaches in the literature. As widely recognised, the complex nature of economic and financial systems necessitates careful attention to nonlinear relationships and conditional interactions among variables. For example:

1. The bidirectional relationship between inflation and the exchange rate may exhibit different responses beyond certain threshold values.
2. The relationship between interest rates and investment may be positive in low-interest environments but become negative in high-interest environments.
3. The relationship between fiscal policy and growth may vary across different regimes depending on the level of public debt.

In the existing literature, approaches such as the Interactive Fixed Effects (IFE) model developed by Bai (2009), the Panel Threshold Regression (PTR) model proposed by Hansen (1999), and the Panel Smooth Transition Regression (PSTR) model introduced by González et al. (2017) are widely used to capture nonlinear and regime-dependent relationships in panel data analysis. While each of these frameworks offers valuable insights into specific dimensions of nonlinearity or cross-sectional dependence, they typically address these features in isolation. In particular, they do not provide a unified structure that simultaneously accounts for interaction effects among explanatory variables and the way in which associated marginal effects evolve across regimes.

The proposed Interactive Panel Data Framework (IPDF) is designed to complement these existing approaches by integrating several analytical dimensions within a single empirical structure. Specifically, the IPDF:

1. Allows economic policies to be evaluated jointly by explicitly modeling interactions among independent variables;
2. Incorporates nonlinear components and threshold mechanisms, facilitating the assessment of variable responses across different economic conditions;
3. Accommodates dynamic processes through the estimation of time-varying interaction parameters;
4. Accounts for heterogeneous panel structures by allowing country- or unit-specific interaction patterns; and
5. Supports the identification of policy-relevant combinations of variables through the computation of conditional marginal effects derived from interaction terms.

In macroeconomic panel data analysis, the reliable estimation and interpretation of interaction effects and nonlinear relationships are highly complex due to methodological challenges such as cross-sectional dependence, slow-moving

dynamics, and pronounced structural heterogeneity. [Canova \(2007\)](#) emphasises that macro panels are often dominated by common shocks, global trends, and low-frequency components, and that when these factors are not adequately controlled for, estimated coefficients tend to reflect properties of the data-generating process rather than underlying structural relationships. This issue is particularly important in interpreting interaction terms between policy-related variables.

In this context, [Canova and Ciccarelli \(2009\)](#) demonstrate that assuming parameter homogeneity in multicountry macroeconomic models can lead to serious biases and argue that cross-country heterogeneity must be explicitly taken into account. The authors note that fixed effects approaches often fail to adequately disentangle common shocks, which may distort both the magnitude and the sign of interaction terms. Since interaction coefficients identified under fixed effects transformations rely solely on within-unit time variation, interpreting them as direct measures of cross-country structural interaction intensity is problematic.

These methodological concerns are addressed more systematically by [Canova and Ciccarelli \(2013\)](#), who highlight that dynamic interactions, nonlinearities, and regime-dependent behaviour in macroeconomic panels often emerge through latent common factors and heterogeneous responses across units. From this perspective, marginal and threshold effects derived from interaction-based modeling should be interpreted not as fixed structural parameters but as conditional relationships that are sensitive to data transformations, sampling variation, and the panel structure. Moreover, the presence of slow-moving macroeconomic variables complicates the identification of interaction coefficients and renders the economic interpretation of estimated threshold values more delicate.

In this study, the methodological concerns raised in the Canova literature are explicitly addressed and mitigated through a series of robustness checks. First, Generalized Estimating Equations (GEE) are employed to account for heteroskedasticity and cross-sectional dependence. Second, marginal and threshold effects derived from interaction terms are tested under alternative model specifications and country-specific estimations to assess the sensitivity of the results. Third, interaction coefficients are interpreted not as structural parameters but as regime-dependent and conditional empirical indicators. This interpretation strategy reduces the risks associated with heterogeneity and unobserved common shocks emphasised by [Canova and Ciccarelli \(2009, 2013\)](#) and allows interaction, marginal, and threshold analyses to be conducted in a more cautious and internally consistent manner within a macroeconomic panel setting.

Panel data models provide a powerful methodological framework for capturing both cross-sectional heterogeneity and temporal dynamics in economics. However, traditional fixed and random effects models may face limitations when confronted with complex data structures such as cross-sectional dependence, threshold effects, and nonlinear transition mechanisms (Pesaran, 2006; Hansen, 1999; González et al., 2017; Bai, 2009). These challenges have encouraged the development of advanced econometric approaches aimed at accounting for nonlinearities, structural breaks, and heterogeneous responses across units. For example, Yang, Yao, and Xie (2025) proposed a panel kink threshold model with multiple covariate-dependent thresholds, while Cai and Zhou (2021) introduced a simplified dynamic panel data framework for macroeconomic policy analysis. In addition, empirical studies on social capital, exchange rate misalignments, income convergence, and institutional quality (e.g., Tekdemir & Varol Iyidoğan, 2024; Krekó & Oblath, 2020; Alemu, Udvari & Kotosz, 2024; Castillo, Santibáñez & Márquez, 2024) emphasise the growing importance of nonlinear dynamics, convergence processes, and institutional factors in shaping macroeconomic outcomes.

In this context, the present study contributes to the literature by developing the Interactive Panel Data Framework (IPDF), which provides an integrated empirical workflow for examining interactions among explanatory variables within panel data settings. The framework builds on the Interactive Effects (IE) approach, allowing unobserved common shocks and heterogeneous responses across units to be jointly accounted for (Bai, 2009; Moon & Weidner, 2015). By organising interaction effects, marginal responses, and threshold behaviour within a coherent analytical structure, the IPDF facilitates a more informative interpretation of interaction-driven relationships than conventional additive panel specifications. The IPDF does not replace existing panel threshold or interactive-effects estimators. Instead, it builds on Hansen (1999), Bai (2009), and the marginal-effects literature by developing a structured workflow that: (i) specifies interaction-augmented panel models, (ii) identifies regime-specific thresholds, (iii) computes and reports conditional marginal effects, (iv) implements robust inference under macro-panel complications.

The IPDF draws on methodological insights from several strands of the literature. The dynamic panel data literature (Arellano & Bond, 1991) provides a reference for the cautious interpretation of interaction coefficients in the presence of potential endogeneity and regime dependence. Nonlinear model extensions (Baltagi & Li, 2002) motivate the specification of interaction and threshold structures, while structural homogeneity tests (Su & Chen, 2013) offer a basis for examining the stability of interaction effects across countries.

At the estimation stage, the Generalized Estimating Equations (GEE) methodology is employed to address heteroskedasticity and cross-sectional dependence, which are commonly observed in macroeconomic panels. This approach allows interaction coefficients derived under the IE structure to be interpreted as conditional and regime-dependent empirical relationships rather than fixed structural parameters. In this way, the IPDF combines the analytical advantages of the interactive effects framework with a robust estimation strategy, enabling a reliable and policy-relevant analysis of interactive, nonlinear, and heterogeneous relationships in panel data.

Below, the relevant literature on the subject is presented:

(i) Dynamic Panel Data Estimators

The foundation of modern panel econometrics was laid by [Arellano and Bond \(1991\)](#), who developed the Generalized Method of Moments (GMM) approach to resolve endogeneity problems arising from lagged dependent variables. Subsequent extensions include maximum likelihood estimation for short panels ([Hsiao, Pesaran & Tahmiscioglu, 2002](#)) and studies such as [Chudik and Pesaran \(2015\)](#), which enhanced robustness under weak exogeneity. In addition, [Cai and Zhou \(2021\)](#) proposed a simplified dynamic panel data framework demonstrating flexibility in capturing time-varying policy effects. [Castillo, Santibáñez, and Márquez \(2024\)](#) also employed a dynamic panel GMM framework to analyse the effects of corruption on human development and highlighted the importance of robust estimation techniques in institutional structures.

(ii) Threshold and Nonlinear Models

Nonlinear mechanisms play a central role in understanding regime-dependent dynamics. [Hansen \(1999\)](#) introduced the Panel Threshold Regression (PTR) model, which was later extended by [Caner and Hansen \(2004\)](#) through the inclusion of instrumental variables. [Kremer, Bick, and Nautz \(2013\)](#) examined nonlinear relationships between inflation and growth. [González et al. \(2017\)](#) proposed the Panel Smooth Transition Regression (PSTR) model, which accounts for the possibility that regime transitions may be gradual rather than abrupt. More recently, [Yang, Yao, and Xie \(2025\)](#) developed a panel kink threshold model with multiple covariate-dependent thresholds. In the same vein, [Tekdemir and Varol Iyidoğan \(2024\)](#) employed a nonlinear threshold framework to investigate the role of government in the social capital–growth relationship and provided empirical evidence of regime-dependent effects.

(iii) Interactive and Factor-Based Models

Another prominent line of research focuses on the role of latent common factors and interactions among variables. Pesaran (2006) developed the Common Correlated Effects (CCE) estimator to capture cross-sectional dependence. Bai (2009) introduced the Interactive Fixed Effects (IFE) model, separating common shocks from unit-specific dynamics. Moon and Weidner (2015) extended these techniques to high-dimensional panels, improving estimation under uncertainty regarding the number of factors. In addition to these methodological advances, Krekó and Oblath (2020) examined the relationship between economic growth and real exchange rate misalignments, providing an empirical setting in which interaction effects and heterogeneity play a crucial role.

(iv) Heterogeneity and Structural Tests

With an awareness of country- or unit-specific characteristics, several studies have focused on structural differences in panel data. Lee, Pesaran, and Smith (1997) analysed stochastic growth convergence, while Eberhardt and Teal (2011) criticised the neglect of structural heterogeneity in conventional growth regressions. Kapetanios, Pesaran, and Yamagata (2011) analysed non-stationary multifactor error structures, and Su and Chen (2013) proposed homogeneity tests within the IFE framework. In addition, Sato and Söderbom (2017) emphasised the value of GMM estimation in environments with time-varying parameters, while Fan and Peng (2024) examined the influence of outliers on GMM estimation in panel models. Finally, Alemu, Udvari, and Kotosz (2024) analysed income convergence in Central and Eastern Europe, providing further empirical evidence of cross-country heterogeneity in growth dynamics.

The main contribution of this study is reflected in five key analytical features of the Interactive Panel Data Framework (IPDF):

1. A framework that integrates interaction effects, threshold mechanisms, and heterogeneity control within a single unified structure,
2. A dynamic interaction structure that enables the estimation of time-varying interaction parameters,
3. The capacity to model complex relationships among three variables through a triple interaction term ($X_1 \times X_2 \times X_3$),
4. The use of the Generalized Estimating Equations (GEE) method, which controls for cross-sectional dependence and heteroskedasticity,
5. A heterogeneous panel structure that allows for the estimation of country-specific interaction coefficients.

The proposed Interactive Panel Data Framework (IPDF), as a unifying empirical framework, is designed to complement existing panel data approaches by integrating interaction effects, marginal responses, and threshold mechanisms within a single analytical structure. These features position the proposed framework as a complementary analytical structure relative to existing panel data approaches (FE, RE, PTR, PSTR, IFE) and support a more transparent and policy-relevant analysis of macroeconomic policy interactions.

Within this framework, the study is structured into five sections. The first section presents the Introduction, outlining the objective of the study, the theoretical background, and the relevant literature. The second section presents the materials and methodology, describing the dataset, variable definitions and econometric methods, and introducing the theoretical and methodological foundations of the Interactive Effects (IE) approach and the Interactive Panel Data Framework (IPDF). The third section reports the empirical findings. The fourth section discusses the results within the context of the existing literature. The fifth and final section, titled Conclusions, provides an overall evaluation, presents policy implications, and offers suggestions for future research. Despite these advances, the literature still lacks a unified empirical framework that integrates interaction effects, marginal responses, and threshold dynamics within a single estimation setting. The proposed Interactive Panel Data Framework (IPDF) is introduced in the next subsection to address this limitation, followed by a detailed presentation of its analytical and mathematical structure.

The empirical analysis of this study is based on a balanced panel data set covering emerging economies, namely Argentina, Brazil, Chile, Colombia, Czechia, Hungary, India, Indonesia, Malaysia, Mexico, South Africa, and Türkiye, over the sample period. The selection of these countries is motivated by both theoretical and empirical considerations. First, these economies exhibit strong interactions among inflation, credit conditions, and economic growth, making them particularly suitable for examining nonlinear, interaction-driven, and regime-dependent macroeconomic relationships. Second, they display substantial heterogeneity in monetary policy frameworks, levels of financial depth, and institutional structures, which allows the proposed Interactive Panel Data Framework (IPDF) to fully exploit its ability to capture country-specific interaction effects. Third, over the sample period, these countries have experienced diverse inflationary episodes, credit expansions, and policy regime shifts, providing a rich empirical environment for identifying threshold behavior and conditional marginal effects. Taken together, this country selection strengthens the empirical relevance of the research question and enhances the external validity of the findings for emerging market economies.

The methodological contribution of this study lies in the Interactive Panel Data Framework (IPDF)—an integrated empirical workflow that systematically combines established panel data methods rather than proposing a new estimator. The IPDF builds on Hansen (1999), Bai (2009), and the marginal-effects literature by organising interaction effects, threshold mechanisms, and conditional marginal-effect computation within a coherent analytical protocol. The IPDF does not replace existing panel threshold or interactive-effects estimators. Instead, it provides a structured workflow that: (i) specifies interaction-augmented panel models, (ii) identifies regime-specific thresholds, (iii) computes and reports conditional marginal effects, and (iv) implements robust inference under macro-panel complications. Through this integrated structure, the framework enables transparent assessment of the conditions under which macroeconomic interactions strengthen, weaken, or change direction, thereby facilitating a direct mapping from empirical results to policy-relevant threshold values.

2. MATERIALS AND METHODS

In this section, the Interactive Panel Data Framework (IPDF), which is developed in the present study, is introduced in detail and its theoretical foundation is presented. First, the dataset, variables, and scope of the sample are described; thereafter, the fundamental mathematical formulation of the IPDF, the interaction terms, marginal effects, and the threshold mechanism are systematically elaborated. In addition, the dynamic IPDF extension, which incorporates the time dimension of the model, is addressed within the theoretical framework. Finally, the theoretical structure of the Generalized Estimating Equations (GEE) approach employed in the empirical implementation of the model is explained in a manner that accounts for potential heteroskedasticity, serial correlation, and cross-sectional dependence in the error terms; and the correlation structure, covariance matrix, and robust standard error estimation techniques adopted in the study are presented in detail. In this way, both the theoretical and applied dimensions of the IPDF framework are comprehensively established, thereby forming a clear analytical basis for the empirical tests conducted on real data in the subsequent Results section.

2.1 Data set

To test the interactive effects model developed in this study, the relationship between consumer price inflation (CPI), the real effective exchange rate (REER), and economic growth in emerging economies is examined. Specifically, the Interactive Panel Data Framework (IPDF) is employed to analyse how interactions

among CPI inflation (inf) and the REER (lndk) influence economic growth. The dataset covers the period 1980–2023 and consists of annual data for 12 emerging economies: Argentina, Brazil, Chile, Colombia, Czechia, Hungary, India, Indonesia, Malaysia, Mexico, South Africa, and Türkiye. The data are obtained from multiple reliable sources, including the World Bank’s World Development Indicators (WDI), the International Monetary Fund’s International Financial Statistics (IFS), and OECD Statistics. The panel structure of the dataset allows for the assessment of cross-country heterogeneity and time dynamics, providing a suitable basis for examining interaction, marginal, and threshold effects among macroeconomic variables. Detailed information on variable definitions, data sources, and transformations is presented in Table 1.

Table 1. Variable Definitions and Data Sources

Variable	Variable Abbreviation	Definition	Source
GDP per capita	lngdp	GDP per capita (constant 2015 US\$) - Gross domestic product divided by midyear population	World Bank (via FRED): https://fred.stlouisfed.org/series/NYGDPPCAPKD*
Inflation (CPI)	inf	Annual % change in consumer price index	IMF International Financial Statistics (via FRED): https://fred.stlouisfed.org/series/FPCPITOTLZG*
Exchange Rate (REER)	lndk	Real Effective Exchange Rate - Local currency unit per US\$, adjusted for inflation differentials	BIS and IMF (via FRED): https://fred.stlouisfed.org/series/CCUSMA02*Q618N
Inflation-Exchange rate interaction	inf_lndk_inter	Interaction term between inflation and exchange rate ($\text{inf} \times \text{lndk}$)	Calculated interaction term
Squared inflation (threshold term)	Inf_r	Squared inflation rate (inf^2), included to capture nonlinear and threshold effects; not a distinct inflation measure	Constructed by authors

Notes: Inflation is measured using the consumer price index (CPI) and denoted as inf. The real effective exchange rate (REER), denoted as lndk, is used as the exchange rate indicator throughout the analysis. An increase in the REER indicates real appreciation. The variable inf_r represents a nonlinear transformation of the inflation rate (inf^2) used exclusively for marginal and threshold analysis. It does not constitute a separate inflation indicator.

Source: Author’s own elaboration based on data from the World Bank, IMF International Financial Statistics, and BIS (via FRED).

Data Preparation and Transformation: Inflation is measured as a percentage change, while GDP and the exchange rate variables are log-transformed. Following these transformations, all variables are standardised (mean = 0, standard deviation = 1) to ensure cross-country comparability and facilitate convergence in the GEE estimation process (See Appendix F for replication package and master_run.do file). Inflation is modeled in percentage terms (levels) due to the presence of negative values in certain periods. Logarithmic transformations are applied exclusively to strictly positive level variables (GDP per capita and REER). Nonlinearity is captured via squared inflation (inf^2), used solely for marginal and threshold analysis. All threshold values implied by interaction terms are back-transformed to original economic units using sample means and standard deviations.

Table 2 reports the descriptive statistics and normality test results for the variables used in the analysis. Panel A presents the descriptive statistics for the logarithmically transformed variables. The mean value of lngdp indicates substantial variation in economic size across countries and over time. Inflation (inf) and the exchange rate (lnrk) display relatively high dispersion, as reflected by their standard deviations and wide ranges between minimum and maximum values. This heterogeneity across observations justifies the use of logarithmic transformations and robust estimation methods. Panel B reports the results of the skewness and kurtosis tests based on bootstrap standard errors. For the residual component (e), both skewness and kurtosis statistics are statistically insignificant ($p > 0.10$), indicating no evidence of asymmetry or excess kurtosis. Similarly, the skewness statistic for the random-effects component (u) is statistically insignificant ($p > 0.10$). Although the kurtosis statistic for u is marginally significant at the 10% level ($p < 0.10$), the corresponding confidence interval includes zero, suggesting that deviations from normality are limited and not severe. Panel C presents the joint normality test results. The null hypothesis of joint normality cannot be rejected for either the residuals (e) or the random effects (u), as indicated by the insignificant chi-square statistics ($p > 0.10$). These results provide further support for the assumption of approximate normality in both error components. Overall, the findings from Panels B and C indicate that the distributional properties of the error terms do not deviate substantially from normality. This supports the reliability of the subsequent estimation results and suggests that non-normality is unlikely to bias inference in the empirical analysis.

Table 2. Descriptive Statistics and Normality Tests

Panel A. Descriptive Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
lngdp	528	26.499	0.948	24.455	28.815
inf	528	2.948	3.879	-21.753	6.727
lndk	528	3.764	3.461	-17.813	9.663
Panel B. Tests for Skewness and Kurtosis					
Test	Coefficient	Bootstrap SE	z	P> z	95% CI
Skewness_e	-0.0086	0.0200	-0.43	0.668	[-0.048, 0.031]
Kurtosis_e	-0.0079	0.0278	-0.28	0.776	[-0.063, 0.047]
Skewness_u	0.1434	0.2337	0.61	0.539	[-0.315, 0.601]
Kurtosis_u	-0.6010	0.3249	-1.85	0.064	[-1.238, 0.036]
Panel C. Joint Normality Tests					
Test	chi2(2)		Prob > chi2		
Joint test for Normality on e	0.26		0.876		
Joint test for Normality on u	3.80		0.150		

Note: N=528 observations from 12 countries (1980-2023). Bootstrap replications=50 based on 12 clusters. e=residuals, u=random effects.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

2.2. Theoretical Structure of the Developed IPDF

The interactive effects panel model provides a flexible framework to analyse how the effect of one independent variable varies depending on the level of another. This feature is particularly relevant in macroeconomic settings where core variables—such as inflation, interest rates, exchange rates, and economic growth—exhibit strong interdependencies. Limitations of Fixed and Random Effects Models: Traditional fixed effects estimators account for within-group (e.g., within-country) variation but fail to capture how the marginal effect of a variable changes conditionally with another variable. For example, if the impact of inflation on growth depends on the exchange rate or interest rate, a standard fixed effects model cannot represent this dependence structure. Random effects models allow for both within- and between-group variation but similarly fall short in modelling joint or conditional effects among variables.

Necessity of an Interactive Framework: Economic relationships are often nonlinear and conditional. The effect of one macroeconomic variable may strengthen, weaken, or even change sign depending on the level of another variable. Such interaction patterns cannot be captured through additive linear

models. Hence, the developed Interactive Panel Data Model (IPDF) incorporates interaction terms that allow the marginal effect of each variable to vary across economic states, regimes, or policy combinations. Figure 1 summarises the theoretical and methodological construction of the developed Interactive Panel Data Model (IPDF). The flowchart illustrates the sequential steps followed in the study, beginning with the development of the model and the theoretical introduction through examples. It then presents the mathematical framework, Monte Carlo simulations used for theoretical validation, and the empirical application based on emerging economy data. The estimation strategy, including the IE estimator, diagnostic tests, and GEE procedure, is also highlighted. Finally, the flowchart expands the “Results” stage into its core analytical components—interaction effects, marginal effects, threshold analysis, and the derivation of optimal inflation levels—demonstrating how the IPDF translates complex interaction structures into policy-relevant outputs.

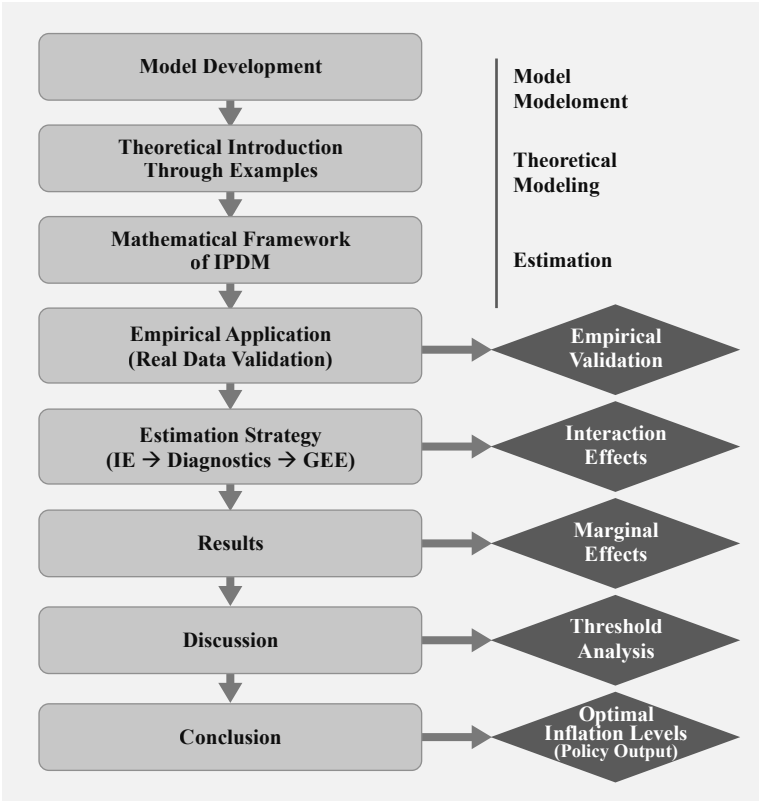


Figure 1. Methodological Framework of the Developed IPDF.
Source: Authors’ illustration

Advantages of the Interactive Model: This model is capable of capturing dynamic relationships among variables and context-specific effects. In some cases, it offers greater explanatory power than traditional fixed or random effects models. It can also serve as a valuable tool for economic policymakers by providing insights for more effective decision-making that accounts for interactions among variables. The mathematical structure of the interactive effects model is presented below. To operationalise the theoretical structure of the IPDF, several model formulations are presented below, illustrating how interaction, marginal and threshold mechanisms function within the workflow. The following formulations are provided for illustrative purposes to clarify the conceptual mechanisms underlying interaction, marginal, and threshold effects within the IPDF framework, while the empirical implementation of these mechanisms is conducted using the estimation strategies described in the subsequent sections.

Example 1: Interaction Between Inflation and Exchange Rate

When modeling economic growth Y_{it} as a function of inflation X_{1it} and exchange rate X_{2it} , both the direct effects of these two variables and their interaction effect should be considered.

Equation (1):

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 (X_{1it} \times X_{2it}) + u_{it} \dots\dots\dots (1)$$

Where: The term $X_{1it} \times X_{2it}$ represents the interactive effect of inflation and exchange rate on economic growth. The sign β_3 indicates whether the marginal effect of inflation on economic growth is amplified or weakened by movements in the exchange rate.

Example 2: Threshold Effects Between Fiscal and Monetary Policies

The impact of fiscal policy (government expenditure G_{it}) and interest rates (r_{it}) on growth may vary depending on whether a certain threshold is exceeded.

Equation (2):

$$Y_{it} = \beta_0 + \beta_1 G_{it} + \beta_2 r_{it} + \beta_3 (G_{it} \times r_{it}) + \beta_4 D(r_{it} > c) + u_{it} \quad (2)$$

Where: $D(r_{it} > c)$ is a dummy variable that equals 1 if the interest rate exceeds a threshold value c , and 0 otherwise.

For instance, if a given threshold value is exceeded, the impact of fiscal and monetary policy on growth may differ depending on the prevailing interest-rate regime. This modeling approach is critical for understanding how fiscal and monetary policies operate in conjunction.

Basic Model: The basic form of the interactive panel data model is given as:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 (X_{1it} \times X_{2it}) + \alpha_i + \lambda_t + u_{it} \dots\dots\dots (3)$$

Where:

Y_{it} : Dependent variable of country i at time t

X_{1it} : First independent variable

X_{2it} : Second independent variable

$(X_{1it} \times X_{2it})$: Interaction term

α_i : Individual-specific fixed effects

λ_t : Time-specific effects

u_{it} : Error term

In the equation above, the interaction term $(X_{1it} \times X_{2it})$ is used to capture the combined effect of the two independent variables on the dependent variable. The structure of the panel data model is suitable for controlling heterogeneity across time and countries. By incorporating fixed or random effects, cross-country differences can be accounted for in the model. For instance, since inflation and exchange rates have both direct and indirect effects on growth, the interaction term helps to understand how these two variables operate together. Given the theoretical framework described above, the following section introduces the Interactive Effects (IE) estimator and its iterative algorithm.

2.3. Interactive Effects (IE) Estimator and Iterative Algorithm

In this study, the empirical analysis is built upon an interactive modeling framework designed to capture conditional, nonlinear, and regime-dependent relationships among macroeconomic variables. While baseline interaction effects are initially examined within a population-averaged setting, particular emphasis is placed on addressing the role of unobserved time-varying common factors that may simultaneously affect all cross-sectional units with heterogeneous intensities.

To this end, the Interactive Effects (IE) estimator is employed as a core methodological component of the proposed framework. Unlike conventional fixed-effects or random-effects models, which treat unobserved heterogeneity as either time-invariant or randomly distributed, the IE approach explicitly models unobserved heterogeneity through time-varying common factors and unit-specific factor loadings. This structure allows the model to capture cross-sectional dependence arising from global or regional shocks while preserving both within- and between-unit variation in the estimation of interaction effects.

2.3.1. Model Specification

The Interactive Effects model is specified as follows:

$$Y_{it} = \alpha + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 (X_{1,it} \times X_{2,it}) + \lambda_i' F_t + \varepsilon_{it} \dots\dots\dots (4)$$

where Y_{it} denotes the dependent variable, $X_{1,it}$ and $X_{2,it}$ represent the explanatory variables of interest, and β_3 captures their interaction effect. The term λ_i is an $r \times 1$ vector of unit-specific factor loadings, while F_t denotes an $r \times 1$ vector of unobserved time-varying common factors affecting all cross-sectional units. The interactive component $\lambda_i' F_t$ captures latent common shocks that cannot be accommodated by standard additive panel data models.

2.3.2. Iterative Estimation Procedure of the Interactive Effects Estimator

The Interactive Effects (IE) estimator is implemented through an explicit iterative estimation procedure that jointly identifies the regression coefficients, unobserved common factors, and unit-specific factor loadings. This algorithmic structure allows the model to account for cross-sectional dependence and unobserved time-varying heterogeneity while preserving both within- and between-unit variation.

In the first step, the baseline model, including the interaction term but excluding the factor structure, is estimated using ordinary least squares (OLS). This initial estimation yields a preliminary coefficient vector, which serves as a starting point for the extraction of common factors. Based on these initial estimates, the residuals are computed as:

$$\hat{u}_{it} = Y_{it} - \hat{\alpha} - \hat{\beta}' X_{it} \dots\dots\dots (5)$$

In the second step, the residuals obtained from the initial OLS estimation are arranged into an $N \times T$ residual matrix. Principal component analysis (PCA) is

then applied to this matrix in order to extract the dominant unobserved time-varying common factors F_t and the corresponding unit-specific factor loadings λ_i . These factors capture latent common shocks that simultaneously affect all cross-sectional units with heterogeneous intensities. In the third step, the model is re-estimated by explicitly controlling for the interactive component $\lambda_i'F_t$. By incorporating the estimated factor structure into the regression, factor-adjusted coefficient estimates are obtained. This step removes the influence of unobserved common shocks from the dependent variable and isolates the structural relationship among the observed regressors.

In the final step, the estimation procedure is iterated by updating the coefficient estimates, common factors, and factor loadings until convergence is achieved. Convergence is defined as changes in parameter estimates falling below a tolerance level of 10^{-6} . This iterative process ensures the joint consistency of the estimated regression coefficients and the latent factor structure.

The number of unobserved common factors is determined using the information criteria proposed by [Bai and Ng \(2002\)](#). According to these criteria, two common factors ($r=2$) are identified in the empirical application, confirming the relevance of interactive heterogeneity and common shocks in the panel.

2.3.3. Estimation Implementation

The Interactive Effects model is estimated using the `xtie` command in Stata, which implements the factor-augmented panel estimator. The baseline specification is estimated as:

xtie lngdp inf lndk inter, fe factors (2)

where `factors (2)` specify the number of unobserved common factors identified by the [Bai and Ng \(2002\)](#) information criteria. This implementation allows for simultaneous estimation of regression coefficients, common factors, and unit-specific factor loadings within a fixed-effects interactive framework.

2.4. Interactive Effects (IE) Estimator as a Structural Validation Framework

A key distinction between the Interactive Effects (IE) estimator and conventional fixed-effects (FE) or reduced-form approaches lies in the identification and interpretation of interaction effects. In fixed-effects models, the interaction coefficient is identified exclusively from within-unit variation, as the within transformation eliminates all between-unit information. Consequently, interaction effects estimated under FE specifications reflect demeaned within-unit dynamics

and may fail to capture structurally relevant cross-sectional heterogeneity and the influence of common shocks.

By contrast, the IE estimator does not rely on within transformation. Instead, unobserved heterogeneity is explicitly modeled through time-varying common factors and unit-specific factor loadings. Once these interactive components are identified and removed, the interaction coefficient β_3 is estimated from factor-adjusted data that preserve both within- and between-unit variation. This feature is particularly important in macroeconomic panels, where interaction effects often operate through cross-country heterogeneity and shared global or regional shocks rather than purely through within-country time-series variation. Within this framework, the IE estimator yields structurally identified and factor-adjusted interaction effects that are purged of latent common dynamics. While reduced-form estimators, such as fixed-effects or population-averaged models, may detect statistically significant interaction terms, they do not distinguish whether such nonlinearities arise from genuine interaction mechanisms or from unobserved common factors. The IE specification resolves this ambiguity by explicitly modeling time-varying common factors and heterogeneous factor loadings across units.

Accordingly, the interaction coefficient β_3 obtained under the IE framework should be interpreted as a factor-adjusted interaction effect, reflecting the true conditional relationship between inflation and the exchange rate after controlling for unobserved common shocks. Although alternative estimators are retained for comparative purposes, the Interactive Effects model provides the most coherent and theoretically consistent structural validation framework for interaction dynamics in the presence of cross-sectional dependence and latent common shocks. From a methodological perspective, the IE estimator is employed in this study primarily as a structural validation tool for interaction effects. The estimation of marginal and threshold effects, by contrast, is conducted within the Generalized Estimating Equations (GEE) framework. This hierarchical modeling strategy ensures both empirical robustness and theoretical coherence, aligning the empirical analysis with the interactive and nonlinear nature of macroeconomic relationships.

2.4.1. Identification of the Interaction Coefficient under IE

The interaction coefficient β_3 is identified from both within- and between-unit variation after controlling for unobserved common shocks through the factor structure. Unlike fixed effects (FE) models, in which the interaction coefficient is identified solely from demeaned within-unit variation, the Interactive Effects

(IE) estimator preserves between-unit information while simultaneously purging latent factor influence.

By explicitly modeling time-varying common factors and unit-specific factor loadings, the IE framework isolates the genuine interaction mechanism from unobserved common dynamics. As a result, the estimated interaction coefficient reflects a structurally identified conditional effect rather than a residual or indirectly inferred relationship. This distinction is particularly important in macroeconomic panel settings, where interaction effects often operate through cross-sectional heterogeneity and shared shocks rather than purely through time-series variation within individual units.

2.4.2. Comparison with FE and RE Estimators

To highlight the methodological advantages of the IE estimator, Table 3 summarises key differences between fixed effects (FE), random effects (RE), and interactive effects (IE) models. Under the IE framework, the interaction coefficient β_3 is identified from both within- and between-unit variation after controlling for common shocks through the factor structure. Unlike FE and RE models, which do not explicitly account for cross-sectional dependence, the IE estimator directly models common shocks affecting all units with heterogeneous intensities. Consequently, the interaction coefficient obtained under the IE framework is factor-adjusted and structurally interpretable, whereas interaction effects estimated under FE or RE specifications may conflate genuine interaction mechanisms with unobserved common dynamics.

Table 3. Comparison with FE/RE

Aspect	FE	RE	IE
Heterogeneity	Time-invariant	Random	Time-varying
Identification	Within only	Within + Between	Within + Between
Cross-dependence	Not modeled	Not modeled	Explicitly modeled
Interaction β_3	Demeaned	Pooled	Factor-adjusted

Source: Authors’ compilation based on the econometrics literature on fixed effects, random effects, and factor models.

2.4.3. Endogeneity Considerations and Robustness

The Interactive Effects (IE) estimator employed in this study offers important advantages in mitigating certain sources of endogeneity that commonly arise in panel data settings. Nevertheless, it is essential to clearly delineate which forms

of endogeneity are addressed by the IE framework and which remain beyond its scope. In this respect, three potential sources of endogeneity merit consideration.

First, reverse causality may be present, as economic growth can simultaneously influence inflation and domestic credit dynamics. Such feedback mechanisms imply that the direction of causality may not be unidirectional, potentially biasing coefficient estimates in standard regression frameworks. Second, omitted variable bias constitutes a major concern. Time-varying but unobserved country-specific or global shocks, such as changes in global financial conditions, geopolitical risks, or common policy regimes, may be correlated with the explanatory variables, leading to biased estimates if not properly controlled for. Third, measurement error may arise, particularly in inflation and credit series, where reporting inaccuracies can be more pronounced during periods of macroeconomic instability. Such errors may attenuate estimated coefficients and distort inference.

The IE estimator mitigates some of these endogeneity concerns primarily through its explicit factor structure. The term $\lambda_i'F_t$ captures unobserved common shocks that affect all countries while allowing for heterogeneous responses across units. By controlling for these latent time-varying factors, the IE framework substantially reduces omitted variable bias stemming from unobserved common confounders. This feature renders the IE approach structurally more flexible than conventional fixed effects (FE) and random effects (RE) models, which do not explicitly model cross-sectional dependence. However, it is important to emphasise that the IE estimator does not directly resolve endogeneity arising from reverse causality or measurement error. In cases where such issues are severe, instrumental variable (IV) approaches or dynamic panel estimators would be required. In the present study, the IE model is primarily employed as a structural validation tool to account for unobserved common factors, and causal interpretations are therefore made with appropriate caution. To further assess the robustness of the empirical findings, several additional checks are conducted. These include the use of lagged explanatory variables ($\ln f_{t-1}$ and $\ln dk_{t-1}$), sub-period analyses distinguishing the pre- and post-2008 global financial crisis periods, and alternative specifications for the number of common factors ($r = 1$ and $r = 3$, with $r = 2$ as the baseline). The results remain broadly consistent across these alternative specifications, reinforcing the stability and reliability of the main conclusions.

2.5. Marginal Effects and Threshold Values

In econometric analysis, a marginal effect refers to the change in the dependent variable associated with a one-unit change in an explanatory variable, holding

other factors constant. In models that incorporate interaction terms, marginal effects are inherently conditional and vary with the level of the interacting variable. Consequently, the impact of an explanatory variable on the dependent variable cannot be summarised by a single constant coefficient (Wooldridge, 2010). This conditionality constitutes a central theoretical feature of interaction-based panel models. When interaction terms are included, the effect of one explanatory variable systematically depends on the level of another, giving rise to state-dependent and potentially nonlinear relationships. Such structures are particularly relevant in macroeconomic settings, where policy regimes, adjustment mechanisms, and transmission channels often differ across economic conditions (Brambor, Clark, and Golder, 2006).

Consider a generic interaction model with two explanatory variables. The marginal effects are obtained from the following partial derivatives:

$$\partial Y_{it} / \partial X_{1,it} = \beta_1 + \beta_3 X_{2,it} \dots\dots\dots (6)$$

$$\partial Y_{it} / \partial X_{2,it} = \beta_2 + \beta_3 X_{1,it} \dots\dots\dots (7)$$

These expressions indicate that the marginal effect of each variable depends explicitly on the level of the other interacting variable. As a result, marginal effects are not fixed but vary across observations, reflecting heterogeneous economic environments. This feature implies that identical policy changes may lead to different outcomes depending on prevailing macroeconomic conditions. The interaction structure further implies the existence of threshold values at which marginal effects may change sign. These thresholds are derived analytically by setting the corresponding marginal effect equal to zero. Specifically, the threshold level of X_2 at which the marginal effect of X_1 becomes zero is given by:

$$X_2^* = -\beta_1 / \beta_3 \dots\dots\dots (8)$$

Similarly, the threshold level of X_1 at which the marginal effect of X_2 changes sign is defined as:

$$X_1^* = -\beta_2 / \beta_3 \dots\dots\dots (9)$$

These threshold values arise endogenously from the interaction structure of the model and do not rely on externally imposed regime classifications. They represent critical regimes in which the direction or magnitude of the relationship between explanatory variables and the dependent variable may differ. Importantly, these thresholds reflect analytical properties of interaction models rather than discrete

policy rules. To clarify the interpretation of marginal and threshold effects, consider two illustrative policy contexts.

In the context of monetary policy, if X_1 denotes the interest rate, X_2 denotes the exchange rate, and Y denotes inflation, the marginal effect of the exchange rate on inflation depends on the level of the exchange rate itself. In a high exchange-rate environment, the effectiveness of inflation-targeting policies may change, reflecting altered transmission mechanisms and cost pressures. Similarly, in the context of fiscal policy, if X_1 represents government expenditures, X_2 represents tax rates, and Y represents economic growth, the effect of government spending on growth depends on the prevailing tax burden. Under high-tax conditions, the growth-enhancing impact of public expenditures may weaken, illustrating how marginal interactions between fiscal instruments generate context-dependent outcomes. These examples demonstrate that marginal interactions between explanatory variables can produce qualitatively different effects on the dependent variable across regimes, underscoring the importance of conditional analysis.

Application to the Inflation–Credit–GDP Framework: Within the empirical framework of this study, the interaction structure is applied to the relationship between inflation, domestic credit, and economic growth. Let

$$X_1 = \ln(\text{Inflation}), X_2 = \ln(\text{DomesticCredit}), \text{ and } Y = \ln(\text{GDP}) \dots\dots\dots(10)$$

The marginal effects are then given by:

$$\partial \ln(\text{GDP}_{it}) / \partial \ln(\text{Inflation}_{it}) = \beta_1 + \beta_3 \ln(\text{DomesticCredit}_{it}) \dots\dots\dots(11)$$

$$\partial \ln(\text{GDP}_{it}) / \partial \ln(\text{DomesticCredit}_{it}) = \beta_2 + \beta_3 \ln(\text{Inflation}_{it}) \dots\dots\dots(12)$$

These expressions imply that the impact of inflation on economic growth depends on the level of domestic credit, and vice versa. Correspondingly, the endogenous threshold levels are defined as:

$$\ln(\text{DomesticCredit})^* = -\beta_1 / \beta_3 \text{ and } \ln(\text{Inflation})^* = -\beta_2 / \beta_3 \dots\dots\dots(13)$$

These thresholds identify critical levels of credit availability and inflation at which their marginal effects on economic growth change direction. Economically, this structure highlights that inflationary pressures and credit expansion cannot be evaluated independently. Instead, their joint effects on growth depend on the broader macro-financial environment. By integrating marginal and threshold

interpretations within an interaction-based panel framework, this approach provides a coherent theoretical basis for analysing conditional relationships among macroeconomic variables. The empirical relevance of these mechanisms is examined in the results section through the estimation of marginal and threshold effects using the econometric strategies described above. Under the regularity conditions of Bai (2009), the threshold implied by the interaction structure, $X_2^* = -\beta_1 / \beta_3$, is consistently estimated via the Delta method. The asymptotic validity of inference for the interaction-based threshold and marginal effects under the interactive effects framework follows from Bai (2009); for completeness, a formal note is provided in Appendix A.

2.6. Interaction Effect

Interaction effects measure the joint impact of two independent variables on the dependent variable. In panel data models that include interaction terms, these effects are formally captured through second-order cross-partial derivatives:

$$\partial^2 Y_{it} / (\partial X_{1it} \partial X_{2it}) = \beta_3 \dots\dots\dots (14)$$

The coefficient β_3 represents the change in the marginal effect of X_1 on Y when X_2 increases by one unit. Accordingly, interaction effects exhibit several important properties. First, the interaction coefficient measures the simultaneous marginal impact of changes in both explanatory variables. Second, interaction terms allow the model to capture nonlinear and state-dependent relationships that cannot be represented within purely additive specifications. Third, the sign and magnitude of β_3 determine the direction and strength of the interaction effect.

Application to Inflation–Credit–GDP. In the empirical specification of this study, the interaction term is defined as follows: X_1 = Inflation, X_2 = ln (Domestic Credit), and Y = ln (GDP). The interaction coefficient β_3 captures how the joint movement of inflation and domestic credit influences economic growth. A positive coefficient indicates that credit expansion amplifies the growth effect of inflation, whereas a negative coefficient implies that rising credit conditions mitigate or reverse inflationary growth effects. In this sense, the interaction structure explicitly tests whether domestic credit moderates the inflation–growth relationship. To accommodate higher-order nonlinearities, the interaction framework can be extended by including quadratic terms:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 (X_{1it} \times X_{2it}) + \beta_4 X_{1it}^2 + \beta_5 X_{2it}^2 + \alpha_i + \lambda_t + u_{it} \dots\dots\dots (15)$$

Methodological Contribution: Building on this structure, the Interactive Panel Data Framework (IPDF) integrates interaction effects with marginal-effect and threshold analysis within a unified panel data framework. Rather than redefining existing panel estimators, the IPDF provides a structured empirical setting that enables a more effective examination of conditional interactions among explanatory variables and allows their effects to vary across different economic states. Table 2 presents a comparative overview of the analytical scope of the IPDF relative to widely used panel data approaches. In this context, the IPDF is designed to complement established methods such as PTR, PSTR, and IFE by organising interaction structures, marginal responses, and threshold behavior within a single empirical framework, thereby enabling a more effective and transparent interpretation of interaction-driven relationships.

Table 4. Comparison of the IPDF Workflow with Alternative Panel Data Approaches

Feature / Model	PTR (Panel Threshold Regression)	PSTR (Panel Smooth Transition Regression)	IFE (Interactive Fixed Effects)	IPDF (Workflow)
Threshold Effects	Yes (fixed threshold)	Yes (smooth transition)	No	Yes (flexible threshold analysis)
Non-linear Relationships	Yes	Yes	Yes (via common factors, indirect)	Yes (explicit via interaction term)
Interaction Terms (X_1 times X_2)	No	No	No	Yes
Marginal-Effect Analysis	No	No	No	Yes
Triple-Interaction Capability	No	No	No	Yes
Time-Varying Parameters	No	Yes	Yes	Yes
Cross-section Dependence	No	No	Yes	Yes
Suitability for Policy Simulation	Limited	Moderate	Indirect	Yes
Implementation Complexity	Moderate	High	High	Moderate
Prevalence in Literature	High	Increasing	Increasing	New

Note: IPDF integrates components from existing methods (interaction terms, threshold mechanisms, marginal-effect reporting) rather than introducing a new estimator. The contribution lies in the systematic combination and implementation strategy.

Source: Authors' compilation based on the econometrics literature on panel data models, including PTR, PSTR, and IFE approaches.

As shown in Table 4, while PTR and PSTR models are effective in capturing threshold effects, they are typically limited in jointly analysing interaction mechanisms and the associated marginal effects across regimes. Similarly, although the IFE approach accounts for unobserved common factors, it does not explicitly focus on nonlinear interaction structures. By contrast, the IPDF provides a more effective analytical framework for evaluating interaction-driven and regime-dependent relationships by jointly incorporating interaction terms together with their marginal and threshold effects. Its ability to accommodate triple interaction terms and time-varying parameters further enhances its empirical usefulness in the assessment of multivariable economic scenarios. Accordingly, the IPDF offers a coherent, interpretable, and policy-relevant framework for applied panel data analysis.

2.7. Econometric Strategy

The empirical implementation of the developed Interactive Panel Data Framework (IPDF) requires an estimation method that is robust to heteroskedasticity, serial correlation, and cross-sectional dependence. For this reason, the model is estimated using the Generalized Estimating Equations (GEE) approach introduced by [Liang and Zeger \(1986\)](#), which provides consistent estimates under flexible correlation structures.

$$\hat{\beta}_{GEE} = \left(\sum_{i=1}^N D_i^T V_i^{-1} D_i \right)^{-1} \left(\sum_{i=1}^N D_i^T V_i^{-1} (Y_i - \mu_i) \right) \dots\dots\dots (16)$$

where: $V_i = A_i^{1/2} R(\alpha) A_i^{1/2}$ is the working covariance matrix, $R(\alpha)$ is the correlation structure. The present study employs an unstructured correlation specification, following [Hardin & Hilbe \(2012\)](#). Heteroskedasticity is tested using White's general test:

$$nR^2 \sim \chi^2(k) \dots\dots\dots (17)$$

The null of homoskedasticity is rejected; therefore, heteroskedasticity-robust standard errors are used ([White, 1980](#)). Serial correlation in panel data is examined using the [Wooldridge \(2010\)](#) test:

$$F(1, N-1) \dots\dots\dots (18)$$

The null hypothesis of no first-order serial correlation cannot be rejected (Wooldridge, 2010). Cross-sectional dependence is tested using Pesaran's CD statistic:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \dots\dots\dots (19)$$

The test strongly rejects the null of cross-sectional independence, validating the use of GEE instead of traditional FE/RE estimators (Pesaran, 2004; 2015).

The empirical implementation of the original Interactive Panel Data Framework (IPDF) developed in this study requires an estimation framework capable of accommodating interaction effects, marginal effects, and threshold mechanisms simultaneously. The baseline IPDF was initially estimated using standard panel-data techniques to evaluate the model's behaviour under conventional assumptions. However, preliminary diagnostics revealed that key classical assumptions, including homoskedasticity, absence of serial correlation, and cross-sectional independence, were violated in the sample. Specifically, the panel exhibits clear heteroskedasticity, cross-sectional dependence among countries, and a dynamic error component structure that necessitates a more flexible correlation specification. Therefore, the initial estimation of the baseline IPDF formulation indicated that its standard error structure did not satisfy the classical panel assumptions, making it necessary to employ a more flexible estimation framework.

The choice of the Generalized Estimating Equations (GEE) estimator is motivated by several econometric considerations. First, diagnostic tests indicate the presence of heteroskedasticity (White, 1980) and potential serial correlation (Wooldridge, 2010), conditions under which conventional FE/RE estimators may yield inefficient or biased standard errors. Second, Pesaran's (2004) CD statistic confirms cross-sectional dependence, rendering classical fixed-effects estimators inappropriate because they assume cross-sectional independence. In contrast, GEE allows for flexible working-correlation structures and produces consistent population-averaged estimates even under model misspecification (Liang & Zeger, 1986). Third, given the data structure with a small number of cross-sectional units (N=12) and a relatively longtime dimension (T=44) system-GMM estimators would suffer from weak-instrument problems (Roodman, 2009), whereas GEE performs well under small-N large-T panels. Following Hardin and Hilbe (2012), an unstructured correlation matrix is employed to accommodate potential contemporaneous correlation across countries.

3. RESULTS

The empirical results presented in this section evaluate the performance of the developed Interactive Panel Data Framework (IPDF) using macroeconomic data for five emerging economies over the period 1980–2023. The empirical application is conducted on a strongly balanced macroeconomic panel consisting of 12 countries—Argentina, Brazil, Chile, Colombia, Czechia, Hungary, India, Indonesia, Malaysia, Mexico, South Africa, and Türkiye—observed over 44 time periods ($T = 44$), yielding a total of 528 observations. This empirical configuration is employed as an illustrative application of the proposed methodology rather than a structural limitation. The Interactive Effects framework and the broader IPDF approach are theoretically designed for panels with large cross-sectional and time dimensions, and their validity does not depend on a specific panel size.

Prior to model estimation, a comprehensive set of preliminary analyses is conducted to characterise the statistical properties of the data and to determine an appropriate econometric strategy. Descriptive statistics are examined for all variables in logarithmic form. Multicollinearity is assessed using the Variance Inflation Factor (VIF), and the results indicate no evidence of serious multicollinearity among the regressors. Distributional properties are evaluated using skewness and kurtosis statistics together with joint normality tests. The results indicate that deviations from normality are limited and not severe, supporting the reliability of subsequent inference.

Panel unit root tests are employed to assess the stationarity properties of the variables. The Cross-sectionally Augmented IPS (CIPS) test and the Im–Pesaran–Shin (IPS) test reveal a mixed order of integration, with some variables stationary in levels and others becoming stationary after first differencing. In addition, the Westerlund variance ratio test does not provide evidence of a long-run cointegration relationship among the variables. This mixed integration structure limits the applicability of methods that rely on strict stationarity or cointegration assumptions.

Cross-sectional dependence is formally examined using Pesaran’s CD test. The results strongly reject the null hypothesis of cross-sectional independence, indicating the presence of common shocks or interdependencies across countries. This finding highlights the empirical relevance of unobserved common factors and motivates the use of factor-augmented and interaction-based panel estimators. The number of unobserved common factors is determined using the information criteria proposed by Bai and Ng (2002). All three criteria (IC1, IC2, and IC3) consistently identify the presence of a dominant common factor. This finding confirms the empirical relevance of interactive heterogeneity and time-varying

common shocks in the data. To assess robustness, alternative specifications allowing for additional factors are also estimated, and the results remain qualitatively unchanged, indicating that the main conclusions are not sensitive to the exact number of factors retained. Following these preliminary analyses, the Interactive Effects (IE) model developed within the IPDF framework is estimated as the baseline specification. This estimation jointly accounts for the interaction between inflation and the exchange rate as well as unobserved common shocks that affect countries with heterogeneous intensities. The IE model serves as a structural benchmark and allows direct comparison with conventional fixed-effects and random-effects estimators.

Subsequently, diagnostic tests are applied to evaluate the adequacy of the IE specification under classical panel-data assumptions. Serial correlation is examined using the Wooldridge test, which provides strong evidence of first-order autocorrelation in the error terms. Groupwise heteroskedasticity is assessed using the Modified Wald test, indicating the presence of heteroskedasticity across cross-sectional units. Together with the previously documented cross-sectional dependence, these results suggest that standard errors obtained from conventional estimators may be inefficient or unreliable. Given the simultaneous presence of heteroskedasticity, serial correlation, and cross-sectional dependence, the IPDF is re-estimated using the Generalized Estimating Equations (GEE) approach. The GEE framework allows for flexible working correlation structures and delivers robust population-averaged estimates under violations of classical assumptions. Accordingly, the GEE estimates constitute the main empirical results of the study. Building on the GEE estimation, the analysis proceeds to the examination of interaction effects, marginal effects, and threshold dynamics embedded in the IPDF structure. Marginal-effect functions are derived to evaluate how the impact of inflation on economic growth varies with the level of the exchange rate, and vice versa. Threshold conditions are computed directly from the estimated interaction coefficients, allowing the identification of critical regime values at which marginal effects change sign.

This integrated approach enables the derivation of country-specific optimal inflation levels based on the interaction between inflation and exchange rate dynamics. While existing studies typically examine marginal or threshold effects in isolation, the joint implementation of both mechanisms within a unified interactive panel framework represents a central empirical contribution of this study. The resulting threshold values and optimal inflation estimates provide analytically grounded and policy-relevant benchmarks for macroeconomic decision-making in emerging economies.

3.1. Testing the Interactive Effects Model: Empirical Analysis

To test the interactive effects model developed in this study, the relationship between inflation, exchange rates, and economic growth in emerging economies is empirically examined within the Interactive Panel Data Framework (IPDF). Specifically, the interactive panel data model is used to analyse how interactions among these variables shape economic growth dynamics. Prior to estimation, unit root tests (Im–Pesaran–Shin and Levin–Lin–Chu) are conducted to assess the time-series properties of the variables. Variables exhibiting non-stationary behavior are treated accordingly through appropriate transformations to ensure stationarity. The empirical models are estimated in levels with fixed effects to control for unobserved heterogeneity across countries, a choice justified by the panel structure and the moderate time dimension ($T = 44$).

The empirical analysis is conducted using annual data obtained from the World Bank's *World Development Indicators (WDI)*, the IMF's *International Financial Statistics (IFS)*, the *Federal Reserve Economic Data (FRED)* database, and *OECD Statistics*. The sample consists of the same twelve emerging economies analysed throughout the study—Argentina, Brazil, Chile, Colombia, Czechia, Hungary, India, Indonesia, Malaysia, Mexico, South Africa, and Türkiye—over the period 1980–2023.

The variables included in the panel data model are defined as follows:

- $\ln gdp$: Logarithm of real GDP
- $\ln f$: inflation
- $\ln dk$: Logarithm of the exchange rate
- inter : Interaction term between inflation and the exchange rate ($\ln f \times \ln dk$)

The core hypothesis of the study concerns the existence of interaction effects:

$H_0: \beta_3 = 0$ (No interaction effect)

$H_1: \beta_3 \neq 0$ (Existence of an interaction effect)

This hypothesis tests whether the interaction between inflation and the exchange rate exerts a statistically significant effect on economic growth. A statistically significant β_3 indicates the presence of meaningful interaction effects that cannot be captured by additive linear panel data models.

In addition, the significance of marginal effects is examined through the following hypothesis:

$H_0: \beta_1 + \beta_3 X_{2_it} = 0$

$H_1: \beta_1 + \beta_3 X_{2_it} \neq 0$

This hypothesis evaluates whether the marginal effect of inflation on economic growth depends on the level of the exchange rate. Rejection of the null hypothesis implies that marginal effects are conditional and state-dependent.

The interactive panel data model analysing the effects of inflation, the exchange rate, and their interaction on economic growth is specified as:

$$\ln gdp_{it} = \beta_0 + \beta_1 inf_{it} + \beta_2 \ln dk_{it} + \beta_3 (inf_{it} \times \ln dk_{it}) + \alpha_i + \varepsilon_{it} \dots\dots\dots (20)$$

where $\ln gdp$ denotes the logarithm of real GDP for country i at time t , inf represents inflation, $\ln dk$ denotes the exchange rate, and α_i captures country-specific effects. The interaction coefficient β_3 measures the joint effect of inflation and exchange rate movements on economic growth and constitutes the central parameter of interest in the IPDF framework. In the empirical implementation, the initial estimator (IE) of the IPDF is operationalised using a user-written Stata routine, `xtie`, developed specifically for this study. The command estimates the Interactive Effects model in panel form, automatically generates interaction terms, and implements an iterative estimation procedure consistent with the theoretical structure of the IPDF. The `xtie` routine supports robust and clustered standard errors, user-defined covariance structures, and includes a post-estimation module (`xtie_margins`) for computing marginal effects implied by the interaction specification, such as;

$$\partial Y / \partial X_1 = \beta_1 + \beta_3 X_2 \dots\dots\dots (21)$$

A full description of the estimation algorithm and the corresponding Stata code are provided in Appendix A. The Interactive Effects (IE) model serves as the baseline structural specification and provides an initial assessment of interaction effects within a factor-augmented framework that explicitly accounts for unobserved common factors and heterogeneous country responses. This specification allows the identification of interaction effects after purging latent common shocks that may bias conventional fixed-effects estimates. However, as documented in subsequent sections, diagnostic tests reveal the presence of heteroskedasticity, serial correlation, and cross-sectional dependence in the panel. These violations of classical panel-data assumptions motivate the use of Generalized Estimating Equations (GEE) as a complementary estimation strategy. Within the IPDF workflow, GEE is employed to accommodate correlated error structures and to deliver robust population-averaged inference for interaction, marginal, and threshold effects. Importantly, GEE does not constitute a separate estimator of the interactive structure. Rather, it complements the IE framework

by providing robust inference once the structural relevance of interaction effects has been validated under the factor-based IE specification. In this sense, the IE model functions as a structural validation step, while GEE constitutes the main empirical framework for inference on interaction-driven marginal and threshold dynamics.

The interactive panel data model employed in this study has the potential to mitigate several common sources of endogeneity frequently encountered in panel settings. As discussed in Section 2.4.3, omitted variable bias arising from unobserved common shocks is largely addressed through the explicit factor structure of the IE model. Nevertheless, other forms of endogeneity, such as reverse causality and measurement error, cannot be entirely ruled out. To enhance the credibility of the empirical findings, the analysis incorporates fixed effects, robust standard errors, regime-dependent marginal effects, and extensive robustness checks. Rather than relying on instrumental variables, the identification strategy emphasises model structure, interaction effects, and consistency across alternative specifications.

3.2. Model Comparison and Baseline Validation: IE versus FE and RE

Table 5 reports a comparison of the Interactive Effects (IE), Fixed Effects (FE), and Random Effects (RE) models for GDP (lngdp). Across all three specifications, the coefficients on inflation (inf) and the exchange rate (lnrk) are positive and statistically significant ($p < 0.01$), indicating that their effects on economic growth are robust across alternative panel data frameworks. Nevertheless, the IE model provides a more flexible and informative specification relative to the conventional FE and RE approaches. The interaction term included in the IE model is negative and statistically significant ($\beta = -0.0502$; $p < 0.01$), implying that the positive effect of inflation on GDP diminishes as the exchange rate increases. This result highlights the presence of conditional and nonlinear dynamics between inflation, exchange rates, and economic growth, which cannot be explicitly identified within standard FE and RE models.

In terms of model fit, the IE specification exhibits a higher explanatory capacity. The within R^2 reaches 0.8093 in the IE model, compared to 0.7005 and 0.7004 in the FE and RE models, respectively, indicating that the IE framework explains a substantially larger share of within-country variation in GDP. Beyond goodness-of-fit measures, the comparison of error-based performance metrics further reinforces the superiority of the IE model. Specifically, the IE specification yields lower prediction errors, with an RMSE of 0.3887 and an MSE of 0.1511, compared to 0.4196 and 0.1716 under the FE model, corresponding to an improvement of

approximately 7.36% in RMSE. Moreover, the IE model achieves a lower mean absolute percentage error (MAPE = 1.21%) relative to the FE model (MAPE = 1.31%), indicating higher relative accuracy. The mean percentage error (MPE) of the IE model is close to zero (0.01%), suggesting negligible systematic bias, whereas the FE model exhibits a small negative bias. An examination of the variance components further supports the suitability of the IE specification. The IE model is characterised by a lower idiosyncratic error variance ($\sigma_e = 0.1053$) and a very high intra-class correlation coefficient ($\rho = 0.9873$), suggesting that variations in GDP are largely driven by common factors and country-specific structural characteristics. The overall statistical significance of the IE model is strongly confirmed by the F-statistic ($F(5,11) = 1041.80$; $p < 0.01$).

Table 5. Model Comparison: IE vs FE vs RE

Variables	IE (Interactive Effects)	FE (Fixed Effects)	RE (Random Effects)
inf	0.1107*** (0.000) [0.0821, 0.1393]	0.1824*** (0.000) [0.1684, 0.1963]	0.1824*** (0.000) [0.1685, 0.1964]
Indk	0.1379*** (0.000) [0.1050, 0.1708]	0.1296*** (0.000) [0.1056, 0.1536]	0.1282*** (0.000) [0.1043, 0.1521]
Inter	-0.0502*** (0.000) [-0.0694, -0.0310]	-	-
_cons	25.6885***	25.3188***	25.3247***
Within R ²	0.8093	0.7005	0.7004
Between R ²	0.0271	0.0281	0.0283
Overall R ²	0.0050	0.0000	0.0000
RMSE	0.3887	0.4196	-
MSE	0.1511	0.1716	-
MPE	0.01%	-0.12%	-
MAPE	1.21%	1.31%	-
F / Wald chi2	F(5,11)=1041.80	F(2,394)=460.66	chi2(2)=915.21
Prob	0.0000	0.0000	0.0000

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors (clustered by country_id) for IE model. IE model includes interaction term (inter) and factor loadings. IE model has highest Within R² (0.8093 vs 0.7005) and lowest RMSE (0.3887 vs 0.4196, 7.36% improvement). Number of obs = 528 | Number of groups = 12 | Obs per group = 34.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

In summary, while FE and RE models provide consistent baseline estimates, the Interactive Effects approach offers a more comprehensive and empirically robust

framework by jointly accounting for interaction effects, unobserved common factors, and superior predictive performance. Accordingly, the IE model is employed as a complementary specification for structural validation, while the main marginal and threshold-based empirical conclusions are subsequently derived from the GEE framework.

3.3. Interactive Effects Model with Common Factors: IE Estimates and PCA Evidence

Table 6 presents the estimation results of the Interactive Effects (IE) model, which explicitly accounts for unobserved common shocks and structural interdependence across countries through a latent factor structure. This framework extends conventional fixed-effects and random-effects models by allowing heterogeneous responses to common global and regional shocks that are not directly observable. The coefficient on inflation is not statistically significant, indicating that inflation does not exert a uniform direct effect on GDP once common factors are controlled for. In contrast, the exchange rate exhibits a positive and statistically significant effect on GDP, suggesting that exchange-rate dynamics remain an important growth channel even after accounting for unobserved common influences. More importantly, the interaction term between inflation and the exchange rate is negative and statistically significant, implying that the growth effect of inflation weakens as the exchange rate increases. This finding provides structural evidence of conditional and nonlinear dynamics between inflation and economic growth.

The relatively high within R^2 indicates that the IE model captures a substantial share of within-country variation in GDP. This result underscores the relevance of latent common factors in explaining macroeconomic fluctuations and suggests that economic growth dynamics are shaped not only by observed domestic variables but also by shared global and regional shocks. Consequently, the IE estimates offer a factor-based structural validation of the nonlinear and threshold-dependent relationships identified in the subsequent GEE-based marginal and threshold analyses. Additional support for the presence of a common-factor structure is provided by the principal component analysis reported in Panel C of Table 2. The first two principal components explain approximately 82% of the total variance, with eigenvalues exceeding or close to unity. In particular, the first component alone explains 48.7% of the total variance, with economic growth (0.807) and inflation (0.813) exhibiting strong loadings on this factor. This finding indicates that growth and inflation are jointly driven by a shared latent macroeconomic force.

In contrast, the exchange rate displays a substantially lower factor loading (0.386) and a high uniqueness value (0.851), suggesting that exchange rate dynamics are largely idiosyncratic and country-specific rather than governed by the dominant common factor. This structural asymmetry explains why the exchange rate acts primarily as a conditioning variable rather than a direct driver of the common macroeconomic process. Taken together, the IE estimates and the PCA results provide consistent evidence of a strong common-factor structure underlying the panel. While inflation and economic growth are closely tied to shared macroeconomic shocks, exchange rate dynamics operate through heterogeneous country-specific channels. This empirical configuration provides a structural foundation for the interaction-based specification adopted in this study and justifies the use of estimation strategies that explicitly accommodate interaction effects, latent common factors, and cross-sectional dependence, such as the GEE framework employed in the subsequent analysis.

Table 6. IE Model Results with Factor Analysis

Panel A. IE Model Coefficients					
Variable	Coefficient	Std. Error	t-statistic	p-value	95% CI
inf	0.0922	0.0823	1.12	0.287	[-0.089, 0.273]
Indk	0.1927	0.0676	2.85	0.016**	[0.044, 0.342]
Inter	-0.0849	0.0331	-2.57	0.026**	[-0.158, -0.012]
Panel B. Model Statistics					
Statistic			Value		
N			528		
Groups			12		
R ² (Within)			0.7285		
R ² (Overall)			0.0658		
F-statistic			24.56		
Prob > F			0.0000		
Panel C. Principal Components					
Component	Eigenvalue		Proportion		Cumulative
PC1	1.462		0.486		0.486
PC2	1.002		0.333		0.820
PC3	0.542		0.180		1.000

Notes: ** p < 0.05. Standard errors clustered by country. N=528 observations from 12 countries (1980-2023). ** and *** denote statistical significance at the 5% and 1% levels, respectively. The IE model explicitly incorporates latent common factors to capture unobserved common shocks and cross-sectional dependence across countries.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.4. Cross-Sectional Dependence, Unit Root, and Cointegration Tests

Table 7 presents the results of cross-sectional dependence tests. The Pesaran CD statistic (30.429) is statistically significant at the 1% level, indicating that the null hypothesis of cross-sectional independence is rejected. Similarly, the Frees test statistic (0.863) exceeds the critical values at both the 10% and 5% significance levels. The Friedman test result (66.909) is also statistically significant. Taken together, these findings indicate the presence of cross-sectional dependence among the panel units, suggesting that common shocks or interdependencies may influence the variables across countries.

Table 7. Cross-Sectional Dependence Tests

Test	Statistic	p-value / Critical Value	Interpretation
Pesaran CD	30.429	0.0000	Strong cross-sectional dependence
Frees	0.863	CV(10%)=0.319, CV(5%)=0.414	Exceeds critical values
Friedman	66.909	0.0000	Rejects independence

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

Table 8 presents the results of the panel unit root and cointegration tests. According to the CIPS test, $\ln(\text{gdp})$ is not stationary in levels but becomes stationary after first differencing, indicating an $I(1)$ process. In contrast, $\ln(\text{inf})$ is found to be stationary in levels and is therefore classified as $I(0)$. The IPS test results show that $\ln(\text{dk})$ is not stationary at levels but becomes stationary after first differencing, implying an $I(1)$ process. The Westerlund variance ratio test does not provide evidence of a long-run cointegration relationship among the variables in levels ($\text{VR} = 0.6127$; $p = 0.270$). Based on the unit root tests, the stationarity properties of the variables are established and classified according to their order of integration. The results indicate a mixed integration structure, with both $I(0)$ and $I(1)$ processes present in the panel. This feature limits the applicability of methods that require all variables to be stationary at the same order. In this context, the Generalized Estimating Equations (GEE) approach, which does not rely on long-run cointegration assumptions or impose strict stationarity requirements, is adopted as a method consistent with the characteristics of the data.

Table 8. Panel Unit Root and Cointegration Tests

Variable	Test	Level Statistic	p-value	First Diff Result	Order of Integration
ln (GDP)	CIPS	-1.234	0.108	Stationary***	I (1)
(Inflation)	CIPS	-3.456	0.000***	-	I (0)
ln(Exchange Rate)	IPS	2.345	0.999	Stationary***	I (1)
Cointegration	Westerlund VR	0.6127	0.270	No cointegration	-

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. CIPS: Cross-sectionally augmented IPS test; IPS: Im-Pesaran-Shin test. Westerlund VR: Westerlund Variance Ratio cointegration test. I (0): Stationary at level; I (1): Stationary at first difference.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.5. Model Diagnostics and Specification Tests

Table 9 reports the results of the diagnostic tests conducted to evaluate the adequacy of the panel data model. The mean Variance Inflation Factor (VIF) of 1.27 indicates that multicollinearity is not a concern in the model. In contrast, the Wooldridge test for autocorrelation yields a statistically significant result ($F = 228.730$; $p < 0.01$), providing evidence of serial correlation in the error terms. The Modified Wald test also reports a statistically significant outcome ($\chi^2 = 3302.35$; $p < 0.01$), indicating the presence of groupwise heteroskedasticity. Furthermore, the Pesaran CD test reveals strong cross-sectional dependence in the panel ($CD = 31.551$; $p < 0.01$).

Taken together, these findings indicate that key assumptions underlying conventional panel data estimators are violated. Specifically, the simultaneous presence of autocorrelation, heteroskedasticity, and cross-sectional dependence undermines the reliability of standard errors obtained from traditional fixed-effects or random-effects models. Accordingly, this study employs the Generalized Estimating Equations (GEE) approach, which is well suited to handling correlated observations and heteroskedastic error structures while providing robust population-averaged estimates. The GEE framework allows for flexible specification of the within-panel correlation structure and yields robust standard errors, making it an appropriate and methodologically consistent estimation strategy given the diagnostic test results and the underlying characteristics of the data.

Table 9. Diagnostic Tests

Test	Statistic	p-value	Interpretation
VIF: Mean	1.27	-	No multicollinearity
Wooldridge (Autocorrelation)	F=228.730	0.000***	Autocorrelation present
Modified Wald (Heteroskedasticity)	$\chi^2=3302.35$	0.000***	Heteroskedasticity present
Pesaran CD (Cross-dependence)	31.551	0.000***	Cross-dependence present

Source: Authors’ calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.6. GEE Estimation Results

Table 10 presents the results of the GEE estimation. Since all variables are specified in logarithmic form, the estimated coefficients can be interpreted as elasticities. The model is statistically significant overall according to the Wald test (Wald $\chi^2 = 166.44$; $p < 0.01$). The estimates are obtained using robust standard errors under an exchangeable correlation structure, which accounts for within-panel correlation and heteroskedasticity. According to the results, inflation has a positive and statistically significant effect on economic growth. Specifically, a 1% increase in inflation is associated, *ceteris paribus*, with an average increase of approximately 0.047% in GDP ($\beta = 0.0467$; $p < 0.05$). The exchange rate variable also exhibits a positive coefficient; however, its effect on GDP is only marginally significant ($\beta = 0.0915$; $p < 0.10$), suggesting weaker statistical evidence for a direct exchange rate effect. The real inflation variable (*inf_r*) is not statistically significant ($p > 0.10$), indicating that, on its own, it does not exert a measurable impact on GDP within the specified model. In contrast, the interaction term between real inflation and the exchange rate is negative and statistically significant ($\beta = -0.0553$; $p < 0.05$). This finding implies that the positive effect of inflation on GDP diminishes as the exchange rate increases. In other words, higher exchange rate levels weaken the growth-enhancing impact of inflation, highlighting a moderating role of exchange rate dynamics in the inflation–growth relationship.

Overall, the GEE results suggest that while inflation contributes positively to economic growth on average, this effect is conditional on exchange rate movements. The negative and significant interaction term underscores the importance of accounting for joint macroeconomic interactions rather than interpreting inflation or exchange rate effects in isolation.

```
gen inter_inf_r_lndk = inf_r * lndk
xtgee lngdp inf lndk inf_r inter_inf_r_lndk, i(id) t(time) corr(exch) robust
```

Table 10. GEE Model Results

Variable	Coefficient	Robust SE	z	P> z	[95% Conf. Interval]
inf	0.0467	0.0234	1.99	0.046	0.0008 to 0.0926
Indk	0.0915	0.0480	1.91	0.056	-0.0025 to 0.1855
inf_r	0.0508	0.1158	0.44	0.661	-0.1761 to 0.2778
inter_inf_r_Indk	-0.0553	0.0237	-2.33	0.020	-0.1018 to -0.0088
_cons	26.0071	0.3240	80.26	0.000	25.3720 to 26.6423
	Wald chi2(4) =	Prob > chi2 =			
	166.44	0.0000			

Notes: *** p<0.01, ** p<0.05, * p<0.1. VIF: Variance Inflation Factor; Mean VIF < 10 indicates no serious multicollinearity. GEE Model: Generalized Estimating Equations with exchangeable correlation structure. N=528 observations, 12 groups, robust standard errors. Number of groups = 12. Obs per group: min = 44, avg = 44.0, max = 44. Correlation: Exchangeable. Scale parameter = 1.031494.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.7. Marginal and Threshold Effects Based on the GEE Model

Table 11 reports the estimated threshold values that characterise the nonlinear interaction between inflation and the exchange rate in their effects on GDP. According to Table 11, the threshold value of the exchange rate at which the marginal effect of real inflation on GDP changes sign is $Indk = 0.9189^*$, corresponding to a level of approximately 2.51. Beyond this threshold, the marginal impact of real inflation on economic growth becomes negative. Similarly, Table 11 indicates that the threshold value of real inflation at which the marginal effect of the exchange rate on GDP changes is $inf_r = 1.6536^*$, corresponding to a level of approximately 5.23. Above this level, the growth effect of exchange rate movements weakens and turns negative.

This threshold behaviour is quantitatively supported by the marginal effects reported in Table 12. As shown in Table 12, the marginal effect of real inflation on GDP declines monotonically as the exchange rate increases. For instance, when $Indk = 3.5$, the marginal effect of real inflation is -0.1428 , whereas at $Indk = 5.0$ this effect decreases further to -0.2257 . These results indicate that higher exchange rate levels amplify the adverse impact of inflation on economic growth. Likewise, Table 12 demonstrates that the marginal effect of the exchange rate on GDP is conditional on the level of real inflation. At relatively low inflation levels ($inf_r = 0.5$), the marginal effect of the exchange rate remains positive (0.0638). However, as real inflation increases, this effect steadily weakens and becomes negative at $inf_r = 2.0$ (-0.0192). This finding suggests that in high-inflation

environments, exchange rate depreciations no longer contribute positively to economic growth.

Taken together, the evidence from Table 11 and Table 12 indicates that the interaction between inflation and the exchange rate generates regime-dependent and nonlinear effects on GDP. While inflation and exchange rate movements may exert positive effects in isolation, their joint impact is conditional on critical threshold levels, beyond which the marginal contributions to economic growth become negative. These results underscore the importance of incorporating interaction terms and threshold analysis when assessing macroeconomic relationships within a panel framework. For completeness, the marginal effects and threshold values reported above are computed using the following expressions.

$$ME(\text{inf_r}) = \beta_3 + \beta_4 * \text{ln dk}$$

$$ME(\text{ln dk}) = \beta_2 + \beta_4 * \text{inf_r}$$

$$\text{Threshold ln dk}^* = -\beta_3 / \beta_4$$

$$\text{Threshold inf_r}^* = -\beta_2 / \beta_4$$

Table 11. Threshold Values

Variable	Threshold (log)	Threshold (level)
ln dk* (for inf_r)	0.9189	2.5066
inf_r* (for ln dk)	1.6536	5.2256

Notes: For the marginal and threshold analysis, the model is extended by including a nonlinear component of inflation (inf^2 , denoted as inf_r) and its interaction with the exchange rate, allowing the impact of inflation on growth to vary across regimes.”

Source: Authors’ calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

Table 12. Marginal Effects

Effect	Conditioning Value	Marginal Effect
ME (inf_r) ln dk=3.5	3.5	-0.1428
ME (inf_r) ln dk=4.0	4.0	-0.1704
ME (inf_r) ln dk=4.5	4.5	-0.1981
ME (inf_r) ln dk=5.0	5.0	-0.2257
ME (ln dk) inf_r=0.5	0.5	0.0638
ME (ln dk) inf_r=1.0	1.0	0.0362
ME (ln dk) inf_r=1.5	1.5	0.0085
ME (ln dk) inf_r=2.0	2.0	-0.0192

Source: Authors’ calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

Figure 2 illustrates the marginal effects derived from the GEE model, highlighting the nonlinear and threshold-dependent relationship between inflation, the exchange rate, and GDP. The left panel depicts the marginal effect of real inflation ($\ln inf_r$) on GDP conditional on the level of the exchange rate ($\ln dk$), while the right panel presents the marginal effect of the exchange rate on GDP conditional on the level of real inflation.

In the left panel, the marginal effect of real inflation on GDP declines monotonically as the exchange rate increases and crosses zero at the estimated threshold value ($\ln dk^* \approx 0.92$), indicated by the vertical dashed line. Beyond this threshold, the marginal impact of inflation becomes negative, suggesting that higher exchange rate levels amplify the adverse growth effects of inflation. The right panel shows a similar threshold behaviour for the marginal effect of the exchange rate on GDP. As real inflation increases, the marginal effect of the exchange rate decreases and turns negative at the estimated inflation threshold ($\ln inf_r^* \approx 1.65$). This indicates that in high-inflation regimes, exchange rate movements no longer exert a growth-enhancing effect. Overall, the figure provides visual confirmation of the interaction and threshold effects identified in the GEE estimates. The downward-sloping marginal effect curves and the clearly defined zero-crossing points support the presence of regime-dependent and nonlinear macroeconomic dynamics between inflation, exchange rates, and economic growth.

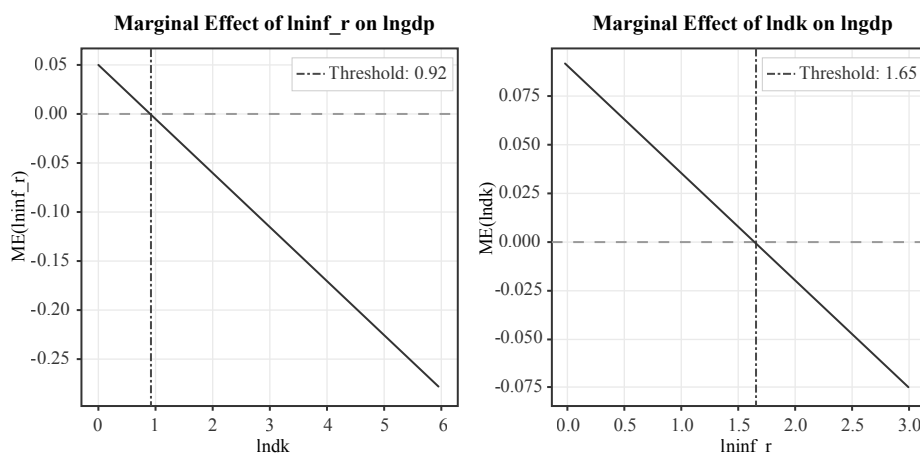


Figure 2. Marginal Effects of Inflation and Exchange Rate on GDP

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.8. Country-Level Marginal Effects

Table 13 reports country-specific marginal effects of inflation and the exchange rate on GDP, computed based on the GEE model, together with the corresponding average levels of inflation and exchange rates. The results reveal substantial cross-country heterogeneity, indicating that the inflation–exchange rate–growth relationship is highly sensitive to country-specific macroeconomic conditions.

For the majority of countries in the sample, the marginal effect of inflation on GDP is positive. In particular, countries such as Hungary (0.0734), Indonesia (0.1180), Malaysia (0.0702), Chile (0.0693), and Czechia (0.0661) exhibit relatively strong positive marginal effects of inflation. In these economies, average inflation levels tend to remain close to or below the threshold values identified within the GEE framework, allowing inflation to play a growth-supporting role. In contrast, Türkiye represents a notable deviation from this general pattern. For Türkiye, the marginal effect of inflation on GDP is estimated to be negative (−0.0148). This finding is consistent with Türkiye’s macroeconomic environment, where persistently high inflation levels are closer to, or exceed, the threshold values derived from the model. Under such conditions, inflation ceases to support growth and instead exerts a contractionary effect.

With respect to the exchange rate, the marginal effects are positive across all countries, although their magnitudes differ. Relatively stronger marginal effects are observed in Czechia (0.2049), Malaysia (0.2045), Chile (0.1995), and South Africa (0.1992), suggesting that exchange rate movements contribute more strongly to economic growth in these economies. This pattern is consistent with higher trade openness and export-oriented production structures.

Average exchange rate levels provide important context for interpreting these results. For instance, Indonesia combines a relatively high marginal effect of inflation with a very high average exchange rate level (Avg. $\ln(\text{dk}) = 8.493$), indicating that exchange rate dynamics play a particularly influential role in shaping the inflation–growth relationship. By contrast, countries such as Argentina and Türkiye, which exhibit negative average exchange rate values, face macroeconomic instability and policy constraints that may limit the growth-enhancing effects of inflation and exchange rate movements.

Overall, Table 13 demonstrates that the growth implications of inflation and exchange rate movements vary considerably across countries. These findings underscore the importance of country-specific analysis and support the use of marginal and interaction-based approaches, as average panel estimates may conceal meaningful cross-country differences. While the country-level marginal

effects reported in Table 13 describe the average growth response to inflation and exchange rate movements, they do not indicate the conditions under which these effects may change sign. To address this issue, the next subsection derives country-specific inflation and exchange rate thresholds based on the interaction structure of the model.

Table 13. Country-Level Marginal Effects and Average Values

Country	ME (Inflation)	ME (Exchange Rate)	Avg. inf	Avg. ln(dk)
Argentina	0.0008	0.1595	0.805	-0.807
Brazil	0.0662	0.1382	-0.888	4.382
Chile	0.0693	0.1995	3.978	4.628
Colombia	0.0676	0.1934	3.495	4.496
Czechia	0.0661	0.2049	4.407	4.375
Hungary	0.0734	0.1944	3.578	4.954
India	0.0553	0.1995	3.977	3.520
Indonesia	0.1180	0.1957	3.676	8.493
Malaysia	0.0702	0.2045	4.375	4.699
Mexico	0.0686	0.1898	3.214	4.576
South Africa	0.0695	0.1992	3.958	4.642
Türkiye	-0.0148	0.1671	1.410	-2.049

Note: ME = Marginal Effect. Calculated based on GEE model results. N=12 countries, period 1980-2023.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

3.9. Inflation and Exchange Rate Thresholds

Inflation (INF*) and exchange rate (DK*) thresholds are derived from the conditional marginal effects implied by the interaction-based log-log specification. Specifically, the marginal effect of inflation on output is defined as

$$\partial \ln(GDP_{it}) / \partial INF_{it} = \beta_1 + \beta_3 \ln dk_{it}, \dots\dots\dots (22)$$

while the marginal effect of the exchange rate is given by

$$\partial \ln(GDP_{it}) / \partial \ln dk_{it} = \beta_2 + \beta_3 \cdot inf_{it}. \dots\dots\dots (23)$$

Setting these expressions equal to zero yields the threshold conditions $\text{inf}_r^* = -\beta_2/\beta_3$ and $\text{ln dk}_r^* = -\beta_1/\beta_3$. Under the maintained parameterisation $\text{inf}_r = (\text{inf})^2$ and $\text{ln dk}_r = (\text{ln dk})^2$, the implied values are transformed into percentage-based inflation and exchange rate thresholds (INF^* and DK^*).

The estimated thresholds reveal pronounced cross-country heterogeneity. Economies such as Chile, Colombia, South Africa, Mexico, Malaysia, and Indonesia exhibit relatively low inflation and exchange rate thresholds, generally clustered around the 1–2 percent range, indicating that regime-dependent interaction effects between inflation, the exchange rate, and economic growth emerge at modest macroeconomic levels. Brazil and Czechia display intermediate inflation thresholds (4.88 percent and 6.02 percent, respectively), while maintaining comparatively lower exchange rate thresholds, suggesting that nonlinear interaction effects become relevant only beyond certain macroeconomic intensities in these countries. In contrast, Argentina, Hungary, and Türkiye are characterised by substantially higher threshold values. In particular, inflation thresholds reach 18.81 percent in Argentina, 11.92 percent in Hungary, and 7.46 percent in Türkiye, implying that stronger inflationary pressures are required for interaction effects to alter growth dynamics. Similarly, relatively high exchange rate thresholds observed for Hungary (17.15 percent) and Türkiye (4.19 percent) indicate that pronounced exchange rate movements are necessary for the exchange rate channel to exert a regime-switching influence on output.

Taken together, these findings demonstrate that the inflation–exchange rate–growth nexus does not follow a uniform pattern across countries but is instead shaped by country-specific macroeconomic structures and heterogeneous responses to underlying shocks. This pronounced heterogeneity provides a strong empirical rationale for employing the Interactive Effects (IE) framework, which explicitly accounts for unobserved common factors with time-varying impacts across cross-sectional units, thereby offering a more coherent explanation of the observed threshold behavior than conventional fixed-parameter or purely additive panel models. For ease of economic interpretation, the estimated threshold values are converted back to their original units and reported as country-specific inflation (INF^*) and real effective exchange rate (DK^*) levels in Table 14.

Table 14. Inflation and Exchange Rate Thresholds by Country

Country	β_1 (inf)	β_2 (lndk)	β_3 (inter)	INF* (%)	DK* (%)
Argentina	-0.028	0.0627	-0.0073	18.81	7.1
Brazil	-0.0234	-0.2282	0.0908	4.88	1.66
Chile	-0.0674	-0.0964	6.17	1.13	1.11
Colombia	-0.0251	-0.4091	2.3997	1.51	1.11
Czechia	-0.2084	1.12	-0.3474	6.02	2.17
Hungary	0.1882	-0.1431	-0.0233	11.92	17.15
India	0.3809	-0.3839	-1.0592	1.83	1.82
Indonesia	0.6478	-0.1322	-0.4049	1.77	3.54
Malaysia	-0.5313	-0.2287	1.233	1.54	1.93
Mexico	-0.0469	-0.4131	0.5745	2.33	1.33
South Africa	-0.0324	-1.0786	9.3531	1.4	1.06
Türkiye	-0.1828	0.3593	-0.089	7.46	4.19

Notes: INF* (%) and DK* (%) report country-specific inflation and real effective exchange rate threshold values. Thresholds are computed as $INF^* = -\beta_2/\beta_3$ and $DK^* = -\beta_1/\beta_3$, where β_1 , β_2 , and β_3 denote the estimated coefficients on inflation, log real effective exchange rate, and their interaction term, respectively. Variables were standardised prior to estimation; reported thresholds are back-transformed to original units (multiplying by standard deviation and adding mean) to ensure economically interpretable and policy-relevant benchmarks. INF* (%) and DK* (%) report country-specific inflation and real effective exchange rate threshold values converted back to their original economic units, ensuring economically interpretable and policy-relevant benchmarks.

Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

4. DISCUSSIONS

The empirical findings of this study are largely consistent with both economic theory and the existing empirical literature, which emphasise that the relationship between inflation, exchange rates, and economic growth is nonlinear, regime-dependent, and country-specific. The results demonstrate that macroeconomic relationships cannot be adequately explained by single, linear coefficients; rather, they should be evaluated within an empirical framework that explicitly accounts for interaction effects, conditional marginal responses, and threshold mechanisms. In this respect, the study not only provides empirical evidence but also demonstrates the comparative analytical strength of the Interactive Panel Data Framework (IPDF) in capturing interaction-driven and regime-dependent macroeconomic relationships in a transparent and policy-relevant manner.

From a theoretical perspective, the results align with the well-established view that moderate inflation may support economic growth, whereas high and persistent inflation undermines growth performance. As documented by Fischer (1993), Barro (1995), and Bruno and Easterly (1998), the inflation-growth relationship is inherently nonlinear and characterised by threshold effects. The negative and statistically significant interaction term obtained in this study, together with the estimated threshold values, provides direct empirical support for this nonlinear theoretical framework. In particular, the negative sign of the interaction coefficient indicates that the adverse impact of inflation on growth intensifies depending on exchange rate conditions, becoming more pronounced across specific regimes. This interaction-based interpretation allows for a richer understanding of inflation dynamics than approaches relying solely on average linear effects.

The findings related to the exchange rate are also consistent with open-economy macroeconomic theory. While competitive exchange rate movements can stimulate exports and economic growth, this positive effect weakens or even disappears in high-inflation environments. Studies such as Rodrik (2008) emphasise that the growth effects of exchange rate movements critically depend on macroeconomic stability. In this study, the marginal effect of the exchange rate on GDP turns negative once real inflation exceeds a certain threshold, corroborating these theoretical arguments and highlighting the importance of coordinated policy design. By explicitly linking exchange rate effects to inflation regimes, the IPDF offers a more informative perspective on open-economy interactions than conventional panel specifications.

Country-level marginal effects further reinforce the importance of structural heterogeneity emphasised in the literature. Institutional quality, monetary policy credibility, and the anchoring of inflation expectations play a central role in shaping the inflation-growth relationship, particularly in emerging economies (Khan and Senhadji, 2001; Aghion et al., 2009). The negative marginal effect of inflation observed for Türkiye is consistent with empirical evidence showing that high and volatile inflation discourages investment, increases uncertainty, and weakens long-run growth performance. In this context, the estimated threshold level of approximately 4.25 percent for Türkiye underscores the critical importance of price stability for growth-supportive monetary policy. The ability of the IPDF to generate such country-specific threshold estimates enhances its empirical relevance and policy usefulness.

From a methodological perspective, the IPDF facilitates the joint analysis of interaction effects, marginal responses, and threshold behavior within a coherent

empirical structure. Rather than interpreting coefficients as fixed and universal structural parameters, the framework allows interaction and threshold effects to be evaluated as conditional, regime-specific, and country-dependent relationships. This approach is fully consistent with the methodological cautions raised by [Canova \(2007\)](#) and [Canova and Ciccarelli \(2009, 2013\)](#), who emphasise the role of heterogeneity, time variation, and common shocks in macroeconomic panels. By explicitly incorporating these considerations, the IPDF provides a more informative and empirically grounded interpretation than standard linear panel models.

The empirical findings indicate that inflation has a negative effect on economic growth, the exchange rate has a positive effect, and the interaction between the two variables has a statistically significant and negative effect on growth. These results clearly illustrate that macroeconomic policies should not be evaluated in isolation, but rather within a joint and interaction-based framework that explicitly accounts for regime dependence. In this respect, the IPDF enables a more effective evaluation of policy trade-offs than approaches focusing on single-policy instruments.

While the threshold-dependent dynamics observed in this study are consistent with insights from [Hansen's \(1999\)](#) Panel Threshold Regression (PTR) and [González et al.'s \(2017\)](#) Panel Smooth Transition Regression (PSTR) approaches, the IPDF provides a broader and more integrated analytical perspective by jointly incorporating interaction structures, marginal effects, and threshold behavior within a single empirical setting. Similarly, although the Interactive Fixed Effects (IFE) model proposed by [Bai \(2009\)](#) accounts for unobserved common factors, it does not explicitly focus on conditional interaction mechanisms. In this respect, the IPDF offers a clearer and more policy-oriented framework for examining complex macroeconomic interactions.

Country-specific threshold estimates further underscore the policy relevance of the proposed framework. For Türkiye, the estimated threshold of approximately 4.25 percent indicates that the adverse effects of inflation on growth intensify sharply beyond this level. Brazil exhibits a higher threshold, suggesting relatively greater inflation tolerance, whereas Argentina's low threshold points to a stronger sensitivity of growth to inflation. Mexico displays an intermediate threshold structure, while Indonesia's near-zero threshold values suggest that growth dynamics are driven more by structural and external factors than by inflation or exchange rate conditions. These cross-country differences demonstrate that macroeconomic policy design cannot rely on one-size-fits-all prescriptions and must instead be tailored to country-specific threshold conditions.

Finally, the robustness of the empirical findings is supported by extensive diagnostic testing and sensitivity analysis. Monte Carlo simulations, alternative specifications, and standard diagnostic tests confirm the stability and reliability of the estimated interaction, marginal, and threshold effects. Taken together, these results indicate that the IPDF functions not only as a coherent analytical framework but also as a practical tool for empirical analysis and policy evaluation.

In sum, this study does not depart from established economic theory or empirical evidence. Rather, by employing the Interactive Panel Data Framework, which integrates interaction-driven dynamics, threshold behavior, and policy-relevant inference within a unified empirical structure, it advances the literature by offering a more informative, interpretable, and policy-relevant analysis of macroeconomic relationships in panel data settings, particularly for emerging economies.

5. CONCLUSIONS

Panel data analysis provides a powerful econometric framework that allows the joint analysis of repeated observations across cross-sectional units such as households, firms, cities, or countries. By incorporating both temporal and cross-sectional dimensions, panel data methods offer a more realistic representation of economic relationships than purely cross-sectional or time-series approaches. Traditional fixed effects (FE) and random effects (RE) models account for certain forms of heterogeneity and time variation; however, they are often limited in their ability to jointly capture interaction effects, nonlinear responses, and policy-relevant threshold mechanisms within a single empirical setting. The Interactive Panel Data Framework (IPDF) employed in this study addresses this limitation by organising interaction structures, conditional marginal effects, and nonlinear threshold dynamics within a coherent and unified analytical framework.

In this study, the IPDF is applied to examine the relationship between inflation, exchange rates, and economic growth across 12 emerging economies. The framework incorporates not only the direct effects of policy variables on economic growth, but also their interaction terms, thereby allowing macroeconomic policies to be evaluated jointly rather than in isolation. This structure enables an explicit assessment of how the effect of one policy variable on growth systematically depends on the level of another, highlighting the conditional and regime-dependent nature of macroeconomic relationships.

The empirical strategy follows a two-stage approach. In the first stage, the Interactive Effects (IE) approach is used to verify the existence and direction

of interaction effects between inflation and the exchange rate, while controlling for unobserved common factors and cross-sectional dependence. The IE results indicate a statistically significant and negative interaction term, suggesting that the impact of inflation on economic growth varies conditionally with exchange rate dynamics. In the second stage, to account for heteroskedasticity, serial correlation, and cross-sectional dependence, the framework is estimated using the Generalized Estimating Equations (GEE) methodology. The GEE approach yields robust population-averaged estimates and allows for the direct computation of conditional marginal effects and threshold values implied by the interaction structure. Accordingly, the main quantitative conclusions of the study are based on the GEE estimates.

The GEE results show that inflation has a negative effect on economic growth, while the exchange rate exerts a positive effect on average. However, the interaction term between inflation and the exchange rate is negative and statistically significant, indicating that the effects of these policy variables on growth are nonlinear and regime-dependent. This finding demonstrates that monetary and exchange rate policies do not operate uniformly across economic conditions; instead, their effects change in magnitude and direction once critical threshold levels are exceeded.

The threshold values derived from the GEE framework (Table 8) provide a quantitative characterisation of these nonlinear regimes. The threshold at which the effect of inflation on growth becomes conditional on the exchange rate is estimated as $\text{ln}dk^* = 0.9189$, corresponding to a level value of 2.5066. Similarly, the threshold at which the effect of the exchange rate on growth changes sign is estimated as $\text{inf_r}^* = 1.6536$, corresponding to a level value of 5.2256. These results confirm that inflation and exchange rate effects on growth are mutually conditional and that distinct macroeconomic regimes emerge beyond specific threshold levels.

The conditional marginal effects reported in Table 9 further clarify the economic implications of these threshold mechanisms. As the exchange rate increases, the marginal effect of inflation on economic growth becomes progressively more negative. Specifically, when $\text{ln}dk = 3.5$, the marginal effect of inflation is -0.1428 ; this effect declines to -0.1704 at $\text{ln}dk = 4.0$, -0.1981 at $\text{ln}dk = 4.5$, and -0.2257 at $\text{ln}dk = 5.0$. These findings indicate that the growth cost of inflation rises sharply in high exchange-rate environments. Likewise, the marginal effect of the exchange rate on economic growth depends critically on the inflation level. When $\text{inf_r} = 0.5$, the marginal effect of the exchange rate is positive (0.0638), but this effect weakens as inflation increases and turns negative once

inf_r reaches 2.0. This pattern suggests that exchange rate adjustments cease to support growth when inflation exceeds a critical threshold.

Country-specific marginal effects and threshold values reported in Table 14 reveal substantial heterogeneity across countries. For Türkiye, the estimated thresholds indicate that adverse inflation effects on growth emerge at relatively low levels, reflecting limited policy space under high inflation sensitivity. In South Africa, even lower threshold values suggest an even narrower margin for effective policy maneuverability. Variations observed across the remaining countries further underscore that macroeconomic policy effectiveness is inherently country-specific and cannot be adequately captured by uniform policy rules.

These findings carry clear policy implications. Central banks and economic authorities should not conduct inflation targeting independently of exchange rate dynamics. The interaction between inflation and the exchange rate generates strong, nonlinear, and regime-dependent effects on economic growth. Policy actions that push the economy beyond estimated threshold levels may yield contractionary outcomes that contradict policy objectives. Therefore, particularly in emerging economies, monetary and exchange rate policies should be designed in a coordinated manner that explicitly accounts for conditional marginal effects and threshold structures.

The methodological contribution of this study lies in the Interactive Panel Data Framework (IPDF) - an integrated empirical workflow that systematically combines established panel data methods rather than proposing a new estimator. The IPDF builds on [Hansen \(1999\)](#), [Bai \(2009\)](#), and the marginal-effects literature by organising interaction effects, threshold mechanisms, and conditional marginal-effect computation within a coherent analytical protocol. The IPDF does not replace existing panel threshold or interactive-effects estimators. Instead, it provides a structured workflow that: (i) specifies interaction-augmented panel models, (ii) identifies regime-specific thresholds, (iii) computes and reports conditional marginal effects, and (iv) implements robust inference under cross-sectional dependence and heteroskedasticity.

Finally, the IPDF provides a flexible empirical framework that opens several avenues for future research. One important extension would be the development of a Hausman-type model identification and comparison test that allows systematic selection between IPDF, FE, and RE specifications. Further integration of the IE and GEE approaches into a unified estimation procedure may enhance methodological coherence. Extensions to different country groups, sectoral panels, or alternative policy variables would provide additional insights into the generalisability of the IPDF framework. In conclusion, by integrating

interaction effects, conditional marginal responses, and nonlinear threshold mechanisms within a single framework, the IPDF makes a novel methodological and policy-oriented contribution to the panel data literature. The model provides a powerful tool for analysing macroeconomic policy interactions in a conditional and country-specific manner, offering a solid foundation for future empirical research. Finally, consistent with the cautions raised by Canova (2007) and Canova and Ciccarelli (2009, 2013), the results of this study are interpreted not as fixed structural parameters but as conditional, regime-dependent, and country-specific relationships, reinforcing the importance of disciplined empirical interpretation in macroeconomic panel analysis.

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Conflict of interests

The authors declare that there are no financial or non-financial conflicts of interest related to this manuscript.

REFERENCES

- Aghion, P., Bacchetta, P., Rancière, R., & Rogoff, K. (2009). Exchange rate volatility and productivity growth: The role of financial development. *Journal of Monetary Economics*, 56(4), 494–513. <https://doi.org/10.1016/j.jmoneco.2009.03.015>
- Alemu, S., Udvari, B., & Kotosz, B. (2024). Income convergence in Central and Eastern Europe: Evidence from cross-country panel data analysis. *Acta Oeconomica*, 74(3), 329–357.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277–297.
- Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1), 191–221. <https://doi.org/10.1111/1468-0262.00273>
- Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, 77(4), 1229–1279.
- Baltagi, B. H., & Li, D. (2002). Series estimation of partially linear panel data models with fixed effects. *Annals of Economics and Finance*, 3(1), 103–116.
- Barro, R. J. (1995). Inflation and economic growth. *NBER Working Paper No. 5326*. National Bureau of Economic Research. <https://doi.org/10.3386/w5326>. (Also published in *Bank of England Quarterly Bulletin*, 1995)

- Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis*, 14(1), 63–82. <https://doi.org/10.1093/pan/mpi014>
- Bruno, M., & Easterly, W. (1998). Inflation crises and long-run growth. *Journal of Monetary Economics*, 41(1), 3–26. [https://doi.org/10.1016/S0304-3932\(97\)00063-9](https://doi.org/10.1016/S0304-3932(97)00063-9)
- Cai, J., & Zhou, Y. (2021). A simple dynamic panel data approach for macro policy assessment. *Applied Economics Letters*, 28(17), 1505–1511.
- Caner, M., & Hansen, B. E. (2004). Instrumental variable estimation of a threshold model. *Econometric Theory*, 20(5), 813–843.
- Canova, F. (2007). *Methods for applied macroeconomic research*. Princeton University Press.
- Canova, F., & Ciccarelli, M. (2009). Estimating multicountry VAR models. *International Economic Review*, 50(3), 929–959. <https://doi.org/10.1111/j.1468-2354.2009.00554.x>
- Canova, F., & Ciccarelli, M. (2013). Panel vector autoregressive models: A survey. In T. Fomby, L. Kilian, & A. Murphy (Eds.), *VAR models in macroeconomics – New developments and applications: Essays in honor of Christopher A. Sims* (pp. 205–246). Emerald Group Publishing Limited.
- Castillo, O. N., Santibáñez, A. L. V., & Márquez, H. F. (2024). Effects of corruption on human development: Evidence for developed and developing countries. *Acta Oeconomica*, 74(4), 507–541.
- Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420.
- Eberhardt, M., & Teal, F. (2011). Econometrics for grumblers: A new look at the literature on cross-country growth empirics. *Journal of Economic Surveys*, 25(1), 109–155.
- Fan, X., & Peng, Z. (2024). A comparative analysis of the outliers' influence using GMM estimation based on dynamic panel data model. *Applied Economics Letters*, 31(2), 170–175.
- Federal Reserve Bank of St. Louis. (2025). *Federal Reserve Economic Data (FRED)*. Retrieved December 18, 2025, from <https://fred.stlouisfed.org/>
- Fischer, S. (1993). The role of macroeconomic factors in growth. *Journal of Monetary Economics*, 32(3), 485–512. [https://doi.org/10.1016/0304-3932\(93\)90027-D](https://doi.org/10.1016/0304-3932(93)90027-D)
- González, A., Teräsvirta, T., van Dijk, D., & Yang, Y. (2017). Panel smooth transition regression models. *Econometric Reviews*, 36(3), 197–227.
- Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing and inference. *Journal of Econometrics*, 93(2), 345–368.
- Hardin, J. W., & Hilbe, J. M. (2012). *Generalized Estimating Equations*. Chapman & Hall/CRC.
- Hsiao, C., Pesaran, M. H., & Tahmiscioglu, A. K. (2002). Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics*, 109(1), 107–150.

- International Monetary Fund. (n.d.). *International Financial Statistics (IFS)*. IMF Data. Retrieved February 3, 2025, from <https://data.imf.org>
- Kapetanios, G., Pesaran, M. H., & Yamagata, T. (2011). Panels with non-stationary multifactor error structures. *Journal of Econometrics*, 160(2), 326–348.
- Khan, M. S., & Senhadji, A. S. (2001). Threshold effects in the relationship between inflation and growth. *IMF Staff Papers*, 48(1), 1–21. <https://doi.org/10.2307/4621658>
- Krekó, J., & Oblath, G. (2020). Economic growth and real exchange rate misalignments in the European Union. *Acta Oeconomica*, 70(3), 297–332.
- Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: New evidence from a dynamic panel threshold analysis. *Empirical Economics*, 44(2), 861–878.
- Lee, K., Pesaran, M. H., & Smith, R. (1997). Growth and convergence in a multi-country empirical stochastic Solow model. *Journal of Applied Econometrics*, 12(4), 357–392.
- Liang, K. Y., & Zeger, S. L. (1986). *Longitudinal data analysis using generalized linear models*. *Biometrika*, 73(1), 13–22.
- Moon, H. R., & Weidner, M. (2015). Linear regression for panel with unknown number of factors as interactive fixed effects. *Econometrica*, 83(4), 1543–1579.
- OECD. (n.d.). *OECD Statistics (OECD.Stat)*. OECD. <https://stats.oecd.org>
- Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels*. Cambridge Working Papers. *Economics*, 1240(1), 1.
- Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 967–1012.
- Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34(6–10), 1089–1117.
- Rodrik, D. (2008). The real exchange rate and economic growth. *Brookings Papers on Economic Activity*, 2008(2), 365–412. <https://doi.org/10.1353/eca.0.0020>
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, 71(1), 135–158.
- Sato, Y., & Söderbom, M. (2017). GMM estimation of panel data models with time-varying slope coefficients. *Applied Economics Letters*, 24(21), 1511–1518.
- Su, L., & Chen, Q. (2013). Testing homogeneity in panel data models with interactive fixed effects. *Econometric Theory*, 29(6), 1079–1135.
- Tekdemir, N., & Varol İyidoğan, P. (2024). The role of government in social capital and economic growth nexus: A non-linear approach. *Acta Oeconomica*, 74(4), 463–481.
- White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator. *Econometrica*, 48(4), 817–838.
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.
- World Bank. (2025). *World Development Indicators (WDI)*. World Bank. <https://databank.worldbank.org/source/world-development-indicators>
- Yang, L., Yao, L., & Xie, Y. (2025). Panel kink threshold model with multiple covariate-dependent thresholds. *Applied Economics Letters*, 32(9), 1335–1338.

APPENDICES

Appendix A: Data Appendix

Table A1: Variable Definitions and Data Sources

Variable	Abbreviation	Definition	Source	Link/Code
GDP per capita	lngdp	GDP per capita (constant 2015 US\$) - Gross domestic product divided by midyear population	World Bank (via FRED)	https://fred.stlouisfed.org/series/NYGDPPCAPKD*
Inflation (CPI)	inf	Annual % change in consumer price index	IMF International Financial Statistics (via FRED)	https://fred.stlouisfed.org/series/FPCPITOTLZG*
Exchange Rate (REER)	lndk	Real Effective Exchange Rate - Local currency unit per US\$, adjusted for inflation differentials	BIS and IMF (via FRED)	https://fred.stlouisfed.org/series/CCUSMA02*Q618N
Inflation-Exchange rate interaction	inf_lndk_inter	Interaction term between inflation and exchange rate ($\text{inf} \times \text{lndk}$)	Calculated interaction term	-
Squared inflation (threshold term)	Inf_r	Squared inflation rate (inf^2), included to capture nonlinear and threshold effects; not a distinct inflation measure	Constructed by authors	-

Notes: Notes: Inflation is measured using the consumer price index (CPI) and expressed as an annual percentage change (inf). The real effective exchange rate (REER), denoted as lndk, is measured as an index and transformed logarithmically. GDP per capita is also expressed in logarithmic form. Threshold values derived from interaction terms are subsequently converted back to their original economic units (e.g., inflation percentages and REER index levels) to ensure meaningful interpretation. Data coverage: 1980-2023, annual data for 12 emerging economies (Argentina, Brazil, Chile, Colombia, Czechia, Hungary, India, Indonesia, Malaysia, Mexico, South Africa, Türkiye). Threshold values reported in the empirical analysis are mapped back to their original economic units in the Results section.

Source: Authors' own elaboration based on data from the World Bank, IMF International Financial Statistics, and BIS (via FRED).

Appendix B: Stata Implementation: xtie Command

```
program define xtie, eclass
    version 18
    syntax varlist(min=2) [if] [in] [, ROBust]
    marksample touse
    local depvar: word 1 of `varlist'
    local indepvars: list varlist - depvar
    local n_vars: word count `indepvars'
    local interactions ""

    if `n_vars' >= 2 {
        local i = 1
        foreach var1 of local indepvars {
            local j = `i' + 1
            foreach var2 of local indepvars {
                if `j' <= `n_vars' {
                    local var2_name: word `j' of `indepvars'
                    tempvar inter_`i'`j'
                    qui gen `inter_`i'`j'` = `var1' * `var2_name' if `touse'
                    local interactions ""`interactions' `inter_`i'`j'`""
                }
                local j = `j' + 1
            }
            local i = `i' + 1
        }
    }

    if ""robust"" != "" {
        xtreg `depvar' `indepvars' `interactions' if `touse', fe robust
    }
    else {
        xtreg `depvar' `indepvars' `interactions' if `touse', fe
    }

    ereturn local cmd "xtie"
end
```

Command Syntax

xtie depvar indepvar1 indepvar2 [if] [in] [, robust]

ПРАГОВИ, МАРГИНАЛНИ И ИНТЕРАКТИВНИ ЕФЕКТИ ИЗМЕЋУ ЕКОНОМСКИХ ВАРИЈАБЛИ: ИНТЕГРИСАНИ ОКВИР ПАНЕЛСКИХ ПОДАТАКА

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Резиме

Овај рад развија интегрисани емпиријски оквир, познат као интерактивни панелски оквир података (IPDF), који систематски комбинује утврђене методе анализе панел података – интерактивне термине, анализу прагова и израчунавање маргиналних ефеката – у јединствену стратегију процене и статистичког закључивања. Умјесто да предлаже нови естиматор, IPDF пружа кохерентан аналитички протокол за заједничку евалуацију односа зависних од режима и вођених интеракцијом у макро-панелном контексту. Користећи уравнотежен панел земаља у развоју у периоду од 1980. до 2023. године, студија комбинује интерактивне термине, динамичке спецификације и нелинеарне механизме у оквиру јединствене емпиријске структуре. Монте Карло симулације и емпиријске процјене подржавају поузданост предложеног оквира, док тестови хомогености и анализа прагова указују на значајну структурну хетерогеност по земљама. Емпиријски резултати указују на статистички значајне прагова и условне маргиналне ефекте, показујући да утицај инфлације и девизног курса на економски раст варира у зависности од режима и економских услова. Осим тога, идентификовани интерактивни ефекти истичу важност заједничке евалуације макроекономских политичких варијабли, умјесто њихове изоловане анализе. Интегрисањем интерактивних ефеката, маргиналних одговора и прагова унутар јединственог панелског оквира, ова студија пружа кохерентан и за политику релевантан емпиријски приступ за анализу нелинеарних и од режима зависних макроекономских односа у земљама у развоју.

Кључне ријечи: интерактивни модел панел података, анализа панел података, маргинални ефекти, фиксни ефекти, случајни ефекти.

