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DOES FOREIGN DIRECT INVESTMENT COMPLEMENT OR SUBSTITUTE DOMESTIC INVESTMENT IN BOTSWANA?[1]

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ABSTRACT

The impact of foreign direct investment (FDI) inflows and outflows on domestic investment in Botswana was examined using data for the period from 1990 to 2022. The study was motivated by Botswana's efforts to attract FDI in support of economic diversification. The question this study sought to answer was: "Does the liberalisation of foreign investment outflows and inflows in Botswana support domestic investment?" The study employed the non-linear autoregressive distributed lag (NARDL) approach to assess whether foreign direct investment complements or the substitutes domestic investment in Botswana. The study found that positive shocks to foreign direct investment inflows complement domestic investment in the short run but substitute it in the long run, while negative shocks to foreign direct investment inflows are insignificant across both time horizons. Positive shocks to foreign direct investment outflows were found to complement domestic investment in the short run but substitute it in the long run. Conversely, negative shocks to foreign direct investment outflows lead to an increase in domestic investment in the long run, although they are insignificant in the short run. Policy implications are also discussed.

1. INTRODUCTION

The neo-classical growth models advocated for capital accumulation, labour force growth, and exogenous technology growth as sources of long-term growth. Various studies have been done expanding on the simple production function where capital has been extended to foreign capital in the form of foreign direct investment or foreign aid (Madondo et al. 2025; Ayenew, 2022; Adusei, E, 2020; Falki, 2009; Durbarry, Gemmell & Greenaway, 1998). Foreign direct investment has been associated with several advantages, apart from expanding the capital base for a country, ranging from technology enhancement and spillover effects to the promotion of good management in the receiving economy. Studies have also pointed to the positive impact of FDI on economic growth (see: Chidoko & Sachirarwe, 2015; Tang & Tan, 2018). Based on these benefits, most African countries have put in place policies that promote foreign direct investment inflows to argument domestic investment. Savings that are insufficient to support domestic investment demand in most African countries have made efforts to attract FDI plausible. To create an enabling environment that can attract FDI, most African countries have formulated investment policies and programmes that support foreign direct investment inflows. Botswana is not an exception on this strategy, aimed at augmenting domestic investment. The investment policies have been revised to make it easy for foreign investors to do business in Botswana. Despite the positive contribution of FDI to domestic investment widely held by African government and vast empirical literature, there is a strand of literature that found FDI inflows and outflows to have negative effects on domestic investment. The overall sentiment is a substitution effect of foreign direct investment on domestic investment. This has long term negative effects on the domestic economy and tends to create dependence on foreign investment to boost domestic investment. This study, therefore, investigates if foreign direct investment has a complementary or substitution effect on domestic investment in Botswana.

Several studies have examined the impact of foreign direct investment inflows on domestic investment. The findings from these studies are mixed, with some studies finding a complementary effect (see Djokoto, 2021; Budang & Hakim, 2020; Oualy, 2019; Ibhagui & Olawole, 2019; Selmi, 2016), while others found a substitution effect (for example, Setiyanto, 2022; Ngeendepl & Phiri, 2021; Gizaw, Dedeho & Lodamo, 2021). There are some studies that found FDI neutrality (see, Polat, 2017). Some studies found both complementarity and substitution effect in the same study depending on regions or time frames considered (see, Jude, 2019; Xu and Yuan, 2012; Adams, 2009). A few studies have investigated the impact of foreign direct investment outflows on domestic investment using non-linear autoregressive distributed lag (NARDL), despite the importance of understanding the link between the two. An examination of the complementarity and substitution effect of FDI on domestic investment provides valuable information in enhancing investment policies currently used in Botswana to advance domestic investment.

The study employs the non-linear autoregressive distributed lag approach (NARDL) to investigate the nature of the impact of FDI inflows and outflows on domestic investment in Botswana. Most studies examining the impact of foreign direct investment inflows and outflows on domestic investment have assumed that positive and negative shocks in FDI exert the same effect on domestic investment, which is not always valid. The NARDL allows an analysis of the impact of FDI on domestic investment taking into account the impact of negative and positive shocks on FDI. This departs from the current body of knowledge and provides more insight to policy makers in Botswana on how to boost domestic investment. The key variables in this study are FDI inflows, FDI outflows and domestic investment.

Botswana is a good case study for this research given that it has managed to grow its economy from a poor country to an upper-middle income country. Botswana has grown its economy in the past based on strategic use of diamond resources. The current investment thrust of the country is to attract investment in other sectors of the economy, apart from diamond. The outcome of this study will contribute to informed policy formulation in attracting foreign investment. To the best knowledge of the researcher, this is the first study that investigated the impact of foreign direct investment inflows and outflows on domestic investment for Botswana using NARDL. This is an area that has not been fully explored to establish if foreign direct investment complement or substitute domestic investment for Botswana.

The rest of the study is structured as follows: Section 2 outlines the literature – country-based and empirical literature, Section 3 dwells on estimation techniques, and Section 4 presents and discusses the empirical results. Section 5 concludes the study.

2. LITERATURE

2.1 FDI and domestic investment dynamics in Botswana

Botswana's investment climate has been strengthened and made competitive through several regulatory reforms. Among the reforms were the Companies Act, investor protection through the Industrial Property Act, Acquisition of Property Act and investment in different economic sectors (Organisation of Economic Cooperation and Development 'OECD', 2014). In 2010, the government launched the Economic Diversification Drive – a guide to economic policy planning anchored on creation of a vibrate private sector (OECD, 2014). In 2011, the merger of the Botswana Export Development and Investment Authority (BEDIA) and Botswana International Financial Services Centre (IFSC) was done to streamline investment in Botswana (OECD, 2014). The successor organisation, Botswana Investment and Trade Centre (BITC) established a facilitation centre to support qualifying investors willing to do business in Botswana (OECD, 2014). The BITC promotes both domestic and foreign investment. To leverage investment promotion, the BITC identifies and promotes growth sectors, offers financial and non-financial incentives to investors (BITC, 2024).

The investment drive in Botswana is guided by the need to diversify from diamonds to other sectors of the economy. The Economic Diversification Drive (EDD) short- and medium- to long-term strategies are designed to create growth and income sources for Botswana to be tied to all sectors of the economy – a move from diamond as a source of income and growth (Republic of Botswana, 2024). The EDD also aims to wean the private sector from government support, aligned with a reduction in government expenditure (Republic of Botswana, 2024).

The government has made concerted effort to attract FDI in export-oriented manufacturing since the late 1990s, to diversify the economy from being sorely diamond-dependent (OECD, 2014). To simplify doing business in Botswana, the Botswana One Stop Service Centre (BOSSC) was established in 2017 (United Nations Trade and Development, 2017). The BOSSC is a facilitation centre within the BITC that focuses on simplifying administrative procedures for investors. In the BOSSC, relevant government agencies are housed to provide prompt, efficient and transparent services to investors such as permitting, visa application, business registration, connection to utilities, income and VAT registration, access to industrial and commercial land, and industrial licensing (United Nations Trade and Development, 2017). Business eligible to the BOSSC service should demonstrate several qualities, for example, potential for export, potential for skills and technology transfer, innovation and creativity, investment in agriculture, mining, agro- processing, information and technology, and transport and hospitality, among other important sectors (United Nations Trade and Development, 2017).

Botswana places priority on private sector participation in advancing economic growth, where the government provides equal playing fields between the public and the private sectors in the infrastructure development, which the country highlights as a cornerstone of economic growth. Aligned to minimise government interference and increase efficiency, the government established the Public Enterprise Evaluation and Privatisation Agency, and the Privatisation Masterplan in 2000 and 2005, respectively. Under the Privatisation Masterplan, services and enterprises suitable for divestiture and outsourcing were identified, thereby creating scope for the private sector to provide such services or undertake outsourced activities where efficiency is enhanced.

Botswana has made progress in creating a regulatory environment that supports investment from both foreign and domestic investors. However, further efforts are required to consolidate fragmented laws in order to facilitate easier access for investors (OECD, 2014). Access to land remains a cumbersome process for investors, especially the change of land use for businesses purposes, which hampers entrepreneurial activities. Skills mismatch remains a challenge in Botswana that humpers investment attraction and competitiveness. Another challenge that has negatively affected investment attraction in Botswana is infrastructure limitation, especially electricity generation. The trends in foreign direct investment and domestic investment in Botswana from 1980 to 2022 are depicted in Figure 1.

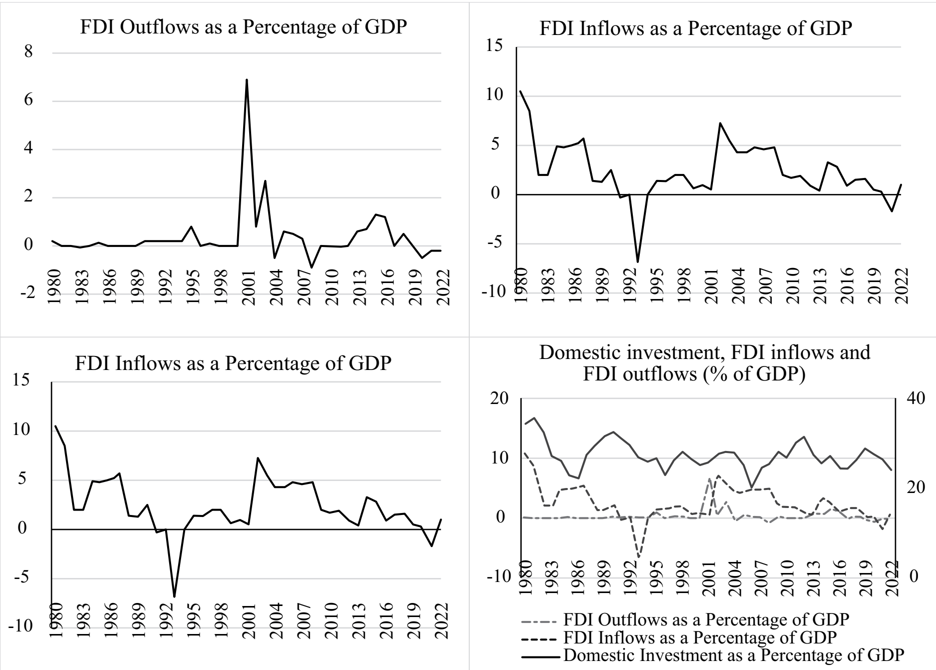

Figure 1: Trends in Foreign Direct Investment and Domestic Investment 1980 -2022
Source: World Bank (2024)

Foreign direct investment outflows have remained depressed over the study period with exceptional years like 2001, 2003, 2015 and 2016 where surges were recorded (World Bank, 2024). Botswana has not received FDI inflows that matched the inflows of 10.5% received in 1980 (World Bank, 2024). FDI inflows declined from 1980 reaching a low of of -6.9% in 1993 (World Bank, 2024). The average annual FDI inflow over the study period registered was 2.4% (World

Bank, 2024). The trend suggests that Botswana has struggled to attract the level of FDI inflows required to accelerate its diversification efforts. This has been worsened by domestic investment that has remained subdued over the study period, with an average of 27.3% between 1980 and 2024 (World Bank, 2024).

2.2 Empirical literature

The link between foreign direct investment and domestic investment can be traced to the economic growth models that proposed capital and labour as the main source of economic growth. Economic growth is buttressed by domestic investment captured by gross capital formation in this study. Solow-Swan model tried to explain the sources of economic growth in the long run where capital accumulation, labour and increase in productivity, largely attributed to technological advancement were proposed. In this study, foreign direct investment is external investment source that complements domestic investment. In addition, foreign direct investment inflows bring other advantages like technology diffusion. Theoretically, positive shocks in FDI inflows are expected to positively contribute to domestic investment, whereas negative shocks in FDI inflows are expected to negatively impact domestic investment. Positive shocks in FDI outflows are expected to negatively impact domestic investment, while negative shocks in FDI inflows are expected to positively impact domestic investment.

Among studies that found foreign investment to positively impact domestic investment is Setiyanto (2022), in a study on Indonesia, using quarterly data from 1990 Q2 to 2020 Q2, the study found a complementary effect of FDI in the primary and secondary sectors and a neutral effect in the tertiary sector. Ngeendepi and Phiri (2021) investigated the complementarity or substitution effect of FDI for 15-countries in the Southern African Development Community (SADC) region using data from 1991 to 2019. Employing panel pool mean group ARDL, the study found that FDI complements domestic investment both in the short and in the long run. Gizaw, Dedeho and Lodamo (2021) analysed the impact of FDI on domestic investment for Ethiopia from 1981 to 2019 using an ARDL approach, and the study found that FDI positively impacts domestic investment. Mushtaq, Shaheen and Khan (2020) studied the impact of FDI and foreign remittances on domestic investment on a sample of five South Asian economies using data from 1976 to 2017. The study found that two capital inflows to increase domestic investment.

Among the studies that found foreign direct investment to negatively impact domestic investment, Djokoto (2021) examined the impact of FDI on domestic investment in the food manufacturing sector using an unbalanced panel dataset of 49 developing, transition and developed countries between 1993 and 2016. Using Generalised Method of Moments (GMM), the study found FDI to negatively impact domestic investment in developed countries in the short run. In the long run, the study found FDI to substitute domestic investment across all the countries. In the same vein, Budang and Hakim (2020) investigated the complementarity or substitution effect of FDI on domestic investment in 38 Asian countries using data for the period 1993-2016. The study found FDI to substitute domestic investment.

In the same spirit, in a study on the impact of FDI on domestic investment for Cote d'Ivoire, Oualy (2019) also found FDI to negatively impact domestic investment, but only in the long run, using time series data from 1975 to 2018. Similarly, Ibhagui and Olawole (2019) found FDI to substitute domestic investment in the Organization of the Petroleum Exporting Countries (OPEC) countries, except Angola and Kuwait. Ahmad et al (2018), employing panel data analysis and data for 30 Chinese provinces, found that FDI substituted for domestic investment when DOLS and GMM approaches were applied. Selmi (2016) also studied the impact of FDI on local investment in the MENA region, using a sample of 7 countries - Algeria, Morocco, Jordan, Syria, Tunisia, Lebanon and Egypt. The study found FDI to negatively impact local investment.

Liu et al. (2015), employing data from 1978 to 2011 for China, examined the impact of FDI on regional growth and inequality. The study found FDI to positively impact growth through enhancement of physical and human capital. However, the study also pointed out the negative impact of FDI through substitution effect on domestic investment and increasing the opportunity cost of technology innovations. Mutenyo, Asmah and Kalio (2010), in a study on 34 Sub-Saharan countries on the crowd-in or crowd-out effect of foreign direct investment on private investment, found a crowd-out effects to prevail for the sample countries.

Some studies found mixed results. Jude (2019) examined the impact of foreign investment on domestic investment for 10 Central and Eastern European countries using data from the period 1995-2015. The study found foreign investment to negatively impact domestic investment in the short run and positively in the long run. Xu and Yuan (2012), in a study examining the impact of foreign investment on domestic investment with particular emphasis on regional differences, found that FDI had a negative effect on domestic investment in the eastern and central regions, while promoting domestic investment in the western region. Adams (2009), in a study on sub-Saharan African countries, using data from 1990 to

2003, found that domestic investment had a positive effect on economic growth. The study also found that FDI had a negative effect on growth in the short run and a positive impact in the long run.

Polat (2017) assessed the impact of FDI on domestic investment for 30 countries within the Organisation for Economic Co-operation and Development (OECD) for the period from 2006 to 2013. By employing the one-step Generalised Method of Moments system, the study found that overall FDI did not have any effect on domestic investment. However, inter-company loans were found to have a positive effect on domestic capital formation.

The literature reviewed points to the mixed results on the impact of FDI on domestic investment. Thus, a country -by -country analysis of the relationship between the two should be done to allow policy makers to come up with relevant FDI-domestic investment policies. The literature indicates a departure from the widely held notion that FDI is invariably beneficial for domestic investment, underscoring the importance of conducting rigorous country-specific analysis prior to formulating FDI policies.

3. ESTIMATION TECHNIQUES

The study employs the non-linear autoregressive distributed lag (NARDL) developed by Shin et al. (2014) to investigate the impact of foreign direct investment on domestic investment. The approach was selected due to numerous advantages it provides over other methods. For example, the approach departs from the traditional ARDL by decomposing the independent variable, in this case, FDI into positive and negative shocks on domestic investment. The results of the study based on the NARDL are more informative on the fluctuations in FDI and the subsequent impact on domestic investment.

Variables

Variables of interest in this study are domestic investment (DI), foreign direct investment inflows (FDII) and outflows (FDIO) captured as a percentage of GDP. Domestic investment is measured by gross fixed capital formation as a percentage of GDP, while FDI inflows and outflows are captured as a percentage of GDP. Other control variables included in the model are inflation (INF) measured by the change in Consumer Price Index, domestic saving as a percentage of GDP (DS) and Gross Domestic Product per Product (GDPPC). All the variables used in this study are in levels.

Table 1: Variable description and data source

Variable	Description	Data Source
DI	Gross fixed capital formation as a percentage of GDP	WDI
FDII	Foreign direct inflows investment as a percentage of GDP	WDI
FDIO	Foreign direct outflows investment as a percentage of GDP	WDI
INF	Change in CPI	WDI
GDPPC	Gross Domestic Product per Product	WDI
DS	Domestic saving as a percentage of GDP	WDI

Note: WDI = World Development Indicators

Source: Author´s calculation

General model specification

$$DI = f\left(FDII, FDIO, INF, GDPPC, DS\right) \quad (1)$$

Where:

DI = domestic investment

FDII = foreign direct investment inflows

FDIO = foreign direct investment outflows

INF = inflation

GDPPC = Gross Domestic Product Per Capita

DS = domestic savings

The model accounts for positive and negative shocks in FDII and FDIO on domestic investment. Foreign direct investment inflows (FDII) and outflows (FDIO) are decomposed into positive and negative partial sum.

$$FDII_t = \rho_0 + FDII_t^+ + FDII_t^- \quad (2)$$

Where:

$$FDII_t^+ = \sum\nolimits_{j=1}^{t} \Delta FDII_t^+ = \sum\nolimits_{j=1}^{t} \max\left(\Delta FDII; 0\right) \quad (3)$$

$$FDII_t^- = \sum\nolimits_{j=1}^{t} \Delta FDII_t^- = \sum\nolimits_{j=1}^{t} \min\left(\Delta FDII_j; 0\right) \quad (4)$$

The positive and negative partial sums for foreign direct investment outflows are given in equation (5) and (6).

$$FDIO_t = \rho_0 + FDIO_t^+ + FDIO_t^- \text{ ....(5)}$$

Where:

$$FDIO_t^+ = \sum_{j=1}^{t} \Delta FDIO_t^+ = \sum_{j=1}^{t} \max\left(\Delta FDIO;0\right) \text{ ....(6)}$$

$$FDIO_t^- = \sum_{j=1}^{t} \Delta FDIO_t^- = \sum_{j=1}^{t} \min\left(\Delta FDIO_j;0\right) \text{ ....(7)}$$

Based on Equation (2) to (7) the NARDL model is given in Equation (8) as:

$$\begin{aligned}\Delta DI_t &= \delta_0 + \sum_{i=1}^{p} \delta_{1i} \Delta DI_{t-i} + \sum_{i=0}^{q1} \delta_{2i}^+ \Delta FDII_{t-i}^+ + \sum_{i=0}^{q2} \delta_{3i}^- \Delta FDII_{t-i}^- + \sum_{i=0}^{q3} \delta_{4i}^+ \Delta FDIO_{t-i}^+ \\ &+ \sum_{i=0}^{q4} \delta_{5i}^- \Delta FDIO_{t-i}^- + \sum_{i=0}^{q5} \delta_{6i} \Delta INF_{t-i} + \sum_{i=0}^{q6} \delta_{7i} \Delta GDPPC_{t-i} + \sum_{i=0}^{q7} \delta_{8i} \Delta DS_{t-i} + \alpha_1 DI_{t-1} \\ &+ \alpha_2^+ FDII_{t-1}^+ + \alpha_3^- FDII_{t-1}^- + \alpha_4^+ FDIO_{t-1}^+ + \alpha_5^- FDIO_{t-1}^- + \alpha_6 INF_{t-1} + \alpha_7 GDPPC_{t-1} \\ &+ \alpha_8 DS_{t-1} + \mu_{1t} \qquad .(8)\end{aligned}$$

Where: δ_0 = constant; δ_1-δ_8= short-run coefficients; α_1-α_8 = long-run coefficients; and μ_1t = error term.

A test for a long-run relation is based on the hypothesis:

H0: α_1=α_2=α_3=α_4=α_5=α_6=α_7=α_8=0, against the hypothesis of a long run relationship among the variables in the model.

H1: α_1 ≠ α_2 ≠ α_3 ≠ α_4 ≠ α_5 ≠ α_6 ≠ α_7 ≠ α_8 ≠ 0.

The NARDL error correction model of Equation 8 is specified in Equation (9) as:

$$\begin{aligned}\Delta DI_t &= \delta_0 + \Delta DI_t = \delta_0 + \sum_{i=1}^{p} \delta_{1i} \Delta DI_{t-i} + \sum_{i=0}^{q1} \delta_{2i}^+ \Delta FDII_{t-i}^+ + \sum_{i=0}^{q2} \delta_{3i}^- \Delta FDII_{t-i}^- \\ &+ \sum_{i=0}^{q3} \delta_{4i}^+ \Delta FDIO_{t-i}^+ + \sum_{i=0}^{q4} \delta_{5i}^- \Delta FDIO_{t-i}^- + \sum_{i=0}^{q5} \delta_{6i} \Delta INF_{t-i} + \sum_{i=0}^{q6} \delta_{7i} \Delta GDPPC_{t-i} \\ &+ \sum_{i=0}^{q7} \delta_{8i} \Delta DS_{t-i} + \lambda ECM_{t-1} + \mu_{2t} \qquad \text{...........(9)}\end{aligned}$$

Where: ECM = Error correction term.

λ is the coefficient on the error term and is expected to have a negative sign confirming that the model converges to the equilibrium after a disequilibrium in the model.

4. EMPIRICAL RESULTS

A test on the stationarity of variables included in the model was done by using the Dickey-Fuller Generalised Least Square (DF-GLS) and the Phillip-Perron (PP) tests. This was done to ensure that the model does not have variables stationary with a higher order than one, which is not acceptable with the approach, and to avoid spurious regression. The results of the unit root test are reported in Table 2.

Table 2: Unit Root Results

Dickey-Fuller Generalised Least Squares (DF-GLS) and Phillip-Perron Tests				
Variable	Dickey-Fuller Generalised Least Square (DF-GLS)		Phillips-Perron (PP)	
	Level	Δ	Level	Δ
DI	0.083	-5.453***	-3.766	-5.673***
FDII	-2.041	-6.687***	-4.028	-8.329***
FDIO	-2.090	-5.762***	-2.830***	-7.548***
INF	-2.100*	-	-2.598	-7.646***
GDPPC	-2.087	-6.301***	-2.497	-9.661***
DS	-1.417	-4.880***	-2.838	-6.355***

Note: *, ** and *** denote stationarity at 10%, 5% and 1% significance levels respectively.

Source: Author´s calculation

Results reported in Table 2 confirm that all the variables included in the model are stationary in either level of first difference. Table 3 reports cointegration results based on the ARDL approach developed by Pesaran and Shin (1999) and expanded by Pesaran et al. (2001).

Table 3: Cointegration Results

F-Statistic			Cointegration Status		
5.226**			Cointegrated		
Asymptotic critical values					
10%		5%		1%	
I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
2.254	3.388	2.685	3.960	3.713	5.326

Note: *, ** and *** denote stationarity at 10%, 5% and 1% significance levels respectively.
Source: Author´s calculation

The calculated F-statistics reported in Table 3 is compared to the upper and lower critical values also reported in the table. If the F-statistic is greater than any upper bound at 1%, 5% or 10%, cointegration is confirmed. However, if the F-statistic is below the lower bound, no long run relationship is confirmed. Results reported in Table 4 confirm long run relationship among the variables in the model given that the F-statistic of 5.226 is greater than the upper bound critical value at 5% level of significance. The next step is a test of long run and short run asymmetry on FDII and FDIO to check the suitability of an NARDL approach. The results are presented in Table 4.

Table 4: Long run and Short Run Asymmetric Test Results

Test	F-statistic	P-value	Decision
W_{LR} - FDI	3.127	0.018*	Asymmetric
W_{SR} - FDI	10.867	0.001***	Asymmetric
W_{LR} -FDIO	8.982	0.002**	Asymmetric
W_{SR} FDIO	8.105	0.003**	Asymmetric

Source: Author´s calculation

W_{LR} = long-run asymmetric test

W_{SR} = short-run asymmetric test

+ and - denotes positive and negative shocks.

*, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively

The results presented in Table 4 confirmed asymmetry on positive and negative values on FDI inflows and outflows. This confirms that the study can proceed with the NARDL approach.

To proceed with the analysis, a parsimonious model is selected based on the Schwarz Bayesian Criteria (SBC) with optimal lags (2, 3, 1, 2, 1, 0, 3, 3) for domestic investment (DI), FDI and partial sums, FDIO and partial sums, inflation (INF), Gross Domestic Product per capita (GDPPC) and domestic savings (DS). The long run and short run results are reported in Table 5.

Table 5. Long-run and short-run Results

Dependent Variable is DI		
Panel A: Long-Run Results		
Regressor	Coefficient	T-ratio [p-value]
$FDII^{+}$	-2.699***	-5.482[0.000]
$FDII^{-}$	1.180	-1.679 [0.103]
$FDIO^{+}$	-5.173*	-1.815[0.080]
$FDIO^{-}$	-6.807**	-2.390[0.023]
INF	-1.040***	-3.522[0. 001]
GDPPC	28.983***	4.525[0.000]]
DS	-0.617***	-4.023[0.000]
Panel B: Short-Run Results		
Regressor	Coefficient	T-ratio [p-value]
$\Delta DI(-1)$	0.561*	2.052 [0.059]
$\Delta FDII^{+}$	11.885	0.522 [0.609]
$\Delta FDII^{+}(-1)$	1.173**	2.716 [0.017]
$\Delta FDII^{+}(-2)$	1.118**	2.803 [0.014]
$\Delta FDII^{-}$	0.1652	0.626 [0.541]
$\Delta FDIO^{+}$	-0.073	-0.233 [0.819]
$\Delta FDIO^{+}(-1)$	3.040**	2.384 [0.032]
$\Delta FDIO^{-}$	-0.598	-0.488 [0.633]
$\Delta GDPPC$	10.196***	3.706 [0.002]
$\Delta GDPPC(-1)$	7.741**	2.364 [0.033]
$\Delta GDPPC(-2)$	8.782***	-.370 [0.005]
ΔDS	-0.109	-0.7214[0.483]
$\Delta DS(-1)$	0.486***	3.285[0.005]
$\Delta DS(-2)$	0.392*	3.060 [0.054]
$ECM(-1)$	-0.654***	-5.427 [0.000]
Panel C: Test statistics		
R- Squared	0.718	
R-Bar-Squared	0.517	
F-statistic [Prob]	3.568 [0.004]	
DW Stat	1.826	
Serial correlation	2.598[0.116]	
Heteroscedasticity	0.775[0.711]	

Note: *, ** and *** denote stationarity at 10%, 5% and 1% significance levels respectively.

Source: Author´s calculation

The results reported in Table 5, Panel A and Panel B confirmed that positive shocks in foreign direct investment inflows have a substitution effect on domestic investment. This was confirmed by the coefficient of $FDII^{+}$ which was negative and statistically significant at 1%. In the short run, positive shocks in FDI were found to have positive impact on domestic investment in Botswana. This was confirmed by $\Delta FDII^{+}(-1)$ and $\Delta FDII^{+}(-2)$ coefficients that are positive and statistically significant at 5% level. Thus, FDI inflows complement domestic investment in the short run. However, the study found that negative shocks in FDI had no significant impact on domestic investment, irrespective of the time considered. Positive shocks in FDII were found to have greater and lasting influence on domestic investment as reported by the dynamic multiplier graphs in Figure 3.

Results on foreign direct investment outflows confirmed that positive shocks have a substitution effect on domestic investment in the long run and a complementary impact in the short run. However, negative shocks on foreign direct investment outflows have a substitution effect on domestic investment in the long run and insignificant in the short run. Overall, negative shocks in foreign direct investment outflows have a deep effect on domestic investment in Botswana according to the dynamic multiplier graph in Figure 3.

Other results reported in Table 4 revealed that inflation has a negative effect on domestic investment in the long run, while Goss Domestic Product per capita has a positive effect on domestic investment regardless of the time considered. Domestic savings were found to negatively effect domestic investment in the long run, and a positive effect was confirmed on domestic investment in the short run. The negative effect could be attributed to a decrease in expenditure as households save more, which negatively affects demand for goods and services. This results in a decrease in aggregate demand, causing a decline in reinvestment or new investment. However, in the short run savings tend to boost resources available for investment through bank intermediation.

The variables included in the model explain 72% of the variability in domestic investment and an error term (ECM) of -0.65 with the expected negative sign. It takes about one year and less than six months to reach convergence back to the equilibrium whenever a disequilibrium is experienced in the system. The model passed heteroscedasticity, serial correlation as reported in Table 5.

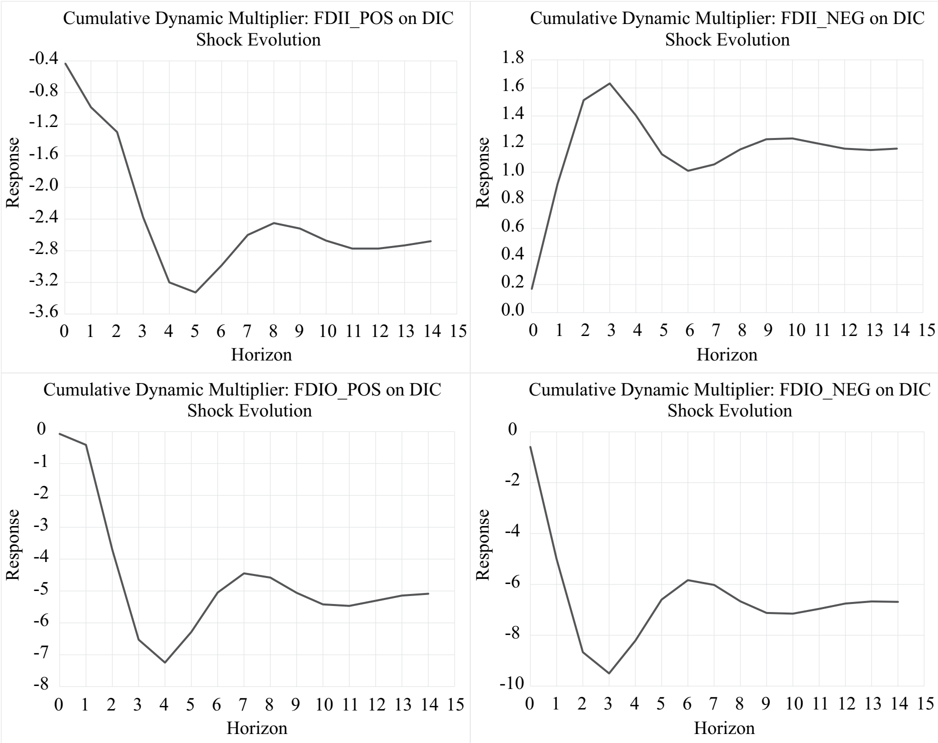

Figure 2: Cumulative Dynamic Multiplier Graphs
Source: Author´s calculation

CONCLUSIONS

The impact of FDI inflows and outflows on domestic investment was investigated for Botswana using data from 1990 to 2022. The study was motivated by the drive that Botswana has taken to attract FDI to support the diversification of the economy. The question this study sought to answer was whether foreign investment inflows and outflows in Botswana complement or substitute domestic investment in Botswana. Using the non-linear ARDL, the study found that positive shocks in foreign direct investment complemented domestic investment in the short run, but substituted domestic investment in the long run. The study also found that positive shocks on foreign direct investment outflows substituteed domestic investment in the long run, while complemented domestic investment in the short run. On the other hand, negative shocks in FDIO are associated with a negative change in domestic investment in the long run, and insignificant in the short run. Overall, positive shocks in FDII have greater weight on domestic investment than negative shocks, while negative shocks on FDIO have greater effect on domestic investment in Botswana than positive shocks, as indicated by the dynamic multiplier graphs of the two key variables.

It can be concluded that foreign direct investment plays an important role in Botswana in supporting domestic investment in the short run, but not in the long run. The results support the the Government of Botswana's decision to open the economy to foreign investors as part of its efforts to diversify the economy. Botswana is therefore encouraged to continue strengthening policies that attract foreign direct investment, such as the use of one-stop shop to simplify administration processes for investors and the provision of a conducive business environment. However, this move needs to be undertaken with caution, as excessive reliance on foreign investment may lead to substitution effect on domestic investment in the long run. These findings further indicate that foreign direct investment outflows tend to compete with domestic investment in the long run when there is a positive shock in FDIO, whereas negative shocks in FDIO are associated with an increase in domestic investment over the same period. Based on these results, it is recommended that policymakers in Botswana encourage domestic investors to prioritise opportunities within the domestic economy, before investing abroad. The Government of Botswana may also introduce targeted incentives to stimulate domestic investment in industries with strong growth potential. In doing so, Botswana can position itself as a preferred destination for domestic investors prior to the consideration of outward investment.

Although efforts were made to ensure the scientific rigour of the study, several limitations should be acknowledged. The study period spans from 1990 to 2022, reflecting constraints related to data availability. The use of alternative datasets may yield different results. Furthermore, domestic investment was proxied by gross fixed capital formation; future research could benefit from the use of disaggregated sectoral data in order to capture the sectore-specific effects of foreign direct investment inflows and outflows.

Conflict of interests

The author declares there is no conflict of interest.

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ДА ЛИ СТРАНЕ ДИРЕКТНЕ ИНВЕСТИЦИЈЕ ДОПУЊУЈУ ИЛИ ЗАМЈЕЊУЈУ ДОМАЋЕ ИНВЕСТИЦИЈЕ У ПОДСТИЦАЊУ ДОМАЋИХ ИНВЕСТИЦИЈА У БОЦВАНИ?

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САЖЕТАК

Утицај прилива и одлива страних директних инвестиција на домаће инвестиције анализиран је за Боцвану коришћењем података за период од 1990. до 2022. године. Студија је мотивисана настојањем Боцване да привуче стране директне инвестиције како би подржала диверсификацију своје економије. Питање на које је ово истраживање настојало да одговори било је: „Да ли либерализација прилива и одлива страних инвестиција у Боцвани подржава домаће инвестиције?" У студији је примијењен нелинеарни ауторегресивни модел расподијељених кашњења како би се испитало да ли постоји комплементарност или супституција између домаћих инвестиција и страних директних инвестиција у Боцвани. Резултати показују да позитивни шокови у приливима страних директних инвестиција допуњују домаће инвестиције у кратком року, али их у дугом року замјењују, док су негативни шокови у приливима страних директних инвестиција статистички безначајни без обзира на посматрани временски период. Позитивни шокови у одливима страних директних инвестиција замјењују домаће инвестиције у дугом року, док их у кратком року допуњују. С друге стране, негативни шокови у одливима страних директних инвестиција изазивају позитивну промјену у домаћим инвестицијама у дугом року, али су у кратком року без значајног утицаја. У раду се такође разматрају импликације за економску политику.

Кључне ријечи: *приливи страних директних инвестиција; одливи страних директних инвестиција; Боцвана; нелинеарни ауторегресивни модел расподијељених кашњења (NARDL); инвестициона политика.*

THE WESTERN BALKANS INSURANCE MARKET: COMPETITION, CONCENTRATION AND MANAGERIAL PRACTICES[1]

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ABSTRACT

This paper analyses the competition and concertation of insurance markets in Bosnia and Herzegovina, Montenegro, Serbia, and North Macedonia. We measure market structure using the Herfindahl–Hirschman Index (HHI) and market development using premiums per capita (EUR) and the share of premiums in GDP. Country-specific linear time trends are estimated with OLS and heteroskedasticity and autocorrelation-consistent standard errors, complemented with rank-based Kendall and Spearman tests designed for short series and potential nonlinearity. We document statistically significant deconcentration in Montenegro and Serbia, a significant increase in concentration in Bosnia and Herzegovina, and an inconclusive pattern for North Macedonia given the limited availability of data. In parallel, premiums per capita trend upward across all markets, with typical annual growth ranging from roughly 9% (Bosnia and Herzegovina) to 14% (Serbia). Taken together, the results support the hypothesis that higher competition is not directly or uniformly associated with market development over the 2019–2024 window. Policy recommendations emphasise proportionate entry facilitation, conduct-focused supervision, and investment in statistical capacity for line-of-business series and longer time frames.

1. INTRODUCTION

In today's dynamic economic environment, competition is a key factor that shapes and influences the development of various industrial sectors, including the insurance sector. Competition within the insurance market has a significant impact on its development, efficiency, and innovation. Understanding the dynamics of competition and its effect on the insurance market is essential for proper sector management and the design of relevant policies.

Within insurance specifically, the Herfindahl–Hirschman Index (HHI) is the standard summary of market structure, computed as the sum of squared market shares. Its interpretation is straightforward: higher values indicate greater concentration and, by implication, less structural competition, while lower values indicate more fragmented structures. HHI's widespread use in merger analysis and regulatory diagnostics makes it a natural starting point for tracking structural trends in small markets. Nevertheless, HHI does not observe pricing to risk, claim-handling quality, or innovation, all of which mediate the mapping from structure to market development and consumer welfare. For this reason, our empirical design deliberately separates structural indicators (HHI) from development metrics, such as premiums per capita and the share of premiums in GDP, in order to study their co-movement.

The policy relevance for the Western Balkans is immediate. Historical legacies of direct state involvement and segmented distribution channels coexist with efforts to harmonise supervision, expand product availability, and digitise distribution. In such settings, market deepening may arise through scale economies and improved efficiency even if concentration rises, or conversely through entry and business-model diversification even if concentration falls. Understanding which of these trajectories is unfolding is a necessary input to proportionate, risk-based supervision and market conduct policy.

Empirically, we assemble annual country–year series for the four markets from 2019 to 2024, measuring concentration via HHI derived from company-level written premiums, and development via premiums per capita (EUR) and premiums/GDP. The data originate from national supervisory authorities and central banks, with local-currency premiums converted to EUR. North Macedonia's published series begins in 2022, which constrains inference for that market and motivates methods that remain valid in very short series.

Methodologically, we estimate country-specific linear time trends in HHI using ordinary least squares while conducting inference with Newey–West heteroskedasticity and autocorrelation-consistent (HAC) standard errors, which are suited for short annual series that may exhibit heteroskedasticity and low-order serial correlation. Since linear trends can be sensitive to functional-form assumptions and outliers, and ultra-short series can yield limited power, we complement the parametric trends with rank-based Kendall and Spearman tests of monotone association between time and HHI. For development indicators, we similarly assess monotone trends and summarise typical dynamics using distribution-free medians of year-over-year growth in premiums per capita.

This study contributes in three ways. First, it integrates a theory-grounded discussion of competitiveness with a short-panel empirical assessment of structural and developmental trajectories in four transitioning insurance markets. Second, it deploys a dual-track inferential strategy, HAC-robust parametric trends alongside rank-based tests, calibrated to the realities of short series in small markets. Third, by analysing structure and development separately, it provides evidence on whether market deepening requires deconcentration or whether these dimensions can decouple over policy-relevant horizons.

The main hypothesis is that market concentration within each country has changed significantly over time during the observation window, as detected by HAC-robust linear trends and corroborated, where possible, by rank-based tests. This hypothesis recognises that even modest year-to-year changes may cumulate to economically meaningful shifts in small markets.

The first auxiliary hypothesis is that the insurance market development, measured by premiums per capita and the share of premiums in GDP, has increased over time across the four markets, consistent with ongoing modernisation and financial-sector deepening in the region. This hypothesis is evaluated using Kendall trend tests and robust summaries of year-over-year growth.

The second auxiliary hypothesis is that a higher level of competition in structure (lower HHI) is not directly or uniformly associated with a higher degree of market development over the sample period; that is, deepening can occur alongside either deconcentration or rising concentration depending on institutional and market-conduct conditions.

These hypotheses deliberately separate questions of change (H1 and H1a) from questions of association (H2a). The first two examine whether there are statistically detectable trends in structure and development within very short samples, while the third examines whether those trends co-move systematically. In this way, the analysis avoids conflating structure with outcomes and situates inference within a framework that is both empirically feasible and policy-relevant for supervisory authorities in the Western Balkans.

2. LITERATURE REVIEW

From 2020 to 2025, numerous studies have linked the structure of insurance markets with managerial practices, competition policy, digitalisation, and firm efficiency. Recent sources emphasise that both competition and market concentration have significant implications for insurers' performance, while managerial decisions and innovation can shape market structure. Regulators and researchers increasingly argue that competitive and efficient insurance markets contribute positively to the broader economy—an especially important point for small markets. For example, analyses of Albania's insurance market indicate that life insurance remains highly concentrated, though concentration is declining as new firms enter, whereas the non-life segment is moderately concentrated with a rising concentration trend. These findings confirm that the entry of new competitors can reduce concentration and strengthen competition. Given the sector's economic importance, researchers stress that the market should be as competitive and efficient as possible to provide consumers with protection at lower cost, and they highlight concentration analysis as a key tool for regulators and policymakers (Bezati, 2024).

Several recent studies examine the link between competition in insurance markets and insurers' performance. For example, an analysis of Eastern European markets finds that greater financial inclusion (broader availability of insurance) is associated with stronger underwriting outcomes, and that these positive effects are significantly more pronounced in more competitive (i.e., less concentrated) markets (Srbinoski et al., 2025). This result suggests that policies promoting competition and higher insurance penetration can yield better outcomes for consumers and firms (Srbinoski et al., 2025).

In other words, competition acts as a catalyst for efficiency: under more intense market rivalry, insurers are incentivised to improve performance and innovate, which translates into lower loss per policy and greater financial stability for the sector (Srbinoski et al., 2025). These findings align with a broader literature that bridges industrial organisation and management in insurance: market structure shapes firm behavior, while managerial decisions (e.g., expanding the customer base or pricing strategies) in turn influence market competitiveness (Srbinoski et al., 2025).

Efficiency of insurance companies as a performance measure is also a focus of recent studies, with Data Envelopment Analysis (DEA) frequently used to assess productivity and resource management. Koprivica et al. (2025) analyse the technical efficiency of insurers in five Western Balkan countries (2015–2022) and find substantial cross-country differences: insurers in Serbia exhibit the highest average efficiency, while those in Albania show the lowest (Milašinovic et al., 2025). Moreover, efficiency levels are significantly influenced by management-controlled factors—such as firm size, degree of specialisation, growth rate, solvency, and profitability—which reflect managerial decisions and strategies (e.g., portfolio diversification, cost control, capital management) that can enhance or constrain efficiency. These findings imply that, through organisational design and business strategy, insurance management can indirectly shape market structure—more efficient firms may grow and capture larger market shares, potentially affecting market concentration (Milašinovic et al., 2025). A global literature review on insurer efficiency, including a bibliometric analysis of DEA studies, highlights a growing emphasis on digital transformation, artificial intelligence, and sustainability in performance evaluation (Kumar & Kumar, 2024). Differences between life and non-life insurers are also observed, partly due to product complexity and the intensity of market competition in those segments. In short, markets with sharper competition display distinct efficiency and productivity patterns, underscoring the importance of incorporating competitive dynamics into performance analyses.

A further key trend in the recent literature is digitalisation in the insurance industry and its implications for competition and management. Although the sector has traditionally been viewed as conservative, newer studies document an accelerated digital transformation that is reshaping how firms operate and compete. Digital technologies, such as InsurTech innovations, big data analytics, and artificial intelligence, have become critical strategic tools for insurance managers. Njegomir et al. (2021) argue that digital transformation permeates the entire insurance value chain, from underwriting and risk management to policy sales and claims handling and/or fundamentally altering operational processes. In this view, technology functions as the “fuel” of organisational strategy, enabling faster, better-informed decision-making across all functions Njegomir et al. (2021).

The adoption of new digital tools also deepens customer orientation: through digital channels and analytics, insurers better understand client needs, tailor products and prices to individual risks, and enhance the user experience

For example, digital platforms and online distribution reduce intermediation costs and expand insurers’ market reach, potentially intensifying competition among firms. At the same time, process automation increases speed and efficiency, lowers operating costs, and can put downward pressure on premiums.

Recent empirical work corroborates these benefits. Bayar et al. (2023) find a positive link between ICT penetration and insurance market growth in new EU member states, with evidence of bidirectional causality suggesting that stronger digital infrastructure supports insurance development, while a growing insurance sector further stimulates ICT investment. Therefore, digitalisation strengthens industry competitiveness and compels managers to adopt new business models. During the COVID-19 period this shift accelerated: major insurers invested in online channels, chatbots, telematics, and automated claims assessment to maintain business continuity and retain customers. These experiences underscore that managerial adaptation to digital change has become essential for survival and growth, as digitally agile firms respond more quickly to market shifts and achieve operational advantages over traditional competitors Bayar et al. (2023).

The theory of competitiveness has its roots in trade theory on competitive advantage. The main views on competitiveness emerged in the 1980s and 1990s, and can be divided into two streams. The first stream links competitiveness with lower labour costs and favourable domestic policies (Brander & Spencer, 1985). The second emphasises productivity as the catalyst of competitiveness and prosperity (Delgado, Ketels, Porter, & Stern, 2012; Krugman, 1990, 1994; Porter, 1990). The productivity-based view as a measure of competitiveness has become the most widely used definition and remains the most common indicator of good performance and competitiveness.

However, from the perspective of policymakers aiming to raise national competitiveness, using productivity to measure competitiveness has two drawbacks. First, it provides no information on the determinants of competitiveness. Policymakers, therefore, would not know which policy instruments to use to improve competitiveness. Second, productivity reflects only a static measure of competitiveness and provides no information on whether the economy is prepared to face changes in the economic environment.

A multitude of components can affect a firm's ability to perform well. These components may be directly linked to firm characteristics or indirectly affect the firm through its business environment. The latter can be further divided into the immediate and the macroeconomic environment, depending on whether it is close to the firm (clients, suppliers, competitors, etc.) or further away (national infrastructure, governance, trade policy, etc.) in terms of connectedness and ability to influence. Moreover, since firms not only need to be competitive today but must remain competitive over time, it is important to consider not only static but also dynamic components of competitiveness.

A firm's ability to compete at a given moment is reflected in its ability to meet market requirements for quality, quantity, and timing at a competitive price. In economic models, this capacity is usually described through the optimisation of the production function under certain constraints, where those constraints mainly reflect access to inputs. In business administration, the same concept is described as the optimisation of the production process, where management plays a key role in designing and monitoring that process.

Indeed, managerial competence has proven to be a good indicator of how well a firm performs in the market. Managerial practices can improve productivity through their influence on the marginal productivity of inputs and resource constraints (Syverson, 2011), as well as on growth and longevity (Bloom & Van Reenen, 2010). It has also been found that managers' years of experience affect firm performance (Bertrand & Schoar, 2003).

Another aspect that influences all four components (quantity, quality, timeliness, and price) of competitive ability is access to inputs and suppliers. Empirical evidence shows that access to foreign intermediate inputs can increase firm efficiency by providing more diverse and higher-quality inputs (Bas & Strauss-Kahn, 2014), especially for small and medium-sized enterprises (SMEs), as they can raise their productivity through learning, variety, and quality (Amiti & Konings, 2007). This aspect includes access to key services such as water and electricity. The ability to perform financial transactions smoothly is also important for production and sales processes.

The time dimension within the "competition" pillar largely depends on the quality of infrastructure and logistics services. Logistics costs make up a significant share of the value of final manufactured goods, especially for SMEs and in developing countries (Schwartz, Guasch, Wilmsmeier, & Stokenberga, 2009). Although logistics costs are influenced by firms' ability to manage logistics, they often depend on external factors. For example, an impact assessment of road network expansion in Peru between 2003 and 2010 estimates that total Peruvian exports in 2010 would have been roughly 20% lower without the road development program (Volpe Martincus, Carballo, & Cusolito, 2017).

Both the economics and business administration literature indicate that access to finance is an important determinant of firm performance in various aspects, including investment, growth, firm size distribution (Ayyagari, Demirgüç-Kunt, & Maksimovic, 2011), and innovation (Demirgüç-Kunt, Beck, & Honohan, 2008). Musso and Schiavo (2008) show how access to external finance in France positively affects firm performance in terms of sales, capital stock, and employment. Access to finance is consistently cited as one of the primary obstacles facing SMEs (Ayyagari, Demirgüç-Kunt, & Maksimović, 2012). It also determines a firm's ability to enter export markets and expand abroad (Bellone, Musso, Nesta, & Schiavo, 2010; Berman & Héricourt, 2010), which are capital-intensive endeavours involving high fixed and variable costs. Access to and the expansion of credit largely depend on a supportive legal and regulatory framework.

Competitiveness is a key factor that shapes the insurance market, influencing its dynamics and prosperity. Through the lens of competitiveness, the state, insurance companies, and clients can either flourish or falter, depending on the quality of competition in the market.

High-quality competition in the insurance market can benefit all stakeholders. Clients benefit from a wide range of products and services, competitive prices, and a high level of service. Quality competition encourages insurance companies to innovate and provide better products tailored to market needs. This leads to improved service quality, greater efficiency, and transparency in the industry. The state also benefits from quality competition through increased consumption, job creation, and higher tax revenues. However, the loyalty and quality of competition are crucial factors. Unsportsmanlike behavior by competitors, such as unfair trade practices, can lead to market distortions, reduced consumer choice, and poor service quality. This can result in the loss of consumer trust, diminished competition, and market stagnation. Under such circumstances, to prosper, clients, the state, and insurance companies must rely on regulatory agencies and legislation that ensure fair and honest competition. It is also important that insurance companies focus their efforts on delivering high-quality products and services and on building long-term relationships with clients.

In the opposite scenario, loss of loyalty and low-quality competition can lead to the decline in all participants in the insurance market. Clients would suffer from a lack of choice, high prices, and poor service. The state would lose due to reduced consumption, job losses, and lower tax revenues. Insurance companies would face declining profits, increased costs, and loss of public trust.

Therefore, high-quality competition in the insurance market can be a key factor for the prosperity of all participants. Through fair and honest competition, clients receive better products and services, the state achieves economic benefits, and insurance companies realise stable growth and development. Managing competitiveness in the insurance market requires the cooperation of all stakeholders and the application of effective regulatory frameworks that promote fair competition and industry integrity.

3. METHODOLOGY

The empirical setting comprises four successor states of the former Yugoslavia that are not members of the European Union: Bosnia and Herzegovina (BIH), Montenegro, Serbia, and North Macedonia. The unit of observation is the country–year. For each market, we assemble annual series on total gross written premiums, market concentration, and two indicators of market depth: premiums per capita (in EUR) and the share of total premiums in domestic GDP. Premiums are collected from national supervisors in local currency and converted to EUR to enable cross-country comparability. Unless otherwise specified in the source documentation, we use the end-of-year exchange rate on 31 December for the conversion. North Macedonia does not publish the relevant premium series before 2022, which constrains the time horizon for that country and motivates the use of inference techniques that are valid in very short series.

Market concentration is measured by the Herfindahl–Hirschman Index (HHI), which summarises the dispersion of market shares across licensed insurers. The HHI is calculated using the data on written premiums of insurance companies operating in respective countries. We further report country-level means, standard deviations, and coefficients of variation to characterise HHI. These descriptive statistics indicate that within-country year-to-year changes are modest relative to cross-country level differences, a feature that is typical of small markets with stable firm configurations and that has implications for the power of formal tests. Graphical inspection of the annual HHI series complements the analysis.

To identify systematic changes in concentration within each market, we estimate simple time trends by country using ordinary least squares (OLS) but conduct inference with heteroskedasticity- and autocorrelation-consistent (HAC) Newey–West standard errors. For each of the countries, we fit

$$HHI_{it} = \beta_0 + \beta_i Year_t + \varepsilon_{it}$$

and interpret as the average annual change in concentration. Negative slopes indicate deconcentration and positive slopes indicate rising concentration. Because annual series in small markets can exhibit both heteroskedasticity and low-order serial correlation, HAC standard errors provide more reliable uncertainty quantification than classical OLS under these conditions (Kiefer, Vogelsang & Bunzel, 2000). For comparison, both HAC and classical p-values are reported. Residual diagnostics include tests for first-order autocorrelation (Durbin–Watson) and for heteroskedasticity (Breusch–Pagan). Given the very short samples, these diagnostics are interpreted descriptively while primary inference rests on HAC standard errors.

Recognising that a linear parametric trend can be sensitive to outliers and that the true trajectory may be non-linear, we complement HAC-OLS with rank-based, non-parametric tests of monotonic association between calendar time and HHI. Specifically, we compute Kendall's τ and Spearman's ρ along with two-sided p-values for each country. These tests do not impose a functional form and are robust in small samples, thereby providing a validity check on the direction of change inferred from . In instances where the time series is extremely short and contains repeated or rounded values, exact small-sample p-values may be uninformative even when the ordering over time is monotonic. In such cases, we report the direction of change and rely on magnitude measures from robust estimators.

Market depth is analysed using two complementary measures, of which premiums per capita, expressed in EUR, serve as a proxy for the intensity of insurance activity per resident, while the share of premiums in GDP scales sectoral activity by macroeconomic size. For premiums per capita, we assess monotonic trends using Kendall's τ and quantify typical dynamics through distribution-free summaries of median year-over-year (YoY) growth rates and their interquartile ranges, which are less sensitive to outliers than mean growth rates. For the share of premiums in GDP, we again compute Kendall's τ, but given the shortness of some series and the prevalence of ties, we emphasise the observed direction and robust magnitude measures over formal small-sample p-values.

4. RESULTS

We collected data on the premiums of insurance companies in the countries of the former Yugoslavia that are not a part of the European Union and analysed the competition on the insurance markets using HHI and premium per capita. The results are presented in the Table 1.

The premiums were collected in local currencies and converted to EUR for the comparability of premiums. The exchange rate on the 31st of December of the respective year was used for the conversion, unless otherwise stated in the methodology of the regulatory body issuing the data.

Table 1: Premiums and HHI indices

Country	Year	Total Premium (local currency)	Total Premium (EUR)	HHI
BIH	2019	762,780,531.58	390,003,493	574.06
BIH	2020	755,894,109.41	386,482,521	581.66
BIH	2021	818,406,455.45	418,444,576	573.83
BIH	2022	881,056,957.44	450,477,269	570.78
BIH	2023	984,030,976.00	503,127,049	619.23
BIH	2024	1,085,511,265.66	555,013,097	630.85
Montenegro	2019	94,763,244.58	94,763,245	1,902.55
Montenegro	2020	93,673,540.74	93,673,541	1,830.12
Montenegro	2021	98,811,849.58	98,811,850	1,844.15
Montenegro	2022	108,283,270.53	108,283,271	1,820.06
Montenegro	2023	119,453,724.61	119,453,725	1,726.81
Montenegro	2024	134,194,150.59	134,194,151	1,688.49
Serbia	2019	107,449,872,000	913,745,331	1,544.70
Serbia	2020	109,916,743,000	934,823,576	1,526.06
Serbia	2021	119,408,670,000	1,015,534,422	1,468.39
Serbia	2022	133,925,041,000	1,141,512,968	1,434.87
Serbia	2023	155,254,730,000	1,324,996,394	1,410.26
Serbia	2024	177,382,869,000	1,515,899,847	1,391.92
North Macedonia	2022	12,785,429,800	207,916,157	894.25
North Macedonia	2023	14,438,596,000	234,793,008	873.02
North Macedonia	2024	15,970,227,000	259,699,602	924.73

Sources: Insurance Agency of Bosnia and Herzegovina (2025); Insurance Supervision Agency of Montenegro (2025); National Bank of Serbia (2025); Insurance Supervision Agency of North Macedonia (2025).

The overview of the main descriptive statistical measures is given in Table 2.

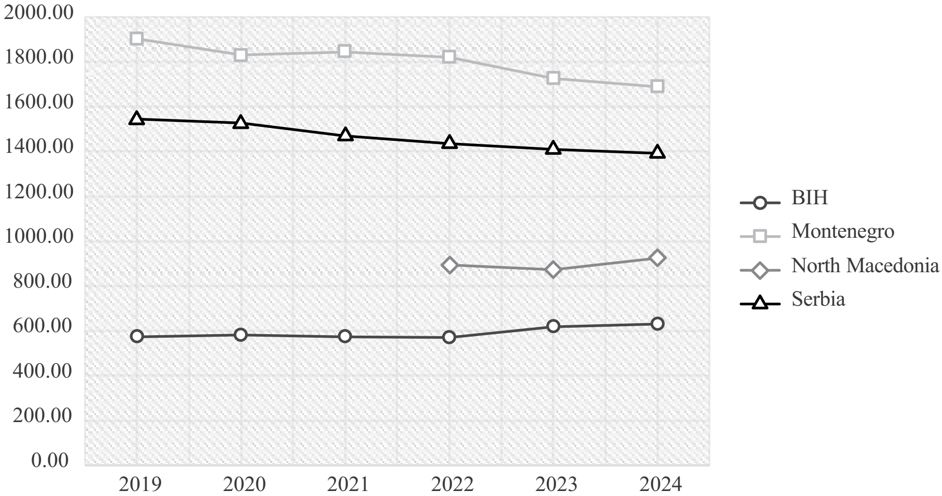
Table 2: Descriptive Statistics

Country	Number of observations	HHI mean	HHI Standard Deviation	HHI Coefficient of Variation (%)
BiH	6	592	26.3	4,45
Montenegro	6	1,802	79.4	4.41
North Macedonia	3	897	26.0	2.90
Serbia	6	1,463	62.2	4.29

Source: authors' calculation

The tabulated panel confirms marked level differences in concentration across markets. Average HHI is lowest in BIH and North Macedonia, and highest in Montenegro and Serbia. Coefficients of variation are modest, between roughly 2.9% and 4.5%, which implies that within-market year-to-year fluctuations are small relative to cross-market level gaps. The graphical series reinforces this finding, with the important caveat that North Macedonia's series begins in 2022 and thus provides only three annual points for inference.

This graphical representation of the HHI indices is given in Graph 1.



Graph 1: HHI Indices
Source: authors' calculation

We also calculated the premium per capita as a measure of the development of the insurance market.

To further examine the concentration of insurance markets, we examine whether the concentration changes monotonically over time for each country separately by estimating a linear trend in the following notation:

$$HHI_{it} = \beta_0 + \beta_i Year_t + \varepsilon_{it}$$

While the estimation of the regression coefficients employs the OLS method, the Newey-West standard errors estimator (HAC) is utilised to account for heteroskedasticity and autocorrelation in the annual data. We report both HAC and OLS p-values for the tes, and check OLS for autocorrelation and heteroskedasticity using Durbin-Watson and Breusch-Pagan tests.

Additionally, to avoid linearity assumptions and limit the sensitivity to outliers, we test for a monotonic association between time and HHI using Kendall's and Spearman's with two-sided p-values (Puth, Neuhäuser & Ruxton, 2015).

The results are given in Table 3.

Table 3: OLS, HAC, Durbin–Watson and Breusch–Pagan Results

Country	OLS slope	HAC SE	p-value (HAC SE)	p-value (not robust)	Durbin–Watson p-value	Breusch–Pagan p-value
BIH	11.24617	2.728044	0.014584	0.056084	0.092	0.66
Montenegro	-40.1239	3.688453	0.000405	0.00444	0.303	0.89
North Macedonia	15.2395	8.594384	0.3269	0.601101	1.000	1.00
Serbia	-32.71	1.747496	4.810^{-05}	0.000344	0.191	0.94

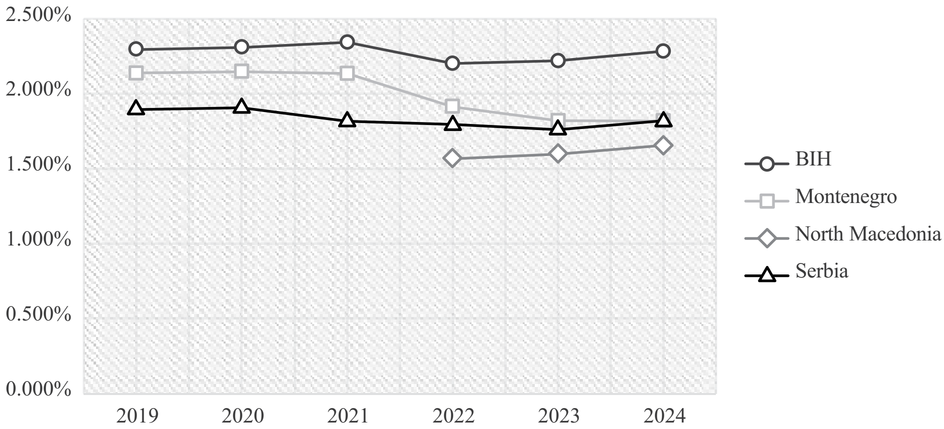
Source: Authors' calculation

Over the observed period, trends in market concentration diverge across the four insurance markets. In Bosnia and Herzegovina (BIH), concentration increased: the HAC-robust linear trend equals +11.2 HHI points per year ($p = 0.0146$). Although the rank-based checks point in the same direction, they are not statistically significant (Kendall $\tau = 0.333$, $p = 0.452$; Spearman $\rho = 0.486$, $p = 0.329$). Residual diagnostics do not reveal major issues beyond a hint of autocorrelation (Durbin–Watson $p = 0.0917$), nor is heteroskedasticity detected (Breusch–Pagan $p = 0.665$), and HAC inference already addresses these concerns.

By contrast, Montenegro and Serbia exhibit a tendency of deconcentration. In Montenegro, the HAC-robust slope is −40.1 HHI points per year ($p = 0.000405$), implying a cumulative reduction of about 200 HHI points. Both Kendall ($\tau = -0.867$, $p = 0.0242$) and Spearman ($\rho = -0.943$, $p = 0.0048$) confirm a downward monotonic trend, and there is no evidence of meaningful curvature or problematic residual structure. Serbia shows a similarly strong decline with a HAC-robust slope of −32.7 HHI points per year ($p = 0.000048$), and the rank tests indicate a perfectly monotonic decrease (Kendall $\tau = -1.000$, $p = 0.0085$; Spearman $\rho = -1.000$, $p < 0.001$).

For North Macedonia, the series is too short to support firm inference. With only three annual observations, the HAC-robust slope of +15.2 HHI points per year ($p = 0.327$) is not statistically different from zero, and neither Kendall nor Spearman provides significant evidence of a monotonic trend. Taken together, these results indicate a statistically significant and accelerating increase in concentration in BIH, pronounced deconcentration in Montenegro and Serbia, and an inconclusive pattern for North Macedonia within the limited sample.

Then, we analysed the premium per capita for the four countries, denoted in EUR, to be comparable. Their trend can be seen in Graph 2.



Graph 2: Premium per capita in EUR
Source: Authors' calculation

Turning to market depth, premiums per capita increased across all four markets, as shown in Table 4.

Table 4: Kendall rank–trend results and median year-over-year growth in premiums per capita

Country	Kendall τ (p-value)	Median YoY growth (%)
BIH	0.867 (0.0242)	0.0896
Montenegro	0.867 (0.0242)	0.101
North Macedonia	1.00 (1)	0.121
Serbia	1.00 (0.00853)	0.136

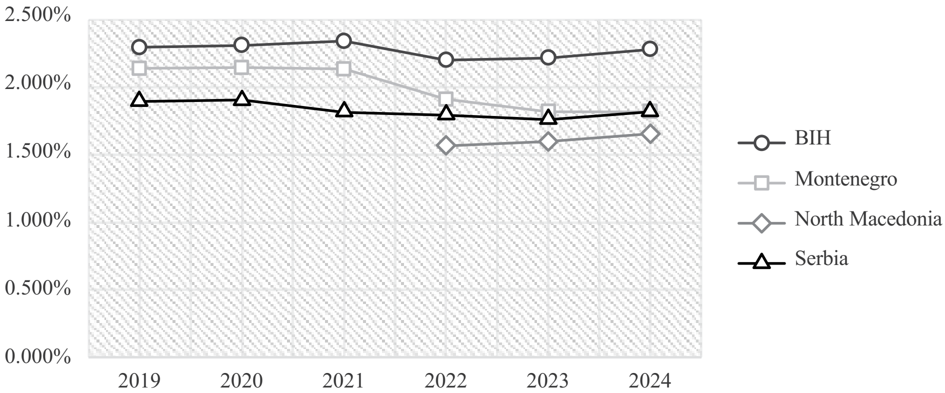
Source: Authors' calculation

The Kendall rank–trend test indicates a statistically significant upward monotonic trend in Bosnia and Herzegovina ($\tau = 0.867$, $p = 0.024$) and in Montenegro ($\tau = 0.867$, $p = 0.024$), and a very strong, statistically significant increase in Serbia

(τ = 1.000, p = 0.0085). North Macedonia also shows an upward pattern (τ = 1.000), but with only three annual observations, the test lacks power and the result is not statistically informative (p = 1.000). The series are short and contain ties due to rounding and limited annual variation. In this setting, Kendall's τ may take an extreme value, while the corresponding exact small-sample p-value is uninformative. We therefore interpret the results primarily in terms of the direction of change and robust magnitude summaries, rather than relying on the exact p-values.

Median year-over-year growth in premiums per capita is about 9.0% in Bosnia and Herzegovina, 10.1% in Montenegro, 12.1% in North Macedonia (based on only two year-over-year observations), and 13.6% in Serbia. Interpreted as typical annual changes, these medians point to sizable compounding over the sample, with the fastest deepening in Serbia and Montenegro and more modest but still positive growth in Bosnia and Herzegovina.

Finally, the share of premiums in GDP trends upward in all four countries, as seen in Graph 3.



Graph 3: Share of total premiums in the country's GDP
Source: Authors' calculation

For the share of premiums in GDP, the Kendall statistics equal τ = 1.000 with p = 1.000 for all four countries. This combination typically arises when the series are nearly monotonic but extremely short and/or contain ties (e.g., repeated rounded values), which makes the exact small-sample p-values uninformative (Brossart, Laird & Armstrong, 2018).

5. DISCUSSIONS

Taken together, the evidence points to a region that has been deepening in insurance activity while experiencing heterogeneous movements in market concentration. On the development side, premiums per capita rise across all four markets; the rank-based trend tests detect statistically significant upward monotonic paths in Bosnia and Herzegovina and Montenegro and an even stronger signal in Serbia, with North Macedonia also increasing but in an ultra-short series that constrains inference. The median year-over-year growth rates, roughly 9% in Bosnia and Herzegovina, 10% in Montenegro, 12% in North Macedonia and 14% in Serbia, suggest economically meaningful compounding over the sample window. These patterns are consistent with a sustained post-pandemic expansion of insurance penetration from relatively low bases, and with the idea that sectoral deepening can proceed even in the presence of frictions typical of small markets.

On the competition side, concentration trends are not uniform. Montenegro and Serbia show robust deconcentration, with HAC-robust slopes of about −40 and −33 HHI points per year, respectively, and corroborating rank-based evidence of monotonic declines. Bosnia and Herzegovina, in contrast, exhibits a statistically significant rise in concentration of roughly +11 HHI points per year, while results for North Macedonia are inconclusive because only three annual observations are available. The level differences are material (mean HHI values range from roughly 600 to 1,800), but within-country dispersion is modest, with coefficients of variation around 3–4%, which implies that trend diagnostics are extracting signal from small year-to-year movements against large cross-country gaps. From an industrial-organisation perspective, declining concentration in Montenegro and Serbia is consistent with either incremental entry and expansion by smaller firms, more aggressive price or product competition by incumbents, or both. Conversely, the increase in Bosnia and Herzegovina suggests consolidation, asymmetric growth among incumbents, or a combination of product and distribution advantages accruing to larger carriers. Because HHI is a structural metric, these contrasting trajectories do not mechanically translate into consumer welfare, but they do signal changes in competitive conditions that deserve regulatory and market attention.

The joint reading of development and concentration provides the most policy-relevant insight. Where premiums per capita are rising while HHI is falling (Montenegro and Serbia), market deepening appears to be taking place in a competitive environment, which is typically favorable for consumer outcomes through pricing discipline, innovation and coverage expansion. In settings where premiums per capita rise alongside increasing concentration (Bosnia and

Herzegovina), the development objective is being met, however, market power may be accruing to a subset of firms. Monitoring should therefore focus on conduct indicators, such as pricing dispersion, broker remuneration structures, ancillary fee dynamics, and claims settlement performance, to ensure that observed scale advantages reflect efficiency rather than anti-competitive behavior. For North Macedonia, a cautiously positive reading on development is warranted, but the paucity of years precludes any reliable statement about competition dynamics; extending the series is a priority for evidence-based supervision. Altogether, the results suggest that supply-side competition and demand-side deepening need not move in lockstep: mixed combinations are feasible and observable in the region over the sample window.

The implications for supervisors and policymakers follow directly. First, deconcentration with rising penetration argues for continuing to remove frictions to entry and growth of smaller or specialised carriers, including digital-first distribution, proportionate capital and reporting for low-risk product lines, and portability of intermediaries across networks. Second, in markets where concentration has risen, the case for granular market-conduct surveillance is strong. Routine tracking of price-to-risk gradients, quote-to-bind conversion rates, renewal spreads for otherwise similar risks, and claims leakage indicators can help distinguish efficiency-driven consolidation from conduct that may harm policyholders. Third, given the fluid cross-country ranking of per-capita premiums, regional peer benchmarking should be dynamic rather than static. Supervisors might emphasise improvement relative to a rolling frontier rather than to a fixed comparator. Fourth, since the share of premiums in GDP exhibits stable ranks, macroprudential or fiscal policies that affect GDP may mechanically influence penetration ratios, so the interpretation of movements in that ratio should separate insurance-side growth from GDP-side fluctuations. These policy priorities are consistent with the dataset, the econometric choices and the cross-checks reported in the paper, and they are implementable with the information systems available to the region's supervisory authorities.

Two data features deserve explicit interpretation. The first is the combination, in the share-of-GDP series, of perfectly monotonic τ values with uninformative exact p-values in very short and tie-heavy samples. This reflects small-sample exact tests that lack power when values repeat and orderings are deterministic. The second concerns the small within-country dispersion of HHI relative to its cross-country level differences. This structure limits the detectability of modest trend shifts over short windows and explains why HAC-robust inference is essential: classical OLS p-values can be borderline even when robust tests reveal statistically reliable slopes, as in the case of Bosnia and Herzegovina. These two features, far from being nuisances, are common in small markets and justify the paper's blend of HAC-OLS, rank-based tests and distribution-free growth summaries.

The study has several limitations that materially shape the interpretation of the results. The most important limitation is the short time dimension of the dataset. A six-year series for Bosnia and Herzegovina, Montenegro, and Serbia, and especially a three-year series for North Macedonia, cannot fully reveal whether the identified changes are structural, cyclical, or event-driven. In practical terms, this means that the paper can detect recent directional movement, but it cannot conclusively establish persistence. This limitation is especially important because insurance markets may react with delay to regulatory reforms, macroeconomic shocks, ownership changes, or consolidation episodes, so the full competitive effects may become visible only over a substantially longer horizon. A second limitation is that the analysis is based on aggregate market indicators and therefore cannot separate developments across life and non-life business lines, nor identify whether concentration changes originate in motor insurance, property insurance, health, life insurance, or another segment. A third limitation is that HHI, while standard and informative, is not the only relevant structural indicator. Because the empirical design intentionally remained parsimonious, the paper does not incorporate additional concentration or inequality measures such as share of the largest enterprises, entropy, or the Gini coefficient. Their inclusion could have provided a richer picture of market structure and allowed more robust triangulation of the findings. A fourth limitation is that the present design does not control for potentially important explanatory factors such as mergers and acquisitions, foreign ownership, regulatory interventions, inflation, GDP shocks, or changes in distribution channels. As a result, the paper identifies structural movement, but not its causal drivers. Finally, converting premiums into EUR using end-of-year exchange rates improves cross-country comparability, yet it may also introduce minor measurement noise when exchange-rate movements and local nominal growth interact.

Future research can address these limitations in concrete ways. The first priority is to extend the time horizon to at least a decade, which would make it possible to distinguish more convincingly between structural change and short-term fluctuation, test for breaks in trend, and evaluate whether recent movements persist once temporary shocks dissipate. Additionally, using control variables, such as the share of the 3 or 5 largest insurance companies, the entropy index or the Gini coefficient, could potentially enable a multidimensional assessment of concentration rather than reliance on HHI alone. The third priority is to introduce explanatory and control variables capable of clarifying the sources of the observed change, including variables capturing mergers and acquisitions, ownership structure, regulatory reforms, macroeconomic conditions, inflation, and digitalisation of insurance distribution. The fourth priority is to disaggregate the analysis by line of business, because aggregate market-level concentration may conceal different competitive dynamics across life and non-life insurance segments. Finally, future work should connect structural indicators with conduct and performance outcomes, such as pricing behaviour, claims settlement, profitability, and consumer choice, in order to evaluate more directly whether changes in concentration improve or weaken effective market competition and welfare.

6. CONCLUSIONS

This study set out to examine how competition relates to insurance market development in four Western Balkan economies: Bosnia and Herzegovina, Montenegro, Serbia, and North Macedonia, over the period 2019–2024. Using the Herfindahl–Hirschman Index (HHI) to track structural concentration and premiums per capita and premiums/GDP as indicators of market deepening, we combined linear time trends with HAC-robust inference and rank-based tests suitable for short annual series. The empirical picture that emerges is clear on two fronts and instructive on a third. First, structural dynamics diverged across markets: Bosnia and Herzegovina experienced a statistically significant increase in concentration, whereas Montenegro and Serbia deconcentrated. North Macedonia did not provide enough data to render a meaningful conclusion. Second, insurance activity deepened across the board, with sustained growth in premiums per capita and rising premiums/GDP despite heterogeneous movements in structure. Third, and most importantly for the policy debate, structure and development did not move in lockstep.

These findings bear directly on the proposed hypotheses. The main hypothesis, positing significant within-market changes in concentration, is partially supported: shifts are significant in Bosnia and Herzegovina, Montenegro, and Serbia, but not inferentially settled in North Macedonia, given the ultra-short series. The first auxiliary hypothesis, anticipating a region-wide increase in market development, is supported by the monotone upward patterns in premiums per capita (and, with caveats about small-sample exact tests, in premiums/GDP). The second auxiliary hypothesis, asserting that lower concentration is not uniformly associated with higher development in the observed window, is supported by the documented decoupling: market deepening coincides with both rising and falling HHI, depending on the market.

Theoretically, the results reinforce a productivity- and conduct-oriented view of competitiveness in services. Structural concentration is an important state variable, but it is not a sufficient statistic for welfare or development. In emerging and transitioning insurance markets, changes in underwriting capacity, distribution channels (especially digital and bancassurance), pricing to risk, and claims-handling efficiency can generate growth in coverage and premiums independent of contemporaneous shifts in structural concentration. Conversely, deconcentration may not translate into deeper markets if entrants remain small, product scope is narrow, or intermediation frictions persist. By separating structural metrics from development indicators and triangulating parametric and rank-based evidence, our design makes explicit that the relevant mechanisms operate through conduct and capabilities as much as through firm counts and market shares.

From a policy perspective, the implication is a two-pillar supervisory strategy. Where deconcentration and deepening occur together (Montenegro, Serbia), proportionate regulation that facilitates entry and scale for efficient carriers can preserve competitive pressure while expanding access. Where deepening accompanies rising concentration (Bosnia and Herzegovina), the emphasis should shift toward market-conduct supervision and transparency. These indicators allow authorities to distinguish efficiency-driven consolidation from exclusionary conduct and to intervene with targeted instruments. For North Macedonia, the priority is to extend the public series and harmonise definitions to enable credible inference before decisive structural policy is considered.

Methodologically, the analysis demonstrates how to extract robust, decision-useful signals from short administrative series. HAC-robust linear trends provide interpretable estimates of direction and magnitude, while Kendall and Spearman statistics offer complementary evidence when functional-form assumptions are tenuous or sample sizes are very small. That said, several limitations should temper interpretation. Our series is short and aggregate, and it cannot reveal line-of-business reallocation, differential growth between life and non-life segments, or within-line pricing dynamics. Currency conversion at year-end and cross-jurisdiction differences in reporting may introduce measurement noise. Finally, without linked microdata on policy prices, risk classes, and claims outcomes, the welfare mapping remains indirect.

This limitation opens a clear agenda for future work. Longer time series, additional concentration indicators, disaggregated line-of-business evidence, and the inclusion of explanatory control variables would substantially improve the capacity to distinguish persistent structural change from temporary fluctuation.

Such extensions would also make it possible to examine whether observed changes in concentration are driven by mergers and acquisitions, regulatory reforms, foreign entry, macroeconomic shocks, or other market-specific developments.

In sum, the paper shows that the Western Balkan insurance markets deepened over the observed period, but not through a single common structural path. Development occurred under both deconcentration and rising concentration, which suggests that the relationship between competition and market development is conditional, country-specific, and sensitive to time horizon. For that reason, any stronger claim about the structural nature of these changes must await longer datasets and richer empirical specifications.

Conflict of interests

The authors declare there is no conflict of interest.

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ТРЖИШТЕ ОСИГУРАЊА НА ЗАПАДНОМ БАЛКАНУ: КОНКУРЕНЦИЈА, КОНЦЕНТРАЦИЈА И МЕНАЏЕРСКЕ ПРАКСЕ

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САЖЕТАК

Овај чланак анализира однос између тржишне структуре и развоја тржишта осигурања у четири земље Западног Балкана: Босни и Херцеговини, Црној Гори, Србији и Сјеверној Македонији, у периоду 2019–2024. Степен конкуренције мјери се Херфиндал–Хиршман индексом док се развијеност тржишта процјењује користећи премије по глави становника (у еврима) и удио премија у БДП-у. Емпиријска анализа комбинује линеарне трендове по земљама са робусним стандардним грешкама и ранговне тестове кратким временским серијама. Резултати показују статистички значајну деконцентрацију у Црној Гори и Србији, раст концентрације у Босни и Херцеговини, те неутврђен образац за Сјеверну Македонију због кратке серије. Истовремено, премије по глави становника расту у све четири земље, што указује да се развој тржишта може одвијати уз пад и уз раст концентрације. Хипотезе о промјенама у концентрацији (дјелимично подржана), расту развијености (подржана) и одсуству јединствене везе између ниже концентрације и већег развоја у кратком временском року (подржана) потврђују да је за регулаторе кључно руковођење на бази емпиријских података, које омогућава јединствен приступ у свакој земљи.

Кључне ријечи: *тржиште осигурања, конкуренција, концентрација, Западни Балкан.*

A CEEMDAN-LSTM MODEL FOR FORECASTING THE USD/DZD EXCHANGE RATE[1]

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ABSTRACT

This study develops a hybrid forecasting model for the USD/DZD exchange rate by combining Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Long Short-Term Memory (LSTM) networks to address high volatility and complex temporal dependencies in currency markets. Using 310 monthly observations, the CEEMDAN procedure decomposes the series into five frequency components and a residual, which are modeled by component-specific LSTM networks. The proposed CEEMDAN-LSTM model achieved the lowest forecast errors among the tested models, with a MAPE of 0.4782%, outperforming traditional LSTM and SVM benchmarks. The 12-month forecast suggests relative exchange rate stability, with a slight decline of about 0.48%. The results indicate that decomposing the original series before LSTM modeling improves predictive accuracy by separating short-term noise from medium- and long-term dynamics. The proposed framework may support exchange-rate risk management, hedging decisions, and short- to medium-term planning in emerging-market settings.

1. INTRODUCTION

Exchange rates represent one of the fundamental components of the macroeconomic structure, given their direct impact on foreign trade patterns, capital flows, balance of payments, and a country's international competitiveness (Plakandaras et al., 2015). The USD/DZD exchange rate stands out as a strategic indicator in the Algerian context, due to the dollar's dominance in pricing key exports, particularly hydrocarbons, on one hand, and the significant dependence of commodity and service imports on it, on the other. In this context, the ability to accurately forecast exchange rate movements becomes a critical tool for monetary authorities, policymakers, and financial market operators—not only for managing and hedging against exchange rate volatility risks, but also for designing more targeted monetary policies and enhancing the efficiency of short- and medium-term financial and budgetary planning, which ultimately reflects on macroeconomic stability.

However, exchange rate time series, particularly in resource-dependent economies, typically exhibit high degrees of instability, volatility, non-linearity, and complex interactions with various financial, economic, and geopolitical factors. These characteristics render many traditional time series analysis models, such as linear regression or ARIMA, limited in their ability to represent the dynamic relationships governing exchange rate movements (De Gooijer & Hyndman, 2006). This has encouraged the use of more flexible methods, including Empirical Mode Decomposition (EMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). EMD, originally proposed by Huang et al. (1998), decomposes non-stationary signals into intrinsic mode functions (IMFs) through an iterative process. CEEMDAN, introduced by Torres et al. (2011), was developed to reduce mode mixing and generate more stable components, thereby improving subsequent forecasting performance (Cao et al., 2019; Wu & Huang, 2009).

Parallel to this development, recent years have witnessed significant expansion in the application of artificial intelligence techniques, particularly machine learning and deep learning models, in financial data and exchange rate forecasting. Support Vector Machines (SVM), pioneered by Vapnik (1995), have proven effective in modeling non-linear relationships within exchange rate data through kernel methods and margin maximization principles. Long Short-Term Memory (LSTM) neural networks, introduced by Hochreiter & Schmidhuber (1997), have demonstrated particular effectiveness in capturing long-term temporal dependencies within series, achieving superior results compared to many traditional models in financial market and exchange rate forecasting (Zhang, 2018). The LSTM architecture addresses the vanishing gradient problem inherent in recurrent neural networks, enabling the network to learn and retain information over extended temporal sequences (Hochreiter & Schmidhuber, 1997). The convergence of these two paths—time series decomposition methods like CEEMDAN and deep learning models like LSTM—has led to the emergence of hybrid models that leverage the strengths of both approaches. In such hybrid frameworks, mode decomposition reduces noise and instability in the original signal, while deep networks extract complex temporal patterns from the resulting components (Fan et al., 2021).

Building on this theoretical and methodological background, this study addresses the following main question: How can a hybrid model that integrates CEEMDAN with LSTM networks improve the accuracy of USD/DZD exchange rate forecasting relative to benchmark single-model approaches such as SVM and LSTM? This problem falls within a broader effort to test the viability of hybrid models in an economic environment with distinctive characteristics such as the Algerian economy, where external and internal factors jointly shape exchange rate movements and make prediction particularly challenging when relying on a single modeling technique.

In light of this, the study aims to achieve several interconnected objectives. First, it decomposes the USD/DZD exchange rate series using CEEMDAN into more stable and modelable sub-components. Second, it constructs benchmark SVM and LSTM forecasting models and evaluates them using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Third, it proposes a CEEMDAN-LSTM hybrid model that feeds the decomposed components into LSTM networks, combining CEEMDAN's capacity to reduce noise and instability with LSTM's ability to capture complex temporal dependencies. Fourth, it compares the hybrid model with the benchmark models in order to assess the forecasting gains generated by the proposed methodology (Fan et al., 2021).

With this framework, the study seeks to contribute to filling part of the research gap in the literature on exchange rate forecasting in emerging economies by presenting an applied model that combines advanced time series analysis techniques with artificial intelligence tools. This could provide a practical framework beneficial to policymakers, monetary authorities, and financial institutions in enhancing the efficiency of exchange rate volatility risk management in the Algerian context, with the potential to generalise the methodology to other currencies and markets with similar characteristics. Furthermore, by demonstrating the superior performance of hybrid approaches over standalone models, this research contributes to the growing body of evidence supporting the use of ensemble and hybrid methods in financial forecasting (Ren et al., 2016).

To systematically address the research question and achieve the stated objectives, this paper is organised as follows. The second section reviews the literature on exchange rate forecasting, covering both traditional econometric approaches and contemporary machine-learning techniques. The third section presents the data, preprocessing steps, and the architecture of the proposed CEEMDAN-LSTM model. The fourth section presents and discusses the empirical results, comparing the forecasting performance of the hybrid model with benchmark LSTM and SVM models using MAE, RMSE, and MAPE. The fifth section concludes and outlines the main limitations and directions for future research.

2. LITERATURE REVIEW

Forecasting foreign exchange rates represents one of the primary challenges in economics and finance, as exchange rates are influenced by multiple factors including inflation, interest rates, monetary policies, and geopolitical events. Accurate forecasting helps in making informed investment decisions, managing financial risks, and promoting economic stability. In this section, we review previous studies related to exchange rate forecasting models, focusing on traditional models, artificial intelligence models, and hybrid models that combine signal decomposition techniques (such as EMD or CEEMDAN) with neural networks like LSTM. We emphasise studies addressing different currencies, while highlighting the gap in applying the CEEMDAN-LSTM model to the US Dollar against the Algerian Dinar (USD/DZD) exchange rate.

Many previous studies rely on traditional time series models, such as ARIMA and SARIMA, which focus on linear and seasonal patterns in the data. For instance, Al-Gounmeein and Ismail (2020) employed a seasonal ARIMA model to forecast the Jordanian dinar against the US dollar using monthly data. Their results showed that SARIMA (1,0,1)(1,0,0)12 outperformed ARIMA (1,0,1) in terms of MAPE, RMSE, and MAE, while also highlighting the limitations of linear models in capturing nonlinear exchange-rate fluctuations.

Similarly, Darvas & Schepp (2025) proposed a monetary model based on the rational-expectations present-value framework for forecasting the pound sterling against the US dollar. Although their model outperformed the random walk benchmark and generated positive economic and statistical returns, the authors also emphasised the persistent difficulty of forecasting major exchange rates under unexpected volatility.

In another context, Flores-Sosa et al. (2022) used a multiple linear regression-heavy ordered weighted average (MLR-HOWA) framework to forecast five Latin American currencies against the US dollar. Their model reduced forecasting error relative to conventional linear regression and highlighted the value of multi-scenario analysis.

With the advancement of artificial intelligence techniques, studies have increasingly adopted neural networks such as ANN, LSTM, and BiLSTM to handle the nonlinear and non-stationary nature of exchange rates. Kamouh (2026) used artificial neural networks to forecast the Egyptian pound against the US dollar by relying on variables such as external debt, GDP, and inflation, and reported higher accuracy than traditional models. García et al. (2024) compared LSTM and BiLSTM models for exchange rates of major currencies against the US dollar, including Bitcoin futures contracts, and found BiLSTM particularly effective for short-term forecasting.

Amri et al. (2025) proposed a deep neural network with a multi-output sliding-window approach for forecasting the Indonesian rupiah against the US dollar and reported improved accuracy through better handling of multiple temporal patterns. Liu et al. (2023) developed a hybrid CNN-STLSTM-AM model for USD/RMB forecasting and found that it outperformed CNN, SVR, LSTM, and GRU-LSTM benchmarks.

To address noise in time series, some studies have adopted decomposition techniques such as Empirical Mode Decomposition (EMD) or CEEMDAN combined with artificial intelligence models. Lin et al. (2012) used an EMD-LSSVR model to forecast multiple currency exchange rates. By decomposing the original series into IMFs and residuals before prediction, the model outperformed both EMD-ARIMA and standalone LSSVR.

Adesina and Obokoh (2025) proposed a SARIMA-LSTM framework for forecasting the South African rand against the dollar, euro, and yuan, reporting gains over ARIMA, SARIMA, GRU, RNN, and standalone LSTM specifications. Lyócsa et al. (2024) examined day-ahead expected shortfall for the EUR/USD rate and showed that implied volatility can improve forecasting accuracy, especially during turbulent periods.

Despite progress in hybrid models, most previous studies have focused on major currencies such as USD/RMB, USD/GBP, or USD/EGP, with few studies on emerging currencies like the Algerian Dinar (DZD). Additionally, the use of CEEMDAN (an improvement over EMD for noise reduction) with LSTM has not been widely applied to USD/DZD. For example, none of the previous studies specifically addressed the USD/DZD exchange rate, which is influenced by local factors such as oil prices and monetary policies in Algeria. This research fills this gap by proposing a CEEMDAN-LSTM model, which combines complete signal decomposition (CEEMDAN) to extract principal components and LSTM to handle long-term temporal dependencies, thereby improving accuracy in forecasting the USD/DZD exchange rate compared to previous models.

3. MATERIALS AND METHODS

3.1 EMD Decomposition

Empirical Mode Decomposition (EMD) is an adaptive time series analysis technique based on the Hilbert-Huang Transform (HHT), specifically designed to handle nonlinear and non-stationary temporal data (Huang et al., 1998). The fundamental principle of EMD lies in decomposing a time series into a set of oscillatory functions called Intrinsic Mode Functions (IMFs), where each function must satisfy two essential conditions: first, the number of extrema (sum of maxima and minima) and the number of zero-crossings must be equal or differ by at most one throughout the entire series; and second, the mean value of the envelopes defined by the local maxima and minima must equal zero at all points. These requirements ensure the extraction of meaningful intrinsic mode functions; otherwise, blind application of the technique to any data may result in physically meaningless harmonics (Huang et al., 1999).

The decomposition process is performed through a systematic procedure called the "Sifting Procedure" applied to any data series $x(t)$, where the process begins by identifying all local extrema of the series, then these values are connected using a curve to create upper and lower envelopes (Yu et al., 2008). Subsequently, the point-wise mean of the envelopes is calculated as:

$$m(t) = \frac{x_{up}(t) + x_{low}(t)}{2}$$

and the details are extracted as:

$$c(t) = x(t) - m(t)$$

This process is repeated until a stopping criterion is satisfied, defined by three conditions related to predetermined thresholds (Huang et al., 1998). The extraction of intrinsic mode functions continues by applying the sifting procedure to the remaining residue until the final residue $r_n(t)$ becomes a monotonic function or contains no more than one local extremum. At the end of the procedure, the original series $x(t)$ can be mathematically expressed as the sum of all extracted intrinsic mode functions and the final residue:

$$x(t) = \sum_j c_j(t) + r_n(t)$$

where $c_j(t)$ represents the intrinsic mode functions that are nearly orthogonal to each other and have means approaching zero, while $r_n(t)$ represents the main trend of the time series. The EMD technique has several clear advantages compared to traditional decomposition methods such as Fourier analysis and Wavelet analysis. First, it is easy to understand and implement; second, it automatically and adaptively selects oscillations within the time series from the series itself, making it powerful in analysing nonlinear and non-stationary time series; and third, it follows a data-driven approach where the data speaks for itself without imposing prior assumptions. The most important advantage of EMD is that it does not require specifying a basis filter function before the decomposition process, unlike Wavelet analysis which requires pre-specifying this function—a difficult task for unknown series (Li, 2006). Studies have also demonstrated that EMD performs better in describing instantaneous frequencies on the local time scale compared to Wavelet analysis and Fourier analysis (Huang et al., 1999), as Fourier analysis when applied to nonlinear time series often produces large sets of physically meaningless harmonics as the degree of nonlinearity and non-stationarity in the series increases. The sifting procedure can be easily implemented using MATLAB software (Yu et al., 2008), making it accessible for practical applications in exchange rate forecasting and other time series analysis tasks.

3.2 Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)

The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise technique was developed by Torres et al. (2011). CEEMDAN represents a significant breakthrough in analysing nonlinear and non-stationary time series signals, with applications including building energy consumption data analysis.

CEEMDAN was specifically designed to address limitations found in previous decomposition methods, particularly Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD). While EMD encounters mode mixing problems caused by intermittent signals, EEMD attempts to resolve this by incorporating white noise but introduces residual noise contamination, especially with low ensemble numbers, and requires increased computational time with higher ensemble sizes. CEEMDAN overcomes these challenges by incorporating adaptive noise at each decomposition stage, thereby improving accuracy while reducing computational complexity. The core objective of CEEMDAN is to decompose an original signal into relatively stable components called Intrinsic Mode Functions (IMFs), plus a residual component. This decomposition facilitates individual prediction of each component, making it particularly valuable for forecasting applications.

The method begins by defining the following parameters:

- $x[n]$: the original signal
- w^i: a white noise series following a normal distribution $N[0,1]$
- ε_k: noise amplitude coefficients
- $Ej(\cdot)$: a function that extracts the j-th mode using EMD.

The decomposition process involves several systematic steps that progressively extract IMFs from the signal:

Step 1: Initial Noise Addition

White noise is added to the original signal:

$$x[n]+\varepsilon_0 w^i[n]$$

Step 2: First IMF Extraction

I realisations of the noise-added signal are decomposed using EMD to extract the first modes. The first IMF is calculated as the average:

$$IMF_1[n]=\frac{1}{I}\sum_{i=1}^{I} IMF_1^i[n]=\overline{IMF_1}[n]$$

Step 3: First Residue Calculation

$$r_1[n]=x[n]-IMF_1[n]$$

Step 4: Second IMF Extraction

The process continues by decomposing $r_1[n]+\varepsilon_1 E_1(w^i[n])$ for $i=1,\ldots,I$ using EMD to extract the first mode, then computing the second IMF:

$$IMF_2[n]=\frac{1}{I}\sum_{i=1}^{I} E_1(r_1[n]+\varepsilon_1 E_1(w^i[n]))$$

Step 5: Iterative Residue Update

For each $k = 2,...,K$, the k-th residue is calculated:

$$r_k[n]=r_{k-1}[n]-IMF_k[n]$$

Step 6: Subsequent IMF Extraction

The decomposition continues by processing $r_k[n]+\varepsilon_k E_k(w^i[n])$ for $i = 1,\ldots,I$, computing the $(k+1)$-th IMF:

$$IMF_{k+1}[n] = \frac{1}{I}\sum_{i=1}^{I} E_1(r_k[n] + \varepsilon_k E_k(w^i[n]))$$

Steps 5 and 6 are repeated until the residue becomes a monotonic function that cannot be further decomposed by EMD.

Step 7: Final Decomposition Result

The process concludes with the complete decomposition of the original signal:

$$x[n] = \sum_{k=1}^{K} IMF_k[n] + R[n]$$

where K represents the total number of IMFs and $R[n]$ is the final residue.

CEEMDAN offers several key advantages over its predecessors. By adding adaptive noise at each decomposition stage, the method significantly reduces mode mixing and maintains component purity. Furthermore, CEEMDAN demonstrates greater computational efficiency than EEMD, as it does not require a substantial increase in ensemble numbers to achieve accurate results.

In the context of exchange rate forecasting, the CEEMDAN method has proven particularly effective when integrated into hybrid forecasting frameworks. The typical workflow involves decomposing the exchange rate time series into a set of intrinsic mode functions (IMFs) using CEEMDAN to address noise and non-linear, non-stationary characteristics. Long Short-Term Memory (LSTM) networks are then applied to forecast each component individually, and the final prediction is obtained by aggregating the forecasts of all decomposed components.

3.3 Support Vector Machine Methodology

Support Vector Machines represent a supervised machine learning approach utilised for solving classification and regression tasks. Credit for developing this methodology belongs to scientist Vapnik in 1995 through his contributions to statistical learning theory. When this approach is applied to regression problems, it is termed Support Vector Regression, which seeks to estimate the values of the dependent variable y′ based on a regression function applied to a training dataset, where values belong to real numbers, such that L denotes the training sample size while D refers to the input space dimensions (García Nieto et al., 2018).

The regression function for the training dataset is mathematically formulated as follows:

$$f(x) = \langle w, x \rangle + b$$

This equation represents the dot product between the weight vector w and the input vector x, while the last variable refers to the intercept or bias coefficient in the model. The core concept of Support Vector Machine regression relies on employing a "loss function" that takes the value zero when the difference between the predicted value and the actual observed value falls within a range defined by the parameter ε, meaning this condition is satisfied. The region defined by this condition for all values is called the "ε-insensitive tube" (García Nieto et al., 2018). Data points that fall outside the boundaries of this tube are subject to penalties through slack variables that are determined based on their position relative to the tube. These constraints are mathematically formulated as follows:

$$\begin{gathered} y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{gathered}$$

Accordingly, the loss function for Support Vector Regression is written in the following mathematical form:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{L} (\xi_i + \xi_i^*)$$

where C represents the regularisation parameter or cost constant, while the other variables constitute the slack variables. The parameter C plays a crucial role in achieving balance between model flatness (margin) and the magnitude of training errors (slack variables).

To reach the optimal solution and minimise the error function, the Karush-Kuhn-Tucker optimality conditions are adopted. These are first-order mathematical conditions necessary for reaching the optimal solution in nonlinear programming problems with inequality constraints. By introducing Lagrange multipliers for all values, the problem is transformed into a Quadratic Programming problem that can be solved using the dual Lagrangian method (García Nieto et al., 2018). In the case of nonlinear data, input vectors from a low-dimensional space are mapped to a high-dimensional linear feature space through a nonlinear transformation. In this context, the nonlinear regression function is formulated as follows:

$$f(x) = \langle w, \phi(x) \rangle + b$$

Among the most commonly used kernel functions that satisfy Mercer's condition are:

Radial Basis Function (RBF) kernel:

$$K(x_i, x_j) = exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2} \right)$$

Polynomial kernel:

$$K(x_i, x_j) = \left(a\langle x_i, x_j \rangle + b \right)^d$$

Sigmoid kernel:

$$K(x_i, x_j) = tanh\left(a\langle x_i, x_j \rangle + b \right)$$

In these equations, the variables represent parameters that determine the characteristics and behavior of the kernel function. The optimal combination of these hyperparameters is selected through applying the Grid Search technique, which is a comprehensive search strategy within a predefined subset space of the algorithm's hyperparameters, using Cross-Validation technique to select parameters that achieve the highest possible accuracy (García Nieto et al., 2018).

3.4 Long Short-Term Memory (LSTM)

Predicting financial time series one step ahead requires more than just the latest data; it also depends on incorporating historical information from previous time periods. Thanks to its self-feedback mechanism in the hidden layer, the Recurrent Neural Network (RNN) model offers significant advantages when dealing with long-term dependency issues. The LSTM unit comprises a memory cell that stores information, with updates managed through three specialised gates: the input gate, the forget gate, and the output gate. At any time step *t*, the fundamental variables include: x_t for the input data entering the cell, h_{t-1} for the previous time step's output, c_t for the memory cell's current value, and h_t for the cell's final output. Figure 1 illustrates the internal architecture of an LSTM unit, demonstrating how information flows through the memory cell and how the three control gates interact to regulate this flow.

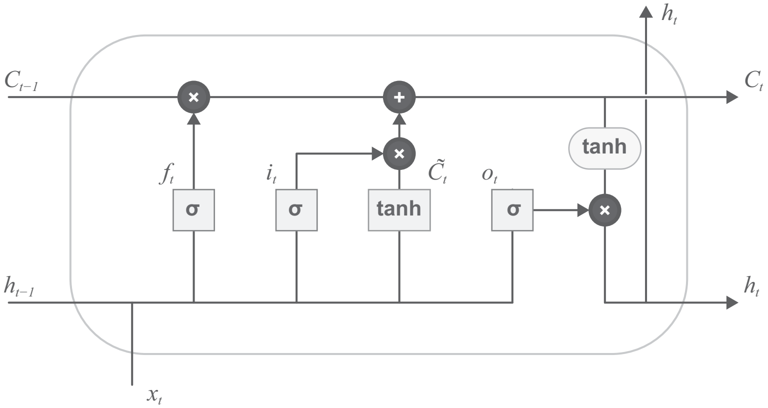

Figure 1: Architecture of LSTM Unit
Source: (Cao et al., 2019)

The LSTM unit's computational process unfolds through several sequential stages. First, the candidate memory cell value $\tilde{c}_t$ is calculated using the weight matrix W_c and bias vector b_c, expressed as: c_t=tanh(W_c·[h_{t-1},x_t]+b_c). Next, the input gate value i_t is determined through the sigmoid function, which regulates how current input data influences the memory cell state: i_t=σ(W_i·[h_{t-1},x_t]+b_i), where W_i represents the weight matrix and b_i the bias vector. The forget gate value f_t is then computed to control how historical information affects the memory cell state: f_t=σ(W_f·[h_{t-1},x_t]+b_f), with W_f as the weight matrix and b_f as the bias vector (Gers et al., 2000). As illustrated in Figure 1, the current memory cell value c_t is subsequently updated through the equation: c_t=f_t*c_{t-1}+i_t*$\tilde{c}_t$, where "*" denotes element-wise multiplication. This update relies on both the previous state c_{t-1} and the candidate cell value, regulated by the input and forget gates. The output gate value o_t is then calculated to determine what information from the memory cell state should be output: o_t=σ(W_o·[h_{t-1},x_t]+b_o), where W_o is the weight matrix and b_o is the bias vector. Finally, the LSTM unit produces its output through: h_t=o_t*tanh(c_t). These three control gates and the memory cell enable the LSTM model to efficiently store, retrieve, reset, and update long-term information. Moreover, the internal parameter sharing mechanism allows researchers to control output dimensions by adjusting the weight matrix dimensions. The architecture creates a substantial temporal delay between inputs and feedback, which prevents both gradient explosion and vanishing because the memory cell's internal state maintains a continuous error flow throughout the network (Cao et al., 2019).

3.5 Hybrid CEEMDAN-LSTM Model

Financial time series data inherently exhibit non-linear, non-stationary, and stochastic characteristics that pose significant forecasting challenges. Traditional single prediction models often struggle to capture the complex dynamics embedded within such data due to their volatility, irregular fluctuations, and multi-scale temporal patterns. Recognising these limitations, researchers have developed hybrid forecasting frameworks that integrate signal decomposition techniques with deep learning architectures. Specifically, combining Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Long Short-Term Memory (LSTM) networks has emerged as a particularly effective approach for financial time series prediction. The fundamental premise underlying this hybrid methodology rests on transforming a complex forecasting problem into multiple simpler sub-problems through decomposition, where each component can be modeled more effectively than the original signal (Lin et al., 2021; Lin et al., 2022).

The first stage of the CEEMDAN-LSTM framework involves decomposing the original financial time series into several Intrinsic Mode Functions (IMFs) with different time scales plus one residual component. CEEMDAN represents an advanced evolution of the original Empirical Mode Decomposition (EMD) method, specifically designed to address the mode mixing problem that plagued earlier decomposition techniques. The fundamental principle of CEEMDAN involves adding adaptive white noise at each stage of the decomposition process, which serves to uniformly distribute different scales of the signal across appropriate IMF components. This adaptive noise addition distinguishes CEEMDAN from its predecessors, including the original EMD and even the Ensemble EMD (EEMD), by adding specific noise realisations at each decomposition stage rather than maintaining the same noise throughout the entire process, resulting in a more complete and stable decomposition with significantly reduced reconstruction error (Lin et al., 2021).

Mathematically, given an original financial time series $X(t)$, the CEEMDAN algorithm decom-poses it through a systematic process. Initially, white noise $\varepsilon^i(t)$ with a specific amplitude is added to the original signal, creating an ensemble of noisy signals: $X^i(t)=X(t)+\varepsilon_0 E_1(\varepsilon^i(t))$, where $i=1,2,...,I$ represents the ensemble member index, $E_1(\cdot)$ denotes the operator that extracts the first EMD mode, and ε_0 represents the noise standard deviation coefficient. Each ensemble member undergoes EMD decomposition to obtain its first mode. The first IMF is calculated as the average across all ensemble members: $IMF_1(t) = \frac{1}{I}\sum_{i=1}^{I} IMF_1^i(t)$. Subsequently, the first residual is computed as: $r_1(t)=X(t)–IMF_1(t)$. For subsequent modes $k=2,3,...,K$, the algorithm adds the noise realisation $E_k(\varepsilon_i(t))$ to the residual $r_{k-1}(t)$, gen-erating: $r_{k-1}(t)+\varepsilon_{k-1}E_k\varepsilon_i(t)$. The k-th mode is obtained by averaging: $IMF_k(t) = \frac{1}{I}\sum_{i=1}^{I} E_1(r_{k-1}(t) + \varepsilon_{k-1}E_k(\varepsilon^i(t)))$, and the corresponding residual becomes: $r_k(t)=r_{k-1}(t)–IMF_k(t)$. This iterative procedure continues until the residual $r_K(t)$ can no longer be decomposed, at which point it becomes the final residual component $R(t)$. The original signal can then be perfectly reconstructed through summation: $X(t) = \sum_{k=1}^{K} IMF_k(t) + R(t)$ (Lin et al., 2022).

The decomposed IMFs represent distinct frequency characteristics of the original financial time series, with each IMF capturing a unique oscillatory mode. High-frequency IMFs typically capture short-term market volatility, rapid price fluctuations, and noise-like components that reflect immediate market reactions and trading dynamics. Medium-frequency IMFs reflect cyclical patterns and periodic behaviors associated with business cycles and seasonal effects. Low-frequency IMFs capture longer-term trends and structural changes in the market. The residual component represents the fundamental long-term trend or drift inherent in the data. This multi-resolution decomposition effectively transforms the non-stationary original series into several relatively stationary sub-series, each exhibiting more regular and predictable pattern. The key advantage of CEEMDAN over traditional EMD lies in its ability to eliminate mode mixing where oscillations of different scales inappropriately appear in the same IMF and to provide a complete decomposition with minimal reconstruction error, thereby ensuring that each characteristic time scale is represented by a unique and meaningful IMF component (Lin et al., 2021; Lin et al., 2022).

Following the decomposition stage, individual LSTM prediction models are established for each IMF component and the residual term. This approach ensures that the historical data's effects on prediction results are appropriately captured for each characteristic frequency component. The CEEMDAN-LSTM model utilises the decomposed data to obtain prediction sequences for each component separately, recognising that different frequency components exhibit distinct temporal patterns that require specialised modeling approaches. The theoretical justification for applying LSTM networks to each decomposed component stems from LSTM's inherent capability to learn long-term dependencies through its memory cell and gating mechanisms. However, in the context of the hybrid CEEMDAN-LSTM model, applying LSTM to decomposed components offers substantial advantages beyond those provided by applying LSTM directly to the original series (Lin et al., 2021).

Each decomposed IMF exhibits considerably more regular oscillatory behaviour and reduced non-stationarity compared to the original signal, making the learning task for individual LSTM networks substantially more tractable. Lin et al. (2022) emphasise that the modified ensemble empirical mode decomposition technique decomposes the original time series into several com-ponents with different frequencies, and each component is predicted separately by the LSTM neural network, which captures the long-term dependencies and complex temporal patterns more effectively. The LSTM network for each component is trained independently using a supervised learning framework. For the *k*-th IMF component $IMF_k(t)$, the input sequence consists of historical values $[IMF_k(t-n), IMF_k(t-n+1),...,IMF_k(t-1)]$, where n represents the lookback window size, and the target output is $IMF_k(t)$. The LSTM network learns to map the historical patterns in each frequency component to future values by adjusting its internal parameters, spe-cifically, the weight matrices and bias vectors for the input gate, forget gate, and output gate, as well as the candidate memory cell, through the backpropagation through time (BPTT) algorithm, minimising a loss function such as mean squared error (MSE): $L=\frac{1}{N}\sum_{t=1}^{N}(IMF_k(t)-\widehat{IMF}_k(t))^2$, where $\widehat{IMF}_k(t)$ represents the LSTM's prediction and N denotes the number of training samples (Lin et al., 2021; Lin et al., 2022).

The architecture of each LSTM network can be customised according to the characteristics of its corresponding IMF component. Typically, high-frequency IMFs require LSTM networks with fewer layers and hidden units due to their simpler and more regular patterns, while low-frequency IMFs and the residual component may benefit from deeper networks with more hidden units to capture their complex long-term dependencies and intricate temporal structures. The training process for each LSTM model is conducted independently, allowing for component-specific hyperparameter optimisation. This modular approach provides considerable flexibility in model design and enables parallel computation during both training and prediction phases, potentially reducing overall computational time compared to monolithic architectures. Furthermore, this decomposition-based strategy allows the model to allocate computational resources more efficiently, dedicating more complex network architectures to components that genuinely require them while using simpler structures for more straightforward patterns (Lin et al., 2022).

The final stage of the CEEMDAN-LSTM model involves reconstructing the predictions from all individual LSTM models to obtain the final forecast of the original time series. Given the predicted values $IMF_k(t)$ from the LSTM model for each k-th IMF component and $R(t)$ from the LSTM model for the residual component, the final prediction $X(t)$ is computed through straightforward summation: $X(t) = \sum_{k=1}^{K} IMF_k(t) + R(t)$. This linear re-construction formula directly follows from the decomposition property of CEEMDAN, where the original signal equals the sum of all its components. The theoretical elegance of this ensem-ble approach lies in its simplicity and interpretability: by accurately predicting each frequency component independently and then reconstructing them, the model effectively captures the mul-ti-scale temporal dynamics of the original financial time series without requiring complex en-semble weighting schemes, meta-learning procedures, or additional optimisation steps (Lin et al., 2021; Lin et al., 2022).

3.6 Evaluation Metrics

To evaluate the predictive capability of the proposed models, the study employed three standard performance indicators. The first of these is the Mean Absolute Error (MAE), which is defined by the equation below (Manowska, 2020):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

The second metric is the Root Mean Square Error (RMSE), expressed by the equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

The third metric is the Mean Absolute Percentage Error (MAPE), which determines the prediction accuracy as a percentage according to the following formula:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| 100\%$$

Here, y_i denotes the observed value and y_i represents the predicted value for the i-th sample, while n refers to the total number of data points in the testing set.

3.7 Statistical Significance, Robustness, and Bootstrap Prediction Intervals

Because error measures alone do not establish whether forecast differences are statistically meaningful, the analysis applies the Diebold–Mariano test of equal predictive accuracy under squared-error loss (Diebold & Mariano, 1995). Given the limited size of the primary test sample, the small-sample modified statistic of Harvey, Leybourne, and Newbold (1997) is reported with two-sided p-values.

Robustness is evaluated by repeating the chronological holdout exercise using an 80/20 split. This alternative test period covers 62 months and permits assessment of whether relative model ranking is stable over a longer out-of-sample horizon.

Finally, the 95% uncertainty bounds for the 12-month forecast are generated through a residual-bootstrap procedure rather than a normal-error assumption. Specifically, centered residuals from the primary CEEMDAN-LSTM holdout are resampled with replacement 5,000 times, and the 2.5th and 97.5th percentiles of the simulated forecasts define the reported prediction limits (Efron & Tibshirani, 1993).

4. RESULTS AND DISCUSSIONS

4.1 Preliminary Data Processing and Descriptive Analysis

This study relied on monthly data for the US dollar exchange rate against the Algerian dinar, spanning a period from January 2000 through October 2025, representing 310 consecutive monthly observations. Table (1) reveals the overall statistical characteristics of this data, where the average exchange rate throughout this period settled at 95.05 dinars per US dollar. However, the substantial standard deviation of 25.92 dinars indicates the presence of sharp fluctuations in currency value. Notably, the lowest recorded price was 61 dinars in the early stages of the study period, while the rate jumped to reach its peak at 145.57 dinars, representing a wide price gap of 84.57 dinars. This considerable range in price volatility clearly underscores the necessity of employing modern and sophisticated forecasting models capable of absorbing and handling this notable degree of market instability.

Table 1. Statistical Characteristics of the USD/DZD Exchange Rate (2000-2025)

Indicator	Mean	Std. Error	Median	Variance	Kurtosis	Skewness	Min	Max	Count
Value	95.05	1.47	79.16	671.87	-1.35	0.55	61.00	145.57	310

Source: Authors' elaboration using python 3.13

Through analysing the skewness and kurtosis coefficients presented in Table (1), we observe that the positive skewness coefficient (+0.55) indicates that the data distribution is skewed to the right, meaning that the majority of observations recorded prices lower than the arithmetic mean. However, the presence of periods that witnessed sharp increases in the exchange rate led to a noticeable elevation of the overall average. As for the negative kurtosis coefficient (-1.35), it suggests that the distribution is flat (Platykurtic), which means the data is widely spread across the price range rather than being concentrated around a specific central value. These statistical characteristics reflect the nature of the Algerian economic environment, which has been influenced by multiple internal and external factors, including oil price fluctuations, monetary policies, and global economic shocks.

Moreover, the substantial gap between the arithmetic mean (95.05) and the median (79.16) clearly demonstrates the impact of extreme values on the distribution. The lower median reflects the actual reality for most of the time period, while the mean is significantly affected by periods that witnessed a sharp decline in the Algerian dinar's value during recent years. This evident discrepancy emphasises the necessity of employing advanced analytical methods that don't rely solely on traditional central statistics, but rather take into account the dynamic structure and non-linear characteristics of the time series. This justifies the selection of the hybrid CEEMDAN-LSTM model in this study.

4.2 Hybrid CEEMDAN-LSTM Model Methodology

The data was divided into two sets: a training set comprising 279 observations (approximately 90% of the total data), and a testing set containing 31 observations (approximately 10%), while maintaining the natural chronological order of the data without random shuffling, to ensure valid evaluation within the time series context. This division is appropriate for long time series, as the testing set of 31 data points (equivalent to roughly 2.5 years) provides sufficient size to assess the model's ability to generalise and forecast accurately.

The analysis process begins by applying CEEMDAN to the original time series. The decomposition process produced five intrinsic mode functions (IMFs) in addition to a residual component, where each component represents a different frequency level in the original data, as illustrated in Figure (2). This multi-level decomposition helps separate short-term fluctuations and irregular shocks from medium- and long-term movements, making it easier for the LSTM models to learn from each pattern individually rather than handling the raw series as a single process.

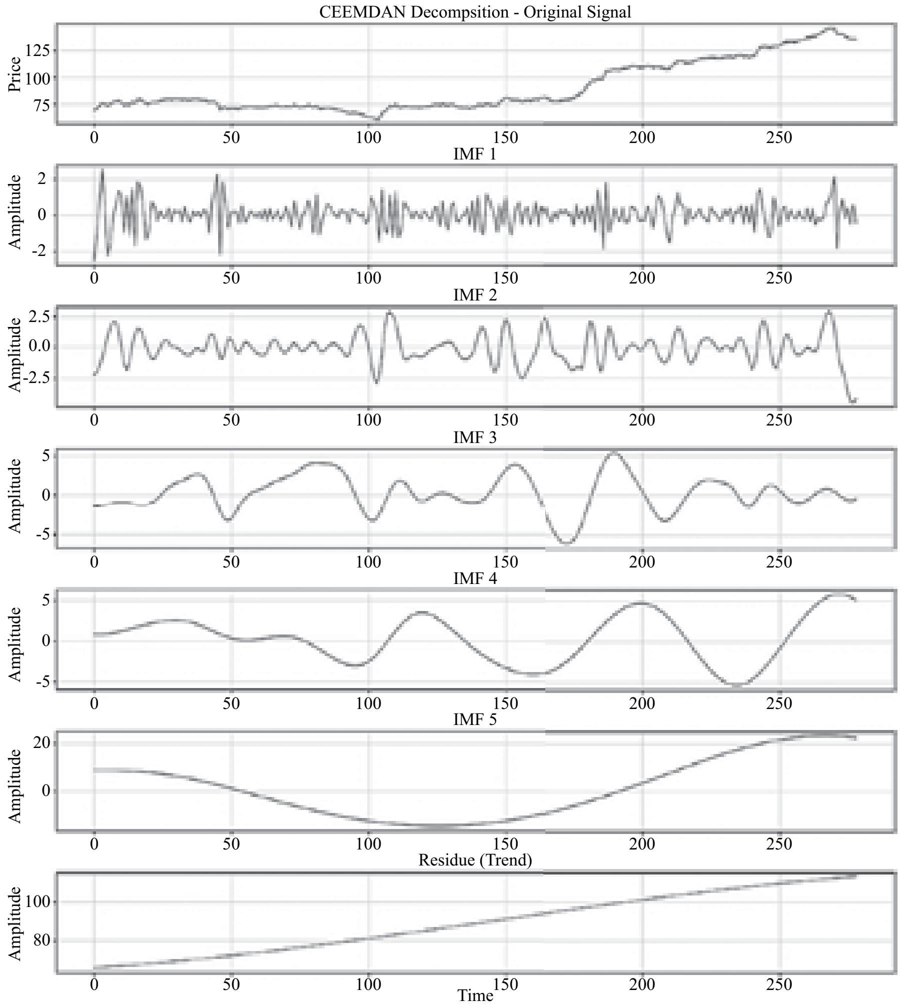

Figure 2: CEEMDAN decomposition of USD/DZD exchange rate into six frequency components

Source: Authors' elaboration using python 3.13

Figure (2) illustrates how the original time series was decomposed into multiple components. IMF1, IMF2, and IMF3 capture higher-frequency movements associated with short-term fluctuations, whereas IMF4, IMF5, and the residual component represent medium- and long-term dynamics. This separation allows the forecasting model to learn patterns at different horizons more effectively.

Each CEEMDAN component was normalised using a scaler fitted on the corresponding training segment only. The LSTM specification uses two stacked layers with 32 and 16 units, trained for 500 epochs with the Adam optimiser (learning rate = 0.001) and mean squared error loss. A parsimonious architecture was retained to limit over-parameterisation in the short monthly series; the same specification was maintained across the primary and robustness evaluations. The lookback window is two months for IMF1–IMF3 and four months for IMF4, IMF5, and the residual; the standalone LSTM uses four lags. The SVR benchmark uses an RBF kernel, with C, gamma, and epsilon selected by grid search under four-fold time-series cross-validation on the training segment only. A fixed random seed of 123 ensures reproducibility. The complete hyperparameter settings and selection procedures for all models are summarised in Table 2.

Table 2. Hyperparameter Specification and Selection Protocol

Model	Hyperparameter	Selected value	Selection protocol
CEEMDAN	Trials; noise amplitude	50; 0.005	Fixed reproducible specification
CEEMDAN-LSTM / LSTM	LSTM layers and units	2 layers: 32, 16	Parsimonious fixed specification
CEEMDAN-LSTM / LSTM	Optimiser; learning rate; loss	Adam; 0.001; MSE	Fixed specification
CEEMDAN-LSTM / LSTM	Epochs; dropout	500; 0.00	Held constant across splits
CEEMDAN-LSTM	Lookback window	2 for IMF1–IMF3; 4 otherwise	Frequency-based rule
Traditional LSTM	Lookback window	4	Held constant across splits
SVR	Kernel; C; gamma; epsilon	RBF; 100; 0.01; 0.001	Grid search + TimeSeriesSplit(4)

Source: Authors' specification and computations using Python 3.13.

4.3 Model Performance During Training

Table (3) reports the final training losses obtained from the six component-specific LSTM models and fully documented specification. The MSE loss function and Adam optimisation algorithm were applied uniformly to all components for 500 epochs.

The residual and IMF5 components exhibit the smallest final losses (0.0001 and 0.0004), reflecting the greater regularity of the lower-frequency dynamics. By contrast, IMF1 and IMF2 are more difficult to fit because they capture higher-frequency fluctuations. The training-loss curves in Figure (3) show declining loss profiles under the documented specification.

Table 3. Training Results of the Component-Specific LSTM Models

Component	Window Size	Final Loss	Number of Epochs	Characteristics
IMF 1	2	0.0188	500	High frequency (short-term fluctuations)
IMF 2	2	0.0132	500	High frequency
IMF 3	2	0.0032	500	Medium frequency
IMF 4	4	0.0027	500	Medium frequency
IMF 5	4	0.0004	500	Low frequency (trend)
Residue	4	0.0001	500	Long-run component

Source: Authors' computations using Python 3.13.

Figure (3) presents the training-loss curves for the six component-specific LSTM models.

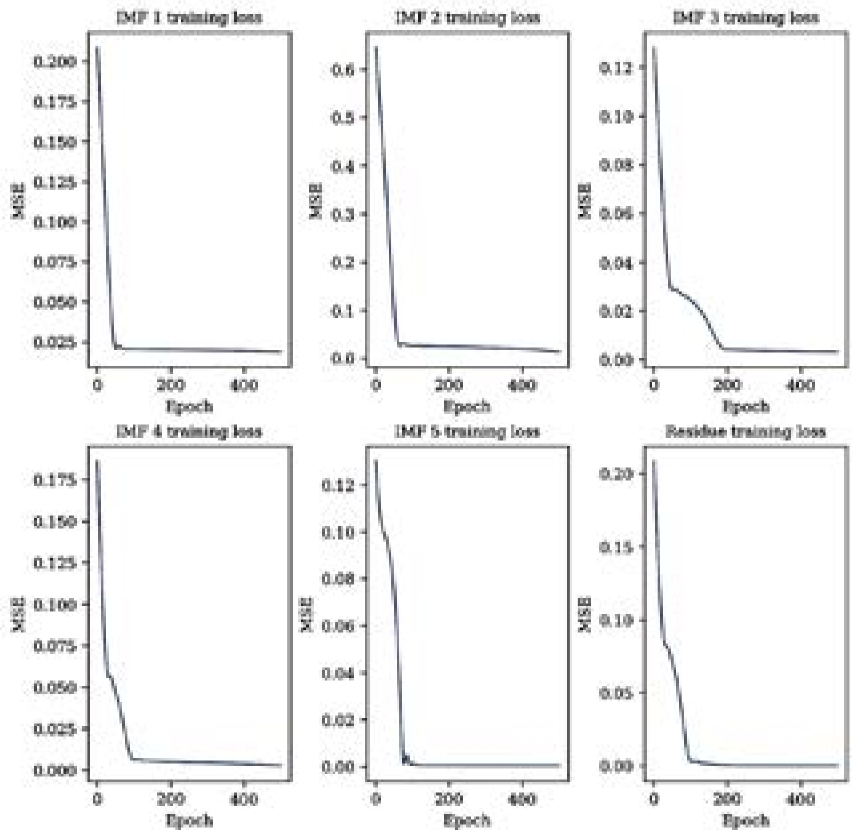

Figure 3: Training-Loss Curves for the Component-Specific LSTM Models
Source: Authors' computations using Python 3.13.

4.4 Model Performance Evaluation on Test Data

After estimation, the component forecasts were aggregated to reconstruct the CEEMDAN-LSTM forecast. Table (4) compares the out-of-sample results on the primary 90/10 chronological holdout with the standalone LSTM and the tuned SVR benchmark.

Table 4. Performance Comparison on the Primary 90/10 Holdout (31 Observations)

Model	MAE	RMSE	MAPE (%)
Traditional LSTM	1.4710	1.8070	1.1094
SVR (RBF)	0.8406	1.0769	0.6304
CEEMDAN-LSTM	0.6393	0.8149	0.4782

Source: Authors' computations using Python 3.13.

On the primary test period, CEEMDAN-LSTM yields the lowest errors on all three metrics. Its MAE of 0.6393 dinars is 56.5% lower than the standalone LSTM error and 23.9% lower than the tuned SVR error. The corresponding MAPE of 0.4782% indicates a close match to the observed USD/DZD values in this holdout.

As shown in Table 5, The modified Diebold–Mariano results support the primary-sample ranking: equal predictive accuracy is rejected at the 5% level against both benchmarks. This provides statistical evidence for the hybrid model's improvement over the primary evaluation window.

Table 5. Modified Diebold–Mariano Tests on the Primary 90/10 Holdout

Model comparison (squared-error loss)	MDM statistic	p-value	Decision at 5%
CEEMDAN-LSTM vs Traditional LSTM	-3.3369	0.0023	Reject equal accuracy; hybrid preferred
CEEMDAN-LSTM vs SVR (RBF)	-2.2930	0.0290	Reject equal accuracy; hybrid preferred

Source: Authors' computations; negative statistic indicates lower loss for CEEMDAN-LSTM.

The improvement is consistent with the decomposition rationale: CEEMDAN isolates components operating at different frequencies, while component-specific LSTM networks learn comparatively homogeneous patterns before their forecasts are recombined.

Figure (4) plots actual observations against the CEEMDAN-LSTM forecasts in the primary holdout period.

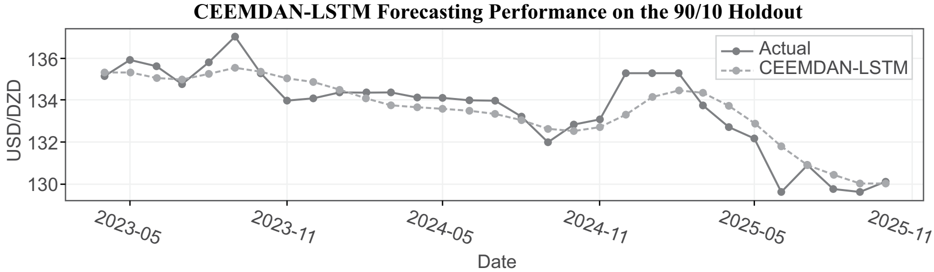

Figure 4: Actual and CEEMDAN-LSTM Forecast Values on the Primary 90/10 Holdout
Source: Authors' computations using Python 3.13.

Figure (4) shows that the hybrid forecast closely follows the observed movements in the primary holdout, although deviations remain at some local turning points.

4.5 Future Forecasting for Twelve Months

The CEEMDAN-LSTM model was re-estimated using the full series and used to generate recursive monthly forecasts from November 2025 through October 2026. In response to the non-normal distributional evidence in Table (1), Table (6) reports residual-bootstrap 95% prediction intervals based on 5,000 resamples rather than intervals obtained under a normal-error assumption.

Table 6. Future USD/DZD Forecasts with 95% Residual-Bootstrap Prediction Intervals

Month	Point Forecast (Dinar)	Lower 95% Bootstrap Bound	Upper 95% Bootstrap Bound
November 2025	130.37	128.12	132.30
December 2025	130.07	127.82	132.00
January 2026	129.85	127.59	131.78
February 2026	129.86	127.60	131.78
March 2026	129.95	127.70	131.88
April 2026	129.90	127.65	131.83
May 2026	129.92	127.67	131.85
June 2026	129.98	127.73	131.91
July 2026	130.05	127.80	131.98
August 2026	130.08	127.82	132.00
September 2026	130.14	127.89	132.07
October 2026	130.21	127.96	132.14

Source: Authors' computations using 5,000 centered residual-bootstrap replications in Python 3.13.

The forecast path indicates relative stability around 130 dinars per US dollar. The point forecast declines from 130.37 in November 2025 to 129.85 in January

2026 and then rises gradually to 130.21 in October 2026, implying only a modest change over the forecast horizon.

The bootstrap limits are asymmetric around the point estimates and avoid imposing normality on future errors. For example, the 95% interval for November 2025 is [128.12, 132.30], while the October 2026 interval is [127.96, 132.14]. These uncertainty bounds should be interpreted as baseline ranges rather than protection against structural breaks or exceptional policy and commodity-price shocks.

Figure (6) presents recent observations, primary-holdout predictions, and the twelve-month forecast path with the residual-bootstrap prediction interval.

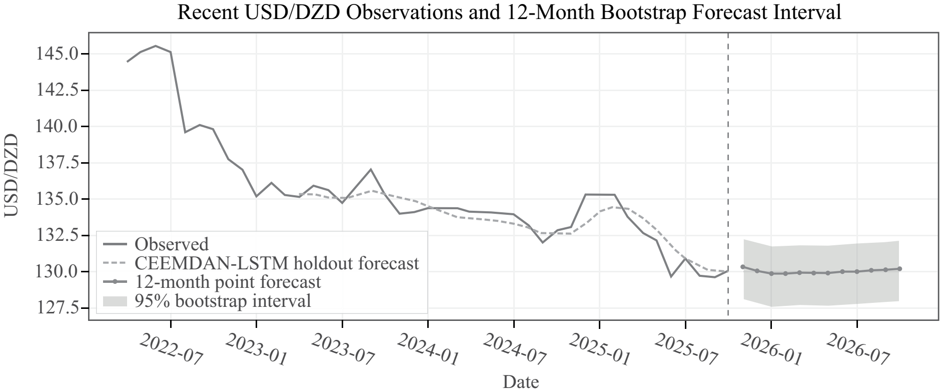

Figure 6: Recent USD/DZD Observations and Twelve-Month Forecast with Bootstrap Interval

Source: Authors' computations using Python 3.13.

The forecast band in Figure (6) makes explicit the uncertainty surrounding the otherwise stable point forecast and provides a more defensible basis for risk analysis than normality-based bounds.

4.6 Discussions and Policy Implications

The results provide evidence in favour of decomposition-based forecasting for the USD/DZD exchange rate. In the primary evaluation, the CEEMDAN-LSTM model achieves lower forecasting errors than both the standalone LSTM and the tuned SVR benchmarks. Furthermore, the modified Diebold–Mariano tests indicate that these improvements are statistically significant, providing empirical support for the forecasting advantage of the proposed hybrid framework.

From an economic perspective, the decomposition results remain meaningful. High-frequency intrinsic mode functions (IMFs) may reflect short-term responses to temporary shocks, market sentiment, and transitory trade or policy disturbances. In contrast, lower-frequency IMFs and the residual component capture more persistent dynamics that may be associated with hydrocarbon export revenues, import demand, inflation differentials, monetary conditions, and exchange-rate management policies. By separating these heterogeneous movements into more homogeneous components, CEEMDAN facilitates more effective pattern learning by the LSTM networks and contributes to improved forecasting performance.

These findings have several policy implications. First, more accurate short-term forecasts can support the timing of foreign-exchange interventions, liquidity planning, and reserve management by monetary authorities. Second, reliable medium-term exchange-rate projections can assist public institutions and import-dependent firms in budgeting, cash-flow management, and hedging decisions. Third, although the twelve-month forecast suggests relative stability in the USD/DZD exchange rate, it should be interpreted as a baseline scenario rather than a guarantee of future stability. Policymakers and market participants should complement baseline forecasts with scenario analysis to assess the potential effects of adverse developments such as oil-price fluctuations, inflationary pressures, or external financial shocks.

Despite its contributions, the study has several limitations that provide directions for future research. The analysis remains univariate and focuses on a single currency pair, while structural changes and exogenous shocks are incorporated only indirectly through the historical exchange-rate series. Future research could extend the framework by incorporating additional macroeconomic variables, including oil prices, inflation rates, interest-rate differentials, and foreign-exchange reserves. Moreover, further comparisons with advanced deep-learning approaches, such as attention-based models and transformer architectures, may provide additional insights into the relative strengths of decomposition-based forecasting methods in exchange-rate prediction.

5. CONCLUSIONS

Overall, the findings demonstrate the effectiveness of the CEEMDAN-LSTM hybrid framework for forecasting the USD/DZD exchange rate using 310 monthly observations covering the period from January 2000 to October 2025. In the primary evaluation, the hybrid model achieved MAE = 0.6393, RMSE =

0.8149, and MAPE = 0.4782%, outperforming both the standalone LSTM and the tuned SVR benchmarks. Furthermore, the modified Diebold–Mariano tests confirmed that these forecasting improvements were statistically significant relative to both competing models.

The prediction intervals generated through the residual bootstrap approach suggest a relatively stable baseline trajectory for the USD/DZD exchange rate over the subsequent twelve months, fluctuating around 130 Algerian dinars per US dollar while explicitly accounting for forecast uncertainty. These results indicate that the CEEMDAN-LSTM framework can serve as a useful tool for exchange-rate forecasting, financial planning, and exchange-rate risk management.

Despite these encouraging findings, practical applications of the model should be accompanied by regular model updating and continuous monitoring of new market information. In addition, forecast-based decisions should be complemented by scenario analysis to account for potential economic and financial shocks. Future research may further enhance forecasting performance by incorporating relevant macroeconomic variables and comparing the proposed framework with more advanced deep-learning architectures.

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Conflict of interests

The authors declare there is no conflict of interest.

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ЦЕЕМДАН-ЛСТМ МОДЕЛ ЗА ПРЕДВИЂАЊЕ ОДНОСА КУРСА АМЕРИЧКОГ ДОЛАРА И АЛЖИРСКОГ ДИНАРА

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САЖЕТАК

Овај рад развија хибридни модел за предвиђање девизног курса америчког долара према алжирском динару комбиновањем ЦЕЕМДАН декомпозиције са ЛСТМ мрежама како би се ријешили изазови високе волатилности и сложених временских зависности на валутним тржиштима. Модел је анализирао 310 историјских опажања са високом волатилношћу (стандардна девијација: 25,92). ЦЕЕМДАН је декомпоновао временску серију на пет фреквентних компоненти и резидуални дио, при чему је свака компонента обрађена независном ЛСТМ мрежом специјализованом за учење образаца унутар свог временског опсега. ЦЕЕМДАН-ЛСТМ модел је постигао најниже вриједности грешке, са МАПЕ од 0,56%, и надмашио традиционалне ЛСТМ и СВМ моделе. Прогноза за 12 мјесеци указује на релативну стабилност девизног курса са благим падом од око 0,48%. Резултати показују да декомпозиција оригиналне серије прије СЛТМ моделирања побољшава тачност предвиђања раздвајањем краткорочног шума од средњорочних и дугорочних кретања. Ова методологија може послужити финансијским институцијама и доносиоцима економских одлука као користан алат за управљање ризиком, стратегије заштите и краткорочно и средњорочно планирање.

Кључне ријечи: *ЦЕЕМДАН, ЛСТМ, предвиђање девизног курса, финансијске временске серије, дубоко учење, управљање ризиком.*

ADOPTION OF ARTIFICIAL INTELLIGENCE AND HUMAN RESOURCE UPSKILLING IN EMERGING MARKETS: EVIDENCE FROM SMALL AND MEDIUM ENTERPRISES IN OYO STATE, NIGERIA[1]

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ABSTRACT

This study investigates how the adoption of artificial intelligence (AI) is associated with workforce upskilling within small and medium-sized enterprises (SMEs) in Oyo State, Nigeria. While AI holds considerable transformative promise for human resource development, a critical knowledge gap persists regarding its regional implementation dynamics, particularly within the context of developing economies. Drawing on an integrated five-theory framework – the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology-Organisation-Environment (TOE) framework, Human Capital Theory, and Sociotechnical Systems Theory – this study develops and tests a conceptual model linking three theoretically grounded AI adoption dimensions (organisational integration, AI training programmes, and data-driven decision-making support) to employee skill enhancement outcomes. Employing a quantitative cross-sectional survey design, the structured questionnaires were administered to 135 respondents comprising HR professionals, SME operators, and employees drawn from approximately 72 SMEs across diverse industry sectors in Ibadan Metropolis. Results indicate that AI integration in HR upskilling practices remains largely nascent ($M = 2.116$). Nevertheless, Pearson correlation and regression analyses revealed significant positive associations between key AI adoption dimensions and employee skill enhancement ($R = 0.750$, $R^2 = 0.562$, $p < 0.001$).

These associations are interpreted as correlational rather than causal given the cross-sectional design. Prominent barriers include infrastructural inadequacies, educational deficiencies, policy gaps, and socio-cultural resistance. The study concludes with actionable policy and practice recommendations, and acknowledges methodological limitations including common method bias risk, absence of formal EFA/CFA, and cross-sectional design constraints.

1. INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technology has been associated with fundamental transformations across various industries globally, including human resource management (HRM). AI has been linked to significant changes in HR processes such as recruitment, performance evaluations, and employee training. Small and medium-sized enterprises (SMEs) face unique opportunities and obstacles in adopting AI, especially in developing countries such as Nigeria. Artificial intelligence is broadly understood as the emulation of human intelligence in machines programmed to think, learn, and make decisions independently (McCarthy, 2007; Russell & Norvig, 2010). Its incorporation into organisational routines is producing significant advantages by enhancing efficiency and enabling data-driven decision-making. In South-West Nigeria, AI-driven automation has been associated with job displacement, especially in low- and middle-skill sectors, potentially exacerbating income disparities (Acemoglu & Restrepo, 2022). AI has been associated with expedited, bias-minimised recruitment, data-informed decision-making, and enhanced training processes (Davenport et al., 2020). Research by Brynjolfsson and McAfee (2014) indicates that human skills remain crucial for interpreting and analysing AI outcomes, despite AI's capacity to automate repetitive tasks. Chui et al. (2016) emphasise the challenges faced by SMEs in implementing AI-driven HR practices. This study examines how AI adoption is associated with HR upskilling in SMEs in Oyo State, Nigeria, with specific focus on how organisational integration, training programmes, and data-driven decision-making support collectively predict employee skill enhancement outcomes.

1.1 Statement of Research Problem

The integration of AI into HR procedures represents a significant technological advancement with potential to enhance workforce development and organisational competitiveness. In Nigeria, where SMEs constitute crucial drivers of economic development, AI integration could fundamentally transform HR operations. Despite national-level initiatives aimed at enhancing the skills of Nigerian professionals (Federal Ministry of Communications, Innovation & Digital Economy, 2024), the localised effects in states such as Oyo remain inadequately understood. Disparities in access to digital infrastructure and training programmes present significant obstacles, while AI implementation risks exacerbating the existing digital skills gap, potentially rendering certain employees inadequately prepared for an AI-centric work environment.

1.2 Research Questions

This study explored the following research questions:

(i) What is the degree of AI adoption in organisational HR upskilling procedures among SMEs in Oyo State, Nigeria?
(ii) What association exists between AI adoption in HR upskilling procedures and employees' enhancement?
(iii) Does AI adoption in HR upskilling procedures have any significant predictive association with employee skill enhancement among SMEs in the study area?

1.3 Research Objectives

The general objective is to evaluate the association between AI adoption and employee upskilling among SMEs. Specifically, the study seeks to:

(i) assess the degree of AI adoption in organisational HR upskilling procedures among SMEs in Oyo State;
(ii) investigate the association between AI adoption in HR upskilling procedures and employee enhancement; and
(iii) evaluate the predictive relationship between AI adoption dimensions and employee skill enhancement among SMEs in the study area.

1.4 Research Hypotheses

H_{01}: The adoption of Artificial Intelligence (AI) is not widespread in organisational HR upskilling procedures.
H_{02}: There is no statistically significant association between AI adoption in HR upskilling procedures and employee enhancement.
H_{03}: AI adoption in HR upskilling procedures does not significantly predict employee upskilling outcomes among SMEs in the study area.

2. LITERATURE REVIEW

2.1 Conceptual Framework on AI Adoption and HR Upskilling

Artificial Intelligence encompasses systems capable of executing tasks requiring human intelligence, including decision-making, learning, and problem-solving. Strohmeier and Piazza (2015) characterise AI as a transformative instrument improving organisational processes by automating operations, analysing datasets, and producing predictive insights, enabling a shift from reactive to proactive HR management. Ogunyemi and Johnston (2012) highlight how technology-mediated information systems — including AI-driven platforms — transform employee management in African organisations, facilitating analytical decision-making for managing personnel data and forecasting workforce requirements. McCarthy (2007) defines AI as creating intelligent machines and computer programmes that reason, solve problems, and adapt autonomously. Russell and Norvig (2016) expand this to systems that act rationally to achieve goals. In the Nigerian context, Gwagwa et al. (2022) examine how socio-cultural values shape responsible AI deployment in Africa, while Hmoud and Laszlo (2019) define AI in HR as sophisticated algorithms replicating human reasoning to resolve workforce challenges, particularly in recruitment and selection.

2.2 Theoretical Framework and Integrated Conceptual Model

This study draws on five complementary theoretical frameworks, each contributing a distinct explanatory layer and directly informing the study's three hypotheses. Rather than treating these theories as parallel background references, this section explicitly maps each framework to the hypotheses it underpins and to the specific AI adoption dimensions selected for analysis. Taken together, they generate an integrated conceptual model in which antecedent adoption conditions shape AI adoption levels (H_{01}), which are in turn associated with employee skill enhancement outcomes (H_{02} and H_{03}).

Human Capital Theory (Becker, 1964) provides the foundational rationale for H_{03}. By positing that investments in employee training yield measurable productivity returns, Human Capital Theory directly justifies the expectation that AI-driven upskilling programmes will be associated with enhanced competencies. The AI Training Programmes predictor operationalises this theoretical claim: organisations investing in AI-centred training are investing in their human capital stock, and this investment is predicted to explain variance in skill enhancement outcomes. The positive AI Training Programmes coefficient ($\beta = 0.312$) is directly interpretable within this framework.

The integrated conceptual model is presented in Figure 1.

ANTECEDENTS	→ H_{01}	→ H_{02} H_{03}
• Perceived Usefulness (TAM) • Perceived Ease of Use (TAM) • Social Influence (UTAUT) • Facilitating Conditions (UTAUT) • Technology Readiness (TOE) • Organisational Capacity (TOE) • Environmental Fit (TOE) Davis, 1989; Venkatesh et al., 2003; Tornatzky & Fleischer, 1990	AI ADOPTION DIMENSIONS • AI Organisational Integration* • Technical Capabilities • Data-Driven HR Insights* • Process Automation • AI Training Programmes* * Retained predictors in regression model TAM • UTAUT • TOE • Sociotechnical Systems Theory	EMPLOYEE SKILL ENHANCEMENT (DV) • Training Participation • Skills Development • Productivity Improvement Becker, 1964; Zawacki-Richter et al., 2019; Brynjolfsson & McAfee, 2014

Figure 1. Integrated Conceptual Model: AI Adoption and Employee Skill Enhancement
Source: Author, 2026

Note: Arrows represent theorised directional associations. H_{01} = AI adoption not widespread (tested via one-sample t-test); H_{02} = association between adoption and enhancement (Pearson correlation, chi-square); H_{03} = AI adoption dimensions predict skill outcomes (multiple regression). * = Constructs retained in the regression model. DV = Dependent Variable. Theoretical sources: TAM (Davis, 1989); UTAUT (Venkatesh et al., 2003); TOE (Tornatzky & Fleischer, 1990); Human Capital Theory (Becker, 1964); Sociotechnical Systems Theory (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012); AST (DeSanctis & Poole, 1994).

The Technology Acceptance Model (TAM; Davis, 1989) underpins H_{01} by establishing that technology adoption is driven by perceived usefulness and perceived ease of use. In the SME context, these perceptions are constrained by infrastructural inadequacies and limited digital literacy, explaining why adoption levels remain nascent (M = 2.116). The AI Organisational Integration construct reflects TAM's concept of actual system usage – the downstream behavioural outcome of favourable technology perceptions.

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) extends TAM by incorporating social influence and facilitating conditions as additional determinants. This is directly relevant to H_{01} and H_{02}: socio-cultural resistance in the Nigerian SME environment – including job displacement fears and AI misconceptions (Gwagwa et al., 2022) – constitutes a negative social influence dampening adoption. Conversely, managerial endorsement and training provision (AI Training Programmes) represent positive facilitating conditions.

The Technology-Organisation-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) illuminates how technological readiness, organisational capacity, and environmental pressures jointly shape AI adoption at the firm level. Inadequate internet connectivity, unstable electricity, and limited computational resources (technological factors), combined with SME resource constraints (organisational factors) and a nascent regulatory environment (environmental factors), converge to explain the low adoption rates documented in H_{01}. The TOE framework additionally justifies the Data-Driven Decision-Making Support predictor.

Sociotechnical Systems Theory (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012) and Adaptive Structuration Theory (AST; DeSanctis & Poole, 1994) address H_{02} and H_{03} from organisational and individual learning perspectives. Sociotechnical Systems Theory posits that AI adoption produces skill enhancement only when the social system – including organisational culture, managerial support, and employee readiness – is aligned with the technical system. This explains AI Integration Level's primacy in the regression model ($\beta = 0.358$). AST further proposes that employees interacting with AI tools engage in iterative adaptation processes that cumulatively build competencies, consistent with the strong training-to-skill-enhancement correlation ($r = 0.758$).

2.3 Empirical Review

Empirical investigations reveal that emerging markets like Nigeria face substantial AI adoption obstacles. Olatunde-Aiyedun (2024) highlight sluggish AI integration in Nigerian educational and organisational settings, particularly in less urbanised areas, necessitating region-specific upskilling initiatives. Brynjolfsson and McAfee (2014) indicate deployment requires proficient workforces, while Hmoud and Laszlo (2019) underscore the importance of addressing skills gaps as AI infiltrates HR functions in sectors including banking and professional services. Eli-Chukwu (2019) notes that Nigeria's agricultural sector faces obstacles despite AI's considerable potential for precision farming. Olatunde-Aiyedun (2024) document minimal AI incorporation in Nigerian educational curricula, while Zawacki-Richter et al. (2019) contend that institutions globally must integrate AI-related courses to prepare future workforces. Zawacki-Richter et al. (2019) further found that AI-related upskilling programmes were associated with significantly improved technical skills, with personalised learning methodologies linked to enhanced skill acquisition. Socio-cultural concerns including technology aversion and fear of job displacement pose further obstacles to AI adoption in African contexts (Gwagwa et al., 2022).

2.4 Research Gap and Theoretical Contribution

Notwithstanding the growing body of literature on AI adoption in HR management, three important gaps remain. First, most empirical studies originate in high-income economies or large enterprises (Davenport et al., 2020; Brynjolfsson & McAfee, 2014), leaving the SME context in sub-Saharan Africa largely understudied. The few Nigeria-focused studies are either sector-specific or qualitative (Eli-Chukwu, 2019; Olatunde-Aiyedun, 2024), limiting generalisability to the mixed-sector SME landscape. Second, prior studies tend to examine AI adoption and skill development as separate phenomena rather than testing the predictive relationship between specific adoption dimensions and skill outcomes through inferential statistics. Third, existing studies are predominantly single-theory accounts (typically TAM alone), whereas the adoption paradox observed in emerging markets — strong associations coexisting with low adoption — requires a multi-theoretical lens.

This study addresses these gaps by: (1) providing multi-sectoral empirical evidence from SMEs in Oyo State; (2) applying an integrated five-theory conceptual model (Figure 1) that explicitly links theoretical constructs to hypotheses and AI adoption dimensions; and (3) identifying specific AI adoption dimensions that predict employee skill enhancement through inferential analysis.

3. MATERIALS AND METHODS

This study examines the association between AI adoption and human resource upskilling within SMEs in Ibadan Metropolis, Oyo State, Nigeria. As a major economic and technological hub, Ibadan serves as a critical centre for commercial activities, education, and administrative functions.

3.1 Research Design and Data Collection

This empirical study employed a quantitative, cross-sectional survey design. Primary data were collected through a structured questionnaire to evaluate the association between AI adoption and human resource upskilling. Item-level missing data were minimal (< 8% per item) and were handled using pairwise deletion for descriptive analyses and listwise deletion for all inferential tests, consistent with standard practice for missing completely at random (MCAR) data patterns (Hair et al., 2019).

3.2 Population, Sample, and Unit of Analysis

The target population comprises approximately 213 HR professionals, SME operators, and employees drawn from SMEs registered with the Oyo State SME Development Agency and the Ibadan Chamber of Commerce and Industry. Within these registered organisations, only those employing at least one HR professional or designated personnel management function were included in the sampling frame.

It is important to clarify the unit of analysis for this study: the unit of analysis is the individual respondent, not the organisation. Respondents were drawn from approximately 72 SME organisations, with between one and three respondents per organisation depending on firm size and the availability of eligible role categories (HR professional, SME operator, and/or employee). This multi-informant approach was adopted to capture different functional perspectives on AI adoption and upskilling within the same organisational context. Readers should note that respondents from the same firm share common organisational experiences, which introduces a degree of non-independence acknowledged in Section 5.1.

Simple random sampling was employed to ensure equal selection probability among eligible respondents. The sample size was determined using the Yamane (1967) formula: $n = N / [1 + N(e)^2]$, where $N = 213$ and $e = 0.05$, yielding $n \cong 139$. Consequently, 139 questionnaires were administered, yielding 135 valid responses (97.1% return rate).

3.3 Research Instrument

The questionnaire was designed using a five-point Likert scale (5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree). All items were adapted from established, peer-reviewed instruments with demonstrated validity and reliability in related technology adoption and HRM contexts. The instrument comprised 24 items distributed across five thematic constructs, as summarised in Table 3. The full instrument is available from the corresponding author upon reasonable request.

The survey also collected seven demographic variables: gender, age group, educational qualification, organisational role, industry sector, years of experience, and organisation size.

Table 3. Questionnaire construct operationalisation (24 items total)

Construct	Items	Theoretical Basis	Adapted From	
AI Organisational Integration	5	TAM (Davis, 1989); TOE (Tornatzky & Fleischer, 1990)	Venkatesh et al. (2003); Olatunde-Aiyedun (2024)	"AI tools are integrated into our core HR processes."
Technical Capabilities	4	UTAUT (Venkatesh et al., 2003)	Hmoud & Laszlo (2019)	"Staff possess adequate skills to use AI tools."
Data-Driven HR Insights	5	TOE; Human Capital Theory (Becker, 1964)	Davenport et al. (2020); Ogunyemi & Johnston (2012)	"AI-generated data informs our HR decisions."
Process Automation	4	Sociotechnical Systems Theory (Trist & Bamforth, 1951)	Strohmeier & Piazza (2015); Hmoud & Laszlo (2019)	"Routine HR tasks are handled through AI automation."
Employee Skill Enhancement (DV)	6	Human Capital Theory; AST (DeSanctis & Poole, 1994)	Zawacki-Richter et al. (2019); Brynjolfsson & McAfee (2014)	"AI-related training improved my job-relevant skills."

Note: DV = Dependent Variable. Items rated on a 5-point Likert scale. Items were adapted from established scales with minor wording modifications to contextualise for the Nigerian SME environment.

3.4 Validity and Reliability

To ensure content validity, the research instrument was subjected to expert review involving specialists in AI, human resource management, and measurement. A pilot study was conducted prior to full-scale deployment. Reliability was assessed using Cronbach's Alpha ($\alpha = 0.839$), exceeding the acceptable threshold of 0.70 (Nunnally, 1978) and indicating sufficient internal consistency.

Regarding construct validity, two acknowledgements are warranted. First, the study measures respondents' perceptions of AI adoption rather than objective indicators of AI tool deployment, introducing a limitation discussed in Section 5.1. Second, while items were adapted from prior validated instruments, formal exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were not conducted. Future studies should include both EFA and CFA to formally establish the factorial structure of the adapted instrument in the Nigerian SME context (Hair et al., 2019). This is acknowledged as a significant limitation of the current study.

3.5 Analytical Techniques

Data were analysed using descriptive statistics (means and standard deviations), a one-sample t-test (H_{01}), Pearson correlation and chi-square test of independence (H_{02}), and multiple linear regression analysis (H_{03}). All analyses were performed using SPSS v.25. The Durbin-Watson statistic was used to assess autocorrelation, and variance inflation factors (VIF) were examined to detect multicollinearity.

Composite score construction: For each construct, a composite score was computed as the arithmetic mean of all item-level responses within that construct following pairwise deletion for items with missing values, producing interval-level scores commensurate with regression analysis assumptions.

One-sample t-test justification (H_{01}): The test value of 2.50 was selected to represent the boundary between the 'Disagree' (2) and 'Neutral' (3) response categories on the five-point scale, operationalising a conservative threshold below which observed means cluster closer to disagreement than to neutrality. A sensitivity analysis using 3.0 as the test value yields $t(134) = -8.84$, $p < 0.001$, reaching the same substantive conclusion. Both thresholds are reported in Table 7.

Chi-square test (H_{02}): Composite scores were recoded into three ordinal categories prior to analysis: Low (1.00–2.49), Moderate (2.50–3.49), and High (3.50–5.00). Categories were assigned prior to and independently of results to avoid post-hoc categorisation bias. The resulting cross-tabulation produced 12 degrees of freedom.

Of the five thematic constructs, the multiple regression model retained three predictors: AI Integration Level, AI Training Programmes, and AI Decision-Making Support. Process Automation demonstrated substantial overlap with AI Integration Level ($r = 0.71$), raising multicollinearity concerns. Technical Capabilities was similarly subsumed within AI Integration Level in preliminary factor analysis. Both were excluded to maintain model parsimony (Hair et al., 2019). The retained predictors exhibited VIF values between 1.389 and 1.523.

3.6 Common Method Bias Precautions

Given that all constructs were measured using a single self-report questionnaire administered on one occasion, the risk of common method bias (CMB; Podsakoff et al., 2003) was explicitly considered at both procedural and analytical stages. Procedural remedies implemented include: (1) anonymity of responses was guaranteed to minimise social desirability bias; (2) participation was voluntary, reducing acquiescence pressure; (3) the survey was framed as having no correct or incorrect answers, reducing evaluation apprehension; and (4) varied item stems were employed across constructs to reduce artificial consistency.

Notwithstanding these precautions, formal CMB diagnostics – including Harman’s single-factor test and common latent factor analysis – were not conducted, which limits the ability to statistically quantify CMB magnitude. The elevated inter-construct correlations (r = 0.681–0.758) may partially reflect shared method variance. Future studies are strongly encouraged to employ temporal separation of predictor and criterion measurements, or multi-source data collection, as additional CMB remedies.

4. RESULTS

4.1 Questionnaire Return Rate

Table 4. Questionnaire return rate

Category	Frequency	Percentage (%)
Not filled/Invalid	4	2.9
Filled correctly	135	97.1
Total Expected	139	100.0

Source: Field Survey, 2025

4.2 Respondent Demographic Profile

Table 5 presents the demographic profile of respondents. The sample comprises slightly more male (52.6%) than female (47.4%) respondents. The majority (39.3%) fall within the 26–35 age bracket. Nearly half hold HND or B.Sc. qualifications (48.9%), with a further 30.4% possessing postgraduate degrees. SME operators represent the largest role category (37.8%), followed by HR professionals (34.1%) and employees (28.1%). The services sector accounts for the largest share (34.8%). The majority of organisations are small-sized (10–49 employees, 46.7%), consistent with the Nigerian SME definition.

While the demographic composition is informative, no systematic comparison with the actual population structure of all SMEs in Oyo State or Ibadan Metropolis was conducted. The sampling frame was limited to SMEs registered with formal agencies, which may over-represent more formalised enterprises relative to the broader informal SME sector. Accordingly, representativeness claims apply specifically to the registered, formalised SME population in Ibadan Metropolis.

Table 5. Demographic profile of respondents (N = 135)

Demographic Variable	Category	Frequency (%)
Gender	Male	71 (52.6%)
	Female	64 (47.4%)
Age Group	18–25 years	23 (17.0%)
	26–35 years	53 (39.3%)
	36–45 years	37 (27.4%)
	46 years and above	22 (16.3%)
Educational Qualification	SSCE / OND	19 (14.1%)
	HND / B.Sc.	66 (48.9%)
	M.Sc. / MBA	41 (30.4%)
	Ph.D.	9 (6.7%)
Organisational Role	HR Professional	46 (34.1%)
	SME Operator / Owner	51 (37.8%)
	Employee	38 (28.1%)
Industry Sector	Manufacturing	27 (20.0%)
	Services	47 (34.8%)
	Agriculture	21 (15.6%)
	Retail / Trade	23 (17.0%)
	ICT / Technology	17 (12.6%)
Years of Experience	Less than 2 years	18 (13.3%)
	2–5 years	43 (31.9%)
	6–10 years	47 (34.8%)
	More than 10 years	27 (20.0%)
Organisation Size	Micro (< 10 employees)	29 (21.5%)
	Small (10–49 employees)	63 (46.7%)
	Medium (50–249 employees)	43 (31.9%)

Source: Field Survey, 2025

4.3 Research Question 1: Degree of AI Adoption in HR Upskilling

Table 6 presents descriptive statistics for AI adoption variables. The composite mean score of 2.116 indicates that AI adoption in HR upskilling procedures is below the conservative threshold of 2.5 and substantially below the conventional neutral midpoint of 3.0, suggesting limited penetration of AI technologies.

Table 6. Descriptive statistics for AI adoption variables

Variable	N	Mean	Std. Dev.	Interp.
AI integrated into HR processes	125	2.080	1.142	Low-Mod.
AI associated with improved recruitment	130	2.462	1.089	Low-Mod.
AI in training and development programmes	130	2.000	0.869	Low
AI associated with improved decision-making	135	2.556	1.095	Moderate
Challenges in adopting AI in HR	130	2.077	0.934	Low-Mod.
Overall AI Adoption Level	135	2.116	1.160	Low-Mod.

Note: Variation in N reflects item-level missing data handled using pairwise deletion for descriptive statistics and listwise deletion for inferential analyses (N = 135). Missing values per item ≤ 7.4% (Hair et al., 2019).

Source: Authors' calculation

4.3.1 Hypothesis Testing: H_{01}

H_{01}: The adoption of AI is not widespread in organisational HR upskilling procedures.

Table 7. One-sample t-test results

Statistic	Value	Interpretation
Test Value (primary)	2.500	Below-neutral adoption benchmark
Sample Mean	2.116	Observed AI adoption level
T-Statistic	−3.847	Significant negative deviation
Degrees of Freedom	134	n − 1
P-Value (2-tailed)	0.000*	Highly significant ($p < 0.001$)
Mean Difference	−0.384	Below test value
95% Confidence Interval	[−0.582, −0.186]	Does not include zero
Sensitivity: test value = 3.0	$t = -8.84$, $p < 0.001$	Same conclusion; adoption below neutral midpoint

*$p < 0.001$. Source: Authors' calculation

Decision: FAIL TO REJECT H_{01}. The result reveals a statistically significant difference between the observed mean AI adoption level ($M = 2.116$, $SD = 1.160$) and the test value of 2.5, $t(134) = -3.847$, $p < 0.001$, 95% CI [−0.582, −0.186]. A sensitivity test using the conventional neutral midpoint of 3.0 yields $t(134) = -8.84$, $p < 0.001$, reinforcing this conclusion. AI adoption is NOT widespread in organisational HR upskilling procedures among SMEs in Oyo State.

4.4 Research Question 2: Association Between AI Adoption and Employee Enhancement

Table 8 presents the Pearson correlation matrix. AI Adoption and Employee Training ($r = 0.724$, $p < 0.001$), Skills Enhancement ($r = 0.681$, $p < 0.001$), and Employee Productivity ($r = 0.697$, $p < 0.001$) all indicate strong positive associations. Employee Training and Skills Enhancement ($r = 0.758$, $p < 0.001$) represents the strongest correlation, indicating that formal training programmes are strongly associated with skill development outcomes. These are correlational findings and do not establish causal direction.

Table 8. Pearson correlation matrix

Variable 1	Variable 2	Pearson r	P-Value
AI Adoption	Employee Training	0.724**	0.000
AI Adoption	Skills Enhancement	0.681**	0.000
AI Adoption	Employee Productivity	0.697**	0.000
Employee Training	Skills Enhancement	0.758**	0.000

**Correlation is significant at the 0.01 level (2-tailed).

Source: Authors' calculation

4.4.1 Hypothesis Testing: H_{02}

H_{02}: There is no statistically significant association between AI adoption in HR upskilling procedures and employee enhancement.

Table 9. Chi-square test of independence results

Test Statistic	Value	df	P-Value	Decision
Pearson Chi-Square	47.823	12	0.000***	Reject H_{02}
Likelihood Ratio	51.247	12	0.000***	–
N of Valid Cases	135	–	–	–

Note: Composite scores were recoded into three categories prior to analysis: Low (1.00–2.49), Moderate (2.50–3.49), High (3.50–5.00), producing a 3 × 4 contingency table (12 df). ***$p < 0.001$.

Source: Authors' calculation

Decision: REJECT H_{02}. The chi-square test, $\chi^2(12, N = 135) = 47.823$, $p < 0.001$, indicates that AI adoption levels and employee enhancement outcomes are not independent. These associations are descriptive and do not imply causality.

4.5 Research Question 3: Predictive Relationship Between AI Adoption and Employee Skill Enhancement

Table 10. Multiple regression — model summary

Model	R	R^2	Adj. R^2	Std. Error	Durbin-Watson
1	0.750	0.562	0.549	1.110	1.847

Source: Authors' calculation

Table 11. ANOVA results

Source	Sum of Sq.	df	Mean Sq.	F (Sig.)
Regression	156.847	3	52.282	42.357*** (0.000)
Residual	161.523	131	1.233	–
Total	318.370	134	–	–

***p < 0.001. Source: Authors' calculation

Table 12. Regression coefficients

Predictor	B	Std. Error	Beta (β)	t (Sig.)	VIF
(Constant)	0.847	0.234	–	3.619 (0.000***)	–
AI Integration Level	0.423	0.089	0.358	4.753 (0.000***)	1.456
AI Training Programmes	0.381	0.095	0.312	4.011 (0.000***)	1.523
AI Decision-Making Support	0.267	0.087	0.218	3.069 (0.003**)	1.389

***p < 0.001; **p < 0.01. VIF values below 5.0 confirm no multicollinearity. Source: Authors' calculation

4.5.1 Hypothesis Testing: H_{03}

H_{03}: AI adoption in HR upskilling procedures does not significantly predict employee upskilling outcomes among SMEs in the study area.

Decision: REJECT H_{03}. The overall model achieves statistical significance, $F(3, 131) = 42.357$, $p < 0.001$, with $R^2 = 0.562$, indicating that 56.2% of variance in employee upskilling outcomes is accounted for by the three retained AI adoption predictors. All three predictors demonstrate individual statistical significance: AI Integration Level ($\beta = 0.358$, $t = 4.753$, $p < 0.001$); AI Training Programmes ($\beta = 0.312$, $t = 4.011$, $p < 0.001$); and AI Decision-Making Support ($\beta = 0.218$, $t = 3.069$, $p = 0.003$). VIF values (1.389–1.523) confirm no multicollinearity. The Durbin-Watson statistic of 1.847 indicates no serial autocorrelation. These coefficients represent predictive associations rather than causal effects.

5. DISCUSSIONS

This study reveals that perceived AI adoption in HR upskilling among Oyo State SMEs remains below moderate levels (M = 2.116), consistent with TAM's (Davis, 1989) prediction that low perceived ease of use and limited facilitating conditions constrain technology uptake. The TOE framework (Tornatzky & Fleischer, 1990) further contextualises these results: inadequate internet connectivity, unstable electricity, resource constraints, and a nascent regulatory environment converge to suppress adoption at the firm level. These findings align with Olatunde-Aiyedun's (2024) documentation of infrastructure and awareness barriers to AI integration in Nigerian institutions, and with Gwagwa et al.'s (2022) observation that socio-cultural dynamics significantly shape technology adoption trajectories across African contexts.

Despite limited adoption, strong positive correlations ($r = 0.681–0.758$) present a noteworthy pattern consistent with Human Capital Theory's (Becker, 1964) expectation that even modest AI-enabled training investments yield measurable competency returns. The robust AI-training association ($r = 0.724$) is consistent with Zawacki-Richter et al.'s (2019) systematic review findings linking AI-supported learning environments to improved skill acquisition outcomes across diverse institutional contexts.

However, an equally plausible interpretation must be acknowledged: the strong associations may partly reflect a selection effect. Organisations that have adopted AI may represent more progressive, resource-endowed SMEs whose employees would report better skill outcomes regardless of AI specifically. This selection effect interpretation underscores the need for longitudinal studies to disentangle genuine AI-upskilling relationships from pre-existing organisational capability differentials.

The regression model demonstrates substantial predictive power ($R^2 = 0.562$), exceeding Cohen's (1988) threshold for large effects. AI Integration Level's primacy ($\beta = 0.358$) aligns with Sociotechnical Systems Theory's emphasis on organisation-wide alignment (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012): skill enhancement is optimised when AI is embedded across organisational functions rather than deployed in isolated pockets. The AI Training Programmes coefficient ($\beta = 0.312$) underscores the urgency of educational reform and is grounded in Human Capital Theory (Becker, 1964); this finding resonates with Strohmeier and Piazza's (2015) conceptual framework positioning structured AI training as central to HRM value creation. The unexplained variance (43.8%) indicates that additional factors, including socio-cultural barriers, AI misconceptions, and infrastructural constraints documented by Gwagwa et al. (2022), warrant further empirical investigation.

This study involved respondents drawn from multiple functional roles within the same organisations. HR professionals, SME operators, and employees may evaluate AI adoption differently; future studies should apply multilevel modelling to account for the nested structure of individuals within firms.

5.1 Limitations

Cross-sectional design. The cross-sectional design prevents causal inference. Longitudinal designs are required to establish temporal precedence.

Common method bias. All variables were collected from a single self-report questionnaire. While procedural remedies were implemented, formal CMB diagnostics were not conducted (Podsakoff et al., 2003). Elevated inter-construct correlations (r = 0.681–0.758) may partially reflect shared method variance.

Perceptual measurement. Reliance on respondents' perceptions of AI adoption rather than objective measures introduces construct validity concerns. Future studies should supplement perceptual measures with organisational records.

Sample scope and representativeness. The sample is confined to Ibadan Metropolis and to registered SMEs. Representativeness claims apply specifically to the registered SME population; generalisations to informal or rural enterprises should be made with caution.

Multi-respondent nesting. Respondents from the same organisation may share contextual influences, introducing non-independence not formally modelled. Future studies should employ multilevel modelling.

Instrument validation. EFA and CFA were not formally conducted, which constitutes a significant limitation. Future research must include full psychometric validation of the adapted instrument (Hair et al., 2019).

Regression model completeness. Exclusion of Process Automation and Technical Capabilities from the regression model means the full five-construct framework was not simultaneously modelled. Future research employing SEM would enable comprehensive simultaneous testing.

6. CONCLUSIONS

This study provides empirical evidence on the associations between AI adoption and HR upskilling among Oyo State SMEs, grounded in an integrated five-theory conceptual model (Figure 1) that explicitly links theoretical constructs to three research hypotheses. The results indicate that current AI adoption remains limited ($M = 2.116$), yet documented strong positive associations ($r = 0.681–0.758$) and substantial predictive power ($R^2 = 0.562$) demonstrate significant potential for AI-enabled workforce development. These conclusions must be interpreted with caution given the cross-sectional design, the potential for selection effects, and the absence of formal EFA/CFA validation. The predictive primacy of AI Integration Level ($\beta = 0.358$) and AI Training Programmes ($\beta = 0.312$) suggests that systemic, organisation-wide AI adoption accompanied by formal training infrastructure is most strongly associated with employee skill development, a finding consistent with both Sociotechnical Systems Theory (Trist & Bamforth, 1951) and Human Capital Theory (Becker, 1964).

Recommendations

1. The three tiers of government in Nigeria should embark on strategic investments and policy reforms enabling broader AI implementation, recognising that the positive AI-upskilling associations documented here are correlational and require longitudinal confirmation.
2. SME managers should prioritise systematic AI integration across organisational functions rather than isolated implementations, investing in employee training programmes for AI-related competencies while actively engaging staff to reduce socio-cultural resistance (Gwagwa et al., 2022).
3. Policymakers need to develop state-specific AI adoption strategies, investing in foundational digital infrastructure and providing targeted financial incentives such as subsidies, tax credits, and loans for SME AI investments.
4. Educational institutions must integrate AI-related content across disciplinary curricula beyond computer science programmes (Zawacki-Richter et al., 2019; Olatunde-Aiyedun, 2024), collaborating with industry to align curricula with actual workplace competency requirements.
5. Future research should adopt longitudinal designs, conduct EFA and CFA for full instrument validation, address CMB through multi-source data collection and formal testing (Podsakoff et al., 2003), employ SEM to simultaneously model all five constructs, apply multilevel modelling for within-firm clustering, and extend the geographical scope beyond Ibadan Metropolis.

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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.

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УСВАЈАЊЕ ВЈЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ И УСАВРШАВАЊЕ ЉУДСКИХ РЕСУРСА НА ТРЖИШТИМА У РАЗВОЈУ: ДОКАЗИ ИЗ МАЛИХ И СРЕДЊИХ ПРЕДУЗЕЋА У САВЕЗНОЈ ДРЖАВИ ОУО, НИГЕРИЈА

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САЖЕТАК

Овај рад испитује у којој мјери усвајање вјештачке интелигенције (ВИ) корелира с усавршавањем људских ресурса у малим и средњим предузећима (МСП) у савезној држави Оуо, Нигерија. Користећи интегративни теоријски оквир који обухвата ТАМ, УТАУТ, ТОЕ, теорију хуманог капитала и социотехничку теорију система, студија развија концептуални модел који експлицитно повезује димензије усвајања ВИ са исходима развоја вјештина запосленика. Подаци су прикупљени од 135 испитаника из око 72 МСП-а путем структурираних упитника. Налази показују ограничено усвајање ВИ (М = 2,116), при чему Пеарсонова корелација и вишеструка регресиона анализа откривају значајне позитивне асоцијације (Р² = 0,562, п < 0,001). Ови резултати тумаче се као корелациони, а не узрочни. У закључном дијелу рада наведене су препоруке за носиоце политика, менаџере и образовне институције, уз јасно препознавање методолошких ограничења.

Кључне ријечи: *вјештачка интелигенција, унапређење вјештина људских ресурса, мала и средња предузећа (МСП), развој радне снаге, тржишта у настајању.*

Прегледни научни чланци
Review Scientific Papers

ENTREPRENEURIAL ACTIVITY AS A FUNCTION OF SUSTAINABLE DEVELOPMENT: PANEL ANALYSIS[1]

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A B S T R A C T
The paper studies the impact of entrepreneurial activity on three components of sustainable development: economic, social and environmental. Three distinct variables, i.e. new businesses, established businesses, and ambitious entrepreneurs, represent entrepreneurial activity. Variables, GDP growth rate, modified human development index and carbon dioxide emissions are used to observe sustainable development. The aim of the paper is to determine whether entrepreneurship affects sustainable development and, if yes, in what form. There are three econometric panel models created for research purposes. A panel analysis was performed on a sample of 35 countries over ten years. The results indicated a contradictory impact of the variables used to measure the level of entrepreneurial activity, while none of them showed an effect on overall sustainable development.

1. INTRODUCTION

In modern society, dominated by problems such as the access to drinking water, the increase in the number of people living below the poverty line, the increase in the number of people with chronic diseases, growing urbanization, endangering the environment, etc., it is not enough to monitor only economic prosperity. Sustainable development models, started emerging in the 1970s, combine economic, social and environmental components, i.e. they promote economic progress without endangering society or the environment. In recent decades, emphasis has been placed on the role of entrepreneurship as a mechanism that can bring solutions to social and environmental problems.

From a theoretical perspective, the relationship between entrepreneurship and economic development can be explained through several approaches. Schumpeter (1934) emphasizes the role of entrepreneurs as innovators who drive economic growth through a process of creative destruction. In contrast, Kirzner emphasizes the role of entrepreneurs in recognizing and exploiting market opportunities. In addition, the theory of endogenous growth (Romer, 1990) suggests that human capital, knowledge and innovation, often driven by entrepreneurial activity, are key determinants of long-term economic growth. These theoretical approaches provide a basis for understanding the potential impact of entrepreneurship on development.

In this paper, the subject of research is the examination of the impact of entrepreneurial activity on sustainable development. The aim of the work is to determine whether encouraging the development of entrepreneurship will lead to a triple final effect - economic growth that does not harm society and the environment. Also, the goal is to determine whether there is a collision between some types of entrepreneurship, i.e. whether they indicate conflicting impacts on different components of sustainable development. More specifically, new businesses are a very complex indicator of entrepreneurial activity. It includes opportunity-entrepreneurship and necessity-entrepreneurship as well as businesses founded with the intention of growth and those started to try one's luck. Bearing in mind such a structure of new businesses, it can be expected that they have the opposite effect on the components of sustainable development in relation to other indicators of entrepreneurial activity or that they do not have a statistically significant impact.

The hypotheses were tested using unbalanced panel models on a sample of 35 countries[2], in the period from 2011 to 2020. Three models were tested, where the first evaluates the impact of entrepreneurship on the economic dimension of sustainable development. The second model evaluates the impact of entrepreneurship on the social dimension of sustainable development, and the third model evaluates the impact of entrepreneurship on the ecological dimension of sustainable development.

H1: Different forms of entrepreneurial activity have heterogeneous effects on economic growth; among new businesses, established businesses, and ambitious entrepreneurs, the last ones have the strongest positive impact.

2 The countries included in the sample are Austria, Croatia, Cyprus, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Panama, Uruguay, Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, Qatar, Iran, China, India, Indonesia, Thailand, Egypt and the Republic of South Africa.

H2: Entrepreneurial activity positively affects the social aspect of sustainable development.

H3: Entrepreneurship may contribute to the reduction of environmental pollution, particularly in the case of new businesses, thus leading to a positive impact on the ecological component of sustainable development.

The paper, in addition to the introduction and conclusion, consists of three chapters: empirical literature, materials and methods, and results and discussions. The *Empirical Literature* delivers a brief overview of studies dealing with a similar topic, i.e. the impact of entrepreneurship on sustainable development or only on some its component. In the chapter *Materials and Methods* a tabular presentation of all used variables and their sources is presented. It is explained how and why the index of human development was corrected. Also, the methodology used to test the set hypotheses was explained. The *Results and Discussion* chapter contains the test results and their interpretation.

2. EMPIRICAL LITERATURE

The relationship between entrepreneurship and development is based on several key economic theories. Schumpeter (1934) views entrepreneurship as an innovative process that radically changes the market order. Romer (1990) through the endogenous growth theory begins to view knowledge as a factor that explicitly explains economic growth. Unlike traditional factors of production, the role of knowledge is particularly significant due to the possibility of spillovers and use by other enterprises. However, knowledge spillovers do not occur automatically; mechanisms are needed to facilitate them. Acs, Audretsch, Braunerhjelm and Carlsson (2011) identified entrepreneurship as a mechanism for the commercialization of knowledge. They examined the role of knowledge and entrepreneurship in stimulating economic growth. The results of a panel analysis conducted on a sample of 18 countries showed that entrepreneurship, measured as the self-employment rate, contributes positively to economic growth.

A review of empirical literature reveals the various variables used by authors to measure entrepreneurial activity level. Among the authors who dealt with this topic, some employed direct measures of the level of entrepreneurial activity, while others used proxy variables. Some authors used the number of patent applications as a productive entrepreneur measure (Salgado-Banda, 2007) since entrepreneurship is often associated with innovation and innovation is sometimes expressed by the number of patents. The limitation of this approach is reflected in the fact that many patents do not go through the commercialization phase, i.e. they do not enter the market but remain at the invention level. Some authors use the research and development variable as a proxy for the level of entrepreneurial activity (Armeanu, Vintila & Gherghina, 2017). Its primary disadvantage is that it can be a measure of innovative activities, but this does not imply it will lead to inventive results.

The percentage of the population that has started or is in the process of starting their own business, the percentage of businesses initiated out of necessity, the percentage of businesses started to seize an opportunity, the number of start-ups, the percentage of businesses with the intention of growth and employment, youth entrepreneurship, growth rate of the number of entrepreneurs in the total number of employees and others are used as direct measures of the entrepreneurial activity level (for more details see Audretsch & Keilbach, 2008; Pinillos & Reyes, 2009; Stam et al, 2010; Linan & Fernandez-Serrano, 2013; Fotoyi & Ncwadi, 2025; Molnar, Josipović & Baškot, 2024). Research on a sample of 43 countries observed in nine years (2004-2012) confirmed that opportunity-driven entrepreneurship positively affects economic growth (Aparicio, Urbano & Audretsch, 2015). The following year, the authors expanded the number of independent variables. Therefore, along with opportunity entrepreneurship, they observed necessity entrepreneurship and the percentage of new businesses. Using the same sample, they proved that the total percentage of new businesses and opportunity entrepreneurship positively influence growth (Urbano & Aparicio, 2016).

Another group of authors used the "growth-oriented entrepreneurs" (ambitious entrepreneurs) variable to denote entrepreneurs with medium and high growth ambitions (Stam et al, 2006). The research employed cross-sectional data (2002), and the sample included 36 countries. Regression analysis indicated that ambitious entrepreneurship contributes to growth more than the percentage of new businesses.

Most of the research papers discovered a positive connection between entrepreneurship and economic growth in samples dominated by developed countries. Yet, negative or statistically insignificant results are present in countries with a lower income level. Regression and cluster analysis applied to a sample of 56 countries of different levels of development revealed a negative relationship between entrepreneurship and growth (Linan & Fernandez-Serrano, 2013). To measure entrepreneurship, the authors utilised the percentage of new businesses, necessity entrepreneurship, and opportunity entrepreneurship. The research of the second group of authors on the example of 43 economies of different development levels from 2009 to 2013, with the application of the fixed effects model, showed that none of the three observed types of entrepreneurship (percentage of new businesses, innovation-based entrepreneurship and opportunity-driven entrepreneurship) does not affect the GDP growth rate (Ferreira et al, 2016).

The most common explanation for the aforementioned results is the inhomogeneity of the observed samples, which is reflected in the final result. The structure of entrepreneurial businesses varies depending on the level of economic development. Opportunity entrepreneurship prevails in developed countries, while necessity entrepreneurship prevails in less developed ones. Entrepreneurs who start a business as the only form to ensure existence for themselves and their families are often insufficiently prepared to navigate the market, and a higher percentage of such businesses fail. The authors' 2016 research approach clarifies the mentioned results in more detail (Prieger et al, 2016). There is no "missed" growth in developed countries because entrepreneurship is almost at the optimum. In developing countries, the optimal rate of entrepreneurship is higher, which is why they have "penalties" for growth. Considering that the Global Entrepreneurship Monitor data show that less developed countries have higher rates of new businesses, higher rates of necessity entrepreneurship and lower rates of opportunity entrepreneurship, the conclusion is that entrepreneurs in those countries are less efficient. As possible reasons, the authors cite market success attained through cooperation with the political elite, not by fighting the competition.

The 2015 United Nations Conference on sustainable development encouraged the actualization of the sustainable development issue. The Global Development Program until 2030, better known as Agenda 2030, was adopted then, containing 17 Sustainable Development Goals (SDGs). It encouraged some authors to examine the link between entrepreneurship and the components of sustainable development (Dhahri & Omri, 2018). They point out that the sustainable development challenges are similar to the *prisoner's dilemma* problem because environmentally conscious behaviour creates a gap between personal and collective goals. They confirmed this on a sample of 20 developing countries, covering a 12-year period. By applying a co-integration analysis, the authors concluded that entrepreneurship contributes positively to economic and social dimensions of sustainable development, but the impact on the environment is negative. The mentioned results display the insufficient environmental awareness of entrepreneurs in developing countries and the preference for individual rewards as opposed to collective sustainability goals. A similar type of research was conducted in 2022 on the example of Slovenia, Croatia, Hungary and Latvia (period 2006-2016). The results showed that entrepreneurship contributes to the economic and social aspect of sustainable development, but not to the ecological one (Almhamad, 2022).

Other authors also point to the connection between entrepreneurship and sustainable development. Zhu, Jia & Lin (2019) point out that entrepreneurship has a key role in promoting the circular model in developing countries, while Markman et al. (2019) explains in more detail the role of entrepreneurship in solving socio-ecological challenges by distinguishing social, ecological and sustainable entrepreneurship. Social entrepreneurship is aimed at solving issues of poverty, unequal opportunities and other social problems. Environmental entrepreneurship deals with solving problems with pollution, climate change and other environmental problems. Sustainable entrepreneurship is a hybrid form of social and ecological entrepreneurship and aims to solve both groups of problems. It is also known as impact entrepreneurship.

3. MATERIALS AND METHODS

The impact of entrepreneurial activity on the sustainable development components in the 2011-2020 period was tested for this paper. The observed sample includes 35 countries, and its size was determined by data availability, primarily for variables measuring the level of entrepreneurial activity. They are collected from the Global Entrepreneurship Monitor (GEM) study. What hindered the research was the fact that only a few countries constantly cooperate with the study publishers, while other countries cooperate only periodically, so no data are available for each year of observation. Thus, an unbalanced panel model was used to test the hypotheses.

Three models were tested. Each one observed a single component of sustainable development as a dependent variable. Three independent variables measure the entrepreneurial activity level (percentage of new businesses, established businesses, and ambitious entrepreneurs). They are the same in all models. However, the choice of the dependent variable determines the control variables. New businesses show the percentage of the adult population (18 to 64 years old) who are starting their own business or have owned and operated a business for 3.5 years or less. This is a composite indicator because it shows the sum of nascent entrepreneurs and newly registered businesses up to 3.5 years old, so it is often called total early-stage entrepreneurial activity (TEA). Established businesses represent the percentage of the adult population that owns and runs an established business, i.e. a business that has been paying salaries/remunerations to owners for more than 3.5 years. Ambitious entrepreneurs are those oriented towards their business growth and represent the percentage involved in new businesses with the expectation to employ six or more people in the following five years.

The first model studies the impact of entrepreneurship on the economic component of sustainable development, expressed by the GDP growth rate. The control variable is gross investments. Investments are used as a control variable because they represent one of the key drivers of economic growth through increasing production capacity, productivity, and employment. The second model tests the impact of entrepreneurship on the social component of sustainable development. The dependent variable is the *Human Development Index* (HDI), taken from *the Human Development Indicators* database, with previous corrections. The HDI is a composite measure of average achievement in three essential human development dimensions, i.e. a long and healthy life, education, and a satisfactory standard of living. A separate sub-index is calculated for each of the mentioned dimensions. The composite index is then calculated by aggregating the previously described three values according to the geometric mean principle. Since the first model already evaluated the impact of entrepreneurship on the GDP growth rate, it is necessary to eliminate the economic dimension from the human development index to avoid overlapping and to obtain a "fully" social component. Hence, the standard of living sub-index was excluded from the human development index, and the square root of the health and education sub-index was calculated instead of the third root of the three sub-indices. The human development index corrected in this way is called the *Modified Human Development Index* (MHDI). The control variable is current health expenditures. The third model examines the impact of entrepreneurship on the ecological dimension of sustainable development, expressed by carbon dioxide emission. Due to the high values of the CO_2 variable, its natural logarithm was used in the model in order to reduce the asymmetry of the distribution and stabilize the variance of the data. The control variables are gross investments and consumption of renewable energy. The data sources for testing the model are the GEM report and the World Development Indicators (WDI) database, edited by the World Bank. A more detailed overview of the variables used is in Table 1.

Table 1: Overview of the variables used in the research

Variable		Abbreviation	Source
Independent Variable	New businesses (total early-stage entrepreneurial activity)	TEA	GEM
	Established Business Ownership Rate	EBOR	GEM
	Percentage of ambitious entrepreneurs	AMB	GEM
Model 1			
Dependent Variable	GDP growth rate	BDP	WDI
Control Variable	Gross investments	Inv	WDI
Model 2			
Dependent Variable	Modified Human Development Index	MHDI	HDI (author's calculations)
Control Variable	Current health expenditure	Health	WDI
Model 3			
Dependent Variable	Carbon Dioxide Emission	CO_2	WDI
Control Variable	Gross investments	Inv	WDI
	Renewable energy consumption	Obn	WDI

Source: author

The stationarity of the variables was tested using the *Fisher panel unit root test* based on *augmented Dickey–Fuller regressions* with an included drift term (Table 2). Given the unbalanced nature of the panel, *Fisher-type panel unit root tests* were considered more appropriate. The results indicated that the variables are stationary at levels, allowing standard panel estimation techniques.

Table 2: Stationarity of the variables

Variable	P (χ^2)	Pm	Conclusion
TEA	197.4193***	11.0976***	Stationary at level
EBOR	220.1124***	13.0435***	Stationary at level
AMB	208.5711***	12.4092***	Stationary at level
BDP	113.3089***	3.6603***	Stationary at level
MHDI	120.4872***	4.2669***	Stationary at level
CO2	202.0375***	11.1592***	Stationary at level
Inv	412.9836***	28.9874***	Stationary at level
Zdravlje	166.4577***	8.1522***	Stationary at level
Obn	163.2140***	8.1645***	Stationary at level

Note: The reported values are *Fisher test* statistics based on augmented *Dickey–Fuller* (*ADF*) tests. The null hypothesis assumes the presence of a unit root in all panels. Asterisks indicate levels of statistical significance: *** $p < 0.01$

Source: author's calculation

The *Modified Wald test* indicates the presence of heteroscedasticity (χ^2=1827.08 for the first model, χ^2=1702.51 for the second model and χ^2=23741.5187 for the third model). Also, the *Wooldridge test* for autocorrelation in panel data was performed. It shows the absence of autocorrelation in the first model (F=1.959) and presence of autocorrelation in the second and third model (F=75.217 and F=33.242, respectively). The results of the *Pesaran CD test* indicate the presence of cross-sectional dependence in all models suggesting that countries are not fully independent. To address heteroscedasticity, autocorrelation and cross-sectional dependence, cluster-robust standard errors at the country level are employed.

Multicollinearity was tested using the *Variance Inflation Factor* (*VIF*). The obtained *VIF* values range from 1.09 to 1.44 for the first model, from 1.05 to 1.35 for the second model, and from 1.06 to 1.52 for the third model, indicating that there is no evidence of multicollinearity among the explanatory variables.

Potential endogeneity may arise due to reverse causality between entrepreneurship and sustainable development indicators, as well as omitted variable bias. In all three models, the *Durbin-Wu-Hausman test* showed the presence of endogeneity, which influenced the choice of instrumental variables model for assessing the impact of entrepreneurship on the components of sustainable development. Although dynamic panel estimators were considered, diagnostic tests and sample characteristics (small T and insufficient observations) indicated that such specifications were not appropriate for the data.

The first model is represented by the equation:

$$BDP_{it} = \beta_0 + \beta_1 TEA_{it} + \beta_2 EBOR_{it} + \beta_3 AMB_{it} + \beta_4 Inv_{it} + u_{it}$$

Due to the endogeneity of the new businesses (TEA), the model is estimated using the instrumental variables method, where TEA is instrumented by its lagged value:

$$TEA_{it} = \alpha_0 + \alpha_1 TEA_{i,t-1} + \alpha_2 EBOR_{it} + \alpha_3 AMB_{it} + \alpha_4 Inv_{it} + \upsilon_{it}$$

The form of the second model is given below:

$$MHDI_{it} = \beta_0 + \beta_1 TEA_{it} + \beta_2 EBOR_{it} + \beta_3 AMB_{it} + \beta_4 Health_{it} + u_{it}$$

and the model that shows the most robust results is the one in which new businesses and established businesses (TEA and EBOR) are instruments:

$$TEA_{it} = \alpha_0 + \alpha_1 TEA_{i,t-1} + \alpha_2 AMB_{it} + \alpha_3 Health_{it} + \upsilon_{it}$$

$$EBOR_{it} = \gamma_0 + \gamma_1 EBOR_{i,t-1} + \gamma_2 AMB_{it} + \gamma_3 Health_{it} + \varepsilon_{it}$$

The final form of the third model is represented by the equation:

$$CO_{2it} = \beta_0 + \beta_1 TEA_{it} + \beta_2 EBOR_{it} + \beta_3 AMB_{it} + \beta_4 Inv_{it} + \beta_5 Obn_{it} + u_{it}$$

and the most robust results are with variables Inv and Obn as instruments:

$$Inv_{it} = \alpha_0 + \alpha_1 Inv_{i,t-1} + \alpha_2 TEA_{it} + \alpha_3 EBOR_{it} + \alpha_4 AMB_{it} + \upsilon_{it}$$

$$Obn_{it} = \gamma_0 + \gamma_1 Obn_{i,t-1} + \gamma_2 TEA_{it} + \gamma_3 EBOR_{it} + \gamma_4 AMB_{it} + \varepsilon_{it}$$

4. RESULTS AND DISCUSSIONS

Table 3 displays the test results for the three models:

Table 3: Test results

	Model 1		Model 2		Model 3
Observations	207		162		181
Number of countries	33		34		35
Wald χ2	23.15		49.71		36.48
Probability > χ2	0.0001		0.0000		0.0000
Root MSE	3.8646		0.0594		1.4337
R-squared	0.1239		0.4196		0.3119
TEA	-0.096*	TEA	-0.0046***	TEA	-0.0812**
Std. Err	0,058	Std. Err	0.0016	Std. Err	0.0354
EBOR	0.070	EBOR	0.0005	EBOR	0.0940*
Std. Err	0.059	Std. Err	0.0019	Std. Err	0.0543
AMB	0.113***	AMB	0.0003	AMB	-0.0050
Std. Err	0.026	Std. Err	0.0004	Std. Err	0.1523
Inv	0.102	Health	0.018***	Inv	0.1200***
Std. Err	0.066	Std. Err	0.0041	Std. Err	0.0394
				Obn	-0.0333**
				Std. Err	0.0166
First-stage results					
Partial R^2 (TEA)	0.7175	**Partial R^2 (TEA)**	0.7122	**Partial R^2 (Inv)**	0.8476
		Partial R^2 (EBOR)	0.7086	**Partial R^2 (Obn)**	0.9867

Note: Models are estimated using the instrumental variables (*2SLS*) approach. Instrumental variables (TEA, EBOR, Inv and Obn) are instrumented by their lagged values. Standard errors are clustered at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

Source: author's calculation based on data from GEM (2011-2020) and World Bank Group (2011-2020)

In all three models, the *partial* R^2 value is very high (from 0.7086 to 0.9867), which shows a strong relationship between the instrument and the endogenous variable and confirms the relevance of the selected instrument.

Model 1

The results of the instrumental variables (*2SLS*) estimation with cluster-robust standard errors indicate that statistically significant variables in the model are TEA (new businesses) and AMB (ambitious entrepreneurs). The coefficient value for new businesses is -0.096 (with a risk level of 10%), which means that one percent increase in new businesses leads to a decrease of approximately 0.096 percentage points in GDP growth, ceteris paribus. On the other hand, coefficient value for ambitious entrepreneurs has a positive sign (β_3=0.113). Specifically, a one percent increase in ambitious entrepreneurs leads to an increase of approximately 0.113 percentage points in GDP growth, ceteris paribus. Lagged TEA is used as an instrument under the assumption that past entrepreneurial activity affects current growth only through current TEA. The first-stage results confirm the strong relevance of the instrument. The *partial R-squared* is high (0.7175), confirming the strong explanatory power of the instrument. Since the model is exactly identified, the validity of the instrument relies on theoretical considerations. The lagged variables were selected as instruments following common practice in panel IV estimation, assuming correlation with the endogenous regressors and no direct effect on the dependent variable. Therefore, the credibility of the results depends on the theoretical assumption that past entrepreneurial activity affects current economic growth only through its impact on current entrepreneurial activity.

The value of the coefficients with new businesses and ambitious entrepreneurs is expected. Ambitious entrepreneurs intend to grow their business by employing six or more people in the following five years. This result indicates the relation between growth at the microeconomic and macroeconomic levels: the aggregated growth of individual businesses causes growth at the entire economic level. Entrepreneurs oriented towards the growth of their own businesses contribute positively to the growth of the gross domestic product (Marjanović, 2023, 70).

New businesses have a negative influence on GDP growth. Such a result can be explained by the structure of the countries in the sample and the structure of the started businesses. The sample represents a combination of developed and developing countries (the range of GDP per capita for the year 2020 for the included countries varies from $1,900 to $116,000). On the other hand, the motive for entrepreneurs to start their business can be opportunity or necessity.

The opportunity can be solving a social problem, doing a job the entrepreneur likes, realizing one's idea, the need for self-affirmation, etc. Necessity entrepreneurship is usually an alternative solution in case of unemployment and inability to find a job. It boils down to starting one's own business to provide the existential needs of the entrepreneurs and their family members. In developed countries, opportunity prevails as a motive, and in developing countries, necessity prevails. This can be seen in the rates of new businesses. Data from the GEM (2020) indicate that the percentage of new businesses is low in most developed countries (Austria: 6.2%, Germany: 4.8%, Italy: 1.9%, Luxembourg: 8%, Netherlands: 11.5%, Sweden: 7.3%), and developing countries show the highest rates (Brazil: 23.4%, Chile: 25.9%, Colombia: 31.1 %, Togo: 32.9%, Uruguay: 21.9%, etc.). Hence, developed economies offer their residents enough opportunities to work and do what they love, so those who start a business are presumably motivated by opportunity. On the other hand, developing countries do not offer as many opportunities, so the population has to start businesses for self-employment, i.e. motivated by necessity. They often lack the knowledge and skills to run a business.

The results obtained by evaluating the first model and their analysis revealed that the paper's first hypothesis can be confirmed. Of the three variables used to measure the level of entrepreneurial activity, ambitious entrepreneurs have an essential influence on the GDP growth rate. Their influence is positive and statistically most significant (risk level 1%). Thus, entrepreneurs oriented towards their businesses' growth and development, have a decisive influence on economic growth.

Model 2

The results in the Model 2 indicate that new businesses (TEA) have a negative and statistically significant effect on human development (β_1= -0.0046). This indicates that higher levels of new businesses are associated with lower levels of human development (MHDI). Specifically, a one percent increase in new businesses leads to decrease of approximately 0.005 percentage points in MHDI. Other variables measuring entrepreneurial activity do not show statistically significant effects. Health has a strong and positive impact on MHDI. Both TEA and EBOR are treated as endogenous variables and instrumented using their lagged values. The first-stage results confirm that the instruments are strong, with high *partial R-squared* values. As in the previous model, the credibility of the results depends on the theoretical assumption that past entrepreneurial activity affects current modified human development index only through its impact on current entrepreneurial activity.

This result suggests that not all forms of entrepreneurship contribute positively to human development. In particular, the increase in new businesses does not necessarily contribute to the improvement of human development, especially in economies dominated by necessity entrepreneurship and entrepreneurship with low productivity and innovation.

The analysis of the second model results indicates that the paper's second hypothesis cannot be accepted, considering that the only statistically significant variable measuring entrepreneurial activity is new businesses and its influence on modified human development index is negative.

Model 3

The results in the Model 3 indicate that investments significantly increase CO_2 emissions, while renewable energy has a mitigating effect. Among the variables measuring the level of entrepreneurial activity, new businesses and established businesses have a statistically significant impact, but with different directions of impact. New businesses (TEA) are associated with lower CO_2 emissions (β_1= -0.0812), suggesting that one percent increase in new businesses leads to decrease of 0.0812 percentages in CO_2 emissions. On the other hand, a one percent increase in established businesses leads to an increase of 0.0940 percentages in CO_2 emissions. Lagged values of the control variables (investments and renewable energy sources) were used as instruments, and their validity was confirmed by the very high values of *partial* R^2 (0.8476 and 0.9867), indicating the absence of a weak instruments problem.

These findings highlight a potential trade-off between economic expansion and environmental sustainability, while also indicating that entrepreneurship may play a role in facilitating a greener transition. Namely, the reduction in pollution caused by new businesses can be explained by the fact that they increase energy efficiency or develop less polluting activities. On the other hand, established businesses imply greater industrial activity and greater use of energy, especially from fossil fuels.

Such a result implies the acceptance of the third hypothesis and shows that new businesses solve the prisoner's dilemma by prioritizing collective rather than individual goals. Bearing in mind that the United Nations adopted the 2030 Agenda as an umbrella document promoting the goals of sustainable development, it is conceivable to expect that entrepreneurs will use the offered incentives for the development of ecological entrepreneurship. This contribution may include launching ventures contributing to reducing pollution, recycling waste, improving agricultural practices, and the like, which Markman et al. (2019) also wrote about.

5. CONCLUSIONS

The results of all three models evaluated in this paper show that the only variable that measures the level of entrepreneurial activity and shows a statistically significant impact on each component of sustainable development is new businesses. However, its effects are contradictory: it reduces economic growth and human development, but has a positive effect on the environment (reduces CO_2 emissions). On the other hand, established businesses have a significant impact only on the environment, but it is negative (increases CO_2 emissions), and ambitious entrepreneurs have a significant impact only on growth, and with a positive sign. The analysis conducted shows that none of the variables measuring the level of entrepreneurial activity can be claimed to have an impact on overall sustainable development. These findings could highlight a potential trade-off between economic expansion and environmental sustainability and lead to the conclusion that a triple bottom line effect is not possible. However, limitations of the observed sample and the data used should be kept in mind.

The sample used in this study includes 35 countries with different levels of development; therefore, future research is recommended to use a more homogeneous sample in order to determine the consistency of the results. This would allow for a more precise discussion of new businesses, as the influence of necessity-driven entrepreneurship would be less pronounced. Furthermore, one of the limitations of this study is the unbalanced nature of the panel data, which may affect the statistical significance of the observed variables. In addition, lagged values were used as instruments in the instrumental variables estimation. Although the first-stage results indicate satisfactory instrument relevance, their validity cannot be fully verified in exactly identified models, but is primarily based on theoretical assumptions regarding the relationship between past and current values of the endogenous variables. It should also be noted that sustainable development was not observed through a single composite indicator, but through separate economic, social and environmental dimensions, which may limit the interpretation of the overall effects of entrepreneurial activity on sustainable development. Finally, the relatively low coefficient of determination in the first model suggests that a considerable share of GDP growth variation is influenced by factors not included in the specification. However, this does not reduce the relevance of the estimated coefficients, particularly in the context of instrumental variables estimation and macroeconomic panel data. Future studies may obtain higher explanatory power by extending the model with additional explanatory variables and broader institutional or macroeconomic indicators.

Conflict of interests

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

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ПРЕДУЗЕТНИЧКА АКТИВНОСТ У ФУНКЦИЈИ ОДРЖИВОГ РАЗВОЈА: ПАНЕЛ АНАЛИЗА

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САЖЕТАК

Овај рад испитује утицај предузетничке активности на три компоненте одрживог развоја: економску, социјалну и еколошку. Предузетничка активност је представљена са три различите варијабле: нови бизниси, уходани бизниси и амбициозни предузетници. Одрживи развој се посматра преко варијабли стопа раста БДП-а, модификовани индекс људског развоја и емисија угљен-диоксида. Циљ рада је да се утврди да ли предузетништво и у ком облику утиче на одрживи развој. За потребе истраживања креирана су три економетријска модела панела. Спроведена је панел анализа на узорку од 35 земаља и у периоду од десет година. Резултати су указали на контрадикторан утицај варијабли којима се мјери ниво предузетничке активности и да ниједна од њих нема ефекат на цјелокупни одрживи развој.

Кључне ријечи: *предузетничка активност, нови бизниси, уходани бизниси, амбициозни предузетници, одрживи развој*

THE IMPORTANCE OF AIR QUALITY MONITORING AND THE NEED TO IMPROVE AIR QUALITY MANAGEMENT IN LOCAL SELF-GOVERNMENT UNITS (LGUS) IN THE REPUBLIC OF SERBIA[1]

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ABSTRACT

The paper will examine the economic impact of Local Self-Government Units (LGUs) on the improvement of air quality and environmental protection in cities and municipalities (one city and one municipality from each district, except Belgrade) in the Republic of Serbia. One of the factors affecting life in cities in the Republic of Serbia is air pollution, which can have a negative impact both on the health of residents living there, as well as on those who come for business or tourism. The subject of research in this paper is general data on air quality in LGUs (cities and municipalities) in the Republic of Serbia, as well as planning and the use of funds by competent LGU institutions for establishing and managing air quality. The aim of this paper is to examine whether the competent LGU authorities apply the planning and legislative framework as a basis for effective and efficient air quality management, implement measures and activities to improve air quality, and whether they collect and allocate funds for this purpose. A survey conducted on a sample of 49 LGUs has shown that most of them do not manage air quality adequately. The research has shown that LGUs insufficiently plan and allocate financial resources in their budgets for maintaining air quality. From the accounting perspective, financial resources that LGUs generate from environmental pollution charges and fees for environmental protection and improvement belong to the budget of the local self-government unit and are important in the planning and incurring expenses (costs) for air quality management.

1. INTRODUCTION

Air pollution is one of the ten leading global risk factors for human health. This is a pressing issue in developed countries and, more recently, in developing countries (Aquino, De Lima, Do Nascimento, & Reis, 2018). Planning and allocating financial resources in the budgets of LGUs to air quality management is very important, primarily for improving air quality, but also for ensuring implementation of the prescribed legislation. Based on the legislation adopted in the Republic of Serbia, LGUs are obliged to establish networks of measuring points/stations, assess air quality, adopt an air quality management plan and an air quality monitoring program, and, if it is determined that the air quality falls into the third category, implement measures to reduce air pollution in order to achieve short-term compliance with permissible values and ensure long-term compliance with limit values. The paper will discuss revenue generated from environmental pollution charges and fees for environmental protection and improvement, as well as expenses incurred by implementing measures aimed at reducing air pollution and maintaining air quality.

The subject of the research presented in this paper is the interdependence of air quality in local self-government units (cities and municipalities) in the Republic of Serbia, as well as planning and the use of financial resources by the competent LGU institutions for the establishment and management of air quality. The objective of this paper is to examine whether competent LGU authorities apply the planning and legislative framework as a basis for effective and efficient air quality management, implement measures and activities to improve air quality, and whether they collect and allocate funds for this purpose. The paper additionally focuses on possible proposals for measures to improve air quality. In accordance with the defined subject and objective of the research, the following research questions have been drafted in the paper:

1) How does the implementation of the legislative and planning framework for air quality management by LGUs affect the maintenance of air quality?
2) How do the monitoring of air pollution levels and measures taken by LGUs to improve air quality affect the maintenance of air quality?
3) What is the impact of revenue generated from environmental pollution charges and fees for environmental protection and improvement on the expenditure incurred by maintaining air quality in LGUs?

The social contribution of this research lies in examining the operation of air quality management in the Republic of Serbia and the effects of the adopted methodology on the implementation and monitoring of air quality management. The scientific contribution of this research lies in accurate examination of the role of elements description, organisation, and operation of competent LGU institutions in monitoring and controlling air quality in the Republic of Serbia. Special attention will be given to air quality monitoring within local self-government units and their operation, as well as to expenses incurred by maintaining air quality.

The scientific toolkit used in this paper is a statistical methodology that includes statistical description and statistical analysis. The paper employs general scientific methods, as well as specific scientific methods and logical reasoning procedures. The specific data collection techniques used in this paper are measurement, case study, and survey. In order to determine whether the competent authorities conducted continuous control and monitoring of air pollution levels (air quality monitoring), data obtained through questionnaires were collected and analysed. Questionnaires related to the adopted air quality monitoring programs for the local network, the expenses incurred by monitoring, and the expenses incurred by implementing measures to reduce air pollution were sent to 49 LGUs.

2. LITERATURE REVIEW

Air pollution is defined as any atmospheric condition in which substances are present in concentrations high enough above their normal levels to produce a measurable effect on humans, animals, vegetation, or materials (Mina, Singh, & Chakrabarti, 2013). According to Bell & Treshow (2002), air pollutants are all substances in the air with the potential to cause harmful effects on humans, plants, animals, or cultural property.

The research conducted by Lapko, Panasiuk, Strulak-Wójcikiewicz, and Landowski (2020) showed that one of the detailed elements determining the attractiveness of an urban tourist destination is air quality, analysed through the emission of solid and gaseous pollutants. The level of air quality, as an element in assessing tourist appeal, determines the tourism competitiveness of an urban destination. Information about air quality in a city that is a travel destination can directly affect decisions on tourist travel, travel according to a specific itinerary, as well as travel cancellations.

Li, Wu, and Zhang (2021) conducted a study on the impact of air quality on the audit process and audit outcomes, observing samples from the Chinese capital market in the period between 2013 and 2018. The results of this study show that client companies located in cities with poorer air quality experience shorter audit delays and lower audit quality. Furthermore, the analyses show that Big 4 auditors can mitigate the effect of air quality on audit delay and audit quality. This study provides a significant contribution to the new literature on behavioural finance by extending the research on ambient air pollution to the audit context and provides new insights into the determinants of audit delay and audit quality. Regardless of the auditing firm in question, its profitability as the sole motive and imperative in business must not be a priority at all costs (Jovković, Karapavlović, & Radojević, 2021).

Awareness of air quality among adults in the USA increases with the number of days with unhealthy air quality warnings. These findings enhance the understanding of the extent to which air quality warnings motivate people to take measures to protect their health amid poor air quality (Mirabelli, Ebelt, & Damon, 2020). These experiences have been incorporated into the Air Quality Management Plan (AQMP). An Air Quality Management Plan describes the current situation and what could be done to ensure clean air in a city or region. It sets objectives and prescribes short-term and long-term policies and controls for improving air quality (Sivertsen & Bartonova, 2012).

Furthermore, numerous authors have examined the impact of air pollution in cities on financial markets. Levy and Yagil (2011) and Zhang, Jiang, and Guo (2017) establish a respective negative correlation between air pollution and stock returns in the USA and China. Meyer and Pagel (2017) indicate that poor air quality affects investors' trading behaviour, as they are less likely to log into their investment accounts and make trading decisions. Similarly, Wu, Hao, and Lu (2018) argue that air pollution induces pessimistic sentiment, leading to lower stock returns, liquidity, and volatility. In addition, Dong, Fisman, Wang, and Xu (2019) find a negative correlation between air pollution during analysts' corporate visits and their subsequent earnings forecasts. Analysts who are exposed to air pollution are less likely to issue timely forecasts compared to analysts who are not exposed to severe air pollution (Li, Luo, & Söderström, 2020).

The trend of increasing air pollution in cities persists, which should serve as a warning that the problem of air pollution must be addressed in the near future (Malinović-Milićević, Mihailović, Nikolić-Đorđić, & Jevtić, 2015). Renewable and alternative energy sources emerge as one of the solutions (Santangeli et al., 2016), and as for transportation, solutions include the use of bioenergy, hybrid and electric propulsion, as well as preventing the access of large transport vehicles into central urban areas (Taefi, Kreutzfeldt, Held, & Fink, 2016).

The legislative framework for air quality management consists of the Air Protection Law, the Environmental Protection Law, as well as numerous by-laws. The Air Protection Law defines three categories of air quality (Pejić, 2015), namely:

- Category I – clean or slightly polluted air, where limit values (LVs) are not exceeded for any pollutant;
- Category II – moderately polluted air, where limit values are exceeded for one or more pollutants, but the tolerance values (TVs) are not exceeded for any pollutant; and
- Category III – excessively polluted air, where tolerance values are exceeded for one or more pollutants.

In accordance with the Air Protection Law (Articles 14 and 15), the competence over the national air quality monitoring network at the level of the Republic of Serbia lies with the Environmental Protection Agency, whereas the competence over the local network of measuring points lies with the LGUs (city/municipality). Air quality is measured using assessment criteria in accordance with the Regulation on Air Quality Monitoring and Requirements (Article 14).

The purpose of air quality monitoring is to protect human health, determine the sources and levels of pollution, track the movement of air pollution, assess the vulnerability of specific locations, and identify critical situations for the purpose of public warning and determining protective measures (Arsenović, Đurić, Đurić, & Senić, 2016). Air quality monitoring is performed at the local, national, and global levels. In our country, numerous local communities monitor air quality (Arsenović et al., 2016). Monitoring results are compared with the relevant legislation, and adequate measures are taken accordingly, such as informing the public and providing recommendations for behaviour during air pollution episodes (Đurkić, Grujić, & Laušević, 2015). Results obtained from the air quality monitoring system, which serve as information for government authorities, local administration, and company management, are scarcely published in the scientific literature (Dimitrijević, Kostov, Tasić, & Milošević, 2008). For this reason, continuous monitoring and investing financial resources are important for air quality management.

According to the Environmental Protection Law, one of the basic principles of environmental protection is the ‘Polluter Pays’ Principle. A polluter pays a fee for environmental pollution when their activities cause or may cause environmental burden, i.e., if they produce, use, or market a raw material, semi-finished product, or product that contains substances harmful to the environment (Environmental Protection Law, Article 9). This Law stipulates that the polluter, in accordance with relevant regulations, bears the total costs of measures undertaken to prevent and reduce pollution, which include the costs of environmental risk and costs of remedying damage caused to the environment. With the entry into force of the Law on Fees for the Use of Public Goods, provisions of Articles 85 and 87 of the Environmental Protection Law, which determine the fee for environmental pollution and the fee for environmental protection and improvement, ceased to be valid on January 1, 2019. The Law on Fees for the Use of Public Goods stipulates the types of fees for environmental pollution, as well as the fee for environmental protection and improvement (Articles 116 and 134). The fees for environmental pollution are: 1) a fee for emissions of SO_2, NO_2, particulate matter, and produced or disposed waste; 2) a fee for substances that deplete the ozone layer; and 3) a fee for plastic bags (Law on Fees for the Use of Public Goods, Article 116).

The party liable to pay the environmental pollution fee includes, inter alia, the producer, i.e. disposer of waste for facilities for which an integrated permit is issued. The allocation of revenue generated from the fees for environmental protection and improvement has changed compared to the provision in the Environmental Protection Law (Article 87, Paragraph 10), which stipulated that "funds obtained from the fee for environmental protection and improvement are to be used through the budgetary fund, specifically for environmental protection and improvement, all in accordance with the adopted programs for the use of the budget fund, i.e. local action and remediation plans". Under the new provision of the Law on Fees for the Use of Public Goods (Article 139), the allocation of revenue generated from fees for environmental protection and improvement shall be as follows: "Revenue generated from fees for environmental protection and improvement belongs to the budget of the local self-government unit".

3. MATERIALS AND METHODS

The research conducted covers 49 LGUs, with the prepared questionnaire sent by email to 49 LGUs, of which 25 are cities and 24 are municipalities. The research was conducted in the second quarter of 2022. The response rate of respondents in the sample was 100%. The target group included district centres, which can be classified as more densely populated cities, as well as one municipality from each district, classified as less densely populated, except for the capital, which was considered a district centre. The sample units were examined based on the air pollution level, using the prescribed limit and tolerance values, as well as based on their status (city, municipality) and the budget-related size of the LGU.

The questionnaire was completed by the heads of environmental protection departments/services in the LGUs, that is, the first level of operations of the services responsible for air quality within the LGU. The questionnaire consists of 12 questions, which are organised into two main sections. At the beginning, through the first six questions, the LGUs provide basic information on air quality measurements and assessments, as well as the funds spent for this purpose. The second section of the questionnaire also contains six questions, which refer to the implementation of measures to reduce air pollution and funds spent for this purpose. Seven questions are designed as YES/NO questions, whereas the remaining five questions require elaborate responses and refer to revenue and expenditure.

Statistical analysis was performed using the SPSS software package, version 26.0. The mean and standard deviation were used to describe numerical variables, whereas frequencies were used to describe the categorical characteristics of the observations. To analyse differences between groups, the Kruskal-Wallis and Mann-Whitney U tests were used, according to the data obtained after testing the normality of data distribution using the One-Sample Kolmogorov-Smirnov test. In addition, the Chi-square (χ^2) test was used to compare categorical variables. The correlation between individual variables was examined using Spearman's rank correlation coefficient. Results were considered statistically significant if the p-value was less than 0.05.

4. RESULTS AND DISCUSSIONS

Based on responses obtained, it can be concluded that first-category air, i.e. clean or slightly polluted air, was identified in nine LGUs, all of which are cities. Third-category air, i.e. excessively polluted air, where tolerance values for one or more pollutants were exceeded, was identified in 13 LGUs (cities). Second-category air, i.e. moderately polluted air, was identified in one LGU (city), whereas one LGU (city) did not respond to this question. On the other hand, seven respondents among LGUs classified as municipalities responded to this question, of which five stated that first-category air was identified, whereas one LGU (municipality) reported second-category air and one reported third-category air. Eighteen (18) LGUs (municipalities) did not respond to this question in the questionnaire. Based on the responses, it can be concluded that LGUs having the status of a city, perform air quality measurements, even though the majority reported third-category air. On the other hand, 17 LGUs classified as municipalities did not respond to this question, which indicates that they do not conduct air quality measurements, as shown in Figure 1. Obtained results are presented in Figure 1.

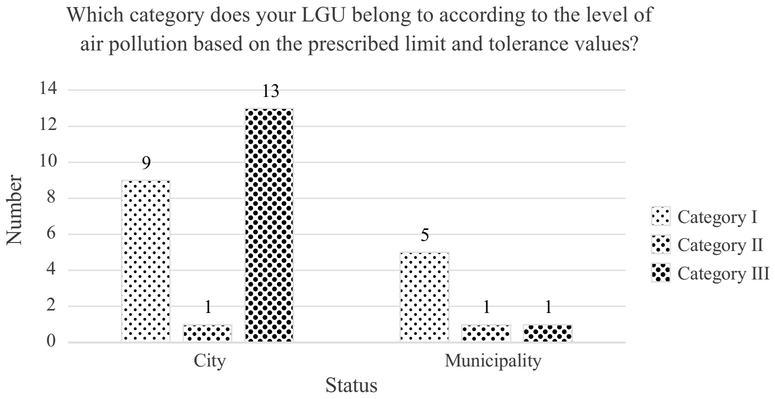

Figure 1: Air quality category by LGU
Source: Author's review

Furthermore, results have demonstrated that there is a statistically significant difference between cities and municipalities in terms of the frequency of positive and negative responses to the questions, except for those questions concerning the adoption of an Air Quality Plan in zones and agglomerations with third-category air quality for the years 2018, 2019, and 2020 (Table 1).

Table 1: Frequency of positive and negative responses to questions in relation to the status of LGU

Question	Status	Yes	No	Significance (χ^2 test value; φ value)
Did the LGU perform quality assessment in the period 2018–2020?	City Municipality	19/25 4/24	6/25 20/24	[a]p<o.oo1* (17.31; -0.594)
Did the LGU, within its competence, provide air quality monitoring in the period 2018–2020?	City Municipality	22/25 19/24	3/25 5/24	[a]p<o.oo1* (22.33; -0.675)
Has a local network of air quality measuring stations and/or monitoring points been established?	City Municipality	22/25 2/24	3/25 22/24	[a]p<o.oo1* (31.10; -0.797)
Was an air quality monitoring program adopted for the local network for 2018?	City Municipality	21/25 3/23	4/25 20/23	[a]p<o.oo1* (24.12; -0.709)
Was an air quality monitoring program adopted for the local network for 2019?	City Municipality	21/25 20/24	4/25 4/24	[a]p<o.oo1* (22.22; -0.673)
Was an air quality monitoring program adopted for the local network for 2020?	City Municipality	20/25 2/23	5/25 21/23	[a]p<o.oo1* (24.53; -0.715)
Are you implementing measures to reduce air pollution in the zone and/or agglomeration where third-category air quality has been determined?	City Municipality	13/21 1/19	8/21 18/19	[a]p<o.oo1* (14.07; -0.593)

Question	Status	Yes	No	Significance (χ^2 test value; φ value)
Did you adopt an Air Quality Plan for 2018 if the air in the zones and agglomerations was classified in the third category?	City	7/18	11/18	[a]p=0.095
	Municipality	0/5	5/5	(2.80; -0.349)
Did you adopt an Air Quality Plan for 20198 if the air in the zones and agglomerations was classified in the third category	City	4/19	15/19	[a]p=0.261
	Municipality	0/5	5/5	(1.26; -0.22)
Did you adopt an Air Quality Plan for 2020 if the air in the zones and agglomerations was classified in the third category?	City	2/15	13/15	[a]p=0.289
	Municipality	0/5	5/5	(0.741; -0.192)

a - $\chi2$ – test; * statistical significance;

Source: Author's review

In the observed period from 2018 to 2020, air quality assessment was performed by 23 LGUs, of which 19 LGUs were cities and 4 LGUs were municipalities, whereas 26 LGUs did not perform air quality assessment, including 5 cities and 21 municipalities. However, air quality monitoring during the observed period was performed by 27 LGUs (22 cities and 5 municipalities), whereas 22 LGUs did not perform air quality monitoring (3 cities and 19 municipalities). It is important to emphasise that 24 LGUs have established a local network of air quality measuring stations and/or monitoring points (22 cities and 2 municipalities), whereas 25 LGUs have not established such a network, of which 22 are municipalities and 3 are cities. Establishing a network of monitoring points and/or stations requires significant financial resources, so municipalities with smaller budgets are unable to finance the supply of a monitoring station without state assistance. An Air Quality Plan in the zone and/or agglomeration, where third-category air quality has been determined, has been adopted by five LGUs which implement measures to reduce air pollution. On the other hand, 36 LGUs responded negatively, i.e. they have not adopted an Air Quality Plan. Additionally, 5 LGUs stated that the air belongs to the first category whereas 3 LGUs indicated that the air is in the second category. In their reasoning, provided next to the given answer, the majority indicated the lack of financial resources as the reason for not adopting an Air Quality Plan, as well as the fact that funds were not allocated in the LGU budget.

When it comes to the comparison of total revenue and expenditure according to the status of LGU (city or municipality), results have shown that there is a statistically significant difference between cities and municipalities with regard to all variables (Table 2).

Table 2: Total revenue-expenditure ratio according to the LGU status

Question	Status: City $\overline{X}$ ± SD	Status: Municipality $\overline{X}$ ± SD	Significance (Test value; z statistics; effect extent)
Expenditure incurred for air quality monitoring in 2018	3,084,400.79 ± 5,774,972.91	156,714.38 ± 476,287,391	[a]p<0.001* (75.00; -4.79; 0.68)
Expenditure incurred for air quality monitoring in 2019	4,033,666.37 ± 6,636,842.63	151,057.71 ± 435,658.97	[a]p<0.001* (54.00; -5.19; 0.74)
Expenditure incurred for air quality monitoring in 2020	4,502,982.48 ± 7,517,514.12	142,605.00 ± 543,511.25	[a]p<0.001* (62.00; -5.16; 0.74)
Total expenditure incurred for implementing measures to reduce air pollution in 2018	37,172,677.83 ± 111,036,269.41	28,007.61 ± 100,446.85	[a]p=0.001* (162.50; -3.21; 0.46)
Total expenditure incurred for implementing measures to reduce air pollution in 2019	54,316,611.93 ± 161,166,308.11	33,901.09 ± 113,757.14	[a]p<0.001* (139.50; -3.64; 0.52)
Total expenditure incurred for implementing measures to reduce air pollution in 2020	52,244,218.38 ± 156,433,191.27	0.00 ± 0.00	[a]p<0.001* (126.50; -4.14; 0.60)
Total revenue generated from charges and fees in 2018	143,663,855.48 ± 243,773,679.28	12,322,465.8 ± 16,773,707.57	[a]p<0.001* (77.00; -4.46; 0.64)
Total revenue generated from charges and fees in 2019	113,276,629.70 ± 247,509,443.44	5,511,691.71 ± 7,102,691.74	[a]p<0.001* (100.00; -4.00; 0.57)
Total revenue generated from charges and fees in 2020	80,408,274.76 ± 135,111,861.34	5,435,693.48 ± 5,560,358.90	[a]p<0.001* (32.00; -5.36; 0.77)
Total expenditure incurred for environmental protection in 2018	128,432,542.31 ± 268,167,179.82	12,354,208.70 ± 13,146,376.83	[a]p<0.001* (98.00; -4.04; 0.58)
Total expenditure incurred for environmental protection in 2019	134,488,647.75 ± 261,809,809.76	21,558,324.26 ± 59,169,677.66	[a]p<0.001* (97.00; -4.06; 0.58)
Total expenditure incurred for environmental protection in 2020	127,238,859.77 ± 271,371,047.16	18,199,448.45 ± 44,852,778.60	[a]p<0.001* (106.00; -3.88; 0.55)

a – Mann – Whitney U test; * statistical significance

Source: Author's review

The expenditure incurred for air quality monitoring and the total expenditure (costs) of implementing measures to reduce air pollution, in relation to the revenue generated from charges and fees (for environmental pollution and for environmental protection and improvement), for the observed period from 2018 to 2020, is not financially significant, as LGUs do not plan and allocate financial resources in their budgets specifically for air quality management, which affects the population living in cities and municipalities. The total expenditure incurred for environmental protection, in relation to the revenue generated from charges and fees (for environmental pollution and for environmental protection and improvement) for the observed period from 2018 to 2020, is not financially significant, since financial resources are not planned and allocated in budgets on the basis of environmental protection, including the maintenance of air quality, even though LGUs generate revenue from the said charges and fees.

When it comes to revenue generated from various types of environmental protection charges and fees and expenditure and costs incurred for environmental protection related to monitoring and implementing measures to reduce air pollution, results show that there is a statistically significant difference between small, medium, and large LGUs (Table 3).

Table 3: Total revenue-expenditure ratio according to LGU budget size

Question	LGU size according to budget			Signifi-cance
	Small $\overline{X} \pm$ SD	Medium $\overline{X} \pm$ SD	Large $\overline{X} \pm$ SD	
Expenditure incurred for air quality monitoring in 2018	30,692.86 ± 105,015.86	1,030,982.67 ± 1,155,328.91	6,166,892.68 ± 8,311,188,342	[a]p<0.001*
Expenditure incurred for air quality monitoring in 2019	37,147.62 ± 118,845.94	1,190,461.05 ± 1,060,237.02	8,225,864.54 ± 9,111,895.20	[a]p<0.001*
Expenditure incurred for air quality monitoring in 2020	37,593.38 ± 172,274.51	1,723,194.61 ± 1,788,345.61	8,419,011.81 ± 10,818,076.43	[a]p<0.001*
Total expenditure incurred for implementing measures to reduce air pollution in 2018	32,227.50 ± 107,502.13	3,051,141.24 ± 11,489,857.44	87,439,602.86 ± 167,190,435.77	[a]p=0.003*
Total expenditure incurred for implementing measures to reduce air pollution in 2019	39,005.00 ± 121,620.25	5,102,485.31 ± 12,921,867.21	126,607,018.76 ± 243,480,930.89	[a]p=0.014*
Total expenditure incurred for implementing measures to reduce air pollution in 2020	39,473.05 ± 176,528.85	6,181,763.28 ± 17,216,657.59	119,404,425.95 ± 237,404,255.45	[a]p=0.003*
Total revenue generated from charges and fees in 2018	9,954,684.94 ± 17,570,473.19	50,285,510.71 ± 64,749,808.60	277,314,798.92 ± 342,901,614.06	[a]p=0.006*
Total revenue generated from charges and fees in 2019	3,022,657.87 ± 4,114,542.28	23,909,119.94 ± 34,658,184.76	247,035,636.93 ± 357,683,145.30	[a]p=0.021*
Total revenue generated from charges and fees in 2020	3,579,491.78 ± 2,778,601.98	18,401,167.44 ± 8,993,918.99	173,427,317.12 ± 180,283,368.92	[a]p<0.001*
Total expenditure incurred for environmental protection in 2018	10,232,011.13 ± 11,088,169.04	41,924,725.49 ± 39,277,412.77	253,779,727.40 ± 399,913,158.87	[a]p<0.001*
Total expenditure incurred for environmental protection in 2019	22,824,703.43 ± 63,436,041.84	35,259,028.73 ± 30,180,057.34	276,563,468.66 ± 379,292,489.33	[a]p=0.027*
Total expenditure incurred for environmental protection in 2020	17,216,670.47 ± 47,747,473.79	38,482,987.86 ± 39,364,068.62	256,351,439.54 ± 403,374,164.06	[a]p<0.024*

Kruskal-Walli’s test; * statistical significance
Source: Author’s review

No statistically significant difference was found between medium and large LGUs with regard to the total expenditure and costs incurred for environmental protection in 2018, nor between small and medium LGUs with regard to the total expenditure incurred for implementing measures to reduce air pollution in 2018, 2019, and 2020 (Table 4).

Table 4: Intergroup comparisons of LGUs of different sizes in relation to revenue and expenditure

Question	LGU	Medium	Large
Expenditure incurred for air quality monitoring in 2018	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p<0.001$*
Expenditure incurred for air quality monitoring in 2019	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p<0.001$*
Expenditure incurred for air quality monitoring in 2020	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.001$*
Total expenditure incurred for implementing measures to reduce air pollution in 2018	Small	$^{a}p=0.478$	$^{a}p<0.001$*
	Medium		$^{a}p=0.003$*
Total expenditure incurred for implementing measures to reduce air pollution in 2019	Small	$^{a}p=0.196$	$^{a}p<0.001$*
	Medium		$^{a}p=0.014$*
Total expenditure incurred for implementing measures to reduce air pollution in 2020	Small	$^{a}p=0.346$	$^{a}p<0.001$*
	Medium		$^{a}p=0.003$*
Total revenue generated from charges and fees in 2018	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.006$*
Total revenue generated from charges and fees in 2019	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.021$*
Total revenue generated from charges and fees in 2020	Small	$^{a}p<0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p<0.001$*
Total expenditure incurred for environmental protection in 2018	Small	$^{a}p=0.002$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.08$
Total expenditure incurred for environmental protection in 2019	Small	$^{a}p=0.004$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.027$*
Total expenditure incurred for environmental protection in 2020	Small	$^{a}p=0.001$*	$^{a}p<0.001$*
	Medium		$^{a}p=0.021$*

a Mann – Whitney U test; * statistical significance

Source: Author's review

Based on the data presented above, there are certain deviations in incurring expenditure among large, medium, and small LGUs, which is understandable, since the size of the LGU also determines the level of revenue generated from environmental pollution charges and from fees for environmental protection and improvement. Results further show that there is a statistically significant, moderately strong correlation between the total revenue generated and expenditure incurred in 2018, 2019, and 2020, considering both municipalities and cities (Table 5).

Table 5: Correlation between total generated revenue and incurred expenditure acceding to the LGU status

Question	Status	Total expenditure incurred for environmental protection in 2018	Total expenditure incurred for environmental protection in 2019	Total expenditure incurred for environmental protection in 2020
Total revenue generated from charges and fees in 2018	City	$r_s = 0.618$; $p = 0.001$*		
	Municipality	$r_s = 0.548$; $p = 0.006$*		
Total revenue generated from charges and fees in 2019	City		$r_s = 0.646$; $p < 0.001$*	
	Municipality		$r_s = 0.482$; $p = 0.017$*	
Total revenue generated from charges and fees in 2020	City			$r_s = 0.685$; $p < 0.001$*
	Municipality			$r_s = 0.419$; $p = 0.041$*

rs – Spearman's rank correlation coefficient; * statistical significance

Source: Author's review

In other words, Table 5 shows that the relationship between generated revenue and expenditure is directly proportional. This means that both cities and municipalities invested more funds during the observed three-year period if their revenue from environmental protection fees and environmental improvement fees were higher.

The research has shown that LGUs follow the legislative framework and align their regulations with the adopted legal provisions, but in practice do not implement the enacted legal acts. Furthermore, this research has shown that LGUs having the status of a city have established a network of monitoring stations and regularly monitor air quality. They have also adopted a monitoring program and an Air Quality Plan. Contrary to that, the majority of LGUs having the status of a municipality have not established these structures and procedures, which indicates that they do not have adequate measures for monitoring and improving air quality. Nevertheless, the research has indicated that LGUs do not pay sufficient attention to the importance of air quality management and maintenance, as in one half of the surveyed LGUs air was classified as Category

III, i.e., excessively polluted air, with tolerance values that were exceeded for one or more pollutants, whereas in one third of the LGUs it was not determined at all which category the air belongs to. In other words, LGUs apply insufficiently the legislative and planning framework for air quality management in their local communities.

The research has shown that LGUs having the status of a city have a more organised approach to air quality management than LGUs having the status of a municipality, primarily in terms of air quality monitoring and adopted Air Quality Plans if in zones and agglomerations the air is classified as Category III. Air quality monitoring in the Republic of Serbia provides early warning in cases of exceeding air pollutant limit values. Therefore, it is very important to implement air quality monitoring measures in order to ensure timely response and prevention aimed at reducing exceedances of limit values. Air quality monitoring is not performed in one half of the surveyed LGUs classified as cities, although continuous monitoring is necessary in order to achieve results, primarily with regard to reducing air pollution.

Based on the research conducted, it can be concluded that LGUs insufficiently plan and allocate funds in their budgets for environmental protection costs, i.e. for maintaining air quality. In addition, revenue generated from (1) environmental pollution fees and (2) fees for environmental protection and improvement in 2020 were lower by 44.93% compared to 2018 and lower by 27.78% compared to 2019. LGUs generate revenue from environmental pollution fees and from fees for environmental protection and improvement. However, as of 2019, the revenue generated from these fees accrue to the budget of the local self-government unit, unlike the earlier period when funds generated from these fees were used by LGUs through a budgetary fund, earmarked for environmental protection and improvement, all in accordance with the adopted programs for the use of budgetary fund resources, i.e. local action and remediation plans. Thus, until 2019, the purpose of these funds was clear because they were collected and spent for a specific aim. However, since 2019 these funds generated from fees have belonged to the budget of the local self-government unit and, therefore, do not necessarily have to be used for environmental protection, including air quality management. This change in the party obliged to pay environmental pollution fees and the modification of the method for calculating and determining the fee for environmental protection and improvement have led to a significant decrease in LGUs revenue generated from this source, which in turn has caused lower expenditure (costs) for maintaining air quality.

The research has shown that LGUs classified as cities and district centres, having a larger population, more developed industry, and higher traffic frequency, generate higher revenue and also plan and allocate greater funds for expenditure (costs) in their budgets for air quality management compared to LGUs classified as municipalities, having smaller population, less developed industry, and lower traffic frequency.

5. CONCLUSIONS

A healthy environment, including clean air, is the foundation for life within an LGU. Therefore, the competent authorities of an LGU should strive to ensure a high-quality and healthy life or to improve it. Based on the research conducted, it can be concluded that not all LGUs (cities and municipalities) with Category III air quality fulfil the legal obligation to adopt measures to improve air quality, which sends a poor message to citizens about the importance of protecting their health from excessive concentrations of air pollutants. In zones and agglomerations where air has been classified as Category III, the competent authorities of LGUs have not required operators to develop plans for reducing air pollution, in the form of adopting an Air Quality Plan and air quality monitoring programs for the local network, which is a legal obligation. Although most LGUs have established an air quality monitoring system, certain elements of the monitoring system are not fully developed, that is, half of the LGUs do not perform air quality monitoring regularly, which is a legal obligation. Continuous air quality monitoring is necessary, especially in LGUs with high levels of air pollution, along with the adoption of measures to reduce it.

Based on the research conducted, an answer can be provided to the first research question: *How does the implementation of the legislative and planning framework for air quality management by LGUs affect the maintenance of air quality?* Although LGUs follow and align their regulations with the legislative framework, the insufficient practical implementation of adopted legal acts significantly reduces the effectiveness of preserving and improving air quality. This gap between the normative framework and the actual situation highlights the need to strengthen the capacity and accountability of LGUs in enforcing regulations. Effective implementation of the legislative and planning framework by LGUs is crucial for maintaining air quality. It is necessary to work on improving the enforcement of laws and strategies, as well as on raising awareness about the importance of environmental protection in local communities.

The answer to the second research question – *How do the monitoring of air pollution levels and measures taken by LGUs to improve air quality affect the maintenance of air quality?* – indicates that LGUs with the status of a city have better organised approach to air quality monitoring and management compared to LGUs with the status of a municipality, which is crucial for timely response to pollution. However, a significant portion of LGUs do not implement adequate measures, leading to excessive pollution and inefficient air quality management.

Finally, an answer can be provided to the third research question – *What is the impact of revenue generated from environmental pollution charges and fees for environmental protection and improvement on the expenditure incurred by maintaining air quality in LGUs?* Based on the research conducted, it is concluded that LGUs invest insufficient efforts to plan expenditure for environmental protection, which leads to reduced effectiveness in maintaining air quality. In addition, a significant decline in revenue generated from environmental pollution fees since 2019 further hampers financing of measures to improve air quality in local communities.

The theoretical contribution of the paper lies in supplementing the existing literature on air quality in LGUs in the Republic of Serbia. According to the author's knowledge, there are few studies in Serbia that address air quality. In addition to its theoretical contribution, this paper also offers a practical contribution. Empirical research results enable the competent authorities within LGUs to understand benefits of implementing air quality management. Air quality monitoring and reporting should be observed as means to improve life in the local community, yet the research shows that LGU institutions are not sufficiently committed to the importance of this matter. Additionally, research results can be useful to the general public in understanding the matter of air quality in LGUs. At the local and national level, the objective of reducing air pollution could be achieved by engaging a team of environmental protection experts, specifically air protection experts, who would conduct a detailed analysis of the causes of air pollution and determine ways to eliminate it. Organising educational training for the population, on the need to preserve and monitor air quality in the future, is one of the priorities of every local community.

The paper is subject to limitations that point to areas for future research. The main limitation in the conducted research is the sample size. Therefore, in addition to LGUs within the country, future research should include competent government institutions dealing with air quality matters, and potentially also LGUs from neighbouring countries that border our state. Furthermore, future research should address the issue of air quality reporting in LGUs and also engage the population living within the territories of these LGUs. Future research may also examine the financing, i.e. planning and allocation of financial resources in the budgets of LGUs, particularly with regard to controlling the use of funds for this purpose. Appropriate mechanisms should be identified at both local and national levels.

Conflict of interests

The authors declare there is no conflict of interest.

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ЗНАЧАЈ ПРАЋЕЊА КВАЛИТЕТА ВАЗДУХА И ПОТРЕБА ЗА УНАПРЕЂЕЊЕМ УПРАВЉАЊА КВАЛИТЕТОМ ВАЗДУХА У ЈЕДИНИЦАМА ЛОКАЛНЕ САМОУПРАВЕ (ЈЛС) У РЕПУБЛИЦИ СРБИЈИ

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САЖЕТАК

У раду ће бити размотрен економски утицај Јединица локалне самоуправе (ЈЛС) на унапређење квалитета ваздуха и заштиту животне средине, у градовима и општинама (из сваког округа по један град и општина, осим Београда) у Републици Србији. Један од фактора који утичу на живот у градовима у Републици Србији јесте загађење ваздуха, које може имати негативан утицај како на здравље становника који живе у њима, тако и на оне који долазе пословно или туристички. Предмет истраживања у раду су општи подаци о квалитету ваздуха у ЈЛС (градови и општине) у Републици Србији, као и планирање и коришћење новчаних средстава од надлежних институција ЈЛС за успостављање и управљање квалитетом ваздуха. Циљ овог рада јесте да испита да ли надлежни органи ЈЛС примјењују плански и законодавни оквир као основу за ефективно и ефикасно управљање квалитетом ваздуха, спроводе мјере и активности на побољшању квалитета ваздуха, као и да ли прикупљају и издвајају новчана средства за ту сврху. Спроводећи анкетно истраживање на узорку од 49 ЈЛС, утврђено је да највећи број њих не управља адекватно квалитетом ваздуха. Истраживање је показало да ЈЛС у буџетима недовољно планирају и издвајају финансијска средства за одржавање квалитета ваздуха. Посматрано из угла рачуноводства, финансијска средства која ЈЛС остварују по основу накнаде загађивања животне средине и накнаде за заштиту и унапређивање животне средине припадају буџету јединице локалне самоуправе и имају значај код планирања и извршења расхода (трошкова) за управљање квалитетом ваздуха

Кључне ријечи: *квалитет ваздуха, загађење ваздуха, мониторинг квалитета ваздуха.*

THRESHOLD, MARGINAL AND INTERACTIVE EFFECTS AMONG ECONOMIC VARIABLES: AN INTEGRATED PANEL DATA FRAMEWORK[1]

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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.

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 (inf × 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 (lndk) 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.

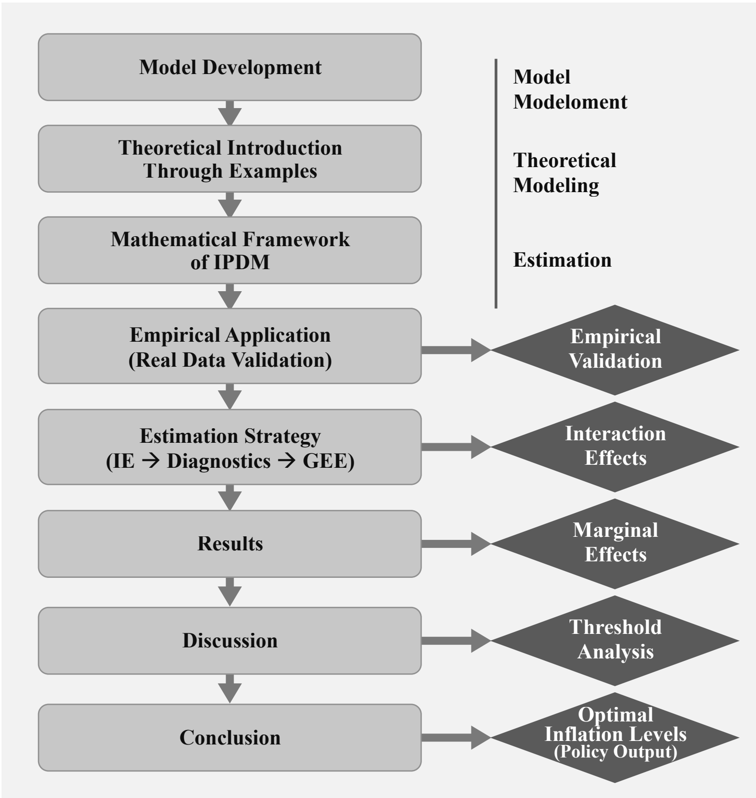

Figure 1. Methodological Framework of the Developed IPDF.
Source: Authors' illustration

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_{1_it} and exchange rate X_{2_it}, both the direct effects of these two variables and their interaction effect should be considered.

Equation (1):

$$Y_{\_it} = \beta_0 + \beta_1 X_{1\_it} + \beta_2 X_{2\_it} + \beta_3 (X_{1\_it} \times X_{2\_it}) + u_{\_it} \quad \text{...(1)}$$

Where: The term $X_{1\_it} \times X_{2\_it}$ 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):

$$Y_{\_it} = \beta_0 + \beta_1 G_{\_it} + \beta_2 r_{\_it} + \beta_3 \left(G_{\_it} \times r_{\_it} \right) + \beta_4 D\left(r_{\_it} > c \right) + u_{\_it} \qquad (2)$$

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:

$$Y_{\_it} = \beta_0 + \beta_1 X_{1\_it} + \beta_2 X_{2\_it} + \beta_3\left(X_{1\_it} \times X_{2\_it}\right) + \alpha_i + \lambda_t + u_{\_it} \quad \text{.........................(3)}$$

Where:

$Y_{\_it}$: Dependent variable of country i at time t
X_{1_it}: First independent variable
X_{2_it}: Second independent variable
($X_{1\_it} \times X_{2\_it}$): Interaction term
α_i: Individual-specific fixed effects
λ_t: Time-specific effects
$u_{\_it}$: Error term

In the equation above, the interaction term ($X_{1\_it} \times X_{2\_it}$) 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:

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

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×1 vector of unit-specific factor loadings, while F_t denotes an r×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:

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

In the second step, the residuals obtained from the initial OLS estimation are arranged into an N × 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 λ_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 (inf_{t-1} and $lndk_{t-1}$), 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:

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

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

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:

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

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

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

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

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

The marginal effects are then given by:

$$\partial \ln(GDP_{it}) / \partial INF_{it} = \beta_1 + \beta_3 \ln(DK_{it}) \quad (11)$$

$$\partial \ln(GDP_{it}) / \partial \ln(DK_{it}) = \beta_2 + \beta_3 INF_{it} \quad (12)$$

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:

$$\ln\left(DK\right)^* = -\beta_1 / \beta_3 \text{ and } INF^* = -\beta_2 / \beta_3 \quad (13)$$

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, $X_2^* = -\text{beta}1 / \text{beta}3$, 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:

$$\partial^2 Y_{it} \Big/ \left(\partial X_{1it} \partial X_{2it} \right) = \beta_3 \qquad (14)$$

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:

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

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 imes 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.

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

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:

$$nR2 \sim \chi 2(k) \qquad (17)$$

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:

$$F\left(1,\ N-1\right) \qquad (18)$$

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

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

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 com-ponent 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 Framewrok (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:

- lngdp: Logarithm of real GDP
- inf: inflation
- lndk: Logarithm of the exchange rate
- inter: Interaction term between inflation and the exchange rate (inf × lndk)

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:

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

where *lngdp* denotes the logarithm of real GDP for country *i* at time *t*, *inf* represents inflation, *lndk* 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;

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

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 (lndk) 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)	0.1824*** (0.000)	0.1824*** (0.000)
	[0.0821, 0.1393]	[0.1684, 0.1963]	[0.1685, 0.1964]
lndk	0.1379*** (0.000)	0.1296*** (0.000)	0.1282*** (0.000)
	[0.1050, 0.1708]	[0.1056, 0.1536]	[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 R^2 (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]
lndk	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 (gdp) is not stationary in levels but becomes stationary after first differencing, indicating an I (1) process. In contrast, inf is found to be stationary in levels and is therefore classified as I (0). The IPS test results show that ln (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 (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)	χ^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 χ^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
lndk	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_lndk	-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) = 166.44	Prob > chi2 = 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 *lndk* = 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 lndk = 3.5, the marginal effect of real inflation is −0.1428, whereas at lndk = 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 (inf_r) = beta3 + beta4*lndk
ME (lndk) = beta2 + beta4*inf_r
Threshold lndk* = -beta3/beta4
Threshold inf_r* = -beta2/beta4

Table 11. Threshold Values

Variable	Threshold (log)	Threshold (level)
lndk* (for inf_r)	0.9189	2.5066
inf_r* (for lndk)	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) | lndk=3.5	3.5	-0.1428
ME (inf_r) | lndk=4.0	4.0	-0.1704
ME (inf_r) | lndk=4.5	4.5	-0.1981
ME (inf_r) | lndk=5.0	5.0	-0.2257
ME (lndk) | inf_r=0.5	0.5	0.0638
ME (lndk) | inf_r=1.0	1.0	0.0362
ME (lndk) | inf_r=1.5	1.5	0.0085
ME (lndk) | 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 (inf_r) on GDP conditional on the level of the exchange rate (lndk), 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 (lndk* ≈ 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 (inf_r* ≈ 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.

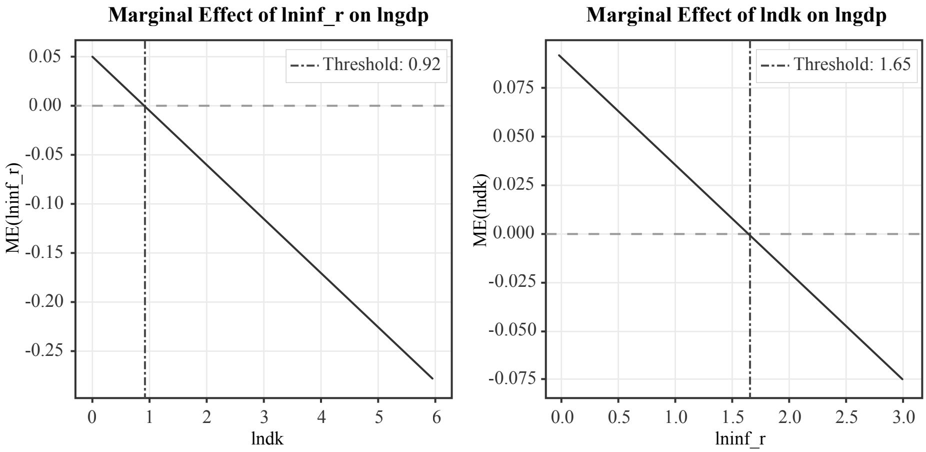

Figure 2. Marginal Effects of Inflation and Exchange Rate on GDP
Source: Authors' calculations using Stata 19, based on data from the World Bank, IMF, and BIS (via FRED).

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(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

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

while the marginal effect of the exchange rate is given by

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

Setting these expressions equal to zero yields the threshold conditions $inf_r^* = -\beta_2/\beta_3$ and $lndk_r^* = -\beta_1/\beta_3$. Under the maintained parameterisation $inf_r = (inf)^2$ and $lndk_r = (lndk)^2$, 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 $lndk^* = 0.9189$, 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 $inf\_r^* = 1.6536$, 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 $lndk = 3.5$, the marginal effect of inflation is -0.1428; this effect declines to -0.1704 at $lndk = 4.0$, -0.1981 at $lndk = 4.5$, and -0.2257 at $lndk = 5.0$. 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 $inf\_r = 0.5$, 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.

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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 (inf × 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 ИЗМЕЂУ 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.*

DIGITAL MOBILE PAYMENT AND ECONOMIC GROWTH IN KENYA AND NIGERIA: A COMPARATIVE ANALYSIS[1]

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ABSTRACT

Mobile payment technology allows digital transactions via smartphones and tablets using methods like NFC, QR codes, and payment apps. This innovation enables consumers to purchase goods and services without physical cards or cash. The global mobile payment market, valued at $2.98 trillion in 2023, is expected to grow to $27.81 trillion by 2032, changing how customers engage with businesses and manage finances. In Nigeria and Kenya, mobile phones serve as vital tools for financial services, e-commerce, and entertainment. This study aims to compare the adoption of digital mobile payments and their impact on economic growth in these countries. It uses quarterly data from Q1 2010 to Q4 2024 from the Central Banks of Kenya and Nigeria, employing the Auto-Regressive Distributed Lag (ARDL) model for analysis. Unit root tests showed variables were integrated of I(0) and I(1), and co-integration tests confirmed long-term relationships. Findings reveal that mobile money payments significantly influence economic growth in both nations, with mixed short-term effects and a positive long-term correlation. The study recommends collaboration among regulators, mobile network operators, fintech firms, and banks to enhance mobile financial services in both countries.

1. INTRODUCTION

Digital and mobile banking have transformed Kenya and Nigeria's financial sectors by increasing financial inclusion, reducing transaction costs, and improving access to services. The rapid adoption of mobile phones, fintech advancements, and better internet connectivity have accelerated the transition from traditional banking to digital financial systems, allowing people to conduct transactions in new ways (Windasari et al., 2022). These services, which mainly require a mobile phone and a bank account have revolutionised the payment system and made financial accessibility easier for many people. Mobile payment, also known as mobile money, mobile money transfer, and mobile wallet, includes various payment processing services that follow financial regulations and are done through a mobile device. Instead of using cash, checks, or credit cards, consumers can use a payment app on their mobile devices to pay for a wide range of services and digital or physical goods. The mobile phone acts as the initiator, authoriser, or confirmer of the transaction, while cellular providers provide a platform that connects to an individual's bank or mobile wallet (Hughes & Lonie, 2007). Although the concept of non-coin-based currency systems has a long history, it is only in the 21st century that the technology supporting such systems has become widely accessible. Mobile payments gained popularity in Japan during the 2000s and then spread globally through various means. The first patent specifically defining a "Mobile Payment System" was filed in 2000 (Japanese Drive Mobile Payment Market, 2011).

Prior to mobile and digital banking, Kenya and Nigeria faced major financial system weaknesses. In Kenya, before M-Pesa was launched in 2007, commercial banks and microfinance institutions mainly served urban areas like Nairobi, Mombasa, and Kisumu. Similarly, Nigeria's banking sector was dominated by traditional banks like First Bank and Guaranty Trust Bank, which catered primarily to urban elites and large corporations, leaving many without access to financial services. Geographic branch concentration, high transaction costs, and bureaucratic hurdles further limited access. The rise of mobile money and digital banking transformed these systems by decentralising services and reducing reliance on physical banks. M-Pesa in Kenya turned mobile phones into financial access tools, while Nigeria's fintech innovations enhanced electronic transfers and mobile banking, greatly improving transaction efficiency and financial inclusion in both countries (Aron, 2018). Kenya is a leader in mobile banking, primarily due to M-Pesa, which has integrated mobile financial services into daily life since its launch by Safaricom in 2007. By 2025, mobile money usage in Kenya was projected to surpass 90%, with around 45-51 million active users and over 400,000 agent outlets (Communications Authority of Kenya, 2025).

M-Pesa has notably reduced poverty and enhanced financial access (Suri & Jack, 2016). In contrast, Nigeria has experienced rapid digital banking growth driven by fintech innovations, increased smartphone adoption, and a cashless policy from the Central Bank. The 2023 cash scarcity crisis further accelerated the move to electronic transactions, with Nigeria reaching about 150 million mobile connections and 107 million internet users by early 2025 (DataReportal, 2025).

In developing nations, digital mobile payment solutions are utilised to offer financial services to the unbanked or underbanked population. This group accounts for approximately 50% of the global adult population, as stated in the Financial Access 2009 Report. According to the Financial Access 2025 Report, 79% of adults globally have a financial account, with 2.3 billion mobile money accounts and mobile transactions totaling 593 million. Additionally, 42% of adults in developing economies use digital merchant payments, highlighting mobile money's rapid growth in financial inclusion worldwide. Mobile payments are now crucial for payment service providers and other market participants to seek out new growth opportunities, according to the European Payments Council. These innovative technology solutions improve operational efficiency, resulting in cost savings and increased business volume. Merchants have also created their own payment platforms like Google Pay, Paypal, and Apple Pay, reducing dependence on traditional payment methods such as cash, bank transfers, cheques, and card payments. The exchange of funds for goods or services has become more convenient in today's world (Harb, Farahat, & Ezz, 2008).

Kenya has experienced a significant shift in its payment landscape in recent times. Businesses and individuals in Kenya have access to a range of payment options, from conventional methods like cards and bank transfers to alternative payment methods (APMs). Mobile payments, especially M-Pesa, have played a vital role in this shift. In Kenya, M-Pesa is the most popular payment method, followed by Paypal, Airtel, and other APMs. The growth of mobile money has been particularly impressive in Africa, making it the top mobile money market globally. The adoption of mobile money in Africa is on the rise, with East Africa, particularly Kenya, at the forefront, while West Africa, led by Nigeria, is making significant progress. Kenya holds the highest position on the continent for cashless transactions, achieving a rate of 75.8%. Meanwhile, Nigeria boasts the highest mobile phone penetration rate in Africa at 85%, with 92% of adult males possessing a mobile device (Diallo, 2024; Micheal, 2024). The extensive utilisation of mobile money services such as M-Pesa has revolutionised transaction methods for both individuals and businesses. In Kenya mobile money has 48% share of payments, which is the highest share of mobile payment, followed by cash on delivery 30%, cards 15%, bank transfer 5% and others 2%

Central Bank of Kenya (CBK, 2023). In 2025, mobile money wallets in Kenya (M-Pesa, Airtel Money) accounted for 50-55% of payments, the highest share among all payment methods, followed by mobile banking apps/bank transfer (35-42%), cash payment (20-30%), debit and credit cards (8-13%) and other digital payment methods (Paypal, fintech wallet, QR, etc) with 3-7%.

M-Pesa, a digital mobile payment service, is widely used in Kenya. It was introduced in 2007 and changed the financial industry. Users can store money, transfer funds, pay bills, and access microloans easily with their smartphones. Safaricom, the operator, claims it has more than 30 million users in Kenya, making it one of the largest mobile payment ecosystems globally. Recent reports indicate that M-Pesa had approximately 35-38 million active users between 2025 and 2026, reflecting the continued expansion of digital financial services in Kenys (Safaricom, 2025; TechCabal, 2025). Following M-Pesa, Paypal is another digital mobile wallet that allows fund transfers between accounts, promoting financial inclusivity. Airtel Money in Kenya also offers mobile payment services, making financial transactions convenient. By the end of 2022, Airtel Money had over 17 million subscribers, establishing itself as a major player in the country and demonstrating the increasing adoption of alternative mobile payment platforms within the country's digital financial ecosystem (Communications Authority of Kenya, 2023). Skrill and Pesapal are other popular digital payment platforms in Kenya, providing users with various payment options. Skrill enables users to receive money in any currency and transfer it to their M-PESA account quickly, while Pesapal allows payments through mobile devices using services like M-PESA and Airtel Money. Pesapal acts as an intermediary between customers and merchants. (CBK, 2022). Oluwole (2022) reported that in Africa, Kenyan businesses have a higher preference for mobile wallets (56%) compared to Nigeria (14%) and South Africa (7%). The survey also revealed that 71% of businesses in Kenya use cash for payments, while businesses in Nigeria (94%) and South Africa (91%) rely more on cash. This indicates that the lower use of cash among Kenyan businesses is reflected in their strong preference for mobile wallets. The study also found that digital payments are widely used in sectors such as food, entertainment, tours and accommodation, agriculture, transport and delivery, and professional services in Kenya.

From 2007 to the present, there have been over 32.5 million active mobile money subscriptions, 5.2 billion transfers, and 264,390 active mobile money agents in Kenya. In 2018, there were 47.7 million mobile accounts compared to 37.39 million in 2017 (CBK, 2019). The use of mobile money services has greatly contributed to financial inclusion and has facilitated cash transfers and investments in various sectors of the economy (Ozili, 2018). In 2018, mobile money transactions in Kenya amounted to Sh3.98 trillion ($38.5 billion), with an average daily value of Sh10.92 billion ($108 million). This represents almost half of the country's GDP and highlights the increasing importance of digital wallets to the economy. The growth of mobile payments has made it possible to pay for both public and private services using a basic mobile phone. In July 2022 alone, there were over 1.2 billion mobile money transactions, totaling over $23 billion. On a daily basis, this translates to approximately 42 million transactions valued at about $730 million (CBK, 2023). In 2007, there were only about one million active mobile money customers in Kenya. By 2022, this number has increased to over half of the country's population of 48 million people. There are approximately 310,000 mobile money agents in 2022, offering services like cash deposits and withdrawals valued at over $6 billion (CBK, 2023). Mobile money is a key player in Kenya's economy, contributing to nearly 70 percent of the GDP (Global Voice Group, 2023).

Nigeria, the largest economy in Africa and the 24th largest in the world, presents great opportunities for businesses looking to expand. With a population of 200 million, 60 percent of whom have access to financial services, Nigeria's digital market is thriving. Mobile money has played a crucial role in this growth, as the country has low bank penetration rates and high mobile acceptance. Through their mobile phones, customers can access a digital account provided by their mobile network operator, with all transactions authorised and recorded in real time using SMS (Paymentwall, 2024). The adoption of digital payments has been remarkable, with penetration rates increasing from 23 percent to 46 percent in less than eight years across Nigeria and other African countries (Okeowo, 2024). In fact, Nigeria alone witnessed a significant surge in digital mobile payments, as evidenced by the 1.35 billion electronic gateway transactions recorded in March 2023, a staggering increase of 448.54 million compared to February 2023. Additionally, cashless transactions grew by 44.84 percent to N126.73 trillion in the first quarter of 2023, up from N87.49 trillion in the same period of 2022 (Okeowo, 2024).

The value of digital mobile payment transactions in Nigeria reached $54.4 billion in 2022. Projections indicate that this value will soar to $150 billion by 2025, highlighting the increasing reliance on digital financial solutions (Global Legal Insights, 2023). From 2025 to 2026, Nigeria's digital mobile payment was valued at roughly $750-$850 billion USD annually based on Fintech (2026) and Nigeria Inter-Bank Settlement System (NIBSS, 2026). Statista (2023) reports that 84.7% of Nigerians own a mobile phone, providing a strong foundation for the widespread adoption of mobile payment apps. During the COVID-19 pandemic, the percentage of active users of mobile payment apps in Nigeria increased significantly, showcasing the crucial role these apps played during challenging times (World Bank, 2023). The growth of mobile payment apps in Nigeria is driven by factors such as the availability of affordable Smartphone's from various brands and the provision of financial services to previously unbanked populations, thus expanding financial inclusion. The highly competitive fintech sector in Nigeria fosters continuous innovation, resulting in the development of new features and services. Additionally, the value of digital mobile payments in Nigeria saw remarkable growth, reaching 387.1 trillion naira by 2022. In the first five months of 2023 alone, the total transactions amounted to 211.1 trillion naira, indicating further acceleration. Mobile payments surged in Nigeria after the 2023 cash shortage, with fintechs like Opay, Palmpay, Moniepoint, and Kuda Bank seeing increased user adoption. By 2024, Nigeria's electronic payment ecosystem exceeded ₦1 quadrillion in instant payment value. This growth in digital mobile money payments has led to increased efficiency in financial transactions, easier access to financial services for a larger population, reduced business transaction costs, and increased profitability and reinvestment (Abimbola, 2024). The value of mobile money transactions as a percentage of GDP has also grown significantly, reaching 16.11 percent from 8.74 percent. CBN (2025) reported mobile payment value of ₦1549.4 trillion or $1.06 million USD for first half of 2024 across broader mobile payment channels. Figure 2 below shows a stable increase of mobile payment from 1.27 billion naira/$8.44 million USD in 2009 to ₦125 trillion/$82.2 billion USD in 2025 (CBN, 2025).

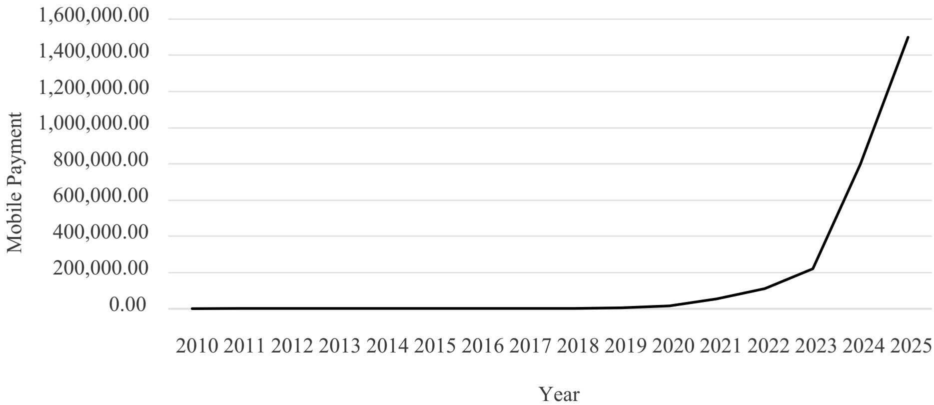

Figure 1: Values of Mobile Payment (₦ billions) in Nigeria
Source: Authors' compilation from CBN (2025)

Mobile money banking in Kenya faces several strategic challenges, including the need for restructuring, customer reluctance, high costs, system failures, network vulnerabilities, software defects, operating mistakes, processing errors, and data loss due to viruses. Additionally, M-Pesa has its own shortcomings, such as fees that prevent small transactions (Comninos, Esselaar, Ndiwalana & Stork, 2008), limited mobile phone access (Jack & Suri, 2011), difficulties for agents managing liquidity and raising capital (Eijkman, Kendall, & Mas, 2010), and complications for integrating with third-party organisations (Sadana et al., 2011). Another challenge is the risk of cash loss through theft from employees or organised individuals targeting M-Pesa shops. In Nigeria, the mobile money payment model requires owning a bank account, which poses a challenge for people in remote areas and villages. Many people in developing countries like Kenya and Nigeria are still unfamiliar with mobile money and have limited knowledge of mobile payments. Furthermore, a significant number of individuals in these countries are financially excluded and lack access to banking services or mobile payments (Mogaji et al, 2021).

Many studies have explored the link between digital payment systems and economic growth. Research indicates that digital payment methods like mobile phones, PoS systems, and web transfers significantly impact Nigeria's economic growth (GDP), while ATMs have an insignificant effect. Some studies suggest PoS and web transactions negatively affect growth, while ATM and mobile payments show a positive but insignificant impact. Other research claims all digital payment methods significantly influence economic growth in Nigeria. Onwere and Oke (2023) compared Kenya and Nigeria, finding mobile banking and PoS systems had an insignificant impact in both countries, with ATMs showing an insignificant effect in Kenya and a negative significant effect in Nigeria. Conversely, Nyaga and Ogollah (2015), Thinguri et al. (2014), and Otieno et al. (2016) focused on the challenges of adopting mobile payment services, highlighting issues such as lack of network coverage in rural areas, few phone money agents, inadequate information on mobile features, and high service charges.

Based on the above empirical findings, this research contributes to knowledge by exploring a specific digital payment method and the most popular digital payment in the countries being studied. Since many people own phones and are familiar with using mobile apps, the study examined the impact of digital mobile phone payments on economic growth in Kenya and Nigeria through a comparative analysis. The research utilised the auto-regressive distributed lag (ARDL) model to understand the relationship between mobile payment and economic growth in both countries using quarterly data from 2010Q1 to 2024Q4. These two countries are chosen because they are regarded as the world's leading mobile banking and mobile money economies dues to the success of M-Pesa and fintech. The upcoming sections will include a literature review, methodology, data analysis, and discussion, as well as conclusions and recommendations.

1.1 Research Hypotheses

Ho_1: Digital mobile payment has no significant effect on economic growth in Kenya

Ho_2: Digital mobile payment has no significant effect on economic growth in Nigeria

2. REVIEW OF LITERATURES

2.1 Theoretical Literatures

Endogenous growth theory: The endogenous growth model focuses on technological innovation, which is developed in the research and development (R&D) areas by incorporating human capital and existing knowledge stock. According to this theory, various factors that create opportunities and incentives for generating technological knowledge are crucial for long-term growth. Additionally, the theory suggests that long-term growth relies on the growth rate of total factor productivity, which is influenced by the rate of technological progress. It argues that enhancing productivity is directly linked to faster innovation and increased investments in human capital by governments and private sector institutions. These efforts aim to foster innovation initiatives and provide incentives for individuals and businesses to be more creative, such as funding for research and development (R&D) and intellectual property.

Diffusion of Innovation Theory: The diffusion of innovation theory, created by E.M. Rogers in 1962, examines how new ideas or products spread through a population over time. The adoption of these innovations occurs when individuals perceive them as new and beneficial. Adoption does not happen all at once, with some people being more likely to adopt early on. Understanding the characteristics of a target population is important when promoting a new innovation. DOI theory elucidates the diffusion of mobile payment innovations, such as mobile wallets and fintech applications, driven by perceived advantages over cash transactions. Key factors influencing adoption include relative advantage, compatibility, complexity, trialability, and observability. The rapid uptake of mobile payments in Nigeria post-2023 cash scarcity exemplifies how environmental pressures enhance innovation diffusion. Thus, DOI theory is vital for analysing mobile payment adoption across socioeconomic groups.

Technology Acceptance Model: Davis' (1985) Technology Acceptance Model (TAM) states that a potential adopter's attitude and expectations towards an innovation determine its likelihood of adoption. TAM focuses on two key concepts: perceived ease of use (how easy the innovation is to learn and implement) and perceived usefulness (how much the innovation improves personal or job-related performance). Davis believed that ease of use directly influences perceived usefulness, as technology that is perceived as easy to use is more likely to be adopted and increase productivity. Ultimately, Davis found that an innovation's perceived usefulness is more important than its ease of use in determining adoption. TAM is widely used in mobile payment studies, as it effectively captures consumer perceptions and intentions. Empirical evidence shows that perceived usefulness and ease of use significantly impact adoption, particularly in rapidly growing fintech markets, making TAM a strong framework for evaluating mobile banking acceptance.

Financial Intermediate Theory: The theory of financial intermediation explains how financial institutions facilitate the efficient distribution of resources, reduce transaction costs, and boost economic activities. It highlights the role of intermediaries like banks and fintech in enhancing market efficiency by linking savers with financial service users. Mobile payment innovations significantly contribute to financial intermediation by increasing access to services for unbanked and underbanked communities. With mobile technology, individuals can conduct transactions, save, transfer money, and access financial products without relying solely on traditional banks. Thus, this theory is crucial for research on the macroeconomic effects of mobile payment innovations, including their influence on financial inclusion, economic growth, and monetary policy effectiveness.

2.2 Empirical Literatures

Gitonga (2025) found that M-Pesa adoption significantly boosted sales, expanded customer bases, improved efficiency, and enhanced sustainability for SMEs in Nakuru Town, Kenya. Batista and Vicente (2025) conducted a randomised field experiment in rural Mozambique, revealing that mobile money reduces remittance costs, improves household welfare, and strengthens resilience to economic shocks like floods and income instability. Anazia & Nwachukwu (2025) argued that M-Pesa transformed Kenya's financial landscape by increasing SME productivity, facilitating cashless transactions, and promoting economic growth, with mobile money improving efficiency and reducing costs. Lambon and Ocansay (2025) analysed panel data from 38 sub-Saharan African countries, including Ghana, and found that mobile money positively influences economic growth, especially when supported by financial stability and job creation, using the Generalized Method of Moments (GMM) to address endogeneity issues.

Okafor and Ibrahim (2024) used the ARDL model on Nigerian data from 2012 to 2014, finding that digital payment platforms positively impact real GDP in both the short and long term, with mobile payments having the most significant effect. Udeh and Chukwu (2024) found that mobile transfers, web payments, and electronic fund transfers positively influence Nigeria's GDP, suggesting that fintech innovations improve financial system efficiency and increase money circulation. Eze and Okoye (2024) examined the effects of monetary policy on electronic money adoption in Nigeria, noting that rapid growth in electronic payment systems could impact money demand stability and monetary policy transmission, altering liquidity behavior and financial intermediation dynamics.

Onwere and Oke (2023) conducted a study comparing the impact of digital banking on the economic growth of Nigeria and Kenya using quarterly data from 2011 to 2021. They analysed mobile banking, ATMs, and point-of-sale terminals with the ARDL model. Results indicated that mobile banking and ATMs in Kenya, as well as point-of-sale terminals, did not significantly contribute to long-term economic growth, while Nigeria's ATMs had a negative effect. The study recommends extending the analysis period to the fourth quarter of 2022 and suggests that the central banks of both countries should promote greater awareness and adoption of digital banking services. Appah, Tebepah, and Newstyle (2023) analysed the effect of digital financial services on Nigeria's economic growth from 2006 to 2021, finding that ATMs and mobile banking had a positive but insignificant influence on real GDP, while point-of-sale (PoS) and web banking significantly impacted growth. Adebisi, Zannu, & Dada (2023) examined digital payment methods' effect on sustainable growth using data from 2015 to 2021, concluding that ATMs and mobile payments had a positive but insignificant effect, whereas PoS and web payments had a negative impact. Both studies propose comparative research between Kenya and Nigeria, extending their studies to 2022Q4, with the latter study attributing impacts to financial illiteracy and inadequate internet access.

Marafa (2022) examined the influence of digital payment systems on Nigeria's economic growth using quarterly data from 2010q1 to 2021q2, employing the ARDL bound test and Granger causality test. The results showed a long-run relationship and significant positive impacts of digital payment variables on economic growth, with unidirectional causality from digital payment platforms to growth. Building on this, a comparative study between Kenya and Nigeria will extend the analysis to 2022Q4. Olofin (2023) investigated the digital economy's effect on growth in Bangladesh, Ethiopia, Kenya, and Nigeria from 1985 to 2017, revealing contributions of the digital economy and institutional quality, while factors like corruption hinder growth. The current study will focus on Kenya and Nigeria, applying the ARDL model and extending the timeline to 2022Q4. Tiony (2023) studied the impact of digital financial services on financial inclusion in Kenya using secondary data from various sources, revealing a notable increase in access to banking services via digital channels, particularly mobile money platforms like M-Pesa. Zwingina, Onoh, and Chukwu (2023) explored the effect of electronic payment systems on Nigeria's economic growth from 2009 to 2018, finding a positive relationship through the use of the ARDL model. Both studies propose comparative analyses between Kenya and Nigeria, with Tiony focusing on digital financial services and Zwingina et al. examining electronic payment systems, extending the research period for Nigeria to 2010Q1-2022Q4.

Hussein and Ritzen (2021) analysed the influence of mobile money payments on economic growth in Sub-Saharan Africa, utilising panel data from 2012 to 2018 across four regions. They identified that total transactions positively impacted economic growth, while active accounts and agents did not significantly affect growth. Building on this, a comparative study focusing on Kenya and Nigeria will extend the research period to 2022Q4. Nyaga and Ogollah (2015) explored barriers to adopting mobile money transfer services in Nairobi, employing descriptive methods and questionnaires. Their findings highlighted considerable challenges facing Mobile Network Operators. The forthcoming study will leverage secondary quarterly data from 2010 to 2022 and apply the ARDL model for a comparative analysis between Kenya and Nigeria. Otieno et al. (2016) explored the challenges of mobile money services in Kenya, using qualitative methods with primary and secondary data. Their findings identified significant obstacles in rural communities, such as lack of information, inadequate cash and e-floats by agents, limited agent availability, and the absence of national ID cards among potential users. The current study aims to conduct a comparative analysis between Kenya and Nigeria from 2010 to 2022, utilising secondary quarterly data and the ARDL model.

3. METHODS

3.1 Theoretical framework

This study focuses on the endogenous growth model, which highlights technology progress as the main driver of long-term economic growth. Unlike the neoclassical growth model, endogenous models consider technological progress as a key factor that can lead to increasing returns to scale. The AK model, developed by Arrow in 1962, suggests that productivity can improve through experience and practice. Many endogenous growth theories, such as those proposed by Lucas (1988), Romer (1986), and Rebelo (1991), emphasise the importance of factors influencing technology (represented by A) and the accumulation of human and physical capital (represented by K).

3.2 The Model

The ARDL model, also known as the bound testing approach, was introduced by Pesaren et al. in 2001 and is used for single equation modeling. It is a co-integration technique that analyses long-run and short-run relationships between variables, regardless of their order of integration, whether the variables in the study are purely $I(0)$ or $I(1)$. The variables were used in their original form

The error correction form of an ARDL *(p q)* (Bound test) regression model is as follows

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{q} \beta_i \Delta x_{1t-i} + \sum_{i=0}^{q} \gamma_k \Delta x_{2t-k} + \phi_0 y_{t-1} + \phi x_{1t-1} + \phi x_{2t-1} + \varepsilon_t \text{ .....(1)}$$

Model Specification

Kenya

$$KRGP = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta KRGDP_{t-i} + \sum_{i=0}^{p} \alpha_{2i} \Delta MPVA_{t-i} + \sum_{i=0}^{p} \alpha_{3i} \Delta MPVO_{t-i}$$
$$+ \sum_{i=0}^{p} \alpha_{4i} \Delta HCAP_{t-i} + \sum_{i=0}^{p} \alpha_{5i} \Delta K_{t-i} + \beta_1 KRGDP_{t-1} + \beta_2 MPVA_{t-1} + \beta_3 MPVO_{t-1}$$
$$+ \beta_4 HCAP_{t-1} + \beta_5 K_{t-1} + \varepsilon_t \text{ ....(2)}$$

Nigeria

$$NRGP = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta NRGDP_{t-i} + \sum_{i=0}^{p} \alpha_{2i} \Delta MPVA_{t-i} + \sum_{i=0}^{p} \alpha_{3i} \Delta MPVO_{t-i}$$
$$+ \sum_{i=0}^{p} \alpha_{4i} \Delta HCAP_{t-i} + \sum_{i=0}^{p} \alpha_{5i} \Delta K_{t-i} + \beta_1 NRGDP_{t-1} + \beta_2 MPVA_{t-1} + \beta_3 MPVO_{t-1}$$
$$+ \beta_4 HCAP_{t-1} + \beta_5 K_{t-1} + \varepsilon_t \text{ ....(3)}$$

Where: KRGDP = Kenya real gross domestic product; NRGDP = Nigeria real gross domestic product, MPVA =Mobile payment value; MPVO = Mobile payment volume; HCAP = Human capital (Education); K = Capital (Gross fixed capital formation). The selection of the variables are guided from the works of Marafa, 2022; Onwere & Oke, 2023; Adebisi, Zannu, & Dada, 2023 and Olofin, 2023.

Real GDP represents the total value of all goods and services produced in a country during a specific time period. It helps estimate the size and growth rate of an economy.

Mobile payment value refers to the money paid for products or services using portable electronic devices like tablets or cell phones. It can also be used to send money to friends and family.

Mobile payment volume measures the increase in mobile money payments made through portable devices.

Human capital represents the economic value of a worker's skills, education, training, intelligence, health, and other factors. This study used secondary education as an indicator of human capital

Gross fixed capital formation includes tangible or intangible assets used in production processes for at least one year.

Lag Length Specification

To circumvent the issue of producing too large models, one of the following two information criteria

The Bayes information criterion (BIC)

$$BIC(p) = log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{log(T)}{T} \quad \text{......} (4)$$

The Akaike information criterion

$$AIC(p) = log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{2}{T} \quad \text{......} (5)$$

3.3 Estimation Test

Unit root Test: Dickey and Fuller developed a regression test in 1979 to detect the presence of a unit root. They later expanded their test by adding lagged terms to eliminate autocorrelation. The Augmented Dickey Fuller test equation is used for this purpose. The possible form of the ADF is given by the following equation.

$$\Delta y_t = a_0 + \lambda y_{t-1} + a_{2t} + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + \mu_t \quad \text{...}(6)$$

Co-integration Test (Bounds Testing Approach of Peseran et al 2001): The ARDL co-integration approach, developed by Pesaran and Shin in 1999 and Pesaran et al. in 2001, is used to analyse both long-term relationships and short-term dynamics between variables. This technique integrates short-term changes with the long-term equilibrium, ensuring that important long-term information is not overlooked (Pesaran & Shin, 1999; Pesaran et al., 2001).

Stability Test: Pesaran and Pesaran (1997) recommend using the CUSUM and CUSUMSQ tests by Brown et al (1975) to assess parameter stability, emphasising the importance of considering short run dynamics when testing for the stability of long run coefficients.

3.4 Sources of Data

This study will analyse quarterly data from 2010q1-2024q4 for Kenya and Nigeria, sourced from the World Development Indicators (WDI, 2025), Central Bank of Kenya (CBK, 2025), and Central Bank of Nigeria (CBN, 2025).

Table 1: Variables for Kenya and Nigeria

Variables	Label	Measure Units	Source
Kenya real gross domestic product	KRGDP	Total value of goods and services	CBK 2024
Nigeria real gross domestic product	NRGDP	Total value of goods and services	CBN 2024
Mobile payment value	MPVA	Money paid for products or services using devices like tablets or cell phones	CBK 2024 CBN 2024
Mobile payment volume	MPVO	Measures the increase in mobile money payments made through portable devices.	CBK 2024 CBN 2024
Human capital (education)	HCAP	Worker's skills, education, training etc.	WDI 2024
Capital (gross fixed capital formation)	K	Tangible or intangible assets used in production processes	WDI 2024

Source: Authors' compilation

4. RESULTS

4.1 Preliminary Analysis and Model Validation

Unit root

Table 2: Unit/Stationarity test for both Kenya and Nigeria

Var	Kenya				Nigeria			
	ADF 5%	Level diff	1st diff	Order of Integration	ADF 5%	Level diff	1st diff	Order of Integration
RGDP	-3.526609	-2.981155	-6.476447	I(1)	-3.508508	-2.23831	-13.54446	I(1)
MPVA	-3.504330	-0.060806	-8.155880	I(1)	-3.526609	-1.597607	-4.143002	I(1)
MPVO	-3.179617	-3.448321		I(0)	-3.526609	-1.878513	-6.060449	I(1)
HCAP	-3.502373	-2.476191	-7.148346	I(1)	-3.502373	-1.876969	-6.997554	I(1)
GFCF	-3.502373	-2.790947	-7.505528	I(1)	-3.508508	-2.734248	-3.530210	I(1)

Source: Authors' computation using E-views 13

The unit root test indicates that the integration order aligns with the autoregressive distributed lag model (ARDL) requirements. Real gross domestic product, mobile payment value, mobile payment volume (Nigeria only), human capital, and gross fixed capital formation are integrated of order one, I(1), while only mobile payment volume (Kenya only) is integrated of order zero, I(0). Therefore, we move forward with the co-integration test (ARDL Bound test).

The ARDL Co-integration Bound test

Table 3: Kenya and Nigeria

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
Kenya			Asymptotic: n=1000	
F-statistic	32.88447	10%	2.2	3.09
K	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Nigeria				
F-statistic	26.11560			
K	4			
Actual Sample Size	48		Finite Sample: n=50	
		10%	2.372	3.32
		5%	2.823	3.872
		1%	3.845	5.15

Source: Authors' computation using E-views 13

In Kenya, the F-statistics value is 32.88447 and the 5% critical value in Pesaran et al. (1999) ranges from 2.56 to 3.49. In Nigeria, the F-statistics value is 26.11560 and the 5% critical value in Pesaran et al. (1999) also ranges from 2.56 to 3.49. Since the F-statistics exceed the upper bound value for both countries, the nominal hypothesis (H0) cannot be accepted and the unconventional hypothesis (H1) is accepted. Therefore, there is a long-term relationship between digital mobile payment and other variables, leading to economic growth. To account for this long-run relationship, we estimate both the short run and the long run using the error correction model (ECM).

Leg Length Selection

Table 4: Leg Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2905.411	NA	2.83e+42	111.9389	112.1265	112.0108
1	-2631.645	484.3555	1.99e+38	102.3710	103.4967	102.8025
2	-2625.154	10.23598	4.17e+38	103.0829	105.1467	103.8741
3	-2612.094	18.08275	7.08e+38	103.5421	106.5440	104.6930
4	-2388.686	266.3711*	3.96e+35*	95.91101*	99.85103*	97.42152*

Using AIC we select lag 4 to estimate both the short-run and long-run estimation of the ARDL.
Source: Authors' compilation

4.2 Short-run Results (Kenya vs. Nigeria)

Table 5: Dependent variable: KRGDP

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D(KRGDP(-1))	0.035294	0.086953	0.405901	0.6872
D(KRGDP(-2))	-0.040498	0.094824	-0.427088	0.6719
D(KRGDP(-3))	-0.026373	0.088586	-0.297716	0.7676
D(KRGDP(-4))	0.299739	0.083939	3.570914	0.0010
D(KMPVA)	-1369.180	542.1910	-2.525272	0.0161
D(KMPVA(-1))	2881.168	529.4592	5.441718	0.0000
D(KMPVO)	3886.377	2369.279	1.640320	0.1096
D(KMPVO(-1))	-2968.175	2984.163	-0.994642	0.3265
D(KMPVO(-2))	9863.934	2659.722	3.708633	0.0007
D(KHCAP)	1856.568	692.7917	2.679836	0.0110
D(KGFCF)	1.46E-05	1.53E-05	0.955327	0.3458
C	3882517.	606627.9	6.400162	0.0000
R-squared	0.996959	Mean dependent var.		7820833.
Adjusted R-squared	0.996030	S.D. dependent var.		1176424.

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
S.E. of regression	74122.98	Akaike info criterion		25.47716
Sum squared resid.	1.98E+11	Schwarz criterion		25.94496
Log likelihood	-599.4518	Hannan-Quinn criter.		25.65394
F-statistic	1073.012	Durbin-Watson stat		1.517288
Prob.(F-statistic)	0.000000			

Source: Authors' computation using E-views 13

The short-term regression analysis of Kenya indicates that mobile payment value (current and lagged by one period), mobile payment volume (lagged by two periods), and human capital all have a significant impact on Kenya's economic growth (RGDP). On the other hand, gross fixed capital formation does not have a significant effect on economic growth. In the short term, a one per cent increase in the value of mobile payments leads to a decline in economic growth in the current period but contributes to an increase in economic growth in the subsequent period. Similarly, a one percent change in the volume of mobile payments increases economic growth in the previous period, while a one percent change in human capital boosts economic growth in the current period in the short term. The Adjusted R-square value indicates a 99% goodness of fit for the results, and the Durbin-Watson statistic of 1.517288 suggests the absence of autocorrelation or serial correlation.

Table 6: Dependent variable: NRGDP

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
NRGDP(-1)	0.148477	0.110692	1.341360	0.1935
NRGDP(-2)	0.061685	0.119477	0.516293	0.6108
NRGDP(-3)	-0.019627	0.120068	-0.163462	0.8716
NRGDP(-4)	0.953634	0.116591	8.179322	0.0000
NMPVA	23547.99	7270.745	3.238732	0.0038
NMPVA(-1)	-16424.56	7658.958	-2.144489	0.0433
NMPVO	-0.028455	0.037016	-0.768710	0.4502
NMPVO(-1)	-0.123924	0.058547	-2.116678	0.0458
NMPVO(-2)	-0.221402	0.071133	-3.112492	0.0051
NMPVO(-3)	-0.707800	0.208093	-3.401358	0.0026
NMPVO(-4)	-0.770676	0.256820	-3.000837	0.0066
NHCAP	-12804.67	12902.26	-0.992436	0.3318
NHCAP(-1)	19989.67	16144.34	1.238185	0.2287
NHCAP(-2)	-13657.71	17406.11	-0.784651	0.4410
NHCAP(-3)	-5892.205	14886.26	-0.395815	0.6961
NHCAP(-4)	60224.81	13564.96	4.439733	0.0002
NGFCF	-12.39135	755.8262	-0.016394	0.9871
C	-5237416.	2589088.	-2.022881	0.0554

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
R-squared	0.992155	Mean dependent var.		67040000
Adjusted R-squared	0.986094	S.D. dependent var.		4745027.
S.E. of regression	559558.8	Akaike info criterion		29.60985
Sum squared resid.	6.89E+12	Schwarz criterion		30.36984
Log likelihood	-574.1970	Hannan-Quinn criter.		29.88464
F-statistic	163.6746	Durbin-Watson stat.		1.577833
Prob.(F-statistic)	0.000000			

Source: Authors' computation using E-views 13

The result above reveals that certain factors have a significant impact on Nigeria's economic growth in the short-run. Specifically, the present and past values of mobile payment, all past volumes of mobile payment and the human capital (lag 4) are significant. On the other hand, the present volume of mobile payment, present and past (up to lag 3) of human capital, and gross fixed capital formation are found to be insignificant in relation to economic growth in Nigeria. In terms of the effects, a one percent change in the values of mobile payment (both present and past) leads to increases and decreases in economic growth in the short-run, respectively. Similarly, a one percent change in the volume of mobile payment in the past results in a decrease in economic growth, while a one percent change in human capital in the past leads to an increase in economic growth in Nigeria in the short-run. Furthermore, the Adjusted R-square indicates a 98% goodness of fit of the result, suggesting a strong relationship between the variables. Additionally, the Durbin-Watson statistic of 1.577833 indicates the absence of auto-correlation or serial correlation in the data.

4.3 Long-run Results (ECM) (Kenya vs. Nigeria)

Table 7: Dependent variable: D(RGDP) (Kenya)

ECM Regression

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(KRGDP(-1))	-0.232868	0.057037	-4.082741	0.0002
D(KRGDP(-2))	-0.273366	0.061114	-4.473061	0.0001
D(KRGDP(-3))	-0.299739	0.063221	-4.741100	0.0000
D(KMPVA)	-1369.180	446.8922	-3.063781	0.0041
D(KMPVO)	3886.377	1974.911	1.967875	0.0568
D(KMPVO(-1))	-9863.934	2179.071	-4.526669	0.0001
CointEq(-1)*	-0.731838	0.048821	-14.99035	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R-squared	0.850700	Mean dependent var.		84583.33
Adjusted R-squared	0.828851	S.D. dependent var.		167890.0
S.E. of regression	69456.38	Akaike info criterion		25.26882
Sum squared resid.	1.98E+11	Schwarz criterion		25.54171
Log likelihood	-599.4518	Hannan-Quinn criter.		25.37195
Durbin-Watson stat.	1.517288			

Source: Authors' computation using E-views 13

CointEq(-1) has a coefficient estimate of 0.731838, meaning 73.18% of disequilibrium movements are corrected within one period. The coefficient is highly significant with a t-statistic of -14.99035, suggesting a long-run relationship between digital mobile payment and economic growth in Kenya. A Durbin-Watson statistic of 1.517288 shows no serial correlation in the regression.

Table 8: Dependent variable: D(NRGDP) (Nigeria)

ECM Regression

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(NRGDP(-1))	-0.995693	0.098919	-10.06575	0.0000
D(NRGDP(-2))	-0.934007	0.096525	-9.676365	0.0000
D(NRGDP(-3))	-0.953634	0.100795	-9.461150	0.0000
D(NMPVA)	23547.99	4448.310	5.293693	0.0000
D(NMPVO)	-0.028455	0.023292	-1.221641	0.2348
D(NMPVO(-1))	1.699877	0.126549	13.43261	0.0000
D(NMPVO(-2))	1.478476	0.112018	13.19850	0.0000
D(NMPVO(-3))	0.770676	0.160563	4.799832	0.0001
D(NHCAP)	-12804.67	9262.768	-1.382380	0.1807
D(NHCAP(-1))	-40674.89	8612.127	-4.722978	0.0001
D(NHCAP(-2))	-54332.60	9375.813	-5.794975	0.0000
D(NHCAP(-3))	-60224.81	9950.698	-6.052320	0.0000
CointEq(-1)*	-0.144170	0.010396	-13.86744	0.0000
R-squared	0.865091	Mean dependent var.		405000.0
Adjusted R-squared	0.805131	S.D. dependent var.		1144205.
S.E. of regression	505097.5	Akaike info criterion		29.35985
Sum squared resid.	6.89E+12	Schwarz criterion		29.90873
Log likelihood	-574.1970	Hannan-Quinn criter.		29.55831
Durbin-Watson stat.	1.577833			

Source: Authors' computation using E-views 13

CointEq(-1), which represents the ECM term, has an estimated coefficient of 0.143170. This means that approximately 14.32% of any imbalances are corrected within one time period. The coefficient is considered significant due to the high t-statistics of 13.86744. This suggests a long-term relationship between digital mobile payment and economic growth in Nigeria. The Durbin-Watson statistic of 1.577833 indicates that there is no serial correlation or autocorrelation in the regression.

4.4 Model Stability

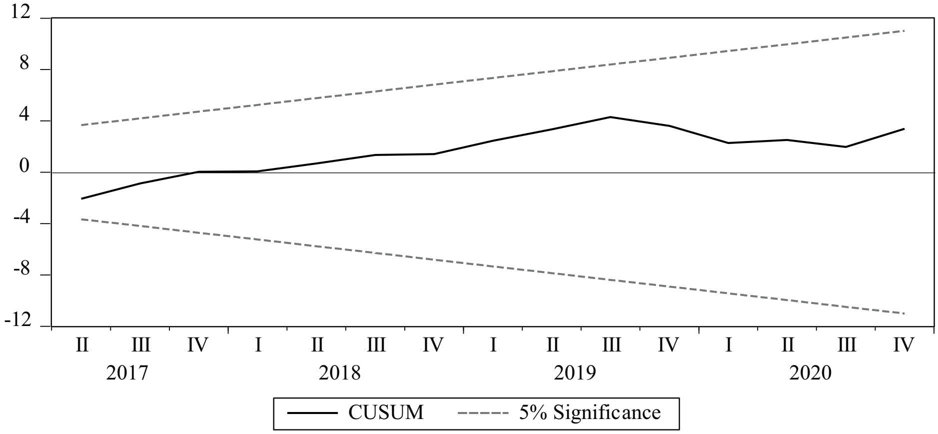

Figure 2: Model Stability
Source: Authors' compilation

The figure shows that the blue line lies between the 5% significant boundary so we can say the model is stable for both Kenya and Nigeria.

5. DISCUSSIONS OF FINDINGS, CONCLUSIONS AND POLICY DIRECTIVES

The study reveals a strong connection between mobile payment adoption and economic growth in Kenya and Nigeria. In Kenya, mobile payments have a notable impact on economic growth in both the short-run and long-term. Similar findings are observed in Nigeria, where mobile payments adoption significantly influences economic growth. These results align with the findings of previous studies conducted by Tiony (2023), Olofin (2023), Hussein and Ritzen (2021), Zwingina, Onoh, and Chukwu (2023), and Marafa (2022). However, the results contradict the findings of Adebisi, Zannu, and Dada (2023), Appah, Tebepah, and

Newstyle (2023), and Onwere and Oke (2023), suggesting that the relationship between mobile payments adoption and economic growth in Kenya and Nigeria varies in the short-run and long-term.

Kenya and Nigeria demonstrate a strong link between mobile and digital payment systems and economic growth. Innovations in mobile money and digital banking have improved transaction efficiency, increased financial inclusion, reduced cash dependency, and stimulated business activities. Data shows that digital payments are vital for SME growth, rural economic integration, productivity enhancement, and financial system development in both countries. The M-Pesa model in Kenya showcases the impact of telecom-based financial innovation, while Nigeria's fintech ecosystem underscores the importance of digital entrepreneurship and instant payments for economic advancement. Nonetheless, challenges like infrastructure issues, cybersecurity risks, and regulatory barriers remain significant hurdles for policymakers to address to ensure inclusive digital financial progress.

A comparative study was conducted to examine the influence of digital mobile adoption on economic growth in Kenya and Nigeria. The study utilised quarterly data and ARDL estimation. Data from the Central Bank of Kenya (CBK, 2025) statistical bulletin, Central Bank of Nigeria (CBN, 2025) statistical bulletin, and World Bank Development Indicator (WDI, 2025) annual data were used. The study revealed a mixed relationship between mobile payments adoption and economic growth in the short term, with both positive and negative effects. In the long term, there was a correlation between the two variables for both Kenya and Nigeria. This implies that mobile payment adoption has had both positive and negative impacts on the economic growth of both countries, and it is expected to continue influencing the future. Based on the findings, the study directs that:

1. The deposit money bank and fintech industries need to work closely with network providers like MTN, Airtel, and Globacom in Nigeria, and Safaricom, Airtel, Equitel, and Telkom Kenya in Kenya to ensure a reliable network in both urban and rural areas for mobile app usage.
2. Enhancing public perception of the ease of use, trust, affordability, usefulness, security, and transparency of mobile money services.
3. Collaboration is essential among regulators, mobile network operators (MNOs), fintech companies, and traditional banks to deliver fast and efficient mobile financial services in Kenya and Nigeria.

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Conflict of Interest

The authors declare there is no conflict of interest.

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ДИГИТАЛНО МОБИЛНО ПЛАЋАЊЕ И ЕКОНОМСКИ РАСТ У КЕНИЈИ И НИГЕРИЈИ: УПОРЕДНА АНАЛИЗА

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САЖЕТАК

Технологија мобилног плаћања омогућава дигиталне трансакције путем паметних телефона и таблета користећи методе попут NFC-а, QR кодова и апликација за плаћање. Ова иновација омогућава потрошачима да купују робу и услуге без физичких картица или готовине. Очекује се да ће глобално тржиште мобилних плаћања, процијењено на 2,98 билиона долара у 2023. години, порасти на 27,81 билион долара до 2032. године мијењајући начин на који купци комуницирају са предузећима и управљају финансијама. У Нигерији и Кенији, мобилни телефони служе као витални алати за финансијске услуге, електронску трговину и забаву. Овај рад има за циљ да упореди усвајање дигиталних мобилних плаћања и њихов утицај на економски раст у овим земљама. У раду су коришћени квартални подаци: од првог квартала 2010. до четвртог квартала 2024. године из централних банака Кеније и Нигерије, те модел ауторегресивног дистрибуираног кашњења (ARDL) за анализу. Тестови јединичних коријена показали су да су варијабле интегрисане од I(0) и I(1), а тестови коинтеграције потврдили су дугорочне везе. Резултати откривају да мобилна плаћања значајно утичу на економски раст у обје земље, са мјешовитим краткорочним ефектима и позитивном дугорочном корелацијом. Студија препоручује сарадњу између регулатора, оператера мобилних мрежа, финансијско-технолошких компанија и банака како би се унаприједиле мобилне финансијске услуге у објема земљама.

Кључне ријечи: *дигитално мобилно плаћање, економски раст, Кенија, Нигерија, ARDL.*