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Climate Change and Stock Market Performance in Nigeria

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Abstract
This study investigates the impact of climate change variables including carbon emissions, rainfall, temperature, inflation, real interest rates, Foreign Direct Investment, and Gross Domestic Product per capita growth rate on stock market performance in Nigeria using the Autoregressive Distributed Lag (ARDL) bound testing approach. Annual data from 1990 to 2022 was analyzed to explore both long-run and short-run dynamics. The results reveal that in the long run carbon emissions and foreign direct investment have a positive and significant effect on stock performance, while inflation has a significantly negative effect. Conversely, in the short run, lag one carbon emission and foreign direct investment one-year lag have a negative and significant effect on stock performance. However, rainfall and temperature did not show any significant effect both in the short and long run. The model demonstrates robust explanatory power, accounting for approximately 96% of the variation in stock market performance. These findings underscore the complex and nuanced interplay between climate change, macroeconomic variables, and financial markets, highlighting the need for policymakers, investors, and corporate managers to address climate and economic risks while leveraging potential opportunities in Nigeria's evolving financial landscape.

Keywords: Climate Change, Stock Market Performance, Carbon Emission, Real Interest Rate, Auto-Regressive Distributed Lag.

1. Introduction

Climate-related anomalies have become a prominent topic in both academic research and practical applications globally. Numerous studies highlight the negative impacts of recent climate change and weather events on various countries (De Frenne et al., 2021; Riris and Arroyo-Kalin, 2019). Climate change has led to crop and livestock losses, which in turn have resulted in reduced agricultural income, higher unemployment, and increased poverty (e.g., Agovino et al., 2019; Ahmad et al., 2022). These consequences underscore climate change's significant risks to economic stability and financial development (Nasir et al., 2019). Interestingly, climate change is increasingly recognized as one of the most pressing global challenges of the 21st century. Its effects, ranging from rising temperatures and sea levels to more frequent and severe weather events, are not only environmental but also economic and financial. As these impacts become more pronounced, they are reshaping industries, influencing regulatory policies, and altering market dynamics (Batten et al., 2017). The global climate is undergoing dramatic changes. Since the mid-20th century, the global average surface temperature has increased by approximately 0.2 ◦C per decade (Kozarcanin et al., 2019). The global average temperature was approximately 1.11 ◦C higher than the preindustrial levels (1850–1900) in 2021, which is close to the lower limit of the Paris Agreement's temperature control target of 1.5 ◦C.

Climate change refers to long-term shifts in temperatures and weather patterns, primarily caused by human activities such as burning fossil fuels, deforestation, and industrial processes (IPCC, 2018). These changes have resulted in more frequent and severe weather events, rising sea levels, and other environmental disruptions, posing risks to various sectors, including agriculture, real estate, and insurance, and potentially destabilizing economies (Hong et al., 2019). As a result, the integration of climate-related risks into investment decisions has gained traction. Investors increasingly recognize the financial implications of environmental factors, as evidenced by the rise of Environmental, Social, and Governance (ESG) investing and the growing adoption of frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD) (Amel-Zadeh & Serafeim, 2018). These frameworks underscore the importance of evaluating how a company's approach to climate change affects its long-term viability and stock performance.

Stock performance, traditionally driven by factors such as economic conditions, interest rates, and corporate earnings, is now also influenced by environmental considerations (Delis et al., 2019). Companies that fail to mitigate their environmental impact or adapt to climate risks may face increased costs, reduced revenues, and reputational damage, negatively affecting their stock prices. Conversely, companies that proactively address climate change and demonstrate strong environmental stewardship may gain favour with investors, leading to improved stock performance (Busch et al., 2018).

Despite the growing recognition of climate change as a significant global challenge, its specific impact on stock performance remains inadequately understood and underexplored. Companies across various sectors face climate-related risks, including physical damages from extreme weather events, regulatory changes aimed at reducing carbon emissions, and shifts in consumer behaviour towards sustainable products (Gibson & Krueger, 2018). These risks can significantly affect financial performance and stock prices. However, there is a lack of comprehensive research quantifying and explaining the extent to which climate change influences stock performance, particularly in developing economies such as Nigeria.

Existing studies produce mixed results. Some suggest that firms with robust environmental practices experience better financial outcomes (Friede et al., 2015), while others indicate that the relationship varies by industry, geography, and time frame (Flammer, 2021). These inconsistencies underscore the need for more nuanced research, particularly in emerging markets where institutional frameworks and climate vulnerabilities differ from those in developed economies. Uncertainty about how to effectively integrate climate risks into financial strategies persists among investors and corporate managers. Varying levels of climate risk disclosure and the absence of standardized reporting frameworks further complicate efforts to assess the impact of climate change on stock performance (Clark et al., 2018). In this context, understanding how climate change affects financial markets, particularly stock performance, is critical for investors, corporate managers, and policymakers.

This study seeks to address the knowledge gap regarding the specific effects of climate change on stock performance in Nigeria. By examining various climate-related factors, including rainfall, temperature, carbon emissions, and other natural or physical risks, this research aims to provide actionable insights. These findings will guide investors, policymakers, and corporate managers in making informed decisions to manage climate risks and leverage opportunities in a rapidly evolving environmental landscape.

2. Literature Review and Hypotheses Development

Theoretical Perspective

The effect of climate change on stock performance has garnered increasing attention in finance and economics. Scholars have proposed various theories to explain the influence of climate change on stock market dynamics globally and in specific markets like Nigeria. However, the theory that underpins the study is the efficient market hypothesis.

The Efficient Market Hypothesis (EMH) is a financial theory proposed by Eugene Fama in the 1970s. It suggests that financial markets are "informationally efficient," meaning that asset prices fully and instantaneously reflect all available information. As a result, it is theoretically impossible for investors to achieve returns that exceed average market consistently returns through stock picking or market timing. The Efficient Market Hypothesis suggest that all available information is already reflected in stock prices, meaning that stock prices are always accurate reflections of all known information at any given time. If any new information becomes available, it will be quickly incorporated into stock prices. A market is considered efficient if asset prices fully reflect all available information at any given time. No investor can consistently "beat the market" by exploiting mispriced assets, as any new information is quickly and accurately incorporated into prices.

Empirical Review

The empirical literature offers extensive insights into the complex interplay between climate change and financial markets, highlighting both regional nuances and methodological diversity. Habibullah et al. (2022) examined the influence of weather catastrophes on the Canadian stock market over nearly three decades (1988–2016). By leveraging accounting ratios and statistical tests, their findings underscored a significant negative impact of extreme weather events on stock returns and volatility, particularly on the Toronto Stock Exchange (TSX) composite and its subsector indices. The IT and financial services sectors appeared most vulnerable, while the consumer staples sector was relatively resilient. These findings underscore the heightened sensitivity of specific sectors to climate risks and the overarching influence of climate warming in Canada, which the study suggests may be more pervasive than in other economies.

Similarly, Barbera-Marin et al. (2023) analyzed the effect of climate change on European stock returns, focusing on 265 companies listed on the Stock 600 index between 2015 and 2021. Their use of econometric panel data revealed that carbon emissions negatively affect corporate performance, while high environmental ratings bolster returns. This aligns with Alessi et al. (2021), whose research on the STOXX Europe Total Market Index highlighted investors' willingness to accept lower compensation for stocks of environmentally responsible companies with lower emission intensity. Alessi et al. also explored the potential global financial implications of reallocating portfolios toward greener assets, finding that institutional losses in such scenarios, while present, were not substantial. However, their study noted limitations, such as the exclusion of secondary effects, which could underestimate the broader financial impacts.

In the U.S., Battiston et al. (2021) employed methodologies including network modelling and financial econometrics to evaluate climate-related financial risks and the role of policy instruments in promoting a low-carbon transition. Complementing this, Dafermos and Nikolaidi (2021) demonstrated that implementing green-supporting and dirty-penalizing factors could modestly mitigate physical risks by influencing credit allocation. Though the impact was small, it became significant when both measures were applied in tandem, offering actionable insights for policymakers aiming to curb carbon emissions.

Flori et al. (2021) took a different approach, exploring the interplay between climate variables (e.g., rainfall, temperature), commodity prices, and financial stability in the U.S. Their innovative application of multidimensional graph theory and econometric techniques revealed that climate variables indirectly influence financial markets by affecting commodity prices. In Italy, Fatica et al. (2021) investigated green bond yields, uncovering varied effects based on issuer type. Supranational institutions and non-financial corporations benefited from lower yields, while financial institutions did not. Notably, repeated green

bond issuances and external certifications were associated with reduced yields, signalling the importance of transparency and consistency in green finance.
In Asia, Liu et al. (2024) examined the impact of climate risks on firm performance in China, finding adverse effects on financial returns, particularly for firms in climate-vulnerable regions. This reinforces the regional disparities in climate risk exposure and the critical need for mitigation strategies tailored to specific geographies. Similarly, Priyadarshani and Perera (2023) assessed the impact of climate risks on Sri Lanka's stock market, noting no significant effect on overall indices but identifying sector-specific vulnerabilities to risks like drought and floods.

Zhang et al. (2015) explored how unexpected climatic events, both domestic and international, impact the Chinese stock market. Their study analyzed data from 21 industry indices listed on the Shenzhen Stock Exchange. The researchers compared the effects of climatic events in China and the USA on the Chinese stock market. Their findings indicate that significant meteorological disasters, such as the 2008 snowstorm and 2011 tropical storm in China, as well as the 2005 hurricane and 2006 snowstorm in the USA, substantially influenced the Chinese stock market. The results reveal that domestic climatic events exert a greater influence on stock market volatility in China than events occurring in the USA. Additionally, the same climatic event may impact different industries in varying ways, while distinct climatic events can have diverse effects on the same industry. The way these events influence industries is also subject to change over time. The study concludes that the degree of impact on each industry depends on its sensitivity to unexpected climatic events

Finally, Liu et al. (2024) adopted an event study methodology to analyze the effects of extreme weather events on the NASDAQ index. Their research demonstrated significant impacts of various climate dimensions, with biological and hydrological disasters exerting negative effects and the climate dimension yielding positive effects. Interestingly, they observed non-linear, time-dependent impacts, with phenomena such as shock reversal suggesting dynamic interactions between climate events and financial markets.

3. Methodology

The study employed the Autoregressive Distributed Lag (ARDL) bound testing technique and error correction model (ECM) following the framework established by Pesaran et al. (2001). This model is advantageous as it addresses endogeneity and simultaneity issues, allowing for inferences to be drawn from the dynamic behaviour of economic variables. In contrast to the Engle-Granger (1987) single equation approach and the maximum likelihood method proposed by Johansen (1991, 1995), the ARDL bound testing approach offers several significant advantages. Firstly, it can analyse long-term relationships between variables regardless of their order of integration (I (0), I (1), or mutually integrated). Secondly, it distinguishes between dependent and explanatory variables, overcoming limitations of the Engle-Granger method while simultaneously estimating short-run and long-run components, mitigating issues related to omitted variables and autocorrelation. Lastly, unlike the Engle-Granger and Johansen cointegration, the ARDL approach yields consistent short-run estimates and super-consistent long-run estimates even with small samples (Pesaran et al., 2001) Annual data from 1990 to 2022 for stock market index, carbon emissions, temperature, rainfall, real interest, inflation, foreign direct investment as a percentage of gross domestic product, gross domestic product per capita growth rate were collected from the World Development Indicators (2023). The real interest rate and inflation were included as control variables

Model Specification
The implicit equation is:

SMI = f (CE, RF, TP, INFL, REINT, FDI, GDPPCGR) …………………………………………………...... (1)

where:

SMI = stock market index, which is a ratio of change in stock market capitalisation to a one-year lag of stock market capitalisation
CE = Carbon Emission
RF = Rainfall or precipitation
TP = Temperature
INFL = Inflation rate
REINT = Real interest rate
FDI = Foreign Direct Investment
GDPPCGR = Gross Domestic Product Per capita Growth rate

Further, the base-line regression equation of the implicit equation in Equation (1) is expressed econometrically as:

$$\begin{aligned} SMI_t = {} & \delta_1\, SMI_{t-1} + \delta_2 CE_{t-1} + \partial_3 RF_{t-1} + \partial_4 TP_{t-1} + \partial_5 INFL_{t-1} + \partial_6 REINT_{t-1} + \partial_7 FDI_{t-1} \\ & + \partial_8 GDPPCGR_{t-1} + \varphi_0 + \sum_{i=1}^{a} \varphi_{1i}\, \Delta SMI_{t-i} + \sum_{i=0}^{b} \varphi_{2i}\, \Delta CE_{t-i} + \sum_{i=0}^{c} \varphi_{3i}\, \Delta RF_{t-i} \\ & + \sum_{i=0}^{d} \varphi_{4i}\, \Delta TP_{t-i} + \sum_{i=0}^{e} \varphi_{5i}\, \Delta INFL_{t-i} + \sum_{i=0}^{f} \varphi_{6i}\, \Delta REINT_{t-1} \\ & + \sum_{i=0}^{g} \varphi_{7i} \Delta FDI_{t-1} + \sum_{i=0}^{h} \varphi_{8i}\, \Delta GDPPCGR_{t-1} \partial ECT_{t-1} + \varepsilon_t \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (\mathbf{2}) \end{aligned}$$

Where ∂ is the coefficient of error correction (EC) term ECT_{t-1}. It shows how quickly variables converge to equilibrium and it should have a statistically significant coefficient with a negative sign. Also, the order of the ARDL (a, b, c, d, f, g and h) model of eight variables as displayed in equation 2. Further, the parameters ∂, where I = 1,2,3,4,5, 6, 7 and 8
Are the appropriate long-run multipliers, where the parameters φ are underlying ARDL model's short-run dynamic coefficients

Trend Analysis of variables (see appendices)
The Stock Market Index (SMI) shows a general upward trend, particularly significant growth after 1995, peaking in 2007, and fluctuating afterward. The substantial increase from 1995 (5092.20) to 2007 (57990.20) suggests economic growth or increased stock market activity. Fluctuations in later years may indicate market instability or corrections. Inflation (INFL) spiked in the early 1990s (e.g., 44.59% in 1992 and 57.17% in 1993) and remained high through the mid-1990s. It stabilizes to single digits post-2000, with occasional spikes. High inflation in the early 1990s likely reflects macroeconomic instability. Improved management may have stabilized inflation post-2000. Real Interest Rate (REAL INT) **is** highly volatile, with negative values in many years (e.g., -31.45% in 1995), indicating borrowing costs were less than inflation. Positive real interest rates are seen intermittently. Negative real interest rates may have stimulated economic activity but can erode savings and investment returns. Temperature is relatively

stable, ranging between 26.59°C and 27.86°C. No significant anomalies or trends are observed. Rainfall fluctuates yearly without a clear trend, ranging from 1051.71 mm (2011) to 1296.78 mm (2019). Carbon emission (CBE) Generally increases over time, starting at 72768.80 in 1990 and reaching 121278.20 in 2022. The steady increase suggests growing fiscal activity, possibly linked to inflationary trends or economic expansion. However, the stock market index grew despite periods of high inflation, indicating potential resilience or nominal growth driven by inflation. Negative real interest rates correspond to years of high inflation, reflecting economic adjustments. The GDP per capita growth rate gradually improved from the mid-1990s and peaked significantly around 2002, indicating a period of strong economic growth or recovery. After the early 2000s peak, the growth rate stabilizes somewhat, fluctuating around positive values. This suggests a relatively steady period for GDP per capita growth. The graph shows a sharp decline starting around 2015, with negative growth rates in 2016 and 2020. After the sharp negative growth in 2020, the graph shows a recovery trend, but the growth rate remains below earlier peaks, suggesting a gradual but incomplete recovery.

4. Results and Discussion

Results

Table 1
Descriptive Statistics

Statistic	SMI	CE	RF	TP	INFL	REINT	FDI	GDPPCGR
Mean	21641.9	97120.9	1183.4	27.306	18.085	3.071	1.315	1.604
Median	23844.5	97215.1	1183.21	27.38	12.88	5.69	1.2	1.51
Maximum	57990.2	121278.2	1296.7	27.86	72.84	18.18	2.9	12.21
Minimum	513.8	72768.8	1051.71	26.59	5.39	-31.45	0.14	-4.6
Std. Dev.	15842.3	12843.3	66.710	0.2919	16.1083	10.1404	0.82102	3.754945
Skewness	0.333214	0.088354	-0.2982	-0.3147	2.19911	-1.3687	0.25221	0.473443
Kurtosis	2.234215	2.106869	2.10531	2.85528	6.82699	5.54406	1.90194	3.530743
Jarque-Bera	1.417012	1.139749	1.58956	0.57358	46.7365	19.2029	2.00774	1.620135
Probability	0.492379	0.565597	0.45168	0.75067	0	6.8E-05	0.36646	0.444828
Sum	714182.7	3204992	39055.1	901.12	596.83	101.36	43.42	52.96
Sum Sq. Dev.	8.03E+09	5.28E+09	142410	2.72773	8303.27	3290.47	21.5702	451.1876
Observations	33	33	33	33	33	33	33	33

Note: Descriptive statistics provide insights into the distribution and properties of the variables.
Source: Author's Computation, 2024

As part of the preliminary analyses, this study explores descriptive statistics to reveal the fundamental and distinctive features of the data distribution of the variables to guide the choice of estimator. Table 1 provides descriptive statistics for eight variables. CE (Carbon Emissions), INFL (Inflation), REINT (Real Interest Rates), RF (Rainfall), SMI (Stock Market Index), TP (Temperature), FDI (Foreign Direct Investment and GDPPCGR (Gross Domestic Product per Capita growth rate. Below is a detailed interpretation of each statistic: The mean provides the central tendency of the data. The average carbon emissions are 97,120.98 units, indicating significant emissions levels, average inflation is 18.086%, suggesting moderately high inflation during the period, real interest rates average 3.072%, showing a positive return on investments when adjusted for inflation, the average rainfall is 1,183.488 mm, typical for regions with substantial precipitation. The stock market index has an average value of 21,641.9, representing overall market performance while the mean temperature is 27.307°C, typical of a warm climate.0 The median represents the middle value, less sensitive to outliers than the mean.

Carbon emissions median value of (97,215.1) is close to the mean, indicating a fairly symmetric distribution for carbon emissions. Inflation median (12.88%) is lower than the mean, suggesting the presence of high inflation outliers. The median value of real interest rate (5.69%) exceeds the mean, pointing to the influence of negative interest rate outliers. The median (1,183.21 mm) closely matches the mean, suggesting a roughly symmetric distribution of rainfall. SMI median (23,844.5) exceeds the mean, indicating some low outliers in the stock market index.TP, t median (27.38°C) aligns well with the mean, indicating symmetry in the temperature data. standard Deviation measures the dispersion of the data from the mean. CE, standard deviation of 12,843.34 suggests moderate variability in carbon emissions. INFL: A high standard deviation (16.108) reflects substantial inflation volatility. REINT, standard deviation of 10.14 indicates significant variation in real interest rates. RF: Rainfall variability is moderate, with a standard deviation of 66.711 mm. SMI: A large standard deviation (15,842.37) shows wide fluctuations in the stock market index. TP: A low standard deviation (0.292) indicates highly stable temperature values. Skewness measures asymmetry in the data distribution. CE, Near-zero skewness (0.088) indicates a nearly symmetric distribution. INFL, positive skewness (2.199) shows a long tail on the right, driven by high inflation outliers. REINT: Negative skewness (-1.369) indicates a left-skewed distribution, influenced by low or negative interest rate outliers.

RF: Slightly negative skewness (-0.298) suggests minor asymmetry to the left in rainfall data. SMI: Positive skewness (0.333) indicates a mild right skew in the stock market index. TP: Slightly negative skewness (-0.315) shows a minor left skew in temperature. Kurtosis measures the "tailedness" of the distribution. CE, RF, and TP Kurtosis values near 3 indicate distributions close to normality. INFL: High kurtosis (6.827) indicates heavy tails, reflecting extreme inflation values. REINT: Kurtosis (5.544) suggests heavy tails, indicating frequent extreme interest rate deviations. SMI: Kurtosis (2.234) is slightly below 3, showing a flatter-than-normal distribution. Jarque-Bera test checks whether the data follows a normal distribution. INFL and REINT Jarque-Bera test yield significant results ($p < 0.05$), rejecting normality due to skewness and kurtosis. CE, RF, SMI, TP: Non-significant results ($p > 0.05$) suggest these variables follow a normal distribution. On average, FDI across the observations is 1.32 units, indicating the average level of foreign direct investment inflow in the data set. The median of FDI is 1.2%, slightly lower than the mean, showing a slight positive skew in the data.

The highest FDI recorded is 2.9%, which suggests that some observations had significant FDI inflows. The lowest FDI recorded is 0.14%, suggesting that some periods had very low FDI. The Standard Deviation (Std. Dev.) of FDI is 0.821020 which indicates a moderate variability in FDI levels across observations. The FDI data is slightly positively skewed, meaning the distribution has a longer tail on the right side. Its kurtosis is below 3, indicating a platykurtic distribution (flatter than a normal distribution). Jarque-Bera (JB) Test: 2.007742 with p=0.36646 The p-value suggests that the FDI distribution is approximately normal. The average GDP per capita growth rate (GDPPCGR) across the observations is approximately 1.60%, suggesting a relatively moderate growth over the period. The median growth rate is close to the mean, indicating a relatively symmetrical distribution. The maximum growth rate is 12.21%, showing periods of exceptional growth. The minimum growth rate is -4.6%, indicating periods of contraction. A high standard deviation suggests significant variability in growth rates over the period. The data is moderately positively skewed, with a tendency for higher growth rates to pull the distribution to the right. The kurtosis is slightly above 3, indicating a leptokurtic distribution (slightly more peaked than normal). The Jarque-Bera (JB) Test value of 1.6201351with p value of 0.444828 suggests that GDPPCGR is approximately normally distributed.

Table 2
Correlation Matrix of Variables

Variables	LMSMI	LNCE	LNRF	TP	INFL	REINT	FDI	GDPPCGR
LNSMI	1.000							
LNCE	0.615	1.000						
LNRF	0.069	0.078	1.000					
TP	0.676	0.291	-0.044	1.000				
INFL	-0.449	-0.236	-0.026	-0.523	1.000			
REINT	0.298	0.144	-0.101	0.502	-0.727	1.000		
FDI	-0.067	-0.504	-0.162	-0.185	0.067	-0.133	1.000	
GDPPCGR	0.134	-169	-0.169	-0.298	0.230	-0.430	0.318	1.000

Note: The table shows the correlation coefficients between variables.
Source: Authors Computation (2024).

For the avoidance of the evidence of multicollinearity among the variables, it suffices to conduct a correlation test on the variables. Table 2 above shows the result of the test. The usual benchmark according to Gujarati (1980) is 0.80 or 80%. Among the explanatory variables, the highest is 0.727 or 72.7% which is between inflation (INFL) and real interest rate (REINT). This test is necessary and important because high collinearity in the regression could inflate the coefficients of standard error and produce spurious estimates and invalid decisions on the statistical significance of the coefficients. This model is free from multicollinearity.

Unit Root Test
The simple time series around a deterministic pattern is commonly believed to be stationary or at least stable; this is not always accurate. Nevertheless, the co-integration technique of ARDL does not require unit roots pretesting. However, to prevent ARDL from crashing in the presence of an embedded stochastic pattern of I (2), the study performs unit root tests to know the number of unit roots in the series. This study used Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to confirm the outcome properties of the time series. The null hypothesis for the test (both ADF and PP) affirms that the data series in question has a unit root. In contrast, the alternative hypothesis affirms that the series is stationary. Table 3 below shows the results of the unit root testing. The results show that rainfall (RF), temperature (TP) and gross domestic product per capita growth rate (GDPPCGR) are stationary at levels, while all other variables in the model became stationary after the first differencing. This depicts that the series has a combination of I (0) and I (1) which makes ARDL appropriate for estimation

Table 3
Augmented Dickey-Fuller and Phillips-Peron Unit Root Test Results

Variables	@ Levels (ADF)	@Levels (PP)	@1st Diff. (ADF)	@1st Diff. (PP)	Order of Integration
INFL	-2.156	-2.852	-4.302***	-4.497***	I (1)
LNCE	-2.759	-2.848	-5.712***	-6.745***	I (1)
LNRF	-6.924***	-6.925***			I (0)
LMSMI	-2.369	-2.443	-4.816***	-4.845***	I (1)
REINT	-2.586	-2.066	-4.273**	-5.423***	I (1)
TP	-4.044**	-4.070**			I (0)
FDI	-2.210	-2.645	-6.652***	-6.946***	I (1)
GDPPCGR	-3.738**	-3.870**			I (0)

Note: **, and *** indicate statistical significance at 5% and 1%, respectively.
Source: Researcher Computation (2024).

Table 4
ARDL Bound Test (Test of Co-Integration)

Significance Level (α%)	Lower Critical Bound I (0)	Upper Critical Bound I (1)	Computed F-Statistic
10	2.03	3.13	3.660316
5	2.32	3.50	
2.5	2.60	3.84	
1	2.96		

Source: Researcher Computation (2024).

In time series analyses, it is common to have mixed stationarity properties of variables which necessitate the test of co-integration. Thus, the estimation technique that captures this is considered in line with Paseran *et al* (2001), this study uses bound testing for the long-run relationship among the variables. Pesaran and Shin (1995, 1998) suggested two critical values to evaluate the relationship (lower and upper bound) due to the limitations of the traditional Wald-test *F*-statistic. The computed *F*-test is then compared with the critical values for the hypothesis test at a 5 per cent level. Therefore, if the calculated *F*-statistic is less than the lower bound value, the null is not rejected. On the contrary, the existence of a long-term relationship between the variables is suggested if the calculated *F*-statistics exceed the upper limit value. The results of ARDL bound testing which explains the long-run relationship among the variables are reported in Table 4 above. It shows that the F-statistic (3.660316) is greater than both the lower and the upper critical values at the benchmark of a 5 per cent significance level. This invalidates the null hypothesis of no co-integration and supports the existence of long-run dynamics

Table 5
Estimated Long-Run and Short-Run Dynamics for the Selected ARDL Model (1, 2, 0, 0, 1, 1, 2, 0)

Panel A: Long-Run Dynamics				
Variables	Coefficient	Standard Error	T-statistics	Probability
LNCE	7.596223***	2.05472	3.696962	0.0020
LNRF	-3.639651	3.397588	-1.071246	0.3000
TP	0.209205	0.901614	0.232034	0.8195
INFL	-0.056437**	0.024304	-2.322164	0.0337
REINT	-0.088085	0.053059	-1.660124	0.1164
FDI	0.743159*	0.36168	2.054742	0.0566
GDPPCGR	-0.010843	0.065148	-0.166437	0.8699
C	-56.84157	38.914046	-1.460695	0.1635
Panel B: Short-Run Dynamics				
D(LNCE)	0.955429	0.783499	1.219439	0.2403
D (LNCE (-1))	-2.216367**	0.819456	-2.704680	0.0156
D(LNRF)	-1.161193	1.078572	-1.076602	0.2976
D(TP)	0.066745	0.291850	0.228696	0.8220
D(INF)	-0.007341	0.008528	-0.860852	0.4020
D(REINT)	-0.009215	0.009112	-1.011380	0.3269
D(FDI)	-0.050137	0.090169	-0.556032	0.5859
D (FDI (-1))	-0.285693**	0.117377	-2.433991	0.0270
D(GDPPCGR)	-0.003459	0.021026	-0.164528	0.8714
CointEq.(-1)	-0.319040	0.104157	-3.063064	0.0074

Cointegrating Equation: LNSMI - (7.5962 * LNCE - 3.6397 * LNRF - 0.0564 * INF - 0.0881 * REINT + 0.2092 * TP + 0.7432 * FDI - 0.0108 * GDPPCGR - 56.814)

Panel C: Good-of-fit Measures

Measures	Value
R-Squared	0.9715
Adj. R-squared	0.9466
F-statistics	39.0146
F-statistics (Prob.)	0.0000
Durbin-Watson Statistics	2.5380

Panel D: Diagnostic Tests

Test	**T-statistics**	**Probability**
Breusch-Godfrey serial correlation LM test	3.858252	0.1453
Breusch-Pagan-Godfrey test for heteroscedasticity	9.156026	0.3293
ARCH test for heteroscedasticity	0.202208	0.6529
RAMSET Reset specification test	0.614554	0.4414

Note: ***, **, * level of significance at 1%, 5% and 10% respectively
Source: The Authors (2024).

Panel A of Table 5 results explore the long-run relationship between stock market performance (SMI) and the independent variables, assuming equilibrium is achieved. The long-run coefficient of carbon emissions (7.5962) is positive and significant (p = 0.0020). This suggests that, in the long term, an increase in carbon emissions is associated with higher stock market performance, possibly due to the high relevance of carbon-intensive industries in Nigeria's economy. The long-run effect of rainfall is negative (-3.6397) but not statistically significant (p = 0.3000). This indicates that rainfall does not play a substantial role in affecting the stock market index. The coefficient for temperature is positive (0.2092) but not statistically significant (p = 0.8195), showing no clear long-term impact. o Inflation has a significant negative effect (-0.0564, p = 0.0337). This suggests that higher inflation erodes stock market performance in the long run. The effect of the real interest rate is negative (-0.0881) but not statistically significant (p = 0.1164), implying no strong influence on the stock market. FDI has a positive and marginally significant impact (0.7432, p = 0.0566). This indicates that an increase in FDI contributes to stock market growth in the long term. The GDP per capita growth effect is negative (-0.0108) but insignificant (p = 0.8699), suggesting a limited influence on stock market performance. The constant term is negative but not significant (p = 0.1635). The negative constant (-156.841) suggests the baseline performance of SMI in the absence of other factors, is not significant.

The short-run results in Part B of the Table examine immediate adjustments and deviations. The short-run coefficient for carbon emissions (LNCE) is positive (0.9554) but not statistically significant (p = 0.2403). This suggests that a short-run increase in carbon emissions does not significantly impact the stock market index. The lagged value of carbon emissions has a significant negative effect on stock market performance (coefficient = -2.2164, p = 0.0156). This implies that past increases in carbon emissions may lead to a short-term decline in stock market performance. Rainfall has a negative but insignificant effect in the short run (p = 0.2976). Other variables, such as temperature (TP), inflation (INF), reinvestment (REINT), foreign direct investment (FDI), and GDP per capita growth (GDPPCGR), do not show significant short-run effects on stock performance. The error correction term is negative (-0.3190) and statistically significant (p = 0.0074). This confirms the existence of a long-run equilibrium relationship between the variables and stock market performance. The speed of adjustment toward equilibrium is approximately 31.9% per year, indicating a moderately fast adjustment process. The model explains approximately 97% of the variance in SMI, indicating excellent explanatory power. The overall model is statistically significant with an F-statistics of 39.14 and a corresponding p-value of 0.0000. Durbin-Watson value of (2.53) indicates no significant autocorrelation. The residuals are homoscedastic and the residuals are normally distributed. The model is correctly specified. The model is stable as suggested by the CUMSUM and CUSUM Square results (see appendices)

Discussion of Results

The long-run positive impact of carbon emissions and temperature on SMI aligns with studies showing that moderate climate variability can enhance productivity in specific sectors (e.g., agriculture, energy) and drive market performance. Nigeria's economy is heavily reliant on oil and gas, which are carbon-intensive industries. This reliance provides a structural explanation for the positive long-run relationship between carbon emissions and stock performance. Companies in the oil sector, like those listed on the Nigerian Exchange, contribute significantly to the market's capitalization and profitability. This dependency aligns with studies in other resource-dependent economies, such as Hammoudeh et al. (2014), which found that oil prices and carbon emissions often drive stock market performance in oil-exporting countries. This contrasts with Oyedeko et al (2024) which show an insignificant effect of carbon emissions in Africa. However, the lack of statistical significance in the current study contrasts with stronger findings in regions where climate policies or investments are more integrated into market performance (e.g., studies by Xie et al., 2019, on ESG activities improving financial performance). The result corroborates the findings of Din et al. (2022) and identifies a significant impact of climate variables, particularly rainfall, on financial metrics.

Like their observation of weather catastrophes negatively affecting stock market returns and volatility. The lagged coefficient of carbon emissions has a significant negative impact on stock market performance. This suggests that past increases in carbon emissions negatively influence stock performance in the short run, potentially reflecting market apprehensions about environmental risks, stricter regulations, or resource inefficiencies. Neither the short-run nor the long-run effects of rainfall are statistically significant. The long-run coefficient is negative (−3.6397) but insignificant (p=0.3000), suggesting that rainfall variability does not materially impact stock performance in Nigeria. This result aligns with studies in tropical economies, such as ling et al. (2025**)**, which found that climate factors like rainfall affect agricultural productivity more than financial markets in resource-dependent economies. In Nigeria, rainfall's effect may be indirect, impacting agriculture or energy production but not stock performance directly. Temperature shows no significant relationship with stock performance in either the short or long run. While temperature changes can influence productivity, energy demand, or agricultural yields, these effects might be insufficient to influence stock market performance in Nigeria. Studies in other regions, such as Bansal et al. (2016**)**, show mixed results.

While temperature extremes have been linked to financial performance globally, their impact tends to be sector-specific. In Nigeria, these sectoral effects might be diffused across the economy, leading to an insignificant aggregate impact. In the long run, inflation has a significant negative effect on stock market performance. This finding is consistent with Fisher's hypothesis and studies like Choudhry (2001**)**, which found that high inflation reduces purchasing power, increases uncertainty, and negatively affects stock valuations. In the Nigerian context, rising inflation may erode investor confidence, especially in a market where inflation rates are often volatile and poorly controlled. The significant negative relationship between real interest rates and SMI corroborates studies like Kyere & Ausloos (2021), which report that macroeconomic instability negatively affects stock performance. In the long run, FDI positively affects stock performance, albeit marginally significant. This aligns with studies like Adesina (2020**)**, which found that FDI boosts capital markets by increasing liquidity and introducing better governance practices.

The lagged short-run coefficient of FDI suggests an initial negative impact on stock performance, possibly due to the repatriation of profits or market distortions caused by foreign entrants. However, the mixed short-term and long-term results highlight the complexity of FDI's impact on financial markets in developing economies. The effect of GDP per capita growth is insignificant in both the short and long run, suggesting that broader economic growth does not translate directly into stock market gains in Nigeria. This finding resonates with Rashid (2015**)**, who argues that in low-income economies, financial markets often lag behind macroeconomic performance due to structural inefficiencies. The significant error correction term indicates the existence of a long-run equilibrium relationship. The speed of adjustment (31.9% per year) suggests that deviations from equilibrium caused by short-term shocks are moderately corrected annually. This aligns with Pesaran et al. (2001), which emphasize that error correction terms highlight the robustness of cointegration relationships in ARDL models.

5. Conclusion and Recommendations

This study explores the interplay between climate change variables and stock market performance in Nigeria, providing critical insights into an emerging area of financial research. While carbon emissions and temperature exhibit positive associations with stock market performance, their statistical insignificance suggests underlying complexities in the climate-financial nexus. Conversely, the significant negative effect of real interest rates underscores the macroeconomic dimensions of stock performance. Rainfall and inflation, though relevant, did not show significant impacts in this context. The presence of a long-run equilibrium relationship among the variables confirms the gradual adjustment of stock market dynamics to climate and macroeconomic shocks. The findings align with global studies emphasizing the importance of environmental, social, and governance (ESG) considerations but also highlight the unique challenges of climate-related financial risks in Nigeria. Given the observed variability in the impact of climate variables, sector-specific policies should be implemented. For instance, industries like agriculture and energy, which are sensitive to temperature and rainfall changes, should adopt climate-resilient strategies. The positive long-term effect of carbon emissions highlights the reliance on carbon-intensive industries in Nigeria. Policymakers should focus on economic diversification, reducing dependency on fossil fuels, and promoting green industries to balance economic growth with environmental sustainability. In addition, they should encourage sustainable FDI which can enhance stock market performance while ensuring environmental and social governance compliance.

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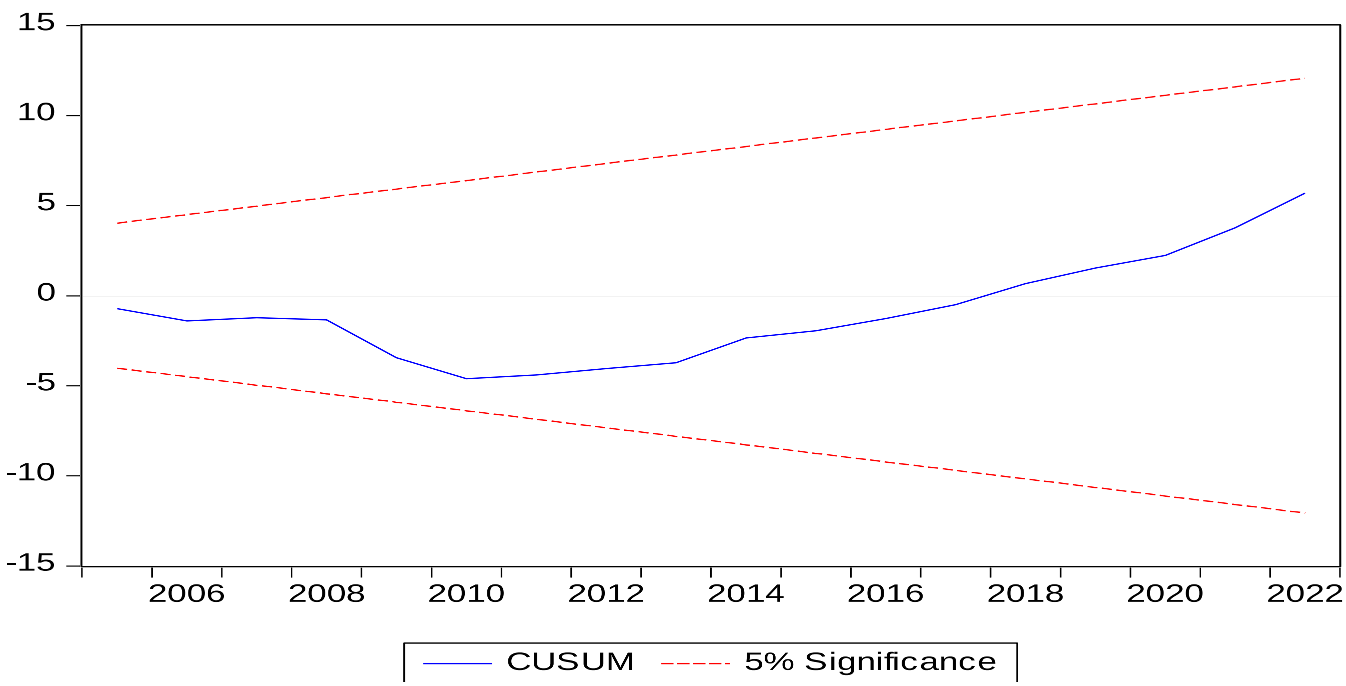
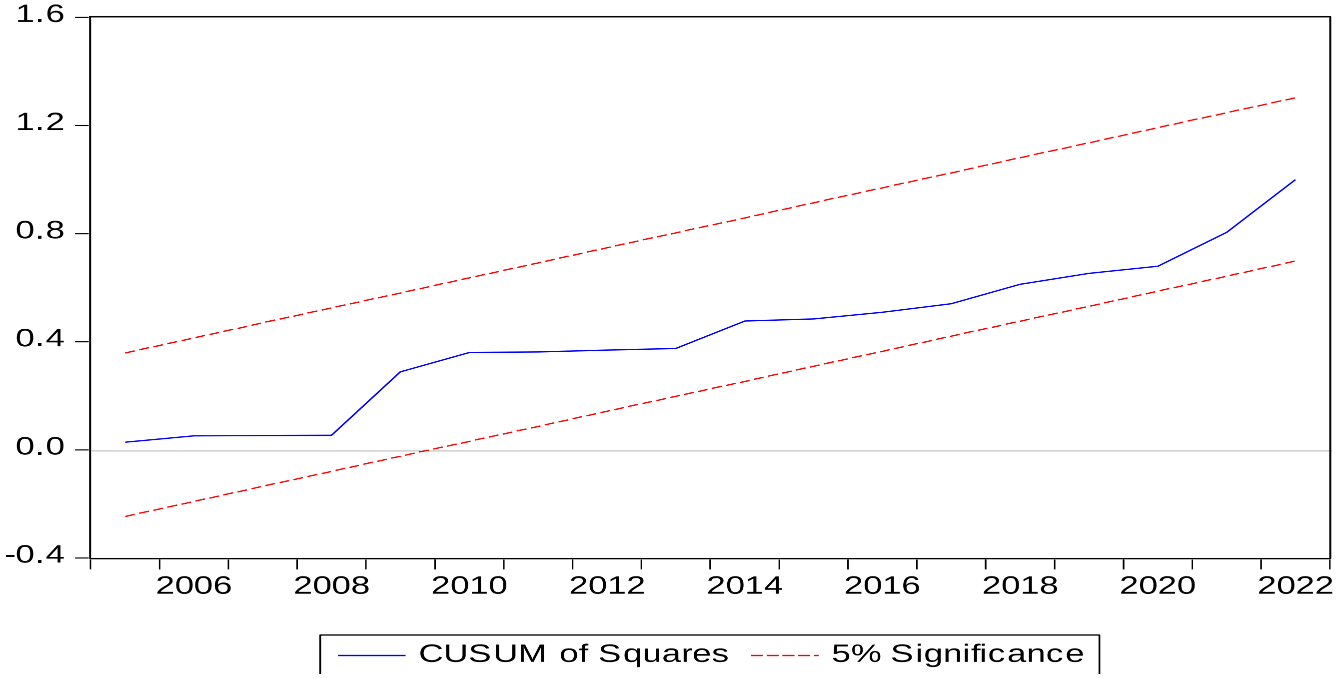
Appendix

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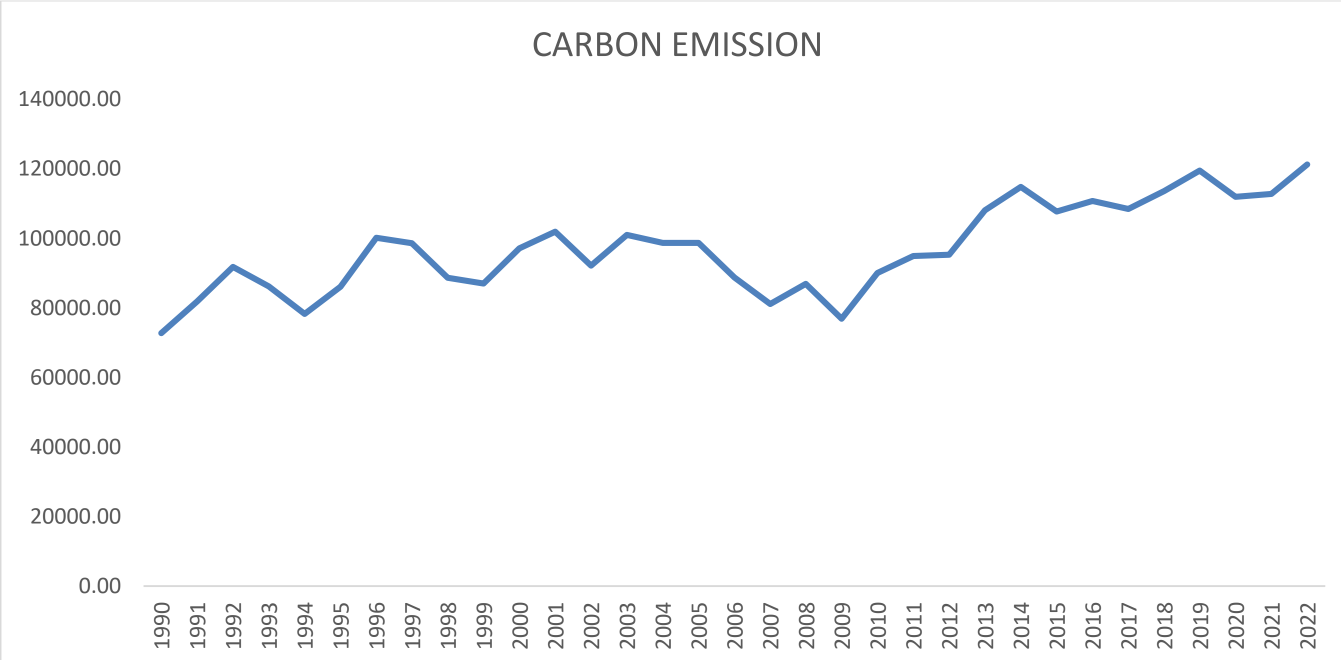
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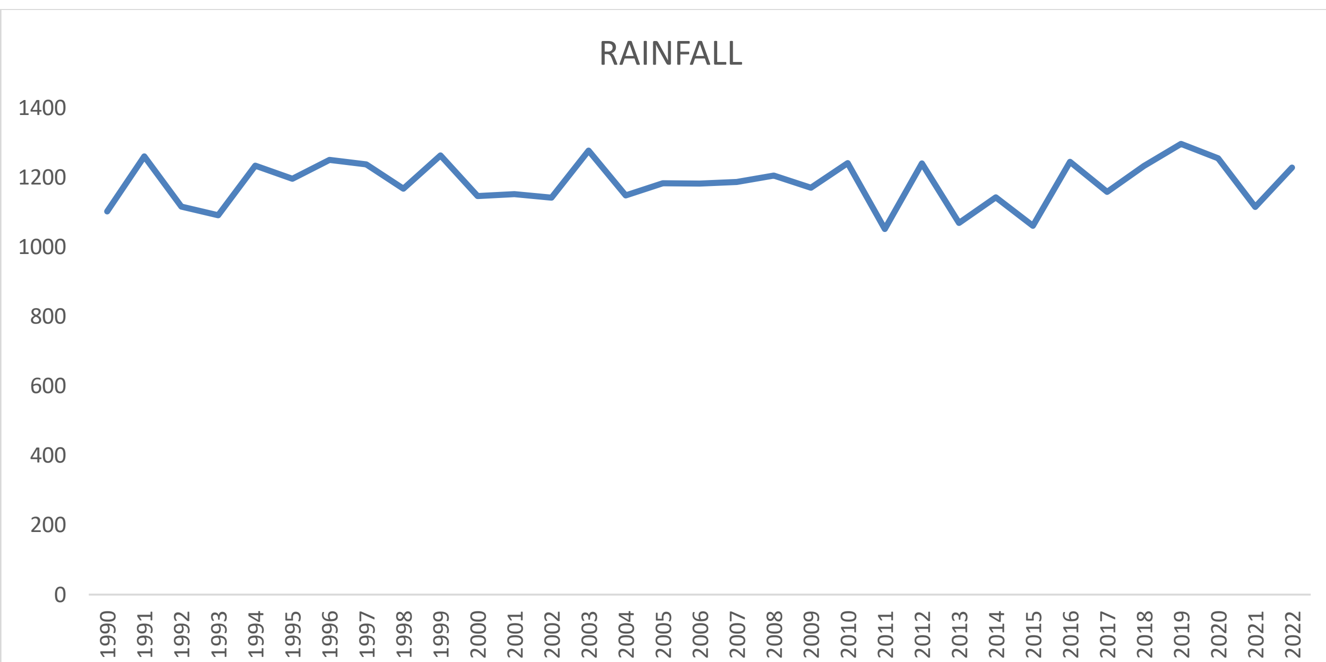
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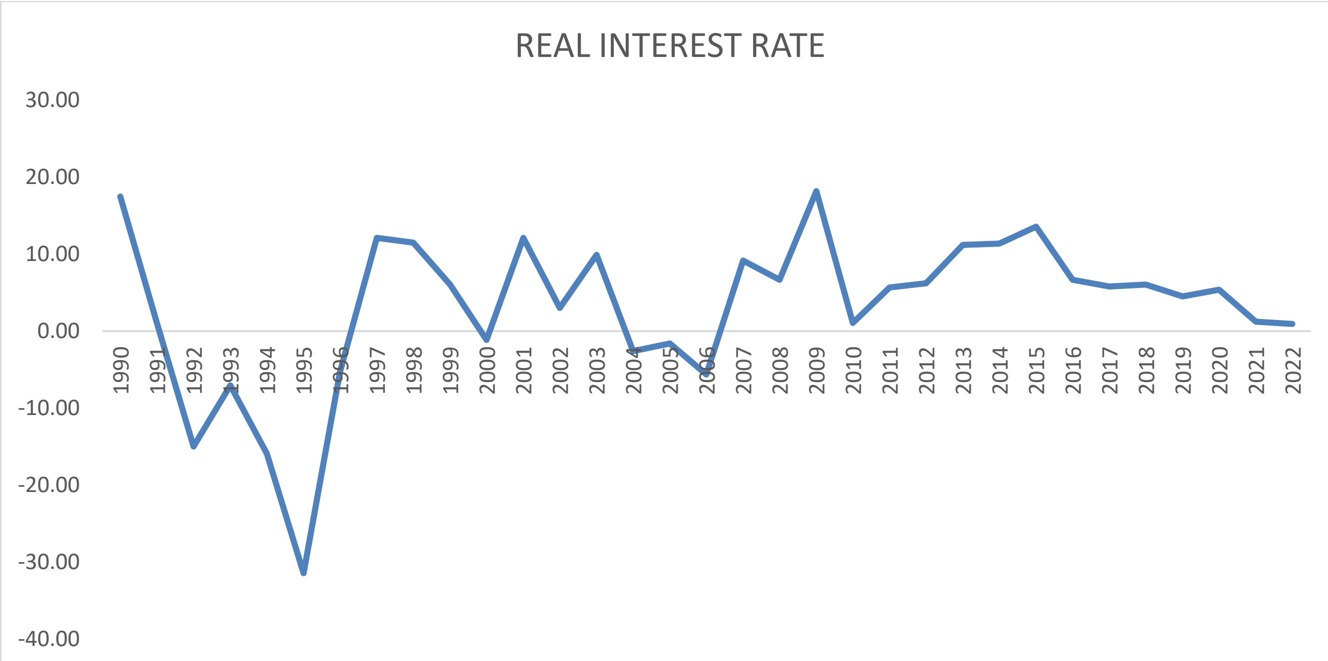
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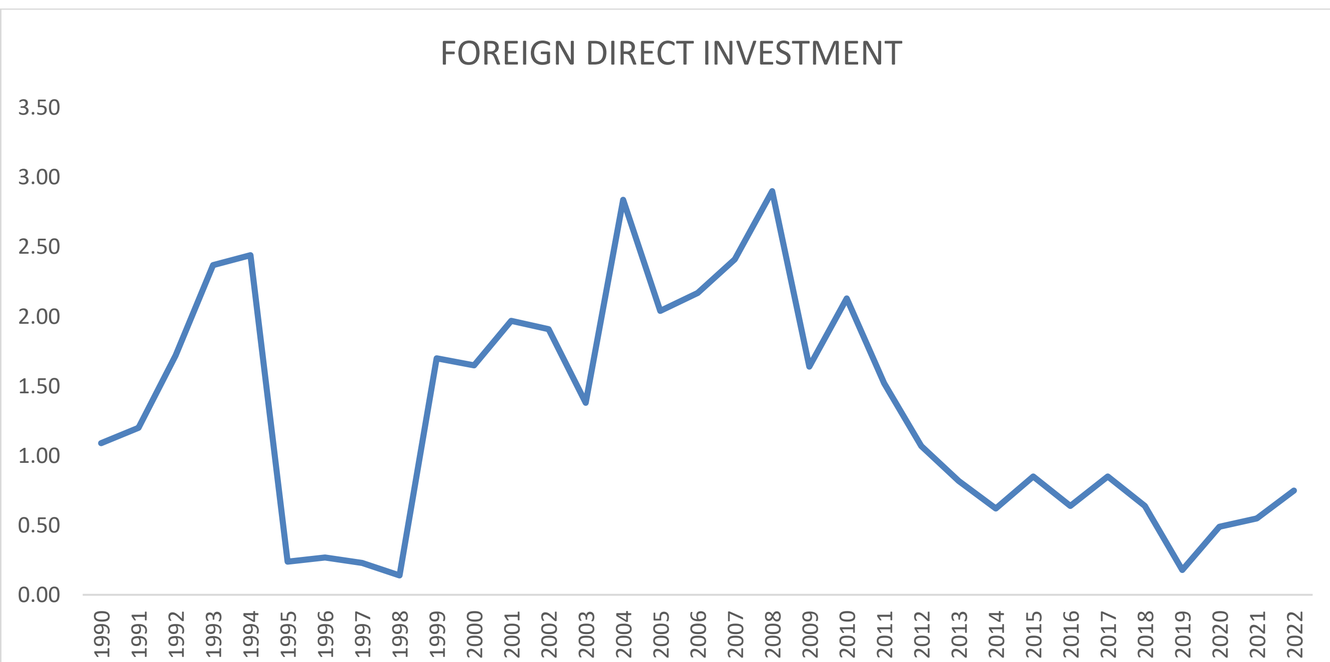
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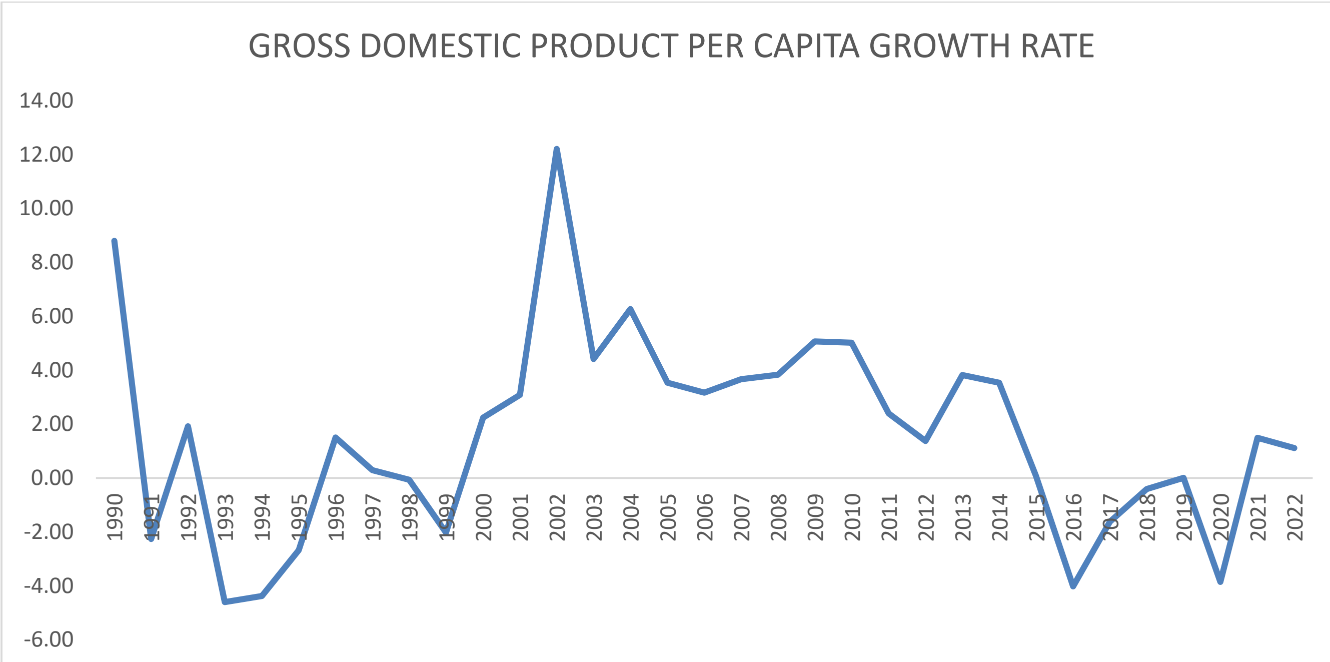
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