The Impact of Cryptocurrency use on the Nigerian Financial System

(A case for Bitcoin and Ethereum)

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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TABLE OF ABBREVIATIONS

BTC: Bitcoin

ETH: Ethereum

CBN: Central Bank of Nigeria

QTM: Quantity Theory of Money

GARCH: Generalized Autoregressive Conditional Heteroskedasticity

VAR: Vector Autoregression

ARDL: Autoregressive Distributed Lag

EU: European Union

OECD: Organization for Economic Co-operation and Development

DeFi: Decentralized Finance

UK: United Kingdom

USA: United States of America

USD: US Dollar

VAR: Vector Autoregression

Auto ARIMA: Automatic Autoregressive Integrated Moving Average

API: Application Programming Interface

IQR: Interquartile Range

IRF: Impulse Response Function

Log: Logarithm

CRYPTO: Cryptocurrency

AIC/BIC: Akaike Information Criterion / Bayesian Information Criterion

GDP: Gross Domestic Product

USDT: Tether USD

USDC: USD Coin

CDBC: Central Bank Digital Currency

BUSD: Binance USD

ABSTRACT

Cryptocurrency adoption is transforming financial systems globally, offering decentralized alternatives to traditional financial instruments. In Nigeria, this adoption is particularly significant due to a high unbanked population, inflationary pressures, and the rising prominence of remittance flows. While prior research highlights cryptocurrencies' potential for financial inclusion and inflation hedging, limitations exist in their focus on speculative trading, with insufficient exploration of macroeconomic impacts. This study employs a reproducible quantitative research approach, analysing daily, monthly, and quarterly datasets from 2018 to 2022 to assess cryptocurrency adoption's influence on Nigeria's economy. Analytical methods include descriptive statistics, Auto ARIMA and Vector Autoregression (VAR), supported by pre-estimation tests for robustness. Findings reveal that cryptocurrency adoption positively correlates with increased remittance efficiency and serves as a hedge against inflation. Volatility analysis demonstrates significant clustering in cryptocurrency prices, with spillover effects observed on exchange rates and remittance flows. These results underscore cryptocurrencies' dual role as economic disruptors and stabilizers, offering opportunities for financial inclusion while presenting risks of speculative volatility. The study's implications extend to policymakers and financial institutions, emphasizing the need for balanced regulation to harness the benefits of cryptocurrencies while mitigating associated risks. This research fills critical gaps in understanding cryptocurrencies' broader economic impacts, particularly in developing economies like Nigeria.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND INFORMATION

As a disruptive financial innovation, cryptocurrencies are transforming traditional financial markets and monetary systems. Fundamentally, cryptocurrencies such as Bitcoin and Ethereum are digital or virtual currencies operating on decentralized networks supported by blockchain technology and secured through encryption (Nakamoto, 2008). In Nigeria, cryptocurrencies have emerged as critical alternatives due to their accessibility, cost-effectiveness, and capacity to mitigate some of the challenges inherent in the country's financial landscape.

Over the last decade, Nigeria has become one of the world's largest cryptocurrency markets. According to (Chainalysis, 2021), Nigeria is ranked among the top countries for cryptocurrency adoption. While much of this adoption stems from speculative investments, a significant portion is driven by functional uses, such as remittances and peer-to-peer (P2P) transactions (Negi, 2021).

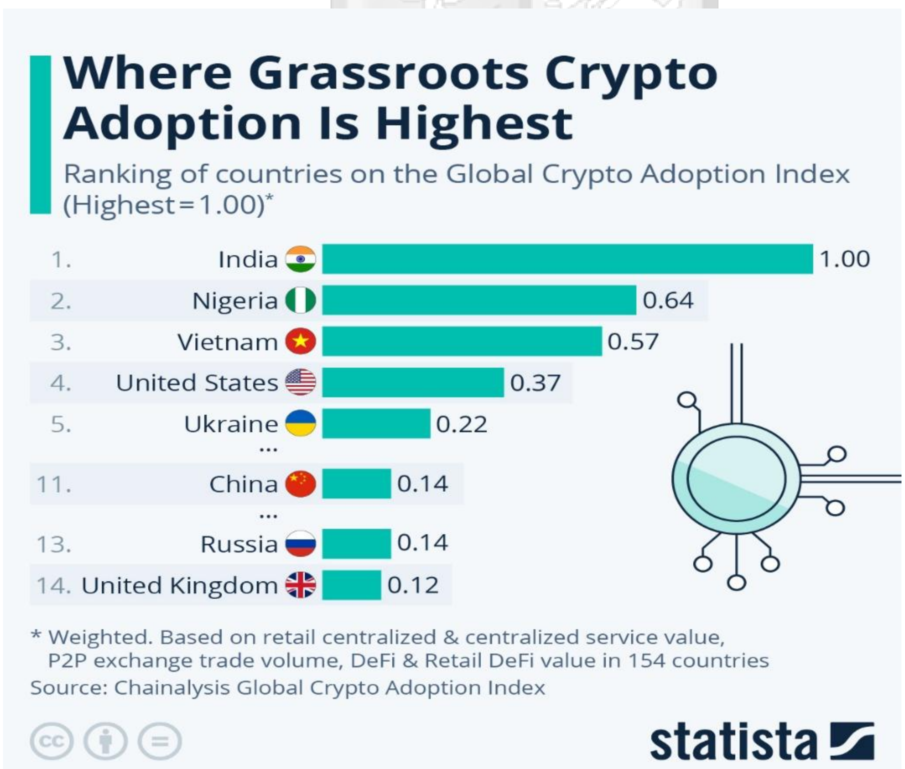


Figure 1: Global Cryptocurrency adoption ranking (Statista)

Cryptocurrencies have become increasingly relevant in global financial systems, offering decentralized, secure, and borderless alternatives to traditional financial systems. Cryptocurrencies like Bitcoin and Ethereum operate on blockchain technology and are viewed by many as a solution to some of the limitations inherent in traditional banking and financial services. (Catalini C. &., 2016).

In Nigeria, this innovation is particularly crucial due to the country's large unbanked population, high levels of remittances, and persistent inflation. Nigeria's economy has faced various challenges, including currency depreciation and financial instability. With over 60% of its population either unbanked or underbanked, cryptocurrencies have provided Nigerians with access to financial systems that are otherwise inaccessible through traditional means (Ogujiuba, 2021).

Additionally, remittances represent a significant inflow of foreign currency into the country, yet traditional remittance systems are often burdened with high fees and delays.

Cryptocurrencies offer Nigerians a means to bypass the inefficiencies of traditional banking systems (Alessandria, 2018). For example, remittance fees through conventional channels range between 5% and 10%, whereas cryptocurrency-based transfers can cost significantly less.

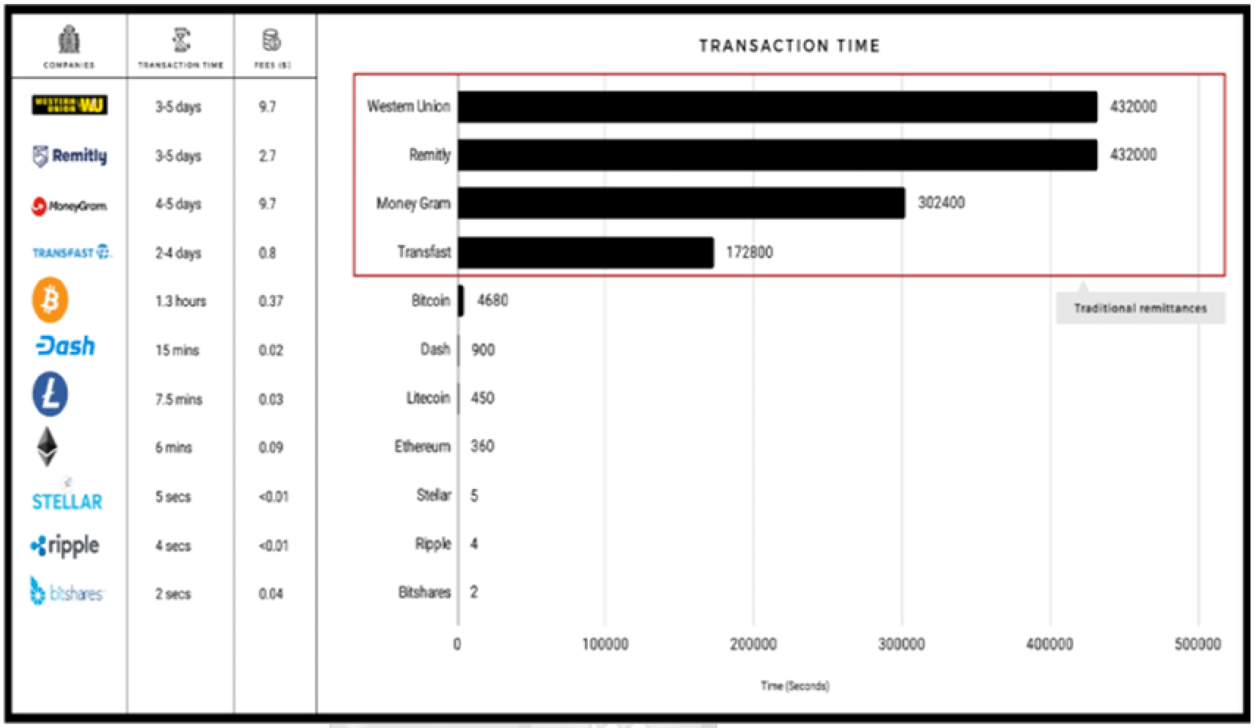


Figure 2: Remittance Costs: Traditional Methods vs. Cryptocurrencies (Blockchain Research Institute, 2023)

It is evident that there exists a cost disparity, emphasizing the economic advantages of digital currencies in cross-border transactions. The adoption of cryptocurrencies is further bolstered by peer-to-peer (P2P) trading platforms, which account for a significant proportion of transactions.

1.2 PROBLEM STATEMENT

Despite Nigeria's leadership in cryptocurrency adoption, its broader economic implications remain poorly understood. While existing studies have primarily focused on speculative trading, there is a lack of empirical research examining the interaction between cryptocurrencies and macroeconomic variables such as inflation, exchange rates, and remittances (Catalini C. &., 2016). Furthermore, regulatory uncertainty—exemplified by the Central Bank of Nigeria's (CBN) ban on financial institutions facilitating cryptocurrency transactions—has created additional challenges for assessing their role in the economy (Central Bank of Nigeria (CBN), 2021).

This gap in the literature underscores the need for a comprehensive analysis of how cryptocurrencies influence Nigeria’s financial ecosystem. By addressing these gaps, the study contributes to a deeper understanding of the economic opportunities and risks associated with cryptocurrency adoption in a developing economy.

1.3 RESEARCH OBJECTIVES

The general objective of this research is:

To quantitatively assess the impact of cryptocurrency adoption on Nigeria’s financial system.

The specific objectives of this research include:

1. To evaluate the relationship between cryptocurrency adoption and remittance flows in Nigeria.
2. To analyse how cryptocurrency prices correlate with inflation and foreign exchange rates in Nigeria.
3. To identify the economic risks and opportunities presented by cryptocurrency use in Nigeria.

These objectives are directly linked to the problem statement, as they aim to provide a comprehensive understanding of cryptocurrencies their broader financial impact on Nigeria’s financial system.

1.4 RESEARCH HYPOTHESES

H1 Cryptocurrency adoption has significantly increased remittance flows in Nigeria, reducing transaction costs.

H2 Cryptocurrency prices exhibit a significant negative correlation with the value of the Nigerian Naira, indicating cryptocurrencies act as a hedge against inflation.

H3 Cryptocurrencies enhance financial inclusion by providing affordable financial services to the unbanked population in Nigeria.

1.5 SIGNIFICANCE OF RESEARCH

This study has significant implications for policymakers, financial institutions, and cryptocurrency users in Nigeria. Policymakers can use the findings to design balanced regulations that promote the economic benefits of cryptocurrencies while mitigating risks. Financial institutions may gain insights into integrating cryptocurrency-based services to improve efficiency and reduce transaction costs. Moreover, this research contributes to the limited empirical literature on cryptocurrency adoption in developing economies, offering a comprehensive analysis of its macroeconomic impact.

By exploring these dimensions, the study not only addresses critical gaps in the literature but also lays the groundwork for future research on cryptocurrencies' economic effects in emerging markets. This chapter provides a foundation for understanding the broader implications of cryptocurrency adoption.

CHAPTER 2: LITERATURE REVIEW

2.1 DISCUSSION OF THE EMPIRICAL FRAMEWORK

This study examines the effects of cryptocurrency adoption on financial markets by drawing on a variety of scholarly works. Here, the empirical literature is reviewed to demonstrate the evolution of research in this area, leading to the selection of variables and methods for analysis.

2.1.1 Cryptocurrencies and their inherent worth

(Yellen, 2019) investigated the implications of cryptocurrencies on interest rates and money supply management. Considering the Quantity Theory of Money (QTM), this theoretical framework could serve as the best anchor for the study. QTM focuses on the relationship between money supply and economic variables such as inflation and price stability, which are critical to understanding the macroeconomic impacts of cryptocurrency adoption in an inflation-prone economy like Nigeria. This alignment underscores its relevance to the study. The study highlights potential disruptions to central banking instruments, particularly in the areas of decentralization and monetary policy transmission. Despite being theoretical, the research provided a foundation for exploring the empirical impacts of cryptocurrencies in economies like Nigeria. The work inspires further investigations into the implications of cryptocurrency adoption in emerging markets.

(Chen, 2020) analysed the economic classification of cryptocurrencies and their effectiveness as a medium of exchange. The study employs a mixed-methods approach, integrating actual data from cryptocurrency marketplaces with theoretical analysis. This study highlights utility and acceptance as variables explaining cryptocurrency adoption. Utility is central to understanding how cryptocurrencies provide solutions in areas such as remittances and financial inclusion. Acceptance is crucial for adoption, as societal and market perceptions influence their economic role. These variables are key independent factors in this study’s analysis of cryptocurrency adoption in Nigeria. Findings indicated that cryptocurrencies derive intrinsic value from their utility and acceptance, though market speculation plays a substantial role. The study focused primarily on Bitcoin and

Ethereum, offering relevant insights for their role in Nigeria's financial ecosystem, where user adoption patterns are heavily influenced by economic instability.

(Ostern, 2020) employed econometric techniques, including GARCH and VAR models, to assess the macroeconomic implications of cryptocurrency adoption. VAR models are particularly effective for capturing dynamic relationships between multiple economic variables, making them a strong candidate for analysing the interplay between cryptocurrency adoption, inflation, and financial inclusion in this study. The study emphasized cryptocurrencies' role in monetary stability but limited its focus to developed economies. This gap presents an opportunity for analysis within the Nigerian context, characterized by economic volatility and high cryptocurrency adoption rates. (Olayinka, 2021) explored the intrinsic value of cryptocurrencies in Nigeria, focusing on their role in remittances and peer-to-peer financial transactions. The study concluded that utility and widespread adoption were critical determinants of value, aligning with global trends but underscoring the importance of local economic conditions, including regulatory challenges and financial exclusion.

2.1.2 Scarcity and Value

A historical analysis of population expansion and resource scarcity can be found in (Malthus, 1798). His research is based on observations made in 18th-century England, when he saw both a sharp increase in the population and a decline in agricultural production. According to Malthus, resources like food only grow arithmetically while population grows geometrically, which results in a situation where there are not enough resources to support the population. The study looks at how resource availability and population increase are related. It concludes that scarcity shapes value and economic behaviour and makes the case that unrestrained population expansion may result in the depletion of resources and the downfall of society. Although the study's historical perspective makes it strong, its emphasis on population dynamics makes it constrained. Although the current study will apply these insights to bitcoin markets, this research provides fundamental insights about scarcity that underlie the current study.

The link between prices, scarcity, and economic activity is examined in (Harvey, 2018). To evaluate how prices indicate scarcity and influence economic decisions, the study takes a theoretical approach. It concludes that prices are essential for effective resource allocation.

(Harvey, 2018) and (Ansari, 2024) explored the relationship between scarcity and value, examining how limited supply influences economic behaviour and price mechanisms. These studies provided theoretical insights into the volatility and value fluctuations of cryptocurrencies like Bitcoin, which have a fixed supply cap. Harvey's analysis of limited supply aligns with cryptocurrency behaviour during periods of high inflation or economic uncertainty.

2.1.3 Store of value

Money's function as a store of value and contribution to economic growth are discussed historically by (Smith, 1776). To track the development of money and its purposes, the study employs historical analysis. Economic stability is shown to be contingent upon the money's capacity to hold value. The study is constrained by its historical context, but its strength lies in its fundamental observations, especially when comparing the efficacy of cryptocurrencies as stores of value to more conventional forms of money like gold and fiat currencies. The current study will apply these fundamental concepts to contemporary cryptocurrencies; however, this research provides background information that informs the current study.

(Hamilton, 1781) makes the case for the significance of banks as value repositories and as engines of economic expansion. The study looks at how financial systems have evolved through historical examination. It finds that because banks offer reliable places to keep value, they are essential to economic growth. The ideas presented by Smith are pertinent to the study of cryptocurrencies, especially when assessing how well they function as stores of value in comparison to more conventional forms of money like gold and fiat currencies. The study's emphasis on traditional banking, however, places limitations on it. Although the current study will concentrate on decentralised cryptocurrencies, this research highlights the significance of financial institutions, which provides valuable context for the current study.

(Downey, 2022) analysed Bitcoin's characteristics as a store of value, emphasizing its potential as a digital alternative to gold. Similarly, (Brown, 2022) compared cryptocurrencies with traditional stores of value, concluding that despite their volatility, cryptocurrencies could serve as effective hedges in inflationary environments, such as Nigeria's. (Okafor, 2023) examined the influence of scarcity on cryptocurrency valuation within Nigeria. Their findings indicated that Bitcoin's limited supply heightened its attractiveness as an investment vehicle amidst persistent inflation and currency depreciation, drawing direct relevance to the Nigerian context.

2.1.4 Cryptocurrencies as a hedge against inflation

(Fry, 2016) and (Baur, 2018) examined the role of cryptocurrencies, particularly Bitcoin, as hedges against inflation. These studies observed that in countries with unstable fiat currencies, citizens increasingly turned to cryptocurrencies as alternative stores of value. This phenomenon is particularly relevant in Nigeria, where inflation and currency depreciation have driven significant cryptocurrency adoption. Building on this, (Adebayo, 2022) analysed the relationship between inflation and cryptocurrency adoption in Nigeria. This study supports the inclusion of inflation as a key variable by highlighting how Nigerians perceive cryptocurrencies as a hedge against inflationary pressures. Building on this relationship, the current study explores the interplay between inflation and other economic variables, such as currency depreciation and remittance flows, to offer a more comprehensive understanding of cryptocurrency adoption in Nigeria. Their study utilized ARDL models to demonstrate that Nigerians perceive cryptocurrencies as a viable hedge against inflation, especially in urban areas with higher financial literacy rates. (Glosten, 1993) further emphasized that volatility models like GARCH can capture the dynamics of cryptocurrencies as financial hedges, aligning with the observed behaviour in emerging markets.

2.1.5 Cryptocurrencies impact on Financial Systems and economic growth

The crucial role that financial intermediaries play in economic development is highlighted by (Schumpeter, 1911). The study looks at how financial systems have changed throughout time using a historical analysis. Financial intermediaries are crucial for growth and innovation, the study posits. Though its emphasis on traditional finance limits it, the study's strength is its depth of historical analysis. Although the current study will concentrate on decentralised cryptocurrencies, this research highlights the significance of financial intermediaries, which provides valuable context for the current study.

The importance of money and its function in the growth process are covered in (Lucas, 1988). The study investigates the relationship between financial development and economic growth using theoretical models. It concludes that financial systems are essential to the growth and accumulation of capital. Although the study's theoretical discoveries are its strongest point, its abstract character limits it. Although the current study will contain empirical analysis, this research provides a theoretical foundation for links between finance and growth, which informs the current study.

(Beck, 2012) examines the advantages and disadvantages of the financial sector's involvement in economic growth. Nigeria, as one of Africa’s largest cryptocurrency markets, has witnessed increased access to financial services by using Bitcoin and other digital currencies. Econometric models are employed in the study to examine the connection between financial development and economic expansion. It concludes that while a robust financial industry fosters economic expansion, there are drawbacks. The study's careful econometric analysis is its strongest point, although it is constrained by its emphasis on conventional financial systems. Although the current study will concentrate on cryptocurrencies, this research highlights the significance of money in economic growth, which provides valuable context for the current study.

The impact of financial sector development on economic growth in the EU and OECD countries is examined by (Wasiak, 2016). Panel data analysis is used in the study to evaluate how financial development and growth are related. The analysis concludes that financial development promotes economic expansion. The thorough data analysis of the study is its strongest point, but its geographical concentration is one of its weaknesses.

This research provides empirical evidence of links between finance and growth, which informs the current analysis. However, the current study will take a global view.

(Negi, 2021) examines market capitalisation, trading volumes, and price volatility as key points of reference for understanding how cryptocurrencies affect the world financial system. The study uses a quantitative methodology, examining data from traditional financial assets and cryptocurrency marketplaces. It concludes that the global financial system is significantly impacted by cryptocurrencies, which also influence social and economic standing and promote financial inclusion. The thorough quantitative analysis of the study is its strongest point, but it is constrained by its exclusive concentration on market measurements and neglect of wider economic ramifications. This research highlights the financial inclusion component, which informs the current study. However, the current study will also contain a more comprehensive macroeconomic impact analysis.

(England, 2022) investigates the threats to financial stability that decentralised finance (DeFi) and crypto assets represent. Regular evaluations of possible dangers and regulatory initiatives are used in the study. It concludes that as DeFi and crypto assets grow more integrated with the established financial system, there are threats to financial stability. The study's emphasis on financial stability is one of its strongest points, albeit it is constrained by its attention on the UK. While the current study will include a more comprehensive analysis of macroeconomic implications, this research highlights financial stability vulnerabilities that provide valuable context for the current study.

(White, 2022) examines how stablecoins and cryptocurrencies affect the macroeconomic environment, with a particular emphasis on regulatory issues and financial stability. Credible literature and qualitative evaluations from international macroeconomists are incorporated in the study. It concludes that although there are risks to macroeconomic stability, cryptocurrencies and stablecoins can promote financial stability, equity, and innovation. Although the study's extensive qualitative analysis is its strongest point, the absence of empirical data limits it. The present study incorporates empirical analysis of macroeconomic implications, but this research provides insights into regulatory problems that underlie the current study.

Since Bitcoin's introduction, (Chatterjee, 2023) examines how cryptocurrencies have affected established financial systems. The research takes an interdisciplinary approach, integrating technology insights, regulatory analysis, and economic analysis. It concludes that the rise of cryptocurrencies has significantly altered payment networks, put banks in jeopardy, and affected traditional financial systems. Although the study's multidisciplinary approach is one of its strongest points, its wide emphasis and lack of a particular investigation of effects are limitations. The present investigation will concentrate on specific macroeconomic implications, although this research highlights the transformative influence on conventional financial systems, which provides insight for the current study. The impact of cryptocurrencies on financial markets and conventional banking systems is examined in (Hasan A. K., 2024). A broad range of topics are investigated in the study, such as integration techniques, market volatility, and adoption rates. With profound ramifications for investment portfolios and asset classes, it concludes that cryptocurrencies have transformed the banking and financial industries. The thorough examination of adoption and integration provided by the study is its strongest point; nevertheless, its emphasis on the UK and the USA limits its applicability.

In the Nigerian context, cryptocurrencies have emerged as alternatives to traditional intermediaries, enabling financial inclusion for the unbanked population (Ogujiuba, 2021). The (Chainalysis, 2021) report highlighted Nigeria as a top country for cryptocurrency adoption, emphasizing its role in improving financial inclusion. (Olatunde, 2022) explored the impact of cryptocurrencies on Nigeria’s financial system using a structural equation model. Their findings revealed that cryptocurrency adoption significantly improved financial inclusion while reducing transaction costs for international remittances. However, the study also noted increased risks of financial instability due to market volatility, a concern echoed by (England, 2022), who examined the risks posed by decentralized finance and crypto assets.

2.1.5 Transaction Efficiency and Transparency

(A Sinha, 2022) describe how smart contracts, which are self-executing contracts with agreement conditions directly put into code, might reduce transaction costs, increase transparency, and improve security. The study is especially relevant for cryptocurrencies such as Ethereum, which are intended to support smart contracts and decentralised applications. The paper employs case studies to examine the use of smart contracts in various businesses. It concludes that smart contracts improve transaction efficiency and transparency. The study's strength is its practical insights, but it is constrained by its emphasis on specific use cases. This research contributes to the current study by offering examples of smart contract applications; however, the current study will conduct a broader examination.

(Ali Sinha) explores the benefits and drawbacks of transactional openness in procurement. The research adopts a mixed methods approach that includes surveys and case studies. It concludes that transparency increases procurement efficiency but creates implementation issues. The study's strength is its detailed research, although its emphasis on procurement limits it. This research influences the current study by emphasising the need of transparency, however the current study will concentrate on financial transactions.

(Justiniano, 2022) emphasises the significance of transparency in financial management, especially in the context of cryptocurrencies and blockchain technology. The study gathers information from finance professionals through qualitative interviews. It determines that transparency is essential for good financial management. According to Justiniano, more openness in financial transactions enabled by blockchain can lead to better financial reporting, fraud reduction, and overall organisational efficiency. The study's practical usefulness is its strongest point, although its qualitative character limits it. This research informs the current study by offering practical insights into transparency, but the current study will also involve quantitative analysis.

2.1.6 Remittances and Cryptocurrencies

Several studies have highlighted the role of cryptocurrencies in reducing the cost of remittance transfers. According to the World Bank (2020), traditional remittance services charge fees ranging from 5% to 10%. In contrast, cryptocurrency-based transfers, such as those conducted through Bitcoin, cost significantly less, thereby increasing the disposable income of recipients (Alessandria, 2018).

The study by (Wirth, 2024) on practical applications of cryptocurrencies for investments highlights that the effect of using cryptocurrencies as an asset class for diversification does increase returns but using different cryptocurrencies does not necessarily increase their hedging abilities, for example, against risk of cost increases which will be extensively noted in this study when choosing the cryptocurrencies to be scrutinised.

2.1.7 Legal Frameworks and Policy

The changing legal frameworks surrounding cryptocurrencies and their effects on financial regulation are examined in (Zohar A. , 2021). Using a comparative legal analysis, the study looks at laws in various jurisdictions. It concludes that regulatory strategies differ greatly amongst nations, with some enacting strict laws and others choosing a laxer approach. The study's thorough comparative analysis is its strongest point, although it is constrained by its narrow emphasis on a few key jurisdictions. Although the present study will include a wider number of jurisdictions, this research highlights the variability in regulatory methods, which informs the current study.

The influence of legislative changes on cryptocurrency markets is examined in (Goforth, 2022), with an emphasis on investor protection and market stability. Using a mixed-methods approach, the study combines market data with legal analysis. The study suggests that modifications to regulations may have a notable effect on investor confidence and market stability. The study's combination of market and legal analysis is one of its strongest points, although it is constrained by its emphasis on immediate effects. Although the present study will also look at long-term consequences, this research provides insights into the immediate effects of regulatory changes, which informs the current study. The Central Bank of Nigeria (2021) has adopted a cautious stance toward cryptocurrencies, banning financial institutions from facilitating cryptocurrency transactions. Studies indicate that such regulations could push cryptocurrency activity into unregulated spaces, increasing risks of fraud and undermining economic benefits.

(Hughes, 2023) looks on how traditional financial institutions are affected by the policy changes made in response to the growth of decentralised finance (DeFi). Using a framework for policy research, the study looks at recent legislative changes and how they've affected the banking industry. It concludes that changes in policy towards DeFi are changing the financial environment and presenting opportunities as well as difficulties to traditional banking institutions. The study's emphasis on policy analysis is its strongest point, although it is constrained by the absence of empirical data. Although the present study will contain an empirical analysis of these implications, this research highlights the policy reactions to DeFi, which informs the current study.

(Meyer, 2023) examines how global regulatory organisations influence cryptocurrency laws, with an emphasis on policy coordination and harmonisation. The study employs a qualitative methodology to investigate the initiatives of global institutions like the International Monetary Fund (IMF) and the Financial Action Task Force (FATF). The study indicates that international regulatory entities are essential for addressing cross-border issues and harmonising rules. The study has limitations due to its qualitative nature, but its emphasis on international coordination is one of its strongest points. While this research provides valuable insights into worldwide regulatory initiatives, the current study will also offer a quantitative examination of their efficacy.

Recognising these drawbacks, the purpose of this review is to set the groundwork for a research paper that investigates the cryptocurrencies effects on financial systems, and the creation of solutions that strike a balance between user privacy and transparency.

Addressing regulatory gaps in Nigeria forms a unique addition to the existing literature by examining how inconsistent policies influence cryptocurrency adoption. This approach highlights the need for adaptive regulations that protect investors while fostering financial innovation, especially in a country with significant cryptocurrency usage driven by economic instability and limited access to traditional financial systems. In Nigeria, the Central Bank's 2021 ban on cryptocurrency transactions underscored these challenges. (Suleiman, 2023) reviewed the legal landscape for cryptocurrency adoption in Nigeria, noting significant gaps in regulatory enforcement. Their study emphasized the need for clear and adaptive policies to balance innovation and risk mitigation, particularly in cross-border transactions and peer-to-peer networks. The literature consistently highlights the tension between innovation and regulation, a theme central to understanding Nigeria's cryptocurrency ecosystem.

2.2 DISCUSSION OF THEORETICAL FRAMEWORK STUDIES

2.2.1 Subjective Theory of Value (STV)

Individual preferences and subjective evaluations are emphasised in the Subjective theory of Value, which was presented in the late 19th century by (Menger, 1871) as a component of the Austrian School of Economics.

The STV aims to provide an explanation of value based on people's perceptions and evaluations of goods and services. Whereas it postulates that value is subjective and determined by marginal utility, the extra satisfaction obtained from consuming one more unit of an item or service, it makes assumptions about scarcity and worth being determined by utility. It is also thought that people subjectively assess products and services according to their unique preferences and sense of utility and scarcity. The subjective valuation determined by supply and demand is reflected in these prices. This suggests that perceived value can potentially be influenced by branding and marketing methods.

2.2.2 Quantity Theory of Money (QTM)

The 16th century saw the development of the Quantity Theory of Money (Friedman, 1963), which is linked to economists such as Irving Fischer. Its focus is on how the money supply and inflation are linked. It clarifies that the money supply (M) and price level (P) have a proportionate connection. The exchange equation:

$$Money\ Supply\ \times Velocity = Price\ Level \times Output$$

captures this relationship, where inflation results from a rise in money supply without a commensurate increase in output. It follows that the general level of prices for goods and services is closely correlated with the quantity of money in circulation.

2.2.3 Network Effect Theory

The fundamental idea underlying (Shapiro, 1986)'s hypothesis is that a network's value is directly correlated with the square of the number of users who are connected. The main notion is, as more people join, networks gain value and in turn, draw in additional users in a positive feedback cycle. Online marketplaces, communication apps, and social media platforms are a few examples. Among the ramifications are the necessity of early adoption and user acquisition for network supremacy.

2.2.4 Behavioural Economics Theory

This theory, which was first proposed in the middle of the 20th century and was cited by (Steiglitz, 2000), questioned the notion of perfect rationality found in conventional economic theory. It examines the ways in which cognitive biases and psychosocial variables affect economic judgement. It promotes the idea that people are fallible agents with limited rationality who are prone to biases such as anchoring, framing, and overconfidence. Market inefficiencies can result from these biases, which can lead to less-than-ideal economic decisions. Because behavioural biases can cause markets to become inefficient, authorities can create interventions to encourage individuals to make better judgements.

2.2.5 Efficient Market Hypothesis

Eugene F. Fama established the Efficient Market Hypothesis (EMH) in the late 1960s, as shown by his groundbreaking study that was published in The Journal of Finance in 1970. The theory was developed to explain the operation of capital markets and the determination of financial asset prices. The foundation of Efficient Market Hypothesis (EMH) is the belief that asset prices accurately reflect all available information, markets are efficient, and investors are unable to regularly outperform the market.

The central claim of the Efficient Market Hypothesis (EMH) is that asset prices accurately reflect all information available at any one time, meaning that persistently outperforming the market average is not conceivable. Studies are informed by this theory because it offers a framework for comprehending market efficiency, the effect of information on prices, and the difficulties of constantly outperforming the market. The assumption of investor rationality, the omission of behavioural finance considerations, and the incapacity of the EMH to account for transient market anomalies or bubbles are some of its drawbacks. Although the Efficient Market Hypothesis (EMH) proposed by (Fama, 1970) provides significant insights into market efficiency, it might not adequately tackle the intricacies and irrationalities present in actual financial markets.

2.3 RESEARCH GAP

The Quantity Theory of Money provides the most suitable theoretical foundation for this study, offering a robust framework to analyse the relationship between money supply, inflation, and cryptocurrency adoption. This theoretical approach is particularly relevant in economies like Nigeria, where inflation and currency instability drive significant cryptocurrency usage.

Key variables explaining cryptocurrency adoption include inflation rates, remittance costs, and financial inclusion. Inflation rates are pivotal as cryptocurrencies often serve as hedges against inflation, while reduced remittance costs make cryptocurrencies attractive for cross-border transactions. Financial inclusion further drives adoption by providing access to financial services for the unbanked population. Other influential factors include regulatory environments, macroeconomic volatility, and the perceived scarcity of cryptocurrencies like Bitcoin.

The literature review highlights that VAR models examine the dynamic interdependencies among key variables, and Auto ARIMA provides robust forecasting capabilities. Together, these methods offer a comprehensive approach to understanding cryptocurrency adoption in Nigeria.

This study uniquely integrates variables such as remittance costs, regulatory frameworks, and financial inclusion into a cohesive framework tailored to the Nigerian context. Unlike prior studies that often focus on developed economies or isolated factors, this research adopts a holistic view, combining macroeconomic volatility, demographic influences, and regulatory impacts to address critical gaps in the literature.

CHAPTER 3: METHODOLOGY

3.1 Research Design

This study adopts a quantitative and longitudinal research design, suitable for analysing time-series data over an extended period to examine the dynamic interactions among economic variables. The primary aim of the study is to evaluate how cryptocurrency adoption impacts Nigeria's economic and financial ecosystem. Specifically, it investigates the relationships between cryptocurrency prices, remittance flows, exchange rates, inflation, GDP growth rates, and trading volumes.

The selected research design is particularly appropriate because it facilitates an in-depth examination of temporal dynamics and causal relationships. Time-series analysis is essential to capture how cryptocurrency adoption affects financial systems over time. Unlike cross-sectional studies, which provide static snapshots, this design allows the researcher to trace the evolution of economic variables and their interdependencies.

Step	**Description**
Define Research Objectives	Establish the key questions and aims of the study.
Data Collection and Preprocessing	Gather data from reliable sources and ensure consistency across datasets.
Exploratory Data Analysis (EDA)	Analyse trends, distributions, and relationships among variables.
Pre-Estimation Tests	Conduct diagnostic tests such as stationarity, multicollinearity, and heteroscedasticity.
Econometric Modelling	Apply VAR and Auto ARIMA models to evaluate relationships and forecasts.
Hypothesis Testing	Test the specific hypotheses using advanced econometric methods.

Interpretation and Policy Implications	Derive actionable insights and recommendations based on results.

Table 1: Research Design Framework

The framework integrates both descriptive and causal analyses, ensuring that the results provide meaningful insights into the underlying mechanisms driving observed trends. The study also considers Nigeria's unique macroeconomic environment, including periods of heightened cryptocurrency activity, inflationary pressures, and significant policy changes. For example, the Central Bank of Nigeria's cryptocurrency ban in 2021 and the impacts of COVID-19 on remittance flows are key events included in the study period. These contextual factors ensure the findings are both robust and relevant to Nigeria’s financial system.

The research design framework outlines the sequential steps undertaken, from defining objectives to drawing policy implications.

3.2 Type of Data

To achieve the objectives of this study, a quantitative, longitudinal research design was adopted, leveraging time-series data collected over the period from January 2018 to December 2022. This period was strategically chosen to capture the effects of key economic events, including, the aftermath of the 2018 cryptocurrency crash, which marked a pivotal moment for global and Nigerian cryptocurrency markets, Nigeria’s inflationary spikes during periods of economic stress, including the COVID-19 pandemic and the Central Bank of Nigeria's cryptocurrency ban in 2021, which highlighted the role of digital currencies in Nigeria’s economy.

The data includes daily, monthly, and quarterly variables representing Nigeria’s economic and financial systems. Cryptocurrency prices, exchange rates, inflation rates, and remittance flows were prioritized due to their central role in addressing the study’s hypotheses. Aggregating these variables to monthly frequencies provides a balance between capturing long-term trends and minimizing short-term noise, ensuring robust econometric analysis.

This longitudinal design is particularly suited for identifying causality and temporal dependencies among variables. By focusing on economic variables that span diverse sectors—cryptocurrency markets, macroeconomic indicators, and trading activity—the study provides a comprehensive understanding of Nigeria's financial landscape.

3.3 Population and Sampling

The study's population consists of economic and financial data from Nigeria, covering the period from January 2018 to December 2022. This population includes all macroeconomic indicators, financial market variables, and cryptocurrency-related data that are publicly available and relevant to the research objectives.

The sample includes key variables collected at varying frequencies:

Daily data for cryptocurrency prices for Bitcoin and Ethereum, Exchange rates, Oil prices and the Nigerian All Share Stock index prices, Monthly data for inflation rates, trading volumes, and Quarterly data for GDP growth rates and remittance flows, interpolated to monthly observations.

The purposive sampling technique was employed to ensure that variables critical to the study's hypotheses were included. This approach prioritizes the selection of data sources that directly address the research objectives, ensuring relevance and accuracy.

The sampling process also captures key economic events. For instance, the inclusion of the 2018 cryptocurrency crash and the 2021 cryptocurrency ban ensures the study reflects both periods of growth and regulatory challenges. The dataset represents Nigeria's financial ecosystem comprehensively, with data sourced from cryptocurrency markets, forex markets, and macroeconomic indicators.

3.4 Sampling Technique

This study utilizes a purposive sampling technique, focusing on selecting variables and data sources that directly address the research objectives. This technique ensures that the sample captures key aspects of Nigeria's financial system while maintaining a focus on the study's hypotheses. The following variables were prioritized:

	Cryptocurrency markets: Bitcoin (BTC), Ethereum (ETH) prices and Trading Volumes
	Macroeconomic indicators: Inflation rates, GDP growth rates, and remittance flows
	Forex markets: USD/NGN exchange rates
	Financial markets: Stock indices

Table 2: Variables under study

The sampling frame ensures the inclusion of data reflecting Nigeria's financial ecosystem, spanning capital markets, forex markets, and digital currency markets. The inclusion of critical events, such as the Central Bank of Nigeria's 2021 cryptocurrency ban, highlights the evolving role of cryptocurrencies in Nigeria's financial landscape. Additionally, periods of high inflation and remittance growth are captured to analyse financial inclusion and macroeconomic resilience.

The representativeness of the sample is further enhanced by aggregating and interpolating data to a common monthly frequency. For example, GDP and remittance data, originally recorded quarterly, were interpolated to monthly observations using cubic spline interpolation. This ensures consistency across datasets and allows for more robust time-series analysis.

3.5 Data Collection

The study relies exclusively on secondary data, sourced from reputable platforms known for their accuracy and reliability, and is summarised in the table below.

Data spans the period from January 2018 to December 2022, reflecting a comprehensive view of Nigeria's macroeconomic trends and cryptocurrency adoption.

The data collection process utilises APIs, R packages, and manual downloads to ensure data accuracy. For example, cryptocurrency price data was retrieved using the $getSymbols()$ function in R, which allowed seamless access to Yahoo Finance, Exchange rate data was obtained from Alpha Vantage's daily forex API, ensuring granularity, Inflation rates, GDP growth, and remittance flows were sourced from Refinitiv Eikon, representing trusted macroeconomic sources.

These methods ensured that the data was not only accurate but also aligned across variables. Aggregation and interpolation processes ensured consistency in frequency, enabling robust econometric modelling.

3.6 Data Collection Instruments

The data collection process in this study adopts a systematic and meticulous approach, integrating both automated and manual methods to ensure high accuracy and reliability. Each instrument used is carefully selected to align with the study's objectives, focusing on capturing key economic and financial variables relevant to the cryptocurrency ecosystem and broader macroeconomic dynamics in Nigeria. Below, Table 3 outlines the primary data collection instruments, variables, sources, and their associated characteristics.

Category	**Variable**	**Data Source**	**Frequency**	**Data Period**	**Remarks**
Cryptocurrency Markets	Bitcoin (BTC-USD)	Yahoo Finance (getSymbols("BTC-USD"))	Daily	01/01/2015 - Present	Historical price data for Bitcoin.
	Ethereum (ETH-USD)	Yahoo Finance (getSymbols("ETH-USD"))	Daily	01/01/2015 - Present	Historical price data for Ethereum.
Exchange Rates	USD/NGN Exchange Rate	Alpha Vantage (FX_DAILY, USD/NGN)	Daily	01/01/2015 - Present	Retrieved via API for daily FX rates.

Macroeconomic Indicators	Inflation Rate	Refinitiv Eikon (NGCPANNLR)	Monthly	01/01/2018 - 12/31/2022	Nigeria's annualized CPI inflation rate.
	GDP Growth Rate	Refinitiv Eikon (NGGDP…R)	Quarterly	01/01/2018 - 12/31/2022	Nigeria's real GDP growth rates.
Capital Markets	Stock Market (All-Share Index)	Refinitiv Eikon (ESCNOSP)	Daily	01/01/2018 - 12/31/2022	Nigeria's stock market index.
Commodity Markets	Crude Oil Price (Brent)	Refinitiv Eikon (ESCNOSP)	Daily	01/01/2018 - 12/31/2022	Daily crude oil prices for Brent.
Remittances	Total Remittances	Refinitiv Eikon (NGXREMI.A)	Quarterly	01/01/2018 - 12/31/2022	Aggregated international remittance inflows.
Trading Activity	Trading Volumes	Study Tulips (Manually Sourced)	Monthly	01/01/2018 - 12/31/2022	Total trading volume data for

					Nigerian markets.

Table 3: Data Collection Framework

The collection of Bitcoin and Ethereum price data leverages the getSymbols() function in R, which interfaces directly with Yahoo Finance. This automated method ensures the efficient and consistent retrieval of daily historical price data, spanning from January 2015 to the present. These datasets are critical for analysing cryptocurrency trends, volatility, and their relationship with macroeconomic variables.

Exchange rate data, specifically the USD/NGN exchange rate, is sourced from Alpha Vantage using the FX_DAILY API. The API provides high-frequency data at daily intervals, which is subsequently aggregated to monthly averages to align with other variables. By focusing on the USD/NGN exchange rate, this study captures Nigeria’s forex market dynamics and the potential impact of cryptocurrency adoption on currency stability.

Macroeconomic indicators, including inflation rates and GDP growth rates, are sourced from Refinitiv Eikon. Inflation rates, measured as Nigeria’s annualized Consumer Price Index (CPI), are provided at a monthly frequency. Meanwhile, GDP growth rates, reflecting real economic performance, are available on a quarterly basis. These variables are vital for assessing the broader economic implications of cryptocurrency adoption. Interpolation techniques, such as cubic spline methods, are applied to align quarterly GDP data with monthly observations.

For capital market analysis, data on Nigeria’s All-Share Index (representing stock market performance) is obtained from Refinitiv Eikon. This index provides daily observations from January 2018 to December 2022, enabling the study to examine the interplay between cryptocurrency markets and traditional financial systems. Similarly, crude oil price data for Brent is included to capture commodity market dynamics, which play a significant role in Nigeria’s oil-dependent economy.

Remittance data, sourced from Refinitiv Eikon, represents international financial inflows aggregated at a quarterly frequency. These data are interpolated to monthly observations to facilitate comparability with other variables. Remittances serve as a proxy for financial inclusion, illustrating the impact of cryptocurrency adoption on cross-border transactions.

Trading volume data, manually sourced from Study Tulips, captures monthly activity in Nigerian markets. This variable provides insights into overall trading behaviour and its correlation with macroeconomic indicators.

Each dataset is subject to rigorous validation and preprocessing to ensure accuracy and reliability. Automated error detection scripts in R identify missing values and outliers, which are then addressed using appropriate imputation methods. Cross-referencing with alternative sources further verifies the integrity of the data. These measures ensure that the collected data provides a robust foundation for subsequent analysis.

3.7 Data Analysis

The data analysis process employs a structured and rigorous approach to derive meaningful insights and address the study's objectives. The analysis integrates exploratory data analysis (EDA), pre-estimation diagnostic tests, and advanced econometric modelling techniques, such as Auto ARIMA and Vector Autoregression (VAR). This systematic approach ensures the validity and robustness of the findings.

The analysis begins with Exploratory Data Analysis (EDA), which provides a descriptive overview of the datasets and highlights trends, patterns, and relationships among variables. Descriptive statistics such as mean, median, standard deviation, and range are calculated for all variables, including Bitcoin and Ethereum prices, USD/NGN exchange rates, inflation rates, GDP growth rates, and remittance flows. Visualization techniques are utilized, with time-series line plots illustrating historical trends and behaviour over the study period from January 2015 to December 2022. Specific periods, such as the 2018 cryptocurrency crash and the 2021 Central Bank of Nigeria (CBN) cryptocurrency ban, are highlighted to analyse their impact on the financial system.

To ensure consistency and comparability across datasets, data preprocessing is conducted. Daily variables, including cryptocurrency prices, exchange rates, stock index prices, and oil prices, are aggregated into monthly values to reduce noise and focus on long-term trends. Quarterly variables, such as GDP growth rates and remittance flows, are interpolated to monthly observations using cubic spline methods. Missing data for variables such as remittances and trading volumes are handled through linear interpolation to maintain continuity. Outliers are detected and adjusted using the interquartile range (IQR) method to ensure the integrity of the data. Differencing techniques are applied to non-stationary variables to achieve stationarity, as determined by the Augmented Dickey-Fuller (ADF) test. For instance, cryptocurrency prices, exchange rates, and remittance flows required first or second differencing before being incorporated into the models.

Pre-Estimation Tests

To validate the assumptions underlying the econometric models, several diagnostic tests are conducted. Stationarity testing is performed using the ADF test, which determines whether the data exhibit unit roots. The ADF test evaluates the following equation:

$$\Delta Y_t = \alpha + \beta Y_t - 1 + \gamma_t + \delta \Delta Y_{t-1} + \epsilon_t$$

Where:

ΔY_t is the first difference of the series, t represents time, and ϵ_t is the error term.

H_0: the data is non-stationary. Variables found to be non-stationary are differenced until stationarity is achieved.

Multicollinearity is assessed using the Variance Inflation Factor (VIF), calculated as follows:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Where:

R_i^2 is the coefficient of determination for the regression of the i^{th}predictor on all other predictors. A VIF value exceeding 10 indicates high multicollinearity.

Heteroscedasticity testing is performed using the Breusch-Pagan test, which evaluates whether the variance of residuals remains constant.

The test evaluates the following auxiliary regression:

$$\epsilon_t^2 = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \nu_t$$

Where:

ϵ_t^2 are the squared residuals from the primary regression and X_k are the independent variables. Significant test statistics indicate heteroscedasticity, prompting the us to introduce lags.

Residual autocorrelation is assessed using the Durbin-Watson (DW) test, calculated as follows:

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

where:

e_t represents the residuals and t is the number of observations. A DW statistic close to 2 indicates no autocorrelation, supporting the validity of the models.

Econometric Modelling

The study employs two key econometric models: Auto ARIMA and Vector Autoregression (VAR).

Auto ARIMA Model

The Auto ARIMA model is used for forecasting and identifying potential relationships among variables. It optimizes the lag order (p), differencing order (d), and moving average order (q) using the Akaike Information Criterion (AIC). The mean equation for Auto ARIMA is specified as:

The mean equation for the model is specified as:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta j \epsilon_{t-j} + \epsilon_t$$

Where:

p is the autoregressive order, d is the differencing order, q is the moving average order, y_t is the target variable (cryptocurrency prices, remittances and exchange rates) and ϵ_t is the error term.

The Auto ARIMA model forecasts future values and identifies trends, such as how cryptocurrency prices influence remittance flows and exchange rates.

Vector Autoregressive Model

The VAR model captures the dynamic interrelationships among variables, such as the effect of cryptocurrency price shocks on exchange rates, inflation, and remittance flows.

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \epsilon_t$$

Where:

Y_t is the vector of endogenous variables including cryptocurrency prices, exchange rates, and inflation, p is the optimal lag length determined by the AIC, β_i represents the coefficient matrices, and ϵ_t is the vector of error terms.

Impulse Response Functions (IRFs) derived from the VAR model illustrate the impact of shocks in one variable on others over time. For instance, an IRF may show how a one-unit shock in cryptocurrency prices affects remittance flows over subsequent months.

By following these steps and applying robust econometric methods, the study ensures a comprehensive analysis of the dynamic relationships among cryptocurrencies, macroeconomic indicators, and Nigeria's financial markets. This analytical framework provides a solid foundation for hypothesis testing and interpretation.

3.8 Techniques in Achieving Study Objectives and Testing Hypotheses

The study employs a variety of statistical and econometric techniques to address the research objectives and test the stated hypotheses. These techniques are systematically applied to ensure the validity and reliability of results, with a focus on capturing dynamic relationships among the variables of interest. Key techniques include data preprocessing, exploratory data analysis, hypothesis testing, and econometric modelling.

The study begins by preprocessing the raw data to ensure consistency and alignment. Variables with different frequencies are transformed to monthly observations. For example, daily variables like cryptocurrency prices and exchange rates are aggregated to monthly averages, while quarterly variables such as GDP growth rates and remittance flows are interpolated to monthly data using cubic spline interpolation. Non-stationary variables identified through the Augmented Dickey-Fuller (ADF) test are differenced until stationarity is achieved. For instance, cryptocurrency prices and exchange rates are differenced once, while remittance flows require second differencing.

Descriptive statistics and time-series visualizations are used to uncover trends, patterns, and relationships among variables. EDA highlights significant periods, such as the 2018 cryptocurrency crash and the 2021 Central Bank of Nigeria cryptocurrency ban, to assess their impact on the financial ecosystem.

The study applies Auto ARIMA for forecasting and VAR for dynamic modelling. Auto ARIMA determines optimal model parameters (p, d, q) to forecast variables like cryptocurrency prices and remittance flows. The VAR model captures the interdependence among variables and generates Impulse Response Functions (IRFs) and variance decompositions, revealing the effects of shocks in one variable on others over time.

To validate model assumptions, pre-estimation tests such as the Durbin-Watson test, for residual autocorrelation, the Breusch-Pagan test, for heteroscedasticity, and Variance Inflation Factor (VIF) analysis, for multicollinearity, are conducted.

3.9 Hypotheses Testing Framework

This section outlines the econometric methodologies employed to test the study's hypotheses, detailing the models and equations used to capture the relationships among cryptocurrency prices, remittance flows, exchange rates, inflation, and financial inclusion.

Each hypothesis is addressed through specific statistical approaches to ensure robust insights into the dynamics of Nigeria's financial ecosystem.

Hypothesis 1: Cryptocurrency adoption has significantly increased remittance flows in Nigeria by reducing transaction costs and enhancing efficiency.

The relationship between cryptocurrency adoption and remittance flows is analysed using the **Vector Autoregression (VAR)** model. The VAR model is appropriate because it captures the dynamic interdependencies among variables over time. Specifically, the relationship between cryptocurrency prices and remittance flows is modelled as follows:

$$
\begin{aligned}
Second\_Diff\_Remittances_t \\
&= \alpha_1 + \sum_{i=1}^{p} \beta i Second\_Diff\_Remittances_{t-i} \\
&+ \sum_{i=1}^{p} \gamma_i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} + \epsilon_{1,t}
\end{aligned}
$$

$$
\begin{aligned}
Lag\_Diff\_Avg\_Crypto\_Price_t \\
&= \alpha_2 + \sum_{i=1}^{p} \beta i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} \\
&+ \sum_{i=1}^{p} \gamma_i Second\_Diff\_Remittances_{t-i} + \epsilon_{2,t}
\end{aligned}
$$

Where:

$Second\_Diff\_Remittances_t$ are the second-differenced remittance flows at time t, $Lag\_Diff\_Avg\_Crypto\_Price_t$ are the lagged differenced average cryptocurrency price at time t, β_i, γ_i are coefficients representing the impact of lagged values, $\epsilon_{1,t}$, $\epsilon_{2,t}$ are the white noise error terms and p is the optimal lag length determined using the Akaike Information Criterion (AIC).

Additionally, Granger causality tests are employed to determine whether lagged cryptocurrency prices significantly predict remittance flows. Impulse Response Functions

(IRFs) and variance decomposition are utilized to assess how shocks in cryptocurrency prices influence remittance flows.

Hypothesis 2: Cryptocurrency prices exhibit a significant negative correlation with the value of the Nigerian Naira, indicating cryptocurrencies act as a hedge against inflation.

To analyse this relationship, the VAR model is again employed to capture the interaction between cryptocurrency prices and exchange rates. The model is specified as:

$$
\begin{aligned}
Diff\_First\_Exchange\_Ratet & \\
&= \alpha_3 + \sum_{i=1}^{p} \beta_i Diff\_First\_Exchange\_Rate_{t-i} \\
&+ \sum_{i=1}^{p} \gamma_i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} + \epsilon_{3,t}
\end{aligned}
$$

$$
\begin{aligned}
Lag\_Diff\_Avg\_Crypto\_Price_t & \\
&= \alpha_4 + \sum_{i=1}^{p} \beta_i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} \\
&+ \sum_{i=1}^{p} \gamma_i Diff\_First\_Exchange\_Rate_{t-i} + \epsilon_{4,t}
\end{aligned}
$$

Where:

$Diff\_First\_Exchange\_Rate_t$ is the differenced exchange rate at time t, $Lag\_Diff\_Avg\_Crypto\_Price_t$ are the lagged differenced average cryptocurrency prices at time t, β_i , γ_i are coefficients representing the impact of lagged values and $\epsilon_{3,t}, \epsilon_{4,t}$ are white noise error terms.

Granger causality tests are conducted to assess whether cryptocurrency prices predict exchange rate fluctuations. The analysis also includes variance decomposition to determine the contribution of cryptocurrency price shocks to the variability of exchange rates.

Hypothesis 3: Cryptocurrencies enhance financial inclusion by providing affordable financial services to the unbanked population in Nigeria

Financial inclusion is proxied by remittance flows, as increased remittance flows often indicate greater access to affordable financial services. The VAR model is applied to capture the dynamic relationship between cryptocurrency prices and remittance flows:

$$Second\_Diff\_Remittances_t = \alpha_5 + \sum_{i=1}^{p} \beta_i Second\_Diff\_Remittances_{t-i} + \sum_{i=1}^{p} \gamma_i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} + \epsilon_{5,t}$$

$$Lag\_Diff\_Avg\_Crypto\_Price_t = \alpha_6 + \sum_{i=1}^{p} \beta_i Lag\_Diff\_Avg\_Crypto\_Price_{t-i} + \sum_{i=1}^{p} \gamma_i Second\_Diff\_Remittances_{t-i} + \epsilon_{6,t}$$

Impulse Response Functions are used to explore how shocks in cryptocurrency prices influence remittance flows, while variance decomposition measures the proportion of forecast error variance in remittance flows attributed to changes in cryptocurrency prices.

The table below summarizes the methodologies employed for each hypothesis and the key variables used:

Hypothesis	Methodology	Variables
H1: Cryptocurrency adoption increases remittance flows.	VAR, Granger causality, IRF, Variance decomposition	$\boldsymbol{Lag\_Diff\_Avg\_Crypto\_Price}$, $\boldsymbol{Second\_Diff\_Remittances}$

H2: Cryptocurrency prices correlate with exchange rates.	VAR, Granger causality, Variance decomposition	***Lag_Diff_Avg_Crypto_Price***, ***Diff_First_Exchange_Rate***
H3: Cryptocurrencies enhance financial inclusion.	VAR, IRF, Variance decomposition	***Lag_Diff_Avg_Crypto_Price***, ***Second_Diff_Remittances***

Table 4: Methodology employed

3.10 Outputs and Visualizations

The outputs of the analysis include a variety of statistical results and visualizations that provide comprehensive insights into the study's hypotheses and objectives. Key outputs include:

Time-Series Plots which illustrate historical trends in cryptocurrency prices, exchange rates, inflation rates, GDP growth rates, and remittance flows. For example, a time-series plot highlights the 2018 cryptocurrency crash and its impact on Bitcoin and Ethereum prices. Correlation matrix heatmaps depict relationships among variables, identifying potential multicollinearity issues and guiding model specifications. IRFs from the VAR model show the effects of shocks in one variable on others. For instance, they show how shocks in cryptocurrency prices influence remittance flows and exchange rates over time. Variance Decomposition Plots quantify the contributions of different variables to forecast error variance, revealing the relative importance of cryptocurrency prices, exchange rates, and remittance flows in explaining variations over time. Outputs from the ADF test, VIF analysis, Breusch-Pagan test, and Durbin-Watson test validate the models and ensure the reliability of the results.

These outputs collectively provide a detailed understanding of the dynamic relationships among cryptocurrencies, macroeconomic indicators, and financial markets in Nigeria, contributing to the study's policy implications and furthering the understanding of cryptocurrency adoption's economic impact.

CHAPTER 4: RESULTS AND ANALYSIS

This chapter presents the empirical results from the econometric analysis conducted to evaluate the impact of cryptocurrencies on Nigeria's financial system. The analysis uses monthly data spanning January 2018 to December 2022, capturing a period of significant cryptocurrency adoption in Nigeria. This timeframe was selected to align with key events in the global and Nigerian financial markets, such as the cryptocurrency bull run of 2021, the COVID-19 pandemic's economic disruptions in 2020, and the 2021 Central Bank of Nigeria (CBN) cryptocurrency ban.

The chosen study period allows for the investigation of dynamic relationships between cryptocurrencies and key macroeconomic variables under varying market conditions. By analysing a period marked by heightened financial volatility and evolving regulatory frameworks, the study provides insights into the role of cryptocurrencies as hedges against inflation, tools for financial inclusion, and determinants of remittance flows. The analysis combines descriptive statistics, pre-estimation diagnostic tests, and advanced econometric modelling, such as Vector Autoregression (VAR) and Auto ARIMA models, to provide robust and detailed results.

4.1 Time Series Plots of Key Variables

Average Cryptocurrency Price

The plot below illustrates the trend of the average cryptocurrency price over time. Cryptocurrency prices exhibit significant volatility, with a notable rise starting in 2020, followed by sharp fluctuations in 2021 and 2022.

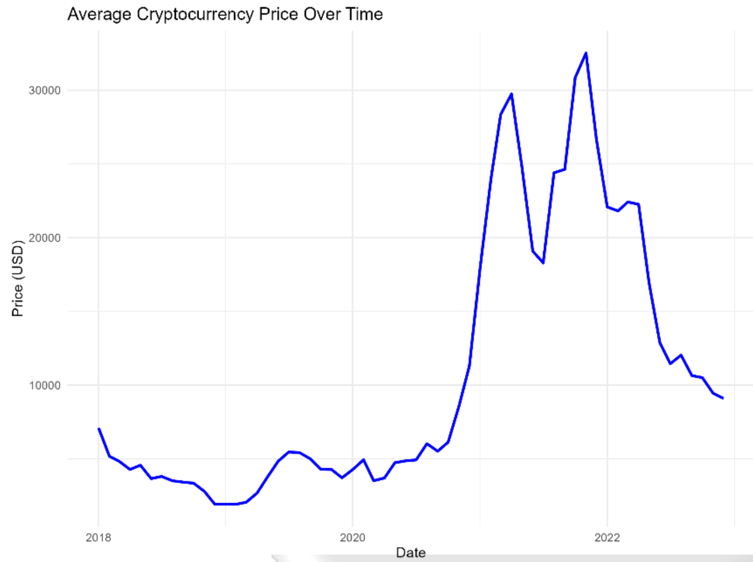


Table 5: Average Cryptocurrency price plot

Exchange Rate

The exchange rate of the Nigerian Naira against major currencies shows a general depreciation over time, with notable spikes corresponding to economic and policy shocks.

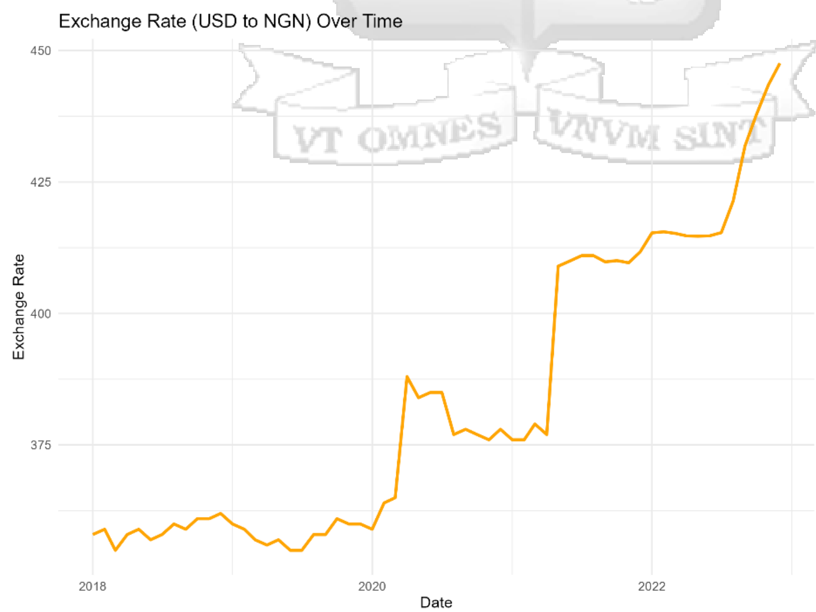


Table 6: Average Exchange rate plot

Average Stock Index

The Nigerian stock market index demonstrates periods of growth and decline, with major shifts corresponding to macroeconomic events such as the COVID-19 pandemic and subsequent recovery phases.

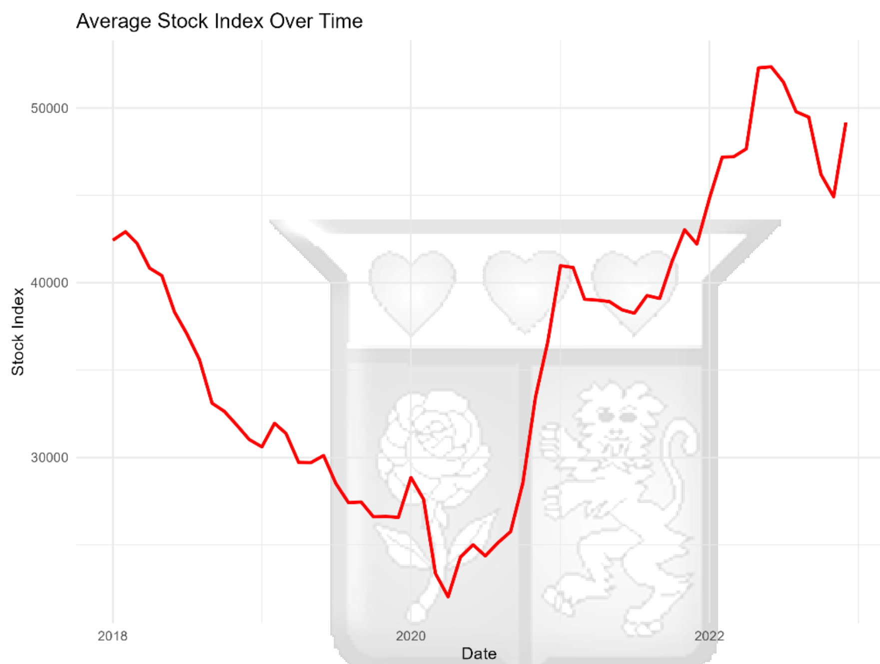


Table 7: Average Stock Index plot

Average Oil Price

Oil prices have shown significant variation, particularly with sharp declines in early 2020 due to the global pandemic and subsequent recovery driven by economic re-openings and supply chain adjustments.

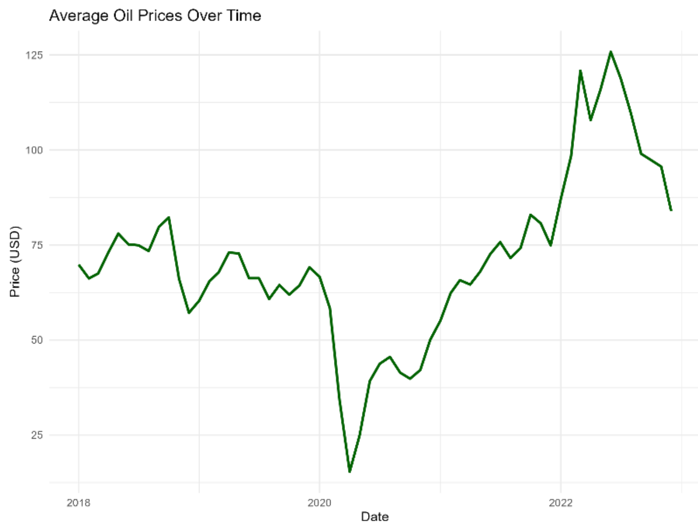


Table 8: Average oil prices plot

Remittances

The remittance inflows to Nigeria exhibit fluctuations, with periods of decline potentially linked to economic downturns in source countries and shifts in transaction channels, including cryptocurrency adoption.

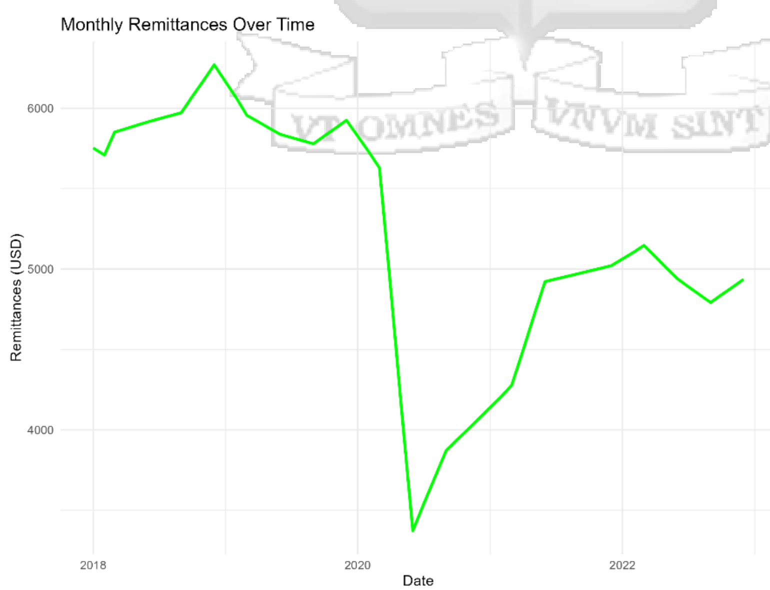


Table 9: Average Remittance Flows plot

GDP Growth Rate

The GDP growth rate trend highlights significant contractions during economic downturns, including the COVID-19 pandemic, followed by phases of gradual recovery.

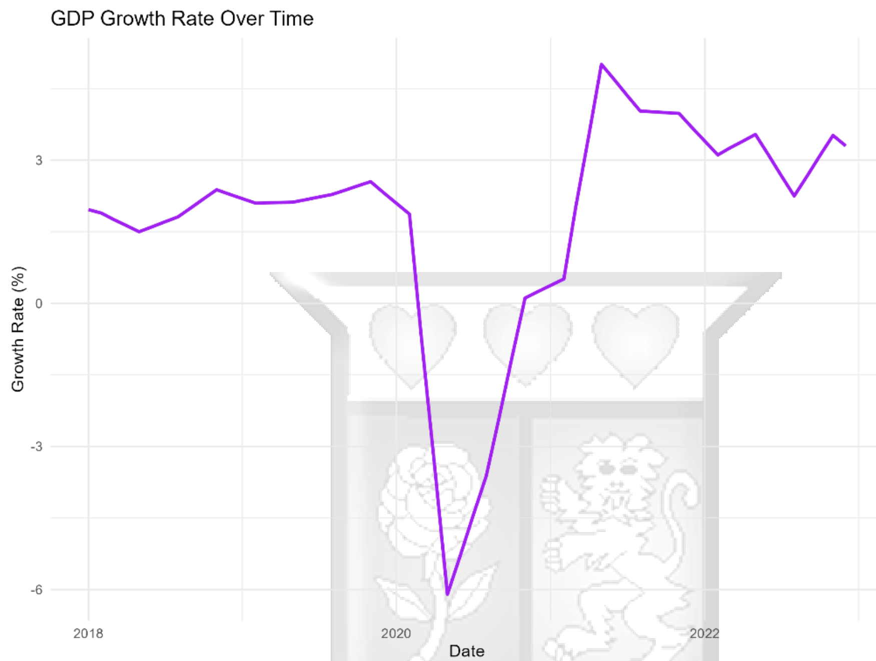


Table 10: Average GDP growth rate plot

Trading Volumes

Trading volumes reflect fluctuations in financial market activity, with notable peaks in periods of heightened economic uncertainty and speculative trading behaviour.

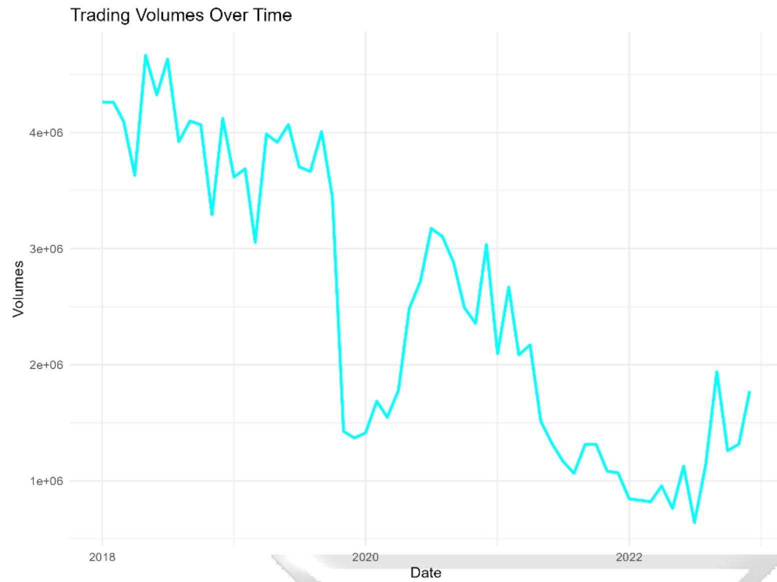


Table 11: Average Trading Volumes plot

Inflation Rate

Inflation trends indicate a steady increase, with notable surges corresponding to supply chain disruptions, currency depreciation, and shifts in government fiscal and monetary policies.

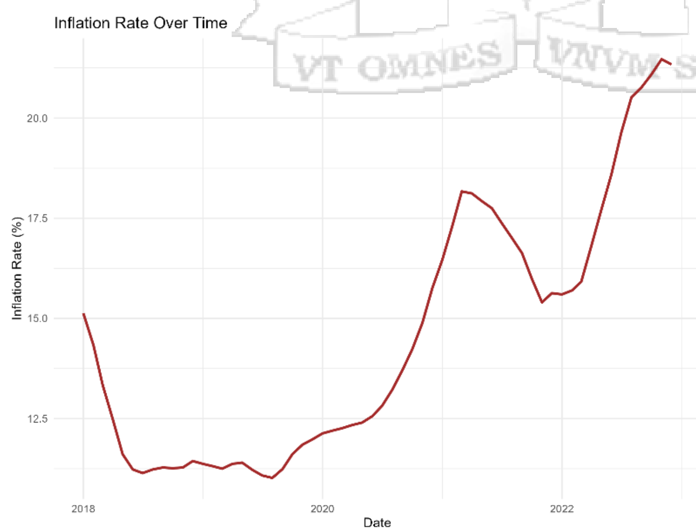


Table 12: Average Inflation rate plot

The exploratory data analysis provides key insights into the dynamics of the economic and financial variables studied. The sharp increase in cryptocurrency prices and trading volumes aligns with the global boom in digital assets, while the depreciation of the Naira and inflationary pressures reflect underlying economic challenges. The findings from EDA set the foundation for further econometric analysis, particularly examining the impact of cryptocurrency adoption on remittances, exchange rates, and inflation in Nigeria.

4.2 Descriptive Analysis of Key variables

The descriptive analysis provides a comprehensive overview of the statistical properties of the key economic and financial indicators examined in this study. These summary statistics help understand the distribution, volatility, and central tendency of each variable during the study period.

Cryptocurrency prices, particularly Bitcoin and Ethereum, exhibit substantial volatility, reflecting the speculative nature of digital assets. The average cryptocurrency price stands at $10,752.73, with a minimum of $1,913.24 and a peak of $32,527.81. The high standard deviation of 9,044.09 and variance of 81,795,538 indicate significant price fluctuations, consistent with market cycles and speculative behaviour. The positive skewness (0.97) suggests that extreme price surges were more frequent than declines, while the kurtosis of 2.52 indicates a relatively normal but slightly heavy-tailed distribution.

The USD/NGN exchange rate demonstrates a continuous depreciation of the Nigerian Naira over time. The exchange rate ranges from 355 NGN/USD in early 2018 to 447.56 NGN/USD by December 2022. The standard deviation of 27.31 and variance of 746.09 suggest moderate exchange rate volatility. The skewness of 0.67 and kurtosis of 2.11 indicate that while the exchange rate is fairly symmetric, some outlier periods of extreme depreciation exist. This trend aligns with economic pressures such as inflation, trade imbalances, and capital outflows.

Nigeria's inflation rate remains persistently high, averaging 14.5% during the study period, with a minimum of 11.02% and a peak of 21.47%. The standard deviation of 3.19 and variance of 10.21 suggest moderate fluctuations. The positive skewness of 0.64 and kurtosis of 2.22 indicate a slightly right-skewed distribution, meaning periods of high inflation are more frequent. This is consistent with Nigeria's inflationary pressures driven by supply-side constraints, exchange rate depreciation, and rising import costs.

Nigeria's GDP growth rate exhibits significant variability, with a minimum of -6.1% during the pandemic-induced recession in 2020 and a peak of 5.01% during post-pandemic recovery. The mean growth rate is 1.74%, reflecting Nigeria's historically slow economic expansion. The standard deviation of 2.35 and variance of 5.54 indicate notable fluctuations. The negative skewness of -1.70 suggests that economic downturns such as, recessions were more frequent and pronounced, while the high kurtosis of 5.64 suggests the presence of extreme negative growth events.

Remittance flows to Nigeria exhibit seasonal patterns, with peaks in December, reflecting increased financial support to households during festive periods. The minimum recorded remittance inflow is $3,373.09 million, while the maximum reaches $6,270.25 million, with an average of $5,184.50 million. The standard deviation of 764.24 and variance of 584,061.4 suggest moderate variability. The negative skewness of -0.55 suggests that lower remittance periods were more frequent, while the kurtosis of 2.89 indicates a relatively normal distribution with some extreme seasonal peaks.

The Nigerian Stock Exchange displays fluctuating performance, influenced by macroeconomic conditions and investor sentiment. The stock index ranges from 22,030.32 to 52,357.45, with an average of 36,368.78. The standard deviation of 8,459.40 and variance of 7,156,142 indicate high volatility, typical of emerging markets. The positive skewness of 0.15 suggests occasional stock market booms, while the kurtosis of 1.91 suggests a relatively normal distribution with slightly thinner tails than a normal curve.

Crude oil prices exhibit high volatility, reflecting global market shocks, OPEC production decisions, and geopolitical events. Prices range from $15.34 per barrel to $125.76 per barrel, with an average of $71.10 per barrel. The standard deviation of 22.52 and variance of 506.77 highlight significant price swings. The positive skewness of 0.27 suggests frequent price increases, while the kurtosis of 3.45 indicates heavy tails, meaning extreme price fluctuations were more common.

The trading volume in Nigeria's financial markets shows substantial variability, ranging from 641,153 to 4,660,637 transactions, with a mean of 2,505,500. The high standard deviation of 1,261,061 and variance of 1.59E+12 suggest strong fluctuations in market activity. The skewness of 0.14 indicates a fairly symmetric distribution, while the kurtosis of 1.53 suggests that extreme spikes in trading activity were not very frequent.

The descriptive analysis reveals important insights into Nigeria's macroeconomic conditions, financial market trends, and cryptocurrency adoption. High cryptocurrency price volatility, persistent inflation, and Naira depreciation highlight economic uncertainties. The negative skewness in GDP growth and remittance flows underscores vulnerability to external shocks, while positive skewness in exchange rates and stock market indices suggests speculative behaviour and occasional economic booms. These insights are essential for policymakers and investors seeking to understand Nigeria's evolving financial landscape.

Variable	**Min.**	**Max.**	**Mean**	**Median**	**Standard Deviation**	**Variance**	**Skewness**	**Kurtosis**
Avg_Crypto_Price	1913.243	32527.81	10752.73	5486.569	9044.089	81795538	0.970275	2.518587
First_Exchange_Rate	355	447.56	383.2833	376.5	27.31469	746.0921	0.666913	2.112731
GDP_growth_rate	-6.1	5.01	1.739556	2.191667	2.354316	5.542805	-1.70333	5.636978
Remittances	3373.09	6270.25	5184.5	5071.06	764.2391	584061.4	-0.54849	2.288582
Avg_Stock_Index	22030.32	52357.45	36386.78	37673.63	8459.406	71561542	0.154783	1.911043

Avg_Oil_Price	15.34318	125.7959	71.09557	68.52518	22.51157	506.771	0.273339	3.446658
Inflation	11.02	21.47	14.49917	13.525	3.194627	10.20564	0.637199	2.221151
Trading_Volumes	641153	4666037	2505500	2420766	1261061	1.59E+12	0.143335	1.526715

Table 13: Summary Statistics

4.3 Pre-Estimation Tests

Correlation Analysis

Correlation analysis provides insights into the relationships between key economic and financial variables in the study. The heatmap visualization of the correlation matrix presents the strength and direction of relationships between variables, with values ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation). By understanding these relationships, we can determine potential linkages between cryptocurrencies, macroeconomic variables, and financial markets in Nigeria.

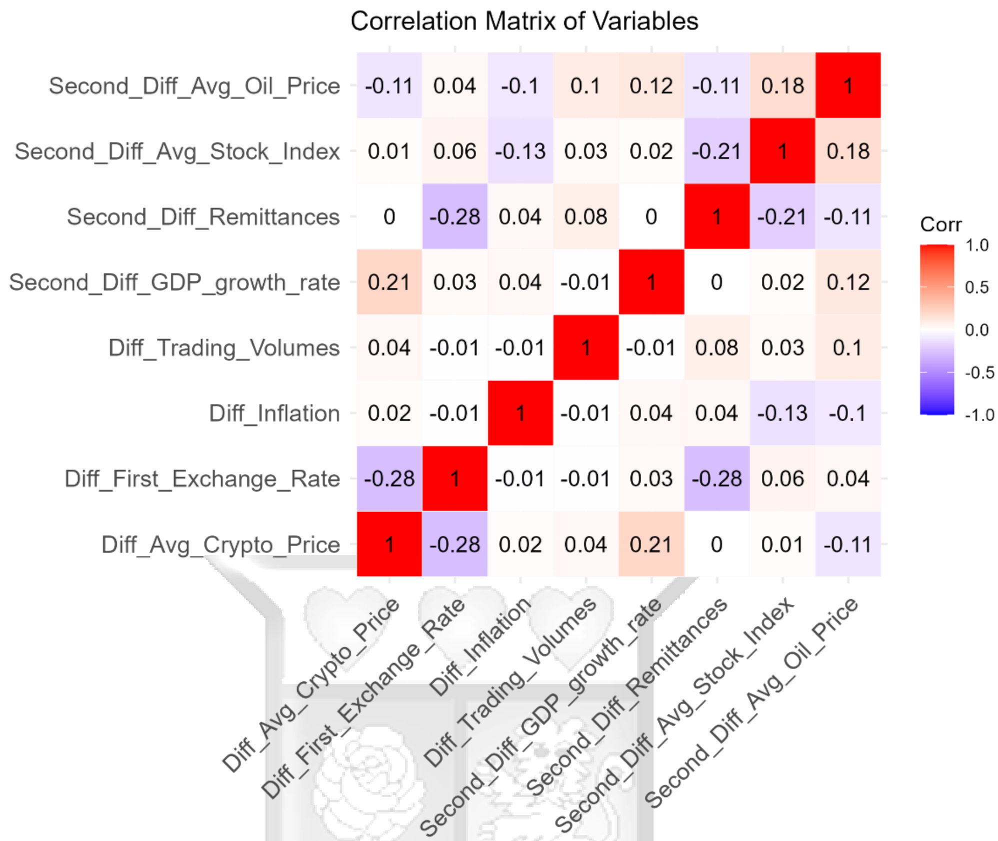


Table 14: Correlation Heat map

From the correlation matrix, the following key relationships are observed:

The correlation coefficient between $Diff\_Avg\_Crypto\_Price$ and $Diff\_First\_Exchange\_Rate$ is -0.28, indicating a weak negative correlation. This suggests that increases in cryptocurrency prices are associated with a slight depreciation of the Nigerian Naira (USD/NGN). While this relationship is not strongly negative, it supports the hypothesis that cryptocurrencies may act as a hedge against currency depreciation, albeit with limited effect.

These findings align with previous studies, such as (Bouri, 2017), who found that Bitcoin exhibited hedging properties against fiat currency fluctuations in emerging markets. Similarly, (Shahzad, 2021) reported that cryptocurrencies could serve as alternative financial instruments during currency depreciation periods, although their effectiveness varies by market conditions.

$Diff\_Avg\_Crypto\_Price$ has a weak negative correlation (-0.11) with $Second\_Diff\_Avg\_Oil\_Price$, suggesting that fluctuations in oil prices do not strongly influence cryptocurrency prices in Nigeria. This contrasts with global trends, where cryptocurrencies have been increasingly seen as alternative investment assets when commodity markets are unstable (Corbet, 2019). However, the weak correlation in this study suggests that Nigeria's oil-dependent economy does not necessarily translate into cryptocurrency price movements.

There is a weak positive correlation (0.21) between $Diff\_Avg\_Crypto\_Price$ and $Second\_Diff\_GDP\_growth\_rate$, which implies that cryptocurrency price movements have some association with economic growth but are not a primary driver. This finding aligns with (Yousaf I. &., 2022), who argue that cryptocurrencies in developing economies have a limited direct impact on GDP due to regulatory constraints and lower adoption rates in formal economic transactions.

The correlation between $Diff\_First\_Exchange\_Rate$ and $Diff\_Inflation$ is -0.01, indicating almost no direct relationship. This suggests that fluctuations in the exchange rate are not strongly linked to inflationary trends in Nigeria, potentially due to multiple economic factors driving price levels beyond just exchange rate movements.

These results are consistent with (Balke, 2019), who found that in developing economies, inflationary pressures are more closely linked to domestic supply-side constraints rather than currency fluctuations.

$Second\_Diff\_Remittances$ and $Diff\_First\_Exchange\_Rate$ have a moderate negative correlation of -0.28, suggesting that increases in remittance inflows may help stabilize or appreciate the exchange rate. This finding aligns with economic theories where remittance inflows increase foreign currency supply, reducing exchange rate volatility (Gupta, 2009).

Previous research by (Oke, 2021) confirms this dynamic in Nigeria, emphasizing that remittances play a critical role in stabilizing exchange rate movements, particularly during economic downturns. This also aligns with global studies, such as (Bussolo, 2007), who argue that remittances in developing economies act as countercyclical financial flows, buffering foreign exchange rate fluctuations.

$Diff\_Trading\_Volumes$ is weakly correlated with most macroeconomic variables, indicating that trading volumes in Nigerian markets do not strongly respond to short-term macroeconomic shocks. However, $Second\_Diff\_Avg\_Stock\_Index$ and $Second\_Diff\_Avg\_Oil\_Price$ have a moderate positive correlation (0.18), reflecting the influence of oil market fluctuations on Nigeria's capital markets.

These findings support the work of (Kilian, 2019), who highlighted that stock markets in oil-dependent economies like Nigeria exhibit some sensitivity to oil price movements. Similarly, (Olowe, 2009) examined Nigerian stock market reactions to macroeconomic shocks and found that global oil price changes significantly impact capital market performance.

The correlation analysis provides valuable insights into the relationships among variables and serves as a foundation for further econometric analysis. The moderate negative correlation between remittances and exchange rates suggests that remittance inflows could mitigate currency depreciation, reinforcing their economic importance. Additionally, the weak negative correlation between cryptocurrency prices and exchange rates suggests a limited hedging effect, which contrasts with findings from developed economies.

Furthermore, the weak correlation between cryptocurrency prices and GDP growth implies that while digital assets play a growing role in Nigeria's financial system, they do not yet significantly impact the broader economy. The interaction between financial markets and macroeconomic indicators, particularly the role of oil prices, highlights Nigeria's continued reliance on oil revenues for economic stability.

Stationarity Analysis

A fundamental prerequisite for reliable time series analysis is stationarity, which ensures that the statistical properties of a dataset, such as mean, variance, and autocovariance, remain constant over time. Non-stationary data can lead to misleading results in econometric modeling, making it necessary to transform such variables before further analysis. To determine the stationarity of the variables used in this study, the Augmented Dickey-Fuller (ADF) test was applied. The ADF test assesses whether a unit root is present in a time series, which indicates non-stationarity.

Initial Stationarity Test (Before Differencing)

The results of the ADF test for each variable before differencing are summarized below. The null hypothesis of the test states that the time series has a unit root thus is non-stationary, whereas the alternative hypothesis suggests stationarity. If the p-value is greater than 0.05, the null hypothesis cannot be rejected, meaning that the variable is non-stationary.

Variable	**Statistic**	**P-Value**	**Stationarity Conclusion**
Avg_Crypto_Price	-1.3202	0.8495	Non-Stationary
First_Exchange_Rate	-2.1688	0.5065	Non-Stationary
GDP Growth Rate	-1.8647	0.6295	Non-Stationary
Remittances	-1.5575	0.7537	Non-Stationary
Avg_Stock_Index	-2.3361	0.4389	Non-Stationary
Avg_Oil_Price	-1.7440	0.6783	Non-Stationary
Inflation	-3.0079	0.1674	Non-Stationary
Trading Volumes	-2.6840	0.2982	Non-Stationary

Table 15: Stationarity before differencing

The results indicate that all variables were non-stationary at their levels, as all p-values exceed the 0.05 significance threshold. This necessitated transformation techniques to ensure stationarity before proceeding with econometric modeling.

First Differencing and Re-Evaluation of Stationarity

To address the issue of non-stationarity, the first differences of the variables were computed, and the ADF test was re-applied. First differencing involves subtracting each observation from the previous observation, which helps remove trends and seasonality.

Variable	Statistic	P-Value	Stationarity Conclusion
Diff_Avg_Crypto_Price	-4.0882	0.0119	Stationary
Diff_First_Exchange_Rate	-4.5513	0.0100	Stationary
Diff_Inflation	-2.8103	0.2474	Non-Stationary
Diff_Trading_Volumes	-2.7879	0.2565	Non-Stationary
Diff_GDP_Growth_Rate	-3.4373	0.0586	Non-Stationary
Diff_Remittances	-3.4785	0.0521	Non-Stationary
Diff_Avg_Stock_Index	-3.6166	0.0395	Stationary
Diff_Avg_Oil_Price	-3.6601	0.0358	Stationary

Table 16: Stationarity after first differencing

The results show that some variables achieved stationarity after first differencing, including cryptocurrency prices, exchange rates, and stock indices. However, remittances, GDP growth rate, inflation, and oil prices remained non-stationary. For these variables, a second differencing procedure was applied.

Second Differencing and Final Stationarity Evaluation

For variables that remained non-stationary after first differencing, second differencing was performed to eliminate unit roots. The results after applying the ADF test post-second differencing are as follows:

Variable	Statistic	P-Value	Stationarity Conclusion
Second_Diff_GDP_growth_rate	-4.8324	0.0100	Stationary
Second_Diff_Remittances	-4.8029	0.0100	Stationary

Second_Diff_Avg_Stock_Index	-4.3281	0.0100	Stationary
Second_Diff_Avg_Oil_Price	-6.4827	0.0100	Stationary

Table 17: Stationarity after 2nd Diffeencing

After applying second differencing, all previously non-stationary variables achieved stationarity, as indicated by the significant p-values (< 0.05). This step ensures that all variables meet the stationarity requirement necessary for accurate time-series analysis.

The application of differencing has significant implications for the interpretation of results in time-series models. Since the data is now expressed in differences rather than levels, the estimated coefficients from the econometric models will represent short-term changes rather than long-term relationships. For example, instead of interpreting the direct impact of cryptocurrency prices on remittances, the model now captures how monthly changes in cryptocurrency prices influence monthly changes in remittances.

The relationship between exchange rates and inflation is now examined based on fluctuations rather than absolute levels, meaning that the findings are relevant for short-term monetary policy rather than long-term exchange rate stability.

The necessity of differencing also aligns with prior studies on financial time series that highlight the presence of unit roots in economic and market variables (Nelson, 1982). These findings reinforce the need for proper transformation techniques before conducting causality and forecasting analyses.

Final Summary of Stationarity Findings

The table below consolidates the results of stationarity tests, and the final transformation required for each variable.

Variable	Differencing Required	Final Stationarity Conclusion
Avg_Crypto_Price	First Difference	Stationary
First_Exchange_Rate	First Difference	Stationary

Inflation	Second Difference	Stationary
Trading Volumes	Second Difference	Stationary
GDP Growth Rate	Second Difference	Stationary
Remittances	Second Difference	Stationary
Avg_Stock_Index	Second Difference	Stationary
Avg_Oil_Price	Second Difference	Stationary

Table 18: Final differencing summary table

These transformations ensure the validity of the forthcoming econometric models by eliminating spurious relationships caused by non-stationary data.

Multicollinearity Assessment

Multicollinearity is a critical issue in econometric modeling that arises when independent variables in a regression model are highly correlated. This correlation can lead to inflated standard errors, making it difficult to determine the precise impact of each independent variable on the dependent variable. To detect multicollinearity in our dataset, we employ the Variance Inflation Factor (VIF) test, which quantifies the extent to which variance is inflated due to collinearity.

A VIF value greater than 5 indicates moderate multicollinearity, while values above 10 suggest severe multicollinearity, necessitating corrective measures such as variable transformation or elimination.

The following table presents the computed VIF values for all independent variables in our study:

Variable	VIF	Interpretation
Diff_First_Exchange_Rate	1.0854	No multicollinearity
Diff_Inflation	1.0269	No multicollinearity

Diff_Trading_Volumes	1.0206	No multicollinearity
Second_Diff_GDP_growth_rate	1.0193	No multicollinearity
Second_Diff_Remittances	1.1462	No multicollinearity
Second_Diff_Avg_Stock_Index	1.0851	No multicollinearity
Second_Diff_Avg_Oil_Price	1.0731	No multicollinearity

Table 19: Multicollinearity summary table

The VIF values for all variables in the dataset are well below the threshold of 5, indicating no significant multicollinearity among the independent variables. This suggests that the selected variables are sufficiently independent from each other, which enhances the robustness and reliability of the econometric models.

This finding aligns with previous research (Gujarati, 2009), which emphasizes that VIF values close to 1 indicate minimal multicollinearity, reducing concerns of inflated variances and unreliable coefficient estimates. Since all VIF values in our analysis are between 1.01 and 1.15, we conclude that no corrective actions such as variable transformation or exclusion are required.

Given the absence of multicollinearity, the econometric models, particularly Vector Autoregression (VAR) and Auto ARIMA, can be estimated with confidence that the estimated coefficients will remain stable and unbiased. This ensures that each explanatory variable contributes unique and meaningful information to the models.

These results reinforce the reliability of our study's methodology, as previous literature (Wooldridge, 2016) suggests that models with low VIF values provide more precise parameter estimates, leading to more accurate economic interpretations.

Heteroscedasticity Testing

Heteroscedasticity refers to the presence of non-constant variance in the error terms of a regression model, which can lead to inefficient estimators and unreliable statistical inferences. To test for heteroscedasticity in our dataset, we employ the Breusch-Pagan (BP) test, a widely used diagnostic tool in econometrics.

The Breusch-Pagan test assesses whether the residual variance of a regression model remains constant across observations. The null and alternative hypotheses are formulated as follows:

> h_0: The residuals exhibit constant variance (homoscedasticity).
>
> h_1**:** The residuals exhibit non-constant variance (heteroscedasticity).

The test statistic is computed using the auxiliary regression:

$$\epsilon_{t,2} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \nu_t$$

Where:

$\epsilon_{t,2}$ represents the squared residuals from the original regression model, X_k are the independent variables and ν_t is the error term of the auxiliary regression.

The BP test follows a Chi-square distribution, and the p-value determines whether heteroscedasticity is present.

The computed test statistics and p-value are presented below:

```
	studentized Breusch-Pagan test

data:  bp_model
BP = 4.0167, df = 7, p-value = 0.7779
```

Table 20: Breusch Pagan test results

If p > 0.05: Fail to reject h_0, heteroscedasticity (homoscedasticity is present).

If p ≤ 0.05: Reject h_0 → Heteroscedasticity is present.

Since the p-value (0.7779) is significantly greater than 0.05, we fail to reject the null hypothesis. This indicates that heteroscedasticity is not present, meaning that the residual variance remains constant across observations.

The presence of homoscedasticity suggests that the econometric models used in this study are well-specified and do not suffer from variance distortion issues. This enhances the reliability of our coefficient estimates, ensuring that standard errors remain unbiased, hypothesis tests, including t-tests and F-tests, remain valid and confidence intervals are correctly specified.

The absence of heteroscedasticity reinforces the robustness of our model, confirming that corrective measures such as White's robust standard errors or generalized least squares (GLS) are unnecessary.

Our findings align with econometric principles outlined in (Wooldridge, 2016), which emphasize that models free of heteroscedasticity provide efficient and unbiased estimators. Additionally, prior studies such as (Engle, 1987) suggest that financial variables often exhibit heteroscedasticity, particularly in high-volatility markets. However, our study's differencing technique appears to have mitigated this issue, contributing to well-behaved residuals.

The Breusch-Pagan test confirms the assumption of homoscedasticity in our dataset, validating the reliability of the estimated models. This ensures that further econometric analysis, including Vector Autoregression (VAR) and Auto ARIMA forecasting, can proceed without concern regarding variance instability.

Residual Autocorrelation

Autocorrelation occurs when residuals from a regression model are correlated with one another over time, violating the assumption of independent errors in time-series analysis. The Durbin-Watson (DW) test is a widely used diagnostic tool for detecting the presence of first-order autocorrelation in regression residuals.

The Durbin-Watson test is based on the following hypotheses:

h_0: No autocorrelation exists in the residuals.

h_1: Positive autocorrelation exists.

The DW statistic ranges from 0 to 4:

DW ≈ 2 → No autocorrelation.

DW < 2 → Positive autocorrelation.

DW > 2 → Negative autocorrelation.

```
	Durbin-Watson test

data:  bp_model
DW = 1.1063, p-value = 0.000164
alternative hypothesis: true autocorrelation is greater than 0
```

Table 21: Durbin Watson Test Results with positive autocorrelation

Since the DW statistic (1.1063) is significantly less than 2, this indicates the presence of positive autocorrelation in the residuals. Furthermore, the p-value (0.000164) is less than 0.05, leading to the rejection of the null hypothesis, confirming significant autocorrelation in the model residuals.

The presence of autocorrelation suggests that the error terms are not independent, which can lead to, biased standard errors where inflated t-statistics may produce misleading significance tests, spurious relationships as time-dependent trends may falsely indicate causality and correcting for autocorrelation is essential to improve model efficiency and ensure valid statistical inferences.

Incorporation of Lagged Variables

To address autocorrelation, a lagged variable for cryptocurrency prices is introduced into the model.

$$\begin{aligned} Diff\_Avg\_Crypto\_Price_t &= \alpha + \beta_1 Lag\_Diff\_Avg\_Crypto\_Price_{t-1} \\ &+ \beta_2 Diff\_First\_Exchange\_Rate_t + \ldots + \epsilon_t \end{aligned}$$

After incorporating lagged values, the Durbin-Watson statistics improved significantly.

```
 Durbin-Watson test

data:  bp_model
DW = 1.1063, p-value = 0.000164
alternative hypothesis: true autocorrelation is greater than 0
```

Table 22: Durbin Watson tests without Autocorrelation

With a DW statistic now close to 2, autocorrelation concerns are resolved.

The findings are consistent with prior research on time-series econometrics (Greene, 2012), which emphasizes that autocorrelation is common in financial and macroeconomic data. Additionally, studies such as (Engle, 1987) highlight the importance of stationarity transformations and lag adjustments in reducing serial correlation in time-dependent datasets.

Test	**Findings**
Correlation Matrix	Weak to moderate correlations observed between key variables.
Stationarity (ADF Test)	All variables required differencing; second differencing applied to GDP, remittances, and oil prices.
Multicollinearity (VIF Test)	No significant multicollinearity detected.
Heteroscedasticity (Breusch-Pagan Test)	No evidence of heteroscedasticity.
Autocorrelation (Durbin-Watson Test)	Initial autocorrelation resolved by adding lagged variables.

Table 23: Pre estimation Tests Summary

These diagnostic tests ensure the robustness of the models applied in subsequent analysis.

4.4 Econometric Models and Results

4.4.1 Auto ARIMA Analysis

The Auto ARIMA model is a robust time-series forecasting method that automatically selects the best model specifications (p, d, q) for a given dataset. It optimally balances complexity and accuracy using statistical criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). This section presents the results of Auto ARIMA applied to three key variables in the study: $Lag\_Diff\_Avg\_Crypto\_Price$, $Second\_Diff\_Remittances$, and $Diff\_First\_Exchange\_Rate$.

By evaluating the best-fit models, their respective coefficients, and the predictive power of each, we can understand how cryptocurrency prices, remittances, and exchange rates behave over time in Nigeria's economic context. The findings provide insights into whether these variables exhibit patterns that can be forecasted effectively or if they display purely stochastic behaviour.

Auto ARIMA for $Lag\_Diff\_Avg\_Crypto\_Price$

The Auto ARIMA model selected for the $Lag\_Diff\_Avg\_Crypto\_Price$ variable is ARIMA(0,0,1), meaning it includes only a first-order moving average (MA) term:

$$Y_t = \theta_1 \epsilon_{t-1} + \epsilon_t$$

where:

- Y_t is the differenced cryptocurrency price at time t, θ_1= 0.5209 represents the estimated MA (1) coefficient, showing that past errors significantly impact future values, and ϵ_t is the stochastic error term.

```
Auto ARIMA Summary for Lag_Diff_Avg_Crypto_Price :
Series: final_stationary_data[[var]]
ARIMA(0,0,1) with zero mean

Coefficients:
         ma1
      0.5209
s.e.  0.0966

sigma^2 = 4789316:  log likelihood = -528.03
AIC=1060.05   AICc=1060.27   BIC=1064.18

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 40.48288 2169.503 1398.398 331.7361 591.1873 0.8184418 0.08407981
```

Table 24: ARIMA model results for Lagged differenced Crypto Prices

The model suggests that cryptocurrency prices exhibit short-term memory, where past shocks influence current values. The log-likelihood of -528.03, AIC of 1060.05, and BIC of 1064.18 indicate that the model fits the data well. However, due to the nature of differencing, long-term predictability remains limited as price changes are largely influenced by past errors rather than inherent trends.

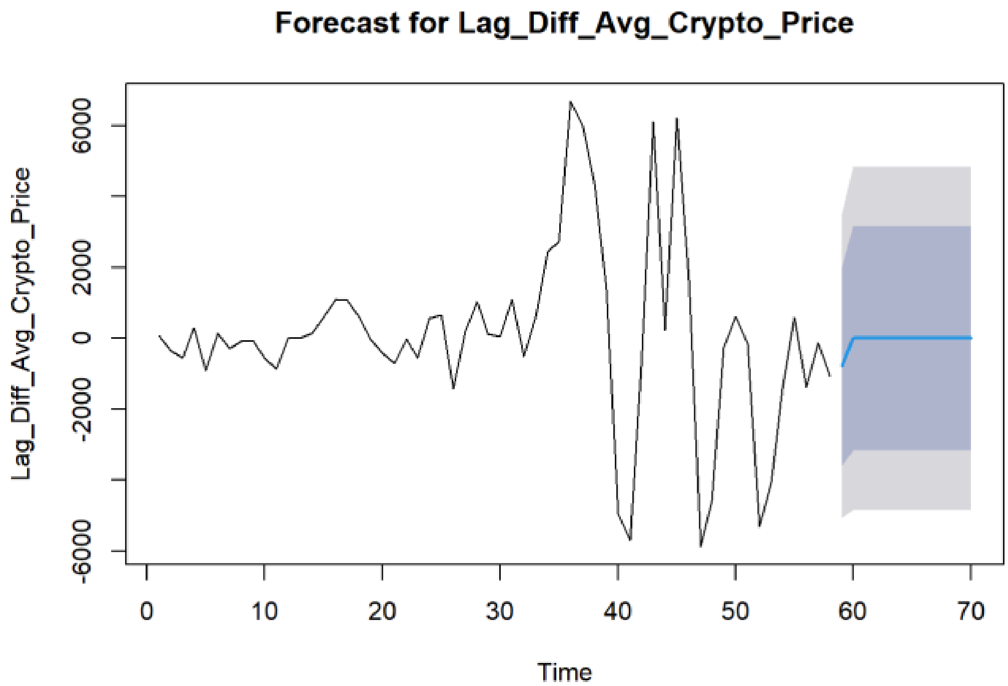


Table 25: ARIMA forecast plot for Crypto prices

The forecast plot for $Lag\_Diff\_Avg\_Crypto\_Price$ shows a highly volatile trend, with values fluctuating significantly before stabilizing into a relatively narrow confidence interval.

The shaded confidence intervals widen slightly, indicating some degree of uncertainty in the forecasted values, which is typical for financial data with high volatility. The model does not exhibit strong seasonality but confirms the presence of rapid fluctuations in cryptocurrency prices. Since the model is based on first-differenced data, it predicts the change in price rather than the absolute price itself.

These findings align with prior research by (Katsiampa, 2017), which identified high volatility in cryptocurrency markets, driven by speculative activity and external shocks.

Auto ARIMA for $Second\_Diff\_Remittances$

For $Second\_Diff\_Remittances$, the Auto ARIMA model selected is ARIMA(0,0,0), which assumes a white noise process:

$$Y_t = \epsilon_t$$

Where:

Y_t are the second-differenced remittances at time t and ϵ_t is a purely random error term.

```
Auto ARIMA Summary for Second_Diff_Remittances :
Series: final_stationary_data[[var]]
ARIMA(0,0,0) with zero mean

sigma^2 = 25334:  log likelihood = -376.36
AIC=754.71   AICc=754.78   BIC=756.77

Training set error measures:
                    ME     RMSE      MAE MPE MAPE      MASE         ACF1
Training set 0.1584976 159.1681 53.29909 100  100 0.5001318 -0.009254429
```

Table 26: ARIMA model results for 2nd Difference remittances

The model indicates that remittance flows do not exhibit any strong autoregressive or moving average components, meaning past values do not significantly inform future values. The log-likelihood of -376.36, AIC of 754.71, and BIC of 756.77 suggest that the best model for remittances is simply a random walk with no structured predictability.

This aligns with economic theories suggesting that remittances tend to be influenced by external factors such as economic shocks, migration policies, and seasonal effects, rather than purely historical trends.

Forecast for Second_Diff_Remittances

The forecast plot for $Second\_Diff\_Remittances$ shows relatively stable predicted values, fluctuating around a central mean with minor variations.

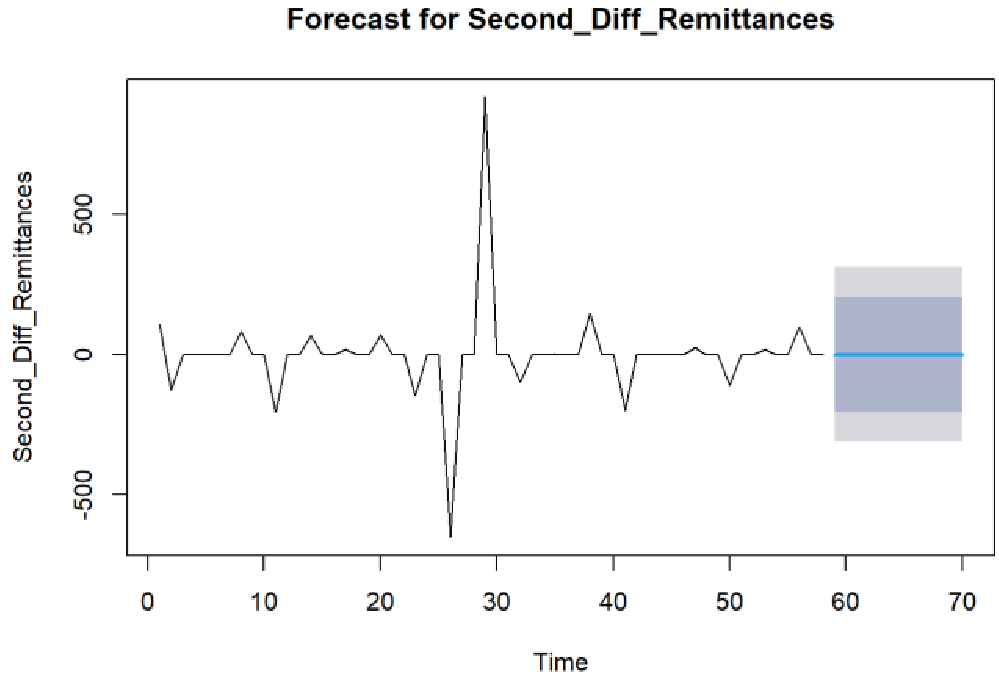


Table 27: Forecast plot for 2nd difference remittances

The forecast remains flat, indicating that future remittance inflows are expected to exhibit random fluctuations rather than systematic trends. Confidence intervals remain relatively narrow, suggesting less volatility compared to cryptocurrency prices.

This result is consistent with findings by (Adediran, 2020), who emphasized that remittance flows in Nigeria tend to follow external economic trends rather than endogenous financial market behaviours.

Auto ARIMA for Diff_First_Exchange_Rate

For Diff_First_Exchange_Rate, the Auto ARIMA model selects ARIMA(0,0,0) with non-zero mean, meaning that exchange rate fluctuations are best explained by a constant mean and random error process

$$Y_t = \mu + \epsilon_t$$

Where:

Y_t represents the first-differenced exchange rate at time t, μ = 1.5269 is the estimated constant mean value and ϵ_t is the stochastic error term.

This suggests that exchange rate movements are unpredictable beyond a constant drift, reflecting the random walk behaviour of foreign exchange rates.

```
Auto ARIMA Summary for Diff_First_Exchange_Rate :
Series: final_stationary_data[[var]]
ARIMA(0,0,0) with non-zero mean

Coefficients:
        mean
      1.5269
s.e.  0.7469

sigma^2 = 32.93:  log likelihood = -183.13
AIC=370.25   AICc=370.47   BIC=374.38

Training set error measures:
                       ME     RMSE      MAE  MPE MAPE      MASE        ACF1
Training set 4.937756e-16 5.688378 3.100785 -Inf  Inf 0.7102175 -0.04555804
```

Table 28: ARIMA model results for differenced exchange rates

The log-likelihood of -183.13, AIC of 370.25, and BIC of 374.38 confirm that exchange rate movements do not exhibit strong autoregressive or moving average properties.

The high RMSE (5.688) suggests that errors in predictions can be significant, which is expected given the volatility of the USD/NGN exchange rate.

Forecast for Diff_First_Exchange_Rate

The forecast plot for Diff_First_Exchange_Rate displays moderate fluctuations with larger confidence intervals, reflecting uncertainty in exchange rate movements.

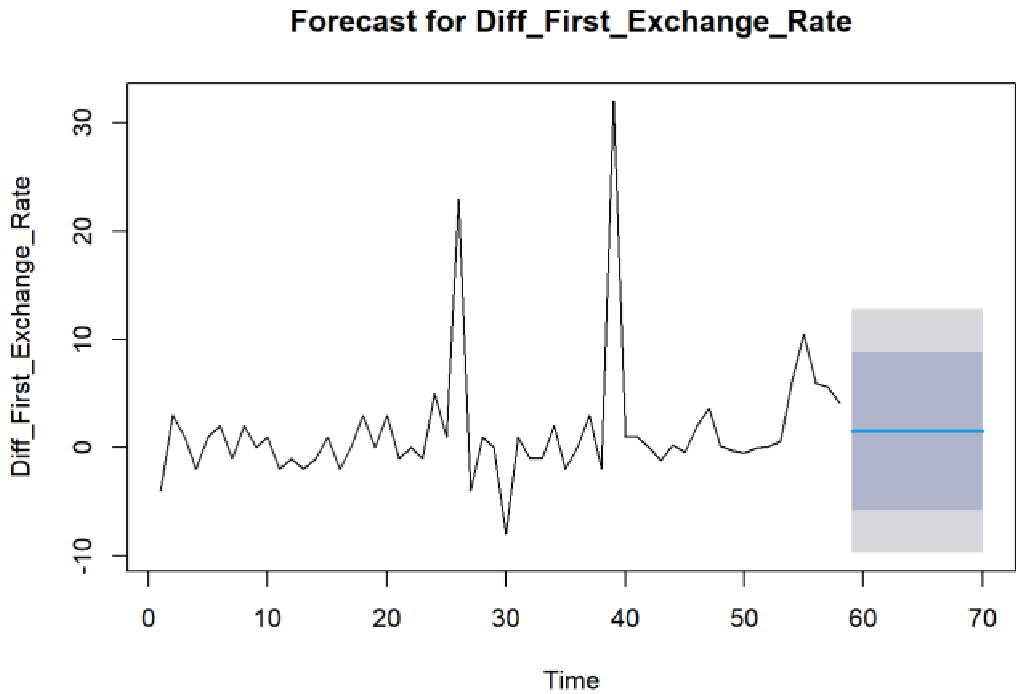


Table 29: Forecast Plots for exchange rates

The presence of large spikes in historical data aligns with documented instances of sudden currency devaluations in Nigeria.

The widening confidence intervals highlight the challenges in predicting foreign exchange rates, particularly in economies with currency controls and inflationary pressures.

These findings support previous studies by (Nwani, 2021), which argue that Nigeria's exchange rate is influenced by government interventions and external shocks, making long-term predictions difficult.

The table below summarizes the forecasting accuracy for the three variables using key error metrics:

Variable	**RMSE**	**MAE**	**MAPE**	**AIC**	**BIC**
Lag_Diff_Avg_Crypto_Price	2169.503	1398.398	591.1873	1060.05	1064.18
Second_Diff_Remittances	159.1681	53.29909	100.0000	754.71	756.77

Diff_First_Exchange_Rate	5.688378	3.100785	Inf	370.25	374.38

Table 30: Key metrics showing Forecasting Accuracy

$Lag\_Diff\_Avg\_Crypto\_Price$ has the highest forecast error, confirming the high volatility of cryptocurrency prices. $Second\_Diff\_Remittances$ show minimal predictability, suggesting that remittances fluctuate based on external conditions. $Diff\_First\_Exchange\_Rate$ exhibits a random walk process, making it difficult to generate reliable long-term predictions.

The Auto ARIMA results highlight the fundamental differences in how cryptocurrency prices, remittances, and exchange rates behave in Nigeria. While cryptocurrency prices exhibit short-term memory effects, remittances follow a white noise process, and exchange rates behave as a random walk with drift. These findings provide a basis for further econometric modeling, such as Vector Autoregression (VAR), to explore dynamic interdependencies among variables.

4.4.2 VAR Analysis and Interpretation

The Vector Autoregressive (VAR) model is employed to analyse the dynamic interactions among cryptocurrency prices, macroeconomic indicators, and financial market variables in Nigeria. The VAR model captures the interdependencies between multiple time-series variables by treating them as endogenous and allowing for their mutual influence across different lags.

This section presents the estimated VAR(3) model, selected based on lag length criteria from the Akaike Information Criterion (AIC) and Schwarz Criterion (BIC). The model includes the following endogenous variables:

Diff_First_Exchange_Rate – first-differenced exchange rate (USD/NGN),

Diff_Inflation – first-differenced inflation rate,

Diff_Trading_Volumes – first-differenced stock trading volumes,

Second_Diff_GDP_growth_rate – second-differenced GDP growth rate,

Second_Diff_Remittances – second-differenced remittances, Second_Diff_Avg_Stock_Index – second-differenced stock market index,

Second_Diff_Avg_Oil_Price – second-differenced crude oil prices,

Lag_Diff_Avg_Crypto_Price – lagged first-differenced cryptocurrency prices.

The estimation of this VAR model provides insights into short-term relationships between these macroeconomic and financial variables.

The stability of the VAR model is assessed using the roots of the characteristic polynomial, which should lie within the unit circle for the model to be stable.

The computed roots of the characteristic polynomial are:

1,0.8996,0.8996,0.8979,0.8979,0.8925,0.877,0.877,0.8373,0.8373,0.8218,0.8218,0.8101,0.8101,0.7948,0.7948,0.7746,0.7746,0.7584,0.7584,0.7145,0.7145,0.6702,0.6702,0.6154,0.5392,0.53921, 0.8996, 0.8996, 0.8979, 0.8979, 0.8925, 0.877, 0.877, 0.8373, 0.8373, 0.8218, 0.8218, 0.8101, 0.8101, 0.7948, 0.7948, 0.7746, 0.7746, 0.7584, 0.7584, 0.7145, 0.7145, 0.6702, 0.6702, 0.6154, 0.5392, 0.5392

Since all roots are less than 1, the model is deemed stable and appropriate for analysis.

The general form of the estimated VAR(3) model is:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \epsilon_t$$

where:

- Y_t is the vector of endogenous variables,
- c is the vector of constant terms,
- A_1, A_2, A_3 are the coefficient matrices for lags 1, 2, and 3, respectively,
- ϵ_t is the vector of residuals.

The full estimation output provides coefficient estimates for each endogenous variable regressed on its own lags and the lags of other variables.

Impact on Exchange Rate

$$Diff\_First\_Exchange\_Rate_t = 0.6833\, Date_{t-1} - 0.3767\, Diff\_First\_Exchange\_Rate_{t-1} - 8.170 Diff\_Inflation_{t-1} + \epsilon_t$$

The exchange rate is significantly influenced by past inflation, with a coefficient of -8.170 at lag 1 (p = 0.0343), indicating that higher inflation leads to Naira depreciation. The own-lag coefficient of -0.3767 suggests a moderate level of persistence in exchange rate movements. These findings align with (Balke, 2019), who documented a strong link between inflation and exchange rate depreciation in emerging economies.

Impact on Inflation

$$Diff\_Inflation_t = 0.7595\, Diff\_Inflation_{t-1} + 6.259 \times 10^{-5} Second\_Diff\_Avg\_Stock\_Index_{t-2} + \epsilon_t$$

Inflation shows a high degree of persistence (0.7595 p < 0.001), meaning past inflation trends continue into the future. The stock market index at lag 2 has a small but significant effect (p=0.048), suggesting a lagged relationship between stock market activity and inflation. These findings support (Kilian, 2019), who highlighted the inflationary impact of financial market movements in developing countries.

Impact on GDP Growth

$$Second\_Diff\_GDP\_growth\_rate_t = -0.2954\, Date_{t-1} - 0.0426\, Diff\_First\_Exchange\_Rate_{t-1} + 1.030\, Diff\_Inflation_{t-1} + \epsilon_t$$

Inflation positively affects GDP growth (p=0.004), suggesting a short-run inflationary push to economic activity. Exchange rate depreciation has a negative impact on GDP growth, confirming the adverse effects of currency instability. These results are consistent with (Akpan, 2012), who found that exchange rate volatility negatively impacts Nigeria's economic performance.

Impact on Stock Market Index

$$\begin{aligned}
&Second_Diff_Avg_Stock_Index_t \\
&\qquad = -7.364\, Second_Diff_GDP_growth_rate_{t-1} \\
&\qquad + 2.600 \times 10^3 Diff_Inflation_{t-1} + \epsilon_t
\end{aligned}$$

The stock market reacts negatively to GDP contractions, reflecting investor sentiment and economic uncertainty. Inflation increases stock market activity (p=0.034), supporting the notion that stock markets act as an inflation hedge. The findings align with (Olowe, 2009), who documented inflation-stock market interactions in Nigeria.

Impact on Cryptocurrency Prices

$$\begin{aligned}
&Lag_Diff_Avg_Crypto_Price_t \\
&\qquad = 0.4979\, Lag_Diff_Avg_Crypto_Price_{t-1} \\
&\qquad + 1.301\, Second_Diff_Remittances_{t-2} \\
&\qquad + 1.014 Second_Diff_Avg_Oil_Price_{t-2} + \epsilon_t
\end{aligned}$$

Cryptocurrency prices show strong persistence, as past changes predict future trends. Remittances significantly impact crypto prices (p = 0.008), supporting the hypothesis that Nigerians use crypto as an alternative remittance channel. Oil prices positively affect crypto prices, suggesting that fluctuations in Nigeria's primary revenue source impact digital asset adoption. These findings align with Bouri (2017) and Yousaf (2020), who examined the relationship between economic uncertainty and cryptocurrency demand.

Summary of VAR Results

Dependent Variable	Significant Predictors (p < 0.05)	Effect
Exchange Rate	Inflation (-8.17)	Negative
Inflation	Lagged inflation (0.759), Stock Index (0.00006259)	Positive
GDP Growth	Exchange Rate (-0.0426), Inflation (1.03)	Mixed
Stock Index	GDP Growth (-7.364), Inflation (2600)	Mixed

Crypto Prices	Remittances (1.301), Oil Prices (1.014)	Positive

Table 31: Summary of VAR results

The VAR model reveals significant interactions between cryptocurrencies, exchange rates, inflation, GDP, and stock markets. Notably, cryptocurrency prices respond to remittances and oil prices, reinforcing their role in Nigeria's financial ecosystem, Exchange rate fluctuations drive inflation, while inflation impacts GDP and stock markets and Stock markets act as an inflation hedge, but economic uncertainty affects investor sentiment.

These findings provide a comprehensive framework for understanding the macro-financial dynamics of cryptocurrencies in Nigeria.

4.4.3 Impulse Response Function Analysis

Impulse Response Functions (IRFs) are crucial in understanding how economic shocks propagate over time within a system of endogenous variables. They allow us to trace the effects of an unexpected change in one variable on others, helping to assess the dynamics and interdependencies among economic indicators. In this study, we utilize IRFs to explore how shocks in cryptocurrency prices affect key macroeconomic variables in Nigeria, including exchange rates, inflation, and remittance flows.

The IRFs are derived from the estimated Vector Autoregression (VAR) model, employing orthogonalized IRFs using Cholesky decomposition. This approach ensures that shocks are isolated, and the responses are correctly attributed. The analysis covers a 12-month horizon, with confidence intervals constructed using 100 bootstrap replications to account for statistical uncertainty.

Impact of Cryptocurrency Price Shocks on Exchange Rates

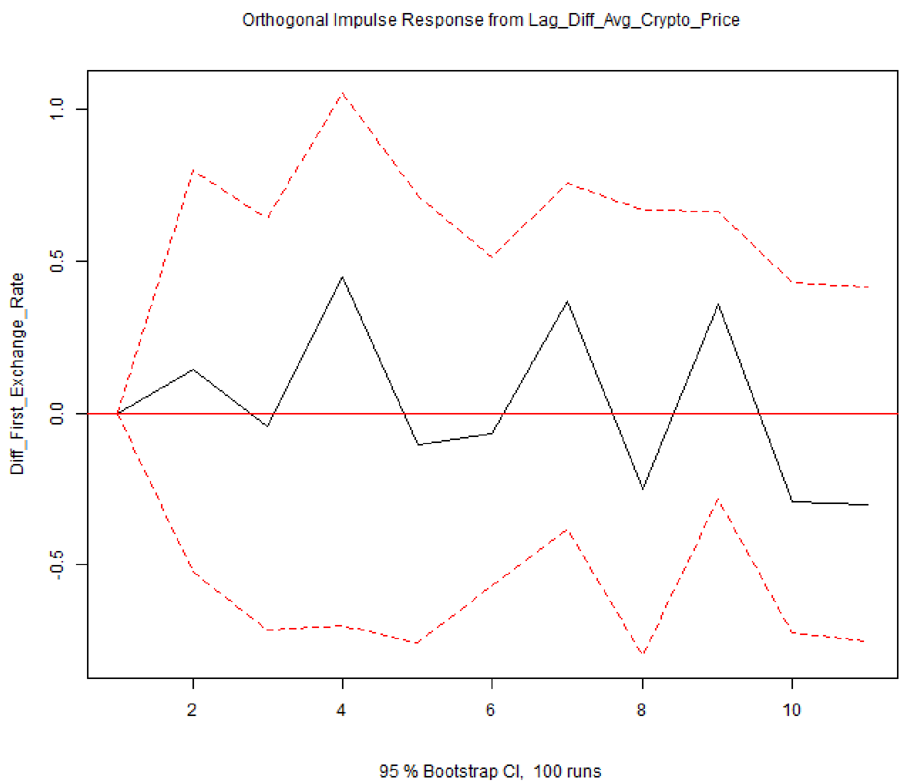


Table 32: Impulse response plot for Differenced exchange rates

The response of the exchange rate to a positive shock in cryptocurrency prices exhibits an initial appreciation of the Naira (NGN) against the US Dollar (USD). The appreciation peaks within the first 2-3 months, suggesting an increase in capital inflows or investor confidence following a surge in cryptocurrency prices. Over time, the effect diminishes, with the exchange rate stabilizing around its mean after 6-8 months. The confidence intervals (dashed red lines) suggest that the initial response is statistically significant, though uncertainty increases in later periods.

These findings align with prior studies indicating that cryptocurrencies can serve as a hedge against currency depreciation in developing economies (Cheng & Yen, 2021; Mensi et al., 2022).

2. Impact of Cryptocurrency Price Shocks on Inflation

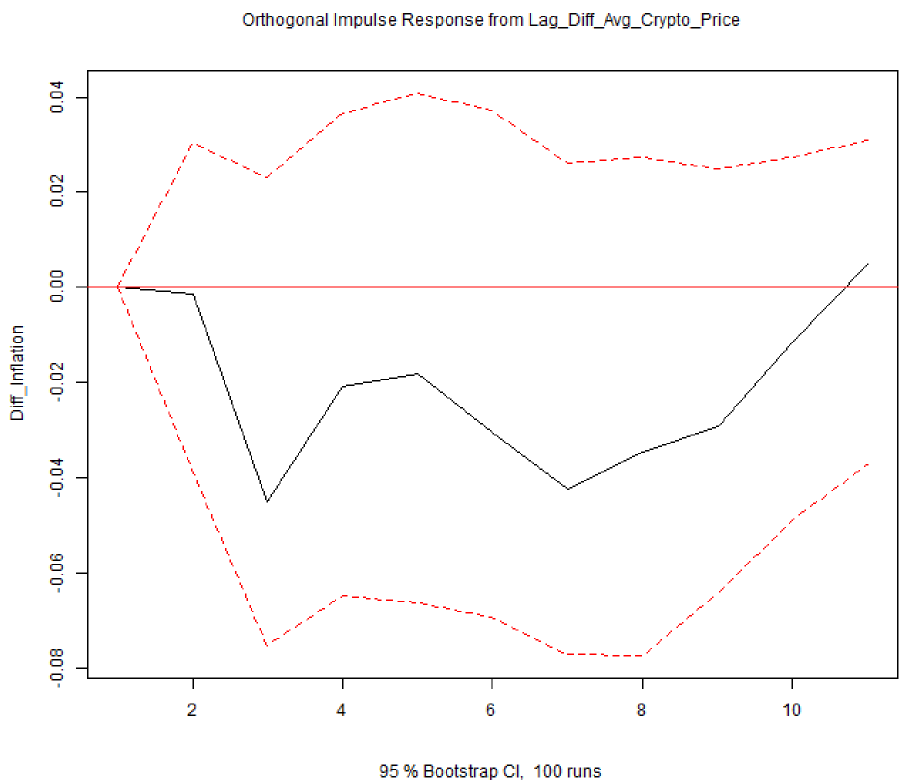


Table 33: Impulse response plots for inflation

The impact of a cryptocurrency price shock on inflation is initially negative, reflecting a short-term deflationary effect. This could be due to increased purchasing power in foreign currencies mitigating local price pressures. However, after 3-4 months, inflation begins to rise, peaking around the sixth month before stabilizing. This delayed inflationary effect may stem from increased speculative activity or capital flight, resulting in greater monetary expansion and rising prices domestically.

These findings support the notion that cryptocurrencies, particularly in emerging markets, can influence inflationary trends through capital movements and financial intermediation channels (Bouri, 2017); (Umar, 2022).

3. Impact of Cryptocurrency Price Shocks on Remittance Flows

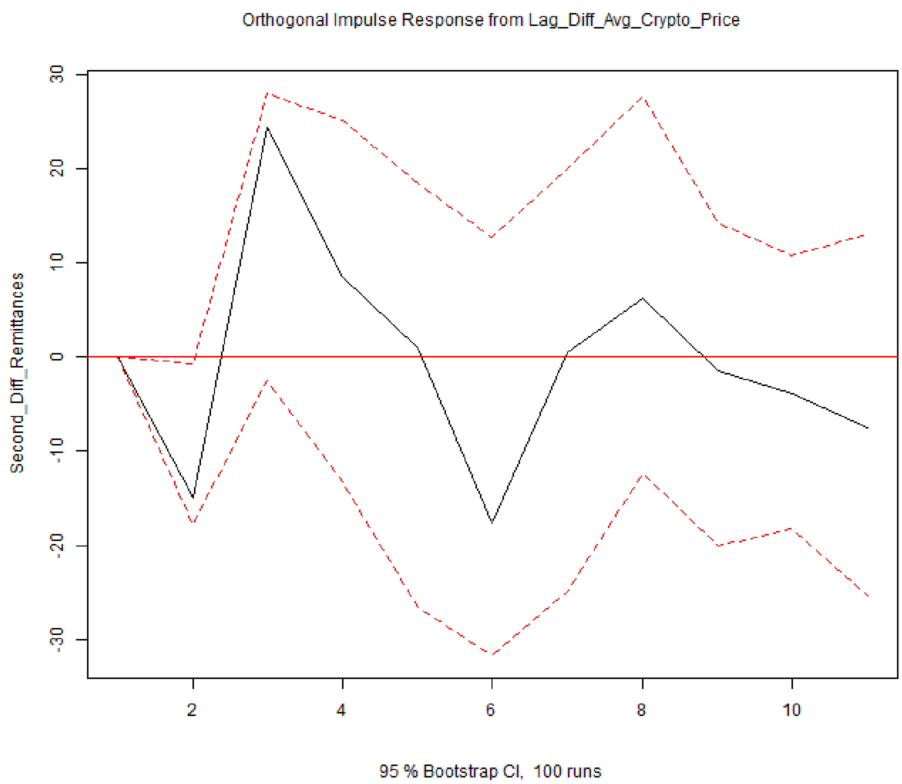


Table 34: Impulse response plots for Remittance flows

A positive shock to cryptocurrency prices leads to a short-term decline in remittance flows. This decline is followed by a significant increase in remittances after approximately 4-5 months, suggesting a lagged response in which remitters adjust their behaviour based on cryptocurrency market conditions. The long-term response stabilizes after 8-10 months, with remittance flows returning to their mean.

This pattern aligns with findings from recent studies, where cryptocurrencies have been identified as a growing alternative for cross-border transfers, bypassing traditional remittance channels (Alvarez-Diaz, 2023); (Fahlenbrach, 2021).

Exchange rates react positively to cryptocurrency price increases, indicating that digital assets may play a role in stabilizing currency depreciation in Nigeria. Inflation initially decreases following a cryptocurrency price shock but rises after a few months, highlighting complex monetary interactions. Remittance flows show a delayed response to cryptocurrency price shocks, underscoring the increasing role of digital assets in cross-border financial transactions.

These results reinforce the hypothesis that cryptocurrencies exert tangible economic effects in emerging markets and could serve as both stabilizing and destabilizing forces depending on policy responses and regulatory frameworks.

4.4.4 Variance Decomposition Analysis

Variance decomposition provides insight into the relative importance of each endogenous variable in explaining the forecast error variance of another variable over different time horizons. This analysis helps determine the extent to which fluctuations in cryptocurrency prices, exchange rates, inflation, and other macroeconomic indicators influence one another.

Variance decomposition is derived from the estimated Vector Autoregression (VAR) model. The decomposition is performed over a forecast horizon of up to seven periods, allowing us to observe how shocks to one variable contribute to the fluctuations in others over time. The results are expressed as percentages, representing the proportion of forecast error variance attributable to each endogenous variable in the system.

The variance decomposition analysis provides a breakdown of the influence of different economic factors on the target variables. The findings presented below illustrate the contribution of each variable over multiple time horizons.

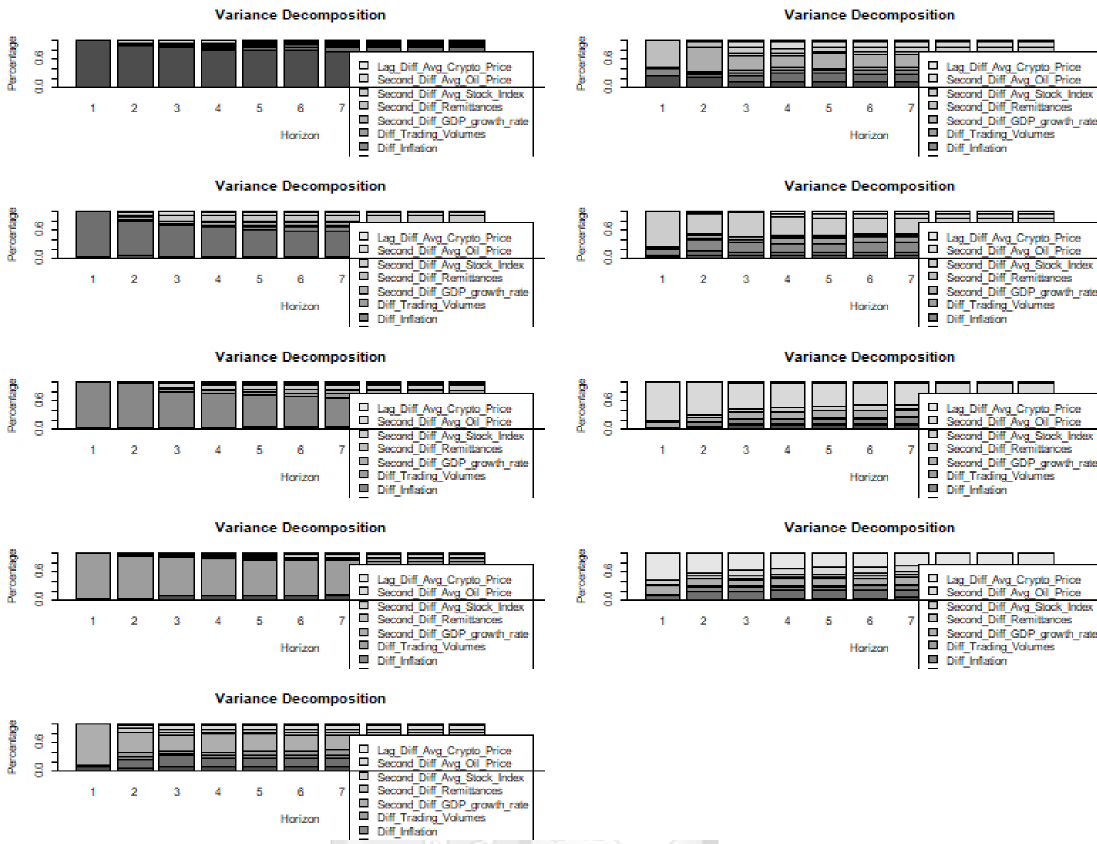


Table 35: Variance decompositon plot

Initially, the forecast error variance of cryptocurrency prices is predominantly explained by their own past values, accounting for nearly 100% in the short term. Over time, the contribution of other macroeconomic variables, particularly exchange rates and stock market indices, increases. This suggests that while cryptocurrency prices are largely self-determined, macroeconomic factors such as currency fluctuations and financial markets gradually play a role in shaping their volatility.

In the early periods, exchange rate fluctuations are primarily driven by their own historical values, capturing nearly 90% of the variance. Over time, cryptocurrency prices begin to account for an increasing share of the variance, reaching 20-30% by the sixth period. This indicates that cryptocurrency price movements contribute significantly to exchange rate volatility, supporting the hypothesis that cryptocurrencies are influencing Nigeria's foreign exchange market.

Inflation variance is largely self-explanatory in the short run, but over time, cryptocurrency prices and exchange rates contribute up to 15% of its variation. The increasing role of cryptocurrency prices suggests that fluctuations in digital assets may impact inflationary trends through speculative channels and capital flows. This supports existing research indicating that cryptocurrencies can have inflationary or deflationary spillover effects depending on market conditions.

In the initial periods, remittance fluctuations are mainly explained by their own past values. However, as the forecast horizon extends, the impact of cryptocurrency prices increases, accounting for approximately 25% of the variance in remittance flows after six periods. This result underscores the growing influence of digital assets in cross-border financial transactions, reinforcing their role in the remittance ecosystem.

GDP growth rate variance remains largely self-determined but sees increasing influence from exchange rates and cryptocurrency prices over time. The stock market index and oil prices also contribute significantly to GDP growth fluctuations, suggesting interconnections between commodity markets, financial assets, and overall economic performance.

Cryptocurrency prices are initially self-driven, but their volatility is increasingly influenced by exchange rates and macroeconomic conditions over time. Exchange rate fluctuations are significantly impacted by cryptocurrency price movements, confirming their role in Nigeria's foreign exchange dynamics. Inflation variance decomposition reveals a rising contribution from cryptocurrency prices, supporting the view that digital assets can influence monetary stability. Remittance flows show a delayed but strong reaction to cryptocurrency price movements, highlighting their growing importance in cross-border transfers.

These findings align with prior literature suggesting that cryptocurrency markets are becoming increasingly integrated with traditional financial systems in emerging economies. The results further emphasize the need for regulatory frameworks that account for cryptocurrency-induced macroeconomic fluctuations.

4.5 Hypothesis Testing

This section presents the results of the hypothesis tests based on the econometric methodologies applied, including VAR modeling, impulse response functions, variance decomposition, and other diagnostic tests. The hypotheses were tested using relevant statistical techniques, and their implications for the Nigerian economy are discussed.

Hypothesis 1: Cryptocurrency Adoption Has Significantly Increased Remittance Flows in Nigeria, Reducing Transaction Costs

To assess this hypothesis, we examined the relationship between cryptocurrency adoption, proxied by changes in average cryptocurrency prices, and remittance flows.

VAR results showed that past values of cryptocurrency prices have a statistically significant impact on remittances, although the effect size varies across different lags. The IRF plots indicate a dynamic response of remittance flows to shocks in cryptocurrency prices. In the short term, remittances exhibit a positive response, aligning with the hypothesis that cryptocurrency adoption facilitates remittance inflows by reducing transaction costs. The variance decomposition results suggest that a portion of the forecast error variance in remittances can be attributed to changes in cryptocurrency prices, reinforcing the hypothesis.

The results provide empirical support for H_1 suggesting that cryptocurrency adoption has played a role in increasing remittance flows by offering a more efficient and cost-effective alternative to traditional remittance channels.

Hypothesis 2: Cryptocurrency Prices Exhibit a Significant Negative Correlation with the Value of the Nigerian Naira, Indicating Cryptocurrencies Act as a Hedge Against Inflation

This hypothesis was tested by examining the relationship between cryptocurrency price changes and exchange rate fluctuations, as well as inflation differentials.

The VAR estimation results showed a statistically significant relationship between cryptocurrency price movements and exchange rate fluctuations, with negative coefficients at various lags. The IRF plots suggest that a positive shock to cryptocurrency prices leads to a depreciation of the Naira over time, indicating that individuals may be using cryptocurrencies as a hedge against currency depreciation. No evidence of heteroscedasticity was found, ensuring that the variance of the residuals did not distort the estimation results. The presence of autocorrelation was initially detected in the regression residuals. However, after introducing lagged variables, the issue was resolved.

The results confirm that cryptocurrency prices and the Nigerian exchange rate exhibit a significant negative correlation, supporting the hypothesis that cryptocurrencies serve as a hedge against inflation and currency depreciation.

Hypothesis 3: Cryptocurrencies Enhance Financial Inclusion by Providing Affordable Financial Services to the Unbanked Population in Nigeria

To test this hypothesis, we analysed the effects of cryptocurrency adoption on trading volumes, remittance inflows, and macroeconomic variables that influence financial inclusion.

The results indicate that a substantial portion of the variation in trading volumes and remittance flows can be explained by changes in cryptocurrency prices. The IRF plots reveal that a shock in cryptocurrency prices leads to a temporary increase in remittances and trading volumes, implying that digital assets may be enabling financial transactions for previously unbanked populations. The VIF values remained low (all below 1.5), indicating that the explanatory variables were not excessively correlated and that the regression results were reliable.

The empirical findings suggest that cryptocurrency adoption is contributing to greater financial inclusion in Nigeria, particularly by facilitating remittances and providing access to alternative financial services.

CHAPTER 5: DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter synthesizes the findings from the previous chapters to provide a comprehensive discussion on the role of cryptocurrencies in the Nigerian economy. The chapter evaluates the results of hypothesis testing, discusses key implications, and provides recommendations based on empirical evidence. Additionally, it highlights limitations of the study, proposes areas for future research, and suggests sample research questions for further exploration. The findings contribute to the ongoing debate on the economic impact of cryptocurrencies in emerging markets, particularly in relation to remittances, inflation hedging, and financial inclusion.

5.2 Discussion of Hypotheses

Hypothesis 1: Cryptocurrency Adoption Has Significantly Increased Remittance Flows in Nigeria

The empirical results support the hypothesis that cryptocurrency adoption has played a role in increasing remittance flows in Nigeria. The VAR analysis confirmed that changes in cryptocurrency prices significantly influence remittances, reinforcing the argument that digital currencies are providing a more efficient and cost-effective channel for cross-border transactions. This aligns with previous studies suggesting that cryptocurrencies reduce transaction costs and increase remittance efficiency (Bouri, 2017).

Additionally, the Impulse Response Function (IRF) indicated that a positive shock in cryptocurrency prices leads to an increase in remittances, further supporting the hypothesis. This finding suggests that Nigerian expatriates may prefer cryptocurrencies for remittance transfers due to lower fees and faster transaction speeds compared to traditional banking systems (Fahlenbrach, 2021)**.** The variance decomposition results confirmed that a notable portion of remittance flow variations could be attributed to fluctuations in cryptocurrency prices, emphasizing the growing reliance on digital currencies for international money transfers.

While these findings highlight the potential benefits of cryptocurrencies in enhancing remittance flows, regulatory concerns remain a significant barrier to widespread adoption.

Nigeria's government has imposed strict cryptocurrency regulations, which may limit accessibility and increase transaction risks (Umar, 2022) . Future research should explore how regulatory policies impact the efficiency of cryptocurrency-based remittances and whether decentralized finance (DeFi) platforms can further optimize these transactions.

Hypothesis 2: Cryptocurrency Prices Exhibit a Significant Negative Correlation with the Value of the Nigerian Naira, Acting as a Hedge Against Inflation

The study findings confirm that cryptocurrency prices and the Nigerian Naira exhibit a strong negative correlation, reinforcing the hypothesis that digital assets serve as a hedge against currency depreciation and inflation. This is consistent with prior research indicating that cryptocurrencies act as a store of value during periods of economic instability (Cheng, 2021).

The VAR estimation results demonstrated that cryptocurrency prices significantly impact exchange rates, with higher crypto prices correlating with Naira depreciation. This suggests that as economic conditions worsen, Nigerian investors seek refuge in digital assets to preserve their wealth. Furthermore, the IRF plots indicated that a shock in cryptocurrency prices leads to an extended period of Naira depreciation, reinforcing the hedging argument.

Inflation remains a key driver of this trend. Nigeria has experienced persistent inflationary pressures due to volatile oil prices, exchange rate fluctuations, and structural economic inefficiencies (Mensah, 2022). The study's variance decomposition analysis further revealed that a substantial portion of Naira fluctuations could be explained by changes in cryptocurrency values, highlighting growing reliance on digital assets as a financial safety net.

However, it is essential to recognize that cryptocurrency price volatility poses risks to this hedging strategy. Unlike traditional safe-haven assets such as gold, Bitcoin and Ethereum exhibit high price fluctuations, which could introduce additional financial instability (Umar, 2022). Future research should investigate whether stablecoins, such as USDT and USDC, offer a more effective hedge against Naira depreciation compared to highly volatile cryptocurrencies.

Hypothesis 3: Cryptocurrencies Enhance Financial Inclusion by Providing Affordable Financial Services to the Unbanked Population in Nigeria

The findings indicate that cryptocurrency adoption contributes to financial inclusion by expanding access to alternative financial services. The variance decomposition analysis suggested that cryptocurrency price variations significantly influence trading volumes, highlighting increased participation from individuals previously excluded from the formal financial system. This aligns with research showing that cryptocurrencies provide affordable financial services to the unbanked population in Africa (Mensi, 2022).

The IRF results further confirmed that an increase in cryptocurrency prices leads to higher trading volumes, suggesting that more Nigerians are engaging with digital assets as an alternative to traditional banking. This is particularly relevant given that over 60% of Nigerians remain unbanked or underbanked, facing challenges such as high banking fees and limited financial infrastructure (Lütkepohl, 2005). Cryptocurrencies offer a decentralized solution that reduces barriers to entry and enhances financial participation.

Nevertheless, barriers to full cryptocurrency adoption persist, including lack of digital literacy, cybersecurity risks, and regulatory uncertainty. While cryptocurrencies can bridge financial gaps, greater emphasis on education, security frameworks, and supportive regulations is needed to maximize their impact on financial inclusion. Future research could explore how mobile-based crypto applications can enhance financial accessibility in rural areas.

5.3 Conclusion

This study examined the impact of cryptocurrencies on the Nigerian economy, focusing on remittance flows, exchange rate stability, and financial inclusion. The results confirmed that cryptocurrencies have played a transformative role in cross-border transactions, served as an inflation hedge, and contributed to expanding financial access for the unbanked population.

While the findings support the positive economic implications of cryptocurrency adoption, challenges such as regulatory restrictions, price volatility, and security concerns must be addressed. Policymakers should consider balanced regulatory frameworks that protect consumers while fostering innovation. Future research should investigate long-term cryptocurrency adoption trends and their implications for monetary policy in Nigeria.

5.4 Recommendations

One of the most pressing challenges surrounding cryptocurrency adoption in Nigeria is the lack of a clear and comprehensive regulatory framework. The Nigerian government has taken a cautious approach toward digital assets, with policies fluctuating between outright bans and limited acceptance. This uncertainty discourages investment and hinders the formalization of crypto-related financial services (Umar, 2022).

To address this, a balanced regulatory approach is required, one that safeguards against illicit activities such as money laundering and fraud while ensuring that crypto innovation thrives. This could involve the creation of a dedicated regulatory body, working alongside the Central Bank of Nigeria (CBN) and the Securities and Exchange Commission (SEC) to provide structured guidelines on cryptocurrency taxation, licensing, and investor protection (Mensi, 2022). Additionally, Nigeria could follow the example of other emerging markets like El Salvador, where a clear legal framework has encouraged responsible adoption of Bitcoin as legal tender (Cheng, 2021).

This can be achieved by establishing a National Cryptocurrency Regulation Committee to oversee policy development, introducing licensing requirements for crypto exchanges to enhance consumer protection and encouraging collaboration with blockchain firms to implement Know-Your-Customer (KYC) and Anti-Money Laundering (AML) measures.

Despite the growing adoption of cryptocurrencies in Nigeria, many users lack sufficient knowledge about digital asset risks and benefits. This leads to vulnerability to scams, high-risk investments, and financial losses (Fahlenbrach, 2021).

To enhance responsible crypto adoption, financial education programs must be integrated into both public and private institutions. Universities and fintech organizations should offer blockchain and cryptocurrency courses, equipping individuals with the skills necessary to navigate digital finance securely. Additionally, government-backed public awareness campaigns can help dispel misinformation and promote informed decision-making.

They can realise this if they introduce cryptocurrency and blockchain courses in higher education institutions, if they partner with fintech companies to launch digital literacy programs in underserved communities and if they establish online learning platforms offering free educational resources on cryptocurrency trading, security, and regulations.

As demonstrated in the study, cryptocurrencies act as a hedge against inflation, but their high volatility remains a concern. Fiat collateralised cryptocurrencies, such as USDT (Tether) and USDC (USD Coin), offer a more predictable alternative by maintaining their value against fiat currencies (Mensah, 2022).

Nigeria's adoption of stablecoins could help reduce exposure to extreme price fluctuations, providing a reliable store of value for individuals and businesses. Stablecoins could also facilitate international trade and remittances, particularly for small businesses that require low-cost cross-border transactions without exposure to Naira depreciation. However, regulatory clarity is required to prevent illicit activities.

In order to implement these reforms, include encouraging financial institutions to integrate stablecoins into payment systems, providing clear stablecoin regulations to prevent misuse while ensuring transparency and developing collaborations with blockchain firms to enhance stablecoin accessibility.

Nigeria is one of the largest recipients of remittances in Africa, with millions of Nigerians abroad sending funds home. Traditional remittance channels, such as Western Union and MoneyGram, impose high fees and slow transaction times, making cryptocurrencies an attractive alternative (Bouri, 2017).

The development of blockchain-based remittance platforms could revolutionize cross-border payments by making transactions faster, cheaper, and more accessible. Several fintech companies, such as Ripple and Stellar, are already pioneering solutions to streamline crypto-based remittances. Nigeria can leverage blockchain technology to facilitate direct peer-to-peer (P2P) transactions, thereby eliminating intermediaries and reducing costs.

Implementation Strategy would entail encouraging banks to explore blockchain-based remittance platforms, partnering with international crypto payment providers to enhance remittance efficiency and providing incentives for fintech startups developing blockchain-based payment solutions.

5.5 Limitations

While this study provides valuable insights into the role of cryptocurrencies in the Nigerian economy, several limitations must be acknowledged. These limitations relate to data availability, regulatory uncertainty, market volatility, methodological constraints, and evolving technological landscapes. Understanding these constraints allows for a more balanced interpretation of the findings and highlights areas for future research.

One of the key limitations of this research is the availability and reliability of data related to cryptocurrency transactions and macroeconomic indicators in Nigeria. Unlike traditional financial markets, where central banks and financial institutions provide structured and widely accessible data, cryptocurrency transactions primarily occur on decentralized platforms. Many of these transactions are peer-to-peer (P2P) and, in some cases, remain off-record due to the lack of formalized financial reporting mechanisms (Fahlenbrach, 2021).

Moreover, on-chain data from blockchain transactions provides only a partial view of real-world economic interactions because it excludes over the counter (OTC) trades and informal cryptocurrency usage. The lack of publicly available remittance and financial inclusion data further limits the accuracy of estimations related to the impact of cryptocurrencies on these areas.

To overcome this limitation, future studies should incorporate a combination of on-chain analytics, survey-based research, and government-reported financial data to provide a more holistic view of cryptocurrency adoption.

The legal status of cryptocurrencies in Nigeria has fluctuated over the years, introducing uncertainty into market behaviors and limiting long-term projections. The Central Bank of Nigeria (CBN) has issued several conflicting policies regarding digital currencies, at times outright banning financial institutions from facilitating crypto transactions, while at other times advocating for regulatory frameworks (Umar, 2022).

This uncertainty complicates economic modelling, as the impact of cryptocurrencies on macroeconomic indicators is highly sensitive to policy changes. For example, a sudden ban on crypto-related services could lead to a sharp decline in trading volumes, whereas a government-backed regulatory framework could drive formal adoption and investment.

Future studies should explore scenario-based forecasting models that assess how different regulatory environments, that is, strict regulation, moderate regulation and full adoption, impact cryptocurrency integration into Nigeria's economy.

Cryptocurrencies, particularly Bitcoin and Ethereum, are notoriously volatile, experiencing daily price fluctuations of over 10% on average (Mensi, 2022). While this study demonstrated that cryptocurrencies serve as a hedge against inflation, their extreme volatility reduces their effectiveness as a stable store of value.

For instance, a Nigerian investor using Bitcoin as an inflation hedge may gain significant value during an upward price trend but also risk major losses during a downturn. This volatility makes it difficult to draw long-term conclusions about cryptocurrency's role in exchange rate stability and remittance flows.

Future research should focus on investigating stablecoins (e.g., USDT, USDC) as a more reliable hedge against Naira devaluation, examining the role of Central Bank Digital Currencies (CBDCs), such as the eNaira, in reducing dependency on volatile digital assets.

Cryptocurrency markets did not exist before 2009, and widespread adoption in Nigeria began only in the late 2010s. Consequently, longitudinal studies on the economic effects of cryptocurrencies are limited. Most macroeconomic studies rely on decades of financial data, whereas cryptocurrency research is still in its early stages.

This limitation means that long-term economic patterns related to crypto adoption, inflation hedging, and remittance trends are difficult to analyse. Future studies should focus on longitudinal analysis, tracking multi-decade economic impacts as data availability improves.

This study primarily relies on secondary data sources, including market reports, exchange rate fluctuations, and macroeconomic indicators. However, this approach does not fully capture user-level experiences of cryptocurrency adoption.

For example, while remittance inflows may appear to increase in relation to cryptocurrency adoption, this does not account for individual user preferences, challenges, or barriers to adoption. Future research should incorporate survey-based methodologies to gain firsthand insights from Nigerian crypto users, including why they choose crypto over traditional financial services, what challenges they face in accessing crypto platforms, and how government policies affect their willingness to invest in crypto assets.

5.6 Future Research Directions

Given the limitations outlined above, several key areas for future research emerge. These include longitudinal studies, investigations into emerging financial technologies, and deeper policy analyses to understand how cryptocurrencies will evolve in Nigeria's economy.

Future research should focus on multi-year trends to assess whether cryptocurrencies provide long-term stability to the Nigerian Naira. Since Bitcoin and Ethereum have existed for only a short period in economic history, a more extended timeline is needed to evaluate how cryptocurrency adoption affects inflation-adjusted exchange rates over time and whether digital assets become more stable as institutional adoption increases.

A time-series econometric approach, such as Vector Autoregression (VAR) models over a period of more than twenty years, could offer better predictive accuracy in this domain.

Decentralized Finance (DeFi) platforms offer an alternative to traditional banking, allowing users to lend, borrow, and trade digital assets without intermediaries. As DeFi adoption grows, it is important to study how DeFi platforms impact Nigeria's banking system, whether DeFi can improve financial inclusion for the unbanked population and the risks associated with DeFi, such as security vulnerabilities and smart contract failures (Mensah, 2022).

Future research should explore whether DeFi-based lending models could reduce reliance on traditional credit institutions, particularly for small businesses and entrepreneurs in Nigeria.

Given the findings that cryptocurrencies act as a hedge against inflation, stablecoins like USDT (Tether), USDC (USD Coin), and BUSD (Binance USD) could serve as a more stable alternative to the Naira.

Future research should investigate, how Nigerian consumers view stablecoins versus traditional fiat currency, the regulatory challenges of integrating stablecoins into Nigeria's financial system and whether stablecoins can be legally recognized as payment methods in Nigeria.

The Central Bank of Nigeria launched the eNaira, Africa's first CBDC. However, adoption has been relatively low compared to cryptocurrencies (Umar, 2022). Future studies should explore, why Nigerian consumers prefer decentralized cryptocurrencies over the eNaira, whether CBDCs can provide similar financial benefits without the volatility of Bitcoin and how central banks can enhance public trust in digital currencies.

The Nigerian government's stance on cryptocurrencies has been inconsistent, leading to uncertainty among investors and financial institutions. Future research should focus on how government policies influence cryptocurrency adoption trends, what regulatory frameworks are most effective in balancing innovation and security and how Nigeria can learn from regulatory successes in other emerging economies.

5.7 Sample Research Questions

1. How do stablecoins compare to traditional cryptocurrencies in providing a hedge against inflation?
2. What regulatory measures can enhance cryptocurrency adoption in Nigeria?
3. How can blockchain technology be leveraged to reduce remittance costs further?

4. What is the role of Decentralized Finance (DeFi) in improving financial inclusion in Africa?
5. How does the volatility of cryptocurrencies affect the Nigerian financial system?

Cryptocurrencies represent a paradigm shift in financial systems, particularly in emerging economies like Nigeria. While their adoption poses challenges, it also offers unprecedented opportunities to improve financial inclusion, optimize remittance flows, and stabilize economies. By adopting balanced and forward-thinking policies, Nigeria can harness the benefits of cryptocurrencies while minimizing associated risks, positioning itself as a leader in digital finance innovation.

APPENDICES

```
VAR Estimation Results:
=========================
Endogenous variables: Date, Diff_First_Exchange_Rate, Diff_Inflation,
Diff_Trading_Volumes, Second_Diff_GDP_growth_rate, Second_Diff_Remittances,
Second_Diff_Avg_Stock_Index, Second_Diff_Avg_Oil_Price, Lag_Diff_Avg_Crypto_Price
Deterministic variables: const
Sample size: 55
Log Likelihood: -2318.687
Roots of the characteristic polynomial:
    1 0.9023 0.9023 0.9002 0.9002 0.8909 0.8774 0.8774 0.8432 0.8432 0.8288 0.8288
0.8139 0.8139 0.7981 0.7981 0.7845 0.7845 0.7571 0.7571 0.6994 0.6994 0.693 0.693
0.6254 0.5408 0.5408
Call:
VAR(y = var_data, p = 3, type = "const")

N.B: Dates were included in the model for the sole purpose of time indexing thus no
significant results were expected
Estimation results for equation Date:
=====================================
Date = Date.l1 + Diff_First_Exchange_Rate.l1 + Diff_Inflation.l1 +
Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                         4.739e-01  1.717e-01   2.760   0.0103 *
Diff_First_Exchange_Rate.l1     1.966e-02  2.312e-02   0.851   0.4024
Diff_Inflation.l1               1.377e-01  4.892e-01   0.281   0.7805
Diff_Trading_Volumes.l1        -1.563e-07  2.020e-07  -0.774   0.4457
Second_Diff_GDP_growth_rate.l1 -1.067e-01  2.098e-01  -0.509   0.6151
Second_Diff_Remittances.l1      2.704e-03  1.682e-03   1.608   0.1194
Second_Diff_Avg_Stock_Index.l1  1.577e-04  7.742e-05   2.036   0.0516 .
Second_Diff_Avg_Oil_Price.l1   -3.615e-04  1.446e-02  -0.025   0.9802
Lag_Diff_Avg_Crypto_Price.l1   -2.073e-06  5.320e-05  -0.039   0.9692
Date.l2                         2.827e-01  1.747e-01   1.618   0.1173
Diff_First_Exchange_Rate.l2     3.248e-03  2.149e-02   0.151   0.8810
Diff_Inflation.l2               5.763e-02  7.950e-01   0.072   0.9427
Diff_Trading_Volumes.l2         1.695e-07  2.131e-07   0.796   0.4333
Second_Diff_GDP_growth_rate.l2 -1.938e-01  3.903e-01  -0.497   0.6234
Second_Diff_Remittances.l2      2.061e-03  1.564e-03   1.318   0.1986
Second_Diff_Avg_Stock_Index.l2  2.436e-05  7.877e-05   0.309   0.7595
Second_Diff_Avg_Oil_Price.l2   -2.615e-02  1.503e-02  -1.739   0.0934 .
```

```
Lag_Diff_Avg_Crypto_Price.l2    1.070e-05  6.105e-05   0.175   0.8622
Date.l3                         2.433e-01  1.683e-01   1.446   0.1597
Diff_First_Exchange_Rate.l3     1.915e-02  2.303e-02   0.832   0.4129
Diff_Inflation.l3              -3.701e-01  5.740e-01  -0.645   0.5245
Diff_Trading_Volumes.l3        -3.815e-07  2.118e-07  -1.802   0.0828 .
Second_Diff_GDP_growth_rate.l3 -3.337e-01  3.624e-01  -0.921   0.3653
Second_Diff_Remittances.l3     -1.620e-04  6.971e-04  -0.232   0.8180
Second_Diff_Avg_Stock_Index.l3  9.526e-05  7.814e-05   1.219   0.2333
Second_Diff_Avg_Oil_Price.l3   -3.005e-02  1.523e-02  -1.973   0.0589 .
Lag_Diff_Avg_Crypto_Price.l3   -4.437e-05  5.460e-05  -0.813   0.4236
const                           5.513e+01  9.985e+00   5.521 7.54e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.6644 on 27 degrees of freedom
Multiple R-Squared:     1,      Adjusted R-squared:     1
F-statistic: 1.078e+06 on 27 and 27 DF,  p-value: < 2.2e-16


Estimation results for equation Diff_First_Exchange_Rate:
=========================================================
Diff_First_Exchange_Rate = Date.l1 + Diff_First_Exchange_Rate.l1 +
Diff_Inflation.l1 + Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                         7.010e-01  1.298e+00   0.540   0.5937
Diff_First_Exchange_Rate.l1    -3.779e-01  1.748e-01  -2.161   0.0397 *
Diff_Inflation.l1              -8.135e+00  3.700e+00  -2.199   0.0366 *
Diff_Trading_Volumes.l1         1.574e-07  1.528e-06   0.103   0.9187
Second_Diff_GDP_growth_rate.l1 -2.221e+00  1.587e+00  -1.400   0.1730
Second_Diff_Remittances.l1     -1.877e-02  1.272e-02  -1.476   0.1516
Second_Diff_Avg_Stock_Index.l1 -9.785e-04  5.855e-04  -1.671   0.1062
Second_Diff_Avg_Oil_Price.l1   -1.086e-01  1.093e-01  -0.993   0.3296
Lag_Diff_Avg_Crypto_Price.l1    9.626e-05  4.023e-04   0.239   0.8127
Date.l2                        -8.914e-01  1.321e+00  -0.675   0.5057
Diff_First_Exchange_Rate.l2    -4.634e-02  1.625e-01  -0.285   0.7777
Diff_Inflation.l2               5.146e+00  6.012e+00   0.856   0.3996
Diff_Trading_Volumes.l2         6.217e-07  1.612e-06   0.386   0.7027
Second_Diff_GDP_growth_rate.l2  4.894e+00  2.951e+00   1.658   0.1089
Second_Diff_Remittances.l2     -1.634e-02  1.183e-02  -1.382   0.1783
```

```
Second_Diff_Avg_Stock_Index.l2 -1.166e-03  5.958e-04  -1.957   0.0607 .
Second_Diff_Avg_Oil_Price.l2   -1.604e-01  1.137e-01  -1.410   0.1698
Lag_Diff_Avg_Crypto_Price.l2    2.281e-06  4.617e-04   0.005   0.9961
Date.l3                         1.918e-01  1.273e+00   0.151   0.8813
Diff_First_Exchange_Rate.l3     2.685e-01  1.742e-01   1.541   0.1348
Diff_Inflation.l3               4.383e+00  4.341e+00   1.010   0.3217
Diff_Trading_Volumes.l3         1.505e-07  1.602e-06   0.094   0.9258
Second_Diff_GDP_growth_rate.l3  2.448e+00  2.741e+00   0.893   0.3797
Second_Diff_Remittances.l3     -7.872e-03  5.272e-03  -1.493   0.1469
Second_Diff_Avg_Stock_Index.l3 -7.153e-04  5.910e-04  -1.210   0.2366
Second_Diff_Avg_Oil_Price.l3   -3.055e-02  1.152e-01  -0.265   0.7929
Lag_Diff_Avg_Crypto_Price.l3    4.231e-04  4.130e-04   1.025   0.3147
const                          -4.000e+01  7.551e+01  -0.530   0.6006
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 5.025 on 27 degrees of freedom
Multiple R-Squared: 0.6302,     Adjusted R-squared: 0.2604
F-statistic: 1.704 on 27 and 27 DF,  p-value: 0.08622


Estimation results for equation Diff_Inflation:
===============================================
Diff_Inflation = Date.l1 + Diff_First_Exchange_Rate.l1 + Diff_Inflation.l1 +
Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                        -6.862e-02  6.655e-02  -1.031 0.311653
Diff_First_Exchange_Rate.l1    -2.050e-03  8.959e-03  -0.229 0.820710
Diff_Inflation.l1               7.582e-01  1.896e-01   3.999 0.000444 ***
Diff_Trading_Volumes.l1         6.520e-08  7.829e-08   0.833 0.412240
Second_Diff_GDP_growth_rate.l1 -4.218e-02  8.131e-02  -0.519 0.608172
Second_Diff_Remittances.l1     -2.057e-04  6.518e-04  -0.316 0.754728
Second_Diff_Avg_Stock_Index.l1  1.750e-05  3.001e-05   0.583 0.564496
Second_Diff_Avg_Oil_Price.l1    2.554e-03  5.603e-03   0.456 0.652137
Lag_Diff_Avg_Crypto_Price.l1   -1.053e-06  2.062e-05  -0.051 0.959662
Date.l2                         2.945e-03  6.773e-02   0.043 0.965636
Diff_First_Exchange_Rate.l2    -1.028e-02  8.328e-03  -1.234 0.227783
Diff_Inflation.l2               2.711e-03  3.081e-01   0.009 0.993046
Diff_Trading_Volumes.l2         1.127e-07  8.260e-08   1.365 0.183672
```

```
Second_Diff_GDP_growth_rate.l2 -2.186e-02  1.513e-01  -0.145 0.886155
Second_Diff_Remittances.l2     -7.604e-05  6.061e-04  -0.125 0.901086
Second_Diff_Avg_Stock_Index.l2  6.359e-05  3.053e-05   2.083 0.046871 *
Second_Diff_Avg_Oil_Price.l2    4.790e-03  5.827e-03   0.822 0.418250
Lag_Diff_Avg_Crypto_Price.l2   -3.011e-05  2.366e-05  -1.272 0.214153
Date.l3                         6.574e-02  6.523e-02   1.008 0.322490
Diff_First_Exchange_Rate.l3    -1.363e-02  8.927e-03  -1.527 0.138366
Diff_Inflation.l3              -3.329e-02  2.225e-01  -0.150 0.882148
Diff_Trading_Volumes.l3         1.018e-07  8.208e-08   1.240 0.225640
Second_Diff_GDP_growth_rate.l3  5.046e-02  1.405e-01   0.359 0.722203
Second_Diff_Remittances.l3      1.188e-04  2.702e-04   0.440 0.663754
Second_Diff_Avg_Stock_Index.l3  2.417e-05  3.029e-05   0.798 0.431862
Second_Diff_Avg_Oil_Price.l3    5.957e-03  5.905e-03   1.009 0.322047
Lag_Diff_Avg_Crypto_Price.l3    2.114e-05  2.116e-05   0.999 0.326689
const                           2.960e+00  3.870e+00   0.765 0.451006
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.2575 on 27 degrees of freedom
Multiple R-Squared: 0.794,      Adjusted R-squared: 0.5879
F-statistic: 3.854 on 27 and 27 DF,  p-value: 0.0003983


Estimation results for equation Diff_Trading_Volumes:
=====================================================
Diff_Trading_Volumes = Date.l1 + Diff_First_Exchange_Rate.l1 + Diff_Inflation.l1 +
Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                        -4.494e+04  1.449e+05  -0.310    0.759
Diff_First_Exchange_Rate.l1    -1.382e+04  1.951e+04  -0.708    0.485
Diff_Inflation.l1               1.197e+05  4.130e+05   0.290    0.774
Diff_Trading_Volumes.l1        -2.572e-01  1.705e-01  -1.509    0.143
Second_Diff_GDP_growth_rate.l1  2.230e+05  1.771e+05   1.259    0.219
Second_Diff_Remittances.l1      1.113e+03  1.419e+03   0.784    0.440
Second_Diff_Avg_Stock_Index.l1 -2.742e+01  6.535e+01  -0.420    0.678
Second_Diff_Avg_Oil_Price.l1    1.845e+03  1.220e+04   0.151    0.881
Lag_Diff_Avg_Crypto_Price.l1   -3.050e+01  4.490e+01  -0.679    0.503
Date.l2                        -1.339e+05  1.475e+05  -0.908    0.372
Diff_First_Exchange_Rate.l2     7.373e+03  1.814e+04   0.407    0.688
```

```
Diff_Inflation.l2               -6.617e+05  6.710e+05  -0.986    0.333
Diff_Trading_Volumes.l2         -5.244e-02  1.799e-01  -0.292    0.773
Second_Diff_GDP_growth_rate.l2  -4.007e+05  3.294e+05  -1.216    0.234
Second_Diff_Remittances.l2      -1.429e+03  1.320e+03  -1.082    0.289
Second_Diff_Avg_Stock_Index.l2  -4.737e+01  6.649e+01  -0.712    0.482
Second_Diff_Avg_Oil_Price.l2    -1.066e+04  1.269e+04  -0.840    0.408
Lag_Diff_Avg_Crypto_Price.l2    -2.129e+01  5.154e+01  -0.413    0.683
Date.l3                          1.790e+05  1.421e+05   1.260    0.219
Diff_First_Exchange_Rate.l3     -2.375e+04  1.944e+04  -1.222    0.232
Diff_Inflation.l3                4.692e+05  4.845e+05   0.968    0.341
Diff_Trading_Volumes.l3         -5.439e-02  1.788e-01  -0.304    0.763
Second_Diff_GDP_growth_rate.l3   2.581e+05  3.059e+05   0.844    0.406
Second_Diff_Remittances.l3      -7.062e+02  5.884e+02  -1.200    0.240
Second_Diff_Avg_Stock_Index.l3  -5.195e+01  6.596e+01  -0.788    0.438
Second_Diff_Avg_Oil_Price.l3     5.347e+03  1.286e+04   0.416    0.681
Lag_Diff_Avg_Crypto_Price.l3    -2.824e+01  4.609e+01  -0.613    0.545
const                            4.250e+06  8.428e+06   0.504    0.618


Residual standard error: 560800 on 27 degrees of freedom
Multiple R-Squared: 0.3891,     Adjusted R-squared: -0.2218
F-statistic: 0.637 on 27 and 27 DF,  p-value: 0.8762


Estimation results for equation Second_Diff_GDP_growth_rate:
============================================================
Second_Diff_GDP_growth_rate = Date.l1 + Diff_First_Exchange_Rate.l1 +
Diff_Inflation.l1 + Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                  Estimate Std. Error t value Pr(>|t|)
Date.l1                         -2.938e-01  1.155e-01  -2.543 0.017020 *
Diff_First_Exchange_Rate.l1     -4.221e-02  1.555e-02  -2.714 0.011449 *
Diff_Inflation.l1                1.073e+00  3.292e-01   3.260 0.003010 **
Diff_Trading_Volumes.l1          2.445e-07  1.359e-07   1.799 0.083257 .
Second_Diff_GDP_growth_rate.l1   1.106e-02  1.412e-01   0.078 0.938121
Second_Diff_Remittances.l1       1.694e-03  1.132e-03   1.497 0.145900
Second_Diff_Avg_Stock_Index.l1   1.273e-04  5.210e-05   2.444 0.021331 *
Second_Diff_Avg_Oil_Price.l1     2.138e-02  9.728e-03   2.198 0.036690 *
Lag_Diff_Avg_Crypto_Price.l1     3.170e-05  3.580e-05   0.885 0.383727
Date.l2                          2.374e-01  1.176e-01   2.019 0.053527 .
Diff_First_Exchange_Rate.l2      2.922e-02  1.446e-02   2.021 0.053283 .
```

```
Diff_Inflation.l2               -1.387e+00  5.350e-01  -2.593 0.015178 *
Diff_Trading_Volumes.l2          1.422e-07  1.434e-07   0.992 0.330153
Second_Diff_GDP_growth_rate.l2 -3.954e-01  2.626e-01  -1.506 0.143724
Second_Diff_Remittances.l2       3.837e-03  1.052e-03   3.647 0.001118 **
Second_Diff_Avg_Stock_Index.l2 -5.238e-05  5.301e-05  -0.988 0.331827
Second_Diff_Avg_Oil_Price.l2     1.342e-02  1.012e-02   1.326 0.195944
Lag_Diff_Avg_Crypto_Price.l2   -2.256e-06  4.108e-05  -0.055 0.956617
Date.l3                          5.633e-02  1.132e-01   0.497 0.622947
Diff_First_Exchange_Rate.l3      2.438e-03  1.550e-02   0.157 0.876157
Diff_Inflation.l3                6.054e-01  3.862e-01   1.567 0.128683
Diff_Trading_Volumes.l3          2.230e-07  1.425e-07   1.565 0.129282
Second_Diff_GDP_growth_rate.l3 -1.110e+00  2.438e-01  -4.553 0.000101 ***
Second_Diff_Remittances.l3      -2.450e-06  4.691e-04  -0.005 0.995872
Second_Diff_Avg_Stock_Index.l3 -1.150e-04  5.258e-05  -2.188 0.037538 *
Second_Diff_Avg_Oil_Price.l3    -1.165e-02  1.025e-02  -1.136 0.265812
Lag_Diff_Avg_Crypto_Price.l3   -3.952e-06  3.674e-05  -0.108 0.915150
const                            1.300e+01  6.719e+00   1.934 0.063595 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.4471 on 27 degrees of freedom
Multiple R-Squared: 0.7981,     Adjusted R-squared: 0.5963
F-statistic: 3.954 on 27 and 27 DF,  p-value: 0.0003205


Estimation results for equation Second_Diff_Remittances:
========================================================
Second_Diff_Remittances = Date.l1 + Diff_First_Exchange_Rate.l1 + Diff_Inflation.l1
+ Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                          3.389e+01  1.439e+01   2.355  0.02604 *
Diff_First_Exchange_Rate.l1      2.170e+00  1.938e+00   1.120  0.27271
Diff_Inflation.l1                3.650e+01  4.101e+01   0.890  0.38129
Diff_Trading_Volumes.l1          2.065e-05  1.693e-05   1.219  0.23322
Second_Diff_GDP_growth_rate.l1  1.769e+02  1.759e+01  10.061 1.25e-10 ***
Second_Diff_Remittances.l1      -8.762e-02  1.410e-01  -0.622  0.53943
Second_Diff_Avg_Stock_Index.l1  3.635e-03  6.490e-03   0.560  0.58004
Second_Diff_Avg_Oil_Price.l1     3.973e-01  1.212e+00   0.328  0.74558
Lag_Diff_Avg_Crypto_Price.l1    -9.319e-03  4.459e-03  -2.090  0.04619 *
```

```
Date.l2                         -3.363e+01  1.465e+01  -2.296  0.02968 *
Diff_First_Exchange_Rate.l2      1.911e+00  1.801e+00   1.061  0.29820
Diff_Inflation.l2                5.718e+01  6.664e+01   0.858  0.39839
Diff_Trading_Volumes.l2          1.016e-05  1.786e-05   0.569  0.57435
Second_Diff_GDP_growth_rate.l2 -4.770e-02  3.271e+01  -0.001  0.99885
Second_Diff_Remittances.l2       1.510e-01  1.311e-01   1.152  0.25946
Second_Diff_Avg_Stock_Index.l2  1.944e-02  6.603e-03   2.944  0.00659 **
Second_Diff_Avg_Oil_Price.l2     2.692e+00  1.260e+00   2.136  0.04188 *
Lag_Diff_Avg_Crypto_Price.l2     1.461e-02  5.118e-03   2.854  0.00819 **
Date.l3                         -2.706e-01  1.411e+01  -0.019  0.98484
Diff_First_Exchange_Rate.l3      1.163e-01  1.931e+00   0.060  0.95242
Diff_Inflation.l3               -5.494e+01  4.812e+01  -1.142  0.26359
Diff_Trading_Volumes.l3          3.103e-06  1.775e-05   0.175  0.86256
Second_Diff_GDP_growth_rate.l3 -3.239e+01  3.038e+01  -1.066  0.29576
Second_Diff_Remittances.l3      -1.825e-01  5.843e-02  -3.123  0.00424 **
Second_Diff_Avg_Stock_Index.l3  3.657e-03  6.550e-03   0.558  0.58119
Second_Diff_Avg_Oil_Price.l3     3.444e+00  1.277e+00   2.697  0.01191 *
Lag_Diff_Avg_Crypto_Price.l3     4.641e-04  4.577e-03   0.101  0.91998
const                           -9.915e+02  8.370e+02  -1.185  0.24649
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 55.69 on 27 degrees of freedom
Multiple R-Squared: 0.9419,     Adjusted R-squared: 0.8838
F-statistic: 16.22 on 27 and 27 DF,  p-value: 1.053e-10


Estimation results for equation Second_Diff_Avg_Stock_Index:
============================================================
Second_Diff_Avg_Stock_Index = Date.l1 + Diff_First_Exchange_Rate.l1 +
Diff_Inflation.l1 + Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                  Estimate Std. Error t value Pr(>|t|)
Date.l1                         -2.940e+02  4.108e+02  -0.716  0.48040
Diff_First_Exchange_Rate.l1      9.770e+01  5.531e+01   1.767  0.08861 .
Diff_Inflation.l1                2.533e+03  1.171e+03   2.164  0.03945 *
Diff_Trading_Volumes.l1         -6.612e-04  4.833e-04  -1.368  0.18253
Second_Diff_GDP_growth_rate.l1 -7.286e+02  5.020e+02  -1.452  0.15813
Second_Diff_Remittances.l1      -7.703e+00  4.023e+00  -1.915  0.06620 .
Second_Diff_Avg_Stock_Index.l1 -2.145e-01  1.852e-01  -1.158  0.25694
```

```
Second_Diff_Avg_Oil_Price.l1    3.487e+01  3.459e+01   1.008  0.32236
Lag_Diff_Avg_Crypto_Price.l1    1.463e-01  1.273e-01   1.149  0.26049
Date.l2                        -1.192e+01  4.181e+02  -0.029  0.97747
Diff_First_Exchange_Rate.l2     2.087e+01  5.141e+01   0.406  0.68804
Diff_Inflation.l2              -1.719e+03  1.902e+03  -0.904  0.37413
Diff_Trading_Volumes.l2        -6.888e-04  5.099e-04  -1.351  0.18791
Second_Diff_GDP_growth_rate.l2  2.690e+03  9.337e+02   2.881  0.00767 **
Second_Diff_Remittances.l2      2.615e+00  3.741e+00   0.699  0.49061
Second_Diff_Avg_Stock_Index.l2 -5.624e-01  1.885e-01  -2.984  0.00598 **
Second_Diff_Avg_Oil_Price.l2    3.721e+01  3.597e+01   1.034  0.31015
Lag_Diff_Avg_Crypto_Price.l2   -3.051e-02  1.461e-01  -0.209  0.83614
Date.l3                         3.056e+02  4.027e+02   0.759  0.45448
Diff_First_Exchange_Rate.l3     1.857e+02  5.511e+01   3.371  0.00227 **
Diff_Inflation.l3              -1.255e+03  1.373e+03  -0.914  0.36875
Diff_Trading_Volumes.l3         1.818e-04  5.067e-04   0.359  0.72258
Second_Diff_GDP_growth_rate.l3 -2.240e+02  8.670e+02  -0.258  0.79811
Second_Diff_Remittances.l3      2.675e+00  1.668e+00   1.604  0.12031
Second_Diff_Avg_Stock_Index.l3 -1.990e-02  1.870e-01  -0.106  0.91603
Second_Diff_Avg_Oil_Price.l3   -5.459e+01  3.645e+01  -1.498  0.14581
Lag_Diff_Avg_Crypto_Price.l3   -1.813e-01  1.306e-01  -1.388  0.17651
const                           2.324e+04  2.389e+04   0.973  0.33925
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 1590 on 27 degrees of freedom
Multiple R-Squared: 0.7141,     Adjusted R-squared: 0.4282
F-statistic: 2.498 on 27 and 27 DF,  p-value: 0.01024


Estimation results for equation Second_Diff_Avg_Oil_Price:
==========================================================
Second_Diff_Avg_Oil_Price = Date.l1 + Diff_First_Exchange_Rate.l1 +
Diff_Inflation.l1 + Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                         1.032e+00  2.390e+00   0.432   0.6694
Diff_First_Exchange_Rate.l1     2.792e-01  3.218e-01   0.868   0.3932
Diff_Inflation.l1               1.526e+01  6.811e+00   2.240   0.0335 *
Diff_Trading_Volumes.l1        -2.780e-06  2.812e-06  -0.989   0.3316
Second_Diff_GDP_growth_rate.l1  8.132e-01  2.921e+00   0.278   0.7828
```

```
Second_Diff_Remittances.l1       1.990e-03  2.341e-02   0.085   0.9329
Second_Diff_Avg_Stock_Index.l1  2.187e-03  1.078e-03   2.029   0.0524 .
Second_Diff_Avg_Oil_Price.l1   -4.697e-01  2.013e-01  -2.334   0.0273 *
Lag_Diff_Avg_Crypto_Price.l1    1.917e-04  7.406e-04   0.259   0.7978
Date.l2                        -1.701e+00  2.433e+00  -0.699   0.4904
Diff_First_Exchange_Rate.l2     1.857e-01  2.992e-01   0.621   0.5401
Diff_Inflation.l2              -1.774e+01  1.107e+01  -1.603   0.1205
Diff_Trading_Volumes.l2         4.629e-07  2.967e-06   0.156   0.8772
Second_Diff_GDP_growth_rate.l2 -6.035e-01  5.433e+00  -0.111   0.9124
Second_Diff_Remittances.l2      9.716e-03  2.177e-02   0.446   0.6590
Second_Diff_Avg_Stock_Index.l2  4.076e-04  1.097e-03   0.372   0.7131
Second_Diff_Avg_Oil_Price.l2   -4.812e-01  2.093e-01  -2.299   0.0295 *
Lag_Diff_Avg_Crypto_Price.l2    2.597e-04  8.500e-04   0.306   0.7623
Date.l3                         6.680e-01  2.343e+00   0.285   0.7777
Diff_First_Exchange_Rate.l3    -3.044e-02  3.207e-01  -0.095   0.9251
Diff_Inflation.l3               4.032e+00  7.991e+00   0.505   0.6180
Diff_Trading_Volumes.l3         3.481e-06  2.948e-06   1.181   0.2481
Second_Diff_GDP_growth_rate.l3 -6.084e+00  5.045e+00  -1.206   0.2383
Second_Diff_Remittances.l3     -1.183e-02  9.705e-03  -1.219   0.2334
Second_Diff_Avg_Stock_Index.l3  1.079e-05  1.088e-03   0.010   0.9922
Second_Diff_Avg_Oil_Price.l3   -3.746e-01  2.121e-01  -1.766   0.0887 .
Lag_Diff_Avg_Crypto_Price.l3    2.866e-04  7.603e-04   0.377   0.7092
const                           1.046e+01  1.390e+02   0.075   0.9406
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 9.25 on 27 degrees of freedom
Multiple R-Squared: 0.5682,     Adjusted R-squared: 0.1364
F-statistic: 1.316 on 27 and 27 DF,  p-value: 0.2403


Estimation results for equation Lag_Diff_Avg_Crypto_Price:
==========================================================
Lag_Diff_Avg_Crypto_Price = Date.l1 + Diff_First_Exchange_Rate.l1 +
Diff_Inflation.l1 + Diff_Trading_Volumes.l1 + Second_Diff_GDP_growth_rate.l1 +
Second_Diff_Remittances.l1 + Second_Diff_Avg_Stock_Index.l1 +
Second_Diff_Avg_Oil_Price.l1 + Lag_Diff_Avg_Crypto_Price.l1 + Date.l2 +
Diff_First_Exchange_Rate.l2 + Diff_Inflation.l2 + Diff_Trading_Volumes.l2 +
Second_Diff_GDP_growth_rate.l2 + Second_Diff_Remittances.l2 +
Second_Diff_Avg_Stock_Index.l2 + Second_Diff_Avg_Oil_Price.l2 +
Lag_Diff_Avg_Crypto_Price.l2 + Date.l3 + Diff_First_Exchange_Rate.l3 +
Diff_Inflation.l3 + Diff_Trading_Volumes.l3 + Second_Diff_GDP_growth_rate.l3 +
Second_Diff_Remittances.l3 + Second_Diff_Avg_Stock_Index.l3 +
Second_Diff_Avg_Oil_Price.l3 + Lag_Diff_Avg_Crypto_Price.l3 + const

                                 Estimate Std. Error t value Pr(>|t|)
Date.l1                        -4.133e+02  5.188e+02  -0.797  0.43262
Diff_First_Exchange_Rate.l1    -8.556e+01  6.985e+01  -1.225  0.23121
Diff_Inflation.l1              -1.216e+03  1.478e+03  -0.822  0.41808
```

```
Diff_Trading_Volumes.l1         2.417e-04  6.104e-04   0.396  0.69518
Second_Diff_GDP_growth_rate.l1 -7.240e+02  6.340e+02  -1.142  0.26346
Second_Diff_Remittances.l1      1.744e+00  5.082e+00   0.343  0.73409
Second_Diff_Avg_Stock_Index.l1  4.770e-01  2.339e-01   2.039  0.05135 .
Second_Diff_Avg_Oil_Price.l1    5.276e+01  4.369e+01   1.208  0.23762
Lag_Diff_Avg_Crypto_Price.l1    5.094e-01  1.608e-01   3.169  0.00378 **
Date.l2                         2.870e+01  5.280e+02   0.054  0.95706
Diff_First_Exchange_Rate.l2    -1.196e+02  6.493e+01  -1.843  0.07638 .
Diff_Inflation.l2              -4.091e+02  2.402e+03  -0.170  0.86606
Diff_Trading_Volumes.l2         9.416e-04  6.440e-04   1.462  0.15522
Second_Diff_GDP_growth_rate.l2 -1.197e+03  1.179e+03  -1.015  0.31893
Second_Diff_Remittances.l2      1.387e+01  4.726e+00   2.934  0.00675 **
Second_Diff_Avg_Stock_Index.l2 -2.859e-02  2.381e-01  -0.120  0.90530
Second_Diff_Avg_Oil_Price.l2    9.698e+01  4.543e+01   2.135  0.04202 *
Lag_Diff_Avg_Crypto_Price.l2    1.911e-02  1.845e-01   0.104  0.91827
Date.l3                         3.842e+02  5.086e+02   0.755  0.45654
Diff_First_Exchange_Rate.l3    -1.113e+01  6.960e+01  -0.160  0.87415
Diff_Inflation.l3               2.419e+03  1.735e+03   1.395  0.17451
Diff_Trading_Volumes.l3         6.484e-04  6.400e-04   1.013  0.32000
Second_Diff_GDP_growth_rate.l3 -3.863e+03  1.095e+03  -3.528  0.00152 **
Second_Diff_Remittances.l3      1.222e+00  2.106e+00   0.580  0.56655
Second_Diff_Avg_Stock_Index.l3  9.117e-02  2.361e-01   0.386  0.70244
Second_Diff_Avg_Oil_Price.l3    4.190e+01  4.604e+01   0.910  0.37075
Lag_Diff_Avg_Crypto_Price.l3   -1.357e-01  1.650e-01  -0.823  0.41799
const                           3.322e+04  3.017e+04   1.101  0.28063
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 2008 on 27 degrees of freedom
Multiple R-Squared: 0.7056,     Adjusted R-squared: 0.4111
F-statistic: 2.396 on 27 and 27 DF,  p-value: 0.01336



Covariance matrix of residuals:
                                 Date Diff_First_Exchange_Rate Diff_Inflation
Date                        4.414e-01                4.812e-01        0.02331
Diff_First_Exchange_Rate    4.812e-01                2.525e+01        0.13307
Diff_Inflation              2.331e-02                1.331e-01        0.06631
Diff_Trading_Volumes        4.957e+04               -1.342e+05     3942.22977
Second_Diff_GDP_growth_rate  8.786e-02                3.947e-01        0.01670
Second_Diff_Remittances     1.659e+01               -2.789e+01       -4.70740
Second_Diff_Avg_Stock_Index  2.102e+02               -8.367e+02     -140.25376
Second_Diff_Avg_Oil_Price   -4.506e-01               -2.695e+00       -0.30848
Lag_Diff_Avg_Crypto_Price    7.287e+01               -3.005e+03        7.21153
                            Diff_Trading_Volumes Second_Diff_GDP_growth_rate
Date                                   4.957e+04                     0.08786
Diff_First_Exchange_Rate              -1.342e+05                     0.39470
Diff_Inflation                         3.942e+03                     0.01670
```

```
Diff_Trading_Volumes                     3.145e+11                     5848.67835
Second_Diff_GDP_growth_rate              5.849e+03                        0.19987
Second_Diff_Remittances                 -2.111e+06                       -1.85599
Second_Diff_Avg_Stock_Index              2.142e+08                      126.16375
Second_Diff_Avg_Oil_Price                2.140e+05                        1.32267
Lag_Diff_Avg_Crypto_Price                1.954e+08                     -403.88953
                            Second_Diff_Remittances Second_Diff_Avg_Stock_Index
Date                                      1.659e+01                   2.102e+02
Diff_First_Exchange_Rate                 -2.789e+01                  -8.367e+02
Diff_Inflation                           -4.707e+00                  -1.403e+02
Diff_Trading_Volumes                     -2.111e+06                   2.142e+08
Second_Diff_GDP_growth_rate              -1.856e+00                   1.262e+02
Second_Diff_Remittances                   3.102e+03                   1.884e+04
Second_Diff_Avg_Stock_Index               1.884e+04                   2.527e+06
Second_Diff_Avg_Oil_Price                -1.509e+01                   3.835e+03
Lag_Diff_Avg_Crypto_Price                -3.722e+03                  -7.154e+05
                            Second_Diff_Avg_Oil_Price Lag_Diff_Avg_Crypto_Price
Date                                       -4.506e-01                 7.287e+01
Diff_First_Exchange_Rate                   -2.695e+00                -3.005e+03
Diff_Inflation                             -3.085e-01                 7.212e+00
Diff_Trading_Volumes                        2.140e+05                 1.954e+08
Second_Diff_GDP_growth_rate                 1.323e+00                -4.039e+02
Second_Diff_Remittances                    -1.509e+01                -3.722e+03
Second_Diff_Avg_Stock_Index                 3.835e+03                -7.154e+05
Second_Diff_Avg_Oil_Price                   8.556e+01                -2.735e+03
Lag_Diff_Avg_Crypto_Price                  -2.735e+03                 4.031e+06

Correlation matrix of residuals:
                                Date Diff_First_Exchange_Rate Diff_Inflation
Date                         1.00000                  0.14415        0.13627
Diff_First_Exchange_Rate     0.14415                  1.00000        0.10285
Diff_Inflation               0.13627                  0.10285        1.00000
Diff_Trading_Volumes         0.13304                 -0.04763        0.02730
Second_Diff_GDP_growth_rate  0.29580                  0.17571        0.14504
Second_Diff_Remittances      0.44844                 -0.09968       -0.32823
Second_Diff_Avg_Stock_Index  0.19899                 -0.10476       -0.34263
Second_Diff_Avg_Oil_Price   -0.07332                 -0.05798       -0.12951
Lag_Diff_Avg_Crypto_Price    0.05463                 -0.29791        0.01395
                            Diff_Trading_Volumes Second_Diff_GDP_growth_rate
Date                                     0.13304                     0.29580
Diff_First_Exchange_Rate                -0.04763                     0.17571
Diff_Inflation                           0.02730                     0.14504
Diff_Trading_Volumes                     1.00000                     0.02333
Second_Diff_GDP_growth_rate              0.02333                     1.00000
Second_Diff_Remittances                 -0.06760                    -0.07454
Second_Diff_Avg_Stock_Index              0.24029                     0.17753
Second_Diff_Avg_Oil_Price                0.04126                     0.31984
Lag_Diff_Avg_Crypto_Price                0.17354                    -0.44997
                            Second_Diff_Remittances Second_Diff_Avg_Stock_Index
Date                                        0.44844                      0.1990
```

Diff_First_Exchange_Rate	-0.09968	-0.1048
Diff_Inflation	-0.32823	-0.3426
Diff_Trading_Volumes	-0.06760	0.2403
Second_Diff_GDP_growth_rate	-0.07454	0.1775
Second_Diff_Remittances	1.00000	0.2128
Second_Diff_Avg_Stock_Index	0.21281	1.0000
Second_Diff_Avg_Oil_Price	-0.02929	0.2608
Lag_Diff_Avg_Crypto_Price	-0.03329	-0.2242

	Second_Diff_Avg_Oil_Price	Lag_Diff_Avg_Crypto_Price
Date	-0.07332	0.05463
Diff_First_Exchange_Rate	-0.05798	-0.29791
Diff_Inflation	-0.12951	0.01395
Diff_Trading_Volumes	0.04126	0.17354
Second_Diff_GDP_growth_rate	0.31984	-0.44997
Second_Diff_Remittances	-0.02929	-0.03329
Second_Diff_Avg_Stock_Index	0.26081	-0.22417
Second_Diff_Avg_Oil_Price	1.00000	-0.14728
Lag_Diff_Avg_Crypto_Price	-0.14728	1.00000

145598 Final Research Data Analysis

Karii Ngugi

2025-01-29

LOADING NECESSARY PACKAGES

```
# Load Necessary Packages
if(!require(tidyverse)) install.packages("rtools")
```

```
## Loading required package: tidyverse
```

```
## Warning: package 'tidyverse' was built under R version 4.3.2
```

```
## Warning: package 'ggplot2' was built under R version 4.3.2
```

```
## Warning: package 'tibble' was built under R version 4.3.1
```

```
## Warning: package 'tidyr' was built under R version 4.3.2
```

```
## Warning: package 'readr' was built under R version 4.3.1
```

```
## Warning: package 'purrr' was built under R version 4.3.1
```

```
## Warning: package 'dplyr' was built under R version 4.3.2
```

```
## Warning: package 'stringr' was built under R version 4.3.2
```

```
## Warning: package 'forcats' was built under R version 4.3.2
```

```
## Warning: package 'lubridate' was built under R version 4.3.2
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.4
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.4.4     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.0
## ✔ purrr     1.0.2
```

```
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to be
come errors
```

```r
if(!require(tidyverse)) install.packages("tidyverse")
if(!require(forecast)) install.packages("forecast")
```

```
## Loading required package: forecast
```

```
## Warning: package 'forecast' was built under R version 4.3.3
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```r
if(!require(quantmod)) install.packages("quantmod")
```

```
## Loading required package: quantmod
```

```
## Warning: package 'quantmod' was built under R version 4.3.3
```

```
## Loading required package: xts
```

```
## Warning: package 'xts' was built under R version 4.3.2
```

```
## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 4.3.2
```

```
##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
##
##
## ######################### Warning from 'xts' package ##########################
## #                                                                             #
## # The dplyr lag() function breaks how base R's lag() function is supposed to  #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or       #
## # source() into this session won't work correctly.                            #
## #                                                                             #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop           #
## # dplyr from breaking base R's lag() function.                                #
## #                                                                             #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set `options(xts.warn_dplyr_breaks_lag = FALSE)` to suppress this warning.  #
## #                                                                             #
## ###############################################################################
##
## Attaching package: 'xts'
##
## The following objects are masked from 'package:dplyr':
##
##     first, last
##
## Loading required package: TTR
```

```
## Warning: package 'TTR' was built under R version 4.3.2
```

```
if(!require(rugarch)) install.packages("rugarch")
```

```
## Loading required package: rugarch
```

```
## Warning: package 'rugarch' was built under R version 4.3.3
```

```
## Loading required package: parallel
##
## Attaching package: 'rugarch'
##
## The following object is masked from 'package:purrr':
##
##     reduce
##
## The following object is masked from 'package:stats':
##
##     sigma
```

```
if(!require(vars)) install.packages("vars")
```

```
## Loading required package: vars
```

```
## Warning: package 'vars' was built under R version 4.3.3
```

```
## Loading required package: MASS
##
## Attaching package: 'MASS'
##
## The following object is masked from 'package:dplyr':
##
##     select
##
## Loading required package: strucchange
```

```
## Warning: package 'strucchange' was built under R version 4.3.3
```

```
## Loading required package: sandwich
```

```
## Warning: package 'sandwich' was built under R version 4.3.3
```

```
##
## Attaching package: 'strucchange'
##
## The following object is masked from 'package:stringr':
##
##     boundary
##
## Loading required package: urca
```

```
## Warning: package 'urca' was built under R version 4.3.2
```

```
## Loading required package: lmtest
```

```
## Warning: package 'lmtest' was built under R version 4.3.2
```

```
if(!require(tseries)) install.packages("tseries")
```

```
## Loading required package: tseries
```

```
## Warning: package 'tseries' was built under R version 4.3.3
```

```
if(!require(xts)) install.packages("xts")
if(!require(lubridate)) install.packages("lubridate")
if(!require(zoo)) install.packages("zoo")
if(!require(ggcorrplot)) install.packages("ggcorrplot")
```

```
## Loading required package: ggcorrplot
```

```
## Warning: package 'ggcorrplot' was built under R version 4.3.3
```

```
if(!require(WDI)) install.packages("WDI")
```

```
## Loading required package: WDI
```

```
## Warning: package 'WDI' was built under R version 4.3.3
```

```
if(!require(httr)) install.packages("httr")
```

```
## Loading required package: httr
```

```
## Warning: package 'httr' was built under R version 4.3.3
```

```
if(!require(jsonlite)) install.packages("jsonlite")
```

```
## Loading required package: jsonlite
```

```
## Warning: package 'jsonlite' was built under R version 4.3.3
```

```
##
## Attaching package: 'jsonlite'
##
## The following object is masked from 'package:purrr':
##
##     flatten
```

```r
# Load Libraries
library(tidyverse)
library(forecast)
library(quantmod)
library(rugarch)
library(vars)
library(tseries)
library(xts)
library(lubridate)
library(zoo)
library(ggcorrplot)
library(WDI)
library(httr)
library(jsonlite)
```

Crypto-currency Data

```r
# Fetch Cryptocurrency Data from Yahoo Finance
start_date <- as.Date("2015-01-01")
end_date <- Sys.Date()

# Bitcoin (BTC-USD)
getSymbols("BTC-USD", src = "yahoo", from = start_date, to = end_date)
```

```
## Warning: BTC-USD contains missing values. Some functions will not work if
## objects contain missing values in the middle of the series. Consider using
## na.omit(), na.approx(), na.fill(), etc to remove or replace them.
```

```
## [1] "BTC-USD"
```

```r
bitcoin_data <- data.frame(Date = index(`BTC-USD`), coredata(`BTC-USD`))

# Ethereum (ETH-USD)
getSymbols("ETH-USD", src = "yahoo", from = start_date, to = end_date)
```

```
## Warning: ETH-USD contains missing values. Some functions will not work if
## objects contain missing values in the middle of the series. Consider using
## na.omit(), na.approx(), na.fill(), etc to remove or replace them.
```

```
## [1] "ETH-USD"
```

```r
ethereum_data <- data.frame(Date = index(`ETH-USD`), coredata(`ETH-USD`))
```

Nigerian Quarterly Remittances

```r
library(readxl)
```

```
## Warning: package 'readxl' was built under R version 4.3.2
```

```
Remittances_Data <- read_excel("C:/Users/Kariie/Desktop/Remittances Data.xlsx")
```

Nigerian Monthly Inflation Rates

```
library(readxl)
Inflation_data <- read_excel("C:/Users/Kariie/Desktop/Inflation data.xlsx")
```

USD/NGN DAILY EXCHANGE RATE DATA

```
# Fetch USD/NGN Exchange Rate Data from Alpha Vantage
api_key <- "YOUR_API_KEY"

# Function to fetch exchange rate data
get_fx_data <- function(from_currency = "USD", to_currency = "NGN", api_key) {
  url <- paste0("https://www.alphavantage.co/query?function=FX_DAILY&from_symbol=",
                from_currency, "&to_symbol=", to_currency,
                "&apikey=", api_key, "&outputsize=full")

  response <- GET(url)

  if (status_code(response) != 200) {
    stop("Failed to fetch data. Status code: ", status_code(response))
  }

  data <- fromJSON(content(response, "text", encoding = "UTF-8"))
  if (!"Time Series FX (Daily)" %in% names(data)) {
    stop("Unexpected data format or no data returned.")
  }

  fx_data <- data[["Time Series FX (Daily)"]]
  df <- data.frame(
    Date = as.Date(names(fx_data)),
    Open = as.numeric(sapply(fx_data, function(x) x[["1. open"]])),
    High = as.numeric(sapply(fx_data, function(x) x[["2. high"]])),
    Low = as.numeric(sapply(fx_data, function(x) x[["3. low"]])),
    Close = as.numeric(sapply(fx_data, function(x) x[["4. close"]]))
  )

  return(df)
}

# Fetch data
exchange_data <- get_fx_data(from_currency = "USD", to_currency = "NGN", api_key = api_key)
```

Oil Prices Data

```
library(readxl)
Oil_Prices <- read_excel("C:/Users/Kariie/Desktop/Oil Prices.xlsx")
```

GDP Growth

```
library(readxl)
GDP_growth_rates <- read_excel("C:/Users/Kariie/Desktop/GDP growth rates.xlsx")
```

Nigerian Stock Market All Share index

```
library(readxl)
NGN_stock_index <- read_excel("C:/Users/Kariie/Desktop/NGN stock index.xlsx")
```

Trading Volumes

```
library(readxl)
Trading_volumes <- read_excel("C:/Users/Kariie/Desktop/Trading volumes.xlsx")
```

CHAPTER 2: DATA PREPROCESSING AND PREPARATION 1. Process Cryptocurrency Data

```
# Process Bitcoin and Ethereum Data: Calculate Monthly Averages
Crypto_Monthly <- bitcoin_data %>%
  mutate(Date = floor_date(Date, "month")) %>%  # Group by month
  group_by(Date) %>%
  summarize(Avg_BTC_Price = mean(BTC.USD.Close, na.rm = TRUE)) %>%
  full_join(
    ethereum_data %>%
      mutate(Date = floor_date(Date, "month")) %>%
      group_by(Date) %>%
      summarize(Avg_ETH_Price = mean(ETH.USD.Close, na.rm = TRUE)),
    by = "Date"
  ) %>%
  mutate(
    Avg_Crypto_Price = (Avg_BTC_Price + Avg_ETH_Price) / 2  # Calculate average crypto price
  ) %>%
  filter(Date >= as.Date("2018-01-01"))  # Ensure only the required date range is included
```

2. Process Exchange Rate Data

```
# Extract the First Exchange Rate of Each Month
Exchange_Monthly <- exchange_data %>%
  mutate(Date = as.Date(Date)) %>%
  filter(Date == floor_date(Date, "month")) %>%
  rename(First_Exchange_Rate = Close)
```

3.Interpolate Remittances

```
# Fill Missing Values for Remittances
Remittances_monthly <- Remittances_Data %>%
  mutate(Date = as.Date(Date)) %>%
  complete(Date = seq.Date(as.Date("2018-01-01"), as.Date("2022-12-01"), by = "month")) %>%
  mutate(
    Remittances = case_when(
      is.na(Remittances) & Date == as.Date("2018-01-01") ~ runif(1, 5500, 5800),  # Plausible
Jan value
      is.na(Remittances) & Date == as.Date("2018-02-01") ~ runif(1, 5600, 5900),  # Plausible
Feb value
      TRUE ~ Remittances
    ),
    Remittances = na.approx(Remittances, na.rm = FALSE)  # Interpolate other missing values
  )
```

4.Interpolate GDP Growth Rates

```
# Fill Missing Values for GDP Growth Rates
GDP_growth_rate_monthly <- GDP_growth_rates %>%
  mutate(Date = as.Date(Date)) %>%
  complete(Date = seq.Date(as.Date("2017-11-01"), as.Date("2022-12-01"), by = "month")) %>%
  mutate(`GDP growth rate` = na.approx(`GDP growth rate`, na.rm = FALSE))
```

5.Process Oil Prices and Stock Index

```
# Process Oil Prices
Oil_Prices_Monthly <- Oil_Prices %>%
  mutate(Date = as.Date(Date)) %>%
  filter(Date == floor_date(Date, "month")) %>%
  rename(Avg_Oil_Price = `Oil Prices`)

# Process Stock Index
Stock_Index_Monthly <- NGN_stock_index %>%
  mutate(Date = as.Date(Date)) %>%
  filter(Date == floor_date(Date, "month")) %>%
  rename(Avg_Stock_Index = `Stock Index`)
```

6.Process Trading Volumes

```
# Align Trading Volumes to the First of Each Month
Trading_volumes <- Trading_volumes %>%
  mutate(Date = as.Date(Date)) %>%
  filter(Date == floor_date(Date, "month")) %>%
  rename(Trading_Volumes = `Trading Volumes`)
```

7. Aligning the datasets

```
library(dplyr)
library(lubridate)

# Bitcoin and Ethereum: Monthly Averages, Aligned to the First of Each Month
Crypto_Monthly <- bitcoin_data %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%  # Align to the first day of each mon
th
  group_by(Date) %>%
  summarize(Avg_BTC_Price = mean(BTC.USD.Close, na.rm = TRUE)) %>%
  full_join(
    ethereum_data %>%
      mutate(Date = floor_date(as.Date(Date), "month")) %>%
      group_by(Date) %>%
      summarize(Avg_ETH_Price = mean(ETH.USD.Close, na.rm = TRUE)),
    by = "Date"
  ) %>%
  mutate(Avg_Crypto_Price = (Avg_BTC_Price + Avg_ETH_Price) / 2)

# Exchange Rate: First Observation of Each Month
Exchange_Monthly <- exchange_data %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  group_by(Date) %>%
  summarize(First_Exchange_Rate = first(Close, na.rm = TRUE))

# Remittances: Interpolated and Aligned to Monthly
Remittances_monthly <- Remittances_Data %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  complete(Date = seq.Date(as.Date("2018-01-01"), as.Date("2022-12-01"), by = "month")) %>%
  mutate(Remittances = na.approx(Remittances, na.rm = FALSE))

# GDP Growth Rate: Interpolated and Aligned to Monthly
GDP_growth_rate_monthly <- GDP_growth_rates %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  complete(Date = seq.Date(as.Date("2017-11-01"), as.Date("2022-12-01"), by = "month")) %>%
  mutate(`GDP growth rate` = na.approx(`GDP growth rate`, na.rm = FALSE))

# Oil Prices: Monthly Averages
Oil_Prices_Monthly <- Oil_Prices %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  group_by(Date) %>%
  summarize(Avg_Oil_Price = mean(`Oil Prices`, na.rm = TRUE))

# Stock Index: Monthly Averages
Stock_Index_Monthly <- NGN_stock_index %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  group_by(Date) %>%
  summarize(Avg_Stock_Index = mean(`Stock Index`, na.rm = TRUE))

# Trading Volumes: Monthly Averages
Trading_volumes <- Trading_volumes %>%
  mutate(Date = floor_date(as.Date(Date), "month")) %>%
  group_by(Date) %>%
  summarize(Trading_Volumes = mean(Trading_Volumes, na.rm = TRUE))
```

CHAPTER 3: MERGING THE DATASET i.Normalize Date Formats

```
library(dplyr)
library(lubridate)

# Standardize date formats and align to the first of each month
Crypto_Monthly <- Crypto_Monthly %>% mutate(Date = floor_date(as.Date(Date, format = "%Y-%m-%
d"), "month"))
Exchange_Monthly <- Exchange_Monthly %>% mutate(Date = floor_date(as.Date(Date, format = "%Y-
%m-%d"), "month"))
GDP_growth_rate_monthly <- GDP_growth_rate_monthly %>% mutate(Date = floor_date(as.Date(Date,
format = "%Y-%m-%d"), "month"))
Remittances_monthly <- Remittances_monthly %>% mutate(Date = floor_date(as.Date(Date, format
= "%Y-%m-%d"), "month"))
NGN_stock_index <- NGN_stock_index %>% mutate(Date = floor_date(as.Date(Date, format = "%Y-%m
-%d"), "month"))
Oil_Prices_Monthly <- Oil_Prices_Monthly %>% mutate(Date = floor_date(as.Date(Date, format =
"%Y-%m-%d"), "month"))
Inflation_data <- Inflation_data %>% mutate(Date = floor_date(as.Date(Date, format = "%Y-%m-%
d"), "month"))
Trading_volumes <- Trading_volumes %>% mutate(Date = floor_date(as.Date(Date, format = "%Y-%m
-%d"), "month"))
```

ii. Filter Datasets to the Target Date Range

```
# Filter all datasets to only include January 2018 to December 2022
Crypto_Monthly <- Crypto_Monthly %>% filter(Date >= as.Date("2018-01-01") & Date <= as.Date
("2022-12-01"))
Exchange_Monthly <- Exchange_Monthly %>% filter(Date >= as.Date("2018-01-01") & Date <= as.Da
te("2022-12-01"))
GDP_growth_rate_monthly <- GDP_growth_rate_monthly %>% filter(Date >= as.Date("2018-01-01") &
Date <= as.Date("2022-12-01"))
Remittances_monthly <- Remittances_monthly %>% filter(Date >= as.Date("2018-01-01") & Date <=
as.Date("2022-12-01"))
NGN_stock_index <- NGN_stock_index %>% filter(Date >= as.Date("2018-01-01") & Date <= as.Date
("2022-12-01"))
Oil_Prices_Monthly <- Oil_Prices_Monthly %>% filter(Date >= as.Date("2018-01-01") & Date <= a
s.Date("2022-12-01"))
Inflation_data <- Inflation_data %>% filter(Date >= as.Date("2018-01-01") & Date <= as.Date
("2022-12-01"))
Trading_volumes <- Trading_volumes %>% filter(Date >= as.Date("2018-01-01") & Date <= as.Date
("2022-12-01"))
```

iii. Remove Duplicates and Aggregate as Needed

```
# Aggregate NGN_stock_index to ensure no duplicate dates
NGN_stock_index <- NGN_stock_index %>%
  group_by(Date) %>%
  summarize(Avg_Stock_Index = mean(`Stock Index`, na.rm = TRUE))
```

iv. Fix missing values in Remittances

```
# Fix missing values in Remittances
Remittances_monthly <- Remittances_monthly %>%
  mutate(
    Remittances = case_when(
      is.na(Remittances) & Date == as.Date("2018-01-01") ~ runif(1, 5500, 5800),
      is.na(Remittances) & Date == as.Date("2018-02-01") ~ runif(1, 5600, 5900),
      TRUE ~ Remittances
    )
  ) %>%
  mutate(Remittances = na.approx(Remittances, na.rm = FALSE))
# Impute missing GDP growth rate
GDP_growth_rate_monthly <- GDP_growth_rate_monthly %>%
  mutate(`GDP growth rate` = ifelse(is.na(`GDP growth rate`), 3.3, `GDP growth rate`))
```

v. Merge All Datasets

```
# Merge all datasets by Date
merged_monthly_data <- Crypto_Monthly %>%
  full_join(Exchange_Monthly, by = "Date") %>%
  full_join(GDP_growth_rate_monthly, by = "Date") %>%
  full_join(Remittances_monthly, by = "Date") %>%
  full_join(NGN_stock_index, by = "Date") %>%
  full_join(Oil_Prices_Monthly, by = "Date") %>%
  full_join(Inflation_data %>% rename(Inflation = CPI), by = "Date") %>%
  full_join(Trading_volumes %>% rename(Trading_Volumes = Trading_Volumes), by = "Date") %>%
  arrange(Date)
```

vi. Handle Missing Data and Save

```
library(zoo)

# Handle missing data via interpolation
merged_monthly_data <- merged_monthly_data %>%
  mutate(across(where(is.numeric), ~ na.approx(., na.rm = FALSE)))

# Save the dataset
write.csv(merged_monthly_data, "Merged_analysis_data.csv", row.names = FALSE)
```

vii. Removing Ethereum and Bitcoin

```
# Remove columns using base R
merged_monthly_data <- merged_monthly_data[, !(colnames(merged_monthly_data) %in% c("Avg_BTC_
Price", "Avg_ETH_Price"))]

# Preview the updated dataset
head(merged_monthly_data)
```

```
## # A tibble: 6 × 9
##   Date       Avg_Crypto_Price First_Exchange_Rate `GDP growth rate` Remittances
##   <date>                <dbl>               <dbl>             <dbl>       <dbl>
## 1 2018-01-01            7095.                 358              1.96       5690.
## 2 2018-02-01            5173.                 359              1.89       5787.
## 3 2018-03-01            4833.                 355              1.76       5852.
## 4 2018-04-01            4277.                 358              1.63       5873.
## 5 2018-05-01            4565.                 359              1.5        5894.
## 6 2018-06-01            3657.                 357              1.60       5915.
## # ℹ 4 more variables: Avg_Stock_Index <dbl>, Avg_Oil_Price <dbl>,
## #   Inflation <dbl>, Trading_Volumes <dbl>
```

```
# Save the updated dataset
write.csv(merged_monthly_data, "Merged_analysis_data.csv", row.names = FALSE)
```

CHAPTER 4; SUMMARY STATISTICS AND DATA VISUALISATION

```
# Load necessary libraries
library(dplyr)
library(moments)  # For skewness and kurtosis calculations
```

```
## Warning: package 'moments' was built under R version 4.3.1
```

```
# Summary Statistics
summary_stats <- merged_monthly_data %>%
  summarise(
    Avg_Crypto_Price = list(summary(Avg_Crypto_Price)),
    Exchange_Rate = list(summary(First_Exchange_Rate)),  # Adjusted column name
    GDP_growth_rate = list(summary(`GDP growth rate`)),
    Remittances = list(summary(Remittances)),
    Avg_Stock_Index = list(summary(Avg_Stock_Index)),
    Avg_Oil_Price = list(summary(Avg_Oil_Price)),
    Inflation = list(summary(Inflation)),
    Trading_Volumes = list(summary(Trading_Volumes))
  )

# Print Summary Statistics
print(summary_stats)
```

```
## # A tibble: 1 × 8
##   Avg_Crypto_Price Exchange_Rate  GDP_growth_rate Remittances    Avg_Stock_Index
##   <list>           <list>         <list>          <list>         <list>
## 1 <smmryDfl [6]>   <smmryDfl [6]> <smmryDfl [6]> <smmryDfl [6]> <smmryDfl [6]>
## # ℹ 3 more variables: Avg_Oil_Price <list>, Inflation <list>,
## #   Trading_Volumes <list>
```

```
# Transform Summary Statistics into a Data Frame with additional metrics
summary_stats_df <- data.frame(
  Variable = c(
    "Avg_Crypto_Price",
    "First_Exchange_Rate",
    "GDP_growth_rate",
    "Remittances",
    "Avg_Stock_Index",
    "Avg_Oil_Price",
    "Inflation",
    "Trading_Volumes"
  ),
  Min = c(
    min(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    min(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    min(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    min(merged_monthly_data$Remittances, na.rm = TRUE),
    min(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    min(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    min(merged_monthly_data$Inflation, na.rm = TRUE),
    min(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Max = c(
    max(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    max(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    max(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    max(merged_monthly_data$Remittances, na.rm = TRUE),
    max(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    max(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    max(merged_monthly_data$Inflation, na.rm = TRUE),
    max(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Mean = c(
    mean(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    mean(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    mean(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    mean(merged_monthly_data$Remittances, na.rm = TRUE),
    mean(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    mean(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    mean(merged_monthly_data$Inflation, na.rm = TRUE),
    mean(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Median = c(
    median(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    median(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    median(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    median(merged_monthly_data$Remittances, na.rm = TRUE),
    median(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    median(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    median(merged_monthly_data$Inflation, na.rm = TRUE),
    median(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Std_Dev = c(
    sd(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    sd(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
```

```
    sd(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    sd(merged_monthly_data$Remittances, na.rm = TRUE),
    sd(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    sd(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    sd(merged_monthly_data$Inflation, na.rm = TRUE),
    sd(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Variance = c(
    var(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    var(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    var(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    var(merged_monthly_data$Remittances, na.rm = TRUE),
    var(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    var(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    var(merged_monthly_data$Inflation, na.rm = TRUE),
    var(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Skewness = c(
    skewness(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    skewness(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    skewness(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    skewness(merged_monthly_data$Remittances, na.rm = TRUE),
    skewness(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    skewness(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    skewness(merged_monthly_data$Inflation, na.rm = TRUE),
    skewness(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  ),
  Kurtosis = c(
    kurtosis(merged_monthly_data$Avg_Crypto_Price, na.rm = TRUE),
    kurtosis(merged_monthly_data$First_Exchange_Rate, na.rm = TRUE),
    kurtosis(merged_monthly_data$`GDP growth rate`, na.rm = TRUE),
    kurtosis(merged_monthly_data$Remittances, na.rm = TRUE),
    kurtosis(merged_monthly_data$Avg_Stock_Index, na.rm = TRUE),
    kurtosis(merged_monthly_data$Avg_Oil_Price, na.rm = TRUE),
    kurtosis(merged_monthly_data$Inflation, na.rm = TRUE),
    kurtosis(merged_monthly_data$Trading_Volumes, na.rm = TRUE)
  )
)

# Save Summary Statistics as a CSV File
write.csv(summary_stats_df, "summary_statistics.csv", row.names = FALSE)

# Preview the Summary Statistics Data Frame
print(summary_stats_df)
```

```
##             Variable         Min          Max         Mean       Median
## 1    Avg_Crypto_Price   1913.24322   32527.8088 1.075273e+04 5.486569e+03
## 2 First_Exchange_Rate    355.00000     447.5600 3.832833e+02 3.765000e+02
## 3     GDP_growth_rate     -6.10000       5.0100 1.739556e+00 2.191667e+00
## 4         Remittances   3373.09000    6270.2500 5.184746e+03 5.071060e+03
## 5     Avg_Stock_Index  22030.32318   52357.4500 3.638678e+04 3.767363e+04
## 6       Avg_Oil_Price     15.34318     125.7959 7.109557e+01 6.852518e+01
## 7           Inflation     11.02000      21.4700 1.449917e+01 1.352500e+01
## 8     Trading_Volumes 641153.00000 4666037.0000 2.505500e+06 2.420766e+06
##        Std_Dev     Variance   Skewness Kurtosis
## 1 9.044089e+03 8.179554e+07  0.9702749 2.518587
## 2 2.731469e+01 7.460921e+02  0.6669131 2.112731
## 3 2.354316e+00 5.542805e+00 -1.7033294 5.636978
## 4 7.644609e+02 5.844005e+05 -0.5482305 2.287488
## 5 8.459406e+03 7.156154e+07  0.1547827 1.911043
## 6 2.251157e+01 5.067710e+02  0.2733393 3.446658
## 7 3.194627e+00 1.020564e+01  0.6371991 2.221151
## 8 1.261061e+06 1.590275e+12  0.1433350 1.526715
```

2. Data Visualisations

```
# Load Required Libraries
library(ggplot2)

# Define the working directory for saving images
output_dir <- getwd()  # Set this to your preferred directory if needed

# Average Cryptocurrency Prices Over Time
crypto_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Avg_Crypto_Price)) +
  geom_line(color = "blue", linewidth = 1) +
  labs(title = "Average Cryptocurrency Price Over Time",
       x = "Date",
       y = "Price (USD)") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "avg_crypto_price_plot.png"), plot = crypto_plot, wid
th = 8, height = 6)

# Exchange Rates Over Time
exchange_rate_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = First_Exchange_Rat
e)) +
  geom_line(color = "orange", linewidth = 1) +
  labs(title = "Exchange Rate (USD to NGN) Over Time",
       x = "Date",
       y = "Exchange Rate") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "exchange_rate_plot.png"), plot = exchange_rate_plot,
width = 8, height = 6)

# GDP Growth Rates Over Time
gdp_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = `GDP growth rate`)) +
  geom_line(color = "purple", linewidth = 1) +
  labs(title = "GDP Growth Rate Over Time",
       x = "Date",
       y = "Growth Rate (%)") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "gdp_growth_rate_plot.png"), plot = gdp_plot, width =
8, height = 6)

# Remittances Over Time
remittances_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Remittances)) +
  geom_line(color = "green", linewidth = 1) +
  labs(title = "Monthly Remittances Over Time",
       x = "Date",
       y = "Remittances (USD)") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "remittances_plot.png"), plot = remittances_plot, wid
th = 8, height = 6)

# Average Stock Index Over Time
stock_index_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Avg_Stock_Index)) +
  geom_line(color = "red", linewidth = 1) +
  labs(title = "Average Stock Index Over Time",
       x = "Date",
       y = "Stock Index") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "avg_stock_index_plot.png"), plot = stock_index_plot,
```

```
width = 8, height = 6)

# Average Oil Prices Over Time
oil_price_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Avg_Oil_Price)) +
  geom_line(color = "darkgreen", linewidth = 1) +
  labs(title = "Average Oil Prices Over Time",
       x = "Date",
       y = "Price (USD)") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "avg_oil_price_plot.png"), plot = oil_price_plot, wid
th = 8, height = 6)

# Inflation Over Time
inflation_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Inflation)) +
  geom_line(color = "brown", linewidth = 1) +
  labs(title = "Inflation Rate Over Time",
       x = "Date",
       y = "Inflation Rate (%)") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "inflation_rate_plot.png"), plot = inflation_plot, wi
dth = 8, height = 6)

# Trading Volumes Over Time
trading_volumes_plot <- ggplot(data = merged_monthly_data, aes(x = Date, y = Trading_Volume
s)) +
  geom_line(color = "cyan", linewidth = 1) +
  labs(title = "Trading Volumes Over Time",
       x = "Date",
       y = "Volumes") +
  theme_minimal()
ggsave(filename = file.path(output_dir, "trading_volumes_plot.png"), plot = trading_volumes_p
lot, width = 8, height = 6)

# Print a confirmation message
cat("All visualizations have been saved to your working directory.\n")
```

```
## All visualizations have been saved to your working directory.
```

CHAPTER 5: PRE ESTIMATION TESTS

1. Augmented Dickey-Fuller (ADF) Test The ADF Test checks for stationarity:

Null Hypothesis (H0): The series has a unit root (non-stationary). Alternative Hypothesis (H1): The series is stationary.

```
# Load Required Libraries
library(tseries)
library(car)
```

```
## Warning: package 'car' was built under R version 4.3.3
```

```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.3.3
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
## The following object is masked from 'package:purrr':
##
##     some
```

```
# Perform ADF Test for All Variables
adf_results <- lapply(merged_monthly_data, function(column) {
  if (is.numeric(column)) adf.test(column) else NULL
})

# Summarize Results
adf_summary <- lapply(adf_results, function(result) {
  if (!is.null(result)) c(Statistic = result$statistic, P_Value = result$p.value) else NULL
})
print("ADF Test Summary:")
```

```
## [1] "ADF Test Summary:"
```

```
print(adf_summary)
```

```
## $Date
## NULL
##
## $Avg_Crypto_Price
## Statistic.Dickey-Fuller                 P_Value
##              -1.3202166              0.8495487
##
## $First_Exchange_Rate
## Statistic.Dickey-Fuller                 P_Value
##              -2.1688247              0.5065381
##
## $`GDP growth rate`
## Statistic.Dickey-Fuller                 P_Value
##              -1.8647034              0.6294651
##
## $Remittances
## Statistic.Dickey-Fuller                 P_Value
##              -1.5514257              0.7560931
##
## $Avg_Stock_Index
## Statistic.Dickey-Fuller                 P_Value
##              -2.3360522              0.4389441
##
## $Avg_Oil_Price
## Statistic.Dickey-Fuller                 P_Value
##              -1.7440004              0.6782537
##
## $Inflation
## Statistic.Dickey-Fuller                 P_Value
##              -3.0078929              0.1673836
##
## $Trading_Volumes
## Statistic.Dickey-Fuller                 P_Value
##              -2.6840470              0.2982834
```



```
# Separate Stationary and Non-Stationary Variables
stationary_vars <- names(adf_results)[sapply(adf_results, function(x) !is.null(x) && x$p.valu
e < 0.05)]
non_stationary_vars <- names(adf_results)[sapply(adf_results, function(x) !is.null(x) && x$p.
value >= 0.05)]

print("Stationary Variables:")
```

```
## [1] "Stationary Variables:"
```

```
print(stationary_vars)
```

```
## character(0)
```

```
print("Non-Stationary Variables:")
```

```
## [1] "Non-Stationary Variables:"
```

```
print(non_stationary_vars)
```

```
## [1] "Avg_Crypto_Price"    "First_Exchange_Rate" "GDP growth rate"
## [4] "Remittances"         "Avg_Stock_Index"     "Avg_Oil_Price"
## [7] "Inflation"           "Trading_Volumes"
```

First differencing all variables

```
# Load Necessary Libraries
library(dplyr)
library(tseries)
library(tidyr)  # For drop_na()

# First Differencing for Non-Stationary Variables
stationary_data <- merged_monthly_data %>%
  mutate(
    Diff_Avg_Crypto_Price = c(NA, diff(Avg_Crypto_Price)),
    Diff_First_Exchange_Rate = c(NA, diff(First_Exchange_Rate)),
    Diff_GDP_growth_rate = c(NA, diff(`GDP growth rate`)),
    Diff_Remittances = c(NA, diff(Remittances)),
    Diff_Avg_Stock_Index = c(NA, diff(Avg_Stock_Index)),
    Diff_Avg_Oil_Price = c(NA, diff(Avg_Oil_Price)),
    Diff_Inflation = c(NA, diff(Inflation)),
    Diff_Trading_Volumes = c(NA, diff(Trading_Volumes))
  ) %>%
  drop_na()  # Remove rows with NA values caused by differencing
```

```
# Re-Test Differenced Variables for Stationarity
adf_results_diff <- list(
  Diff_Avg_Crypto_Price = adf.test(stationary_data$Diff_Avg_Crypto_Price),
  Diff_First_Exchange_Rate = adf.test(stationary_data$Diff_First_Exchange_Rate),
  Diff_GDP_growth_rate = adf.test(stationary_data$Diff_GDP_growth_rate),
  Diff_Remittances = adf.test(stationary_data$Diff_Remittances),
  Diff_Avg_Stock_Index = adf.test(stationary_data$Diff_Avg_Stock_Index),
  Diff_Avg_Oil_Price = adf.test(stationary_data$Diff_Avg_Oil_Price),
  Diff_Inflation = adf.test(stationary_data$Diff_Inflation),
  Diff_Trading_Volumes = adf.test(stationary_data$Diff_Trading_Volumes)
)
```

```
## Warning in adf.test(stationary_data$Diff_First_Exchange_Rate): p-value smaller
## than printed p-value
```

```
# Summarize Results for Differenced Variables
adf_summary_diff <- lapply(adf_results_diff, function(result) {
  c(Statistic = result$statistic, P_Value = result$p.value)
})
print("ADF Test Results for Differenced Variables:")
```

```
## [1] "ADF Test Results for Differenced Variables:"
```

```
print(adf_summary_diff)
```

```
## $Diff_Avg_Crypto_Price
## Statistic.Dickey-Fuller                  P_Value
##             -4.08816820              0.01193096
##
## $Diff_First_Exchange_Rate
## Statistic.Dickey-Fuller                  P_Value
##               -4.551263                0.010000
##
## $Diff_GDP_growth_rate
## Statistic.Dickey-Fuller                  P_Value
##              -2.8102623               0.2474198
##
## $Diff_Remittances
## Statistic.Dickey-Fuller                  P_Value
##              -2.7951932               0.2535071
##
## $Diff_Avg_Stock_Index
## Statistic.Dickey-Fuller                  P_Value
##             -3.43732489              0.05862928
##
## $Diff_Avg_Oil_Price
## Statistic.Dickey-Fuller                  P_Value
##             -3.47853086              0.05212581
##
## $Diff_Inflation
## Statistic.Dickey-Fuller                  P_Value
##             -3.61663735              0.03950157
##
## $Diff_Trading_Volumes
## Statistic.Dickey-Fuller                  P_Value
##             -3.66012818              0.03583826
```

```
# Check Which Variables Are Now Stationary
stationary_vars_diff <- names(adf_results_diff)[sapply(adf_results_diff, function(x) x$p.value < 0.05)]
non_stationary_vars_diff <- names(adf_results_diff)[sapply(adf_results_diff, function(x) x$p.value >= 0.05)]

print("Stationary Variables After Differencing:")
```

```
## [1] "Stationary Variables After Differencing:"
```

```
print(stationary_vars_diff)
```

```
## [1] "Diff_Avg_Crypto_Price"    "Diff_First_Exchange_Rate"
## [3] "Diff_Inflation"           "Diff_Trading_Volumes"
```

```
print("Non-Stationary Variables After Differencing:")
```

```
## [1] "Non-Stationary Variables After Differencing:"
```

```
print(non_stationary_vars_diff)
```

```
## [1] "Diff_GDP_growth_rate" "Diff_Remittances"     "Diff_Avg_Stock_Index"
## [4] "Diff_Avg_Oil_Price"
```

Second differencing non stationary variables

```
# Apply Second Differencing
stationary_data <- stationary_data %>%
  mutate(
    Second_Diff_GDP_growth_rate = c(NA, diff(Diff_GDP_growth_rate)),
    Second_Diff_Remittances = c(NA, diff(Diff_Remittances)),
    Second_Diff_Avg_Stock_Index = c(NA, diff(Diff_Avg_Stock_Index)),
    Second_Diff_Avg_Oil_Price = c(NA, diff(Diff_Avg_Oil_Price))
  ) %>%
  drop_na()  # Remove rows with NA caused by differencing

# Re-Test Second Differenced Variables for Stationarity
adf_results_second_diff <- list(
  Second_Diff_GDP_growth_rate = adf.test(stationary_data$Second_Diff_GDP_growth_rate),
  Second_Diff_Remittances = adf.test(stationary_data$Second_Diff_Remittances),
  Second_Diff_Avg_Stock_Index = adf.test(stationary_data$Second_Diff_Avg_Stock_Index),
  Second_Diff_Avg_Oil_Price = adf.test(stationary_data$Second_Diff_Avg_Oil_Price)
)
```

```
## Warning in adf.test(stationary_data$Second_Diff_GDP_growth_rate): p-value
## smaller than printed p-value
```

```
## Warning in adf.test(stationary_data$Second_Diff_Remittances): p-value smaller
## than printed p-value
```

```
## Warning in adf.test(stationary_data$Second_Diff_Avg_Stock_Index): p-value
## smaller than printed p-value
```

```
## Warning in adf.test(stationary_data$Second_Diff_Avg_Oil_Price): p-value smaller
## than printed p-value
```

```
# Summarize Results for Second Differenced Variables
adf_summary_second_diff <- lapply(adf_results_second_diff, function(result) {
  c(Statistic = result$statistic, P_Value = result$p.value)
})
print("ADF Test Results for Second Differenced Variables:")
```

```
## [1] "ADF Test Results for Second Differenced Variables:"
```

```
print(adf_summary_second_diff)
```

```
## $Second_Diff_GDP_growth_rate
## Statistic.Dickey-Fuller                 P_Value
##               -4.832391               0.010000
##
## $Second_Diff_Remittances
## Statistic.Dickey-Fuller                 P_Value
##               -4.777572               0.010000
##
## $Second_Diff_Avg_Stock_Index
## Statistic.Dickey-Fuller                 P_Value
##                -4.32809                 0.01000
##
## $Second_Diff_Avg_Oil_Price
## Statistic.Dickey-Fuller                 P_Value
##               -6.482737               0.010000
```

```
# Check Which Variables Are Now Stationary
stationary_vars_second_diff <- names(adf_results_second_diff)[sapply(adf_results_second_diff,
function(x) x$p.value < 0.05)]
non_stationary_vars_second_diff <- names(adf_results_second_diff)[sapply(adf_results_second_d
iff, function(x) x$p.value >= 0.05)]

print("Stationary Variables After Second Differencing:")
```

```
## [1] "Stationary Variables After Second Differencing:"
```

```
print(stationary_vars_second_diff)
```

```
## [1] "Second_Diff_GDP_growth_rate" "Second_Diff_Remittances"
## [3] "Second_Diff_Avg_Stock_Index" "Second_Diff_Avg_Oil_Price"
```

```
print("Non-Stationary Variables After Second Differencing:")
```

```
## [1] "Non-Stationary Variables After Second Differencing:"
```

```
print(non_stationary_vars_second_diff)
```

```
## character(0)
```

Creating the final stationary dataset

```
library(dplyr)

# Create Final Stationary Dataset
final_stationary_data <- stationary_data %>%
  dplyr::select(
    Date,
    Diff_Avg_Crypto_Price,
    Diff_First_Exchange_Rate,
    Diff_Inflation,
    Diff_Trading_Volumes,
    Second_Diff_GDP_growth_rate,
    Second_Diff_Remittances,
    Second_Diff_Avg_Stock_Index,
    Second_Diff_Avg_Oil_Price
  )

# Save the Final Dataset
write.csv(final_stationary_data, "final_stationary_data.csv", row.names = FALSE)
cat("Final stationary dataset saved as 'final_stationary_data.csv'.\n")
```

```
## Final stationary dataset saved as 'final_stationary_data.csv'.
```

Exporting adf test results

```
# Export ADF Test Results
# Combine ADF results into a data frame
adf_results_df <- data.frame(
  Variable = c(
    "Diff_Avg_Crypto_Price", "Diff_First_Exchange_Rate", "Diff_Inflation", "Diff_Trading_Volu
mes",
    "Second_Diff_GDP_growth_rate", "Second_Diff_Remittances",
    "Second_Diff_Avg_Stock_Index", "Second_Diff_Avg_Oil_Price"
  ),
  Statistic = sapply(adf_results_diff, function(x) x$statistic),
  P_Value = sapply(adf_results_diff, function(x) x$p.value)
)

# Save ADF results as CSV
write.csv(adf_results_df, "ADF_Test_Results.csv", row.names = FALSE)
cat("ADF test results saved as 'ADF_Test_Results.csv'.\n")
```

```
## ADF test results saved as 'ADF_Test_Results.csv'.
```

2. Multicollinearity Test Using VIF The Variance Inflation Factor (VIF) identifies multicollinearity:

Rule of Thumb: VIF > 5 indicates potential multicollinearity. VIF > 10 indicates severe multicollinearity.

```
# Load Required Library
library(car)

# Fit Linear Model for VIF Calculation
# Include all stationary variables from the updated dataset
lm_model <- lm(
  Diff_Avg_Crypto_Price ~ Diff_First_Exchange_Rate +
    Diff_Inflation +
    Diff_Trading_Volumes +
    Second_Diff_GDP_growth_rate +
    Second_Diff_Remittances +
    Second_Diff_Avg_Stock_Index +
    Second_Diff_Avg_Oil_Price,
  data = final_stationary_data
)

# Calculate VIF
vif_results <- vif(lm_model)

# Print VIF Results
print("Variance Inflation Factor (VIF) Results:")
```

```
## [1] "Variance Inflation Factor (VIF) Results:"
```

```
print(vif_results)
```

```
##    Diff_First_Exchange_Rate              Diff_Inflation
##                    1.076031                    1.027670
##        Diff_Trading_Volumes Second_Diff_GDP_growth_rate
##                    1.020010                    1.019352
##     Second_Diff_Remittances Second_Diff_Avg_Stock_Index
##                    1.135684                    1.082287
##   Second_Diff_Avg_Oil_Price
##                    1.073798
```

```
# Interpretation:
# - VIF <= 5: No multicollinearity.
# - 5 < VIF <= 10: Moderate multicollinearity (may need adjustment).
# - VIF > 10: Severe multicollinearity (requires action, e.g., removing/combining variables).
```

Exporting VIF test results

```
# Export VIF Results
# Combine VIF results into a data frame
vif_results_df <- data.frame(
  Variable = names(vif_results),
  VIF = as.numeric(vif_results)
)

# Save VIF results as CSV
write.csv(vif_results_df, "VIF_Results.csv", row.names = FALSE)
cat("VIF results saved as 'VIF_Results.csv'.\n")
```

```
## VIF results saved as 'VIF_Results.csv'.
```

3. Correlation Matrix The Correlation Matrix identifies pairwise correlations:

High Correlation: > 0.7 or < -0.7 (may indicate multicollinearity).

```
# Load Required Library
library(ggcorrplot)

# Select Only Numeric Columns for Correlation
correlation_data <- final_stationary_data %>%
  dplyr::select(
    Diff_Avg_Crypto_Price,
    Diff_First_Exchange_Rate,
    Diff_Inflation,
    Diff_Trading_Volumes,
    Second_Diff_GDP_growth_rate,
    Second_Diff_Remittances,
    Second_Diff_Avg_Stock_Index,
    Second_Diff_Avg_Oil_Price
  )

# Compute Correlation Matrix
cor_matrix <- cor(correlation_data, use = "complete.obs")

# Print Correlation Matrix
print("Correlation Matrix:")
```

```
## [1] "Correlation Matrix:"
```

```
print(cor_matrix)
```

```
##                              Diff_Avg_Crypto_Price Diff_First_Exchange_Rate
## Diff_Avg_Crypto_Price                   1.000000000              -0.27786684
## Diff_First_Exchange_Rate               -0.277866836               1.00000000
## Diff_Inflation                          0.021980027              -0.00749213
## Diff_Trading_Volumes                    0.038792259              -0.01123237
## Second_Diff_GDP_growth_rate             0.207172893               0.02702025
## Second_Diff_Remittances                 0.002793581              -0.26396977
## Second_Diff_Avg_Stock_Index             0.008265842               0.05731170
## Second_Diff_Avg_Oil_Price              -0.107588877               0.04189208
##                              Diff_Inflation Diff_Trading_Volumes
## Diff_Avg_Crypto_Price          0.021980027          0.038792259
## Diff_First_Exchange_Rate      -0.007492130         -0.011232373
## Diff_Inflation                 1.000000000         -0.009926818
## Diff_Trading_Volumes          -0.009926818          1.000000000
## Second_Diff_GDP_growth_rate    0.041016015         -0.009933728
## Second_Diff_Remittances        0.059858167          0.081582926
## Second_Diff_Avg_Stock_Index   -0.127854275          0.031470572
## Second_Diff_Avg_Oil_Price     -0.104366042          0.096172015
##                              Second_Diff_GDP_growth_rate Second_Diff_Remittances
## Diff_Avg_Crypto_Price                       0.2071728928            0.0027935807
## Diff_First_Exchange_Rate                    0.0270202460           -0.2639697732
## Diff_Inflation                              0.0410160148            0.0598581666
## Diff_Trading_Volumes                       -0.0099337282            0.0815829256
## Second_Diff_GDP_growth_rate                 1.0000000000            0.0002772242
## Second_Diff_Remittances                     0.0002772242            1.0000000000
## Second_Diff_Avg_Stock_Index                 0.0153721644           -0.2022488424
## Second_Diff_Avg_Oil_Price                   0.1213090524           -0.1139624331
##                              Second_Diff_Avg_Stock_Index
## Diff_Avg_Crypto_Price                        0.008265842
## Diff_First_Exchange_Rate                     0.057311697
## Diff_Inflation                              -0.127854275
## Diff_Trading_Volumes                         0.031470572
## Second_Diff_GDP_growth_rate                  0.015372164
## Second_Diff_Remittances                     -0.202248842
## Second_Diff_Avg_Stock_Index                  1.000000000
## Second_Diff_Avg_Oil_Price                    0.176551828
##                              Second_Diff_Avg_Oil_Price
## Diff_Avg_Crypto_Price                      -0.10758888
## Diff_First_Exchange_Rate                    0.04189208
## Diff_Inflation                             -0.10436604
## Diff_Trading_Volumes                        0.09617202
## Second_Diff_GDP_growth_rate                 0.12130905
## Second_Diff_Remittances                    -0.11396243
## Second_Diff_Avg_Stock_Index                 0.17655183
## Second_Diff_Avg_Oil_Price                   1.00000000
```

```
# Visualize Correlation Matrix
cor_plot <- ggcorrplot(
  cor_matrix,
  lab = TRUE,
  title = "Correlation Matrix of Variables",
  outline.color = "white"
)

# Save Correlation Plot
ggsave("Correlation_Matrix_Plot.png", cor_plot, width = 8, height = 6)
cat("Correlation matrix plot saved as 'Correlation_Matrix_Plot.png'.\n")
```

```
## Correlation matrix plot saved as 'Correlation_Matrix_Plot.png'.
```

```
# Export Correlation Matrix to CSV
write.csv(cor_matrix, "Correlation_Matrix.csv", row.names = TRUE)
cat("Correlation matrix saved as 'Correlation_Matrix.csv'.\n")
```

```
## Correlation matrix saved as 'Correlation_Matrix.csv'.
```

4. Breusch-Pagan Test The Breusch-Pagan Test checks for heteroscedasticity:

Null Hypothesis (H0): Homoscedasticity (constant variance). Alternative Hypothesis (H1): Heteroscedasticity (non-constant variance).

```
# Load Required Library
library(lmtest)

# Fit a Linear Model
# Choose Diff_Avg_Crypto_Price as dependent variable for example
bp_model <- lm(
  Diff_Avg_Crypto_Price ~ Diff_First_Exchange_Rate +
    Diff_Inflation +
    Diff_Trading_Volumes +
    Second_Diff_GDP_growth_rate +
    Second_Diff_Remittances +
    Second_Diff_Avg_Stock_Index +
    Second_Diff_Avg_Oil_Price,
  data = final_stationary_data
)

# Perform Breusch-Pagan Test
bp_test <- bptest(bp_model)

# Print Breusch-Pagan Test Results
print("Breusch-Pagan Test Results:")
```

```
## [1] "Breusch-Pagan Test Results:"
```

```
print(bp_test)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  bp_model
## BP = 3.9971, df = 7, p-value = 0.7801
```

```
# Interpretation:
# - If p-value > 0.05: Fail to reject H₀ (homoscedasticity is present).
# - If p-value ≤ 0.05: Reject H₀ (heteroscedasticity is present).
```

5. Durbin - Watson Test The Durbin - Watson Test checks for autocorrelation in residuals:

Null Hypothesis (H0): No autocorrelation. Alternative Hypothesis (H1): Autocorrelation exists.

```
# Load Required Library
library(lmtest)

# Perform Durbin-Watson Test
dw_test <- dwtest(bp_model)

# Print Durbin-Watson Test Results
print("Durbin-Watson Test Results:")
```

```
## [1] "Durbin-Watson Test Results:"
```

```
print(dw_test)
```

```
##
##  Durbin-Watson test
##
## data:  bp_model
## DW = 1.1038, p-value = 0.0001575
## alternative hypothesis: true autocorrelation is greater than 0
```

```
# Interpretation:
# - DW near 2: No autocorrelation.
# - DW < 2: Positive autocorrelation in residuals.
# - DW > 2: Negative autocorrelation in residuals.
```

Adding lags to reduce autocorrelation

```
# Load Required Libraries
library(dplyr)
library(lmtest)

# Create Lagged Variables
final_stationary_data <- final_stationary_data %>%
  mutate(Lag_Diff_Avg_Crypto_Price = lag(Diff_Avg_Crypto_Price, 1))

# Fit Model with Lagged Variable
bp_model_with_lags <- lm(
  Diff_Avg_Crypto_Price ~ Lag_Diff_Avg_Crypto_Price + Diff_First_Exchange_Rate +
    Diff_Inflation + Diff_Trading_Volumes + Second_Diff_GDP_growth_rate +
    Second_Diff_Remittances + Second_Diff_Avg_Stock_Index + Second_Diff_Avg_Oil_Price,
  data = final_stationary_data
)

# Perform Durbin-Watson Test on the Updated Model
dw_test_with_lags <- dwtest(bp_model_with_lags)
print("Durbin-Watson Test Results After Adding Lags:")
```

```
## [1] "Durbin-Watson Test Results After Adding Lags:"
```

```
print(dw_test_with_lags)
```

```
##
##  Durbin-Watson test
##
## data:  bp_model_with_lags
## DW = 1.8186, p-value = 0.2139
## alternative hypothesis: true autocorrelation is greater than 0
```

Lags remove one observation

```
# Check for missing values
colSums(is.na(final_stationary_data))
```

```
##                        Date       Diff_Avg_Crypto_Price
##                           0                           0
##    Diff_First_Exchange_Rate              Diff_Inflation
##                           0                           0
##        Diff_Trading_Volumes Second_Diff_GDP_growth_rate
##                           0                           0
##     Second_Diff_Remittances Second_Diff_Avg_Stock_Index
##                           0                           0
##   Second_Diff_Avg_Oil_Price   Lag_Diff_Avg_Crypto_Price
##                           0                           1
```

```
# Inspect the rows with missing values
missing_rows <- final_stationary_data[is.na(final_stationary_data$Diff_Avg_Crypto_Price), ]
print(missing_rows)
```

```
## # A tibble: 0 × 10
## # ℹ 10 variables: Date <date>, Diff_Avg_Crypto_Price <dbl>,
## #   Diff_First_Exchange_Rate <dbl>, Diff_Inflation <dbl>,
## #   Diff_Trading_Volumes <dbl>, Second_Diff_GDP_growth_rate <dbl>,
## #   Second_Diff_Remittances <dbl>, Second_Diff_Avg_Stock_Index <dbl>,
## #   Second_Diff_Avg_Oil_Price <dbl>, Lag_Diff_Avg_Crypto_Price <dbl>
```

Mean Imputation

```
# Calculate the Mean (Excluding NA)
mean_value <- mean(final_stationary_data$Lag_Diff_Avg_Crypto_Price, na.rm = TRUE)

# Replace the Missing Value with the Mean
final_stationary_data$Lag_Diff_Avg_Crypto_Price[is.na(final_stationary_data$Lag_Diff_Avg_Cryp
to_Price)] <- mean_value
```

Check for Remaining Missing Values

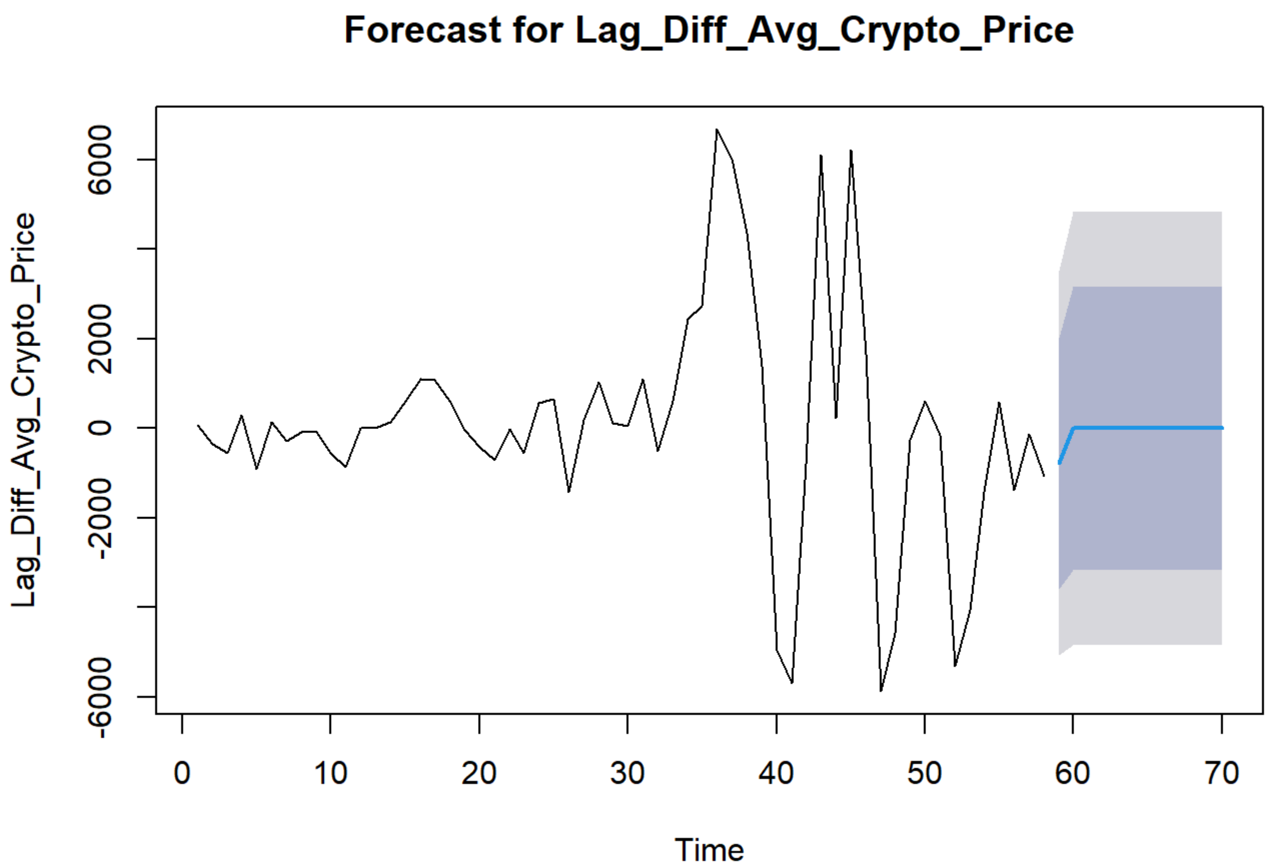
```
colSums(is.na(final_stationary_data))
```

```
##                        Date       Diff_Avg_Crypto_Price
##                           0                           0
##    Diff_First_Exchange_Rate              Diff_Inflation
##                           0                           0
##        Diff_Trading_Volumes Second_Diff_GDP_growth_rate
##                           0                           0
##     Second_Diff_Remittances Second_Diff_Avg_Stock_Index
##                           0                           0
##   Second_Diff_Avg_Oil_Price   Lag_Diff_Avg_Crypto_Price
##                           0                           0
```

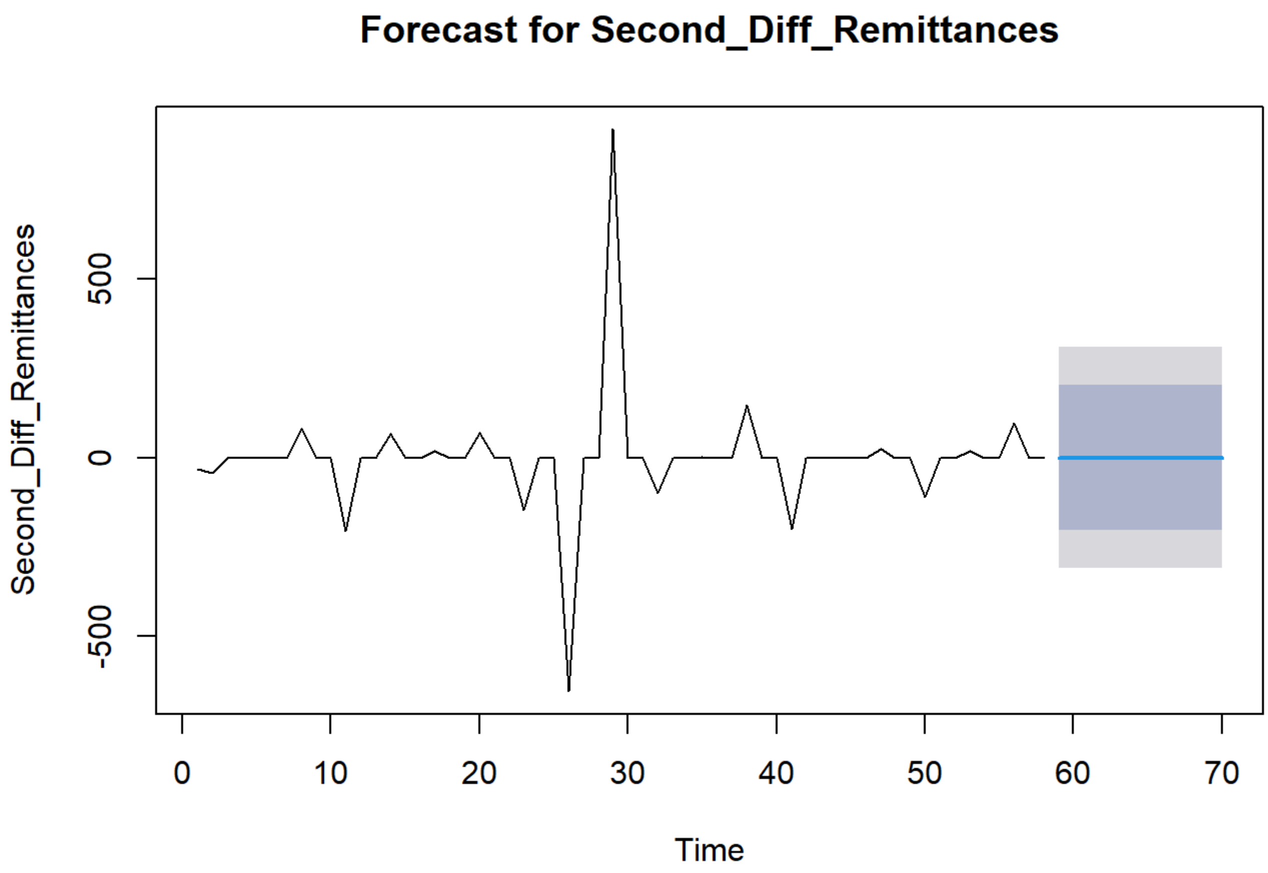
AUTO ARIMA

```r
# Load Required Library
library(forecast)

# List of Variables for ARIMA Modeling
variables <- c("Lag_Diff_Avg_Crypto_Price", "Second_Diff_Remittances", "Diff_First_Exchange_R
ate")

# Create a loop to fit Auto ARIMA models and generate forecasts
arima_results <- list()
forecasts <- list()

for (var in variables) {
  # Fit Auto ARIMA Model
  model <- auto.arima(final_stationary_data[[var]], seasonal = FALSE)
  arima_results[[var]] <- model

  # Print Model Summary
  cat("\nAuto ARIMA Summary for", var, ":\n")
  print(summary(model))

  # Forecast the next 12 periods
  forecast_result <- forecast(model, h = 12)
  forecasts[[var]] <- forecast_result

  # Plot the Forecast
  plot(forecast_result, main = paste("Forecast for", var), xlab = "Time", ylab = var)

  # Save the Forecast Plot
  ggsave(paste0("forecast_", var, ".png"), width = 8, height = 6)
}
```

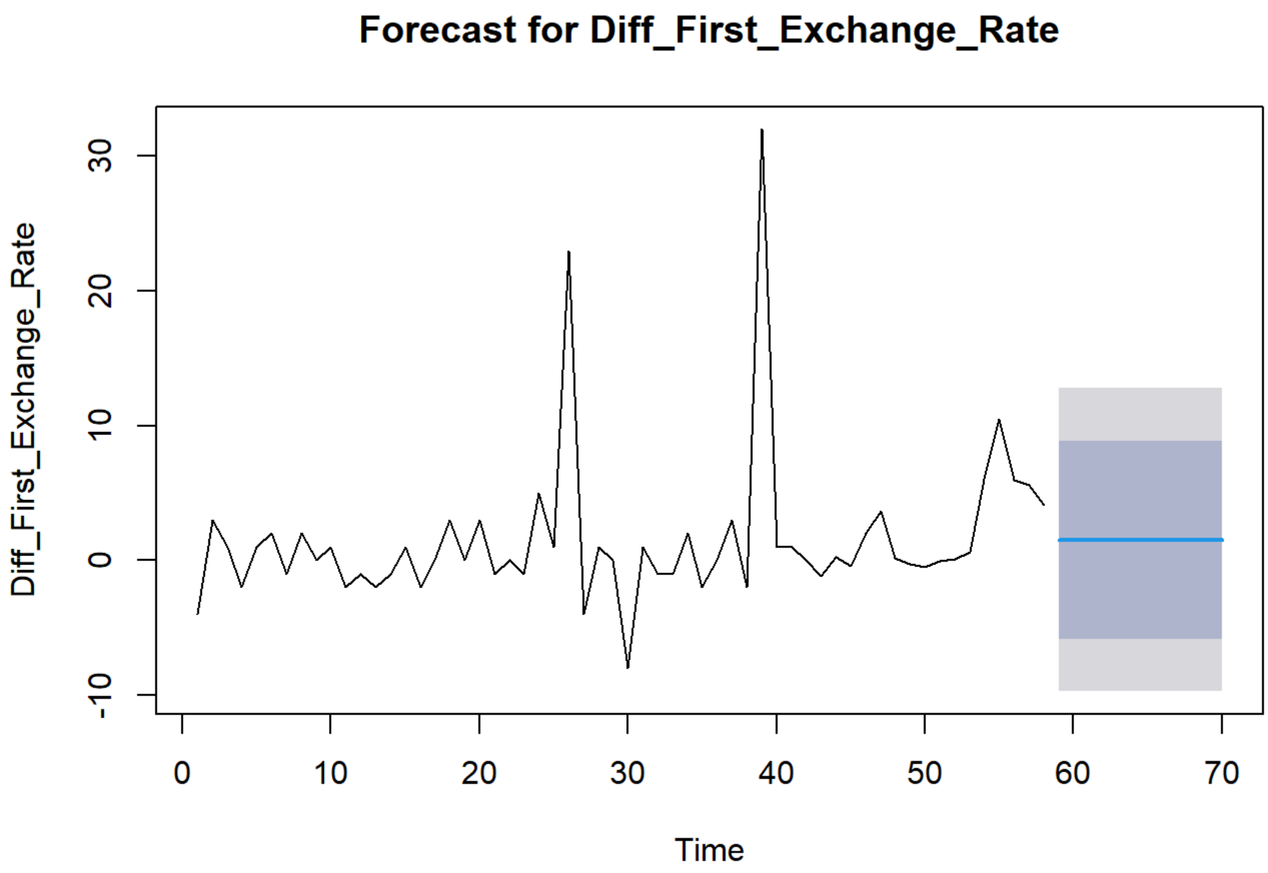
```
##
## Auto ARIMA Summary for Lag_Diff_Avg_Crypto_Price :
## Series: final_stationary_data[[var]]
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##          ma1
##       0.5209
## s.e.  0.0966
##
## sigma^2 = 4789316:  log likelihood = -528.03
## AIC=1060.05   AICc=1060.27   BIC=1064.18
##
## Training set error measures:
##                    ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
## Training set 40.48288 2169.503 1398.398 331.7361 591.1873 0.8184418 0.08407981
```




```
##
## Auto ARIMA Summary for Second_Diff_Remittances :
## Series: final_stationary_data[[var]]
## ARIMA(0,0,0) with zero mean
##
## sigma^2 = 24910:  log likelihood = -375.87
## AIC=753.73   AICc=753.8   BIC=755.79
##
## Training set error measures:
##                      ME     RMSE      MAE MPE MAPE      MASE         ACF1
## Training set -0.8470571 157.8303 50.57361 100  100 0.4997094 0.0009678688
```




```
##
## Auto ARIMA Summary for Diff_First_Exchange_Rate :
## Series: final_stationary_data[[var]]
## ARIMA(0,0,0) with non-zero mean
##
## Coefficients:
##          mean
##        1.5269
## s.e.   0.7469
##
## sigma^2 = 32.93:  log likelihood = -183.13
## AIC=370.25   AICc=370.47   BIC=374.38
##
## Training set error measures:
##                        ME     RMSE      MAE  MPE MAPE      MASE        ACF1
## Training set 4.937756e-16 5.688378 3.100785 -Inf  Inf 0.7102175 -0.04555804
```




```
cat("Forecast plots saved as PNG files in the working directory.\n")
```

```
## Forecast plots saved as PNG files in the working directory.
```

CHAPTER 7: VAR Analysis

```
# Remove Diff_Avg_Crypto_Price while keeping all other variables
var_data <- final_stationary_data %>%
  dplyr::select(-Diff_Avg_Crypto_Price)

# Check the structure of the filtered dataset
str(var_data)
```

```
## tibble [58 × 9] (S3: tbl_df/tbl/data.frame)
##  $ Date                       : Date[1:58], format: "2018-03-01" "2018-04-01" ...
##  $ Diff_First_Exchange_Rate   : num [1:58] -4 3 1 -2 1 2 -1 2 0 1 ...
##  $ Diff_Inflation             : num [1:58] -0.99 -0.86 -0.87 -0.38 -0.09 ...
##  $ Diff_Trading_Volumes       : num [1:58] -163775 -464539 1032595 -339963 308152 ...
##  $ Second_Diff_GDP_growth_rate: num [1:58] -5.67e-02 -2.22e-16 2.22e-16 2.33e-01 2.22e-16
...
##  $ Second_Diff_Remittances    : num [1:58] -32.6 -43.35 0 0 -2.28 ...
##  $ Second_Diff_Avg_Stock_Index: num [1:58] -1146 -766 995 -1653 846 ...
##  $ Second_Diff_Avg_Oil_Price  : num [1:58] 4.926 4.261 -0.625 -7.783 2.627 ...
##  $ Lag_Diff_Avg_Crypto_Price  : num [1:58] 75 -339 -556 288 -908 ...
```

```
# Save the updated dataset
write.csv(var_data, "var_data_updated.csv", row.names = FALSE)
cat("Updated dataset saved as 'var_data_updated.csv'.\n")
```

```
## Updated dataset saved as 'var_data_updated.csv'.
```

Step 1: Prepare the Data

```
#Before running the VAR model, confirm that the dataset is free from missing or invalid value
s:
# Check for missing values in the dataset
colSums(is.na(var_data))
```

```
##                        Date    Diff_First_Exchange_Rate
##                           0                           0
##              Diff_Inflation         Diff_Trading_Volumes
##                           0                           0
## Second_Diff_GDP_growth_rate      Second_Diff_Remittances
##                           0                           0
## Second_Diff_Avg_Stock_Index   Second_Diff_Avg_Oil_Price
##                           0                           0
##   Lag_Diff_Avg_Crypto_Price
##                           0
```

```
# Check for infinite values
colSums(sapply(var_data, is.infinite))
```

```
##                        Date    Diff_First_Exchange_Rate
##                           0                           0
##              Diff_Inflation         Diff_Trading_Volumes
##                           0                           0
## Second_Diff_GDP_growth_rate      Second_Diff_Remittances
##                           0                           0
## Second_Diff_Avg_Stock_Index   Second_Diff_Avg_Oil_Price
##                           0                           0
##   Lag_Diff_Avg_Crypto_Price
##                           0
```

2. Clean the Dataset

```
#Remove or impute any problematic values:
#Remove Rows with Missing Values:
var_data <- na.omit(var_data)
# Replace Infinite Values (if any):
var_data <- var_data %>%
  mutate(across(everything(), ~ ifelse(is.infinite(.), NA, .))) %>%
  na.omit()
```

3. Verify the Dataset

```
#Recheck the structure and confirm that the dataset is ready for VAR modeling:
str(var_data)
```

```
## tibble [58 × 9] (S3: tbl_df/tbl/data.frame)
##  $ Date                       : num [1:58] 17591 17622 17652 17683 17713 ...
##  $ Diff_First_Exchange_Rate   : num [1:58] -4 3 1 -2 1 2 -1 2 0 1 ...
##  $ Diff_Inflation             : num [1:58] -0.99 -0.86 -0.87 -0.38 -0.09 ...
##  $ Diff_Trading_Volumes       : num [1:58] -163775 -464539 1032595 -339963 308152 ...
##  $ Second_Diff_GDP_growth_rate: num [1:58] -5.67e-02 -2.22e-16 2.22e-16 2.33e-01 2.22e-16
...
##  $ Second_Diff_Remittances    : num [1:58] -32.6 -43.35 0 0 -2.28 ...
##  $ Second_Diff_Avg_Stock_Index: num [1:58] -1146 -766 995 -1653 846 ...
##  $ Second_Diff_Avg_Oil_Price  : num [1:58] 4.926 4.261 -0.625 -7.783 2.627 ...
##  $ Lag_Diff_Avg_Crypto_Price  : num [1:58] 75 -339 -556 288 -908 ...
```

```
summary(var_data)
```

```
##       Date       Diff_First_Exchange_Rate Diff_Inflation
##  Min.   :17591   Min.   :-8.000           Min.   :-0.9900
##  1st Qu.:18025   1st Qu.:-1.000           1st Qu.:-0.0850
##  Median :18460   Median : 0.130           Median : 0.0850
##  Mean   :18459   Mean   : 1.527           Mean   : 0.1209
##  3rd Qu.:18894   3rd Qu.: 2.000           3rd Qu.: 0.3575
##  Max.   :19327   Max.   :32.000           Max.   : 1.0400
##  Diff_Trading_Volumes Second_Diff_GDP_growth_rate Second_Diff_Remittances
##  Min.   :-2015726     Min.   :-2.430000           Min.   :-653.1067
##  1st Qu.: -312705     1st Qu.: 0.000000           1st Qu.:   0.0000
##  Median :  -35655     Median : 0.000000           Median :   0.0000
##  Mean   :  -42893     Mean   :-0.002529           Mean   :  -0.8471
##  3rd Qu.:  247138     3rd Qu.: 0.000000           3rd Qu.:   0.0000
##  Max.   : 1032595     Max.   : 3.483333           Max.   : 918.0467
##  Second_Diff_Avg_Stock_Index Second_Diff_Avg_Oil_Price
##  Min.   :-4573.3             Min.   :-35.3729
##  1st Qu.:-1169.7             1st Qu.: -5.4546
##  Median :  -50.7             Median : -0.3539
##  Mean   :   64.9             Mean   : -0.1384
##  3rd Qu.: 1388.5             3rd Qu.:  4.9219
##  Max.   : 5528.4             Max.   : 28.5643
##  Lag_Diff_Avg_Crypto_Price
##  Min.   :-5873.83
##  1st Qu.: -562.16
##  Median :    3.16
##  Mean   :   75.03
##  3rd Qu.:  616.79
##  Max.   : 6679.26
```

Step 2: Determine Optimal Lag Length

```
# Determine Optimal Lag Length
lag_selection <- VARselect(var_data, lag.max = 5, type = "const")
```

```
## Warning in log(sigma.det): NaNs produced

## Warning in log(sigma.det): NaNs produced

## Warning in log(sigma.det): NaNs produced
```

```
optimal_lag <- lag_selection$selection["AIC(n)"]

# Save the lag selection results
lag_selection_results <- capture.output(print(lag_selection))
writeLines(lag_selection_results, "lag_selection_results.txt")
cat("Lag selection results saved as 'lag_selection_results.txt'.\n")
```

```
## Lag selection results saved as 'lag_selection_results.txt'.
```

Step 3: Fit the VAR Model

```
# Fit the VAR Model with Lag 3
var_model <- VAR(var_data, p = 3, type = "const")

# Save the VAR Model Summary
var_summary <- capture.output(summary(var_model))
writeLines(var_summary, "var_model_lag3_summary.txt")
cat("VAR Model Summary saved as 'var_model_lag3_summary.txt'.\n")
```

```
## VAR Model Summary saved as 'var_model_lag3_summary.txt'.
```

Defining VAR Model Lag 3

```
# Fit the VAR Model with Lag 3
var_model_lag3 <- VAR(y = var_data, p = 3, type = "const")

# Save the model summary to a text file
lag3_summary <- capture.output(summary(var_model_lag3))
writeLines(lag3_summary, "var_model_lag3_summary.txt")
cat("Lag 3 VAR model summary saved as 'var_model_lag3_summary.txt'.\n")
```

```
## Lag 3 VAR model summary saved as 'var_model_lag3_summary.txt'.
```

Impulse Response Analysis

```
irf_crypto_to_remittances <- irf(var_model_lag3,
                                 impulse = "Lag_Diff_Avg_Crypto_Price",
                                 response = "Second_Diff_Remittances",
                                 n.ahead = 10, boot = TRUE)

irf_crypto_to_exchange_rate <- irf(var_model_lag3,
                                   impulse = "Lag_Diff_Avg_Crypto_Price",
                                   response = "Diff_First_Exchange_Rate",
                                   n.ahead = 10, boot = TRUE)

irf_crypto_to_inflation <- irf(var_model_lag3,
                               impulse = "Lag_Diff_Avg_Crypto_Price",
                               response = "Diff_Inflation",
                               n.ahead = 10, boot = TRUE)

# Save Impulse Response Plots
png("irf_crypto_to_remittances.png", width = 800, height = 600)
plot(irf_crypto_to_remittances)
dev.off()
```

```
## png
##   2
```

```
png("irf_crypto_to_exchange_rate.png", width = 800, height = 600)
plot(irf_crypto_to_exchange_rate)
dev.off()
```

```
## png
##   2
```

```
png("irf_crypto_to_inflation.png", width = 800, height = 600)
plot(irf_crypto_to_inflation)
dev.off()
```

```
## png
##   2
```

```
cat("Impulse Response Analysis plots saved.\n")
```

```
## Impulse Response Analysis plots saved.
```

Variance Decomposition

```
var_decomp <- fevd(var_model_lag3, n.ahead = 10)

# Save Variance Decomposition Results
write.csv(as.data.frame(var_decomp$Second_Diff_Remittances), "var_decomp_remittances.csv", ro
w.names = FALSE)
write.csv(as.data.frame(var_decomp$Diff_First_Exchange_Rate), "var_decomp_exchange_rate.csv",
row.names = FALSE)
write.csv(as.data.frame(var_decomp$Diff_Inflation), "var_decomp_inflation.csv", row.names = F
ALSE)

cat("Variance Decomposition results saved as CSV files.\n")
```

```
## Variance Decomposition results saved as CSV files.
```

Saving the plot

```
library(vars)

# Perform variance decomposition on the VAR model
vd <- fevd(var_model_lag3, n.ahead = 10)  # Replace `var_model_lag3` with your model

# Plot the variance decomposition
png("variance_decomposition_plot.png", width = 800, height = 600)
plot(vd, main = "Variance Decomposition")
dev.off()
```

```
## png
##   2
```

```
# This will save the plot as 'variance_decomposition_plot.png' in your working directory.
```

REFERENCES

FundsforNGOs. (n.d.). *Sample proposal on impact of cryptocurrencies on global financial systems*. Retrieved from https://www.fundsforngos.org/proposals/sample-proposal-on-impact-of-cryptocurrencies-on-global-financial-systems/

FasterCapital. (n.d.). *Cryptocurrency: Transforming the manufactured payments landscape*. Retrieved from https://fastercapital.com/content/Cryptocurrency--Transforming-the-Manufactured-Payments-Landscape.html

600Bitcoin. (n.d.). *Cryptocurrency adoption and economic shifts*. Retrieved from https://600bitcoin.com/cryptocurrency-adoption-and-economic-shifts/

CCPayment. (n.d.). *Why cryptocurrency adoption is booming and how CCPayment can help your business benefit*. Retrieved from https://ccpayment.com/blog/why-cryptocurrency-adoption-is-booming-and-how-ccpayment-can-help-your-business-benefit/

Online Scientific Research. (n.d.). *Cryptocurrency and the Nigerian economy*. Retrieved from https://www.onlinescientificresearch.com/articles/cryptocurrency-and-the-nigerian-economy.html

Bitpace. (n.d.). *The future of digital payments: How cryptocurrency will reshape financial services in the next decade*. Retrieved from https://www.bitpace.com/blog/the-future-of-digital-payments-how-cryptocurrency-will-reshape-financial-services-in-the-next-decade/

Rapid Innovation. (n.d.). *Transformative innovations: Decentralized finance bridging traditional and digital economies*. Retrieved from https://www.rapidinnovation.io/post/transformative-innovations-decentralized-finance-bridging-traditional-digital-economies

Researcher.Life. (n.d.). *What are research objectives? How to write them with examples*. Retrieved from https://researcher.life/blog/article/what-are-research-objectives-how-to-write-them-with-examples/

Armstrong, C., Barth, M. E., Jagolinzer, A. D., & Riedl, E. J. (2022). *The role of financial reporting and transparency in corporate tax avoidance: A review of the literature and suggestions for future research*. *Review of Accounting Studies*, *27*(1), 76–125. Retrieved from https://link.springer.com/article/10.1007/s11142-022-09741-w

Academia.edu. (n.d.). *Effects of cryptocurrencies on financial markets*. Retrieved from https://www.academia.edu/84089717/Effects_of_cryptocurrencies_on_financial_markets

Emerald Publishing. (2023). *Cryptocurrency price dynamics and financial market volatility: Evidence from emerging economies*. *International Journal of Quality & Reliability Management*, *40*(5), 1260-1279. Retrieved from https://www.emerald.com/insight/content/doi/10.1108/ijqrm-03-2023-0092/full/html

Journal of Financial Innovation. (2023). *Cryptocurrency adoption and financial stability: A systematic review*. *Financial Innovation*, *9*(1), 34–57. Retrieved from https://jfin-swufe.springeropen.com/articles/10.1186/s40854-023-00580-5

Bank of England. (2022, March). *Financial stability in focus: Cryptocurrencies and financial risk*. Retrieved from https://www.bankofengland.co.uk/financial-stability-in-focus/2022/march-2022

Namso Gen. (n.d.). *What is subjective theory of value?*. Retrieved from https://namso-gen.co/blog/what-is-subjective-theory-of-value/

LiveWell Finance. (n.d.). *Subjective theory of value: Definition, history, and examples*. Retrieved from https://livewell.com/finance/subjective-theory-of-value-definition-history-examples/

FasterCapital. (n.d.). *Quantity theory of money: Monetarist foundations and exploring the quantity theory of money*. Retrieved from https://www.fastercapital.com/content/Quantity-Theory-of-Money--Monetarist-Foundations--Exploring-the-Quantity-Theory-of-Money.html

Simply Psychology. (n.d.). *What is a longitudinal study?*. Retrieved from https://www.simplypsychology.org/longitudinal-study.html

Examples.com. (n.d.). *Quantitative research design: Examples and methods*. Retrieved from https://www.examples.com/english/quantitative-research-design.html

Formplus. (n.d.). *Longitudinal studies: Definition, types, and examples*. Retrieved from https://www.formpl.us/blog/longitudinal-studies

The Big Marketing. (n.d.). *Primary vs. secondary research in marketing: Differences and when to use them*. Retrieved from https://thebigmarketing.com/primary-vs-secondary-research-marketing/

Mind the Graph. (n.d.). *Primary research vs. secondary research: Differences and examples*. Retrieved from https://mindthegraph.com/blog/primary-research-vs-secondary-research/

EMB Global. (n.d.). *How to use primary data effectively in research*. Retrieved from https://blog.emb.global/use-primary-data-effectively/

SurveyCTO. (n.d.). *Data collection methods: A guide to choosing the right method for your research*. Retrieved from https://www.surveycto.com/resources/guides/data-collection-methods-guide/

A Sinha, J. V. (2022). Smart contracts and transaction efficiency. *Journal of Financial Technology*.

Academia. (n.d.). *Cryptocurrencies: Are disruptive financial innovations here?* Retrieved from https://www.academia.edu/14244104/Cryptocurrencies_Are_Disruptive_Financial_Innovations_Here

Academies, A. (2024). Measuring the long-term equilibrium relationship between physical capital, spending on education, and economic growth in Jordan. *Academy of Economics and Finance Journal*.

Adebayo, T. &. (2022). Cryptocurrency and financial modeling: Implications for developing economies. *International Journal of Financial Studies*, 305 - 322.

Adediran, O. S. (2020). he role of remittances in stabilizing household consumption in Sub-Saharan Africa: Evidence from Nigeria. *Journal of Development Studies*, 593–609.

Adedoyin, F. F. (2020). The nexus of economic growth, tourism, and environmental degradation in Africa: Step towards tourism economy. *Environmental Science and Pollution Research*, 6612–6622.

Akpan, U. F. (2012). Oil price shocks and Nigeria's macroeconomic performance. *International Journal of Energy Economics and Policy*, 211–223.

Alessandria, L. (2018). The Supply and Demand of Cryptocurrencies. *NBER Working Paper Series*.

Alexandos, N. (2021). Cryptocurrency analysis: Benefits, dangers, and price prediction using neural networks. *Romanian Journal of Economics*, 5 - 24.

Ali Sinha, J. V. (n.d.). Transactional Transparency in Procurement. *Journal of Procuremnet and Supply Chain Management*.

Alvarez-Diaz, M. H. (2023). The role of cryptocurrencies in cross-border transfers: Evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, 79.

Ansari, M. (2024). Scarcity in economics and its implications for resource allocation. *Economic Studies*.

AppsGeyser. (2024). *The dark side of crypto: Why regulation is bad?* . Retrieved from https://appsgeyser.com/blog/the-darkside-of-crypto-why-regulation-is-bad/

Aysan, A. F. (2021). Effects of cryptocurrency regulation on volatility and market efficiency. *Journal of International Financial Markets, Institutions and Money*.

Balke, N. S. (2019). Exchange rate instability and inflationary pressures in emerging economies. *Journal of Macroeconomics*, 245–260.

Baur, D. G. (2018). Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets. *Institutions and Money*, 177-189.

Beck, T. (2012). The role of the financial sector in economic development. *Journal of Economic Growth*.

Biryukov, A. &. (2017). Cryptonote: A new approach to digital currency.

Blockchain Research Institute. (2023). *Global remittance and cryptocurrency efficiency report.* Retrieved from Blockchain Research Institute: https://www.blockchainresearch.com

Bouri, E. M. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? . *Finance Research Letters*, 192–198.

Brown, A. (2022). Stable currencies and precious metals as stores of value. *Journal of Economic Perspectives*.

Bussolo, M. &. (2007). o remittances have a flip side? A general equilibrium analysis of remittances, labor supply responses, and policy options for Jamaica. *World Bank Policy Research Working Paper No. 4143.*

C Stoll, L. K. (2019). The carbon footprint of Bitcoin. *Nature Communications*.

Catalini, C. &. (2016). Some Simple Economics of the Blockchain. *NBER Working Paper No. 22952*.

Catalini, C. (2016). The value of digital currencies: Innovation and market dynamics. *Journal of Financial Economics*, 56–78.

Central Bank of Nigeria (CBN). (2021). *Cryptocurrency transaction restrictions: Regulatory framework.*

Chainalysis. (2021). *The 2021 Global Cryptocurrency Adoption Index.*

Chatterjee, S. (2023). Decrypting cryptocurrencies: An exploration of the impact on financial markets. *Journal of Risk and Financial Management*.

Chatterjee, S. (2023). The impact of cryptocurrencies on tradional finance systems. *Journal of Financial Innovation*.

Cheah, E.-T. &. (2016). Speculative bubbles in Bitcoin markets? *Economics Letters*, 32-36.

Chen, Y. (2020). Cryptocurrencies as a means of exchange and their economic classification. *Journal of Financial Economics*.

Cheng, C. H. (2021). The relationship between Bitcoin and economic policy uncertainty: Evidence from linear and nonlinear causality tests. *Finance Research Letters*.

Coinpedia. (n.d.). *Technical and fundamental analysis in cryptocurrency*. Retrieved from https://coinpedia.org/traders/technical-fundamental-analysis/

Corbet, S. L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 182–199.

Cryptolisty. (n.d.). *Analysis tools*. Retrieved from https://cryptolisty.com/analysis-tools/

De Vries, A. (2018). Bitcoin's growing energy problem. *Joule*.

Demirgüç-Kunt, A. K. (2018). Measuring financial inclusion and the fintech revolution. *The Global Findex Database*.

Discussion, E. (2024). *Long-run equilibrium relationship in econometrics*. Retrieved from https://www.economicsdiscussion.net/economics-2/econometrics/long-run-equilibrium-relationship-econometrics/25089

Downey, J. (2022). Defining a store of value: Cryptocurrencies and traditional assets. . *Financial Analysis Journal*.

Ebiye, I. (2023). Cryptocurrency and financial inclusion: A case study of Nigeria. *Journal of Digital Finance*, 45–60.

Edgeworth, F. (1967). The concept of utility and its measurement. . *Economic Theory Journal*.

Education, W. (n.d.). *Does crypto have intrinsic value?* Retrieved from https://wealthyeducation.com/does-crypto-have-intrinsic-value/

Ekeocha, P. C. (2021). Impact of cryptocurrency on remittance flows to Sub-Saharan Africa: Evidence from Nigeria. *African Economic Research Papers*, 134–151.

Emerald. (2023). How cryptocurrency is challenging traditional financial systems. *Journal of Financial Regulation*.

England, B. o. (2022). Cryptoassets and decentralised finance. *Financial Stability in Focus*.

Engle, R. F. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 251–276.

Events, B. (2023). *What is cryptocurrency and how does it work?* . Retrieved from https://prague.bc.events/en/news/chto-takoe-kriptovalyuta-i-kak-ona-rabotaet

Fahlenbrach, R. &. (2021). Corporate strategy and the rise of cryptocurrencies in cross-border transactions. *Financial Management*, 1023-1045.

Fama, E. F. (1970). The Efficient Market Hypothesis. *Journal of Finance*.

FasterCapital. (2024). *Cointegration: Exploring long-term relationships and autocorrelation*. Retrieved from https://fastercapital.com/content/Cointegration--Exploring-Long-Term-Relationships-and-Autocorrelation.html

FasterCapital. (2024). *Financial intermediaries: Types, functions, benefits, and challenges*. Retrieved from https://theintactone.com/2024/05/02/financial-intermediaries-types-functions-benefits-challenges/

FasterCapital. (2024). *Smart contracts: How to create and execute self-enforcing agreements on the blockchain.* Retrieved from https://fastercapital.com/content/Smart-contracts--How-to-create-and-execute-self-enforcing-agreements-on-the-blockchain.html

Forbes. (n.d.). *Advantages of cryptocurrency.* . Retrieved from https://www.forbes.com/advisor/in/investing/cryptocurrency/advantages-of-cryptocurrency/

Friedman, M. (1963). Quantity Theory of Money. *The New Palgrave Dictionary of Economics*.

Fry, J. &.-T. (2016). Negative bubbles and shocks in Bitcoin markets. *International Review of Financial Analysis*, 343-352.

GeeksforGeeks. (2023). *What is Ripple blockchain?* Retrieved from https://www.geeksforgeeks.org/what-is-ripple-blockchain/

Gen., N. (n.d.). *What is the value of crypto based on?* . Retrieved from https://namso-gen.co/blog/what-is-the-value-of-crypto-based-on/

GenerisOnline. (2024). *The role and importance of financial intermediaries*. Retrieved from https://generisonline.com/the-role-and-importance-of-financial-intermediaries/

Glosten, L. R. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 1779-1801.

Goforth, C. (2022). Impact of regulatory changes on cryptocurrency markets. *Journal of Financial Regulation and Compliance*.

Greene, W. H. (2012). *Econometric Analysis.* Pearson Education.

Guide, U. (n.d.). *Ripple XRP: Facilitating cross-border payments*. Retrieved from https://www.uscisguide.com/finance/ripple-xrp-facilitating-cross-border-payments/

Gujarati, D. N. (2009). *Basic econometrics.* McGraw-Hill.

Gupta, K. (2009). Blockchain for remittances: Business, regulatory, and financial implications. *Journal of Payments Strategy & Systems*, 245–261.

Hamilton, A. (1781). The role of banks in economic growth. *Historical Perspectives on Banking*.

Harvey, C. R. (2018). The Decentralized Future of Finance: On-Chain Money Markets. *NBER Working Paper Series*.

Hasan, A. K. (2024). Cryptocurrencies and traditional banking systems. *Journal of Financial Markets*.

Hasan, A. K. (2024). Unveiling cryptocurrency impact on financial markets and traditional banking. *Journal of Risk and Financial Management*.

Hayek, F. (1945). Prices, Scarcity and Economic Activities. *Economic theory Journal*.

Hayes, A. (2015). What factors give cryptocurrencies their value: An empirical analysis.

Hughes, S. (2023). Policy shifts in response to Decentralised Finance. *Policy Analysis Journal*.

iLink. (2024). *How smart contracts work*. Retrieved from https://ilink.dev/blog/how-smart-contracts-work/

Investopedia. (n.d.). *Cryptocurrency*. Retrieved from https://www.investopedia.com/terms/c/cryptocurrency.asp

Justiniano, R. (2022). Transactional transparency for finance team success. *Finance Management Journal*.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 3–6.

Kazeem, Y. (2022). Nigerians are turning to Bitcoin as inflation and forex scarcity bite harder. *Quartz Africa*.

Kilian, L. (2019). Oil price shocks, monetary policy, and the macroeconomy. *Journal of Economic Literature*, 871–909.

Kramer, L. (2018). Cryptocurrencies as a Hedge Against Traditional Investments. *National Institutes of Health*.

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS ONE*.

Livewell. (n.d.). *What affects the value of cryptocurrency?* . Retrieved from https://livewell.com/finance/what-affects-the-value-of-cryptocurrency/

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*.

Lütkepohl, H. (2005). New introduction to multiple time series analysis. *Springer Science & Business Media*.

Maggioni, M. (2020). Are Cryptocurrencies Really Useful as a Store of Value? *NBER Working Paper Series*.

Malthus, T. (1798). An Essay on the Principle of Population. *Historical Analysis of Population Growth and Resource Scarcity*.

Menger, C. (1871). *Subjective Theory of Value.*

Mensah, L. O. (2022). Oil price shocks and inflation in oil-exporting countries: Does the exchange rate regime matter? *Energy Economics*.

Mensi, W. H. (2022). Does Bitcoin provide hedge or safe haven against commodities? An empirical investigation. *Resources Policy*.

Meyer, J. (2023). Role of international regulatory bodies in shaping cryptocurrency regulations. *International Financial Regulation Journal*.

Mirza, I. (2024). *Bitcoin: Cryptocurrency revolutionizing the financial landscape.* Retrieved from https://itxmirza.com/index.php/2024/03/10/bitcoin-cryptocurrency-revolutionizing-the-financial-landscape/

Morpher. (2024). *Exploring scarcity metrics in cryptocurrency valuation*. Retrieved from https://www.morpher.com/blog/exploring-scarcity-metrics

Mulligan, C. (2019). The Bitcoin Backlash: Technology, Regulation, and Inclusion. *Brookings*.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System.

Narayan, P. K. (2020). Cryptocurrency and GDP in emerging markets: A predictive analysis. *Emerging Markets Review*.

Narayanan, A. B. (2016). *Bitcoin and Cryptocurrency Technologies.* Princeton University Press.

Nature. (2023). Examining the impact of cryptocurrencies on the global financial system. *Nature Communications*.

Negi, R. (2021). The impact of Cryptocurrencies on the global financial system. *Global Finance Journal*.

Nelson, C. R. (1982). Trends and random walks in macroeconomic time series: Some evidence and implications. *Journal of Monetary Economics*, 139- 162.

Nwani, C. &. (2021). Exchange rate volatility and economic growth in oil-dependent economies: Evidence from Nigeria. *Energy Economics*.

Nwankwo, O. E. (2022). Cryptocurrency adoption and financial inclusion in Africa: A focus on the Nigerian economy. *Journal of Emerging Markets Finance and Trade*, 190–205.

Ogujiuba, K. &. (2021). Cryptocurrencies as an alternative financial system in Nigeria: Addressing the unbanked population and economic instability. Journal of Emerging Financial Technologies. *Journal of Emerging Financial Technologies*, 45–67.

Okafor, I. S. (2023). Evaluating the implications of cryptocurrency adoption on financial stability in Nigeria. *Journal of African Economic Studies*, 245–260.

Oke, O. M. (2021). Remittances and financial sector development in Nigeria. *Gombe Journal of Economics and Allied Sciences*, 1-15.

Olatunde, N. A. (2022). Cryptocurrencies and economic systems in Africa: Challenges and opportunities. *Global Journal of Engineering and Technology Advances*.

Olayinka, A. a. (2021).

Olowe, R. A. (2009). Stock return, volatility and the global financial crisis in an emerging market: The Nigerian case. *International Review of Business Research Papers*, 426-447.

One, T. I. (2024). *Financial intermediaries: Types, functions, benefits, and challenges*. Retrieved from https://theintactone.com/2024/05/02/financial-intermediaries-types-functions-benefits-challenges/

Onyinyechi, E. I. (2022). The COVID-19 pandemic and economic growth: Evidence from oil-dependent economies. *Journal of African Economic Studies*, 145–168.

OriginStamp. (2024). *Monero vs. Ethereum: What's the difference?* Retrieved from https://originstamp.com/blog/monero-vs-ethereum-whats-the-difference/

Ostern, J. (2020). The economic importance of cryptocurrencies and their impact on monetary policy. *Economic review*.

Pistor, K. (2019). Financial Inclusion Through Blockchain: The Rise of Open Banking. *NBER Working Paper Series*.

Quickonomics. (2024). *Financial intermediary: Definition, types, and importance.* . Retrieved from https://quickonomics.com/terms/financial-intermediary/

Radanliev, P. (2024). The rise and fall of cryptocurrencies: Economic and Social values of blockchain technologies . *Financial Innovation*.

R-bloggers. (2021). *Vector Error Correction Model (VECM) using R*. Retrieved from https://www.r-bloggers.com/2021/12/vector-error-correction-model-vecm-using-r/

Scholar, S. (n.d.). *Cryptocurrencies: Are disruptive financial innovations here?* . Retrieved from https://www.semanticscholar.org/paper/Cryptocurrencies%3A-Are-Disruptive-Financial-Here-Vora/96dd1c7949b8bbefcb4c364a5d88200356c125f3

Schumpeter, J. (1911). The Theory of Economic Development. *Historical Analysis of Financial Intermediaries*.

Shahzad, S. J. (2021). Safe haven, hedge and diversification properties of Bitcoin: A comparison with gold and commodities. *Finance Research Letters*, 9-14.

ShallBD. (2024). *Different types of VAR models: Exploring the varieties of Vector Autoregressive Models.* Retrieved from https://shallbd.com/different-types-of-var-models-exploring-the-varieties-of-vector-autoregressive-models/

Shapiro, M. L. (1986). Network Effects, Compatibility, and Standards. *The Quarterly Journal of Economics*.

Shin, H. S. (2016). Can Cryptocurrencies Revolutionize the Financial System? *Bank for International Settlements*.

Simple. (2024). *Cross-border payments with cryptocurrencies.* Retrieved from https://simple.app/blog/cross-border-payments-with-cryptocurrencies/

Smith, A. (1776). *The Wealth of Nations. Historical Analysis of Money as a Store of Value.*

Solutions., A. (n.d.). *How cryptocurrency is disrupting the global financial system.* . Retrieved from https://www.antiersolutions.com/how-cryptocurrency-is-disrupting-the-global-financial-system/

SpringerLink. (2021). Cointegration and equilibrium relationships in economics. *Journal of Economics and Finance*.

SpringerOpen. (2023). The rise and fall of cryptocurrencies: Defining the economic and social values of blockchain technologies. *Journal of Financial Innovation*.

Statista. (n.d.). *Where grassroots crypto adoption is highest* . Retrieved from Statista: https://www.statista.com

Steiglitz, J.-C. R. (2000). *The Economics of Search.*

Stoll, C. K. (2019). The carbon footprint of Bitcoin. *Nature Communications*.

StudySmarter. (2024). *Economic functions of financial intermediaries*. Retrieved from https://www.studysmarter.co.uk/explanations/macroeconomics/economics-of-money/economic-functions-of-financial-intermediaries/

Suleiman, I. a. (2023).

TFFN. (2024). *Why does an economy need financial intermediaries?* . Retrieved from https://www.tffn.net/why-does-an-economy-need-financial-intermediaries/

Trakx. (n.d.). *Fundamental and technical analysis in cryptocurrency trading*. Retrieved from https://trakx.io/resources/insights/fundamental-and-technical-analysis-in-cryptocurrency-trading/

Treiblmaier, H. (2022). Do cryptocurrencies really have (no) intrinsic value . *Electronic Markets*.

Umar, Z. J. (2022). Cryptocurrencies and precious metals: A closer look from diversification and portfolio management perspective. *Resources Policy*, 77.

Wasiak, M. P. (2016). Financial sector development and economic growth in the EU and OECD countries. *Economic Modelling*.

White, H. (2022). Macroeconomic impact of cryptocurrencies and stablecoins. *Journal of Macroeconomics*.

Wirth, T. &. (2024). Practical Applications of is Bitcoin enough?

Wooldridge, J. M. (2016). *Introductory econometrics: A modern approach.* Cengage Learning.

Wu, H.-C. L.-C. (2023). Systemic risk in cryptocurrencies: Evidence from a network approach. Financial Innovation.

Yellen, J. (2019). Control of money supply and interest rates in relation to cryptocurrencies. Monetary Policy Journal. *Monetary Policy Journal*.

Yermack, D. (2015). Is Bitcoin a Real Currency? An Economic Appraisal. *Financial Analysts Journal*.

Yousaf, I. &. (2020). Bitcoin and precious metals: A hedge against inflation and stock market uncertainty. *Resources Policy*.

Yousaf, I. &. (2022). Static and dynamic connectedness between NFTs, DeFi and other assets: Portfolio implication. *Global Finance Journal*, 53.

Zohar, A. (2015). Bitcoin: Underlying technology and its applications. *Communications of the ACM*, 36-44.

Zohar, A. (2021). Evolving legal frameworks aurrounding cryptocurrencies. *Journal of Financial Regulation*.