BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

DEPARTMENT OF STATISTICS AND MATHEMATICS

ZIMBABWE'S FDI CONUNDRUM: UNPACKING THE ROLE OF SOCIOPOLITICAL FACTORS AND FORECASTING

BY

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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS OF THE BACHELOR OF SCIENCE HONOURS DEGREE IN STATISTICS AND FINANCIAL MATHEMATICS

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JUNE 2024

APPROVAL FORM

This is to certify that this research project is the result of my own research work and has not been copied or extracted from past sources without acknowledgement. I hereby declare that no part of it has been presented for another degree in this University or elsewhere.

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DEDICATION

In loving memory of Dennis and Gift.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my Lord and personal Saviour, Jesus Christ, for His guidance, strength, and blessings throughout this journey. Without His grace and mercy, this accomplishment would not have been possible. I would also like to give special thanks to two remarkable ladies, Mrs. S. Chitongo and Mrs. M. Dengu, who have been a constant source of inspiration and motivation. Their unwavering faith in my potential and consistent encouragement to look on the bright side have been invaluable to me. I would like to extend my heartfelt thanks to my supervisor, Mr. B. Kusotera, for his invaluable support, insightful feedback, and encouragement throughout the course of this study. His expertise and dedication have been instrumental in shaping this research. Additionally, I am profoundly grateful to my classmates for their continuous support, collaboration, and camaraderie. Their shared knowledge and constructive discussions have greatly enriched this work. To all who have contributed to this study in various ways, your support and encouragement have been invaluable. Thank you.

ABSTRACT

Foreign Direct Investment stands as a pivotal force to propel growth in developing countries, therefore having a thorough understanding of its dynamics is of paramount importance. This study investigates the relationship that political stability and corruption has with FDI inflows in Zimbabwe and compares the predictive power of the ARIMA model and LSTM neural network. Utilizing a Vector Autoregressive (VAR) framework, the analysis incorporates different factors including inflation, GDP, Control of Corruption (COC), and the political stability index (PSI). The results reveal a short-run negative correlation between GDP and FDI, with GDP showing a positive influence on FDI in the long term. Political stability exhibits a positive influence on FDI in the long run, on the other hand control of corruption negatively impacts FDI inflows for both the short-term and long-term, supporting the "helping hand" hypothesis in a weak regulatory context. The study also finds that LSTM outperforms ARIMA in predicting FDI, accurately reflecting the volatile nature of FDI inflows. FDI inflows were forecasted using the LSTM from 2023 to 2026. These findings underscore the complex interplay between socio-political factors and FDI, providing critical insights for policymakers in Zimbabwe to enhance the investment climate. Constraints of the study included limited data availability and a short research duration. The study recommends a firmer grip on corruption by stakeholders, political tolerance and engagement of both ruling and opposition parties in the government to fostering a more conducive investment environment in Zimbabwe.

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ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criteria
COC	Control of Corruption
CUSUM	Cumulative Sum Control Chart
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
PACF	Partial Autocorrelation Function
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
ZRP	Zimbabwe Republic Police
ZACC	Zimbabwe Anti-Corruption Commission
ZIC	Zimbabwe Investment Centre

CHAPTER 1: INTRODUCTION

1.0 Introduction

Foreign capital plays a crucial for global economic growth, yet Zimbabwe faces significant economic challenges in attracting it. Zimbabwe, rich in resources, navigates complex investment regulations influenced by socio-political factors. Sikwila (2014) highlights the impact of production, trade liberalization, political stability, local investment, and inflation on FDI. This study explores these dynamics to elevate economic development through industrial advancements, a strong financial sector, and new technologies, promoting technical innovation and global managerial skills. The introductory chapter addresses the background of the study, issue statement, purpose, goals, importance, assumptions, constraints, and methodology. This sets the stage for a comprehensive five-chapter study, covering literature review, methodology, data analysis, and concluding with findings and recommendations.

1.1Background of the study

Following its independence in 1980, the newly formed government of Zimbabwean engaged a tightly regulated, inward-focused economic approach. During this period, around 70% of the entire capital stock comprised of international investment, notably with Foreign Direct Investment (FDI) being the primary component among various inflows (Clarke, 1980). However, for the first decade post-independence, FDI inflows remained relatively low, reflecting the highly regulated policy environment. Foreign firms faced cumbersome processes, requiring approval from the Foreign Investment Centre for any new businesses in the country. Despite the presence of political stability, low corruption levels, and secure property rights, FDI inflows remained subdued.

In 1989, a pivotal shift occurred with the implementation of a revised investment code, ushering in significant changes. (Gwenhamo, 2009) highlighted that during the 1990s, the policy environment featured tax holidays, tariff exemptions, and alterations in profit repatriation proportions for multinational companies, surging FDI inflows to an average exceeding $50 million annually between 1990 and 1997. However, political instability arising from compulsory land acquisition in 2000 led to a substantial drop in FDI, coupled with economic inefficiencies, reflected in a decline in FDI contribution to the GDP from 25% in 1995 to 17% in 2005. Post-independence corruption became rampant following the liberalisation of the economy, the extent of bureaucratic corruption worsened, with bodies like the Zimbabwe Investment Centre which was created for the purpose of facilitation of FDI was being used as a restriction mechanism to illicit private wealth for the ruling elite who used state power to have access to state resources, Muzurura (2016).

The subsequent years were marked by further challenges, including Zimbabwe's expulsion from the IMF and a subsequent reduction in its borrowing limit, disrupting FDI inflows and exacerbating unemployment and poverty issues (Gwenhamo, 2009). Notably, within the broader context of developing nations, Sub-Saharan Africa, where Zimbabwe is situated, has experienced comparatively lower FDI levels than South American and Asian counterparts, contributing to increased poverty, sectoral deterioration, and slow economic growth due to inadequate funding and a weakened monetary system. (Biti, 2013) emphasized that Zimbabwe's unemployment rate reached approximately 80% in 2012, exacerbating pervasive poverty among the majority of the population. Since 2013 weak governance, lack of transparency within the bureaucracy paved way for inefficiencies in the system particularly in the organisations deemed to be watchdogs such as the ZACC and ZRP who have been rendered as toothless bulldogs by rent seeking public officials (Muzurura, 2016). It is without question the rampant increase in abuse of public office by civil servants, bureaucrats since they are in an economy with high levels of government regulations, they resort to use office as an enterprise to supplement their low incomes by assisting business owners in evading state statutes and laws through corruption (Muzurura, 2016)

From the start of the 21st century, the foreign investment landscape in Zimbabwe can be characterized as a stochastic process. Notably, there were record low inflows of US$3,799,999 in both 2001 and 2003, marking the lowest points within the decade spanning from 2000 to 2010. Conversely, the highest FDI inflow was recorded in 2010, reaching US$122,586,666.67. The subsequent decade witnessed a relative growth in FDI inflows, peaking in 2014. However, starting from 2015, there has been a consistent and steady decline in the amount of FDI. In 2015, 2016, and 2017, the inflows were US$399,200,000, US$343,013,813, and US$307,187,738, respectively. A noteworthy shift occurred in 2018 when Zimbabwe experienced a record-high FDI inflow of US$717,865,322, showcasing a remarkable growth of over 100% compared to the previous year (UNCTAD, 2018). Despite this peak, FDI inflows sharply decreased to

US$249,500,000 in 2019 and continued to decline in the subsequent years. The pattern of FDI inflows exhibited a slow but steady decline without any discernible pattern. However, certain years stood out with surges in FDI, often closely associated with significant political events within the country. This study is premised on the researcher's position as part of a cohort focusing on narrowing the gap in understanding the relationship between FDI and the socio-political factors that influence investor sentiment in the country.

1.2 Statement of the problem

Zimbabwe has been confronted with a persistent and concerning trend of declining Foreign Direct Investment (FDI) inflows over recent years. Despite sporadic surges, the overall trajectory reflects a consistent decrease in foreign capital entering the country. This decline raises significant concerns about the economic implications and potential barriers that deter foreign investors. Recognizing the multifaceted nature of this issue, our research specifically aims to comprehensively investigates the impact of socio-political variables on the observed decline of Zimbabwe's FDI. Understanding how political and social dynamics influence investor sentiment is crucial for policymakers, business leaders, and stakeholders seeking to revitalize Zimbabwe's economy. This study, therefore, endeavours to provide nuanced insights into the interplay between FDI and socio-political conditions, identify key determinants affecting investor confidence, and propose strategic measures to reverse the downward trend, fostering a more conducive environment for foreign investment.

1.3 Objectives of the study

1. Analyse the relationship between socio-economic variables and FDI inflows in Zimbabwe.
2. Develop and compare the performance of LSTM and Box-Jenkins (ARIMA) models in forecasting FDI inflows.
3. Use the best performing model (LSTM or Box Jenkins) to forecast FDI inflows for 2023-2026

1.4 Research question

1. To what extent socio-economic factors impact the quantity and pattern of FDI inflows in Zimbabwe?
2. Will the FDI fitted models be valid or not?
3. Will the inflows of FDI in Zimbabwe be constant or not constant?

1.5 Significance of the study

This research has both academic and practical significance by advancing our understanding of FDI dynamics in the Zimbabwe. The evaluation of ARIMA and LSTM models contributes to forecasting methodologies specific to the country, enhancing predictive accuracy. Furthermore, the exploration of political stability, corruption, and good governance as determinants of FDI provides crucial insights for policymakers, facilitating the development of targeted strategies to attract and sustain investments. The study's findings will inform stakeholders, including government agencies and investors, aiding evidence-based decision-making for the formulation of policies that foster a conducive investment climate. Ultimately, the research contributes to both scholarly knowledge and practical initiatives, guiding sustainable economic development in Zimbabwe.

1.6 Assumption of the study

FDI inflows are in United States Dollars.

Regression analysis assumes a linear association between FDI inflows and the selected socio-political factors.

1.7 Limitations of the study

The limitations that are there, are the availability of data on the socio-political factors that affect FDI inflows for the period being examined. Another limitation of the research is that the researcher is not able to ascertain the extent to which policies regarding FDI were implemented.

1.8 Definition of terms

Foreign Direct Investment: Is interpreted as the rate at which capital inflows accumulate and contribute to the fixed capital stock of the host country over time (Sikwila, 2014).

Time Series: Information gathered from observations gathered in a sequential manner over a period of time (Cryer & Chan, 2008).

Socio-Political: Concerning, connected with, or encompassing a fusion of social and political elements (Merriam-Webster,2023)

Political Stability: Kim and Haksoon (2010) assess political stability based on criteria like free elections, empowered elected officials, competitive political groups, influential opposition, and entity autonomy.

Economic Growth: This concerns the augmentation and growth of a country's GDP, wherein adjustments are made for inflation during a specified period. It embodies the consistent, enduring growth in economic output over an extended period (Smith, 2020).

Recurrent Neural Network: A type of network in which neurons provide feedback signals to one another (Grossberg, 2013)

1.9 Chapter summary

This chapter has highlighted the critical significance of analysing FDI in Zimbabwe, seeking to unravel the complexities behind the country's irregular FDI inflow patterns. With a clear emphasis on time series analysis utilising advanced neural network techniques and ARIMA models, the exploration aims to understand the trends in FDI inflows and forecast observed patterns. Moreover, the application of a regression model delves deeper into comprehending FDI patterns by shedding light on the socio-political factors that influence inflows and the extent of their impact. In addition to addressing sporadic patterns, the chapter aims to overcome historical challenges where FDI values were susceptible to overestimation or underestimation due to inherent model weaknesses. The research objectives are strategically designed to identify a more robust forecasting model, comparing the effectiveness of ARIMA and neural networks in time series modelling. As we transition to the subsequent section, the study is poised to conduct a comprehensive analysis of both theoretical and empirical literature, providing a more nuanced understanding of the intricate relationship between FDI patterns and socio-political influences.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This section offers a systemic examination theoretical and empirical works to understand the complex relationship between FDI, socio-political factors, and forecasting methodologies. This study evaluates FDI inflow forecasting in Zimbabwe using the ARIMA model and LSTM, a type of Recurrent Neural Network. Adebiyi et al. (2014) find ARIMA models effective for accurate financial projections, often outperforming more complex models. Jere et al. (2017) compares forecasting methods in Zambia, noting ARIMA's superior performance with minimal errors, predicting a 44.36% annual net FDI inflow growth by 2024. However, the literature on AI in FDI forecasting is limited. Roy (2021) argues that AI approaches outperform traditional methods in predicting FDI trends and uncovering hidden information. The study addresses the efficacy of these models in Zimbabwe. Bruce (2005) highlights institutional effectiveness in influencing FDI, noting that inadequate legal protection and corruption deter investment by raising business costs. Poor infrastructure, resulting from weak institutions, further impedes FDI by reducing expected profitability. Kim and Haksoon (2010) assert that political risks affect FDI inflows, with unstable countries attracting more FDI and stable ones seeing outflows. Despite a global increase in FDI to developing countries since 1985 (World Bank, 2002), Zimbabwe has not benefited significantly, partly due to socio-political instability. Other macroeconomic factors also drive FDI, impacting shareholder wealth and influenced by stock market liberalization and corporate governance (Admati and Pfleiderer, 2000). This review aims to deepen the understanding of these dynamics and their implications for Zimbabwe's FDI.

2.1 Theoretical Literature Review

2.1.1 Theoretical Framework

FDI is crucial for the economic growth of developing countries. This theoretical framework explores the impact of corruption and political stability on attracting foreign capital into the country. It employs the "Helping" and "Grabbing" hand hypotheses, along with concepts from rent-seeking, public choice theory, and transaction cost economics, to provide a comprehensive analysis.

Helping Hand and Grabbing Hand Hypotheses

The "Helping Hand" hypothesis ascertains that corruption can sometimes facilitate business operations by helping firms navigate bureaucratic red tape, potentially attracting FDI (Méon & Weill, 2010). Bhattacharya et tal (2018) points out that government intervention can positively impact FDI inflows by providing a conducive environment. Conversely, the "Grabbing Hand" hypothesis posits that corruption creates an unpredictable business environment, increasing the cost of doing business and deterring FDI (Quazi, 2014). In the context of Zimbabwe, the "Grabbing Hand" hypothesis is more applicable due to pervasive corruption and the lack of transparency, which create significant barriers to investment (Mugabe et al., 2018). Corruption in Zimbabwe is characterized by high-level officials demanding bribes, increasing transaction costs and creating uncertainty for investors.

Rent-Seeking

Rent-seeking entails individuals or entities endeavouring to augment their personal wealth without generating additional wealth, often by influencing the political landscape (Krueger, 1974).. In Zimbabwe, rent-seeking behaviour is evident in the way government officials exploit their positions to extract rents from businesses, discouraging FDI (Acemoglu & Robinson, 2012). This behaviour distorts market incentives and resource allocation, making the country less attractive to foreign investors.

Public Choice Theory

Public choice theory employs economic principles to analyse political decision-making, proposing that politicians and bureaucrats prioritize their self-interest over the welfare of the public (Buchanan & Tullock, 1962). In Zimbabwe, public choice theory helps explain why corruption is rampant: politicians and officials prioritize personal gains over national development. This self-interested behaviour leads to policies that are not conducive to attracting FDI, such as inconsistent regulations and high levels of bureaucratic interference (Moyo, 2016).

Transaction Cost Economics

Transaction cost economics centres on the expenses linked with economic transactions, particularly in the presence of uncertainties and complexities (Williamson, 1985). High levels of corruption and political instability increase transaction costs by creating risks and uncertainties. In Zimbabwe, the unpredictability of both political and economic policies elevates these costs, thus deterring FDI (North, 1990).

Zimbabwe's economic landscape has been significantly affected by corruption and political instability, which are critical barriers to FDI. The country's governance issues align with the "Grabbing Hand" hypothesis, where corruption increases transaction costs and creates a hostile investment climate. Rent-seeking behaviour further exacerbates these issues by diverting resources away from productive uses. Political instability in Zimbabwe, characterized by frequent changes in leadership and policy unpredictability, aligns with public choice theory, suggesting that the personal interests of politicians often override the need for stable and conducive investment policies. This instability increases transaction costs and risks, further discouraging foreign investors. To effectively analyse the effect of corruption and political stability on foreign capital inflows in Zimbabwe, this framework provides a robust theoretical foundation. By integrating the "Helping Hand" and "Grabbing Hand" hypotheses with rent-seeking, public choice theory, and transaction cost economics, we can comprehensively assess how these factors interact to influence FDI inflows.

The combined theoretical perspectives offer a nuanced understanding of how corruption and political stability affect FDI. In Zimbabwe, the prevalence of corruption and political instability acts as significant deterrents to foreign investment. The integration of these theories into the analysis will provide a comprehensive assessment of the barriers to FDI in Zimbabwe and offer insights into potential policy reforms to attract more foreign investment.

2.1.2 Socio-Political Factors Influencing FDI

Foreign capital is a critical driver of economic development, and understanding the socio-political factors shaping FDI inflows in developing countries, such as Zimbabwe, is paramount. This theoretical literature review delves into key scholarly works that elucidate the nuanced influence of socio-political factors, with a specific focus on the Political Stability Index (PSI) and the Control on Corruption (COC) scale. There exists a number of socio-political factors that influence FDI like Minorities at Risk (MAR), Environmental Performance Index (EPI), Social Progress Index (SPI)…etc. these are all variables that have an effect on FDI inflow, but PSI and COC stand out as the most significant in the case of Zimbabwe for the examined timeframe, as it is characterised by quite a number of paramount socio-political events of great magnitude.

Political Stability and Corruption

Zimbabwe's FDI inflows from dropped from USD 745 million in 2018 to USD 166 million in 2021, this was attributed to the lack of predictability in the bureaucracy's economic regulation and the turbulent political and economic environment in yester years have eroded confidence among foreign investors, hampering their willingness to invest (UNCTAD, 2022). Foreign investors have influenced most of the mergers and acquisitions in Zimbabwe since June 2017 with 73% of all approved mergers and in 2013 a piece of legislation was put which forbade foreign investors from owning small businesses in Zimbabwe (Lloyds Bank, 2023). The interplay between the legislative machine and FDI cannot be taken lightly as it is a major driver, especially in the context of Zimbabwe. Certain scholars have identified a connection between the two variables, contending that foreign investors are inclined to avoid incurring extra expenses in the shape of bribes for acquiring business licenses. The rationale behind this inclination is the potential diminution of their returns on investments (ROI) (Freckleton et al., 2012). In this view corruption then has a negative on the FDI inflows in the host country, as providing bribes involves a significant default risk, as there is no legal recourse for the briber if the agreed-upon actions are not fulfilled by the recipient. Unlike legitimate contracts, bribes lack legal binding and cannot be enforced in a court of law (Cuervo-Cazurra, 2008).

Political stability allows governments to lessen the risk of seizing private property for public purposes, enabling them to allocate resources towards bolstering the financial market. This promotes the use of internalization benefits, resulting in increased FDI inflows (Khandaker, 2015). The rationale behind this is that stability enhances the trust of foreign investors, encouraging them to contribute a much larger capital to the intended foreign nation. The degree of instability related to investment risk holds greater sway over foreign investment choices in

Middle Eastern and North African nations compared to developing nations with lower investment risk levels Chan and Gemayel (2004). Kim and Haksoon (2010) highlight the intricate relationship between measures of political stability and the overall performance of the private sector, including their impact on inward Foreign Direct Investment (FDI). Sikwila (2014) underscores the crucial role of political stability in attracting or deterring FDI in Zimbabwe. There is a prevalent belief that policies concerning indigenization and property rights act as barriers to FDI inflows.

The Control of Corruption (COC), as defined by The World Bank (2022), evaluates perceptions of the degree to which governmental authority is utilized for personal benefit, encompassing various levels of corruption, including the influence of elites and private entities on state matters. This metric spans from -2.5 (representing limited control of corruption) to 2.5 (indicating robust control of corruption), with higher values reflecting more effective corruption management. As emphasized by Chamisa (2020), there exists a direct relationship between investor confidence and the COC score. Nations with higher COC scores are more likely to attract substantial Foreign Direct Investment (FDI). However, there are occasional instances where a positive correlation is observed between FDI inflows and corruption. Elfakhani and Mackie (2015) highlight this trend by referencing China, where despite increasing corruption levels and diminishing protection of property rights from 1980 to 2008, FDI inflows continued to rise. Quazi et al. (2014) further illustrate the positive influence of corruption on FDI inflows in their study of 53 African countries.

2.1.3 Forecasting Methodologies

Box-Jenkins ARIMA

The examination of Foreign Direct Investment (FDI) forecasting in developing nations has garnered considerable scholarly attention, with the Box-Jenkins ARIMA methodology emerging as a pivotal analytical tool. The seminal work by Reinsel et al. (2016) in time series analysis has substantially contributed to the application of ARIMA models, rendering them particularly pertinent for prognosticating FDI trends. Comprising autoregressive (AR), differencing (I), and moving average (MA) components, the ARIMA model has been extensively utilized due to its adeptness in accommodating both linear and nonlinear features inherent in time series data (Hyndman & Athanasopoulos, 2018). The versatility of ARIMA extends its utility to diverse fields such as finance, economics, and epidemiology, as articulated by Cowpertwait and Metcalfe (2009). Its applicability is further underscored by its capacity to accommodate seasonality, trends, and autocorrelation within datasets (Wei, 2006). The iterative process advocated by Box and Jenkins, encompassing model identification, estimation, and diagnostic checking, ensures a methodologically rigorous approach to time series analysis (Chatfield, 2019).

Recent advancements in ARIMA methodology involve enhancing forecasting accuracy through the integration of exogenous variables, as demonstrated by the ARIMAX hybrid approach (Hipel & McLeod, 1994; Zhang & Qi, 2005). This augmentation broadens the model's scope by considering external factors that may influence time series behaviour.

However, notwithstanding the widespread use of ARIMA, critiques have emerged regarding its assumptions of linearity and stationarity. Scholars, such as Tong (1990), have proposed nonlinear extensions like the Threshold Autoregressive (TAR) model to address these limitations. Nevertheless, this study aimed to circumvent these shortcomings by employing a recurrent neural network model. The intricacies and dynamism of FDI flows in developing nations necessitate robust forecasting methodologies. ARIMA models, adept at capturing underlying patterns and trends, have proven efficacious in this realm (Borensztein et al., 1998). The incorporation of autoregressive and moving average components allows for the consideration of historical FDI values and the discernment of potential cyclical patterns.

Application of ARIMA models in forecasting FDI in specific developing regions, such as Asia and Africa, attests to the methodology's adaptability across diverse economic contexts (Li & Reza, 2018; Ofori, 2018). The iterative process of Box-Jenkins, which entails careful model identification, estimation, and diagnostic assessment., ensures a rigorous analysis of FDI time series data in these regions. Despite the promises of ARIMA, some studies underscore the imperative of considering additional variables and external factors that may influence FDI dynamics (Asiedu, 2002). The integration of exogenous variables, as exemplified by Zhang and Qi (2005) through the ARIMAX approach, facilitates a more comprehensive forecasting model, encompassing not only historical FDI patterns but also the impact of external economic and policy variables.

Challenges inherent in forecasting FDI in developing nations, such as political instability and policy changes, necessitate models, including ARIMA, to account for these uncertainties (Alfaro et al., 2004).

Long Short-Term Memory (LSTM)

Over the years, LSTM has emerged to show its prowess among tools for sequence modelling and time series analysis. Invented by Hochreiter and Schmidhuber in 1997, LSTM resolves the disappearing gradient issue found in conventional recurrent neural networks (RNNs), enabling the modelling of long-term dependencies within sequential data. With its distinctive structure featuring memory cells and gates for input, output, and forget, LSTM can effectively retain or discard information across prolonged sequences, rendering it fit to carry out tasks involving contextual and short-term dependencies (Hochreiter & Schmidhuber, 1997).

LSTM has found wide applications across diverse domains, demonstrating effectiveness in natural language processing (Graves et al., 2013), speech recognition (Hannun et al., 2014), and financial time series forecasting (Fischer & Krauss, 2018). Its proficiency in capturing patterns of varying durations proves advantageous, especially where conventional models encounter limitations. Studies focusing on specific regions highlight LSTM's adaptability to different economic contexts. For instance, Zhang et al. (2019) applied LSTM to forecast Foreign Direct Investment (FDI) in Asia, emphasizing its ability to learn from past observations and adapt to changing economic conditions. This adaptability is particularly valuable in developing countries where FDI patterns are influenced by multifaceted factors.

Roy (2021) observes that linear models face challenges in accurately predicting FDI due to significant noise in the data. Instead, the study advocates for non-linear approaches, such as neural networks, which can capture irregular patterns without requiring parameter estimation during forecasting. While LSTM shows promise in FDI forecasting, scholars acknowledge the significance of feature selection and model tuning. The incorporation of relevant economic indicators as input features enhances LSTM's predictive accuracy (Nair et al., 2021), aligning with the broader trend in machine learning applications where domain knowledge integration is crucial for improved forecasting.

The versatility of LSTM in handling various data types and addressing challenges related to sequential data has led to its widespread use. Chung et al. (2014) introduced the Gated Recurrent Unit (GRU), a version of LSTM, further expands the repertoire available to researchers and practitioners in deep learning. However, despite its successes, LSTM is not without limitations. Challenges related to model interpretability have been explored, prompting ongoing efforts to enhance transparency and understanding of the decision-making process within LSTM networks (Karpathy et al., 2016).

Turning attention to developing countries like Zimbabwe, FDI forecasting using LSTM faces challenges related to the quality of FDI data. Incomplete or noisy data introduces uncertainty into LSTM training, potentially compromising its ability to discern meaningful patterns and leading to inaccurate forecasts (Roy, 2021). Additionally, LSTM's capacity to capture complex patterns raises the risk of overfitting, particularly when dealing with limited FDI data, potentially affecting the model's generalization to unseen data (Zhang et al., 2019). Furthermore, LSTM's inherent complexity poses challenges in interpreting its decision-making process, crucial for stakeholders, policymakers, and analysts in Zimbabwe. The lack of interpretability may hinder the adoption and trust in LSTM-based predictions (Karpathy et al., 2016).

In conclusion, while LSTM holds considerable promise for FDI forecasting, addressing challenges related to data quality, overfitting, and interpretability is paramount, especially in the context of developing countries like Zimbabwe. Continuous refinement and adaptation of LSTM models are essential for improving their reliability and effectiveness in capturing the dynamics of FDI trends.

2.2 Conceptual Framework

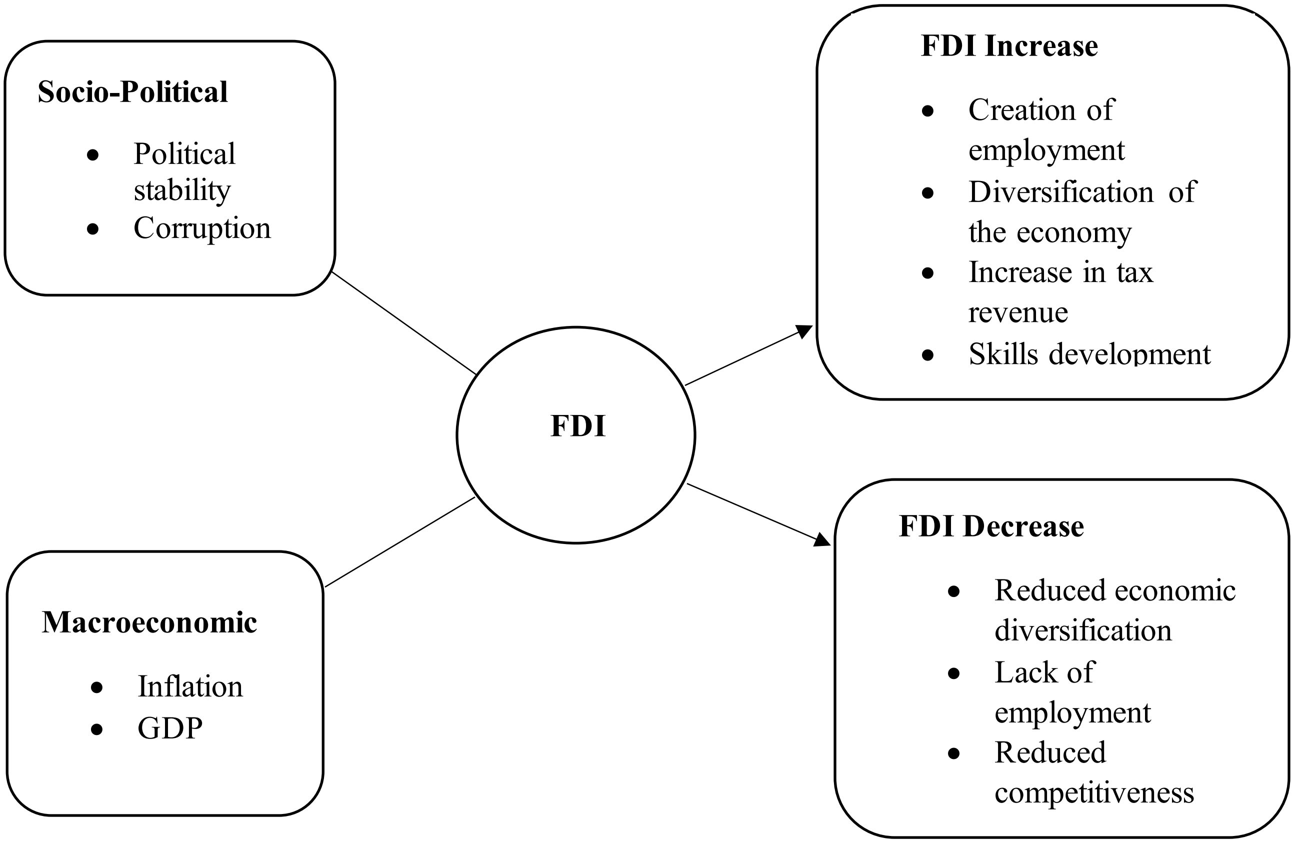


Figure 2. 1 Conceptual Framework

The framework depicts a relationship that exists between macroeconomic and socio-political factors, and FDI inflows. Here it is shown how healthy management of both factors leads to creation of employment, diversification of the economy, skills development and technological advancement with an improvement if FDI inflows. While on the other hand it is shown how unhealthy management of both factors leads to decrease in FDI resulting in lack of employment, reduced competitiveness in industry.

2.3 Empirical Literature Review

In research conducted in Pakistan, Arfan and Abdullah (2014) conducted a thorough analysis of Foreign Direct Investment (FDI) inflows spanning 21 years from 1999 to 2011. Their investigation focused on unravelling the moderating impact of political stability in conjunction with macroeconomic variables on FDI inflows. Employing a hierarchical multiple linear regression model, the study emphasized the interplay of political stability. To validate their results, the researchers tested yearly data, which included variables such as inflation rate, imports, GDP growth rate, and political stability, for stationarity using the Augmented Dickey Fuller (ADF) test, considering factors like GDP and BOP growth rate. With all assumptions duly examined, the research employed SPSS 19.0 for regression analysis. The outcomes revealed a noteworthy and positive moderation effect of political stability on both GDP growth rate and Balance of Payments (BOP), subsequently influencing FDI inflows. The study's implications underscored the necessity for a revaluation of Pakistan's FDI policies, urging policymakers to consider strategic adjustments to attract more investments into the country. Proposals were put forth, including the delineation of a positive list comprising sectors conducive to FDI encouragement, and a negative list specifying areas where FDI should be restricted, such as defence goods and the service sector.

In a study in Turkey to assess the interplay between foreign trade balance and terms of trade, Ucan et tal (2018) employed the VECM. The ADF test was employed to check for stationarity in the data and both variables were found to be stationary at the first difference and for the lag length criteria, AIC was used and it selected lag length 3 as the optimal lag (Ucan et tal 2018). The Johansen cointegration test was used to assess to the presence cointegration equations, at 5% significance level the null hypothesis that there is no cointegration was rejected and concluding that there is at least one cointegrating relationship. The error correction model was then used to assess what type of process by which this long-term relationship passes in the short run. Granger causality was also employed to for causality between the variables and the results at 5% significance level show the existence of unilateral causality from foreign trade to terms of trade in the short term. The study concluded that there exists a long-run interplay among variables foreign trade and terms of trade on top of the short-run unilateral causality from foreign trade balance to terms of trade.

Ahmed et al. (2018) conducted an in-depth analysis using a Panel Fully Modified Ordinary Least Squares (FM-OLS) model to thoroughly examine the influence of corruption, trade openness, and political stability on the combined economies of Brazil, Russia, India, and China, known collectively as BRIC. Corruption levels were assessed using Transparency International's CPI, while political stability was evaluated using the Political Stability and Absence of Violence Index from the World Bank., and trade openness data were sourced from World Bank databases. The study spanned 15 years, from 2002 to 2016. initially, the Levin-Lin Chu test was used to evaluate panel data stationarity, revealing non-stationarity. Following this, first differencing was applied, and a subsequent Levin-Lin Chu test showed stationarity, with all p-values below 0.05. When the model was executed, it was found that 69.17% of FDI variations in BRIC countries could be explained by corruption, trade openness, and political stability, as indicated by a Coefficient of Determination (R-squared) of 0.69. The adjusted R-squared, at 0.67, suggested that 67.87% of FDI variation in BRIC nations could be attributed to the independent variables, meeting the generally accepted fitness threshold of over 60%. The Standardized Coefficient (beta) of Corruption was -0.02, with a p-value of 0.18, indicating a statistically insignificant negative impact of corruption on FDIs in BRIC countries, implying that corruption does not influence foreign direct investments in these nations. Notably, the research underscored a positive long-term relationship between FDI and political stability in BRIC countries. Therefore, policymakers are encouraged to focus on governance improvement, promote efficiency through regulatory quality, establish a robust rule of law, and ensure enduring political stability to attract increased FDI inflows

Sikwila (2014) employed E-Views for Ordinary Least Squares (OLS) estimations in a study scrutinizing Foreign Direct Investment (FDI) inflows into Zimbabwe. The investigation centred on discerning the determinants of these inflows, encompassing trade output, trade openness, political stability, domestic investment, and inflation. The study was grounded in the modified acceleration theory, utilizing time series data sourced from World Bank databases. The results, attaining significance at a 5% level, underscored the importance of all the variables under study with all significant t-ratios. Trade output demonstrated significance at a 10% level, yielding a t-ratio of 1.8. Notably, the study concluded that indigenization posed no obstacle to FDI inflows, as indicated by the insignificant t-ratios associated with all variables. Similarly, the data failed to substantiate the notion that property rights policies negatively impacted inflows. Sikwila (2014) underscored the policy implications of these findings for Zimbabwean and regional policymakers. Furthermore, the study advocated for potential investors contemplating countries like Zimbabwe to consider forging joint ventures with local counterparts. This strategic approach, particularly in sectors such as mining and manufacturing, was deemed imperative for ensuring the sustained success of FDI.

Kim and Haksoon (2010) conducted a study encompassing 28 countries, utilizing a comprehensive dataset spanning from 1990 to 2002. The primary objective was to investigate the interplay between FDI and political balance. Both OLS and GLS models were employed in this study to discern the nuanced characteristics of political stability and FDI inflows across diverse countries. The study revealed that politically unstable countries, despite their inherent instability, exhibited a heightened FDI inflow, particularly when demonstrating control over macro-economic factors. In alignment with Kim et al. (2010), the study established a positive correlation between a host country's Gross Domestic Product (GDP) and FDI flows. To fortify their empirical findings, three pertinent econometric techniques were employed in panel data analysis: pooled Ordinary Least Squares (OLS) estimation with robust standard errors, cross-sectional time-series feasible Generalized Least Squares (GLS) estimation, and random effects estimation. The integration of these methodologies contributes to the robustness and reliability of the empirical results. The outcomes underscored that FDI inflows were notably pronounced in countries characterized by political instability. Intriguingly, the study identified high capital outflows as a distinctive characteristic of politically stable countries, thereby shedding light on the intricate dynamics between political stability and FDI trends.

In the investigation conducted by Sibanda (2022), the focus was on forecasting Foreign Direct Investment (FDI) inflows in Zimbabwe using data of 52 years from 1970. The study employed the Box-Jenkins (ARIMA) model, with diagnostic checks revealing that ARIMA (0, 1, 1) was deemed optimal based on the AIC. To affirm model adequacy, a unit root test (ADF) was employed to assess the residuals for stationarity. In addition to the ARIMA model, a General Additive Model (GAM) was utilized for predictions, with a Mean Squared Error (MSE) serving as a metric to compare the predictive capabilities of both models. The study's findings indicated that the ARIMA model surpassed the GAM model in terms of in-sample forecasts. However, challenges were encountered when extending predictions to out-of-sample scenarios. Sibanda (2022) highlighted the inherent difficulty in predicting economic variables like FDI values, attributing the challenge to structural breaks within the economy. The study emphasized the significance of a stable political environment as an indicator of a conducive investment atmosphere. Furthermore, Sibanda (2022) suggested potential avenues for further research, proposing the exploration of non-linear models to address the inherent volatility in the FDI series.

In a study to predict FDI inflows in India, Roy (2021) employed an AI approach for forecasting methodology through a special kind of a neural network the LSTM. FDI inflows were collected from 1947 to 2020. In this study it was pointed out how conventional linear models are inefficient in forecasting when the data contains too much noise, to come to this conclusion an ARIMA and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) to perform predictions on the same data. A Root Mean Squared Error (RMSE) was employed to test for the accuracy of the predictive models. The accuracy of machine learning is increases with the volume of data; the data base used was fairly small so a conclusion was reached that the accuracy of the results could be perfected by using larger data set. Roy (2021) underscored that the traditional linear models such as ARIMA and GARCH perform well for small amounts of data, however their performances degrade when the volume of data increases. Roy (2021) also pointed out that the nature of FDI data was noisy and inflated, traditional models do not perform well with this type of data and they also require a series of parameters to be calculated based on the data, thus the superiority of a non-linear approach to deal with the data.

2.3 Research issues and research gap

While extensive research has explained factors that have effect of Foreign Direct Investment (FDI) inflows, significant gaps remain within understanding the nuanced impact of political uncertainty and corruption on FDI, particularly within the specific context of Zimbabwe. Existing studies often generalize findings across multiple countries or focus on broad macroeconomic indicators, lacking a deep dive into the unique socio-political and economic conditions of individual nations. Notably, research on Zimbabwe has not fully explored the direct interactions between political stability, corruption, and other economic variables, nor the long-term effects of political instability and corruption on investor confidence and decision-making. Additionally, there is a scarcity of advanced predictive models, such as those utilizing artificial intelligence or machine learning, to accurately forecast FDI inflows in politically volatile and corrupt environments. Addressing these gaps could yield more precise policy recommendations and strategic insights for enhancing FDI in Zimbabwe and similar contexts.

2.4 Chapter summary

The literature review offers a comprehensive exploration of the intricate factors influencing Foreign Direct Investment (FDI), combining theoretical frameworks, empirical studies, and forecasting methodologies. It underscores the critical role of political stability, corruption perceptions, and advanced forecasting techniques. "*Helping*" and "*Grabbing*" hand hypothesis, rent seeking theory, public choice theory and Transaction cost of economics frameworks stands out as a fundamental theoretical lens, providing enlightenment into the factors affecting FDI and their relevance. The empirical studies discussed shed light on the moderating impact of political stability on FDI inflows and the varied influence of corruption. The review advocates for the integration of non-linear approaches like LSTM due to the challenges posed by noisy and dynamic FDI data. Overall, the literature review not only deepens our understanding of the multifaceted factors shaping FDI but also positions advanced forecasting methodologies as essential for accurate predictions, offering valuable guidance for policymakers in fostering an attractive environment for FDI.

CHAPTER 3: RESSEARCH METHODOLOGY

3.0 Introduction

The methodology aims to systematically address the research's objectives and questions by employing regression time series analysis. The study concentrated on investigating the effects that socio-political factors have on acquiring foreign capital in Zimbabwe, identifying a time series model, estimating model parameters, diagnosing the model, and predicting and forecasting FDI inflows from 2023 to 2026. Additionally, the study evaluated the predictive accuracy of a neural network and traditional Box Jenkins models. To explore the enduring associations between variables, the study will employ the Vector Auto Regressive (VAR) model, Johansen co-integration, Granger causality and VECM. This detailed examination is designed to enhance our understanding of the intricate dynamics governing FDI inflows throughout the specified time period. Building on the introductory context, the subsequent section delves into the researcher's chosen methodology and provides insight into the rationale driving the research.

3.1 Research Design

The research adopted a quantitative research design grounded in Burn and Grove's (1993) perspective. Quantitative research is characterized as a structured, objective, and systematic process relying on numerical data to investigate variables concerning about the universe. This design is causal, particularly suitable when exploring cause-and-effect relationships between variables. The researcher's role in this approach is centred on effective data collection and interpretation, with a focus on investigating observable and quantifiable phenomena.

3.2 Data Sources

The research leverages secondary data on FDI inflows, political, economic growth and control of corruption from the World Bank. Inflation data was obtained from the Reserve Bank of Zimbabwe (RBZ). Utilizing these sources provides a robust foundation, tapping into widely recognized repositories for comprehensive and reliable global economic datasets. This enhances the credibility of the study and ensures a nuanced analysis of the effects of political uncertainty and corruption on foreign capital.

3.2.1 Data Collection

a. Time Series Data on FDI Inflows: The researcher acquired annual data on FDI inflows in Zimbabwe from World Bank.

a. Socio-Political Factors Data: The researcher gathered data on socio-political factors that is political stability and control of corruption from World Bank.

3.3 Target population

The study focuses on foreign investors, businesses, government agencies, and other stakeholders engaged in economic activities within Zimbabwe.

3.4 Variable Selection

a. Dependent Variable: The researcher saw it fit to use FDI inflows as the dependent variable.

b. Independent Variables: Socio-political factors mentioned in the literature review will be considered as independent variables.

The primary objective is to explore the influence of socio-political factors, namely political stability and corruption, on FDI inflows. Brief descriptions of each variable are provided below, accompanied by justifications for their inclusion in the research.

Table 3. 1 Description of Variables

Variables	Symbol	Indicator	Source
Foreign Direct Investment inflows	FDI	Cross-border investment with significant influence	World Bank
Political Stability	PSI	Political stability and security	World Bank
Corruption	COC	Control of Corruption	World Bank
Economic Growth	GDP	Economic growth	World Bank
Inflation	INF	Loss of value in money	Reserve Bank of Zimbabwe

3.5 Political Stability Index

This is a measure that assesses the level of political balance and or rest within a country. It is often used as an indicator of the overall political environment's stability and security.

Justification:

Sikwila (2014) emphasizes that political stability stands as a pivotal factor influencing the attraction or hindrance of foreign investment in Zimbabwe. The rationale behind this is that stability enhances the trust of foreign investors in the investment landscape, encouraging them to contribute more capital to the host nation.

3.6 Control of Corruption

This refers to the general views on the extent to which governmental authority is exploited for personal gain, encompassing various degrees of corruption, along with the impact of influential individuals and private entities on governmental affairs (World Bank, 2022).

Justification:

Muzurura (2016) points out that corruption increases the cost of doing business by raising uncertainty as far as expected payoffs to fixed capital investment, which in turn has an effect of the FDI inflows.

3.7 Economic Growth

This metric calculates the total value generated by all resident producers in the economy, including product taxes and excluding any subsidies not factored into the product values.

Justification:

Gwenhamo (2009) emphasizes the significance of GDP as an indicator of the host country's market size, which is considered a crucial factor influencing horizontal FDI. The underlying assumption is that foreign investors are inclined to invest in expanding markets to capitalize on opportunities.

3.8 Inflation

The continuous increase in the overall cost level of goods and services within an economy, leading to a decline in the value of money's purchasing power.

Justification:

The inflation rate serves as an indicator of economic stability, reflecting both economic pressures and the government's capacity to manage its budget. High inflation erodes the actual earnings of foreign investors operating in the local currency, thus lower inflation rates promote increased foreign direct investment (FDI) inflows, as suggested by Boateng et al. (2009).

3.9 Foreign Direct Investment

FDI can be perceived as the rate of increase in incoming capital that contributes over time to the accumulated fixed capital of the domestic nation (Sikwila, 2014).

Table 3. 2 Expected Variable Signs/ Effects on FDI inflows

Variable	Expected Sign	Possible Explanation
Political Stability	+	positive relationship between Political Stability and FDI inflows (Sikwila,2014)
Control of Corruption	+	A positive exists relationship between Control of Corruption and FDI inflows
Economic Growth	+	There is positive relationship between economic growth and FDI Inflows
Inflation	-	There is a negative relationship between FDI and Inflation

3.10 Vector Auto-Regressive (VAR)

The study adopts a comprehensive approach to uncover the temporal dynamics governing Foreign Direct Investment (FDI) inflows in Zimbabwe, with a specific focus on the influence of political stability. The VAR model is chosen as it accommodates the dynamic nature of the relationships between these key variables over time. The researcher initiates the VAR process by estimating model parameters, which involve determining the lag structure that best captures the temporal dependencies among FDI, PSI, GDP and INF. The VAR model is structured to account for the simultaneous interactions among the variables, allowing for a more nuanced understanding of their interplay. The study leverages this methodology to discern the short run and long run implications of changes in political stability on FDI inflows. By incorporating lagged values of each variable, the VAR model captures how past values influence the current state, uncovering potential feedback mechanisms that contribute to the overall system dynamics.

To ensure the validity of the VAR model, the researcher conducts thorough diagnostics. This involves assessing the stationarity of the data through techniques like the ADF test, Jacque-Bera (JB) test, Johansen co-integration test and Granger Causality test. The model applied can be explained by the following equations,

$$FDI_t = \phi_{11} FDI_{t-1} + \phi_{12} PSI_{t-1} + \phi_{13} INF_{t-1} + \phi_{14} GDP_{t-1} + \varepsilon_{FDI} \quad [1]$$

$$PSI_t = \phi_{21} FDI_{t-1} + \phi_{22} PSI_{t-1} + \phi_{23} INF_{t-1} + \phi_{24} GDP_{t-1} + \varepsilon_{PSI} \quad [2]$$

$$INF_t = \phi_{31} FDI_{t-1} + \phi_{32} PSI_{t-1} + \phi_{33} INF_{t-1} + \phi_{34} GDP_{t-1} + \varepsilon_{INF} \quad [3]$$

$$GDP_t = \phi_{41} FDI_{t-1} + \phi_{42} PSI_{t-1} + \phi_{43} INF_{t-1} + \phi_{44} GDP_{t-1} + \varepsilon_{GDP} \quad [4]$$

3.10.1. Augmented Dickey-Fuller (ADF) Test

Unit root tests assess whether a time series is stationary. The Dickey-Fuller test checks the null hypothesis that the series has a unit root against the alternative, under the assumption that the errors are white noise. If the raw data is non-stationary, differencing is used, and the Augmented Dickey-Fuller (ADF) test confirms stationarity. Stronger rejection of the unit root hypothesis at a given confidence level indicates greater stationarity, evidenced by a more negative result. The ADF test is essential for identifying a unit root, which is required for VAR modelling.

3.10.2 Johansen Co-integration Test

In investigating the impact of political stability on FDI inflow, the research adopted the Johansen co-integration approach, a robust method for assessing long-term relationships without necessitating a prior separation of endogenous and exogenous variables. The hypothesized relationships can be expressed as follows:

H_0 = No Co-integration

H_1 = Co-integration exists

Given the expectation that the independent variables are not stationary at their levels but become stationary in their first differences, the study utilizes the trace test and maximum eigenvalue test to assess these hypotheses. Rejecting the null hypothesis indicates the presence of co-integration, signifying a long-term relationship among the variables. The Johansen co-integration approach provides two specific tests: the trace test and the maximum eigenvalue test. The trace test evaluates the null hypothesis of having r co-integration vectors against the alternative hypothesis of having n co-integration vectors. In contrast, the maximum eigenvalue test evaluates the null hypothesis of r co-integrating vectors against the alternative of r+1 co-integrating vectors, with r ranging from 1 to n. Generally, neither test statistic conforms to a chi-square distribution; instead, asymptotic critical values are referenced (Johansen & Juselius, 1990). Johansen's method assumes that all variables in the system are integrated of order I (1), so the presence of stationary variables does not pose theoretical concerns (Johansen, 1995). Additionally, pretesting the variables in the system to determine their integration order is considered unnecessary. If a single variable in the system is integrated of order I (0) instead of I (1), this results in a co-integrating vector defined by the sole stationary variable in the model. The long-term coefficients or relationships are derived from Johansen's Co-integration tests (Johansen, 1992). The tests are depicted below.

,

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln (1 - \lambda_i) \qquad [5]$$

$$J_{max} = -T ln(1 - \lambda_{r+1}) \qquad [6]$$

3.10.3 Vector Error Correction Model (VECM)

Granger's theoretical framework posits that variable, while individually subject to permanent shocks (integrated), manifest mean reversion in their amalgamated weighted sums (co-integrated). As delineated in the seminal Granger representation theorem (Engle & Granger, 1987), the co-integration of variables driven by enduring shocks necessitates the existence of VECM) tailored to the dataset. This methodological framework, widely endorsed in empirical research, confers a dual analytical advantage, encapsulating both the enduring levels and immediate fluctuations of nonstationary variables. VECM, an esteemed derivative of the Vector Autoregressive (VAR) model, imposes co-integration constraints and integrates short-term coefficients, thereby enriching the analytical rigor of the model. Given the co-integrated properties of the variables under scrutiny within the VAR framework, subsequent analytical endeavours entail the delineation and estimation of a VECM, wherein the error correction term assumes primacy in delineating the model's dynamic behaviour (Johansen, 1991). Upon the imposition of equilibrium constraints, the VEC model orchestrates a nuanced depiction of the gradual adjustment dynamics exhibited by the model against its long-run equilibrium state. The dynamic specification of the model affords methodological parsimony, facilitating the judicious removal of statistically insignificant variables while upholding the structural integrity conferred by the error correction mechanism. The magnitude of the error correction term functions as a pivotal metric, furnishing insight into the temporal dynamics governing the convergence of prevailing disequilibria towards a long-term equilibrium state (Engle & Granger, 1987). VAR does not cover for presence of long-term impact among variables, the relationship is given as follows

$$\mathrm{ECT}_{t-1} = [Y_{t-1} - \eta_j X_{t-1} - \xi_m R_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots \text{[7]}$$

Y_{t-1} is the target variable, X_{t-1} and R_{t-1} are endogenous variables.

While for the short run the relationship is estimated as follows

$$\Delta y_t = \sigma + \sum_{i-1}^{k-1} y_i \Delta y_{t-1} + \sum_{j-1}^{k-1} \eta_j \Delta X_{t-j} + \sum_{m-1}^{k-1} \xi_m \Delta R_{t-m} + \lambda ECT_{t-1} + u_t \ldots \text{[8]}$$

Δy_t is the change in the dependent variable y at time t.

σ r the baseline level of Δy_t when all other predictors are zero.

$\sum_{i-1}^{k-1} y_i \Delta y_{t-1}$ The sum of lagged differences of the dependent variable. This term accounts for the autoregressive component of the model, where y_i are the coefficients of the lagged differences Δy_{t-1}.

$\sum_{j-1}^{k-1} \eta_j \Delta X_{t-j}$ The sum of lagged differences of an independent variable **X**. Here, η_j are the coefficients for the lagged changes in **X**, indicating how past changes in **X** affect the current change in y.

$\sum_{m-1}^{k-1} \xi_m \Delta R_{t-m}$ The sum of lagged differences of another independent variable **R**. The ξ_m coefficients represent the impact of past changes in **R** on the current change in y.

λECT_{t-1} The error correction term (ECT) from the previous period, multiplied by its coefficient λ. The ECT represents the deviation from the long-term equilibrium in the previous period. The coefficient λ indicates the speed of adjustment back to the equilibrium.

3.10.4 Granger Causality Test

The Granger Causality assws is employed in time series analysis to assess whether past values of one variable can predict the current values of another variable (Granger, 1969). In the context of VAR model for studying the impact of PSI, COC, INF and GDP on FDI inflows, the test becomes relevant to investigate the directional influence among these variables. The need for Granger Causality test arises from the following considerations,

i. Temporal relationships which the model captures between the variables indicating how past values may influence the current and future values
ii. Understanding the causal relationship is crucial for policy makers
iii. The test provides statistical means to validate the assumed causal relationships within the VAR model.

Odhiambo (2009) the Granger Causality test is based on the following hypothesis,

$$\mathrm{H}_0 = \mathrm{X}_t \text{ does not Granger cause } \mathrm{Y}_t$$

$$\mathrm{H}_1 = \mathrm{X}_t \text{ Granger cause } \mathrm{Y}_t$$

Assuming X_t and Y_t are time series. The hypothesis is tested using the following system of equations

$$X_t = b_0 + \sum_{i=1}^{k} a_{2i} Y_{t-1} + \sum_{i=1}^{k} X_{t-1} + \mu_t \qquad [9]$$

$$Y_t = a_0 + \sum_{i=1}^{k} a_{1i} Y_{t-1} + \sum_{i=1}^{k} b_{1i} X_{t-1} + \varepsilon_t \qquad [10]$$

μ_t and ε_t are random processes and k denotes the number of lagged variables, the rejection criterion is rejected H_0 if b_{1i} are jointly significant (Odhiambo, 2009)

3.10.5 Normality Test

In the context of regression analysis, the Jacque-Bera test is applied to assess whether the residuals from the regression model are normally distributed. The normality assumption is crucial for making valid statistical inferences. The test statistic is based on the skewness and kurtosis. In a normal distribution the skewness is 0 and the Kurtosis is 3. The test produces a p value and if this p value is below the significance level, we reject the null hypothesis that the residuals are normally distributed. Nevertheless, it embraces a nuanced perspective as outlined by Greene (2003), challenging the rigid necessity of adhering to stringent normality assumptions in regression models.

3.11 Box Jenkins methodology

The approach utilises ARIMA models to identify the optimal model needed to fit historical values in time series analysis. The methodology is split into three stages that is model identification, model selection and model estimation. The general equation for the ARIMA model is as follows

$$\Phi_p(B)(1-B)^d Y_t = \theta_q(B)\alpha_t \sim ARIMA(p,d,q) \qquad [11]$$

Model Identification: In the initial phase of the Box–Jenkins modelling methodology, emphasis is placed on scrutinizing the stationarity of the temporal series and discerning notable seasonality. The assessment of stationarity is facilitated through the utilization of run sequence graphics, wherein the imperative is the manifestation of consistency in both position and scale. Remedial procedures, including differencing, curve fitting, or judicious data point removal, are invoked to impart stationarity and redress seasonality. Subsequent to these adjustments, the subsequent stage involves ascertaining the AR and moving average MA components' order, conventionally denominated as p and q.

Model Selection: Estimating parameters for Box–Jenkins models involve solving nonlinear equations, a process well-supported by modern statistical packages. Two primary techniques, nonlinear least squares and maximum likelihood estimation, are commonly used for fitting Box–Jenkins models. Maximum likelihood estimation is often recommended due to its favourable statistical properties.

Model Estimation: After model fitting, diagnostics are essential to validate the model's appropriateness. Residuals, representing the differences between predicted and observed values, should adhere to specific characteristics. They should be drawn from a stationary distribution, demonstrate homoscedasticity (constant variance), and ideally exhibit properties of white noise. Meeting these assumptions ensures that the residuals provide the best fit to the data. Diagnostic tools include visual examination of residuals and scrutiny of the Box–Ljung statistic, which tests for the absence of autocorrelation in the residuals.

3.11.1 Diagnostic Checking

3.11.1.1Stationarity

The research employed the ADF test to validate stationarity. Autocorrelation (ACF) and partial autocorrelation (PACF) functions are used to determine which model represent the series. The visual analysis aids in specifying the appropriate parameters (p, d, q) for the ARIMA model, guiding the selection of Autoregressive and moving average orders. The overall goal is to identify a parsimonious and effective model for forecasting, capturing the key temporal patterns in the data.

3.11.1.2 Akaike Information Criterion (AIC)

AIC balances off the trade-off between the goodness of fit and the complexity of the model, penalising overly complex models (Ruey, 2010). The model with the lowest AIC values is considered the most suitable, as it achieves a good balance between explaining the data and avoiding over fitting. The AIC is calculated as following,

$$AIC = -2 * \ln(\hat{L}) + 2k \qquad [12]$$

$(\hat{L})$ Is the maximum likelihood of the model, k is the number of parameters in the model

3.12 Long Short-Term Memory (LSTM)

Long Short-Term Memory networks are a specialised type of recurrent neural network (RNN) designed to capture and learn patterns in sequential data. LSTM excel at handling long term dependencies, making them well suited to forecast FDI inflows. The core of an LSTM unit involves various gates and memory states to control information inflow. The general equation for LSTM is given as follows:

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \qquad [13]$$

Cell state (C_t): The cell state is a continuous vector that runs through the entire sequence of an LSTM network. It acts as a form of memory, allowing the LSTM to capture long term dependencies and remember relevant information over extended periods. The cell state is updated through a combination of the forget gate, input gate and a new candidate values vector.

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \qquad [14]$$

Forget gate (f_t): The forget gate decides which information to remove from the cell state or keep. It takes input from the previous hidden state (h_{t-1}) and the current input (x_t). The sigmoid activation function (σ) squashes values between 0 and 1, representing the extent to which the information in the cell state should be forgotten

$$f_t = \sigma\ (W_f * [h_{t-1}, x_t] + b_f) \qquad [15]$$

Input gate (i_t): The input gate determines what new information to store in the cell state. Like the forget gate, it employs a sigmoid activation function to control the flow of new information. The tanh activation function is applied to a combination of the previous hidden state and the current input to generate new candidate values.

$$i_t = \sigma\ (W_i * [h_{t-1}, x_t] + b_i) \qquad [16]$$

New Candidate Values ($\widehat{C}_t$)

The values represent the information that can be added to the cell state. These values are obtained by employing the tanh activation function to a linear transformation of the previous hidden state and the current input.

$$\hat{C}_t = tanh\ (W_c * [ht - 1, x_t] + b_c) \qquad [17]$$

3.12.2 Data Pre-processing

Pre-processing data for LSTM networks is essential to ensure that the model can effectively learn from the input features and produce accurate forecasts. Normalising the data is of key importance to facilitate the training process, common techniques include min-max or Z score normalisation (Kheikhah et tal, 2013). The researcher employed the min- max scaling for this study.

$$X_{normalised} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad [17]$$

The data needs to be divided into training and testing sets using an 80:20 ratio, with the larger portion assigned to training (Tsai, 2008).

LSTM Model Training

The training phase entails optimizing the model's parameters to minimize the discrepancy between predicted and actual values in the training data. This process involves a series of steps, including forward and backward passes, utilizing the backpropagation algorithm.

Forward pass: The input data is fed into the LSTM model. The data has a three-dimensional shape that is samples, time steps and features. The LSTM processes the input data updating hidden states (h_t) and cell state (C_t) through each time step (*t*). These are calculated using various gates and activation functions as follows:

$$f_t = \sigma\,(W_f * [h_{t-1}, x_t] + b_f)\text{.... forget gate} \quad [18]$$

$$i_t = \sigma\,(W_i * [h_{t-1}, x_t] + b_i)\text{....... Input gate} \quad [19]$$

$$\hat{C}_t = tanh\,(W_c * [ht - 1, x_t] + b_c)\text{.... new candidate values} \quad [20]$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t\text{..... Cell state} \quad [21]$$

$$o_t = W_O * [ht - 1, x_t] + b_0\text{..... Output gate} \quad [22]$$

$$h_t = o_t * \tanh(C_t)\text{..... Hidden state} \quad [23]$$

The hidden states are used as inputs to the output layer, producing the model's predictions

$$\hat{y}t = Wout * h_t + b_{out} \quad [24]$$

Loss Computation: The Mean Squared Error (MSE) approach is used to calculate the error between the predicted values ($\hat{y}t$) and the actual values (*yt*)

Backward Pass (Back propagation): Gradients of the loss with respect to the model parameters using back propagation. Starting from the output layer, the partial derivatives of the loss with respect to each parameter are calculated layer by layer, moving backward through the network,

$$\frac{\partial L}{\partial W} \text{ and } \frac{\partial L}{\partial b} \quad [25]$$

The calculated gradients guide the adjustment of weights and biases to reduce loss. This is typically done by optimisation through the method of gradient descent,

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W} \ , \ b_{new} = b_{old} - \eta \frac{\partial L}{\partial b} \quad [26]$$

…….. Here(η) represents the learning rate, controlling the size of the steps taken during optimisation. W_{new} ,W_{old}, b_{new} and b_{old} represent the new and old weights and biases, respectively, after and before an iteration of the optimisation process. The learning rate (η) is a hyper parameter that requires adjusting, if the learning rate is too large, it may lead to over fitting

3.13 Prediction and Forecasting

Following the attainment of the results, this study will made use of the selected models to predict and forecast FDI inflows for the period 2023-2026. Hence, the evaluation of predictive accuracy is to compare the predictions of ARIMA and LSTM against actual FDI inflows. Also, the relevant accuracy metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

3.14 Ethical Considerations

Data was sourced from relevant sources using the approved domains and libraries which were deemed to be free to the public.

3.15 Discussion and Validation

The researcher interpreted the results in the context of the research questions, discussing the impact of socio-political factors on FDI, the validity of the fitted models, and the constancy of FDI inflows. To validate the robustness of the fitted regression model, the researcher employed the Godfrey LM test to test for serial correlation, Breusch-Pagan test for the presence of homoskedasticity, Ramsey RESET and Cumulative Sum Control Chart (CUSUM) were used to test for stability of the model. Therefore, the limitations and sensitivity analysis were adopted, to acknowledge and discuss potential limitations of the methodology and conduct sensitivity analysis to assess the robustness of the findings.

3.16 Chapter summary

By following this methodology, the researcher aied4d was to provide valuable insights into the relationship between socio-political factors and FDI inflows in Zimbabwe, incorporating advanced time series analysis techniques for accurate prediction and forecasting.

CHAPTER 4: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

In this chapter, the research thoroughly explored, analysed\ data and as well as the presentation and discussion of findings. This section begins by giving the descriptive statistics of the variables that are in the study, pre-tests, Granger causality test, Johansen Cointegration test, Augmented Dickey Fuller Test, Jacque- Bera test, the analysis was done using EViews 12 SV Lite R Studio, Excel and Python. The results allowed the researcher to give answers to the research questions as to how the selected factors affect is related to the FDI inflows in Zimbabwe. Furthermore, the study aims at comparing the predictive capabilities of Traditional Box Jenkins ARIMA and Artificial Neural Network.

4.1 Descriptive Statistics

Table 4. 1Descriptive Statistics

	FDI	GDP	INF	PSI	COC
Mean	211,083,197	14,569,249,152	325.7382	0.171739	-1.299824
Median	150,360,000	14,101,920,300	0.121	0.170000	-1.298485
Maximum	717,865,322	34156069918	6657.741	0.250000	-1.27275
Minimum	3,800,000	4415702800	-0.0241	0.110000	-1.425627
Std. Dev	187,869,802	8,765,116,598	1384.704063	0.044174	0.90354
Skewness	0.864445911	0.537914681	4.432547	0.402155	0.461160
Jarque – Bera	2.536610	1.565904	378.3223	1.784752	1.324486
Probability	0.281308	0.457055	0.00000	0.409681	0.515693

Sum	4,854,913,541	3.35093E+11	3.95	3.950000	-29.89594
Sum Sq. Dev	7.76E+17	1.69E+21	4.22E+11	0.042930	0.179604
Observations	23	23	23	23	23

The mean for all the variables is represented in the Table 4.1, for FDI the mean and skewness is positive showing that FDI is on the rise with a mean of $211,083,197, and for a developing country this figure is well-thought-out to be moderate. Inflation has both positive mean and skewness showing that lending rates are increasing. The median inflation rate was 0.121. Political stability also exhibits a positive mean and positive skewness indicating an increasing trend in the political stability. The median value for political stability is 0.170000. The maximum and minimum indicate the highest values for each variable. FDI has a minimum of $3,800,00 and $717,865,322 as the maximum. COC has a negative mean and positive skewness indicating that control of corruption is on the decrease.

Standard deviation is the deviation from the mean with respect to each variable. Inflation has a large standard deviation of 1384.704063. Skewness mirrors the variables' tendency to follow normal distribution, the normal skewness is for values close to 0. FDI has 0.864445911%, PSI has 0.402155% and GDP has 0.53791468%, showing a relative normal distribution. The coefficient of skewness for inflation is large and positive 4.432547%, indicating that is has heavier right tail than the normal distribution and most of the inflation values are on the extreme end. Coefficient of kurtosis of 3 implies that normality exists, FDI and PSI has kurtosis values of 0.571314614 and 1.897532 respectively, these values are well below 3 are they are described as platykurtic indicating the existence of lighter tails and a flatter peak. GDP and INF have negative kurtosis values, again showing the presence of platykurtic kurtosis, the values are -0.679777027% and -1.07167%. The Jarque-Bera statistic evaluates how much the skewness and kurtosis of a series deviate from a normal distribution. The null hypothesis posits that the distribution is normal. If the probability is less than α = 0.05, we reject the null hypothesis. For foreign direct investment, inflation, economic growth, and political stability, since the probabilities are below the critical value, we conclude that these variables are not normally distributed4.2 Pre-test

4.2.1 Correlation

Table 4. 2 Correlation Matrix

	FDI	GDP	INF	PSI	COC
FDI	1				
GDP	0.850715	1			
INF	-0.217978	-0.255379	1		
PSI	0.711058	0.507779	0.016869	1	
COC	-0.3283764	-0.0753045	-0.1860043	-0.4212599	1

Table 4.2. shows correlations between the variables, FDI and GDP have a strong positive correlation. A strong positive correlation exists between FDI and PSI. PSI and COC exhibit a weak negative correlation. We use correlations to suspect multicollinearity in the variables if they have correlations above 0.8 (Dzapasi, 2020), all the variables as shown in the table have correlation below 0.8 except for the one between FDI and GDP which must be ignored since FDI is the dependent variable, this infers that multicollinearity is absent among the variables.

4.2.2 Multicollinearity

VIF test was used to test for multicollinearity among variables. If the VIF values falls below 5 there is no evidence to support multicollinearity, while a VIF value which ranges 5<VIF<10 shows that there is moderate multicollinearity and a VIF value of greater than 10 provides sufficient evidence for the presence of high multicollinearity. The Table 4.3 shows all VIF values for the variables GDP, INF, PSI and COC fall under 5 suggesting no evidence for multicollinearity (Dzapasi, 2020).

Table 4. 3 VIF test results

Variable	Coefficient Variance	Centred VIF
GDP	5.66E-06	1.510772
INF	1.70E+08	1.130250
PSI	2.50E+16	1.696310

COC	4.53E+16	1.285162

4.2.3 Stationarity Tests

The Augmented Dickey Fuller (ADF) test was used to assess for the presence of a unit root, to check the stationarity of variables. The results are reported in the Table 4.3 below.

Table 4. 4 ADF Test

Variable	Intercept		Trend and Intercept		
	Level	1st Difference	Level	1st Difference	Decision
FDI	0.2548	0.0014*	0.1429	0.0066*	I (1)
GDP	0.9141	0.0002*	0.0228*		I (1)
INF	0.0036*		0.0129*		I (0)
PSI	0.2338	0.0003*	0.5385	0.0018*	I (1)
COC	0.2893	0.0182*	0.8486	0.0113*	I (1)

Note: (*) stationarity at 5% significance level

Foreign direct investment, economic growth and political stability were found to be stationary at the first difference under the intercept at 5% significance level. Inflation was found to be stationary at level for both intercept and trend and intercept. Economic growth under trend and intercept, was found to be stationary at level, while foreign direct investment and political stability under trend and intercept were stationary at the first difference at 5% significance level. Control of corruption was found to be stationary at the first difference at both trend and intercept and trend. All the variables were found to be stationary either at level or at 1st differencing under the 5% critical values.

4.2.4 Determination of Lags

Lag order selection statistics are shown below in the Table 4.4. The results indicate lags at one as shown by the selection criterion of the HQ, SC, AIC, EPE, LR and LogL so the researcher employed the tests with one lag.

Table 4. 5 Determination of Lags

Lag	LogL	LR	FPE	AIC	SC	HQ

0	-1035.079	NA	7.19e+36	99.05512	99.30382	99.10910
1	-987.2105	68.38332*	8.84e+35*	96.87719*	98.36936*	97.20103*
2	-962.3469	23.67962	1.47e+36	96.89018	99.62583	97.48389

(*Indicates lag order selected by the criterion)

AIC was employed by the researcher because it out performs the other information criteria and the lower the value the better the information criterion. The AIC is employed to all the variables in the study and the selected lags are presented in the Table 4.5

Table 4. 6 Lags

Variable	Lag
FDI	1
GDP	1
INF	1
PSI	1
COC	1

4.3 Johansen co-integration results

To check for long term relationships between the variables the Johansen cointegration test was used with all variables at lag 1 and the trace test was at 5% level. The outcome is displayed below in **Table 4.7**.

Table 4. 7 Johansen co-integration

		Trace		
Hypothesized No. of CE(s)	**Eigen Value**	**Trace Statistic**	**Critical Value 0.05**	**Prob****
None*	0.747157	71.89875	69.81889	0.0338
At most 1	0.655462	43.02403	47.85613	0.1320
At most 2	0.450416	20.64743	29.79707	0.3800

At most 3	00.314549	8.076952	15.49471	0.4572
At most 4	0.006914	0.145709	3.841465	0.7027
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level (*) denotes rejection of the hypothesis at the 0.05 level				

We reject the null hypothesis at 5% significance level that there is no cointegration and conclude that there is at least 1 co-integrating equation among the variables because trace is greater than 0.05 as presented, in Table 4.6 above. Because of cointegration there exists long run relationships between the variables illustrated by the normalised cointegrated equation in **Table 4.8**.

Table 4. 8 Normalized Cointegrating Equation

Normalized cointegrating coefficients (Standard Error in Parentheses)				
FDI	**GDP**	**INF**	**PSI**	**COC**
1.000000	-0.013929 (0.00168)	9410.054 (10212.3)	-2.20E+09 (3.1E+08)	3.55E+08 (1.2E+08)

The cointegration equation shows that in the long run, economic growth (GDP) and political stability (PSI) positively influence foreign direct investment (FDI) (because the signs are reversed in the long run). While inflation and control of corruption (COC) has a negative influence on FDI, on average ceteris paribus in the long run. These findings are in agreement with a Nguyen, (2021) research on the influence of control of corruption and macroeconomic factors on FDI inflows. These findings demonstrate the long-term association FDI and, PSI and COC.

4.4 VECM Results

The short run relationships are represented in the **Table 4.9**, the long run relationships have been presented through the Johansen co-integration test. The error correction term represents the rate at which the differences between long-term and short-term estimates are adjusted. The number of lags used is 1 and co-integration of rank = 1.

Table 4. 9 VECM Results (short-run estimates)

Error Correction	D(FDI)	D(GDP)	D(INF)	D(PSI)	D(COC)
CointEq1	-1.641034 (0.50388) [-3.25680]	-35.95999 (17.8069) [-2.01945]	2.54E-06 (7.8E-06) [0.47225]	7.26E-11 (1.5E-10) [0.47225]	-2.48E-10 (1.6E-10) [-1.58792]
D (FDI (-1))	0.933863 (0.51334) [1.81918]	35.83925 (18.1413) [1.97556]	5.76E-06 (8.0E-06) [0.72165]	1.41E-10 (1.6E-10) [0.90247]	3.27E-10 (1.6E-10) [2.05363]
D (GDP (-1))	-0.026625 (0.01498) [-1.77694]	-1.266885 (0.52952) [-2.39252]	-1.50E-07 (2.3E-07) [-0.64527]	-4.85E-12 (4.6E-12) [-1.06072]	-9.16E-12 (4.6E-12) [-1.97342]
D (INF (-1))	17543.80 (17084.7) [1.02687]	600023.0 (603764.) [0.99380]	-0.325957 (0.26555) [-1.22750]	1.46E-06 (5.2E-06) [0.28070]	-2.62E-0.6 (5.3E-06) [-0.49501]
D (PSI (-1))	-1.72E+09 (1.1E+09) [-1.54862]	-4.95E+10 (3.9E+10) [-1.25988]	-10506.47 (17270.8) [-0.60834]	-0.118527 (0.33921) [-0.34942]	-0.281729 (0.34423) [-0.81843]
D (COC (-1))	-5.17E+08 (8.2E+08) [-0.62704]	1.50E+10 (2.9E+10) [0.51519]	2250.106 (12813.6) [0.17560]	0.034031 (0.25167) [0.13522]	0.394940 (0.25539) [0.298282]
C	34473393 (3.1E+07) [1.10337]	2.11E+09 (1.1E+09) [1.91047]	131.4575 (485.618) [0.27070]	0.005874 (0.00954) [0.61581]	0.002887 (0.00968) [0.29828]

D (FDI): The prior year's deviation from the long-term equilibrium is corrected in the current period at an adjustment rate of 1.641034%, as demonstrated by the adjustment coefficient in the co-integrating equation. In the short term, a 1% change in GDP results in a 0.02% decrease in FDI. Likewise, a 1% change in political stability leads to a 1.72% decline in FDI inflows, while a 1% change in control of corruption results in a 5.17% decrease in FDI.

D (GDP): A 1% rise in FDI inflows is associated with a 35.83925% increase in GDP. The deviation from long-term equilibrium in the previous year is rectified in the current period at a rate of (-35.95999) %, as indicated by the adjustment coefficient in the cointegration equation.

D(PSI): A 1% shift in foreign direct investment results in a 1.14% increase in political stability. The deviation from long-term equilibrium in the previous year is corrected at a rate of 7.26%. Regarding the control of corruption (COC), a 1% inflation increase leads to a -2.62% decrease in COC. The previous year's deviation from long-term equilibrium is rectified at an adjustment rate of -2.48%.

4.5 Granger Causality Testing

Table 4. 10 Results for Granger Causality

Null hypothesis	F-statistics	Obs	Prob	Decision
GDP does not Granger Cause FDI	0.29916	22	0.5908	Fail to reject
FDI does not Granger Cause GDP	0.38119		0.5443	Fail to reject
INF does not Granger Cause FDI	0.14627	22	0.7064	Fail to reject
FDI does not Granger Cause INF	0.37888		0.5455	Fail to reject
PSI does not Granger Cause FDI	3.12652	22	0.0931	Fail to reject
FDI does not Granger Cause FDI	0.81648		0.3775	Fail to reject
COC does Granger Cause FDI	2.59507	22	0.1237	Fail to reject
FDI does Granger Cause COC	2.01809		0.1716	Fail to reject
INF does Granger Cause GDP	0.29098	22	0.5959	Fail to reject
GDP does Granger Cause INF	1.14215		0.2986	Fail to reject
PSI does not Granger Cause GDP	0.14581	22	0.7068	Fail to reject
GDP does not Granger Cause PSI	0.03459		0.8544	Fail to reject
COC does not Granger Cause GDP	1.03846	22	0.3210	Fail to reject
GDP does not Granger Cause COC	1.93214		0.1806	Fail to reject
PSI does not Granger Cause INF	1.47760	22	0.2390	Fail to reject
INF does not Granger Cause PSI	0.78478		0.3868	Fail to reject
COC does not Granger Cause INF	0.00387	22	0.9511	Fail to reject
INF does not Granger Cause COC	1.32611		0.2638	Fail to reject

COC does not Granger Cause PSI PSI does not Granger Cause COC	2.57729 1.22420	22	0.1249 0.2824	Fail to reject Fail to reject

Outcomes for the analysis of Granger causality tests are presented to support VECM results. There is no directional causality among GDP and FDI, INF and FDI, PSI and FDI, INF and GDP, PSI and INF, COC and PSI, FDI and COC. This implies that the variables do not Granger cause each other. In other words, the past values of variables do not provide any useful information for predicting the future variables of other variables in the system and vice versa. The lack of Granger causality does not necessarily imply independence or lack of relationship between variables that are not captured by the Granger Causality test.

4.6 Model Validation

4.6.1 Godfrey LM test

Table 4. 11 test for serial correlation

Lag	**LRE*stat**	**Df**	**Prob**	**Rao F-stat**
1	39.00961	25	0.2633	1.959273

The results in the table above indicate that the null hypothesis of no serial correlation is accepted for the Godfrey LM test at lag 1, as the p-value exceeds the significance level of 0.05. Consequently, it is concluded that there is no serial correlation, since the majority of lag 1 results support the hypothesis. This may be attributed to the data not being normally distributed.

4.6.2 Test for normality

Table 4. 12 Results for VECM test for normality

Component	**Jarque-Bera**	**Df**	**Prob**
1	0.929060	2	0.6284
2	0.356512	2	0.8367

3	14.35648	2	0.0008
4	0.321893	2	0.8513
5	0.655203	2	0.7207

Table 4.12 shows the results for the Jarque-Bera test for normality which shows that FDI, GDP, PSI and COC residuals are normally distributed and INF is not normally distributed, because they have probability values greater than 0.05, we fail to reject the null hypothesis that the residuals are normally distributed at 5% significance level. On the other hand, only INF was found not to follow the normal distribution at the 5% significance level.

4.6.3 Ramsey RESET

The test confirms the stability of the model at both the t and F statistic, with both greater than the critical value of 0.05. These results shows that the model has been accurately specified. The table below shows a detailed outline of the results.

Table 4. 13 Results for Ramsey RESET test

	Value	**Df**	**Probability**
t-statistic	0.810832	14	0.4310
F-statistic	0.657448	(1, 14)	0.4310
Likelihood ration	1.009608	1	0.3150

4.6.4 Heteroscedasticity test

The p-values shown in the **Table 4.14** are greater than the critical value of 0.05, therefore there is not enough evidence at 5% significance level that the variances are heteroskedastic.

Table 4. 14 Results for Breusch-Pagan Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey Null hypothesis: Homoskedasticity			
F-statistic	0.580298	Prob.F(6,15)	0.7407
Obs*R-squared	4.144584	Prob.Chi-Square (6)	0.6571
Scaled	2.489927	Prob.Chi-Square (6)	0.8696

4.6.5 Cumulative Sum Control Chart (CUSUM) Plots

Figure 4. 1 CUSUM plot

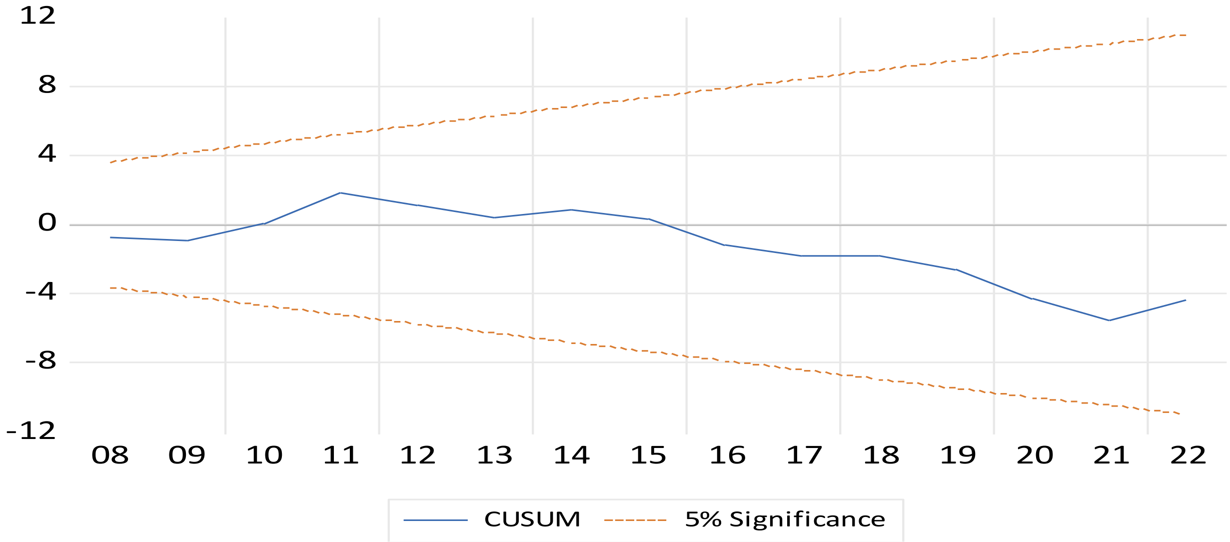
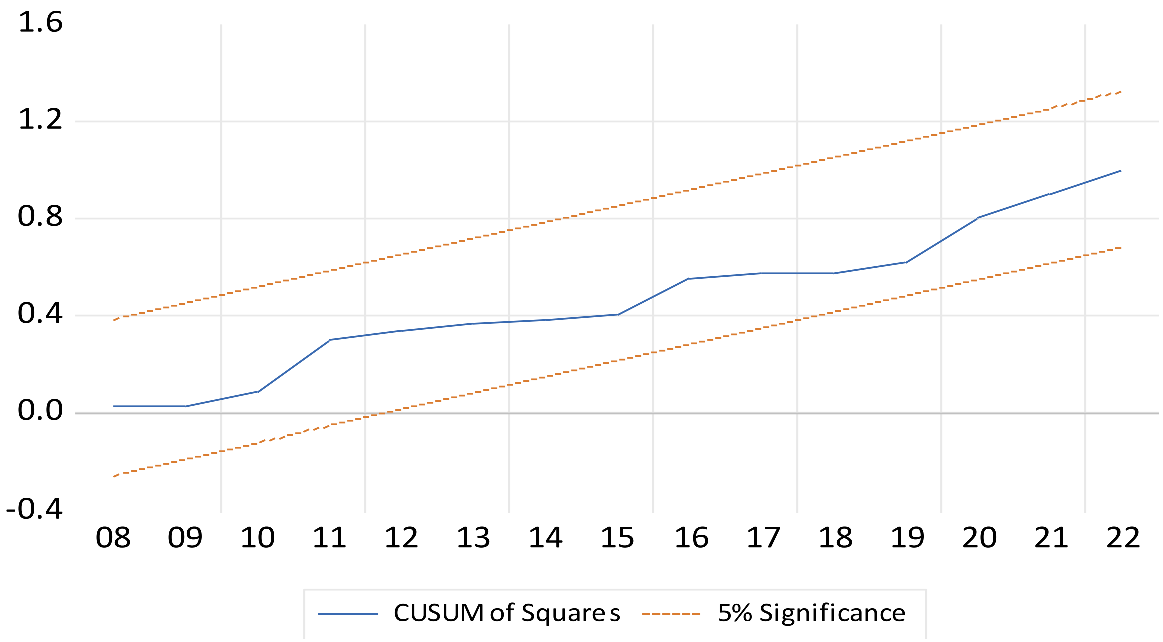


Figure 4. 2 CUSUM Squared plot



The CUSUM plots in figures 4.1 and 4.2 show the CUSUM lines within the confidence bounds, this suggests that the process is in control, with no significant structural changes or shifts in the parameters.

4.7 Forecasting Methodologies

In this section the researcher compared two forecasting methodologies that is the traditional Box Jenkins ARIMA and a Recurrent neural network for both in sample and out sample performance when it comes to FDI using inflow data from 1992 to 2022.

4.7.1 Box-Jenkins Methodology (ARIMA)

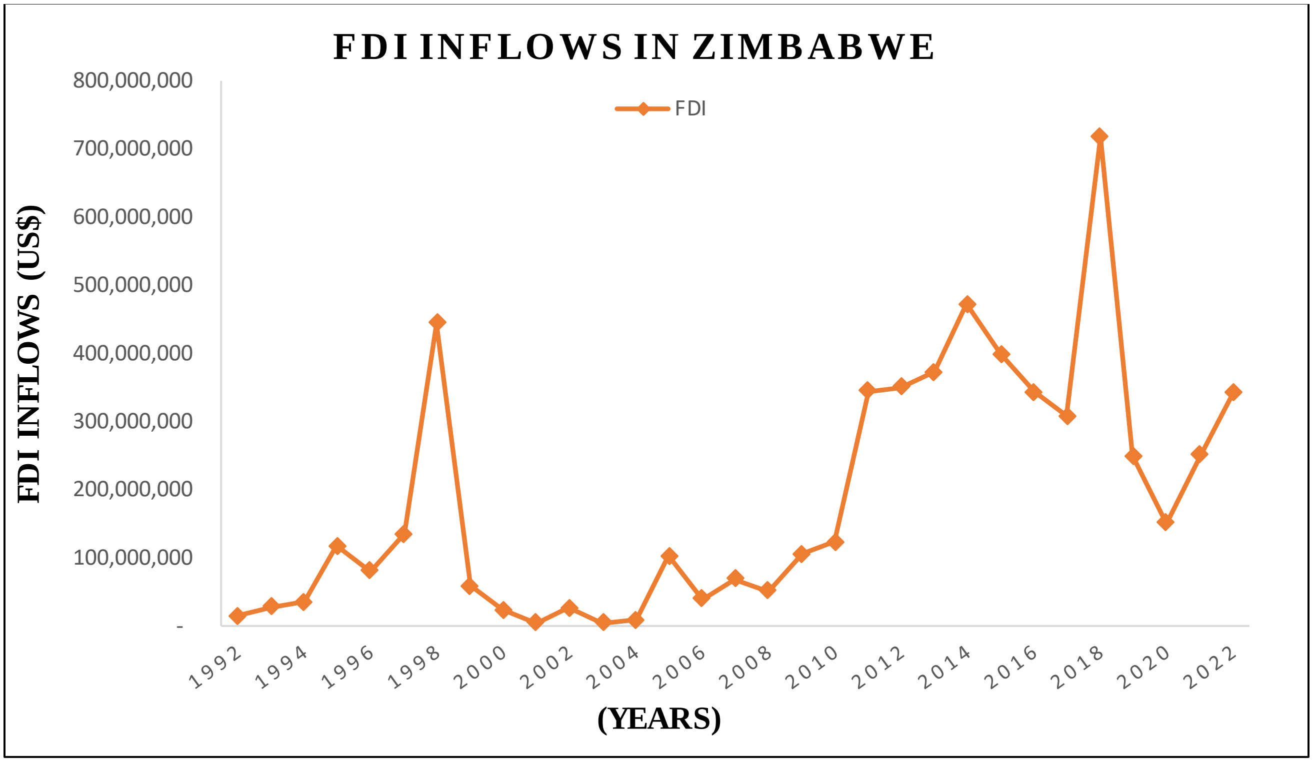
4.7.1.1Descriptive Statistics

Table 4. 15 Descriptive Statistics for FDI

FDI INFLOW (US$)	**Min**	**1st Qu**	**Median**	**Mean**	**3rd Qu**	**Max**
	3800000	37324440	117700000	186111853	342256906	717865322

The descriptive table shows the minimum, lower quartile, upper quartile, median, mean and the maximum FDI inflows recorded over the 30-year period from 1992 to 2022 in United States dollars. Below is a graphical representation of the pattern of FDI inflow into Zimbabwe for the period.

Figure 4. 3 Raw FDI Inflows



4.7.1.2 Stationarity Test

Table 4. 16 ADF Test

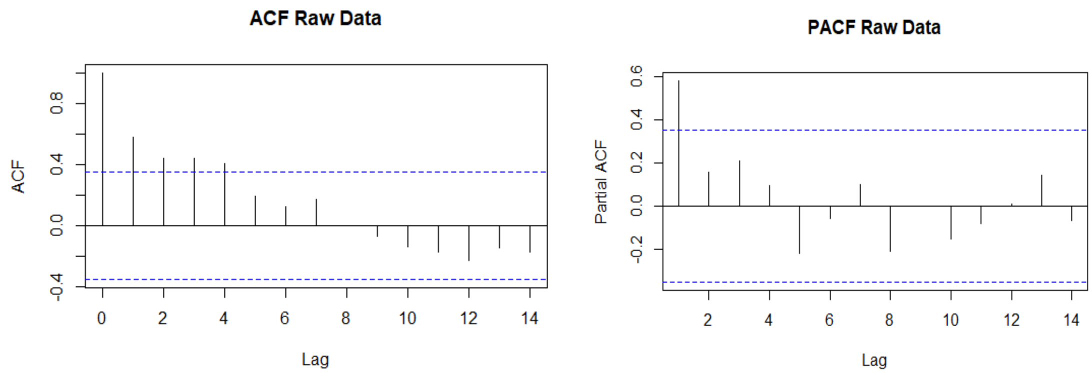
Augmented Dickey-Fuller Test	data: diff_2FDI	
Dickey-Fuller = -4.3855	Lag order = 3	p-value = 0.01
alternative hypothesis: stationary		

The ADF test result concluded the existence of a unit root after the 2nd difference as shown by the p value which is greater than 0.05, therefore the time series was determined to exhibit stationarity. Henry et al (2019) concluded that their time series data was stationary after the first difference and Nyoni (2018) concluded that the FDI series is integrated into order one I (1)

4.7.1.3 ACF and PACF

Methembeni (2022) points out that if an ACF does not quickly, it is assumed to be non-stationary. The figures below exhibit the correlation on the most lags and the plot has not died out quickly.

Figure 4. 4PACF and ACF Plots for Raw Data



4.7.1.4 Model Identification

To select the best fitting models the AIC was used and the model with the lowest AIC value was chosen. Idowu (2021) concludes that depending on the greatest coefficient of determination, percentage of significant coefficient and the lowest AIC and volatility, the study went to recommend ARIMA (1, 1, 3) as the optimal model. After applying the same technique, the researcher chose ARIMA (0, 1, 1) as the appropriate model for this analysis. The model was chosen after careful consideration of a variety of factors including, the white noise property since the residuals have been proved to exhibit stationarity. Methembeni (2022) points out that even though potential numerical models can to a greater extent reflect the properties of the data, the principle of parsimony is used to select the model that perfectly fits the data based on the number of parameters.

Table 4. 17 Model identification

ARIMA (2,1,2) with drift	: Inf
ARIMA (0,1,0) with drift	: 1222.603
ARIMA (1,1,0) with drift	: Inf
ARIMA (0,1,1) with drift	: 1218.363

ARIMA (0,1,0)	: 1220.442
ARIMA (1,1,1) with drift	: Inf
ARIMA (0,1,2) with drift	: Inf
ARIMA (1,1,2) with drift	: Inf
ARIMA (0,1,1)	: 1216.473
ARIMA (1,1,1)	: 1218.768
ARIMA (0,1,2)	: 1218.687
ARIMA (1,1,0)	: 1219.212
ARIMA (1,1,2)	: 1221.283

Best model: ARIMA (0,1,1)	
Log likelihood = -606.01	**AICc = 1126.398**
AIC = 1216.03	**BIC = 1128.749**

4.7.1.5 Model Structure

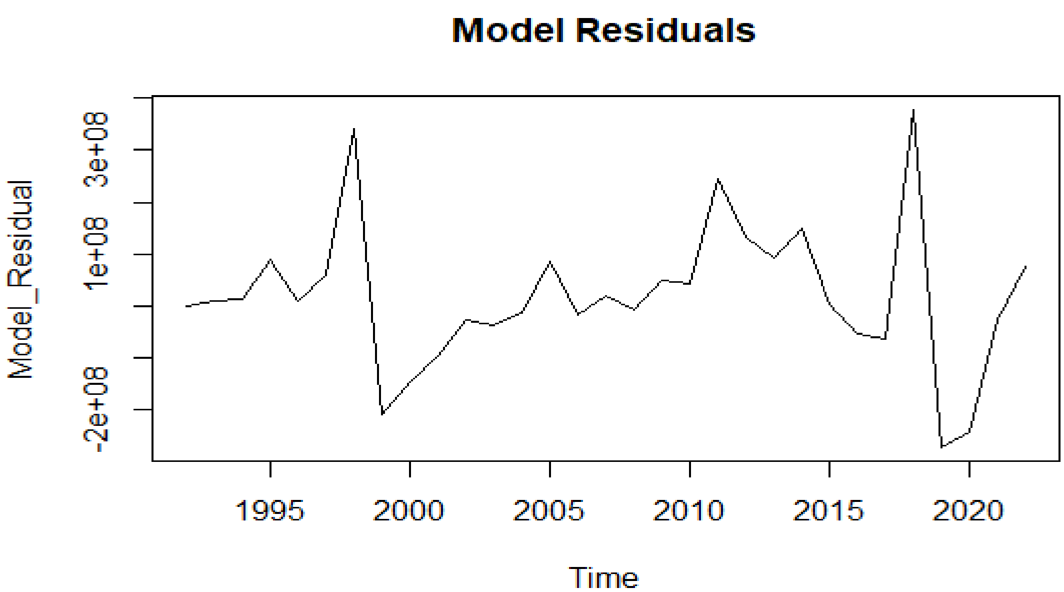
$$\boldsymbol{X_t = -0.5248_{\ t-1} + \varepsilon_t}$$

Above is a is a representation of the chosen model. The standard error obtained is 0.1648 and sigma^2 that was estimated was 2.106e+16. The findings show that FDI inflow has a negative coefficient (0.5248), implying that FDI Inflows contribute to the socio-economic growth of the country as concluded by Idowu (2021).

4.7.1.6 Diagnostic Checking

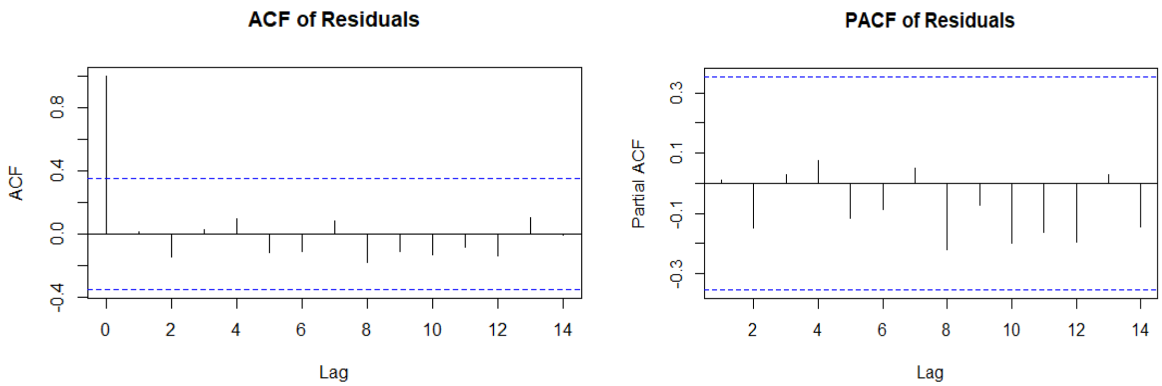
The examination of residuals entailed a comprehensive utilization of various diagnostic tools, including ACF and PACF) plots, as well as density plots and histograms. Through these analytical instruments, the study sought to discern patterns and trends within the residuals, thereby illuminating insights into the underlying structure of Foreign Direct Investment (FDI) inflows in Zimbabwe. Upon meticulous scrutiny of the residuals plot, it became apparent that the trajectory of FDI inflows exhibited a discernible pattern characterized by a steady decline. Despite occasional deviations from the expected zero mean and consistent variance, the overarching structure of FDI inflows remained relatively stable and persistent. This observation underscores the enduring nature of FDI dynamics within the Zimbabwean context. Moreover, the findings were reinforced by the insights offered by Idowu (2021), who highlighted that diagnostic testing corroborated the consistency and alignment of the estimated model with the empirical observations. This affirmation lends credence to the reliability and validity of the model in capturing the nuances of FDI behaviour in Zimbabwe. Furthermore, Methembeni (2022) further validated the efficacy of the ARIMA (0, 1, 1) model in forecasting FDI inflows within the Zimbabwean context. This assertion underscores the utility and effectiveness of the chosen modelling approach in accurately predicting the trajectory of FDI inflows, thereby facilitating informed decision-making processes and strategic planning initiatives within the realm of economic policy formulation and implementation.

Figure 4. 5 Model Residuals Results



4.7.1.7 Model Residuals Results

Figure 4. 6 Testing for Independence of Residuals

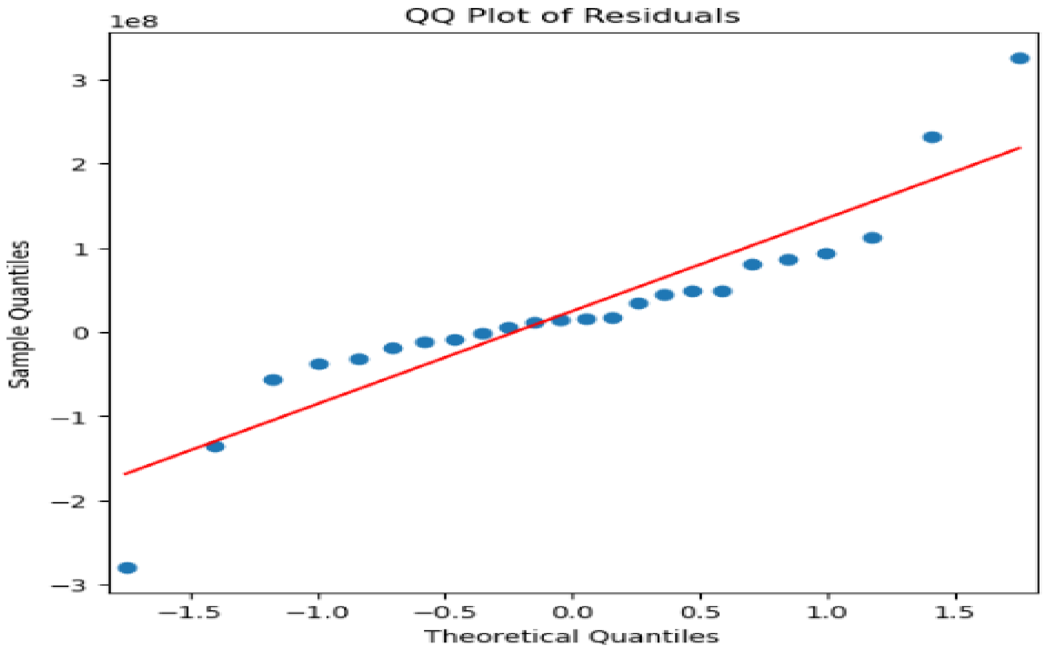


The examination of autocorrelation plots reveals that, apart from lag 1, the sample autocorrelation remains within the 95% confidence interval for the first 15 lags, while the Partial Autocorrelation Function (PACF) of the residuals displays uniform null autocorrelation across all lags. This implies a consistent variance in the residuals and validates the selection of the ARIMA (0, 1, 1) model, with the residual mean approximating zero. Moreover, aligning with prior research by Henry, Elijah, Gwani, & Simon (2019), the ACF and PACF plots of residuals from the ARIMA (1, 1, 2) model demonstrate correlations within acceptable limits, indicative of behaviour akin to white noise. These findings not only affirm the robustness of the chosen modelling approach but also provide valuable insights into the underlying structure of the data, enhancing the interpretability and utility of the analytical outcomes.

4.7.1.8 Testing for Independence of Residuals

The Q-Q plot illustrates the normal distribution, giving a satisfactory fit for this model since extreme values tail off and the majority of the values are on the line, indicating that the residuals are normally distributed.

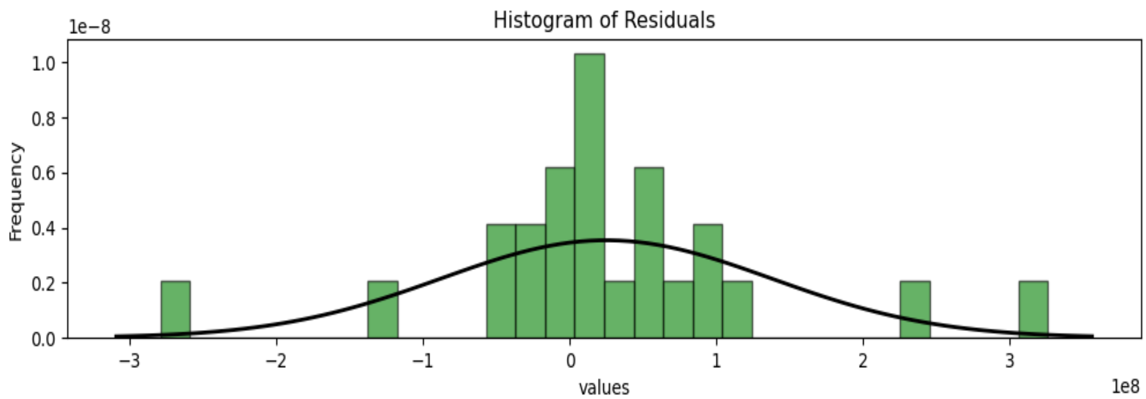
Figure 4. 7 Testing for Normality of plot residuals



4.7.1.9 Testing for the Normality plot of Residuals

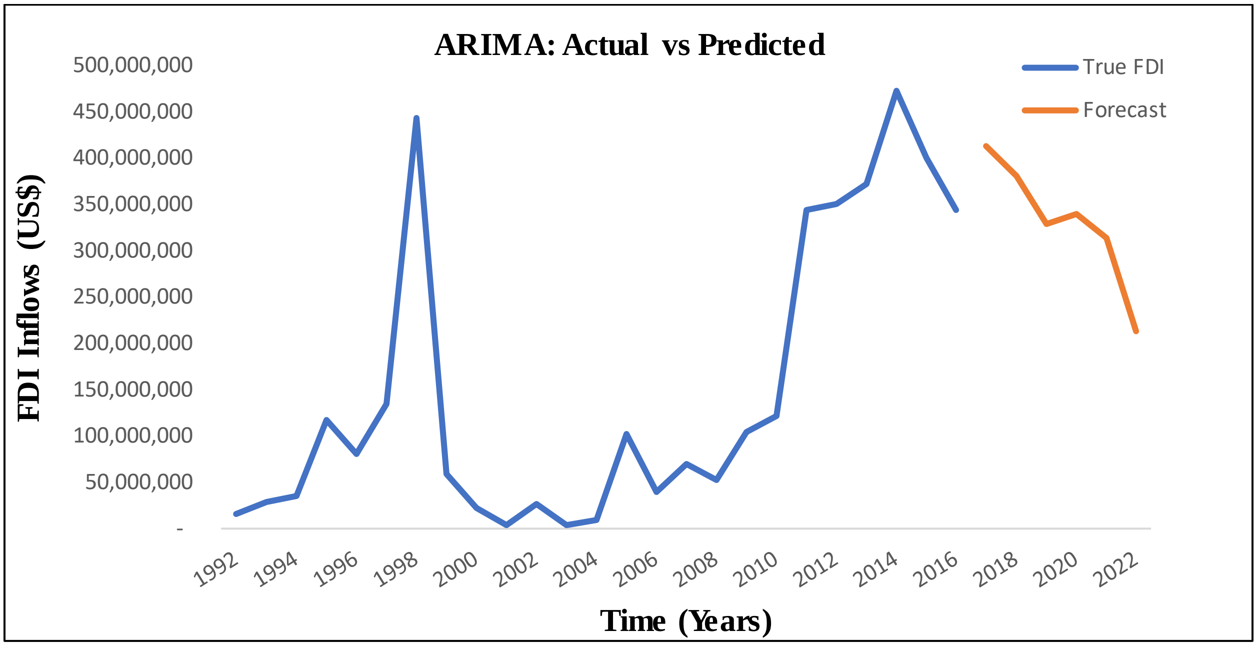
The graphical representation, show that the residuals depict a bell-shaped distribution, highlighting that they follow a near normal distribution. This is further supported by the mean of zero, indicating that qualify as white noise and homoscedasticity property is met (Henry et al 2019).

Figure 4. 8 Normality plot of Residuals



4.7.1.10 Forecasting ARIMA (0,1,1)

Figure 4. 9 Forecasted Values Plot



The diagram shows the forecasted values of the FDI inflows for the 20% test split from 2017 to 2022. The forecasted values for the six years show a gradual rise and a sharp fall in FDI

Table 4. 18 Forecasted FDI ARIMA (0,1,1)

Year	Predicted Values
2017	413056000
2018	380134500
2019	329128800
2020	340129200
2021	313129200
2022	213129200

It comes without question the need to critic these results, as they show a rather constant trajectory in the inflows of FDI for the next six years.

4.8 Long Short-Term Memory (LSTM)

The descriptive statistics of the FDI data have been described in the previous section of the ARIMA methodology, in this section we are forecasting FDI inflows from 2023 to 2026 using a recurrent neural network. To assess the performance of the model in performing the task, we have employed various accuracy measure metrics.

4.8.1 Data preprocessing

Neural networks require data to be to be normalised, to do this the researcher employed the MinMaxScaler from the sklearn. preprocessing library in python. The data was then transformed into three-dimensional data using the fit_transform function in python. To build the model the data was split using the ratio 80:20 for training and testing respectively.

4.8.2 Hyper-parameter Estimation

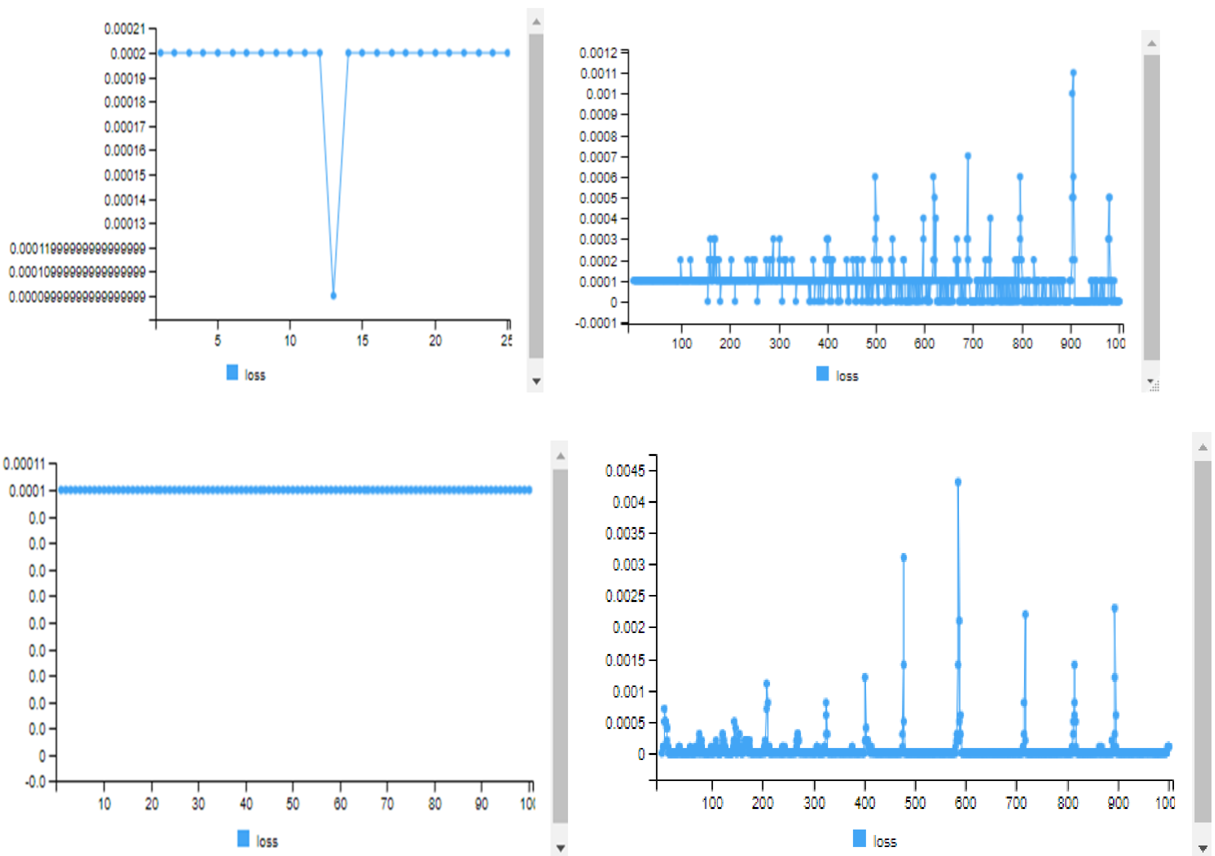
The most important hyper-parameters for LSTM are the batch size, number of epochs and number of neurons. Roy (2021) points out that hyper-parameters determine the success of the model and that there is no set rule to select these hyper-parameters. Using this method, we employed a variety of hyper-parameters to train the model; while keeping the number of nodes as little as possible, **Table 4.20** shows the different hyper-parameters and the RMSE of that model

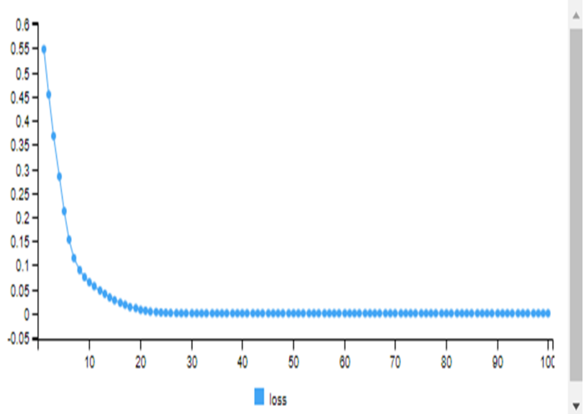
Table 4. 19 Hyper-parameter estimates

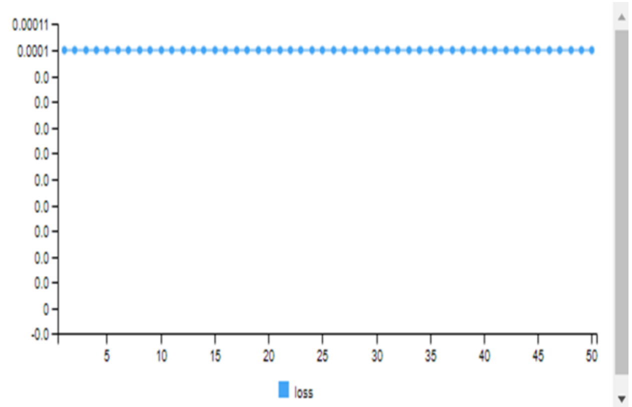
Epoch	Batch size	RMSE
100	31	0.149978531354136
50	31	0.14997853135136
100	1	0.142119027775133
500	31	0.149051525623674
100	20	0.148788927077685
50	20	0.148652228842914
1000	1	0.0283941875659475
25	1	0.160724173749713

On top of the RMSE values as a way to select the optimal hyper-parameters for the best performing model, we also employed the training curves for the various parameters. The training curves' main purpose was to visualize how the loss of the model changes over the course of the training epochs. The loss should ideally decrease indicating that the model is learning and improving its predictive performance. Training curves also provide a visual method to check if the model is overfitting, underfitting or an optimal fit. An overfit training fit would have the training loss continuing to decrease while the validation loss starts to increase or remains stagnant, in the same light an underfit model would have both training and validation losses high and showing little improvement over time on the other hand an optimal fit would show decreasing training and validation loses that converge to a minimum value. Ideally the training loss should converge to a stable minimum value.

Figure 4. 10 Training curves from different models







4.8.3 Optimal Model selected

After careful evaluation of various machine learning models for the task at hand, we have chosen a model that exhibits a perfect training curve and loss. This decision is based on several key factors outlined below:

1.Optimal Generalization: The selected model demonstrates exceptional performance on both the training and validation datasets, as indicated by its perfect training curve and loss. This suggests that the model has learned to generalize well to unseen data, striking an ideal balance between bias and variance. The convergence of the training and validation losses to low, stable values signifies that the model has captured the underlying patterns in the data without overfitting or underfitting.

2. Robust Learning Dynamics: Throughout the training process, the model consistently reduces its loss over successive epochs, indicating effective learning and adaptation to the training data. The smooth and steady decline of the loss curve without significant fluctuations or erratic behaviour reflects the robust learning dynamics of the model. Such behaviour is indicative of a well-structured and appropriately parameterized model architecture.

3. Efficient Training: The efficiency of the training process is another crucial consideration. The model's ability to achieve optimal performance within a reasonable number of training epochs demonstrates its efficiency in learning complex patterns from the data. By converging to a minimum loss value quickly and consistently, the model minimizes computational resources and training time while maximizing predictive accuracy.

Figure 4. 11 Training curve of the optimal model selected

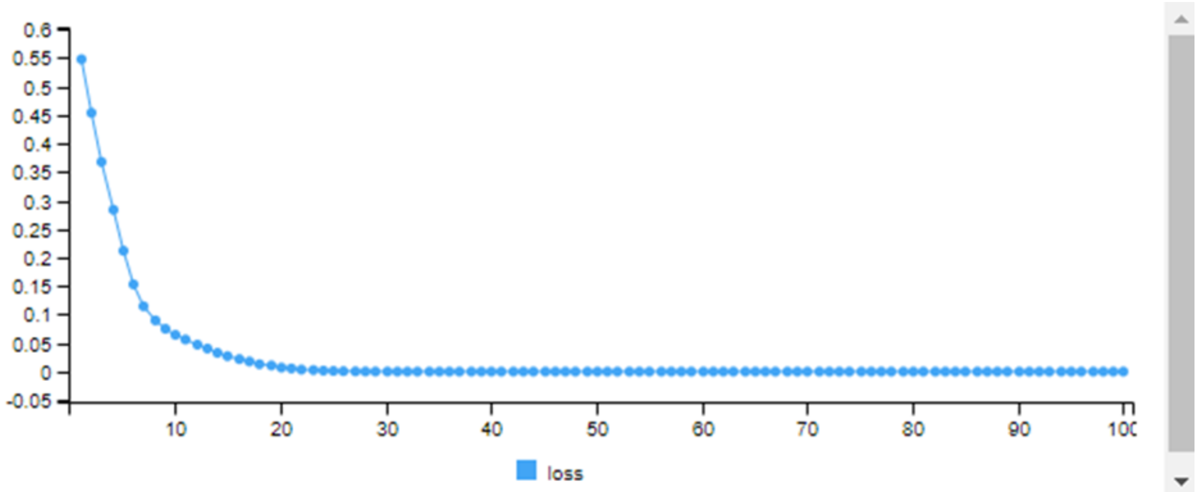


Table 4. 20 Optimal Hyper Parameters

Epoch	**Batch size**	**RMSE**
100	1	0.142119027775133

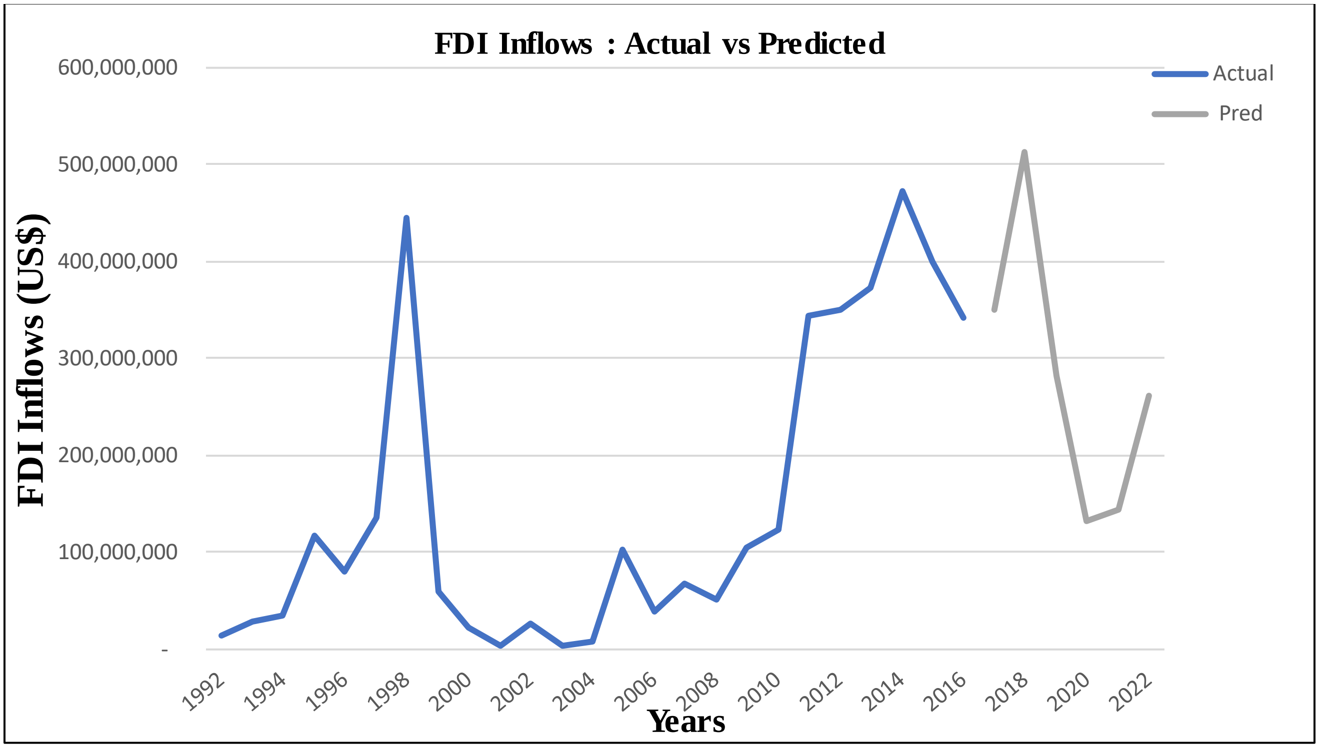
4.8.4 Forecasting

The remaining 20% of the data was then forecasted using the optimal neural network selected. The results of the forecast are given in the table below and they show rapid growth before a fall in the consequent years from 2019 to 2021. In 2022 a rise starts to be noticed.

Table 4. 21 Forecasted FDI LSTM

Year	**Forecast**
2017	349577024
2018	513134500
2019	283118976
2020	132400384
2021	144295104
2022	260881152

Figure 4. 12 LSTM: Actual vs Predicted



4.8.5 Model Performance Evaluation

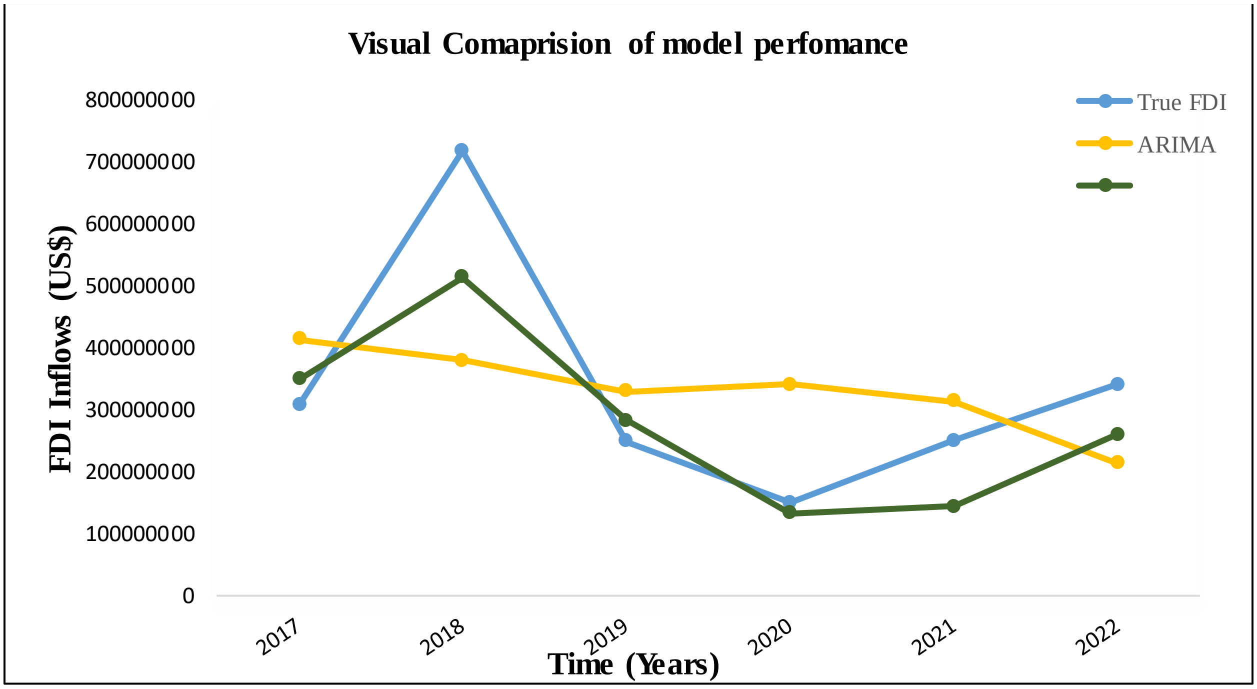
Table 4. 22 Comparative Analysis of Accuracy

		Forecast	
Year	**Actual**	**ARIMA (0,1,1)**	**LSTM**
2017	307187739	413056000	349577024
2018	717865322	380134500	513134500
2019	249500000	329128800	283118976
2020	150360000	340129200	132400384
2021	250000000	313129200	144295104
2022	341500000	213129200	260881152

Error Measure	**MAE**	70,617,694	55,500,987*
	RMSE	160,279,270	102,337,080*

In comparing the performance of ARIMA and LSTM models based on various error metrics, it is evident that the LSTM model generally provides more accurate predictions. The LSTM model has lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) indicating more precise and consistent predictions. The LSTM model shows superior performance in most of the evaluated metrics, suggesting it is a better choice for prediction in this scenario. **Table 4.22** shows the detailed metrics.

Figure 4. 13 Model Performance, ARIMA (0,1,1) and LSTM



With the aid of a line graph the forecasting power of the two models was depicted along with the actual FDI inflows recorded from 2017 to 2022. The LSTM model exhibits more prowess in following the trend shown by FDI inflows for the period. ARIMA (0,1,1) shows a rather constant trend of FDI for the six years, the model does not mimic the trend exhibited by the actual inflows from 2017 to 2022. ARIMA (0,1,1) fails to discern the underlying pattern in FDI while LSTM has managed to capture the underlying patterns of foreign investment inflow. The better performing model is the recurrent neural network.

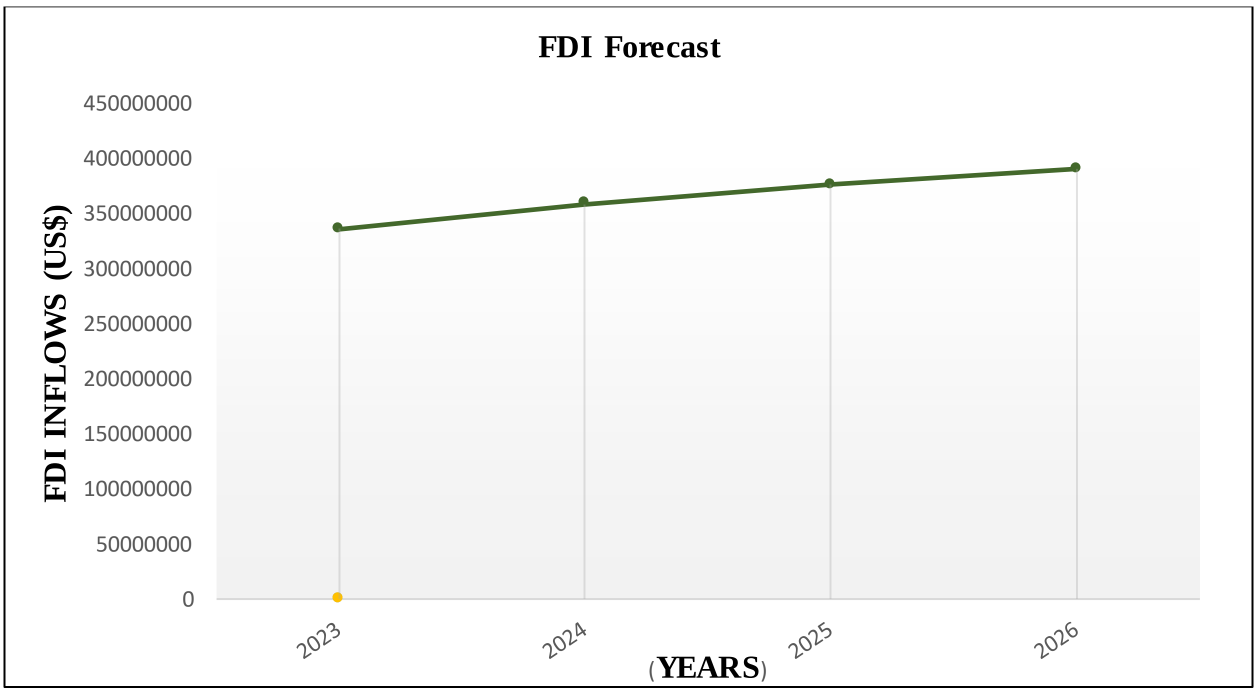
4.9 Out of Sample Forecast

To forecast FDI inflows from 2023 to 2026, the researcher employed the better performing LSTM, **Table 4.25** show the forecasted values exhibiting a rather constant inflow of FDI with little volatility for the four years.

Table 4. 25 Forecasted values

Year	Forecast
2023	335667230
2024	358511460
2025	375643870
2026	390540960

Figure 4.14 FDI Forecast



4.10 Discussion of Findings

The Granger causality tests, indicate no directional causality between GDP, inflation, political stability, control of corruption and FDI, implying that past values of these variables do not predict future values with statistical significance. Notably, FDI exhibits a wide range of values, suggesting fluctuations in investment activity, while GDP shows steady growth trends. The Augmented

Dickey-Fuller (ADF) test confirms the stationarity of FDI, GDP, and PSI at the first difference level, indicating a stable long-run relationship.

Political stability (PSI) and economic growth (GDP) in the long run has a positive relationship with FDI inflow, that is if PSI and GDP increases this will positively influence foreign direct investment (FDI). These findings are in agreement with the findings (Quazi, 2014) who found out that political stability attracts direct investment by boosting confidence in the host country by the investors whereas political instability does the opposite. Inflation was found to have a positive relationship FDI inflows that is if inflation increases then the FDI inflows increases, this is in contradiction to the results obtained by (Boateng, 2015), who found out that low inflation signals for internal national economic stability and encourages inward capital injection from foreign markets. Control on corruption was also found to have a negative influence on FDI inflow in both the long-run and short-run. These findings are in contradiction in the context of Zimbabwe to the studies by (Nguyen, 2021) in the South Asia and concluded that there is a positive relationship between control of corruption and FDI inflows.

The results also showed that there is a positive relationship between foreign direct investment and economic growth. These results are supported by the findings by (Boateng, 2015), who concluded that macroeconomic factors such as GDP were important factors that determine the inflows of capital into the host country and that there is appositive relationship between the two.

Furthermore, the forecasting methodologies, including the Traditional Box-Jenkins ARIMA and the LSTM recurrent neural network, offer contrasting perspectives on FDI trends. While the ARIMA model predicts a fixed FDI inflows over the forecast horizon, the LSTM model suggests a more nuanced picture with fluctuations in FDI levels but a gradual rise. The discussion of these findings underscores the complexity of FDI dynamics and the challenges in accurately predicting future trends. The discrepancies between the forecasted values highlight the importance of selecting appropriate modelling techniques and considering the inherent uncertainties in economic forecasting. Overall, to compare the predictive capabilities of the LSTM and Box-Jenkins ARIMA, we employed error measures to compare the accuracy of the two models during the training stages these include MAE and RMSE. We also employed a line graph to compare visually the forecasting power of the two models. The recurrent neural network emerged as the outstanding one between the two, and consequently it was used to forecast FDI for the next four years. The forecast shows a constant rise in FDI.

4.10 Chapter summary

The chapter presents a thorough examination of the research findings derived from a diverse array of data sources, meticulously analysed to provide valuable insights. Utilizing tabular formats, the study offers a structured depiction of results, with descriptive statistics shedding light on the fundamental characteristics of the variables under investigation. Augmented by Jacque-Bera tests to assess normality, the chapter's pre-testing phase encompasses correlation analyses, lag determination via the AIC criterion, and the crucial application of Augmented Dickey-Fuller (ADF) tests to ascertain data stationarity. Noteworthy is the validation of the inter-variable relationships' integrity, evidenced by the absence of serial correlation at lag 1, as revealed by the Godfrey LM test. Moreover, the investigation ventures into examining the long-run associations among variables through Johansen co-integration tests, while short-run effects of socio-economic determinants on FDI inflows are explored using the VECM. Granger causality testing enriches the analysis by unravelling directional causal linkages among the variables of interest. Diagnostic assessments, including Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) analyses, bolster confidence in the suitability of the ARIMA model. Further insights into residual normality are gleaned through Q-Q plots. Notably, model validation via various accuracy measures emerges as a pivotal metric, affirming the accuracy of the analyses. The chapter's culmination highlights the adoption of Long Short-Term Memory (LSTM) modelling techniques for FDI forecasting, signifying the study's commitment to harnessing advanced methodologies for robust predictive capabilities. This sets the stage for subsequent sections, which will encompass summary, conclusive insights, and policy recommendations, thereby providing a comprehensive framework for informed decision-making.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This section represents the summary of the study's results in relation to the objectives and with a clear indication the degree to which the objectives have been met. Furthermore, this chapter recommends rational measures to policy makers in Zimbabwe.

5.1 Constraints of the study

The study was met with a few constraints the first one being time, the duration of the study was rather short and thus did not allow for an in-depth analysis. The second one was unviability of data particularly the corruption perception index which only had data from 2012 to 2022. The sample size for application of the recurrent neural network was very small and monthly data for FDI inflows would have been ideal since neural networks generally require large data sets.

5.2 Summary of findings from the study

There are two main objectives in this study (i) to analyse the impact of political stability and corruption on foreign direct investment in Zimbabwe, (ii) to compare the predictive power of ARIMA and LSTM on FDI with data from 1992 to 2022. Regarding the first objective, the study incorporated variables such as inflation (INF), gross domestic product (GDP), Control of Corruption (COC) and the political stability index (PSI) within a Vector Autoregressive (VAR) framework.

The analysis uncovered a weak negative correlation between GDP and FDI, supported by the Vector Error Correction Model (VECM) results. This counterintuitive finding suggests that as GDP increases, FDI decreases in the short run ceteris paribus, contrary to the expected positive relationship indicating internal stability attracting external capital. In the long-term however GDP has a direct relationship with FDI inflows. Similarly, political stability demonstrated a positive association with FDI in the long run supporting the theoretical assumptions of the Eclectic paradigm's ownership aspect. While increased political stability traditionally attracts foreign capital, in developing countries like Zimbabwe, multinational corporations (MNCs) often benefit from political instability, capitalizing on resources at reduced costs, as seen in cases like this one where China has been involved in Congo's internal conflict and economy. During Joseph

Kabila's regime, deals with Congolese leaders have enabled Chinese firms to obtain significant access to metals crucial for mass-producing electronics and clean energy solutions.

(Global Conflict Tracker, 2024). Control on corruption was found to exhibit long-run and short-run negative influence on the FDI inflows, these findings are validated by the findings of (Quazi et tal, 2014) who concluded that corruption had a positive relationship with FDI inflows under the "helping hand" hypothesis which suggests that corruption loosens the burden of business in the presence of weak regulatory framework. The study also points out that Africa has relatively weak regulatory framework. In this light the study hints the presence of a relatively strong regulatory framework in Zimbabwe thus the negative relationship between control of corruption in Zimbabwe. However, this view is not without conflicting opinions as (Chamisa, 2020) concludes that corruption negatively affects FDI inflows in a study carried out in the SADC region. These conflicting views, further cements the need for a study such as this one to paint a clear picture of the effect of corruption in the specific context of Zimbabwe.

In terms of predictive performance, LSTM outperformed the ARIMA (0, 1, 1) model, as evidenced by the prowess shown in the following metrics these are MAE and RMSE values and the nature of the forecasts. While both models predicted lower FDI values, ARIMA exhibited a rather constant graph, whereas LSTM reflected volatility and a gradual upward trend, aligning more closely with the erratic nature of FDI inflows.

These findings underscore the complex interplay between socio-political factors and FDI dynamics, suggesting avenues for further research and policy implications aimed at fostering a conducive investment climate in Zimbabwe and similar developing economies.

5.3 Conclusion

This study examined the effect of political stability and corruption on foreign direct investment (FDI) in Zimbabwe, while also comparing the predictive performance of the ARIMA model and neural network in forecasting FDI. The analysis revealed conflicting long run relationships with FDI, for political stability and control of corruption, that is political stability is set to positively influence FDI inflows while control of corruption negatively impacts inflows. Short run negative relationship between GDP and FDI, contrary to expectations, and a negative association between political stability and FDI, reflecting the nuanced dynamics of investment in developing countries.

Additionally, a direct relationship between inflation and economic growth was identified. LSTM demonstrated superior predictive prowess over ARIMA, showcasing a more realistic portrayal of the volatile nature of FDI inflows. These findings highlight the complexities underlying FDI dynamics and provide insights for policy formulation to enhance the investment climate in Zimbabwe and similar contexts.

5.4 Recommendations

The study has derived recommendations derived from the findings of the study.

1. **Encouragement of Political tolerance:** The government should prioritize efforts to enhance political tolerance within the country to foster a conducive political sphere in order to boost investor confidence towards the country. Involvement of both the ruling and opposition, through coalitions in all levels of government can promote a conducive political sphere.
2. **Tightening the grip on Corruption:** The government, through its agencies such as the Zimbabwe Anti-Corruption Commission (ZACC), should strengthen controls, checks, and balances within the investment sector. This approach aims to reduce corruption, promote the fair distribution of resources, and prevent abuse of office. By implementing rigorous oversight mechanisms, the government can create a more transparent and equitable environment for investors, fostering economic growth and stability

3. **Currency Reforms:** Implement currency reforms to bolster investor confidence, such as joining the Rand Monetary Union and adopting policies that promote industrialization for job creation. These measures aim to minimize arbitrage arising from illegal money changing and address the issues caused by parallel exchange rates, which have contributed to the depreciation of the local currency and undermined confidence both locally and internationally. Strengthening the currency will enhance economic stability and attract more investment.

4. **Reviewing Investment policies:** The government could reassess the Indigenization and Economic Empowerment Act, which mandates that foreign investors hold only 49% ownership of enterprises, with the majority 51% owned by indigenous Zimbabweans. Relaxing these ownership requirements in key sectors could significantly enhance foreign capital inflows, as

investors are more likely to commit if they can retain greater ownership and decision-making powers.

5. **Sectoral Prioritization:** government to persist in prioritizing investments in critical sectors like mining, agriculture, manufacturing, tourism, and infrastructure. Through dedicated allocation of resources and assistance to these sectors, the government can spur employment opportunities, draw foreign investments, and nurture sustained economic progress. Furthermore, introducing tailored policies and incentives aimed at promoting investment in these sectors will amplify their growth prospects and bolster the nation's prosperity at large.

5.5 Chapter summary

This study was to ascertain the impact of political stability on foreign capital inflows and to compare the forecasting capabilities of ARIMA and LSTM models. According to the findings political stability and control of corruption have great impact on foreign capital inflows and the better performing model is the LSTM. This chapter discussed summary of the findings from the study, conclusions and recommendations.

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APPENDICES

Descriptive statistics

FDI	GDP	INF	PSI	COC
2.11E+08	1.46E+10	325.7392	0.171739	-1.299824
1.50E+08	1.41E+10	0.121000	0.170000	-1.298485
7.18E+08	3.42E+10	6657.741	0.250000	-1.127275
3800000.	4.42E+09	-0.024100	0.110000	-1.425627
1.88E+08	8.77E+09	1384.704	0.044174	0.090354
0.807015	0.502178	4.432547	0.402155	0.461160
3.204455	2.209268	20.78148	1.897532	2.271030
2.536610	1.565904	378.3223	1.784752	1.324486
0.281308	0.457055	0.000000	0.409681	0.515693
4.85E+09	3.35E+11	7492.003	3.950000	-29.89594
7.76E+17	1.69E+21	42182918	0.042930	0.179604
23	23	23	23	23

Correlation

	FDI	GDP	INF	PSI	COC
FDI	1	0.85071493...	-0.2179782...	0.71105770...	-0.3283764...
GDP	0.85071493...	1	-0.2553794...	0.50777866...	-0.0753045...
INF	-0.2179782...	-0.2553794...	1	0.01686883...	-0.1860043...
PSI	0.71105770...	0.50777866...	0.01686883...	1	-0.4212599...
COC	-0.3283764...	-0.0753045...	-0.1860043...	-0.4212599...	1

VIF Test

Variance Inflation Factors
Date: 06/10/24 Time: 13:18
Sample: 2000 2022
Included observations: 23

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
GDP	5.66E-06	5.874552	1.510772
INF	1.70E+08	1.195639	1.130250
PSI	2.50E+17	28.50073	1.696310
COC	4.53E+16	279.3451	1.285162
C	6.41E+16	233.0180	NA

Unit Root Tests

Null Hypothesis: D(FDI) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.744956	0.0014
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.610320	0.0002
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

Null Hypothesis: INF has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.231981	0.0036
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

Null Hypothesis: D(PSI) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.365959	0.0003
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

Null Hypothesis: D(COC) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.508676	0.0182
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

Lag Selection

Included observations: 21

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1035.079	NA	7.19e+36	99.05512	99.30382	99.10910
1	-987.2105	68.38332*	8.84e+35*	96.87719*	98.36936*	97.20103*
2	-962.3469	23.67962	1.47e+36	96.89018	99.62583	97.48389

Johansen Cointegration

Sample (adjusted): 2002 2022
Included observations: 21 after adjustments
Trend assumption: Linear deterministic trend
Series: FDI GDP INF PSI COC
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.747157	71.89875	69.81889	0.0338
At most 1	0.655462	43.02403	47.85613	0.1320
At most 2	0.450416	20.64743	29.79707	0.3800
At most 3	0.314549	8.076952	15.49471	0.4572
At most 4	0.006914	0.145709	3.841465	0.7027

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

1 Cointegrating Equation(s): Log likelihood -983.8589

Normalized cointegrating coefficients (standard error in parentheses)

FDI	GDP	INF	PSI	COC
1.000000	-0.013929	9410.054	-2.20E+09	3.55E+08
	(0.00168)	(10212.3)	(3.1E+08)	(1.2E+08)

Vector Error Correction Estimates
Date: 05/19/24 Time: 14:01
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
FDI(-1)	1.000000
GDP(-1)	-0.013929 (0.00168) [-8.28344]
INF(-1)	9410.054 (10212.3) [0.92144]
PSI(-1)	-2.20E+09 (3.1E+08) [-7.09442]
COC(-1)	3.55E+08 (1.2E+08) [2.87555]
C	8.30E+08

Error Correction:	D(FDI)	D(GDP)	D(INF)	D(PSI)	D(COC)
CointEq1	-1.641034 (0.50388) [-3.25680]	-35.95999 (17.8069) [-2.01945]	2.54E-06 (7.8E-06) [0.32412]	7.26E-11 (1.5E-10) [0.47225]	-2.48E-10 (1.6E-10) [-1.58792]
D(FDI(-1))	0.933863 (0.51334) [1.81918]	35.83925 (18.1413) [1.97556]	5.76E-06 (8.0E-06) [0.72165]	1.41E-10 (1.6E-10) [0.90247]	3.27E-10 (1.6E-10) [2.05363]
D(GDP(-1))	-0.026625 (0.01498) [-1.77694]	-1.266885 (0.52952) [-2.39252]	-1.50E-07 (2.3E-07) [-0.64527]	-4.85E-12 (4.6E-12) [-1.06072]	-9.16E-12 (4.6E-12) [-1.97342]
D(INF(-1))	17543.80 (17084.7) [1.02687]	600023.0 (603764.) [0.99380]	-0.325957 (0.26555) [-1.22750]	1.46E-06 (5.2E-06) [0.28070]	-2.62E-06 (5.3E-06) [-0.49501]
D(PSI(-1))	-1.72E+09 (1.1E+09) [-1.54862]	-4.95E+10 (3.9E+10) [-1.25988]	-10506.47 (17270.8) [-0.60834]	-0.118527 (0.33921) [-0.34942]	-0.281729 (0.34423) [-0.81843]
D(COC(-1))	-5.17E+08 (8.2E+08) [-0.62704]	1.50E+10 (2.9E+10) [0.51519]	2250.106 (12813.6) [0.17560]	0.034031 (0.25167) [0.13522]	0.394940 (0.25539) [1.54641]
C	34473393 (3.1E+07) [1.10337]	2.11E+09 (1.1E+09) [1.91047]	131.4575 (485.618) [0.27070]	0.005874 (0.00954) [0.61581]	0.002887 (0.00968) [0.29828]
R-squared	0.545241	0.451378	0.311373	0.185318	0.379612
Adj. R-squared	0.350345	0.216255	0.016248	-0.163832	0.113732
Sum sq. resids	2.27E+17	2.83E+20	54749370	0.021120	0.021750
S.E. equation	1.27E+08	4.50E+09	1977.541	0.038840	0.039415
F-statistic	2.797593	1.919748	1.055054	0.530769	1.427756
Log likelihood	-417.4322	-492.2972	-184.9221	42.67406	42.36546
Akaike AIC	40.42211	47.55211	18.27830	-3.397529	-3.368139
Schwarz SC	40.77028	47.90029	18.62647	-3.049355	-3.019965
Mean dependent	16080952	9.80E+08	-0.048895	0.001905	-0.006089
S.D. dependent	1.58E+08	5.08E+09	1993.805	0.036003	0.041868

Determinant resid covariance (dof adj.)	2.58E+35
Determinant resid covariance	3.40E+34
Log likelihood	-983.8589
Akaike information criterion	97.51037
Schwarz criterion	99.49994
Number of coefficients	40

Pairwise Granger Causality Tests
Date: 05/21/24 Time: 16:47
Sample: 2000 2022
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause FDI	22	0.29916	0.5908
FDI does not Granger Cause GDP		0.38119	0.5443
INF does not Granger Cause FDI	22	0.14627	0.7064
FDI does not Granger Cause INF		0.37888	0.5455
PSI does not Granger Cause FDI	22	3.12652	0.0931
FDI does not Granger Cause PSI		0.81648	0.3775
COC does not Granger Cause FDI	22	2.59507	0.1237
FDI does not Granger Cause COC		2.01809	0.1716
INF does not Granger Cause GDP	22	0.29098	0.5959
GDP does not Granger Cause INF		1.14215	0.2986
PSI does not Granger Cause GDP	22	0.14581	0.7068
GDP does not Granger Cause PSI		0.03459	0.8544
COC does not Granger Cause GDP	22	1.03846	0.3210
GDP does not Granger Cause COC		1.93214	0.1806
PSI does not Granger Cause INF	22	1.47760	0.2390
INF does not Granger Cause PSI		0.78478	0.3868
COC does not Granger Cause INF	22	0.00387	0.9511
INF does not Granger Cause COC		1.32611	0.2638
COC does not Granger Cause PSI	22	2.57729	0.1249
PSI does not Granger Cause COC		1.22420	0.2824

Godfrey LM Test

VEC Residual Serial Correlation LM Tests
Date: 05/19/24 Time: 14:04
Sample: 2000 2022
Included observations: 21

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	39.00961	25	0.0368	1.959273	(25, 20.1)	0.0641

Normalised Cointegrating Coefficients

Component	Jarque-Bera	df	Prob.
1	0.929060	2	0.6284
2	0.356512	2	0.8367
3	14.35648	2	0.0008
4	0.321893	2	0.8513
5	0.655203	2	0.7207
Joint	16.61915	10	0.0832

*Approximate p-values do not account for coefficient estimation

Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.580298	Prob. F(6,15)	0.7407
Obs*R-squared	4.144584	Prob. Chi-Square(6)	0.6571
Scaled explained SS	2.489927	Prob. Chi-Square(6)	0.8696

PROJECT DATA

REGRESSION DATA

Date	FDI	GDP	PSI	INF
2000	23,200,000	6,689,957,600	12%	68.15%
2001	3,800,000	6,777,384,700	13%	144.58%
2002	25,900,000	6,342,116,400	11%	432.30%
2003	3,800,000	5,727,591,800	19%	3019.90%
2004	8,700,000	5,805,598,400	14%	7028.70%
2005	102,800,000	5,755,215,200	12%	48205.60%
2006	40,000,000	5,443,896,500	18%	665774.10%
2007	68,900,000	5,291,950,100	15%	24411.03%
2008	51,600,000	4,415,702,800	13%	0.00%
2009	105,000,000	9,665,793,300	14%	0.00%
2010	122,586,667	12,041,655,200	14%	3.03%
2011	344,300,000	14,101,920,300	19%	3.48%
2012	349,850,000	17,114,849,900	22%	3.72%
2013	373,050,000	19,091,020,000	24%	1.63%
2014	472,800,000	19,495,519,600	22%	-0.21%
2015	399,200,000	19,963,120,600	25%	-2.41%
2016	343,013,813	20,548,678,100	25%	-1.57%
2017	307,187,739	17,584,890,937	21%	0.91%
2018	717,865,322	34,156,069,918	20%	10.62%
2019	249,500,000	21,832,234,921	15%	23.00%
2020	150,360,000	21,509,698,407	13%	12.10%
2021	250,000,000	28,371,238,666	17%	19.70%
2022	341,500,000	27,366,627,153	17%	41.90%

TIME SERIES DATA

Date	FDI
1992	14,949,900
1993	27,955,135
1994	34,648,880
1995	117,700,000
1996	80,900,000
1997	135,100,000
1998	444,300,000
1999	59,000,000
2000	23,200,000
2001	3,800,000
2002	25,900,000
2003	3,800,000

2004	8,700,000
2005	102,800,000
2006	40,000,000
2007	68,900,000
2008	51,600,000
2009	105,000,000
2010	122,586,667
2011	344,300,000
2012	349,850,000
2013	373,050,000
2014	472,800,000
2015	399,200,000
2016	343,013,813
2017	307,187,739
2018	717,865,322
2019	249,500,000
2020	150,360,000
2021	250,000,000
2022	341,500,000

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