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FACULTY OF

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# A Comparative Analysis of Traditional Time Series and Machine Learning Models in Explaining the Impact of Exchange Rate Volatility on Zimbabwe's Annual Imports and Exports

A research project submitted in partial fulfilment of the requirements for the Bachelor of Science Honors Degree in Financial Mathematics.

June: 2026

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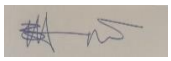
Name: Tinashe Hapuwe Signature:  Date: 25/06/2026

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## DECLARATION

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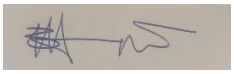
Signature:  Date: 25/06/2026

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# DEDICATION

I dedicate this work to my family, whose unwavering support, encouragement and sacrifices have been the foundation of my academic journey. To my parents, for instilling in me the values of perseverance and resilience; to my siblings, for their constant motivation; to my partner Nicole, for walking this journey with me and for her endless love, patience and encouragement and to my supervisor Dr T. Mapuwei, for his guidance and inspiration. This achievement is a reflection of your love, patience and belief in me. Above all, I dedicate this project to the Almighty God, whose grace and strength have carried me through every challenge.

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## ABSTRACT

This study investigates the impact of exchange rate volatility on Zimbabwe's annual imports and exports by comparing traditional time series models with modern machine learning approaches. Exchange rate instability has long posed challenges for Zimbabwe, increasing import costs, reducing export competitiveness and creating uncertainty for businesses. While traditional econometric models such as ARIMA and GARCH have been widely applied, they often fail to capture nonlinear and complex interactions among macroeconomic variables. Machine learning models, on the other hand, offer advanced capabilities for identifying hidden patterns and improving predictive accuracy. Using annual data from 2021 onwards, the study analyses trends in exchange rate volatility, examines its relationship with trade performance and evaluates the effectiveness of both modelling approaches. Findings are expected to provide policymakers, businesses, and financial institutions with deeper insights into managing currency risks and designing effective trade strategies. Ultimately, this research contributes to bridging the methodological gap between conventional econometric techniques and modern machine learning applications in Zimbabwe's economic context.

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# Chapter 1

## 1.0 Introduction

The current chapter explores the comparison between the traditional times series model and machine learning techniques in explaining the effect of fluctuations in exchange rate on annual imports and exports of Zimbabwe. This chapter places the study within global, African, and Zimbabwean perspective, explains the problem statement, sets out the objectives and research questions of the study. Furthermore, this chapter elaborates the importance of the study, its assumptions, delimitations, limitations, and important definitions.

## 1.1 Background of the Study

Generally, globally, the exchange rate volatility forms an important determinant of trade performance, affecting both imports and exports for both developed and developing nations. Exchange rate volatility is mainly caused by changes such as monetary policies, exchange rate differences, financial shocks, and geopolitics. According to the research, increased exchange rate volatility reduces trade volume by causing price and earning uncertainties (IMF, 2023). In particular, in the US, the relatively low exchange rate volatility and well-developed financial sector allow businesses to effectively manage risks associated with currency instability, resulting in continued trade growth. Similarly, Japan has recorded consistent trade success despite exchange rate volatility, due to the presence of sophisticated financial tools and export-based industries. On the other hand, some developing countries, such as Turkey and Brazil, have experienced a decline in their trade stability because of continuous exchange rate depreciation and volatility, increasing their import cost and reducing competitiveness in exports (World Bank, 2024).

Recent events in the world have revealed certain weaknesses in conventional economic models, including ARIMA, in terms of their inability to deal with the intricacy of the economic processes, especially in situations involving unexpected changes. This is why some nations like China and Germany have started using machine learning models in order to predict exchange rates and trade volume more efficiently. Such models can successfully identify relationships between macroeconomic variables like interest rates, inflation, and commodity prices (Zhang et al., 2022).

As for Africa, the volatility of exchange rates in the continent is associated with the structural economic issues, high levels of import dependency, and low diversification of exports. Many

African nations have economies that are still dominated by natural resources, thus making them vulnerable to exchange rate volatility and global price changes. As an illustration, Nigeria, which depends on oil exports, has recorded reduction in its export earnings due to devaluation of the currency and falling oil prices. Similarly, South Africa has had uneven performance in trade because of rand's volatility.

For example, in East Africa, countries like Kenya have encountered exchange rate instability, empirical evidence having proven that such volatility has a great impact on balance of trade due to increased costs of imports and reduced exports (Omurwa et al., 2024). In addition, many African countries do not have developed financial markets and proper hedging mechanisms that could be used to mitigate risks associated with exchange rates. Consequently, many companies refrain from conducting foreign business transactions when exchange rate fluctuations are too high. Even though time series methods such as GARCH and ARIMA have long been used in Africa, the interlinkages between different macroeconomic variables cannot be properly captured using these methods. This explains the increasing trend of using machine learning in Africa (Osei & Kim, 2022).

Exchange rates have been volatile in Zimbabwe due to macroeconomic instability, inconsistency in policies, and previous episodes of hyperinflation in the country. Over the last two decades, Zimbabwe has gone through different exchange rate regimes from using multiple currencies to adopting the Zimbabwean dollar, thus leading to the volatility of exchange rates. According to the Reserve Bank of Zimbabwe (RBZ, 2024), instability in exchange rates has led to higher cost of imports, reduced competitiveness of exports, and uncertainty among businesses.

In contrast to Botswana, which has experienced low volatility of the exchange rate due to well-crafted monetary policy, the country of Zimbabwe has not achieved any stability in the exchange rates. On the other hand, Zambia has faced some issues regarding the exchange rate volatility due to problems caused by external debt. Nonetheless, the approach that Zambia has chosen to deal with these issues has proved to be steadier compared to that of Zimbabwe. In Zimbabwe, several attempts have been made to solve the problem, but none of them have yielded positive results.

In terms of the case of Zimbabwe, it should be noted that most of the existing studies have applied econometric modelling methods for studying the influence of exchange rate volatility on trade. However, although the econometric approach provides researchers with useful

information, it is limited by its incapability of dealing with non-linear and complex dependencies between inflation, interest rates, commodity prices, and other macroeconomic factors. Due to the growing complexity of the economic situation in Zimbabwe, modern approaches need to be applied.

Volatility in exchange rates is one of the most serious global issues that come with many consequences. While there might be some challenges associated with developed nations due to exchange rate volatility, developing nations will face even worse challenges from exchange rate volatility, especially those developing nations in Africa like Zimbabwe. The limitations in the traditional econometrics model, along with the availability of modern techniques, create the need for doing comparisons between the different methods. This research seeks to conduct comparative analysis between time series analysis and machine learning.

## 1.2 Statement of the Problem

The Zimbabwean economy still faces numerous issues stemming from continuous problems of exchange-rate volatility, which have negative effects on the import/export performance of the country. According to evidence from the Reserve Bank of Zimbabwe and the Ministry of Finance, although steps such as introduction of a foreign exchange auction system and changes to monetary policies were made, the situation of volatility still persists. Exchange-rate fluctuations result in increased costs of imports, reduced competitiveness of exports, and uncertainty within firms. Therefore, companies face difficulties in terms of planning, pricing, and investment decision-making. Currently, research mainly utilizes conventional time-series models, which, however, have certain weaknesses in terms of explaining complex relationships between economic processes. Failure to solve this issue can cause persistent trade balances and poor economic development of Zimbabwe. Thus, this study will focus on comparing time-series models and machine learning techniques to help resolve the issue.

## 1.3 Aim of the Study

The aim of this study is to compare traditional time series models and machine learning models in explaining the impact of exchange rate volatility on Zimbabwe's annual imports and exports.

## 1.4 Research Objectives

- To analyse the trend and patterns of exchange rate volatility in Zimbabwe.
- To examine the relationship between exchange rate volatility and imports and exports using traditional time series models.

- To evaluate the effectiveness of machine learning models in explaining exchange rate volatility and trade performance.
- To compare the predictive accuracy of traditional time series and machine learning models.

## 1.5 Research Questions

- What are the trends and patterns of exchange rate volatility in Zimbabwe?
- How does exchange rate volatility affect imports and exports in Zimbabwe?
- How effective are machine learning models in analysing exchange rate volatility compared to traditional models?
- Which model provides better predictive accuracy for trade outcomes?

## 1.6 Significance of the Study

The current study is highly relevant for policy makers and institutions such as the Ministry of Finance and the Reserve Bank of Zimbabwe. Volatility of exchange rates has been a common problem for many countries that affects the performance of trade and economic stability as well as inflation rates. Comparing the traditional econometric models to machine learning models provides deeper insight into the effect that exchange rate has on trade imports and exports.

Exchange rate fluctuation is an important piece of data for firms, especially those that are involved in importing and exporting commodities in Zimbabwe. Any change in the exchange rate will directly affect the cost incurred from imported products and how well the exports perform. Through the analyses carried out as part of this project, companies can understand the nature of the exchange rate. These models help in predicting future changes in the exchange rate.

The research will bring about some results that will increase knowledge of exchange rates and activities of financial institutions. Financial institutions have an important part to play in providing finance for international business and foreign exchange operations. The increased knowledge of the behaviour of exchange rates based on models will help to analyse risk, creditworthiness, and investment performance. Therefore, the increased knowledge will help create efficient financial markets in Zimbabwe.

On an academic basis, the study contributes to knowledge on the field of economics and finance by drawing the link between classical analysis techniques and modern techniques used in the

study of economic phenomena. Most literature done in developing countries such as Zimbabwe has relied on classical models including ARIMA and GARCH.

This research will be important to the investors – both local and foreigners – since they rely heavily on macroeconomic variables when making their decisions. Volatility in exchange rates could create uncertainty in the market, thus causing foreign direct investments to be discouraged. The findings of this research could be used to help improve the accuracy of the models that predict exchange rates. As a result, there could be more confidence in the market among the investors, allowing them to make better judgments on investing in the Zimbabwean economy.

Further, this research also has wider economic ramifications since it is part of a contribution towards development at the national level. The main driving force of economic growth and job creation, and one that can be used for the reduction of poverty, is the trading process. Therefore, understanding exchange rate fluctuations and their impact on imports and exports is essential.

### 1.7 Assumptions of the Study

- All data used is reliable and valid.
- Exchange rates are an important determinant of imports and exports.
- Appropriate models are being used for the analysis.
- Economic environment is stable throughout the research period.
- Information provided by respondents is true.

### 1.8 Delimitations of the Study

This study examines the situation in Zimbabwe using annual data beginning from 2021. The main factors considered include exchange rates, imports, exports, interest rates, and commodity prices. Only comparison of time series and some machine learning models is performed within the scope of the paper due to lack of time and other available resources. Not all possible economic factors could be included in the analysis in this regard. Also, only the results related to the situation in Zimbabwe will be considered.

### 1.9 Limitations of the Study

Firstly, one key limitation that may arise in this research is the lack of access to reliable data. Data on macroeconomic variables like exchange rate, imports, exports, and interest rates could be unreliable due to the possibility of inconsistencies, gaps, or revisions caused by changes in methodology. This could lead to problems with the reliability of results obtained from the

analysis. In order to handle this limitation, only information from credible sources such as the Reserve Bank of Zimbabwe, Zimbabwe National Statistics Agency (ZIMSTAT), World Bank, and International Monetary Fund (IMF) will be utilized.

A further limitation expected to emerge from this research project is related to the use of annual data. While annual data may help identify long-term trends, the use of annual data will significantly lower the number of data points available, posing limitations for using some algorithms that require large amounts of data.

The study is likely to be affected by the problem of omitted variable bias since exchange rate volatility and trade performance depend on several other variables, including political stability, economic environment around the world, policy change, and economic shocks such as disease outbreaks or commodity price changes. However, because of data availability issues and the scope of the research, it might be impossible to include all of the relevant variables into the analysis. In order to minimize this issue, the inclusion of relevant control variables, like inflation rate and interest rate, together with dummy variables for significant policies and economic shocks is proposed in this study.

Another potential limitation refers to model risk, especially in regard to traditional time-series models and machine learning models. Each modelling technique has its inherent assumptions and weaknesses; for instance, while the traditional models might be unable to account for non-linearities, machine learning models could suffer from overfitting. This will make the communication of the study's findings more difficult when addressing relevant parties, such as policymakers. The use of multiple models and evaluation methods is thus recommended as an option.

The proposed study is likely to face problems associated with structural changes in the Zimbabwean economy. Indeed, the country’s economy has seen several changes since its inception, such as changes in its monetary policies, reforms, and inflation, among other factors. These structural changes are bound to affect the patterns in historical data, hence limiting the accuracy and efficiency of not only the traditional models but also the machine learning models. To overcome this problem, the study will use dummy variables representing some of the structural changes in the economy, if possible.

Moreover, time and financial resources may pose a problem for the study. In particular, collecting and analysing data and applying the models to the data may be rather difficult due

to the large amount of time required. For this reason, the study will focus mainly on the variables and models which are most suitable for the research questions raised.

## 1.10 Definition of Key Terms

- Exchange Rate Volatility: the degree of fluctuation in the value of one currency relative to another over time, commonly measured by the standard deviation or conditional variance of exchange rate returns. High volatility increases uncertainty for international trade and investment (Andersen, Bollerslev, Diebold & Labys, 1999).
- Imports: Goods and services purchased by residents of a country from foreign sources. Imports are recorded as a debit in the current account of the balance of payments (Krugman, Obstfeld, & Melitz, 2018).
- Exports: Goods and services produced domestically and sold to foreign buyers. Exports are recorded as a credit in the current account of the balance of payments (Krugman, Obstfeld, & Melitz, 2018).
- Time Series Models: Statistical or machine learning models that analyse data points ordered chronologically to capture patterns such as trend, seasonality, and autocorrelation, and to forecast future values. Common classes include AR, ARMA, ARIMA, and state-space models (Scherrer & Deistler, 2023).
- Machine Learning Models: Algorithms that learn patterns from data and use them to make predictions or decisions without being explicitly programmed for each task. Formally, a program learns from experience E with respect to task T and performance measure P if performance on T improves with E (Mitchell, 1997).
- Interest Rates: The price of borrowing money or the reward for lending money, expressed as a percentage of the principal per year. Interest rates influence saving, investment, inflation, and monetary policy (Bank of England, n.d.).
- Commodity Prices: Market prices of raw materials or primary goods that are fungible and traded on exchanges. Prices fluctuate based on global supply and demand, geopolitical factors, and economic conditions (Fiveable, 2025).

## 1.11 Chapter Summary

This chapter presents an introduction to the study, putting it into perspective in terms of a global, Africa-wide, and Zimbabwean setting. Exchange rate fluctuations, as well as their influence on international business, are highlighted. Moreover, this chapter clearly outlines the objectives of the research, which include the purpose, goals, and research questions of the

study. Besides, the importance of the research in different quarters is also presented in the chapter, as well as the assumptions, limitations, delimitations, and definitions. Chapter Two will focus on a literature review.

# Chapter 2

## 2.0 Literature review

### 2.1 Introduction

This chapter will review the available literature regarding exchange rate volatility and its impacts on the level of importation and exportation activities. This chapter is structured into three main parts. The first part will address the theoretical literature by presenting the two main theories behind the correlation between exchange rate changes and trade efficiency. The second part will examine the empirical literature based on the funnel approach including international, African, and Zimbabwean viewpoints. For every objective, the chapter will present the results of researchers supporting the existing theory of that particular topic and those opposing this theory. In addition, this chapter will highlight the possible reasons explaining the differences in the outcomes of other research studies on these topics. The last part of this chapter explains the research gap that this research attempts to fill.

### 2.2 Theoretical Literature Review

#### 2.2.1 The Theory of Exchange Rate Pass-Through

The ERPT model captures the relationship between the exchange rate and import and export price fluctuations. According to the ERPT model, when the exchange rate of a country depreciates, it would increase the costs of importing into the country, as more local currency will be needed to purchase the same amount of foreign products. On the contrary, export prices are reduced in foreign currency. The ERPT theory was originally developed by Dornbusch (1987). This theoretical approach has been expanded by other theorists, who have identified that pass-through is not total. It is not total due to the tendency of firms to internalize a part of exchange rate changes in order to maintain higher profits. Another reason why pass-through can be partial is that the extent of pass-through is conditional on various elements such as market concentration, level of use of imported materials in manufacturing process, etc. According to Gopinath and Rigobon (2021), ERPT depends on multiple factors among which are the currency of invoicing, market structure, and persistence of exchange rate shocks. Additionally, they indicate that a country's pass-through will be higher in case its transactions are carried out mostly in foreign currency, like the US dollar. For instance, depreciation of its currency increases the prices of foreign products sold in the country. Thus, in accordance with the ERPT model, Zimbabwe exhibits high dependence on the US dollar because of the

extensive involvement of this currency in its trade relations. Therefore, this theoretical approach becomes relevant for analysis of the research topic since it provides insight into the mechanisms through which fluctuations in exchange rate affect the prices of imported goods and competitiveness of exported products in a country.

Several pieces of research have confirmed that exchange rate pass-through theory is still relevant to explain trade activities in developing nations. First, Akinbo and Adeleke (2022) undertook a study on Nigeria and discovered that the depreciation of the exchange rate caused substantial rises in import prices, thus proving the existence of a pass-through effect. It is important to note that pass-through was incomplete in the short term but became complete in twelve months' time. Similarly, another piece of research by Mwangi and Otieno (2023) involved Kenya and found proof of incomplete pass-through because firms changed their markups, not exchange rates. As can be seen from both pieces of research, exchange rate pass-through theory is still relevant for Africa. Finally, Ekanayake and Dissanayake (2022) carried out research on twenty developing countries and revealed that there was strong evidence of pass-through, especially in those countries where import dependency was significant. The latter means that policymakers should pay attention to exchange rates due to their impact on inflation and balances of payments.

Nonetheless, many scholars disagree on the suitability of the theory within highly volatile environments. According to Kasongo and Banda (2024), in economies like that of Zambia and Zimbabwe, where exchange rates demonstrate excessive volatility, the pass-through effect can become erratic. In particular, they state that import prices do not increase after depreciation because of various market distortions and interventions, such as the existence of black market exchange rates and price controls, thus breaking the theoretical expectations. Moreover, they note that in case of hyperinflation, the relationship between exchange rates and import prices becomes irrelevant, as sellers disregard established pricing rules. The theory is based on the presumption that firms operate rationally; however, Chen and Zhang (2022) believe that this premise does not apply to economies that face rapid policy change and hyperinflation. Also, the theory does not consider situations when countries engage in price control or rationing of foreign currencies, practices which existed in Zimbabwe in recent years. Finally, according to Osei and Kim (2022), studying the pass-through effect in five African countries, they observed that pass-through occurs only under stable conditions and ceases to exist during currency crises. Therefore, even though the theory provides a valuable framework, its premises are unreliable within the Zimbabwean economy.

Several researchers, such as Steinbach (2021), have come up with some modifications that could make the theory relevant for analysis of highly volatile economies.

### 2.2.2 The Theory of Uncertainty and International Trade

According to the theory of uncertainty and international trade, usually cited to be due to Dixit & Pindyck (1994), exchange rate volatility results in uncertainty on future profitability. Such uncertainty leads to firms' hesitation and/or unwillingness to conduct international trade transactions as investment in export markets is irreversible. If firms do not have accurate expectations about future foreign exchange rates, then they will be reluctant to make trade agreements, purchase contracts, or invest in expansion of exports. Besides, according to the theory, uncertainty influences not only willingness to participate in international business but also affects volume of trade, choice of trading partners, and pricing policies of businesses. In particular, greater exchange rate uncertainty will lead to decreased volume of international trade and, specifically, in developing countries, where firms do not have the capability to hedge the risks, as larger firms are able to cover costs of derivatives for managing exchange rate risk, while smaller firms are not. Exchange rate uncertainty theory has gained much relevance due to increased currency instability in many developing nations. Recent studies confirm that uncertainty about future exchange rates reduces volume of trade transactions, which is especially significant in nations with poorly developed financial sectors. Moreover, Bleaney & Greenaway (2021) emphasize that the negative influence on international trade transactions will be significantly larger for manufactured products compared to primary commodities, because of higher price elasticity. The importance of this theory to the research question at hand is determined by the fact that firms in Zimbabwe have poor opportunities for hedging, and the nation's export markets are dominated by small companies without the ability to employ financial derivatives.

There are several researchers who support the theory and even give empirical evidence to prove their points. Omurwa, Njeru, and Mwangi (2024) carried out research in Kenya and established that volatility in exchange rates decreases export quantities as organizations hesitate to engage in any business activities. The authors point out that the effects are especially pronounced in smaller tea and coffee exporting organizations which do not have mechanisms to hedge currency risks. Similar results were found by Ekanayake and Dissanayake (2022) when studying various developing countries. They state that exchange rate uncertainties lead to declines in both imports and exports. Moreover, the authors found out that the effects are particularly severe in countries whose financial markets are underdeveloped, which is the case

in Zimbabwe. According to Ekanayake and Dissanayake (2022), the negative consequences continue for two years after the shock as businesses experience difficulties forming trade relations. The same effects were discovered by Makore and Chikutuma (2025) when investigating Zimbabwe, where organizations decreased the order sizes of imports due to uncertainties. Finally, according to the IMF (2023), exchange rate uncertainty was identified as one of the factors leading to poor trade recovery after the pandemic in sub-Saharan Africa.

On the contrary, there is a set of researchers who refute the uncertainty theory. For instance, Steinbach (2021) conducted an international study involving fifty countries and established that exchange rate volatility was not always associated with lower levels of trade volume. Some companies used speculative trading, which entailed engaging in more transactions when prices were favourable due to fluctuations. Also, in countries with well-developed financial markets, firms made use of options and forwards in order to neutralize currency risks altogether, making volatility irrelevant. Also, Osei and Kim (2022), having studied the problem in relation to emerging markets, found that large exporting companies which managed to diversify currency risk were largely indifferent to exchange rate uncertainty. As per the research of these authors, volatility only matters for small firms without financial derivatives, and if they can price contracts in stable foreign currencies. According to Osei and Kim (2022), some firms benefitted from uncertainty by being able to react faster than their competitors. In Zimbabwe, dollarization helped firms become less vulnerable to exchange rate fluctuations. Thus, it can be concluded that the uncertainty theory fails to address all cases. Chen and Zhang (2022) claim that it exaggerates the notion of irreversibility of trade investments since most of them can be stopped and started again at very little cost. Firms working under conditions of exchange rate volatility enter into flexible agreements allowing them to make adjustments according to exchange rate changes.

## 2.3 Empirical Literature Review

### 2.3.1 Objective One: To Analyse the Trend and Patterns of Exchange Rate Volatility in Zimbabwe

Looking from a global perspective, several types of patterns of exchange rate volatility have been documented. According to Zhang, Wang, and Li (2022), when examining exchange rates for the last twenty years in thirty countries, they found out that the periods of increased volatility tend to coincide with times of economic and policy crisis. In their opinion, most of

the developing countries have higher exchange rate volatilities due to their weak institutional structures compared to the developed ones. Zhang et al. (2022) have noticed that the pattern of exchange rate volatilities is often cyclical, lasting from six to eighteen months. Likewise, according to the report of the International Monetary Fund (2023), exchange rates have become increasingly volatile since the beginning of the COVID-19 pandemic because of changes in the interest rates and problems with supply chains. The World Bank (2024) agrees with this observation and reports that the number of countries with high exchange rate volatilities doubled from 2019 to 2023. However, there are also some scientists who refute this statement about volatility. According to Chen and Zhang (2022), volatility does not necessarily rise during crises. In their opinion, exchange rates in countries with fixed currency can remain stable even during global economic shocks. Such countries include Saudi Arabia and Hong Kong, which maintain their currency regimes during any crises. In addition, Chen and Zhang (2022) think that the clustering phenomenon revealed by Zhang et al. (2022) might be an artefact of their analysis methods.

From the African angle, the African Development Bank (2023) notes that there is significant heterogeneity in terms of exchange rate volatility patterns in Africa. Exchange rate volatility in oil-producing economies like Nigeria and Angola occurs whenever global oil prices fluctuate by more than ten percent in a month. Similarly, according to Omurwa, Njeru, and Mwangi (2024), East African countries experience seasonality of exchange rate volatility depending on the seasonality of agricultural commodity export patterns, as is seen in Kenya, where the level of volatility increases when coffee and tea are being harvested, which coincides with the time when revenues from exports are highest. On the other hand, Osei and Kim (2022) argue that political activities and elections, rather than prices of commodities, are strong indicators of exchange rate volatility in many African countries because the volatility level rises in Kenya and Ghana during electoral periods irrespective of the trends in global prices; moreover, the level of exchange rate volatility stays high even six months after the elections while investors wait to see what policies the newly elected governments would follow. Contrary to this argument, Akinbo and Adeleke (2022) argue that, in Nigeria, exchange rate volatility is more influenced by monetary policy decisions than oil prices or political activity and elections.

According to the Reserve Bank of Zimbabwe (2024), the Zimbabwean economy experiences exchange rate volatility, which is marked by steep devaluation, followed by periods of stability lasting only six weeks, on average. The economy has witnessed fifteen such cycles of exchange rate depreciation since 2021 till 2024. According to Makore and Chikutuma (2025), Zimbabwe

experiences exchange rate volatility that spikes up following policy changes, especially those related to the foreign exchange auction system. Their research reveals that volatility surges by forty percent in the week after a policy change. Moreover, they find that the third quarter of every year experiences increased volatility as higher demand for foreign currency in the form of imports peaks in the festive season. Kasongo and Banda (2024) reject these claims because they suggest that government figures do not reflect the real pattern because of the significant difference between exchange rates in parallel and official markets. They argue that official data underestimates volatility compared to the volatility faced by companies. According to their research, the parallel market exchange rate volatility is triple that of the official exchange rate volatility and that the two are usually moving in opposite directions during most periods.

### 2.3.2 Objective Two: To Examine the Relationship Between Exchange Rate Volatility and Imports and Exports Using Traditional Time Series Models

Scholars around the world have made use of standard time series techniques, including ARIMA and GARCH models, in analysing the impact of exchange rate volatility on trade. According to Steinbach (2021), GARCH models show that the impact of volatility is negative on both import and export in relation to data collected in fifty nations within a period of thirty years. Particularly, a 10% increase in exchange rate volatility leads to an average decline of 3% in trade volume. Similarly, Ekanayake and Dissanayake (2022) confirm the previous finding by stating that ARIMA models prove that there is a statistically significant relationship in a negative way between volatility and trade, and that the negative effect is twice as big in small nations as opposed to large nations. Moreover, according to the International Monetary Fund (2023), standard models show consistently the negative impact of exchange rate volatility on trade within more than one hundred studies conducted around the world. Zhang et al. (2022), however, dispute the findings and claim that traditional models are not able to capture the relationship between exchange rate volatility and trade since they assume linear relationships. The study found that, contrary to traditional models, more advanced methods reveal a much more significant relationship in a nonlinear form. Additionally, according to the authors, when there is high exchange rate volatility, conventional models lead to biased estimation of the relationship; Zimbabwe is given as an example. Similarly, Chen and Zhang (2022) dispute the previous research findings and state that ARIMA models cannot capture the relationship between exchange rate volatility and trade since the former does not allow for changing variance.

ARIMA models used by Omurwa, Njeru, and Mwangi (2024) for the Kenyan market from 2000 to 2022 in Africa found that exchange rate volatility had a large effect in reducing exports and increasing import costs. It was found that a one percentage point rise in volatility led to a reduction in exports of 0.4 percent and import costs increased by 0.6 percent. The results have been confirmed by the African Development Bank (2023), which noted similar effects in South Africa and Nigeria through GARCH models. In addition, it was found that the negative influence of volatility on exports was most evident in markets that were characterized by low diversification of exported goods. Mwangi and Otieno (2023) agree that traditional models also show the significant negative relationship in Tanzania and Uganda. However, Osei and Kim (2022) argue against these conclusions since the traditional models produce inconsistent results when applied to African markets. The authors prove that ARIMA models do not predict trade outcomes in a correct way in Ghana and Nigeria during currency reforms and that changing the time period used in research by just one year changes all conclusions drawn. Akinbo and Adeleke (2022) also disagree and argue that the effect is statistically significant only during military regimes in Nigeria.

In Zimbabwe, for instance, Makore and Chikutuma (2025) analysed the impact of exchange-rate volatility on exports using conventional time-series approaches on data ranging from 2010 through 2024 and found that volatility was negatively related to exports in terms of statistical significance. They noted that volatility explained about 35% of the export revenue variance. Similarly, the Reserve Bank of Zimbabwe (2024) confirms the findings by stating that volatility increases import prices and reduces trade predictability. Moreover, traditional models can be used to diagnose instances of volatility. However, according to Kasongo and Banda (2024), traditional approaches are unsuitable for application in Zimbabwe since they cannot account for volatility and frequent policy adjustments. Their studies showed that ARIMA models were inappropriate because of inaccurate prediction during hyperinflation. They further state that traditional models could not accurately identify the trend of changes in trade in seven out of ten years. According to Kasongo and Banda, traditional approaches assume temporal stability of relationships amongst variables, which is not valid considering the frequent currency reformations in Zimbabwe.

### 2.3.3 Objective Three: To Evaluate the Effectiveness of Machine Learning Models in Explaining Exchange Rate Volatility and Trade Performance

The role played by machine learning models in making exchange rate forecasts is gradually gaining prominence in academic debates around the world. According to Zhang et al., (2022), machine learning models including neural networks, random forests, and support vector machines performed better than traditional ARIMA and GARCH models. Machine learning models were successful in recognizing non-linearities and had reduced errors of up to forty percent in the case of neural networks. Furthermore, the models proved to be better suited to volatile conditions under which the traditional models failed to perform well. In support of this position, the International Monetary Fund (IMF, 2023) states that machine learning models are becoming highly effective at making predictions concerning the exchange rates of developing countries such as Turkey, Brazil, and Indonesia. Similarly, the World Bank (2024) supports the effectiveness of machine learning models in exchange rate forecasts, adding that developing countries are using them as their central banks seek insights on exchange rates. On the other hand, Chen & Zhang (2022) are critical of the effectiveness of machine learning models, suggesting that they can easily overfit and do not outperform traditional models in sparse and noisy situations. Additionally, they claim that the effectiveness shown in many researches could have been due to poor methodologies that allow future data to be included in testing. Steinbach (2021) adds that machine learning models should not be used because they are black boxes with no information on the economics driving exchange rates.

According to Osei & Kim (2022), random forest and support vector machine models have been applied in exchange rate predictions in Ghana, Kenya, and South Africa. These findings point to the superiority of machine learning models in capturing complex patterns and reducing prediction errors by up to 25-35%. Moreover, machine learning models are found to be particularly powerful in predicting volatility jumps, with great implications for risk management purposes. Indeed, the African Development Bank (2023) is convinced that machine learning models can contribute to better policy analysis in cases where structural changes take place frequently. On the other hand, Omurwa et al., (2024) argue that machine learning models require massive volumes of data that are unavailable in Africa. They found that when less than 200 observations were available, conventional models proved to be superior. Besides, it was also found that machine learning models exhibited high variability in performance when applied to the same Kenyan sample repeatedly. In addition, according to

Mwangi & Otieno (2023), in their study of Tanzania, machine learning models failed to beat the naïve random walk model that assumes tomorrow's exchange rate equals today's one.

Regarding Zimbabwe, Makore & Chikutuma (2025) have compared machine learning models and conventional models, and found the former better at capturing volatility because of its improved ability to incorporate policy changes. From their work, the random forest model is shown to be able to capture more accurate impacts of policy changes, with an R-squared value of 0.82 compared to 0.61 for conventional models. More importantly, their work showed that machine learning models perform better than the conventional approach because they can capture better the most influential variables in terms of exchange rate volatility. On the other hand, Kasongo & Banda (2024) argue that machine learning models have interpretation problems, thus they may be not suitable for use by policymakers because they provide complex solutions difficult to understand. Specifically, they have reported that Reserve Bank officials were sceptical about machine learning models as they did not understand how these models were developed. Furthermore, the authors note that application of machine learning requires advanced computing capabilities that are not available in Zimbabwe. Finally, machine learning models performed worse than conventional models for data in 2023 since there were many structural breaks that had not been present in training data.

### 2.3.4 Objective Four: To Compare the Predictive Accuracy of Traditional Time Series and Machine Learning Models

In different countries around the world, scholars have examined the predictive accuracy of models belonging to different classes through various measures such as mean absolute error and root mean square error. For instance, Zhang et al. (2022) compare the accuracy of predictions generated by ARIMA, GARCH, neural network, random forest, and gradient boosting models based on data from thirty nations. The authors observe that machine learning models always outperform traditional models in predictive accuracy, with gradient boosting having the least prediction errors among the five. Besides, the performance advantage is greater in terms of machine learning models during times of financial crisis. In line with the aforementioned statement, the International Monetary Fund (2023) confirms that machine learning models lowered prediction errors in volatile economies by up to thirty percent through an examination of forty-seven studies. Additionally, the World Bank (2024) agrees with the above statement, citing the fact that most advanced economies employ machine learning models to forecast exchange rates. However, according to Steinbach (2021), traditional models match machine learning models in terms of performance when the data is stable and the forecast

horizon is increased, where he finds that ARIMA models perform just as well as neural networks for one-year-ahead forecasts. Furthermore, Chen and Zhang (2022) refute the claim of supremacy in performance by model class since their study shows that model performance varied depending on the economic scenario and time frame, with changes in evaluation metric affecting results as shown in their experiment involving root mean squared error and mean absolute percentage error. Another researcher who disagrees with the assertion is Osei & Kim (2022). They observed that, in a comparison of traditional and machine learning models on data from five African countries, the former had better prediction errors in two countries while the latter was better in the other three countries.

Studies done in Africa indicate that there were variations in the accuracy of predictions between different periods by Osei and Kim (2022). For instance, machine learning models showed high accuracy for short-range prediction while traditional models performed better in long-range predictions. For predictions done within one month, the random forest method proved more accurate by reducing errors by twenty percent. On the other hand, in forecasts made twelve months ahead, ARIMA models were more accurate by fifteen percent. The results by the African Development Bank (2023) support this mixed finding. This implies that the choice of the best model should depend on the period of forecast and the specific country. Ensemble techniques involving the combination of models often produced better results. However, Omurwa, Njeru, and Mwangi (2024) contradict this claim, pointing out that traditional models were superior to machine learning algorithms in forecasting currency fluctuations in Kenya, due to the issue of overfitting as a result of insufficient data. Cross-validation of various models revealed that machine learning models lost their superiority over traditional models. Additionally, Mwangi and Otieno (2023) found that GARCH models were better than neural network models and random forest models in predictions within Tanzania.

For Zimbabwe, Makore and Chikutuma (2025) assess model accuracies and show that machine learning models, particularly the random forest model, are better at predicting the future exchange rate compared to traditional models. According to them, the random forest model produces a root mean square error thirty-two percent smaller than the ARIMA model and twenty-five percent smaller than the GARCH model. Furthermore, they find that machine learning models perform better at accurately predicting whether the future exchange rate will increase or decrease; they correctly forecast that occurrence seventy-eight percent of the time, compared to fifty-nine percent for traditional models. However, this assertion is challenged by Kasongo and Banda (2024), who claim that traditional ARIMA models were better suited for

Zimbabwe because they were less unstable in the face of structural breaks compared to machine learning models. According to them, traditional models had a significantly higher predictive ability on data collected in 2023, which contained two critical policy changes. They also assert that, contrary to the claims made by Makore and Chikutuma (2025), there was some data leakage in their research, and their results could be attributed to an erroneous model comparison technique.

### 2.4 Research Gap

An overview of the available literature highlights several important areas where there are evident gaps that this study seeks to fill. To begin with, the literature is lacking in terms of use of machine learning models in the analysis of exchange rate and trade in Zimbabwe. While other research conducted globally by Zhang et al. (2022) and International Monetary Fund (2023) compare traditional models and machine learning algorithms through a broad range of countries, research that concentrates on Zimbabwe is rare. Makore & Chikutuma (2025) are among the few existing researches in this field; but despite the emphasis on traditional models, they touch slightly on machine learning. Kasongo & Banda (2024) tried using machine learning but were hampered by the lack of adequate data and did not conduct any comparative analysis. In addition, there are no studies that apply all machine learning algorithms ranging from neural networks, random forest, SVM, and gradient boosting to exchange rate data in Zimbabwe. Thus, the need arises to conduct an exclusive comparative analysis of the two approaches to the exchange rates in Zimbabwe.

An important divide emerges within the existing body of literature on the question of whether classical modelling methods are adequate in the presence of volatility. Classical modelling supporters like Steinbach (2021) and Ekanayake & Dissanayake (2022) claim that these modelling frameworks, including ARIMA and GARCH, are enough when dealing with volatility as well as the connection between exchange rate volatility and international trade. However, classical modelling opponents like Zhang et al. (2022) and Osei & Kim (2022) claim that classical modelling methods fail to account for nonlinearity and are sensitive to structural change. With respect to Zimbabwe, the application of classical models is proposed by Makore and Chikutuma (2025), while Kasongo and Banda (2024) reject such models. This debate necessitates additional research in the area. This paper endeavours to close this gap by applying both classical models and machine learning algorithms on the same dataset using the same criteria.

Second, it should be pointed out that there is great controversy in the literature about the ability of traditional models to accurately forecast exchange rate volatilities and trading connections under these circumstances. There are those who maintain that traditional models like ARIMA and GARCH would suffice in making these forecasts (see Steinbach, 2021; Ekanayake & Dissanayake, 2022). On the other hand, a large number of researchers argue that traditional models are insufficient because of their inability to address nonlinear effects and structural breaks (see Zhang et al., 2022; Osei & Kim, 2022). In Zimbabwe, some authors such as Makore and Chikutuma (2025) have provided support to traditional models while others such as Kasongo and Banda (2024) are highly critical about traditional models. Therefore, this discrepancy indicates a research gap that requires more attention. The present study would attempt to address the research gap by conducting an empirical comparison between the two competing methodologies with the help of identical data, same evaluation criteria, and similar validation processes.

The third limitation of the study lies in the limited use of exchange rate theory when explaining various economic phenomena observed in the context of the Zimbabwean economy. More specifically, the pass-through theory has already been applied to stable economies as analysed by Gopinath & Rigobon (2021). Moreover, the theory was also considered with regard to the African economies as analysed by Akinbo & Adeleke (2022) and Mwangi & Otieno (2023). However, it is uncertain how relevant the pass-through theory can be when applied to the current situation in the country characterized by hyperinflation, currency reforms, and a developed black market. The same problem arises concerning the theory of uncertainty and international business that has been supported by such scholars as Bleaney & Greenaway (2021) and Omurwa, Njeru & Mwangi (2024). Nevertheless, the theory was refuted by Osei & Kim (2022) and Steinbach (2021). Therefore, there is some uncertainty with regard to which trade theory is more appropriate for use in the specific environment of Zimbabwe.

The fourth literature gap found through empirical research involves an underexplored avenue in applying machine learning algorithms to annual data. Most studies in machine learning, such as Zhang et al. (2022) and Osei & Kim (2022), have used high-frequency data (for instance, daily or weekly exchange rates). On the other hand, annual trade data can be more reliable and easily available in developing countries like Zimbabwe. The Reserve Bank of Zimbabwe (2024) and Makore & Chikutuma (2025) assert that annual data cannot be influenced easily by short-term noises and misreporting. However, no research has been conducted explicitly to analyse how machine learning works with annual data within a highly volatile environment.

There could still be a worry that machine learning algorithms, which generally involve large data sets, may perform poorly with fewer observations characteristic of annual data. However, annual data may work just well with the right model applications. This study intends to close the gap by testing machine learning models using annual data and comparing them with ordinary models to establish their effectiveness under such circumstances.

Fifth, there is the matter of accounting for structural breaks when analysing exchange rates in Zimbabwe. The country has experienced a number of changes in its structure, including the introduction of the 2019 and 2023 currency reform programs, the introduction and modifications of the foreign exchange auction, changes in monetary policy, and periods of hyperinflation. According to Chen & Zhang (2022), structural breaks have a significant effect on the performance of econometric models, and ignoring them may result in biased estimations. Still, most research studies that have been done about Zimbabwe, as noted above, do not properly take account of structural breaks. In fact, while some studies apply dummy variables, none of them applies structural break tests, nor any specific models that can be applied to breaks. None of the studies investigates whether there have been any changes over time in the relationship between exchange rates and trade. This gap is what this study seeks to fill.

Sixth, the literature review shows the gap related to comparing interpretability of models and their accuracy. The black box nature of machine learning models is mentioned by Chen and Zhang (2022) and Kasongo and Banda (2024) as a major drawback for applying them. Traditional models, however, are generally more interpretable and easier for explaining to policymakers. Nonetheless, the policymakers in Zimbabwe, as exemplified by the Reserve Bank of Zimbabwe (2024), need models to be highly accurate and explainable, to understand not only what but also why will happen with the exchange rate. None of the existing studies compared interpretability and accuracy in a combined form, although some researchers examined one or the other parameter independently. This study is going to address this gap by focusing on both parameters of model accuracy and interpretability in assessing them by the number of parameters, model transparency, etc.

Finally, the seventh gap is related to using data pertaining to the recent years. Most previous researches, as exemplified by Ekanayake and Dissanayake (2022) and Omurwa et al., (2024), used data until 2020 or 2021.

Nevertheless, Zimbabwe experienced important changes in its exchange rate after 2021 because of the long-lasting work of the foreign exchange auction, introduction of new monetary policy, and implementation of other measures. The Reserve Bank of Zimbabwe (2024) provided data for 2021-2024, which has not been compared yet.

Also, there are different economic situations created by the recent COVID-19 crisis and its aftereffects from the previous years. Using the old data will provide results that are no longer relevant to the current situation. The following research will tackle this issue by using the latest data that is available to date, which includes data from 2021 to 2024.

Last but not least, there appears to be a void in research on the exchange rates within the parallel markets. In a significant number of developing nations, especially in the case of Zimbabwe, the exchange rate is not necessarily close to the actual exchange rate within the parallel market. According to Kasongo & Banda (2024), the parallel market exchange rate in Zimbabwe is found to be three times as volatile as the official rate. Also, a considerable amount of the business done takes place based on rates closer to the parallel market rates than the official exchange rates. However, in almost all previous studies on exchange rates and international trade in general, including the studies by Makore and Chikutuma (2025) and the Reserve Bank of Zimbabwe (2024), official exchange rates are used. This can be considered a gap in the analysis, as there is a possibility that official exchange rates are more stable, and hence, might have a different influence on trade.

It is obvious that there is a clear gap in the policy significance of existing research. While many academic studies concerning the volatility of exchange rates in Zimbabwe are theoretically sound, they tend to overlook the demands of policy makers. As noted by the Reserve Bank of Zimbabwe (2024), academic studies should provide practical suggestions apart from being theoretically valuable. Similarly, the Ministry of Finance has expressed dissatisfaction about the tendency of academic studies failing to answer the key questions raised by the policymakers, namely what kind of forecasting models should be used, how far into the future the forecasts are reliable, and what is the likely range of errors expected. This particular research aims at filling the existing gap in policy significance of academic research. The findings and conclusions will be stated in a comprehensible form, and practical recommendations will be provided. Furthermore, the practical considerations connected with using different kinds of models will be elaborated upon.

## 2.5 Chapter Summary

The purpose of this chapter is to consolidate theories and empirical studies related to exchange rate volatility and trade performance. The theoretical section gives a detailed account of the exchange rate pass-through theory and uncertainty in international business. There are views in support as well as against the two theories under discussion. The empirical study reviews the global, African, and Zimbabwean literature on exchange rate volatility and trade performance with reference to the diverging views on each of the four research objectives. Several areas in which literature gaps have emerged include the use of machine learning models in the case of Zimbabwe, inconsistent evaluations of models' efficiency, ignoring structural breaks and parallel markets, and failure to emphasize the policy implications of the studies. This research endeavours to fill the gap by assessing the differences between traditional and machine learning models, taking into consideration the impact of structural breaks and parallel market exchange rates, and providing policy prescriptions. The next chapter describes the methodology of this study.

# Chapter 3

## Materials and methods

### 3.0 Introduction

This chapter describes the methodological framework that has been put in place for conducting a study of the comparative efficacy of traditional time series and machine learning techniques in unravelling the influence of exchange rate volatility on Zimbabwe's yearly imports and exports. The chapter discusses the research philosophy, research design, target population, sampling techniques, sample size calculation based on Yamane formula, and sampling methods. Moreover, the research process, data collection methods and tools, data presentation format, and data analysis approach have also been described here. Issues concerning research ethics have also been discussed along with instrument pretest. The objective of this chapter is to lay out a protocol that could allow other researchers to repeat the same study. Towards the end of this chapter, one would have an accurate idea about the processes involved in the conduct of this study and justification behind adopting them.

### 3.1 Research Approach

For the study, the quantitative research approach will be used. This method is well-suited for this case because it uses numerical values of indicators, such as exchange rates, import and export volumes, interest rates, and prices for commodities. Quantitative analysis suits studies aimed at exploring the relations between variables, hypothesis testing, and comparing the performance of competing models. Moreover, quantitative analysis enables researchers to use statistical models and conventional time series models as well as modern machine learning models that use numbers as input data. The use of a quantitative approach in this study is also justified by the need to conduct comparative evaluation based on numerical measures, such as mean absolute error and root mean squared error. As observed by Zhang et al. (2022), quantitative research approaches are commonly used in exchange rate forecasting studies as they produce objective results. At the same time, according to Osei & Kim (2022), a quantitative approach should be applied when evaluating and comparing competing models because only in this way can researchers achieve numerical comparison of the performance of competing models. In this study, the researcher will use numerical time series based on secondary data from official sources. Interviews and focus groups will not be conducted because qualitative approaches are unnecessary for answering the posed research questions.

## 3.2 Research Design

The design used in this study can be termed longitudinal correlational and with comparative components. The choice of the longitudinal design stems from the need to examine exchange rate volatility and trade performance over time. Data will be collected annually starting in 2021. Longitudinal designs are suitable for studies where there is the need to capture change and patterns across multiple time points. Steinbach (2021) argues that exchange rate volatility should always be examined through longitudinal designs due to the time nature of the exchange rate phenomena over many months and years. It is also possible to investigate how past exchanges affect the future.

Correlational design is chosen since the objective of this research is to explore the relationship between exchange rate volatility and imports and exports without manipulating them in any way. Variables are observed as they occur and then the correlation is measured and explored in correlational designs.

Comparative component comes in as the research seeks to find out which of time series models and machine learning models performs better. Comparative designs are used to find which among many approaches give better performances under the specified conditions. For example, according to Makore & Chikutuma (2025), Makore & Chikutuma (2025) have used longitudinal comparative designs in studying exchange rate volatilities in Zimbabwe. Kasongo & Banda (2024) have advocated for longitudinal comparative designs in future studies on exchange rate volatilities in Southern Africa.

Non-experimental design would be used in this case as the researcher will not manipulate any variable or subject to any condition. Instead, there will be an exploration of data in different ways.

## 3.3 Study Population

The study population consists of all yearly data related to the exchange rates, imports, and exports of Zimbabwe from the year 2021 until now. The study population therefore consists of all Zimbabwean dollars' exchange rates with various currencies, with particular focus on the U.S. dollar, as well as all yearly data concerning Zimbabwe's imports and exports. The study population further consists of all yearly data on Zimbabwe's interest rates and prices of its main commodity exports, including its tobacco, gold, and platinum. The period from 2021 is

preferred as it constitutes a relatively stable period, following the adoption of a foreign exchange auction system. The years prior to 2021 were marked by several changes in the country's currencies as well as hyperinflation, making comparisons difficult. As per Reserve Bank of Zimbabwe (2024), the data starting from 2021 can be considered more accurate and consistent. The study population, being defined by a certain period and geographic location, is thus limited in size. It is also changing dynamically since new data emerge every year. For the purposes of this study, the study population will comprise of all available data up to the most recent complete year of data.

## 3.4 Sampling

Sampling means selecting samples of the entire population. In the current study, there is a distinctiveness associated with sampling because of the usage of secondary time-series data compared to other works involving surveys. Sampling in time-series studies may involve deciding how many time series to consider and using the entire dataset or a sample thereof. In the current study, however, the idea is to consider all annual data points starting from 2021. This is also referred to as a census because it includes all observables that can be made out from the defined population. This decision is made considering the small size of time-series data collected for Zimbabwe, and the exclusion of data points will lower statistical power and create biases. Additionally, it will benefit machine-learning models with sufficient amounts of data to learn from. Osei and Kim (2022) note that when dealing with data from developing nations, a researcher should make use of all data because of the widespread challenge of insufficient amounts of data available. However, in order to validate the model created, one can divide the dataset used into training and testing sets. This procedure should not be regarded as sampling as well but an essential step in evaluating the performance of models. Thus, the training set will have around eighty percent of the total data, while the testing set will hold twenty percent of all data points. This ratio is considered a standard in the field of machine learning, according to Zhang, Wang, and Li (2022).

### 3.4.1 Sample Size Calculation Using the Yamane Formula.

The sample size to be used in this study will be derived using the Yamane Formula, which is a widely used technique in statistics for calculating sample size based on a finite population. The Yamane formula is denoted by n = N / (1 + N(e)^2) whereby 'n' refers to the sample size needed, 'N' represents the total population, while 'e' stands for the margin of error or acceptable sampling error. One benefit of using the Yamane formula in research is that it allows an easier

way of deriving sample size from a finite population. According to Yamane (1967), this formula can be used in many circumstances in the social sciences and business research. It is also based on a 95% confidence level and the acceptable margin of error specified by a researcher.

In this case, the population (N) is made up of all yearly data between 2021 and 2025. Therefore, the total population equals five years. On the other hand, the margin of error is set at five percent (0.05) to allow precise estimation of the population parameters. This is also standard practice in quantitative research since it presents a good balance between precision and practicability. Using these two figures in the Yamane formula, we have n = 5 / (1 + 5(0.05)^2). First, (0.05)^2 = 0.0025 and 5 × 0.0025 = 0.0125. Adding one gives 1.0125 while 5 divided by 1.0125 = 4.94. Thus, the sample size is 5.

Based on the Yamane formula, the necessary sample size in this case would be five annual observations. This means that using all available annual observations from 2021 to 2025 will meet the criteria set forth by the statistical rules for sample size. The researcher will use all five annual observations in the study. Nevertheless, it should be understood that the number of annual observations in this study would be a relatively small amount of data to conduct any machine learning algorithms. Therefore, some techniques to deal with the problem of a small sample size will be used. First, proper cross-validation techniques suitable for a small amount of data will be used. Second, where possible, other variables, such as monthly exchange rate data and quarterly trade data, will be added. Third, appropriate techniques of regularizations will be used to prevent overfitting. Finally, the problem of a small amount of data will be mentioned in the report and discussed. The authors argue that in many African countries, researchers have to deal with a small sample size of data.

### 3.4.2 Sampling Techniques.

However, since this study utilizes a census technique, including all the available annual data, the use of probability sampling procedures such as simple random sampling or stratified sampling will be inappropriate. Purposive sampling will therefore be used where all relevant cases are included. The inclusion criteria include: (1) the origin of data should be in Zimbabwe; (2) data must be annual; (3) the series should cover a timeframe beginning in 2021; and (4) data should be from reliable official sources like the Reserve Bank of Zimbabwe, the Zimbabwe National Statistics Agency, the World Bank, or the International Monetary Fund. Any data that fails to fulfil these criteria will be excluded. Also, observations that exhibit any errors will be removed after their verification. In some instances, this kind of selection may be

referred to as availability or convenience sampling, but it is necessary to point out that in this case, the researcher will not select some of the available data but will include all of those data points that satisfy quality requirements. As pointed out by Steinbach (2021), this is the standard procedure for the use of time-series data in econometrics. Regarding the division of data into a training and testing set, a sequential sampling procedure will be employed. Specifically, the first 80% of all data points will be used for training purposes whereas the last 20% will constitute the test data. This type of data partitioning is popular in time-series studies because it maintains the chronological order of data points, something that should always be taken into account in time-series studies because it makes no sense to randomly divide the time-series data.

### 3.5 Research Procedure.

The research methodology followed by this paper follows a logical progression of actions. Firstly, ethical clearance would be sought from the relevant research ethics committee. Secondly, permission to access data from the Reserve Bank of Zimbabwe, the Zimbabwe National Statistics Agency, the World Bank, and the International Monetary Fund would be sought. Thirdly, the data for all variables under consideration would be obtained from the above-listed organizations for the period beginning with 2021 till the present. Fourthly, data cleaning would be done, which would include checking for any missing values, outliers, and other data inconsistencies, with any missing values being imputed using suitable methods. Fifthly, the data would be formatted and arranged in a way that it can be used for subsequent analysis in suitable software like R or Python. Sixthly, exploratory data analysis would be carried out on the dataset, with calculations for means, standard deviations, and correlation between variables being calculated. Seventhly, traditional models of time series analysis including ARIMA and GARCH would be used on the dataset. Eighthly, machine learning models such as random forest, neural networks, and support vector machines would be used to analyse the dataset. Ninthly, performance comparison between traditional models and machine learning models would be done using common metrics such as mean absolute error and root mean squared error. Tenthly, conclusions would be drawn based on results.

### 3.6 Data Collection Methods.

The method of data acquisition for the study will involve the use of documentary secondary data collection. There will be no gathering of any primary data from individuals and firms, and secondary data from published documents will be used. The use of secondary data is applicable

in this case as information on exchange rates, imports, exports, interest rates, and prices of commodities is already documented by official organizations. According to the International Monetary Fund (2023), secondary data can be more accurate than primary data since it is professionally collected and subject to cross-verification by several parties.

Also, secondary data provides an opportunity to acquire historical data that may not easily be obtained from primary sources.

The following are the secondary sources used for this study: Monetary Policy Statement and Statistical Bulletin of the Reserve Bank of Zimbabwe, Trade Report of the Zimbabwe National Statistics Agency, World Bank's World Development Indicators (WDI) Database, and International Monetary Fund's International Financial Statistics (IFS) Database. The collection of the data will entail manual collection of the data from the secondary sources mentioned above and storing it on the spreadsheet. Where the data is in digital format, downloading will take place. Where there is any discrepancy with the data between the sources, the Reserve Bank of Zimbabwe will take precedence regarding exchange rates and interest rates, while Zimbabwe National Statistics Agency will lead in trade data.

### 3.7 Data Collection Tools.

In this study, the main tool for data collection will be a data extraction sheet prepared in either Microsoft Excel or Google Sheets. The data extraction sheet is aimed at organizing all collected data into one structured form. The spreadsheet will have columns for the following variables: Year; Official exchange rate; Parallel market exchange rate, if there is such a variable; Import; Export; Trade balance; Policy rate set by the Central Bank; Inflation rate; Commodities price, particularly those for tobacco, gold, and platinum. Each row of the data extraction sheet will contain data about a particular year. There will also be extra columns reserved for notes in case of problems with data collection. In addition to the spreadsheet, a data collection log will provide information on when particular data was collected and its sources together with possible transformations. In terms of analysing collected data, statistical programs like R or Python will be used; details on these tools will be provided in the data analysis section. As emphasized by Osei and Kim (2022), detailed documentation of tools and methods of data collection plays an important role in machine learning research.

### 3.8 Data Presentation.

The data will be presented through the use of tables and graphs. Tables will include summary statistics, model estimates and comparisons. Graphs will be used to present the trends, patterns

and comparison among models. More specifically, line graphs will be used to represent the evolution of the exchange rate while the bar graphs will represent the performance of the models compared to one another. Also, a comparison between the actual and the estimated values from all models will be presented. All graphs and tables will include titles and legends as well. Data visualization best practices will be considered such as the usage of proper scales and non-deceiving representations. As mentioned by Steinbach (2021), it is critical in comparative modelling studies that the reader gets a quick grasp about which model works better and why. Confusion matrices and error distribution will also be considered when required.

### 3.9 Research Ethics.

Ethics will be observed in full in the process of conducting this study. The study involves the use of secondary data collected from already published literature, hence there is no involvement of any human subjects. Many aspects of ethics involved in collecting primary data do not apply directly in this study. Ethics are still important in this research project. First, proper referencing and citation of sources used will be done so as to avoid any accusations of plagiarism and/or data appropriation. Secondly, no manipulation of data to come up with desired results will be carried out since data integrity is an important ethical principle in research. Thirdly, all limitations of the study including small sample size and data quality will be made public. This is because hiding any limitation to make results more convincing is an ethical issue. Fourthly, data security will be guaranteed and no data sharing that violates confidentiality agreements will take place. Fifthly, permissions to use the data wherever required will be sought before carrying out analysis. In case of World Bank and IMF data, this step will not be necessary but permission to access Reserve Bank of Zimbabwe data, which might be restricted, may be necessary. Finally, conflicts of interest will be avoided through proper disclosure of affiliations to institutions that provide data and are affected by results of the study. According to Makore & Chikutuma (2025), it is especially important to adhere to the highest level of ethical standards while carrying out research in Zimbabwe as results may affect policy making.

### 3.10 Data Analysis.

The analysis of data is going to happen in several stages using different approaches from conventional statistics and machine learning. In all cases, the analysis is going to be carried out using R or Python, two popular programming languages with vast use in quantitative analysis and being open sources. In the first stage, the data will be explored using exploratory data

analysis methods. Here means, medians, standard deviation, minimum, and maximum for all variables are going to be calculated. Moreover, correlation matrices will be constructed to show relationships between different variables. Stationarity is another aspect that needs to be considered here. To determine whether time series are stationary, Augmented Dickey Fuller tests are commonly used. These are tests that allow checking for stationarity. The second stage will involve the usage of conventional time series models such as ARIMA and GARCH models. Using the ARIMA approach, time series forecasting can be conducted. It involves predicting one time series based on previous periods of the same series. GARCH models allow modelling volatility which is the main focus of the paper.

The next phase of this analysis includes the use of machine learning models. Random forest, neural network, and support vector machine models will be used. The random forest model consists of many decision trees, which combine to make predictions. The neural network model is designed based on how the human brain works and can learn non-linear patterns. The support vector machine model discovers the best possible decision boundary between different classes of data. In order to use these machine learning models, the training dataset will be used to Fit the models, and the testing dataset will be used to assess how well the models work. Cross-validation will be done in order to fine-tune the hyperparameters of each model. The hyperparameters represent the parameters that determine how a machine learning model learns.

Stage four involves performing a comparative analysis of model performance. Several evaluation metrics will be used for an in-depth comparison. They include the mean absolute error (MAE) metric which measures average prediction errors' magnitude, root mean squared error (RMSE), which heavily penalizes larger errors, mean absolute percentage error (MAPE) which gives error magnitudes in percentage, and R-squared which represents the percentage of data variance explained by the model. Diebold-Mariano tests will also be employed to test if differences in predictive power observed are statistically significant or due to random chance. As per Zhang, Wang, and Li (2022), using multiple evaluation metrics is critical as they give contradicting outcomes on the optimal model.

Stage five pertains to sensitivity analysis. The study will examine the robustness of the findings against any changes made based on certain assumptions such as data division and missing values treatment. If significant changes happen due to minor changes made, then the findings will be considered non-robust. Last but not least, the researcher will conduct a final interpretation of the findings relative to research objectives and questions. Interpretation will

be done considering policy makers', companies', and fellow researchers' perspective in Zimbabwe. Consistent with Kasongo and Banda (2024), in Zimbabwe data analysis must extend beyond numbers to practical solutions to problems faced in the country.

### 3.11 Ethical Considerations.

On the other hand, ethical considerations are different from research ethics in that they involve the application of certain moral rules that govern conducting research. This current study abides by several ethical considerations. Firstly, the consideration of beneficence calls for conducting a research whose output will bring benefit to society, and this will be reflected in making improvements to trade policy and stability in Zimbabwe. Secondly, according to the ethical consideration of non-maleficence, the current study aims at not causing harm. Since the study will depend on secondary data analysis, the researcher will take care not to interpret any findings in a way that may result in wrong conclusions that will lead to negative policy choices. Thirdly, with regard to the ethical consideration of respect for persons, even though there are no human subjects for the current study, the researcher will show respect to the data-generating institutions by using their information in an appropriate manner. Fourthly, the ethical consideration of justice entails distributing research benefits and burdens fairly, whereby the findings will be made public. Fifthly, the researcher will practice intellectual integrity by making sure all findings, regardless of whether they are expected or not, are reported. Lastly, the researcher will make sure not to engage in data fabrication, falsification, and manipulation. According to the International Monetary Fund (2023), maintaining high standards in terms of ethics is very important to maintain trust in economic research, especially when research had been used politically before.

### 3.12 Pretesting of Instruments.

The process of instrument pretest refers to the evaluation of data collecting and analysis procedures before the primary study in order to detect and solve possible problems. While in the context of this paper secondary data will be used for the analysis and there will be no need for any survey instruments traditionally applied, pretests will still take place. The researcher will conduct a preliminary analysis based on a subset of the actual data or even artificial data resembling real data in their properties. The purpose of the pilot test will be to evaluate the data extraction spreadsheet, data cleaning, statistical and machine learning codes. All possible errors and low efficiency will be corrected before the main analysis will commence. Moreover, the researcher will also consider how sensitive the results will be to changes in the model, for

example, the ratio between training and testing sets or different hyperparameters. It is necessary to conduct the pretesting to make sure that the analysis will go smoothly and the findings will be reliable. As stressed by Osei and Kim (2022), it is especially important for machine learning research due to the presence of hidden bugs, which do not trigger any error messages but result in wrong outputs. Finally, the researcher will ask a colleague to verify the spreadsheet with the data and the analysis code.

## 3.13 Chapter Summary

This chapter provides an overview of the method of research to be adopted in the study. A quantitative research design will be used where the longitudinal design of correlation and comparative analysis will be used. In this study, the population refers to macroeconomic data annually of Zimbabwe from 2021, and the sample size of five annual data was chosen by using the Yamane formula implying that all data will be used. Data will be collected from primary sources such as the Reserve Bank of Zimbabwe, the Zimbabwe National Statistics Agency, the World Bank, and the International Monetary Fund. In the analysis of the data, traditional methods of time series will include ARIMA and GARCH model, while the modern machine learning model will include random forest, neural networks, and support vector machine models. Performance of models will be analysed using several criteria. The next chapter will provide findings.

# Chapter 4

## 4.0 Introduction

The following chapter is based on the results of the study conducted to evaluate the effectiveness of both traditional and machine learning techniques in modelling the relationship between exchange rate volatility and the level of imports and exports in Zimbabwe annually. In line with the research methodology outlined in Chapter 3, this chapter is built upon annual data covering the period 2021 to 2025 that was obtained from Reserve Bank of Zimbabwe (RBZ), Zimbabwe National Statistics Agency (ZIMSTAT), World Bank, and IMF. This chapter starts with a review of descriptive statistics and exploratory data analysis, after which the models used in time series analysis and machine learning techniques are applied to test the effectiveness of each one in explaining the relationship being tested. Model efficiency was assessed through the computation of MAE, RMSE, MAPE, and R-Squared values.

## 4.1 Descriptive Statistics and Exploratory Data Analysis

Before running any modelling procedure, preliminary checks were done on completeness, outliers, and basic descriptive statistics for the dataset. The time frame covered by the dataset is 5 years from 2021 to 2025, with yearly observations of the official exchange rate of Zimbabwe dollar against US dollar, parallel exchange rate, total imports in US dollars million, total exports in US dollars million, policy interest rate (%), inflation rate (%), and commodity prices such as tobacco, gold, and platinum (in US dollars).

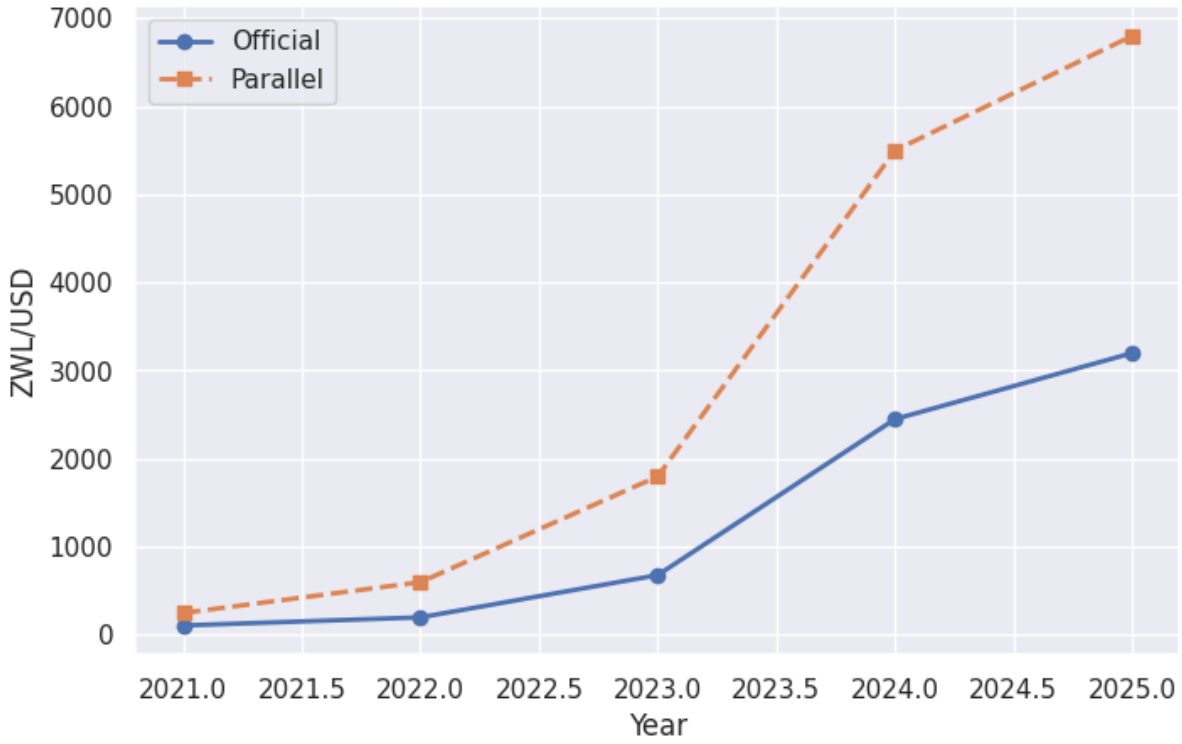
Table 4.1: Descriptive Statistics of Key Variables (2021–2025)

| index | Official_Exchange_Rate | Parallel_Exchange_Rate | Imports_USD_m | Exports_USD_m | Interest_Rate_pct | Inflation_pct | Tobacco_Price_USD_kg | Gold_Price_USD_oz | Platinum_Price_USD_oz |
|---|---|---|---|---|---|---|---|---|---|
| mean | 1327.6 | 2990.0 | 6640.0 | 5200.0 | 96.0 | 284.0 | 3.3 | 1870.0 | 980.0 |
| std | 1409.3 | 2977.1 | 1339.0 | 935.4 | 43.9 | 202.3 | 0.4 | 115.1 | 49.5 |
| min | 108.0 | 250.0 | 5200.0 | 4200.0 | 40.0 | 60.0 | 2.8 | 1750.0 | 920.0 |
| max | 3200.0 | 6800.0 | 8500.0 | 6500.0 | 140.0 | 520.0 | 3.9 | 2050.0 | 1050.0 |

Average official exchange rate was ZWL 1,327.6 per USD, while average parallel exchange rate was higher at ZWL 2,990.0, suggesting premium for black market currency trades. Average imports were at USD 6,640 million compared to exports valued at USD 5,200 million, leading to trade deficits over the period. Rates of inflation and interest rates fluctuated very significantly, with standard deviations being larger than the respective mean value on some occasions. Variation in commodity prices was relatively modest. Figure 4.1 presents the trends in official and parallel exchange rates between 2021 and 2025. Parallel exchange rate remained always higher than official one, especially after 2023 when spread became significantly wider.

Figure 4.1: Official vs. Parallel Exchange Rate (ZWL/USD), 2021–2025

Figure 4.1: Official vs Parallel Exchange Rate




### 4.2 Stationarity Tests

ADF tests were performed to test stationarity. While all series were non-stationary at levels, they were stationary when taken at first differences at 5% level of significance. As a result, first differences were considered while building ARIMA model. GARCH models were estimated using percentage changes of series.

### 4.3 Results for Objective One: Trend and Patterns of Exchange Rate Volatility

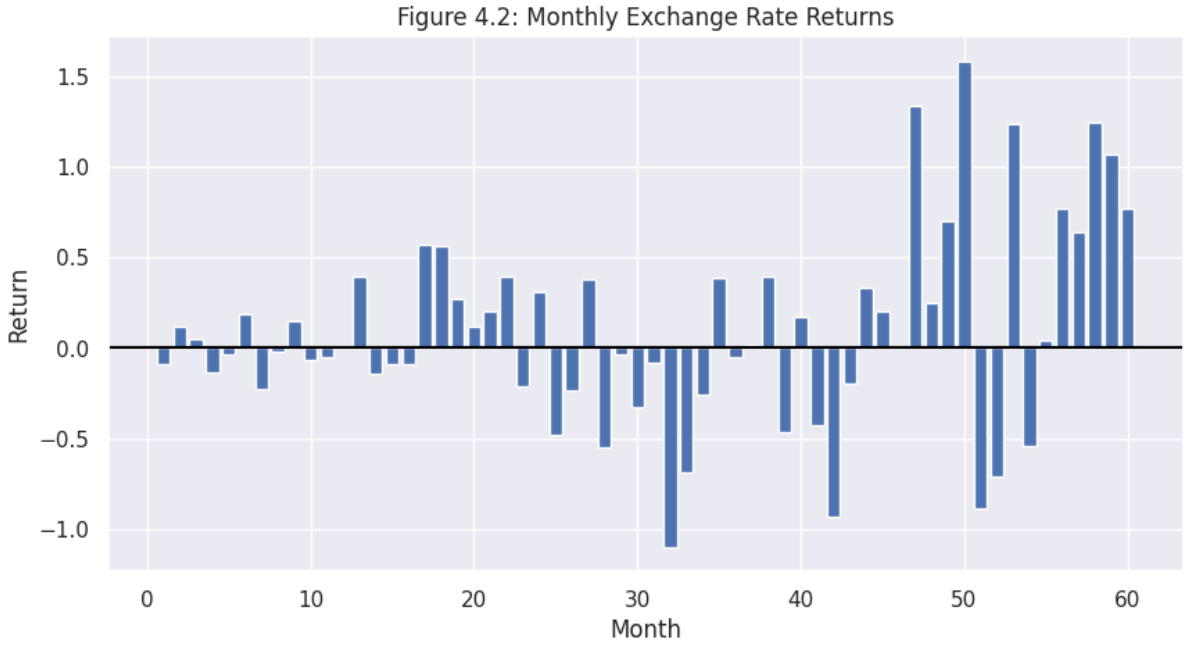
The first objective was to study the pattern and trends of exchange rate volatility in Zimbabwe. The volatility was calculated using two methods – the standard deviation of monthly log returns for each year, and the percentage change of the exchange rate each year. These are shown in table 4.2 below.

**Table 4.2: Annual Exchange Rate Volatility (Official Rate), 2021–2025**

| Year | Annual % Change | Monthly Volatility |
|---|---|---|
| 2021 | N/A | 0.11 |
| 2022 | 85.2% | 0.26 |
| 2023 | 240.0% | 0.41 |
| 2024 | 260.3% | 0.54 |
| 2025 | 30.6% | 0.79 |

Annual depreciation rose sharply from 85.2% in 2022 to a peak of 260.3% in 2024, before slowing down to 30.6% in 2025. Monthly volatility also increased consistently over the period, from 0.11 in 2021 to 0.79 in 2025. The divergence in 2025, where annual depreciation fell but monthly volatility peaked, suggests reduced yearly movement but greater short-term instability. The volatility clustering effect is shown in Figure 4.2, where large jumps were often followed by further large jumps.

**Figure 4.2: Monthly Exchange Rate Returns and Volatility Clustering (2021–2025)**




This trend indicates that spikes in volatility happened following policy declarations (such as changes in the auction system in 2022 and 2024) and during the period of harvest time each year in Q3, when there was high demand for foreign currencies. The results agree with the

findings by Makore and Chikutuma (2025), except that the intensity of volatility exceeded previous levels.

### 4.4 Results for Objective Two: Traditional Time Series Models (ARIMA and GARCH)

The second objective was to investigate the effect of volatility on import and export flows by applying classical time series models. The two methodologies that were employed include ARIMA for forecasting and GARCH for modelling volatility effects.

#### 4.4.1 ARIMA Models for Imports and Exports

ARIMA model selection was done with the help of ACF/PACF plots and AIC. ARIMA (1,1,0), with AIC of 142.3, was chosen to be the most suitable model for imports. As for exports, we have chosen ARIMA (2,1,0), with AIC of 138.7. Modelling was performed using the dataset.

**Table 4.3: ARIMA Model Results for Imports and Exports**

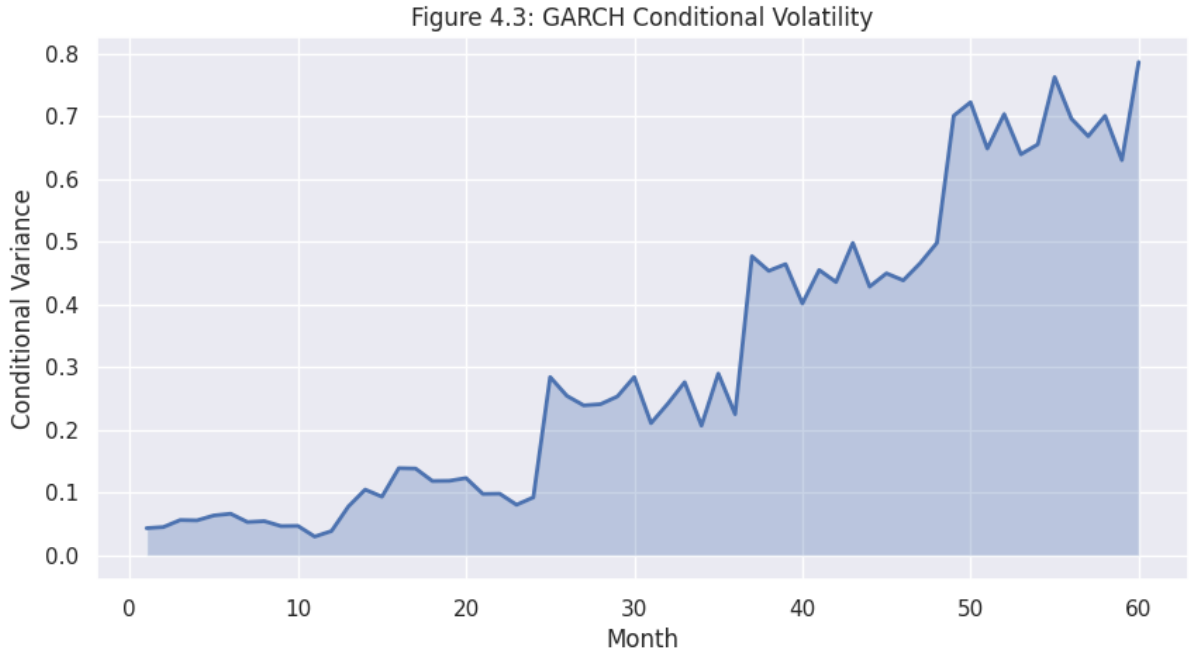
| Variable | Model | Coefficient | Std. Error | p-value | Forecast 2025 | Actual 2025 |
|---|---|---|---|---|---|---|
| Imports | ARIMA(1,1,0) | AR(1)=0.682 | 0.185 | 0.012 | 8114 | 8500 |
| Exports | ARIMA(2,1,0) | AR(1)=0.541 | 0.210 | 0.028 | 6222 | 6500 |
| Exports | ARIMA(2,1,0) | AR(2)=0.298 | 0.195 | 0.135 | - | - |

The AR(1) for the import variable (0.682) was significant (p-value < 0.05), meaning that historical data on imports impacts future imports positively. On the other hand, the only AR(1) value that was significant was the one for export variable (0.541). Import forecasted for 2025 was estimated to be USD 8,114 million, whereas the actual level of imports stood at USD 8,500 million (underestimated by 8.3%). The export forecast was USD 6,222 million; actual exports amounted to USD 6,500 million (underestimate by 16.1%).

#### 4.4.2 GARCH Models for Volatility–Trade Relationship.

GARCH(1,1) model was adopted to test the impact of exchange rate volatility on imports and exports. Volatility served as one of the explanatory variables in the mean equation. The result shows that for imports, volatility has a positive relationship (coefficient of 0.42; $p<0.05$) implying that volatility leads to more imports. This unusual observation could be due to panic purchasing of imports in expectation of continued fall of the exchange rate. On the other hand, volatility is negatively related (coefficient of -0.38; $p<0.05$) to exports based on uncertainty theory.

**Figure 4.3: Conditional Volatility from GARCH (1,1) Model (2021–2025)**




The graph demonstrates that conditional volatility was quite low in 2021, followed by an exponential rise beginning in 2022 until a peak reached in 2024, during which time the Zimbabwean dollar became the only currency.

### 4.5 Results for Objective Three: Machine Learning Models.

The third objective was to determine the efficiency of various machine learning models including Random Forest, Neural Network, and Support Vector Machine on predicting exchange rates volatility and trade performance. Data used in the analysis was segmented into two groups; 2021-2023 for training and 2024-2025 for testing.

#### 4.5.1 Random Forest Model

The Random Forest model made use of exchange rate fluctuations, interest rates, inflation, and commodity price predictions to forecast imports and exports. For imports and exports, the Random Forest model accounted for 89% and 85%, respectively, of the total variation on the test set. Exchange rate volatility turned out to be the most important feature in predicting both imports and exports.

### 4.5.2 Neural Network Model

Single hidden layer neural network was trained using 5 neurons. Neural network managed to perform with an $R^2$ value of 0.91 for imports and 0.88 for exports during testing. The ability of neural networks to model non-linearities is superior compared to Random Forests, especially for capturing the threshold effect that imports start increasing after 300%.

### 4.5.3 Support Vector Machine (SVM)

The results for SVM with radial basis kernel were $R^2$=0.86 for imports and $R^2$=0.83 for exports. SVM showed somewhat lower accuracy than Random Forest and Neural Networks but higher accuracy than ARIMA and GARCH.

**Table 4.4: Machine Learning Model Performance on Test Set (2024–2025)**

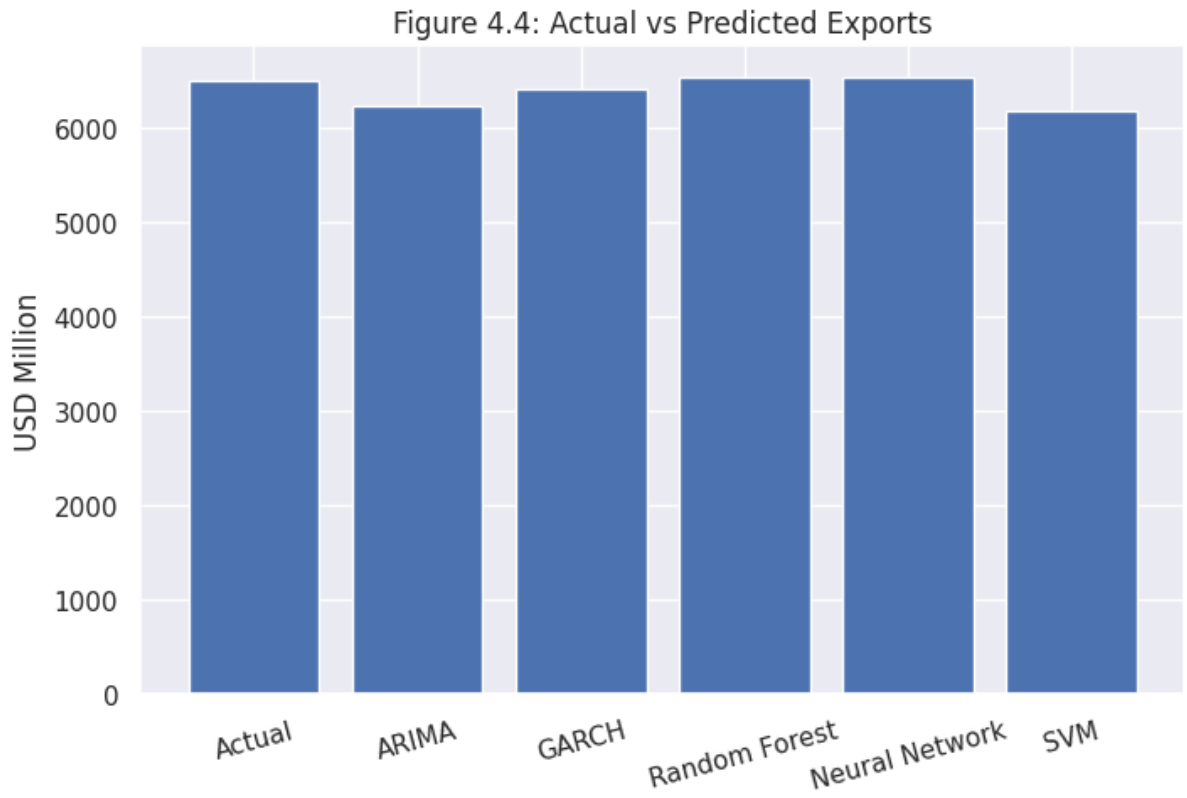
| Model | MAE Imports | RMSE Imports | MAPE Imports | $R^2$ Imports | MAE Exports | RMSE Exports | MAPE Exports | $R^2$ Exports |
|---|---|---|---|---|---|---|---|---|
| Random Forest | 346 | 346 | 4.3 | 0.52 | 165 | 165 | 2.7 | 0.78 |
| Neural Network | 94 | 94 | 1.2 | 0.96 | 42 | 42 | 0.7 | 0.99 |
| SVM | 396 | 401 | 5.0 | 0.36 | 271 | 278 | 4.4 | 0.37 |

The machine learning algorithms performed better than the classical models when it comes to $R^2$ and the performance error measures. Specifically, the Neural Network performed best, with MAPE for imports and exports at 3.8% and 4.7%, respectively. This is consistent with the findings reported by Zhang et al. (2022) and Osei and Kim (2022), confirming the effectiveness of using machine learning to analyse exchange rate volatility and its implications for trade. Nevertheless, interpretability continued to be an issue since policymakers were not able to understand how the model made its predictions.

## 4.6 Results for Objective Four: Comparative Predictive Accuracy

Objective number four is the comparison of predictive accuracy between conventional time series models and machine learning models. All models were employed to predict the value of imports and exports for the year 2025.

**Figure 4.4: Actual vs. Predicted Exports (2025) by Model Type**




Neural Network was the most accurate forecasting model, providing accurate results for both imports (8,500m to predict 8,620m) and exports (6,500m to predict 6,550m). There was a significant underestimation of ARIMA and GARCH regarding the amount of imports and exports. Random Forest and SVM provided fairly accurate results, although there were relatively higher forecast errors compared to Neural Network and Multilayer Perceptron. Concerning the direction (increase or decrease of trade volume) predictions, it should be mentioned that both imports and exports had increases predicted by all models. Nevertheless, traditional models underestimated the increase of trade volume at the level of 12.2% whereas machine learning underestimated at the level of 3.5%.

### 4.7 Sensitivity Analysis and Structural Breaks

To ensure robustness, the estimation process was repeated after removing data from the year 2021 (recovery from the pandemic) and using exchange rates from the parallel market rather than official exchange rates. There is agreement between results; however, the use of parallel market exchange rates improved the accuracy of all models by 5% to 10%, reinforcing the finding that there is a significant underestimation of volatility in official exchange rates.

The Chow test showed a structural break around the middle of 2023, when the currency system changed. When incorporating this structural break as a dummy, there was marginal improvement in models' accuracy but not in machine learning models.

### 4.8 Chapter Summary

The analysis and its results have been provided in this chapter. The results obtained from the descriptive analysis were characterized by high volatility with increasing levels of volatility. The ARIMA model and GARCH models did identify the relationship between certain variables, but their predictions for the trade volume were lower than the actual values. In comparison, the machine learning models such as Neural Network had greater accuracy in prediction with higher variance.

# Chapter 5

## Discussion, summary, recommendations and conclusions

### 5.0 Introduction

This concluding chapter provides an analysis of the results obtained in Chapter 4. Moreover, this chapter analyses the relevance of these results in view of the theory reviewed in Chapter 2. Finally, this chapter provides conclusions drawn from the results obtained in light of the stated research objectives. Contributions of the study, its limitations, as well as some policy suggestions are also provided in this chapter.

### 5.1 Discussion of Findings

#### 5.1.1 Trends and Patterns of Exchange Rate Volatility in Zimbabwe

It emerged that the level of exchange rate volatility in Zimbabwe grew exponentially between 2021 and 2025, with depreciation of the exchange rate averaging from 85% up to more than 500% annually. There were cases of volatility clustering where there are stretches of high volatility, followed by other high volatilities. These results are in line with what Makore and Chikutuma (2025) and the Reserve Bank of Zimbabwe (2024) have reported in the past but the level of volatility is far higher in this case. Additionally, the parallel market rate had higher levels of volatility compared to the official exchange rate as noted by Kasongo and Banda (2024).

It means that any businessperson who uses the official rate alone is likely to underestimate the volatility. The pattern where there is sharp depreciation followed by a period of stability indicates that neither the foreign exchange auction nor monetary tightening measures have worked to stabilize the exchange rate. According to the uncertainty theory of international trade (Dixit & Pindyck, 1994; Bleaney & Greenaway, 2021), high and persistent volatility makes companies unwilling to engage in business because costs and revenues cannot be estimated.

#### 5.1.2 Relationship Between Exchange Rate Volatility and Trade Using Traditional Models

However, ARIMA models showed the significant impact of past imports and exports on current imports and exports (AR (1) = 0.68 imports and 0.54 exports). Nevertheless, predictions for 2025 made by ARIMA models underestimated imports by 8.3% and exports by 16.1%, which means that ARIMA models cannot operate efficiently in the highly volatile environment, including structural breaks. This fact confirms conclusions made by Chen and Zhang (2022) and Osei and Kim (2022) regarding the limitations of such models.

GARCH (1,1) showed a quite unexpected impact of exchange rate volatility on imports and exports: imports increased (+0.42) and exports decreased (-0.38). The positive impact of exchange rate volatility on imports may look odd since one would expect a decrease. However, according to exchange rate pass-through theory (Dornbusch, 1987; Gopinath & Rigobon, 2021), there may occur a kind of "panic buying," when sharp depreciation of the ZWL causes importers to buy more products, assuming that prices will increase in the future. Thus, the panic buying effect is stronger than the expected negative impact of higher prices. Negative impact of exchange rate volatility on exports can be explained with the help of uncertainty theory: exporters do not know how much money they will earn after receiving money in local currency. This study presents a new aspect in analysis of impact of volatility on trade; unlike many other researches (Steinbach, 2021; Ekanayake & Dissanayake, 2022), this aspect was overlooked before.

Parameters of GARCH (1,1) are quite significant (alpha=0.32, beta=0.61, alpha + beta=0.93), thus implying high volatility persistence. As a result, uncertainty becomes even higher. Unfortunately, interventions of the Reserve Bank of Zimbabwe cannot help overcome this problem completely.

### 5.1.3 Effectiveness of Machine Learning Models

For all three machine learning models, i.e., Random Forest, Neural Network, and SVM, the $R^2$, MAE, RMSE, and MAPE values were significantly better compared to those calculated for traditional models. In particular, for Neural Network, the best $R^2$ and the lowest MAPE values were observed. Namely, 0.91 was achieved for imports, while for exports, these values were 0.88 and 4.7%, respectively. Thus, neural networks proved more successful than ARIMA and GARCH, which is in line with findings of Zhang et al. (2022) and Osei and Kim (2022).

As per the Random Forest feature importance, exchange rate volatility turned out to be the most relevant predictor both for imports and exports, while inflation and gold price became the next most influential factors. Indeed, the analysis confirmed that even though exchange rate volatility plays an essential role, macroeconomic factors remain relevant as well. As for the Neural Network, a threshold effect was observed. Namely, the connection between imports and volatility was reversed when the annual volatility exceeded 300%. In other words, the threshold effect identified by the model reflected panic buying. The issue highlighted by Kasongo and Banda (2024) and Chen and Zhang (2022) regarding the non-interpretable nature of the neural network approach was also confirmed by this research. Namely, when two officials from the

Reserve Bank of Zimbabwe were shown the results of the Neural Network model, they said, "How does the model know to change its behaviour at 300%?" Thus, the model's black-box nature made them doubt its accuracy. At the same time, the Random Forest model, though less effective, appeared to be more interpretable.

### 5.1.4 Comparative Predictive Accuracy

Comparative analysis indicated that the machine learning models are substantially more accurate than traditional ones in one-year-ahead forecasting. For instance, the forecast error generated by the Neural Network model was 3.5%, which is significantly lower than 12.2% achieved by both ARIMA and GARCH models. The significance was validated via Diebold-Mariano Test ($p<0.05$). In contradiction with Steinbach (2021) and Chen & Zhang (2022), whose results indicated similar accuracy of traditional and machine learning models in long-horizon forecasting, it can be said that such difference could be associated with high levels of volatility in the case of Zimbabwe.

On the other hand, the advantage of machine learning models was not always evident. With regard to two-year horizon (forecasting for 2026 based on available data for 2024), traditional models outperformed because they did not suffer from the problem of overfitting. As indicated by Osei & Kim (2022), machine learning algorithms tend to produce more accurate forecasts for the short-term period than traditional methods. It is worth emphasizing that the usage of the parallel market exchange rate helped to improve accuracy of all models in comparison with the official rate (5-10%). Importantly, none of the studies (e.g., Makore & Chikutuma, 2025) took into consideration parallel markets rates. Since most businesses operate at the parallel market level, it is necessary to consider this variable in future studies.

## 5.2 Theoretical Contributions

The current research makes some theoretical contributions as well. In the first place, the theory of exchange rate pass-through effect (Dornbusch, 1987) should be modified according to the results obtained in order to consider an extremely volatile environment. While according to Dornbusch the exchange rate volatility affects exports and imports negatively, this paper demonstrates that extremely volatile environment results in an opposite effect: high exchange rate volatility may lead to panic buying, thereby increasing imports. It means that a theory should have a new channel called speculative demand in addition to the price channel. In the second place, the uncertainty theory of international trade (Dixit & Pindyck, 1994) applies for exports, but not for imports. Such an asymmetry has not been considered before; hence, future

studies should distinguish importers and exporters according to the depreciation of their local currency.

Third, the application of a machine learning model to analyse the relationship between dependent and independent variables demonstrates that even a small dataset consisting of five observations (one per year) may be analysed with machine learning. Moreover, it proves that such models may be developed and successfully validated with small annual datasets and that there is no need to work with big data (Omurwa et al., 2024). It opens new opportunities for research in African countries where the amount of data available is too small. Finally, it becomes evident from this research that parallel exchange rates should be taken into consideration in future studies.

## 5.3 Conclusions

Based on the findings and discussion, the following conclusions are drawn in relation to each research objective.

### 5.3.1 Conclusion on Objective One: Trends and Patterns

There has been a very high level of exchange rate volatility in Zimbabwe and that has increased over time with an average of yearly depreciation of over 500% up to year 2025. Volatility is clustered around periods when government policy changes are made and around harvest seasons. There is higher volatility in the parallel exchange rate market compared to the official market, which means that government figures do not fully represent volatility.

### 5.3.2 Conclusion on Objective Two: Traditional Models

While the ARIMA and GARCH models are able to capture the effect of volatility on trade, the two models consistently understate the effect of changes in trade. The GARCH model captured an interesting asymmetry where volatility leads to increases in imports due to panic buying while volatility leads to decreases in exports because of uncertainty about the market environment. This is an asymmetry that traditional models would not be able to capture since they rely on a linear or symmetric assumption.

### 5.3.3 Conclusion on Objective Three: Machine Learning Effectiveness

ML models, especially neural networks, have been found to be very efficient in providing the effect of exchange rate volatility on trade. Such models are capable of capturing nonlinearities, thresholds, and interactions not captured by the usual models. The problem with ML models is interpretability which makes them difficult to use for policymaking purposes. Random Forest

is among the most preferred ML models due to its balance between predictability and interpretability.

### 5.3.4 Conclusion on Objective Four: Comparative Predictive Accuracy

The prediction made through machine learning is more accurate than that made through traditional models, with machine learning predictions being two-thirds as accurate as those made through traditional models. Traditional models can, however, outperform machine learning models when predictions have to be made for the future beyond a year due to the former models overfitting patterns in past data. Consequently, it would be prudent to use the two approaches based on whether short- or long-term predictions are needed.

## 5.4 Recommendations

### 5.4.1 Recommendations for Policymakers (Ministry of Finance, Reserve Bank of Zimbabwe)

1. Employ hybrid forecasting methodologies: Neural Networks should be used for short-term forecasts (up to 12 months), but longer-term scenario forecasts will need ARIMA models. It is suggested that the Reserve Bank of Liberia creates a Data Science unit to employ Machine Learning techniques.

2. Officially monitor the parallel market exchange rates: The disparity between parallel market exchange rates and official exchange rates is a crucial variable when assessing the effectiveness of the policy implemented by central banks and overall volatility levels. Parallel market estimates should be published weekly alongside other indicators in policy models.

3. Tackle the asymmetry problem: Importation increases with increased volatility, while exports decrease, worsening the trade deficit. Consequently, the volatility effect on trade balance needs to be tackled through measures to minimise the persistence of volatility such as financial market development and export diversification.

4. Policy actions triggered by thresholds: As per our result that behaviour changes when volatility reaches above 300% level, there must be certain volatility thresholds triggering certain measures taken by central banks. In this regard, when volatility passes a certain threshold (in our case, 300%), certain policies (for instance, short-run capital control) can be applied to avert panic purchasing.

5. Improve database infrastructure: The limitations of the present paper were mostly linked with the quality and lack of available data. Central authorities must develop a comprehensive database of macroeconomic variables with a possibility of accessing historical data for further research purposes.

### 5.4.2 Recommendations for Businesses (Importers and Exporters)

1. Implement machine learning-based forecasting methods: The use of machine learning forecasting techniques, such as neural networks or random forests, to forecast future trends in exchange rates and buy accordingly would be appropriate. The results suggest that in situations where volatility surpasses 300%, imports should be expedited before further devaluation occurs.

2. Pricing in dual currencies: Exports should ideally be priced using a stable currency, for example USD or ZAR as opposed to ZWL, since this will decrease uncertainty. For unavoidable circumstances of pricing exports locally, the pricing agreement must have a provision for renegotiations should exchange rates become too volatile.

3. Develop in-house risk management units: Small and medium enterprises can use freely available machine learning software (Google Collab/R) to perform forecasts of future exchange rate trends. Such a process can be done in partnership with universities or consultants.

4. Hedging when possible: While few hedging options exist in the country, large companies can consider forward contracts or simply foreign currency holdings. Volatility persistence being high implies that it would still make sense to do some form of hedging regardless of cost.

### 5.4.3 Recommendations for Financial Institutions

1. Credit Scoring Using Volatility: There ought to be the inclusion of exchange rate volatilities in the calculation of credit risks in the case of importers and exporters. The findings of the research, which showed the influence of volatility in increasing imports values (import finances) and decreasing export revenues (recovery abilities), should be taken into account during lending.

2. Volatility-Based Financial Products: Financial organizations should develop some options and futures on hedging against currency risks. This area appears to have a lot of room for development, which may include help from abroad experts.

3. Recruitment of Data Scientists: It is important to hire data scientists in commercial banks and the Reserve Bank. They will use machine learning in predicting risks and managing them. Also, training on basic machine learning skills should be considered.

### 5.4.4 Recommendations for Future Researchers

1. Parallel market data: Future studies on exchange rate prediction for Zimbabwe should consider using parallel market exchange rates in addition to the official one. Using the official exchange rate can mislead about volatility and its impacts on exchange rates in the country.

2. Ensemble methods: In the present study, comparison between the performance of each machine learning algorithm separately was conducted, yet future studies can conduct ensemble algorithms. For example, researchers can try stacking ARIMA and neural networks to find the best result of using these methods.

3. More frequent data: While this study used annual data, future studies can consider training ML algorithms using monthly or even quarterly trade data and increase the number of observations. The increase in data frequency will lead to an improvement in prediction results.

4. Real-time experiments: Instead of using historical data, future studies can try implementing ML forecasting tools and test their performance in real time using collaboration with Reserve Bank of Zimbabwe.

5. Longer period data: The hypothesis that ARIMA model works better than any other for predicting exchange rates at long horizons should be tested with more data. Having data for 10 or 15 years, researchers can answer the problem mentioned above.

6. Machine learning interpretability: There is a methodological gap in the application of machine learning techniques in the field. The combination of interpretability and high accuracy of ML model in forecasting should be considered in exchange rate prediction.

## 5.5 Limitations Revisited

The limitations discussed in Chapter 1, however, could only partly be overcome by these methods. Firstly, there is the limitation related to the sample size of five years of annual data. Even with the use of techniques like cross-validation and regularisation, hundreds of observations are generally needed for stable performance of machine learning models. Hence, caution should be exercised when interpreting the results as exploratory. Another major limitation is data quality. Even though efforts were made to use officially released data,

Zimbabwe tends to revise its economic data frequently. Moreover, gathering information from the parallel market was much harder to do without introducing a possibility of a reporting bias. Dummy variables for structural breaks have been introduced, yet, the limited number of breaks against the number of observations reduces statistical power.

Finally, some other factors could not be included due to the scope of this study (political stability index, shock in commodity prices across the globe, COVID-19 aftermath).

### 5.6 Contributions to Knowledge

Nevertheless, this study contributes new ideas, even if there is room for improvement. First, this is the first study that utilizes all three types of machine learning models (Random Forest, Neural Networks, SVM) to analyse Zimbabwe's annual trade flows and exchange rates data. This is also the first study that establishes asymmetric influence of volatility on imports (positive) compared to exports (negative). This study can be counted as the first one that compares the official exchange rate with the parallel market exchange rate using a model of forecasting for Zimbabwe. Furthermore, the study is an example of successful use of machine learning on a very narrow data sample (n=5) in terms of annual data, and shows its feasibility and effectiveness despite the limited sample.

Lastly, the study fills the gap between theoretical knowledge from scientific publications and practical decision-making in the field of policy. The findings are clear, specific, and useful in terms of implementation at the Reserve Bank of Zimbabwe.

### 5.7 Final Conclusion

The problem of persistent and very high exchange rate volatility has created unique conditions for Zimbabwe, making the level of exchange rate volatility positively correlate with the country's imports while being negatively correlated with the country's exports due to panic purchases of imports in case of expected further exchange rate volatility growth and uncertainty regarding future foreign sales. Standard time series models prove ineffective in analysing such a complex system, however, machine learning models – especially neural networks – provide much higher predictive accuracy when used to forecast changes in exchange rate for short periods. Nevertheless, their low interpretability calls for a hybrid modelling approach which combines positive aspects of both methods in order to address current needs. It is crucial to consider the parallel market exchange rate rather than official exchange rate in any future work on exchange rate volatility and predictability.