An Ensemble Learning of Volatility Spillovers among Emerging Currency Markets

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Declaration

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

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Abstract

The accurate prediction of volatility spillovers enables policy makers and traders to create more efficient investment and hedging strategies. There is an overall lack of research that focuses on the shocks that the Kenyan currency receives from other currency markets.Therefore,this paper estimates the degree of volatility spillovers from select exchange rates to the KES/USD using a GARCH-LSTM (General Auto-Regressive Conditional Heteroskedasticity-Long Short Term Memory) model. The study focuses on daily exchange rate data from 2017 to 2024. This timeline captures the recent significant events that have affected emerging economies: BREXIT, the COVID pandemic, the Russia -Ukraine war, and the increase of Federal Reserve interest rates. The selected currencies are the BRICS currencies: the South African Rand, the Brazilian Real, the Chinese Yuan, the Russian Ruble, the Indian Rupee,and the two dominant Western currencies:the Euro,and the British Pound. Daily volatilities are estimated by the GARCH(General Auto-Regressive Conditional Heteroskedasticity model and then forwarded to the LSTM (Long Short Term Memory) model which captures dependencies in the non-linear and complex volatility patterns. The results of the GARCH-LSTM ensemble model show that for the full period (2017-2024),the KES/USD incurred the highest degree of volatility spillover from the INR/USD at 1.3131 and RUB/USD at 1.1609.While the ZAR/USD transferred the least volatility at 0.0098. CNY/USD followed closely at 0.0137 . Therefore, the study recommends the implementation of hedging strategies, especially during trade with the Indian and Russian markets as they demonstrate the highest contagion risk to the KES/USD exchange rate. In addition, among the forex markets studied, the South African and Chinese markets are safer to trade as they pose the least risk of contagion to the KES / USD exchange rate.Besides,research centers should focus more on the application of ensemble learning systems in macroeconomic issues.This is because they give more layered information about financial time series than traditional GARCH models.For example, in this paper, the GARCH-LSTM model outputs a close estimate of the degree of shock transmission, while a GARCH model could only give us the correlation between the volatilities.

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List of abbreviations

ANN	Artificial Neural Network	GFC	Global Financial Crisis
BEKK	Baba Engle kraft Kroner	GJR-GARCH	Glosten Jagannathan Runkle Generalized Autoregressive Conditional Heteroskedasticity
BRICS	Brazil, Russia, India, China, South Africa	INR-	Indian Rupee
BRL-	Brazilian Real	LSTM	Long-short Term Memory
BWP	Botswana Pula	MAD	Moroccan Dirham
CNN	Convolutional Neural Network	M-GARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
CNY-	Chinese Yuan	NSE	Nairobi Securities Exchange
COVID-19	Coronavirus disease 2019		
DCC-GARCH	Dynamic Conditional Correlation	RUB	Russian Ruble
E-GARCH-	Exponential Generalized Autoregressive Conditional Heteroskedasticity	TND	Tunisian dollar
EUR-	Euro	VAR	Vector AutoRegressive
GARCH	Generalized Autoregressive Conditional Heteroskedasticity		
GBP-	Great Britain Pound	ZAR-	South African Rand

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Dedication

I dedicate this project to all the Kenyans for a better tomorrow.

Chapter 1

Introduction

1.1 Introduction

Volatility spillovers are a major contribution of fluctuation in the financial markets.There is an overall lack of research that focuses on the shocks that the Kenyan currency receives from other currencies through the exchange rate channel. This research aims at using a GARCH-LSTM algorithm to estimate the degree of volatility spillovers transmitted from five BRICS currencies,the Euro and the British pound to the Kenyan shilling. This chapter will provide an introduction to the study by first discussing the background,research problem ,followed by objectives,significance and limitations.

1.2 Study Background

The spread of shocks is as old as time, but the phenomenon of volatility spillovers came to light after the Asian crisis in 1997 as highlighted in Baig's 1999 paper. What started as a minor currency crisis in Thailand spread through East Asia to affect major economies such as Brazil and Russia (Chancharoenchai and Dibooglu, 2006). The cause was Bangkok's unpegging of the Thai Baht from the US dollar (Baig and Goldfajn, 1999).After,the ruble's value went down and the Russian central bank defaulted on its debt. But even before that, the collapse of the Bretton Woods model in 1973 had brought about spillover effects (Bordo, 2020). Research can trace the first crisis in which volatility spillover was major causal factor back to 1825. The irrationality in the London Stock Exchange spread to Latin America, cutting off their overseas loans (Anastasopoulos, 2018). However, the Asian crisis inspired heavy research on the spillover of volatility and its effects. Since then, more focus has been on Asian, European, and American markets. Partially, because the markets have existed longer than African markets. Engle (2002) observed that every time developed countries go through an economic issue, developed and emerging markets suffer from it no matter the strength of their fiscal accounts.

Research attributes the spread of shocks as a key influence in investor behavior (Claessens and Forbes, 2001). At the beginning of a crisis, lenders and stockholders may resolve to pull out their investments and pour into more profitable assets. The economies decline in value if a significant portion of the investors pull-out around the same time. While Caporale et al. (2021) linked it to information asymmetries and liquidity problems. (Group, 2013) The World Bank Group defined contagion as the process in which shock is transmitted between economic regions in times of crisis. Another researcher Rigobon (2016) had the same idea and added that the main difference between volatility spillover and contagion is the magnitude. He concluded that it is a volatility spillover if the degree of shock matches the figure in the hypothesis of that particular study. However, it is contagion, if the degree of the shock is greater than what is stated in the hypothesis of that particular study (Rigobon, 2016). This paper will use the term ' volatility spillovers' because the entire timeline(2017-2024) will involve crisis and non-crisis moments.

In the recent past, the world has gone through radical change. The pandemic in 2019, BREXIT fully taking effect in 2020, and the Russian-Ukraine war in 2022. Not to mention that during the 2022 to 2023 financial cycle, the federal reserve rates increased about eleven times (Saving, 2023). Making it harder for emerging economies to borrow money or repay their loans in US dollars. This resulted in many economies seeking a new world order. The recent geo-economic and political alliances are leading to a gradual decline of the Western systems and the rise of the BRICS group. Ever since the Bretton Woods system in 1945 the US dollar has been at the center of foreign exchange transactions worldwide. The dominance of the dollar continued even after the collapse of the gold-backed system in 1971. The Euro is second in global dominance. According to Mühleisen (2022) a third of global transactions involve the Euro. The British Pound and the Japanese Yen follow closely in dominance, but this paper will concentrate on the three Western currencies. BRICS is a political and economic group comprising

China, India, Brazil, Russia, and South Africa which joined the platform in 2010. On the 1st of January 2024, the powerful bloc welcomed six more countries into the group: United Arab Emirates, Ethiopia, Iran, and Argentina (Iankovskii, 2022). This study will concentrate on the five original member states due to the timeline of the data set. BRICS is committed to sustainable development and accelerated economic growth of the global south (Antony, 2024). The member countries share national interests that push for a non-dollar-based monetary order. This has caused some restlessness among Western powers. More so, the states contribute to 31.5% of the world's GDP, 26% of global oil production, 50% of Iron ore,46% of wheat, and 40% of corn as stated by Iankovskii (2022).

Among the five BRICS countries,the USD is used as a reserve currency making USD/BRL,USD/RUB ,USD/INR,USD/CNY, USD/ZAR the most traded pairs across the countries. Post 2022 , there has been a rise of the use of RUB/CNY and RUB/INR. However, for econometric consistency with the KES/USD , the study will use the USD as the common base currency for the trading pairs. Thus, any volatility in the cross rates such as in RUB/CNY will be assumed to be reflected in USD-based currency fluctuations. The Kenyan economy has not been immune to all the global turbulent changes. Various studies agree that the probability of the spread of shock is proportional to the level of interdependence between countries (Morales and Andreosso-O'Callaghan, 2014). The more dependent the economy is on others, the more it is exposed to spillover effects. Is the Kenyan economy a net receiver of shock, if so how much degree of shock does it receive from the select economies? In other words, how should Kenya align itself with the current global shift? This paper seeks to answer these questions by studying the relationship between the Kenyan shilling, BRICS currencies, and two dominant Western currencies. Following Dornbusch et al. (2000) observation that one can detect the spread of shocks through co-movements in capital flows, differences in bond yields, share prices, and exchange rates.The study will analyze the degree of shocks that is transmitted from each currency to the Kenyan shilling via the exchange rates channel and suggest economic allegiance with the currencies that promise the least spillover risk to the Kenyan shilling.

1.3 Research Problem

Analyzing the spread of shocks among economic regions is paramount when informing macro-economic policies. However, the existing research on volatility spillovers falls short in some areas making it inadequate in influencing fiscal policies in Kenya effectively.

a) The existing research has used less accurate methods to analyze volatility spillover and financial contagion among African markets. Papers have relied on GARCH Dukundane (2023), BEKK-GARCH (Panda et al., 2019), (Niyitegeka and Tewari, 2020), (Emenike, 2023)) M-GARCH (Debalke, 2023), EGARCH (Humavindu and Floros, 2006), (Raputsoane, 2008), GJR-GARCH (KARAKAYA and KUTLU, 2023), (Aawaar et al., 2023) and DCC-MGARCH (Tripathy and Panda, 2023) models to analyze volatility spillovers. The various GARCH models are instrumental with each variation adding to their efficiency and the accuracy of the results. (Dornbusch et al., 2000) explains that most practical research aims to quantify the degree of shock and the channels of transmission. Various research agrees that GARCH models have been reliable but deep learning methods outperform them in accuracy (Amirshahi and Lahmiri, 2023), (Sahiner, 2023).These past models are linear making them inadequate for complex exchange rate data. This paper will focus on the application of a GARCH-LSTM for the estimation of volatility spillovers.The latter method can effectively capture patterns in non-linear complex time series data like exchange rates (Adams and Uchema, 2024).

b) Previous papers on African markets have focused on spillovers channels like daily returns, cryptocurrencies (Amirshahi and Lahmiri, 2023) and stock market indices (Akunga et al., 2023), (Panda et al., 2019), (Tripathy and Panda, 2023).However,these studies have failed to cover the spillovers transmitted through the exchange rates channel to the Kenyan shilling in recent years. The foreign exchange market is unique (Baruník et al., 2017). Besides, it is one of the most liquid globally integrated, and highly decentralized financial markets (Diebold and Yilmaz, 2015). The exchange rate is a key macroeconomic aggregate that is used to rank a country's trade performance. Focusing on the exchange rates rather than stock market indices like most research before, will give a unique perspective on the spread of shocks.

c) Numerous studies modeling financial contagion in African currencies have used earlier data sets (Akunga et al., 2023), (Boakye et al., 2023).However, there is a need for a study that focuses on the Kenyan shilling during recent times. A series of events and past economic decisions of higher trading powers attributes to the current financial turbulence (Muchiri, 2017). The Russia-Ukraine war has derailed the economic recovery from the COVID-19 pandemic (Orhan, 2022).Not forgetting the constant increase in federal reserve rates has caused a strain on dollar-based transactions. More than that, the turbulence has caused nations to exit((Kohnert, 2020)) and enter new trade agreements (Skaricic, 2023). The current economic debate focuses on the tug between BRICS and Western powers. This paper will focus on a recent data set 2017-2024 and more specifically on the relationship between the Kenyan shilling and the select currencies. This will give a clear understanding on which trade alignment among the select currencies would lead to the least contagion risk to the Kenyan shilling.

1.4 Research Aims, Objectives, and Questions

1.4.1 Research Aim

The main aim is to identify the degree of the exchange rate volatility spillovers from each select currency to the Kenyan shilling from 2017 to 2024.

1.4.2 Research Objectives

a) To quantify the degree of volatility spillover transmitted to the KES/USD currency pair from the (BRICS currency pairs: ZAR/USD,BRL/USD,CNY/USD,RUB/USD, INR/USD,and the two dominant Western currency pairs; EUR/USD, GBP/USD).

b) To identify the select currency markets transmitting the highest contagion risk to the Kenyan shilling.

c) To estimate the degree of exchange rate volatility spillovers using a GARCH-LSTM model.

1.4.3 Research Questions

a) Which degree of volatility spillover is transmitted from the seven currency pairs - ZAR/USD,BRL/USD,CNY/USD,RUB/USD,INR/USD,EUR/USD, GBP/USD to the KES/USD?

b) How does the degree of contagion risk to the KES/USD differ between BRICS currency markets (ZAR/USD,BRL/USD,CNY/USD,RUB/USD,INR/USD) and Western currency markets (EUR/USD, GBP/USD)?

c) How can we incorporate GARCH together with a recurrent neural network algorithm to estimate and analyze the degree of exchange rate volatility spillovers?

1.5 Scope

a) The dataset includes daily exchange rates of the select currencies between 2017 and 2024. 2017-2020 is a pre-crisis period because a sharp change in the currency value can be observed at the beginning of 2020.

b) Raw exchange rate data was downloaded from the Central Bank of Kenya's website.

c) The study looked into the contagion effects between the Kenyan currency and selected currencies, BRICS currencies: The South African Rand, the Brazilian Real, the Chinese Yuan, the Russian Ruble, the Indian Rupee, and the three Western currencies: the US dollar, the British Pound, and the Euro.

1.6 Significance

With the ever-increasing globalization of financial markets, contagion is inevitable. An understanding of the current financial layout is needed to improve the value of African currencies.

a) This research has contributed to the existing literature on the spread of shocks to African currency markets. More specifically, the relationship between the Kenyan shilling and major trade currencies.

b) Regulators are put in place to monitor currency contagion risk. However, much accuracy is needed when quantifying these risks.This paper has incorporated a GARCH and LSTM model to produce an accurate estimate of the degree of volatility spillovers. Thus, it contributes to the current literature on the application of ensemble learning algorithms in analyzing volatility spillovers.

c) In addition, this study classified the currency markets according to the risk of contagion they impose on the KES / USD exchange rate, giving policymakers critical information in these turbulent times.

1.7 Study Limitations

a) This study focused on the last 7 years. Even though the timeline is limiting ,it allowed the study to focus on the interaction of the exchange rates during recent years.

b) The study focuses on the shocks that seven exchange rate series transmit to the KES/USD exchange rate. There is acknowledgment that the study could be broader. However,the focus of the study is the relationship between the Kenyan shilling, the BRICS currencies, the Euro and the British Pound.

c) The study focused on the currency pairs against USD mainly for econometric consistency with the KES/USD and the availability of data. Thus, the study does not explore volatility in the cross rates such as RUB/CNY, EUR/GBP.

1.8 Structural Outline

In chapter one the background of the study has been introduced .The research objectives and questions have been outlined and the significance discussed.Chapter two,reviews the existing literature and identifies the main research gap.Chapter three, presents the methodology. It justifies the application of recurrent neural networks in the estimation of volatility spillovers and, discusses the research design.Results are presented and, data described in Chapter 4 then Chapter 5 holds the interpretation and explanation of results. Finally, Chapter 6 summarizes the study .

Chapter 2

Literature Review

2.1 Introduction

This chapter explores past literature with a focus on the main topic. Following a thematic approach, it discusses past literature in relation to volatility spillovers, its effect on African currencies and the application of deep learning algorithms in the analysis of financial time series.

2.2 Volatility Spillovers

The definition of volatility spillovers and financial contagion has sparked debate since early research following the 1997 crisis in East Asia (Chancharoenchai and Dibooglu, 2006). Previous research (Edwards and Susmel, 2001), (Edwards and Susmel, 2003), (Gallo and Otranto, 2008) defined volatility spillover as the situation in which a shift in the system of the dominant market results in a shift in the system of emerging and developing markets. Dornbusch et al. (2000) defined contagion as a notable increase in inter-market correlations after an economic disturbance in one or a group of economic regions.

The phenomenon is measured by comparing the degree of co-movements of financial flows in tranquil and turbulent times. Rigobon (2016) added that the main difference between volatility spillover and contagion is the magnitude. He concluded that it is a volatility spillover if the degree of shock matches the figure in the hypothesis. However, it is contagion, if the degree of the shock is greater than what is stated in the hypothesis.This paper will focus on the volatility spilled from seven select currencies to the Kenyan shilling.

2.2.1 Spillover Channels

Dornbusch et al. (2000) confirmed that the spread of economic shocks can be studied through similar movements in capital flows, differences in bond yields, share prices, and exchange rates. Therefore, trade links, similar investment trends, and regional patterns can lead to market volatility.

2.2.2 Types of Contagion

Different authors (Masson, 1998), (Wolf, 1999), (Forbes and Rigobon, 2002), (Pritsker, 2001), (Dewandaru et al., 2017) agree that contagion is a result of two key factors which give rise to the two types: Pure and fundamental-based contagion. Calvo and Reinhart (1996) defined fundamental-based contagion as the systemic risk that occurs due to financial linkages in the market. Notably, movements in macroeconomic variables are only classified as contagion in times of financial crisis when the effects become too much. Further research added that this type of contagion can be spread through shared market volatilities, regional patterns,economic linkages and similar trade affairs which tend to have longer shock periods ((Pesenti and Tille, 2000)).

The second category is pure contagion. Forbes and Rigobon (2002), and Eichengreen et al. (1996)), defined as the excessive transmission of volatility that is higher than the individual and basic risks, which affects temporary trends. The World Bank research (2000) attributed pure contagion to herd behavior and risk aversion in investors. Any speculation of a crisis causes investors to pull out their funding. A clear observation can be seen in one of the first contagion crises of 1825 when irrationality in the London Stock Exchange caused investors to withdraw funding (Anastasopoulos, 2018). The fund pullout affected investments in Latin America. Researchers suggested that pure contagion can lead to fundamental-based contagion and vice versa. Thus, the two will be considered when analyzing contagion in exchange rate markets (Pesenti and Tille, 2000). This is because herd behavior can lead to systemic risk while systemic risk can lead to mass losses. Dornbusch et al. (2000) explains that most practical research aims to quantify the degree of shock and the channels of transmission. Thus, both crisis and non-crisis contagion will be studied in this paper.

2.3 Spillover Effects on African Currencies

Previous research has focused on studying the behavior of African currencies during financial crises (Coleman, 2008), (Mwega, 2010), (Raputsoane, 2008). These currencies are sensitive to domestic politics and changes in international markets. Most African countries, including Kenya, have adopted a free-floating regime (Musembi, 2013). Thus, it is imperative to quantify the financial contagion from regional and global markets to capture the correlation between the extreme shocks. Using an EGARCH model, Raputsoane (2008)investigated the behavior of the shock spillovers between the South African currency and those of dominant and emerging markets. The study concluded that European markets had significant negative volatility spillovers to the rand. Could this also be the case for the Kenya shilling? Besides, Asian and Latin markets were found to have no spillover effects on the rand. Coleman (2008) explained that developed stock markets linked to the global financial crisis experienced a decline almost immediately from November 2008. He observed a sharp drop of 30-40% in major African securities markets; the Nigerian Stock Exchange, the Johannesburg Stock Exchange, and the Nairobi Stock Exchange.

Mwega (2010) reported a 48% drop in the NSE 20 share index between mid-2008 and mid-2009. Much of the decline was credited to the GFC and the political unrest in Kenya following the election of December 2007. Mwega (2010) also reported poor regulations in stock brokerage firms attributed to the drop. Terfa (2011) studied the effect of the GFC on African stock exchanges from November 2007 to November 2012. He found that African Capital markets fell by 30% to 40%, but private equity

investors remained committed to Africa. Further research attributed the sharp decline in early 2009 to a lack of heavy foreign direct investments (Koech and Rotich, 2013). Boako and Alagidede (2017) went further to quantify and test the effects that extreme turbulence in developed markets has on African stock markets. The study analyzed contagion by comparing CoVAR values for African stocks for consecutive periods from 2007 to 2009. The study confirmed that there was contagion from dominant economies to African stock markets. The results agree with earlier studies (Raputsoane, 2008). Kipruto et al. (2018) sort out to confirm the applicability of artificial neural networks in investigating the Kenyan shilling exchange rate against; the Japanese Yen, the US dollar, the Great Britain Pound, and the Euro. After tests on the models, they found the average value of the neural network to have low error. The study indicated that ANN has high accuracy in forecasting exchange rates in Kenya. The study encouraged further research on neural networks for forecasting purposes. In addition, Makiya (2020) analyzed a time series with a resilient back propagation neural network to forecast forex prices. Successful predictions on data sets from 2016 to 2019 were conducted with an accuracy of 88%-98%. The high accuracy rates indicate that the combination of neural networks and a supplement technique is optimal for time series analysis.
Karungu et al. (2020) investigated the influence of financial contagion on stock performances in the Nairobi stock exchange (NSE). With the use of Excel and SPSS tools, the study analyzed data from April 2006 to December 2008. There was evidence of contagion effects on firms listed in the NSE during the GFC. Niyitegeka and Tewari (2020) was curious about the effects that the Eurozone debt crisis had on the relationship between the South African rand and the Euro. The research applied BEKK-GARCH and DCC-GARCH models. The study found evidence of heightened spread of shocks from the Euro to the Rand during the eurozone crisis.

Atenga and Mougoue (2021), extended the data set to examine global and regional volatility spillovers to African currencies using (Diebold and Yilmaz, 2009;2012;2014) network framework. The study concluded that African currencies reacted more quickly to variables in their markets than global volatility spillovers with a few exceptions: BWP, MAD, TND, and ZAR. Boakye et al. (2023) adopted the same model as Atenga and Mougoue (2021) but used an extension of the 2016 version to examine interdependence amongst African currencies. After analyzing data over the period June 2004 and June 2021, Boakye et al. (2023) confirmed the presence of volatility spillovers during the eurozone sovereign debt crisis and the global financial crisis. The study also found that among African currencies, the South African rand, the CFA franc, and the Moroccan dirham were the highest net transmitters of shocks. However, the Botswana Pula and the Kenyan Shilling were net receivers of shocks from other currencies. Thus, it is paramount to find out the degree of shock transmitted to the Kenyan shilling from dominant trade currencies.

Opoku et al. (2023) examined the spread of shocks between the exchange rates of sub-Saharan African countries and exports. The study applied the Barunik and Krehlik spillover index to capture time-dependent and non-stationary co-movements. The study found that South Africa's exchange rates transmit risk spillovers among metal-producing countries. Agricultural countries receive shock from Cote d'Ivoire's exchange rates. This conclusion agrees with the findings of (Boakye et al., 2023), that South Africa is a net transmitter of a shock to other African currencies. Mensah et al. (2023), examined the volatility spillovers of the Eurobond issue in the exchange rates of four African currencies. Using data from 2006 - 2021 subdivided into three periods. The study found heavy volatility spillovers during the GFC and the Eurobond era. The authors concluded that various currency exchange rates attracted varying degrees of volatility shocks providing portfolio diversification opportunities for investors.

Das and Roy (2023) applied an MGARCH model to investigate the spread of shocks among the currencies of BRICS member countries and four major developed countries from 2006 - 2019. After employing a DCC-GARCH model and a VAR index. The study concluded that China, South Africa, and India were net receivers of shock from more developed markets. Besides, the research noted that Brazil and Russia passed on volatility shocks to other markets. These results varied with Akhtaruzzaman et al. (2021) who analyzed volatility spillovers between G7 countries and China on a later data set. China and Japan were found to be the main transmitters of shock during the pandemic period.

Studies highlight the differences in volatility transmission behavior between pre-pandemic and post-pandemic periods. Moreso, the accelerated effects of the Russia -Ukraine war that commenced in early 2022 (Orhan, 2022). The study observed that the two countries have a huge influence on the global commodity market. They contribute 30% of global wheat exports, 20% of corn, mineral fertilizer, and natural gas, and 11% of oil. Moreover, their metal exports support global supply chains. Cormann and Boone (2022) observed that since the war began, there has been a sharp increase in the prices of these commodities. Kammer et al. (2022) commented that the war could potentially lead to capital outflows from emerging markets. This study recognizes the importance of finding out exactly how the turbulence has affected the Kenya shilling.

2.4 Deep Learning Methods

Machine learning is field of artificial intelligence that trains the algorithms to learn the learn the data without much of the programmers interference (García-Medina and Aguayo-Moreno, 2024). Their high computing power has earned these deep learning methods popularity among staticians.Several research studies analyzing the financial markets have employed these methods. Gunduz et al. (2017) used a convolutional neural network (CNN) to forecast the movements of Borsa Istanbul 100 stock prices. The study concluded that the CNN model with ordered features was better than the one with randomly ordered features. And that, it outperformed a logistic regression model in the prediction of a nonlinear, noisy, non-stationary structure. Maqsood et al. (2020) explored the contagion effects of major crises from 2012 to 2016 on four economies; for developed markets, they studied the US, and Hong Kong, for emerging markets they studied Turkey and for developing markets, they studied Pakistan. They combined linear regression, support vector regression, and a deep learning algorithm on a data set containing 11.42 million tweets for stock exchange forecasting. The study concluded that a structured stock forecast algorithm should include public opinion such as Twitter data.

More so, the study highlighted that deep learning methods can capture the non-linearity of these data. Other studies (Hiransha et al., 2018), (Vargas et al., 2017), Wang et al. (2021) contributed to the financial literature on deep learning methods in Stock market forecasting. Besides, recent studies (Awoke et al., 2020), (Jamshed and Dixit, 2022), (McNally et al., 2018) have applied deep learning techniques to cryptocurrency analysis. The application of non-linear time series has been extended to predicting exchange rates by various researchers (Dautel et al., 2020), (Fisichella and Garolla, 2021), (Ni et al., 2019). Thakkar and Chaudhari (2021) and Chopra et al. (2021) advocate for the use of machine learning models stating that they possess superior capabilities and high accuracy. The literature exposes the need for more research concerning the role of machine learning in volatility spillover analysis; especially on asymmetric shock transmissions.

Coupling deep learning algorithms with MGARCH methods has proven to be effective in studies such as ((Amirshahi and Lahmiri, 2023), (Sahiner, 2023)). After much analysis of recent papers, the author has not come across any study that combines a deep learning technique with a DCC-GARCH to calculate the degree of exchange rate volatility spillovers from BRICS and Western currency markets to the Kenyan shilling. This research will contribute to the much-needed financial literature on contagion effects to African currencies paying special attention to the Kenyan shilling.

Chapter 3

Methodology

3.1 Introduction

This chapter focuses on intergrating GARCH and LSTM in the estimation of the degree of volatility spillovers from select exchange rates to the KES/USD from 2017 to 2024.The historical data was downloaded from the CBK website. The GARCH model was used to output the daily volatilities. The Long Short Term Memory (LSTM) model under Recurrent Neural Networks (RNN) was used due to its ability to capture patterns in non-linear and complex time series data like exchange rates (Adams and Uchema, 2024).

The chapter will go on to discuss the research design choices, methodological limitations and give a concluding summary after that.

3.2 Research Design

3.2.1 Research Strategy

The overall strategy of this study was to incorporate a GARCH model with an LSTM model to produce an accurate degree of spillover from the various exchange rates. After which, we ranked the various degrees according to the level of contagion risk they impose on the KES/USD.

3.2.2 Time Horizon

This study took a longitudinal approach because it sought to analyze several exchange rates time series data over the past seven years from 2017 to 2024 .

3.2.3 Sampling Strategy

This study applied a non-probability sampling technique. Purposive sampling because the researcher intended to find out the specific relationship ,the Kenyan shilling has with BRICS currencies: The South African Rand, the Brazilian Real, the Chinese Yuan, the Russian Ruble, the Indian Rupee, and the specific relationship it has with the two dominant Western currencies: the Euro, the British Pound.All the select seven exchange rates represent major trading currencies((Anastasopoulos, 2018), (Muchiri, 2017))

3.2.4 Data Collection Methods

Due to the nature of our study ,we had to collect secondary data.The daily exchange rate data was downloaded from the Central Bank of Kenya (CBK) website. This is because the Central Bank of Kenya is a reliable data source. The exchange rate data between KES and other currencies is accurate and updated on a real-time basis. More so, the data is available for download by the public.

3.3 Data Analysis

For this specific study ,we have eight exchange rates. BRL/USD, RUB/USD, INR/USD, CNY/USD,ZAR/USD, GBP/ USD, EUR/USD and KES/USD. The latter is the target currency. Raw exchange rate data from 01-09-2017 to 01-09-2024 was downloaded from the CBK website . The aim is to calculate the volatility spillover degree from seven currencies to the KES currency using a GARCH-LSTM model.

3.3.1 Data Pre-processing

Missing data and duplicates are dropped. After exploratory data analysis, the exchange rate series are scaled using a min-max scaler from the scikit-learn Python libraries to facilitate LSTM training. Then, data was split using a 80:20 ratio for train and test data respectively.

3.3.2 The LSTM Model

Under deep learning methods, are artificial neural networks which use neurons to relay information (Kipruto et al., 2018). An ANN model receives an input vector x weights it depending on what is has learned from the data , generates an output (fx) through an activation function $g()$ but not before it recognizes some bias b

$$f(x) = g(x * w) + b, \tag{3.1}$$

For a while, modeling exchange rate data had been quite tasking due to its non-stationary (Xu et al., 2019) and complex nature. However, Recurrent Neural Networks(RNNs) are more layered and thus more equipped Hu et al. (2021) to handle sequential data like financial time series (Adams and Uchema, 2024).The RNN model extracts information from sequential data, pushes the information while learning patterns in the time series (Zhao and Yan, 2024). If an RNN unit has an input x_t that generates a value h_t, then the sequential model uses the output of the cell state at time $t-1$ as the input for time t , and the t output as the input for time $t+1$.

Hochreiter, Sepp,and Schmidhuber Hochreiter and Schmidhuber (1997) were the first to introduce the LSTM model, but it had long-term dependence problems. Graves et al. (2013) rectified the error resulting in the current model. Each unit in the model has 3 gates: an input gate, a forget gate, and an output gate. Thus the network pushes the insignificant information towards the forget gate and significant data is pushed forward. The gating system differentiates it from a typical RNN unit and allows the LSTM unit

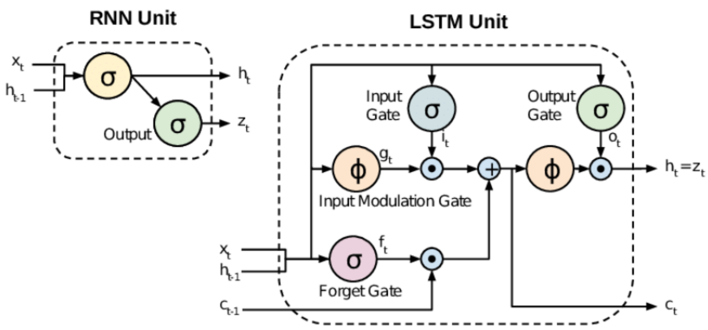

Figure 3.1: LSTM and RNN Source:Tripathi (2021)

to pick the non-linearity in time series data, in this case, the increased spikes in volatility (Sahiner, 2023). The input x of this LSTM model is a multivariate time-series data set

$$X \in R^{(b,s,n)} \tag{3.2}$$

where

i) $b =$ batch size.

ii) $s =$ sequence length

iii) $n =$ Number of exchange rate series

Each LSTM cell maintains two states throughout. The memory state C_t- stores long-term dependencies in volatility patterns. while the hidden state h_t holds short term info.

Step 1:

Each channel linking a neuron in the input layer to a neuron in the hidden layer is assigned a weight .With each neuron in the next layer having its own bias. The input is multiplied by the weight and the bias is added. This is then passed through an activation function which determines whether shock will be passed through the next input gate or the forget gate. The input gate controls how much recent shock should be added:

$$i_t = \sigma[W_i(h_{t-1}, x_t) + b_i] \tag{3.3}$$

Step 2:

The past volatility information to forget is passed through the forget gate.

$$f_t = \sigma[W_f(h_{t-1}, x_t) + b_f] \tag{3.4}$$

Step 3:

The memory cell becomes .

$$\tilde{C}_t = tanh[W_c(h_{t-1}, i_t) + b_c] \tag{3.5}$$

Step 4:

The current memory cell is then updated through combining past and new volatility signals.

$$C_t = (f_t * C_{t-1}) + (i_t * \tilde{C}_t) \tag{3.6}$$

step 5:

The output gateO_t decides how much shock will passed onto the next step:

$$O_t = \sigma[W_o(h_{t-1}, x_t) + b_o] \tag{3.7}$$

Step 6: The new hidden state becomes:

$$h_t = O_t * tanh(C_t) \tag{3.8}$$

step 7: The final hidden state is passed through a dense layer to produce the degree of shock transmission.

$$\tilde{S}_t = [W_y h_T + b_y] \tag{3.9}$$

3.3.3 GARCH Model

Bollerslev (1990) introduced the GARCH model to capture the conditional variance. This mean equation gives us the residuals. Where g denotes the first currency, and h denotes the second currency.

$$\sigma_{gt}^2 = \mu_g + \sum_{i=1}^{n} \alpha_{gt}\sigma_{gt-1} + \sum_{i=1}^{n} \beta_{gt}\sigma_{ht-1} + \varepsilon_{gt} \tag{3.10}$$

$$\sigma_{ht}^2 = \mu_h + \sum_{i=1}^{n} \alpha_{ht}\sigma_{ht-1} + \sum_{i=1}^{n} \beta_{ht}\sigma_{gt-1} + \varepsilon_{ht} \tag{3.11}$$

The second step is where the variances are calculated.

$$\sigma_{gt}^2 = \alpha_{g0} + \alpha_{g1}\varepsilon_{gt-1}^2 + \beta_{g1}\sigma_{gt-1}^2 \tag{3.12}$$

$$\sigma_{ht}^2 = \alpha_{h0} + \alpha_{h1}\varepsilon_{ht-1}^2 + \beta_{h1}\sigma_{ht-1}^2 \tag{3.13}$$

Where

i) α_0 and ε are constants.

ii) σ_t^2 - the conditional variance

iii) α_1 - ARCH variable

iv) β_1 - GARCH variable.

3.4 Construction of the Model

The data is loaded and missing data and duplicates are dropped. The returns are calculated using the following formula :

$$R_t = \frac{E_t}{E_{t-1}} - 1$$

where:

i) R_t is Return at time t

ii) E_t is exchange rate at time t

iii) E_{t-1} is exchange rate at time $t-1$

The returns are scaled to ensure smooth training by the LSTM model. The GARCH model is applied to the return series to capture the variances. $\sigma_t = \sqrt{\sigma_t^2}$, the square root of which gives the daily volatilities σ_t. Besides,defining the time step of 60 days. We divided 80% data for training and 20% for testing .Then the main LSTM model was defined. in the cell state, the tangent function was used to create the vectors while the sigmoid function was applied in the input and output gates. After importing the necessary libraries from Keras, we defined our LSTM model as a sequential model with one input layer, two hidden layers, one dense layer and one output layer. We used adam as an optimizer because its able to adjust learning rates based on first and second gradient estimates. Early stopping was used to prevent overfitting Anam et al. (2024).Signals were verified by the MSE to control the detection of false signals Sevim et al. (2014). Finally the RMSE,MSE,MAE were used to estimate the accuracy of the models.

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(\delta_t^2 - \hat{\delta}_t^2\right)^2} \tag{3.14}$$

MAE

$$MAE = \frac{1}{k}\sum_{t=1}^{k}\left|\delta_t - \hat{\delta}_t\right| \tag{3.15}$$

and MSE

$$MSE = \frac{1}{k}\sum_{t=1}^{k}\left(\delta_t^2 - \hat{\delta}_t^2\right)^2 \tag{3.16}$$

3.5 Methodological Challenges

The LSTM model can capture dependencies despite the non-stationarity of the exchange rates (Adams and Uchema, 2024).Besides, Early stopping was used to prevent overfitting of the LSTM model. Combining GARCH and LSTM models was labor intensive and the selection of parameters, sensitive to slight changes.

Chapter 4

Results

4.1 Introduction

This chapter presents the descriptive statistics of the eight exchange rate datasets with a focus on the KES/USD. Next, the hypothesis test results are discussed and the final results presented.

4.2 Preliminary Analysis

For this specific study ,the data is retrieved from the Central Bank of Kenya website and covers closing prices of exchange rates from eight currencies i.e BRL/USD, RUB/USD, INR/USD, CNY/USD,ZAR/USD, GBP/USD, EUR/USD and KES/USD. The latter is the target currency .The full sample period of the study consists of 1823 exchange rate prices from each currency dating from 01 September 2017 to 01 September 2024. It covers the daily exchange prices without the weekends. Figure(4.1) shows that the Kenyan shilling was quite stable up until 2020 where there was a sharp decline.The drop continued until the end of 2023 and then a sharp rise was witnessed. While (**??**) shows that before 2020,the exchange rates for all the currency were a bit steady. However, after 2020, as the GBP/USD and EUR/USD started to rise the KES/USD started to drop while other currencies like the CNY/USD have remained quite stable for the full period. However, another thing that is quite clear from the graph is that the exchange rates for the two western currencies have a much higher value than the BRICS currencies. Besides, they show more volatile movements especially at the beginning of 2020 and the end of 2022.

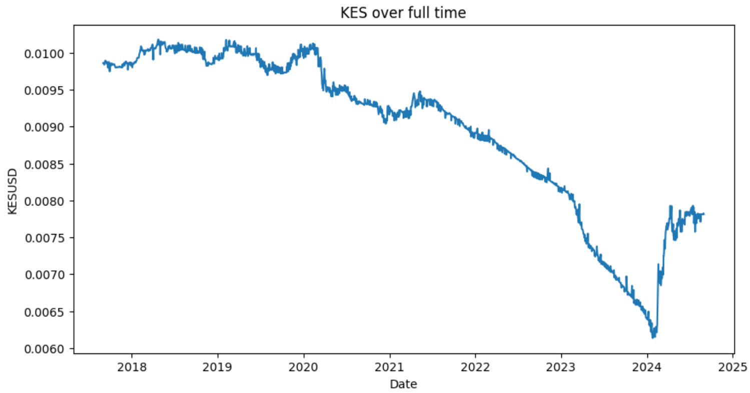

Figure 4.1: KES 2017-2024.

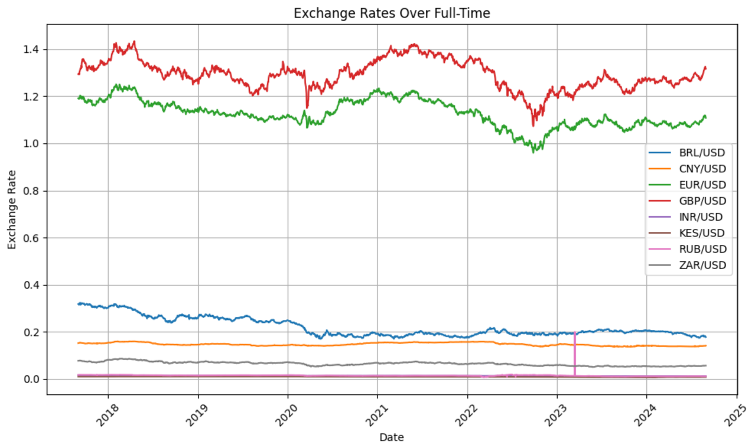

Figure 4.2: Exchange Rates 2017-2024

4.3 Descriptive statistics

Tables(4.1),(4.2), (4.3) and(4.4) demonstrate that the GBP/USD has the highest mean value of 1.2919 with a standard deviation of 0.0628 while the KES/USD has the least mean value of 0.0101 with a standard deviation of 0.001 .The GBP/USD has the highest max value with 1.4342,and the KES/USD has the least max at 0.0101.Which also happens to have the least minimum value at 0.0061 followed closely by RUB/USD at 0.0072. GBP/USD has the greatest range with 0.3615. This is backed-up by its high standard deviation 0f of 0.0628 compared to other exchange rates. KES/USD and INR/USD have the smallest range with 0.004044, and 0.004069 respectively. This is also supported by their negligible standard deviations of 0.001 for the INR/USD and 0.00108 for the KES/USD.

Table 4.1: 2017-2020 Descriptive Statistics Source: Kariuki (2024a)

Pre(2017-2020)	min	max	mean	std
BRL/USD	0.2230	0.3228	0.2692	0.0257
RUB/USD	0.0142	0.0179	0.0159	0.0009
INR/USD	0.0134	0.0158	0.0145	0.0006
CNY/USD	0.1393	0.1596	0.1483	0.0054
ZAR/USD	0.0646	0.0865	0.0726	0.0055
EUR/USD	1.0788	1.2510	1.1514	0.0409
GBP/USD	1.2022	1.4342	1.3090	0.0467
KES/USD	0.0097	0.0102	0.0099	0.0001

Table 4.2: Mid Descriptive Statistics Source: Kariuki (2024i)

mid(2020-2022)	min	max	mean	std
BRL/USD	0.1698831171	0.2251593024	0.1867635366	0.008416627483
RUB/USD	0.01177648269	0.01511039585	0.01350746888	0.0004445855602
INR/USD	0.01289158221	0.01386001334	0.01345284977	0.0001900544081
CNY/USD	0.1395050287	0.1584208608	0.1511200013	0.005814231488
ZAR/USD	0.05195182934	0.07452708483	0.06425304266	0.00500941896
EUR/USD	1.065734506	1.234110832	1.165204135	0.03951851782
GBP/USD	1.1494385	1.422677517	1.334067328	0.05639166869
KES/USD	0.008802817203	0.0100627793	0.00925566236	0.0002156145543

Table 4.3: Post Descriptive statistics .Source: Kariuki (2024j)

Post(2022-2024)	min	max	mean	std
BRL/USD	0.1738948971	0.2176847011	0.1967786829	0.008298052987
RUB/USD	0.007196051069	0.200000003	0.01303693701	0.007718731396
INR/USD	0.01173791569	0.01328289416	0.01225044857	0.0003453914571
CNY/USD	0.1364666075	0.1585187912	0.1427563606	0.005434108603
ZAR/USD	0.05057017878	0.06905028224	0.0563744261	0.004130281638
EUR/USD	0.9596191645	1.123759627	1.068060619	0.03302297073
GBP/USD	1.072754145	1.342281818	1.241620299	0.04571605492
KES/USD	0.006134969182	0.008864462376	0.007687839022	0.0007316182481

Table 4.4: Full Descriptive Statistics Source: Kariuki (2024c)

Full(2017-2024	min	max	mean	std
BRL/USD	0.1698831171	0.3228305876	0.2196571482	0.04060021471
RUB/USD	0.007196051069	0.200000003	0.01420472892	0.004835979795
INR/USD	0.01173791569	0.01580652781	0.01340345915	0.001059004993
CNY/USD	0.1364666075	0.1595506966	0.1471083303	0.006526328321
ZAR/USD	0.05057017878	0.08647676557	0.06440182462	0.008423576661
EUR/USD	0.9596191645	1.251000881	1.125447325	0.0574959524
GBP/USD	1.072754145	1.43420577	1.291979885	0.06284350801
KES/USD	0.006134969182	0.01017894596	0.008942358608	0.001079933982

Skewness

From the table(4.5), we can observe that for the full period, the EUR/USD, GBP/USD,and KES/USD are negatively skewed .Eastman and Lucey (2008) affirm that investors prefer the case of negative skewness in Forex markets because it indicates that most returns are higher than the mean. The rest of exchange rates (4.5)are positively skewed.The RUB/USD has a high degree of non-normality,given that its skewness is way > 2. This findings confirms early research of Simkowitz and Beedles (1978) that stated that returns are not symmetrical and thus lack a normal distribution.

Table 4.5: Skewness Source: Kariuki (2024k)

Skewness	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	0.608115	0.904133	-0.257523	0.952392
RUB/USD	0.652162	0.209736	21.839258	31.108973
INR/USD	0.566849	-0.259884	1.469265	0.30256
CNY/USD	0.551307	-0.715968	1.175564	0.225898
ZAR/USD	0.956863	-0.449043	1.343366	0.325487
EUR/USD	0.627723	-0.491416	-1.241668	-0.108206
GBP/USD	0.365786	-0.734119	-0.882009	-0.145677
KES/USD	-0.259691	0.195331	-0.275776	-0.845184

Kurtosis

Kurtosis is a measure of the thickness of a tail of a distribution (DeCarlo, 1997).The significance of this information is that the thickness of a tail can tell us the peakness of a distribution. Therefore, kurtosis can explain extreme sharp events. Emenike and Enock (2020) adds that a high kurtosis is indicative of large shocks despite the nature of the sign $+/-$. For a normal distribution, the kurtosis is 3.Lepto-kurtosis is positive and has a sharp peak , while platy-kurtosis is negative (Chissom, 1970). The table (4.6) shows the values of kurtosis are only positive in the RUB/USD currency while the other currencies demonstrate platy-kurtosis.

Table 4.6: Kurtosis Source: Kariuki (2024h)

Kurtosis	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	-0.877996	2.104393	-0.317831	-0.314176
RUB/USD	-0.700391	1.41836	529.013592	1196.151171
INR/USD	-0.999609	-0.351576	1.014009	-0.706255
CNY/USD	-0.755778	-1.070304	0.762658	-1.211538
ZAR/USD	-0.098463	-0.635803	1.121575	-0.565797
EUR/USD	-0.484294	-0.669535	1.02167	-0.357384
GBP/USD	0.222682	-0.265596	1.046639	-0.05652
KES/USD	-0.993151	0.65386	-1.023773	-0.417505

4.4 Tests

4.4.1 Jarque-Bera Test

H_0 : The time series follows a normal distribution

H_A : The time series follows a non-normal distribution

Table (4.7) holds the p-values of the Jarque-Bera test.All the values for all exchange rates are < 0.05 . Thus, none of them follow a normal distribution (Thadewald and Büning, 2007) . This echoes the skewness(4.5) findings.The more reason to use a neural network algorithm which is better for handling complex non-linear data.

Table 4.7: Jarque Bera P-values. Source: Kariuki (2024g)

Exchange rates	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	6.6415e-14	2.6461e-36	0.0065	3.1452e-62
RUB/USD	1.4585e-13	1.0579e-10	0.0	0.0
INR/USD	4.1956e-14	0.0133	1.8023e-57	4.7365e-15
CNY/USD	3.3548e-11	9.4929e-16	1.3571	2.6884e-28
ZAR/USD	3.6311e-22	1.9129e-06	1.8694e-50	4.6998e-13
EUR/USD	2.4846e-11	2.1253e-07	5.0417e-43	0.0012
GBP/USD	0.0004	3.4776e-11	2.5112e-25	0.0342
KES/USD	4.2089e-08	0.0024	9.7689e-50	1.5327e-50

4.4.2 Unit Root Test

The Augmented Dickey-Fuller test

H_0 : The time series is non-stationary.

H_A : The time series is stationary .

Table (4.8) with p-values from the ADF test show that the values are > 0.05 .Thus, we should fail to reject the null hypothesis and conclude that all the exchange rates are non-stationary. Dickey and Fuller (1981) explained that for a stationary time series ,the mean and variance remain constant over time. Such kind of distribution is susceptible to random shocks and lacks long-term stability (Dickey and Fuller, 1981).

Table 4.8: ADF Test P-values. Source: Kariuki (2024b)

ADF Test P-values	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	0.7533	9.2976e-05	0.1756	0.2365
RUB/USD	0.3774	0.0121	3.9543e-10	4.70853e-05
INR/USD	0.5043	0.0611	0.0804	0.4963
CNY/USD	0.8206	0.8845	0.03467	0.3951
ZAR/USD	0.5615	0.5913	0.1531	0.3732
EUR/USD	0.6345	0.4975	0.1982	0.2863
GBP/USD	0.3621	0.4723	0.1664	0.1414
KES/USD	0.2718	0.0489	0.4856	0.8767

4.4.3 Correlation Coefficient Test

Even if correlation does not imply causation ,it is still an important measure when assessing time series data . The Pearson correlation coefficient is a measure of the linear linkage between any two data sets (Sahiner, 2023).This coefficient between any two exchange rates a and b is calculated as follows:

$$P_{ab,t} = \frac{E_{t-1}(R_{a,t}R_{b,t}) - (R_{a,t})(R_{b,t})}{\sqrt{E_{t-1}R^2_{a,t} - (R_{a,t})}\sqrt{E_{t-1}(R^2_{b,t} - (R^2_{b,t}}} \tag{4.1}$$

Figures((2017-2020) heat map (4.3), (2020-2022) heat map(4.4), (2022-2024) heat map (4.5), and (2017-2024) heat map (4.6) indicate the correlation between the exchange rates. Looking at the((2017-2020) heat map (4.3), we see that the KES/USD has a weak negative correlation with the RUB/USD, INR/USD and BRL/USD. A weak positive correlation to other currencies with its highest at a positive correlation of 0.46 with the GBP/USD and the weakest at -0.097 against the RUB/USD. During 2020-2022 (4.4), the KES/USD had a negative correlation with all the exchange rates apart from the BRL/USD and RUB/USD. During 2022-2024 (4.5),the KES/USD had a negative correlation with BRL/USD at -0.35 and EUR/USD at -0.43. It had a positive correlation with the Rand, Indian Rupee and the Chinese Yuan. However,for the full period, the heat map (4.6) shows the correlation between the other currencies and the KES.The Indian Rupee has the highest at 0.86. Followed by the Euro together with the Brazilian Real at 0.56 ,followed by the Chinese Yen at 0.5. The least is the South African Rand at 0.28.It's interesting to note that the Rand is least correlated to Russian Ruble.

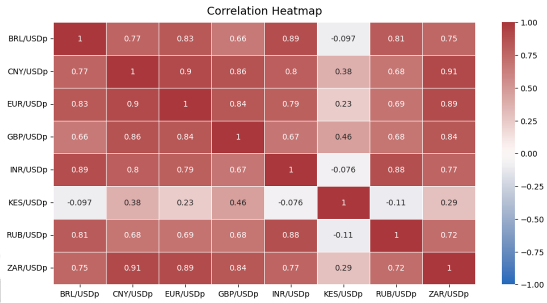

Figure 4.3: 2017-2020 Correlation

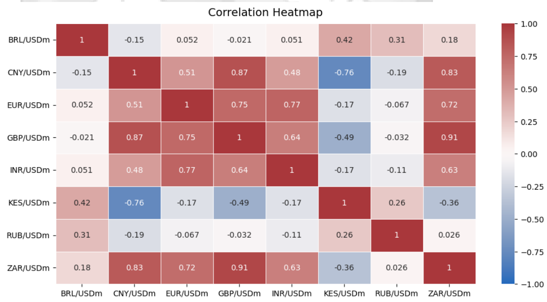

Figure 4.4: 2020-2022 Correlation

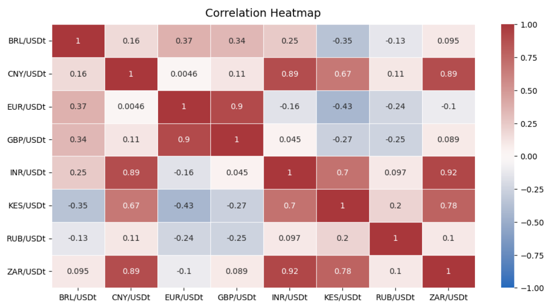

Figure 4.5: 2022-2024 Correlation

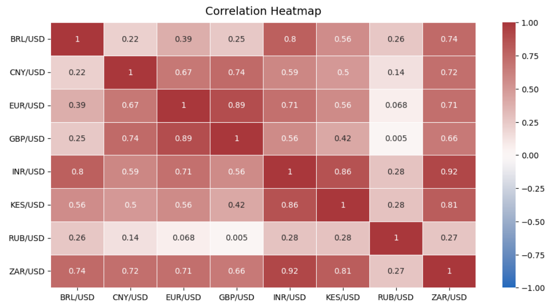

Figure 4.6: 2017-2024 Correlation

4.5 Spillover Degrees

Table (4.9) outlines the final results output by the LSTM model. It holds the degree of volatility the Kenyan forex market received from select forex markets. Table (4.9) shows that during 2017 to 2020, INR/USD transmitted the highest degree of volatility to the KES/USD at 1.2561 followed closed by RUB/USD at 1.1206. We can see that ZAR/USD transmits the least volatility at 0.0099 with CNY/USD at a close second least at 0.0141. The GARCH-LSTM model (4.10) used to calculate these results had low RMSE(0.0988), MAE(0.0730), and MSE(0.0098) values indicating a high accuracy. During the mid period 2020 to 2022, the INR/USD transmitted the highest degree of volatility of the KES/USD at 1.3702 followed closed by RUB/USD at 1.1486. We can see that ZAR/USD transmits the least volatility at 0.0091 with CNY/USD at a close second least at 0.0134. The mid-period model (4.10) had low RMSE(0.1042), MAE(0.0840), and MSE(0.0109) values indicating a great performance, but it had higher errors than the model for the pre-period. In the post period (2022 to 2024),INR/USD transmitted the highest degree of volatility of the KES/USD at 1.3394 followed closed by RUB/USD at 1.1938. We can see that ZAR/USD transmits the least volatility at 0.0095 with CNY/USD at a close second least at 0.0131. The post-period model (4.10) had low RMSE(0.0866), MAE(0.0671), and MSE(0.0075) values indicating a greater performance than the models for the previous periods. The ranking(4.9) show that India and Russia have the highest degree of volatility spillovers to the Kenyan currency.Even though the Euro is third,it is almost a half of Russia's degree.The other four currencies have an almost negligible degree with the South African Rand having the least spillover degree at 0.0098.Notably,the full-period model (4.10) had the least errors with RMSE(0.0831), MAE(0.0702), and MSE(0.0069) values. In comparison , when using the GARCH only model, we could only output the daily volatilities, so we ran a correlation to the volatilities in the KES/USD. Table (4.11)shows that the correlation between volatilities has increased over time. The highest positive correlation in the full period, KES/USD has the highest correlation with EUR/USD at (0.5243) and the weakest negative correlation with ZAR/USD at (-0.2134) .Table(4.12) show low MAE results of the GARCH ranging from the lowest at (0.0024) to (0.1255) indicating a great performance in estimating the correlations.

Table 4.9: GARCH-LSTM Model Degree of Volatility Spillovers. Source: Kariuki (2024d)

Degree of Spillovers	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	0.1425	0.1559	0.1426	0.1439
RUB/USD	1.1206	1.1486	1.1938	1.1609
INR/USD	1.2561	1.3702	1.3394	1.3131
CNY/USD	0.0141	0.0134	0.0131	0.0137
ZAR/SUD	0.0099	0.0091	0.0095	0.0098
GBP/USD	0.0154	0.0138	0.0119	0.0143
EUR/USD	0.0678	0.0688	0.0575	0.0681

Table 4.10: Accuracy Metrics for the GARCH-LSTM Models

Accuracy Metrics	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
RMSE	0.098779	0.104185	0.086625	0.083149
MAE	0.073002	0.083964	0.067063	0.070172
MSE	0.009757	0.010855	0.007504	0.006914

Table 4.11: GARCH Correlation of volatility. Source: Kariuki (2024e)

Volatility Correlation	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	0.028912	0.814230	0.814230	-0.125324
RUB/USD	0.113886	0.735518	0.735518	0.379100
INR/USD	0.054629	0.766008	0.766008	0.432366
CNY/USD	0.146803	0.753633	0.753633	0.404727
ZAR/USD	-0.067606	0.0091	0.185232	-0.213435
GBP/USD	0.111023	0.0138	0.563123	-0.01905
EUR/USD	0.178768	0.829337	0.829337	0.524318

Table 4.12: GARCH MAE Metrics. Source: Kariuki (2024f)

GARCH MAE	Pre 2017-2020	Mid 2020-2022	Post 2022-2024	Full 2017-2024
BRL/USD	0.072445	0.814230	0.064856	0.050283
RUB/USD	0.089678	0.735518	0.107381	0.072171
INR/USD	0.101422	0.056641	0.059748	0.056467
CNY/USD	0.084863	0.062106	0.038975	0.052106
ZAR/USD	0.081942	0.102103	0.048600	0.038878
GBP/USD	0.075019	0.055470	0.004876	0.002419
EUR/USD	0.101422	0.103552	0.12551	0.095711

Chapter 5

Discussion

5.1 Introduction

This chapter discusses the answers to the research questions in great detail while acknowledging the limitations of the study. It adds some recommendations for further research.

The main research sought to find out

a) Which degree of volatility spillover is transmitted from the seven currency pairs - ZAR/USD,BRL/USD,CNY/USD,RUB/USD,INR/USD,EUR/USD, GBP/USD to the KES/USD?

b) How does the degree of contagion risk to the KES/USD differ between BRICS currency markets (ZAR/USD,BRL/USD,CNY/USD,RUB/USD,INR/USD) and Western currency markets (EUR/USD, GBP/USD)?

c) How can we incorporate GARCH together with a recurrent neural network algorithm to estimate and analyze the degree of exchange rate volatility spillovers?

5.2 Key Findings

Using a GARCH-LSTM model, we were able to estimate the degree of spillovers. For all the time periods (2017-2020, 2020-2022, 2022-2024,2017-2024) the INR /USD transmitted the highest degree of volatility spillovers to the KES/USD. Table(4.9) shows that the lowest degree was in the (2017-2020) pre- period at 1.2561. However, its highest was 1.3702 during the mid period (2020-2022). It drops during the post period

(2022-2024) to 1.3394 .At a close second,the RUB/USD follows. Interestingly,the degree os spillover for the RUB/USD increases with every time period. Such that, the degree for pre-period $<$ mid-period $<$ post-period. (1.1206< 1.1486 < 1.1938)
Interestingly ,for the full period (2017-2024) the highest degree of volatility spillover comes from two BRICS currencies the Rupee (1.3131) and the Ruble forex markets(1.1609), while the least degrees of spillovers is transmitted from a BRICS currency,the south African Rand at 0.0075. For the western currencies,Table (4.9) shows the GBP/USD transmits a low degree of volatility at 0.0149 and but the EUR/USD transmits the third highest degree to the KES/USD at 0.056.
The GARCH-LSTM proved an important tool in estimating the degree of volatility spillovers between exchange rates. After calculating the daily volatilities through GARCH, the data was forwarded to an LSTM model to retain the relevant volatility information and, output a degree of shock transmission. As shown in table (4.9). However, we only get daily volatilities when using a GARCH model. So to get a measure of relationship between daily volatilities of KES/USD and other exchange rates, we estimated the correlation between the volatilities of various exchange rates. Table (4.11) shows those correlation results.

5.3 Discussion of Results

From the table (4.9), The GARCH-LSTM results show that the INR/USD exchange rate transmits the highest degree of volatility spillover to the KES/USD .This suggests a strong interconnection between the Indian currency market and the Kenyan economy. Interestingly, the findings concur with Anna's Mishra (2024) research on the trade links between India and Africa. Notably ,India's trade links with Africa continue to grow making it the third largest trade partner for Africa as of 2023 (Mishra, 2024). India's strong ties to Kenya to the fact that trade began on the east coast of Africa centuries ago. Kenya among Egypt,South Africa,Tanzania, Nigeria are the top 5 African destinations for Indian exports (Mishra, 2024). Kenya alone has witnessed a growth of 22% over the past year (hci, 2024) (oec, 2024a). Kenya mainly imports Pharmaceuticals, Machinery,transport,petroleum products, steel from India While it exports leather,metal scraps,soda ash and vegetables (hci, 2024). The imbalance in the export import value can be one of the reasons why Kenya is a net receiver of shock from the Indian economy. More trade links between Kenya and India are expected as India continues to invest more in Kenya especially, telecommunications and manufacturing sectors (hci, 2024). The data in table(4.9)shows that the degree of the Russian Ruble (1.1609) comes in close proximity to the India Rupee with a volatility spillover degree of 1.3131 for the full period (2017-2014).This could be explained by the findings of Hussain et al. (2024) that Russia has a high shock linkage to India .Therefore,if the Rupee has high shock transmission to Kenya it follows that the Ruble will as well, due to the systemic risk nature of contagion. Besides, Russia itself has strong trade linkages. While Kenya exports ,Tea, Cut flowers and Tropical Fruits to Russia oec (2024b), It imports Wheat, Fertilizers ,Semi-Finished Iron among other products. It is important to Note that Kenya's exports to Russia have decreased at an annual rate of 4.51% while Kenya's imports from Russia have increased at annual rate of 4.16% over the past five years oec (2024b) . The second highest volatility degree(RUB/USD) is significantly higher than third (BRL/USD).The data in table (4.9) suggests that the Euro Forex markets transmits a degree of volatility spillover that is about half that of the Rupee.The CNY/USD transmit the second least volatility to the KES/USD.This agrees with Hussain et al. (2024) they explained that China has weak volatility connectedness to the rest of the BRICS countries. Its interesting that even though Brazil transmits high volatility to South Africa (Hussain et al., 2024), The ZAR/USD transmit the lowest volatility to the KES/USD as observed in table (4.9) while the BRL/USD transmits the third highest volatility to the KES/USD,

5.4 Limitations of the Study

This study estimates the volatility transmitted to the KES/USD through the exchange rate channel. We acknowledge that it does not account for all macro-economic factors and geopolitical events that can influence the movements in the Kenyan Forex Market . However ,it does shed a light to the current state of risk transmission.The study only focus on the past 7 years .Even though the main aim is to focus on recent years it would also the important to have a research that covers a good period of about 50 years.While this paper focus more on the global south,Euro and the Pound. More research that focus on the Kenyan shilling against wider markets like the Asian Forex markets and through other channels like stock indices and other macro-economic indicators.

5.5 Recommendations

Based on the findings above,this study recommends that stakeholders, policy makers , trade representatives and people looking to invest in the Kenyan market should: closely monitor the behavior of the Indian Rupee and the Russian Ruble by enforcing an efficient framework that combines both macroeconomic factors and real time market data to better estimate contagion risks.The parties involved should also implement policies that include hedging strategies through options or futures especially when dealing imports from the Indian and Russian markets. Research centers could invest more in large-scale deep learning techniques to create real-time predictive tools. These tools can not only accommodate more time series but also capture a longer time line. This will help policymakers and government trade representatives with informed decisions. Besides, investors could consider diversify their portfolios by investing in lower risk currencies like the Chinese and South African markets.

Chapter 6

Conclusion

Through this research,we enhance our understanding of the degree of volatility transmitted to Kenyan Forex Market in specific its main trading exchange rate(KES/USD). We have investigated seven select currencies i.e 5 BRICS countries(Brazil, Russia, India,China,South Africa) due to the rise of the global south trading bloc, the Euro as the second largest trading currency and the British Pound for its long standing history with the Kenyan shilling. This study is unique from existing literature by focusing on the degree of volatility transmitted to the KES/USD through a GARCH-LSTM model. The study acknowledges the exchange rates as a main channel of volatility transmission. Besides,we focus on the past seven years due to the recent timeline of financial events that have de-stabilized exchange rates and trade linkages globally. The results show that there is indeed a level of shock transmitted from each of the select exchange rates. There is evidence that the Indian Rupee and the Russian Ruble transmits very high degrees of volatility to the KES/USD.This is backed up by trade linkages between the countries as we observed that Kenya is a net importer in both cases.The study also finds that the South African rand and Chinese Yuan currency markets transmit the lowest and second least degrees of shock.Thus, this paper recommends that stakeholders, policy makers, trade representatives and people looking to invest in the Kenyan market should closely monitor the behavior of the Indian Rupee and the Russian Ruble by the enforcement of an efficient monitoring framework that combines both macroeconomic factors and real time market data to better estimate contagion risks.Besides, the implementation of policies that include hedging strategies especially when trading with the Indian and Russian markets. Another recommendation is that research centers should focus more on the application of ensemble learning systems in macroeconomic issues.This is because they give more layered information about financial time series than traditional

GARCH models.For example, in this paper, the GARCH-LSTM model outputs a close estimate of the degree of shock transmission, while a GARCH model could only give us the correlation between the volatilities.

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Appendix A

Similarity Report

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Appendix B

Ethical Clearance Confirmation

24th April 2024

Ms Kariuki Purity,
purity.wanjiku@strathmore.edu

Dear Ms Kariuki,

RE: A Deep Learning Analysis of Volatility Spillovers from Select Currencies to the Kenyan Shilling

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC2120/24.** The approval period is from **24th April 2024 to 23rd April 2025.**
This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

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