KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

THE IMPACT OF EXCHANGE RATES VOLATILITY ON STOCK PRICES IN GHANA

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A THESIS SUBMITTED TO THE DEPARTMENT OF ACTUARIAL SCIENCE AND STATISTICS, KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF BACHELOR OF SCIENCE IN ACTUARIAL SCIENCE.

Declaration

I hereby declare that this submission is my own work towards the award of undergraduate degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which had been accepted for the award of any other degree of the university, except where due acknowledgment had been made in the text.

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Dedication

We dedicate this thesis first and foremost to God Almighty and our parents, who have been our constant source of inspiration. They have given us the drive and discipline to approach any task with determination and enthusiasm. Their love and support made our work possible, and we pray that God will bless them abundantly and replenish all that they have sacrificed for our success.

Abstract

The objective of this research is to investigate whether there is a Granger-causal relationship between exchange rates and stock prices. We utilized the Granger-Causality model and analyzed daily data from the Ghana Stock Exchange Composite Index (GSE-CI) and the USD-Cedi exchange rate spanning from 2012 to 2022.

We collected our data from the Bank of Ghana and the Ghana Stock Exchange. After conducting Granger-causality tests to assess causality from exchange rate movements to changes in stock prices and vice versa, our findings revealed that neither variable significantly influenced the other. Therefore, we concluded that changes in exchange rates do not Granger-cause changes in stock prices, and conversely. Nevertheless, investors should consider other potential impacts of exchange rate fluctuations when making investment decisions in the stock market.

Acknowledgements

We wish to express our sincere gratitude to the Almighty God for helping us complete our project through his love, protection, and wisdom. We would like to thank our supervisor, Miss Sandra Addai-Henne, once more for her advice, modifications, patience, motivation, enthusiasm, and immense knowledge throughout our project. She taught us a lot, and we want to continue learning from her in the future. We would like to thank all lecturers and staff of the Department of Statistics and Actuarial Science, for their knowledge shared since we first enrolled at this prestigious institution. Finally to our family and others who have contributed in one way or the other to make the writing of this thesis possible.

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Chapter 1

Introduction

1.0.1 Background of Study

Stock exchange markets play a crucial role in economies as they provide long-term funding to businesses. The stock market is influenced by various external and internal factors, including exchange rates. Exchange rate volatility is defined as the risk associated with unexpected movements in the exchange rate. The world's stock markets are investments for international investors. The importance of developing nations for the diversification of global assets cannot be ignored by international investors. Foreign currency rates affect the profitability of foreign investors' stock market investments. It is widely accepted that fluctuating exchange rates have an impact on how competitively strong businesses are in global markets (Stavarek, 2005). If the prices of their inputs and outputs are impacted by currency changes, even businesses with entirely domestic operations may be impacted by exchange rates (Adler and Dumas, 1984). The Ghanaian economy began to exhibit chronic foreign exchange rate volatility and deviations from purchasing power parity. Economic problems have recently harmed the Ghanaian economy. These unfavorable economic conditions have an impact on businesses operating in the nation because they incur more business and foreign exchange risk. One of the main causes of macroeconomic uncertainty that affects businesses is exchange rate volatility. This volatility can be attributed to the post-1970s rapid growth in global trade. The only venue for Ghanaian stock market activity is the Ghana Stock Exchange (GSE). The Ghana Stock Exchange (GSE), which lists stocks in two listing categories, the Official List and the Ghana Alternative Market (GAX), has about forty-three (43) listed stocks and an average total market capitalization of GHS 65 billion (GSE, 2018). As a result, the GSE is a dependable source of equity financing for both larger companies and relatively smaller businesses operating in Ghana. As part of the structural reform program started under the watchful eye of the World Bank and the IMF, Ghana was exposed to the flexible exchange rate regime in 1983. According to Winful, Sarpong, and Kumi (2012), these reforms included changes to interest rates, the elimination of credit restrictions, and the implementation of a floating exchange rate regime. The managed flexible exchange rate policy, which Ghana now uses, involves some intervention by monetary authorities in addition to market forces like supply and demand dictating currency prices. Free currency exchange in Ghana was made possible by the floating exchange rate regime, but it also had some negative effects on the cedi's value among its key trading partners, the US Dollar, Euro, and Great Britain Pound. According to statistics from the Bank of Ghana, the Cedi has undergone significant exchange rate depreciation and volatility since the flexible exchange rate regime was implemented. From 2007 to 2018, the cedi's value relative to its main trading partner currency (the dollar) decreased by nearly 300 percent, falling from the equivalent of one dollar to one cedi to roughly eleven cedis. Therefore, the exchange rate is crucial for assessing stock market volatility. Using data from the Ghana Stock Exchange from 2012 to 2022, the current study attempts to determine a causal relationship between stock prices and exchange rate volatility in Ghana. When deciding to invest in the stock market, investors are motivated by share prices. Prices in the stock market fluctuate irregularly and unpredictably. It is believed that price volatility in the stock market is a sign of a healthy stock market. Most changes in stock market values are the consequence of speculative activity. Therefore, exchange rate rumors could have an impact on stock market values. Investors become uneasy due to price fluctuations in the stock market, thus to avoid risks, the investors decrease investment in the capital market. In this manner, a long-term source of finance begins to decline, which causes a decrease in the amount of investment in the economy and a decline in capital formation. A recession may be on the horizon for the economy. There is conflicting evidence in the literature about the causal link between exchange rate volatility and stock market price volatility. Many economists, particularly in the world's developing nations, have previously been interested in empirical studies of the relationship between exchange rate variability and stock prices. Even though economic theory suggests that fluctuations in foreign exchange affect cash flow, investments, and business profitability, actual research is still divided on the subject. The relationship between exchange rate variability and the response of stock prices is revealed in the empirical experiments that follow. However, both in theory and empirical research, the arrow of causation is still ambiguous. Therefore, the purpose of this study is to investigate the actual causal link between stock prices and exchange rates. In this context, the pertinent empirical issue is: How do changes in exchange rates and stock prices relate to one another in the Ghanaian economy?

1.0.2 Problem Statement

The assessment of the influence of exchange rate volatility on Ghana's financial position has provided divergent views, primarily due to differences in research conclusions. Adjasi et al (2008) found an inverse relationship while Gatsi et al. (2016) concluded that there was no causal relationship. In line with these results, we would consider the impact of exchange rate volatility on stock prices in Ghana including the covid period which others failed to look at.

1.0.3 Reseach Objective

The objective of this work is to examine the causal relationship between exchange rate and stock prices in Ghana with special reference to the Ghana Stock Exchange.

1.0.4 Significance of the study

The findings of the study would be especially relevant to investors, government, and other institutions in identifying the impact of exchange rate fluctuation on the stock market performance, especially given the unstable exchange rate situation in Ghana over the past decade, and particularly in recent years. In addition, there have been few studies on the impact of exchange rate changes on stock price movement in Ghana. This study, therefore, adds to the breadth of the studies conducted from a Ghanaian perspective on this topical issue. Furthermore, this study used data from the period after the redenomination of the Ghana cedi, specifically from 2012 to 2022, in the development of a current perspective on the subject.

1.0.5 Organisation of Study

There are five chapters in this research. The first chapter of this study discusses the background information and the foundations for our research. Our problem statement and a summary of the study's goals are also included. The second chapter of this study contains a literature review of some very important information about this work. It also includes several studies that have been conducted to look into the relationships between exchange rate volatility on stock prices. The third section which is the methodology provides more details on the mathematical computation of the models used for this work. The fourth chapter presents the practical outcome, which includes data representation, analysis, and discussion. The fifth chapter contains the study?s conclusions as well as some recommendations that can be made.

1.0.6 Limitations of the Study

Some codes were difficult to comprehend and run at the start of the work and hence caused the study to be delayed. We were also limited by the easy access to certain study materials since some of them required payments and others were out of the jurisdiction of the country. Overall, the study was a challenging one but as we progressed on the project, we worked out all of these.

Chapter 2

Literature Review

2.1 Introduction

It is true that financial economists, policymakers and investors have long-attempted to understand the dynamic interactions between exchange rate and stock returns, the exact patterns of the interactions remain unclear, though the nature and strength of the dynamic interactions between them are of high interest and need to be evaluated empirically. Ghana adopted a floating exchange rate regime in 1983, an event that positions the subject of exchange rate volatility as pertinent to its financial sector, notably the stock market. Over the past decade, the country has experienced considerable exchange rate volatility. Consequently, exchange rate volatility has assumed topical eminence in contemporary economic and political arguments, albeit not directly related to the stock market. It is imperative; however, we investigate the relationship between exchange rate and stock prices since the GSE serves as a reliable investment alternative for investors in the country. This section explains the theoretical and empirical literature on the relationship between exchange rate and stock prices in Ghana. The first section explains the theoretical grounds of the study. It discusses how the theoretical models, the VAR (Vector Autoregressive Model) and the Granger Causality model explain the connection between exchange rate and stock prices. The second section provides information on empirical methods and findings related to the issue of how the exchange rate affects stock prices in Ghana. 2.2 Review of Theoretical Literature. The two models that describe the dynamic relationship between changes in the exchange rate and stock prices are the VAR model and the Granger Causality model. The final goal of this part is to provide a theoretical overview of the relationship between these two models.

2.2 Vector Autoregressive Model

Vector Autoregression (VAR) is a forecasting algorithm that can be used when two or more time series influence each other, i.e. the relationship between the time series involved is bi-directional and the flow of data is mutual and each variable alters the other. The VAR model connects recent data on one variable to older data on that same variable as well as to earlier data on other variables in the system. It is a straightforward multivariate time series model. VAR models differ from univariate autoregressive models in that they allow feedback between the variables in the model.(Eric,2021) . When two or more time series interact with one another, or when the relationship between the time series is bidirectional, the forecasting algorithm known as vector autoregression (VAR) can be utilized. VAR models make excellent forecasting tools. Their setup allows the current values of a set of variables to be partially explained by their prior values. (Helmut Lutkepohl). Because each variable (Time Series) is modeled as a function of previous values, the predictors are nothing more than the lags (time-delayed values) of the series; this model is known as an autoregressive one.

2.2.1 History of the Vector Autoregressive Model

One of the most effective, adaptable, and simple methods for the study of multivariate time series is the vector autoregressive (VAR) model. Dynamic multivariate time series are a logical extension of the univariate autoregressive model. These four tasks: data description, forecasting, structural inference, and policy analysis were carried out in the 1970s using a number of methods. These ranged from complex models with hundreds of equations to simple univariate time series models with only one equation that concentrated on interactions between a few variables, only one variable. But following the macroeconomic instability of the 1970s, none of these strategies seemed very reliable. Vector auto-regressions (VARs), a fresh macroeconomic paradigm introduced by Christopher sins in 1980, held a lot of promise in offering a consistent and reliable approach to data description, forecasting, structural inference and policy analysis, as Sims(1980) and others emphasized in a number of key early works. A single equation, one-variable linear model called a univariate auto-regression explains a variable?s current value using its own lagged data. A VAR is an n-equation, n-variable linear model where each variable is described by its own lagged values as well as the present and past values of the other variables. The statistical toolkit that came with VARs was straightforward to use and understand and it offered a systematic technique to capture rich dynamics in various time series (Watson, 2001)

2.2.2 Types of the VAR Model

There are mainly three broad types of VAR models, the reduced form, the recursive form, and the structural VAR model.

- Reduced Form: The reduced form of the Var model assumes that each variable is a function of either its historical values or the historical values of other variables in the model. Even though reduced-form models are the most straightforward VAR models, they have drawbacks. The error terms in different equations will be interrelated. As a result, we are unable to predict the effects of individual shocks on the system.

- Recursive Var Models: All the elements of the reduced-form model are included here, however, certain variables may also be functions of concurrent variables. We can model structural shocks using the recursive model by enforcing these short-run relationships. The error terms in each regression equation are created by a recursive VAR such that they are unrelated to the error in the previous equations. To achieve this, carefully choose a few current values to act as regressors.

- Structural Var Models: This contains constraints that extend the scope of the casual relationships that can be discovered using reduced-form or recursive models. The effects of individual shocks, like policy decisions, can be predicted and modeled using these ad hoc relationships. (Eric, 2021).

2.2.3 Applications of The VAR Model

The VAR model is particularly effective for forecasting and characterizing the dynamic behavior of economic and financial time series. It frequently offers forecasts that are better than those from complex simultaneous equation models and univariate time series models. Because they can be made conditional on the likely future course of certain model variables, forecasts using VAR models can be highly flexible.(Eric Zivot and Jiahui Wang 2007) The VAR model has been widely used to simulate the temporal dependence of multivariate time series. Sims (1980) brought vector autoregressions (VARs) into empirical economics by demonstrating that they provide a flexible and manageable framework for assessing economic time series. James H. Stock and Mark W. Watson, 2001). When Sims (1980) suggested Vector Autoregressive (VAR) models as alternatives, multivariate simultaneous equations were widely employed for macroeconomic analysis. Models that described the dynamic structure of the variables were needed at the time due to the longer and more often recorded macroeconomic time series, and VAR models are well suited for this. VAR models often concentrate on stationary variables without considering temporal trends. The importance of stochastic trends in economic variables was identified in the 1980s by Granger (1980), Engle and Granger (1987), Johansen (1995), and others. They also created the concept of cointegration, showing that stochastic trends can also be captured by VAR models (Helmut Lutkepohl).

- Medicine: In the field of medicine, VAR models are quite useful. It can be used to simulate both past and present heart rate, respiration rate, and blood pressure correlations. Electronic diaries have been utilized more frequently recently in medical research and practice to examine patient processes and changes in symptoms over time. A multivariate time series approach must be used to simulate dynamic dependence structures and feedback mechanisms between symptom-relevant variables. In a study by Wild, the electronic diary data of 35 obese patients with and without binge eating disorders (BED) were subjected to the graphical VAR method. Two path diagrams were used to show the dynamic interactions between eating behavior, depression, anxiety, and eating control for the two subgroups. The findings demonstrated that the temporal patterns that influenced each category of obese patients?those with and those without BED?could be distinguished. The use of a graphical VAR technique for the analysis of electronic diary data was found to provide a greater understanding of the dynamics and dependent patterns of the patient. In various fields of medical care and research, increased adoption of this modeling strategy might result in a better understanding of intricate psychological and physiological mechanisms. (Wild et al.2010)

- Economics: The link between income and consumption over time is modeled using a two-equation VAR system. Ranjith Bandara (2011) claims that Granger Causality Tests were also employed in conjunction with Vector Auto-Regressive (VAR) models to determine the most relevant causes of inflation. Overall, the results of estimated VAR models suggested that information about Sri Lankan inflation bbehaviorcan be found in the money supply, exchange rate, and GDP. Also in Soren's 2001 studies, where the terms "instrument," "intermediate target," and "final target" were defined in the context of the cointegrated VAR and "target variable" was defined as "controllable" if it could be made stationary around a desired target value by using the instrument, which can be expressed as a condition on the long-run impact matrix," it was found that the empirical findings did not support the widely held belief that the Federal Reserve Bank can control the economy. The dynamics of the process are altered when a control rule is used to intervene in the market, necessitating the derivation of the attributes of the new regulated process. On a daily and monthly basis, the theoretical conclusions were applied to US monetary data. (Soren Johansen 2001).

- Biology: Using a sparse structural VAR, the relationships among huge networks of genes are modeled. According to a study by Andre Fujita, the proposed SVAR method can model gene regulatory networks in situations where there are fewer samples than genes. This makes it possible to infer partial Granger causalities on the fly without any a priori knowledge. We also provide a statistical test to manage the false discovery rate, which was previously not attainable using other gene regulation networks.

2.2.4 Advantages of the VAR Model

- The VAR model is a systematic but flexible approach for capturing complex real-world behavior.
- Better forecasting performance.
- Ability to capture the intertwined dynamics of time series data.

2.2.5 Disadvantages of the VAR Model

- One of the main disadvantages of using VAR for forecasting is that it requires a large amount of data and a careful selection of the lag length. If you have too few observations or too many lags, you may over-fit the model and produce inaccurate forecasts. If you have too many variables or too few lags, you may omit important information and produce biased forecasts.
- Another challenge of using VAR for forecasting is that it may not account for structural changes or nonlinearities in the data. You may have to test for stability, heteroscedasticity, and nonlinearity, and use alternative methods such as structural VAR, threshold VAR, or vector error correction models.

2.3 Granger Causality

A statistical theory of causation that is based on prediction is called Granger causality, according to Anil. Since its development in the 1960s, it has been frequently applied in economics. Applications in neuroscience have only recently gained popularity. Granger Causality states that if a signal X_1 "causes" a signal X_2, then past values of X_1 should provide knowledge that aids in predicting X_2 in addition to that provided by past values of X_2 alone. (Anil 2007) Eric, in his study also established that the Granger Causality test determines if a variable is useful in predicting how another variable will behave. It's crucial to remember that Granger Causality allows us to conclude forecasting ability rather than actual causality. The Granger Causality statistics are F-statistics that determine if all of a variable's lag coefficients in an equation for another variable are collectively equal to zero. Evidence that a variable is important for predicting another variable grows as the P-value of the F-statistic drops. Eric (2021).

According to Anil, the basic Granger Causality definition is quite simple. Suppose that we have three terms, X_t, Y_t, and W_t and that we first attempt to forecast X_{t+1} using past terms of X_t and W_t. We then try to forecast X_{t+1} using past terms of X_t, Y_t and W_t . If the second forecast is found to be more successful, according to standard cost functions, then the past of Y_t appears to contain information helping in forecasting X_{t+1} that is not in past X_t or W_t. In particular, W_t could be a vector of possible explanatory variables. Thus, Y_t would Granger Cause X_{t+1} if; Y_t occurs before and It contains information useful in forecasting X_{t+1} that is not found in a group of other appropriate variables. (Anil,2007).

2.4 Empirical Evidence

Several studies have looked at the causal connection between exchange rates and stock prices. These investigations yield contradictory findings. To provide investors with the necessary understanding of the effects, if any, of exchange rate volatility on the stock market in Ghana, the study would aim to examine the impact of exchange rate volatility on the Ghana Stock Exchange. There was no agreement found in some research on the connection between Ghana's stock prices and currency rates.

According to studies like those by Adjasi, Harvey, and Agyapong (2008), there is an inverse relationship between stock market volatility and exchange rate volatility. They discovered that, in the long term, a depreciation in the local currency increases stock market returns using the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model (Adjasi et al., 2008). However, research by Gatsi, Appiah, and Wesseh (2016) found no connection between variations in the exchange rate and stock prices. These many empirical findings support Mishra's (2016) claim that there is no theoretical agreement regarding the connection between exchange rate and stock market volatility.

Using a VAR model, Adjasi and Biekpe (2005) looked into the correlation between stock prices and changes in currency rates in South Africa, Ghana, Egypt, Nigeria, Kenya, and Mauritius. For South Africa, Ghana, Egypt, Nigeria, Kenya, and Mauritius, their study's findings suggested that there was no long-term stable association between currency rates and stock market values. In a different investigation, Pilinkus and Boguslauskas (2009) tested the hypothesis of a short-run association between macroeconomic factors and stock market prices using the impulse response function. Their research revealed that short-term interest rates, the unemployment rate, and currency rates all hurt stock market prices.

A study by Muhammad and Rasheed (2011) examined the correlation between stock prices and exchange rates for Pakistan, India, Bangladesh, and Sri Lanka from January 1994 to December 2000. The study looked at the long-run and short-run relationships between stock prices and exchange rates using cointegration, vector error correction modelling, and traditional Granger causality testing. The study's findings for all four countries indicated that there was no short-run correlation between the factors. For Pakistan and India as well, there was no long-term correlation between stock values and currency rates. However, it appears that there was a bi-directional causal relationship between these two financial variables in Bangladesh and Sri Lanka.

Using the squared residuals from the autoregressive moving average (ARMA) models, Sekmen (2011) investigated the effects of exchange rate volatility on stock returns for the United States from 1980 to 2008. Since the availability of hedging mechanisms was insufficient to mitigate the negative impact of exchange rate volatility on trade volume, the study revealed that exchange rate volatility hurt U.S. stock returns. In a different study, Olugbenga (2012) used the Johansen cointegration tests to analyse the long- and short-term effects of exchange rate development on Nigerian stock market development throughout the period 1985:1?2009:4. According to the findings, stock market performance relative to the exchange rate was significantly positive in the short run and significantly negative in the long run.

The exchange rate had a major impact on stock price movement in Ghana, according to Adam and Tweneboah (2008), who also looked into several other macroeconomic factors that affected stock price movement in Ghana. He concluded that the Ghana Stock Exchange All-Share Index (GSE-ASI) data from 2006 to 2014 may be used to analyse data using the Arbitrage Pricing Theory (APT) framework. Adu (2012), who used the Arbitrage Pricing Theory to examine the connection between exchange rate and stock price movement, discovered results that were incompatible with those of Adam and

Tweneboah (2008). Adu (2012) discovered that stock price movements in Ghana are not significantly impacted by changes in exchange rates.

Using the Co-integration technique and Granger causality, Zia and Rahman (2011) conducted a study in Pakistan to investigate the relationship between exchange rates and sock prices. According to the study, there are no lasting relationships. The findings also highlighted the lack of a causal connection between these variables.

In a study published in 2012, Olubgenga (2012) looked at how exchange rates affected the growth of the Nigerian stock market between 1985 and 2009. The investigation, which used Johansen co-integration tests, showed that there is a considerable positive association between exchange rates and stock market performance, but that the relationship is significantly negative over the long term. The Granger causality test, which was also included in the study, offered convincing proof that changes in the exchange rate cause changes in stock market performance.

Sui and Sun (2016) researched to examine the relationships between regional exchange rates, stock market returns, and the BRICS (Brazil, Russia, India, China, and South Africa). Through the use of a VAR model, they discovered a significant correlation between exchange rate volatility and stock market performance. Using the Error Correction model, Subair and Salihu (2013) discovered a negative correlation between the volatility of the exchange rate and the Nigerian stock market. This supports the findings of Nkoro and Uko's (2016) investigation, which found a substantial inverse association between the factors.

2.4.1 Conclusions on Empirical Review

The study's analysis of empirical literature reveals that there are differing opinions regarding the relationship between the exchange rate and the stock market, making it impossible to draw a firm conclusion about this relationship based solely on the body of available research. Studies by Alam and Tafiques (2007) acknowledge the necessity for ongoing research in the fields of stock markets and exchange rate volatility. The studies mentioned above used a variety of techniques as well as various time observations of the study's data. The various assessments of the importance of exchange rate movements in explaining stock price changes may be explained by these considerations.

Chapter 3

Methodology

3.1 Introduction

The objective of the study is to find out whether exchange rate volatility influences stock price movement in Ghana. This chapter contains the research design, data collection method, and data analysis models and tools that the study would deploy in achieving this objective.

3.2 Research Design

The study employs an explanatory research design. An explanatory research design is a research design that seeks to investigate a phenomenon that has not been studied or explained properly. It tends to explain an occurrence when limited information is available. The Ghana Stock Exchange Composite Index (GSE-CI) is the dependent variable and the independent variable is the USD-CEDI exchange rate.

3.3 Hypothesis

The Flow-Oriented Model by Dornbusch and Fischer (1980) is a theoretical model that suggests the existence of a relationship between exchange rate and stock prices. The model suggests that exchange rates change cause movement in stock prices. The hypothesis of the paper derives from the exchange rate causality claims of the Flow-Oriented Model. Thus, from a unidirectional viewpoint, there is the existence of causality from exchange rate and stock prices. This perspective informs the following hypothesis that was tested in this study:

H_0:Exchange rate volatility does not affect stock price movement in Ghana
H_1:Exchange rate volatility affects stock price movement in Ghana

3.4 Data Collection

The dataset for the study was collected from secondary sources. The dataset includes stock price data (Ghana Stock Exchange Composite Index (GSE-CI)) and the cedi-dollar exchange rate over the period 2012-2022. The stock price data was obtained from the Ghana Stock Exchange website and the exchange rate data was obtained from the Bank of Ghana website.

3.5 Data Sample

The sample for the study is made up of the Ghana Stock Exchange Composite Index (GSE-CI), which is the principal stock index on the Ghana Stock Exchange. The GSE-CI is a market capitalization-weighted index of all 42 listed stocks from 37 companies and thus is appropriate for the study because it fully captures the market information of all stocks on the Ghana Stock Exchange. Daily observations of the GSE-CI and USD-Cedi Exchange rates for the period 2012-2020 were considered for the study. Compared to other studies, particularly in larger and developed countries, there are fewer firms on the GSE-CI. However, this does not affect the accuracy of this study.

3.6 Descriptive Statistics

Central tendency measures encompass the mean (which calculates the average of observed data), the median (the middle value after sorting data), and the mode (the most frequently occurring value). Measures of dispersion, on the other hand, examine how data spreads out and include the range (the difference between the highest and lowest values), variance (indicating the extent of variation in observations), and standard deviation (measuring how far observations deviate from the sample average).

3.7 Test for Stationarity

Stationarity for time series data can be tested using the Augmented Dickey-Fuller(ADF) test, Philip-Perron(PP) test, and the Kwiatkowski Philips-Schmidt-Shin(KPSS) test. This study will specifically use the Augmented Dickey-Fuller (ADF) test to check for stationarity of both the exchange rate and stock price variables.

3.7.1 Augmented Dickey-Fuller (ADF) Test

The ADF test is a statistical test used to determine whether a time series data is stationary or non-stationary. It is an extension of the simpler Dickey-Fuller test. The Dickey-Fuller test checks for the presence of a unit root, which implies that a time series is non-stationary. The ADF test builds upon this by considering higher-order autoregressive processes and accounting for the possibility of serial correlation in the data.

The null hypothesis of the ADF test is that the time series has a unit root, indicating that it is non-stationary against the alternative hypothesis that suggests that the time series is stationary. The ADF uses an autoregressive model and includes lagged differences of the time series in the regression equation. The lag order is determined based on criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). The ADF test calculates a test statistic which is compared to critical values from statistical tables to determine the level of significance. If the calculated ADF statistic is less than the critical value, the null hypothesis of a unit root is rejected, indicating that the series is stationary. Conversely, if the test statistic is greater than the critical value, the null hypothesis cannot be rejected, suggesting the presence of a unit root and non-stationarity. In addition to comparing the test statistic to critical values, the ADF test provides p-values that indicate the probability of obtaining the observed test statistic under the null hypothesis. A smaller p-value suggests stronger evidence against the null hypothesis of a unit root and supports the conclusion of stationarity. The ADF test estimates the regression model;

$$Y_t' = \alpha + \beta + \phi Y_{t-1} + \gamma_1 Y_{t-1}' + \gamma_2 Y_{t-2}' + ... + \gamma_k Y_{t-k}' \tag{3.1}$$

where Y_t' denotes the first difference of the series;
k is the number of lags,
α is a constant
β is the coefficient of the time trend
The following are hypotheses of the ADF test;
H_0: The series is not stationary
H_1: The series is stationary

3.8 Univariate Time Series

A univariate time series refers to a sequence of data points collected over time, where each data point corresponds to a single variable or measurement. In other words, it involves the observation of a single variable at different points in time.

3.8.1 Autoregressive(AR) Model

An autoregressive model is one where the current value of a variable, y, depends upon only the values that the variable took in previous periods plus an error term. A simple way to model dependence between consecutive observations is $Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t$ where ϵ is white noise. Such a process is called a first-order autoregressive process or AR(1) process. It is stationary if the coefficient $\phi_1 < 1$. Since E$[\epsilon] = 0$ it follows that under the stationarity condition the mean of the process $E[Y_t] = \frac{\phi_0}{1-\phi_1}$ and variance $var[Y_t] = \frac{\sigma_\epsilon^2}{1-\phi_1^2}$ where $\sigma_\epsilon^2 = var(\epsilon)$.
A more general representation of the autoregressive process is

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + ...\phi_p Y_{t-p} + \epsilon_t \tag{3.2}$$

and called an autoregressive process of order p, or in short, AR(p).

3.8.2 Autocovariance Function

The autocovariance measures the linear dependence between two points on the same series observed at different times. For a stochastic process

$Y_t : 0, \pm 1 \pm 2 \pm 3, ...,$ the mean function is defined by $\mu_t = E(Y_t)$ for t=$0, \pm 1 \pm 2, \pm 3$...That is μ_t is just the expected value of the process at time t. In general, μ_t can be different at each time point t.The autocovariance function

$$\gamma_{t,s} = Cov(Y_t, Y_s) \tag{3.3}$$

for s,t=$0, \pm 1, \pm 2 \pm 3$...

$$Cov(Y_t, Y_s) = E[(Y_t - \mu_t)(Y_s - \mu_s)] = E(Y_t Y_s) - \mu_t \mu_s \tag{3.4}$$

3.8.3 Autocorrelation Function

The autocorrelation function is used to analyze the correlation between a time series and its lagged values. The ACF measures the linear relationship between a time series observation at a particular time point and its past values at different lags. The autocorrelation function is given by;

$$\rho_{t,s} = corr(Y_t, Y_s) \tag{3.5}$$

for s,t= $0, \pm 1, \pm 2, \pm 3$... where

$$corr(Y_t, Y_s) = \frac{cov(Y_t, Y_s)}{\sqrt{var(Y_t)var(Y_ts)}} = \frac{\gamma_{t,s}}{\sqrt{\gamma_{t,t}\gamma_{s,s}}} \tag{3.6}$$

The values of $\rho_{t,s}$ near ± 1 indicate strong linear dependence, whereas values near zero(o) indicate weak linear dependence.If $\rho_{t,s} = 0$ we say Y_t and Y_s are uncorrelated.

3.8.4 Partial Autocorrelation Function

The partial autocorrelation function(PACF) is similar to an ACF. In time series analysis, the partial autocorrelation function (PACF) is used to determine the direct relationship between observations at different time lags while controlling for the effects of intermediate time points. It is commonly used to determine the order of an autoregressive (AR) model.

Given a time series Y_t, the partial autocorrelation of lag k denoted $\phi_{k,k}$, is the autocorrelation between Y_t and Y_{t+k} with the linear dependence of Y_t on Y_{t+k} through Y_{t+k-1} removed. Equivalently, it is the autocorrelation between Y_t and Y_{t+k} that is not accounted for by lags 1 through k-1 inclusive.

$$\phi_{1,1} = corr(Y_{t+1}, Y_t)\ for\ k = 1, \tag{3.7}$$

$$\phi_{k,k} = \operatorname{corr}\left(Y_{t+k} - \hat{Y}_{t+k}, Y_t - \hat{Y}_t\right) \text{ for all } k \tag{3.8}$$

where $\hat{Y}_{t+k}$ and $\hat{Y}_t$ are linear combinations of $\{Y_{t+1}, Y_{t+2}, \ldots, Y_{t+k-1}\}$ that minimize the mean square error of Y_{t+k} and Y_t, respectively.

3.9 Multivariate Time series

Multivariate time series analysis considers simultaneously multiple time series. It is a branch of multivariate statistical analysis but deals specifically with dependent data. It is, in general, much more complicated than the univariate time series analysis, especially when the number of series considered is large.is investigates dependence and interactions among a set of variables in multi-values processes. One of the most powerful methods of analyzing multivariate time series is the vector autoregression model. It is a natural extension of the univariate autoregressive model to the multivariate case.

3.9.1 The Vector Autoregressive Model

The VAR was introduced by Sims(1986) as a technique that could be used to characterize the joint dynamic behaviors of a collection of variables without requiring strong restrictions of the kind needed to identify underlying structural parameters. A VAR system contains a set of m variables, each of which is expressed as a linear function of p lags of itself and of all of the other m-1 variables, plus an error term.

VAR(p)

Let $y_t = (y_{1t},...,y_{kt})$; $t \in Z$ be a k-variable random process. We say that the process $\{y_t; t \in Z\}$ follows a vector autoregressive model of order p, denoted as VAR(p) if

$$y_t = V + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t, t \in Z; \tag{3.9}$$

where p is a positive integer
A_i are $(K \times K)$ coefficient matrices
$V = (V_1, ..., V_k)$ is a fixed $(K \times 1)$ vector of intercept terms
and $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{kt})$ is a K-dimensional white noise with covariance matrix Σ_ε

Matrix Formulation of VARs

The simplest possible VAR features two variables and one lag i.e VAR(1)

$$y_{1t} = a_{11} y_{1,t-1} + a_{12} y_{2,t-1} + u_{1t} \tag{3.10}$$

$$y_{2t} = a_{21} y_{1,t-1} + a_{22} y_{2,t-1} + u_{2t} \tag{3.11}$$

The matrix form is;

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix}$$

Assumptions of the VAR Model

- Stationarity: The time series variables are assumed to be stationary, meaning their mean and variance are constant over time. Stationarity is important to ensure stable relationships between variables and reliable estimation results.
- No Perfect Multicollinearity: The variables included in the VAR model are assumed to be linearly independent and not perfectly correlated with each other. Perfect multicollinearity can lead to estimation problems and unreliable results.
- The error term's conditional mean is zero
- The possibility of large outliers is low

3.9.2 Optimal Lag Selection

A reasonable strategy on how to determine the lag length of the VAR model is to fit VAR(p) models with different orders p = 0, ..., pmax and choose the value of p which minimizes some model selection criteria. Model selection criteria for VAR(p) could be based on Akaike (AIC), Schwarz-Bayesian (BIC) and Hannan-Quinn (HQ) information criteria:

$$AIC(p) = ln\Sigma(p) + \frac{2}{T}pn^2 \tag{3.12}$$

$$BIC(p) = ln\Sigma(p) + \frac{lnT}{T}pn^2 \tag{3.13}$$

$$HQ(p) = ln\Sigma(p) + \frac{2lnT}{T}pn^2 \tag{3.14}$$

3.9.3 Granger Causality Test

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about a variable's or a group variable's forecasting ability for other variables. If a variable, or group of variables, y_1 is found to help predict another variable, or group of variables,y_2, then y_1 is said to granger-cause y_2; otherwise, it is said to fail to granger-cause y_2. This study deployed the Granger Causality Model developed by Granger(1969) in determining the causality relationship between exchange rate and stock prices in Ghana. Granger Causality test is preferred to other methods because of its favorable response to both small and large sample sizes,(Odhiambo,2008). The VAR is a natural framework for examining the Granger causality. The VAR is expressed as;

$$\Delta \ln \mathrm{GSE}_t = a_0 + \sum a_{1i} \Delta \ln \mathrm{GSE}_{t-1} + \sum a_{2i} \Delta \ln \mathrm{ER}_{t-1} + u_t \tag{3.15}$$

$$\Delta \ln \mathrm{ER}_t = b_0 + \sum b_{1i} \Delta \ln \mathrm{GSE}_{t-i} + \sum b_{2i} \ln \Delta \mathrm{ER}_{t-i} + v_t \tag{3.16}$$

Chapter 4

Analysis and Findings

4.1 Introduction

This chapter presents the findings of the empirical tests conducted and their interpretations. This study employed daily data observations of stock price and USDGHS exchange rate data for the period 2012-2022. Unlike other studies, which deploy weekly, monthly, or yearly data observations, daily data observations were used for the study, as they are more likely to find Granger causality (Granger et al., 2000). The sample period for the study is before COVID-19 (2012-2019), during COVID-19 (2020-2021) and after COVID-19 (2022).

4.2 Results of Descriptive Statistics

Descriptive analysis was conducted on the two variables namely ?lnSI (change in natural log of the GSE-CI prices) and lnER (change in natural log of the Exchange rate). Daily data on the GSE-CI and Exchange rate collected for the period 2012 to 2022 was used to generate the return series for both the stock index and the exchange rates. The return series was calculated as follows:

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \times 100 \tag{4.1}$$

STATISTICS	GSE	PRICE
Mean	0.031766541	0.055648837
Median	0	0
Maximum	4.952673708	9.92549581
Minimum	-5.049732482	-7.779971608
Standard Deviation	0.669834512	0.96830453

Table 4.1: Descriptive Statistics

4.3 Estimation Techniques

Studies have used various econometric approaches in determining causal relationships between multiple phenomena. This study adopted the Vector Autoregressive Model and the Granger Causality Model to determine the relationship between exchange rate returns and stock price changes. As noted by Engle and Granger (1987), many empirical studies have refuted the assumption that studies premised on time series data are stationary. Hence, stationarity test was conducted to avoid spurious results resulting from the use of non-stationary time series data in regression analysis (Granger and Newbold, 1974).

4.3.1 Line plots for the Data Sets

The chart displays the daily performance of stocks enlisted on the Ghana Stock Exchange composite index during an 11-year period, from January 2012 to December 2022. Dates are displayed on the x-axis, while the stock price in US dollars is displayed on the y-axis. Over the years, there have been huge swings in the stock price. In January 2014, it spiked to a peak of GHC2,500 before falling to a low of GHC1500 in January 2017. In February 2018, it rose to a peak of GHC3,500 before falling once more to a low of GHC1,800 around December 2020.In November, it rose again to GHC3000 and it is now selling at almost GH2,500. The chart has a few noteworthy characteristics. Even though there have been a few severe losses along the road, the stock price generally follows an upward trend. Second, compared to the long run, the stock price is typically more erratic in the short term. This indicates that while the price can vary dramatically from day to day or week to week, it is less likely to do so over the course of several years.

Figure 4.1: Line Plot for Stock Prices

The graph depicts the rate of exchange between the US dollar (USD) and Ghanaian cedi (GHC) from January 2012 to August 2023, a period of 11 years. Dates are displayed on the x-axis, while the GHC to USD conversion rate is displayed on the y-axis.

Over the years, the exchange rate has seen enormous fluctuations. It peaked in January 2012 at about 2.8 GHC per USD and rose to a peak of 4 GHC per USD around December 2014. It fell to about 3.1 GHC per USD at the end of 2014 and increased again to around 4.2 GHC per USD in 2015. Since then we experienced an increase to a peak of 6.2 GHC per USD in August 2022, and it is currently trading around 7.8 GHC per USD. The chart has a few noteworthy characteristics. First off, there is an overall rising tendency in the exchange rate, despite some notable falls along the way. Second, compared to the long term, the exchange rate is typically more volatile in the near term. This indicates that while the rate can vary dramatically from day to day or week to week, it is less likely to do so over the course of several years.

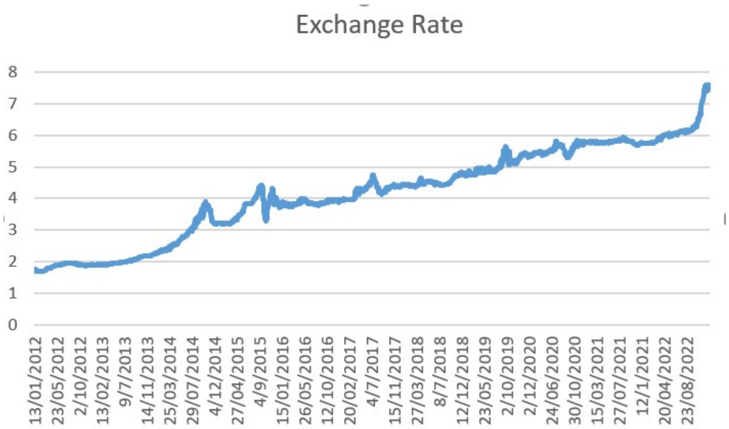

Figure 4.2: Line Plot for Exchange Rate

4.3.2 Time Series Plots for the Returns of the Data sets

Figure 3 shows a plot of the returns of the daily stock price (USD/GHS) from January 2012 to December 2023. There is a presentation of the time intervals in years on the horizontal axis and the vertical axis displays the exchange rate data points. The plot was used for graphical analysis of the data points. There is no trend in the return series which indicates that the series is stationary. There are no seasonality and cyclical movement in the series. This means that the monthly exchange rate series is characterized by a constant mean but a changing variance.

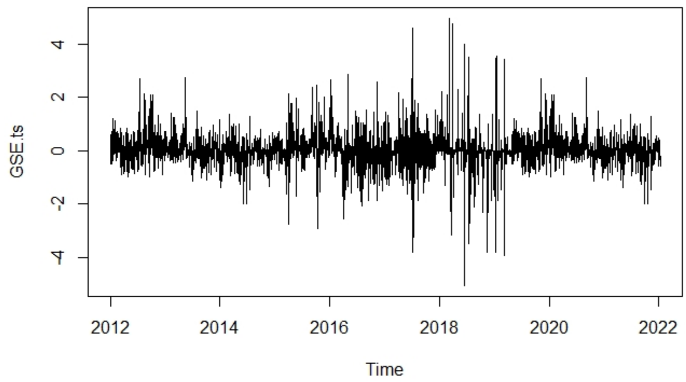

Figure 4.3: Time Series Plot for the Returns of Stock Prices

Figure 4 presents a graph representing the daily returns of the exchange rate(USD/GHS) over the period from January 2012 to December 2023. The horizontal axis displays time intervals in years, while the vertical axis shows the exchange rate data points. The plot was employed for the graphical analysis of the data. The analysis of the plot indicates that there is no discernible trend in the return series, suggesting that the series is stationary. This means that the monthly exchange rate series maintains a constant mean but a changing variance without any significant seasonality or cyclical patterns.

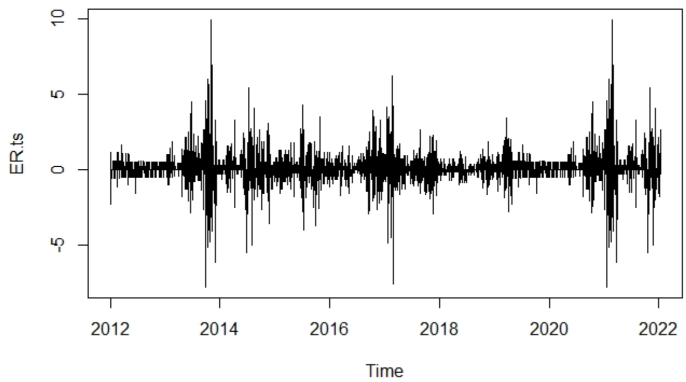

Figure 4.4: Time Series Plot for the Returns of Exchange Rate

4.3.3 ACF and PACF plots for the Returns of the Data

ACF and PACF plots for Stock Price

The ACF plot displays how a time series relates to its past observations at various time lags. The x-axis represents these lags, indicating how many time steps back we're looking. On the y-axis, you find the correlation coefficient, which measures the strength of this relationship. In most cases, the correlation coefficient is significant, signifying a positive correlation between the current observation and past observations at these lags.

On the other hand, the PACF plot reveals significant spikes at specific lag values, suggesting a strong positive correlation between the current observation and observations at those specific time intervals. However, this correlation might not extend to observations at other time lags.

For instance, in the ACF plot, a notable spike at lag 1 implies a positive correlation between the current observation and the observation one time step in the past.

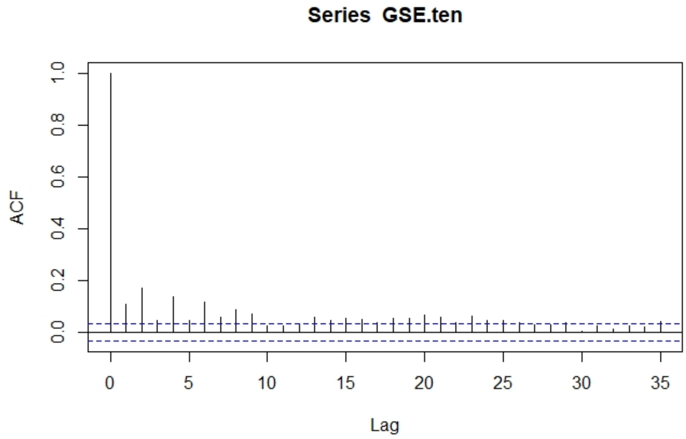

Figure 4.5: ACF Plot for the Returns of Stock Price

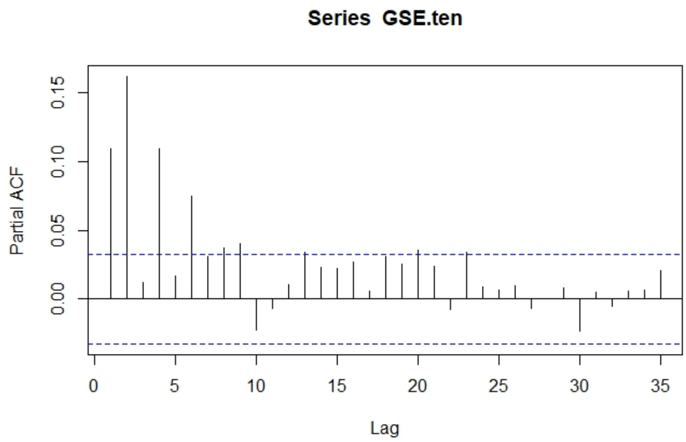

Figure 4.6: PACF Plot for the Returns of Stock Price

ACF and PACF plots for Exchange Rate

In the ACF plot, there is a significant spike at lag 1. This means that there is a correlation between the current observation and the observation 1 time step ago.

In the PACF plot, there is a significant spike at lags 1 and 2. This means that there is a positive correlation between the current observation and the observation 1-time step ago, but this correlation is not affected by the intervening observations.

The fact that the ACF plot has a significant spike at lag 1 suggests that the time series is autoregressive. This means that the current observation can be predicted from the previous observation.

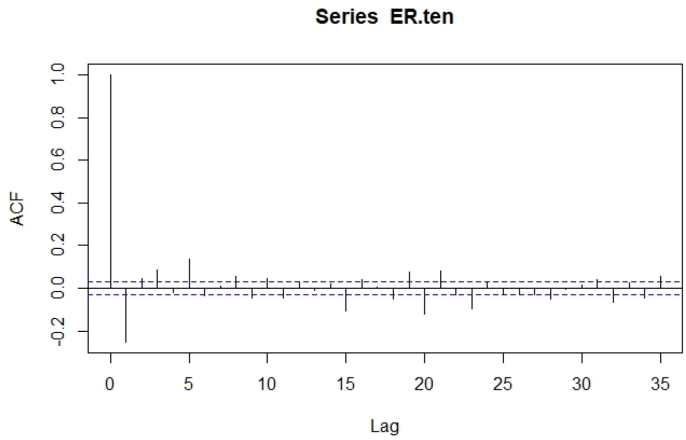

Figure 4.7: ACF Plot for the Returns of Exchange Rate

The PACF plot also shows that the correlation between the time series and its lagged values decreases rapidly after lag 2. This suggests that the time series is not a moving average (MA) process, as MA processes typically have significant correlations at longer lags.

Overall, the PACF plot suggests that the time series for Exchange Rate is an AR(2) process. This means that a good model for this time series would be an AR model with two auto-regressive terms.

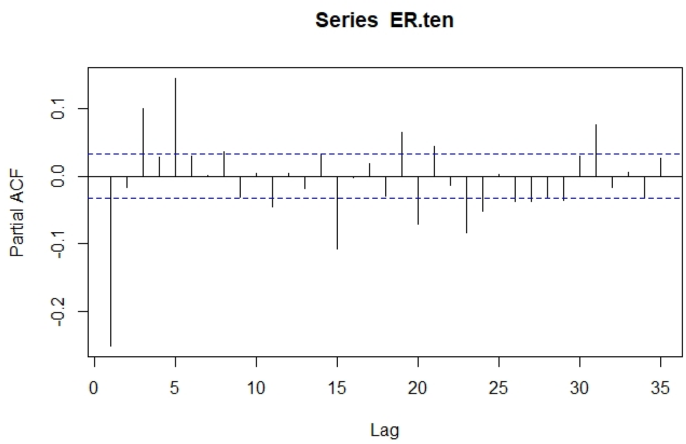

Figure 4.8: PACF Plot for the Returns of Exchange Rate

DATA	**Ho**	**P-VALUE**	**DECISION**
GSE	Not Stationary	$< 2.2 \times 10^{-16}$	Reject
PRICE	Not Stationary	$< 2.2 \times 10^{-16}$	Reject

Table 4.2: Stationary Test

4.4 Test for Stationarity

The Augmented Dickey-Fuller (ADF) test is applied to the returns of both exchange rates and stock prices data sets to account for the presence of stationarity.

Test Results Null Hypothesis: There is a unit root (The mean is not stationary) Alternative Hypothesis: There is no unit root(The mean is stationary)

The p-value associated with each of the tests is less than the significance level of 0.05 therefore we reject the null hypothesis. Hence the data sets are stationary.

4.5 Multi-collinearity Test

Based on the information provided in Table 4.3, we can observe a weak negative correlation (-0.01405) between exchange rates and stock prices. This weak correlation indicates the absence of significant multi-collinearity between these two variables. This lack of multi-collinearity is beneficial as it enhances the stability and reliability of the coefficients estimated for both exchange rates and stock prices within the VAR (Vector Autoregression) model.

This implies that the parameter estimates are less susceptible to being highly influenced by minor fluctuations in the data. Furthermore, the absence of multi-collinearity allows us to confidently attribute variations in the dependent variables (GSE and ER) to changes in their independent variables. This clarity is achieved without the ambiguity introduced by correlated predictors.

	STOCK PRICE	EXCHANGE RATE
STOCK PRICE	1	-0.01422
EXCHANGE RATE	-0.01422	1

Table 4.3: Correlation Matrix

4.5.1 Model Selection

Model	AIC	BIC
VAR(1)	16806.81	16844.04
VAR(2)	16722.51	16784.56
VAR(3)	16681.36	16768.22
VAR(4)	16626.54	16738.23
VAR(5)	16535.89	16672.39
VAR(6)	16505.33	16666.63
VAR(7)	16501.35	16687.47
VAR(8)	16488.29	16699.21
VAR(9)	**16478.58**	**16714.3**
VAR(10)	16482.42	16742.95

Table 4.4: Model Selection

From Table 4.4 VAR(9) is the best model because it has the least AIC and BIC.

4.5.2 VAR Estimation Results

VAR Estimation Results:

========================

Endogenous variables: GSE.ts, ER.ts

Deterministic variables: const

Sample size: 3653

Log Likelihood: -8201.288

Roots of the characteristic polynomial:

0.8761 0.7797 0.7797 0.7362 0.7362 0.6977 0.6977 0.6964 0.6964 0.6865 0.6807 0.6749 0.6749 0.6683 0.6683 0.6644 0.6644 0.5858

Call:

VAR(y = dat.bv, p = 9, type = "const", exogen = NULL)

Estimation results for the equation of Stock Price (GSE.ts):

=== GSE.ts = GSE.ts.l1 + ER.ts.l1 + GSE.ts.l2 + ER.ts.l2 + GSE.ts.l3 + ER.ts.l3 + GSE.ts.l4 + ER.ts.l4 + GSE.ts.l5 + ER.ts.l5 + GSE.ts.l6 + ER.ts.l6 + GSE.ts.l7 + ER.ts.l7 + GSE.ts.l8 + ER.ts.l8 + GSE.ts.l9 + ER.ts.l9 + const

	Estimate	Std. Error	t value	Pr(>|t|)	
GSE.ts.l1	0.072745	0.016566	4.391	1.16e-05	***
ER.ts.l1	-0.006125	0.009853	-0.622	0.53425	
GSE.ts.l2	0.114610	0.016600	6.904	5.93e-12	***
ER.ts.l2	-0.012651	0.010195	-1.241	0.21471	
GSE.ts.l3	-0.004956	0.016695	-0.297	0.76661	
ER.ts.l3	-0.024318	0.010194	-2.386	0.01711	*
GSE.ts.l4	0.100753	0.016641	6.054	1.55e-09	***
ER.ts.l4	0.011483	0.010236	1.122	0.26203	
GSE.ts.l5	0.014440	0.016724	0.863	0.38795	
ER.ts.l5	-0.007432	0.010132	-0.733	0.46331	
GSE.ts.l6	0.080917	0.016649	4.860	1.22e-06	***
ER.ts.l6	0.002321	0.010221	0.227	0.82033	
GSE.ts.l7	0.031089	0.016683	1.863	0.06247	.
ER.ts.l7	0.018946	0.010178	1.861	0.06276	.
GSE.ts.l8	0.047576	0.016581	2.869	0.00414	**
ER.ts.l8	0.008929	0.010181	0.877	0.38057	
GSE.ts.l9	0.049737	0.016566	3.002	0.00270	**
ER.ts.l9	0.011082	0.009852	1.125	0.26074	
const	0.017161	0.009772	1.756	0.07915	.

Table 4.5: VAR output for Stock Price

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1 Residual standard error: 0.6053 on 3631 degrees of freedom

Multiple R-Squared: 0.06285, Adjusted R-squared: 0.05769

F-statistic: 12.18 on 20 and 3631 DF, p-value: $< 2.2 \times 10^{-16}$

Estimation results for the equation of Exchange Rate (ER.ts)

==

ER.ts = GSE.ts.l1 + ER.ts.l1 + GSE.ts.l2 + ER.ts.l2 + GSE.ts.l3 + ER.ts.l3 + GSE.ts.l4 + ER.ts.l4 + GSE.ts.l5 + ER.ts.l5 + GSE.ts.l6 + ER.ts.l6 + GSE.ts.l7 + ER.ts.l7 + GSE.ts.l8 + ER.ts.l8 + GSE.ts.l9 + ER.ts.l9 + const

	Estimate	Std. Error	t value	Pr(>|t|)	
GSE.ts.l1	-0.053103	0.027877	-1.905	0.05687	.
ER.ts.l1	-0.264980	0.016580	-15.982	< 2e-16	***
GSE.ts.l2	0.004125	0.027933	0.148	0.88260	
ER.ts.l2	-0.008451	0.017155	-0.493	0.62233	
GSE.ts.l3	-0.035949	0.028093	-1.280	0.20076	
ER.ts.l3	0.095750	0.017154	5.582	2.56e-08	***
GSE.ts.l4	-0.022286	0.028004	-0.796	0.42619	
ER.ts.l4	0.069184	0.017225	4.016	6.03e-05	***
GSE.ts.l5	0.077825	0.028142	2.765	0.00571	**
ER.ts.l5	0.152720	0.017050	8.957	< 2e-16	***
GSE.ts.l6	0.001733	0.028017	0.062	0.95069	
ER.ts.l6	0.033520	0.017199	1.949	0.05138	.
GSE.ts.l7	0.018331	0.028074	0.653	0.51384	
ER.ts.l7	0.011482	0.017128	0.670	0.50266	
GSE.ts.l8	0.048134	0.027902	1.725	0.08459	.
ER.ts.l8	0.028043	0.017133	1.637	0.10177	
GSE.ts.l9	0.002329	0.027876	0.084	0.93343	
ER.ts.l9	-0.033150	0.016579	-2.000	0.04563	*

Table 4.6: VAR output for Exchange Rate

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 0.967 on 3634 degrees of freedom

Multiple R-Squared: 0.09936, Adjusted R-squared: 0.0949

F-statistic: 22.27 on 18 and 3634 DF, p-value: < 2.2e-16

From the estimation results of the VAR model, it's evident that all the roots of the characteristic polynomial fall within the unit circle. This observation indicates that the model is stable and doesn't exhibit explosive behavior.

Since the p-values linked to most of the lag coefficients are below the selected alpha threshold, the corresponding lags are deemed statistically significant. This signifies that the past values of the variable at those particular lags exert a meaningful influence on the current value of the variables being studied.

4.6 Granger Causality Test

We utilized the Granger causality model developed by Granger (1969) to investigate the causal relationship between returns in foreign exchange rates and stock prices. The Granger causality test was chosen due to its suitability for both small and large sample sizes, as noted by Odhiambo (2008).

Our findings indicate that we do not have sufficient evidence to reject the null hypothesis that changes in exchange rate returns do not lead to changes in stock price returns. This conclusion is supported by the fact that the F-statistic falls below the critical values. The associated P-value (0.5835) further reinforces this conclusion, as it is higher than the commonly used significance level of 0.05 (as shown in Table 2).

Similarly, we also find no grounds to reject the null hypothesis that alterations in stock price returns do not cause variations in exchange rate returns. This is substantiated by the F-statistic being lower than the critical values, and the P-value being greater than 0.05 (as indicated in Table 2).

In essence, our analysis suggests that historical trends in stock prices do not offer valuable insights for predicting current exchange rate values, and conversely, past exchange rate data does not provide meaningful information for forecasting current stock prices.

Ho	**F-Statistic**	**P-Value**	**Decision**
GSE doesn't granger-cause ER	1.5734	0.1078	Fail to reject
ER doesn't granger-cause GSE	1.5478	0.1158	Fail to reject

Table 4.7: Granger Causality Test

Chapter 5

Conclusion and Recommendations

5.1 Introduction

The research focused on examining the connection between exchange rates and stock prices within the Ghana Stock Exchange. Through the utilization of the Granger Causality test, it was determined that there is no relationship between exchange rates and stock prices. A corresponding causal assessment regarding the potential Granger-causing relationship between stock prices and exchange rates also revealed a lack of significant correlation. Therefore, the outcomes of this investigation challenge both the Flow-Oriented Model Theory, which proposes that alterations in exchange rates influence stock price movement, and the Stock-Oriented Model Theory, which suggests that changes in stock prices impact exchange rates.

These findings are in alignment with prior studies conducted by Gatsi et al. (2016) and Asare-Kyere (2019), wherein no Granger-causing relationship between exchange rates and stock prices was identified during the post-cedi redenomination period. The study's outcomes indicated that bidirectional causal connections were statistically insignificant at a 5 percent significance level. Consequently, from a statistical perspective, it can be inferred that despite fluctuations in exchange rates during the height of the COVID-19 pandemic in 2020 and beyond, the stock market remained unaffected by these changes. A comparable conclusion was drawn concerning the potential influence of stock price changes on exchange rate movements.

5.2 Conclusions

Past research into the relationship between exchange rates and stock prices has yielded inconsistent results. The outcomes of this study align with those of Adu (2012), Gatsi et al. (2016), and Asare-Kyere (2019), all of whom similarly concluded that the exchange rate does not significantly account for variations in stock price movements. This current study expanded its timeframe to encompass the COVID-19 period (2020-2022), yielding a comparable outcome. Nonetheless, this result contrasts with certain findings from other studies such as those by Adam and Tweneboah, and Agyapong et al., which indicated the presence of an opposing relationship between exchange rates and stock prices.

5.3 Recommendations

In line with the conclusions of the study, the following recommendations are made in the areas of policymaking for investment decision-making. Areas for further research hereafter recommended.

5.3.1 Investors

When making investment choices related to stocks on the Ghana Stock Exchange, investors need not overly prioritize the impact of exchange rate fluctuations. While the exchange rate holds significance for individuals, businesses, and the overall economy, its ability to explain the shifts observed within the Ghana Stock Exchange is limited and lacks significance. Nevertheless, investors should remain attentive to other systematic risk factors such as interest rates and inflation rates, which have been demonstrated in certain studies to exert influence on changes in stock prices.

5.3.2 Government

The government should implement significant measures to tackle the devaluation of the cedi. While it may not have a direct impact on shifts in stock prices, the exchange rate does affect the returns (dividends) acquired by investors. Therefore, the depreciation of the domestic currency is unfavorable for global investors, as it leads to trading losses when converting into foreign currencies like the US Dollar.

5.3.3 Further research

Additional research can be conducted on various aspects of the Ghanaian stock market. As an emerging stock market within the sub-region, a wide range of studies on stock market operations will offer essential insights necessary for both investors and policymakers to make informed decisions.

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