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MACRO-FINANCIAL LINKAGES IN EMERGING MARKETS: THE INTERCONNECTEDNESS BETWEEN MACROECONOMIC VARIABLES AND FINANCIAL MARKETS

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Macro-Financial Linkages in Emerging Markets: The Interconnectedness between Macroeconomic Variables and Financial Markets Dynamics

Abstract

This study investigates the intricate relationship between stock market returns and macroeconomic indicators - specifically, interest and exchange rates in Ghana's emerging market. It aims to evaluate the forecasting power of these variables in predicting stock market trends. Employing ARIMA and SARIMAX models, the research examines temporal patterns in stock market returns and the influence of these macroeconomic factors as exogenous variables. This methodological framework is designed to dissect the complex interplay between economic conditions and stock market fluctuations.

The results reveal significant autoregressive components in stock returns, highlighting the data's temporal dependencies. The influence of exogenous factors, such as exchange rates, demonstrates variability across different model specifications, pointing to a multifaceted connection between macroeconomic elements and market performance. The findings underscore the intricate nature of these relationships in an emerging economy context, suggesting that while interest and exchange rates provide critical insights, their predictive value is potentially limited by additional, unexplored variables and the inherent temporal dynamics of the market.

Keywords: Stock market, Emerging market, Macroeconomic factors, Interest rates, Exchange rates, ARIMA/ SARIMAX models, Predictive modeling,

1 Introduction

Financial markets play a pivotal role in most economies, contributing substantially to economic growth, trade, and investment flows. However, in economies where financial markets finds it place, are often characterized by inherent volatilities backed by uncertainties including volatile capital flows, currency fluctuations, and exposure to external shocks. Over the past few years, there has been a renewed focus on understanding the connection between financial markets and economic growth. [1] and [2] provided substantial evidence indicating a correlation between financial markets development and economic growth underscoring the need to have an effective financial market for an economy to function properly. Macroeconomic variable play a pivotal role in shaping financial markets. Fluctuations in macroeconomic indicators have the potential to indicate alterations in investor confidence, thereby influencing consumer expenditure, corporate investment decisions, and the holistic performance of financial markets [3]. Central banks often use monetary policy tools to influence macroeconomic factors, aiming to achieve economic stability. Thus, understanding the intricate relationship and dynamics between financial markets and macroeconomic variables is crucial for policymakers, investors, and businesses alike.

Financial markets function are essential conduits where individuals, corporations, and governmental entities converge to engage in the trading of diverse financial instruments, encompassing stocks, bonds, currencies, and derivatives. These markets serve as pivotal mechanisms for capital allocation, risk mitigation, and price determination, thereby assuming a fundamental role in the operational dynamics of contemporary economies. Among the various forms of financial markets, the stock market stands out prominently, functioning as a dynamic arena where publicly listed enterprises issue equities to garner capital, subsequently facilitating investors' transactions involving the purchase and sale of these securities. The stock market not only furnishes firms with a channel for augmenting their financial resources to fuel expansionary endeavors but also affords investors the prospect of realizing returns via capital appreciation and dividend distributions. Predicting the stock market holds immense importance for investors, financial institutions, and policymakers alike. Accurate forecasts are instrumental in guiding investors towards informed decisions pertaining to asset allocation, portfolio management, and the implementation of strategies aimed at mitigating risks.[4]. Financial institutions rely on market predictions to optimize trading strategies, manage investment portfolios, and offer advisory services to clients. Moreover, policymakers utilize stock market forecasts to gauge economic sentiment, assess the effectiveness of monetary and fiscal policies, and anticipate potential financial crises. A conventional approach to prediction involves identifying factors that exert influence on the response variable, a practice observed across diverse methodologies. In the context of stock market data, typically univariate, various time series techniques such as the ARIMA/SARIMA class of models and GARCH models, utilizing lag periods, are commonly employed to forecast future prices [5]. In multivariate scenarios, extensive research has explored the determinants of stock market prediction, with many studies asserting the significance of macroeconomic factors such as interest rates, GDP, and exchange rates. [6] underscored the need incorproate feedback effect when building models for the financial markets to explain market phenomena. [7] explained that the volatility of stock returns can be attributed to abrupt fluctuations and atypical movements in macroeconomic variables, inducing uncertainty regarding prospective profits.

In developed nations, the stock market dynamics are distinguished by mature regulatory frameworks, advanced financial infrastructure, and ample market liquidity. Investors derive advantages from stable political climates, robust economic fundamentals, and firmly established corporate governance norms, collectively fostering a relatively predictable market environment. Conversely, the stock markets of emerging economies manifest unique dynamics. These markets frequently demonstrate elevated volatility, heightened vulnerability to external perturbations, and regulatory frameworks that are comparatively less mature than those observed in developed nations. Emerging markets may undergo periods of rapid economic expansion, intermingled with instances of political instability, currency fluctuations, and regulatory ambiguities, all of which can markedly influence investor sentiment and market dynamics. Nonetheless, notwithstanding these challenges, emerging markets present opportunities for potentially higher returns and diversification advantages for investors who are prepared to navigate the associated risks. The disparity in dynamics has led to the establishment of a long-run equilibrium relationship, resulting in interdependence between developed countries and emerging economies due to diversification [8].

In this paper, our attention will be directed towards the emerging market, with Ghana being examined as a case study. It has been established that macro-economic factors significantly influence emerging economies financial system. Key indicators such as GDP growth, inflation rates, exchange rates, and interest rates exert considerable impact. For instance, [9] found out that stock markets is influenced by various macroeconomic factors, including income levels, gross domestic investment, the degree of advancement in the banking sector, the influx of private capital flows, and the level of liquidity in the stock market. For emerging economies such as Ghana, being an export-oriented economy, the fluctuation of exchange rates significantly affects export revenues and import expenditures, thereby exerting a notable influence on different sectors of the economy. Additionally, changes in interest rates impact the cost of borrowing, influence patterns of saving, and guide investment decisions, consequently molding the trajectory of credit expansion and liquidity within the financial system. [10] discovered that fluctuations in exchange rates influence stock market volatility, with the enduring effects of shocks delineating a nuanced association between currency movements and stock market dynamics. [11] concluded that dynamic interconnections are present between foreign exchange and stock markets across East Asian economies, characterized by fluctuating levels of causal associations between exchange rates and stock prices, as well as reciprocal causality between stock prices and exchange rates. In studying the factors influencing emerging market, [12] highlighted the resilience of institutional factors, particularly within the legal and regulatory framework ensuring investor protection and transaction transparency in the Ghana stock market, while also proposing potential improvements such as the adoption of a centralized clearing system.

The impact of macroeconomic factors, notably interest rates and exchange rates, on emerging markets remains a subject of ongoing debate within academic and policy circles. Despite extensive analysis, a definitive consensus on the matter has yet to be reached, our research endeavors to investigate the viability of utilizing interest rates and exchange rates as predictive indicators for stock market behavior. Specifically, we aim to assess the extent to which variations in interest rates and exchange rates can inform predictions of stock market movements. Furthermore, our inquiry delves into exploring the potential influence of lag periods within these factors on stock market prediction, considering the inherent lag periods within the stock market data itself.

The paper is structured as follows: Section 2 provides a brief overview of the dataset used in this study, along with some visualizations. The Methods and Modeling Section **??** details the three models used in this paper: ARIMA(2,0,0), SARIMAX and SARIMAX with lags. These models deliver promising results in characterizing and predicting the Ghanaian Stock Exchange Composite Index (GSE-CI), presented in Section 4. Finally, we conclude this paper with a discussion of our findings in Section 5 and possible directions for future research in Section 6.

2 Materials

In this section of the paper, we present an overview of the dataset employed for modeling and analysis.

2.1 Data Gathering and Analysis

The study sourced data from the Ghana Stock Exchange (GSE) regarding the GSE Composite Index, a metric for assessing stock market performance derived from the aggregate market capitalization of all listed companies on the exchange. Additionally, macroeconomic indicators such as interest rates (represented by the Interbank Weighted Average, IWA) and exchange rates were obtained from the Bank of Ghana. The data collection period spanned from 2011 to 2022, encompassing monthly observations.

In conducting our investigation, we opted to employ the natural logarithm of monthly returns pertaining to the GSE-CI closing index and exchange rate. Interest rates, already expressed as percentages, were transformed by taking the logarithm of the rate. This methodological choice was informed by the mathematical expediency associated with log returns, as elucidated by [13]. Specifically, log returns offer the advantageous feature of being directly summable over 'n' periods to ascertain the total return across those intervals, while also affording a normal distribution, facilitating analytical procedures. Moreover, log returns provide a close approximation to simple returns in instances where the latter approach zero.

The monthly log returns are calculated using the following formula:

$$Y_t = \ln(\frac{X_t}{X_{t-1}}) \tag{2.1}$$

where,

Y_t denotes the series at time t,

X_t represents the observation at time t, and

X_{t-1} is the observation at time t-1.

2.2 Preliminary Analysis

Following analysis, descriptive statistics were computed for the daily returns of the GSE-CI, Interbank Weighted Average (IWA), and the Exchange rate. These statistics offer a summary of the central tendency, dispersion, and distributional shape of the daily returns, facilitating an initial comprehension of the data characteristics.

These are illustrated in Table 1 below.

Table 1: Descriptive Statistics of Monthly Returns of the GSE-CI, IWA and Exchange Rate.

	Mean	Standard Deviation	Skewness	Kurtosis
GSE Return	0.006415	0.050105	0.867234	2.642124
Exchange Return	0.015576	0.038764	2.319489	14.565352
IWA	2.846897	0.294005	-0.490965	0.188525

From Table 1 above the descriptive statistics of monthly returns for three key financial indicators: the GSE-CI (Ghana Stock Exchange Composite Index) return, Exchange Rate return, and Interbank Weighted Average (IWA). For the entire period under consideration, the mean GSE-CI return is 0.006415, Exchange Rate return is 0.015576, and IWA return is 2.846897. These values indicate the average monthly returns for each respective financial indicator. Positive mean values for the GSE-CI and Exchange Rate returns suggest overall positive returns on average, while the mean IWA return represents the average interest rate over the period. Standard deviation is commonly interpreted as a measure of risk. A higher standard deviation implies greater variability and thus higher risk associated with the investment. The standard deviations for the GSE-CI, Exchange Rate, and IWA were 0.050105, 0.038764, and 0.294005, respectively. The relatively higher standard deviation for the IWA indicates higher variability and thus greater risk associated with interest rate fluctuations compared to stock market returns and exchange rate fluctuations. Thirdly, skewness measures the asymmetry of the distribution of returns. Positive skewness indicates a distribution with a tail extending to the right, while negative skewness indicates a tail extending to the left. The skewness values for the GSE-CI, Exchange Rate, and IWA are 0.867234, 2.319489, and -0.490965, respectively. Positive skewness for the GSE-CI and Exchange Rate returns suggests the presence of more extreme positive returns, while negative skewness for the IWA implies a slight leftward skew in interest rate returns. Lastly, kurtosis measures the peakedness or flatness of the distribution of returns. Positive kurtosis indicates a more peaked distribution with heavier tails, while negative kurtosis indicates a flatter distribution with lighter tails. The kurtosis values for the GSE-CI, Exchange Rate, and IWA are 2.642124, 14.565352, and 0.188525, respectively. The relatively higher kurtosis for the Exchange Rate suggests a more peaked distribution with heavier tails, potentially indicating higher probabilities of extreme returns or volatility.

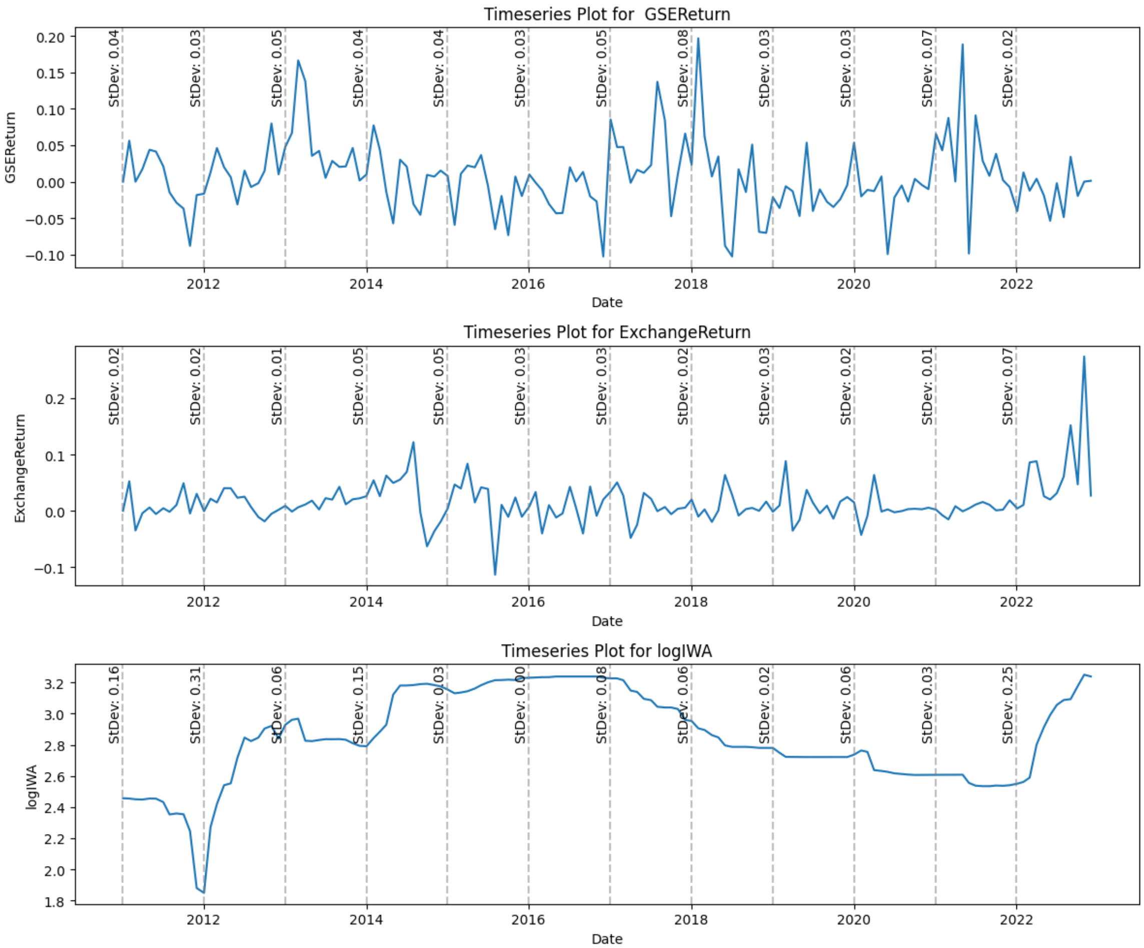

Figure 1: Time Series Plot of GSE-CI, Exchange Rate, and Interbank Weighted Average (IWA) over 2011-2022 Period.

We continue to explore and ascertain whether indeed, a higher interest rate period produces a lower stock market return. In Figure 1 above the year-on-year comparison of standard deviation figures for GSE-CI (Ghana Stock Exchange Composite Index) returns and Exchange Rate returns provides insights into the relationship between interest rates and stock market volatility from 2011 to 2022.

In 2011, the standard deviation for GSE-CI returns was 0.040475, while for Exchange Rate returns, it stood at 0.024607. This period coincided with a relatively lower interest rate environment, as indicated by the IWA standard deviation of 0.165434. Moving to 2012, there was a decrease in volatility for both GSE-CI and Exchange Rate returns, with standard deviations of 0.028838 and 0.019124, respectively. Despite a slight increase in the IWA standard deviation to 0.322087, the stock market and exchange rate remained relatively stable. In 2013, volatility increased significantly for GSE-CI returns (standard deviation: 0.050768), while Exchange Rate returns maintained stability (standard deviation: 0.011668). This period coincided with a notable rise in the IWA standard deviation to 0.059533, suggesting a potential impact of higher interest rates on stock market volatility. The trend continued in 2014, with moderate volatility observed for GSE-CI returns (standard deviation: 0.037920) and increased volatility for Exchange Rate returns (standard deviation: 0.051445). The IWA standard deviation further increased to 0.158789, indicating continued upward pressure on interest rates and potentially contributing to heightened market uncertainty. In 2015, both GSE-CI and Exchange Rate returns maintained stability, with standard deviations of 0.036665 and 0.048210, respectively. Despite a slight increase in Exchange Rate return volatility, the stock market remained relatively steady. The IWA standard deviation continued to rise to 0.036488, reflecting ongoing fluctuations in interest rates. By 2016, volatility in both GSE-CI and Exchange Rate returns decreased, with standard deviations of 0.033714 and 0.027954, respectively. The IWA standard deviation remained relatively stable at 0.003216, indicating a period of relative calm in the financial markets. In 2017, GSE-CI returns experienced increased volatility (standard deviation: 0.048667), while Exchange Rate returns remained stable (standard deviation: 0.027102). The IWA standard deviation slightly decreased to 0.087420, suggesting a potential impact of lower interest rates on stock market volatility. In 2018, GSE-CI returns exhibited high volatility (standard deviation: 0.082706), while Exchange Rate returns remained stable (standard deviation: 0.021856). Despite a decrease in volatility for Exchange Rate returns, the stock market experienced increased uncertainty. The IWA standard deviation declined to 0.060462, indicating a potential relationship between lower interest rates and higher stock market volatility. In 2019 and 2020, both GSE-CI and Exchange Rate returns showed relatively low volatility, with standard deviations hovering around 0.026-0.034 for GSE-CI returns and 0.024-0.034 for Exchange Rate returns. These periods coincided with stable IWA standard deviations, suggesting a potential impact of interest rate stability on market volatility. In 2021, volatility in GSE-CI returns increased (standard deviation: 0.069476), while Exchange Rate returns remained stable (standard deviation: 0.009595). The IWA standard deviation remained relatively steady, indicating that other factors may have contributed to the increased stock market volatility. Finally, in 2022, GSE-CI returns exhibited reduced volatility (standard deviation: 0.025960), while Exchange Rate returns experienced increased volatility (standard deviation: 0.076883). The IWA standard deviation rose to 0.259646, suggesting a potential impact of higher interest rates on stock market stability. Overall, the comparison underscores the complex interplay between interest rates and stock market volatility, with higher interest rates potentially contributing to increased market uncertainty and volatility in certain periods.

Furthermore the figure showed a fluctuating return, possibly of the stock market. The returns fluctuate above and below a zero line, indicating periods of positive and negative returns. The overall trend does not seem to indicate a consistent increase or decrease over time, but rather cyclical patterns of volatility. Notably, there were several sharp peaks and troughs, with the most volatile periods appearing to be around early 2020. Volatility appears to be quite pronounced at certain intervals, notably around 2015-2016, and there's a very volatile period around early 2020, which could correspond to the start of the COVID-19 pandemic as it had widespread impact on financial markets. There doesn't appear to be a persistent long-term upward or downward trend; instead, the return seems to revert back to a mean level after extreme movements.

Similar to the stock market return, the exchange rate oscillate above and below the zero line. There's a noticeable spike towards the end of the series in 2022, suggesting a significant increase in returns at that time. Prior to this, the returns show a mix of ups and downs without a clear long-term trend. The plot showed moderate volatility, with less extreme swings compared to the GSE Return. The volatility increases substantially towards the end of 2022. Consistent fluctuations, with no apparent long-term trend until the spike at the end were observed. Similar to GSE Return, there's no clear persistence in the trend until the spike at the end of the time series. The spike could suggest a major event or change in the underlying factors influencing the Exchange Return.

In contrast, this interest rate plot showed a more distinct upward trend over time, despite some periods of decline or plateau. This suggests that the underlying asset or index has been generally increasing in value, particularly after 2016, with a more pronounced rise from about 2020 onwards. The volatility in this plot is less apparent compared to the GSEReturn. There's a sharp drop early in the series, but after that, the trend is smoother, especially after 2016. There are periods of increase and relative stability, especially after 2016. Before that, the plot shows a significant drop and then a period of recovery. The initial drop brings the plot to its lowest point early in the series. After a period of recovery, the trend gradually moves to higher values, with a notable increase starting from around 2020 onwards. This plot shows the most persistence among the three. After the early drop and recovery, the trend stabilizes, and then from about 2020, there is a persistent upward trend, suggesting steady growth.

2.2.1 Relationship Analysis

We further investigate the relationships among the three variables and study their effects.

Table 2: Correlation Matrix

	GSEReturn	ExchangeReturn	logIWA
GSEReturn	1.000000	-0.000974	-0.002141
ExchangeReturn	-0.000974	1.000000	0.104238
IWA	-0.002141	0.104238	1.000000

From the correlation matrix, the correlation coefficient between GSE Return and Exchange Return is approximately -0.000974, indicating a very weak negative correlation. This suggests that there is almost no linear relationship between the returns of the Ghana Stock Exchange and exchange rates. The correlation coefficient between GSE Return and IWA is approximately -0.002141, also indicating a very weak negative correlation. Similarly, this suggests that there is almost no linear relationship between the returns of the Ghana Stock Exchange and the Interbank Weighted Average interest rate. The correlation coefficient between Exchange Return and IWA is approximately 0.104238, indicating a weak positive correlation. This suggests that there is a slightly positive linear relationship between exchange rates and the Interbank Weighted Average interest rate.

The cross-correlation table below provides insights into the relationships between different lag periods of the stock return and the variables Exchange and IWA.

At a lag of -5 periods, there is a positive cross-correlation of approximately 0.093177 with Exchange and a negative cross-correlation of approximately -0.090914 with IWA. This indicates a weak positive relationship with Exchange and a weak negative relationship with IWA

Table 3: Cross-Correlation Analysis Results

Lag	Cross-Correlation with Exchange	Cross-Correlation with IWA
-5	0.093177	-0.090914
-4	0.025488	-0.06119
-3	-0.118599	-0.031758
-2	-0.064249	-0.0119
-1	-0.075566	-0.012559
0	-0.000974	-0.002141

at this lag. The cross-correlation decreases slightly at a lag of -4 periods, with a positive value of approximately 0.025488 for Exchange and a negative value of approximately -0.06119 for IWA. This suggests weaker correlations compared to the previous lag. At a lag of -3 periods, the cross-correlation becomes more negative, with values of approximately -0.118599 for Exchange and approximately -0.031758 for IWA. This indicates a stronger negative relationship between the variables at this lag. The negative cross-correlation continues to decrease at a lag of -2 periods, with values of approximately -0.064249 for Exchange and approximately -0.0119 for IWA. Although still negative, the correlations are weaker compared to the previous lag. At a lag of -1 period, the cross-correlation remains negative, with values of approximately -0.075566 for Exchange and approximately -0.012559 for IWA. Again, these values suggest a weak negative relationship between the variables at this lag. At lag 0 (no lag), the cross-correlation values are close to zero for both Exchange and IWA, with values of approximately -0.000974 and -0.002141, respectively. This indicates almost no correlation between the variables at this point in time.

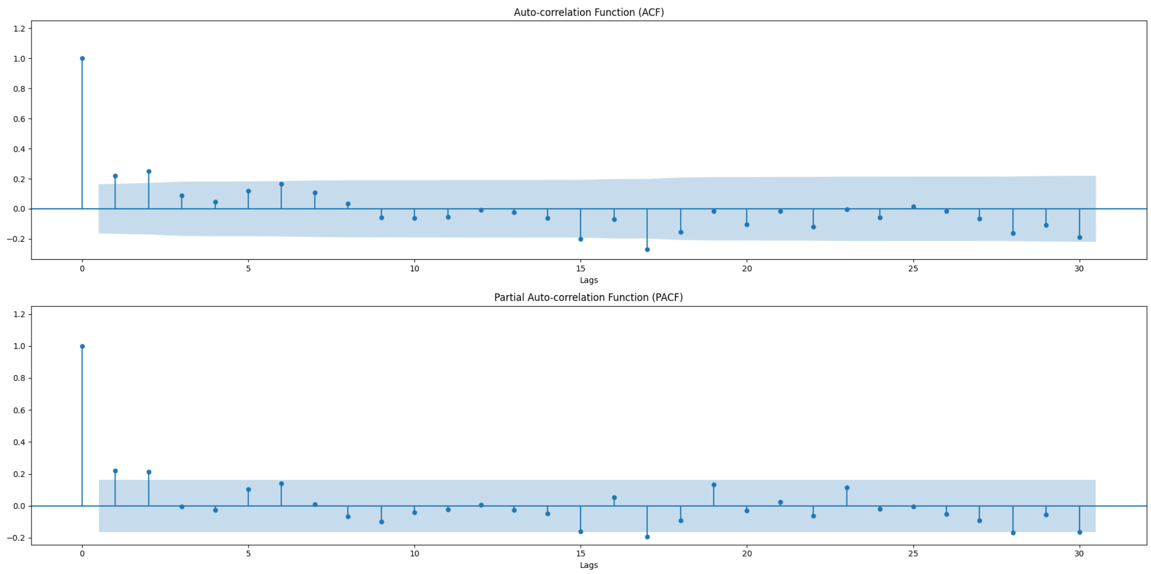

Figure 2: ACF & PACF Plot of GSE-CI.

The Autocorrelation Function (ACF) analysis of the stock return series reveals a cessation of correlation at lag 2. This observation suggests a lack of significant autocorrelation within the stock return series beyond a lag of 2 periods, indicating that present stock return values exhibit no discernible systematic relationship with their own past values beyond this point. This outcome underscores a brief memory effect within the stock return series, as the influence of past returns on current returns diminishes notably after two periods. Conversely, the Partial Autocorrelation Function (PACF) evaluates the correlation between a time series and its lagged values while accounting for the impact of other intermediate lags. Similar to the ACF, the PACF's truncation at lag 2 in the stock return series signifies the absence of significant partial autocorrelation between the stock return and its values at lag 2, once the influence of intervening lags is factored in. Put simply, any correlation between the stock return and its values at lag 2 can be adequately explained by correlations at shorter lags. This outcome indicates a limited predictive utility of past stock returns for forecasting future returns beyond a short-term horizon of two periods. Consequently, investors and analysts should be cognizant of this temporal dependency structure when constructing forecasting models and formulating investment strategies in the financial markets.

3 Methods

This section discusses approach used to investigate the interdependence between stock market returns and interest rates and exchange rates.

3.1 ARIMA Models

ARIMA processes represent a category of stochastic processes utilized in the examination of time series data. The utilization of ARIMA methodology in time series analysis was pioneered by Box and Jenkins [14]. In this study, we implemented the autoregressive model, a subtype of the ARIMA model, to delineate the proposed ARIMA framework.

3.1.1 Autoregressive Moving Average Models

Autoregressive models operate under the premise that the present value of a series y_t can be represented as a function of its k prior values $y_{t-1}, y_{t-2}, ..., y_{t-k}$ where k denotes the requisite number of historical steps to predict the current value.

An autoregressive model of order k, AR(k) can be written as;

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_k y_{t-k} + w_t$$

where y_t is stationary and the series of intrest

$\phi_1, \phi_2, \ldots, \phi_k$ are constants

w_t is the noise.

3.1.2 Autoregressive (AR) Models augmented with Exogenous Variables

This study utilizes Autoregressive (AR) models enriched with exogenous variables to explore the relationship between stock market returns and macroeconomic factors, particularly interest rates and exchange rates. By integrating exogenous variables like interest rates and exchange rates, AR models can better predict stock market behavior by considering external influences on the variable under scrutiny. This approach enables a more holistic examination of the forces guiding stock market fluctuations in emerging markets. Specifically, interest rates and exchange rates are theorized to influence stock market returns via their effects on investor sentiment, capital movements, and overall macroeconomic conditions.

To operationalize the AR models with exogenous variables, we specify the following equation:

$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \beta_1 u_{t-1} + \beta_2 u_{t-2} + w_t$

where y_t represents the stock market returns at time t, y_{t-1}, y_{t-2} are lagged values of the stock market returns. u_{t-1} and u_{t-2} denote the lagged values of the exogenous variables (interest rates and exchange rates), ϕ_1 and ϕ_2 are the coefficients associated with the lagged stock market returns, β_1 and β_2 are the coefficients associated with the lagged exogenous variables, and w_t is noise.

4 Results

In this section, we delve into the estimation, modeling techniques, and predictive methodologies employed for forecasting the Ghana Stock Exchange Composite Index (GSE-CI) utilizing exchange rate and interest rate data.

Our preliminary analysis indicated that both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) exhibit cutoffs at lag 2, suggesting a potential Autoregressive model of order 2, denoted as AR(2). In the second model iteration, we integrate interest rates and exchange rates as exogenous variables alongside the AR(2) model structure. This allows us to assess the impact of these external factors on the predictive power of the model. Building upon this framework, our third model iteration mirrors the second model but introduces adjustments to the lag specifications for the exogenous variables. Specifically, we consider a lag of 5 periods for the interest rate variable and a lag of 3 periods for the exchange rate variable. By modifying the lag specifications, we aim to capture potentially more nuanced relationships between these exogenous factors and the GSE-CI. Through these sequential model iterations, we aim to refine our predictive framework for the GSE-CI by systematically incorporating relevant exogenous variables and adjusting lag specifications to enhance model accuracy and predictive performance.

4.1 ARIMA (2,0,0)

The table presents the results of a AR(2) model applied to the dataset. The constant coefficient has a value of 0.0071 with a standard error of 0.008. This suggests that the constant term in the SARIMAX model is estimated to have a small positive effect on the dependent variable, but the estimate is associated with relatively high uncertainty. The coefficient for X_{t-1} (ar.L1)

Table 4: AR(2) Results

	Coefficient	Standard Error	p-value
const	0.0071	0.008	0.401
ar.L1	0.3498	0.100	0.000
ar.L2	0.0462	0.122	0.706
Ljung-Box (L1) (Q)			0.00

is 0.3498 with a standard error of 0.100, indicating a significant positive effect of the lagged value of the dependent variable (order 1) on its current value. This implies that past values of the dependent variable have a moderate positive influence on its present value. The coefficient for X_{t-2} (ar.L2) is 0.0462 with a standard error of 0.122, indicating a non-significant positive effect of the lagged value of the dependent variable (order 2) on its current value. This suggests that the influence of the second lag on the current value is relatively weak and uncertain.

For ar.L1, the p-value is 0.000, which is less than any conventional significance level ($\alpha = 0.05$). This low p-value suggests that the coefficient of ar.L1 is statistically significant. In other words, we have strong evidence to reject the null hypothesis that the coefficient of ar.L1 is zero. This indicates that the lagged value at time $t-1$ significantly contributes to the current value of the time series.On the other hand, for ar.L2, the p-value is 0.655, which is much higher than a conventional significance level. This high p-value suggests that the coefficient of ar.L2 is not statistically significant. In other words, we fail to reject the null hypothesis that the coefficient of ar.L2 is zero. This indicates that the lagged value at time $t-2$ may not significantly contribute to the current value of the time series. The Ljung-Box (L1) (Q) statistic of 0.00 has a non-significant p-value, indicating that there is no evidence of autocorrelation in the residuals of the model at lag 1. This suggests that the residuals are independent.

4.2 ARIMA(2,0,0) with Exogenous Variable

Table 5: AR(2) with Intrest rate and Exchange Rate Results

	Coefficient	Standard Error	p-value
Exchange Return	0.0647	0.159	0.683
IWA	0.0022	0.003	0.463
ar.L1	0.3512	0.100	0.000
ar.L2	0.0465	0.124	0.709
Ljung-Box (L1) (Q)			0.000

Table 5 presents the results of an AR(2) model with interest rate (IWA) and exchange rate (Exchange Return) as exogenous variables.

Firstly, we observe that the coefficient for Exchange Return is 0.0647, indicating that a one-unit increase in the exchange rate leads to an estimated increase of 0.0647 units in GSE Return, holding other variables constant. Similarly, the coefficient for IWA is 0.0022, suggesting that a one-unit increase in the interest rate leads to an estimated increase of 0.0022 units in GSE Return, while controlling for other factors.

However, it is essential to consider the standard errors associated with these coefficients. The standard error for Exchange Return is 0.159, suggesting a certain level of variability or uncertainty in the estimated effect of the exchange rate on GSE Return. Likewise, the standard error for IWA is 0.003, indicating the level of uncertainty in the estimated effect of the interest rate on GSE Return. Furthermore, examining the p-values associated with each coefficient provides insights into their statistical significance. The p-value for ExchangeReturn is 0.683, implying that the effect of the exchange rate on GSE Return is not statistically significant at conventional significance levels. Similarly, the p-value for IWA is 0.463, indicating that the impact of the interest rate on GSEReturn is also not statistically significant. The coefficient for ar.L1 is 0.3512 with a significant p-value of 0.000, suggesting that lagged values of GSEReturn significantly influence its current value. Conversely, the coefficient for ar.L2 is 0.0465 with a non-significant p-value of 0.709, indicating that the second lag of GSEReturn does not have a statistically significant impact on its current value.

Lastly, the Ljung-Box test statistic is presented as an indicator of autocorrelation in the residuals. The p-value associated with this statistic is 0.000, suggesting that there is significant evidence against the null hypothesis of no autocorrelation in the residuals.

4.3 ARIMA(2,0,0) with Lag Exogenous Variable

Table 6 presents the results of an Autoregressive model of order 2 (AR(2)) with lagged interest rates and exchange rates as exogenous variables.

The coefficient of ExchangeReturnlag is 0.1224, indicating that a one-unit increase in the lagged exchange rate corresponds to an estimated increase of 0.1224 units in the response variable, holding other variables constant. However, the high standard error of 0.170 suggests

Table 6: AR(2) with Lag Intrest rate and Exchange Rate Results

	Coefficient	Standard Error	p-value
ExchangeReturnlag	0.1224	0.170	0.721
IWAlag	0.0021	0.003	0.732
ar.L1	0.3559	0.104	0.001
ar.L2	0.0531	0.117	0.455
Ljung-Box (L1) (Q			0.000

considerable uncertainty in this estimate. Additionally, the p-value of 0.721 implies that this coefficient is not statistically significant at conventional levels, indicating that the lagged exchange rate does not have a significant effect on the response variable. The coefficient of IWAlag is 0.0021, indicating that a one-unit increase in the lagged interest rate results in a 0.0021 unit increase in the response variable, controlling for other factors. Similar to the exchange rate, the standard error of 0.003 suggests uncertainty in this estimate. The p-value of 0.732 indicates that this coefficient is not statistically significant, suggesting that the lagged interest rate does not have a significant effect on the response variable.

Taking the AR(2) component into consideration, the coefficient of $X_{t-1}$is 0.3559, suggesting that the immediate past values of the response variable significantly influence its current value. The low standard error of 0.104 indicates relatively low uncertainty in this estimate. Importantly, the p-value of 0.001 is less than the conventional significance level of 0.05, indicating that this coefficient is statistically significant. This implies that the first lag of the response variable has a significant effect on its current value. The coefficient of X_{t-2} is 0.0531, suggesting that the second lag of the response variable has a modest influence on its current value. The standard error of 0.117 indicates some uncertainty in this estimate. However, the high p-value of 0.455 suggests that this coefficient is not statistically significant, indicating that the second lag of the response variable does not have a significant effect on its current value.

The Ljung-Box test statistic assesses autocorrelation in the residuals of the model. The p-value of 0.000 indicates significant evidence against the null hypothesis of no autocorrelation in the residuals.

4.4 Model Selection

We conduct a comparative analysis of three forecasting models based on Mean Squared Error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) to determine their predictive performance and model fit.

Table 7: Comparative Analysis of Forecasting Models

Model	MSE	AIC	BIC
ARIMA(2,0,0)	0.002431	-319.747908	-311.932398
SARIMAX(2,0,0)	0.002475	-317.367767	-304.341916
SARIMAX(2,0,0) with Lags	0.002511	-316.805975	-303.780124

The MSE measures the average squared difference between predicted and actual values. Among the three models, the ARIMA(2,0,0) model exhibits the lowest MSE, indicating slightly superior prediction accuracy compared to SARIMAX(2,0,0) and SARIMAX(2,0,0) with Lags models. However, the differences in MSE values are relatively small, suggesting comparable predictive performances across models.

The AIC evaluates the relative quality of statistical models, considering both goodness of fit and model complexity. The SARIMAX(2,0,0) model demonstrates the lowest AIC among the three models, indicating a better balance between model fit and complexity. Conversely, the ARIMA(2,0,0) model shows the highest AIC, suggesting relatively poorer model fit or higher complexity compared to SARIMAX models.

Similar to AIC, BIC penalizes models for complexity, emphasizing parsimonious model selection. Consistent with AIC results, the SARIMAX(2,0,0) model exhibits the lowest BIC, signifying superior model fit with optimal complexity. While the ARIMA(2,0,0) model has a higher BIC than SARIMAX models, it still demonstrates competitive performance.

5 Discussion

Our research delved into the nuanced relationship between macroeconomic factors, particularly interest rates and exchange rates, and stock market behavior in emerging markets, focusing on Ghana. Through analysis of descriptive statistics, correlation matrices, and predictive modeling techniques, we aimed to discern the impact of these economic indicators on stock market movements and ascertain their predictive utility.

The study unveiled crucial insights into the average returns, volatility, skewness, and kurtosis of financial indicators over the study period. Positive average returns for the Ghana Stock Exchange Composite Index (GSE-CI) and exchange rates indicated overall market positivity, while interest rate fluctuations exhibited higher variability, implying greater risk associated with interest rate movements.

Correlation analysis revealed weak relationships between stock returns and both exchange rates and interest rates, suggesting that while these macroeconomic factors may exert some influence on stock market movements, their predictive power alone may be limited. Autocorrelation and partial autocorrelation functions provided insights into temporal dependencies within stock returns, indicating limited predictive utility beyond short-term horizons. Model iterations incorporating autoregressive components and exogenous variables (interest rates and exchange rates) offered valuable insights into predictive modeling. While autoregressive terms exhibited significant influence on current stock returns, the impact of exogenous variables varied, with exchange rates demonstrating statistically insignificant effects in some instances.

Evaluation metrics such as mean squared error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) facilitated model comparison. SARIMAX models demonstrated competitive predictive performance compared to traditional ARIMA models, with SARIMAX(2,0,0) exhibiting the lowest AIC and BIC, suggesting superior model fit with optimal complexity. The findings underscore the intricate nature of these relationships in an emerging economy context, suggesting that while interest and exchange rates provide critical insights, their predictive value is potentially limited by additional, unexplored variables and the inherent temporal dynamics of the market..

6 Conclusion and Future Work

In conclusion, our study has shed light on the intricate relationship between macroeconomic factors, particularly interest rates and exchange rates, and stock market prediction in emerging economies, with a specific focus on Ghana. Through meticulous analysis and modeling, we have contributed valuable insights to the ongoing discourse surrounding this topic. Our findings highlight the significance of interest rates and exchange rates as indicators of market movements in emerging economies. However, we also acknowledge the limitations of relying solely on these variables for predictive purposes. While interest rates and exchange rates offer valuable insights, their predictive power may be subject to influence from other unaccounted variables and temporal dependencies within the data. Moreover, our study underscores the importance of employing sophisticated modeling techniques to capture the complex dynamics of emerging markets. By incorporating autoregressive components and exogenous variables into our models, we have been able to enhance our understanding of stock market behavior and improve predictive accuracy.

Looking ahead, there are several avenues for future research that could further advance our understanding of the relationship between macroeconomic factors and stock market prediction in emerging economies. Future studies could explore the impact of additional macroeconomic variables, such as inflation rates, GDP growth, and political stability, on stock market behavior. By considering a broader range of factors, researchers can gain a more comprehensive understanding of market dynamics. Temporal dependencies within the data warrant further investigation. Future research could employ more sophisticated time series analysis techniques to explore the temporal dynamics of stock market returns and macroeconomic variables, potentially uncovering long-term trends and patterns. Utilizing machine learning algorithms, such as deep learning and ensemble methods, could offer new insights into stock market prediction in emerging economies. These approaches have the potential to capture nonlinear relationships and complex interactions between variables, enhancing predictive accuracy.

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