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PREDICTING STOCK MARKET TRENDS: A BIVARIATE REGRESSION ANALYSIS OF TRADING VOLUME IMPACT

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Predicting Stock Market Trends: A Bivariate Regression Analysis of Trading Volume Impact

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Abstract

Stock market prediction presents a perennial challenge for investors attempting to forecast the future value of traded stocks at the exchange. The allure of successful predictions, which can yield substantial profits, has driven this pursuit since the inception of stock markets. The 2008 financial crisis highlighted the complexity of market behaviour, emphasizing the need for a deeper understanding of stock market prediction. Regression analysis, a quantitative research method, quantifies relationships between dependent and independent variables. This study conducted a bivariate regression analysis to assess the predictive potential of traded volume on equity price movements within the Nigerian Exchange Limited (NGX or The Exchange), using Guaranty Trust Holding Company Plc (GTCO) historical data. The results revealed a statistically significant correlation (r=0.59) between volume (X) and price (Y). The regression equation (Y = 44.164 + 0.179X) demonstrated that 34.5% of price variance can be predicted from traded volume, indicating a reasonably strong relationship. These findings suggest a moderately robust association between trading volume and stock price movements. This implies that, to some extent, trading volume can guide predictions of stock prices. As investors seek to outperform the market, using linear Regression for stock price prediction remains an engaging area for further research, aiming to enhance return on investment. In conclusion, our linear regression model can generate more precise stock price predictions with a more extensive dataset.

Keywords: *Efficient market hypothesis, linear Regression, Price prediction, trading volume, Stock market.*

1.0 Introduction

Stock market prediction, the endeavour to forecast the future value of company stocks and other financial instruments traded on exchanges has always captivated the attention of investors. The successful prediction of a stock's future price holds the promise of substantial profits [1]. However, the efficient-market hypothesis, a cornerstone of financial theory, posits that stock prices inherently reflect all currently available information. According to this hypothesis, any price changes not rooted in newly revealed information are unpredictable. Nonetheless, dissenting voices persist, armed with many methods and technologies they claim can unveil future price trends [2].

For as long as financial markets have existed, predicting the stock market has tantalized and bedevilled investors. Each day, trillions of dollars are exchanged on stock exchanges, with every dollar representing an investor's aspiration for financial gain. The fortunes of entire companies can rise and fall in the blink of an eye, dictated by market behaviour [1]. The ability to accurately forecast market movements carries the promise of wealth and influence, making it a perennial pursuit. Consequently, with its inherent challenges and rewards, the stock market captures the collective imagination whenever it exhibits erratic behaviour [3]. The 2008 financial crisis is a poignant example, as evidenced by the deluge of films and documentaries inspired by the crash. A common theme among these productions was the widespread lack of comprehension regarding how the market operates and responds. A deeper understanding of stock market prediction could offer insights to mitigate the impact of similar future events [4].

Beyond the allure of profits, the prediction of stock market direction plays a vital role. It can function as an early recommendation system for short-term investors and an early warning system for long-term shareholders in financial distress [5]. While numerous stock prediction studies focus on using macroeconomic indicators like the Consumer Price Index (CPI) and Gross Domestic Product (GDP) to train prediction models, obtaining daily data for these indicators can be a daunting task [6]. Consequently, such methods are challenging to apply in practice. This paper proposes a novel approach that directly utilizes price data to predict market index direction and stock price movement. This approach promises to provide a pragmatic and effective means of navigating the complex landscape of stock market prediction.

2.0 Literature Review

The efficient market hypothesis (EMH) suggests stock prices are unpredictable due to the inherent informational nature of stock prices [7]. However, dissenting voices challenge this hypothesis using regression analysis, a quantitative research technique [8]. This study focuses on the Nigerian Exchange Group (NGX) and examines the relationship between trading volume and stock price movements, using a bivariate regression analysis to assess the predictive potential of trading volume in this specific market context.

2.1. Prediction methods

According to [10], prediction methodologies fall into three broad categories which can (and often do) overlap. They are fundamental analysis, technical analysis (charting) and technological methods.

2.1.1 Fundamental analysis

Fundamental Analysts are concerned with the company that underlies the stock itself. They evaluate a company's past performance as well as the credibility of its accounts [11]. Many performance ratios are created that aid the fundamental analyst with assessing the validity of a stock, such as the P/E ratio. Warren Buffett is perhaps the most famous of all Fundamental Analysts [1]. Fundamental analysis is built on the belief that human society needs capital to make progress and if a company operates well, it should be rewarded with additional capital and result in a surge in stock price. Fundamental analysis is widely used by fund managers as it is the most reasonable, objective and made from publicly available information like financial statement analysis [12].

According to [6], another meaning of fundamental analysis is beyond bottom-up company analysis; it refers to top-down analysis from first analyzing the global economy, followed by country analysis and then sector analysis, and finally the company level analysis.

2.1.2 Technical analysis

Technical analysts or chartists are not concerned with any of the company's fundamentals. They seek to determine the future price of a stock based solely on the (potential) trends of the past price (a form of time series analysis) [5]. Numerous patterns are employed such as the head and shoulders or cup and saucer. Alongside the patterns, techniques are used such as *the exponential moving average* (EMA). Candle stick patterns, believed to have been first developed by Japanese rice merchants, are nowadays widely used by technical analysts [3].

2.1.3 Data Mining Technologies

With the advent of the digital computer, stock market prediction has since moved into the technological realm [13]. The most prominent technique involves the use of *artificial neural networks* (ANNs) and Genetic Algorithms (GA). ANNs can be thought of as mathematical function approximators [14]. The most common form of ANN in use for stock market prediction is the feed forward network utilizing the backward propagation of errors algorithm to update the network weights. These networks are commonly referred to as Back propagation networks. Another form of ANN that is more appropriate for stock prediction is the time recurrent neural network (RNN) or time delay neural network (TDNN) [15]. Examples of RNN and TDNN are the Elman, Jordan, and Elman-Jordan networks.

2.1.4 Internet-based data sources for stock market prediction

[16] introduced a method to identify online precursors for stock market moves, using trading strategies based on search volume data provided by Google Trends. Their analysis of Google search volume for 98 terms of varying financial relevance, published in Scientific Reports, suggests that increases in search volume for financially relevant search terms tend to precede large losses in financial markets. Out of these terms, three were significant at the 5% level ($|z| > 1.96$). The best term in the negative direction was "debt", followed by "color". In a study published in Scientific Reports in 2013, [16] demonstrated a link between changes in the number of views of English Wikipedia articles relating to financial topics and subsequent large stock market moves. The use of Text Mining together with Machine Learning algorithms received more attention in the last years, with the use of textual content from Internet as input to predict price changes in Stocks and other financial markets [17].

2.1.5 Applications of Complexity Science for stock market prediction

Using new statistical analysis tools of complexity theory, researchers at the New England Complex Systems Institute (NECSI) performed research on predicting stock market crashes. It has long been thought that market crashes are triggered by panics that may or may not be justified by external news. This research indicates that it is the internal structure of the market, not external crises, which is primarily responsible for crashes. The number of different stocks that move up or down together were shown to be an indicator of the mimicry within the market, how much investors look to one another for cues. When the mimicry is high, many stocks follow each other's movements - a prime reason for panic to take hold. It was shown that a dramatic increase in market mimicry occurred during the entire year before each market crash of the past 25 years, including the financial crisis of 2007–08 [18].

2.2 Regression Analysis

Regression analysis is a form of predictive modelling technique which investigates the relationship between a dependent (target) and independent variable(s) (predictor). This technique is used for forecasting, time series modelling and finding the causal effect relationship between the variables [19]. For example, relationship between traded volume and price movement at the Exchange is best studied through Regression. Regression analysis is an important tool for modelling and analysing data [9]. In line with the theory of linear Regression, we fit a curve and or line to the data points, in such a manner that the differences between the distances of data points from the curve or line is minimized. There are multiple benefits of using regression analysis. They are as follows [20]:

i. It indicates the significant relationships between dependent variable and independent variable.
ii. It indicates the strength of impact of multiple independent variables on a dependent variable.

Regression analysis also allows us to compare the effects of variables measured on different scales, such as the effect of price changes and the volume traded. These benefits help market researchers' / data analysts' / data scientists and or investors to eliminate and evaluate the best set of variables to be used for building predictive models [19].

2.3 Types of Regression Techniques

According to [20], there are various kinds of regression techniques available to make predictions. These techniques are mostly driven by three metrics (number of independent variables, type of dependent variables and shape of regression line).

2.3.1 Linear Regression

It is one of the most widely known modelling technique. Linear Regression is usually among the first few topics which people pick while learning predictive modelling [20]. In this technique, the dependent variable is continuous, independent variable(s) can be continuous or discrete, and nature of regression line is linear. Linear Regression establishes a relationship between dependent variable (Y) and one or more independent variables (X) using a best fit straight line (also known as regression line). It is represented by an equation $Y = a + b * X + e$, where a is intercept, b is slope of the line and e is error term. This equation can be used to predict the value of target variable based on given predictor variable(s). The difference between simple linear Regression and multiple linear Regression is that, multiple linear Regression has (>1) independent variables, whereas simple linear Regression has only 1 independent variable [20].

2.3.2 Logistic Regression

Logistic Regression is used to find the probability of event=Success and event=Failure [19]. We should use logistic Regression when the dependent variable is binary (0/ 1, True/ False, Yes/ No) in nature. Here the value of Y ranges from 0 to 1 and it can be represented by following equation. odds= p/ (1-p) = probability of event occurrence / probability of not event occurrence

2.3.3 Polynomial Regression

A regression equation is a polynomial regression equation if the power of independent variable is more than 1 [9]. The equation below represents a polynomial equation: y=a + b*x^2. In this regression technique, the best fit line is not a straight line. It is rather a curve that fits into the data points.

2.3.4 Stepwise Regression

This form of Regression is used when we deal with multiple independent variables. In this technique, the selection of independent variables is done with the help of an automatic process, which involves no human intervention [19]. This feat is achieved by observing statistical values like R-square, t-stats and

AIC metric to discern significant variables. Stepwise Regression basically fits the regression model by adding/dropping co-variates one at a time based on a specified criterion.

2.3.5 Ridge Regression

Ridge Regression is a technique used when the data suffers from multicollinearity (independent variables are highly correlated) [20]. In multicollinearity, even though the least square estimates (OLS) are unbiased; their variances are large which deviates the observed value far from the true value. By adding a degree of bias to the regression estimates, ridge regression reduces the standard errors.

2.3.6 Lasso Regression

Similar to Ridge Regression, Lasso *(Least Absolute Shrinkage and Selection Operator)* also penalizes the absolute size of the regression coefficients. In addition, it can reduce the variability and improve the accuracy of linear Regression [21]. Lasso regression differs from ridge regression in a way that it uses absolute values in the penalty function, instead of squares. This leads to penalizing (or equivalently constraining the sum of the absolute values of the estimates) values which causes some of the parameter estimates to turn out exactly zero [20].

2.3.7 Elastic Net Regression

Elastic-Net is a hybrid of Lasso and Ridge Regression techniques. Elastic-net is useful when multiple features are correlated [21]. Lasso will likely pick one of these at random, while elastic-net will likely pick both. A practical advantage of trading off between Lasso and Ridge is that it allows Elastic-Net to inherit some of Ridge's stability under rotation [19].

2.4 Gap from Literature Review

The literature on stock market prediction methodologies is extensive, but there is a gap that needs further exploration. The efficient market hypothesis and the random walk pattern in stock prices highlight the challenges of predicting stock prices solely based on historical trends and publicly available information [9]. Research consistently reaffirms the effectiveness of the efficient market hypothesis in practice, revealing that most portfolios managed by professional stock predictors do not outperform the average market return when considering management fees [12].

Prediction methodologies can be categorized into fundamental analysis, technical analysis, and technological methods [10]. Fundamental analysis examines a company's past performance and credibility, while technical analysts focus on potential trends in past prices to determine future stock prices. Technological methods, such as data mining technologies and complexity science applications, have introduced innovative approaches, such as artificial neural networks and genetic algorithms. Complexity science, as studied by researchers at the New England Complex Systems Institute, introduces new statistical analysis tools to predict stock market crashes.

However, there is a gap in exploring alternative methodologies, such as linear regression analysis, in the context of prevailing market conditions and challenges. Existing studies address limitations of historical data and resistance of markets to systematic prediction, but a focused investigation into bivariate regression analysis and its impact on trading volume remains relatively unexplored. This study aims to bridge this gap by providing fresh insights into stock price prediction, considering the nuanced dynamics of the market and the potential influence of trading volume.

3.0 Research Methodology

The research methodology employed in this study adopts a quantitative approach and utilizes an experimental research design to investigate the strategic influence and impact of trading volume on the price movements of stocks listed on the Nigerian Exchange Limited (NGX) [22]. The primary objective of this research is to predict stock price movements using daily traded volume as a key variable.

3.1 Data Sources

To conduct our analysis, we collected empirical data related to daily stock prices and trading volume for the month of January 2018. These datasets were meticulously obtained from the Nigerian Stock Exchange's (NSE) daily transaction records. We selected this specific period to provide a representative snapshot of stock price movements and trading volume trends within the Nigerian Stock Exchange.

3.2 Case Study

For our analysis, we focused on the stock of Guaranty Trust Holding Company Plc (GTCO) as our case study. By concentrating on a specific stock, we aimed to gain a nuanced understanding of the relationship between traded volume and price movement within a real-world context. GTB's stock serves as a concrete and relevant example to investigate the impact of trading volume on stock prices within the Nigerian Stock Exchange.

3.3 Empirical Analysis

The empirical analysis in this study seeks to forecast the daily directional movements of stock prices by leveraging the daily traded volume data for GTCO. To achieve this, we employed a linear regression model, which allows us to examine how changes in traded volume relate to price changes and, consequently, make predictions regarding future stock price movements. This rigorous empirical investigation facilitates the evaluation of the effectiveness of traded volume as a predictive variable for stock price movements.

In summary, this research methodology underscores the quantitative nature of our study and outlines the data sources and design. By focusing on a specific case study within the Nigerian Stock Exchange, we aim to contribute valuable insights to stock market prediction. The empirical analysis, utilizing a linear regression model, serves as a powerful tool to investigate the relationship between traded volume and stock price movements.

3.4 Linear Regression Model

Regression analysis is a foundational quantitative research method employed to model and analyze relationships among multiple variables. It allows us to quantify the nature of relationships between dependent variables (such as stock prices) and independent variables (such as trading volume). In the context of our study, the linear regression model provides insights into how changes in traded volume are associated with changes in stock prices.

At the core of the linear regression model are several key components. The model involves estimating unknown parameters (β coefficients) that quantify the relationship between the independent variable (trading volume, denoted as X) and the dependent variable (stock price, denoted as Y). The regression equation takes the form:

$$Y = a + b^{*}X + \varepsilon \quad \text{………………………………. Equation (i)}$$

In this equation, 'a' represents the intercept, 'b' represents the slope coefficient, and ε represents the error term. The goal of the regression analysis is to estimate the values of 'a' and 'b' that minimize the differences between the observed stock prices and the values predicted by the regression line.

The linear regression model allows us to assess the strength and direction of the relationship between trading volume and stock prices. The estimated β coefficients provide quantitative insights into the impact of changes in trading volume on stock price movements. By analyzing the statistical significance and magnitude of these coefficients, we can determine the predictive potential of trading volume within the context of our study.

It is important to note that linear regression analysis is based on several key assumptions. These assumptions include linearity (assuming a linear relationship between trading volume and stock prices), homoscedasticity (equal variance of errors), absence of multicollinearity (no significant correlation between independent variables), and normal distribution of errors. Violations of these assumptions can affect the accuracy and reliability of the regression analysis results.

By employing the linear regression model in our empirical analysis, we aim to assess the predictive power of trading volume on stock price movements within the Nigerian Stock Exchange. The analysis of the regression coefficients and statistical significance will provide valuable insights into the relationship between trading volume and stock prices, allowing us to make predictions and enhance our understanding of stock market dynamics.

4.0 Data Presentation, Analysis, Empirical Result, and Discussion.

4.1 Data Presentation

The secondary data collated for this study is presented below:

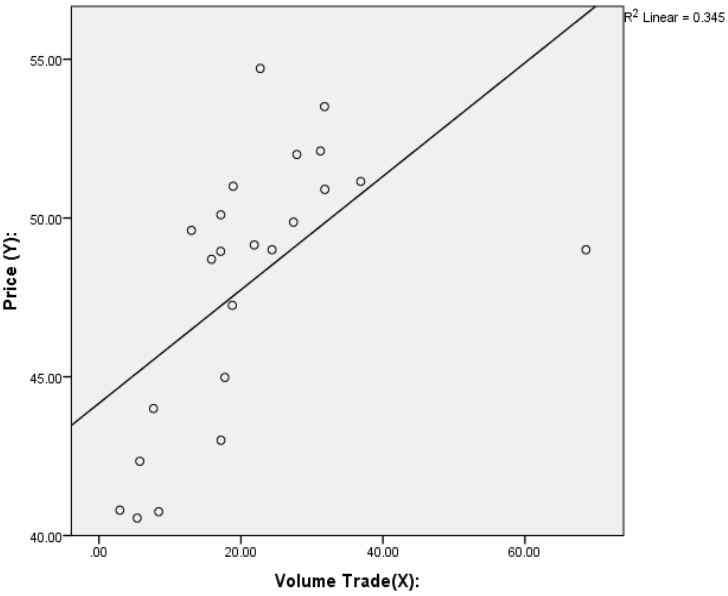
Table 1 contains the transaction details of GTCO Plc:

S/N	Date	Prev Close ₦	Open ₦	High ₦	Low ₦	Close ₦	Change ₦	Deals	Volume	Value ₦
Jan 2018										
1	01 Jan 2018	40.53	40.66	41.65	40.66	40.75	0.22	123	8,409,916	343,663,191.32

2	02 Jan 2018	40.75	39.05	40.55	39.05	40.55	-0.20	123	5,390,824	214,269,863.52
3	03 Jan 2018	40.55	40.63	40.90	40.61	40.80	0.25	151	2,938,186	119,705,705.58
4	04 Jan 2018	40.80	41.00	42.35	40.81	42.34	1.54	232	5,745,511	240,397,661.62
5	05 Jan 2018	42.34	42.00	43.01	42.35	43.00	0.66	272	17,184,311	737,968,479.00
6	08 Jan 2018	43.00	43.07	44.00	43.07	44.00	1.00	229	7,690,811	337,559,027.91
7	09 Jan 2018	44.00	44.00	45.00	44.00	44.98	0.98	304	17,729,113	789,245,591.71
8	10 Jan 2018	44.98	45.00	47.25	45.50	47.25	2.27	173	18,776,266	886,480,006.56
9	11 Jan 2018	47.25	48.90	49.61	48.90	49.61	2.36	218	13,017,460	645,264,259.87
10	12 Jan 2018	49.61	49.65	51.00	47.16	49.00	-0.61	533	68,592,842	3,444,846,895.04
11	15 Jan 2018	49.00	49.50	50.10	47.15	50.10	1.10	345	17,168,137	851,676,107.89
12	16 Jan 2018	50.10	50.00	51.50	50.00	51.00	0.90	388	18,911,512	964,308,596.05
13	17 Jan 2018	51.00	49.86	51.15	49.86	51.15	0.15	412	36,874,616	1,870,978,240.35
14	18 Jan 2018	51.15	50.50	53.70	50.50	52.11	0.96	526	31,189,920	1,600,983,597.78
15	19 Jan 2018	52.11	50.26	54.71	50.26	54.71	2.60	379	22,715,334	1,223,017,283.43
16	22 Jan 2018	54.71	54.99	57.00	53.00	53.51	-1.20	522	31,772,388	1,763,445,855.12
17	23 Jan 2018	53.51	52.25	53.00	50.84	52.00	-1.51	611	27,869,693	1,442,132,665.20
18	24 Jan 2018	52.00	50.00	51.00	50.00	50.90	-1.10	622	31,813,081	1,607,432,958.58
19	25 Jan 2018	50.90	50.00	50.00	49.02	49.87	-1.03	318	27,396,463	1,365,611,471.81
20	26 Jan 2018	49.87	49.01	49.05	48.80	49.00	-0.87	330	24,383,546	1,193,453,550.69
21	29 Jan 2018	49.00	48.85	49.05	48.70	48.70	-0.30	452	15,852,622	774,900,560.10
22	30 Jan 2018	48.70	48.75	49.15	48.75	48.95	0.25	427	17,135,756	839,215,244.10
23	31 Jan 2018	48.95	49.00	49.15	48.75	49.15	0.20	328	21,871,676	1,072,102,425.70

Sources: *NGX Statistical Bulletin, 2018*

4.2 Data Analysis



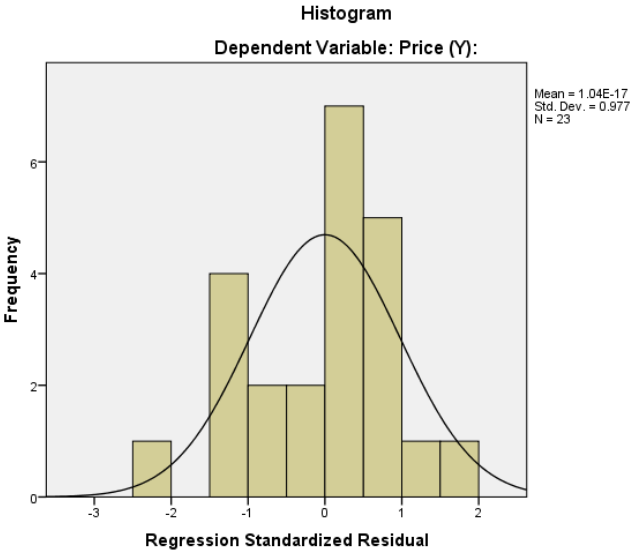


Figure 1 shows the linearity between variables. Figure 2 shows that data are normally distributed.

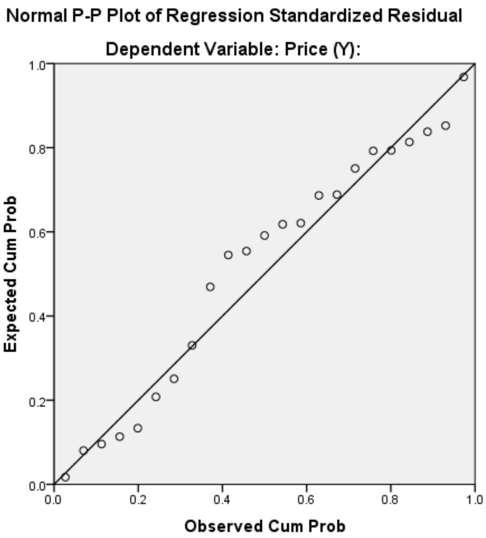


Figure 4 shows homoscedasticity.

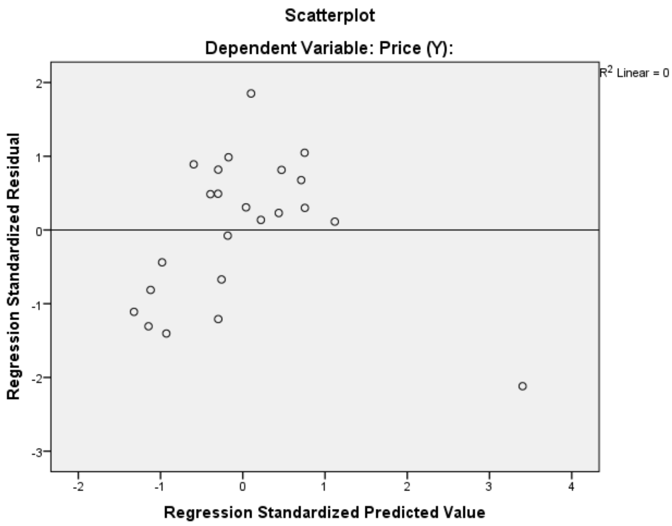


Figure 3 shows the normality of the dataset

4.3 Empirical Results

Table 2 shows the value of $R^2 = 0.345$ and $R = 0.587$, Durbin-Watson = Data Independence

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.587[a]	.345	.314	3.50341	1.121

Table 3 shows that our Regression is better. $p < 0.005$

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	135.681	1	135.681	11.055	.003[b]
	Residual	257.751	21	12.274		
	Total	393.432	22			

Table 4 shows the equation for our regression (i.e., regression model. PRICE =44.164 + 0.179* (Volume Traded)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	44.164	1.359		32.490	.000	41.337	46.991
	Volume Trade(X):	.179	.054	.587	3.325	.003	.067	.291

a. Dependent Variable: Price (Y):

4.4 Discussion of Findings

This study examines the predictive power of traded volume on the price movement of equity listed on the Nigerian Exchange Limited (NGX) using historical data from GTCO Plc as a case study. The initial analysis revealed a positive and linear correlation, with no outliers, indicating a stable dataset. The statistical analysis revealed a significant correlation between traded volume and price movement, with a correlation coefficient of $r = 0.59$, indicating the relevance of traded volume as a predictor of stock price movement.

The regression equation, $Y = 44.164 + 0.179(X)$, provides a quantitative framework for predicting stock price movements based on changes in traded volume. The coefficient of determination, r^2, is 0.345, suggesting that approximately 34.5% of the variance in stock price can be accounted for by variations in traded volume.

To gauge the robustness of the regression model, bootstrapping techniques were employed to generate a 95% confidence interval for the slope coefficient used to predict price from volume. The results substantiate a positive and statistically significant relationship between traded volume and stock price movement for GTCO Plc on the Nigerian Exchange Limited. The regression equation and coefficient of determination emphasize the predictive potential of traded volume, accounting for a substantial portion of price variance.

4.5 Forecast

This section presents the forecasting results for stock price movements based on traded volume. **Table 5** below summarizes the key findings:

S/N	VOLUME TRADED	PRICE CLOSED	FORECAST	ABS ERROR	ERROR ^2	% ERROR
1	8.41	40.75	45.67	4.92	24.18	12%
2	5.39	40.55	45.13	4.58	20.95	11%
3	2.94	40.8	44.69	3.89	15.13	10%
4	5.75	42.34	45.19	2.85	8.13	7%
5	17.18	43	47.23	4.23	17.93	10%
6	7.69	44	45.54	1.54	2.37	3%
7	17.73	44.98	47.33	2.35	5.53	5%
8	18.78	47.25	47.52	0.27	0.07	1%
9	13.02	49.61	46.49	3.12	9.73	6%
10	68.59	49	56.42	7.42	55.07	15%
11	17.17	50.1	47.23	2.87	8.22	6%
12	18.91	51	47.54	3.46	11.95	7%
13	36.87	51.15	50.75	0.40	0.16	1%
14	31.19	52.11	49.74	2.37	5.63	5%
15	22.72	54.71	48.22	6.49	42.07	12%
16	31.77	53.51	49.84	3.67	13.46	7%
17	27.87	52	49.14	2.86	8.15	5%
18	31.81	50.9	49.85	1.05	1.11	2%
19	27.4	49.87	49.06	0.81	0.66	2%
20	24.38	49	48.52	0.48	0.23	1%
21	15.85	48.7	47.00	1.70	2.90	3%
22	17.14	48.95	47.23	1.72	2.97	4%
23	21.87	49.15	48.07	1.08	1.16	2%

Computation of Error Term: ε

Discussion of Forecasting Results:

The study reveals a moderately strong relationship between trading volume and stock price movements in the Nigerian Stock Exchange, suggesting that trading volume can be a useful guide for predicting stock prices. This study provides a localized perspective on stock market prediction, focusing on the Nigerian market. However, the analysis is subject to potential limitations, as it was based on historical data from a single month and may not account for all factors influencing stock price movements, such as macroeconomic indicators or company-specific fundamentals. Despite these limitations, the findings contribute to the understanding of stock market prediction and offer valuable insights for investors and market participants. The statistically significant correlation between trading volume and stock prices suggests that trading volume can be a useful factor in predicting stock price movements. However, further research is needed to enhance the accuracy of prediction models and consider additional variables. Future research could explore other prediction methods, incorporate more variables, or analyse longer time periods to gain a more comprehensive understanding of stock price movements. Additionally, studying the impact of other factors such as market sentiment, investor behaviour, or regulatory changes could provide additional insights into the dynamics of the Nigerian stock market.

5.0 Conclusion

In summary, this study has examined the relationship between trading volume and stock price movements within the Nigerian Exchange Limited. Through a rigorous analysis of historical data from GTCO Plc, we have identified a moderately strong positive correlation between trading volume and stock prices. This finding suggests that trading volume can serve as a useful predictor of stock price movements in the Nigerian market. While stock market prediction remains complex and subject to various factors, our study contributes to the ongoing quest for improved methodologies in this field. By focusing on the Nigerian Exchange Limited, we provide a localized perspective that enhances our understanding of the dynamics within this specific market.

Despite the significant correlation we found, it is important to acknowledge the limitations of this study. The analysis was based on a single case study and a limited timeframe, which may not capture the full breadth of market conditions. Additionally, there are other variables and external factors that could influence stock price movements, such as macroeconomic indicators, investor sentiment, and regulatory changes.

To further enhance stock price prediction models, future research should consider incorporating additional variables, utilizing more extensive datasets, and exploring other prediction methods. Additionally, studying the impact of factors specific to the Nigerian market, such as cultural and economic dynamics, could provide further insights.

Ultimately, the findings of this study have practical implications for investors and market participants in the Nigerian Exchange Limited. Understanding the relationship between trading volume and stock price movements can inform investment strategies and risk management decisions. By incorporating trading volume as a factor in stock price prediction models, investors can potentially improve their returns and navigate the Nigerian market more effectively.

In conclusion, while stock market prediction remains challenging, our study highlights the significance of trading volume as a predictor of stock price movements in the Nigerian Exchange Limited. By considering the limitations and further exploring the dynamics of the market, we can continue to refine our understanding and develop more accurate prediction models. This research contributes to the broader body of knowledge in stock market prediction and provides valuable insights for investors operating in the Nigerian market.

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