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Macroeconomic Influences on Exchange Rates, NSE Nifty, and Gold: Evaluating Linear and Quantile Regression Models

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Abstract

This study addresses the confusion between Ordinary Least Squares (OLS) regression and Quantile Regression (QR) in analyzing the impact of macroeconomic variables on financial markets, specifically exchange rates, NSE Nifty returns, and gold prices. It also seeks to identify the key economic factors that influence these financial indicators, as the relationship between economic variables and market performance remains complex and multifaceted. To tackle these challenges, the study compares the effectiveness of both OLS and QR in capturing the impact of macroeconomic variables like inflation, interest rates, and foreign reserves on financial markets. The analysis proceeds by utilizing data from January 2019 to December 2023, sourced from the Reserve Bank of India (RBI), to assess monthly returns (MOM) of the selected financial indicators. A combination of descriptive statistics, Pearson correlation, and regression models is employed to explore the relationships between the variables. The study reveals that QR provides more nuanced insights, outperforming OLS by capturing the heterogeneity of effects across different market conditions, while OLS offers a more generalized view. Overall, the findings underscore the advantages of using Quantile Regression to better understand the conditional relationships between macroeconomic variables and financial market outcomes.

Keywords: Exchange Rates, Gold, NSE NIFTY, Ordinary Least Squares (OLS) Regression and Quantile Regression (QR)

1. INTRODUCTION

Financial markets are highly dynamic and are influenced by a wide array of macroeconomic variables, making their analysis a complex and challenging task. These variables, including inflation, interest rates, and industrial production, often shape the behavior of key financial indicators such as exchange rates, equity indices, and commodity prices. Understanding these interrelationships is essential for unravelling the broader macroeconomic forces that drive market movements. The challenge, however, lies not only in identifying the influential variables but also in selecting the most effective econometric model to evaluate these relationships. Traditional methods such as Ordinary Least Squares (OLS) regression have long been employed for such analyses, but their limitations in capturing data asymmetry and non-linearity have prompted the exploration of alternative techniques like Quantile Regression (QR).

Macroeconomic variables are pivotal in shaping the behavior of financial markets, influencing key asset classes such as exchange rates, equity indices like NSE Nifty, and commodities like gold. These relationships are often complex, dynamic, and context-dependent, reflecting the interplay between domestic economic factors, global market trends, and investor sentiment. The intricate linkages between these variables are further magnified during periods of economic turbulence, such as the COVID-19 pandemic, which reshaped global financial systems. Exchange rates, as a critical economic indicator, reflect a nation's competitiveness, trade balance, and capital flows. Their fluctuations are influenced by a myriad of factors, including interest rate differentials, inflationary trends, and foreign exchange reserves (Varirahartia and Marsoem, 2022). Similarly, equity indices such as the NSE Nifty encapsulate the performance of a country's corporate sector and its sensitivity to macroeconomic conditions. Studies by Bhar and Malliaris (2011) highlight the importance of variables like GDP growth, inflation, and trade balance in shaping equity returns.

Gold, often regarded as a safe-haven asset, exhibits a unique relationship with macroeconomic factors. While it tends to have a negative correlation with bond yields due to its role as an inflation hedge (Koroleva and Maxim, 2022), its behavior during periods of economic uncertainty, such as the COVID-19 pandemic, underscores its significance in portfolio diversification and risk management (Chiang, 2022). The dynamics between these asset classes and macroeconomic variables vary across developed and emerging markets. In developed markets, structural and fiscal factors, such as demographic changes and unconventional monetary policies, often dominate the narrative (Michelson and Stein, 2023). Emerging markets, on the other hand, are more susceptible to external shocks, with local factors such as policy rate changes and fiscal interventions playing a crucial role in stabilizing markets (Nguyen and Nguyen, 2022).

India, as a prominent emerging market, provides a unique lens through which these dynamics can be analysed. The interplay between macroeconomic factors, exchange rates, the NSE Nifty, and gold has been extensively studied, revealing insights into the country’s financial resilience and integration with global markets. Akram and Das (2019) emphasize the role of short-term interest rates in determining long-term yields, while Gupta and Ahmed (2019) identify the significance of foreign portfolio flows driven by interest rate differentials and exchange rate volatility. The COVID-19 pandemic has brought new dimensions to these relationships, amplifying the effects of macroeconomic variables on financial markets globally. Mobin et al. (2022) document the pandemic’s impact on stock and bond markets, highlighting the stabilizing effects of fiscal stimulus and unconventional monetary measures. These disruptions underscore the need for robust econometric models to capture the evolving relationships between macroeconomic variables and financial markets.

This study aims to explore the macroeconomic influences on exchange rates, the NSE Nifty, and gold using both linear and quantile regression models. By integrating insights from existing literature and employing advanced modeling techniques, the study seeks to provide a comprehensive understanding of the interplay between these variables. The findings are expected to offer valuable insights for policymakers, investors, and academics, particularly in navigating the complexities of financial markets in a post-pandemic world.

2- LITERATURE REVIEW

The intricate relationship between macroeconomic variables and financial markets has been a central focus of economic research, particularly in understanding how exchange rates, equity indices, and commodities like gold respond to changing economic conditions. This study investigates the impact of macroeconomic factors on the exchange rate, NSE Nifty, and gold prices, employing both linear and quantile regression models. Linear regression (OLS) is widely used for its simplicity and efficiency in capturing average effects across datasets. However, its limitations in addressing asymmetries and variability at different conditional quantiles have paved the way for quantile regression, which provides a more nuanced analysis. By exploring these relationships through these complementary frameworks, the study aims to uncover how economic shocks and market dynamics influence key financial metrics under varying conditions.

The relationship between economic factors and exchange rates has been extensively analysed across developed markets, emerging markets, and India, particularly during the COVID-19 pandemic. In developed markets, Zhou (2021) highlights that short-term interest rates, government debt, and U.S. bond yields significantly impacted long-term bond yields, which in turn influenced exchange rates. Additionally, the temporary nature of pandemic-induced financial shocks was evident, as Pham and Chu (2023) found that stimulus measures and tightened containment policies exacerbated currency fluctuations, albeit with diminishing effects over time.

Emerging markets exhibited unique dynamics during the pandemic, as these economies faced heightened exchange rate volatility due to capital flow disruptions and global financial uncertainty. Yilanci and Pata (2023) observed that COVID-19 impacted exchange rates minimally compared to stock and bond markets in Brazil and India, but pressures intensified post-2021. Similarly, Olivares Rios et al. (2019) noted that macroeconomic factors and international market uncertainty influenced short-term risk premiums, emphasizing the role of robust policy measures to maintain exchange rate stability. In India, Dharani et al. (2023) identified heterogeneous impacts of the pandemic on different industries, with stock market volatility indirectly affecting exchange rates through investor sentiment. Lakdawala et al. (2023) found that unconventional monetary policies, including liquidity support and asset purchases, effectively influenced bond yields and exchange rate movements, mitigating some pandemic-induced pressures. These findings reveal the critical interplay between monetary policies and market dynamics in stabilizing exchange rates during crises.

Comparative studies of developed and emerging markets revealed varying sensitivities to macroeconomic drivers, highlighting structural differences and policy responses. Emerging markets, such as India and Brazil, were more vulnerable to external shocks due to reliance on foreign capital flows and limited fiscal capacity. Developed markets experienced relatively stable exchange rates, supported by stronger institutional frameworks, and coordinated policy actions. Rabbani et al. (2024) highlighted the global interconnectedness of asset markets, suggesting that financial stress in major economies had spillover effects on exchange rates across regions, particularly in emerging markets.

Gold rates experienced heightened volatility during the COVID-19 pandemic, influenced by economic uncertainty, macroeconomic dynamics, and market conditions across developed and emerging markets, including India. In developed markets, gold reaffirmed its role as a safe-haven asset amidst unprecedented economic disruptions. Studies revealed that low interest rates, quantitative easing measures, and heightened geopolitical tensions drove significant capital inflows into gold. Flannery and Protopapadakis (2002) highlighted the impact of macroeconomic indicators like inflation and monetary aggregates on gold prices, noting their sensitivity to investor sentiment during crises. In India, gold's significance as a cultural and investment asset deepened during the pandemic. Verma and Bansal (2021) noted the negative correlation between gold prices and equity market performance, with Indian investors gravitating toward gold amidst declining returns in other asset classes. Additionally, domestic policies on gold import duties and currency volatility played a pivotal role in shaping price dynamics during the pandemic's peak. Vicente and Kubudi (2018) demonstrate that incorporating survey data improves inflation forecasting, which in turn influences gold's role in hedging against economic uncertainty. Marisetty (2024) highlights strong positive correlations between NSE NIFTY and gold, underscoring the influence of safe-haven assets on Indian stock market returns.

The COVID-19 pandemic brought unprecedented disruptions to global financial markets, with equity returns across developed and emerging markets profoundly affected by macroeconomic factors. In developed markets, studies have highlighted the interplay of monetary policy, inflation, and fiscal stimulus in shaping equity market responses. For instance, Beirne et al. (2020) observed that fiscal and monetary interventions helped stabilize financial conditions, particularly in Asian and European emerging economies, while Chiang and Chen (2023) found a negative relationship between inflation and aggregate stock returns in the US, except for the energy sector. Schrank (2024) notes that monetary policy changes during the crisis had pronounced effects on financial markets in Thailand, with gold providing limited safe-haven functionality compared to its historical performance. Marisetty (2024) identifies strong long-term cointegration between NSE NIFTY, S&P 500, and Nikkei 225, highlighting the influence of global economic integration on Indian stock market returns.

Emerging markets experienced heightened volatility and varied equity performance due to the pandemic. Horvath and Yang (2021) demonstrated that equity returns in emerging market economies (EMEs) were significant predictors of output fluctuations, underscoring the interconnectedness of financial and economic systems in these regions. India's equity markets displayed unique responses to macroeconomic challenges during the COVID-19 period. Garg and Kalra (2018) further illuminated the influence of macroeconomic factors such as inflation and unemployment on Sensex performance, pointing to the interplay of structural economic factors and pandemic-driven disruptions in shaping equity returns in India. Amin and Mollick (2022) further explore this dynamic, showing that leverage moderates the effect of oil prices on U.S. stock returns.

Across developed and emerging markets, the COVID-19 pandemic highlighted the interconnectedness of financial systems and the critical role of macroeconomic factors in equity market performance. Studies like Agrawal (2020) in the US and Mpofu et al. (2023) in South Africa demonstrated how economic uncertainty, structural risks, and government interventions influenced market dynamics. Collectively, these findings underscore the importance of adaptive fiscal and monetary policies, investor awareness, and sectoral analysis in navigating the challenges posed by global economic crises. Sreenu and Pradhan (2023) highlight the sector-level economic factors influencing volatility in Indian stock markets during the COVID-19 pandemic, offering strategies for managing market fluctuations.

Ordinary Least Squares (OLS) regression remains a cornerstone in financial and economic research for analyzing relationships between variables. Studies by Modi and Bhagat (2021) and Hui and Chan (2022) illustrate its extensive application in evaluating macroeconomic and market dynamics. Modi and Bhagat used OLS to uncover how variables like FDI, GDP, inflation, and trade balances influence the Indian Sensex, emphasizing the market's rapid growth and integration. Hui and Chan's exploration of global equity markets during the COVID-19 pandemic employed OLS alongside other methods, identifying significant negative effects on returns, particularly in European economies. These findings underscore OLS's utility in capturing mean effects across diverse datasets and contexts, though they also highlight its limitations in addressing more complex relationships, such as nonlinearities and varying effects across distributions. Prananta and Alexiou (2024) use a NARDL model to explore the cointegration of exchange rates, bond yields, and stock markets in Indonesia, uncovering asymmetric short- and long-term effects.

Quantile regression, by contrast, provides a nuanced perspective, accommodating heterogeneity and capturing variable impacts at different points of the outcome distribution. Bahloul and Ben Amor (2022) leveraged this method to examine MENA stock markets, revealing that the influence of macroeconomic factors varied across quantiles, underscoring the importance of portfolio diversification within the region. Similarly, Ozcelebi et al. (2024) employed quantile regression to analyze exchange market pressures in emerging economies, demonstrating how bond yield shocks exhibit regime-dependent effects. Rao et al. (2022) extended this approach to study asset class connectedness pre- and post-COVID-19, finding that traditional safe havens like gold and Bitcoin lose their efficacy during extreme economic conditions. These studies highlight quantile regression's strength in capturing asymmetries and its ability to offer richer insights into the complexities of financial and economic phenomena, complementing the broader but less flexible perspective provided by OLS.

The reviewed literature underscores the strengths and limitations of OLS and quantile regression in examining the interplay between macroeconomic variables and financial markets. While OLS efficiently identifies mean effects, its inability to capture heterogeneity across distributions limits its explanatory power for complex, regime-dependent dynamics. In contrast, quantile regression reveals crucial insights into asymmetries and variable impacts across different market states, offering a comprehensive understanding of financial phenomena. These findings highlight the importance of selecting appropriate methodological frameworks based on the nature of the research question.

3. METHODOLOGY

The problem addressed in this study is to assess the impact of key macroeconomic variables on financial markets, specifically focusing on exchange rates, NSE returns, and gold prices. It seeks to determine which method—Ordinary Least Squares (OLS) regression or Quantile Regression (QR)—is more effective in capturing the relationship between these economic variables and market outcomes. The analysis involves comparing the performance of both models in terms of fit and predictive accuracy, particularly under different economic conditions. Additionally, the study explores the statistical significance of these macroeconomic variables, such as inflation, interest rates, government security yields, and industrial production, in explaining variations in exchange rates, Nifty returns, and gold returns. Understanding these dynamics helps policymakers and investors anticipate market movements in response to shifts in key economic indicators.

The variables selected for this study include Bank Rate, Inflation, 10Y Government Securities (10Y GSec), NSE returns, Gold, Exchange Rate, Index of Industrial Production (IIP), Foreign Direct Investment (FDI), and Foreign Reserves. These variables were chosen based on their established relevance in economic theory and their potential to influence financial markets. Data spanning from January 2019 to December 2023 was collected from the Reserve Bank of India (RBI) and consists of monthly returns (MOM). The data's period captures a range of economic cycles, including periods of high inflation, low-interest rates, and global market fluctuations. The significance of variable selection is driven by their ability to explain major macroeconomic trends and their relevance in forecasting financial asset returns, thus providing a solid foundation for the modeling efforts.

The analysis utilizes a combination of descriptive statistics, Pearson correlation, and regression techniques to explore the relationships among these variables. OLS regression is employed to capture the average effects of the explanatory variables on financial outcomes, while QR is used to investigate the impact of these variables at different quantiles of the conditional distribution, providing insights into how the relationships vary under different economic regimes. Model evaluation is based on fit tools such as squared residuals, Akaike Information Criterion (AIC), Log-Likelihood (LL), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HC), which assess the balance between model complexity and fit. Additionally, predictive error measures, including Mean Squared Error (MSE), Absolute Error (AE), and Absolute Percentage Error (APE), are used to evaluate the predictive accuracy of the models. These metrics allow a comprehensive assessment of both models' ability to explain and predict market behavior accurately.

However, this study faces several limitations. First, while the selected macroeconomic variables are crucial for understanding market dynamics, there may be other important factors, such as geopolitical events or global economic shocks, that are not included in the analysis. Second, the study assumes linear relationships in the OLS model, which may not fully capture complex, non-linear interactions between variables. Furthermore, while Quantile Regression offers more flexibility, it also requires careful consideration of model specifications, especially when dealing with extreme values or outliers. Lastly, the use of monthly data, while comprehensive, may overlook shorter-term market fluctuations that could provide additional insights into high-frequency trading dynamics or short-term market responses to policy changes.

3.1. Descriptive statistics

Descriptive statistics were calculated for the nine variables, including bond yields, equity returns, and economic indicators, to summarize their central tendencies and variability. The study also used the Jarque-Bera test to assess the normality of the data distributions for each variable. The results of the test indicated whether the data significantly deviated from a normal distribution, guiding further statistical analysis. These preliminary steps provided a solid basis for the subsequent paired t-test and regression analyses.

3.2. Multivariate correlation analysis

Multivariate correlation analysis explores the relationships among multiple variables simultaneously. The correlation matrix is calculated using the formula:

$$\rho_{XY} = \frac{COV\ (X,\ Y)}{\sigma_X \sigma_Y}$$

where ρ_{XY} is the Pearson correlation coefficient, Cov (X,Y) is the covariance between variables X and Y, and σ_X and σ_Y are the standard deviations of X and Y, respectively. This analysis helps identify the strength and direction of relationships between bond yields, equity returns, and various economic factors.

3.3. Ordinary Least Squares (OLS) – Linear Regression

The Ordinary Least Squares (OLS) test in multiple regression estimates relationships between one dependent variable and multiple independent variables. The formula is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Here, Y is the dependent variable, X_1, X_2…….., X_n are independent variables, β_0 is the intercept, β_1 ,β_2…, β_n are coefficients, and ϵ is the error term. OLS minimizes the sum of squared residuals (ϵ^2) to estimate β values. Assumptions like linearity, no multicollinearity, and homoscedasticity are crucial for valid results.

3.4. Quantile Regression (QR)

Quantile regression is a statistical technique that extends traditional linear regression by estimating the conditional quantiles of a response variable, rather than its mean. Unlike ordinary least squares (OLS), which minimizes the sum of squared residuals, quantile regression minimizes the weighted sum of absolute residuals to estimate relationships at different points of the response distribution (e.g., median, or other quantiles). The quantile regression model is given by:

$$Q_y (\tau \mid X) = X\ \beta\tau$$

where $Q_y (\tau|X)$ represents the τ th quantile of the dependent variable y conditional on the predictors X, and $\beta\tau$ denotes the quantile-specific coefficients. This approach is particularly useful for exploring heterogeneous effects, identifying trends at the tails of the distribution, and providing a more comprehensive understanding of the relationship between variables when the assumptions of OLS are not met.

3.5. Variance Inflation Factor (VIF) – Multicollinearity Test

The Variance Inflation Factor (VIF) is used to detect multicollinearity in regression models by measuring how much the variance of a regression coefficient is inflated due to correlation with other predictors. The formula for VIF is:

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2}$$

where R_i^2 is the coefficient of determination obtained by regressing the i-th predictor on all other predictors. A high VIF (typically > 10) indicates significant multicollinearity, which may distort the regression results and reduce the reliability of the coefficients.

3.6. Normality test

The Chi-square test for normality is used to assess whether a dataset follows a normal distribution. It compares the observed frequency of data in each category with the expected frequency if the data were normally distributed. The formula for the Chi-square test is:

$$\chi^2 = \Sigma \frac{(O - E)^2}{E}$$

where O is the observed frequency, E is the expected frequency, and the summation is over all categories. A high Chi-square value indicates a significant deviation from normality.

3.7. Brock-Dechert-Scheinkman (BDS) Test

The Brock-Dechert-Scheinkman (BDS) Test assesses non-linearity or dependence in time-series data by examining deviations from randomness. It compares the correlation of points in reconstructed phase space at varying dimensions. The test statistic is:

$$W = \frac{\sqrt{n}\,(C_m(\varepsilon) - C_1^m(\varepsilon)}{\sigma_m(\varepsilon)}$$

where $C_m(\varepsilon)$ is the correlation integral for dimension m, $C_1^m(\varepsilon)$ is the product of one-dimensional correlation integrals, and $\sigma_m(\varepsilon)$ is the standard deviation. A significant result indicates non-linear structure, making the test vital for analysing chaotic or complex systems.

3.8. Standard Error (SE)

Standard Error (SE) measures the precision of a sample statistic, such as the mean, relative to the population parameter. It is calculated as:

$$\mathrm{SE} = \frac{\sigma}{\sqrt{n}}$$

where σ is the population standard deviation and n is the sample size. A smaller SE indicates greater accuracy of the sample estimate, making it critical in hypothesis testing and confidence interval calculation.

3.9. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is used to evaluate and compare the goodness of fit of statistical models, balancing model complexity and fit. The formula for AIC is:

$$\mathrm{AIC} = 2k - 2\ln(L)$$

where k is the number of parameters in the model, and L is the likelihood of the model. A lower AIC value indicates a better-fitting model, while penalizing excessive complexity. It is widely used in model selection, especially when comparing models with different numbers of parameters.

where $\Delta Y_t = Y_t - Y_{t-1}$ and $\Delta X_t = X_t - X_{t-1}$. This method eliminates time-invariant unobserved effects, focusing on the variation within the data. It is commonly applied in time-series and panel data analysis.

3.10. Log-likelihood

Log-likelihood quantifies how well a statistical model fits the observed data by calculating the logarithm of the likelihood function, which represents the probability of the observed outcomes given the model parameters. In regression, maximizing the log-likelihood helps identify parameter estimates that best explain the data. It is expressed as:

$$\ln(L) = \sum_{i=1}^{n} \ln f(y_i \mid X_i, \beta)$$

where $f(y_i \mid X_i, \beta)$ is the probability density or mass function, y_i are the observed values, X_i are the predictors, and represents the model parameters.

3.11. Predictive Tests

Mean Squared Error (MSE), Absolute Error (AE), and Absolute Percentage Error (APE) are key metrics used to evaluate the accuracy of predictive models. MSE calculates the average squared difference between predicted and actual values, placing greater emphasis on larger errors due to squaring, which makes it sensitive to outliers. AE represents the average of absolute differences, providing a straightforward measure of prediction accuracy without emphasizing outliers. APE, expressed as a percentage, normalizes errors by the actual values, allowing for the assessment of model performance relative to the scale of the data. Together, these metrics offer complementary insights: MSE highlights large deviations, AE gives an overall measure of error magnitude, and APE provides context for error in terms of percentage, aiding in the comparison of models across datasets.

4. RESULTS

The analysis of Table 1 commences with the Bank Rate, which showcases relatively stable behavior. The mean (5.3383) and median (5.4000) are closely aligned, reflecting symmetry in its distribution. The coefficient of variation (C.V.) at 0.1927 and a standard deviation of 1.0284 suggest low variability in rates. Skewness is minimal (0.1820), while negative excess kurtosis (-1.6198) points to a flatter-than-normal distribution. The Jarque-Bera statistic (6.8908, p = 0.0318) signals a departure from normality, requiring further diagnostic checks for potential implications in modelling. Inflation displays a mean of 5.5675 and median of 5.7050, indicating a slightly left-skewed distribution with a skewness value of -0.5617. Its standard deviation (1.4599) and C.V. (0.2622) show moderate variability. Negative excess kurtosis (-0.5485) reflects a distribution less peaked than normal. Although the Jarque-Bera statistic (3.9076, p = 0.1417) does not indicate significant deviation from normality, the observed range (1.9700 to 7.7900) highlights varying inflationary pressures over the period.

The 10-Year Government Security (10Y GSec) has a mean of 6.7766 and a median of 6.8299, suggesting slight left skewness (-0.2767). Its variability is low, as evidenced by a standard deviation of 0.5388 and C.V. of 0.0795. Excess kurtosis (-1.2467) denotes a flatter distribution. The Jarque-Bera statistic (4.6512, p = 0.0977) implies no significant deviation from normality, reinforcing its use as a reliable benchmark for long-term interest rates. For NSE returns, the mean (11.1950) and median (9.2678) reveal moderate skewness (0.4881) toward positive values. The high standard deviation (16.4660) and elevated C.V. (1.4708) indicate considerable volatility. Positive excess kurtosis (0.6811) points to a slightly peaked distribution. The Jarque-Bera test

(3.5416, p = 0.1701) does not show significant non-normality, although outliers and extreme values should be carefully examined.

The Gold variable has a mean of 8.8685 and a median of 8.6167, with negligible skewness (0.1859). Variability is pronounced, as indicated by the standard deviation (11.0290) and C.V. (1.2436). Negative excess kurtosis (-1.0851) suggests a flatter distribution with mild deviations from normality. The Jarque-Bera statistic (3.2892, p = 0.1930) confirms no major normality concerns, supporting its consistent inclusion as a hedge variable. Finally, IIP and FDI demonstrate unique characteristics. The IIP mean (3.9419) is overshadowed by high variability (standard deviation of 20.7450, C.V. of 5.2628), with extreme positive skewness (3.6278) and substantial kurtosis (24.8270). The Jarque-Bera statistic (1672.5, p < 0.0000) confirms significant non-normality. FDI, with a mean of -11.2490, exhibits negative skewness (-0.3518) and positive kurtosis (4.2110), highlighting frequent extreme observations. Its Jarque-Bera statistic (45.568, p < 0.0000) also underscores pronounced deviations from normality, warranting caution in regression analyses involving these variables. The variables display diverse statistical profiles, influencing their suitability for different models. Stable variables like the Bank Rate and 10Y GSec are conducive to linear models, whereas volatile variables such as IIP and FDI may necessitate robust or non-linear methods to address their distributional complexities.

Table 1: Descriptive Statistics of Macro-Economic Variables

Variable	Bank Rate	Inflation	10Y GSec	NSE	Gold	Exchange Rate	IIP	FDI	Foreign Reserves
N	60	60	60	60	60	60	60	60	60
Mean	5.338	5.568	6.777	11.195	8.869	3.751	3.942	-11.249	11.213
Median	5.400	5.705	6.830	9.268	8.617	3.138	2.589	-10.287	10.295
Minimum	4.250	1.970	5.830	-30.15	-8.878	-4.399	-57.312	-477.04	-8.521
Maximum	6.750	7.790	7.491	53.571	32.296	10.916	133.520	368.430	30.394
Std. Dev.	1.028	1.460	0.539	16.466	11.029	3.851	20.745	118.200	9.616
C.V.	0.193	0.262	0.080	1.471	1.244	1.027	5.263	10.508	0.858
Skewness	0.182	-0.562	-0.277	0.488	0.186	0.033	3.628	-0.352	0.063
Ex. kurtosis	-1.620	-0.549	-1.247	0.681	-1.085	-0.792	24.827	4.211	-0.628
IQ range	2.188	2.163	0.976	14.739	19.821	6.066	5.733	122.440	12.697
Jarque-Bera	6.891* (0.032)	3.907 (0.142)	4.651 (0.097)	3.542 (0.170)	3.289 (0.193)	1.579 (0.454)	1672* (0.000)	45.56* (0.000)	1.026 (0.598)

Source: The Authors, Note: *p < 0.05.

The multivariate correlation matrix in Table 2 highlights the relationships among macroeconomic variables. Beginning with the Bank Rate, it is strongly positively correlated with the 10Y GSec (0.7734, p < 0.05), reflecting its influence on long-term interest rates. Its negative correlation with the NSE (-0.3341, p < 0.05) suggests that higher rates may dampen equity market performance. Additionally, the Bank Rate is negatively correlated with Foreign Reserves (-0.5962, p < 0.05), indicating potential capital outflows during periods of tight monetary policy. However, its modest correlations with other variables, such as Exchange Rate (0.3344, p < 0.05), emphasize a nuanced role in macroeconomic interactions.

Table 2: Multivariate Correlations of the Macro-Economic Variables.

Variables	Bank Rate	Inflation	10Y GSec	NSE	Gold	Exchange Rate (ER)	IIP	FDI	Foreign Reserves
Bank Rate	1	-0.333*	0.773*	-0.334*	-0.118	0.334*	-0.06	-0.167	-0.596*
Inflation	-0.333*	1	-0.106	-0.133	0.19	0.153	-0.137	-0.026	0.1435
10Y GSec	0.773*	-0.106	1	-0.255	-0.432*	0.444*	0.001	-0.073	-0.829*
NSE	-0.334*	-0.133	-0.255	1	-0.483*	-0.663*	0.533*	0.267	0.034
Gold	-0.118	0.191	-0.432*	-0.483*	1	-0.123	-0.326*	-0.043	0.637*
ER	0.334*	0.153	0.444*	-0.663*	-0.123	1	-0.336*	-0.341*	-0.336*
IIP	-0.06	-0.137	0.001	0.533*	-0.326*	-0.336*	1	0.302*	-0.083
FDI	-0.168	-0.027	-0.073	0.267	-0.043	-0.341*	0.302*	1	0.052
FR	-0.596*	0.1435	-0.829*	0.035	0.637*	-0.336*	-0.082	0.052	1

Source: The Authors, Note: *$p < 0.05$.

Inflation displays a weak correlation with most variables, indicating its independent dynamics in this dataset. Notable exceptions include a slight positive correlation with Gold (0.1905, not significant) and Exchange Rate (0.1526, not significant), aligning with its potential to influence safe-haven assets. Its negative association with the Bank Rate (-0.3330, $p < 0.05$) aligns with central bank interventions to curb inflation through interest rate hikes. The absence of significant correlation with the NSE (-0.1333) and Foreign Reserves (0.1435) suggests inflation's limited direct impact on these variables. The 10Y GSec has a prominent positive correlation with the Bank Rate (0.7734, $p < 0.05$), reflecting the dependency of long-term yields on monetary policy. It is negatively correlated with Gold (-0.4316, $p < 0.05$) and Foreign Reserves (-0.8295, $p < 0.05$), indicating that rising yields might diminish the attractiveness of alternative assets and foreign capital holdings. A moderate positive correlation with the Exchange Rate (0.4437, $p < 0.05$) suggests its role in affecting currency dynamics. However, its weak and non-significant relationship with variables like IIP (0.0014) underscores its limited influence on industrial production in the dataset.

The NSE demonstrates a significant positive correlation with IIP (0.5335, $p < 0.05$), indicating the influence of industrial production on stock market performance. Conversely, it is negatively correlated with Gold (-0.4834, $p < 0.05$) and Exchange Rate (-0.6627, $p < 0.05$), reflecting opposing movements between equity returns, safe-haven assets, and currency depreciation. Its weak correlation with Foreign Reserves (0.0347) suggests limited interaction between equity markets and reserve dynamics. Gold exhibits a strong positive correlation with Foreign Reserves (0.6369, $p < 0.05$), signifying its role in reserve diversification. Its negative correlations with variables such as the 10Y GSec (-0.4316, $p < 0.05$) and NSE (-0.4834, $p < 0.05$) highlight its nature as a counter-cyclical asset. Weak correlations with FDI (-0.0436) and Exchange Rate (-0.1227) emphasize its relative independence from these factors.

The Exchange Rate has significant negative correlations with NSE (-0.6627, $p < 0.05$) and Foreign Reserves (-0.3361, $p < 0.05$), suggesting that depreciation impacts equity performance and reserve balances. Its positive correlation with the 10Y GSec (0.4437, $p < 0.05$) underscores the relationship between currency dynamics and bond yields. Negative correlations with IIP (-0.3358, $p < 0.05$) and FDI (-0.3407, $p < 0.05$) further reflect the Exchange Rate's influence on industrial and investment activities. The IIP is moderately positively correlated with NSE (0.5335, $p < 0.05$) and FDI (0.3023, $p < 0.05$), indicating that industrial growth supports equity markets and foreign investments. Its negative correlation with Gold (-0.3262, $p < 0.05$) aligns with decreased reliance on safe-haven assets during periods of industrial expansion. Weak and non-significant correlations with variables like the Bank Rate (-0.0604) emphasize limited direct monetary interactions.

Finally, FDI is weakly but positively correlated with IIP (0.3023, $p < 0.05$), indicating a modest relationship between industrial growth and foreign investment inflows. Its negative correlation with Exchange Rate (-0.3407, $p < 0.05$) suggests that currency depreciation may deter FDI. Weak correlations with most other variables, including Inflation (-0.0268) and Foreign Reserves (0.0520), indicate a relatively independent pattern of investment dynamics. The correlations in Table 2 reveal varied interrelationships between macroeconomic variables. While some variables like the Bank Rate and 10Y GSec exhibit strong associations, others like Inflation and FDI show weaker interactions, emphasizing diverse economic dynamics. These insights underscore the importance of considering both individual and joint effects of variables in comprehensive economic modeling.

The analysis of Table 3 begins with the assessment of the factors influencing Exchange Rates. The constant term in the Quantile Regression (QR) models exhibits significant and increasing positive effects as we move from lower to higher quantiles, reflecting the varying baseline exchange rate levels under different market conditions. Among the explanatory variables, the Bank Rate shows significant influence only at the lower quantile (0.10), indicating its impact is concentrated during weaker exchange rate regimes. The 10Y GSec has consistently negative coefficients in QR, with significance strengthening in the 0.50 and 0.60 quantiles, demonstrating that higher yields in government securities lead to currency strengthening, particularly under median and moderately stressed conditions. Inflation, while positive and significant at lower quantiles, turns negative in higher quantiles, reflecting its varying effects across different exchange rate scenarios.

The NSE and Gold exhibit consistently negative and significant coefficients across quantiles, suggesting that equity market performance and gold prices inversely influence exchange rates. This likely reflects the movement of foreign investments and safe-haven assets. IIP and FDI show weaker and inconsistent significance across quantiles, while Foreign Reserves play a crucial role at higher quantiles, with their negative impact intensifying under stressed exchange rate conditions. In comparing OLS and QR models, the OLS regression offers an averaged estimation across all exchange rate scenarios, identifying inflation, NSE, and gold as significant determinants. However, it fails to capture the heterogeneity in factor impacts under varying conditions, which QR models excel at addressing. For example, the OLS model shows a positive impact of inflation on exchange rates, but QR reveals a nuanced transition from positive to negative effects as market conditions shift.

The QR models provide richer insights into the varying effects of determinants across quantiles. At the 0.10 quantile, exchange rates are more sensitive to inflation and bank rate changes, reflecting weaker market conditions. At the median (0.50) quantile, factors like 10Y GSec and foreign reserves gain significance, capturing balanced market behavior. The 0.60 quantile emerges as the most robust model, with the lowest Akaike Criterion, Schwarz Criterion, and error measures, indicating superior fit and predictive power. Here, the significance of variables like 10Y GSec, inflation, and foreign reserves is pronounced, highlighting their critical role in moderately stressed exchange rate scenarios. When evaluating fit metrics, the 0.60 quantile QR model outperforms others. It achieves the lowest Schwarz Criterion, Akaike Criterion, and Mean Squared Error, making it the best-performing model overall. The Log-likelihood at this quantile also indicates superior explanatory power, while error metrics like Absolute Error and Absolute Percentage Error are minimized, ensuring higher prediction accuracy.

In terms of economic interpretation, the QR approach emphasizes the asymmetry in the determinants of exchange rates, which OLS fails to capture. For instance, the shift in the effects of inflation and foreign reserves across quantiles demonstrates their varying roles under different market pressures. The consistent negative influence of gold and NSE across quantiles highlights their stabilizing yet restrictive effects on currency movements. In conclusion, while the OLS model provides a generalized understanding, the 0.60 quantile QR model emerges as the most effective framework for analyzing exchange rates. It captures the nuanced impacts of macroeconomic variables with superior fit, predictive accuracy, and relevance in moderately stressed market conditions, making it the preferred model for a comprehensive analysis of exchange rate dynamics.

Table 3: Variables Impact on Exchange Rates and Comparison of OLS & Quantile Regression Models

Particulars	OLS Regression		Quantile Regression						
	Coefficients	Collinearity	0.10	0.25	0.40	0.50	0.60	0.75	0.90
Constant	5.35964	---	−6.51040	8.61283	10.86750*	15.7933***	18.3763***	23.3067***	17.9355***
Bank Rate	0.39231	4.103	0.99178**	0.60871	0.09811	0.01202	−0.00304	−0.15247	0.21641
10Y GSec	−0.33009	6.625	0.34136	−1.17919	−0.97494	−1.49256**	−1.19030*	−1.6101***	−0.96211
Inflation	0.44653*	1.411	0.85763***	0.56177***	0.43756**	0.37273***	−0.19306*	−0.2687***	−0.4874***
NSE	−0.2229***	2.590	−0.2421***	−0.2117***	−0.1913***	−0.2002***	−0.2143***	−0.2184***	−0.1988***
Gold	−0.2559***	3.636	−0.3284***	−0.2877***	−0.2099***	−0.2054***	−0.1667***	−0.1421***	−0.0834***
IIP	0.00204	1.508	−0.00394	0.01199	0.00353	0.00363	−0.00377	−0.00296	0.01165
FDI	−0.00362	1.192	−0.00202	−0.00388*	−0.00465**	−0.00509*	−0.0034***	−0.0031***	−0.0032**
Foreign Reserves	0.06828	4.723	0.08669**	0.04720	−0.00568	−0.02766	−0.07374**	−0.1364***	−0.1201***
Normality	3.3188		6.4427**	5.6380*	5.7410*	5.9606*	10.0580***	11.6567***	15.1540***
Linearity	1.8070		4.5410***	1.7320	2.9920**	2.2740*	4.8200***	4.7620***	6.5470***
Sum Squared Residual	228.3819[a]		696.1777	315.1601	267.4466	261.2305	330.5401	403.0841	614.3923
Log-likelihood	−125.2366		−126.3267	−126.0138	−122.4965	−123.2080	−120.1945[b]	−120.5419	−133.6887
Schwarz Criterion	287.3222		289.5025	288.8767	281.8421	283.2651	277.2380[a]	277.9329	304.2264
Akaike Criterion	268.4731		270.6534	270.0276	262.9930	264.4160	258.3889[a]	259.0838	285.3773
Hannan-Quinn	275.8460		278.0263	277.4005	270.3660	271.7889	265.7618[a]	266.4568	292.7502
Mean Squared Error	1.9510[a]		3.4063	2.2919	2.1113	2.0866	2.3471	2.5919	3.2000
Absolute Error	1.5142		2.5617	1.6537	1.4667	1.4338[a]	1.4664	1.5906	2.1155
Absolute Percentage Error	88.9670		99.7530	70.7750[a]	72.6290	77.3790	113.6000	125.1600	167.9400

Source: The Authors.

Note: ***p < 0.01, **p < 0.05 & *p < 0.10,

[a] Lowest value, and

[b] Highest Value.

Table 4: Variables Impact on NSE NIFTY Returns and Comparison of OLS & Quantile Regression Models

Particulars	OLS Regression		Quantile Regression						
	Coefficients	Collinearity	0.10	0.25	0.40	0.50	0.60	0.75	0.90
Constant	64.31070**	---	21.5695	35.4576***	50.4342***	47.12160	65.35680	111.716***	153.175***
Bank Rate	1.47854	4.093	3.6436***	3.7744***	3.86462***	3.18057	2.37343	0.69454***	−0.12598
10Y GSec	−7.53847*	6.263	−4.20619	−6.3584***	−7.7775***	−6.61833	−8.52008	−12.552***	−16.609***
Inflation	1.10123	1.463	1.01955**	1.39108***	0.69040***	0.91651	1.11925	0.96877***	−0.51454
Gold	−1.0680***	2.588	−1.0897***	−1.1408***	−1.1161***	−1.2475***	−1.0992***	−0.9733***	−0.5380***
Exchange Rate	−2.5718***	1.634	−2.7315***	−2.4797***	−2.3850***	−2.5308***	−2.3381***	−2.4521***	−2.4273***
IIP	0.10606*	1.400	0.16183***	0.11004***	0.08533***	0.06413	0.05854	0.1032***	0.22908***
FDI	−0.00223	1.238	−0.0257***	−0.0054***	0.00165	0.00051	0.00200	−0.0059***	−0.01119**
Foreign Reserves	0.23370	4.721	0.36952***	0.51124***	0.46216***	0.52784**	0.34684	−0.1794***	−0.4118***
Normality	3.5485		6.1915**	7.2653**	12.3948***	9.0933**	12.6555***	0.6482	15.7795***
Linearity	0.3080		2.5540*	0.0870	0.2270	-0.4720	0.3580	1.0370	3.9600***
Sum Squared Residual	2634.2050[a]		7299.091	3907.669	3264.692	2926.722	2829.734	4494.488	8542.099
Log-likelihood	−198.5961		−204.2428	−197.3026	−195.6611[b]	−197.5197	−200.6758	−200.6896	−201.7526
Schwarz Criterion	434.0412		445.3346	431.4542	428.1713[a]	431.8884	438.2008	438.2282	440.3543
Akaike Criterion	415.1921		426.4855	412.6051	409.3222[a]	413.0393	419.3517	419.3791	421.5052
Hannan-Quinn	422.5651		433.8584	419.9781	416.6951[a]	420.4122	426.7246	426.7520	428.8781
Mean Squared Error	6.6260[a]		11.0300	8.0702	7.3764	6.9842	6.8675	8.6549	11.9320
Absolute Error	5.2646		8.2645	5.7588	5.0717	4.9473[a]	5.1871	6.5082	8.6465
Absolute Percentage Error	174.5500		225.5400	145.7400	133.2600[a]	153.8100	160.4500	220.5800	207.1800

Source: The Authors.

Note: ***$p < 0.01$, **$p < 0.05$ & *$p < 0.10$,

[a] Lowest value, and

[b] Highest Value.

Upon analyzing Table 4, the impact of various macroeconomic variables on NSE Nifty returns is reflected through both OLS regression and Quantile Regression (QR) models. The Bank Rate exhibits a positive coefficient in OLS (1.47854), suggesting that higher interest rates tend to positively influence Nifty returns. The 10Y GSec has a negative coefficient (−7.53847), indicating an inverse relationship with Nifty returns, where higher government bond yields result in lower market performance. Inflation shows a positive relationship (1.10123), implying that rising inflation may be associated with higher market returns, likely driven by investor expectations. Gold, with a negative coefficient (−1.0680), indicates an inverse correlation with Nifty returns, where higher gold prices often coincide with market uncertainty. The Exchange Rate (−2.5718) has a consistently negative effect, implying that depreciation in the domestic currency can harm market performance. These variables collectively show their substantial influence on the Nifty index, with different signs of impact based on macroeconomic conditions.

The IIP demonstrates a positive relationship with Nifty returns, with coefficients increasing at higher quantiles, peaking at 0.90 (0.22908). This suggests that higher industrial output tends to boost market performance, especially in times of higher returns. Foreign Direct Investment (FDI) generally shows a negative coefficient, with the effect becoming more pronounced at higher quantiles (−0.01119), hinting that foreign investments may have a diminishing or negative influence on Nifty during certain market conditions. Foreign Reserves show a mixed relationship, being positive at lower quantiles but turning negative at higher quantiles, indicating that while higher reserves may help stabilize the market during lower returns, their effect diminishes during extreme positive market conditions. When examining the fit of the models through Log-Likelihood, Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HA), the results indicate that Quantile Regression at the 0.40 quantile performs better than OLS. The Log-Likelihood for the 0.40 quantile (−195.6611) is superior to OLS (−198.5961), indicating that the QR model fits the data better at this quantile. Similarly, the AIC for the 0.40 quantile (409.3222) is lower than that of OLS (415.1921), suggesting that the 0.40 quantile model strikes a better balance between model fit and complexity. The SIC for 0.40 quantile (431.8884) is also lower than OLS (434.0412), and the HA for 0.40 quantile (416.6951) is better compared to OLS (422.5651), further supporting the conclusion that QR at the 0.40 quantile provides a superior fit when assessed through these model selection criteria.

In terms of predictive power, Quantile Regression at the 0.40 quantile stands out, particularly in Absolute Percentage Error, where it achieves the lowest value (133.26). This shows that the 0.40 quantile model is more effective in minimizing the relative error compared to other models, indicating its strength in making predictions that align more closely with actual market outcomes. Additionally, QR at the 0.50 quantile performs best in Absolute Error (4.9473), demonstrating superior accuracy in predicting the median values of Nifty returns. While OLS is strong in traditional fit metrics, QR at the 0.40 quantile provides more reliable predictions in capturing the conditional distributions and minimizing relative errors. Overall, OLS regression excels in traditional fit metrics such as Mean Squared Error (MSE) and Sum Squared Residual (SSR), making it the best model for capturing the general relationship between the explanatory variables and Nifty returns. However, when it comes to predictive power, Quantile Regression at the 0.40 quantile emerges as the superior model. It performs better in minimizing Absolute Percentage Error and offers a more accurate fit when evaluated using Log-Likelihood, AIC, SIC, and HA. Therefore, while OLS remains a strong model for overall fit, QR at the 0.40 quantile proves to be the best choice for understanding and predicting Nifty returns in a more detailed, quantile-specific manner.

Table 5: Variables Impact on Gold and Comparison of OLS & Quantile Regression Models

Particulars	OLS Regression		Quantile Regression						
	Coefficients	Collinearity	0.10	0.25	0.40	0.50	0.60	0.75	0.90
Constant	27.85960	---	2.28322	17.5033***	32.87760*	27.50450*	45.52160*	53.0061***	60.2671**
Bank Rate	3.57870***	3.511	5.32903***	3.81222***	3.12106***	2.85986***	3.45839**	2.6574***	4.39143***
10Y GSec	−5.93577*	6.154	−4.16606**	−4.8747***	−5.38891*	−4.50227*	−7.82669*	−8.3349***	−11.682***
Inflation	1.37607***	1.332	1.95152***	1.55326***	0.54064	0.64580	1.25809*	1.4051***	2.8015***
NSE	−0.51085***	2.759	−0.5846***	−0.5408***	−0.6494***	−0.6211***	−0.5597***	−0.5013***	−0.3639***
Exchange Rate	−1.41237***	2.446	−2.1302***	−1.8508***	−1.8253***	−1.8079***	−1.5977***	−1.2849***	−1.1984***
IIP	−0.00398	1.508	0.06555**	−0.0338***	0.03164	0.01389	0.00934	−0.0194*	−0.06283
FDI	0.00112	1.239	0.00639	−0.0066***	−0.00428	−0.00163	0.00042	0.00366**	0.01232
Foreign Reserves	0.49164***	3.787	0.30797***	0.4745***	0.49352***	0.56659***	0.36221*	0.36832***	0.37562**
Normality	1.3465		13.1257***	2.5401	3.7683	3.3402	2.3818	1.7727	10.7221***
Linearity	1.6950		6.8110***	2.5510**	0.5660	1.1390	1.3250	4.2910***	8.0310***
Sum Squared Residual	1260.006[a]		4711.218	1980.57	1571.417	1442.262	1349.511	2011.041	4543.246
Log-likelihood	−176.4721		−182.7072	−176.5631	−174.9051[b]	−175.3783	−176.9842	−178.1366	−181.4228
Schwarz Criterion	389.7933		402.2634	389.9752	386.6593[a]	387.6057	390.8175	393.1224	399.6947
Akaike Criterion	370.9442		383.4143	371.1261	367.8102[a]	368.7566	371.9684	374.2733	380.8456
Hannan-Quinn	378.3172		390.7873	378.4990	375.1831[a]	376.1295	379.3414	381.6462	388.2185
Mean Squared Error	4.5826[a]		8.8612	5.7454	5.1176	4.9028	4.7426	5.7894	8.7018
Absolute Error	3.5732		6.5105	4.1848	3.5077	3.4206[a]	3.5560	4.3087	6.5873
Absolute Percentage Error	212.83		443.26	341.47	265.79	276.17	206.25[a]	221.24	224.58

Source: The Authors.

Note: ***p < 0.01, **p < 0.05 & *p < 0.10,

[a] Lowest value, and

[b] Highest Value.

Upon analyzing Table 5, the relationship between various macroeconomic variables and Gold returns using both OLS regression and Quantile Regression (QR) models provides valuable insights. The Bank Rate has a positive and statistically significant coefficient in both models, especially at the 0.10 quantile (5.32903), indicating that a higher interest rate positively impacts

Gold returns, which is consistent with traditional financial theory. Conversely, 10Y GSec shows a negative relationship across all models, with the most significant negative impact at the 0.90 quantile (−11.682), which suggests that higher long-term bond yields are associated with lower Gold returns. Similarly, Inflation exhibits a positive coefficient, with the strongest impact at the 0.90 quantile (2.8015), suggesting that inflationary pressures are positively correlated with Gold prices, typically acting as a hedge against inflation. The NSE returns have a consistently negative relationship with Gold returns, particularly across quantiles, indicating that higher stock market performance tends to be associated with lower demand for Gold as a safe-haven asset.

Other variables, such as the Exchange Rate and Foreign Reserves, also show significant relationships with Gold returns across all quantiles, with the most pronounced effect seen at the 0.10 quantile for Exchange Rate (−2.1302) and at the 0.90 quantile for Foreign Reserves (0.37562). These results suggest that a weaker domestic currency and lower foreign reserves may result in lower Gold prices. The Index of Industrial Production (IIP), which shows mixed results across quantiles, indicates its minimal impact on Gold returns, particularly at the 0.90 quantile, where the relationship becomes negative (−0.06283), suggesting that industrial production levels have a diminishing effect on Gold prices. FDI also displays limited impact, with coefficients varying across quantiles but remaining generally small, indicating that foreign direct investment has a minor influence on Gold returns.

When evaluating the fit of the models through various criteria, such as Log-Likelihood (LL), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HC), we find that Quantile Regression at the 0.40 quantile performs the best in these aspects. For instance, the Log-Likelihood for the 0.40 quantile (−174.9051) is higher compared to other quantiles and OLS (−176.4721), indicating a better fit. Similarly, AIC, SIC, and HC values are all lowest at the 0.40 quantile, which suggests that this quantile regression model offers the most efficient balance between fit and model complexity. This performance is superior to OLS, which, while strong in traditional fit measures like Mean Squared Error (MSE) and Sum Squared Residual (SSR), does not provide the best fit according to these advanced criteria.

In terms of predictive power, OLS regression excels in traditional metrics like Mean Squared Error (MSE), where it achieves the lowest value (4.5826), indicating that it has the smallest overall squared residuals. However, Quantile Regression at the 0.50 quantile performs best in terms of Absolute Error (3.4206), indicating its superior accuracy in predicting the central tendency of Gold returns. When considering the Absolute Percentage Error, the 0.60 quantile performs the best with the lowest value (206.25), highlighting that this quantile-based model is more effective in minimizing the relative prediction errors. This suggests that QR at the 0.60 quantile captures the underlying variations and provides more reliable predictions for the tail behaviours, where Gold prices exhibit more volatility.

Overall, OLS regression remains the most effective model in terms of traditional fit metrics like Mean Squared Error (MSE) and Sum Squared Residual (SSR), but Quantile Regression at the 0.40 quantile is superior when it comes to model selection criteria (Log-Likelihood, AIC, SIC, HC). In terms of predictive power, QR at the 0.50 quantile excels in Absolute Error, while QR at the 0.60 quantile is best in minimizing Absolute Percentage Error, demonstrating its strength in handling data variability. Therefore, while OLS is optimal for capturing the overall relationship, QR at the 0.40 quantile provides a more reliable fit when assessed using advanced model selection criteria, making it the better choice for understanding and predicting Gold returns in a more detailed manner.

5. DISCUSSION AND CONCLUSION

The comprehensive analysis of the macroeconomic variables and their influence on key financial indicators provides important insights into the behavior of the economy. Descriptive statistics reveal that stable variables such as the Bank Rate and 10Y GSec have low variability, suggesting they are conducive to traditional linear modeling approaches. In contrast, more volatile variables, such as IIP and FDI, exhibit significant deviations from normality, indicating that non-linear or robust models may be necessary to handle extreme observations effectively. The diverse statistical profiles of these variables emphasize the importance of selecting appropriate modeling techniques based on their distributional characteristics. The multivariate correlation matrix further illuminates the complex interrelationships among the variables, highlighting significant associations, such as the Bank Rate's positive correlation with the 10Y GSec and negative correlation with the NSE, suggesting how monetary policy impacts both long-term rates and equity market performance.

The multivariate correlation analysis reveals the intricate relationships between the variables, emphasizing that factors such as the Bank Rate, 10Y GSec, and inflation are strongly interlinked. For instance, the Bank Rate's negative correlation with the NSE indicates that higher interest rates may suppress equity market performance, while its positive correlation with the 10Y GSec demonstrates the influence of monetary policy on long-term bond yields. Gold, on the other hand, shows negative correlations with the NSE and Exchange Rate, reinforcing its role as a safe-haven asset during periods of market uncertainty or currency depreciation. The correlation matrix underscores the importance of considering both individual and joint effects of these variables in comprehensive economic modeling, highlighting how different macroeconomic forces interact with one another.

Quantile Regression (QR) models, particularly at the 0.40 and 0.60 quantiles, offer a deeper understanding of the varying impacts of macroeconomic variables under different market conditions. These models outperform traditional OLS regression by capturing the heterogeneity of factor effects across different market scenarios, which OLS fails to address. For example, QR reveals that inflation's effect on exchange rates transitions from positive to negative across quantiles, indicating the varying influence of inflation under different market stresses. Similarly, factors like the 10Y GSec and foreign reserves show increasing significance at higher quantiles, reflecting their greater impact during moderately stressed market conditions. These findings highlight the value of QR in capturing asymmetries in the data, providing a more nuanced understanding of the relationships between economic variables and their effects on financial markets.

In conclusion, while OLS regression is useful for providing a generalized understanding of relationships between macroeconomic variables and financial indicators, Quantile Regression offers richer insights, particularly in terms of capturing the varying effects of these variables under different economic conditions. QR's ability to account for heterogeneity across quantiles makes it a more powerful tool for modeling the complexities of financial and economic data. The multivariate correlation analysis further emphasizes the importance of understanding the joint dynamics between variables, as correlations like those between the Bank Rate and 10Y GSec suggest interconnected economic forces. Overall, incorporating Quantile Regression into economic modeling improves predictive accuracy and provides a more comprehensive framework for understanding the conditional relationships within the data.

5.1. Scope for Further research

Further research could explore the use of more advanced machine learning techniques, such as random forests or neural networks, to capture non-linear relationships and interactions between macroeconomic variables and financial indicators. Additionally, expanding the scope to include global economic factors, such as international trade volumes, geopolitical events, and global monetary policies, could provide a more holistic view of the interconnectedness between domestic and global financial markets. Moreover, incorporating time-series analysis techniques like Vector Autoregression (VAR) or Cointegration tests could enhance the understanding of dynamic relationships and causalities over time, offering deeper insights into how economic policies and shocks propagate across different sectors.

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