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Exploring The Dynamics Of Inflation, Interest Rates, And Bond Yields: A Comprehensive Regression Model Comparison

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Abstract
This research presents a comprehensive analysis of the impact of key macroeconomic indicators, including 10-year Government Securities (10Y GSec) yields, 91-day Treasury Bill (TB) rates, interest rates, inflation, exchange rates, foreign reserves, gold prices, equity market indices (NSE Nifty), FDI, and Month-on-Month (MoM) basis returns, on interest rates, inflation, yields and vice-versa in India, using data from 2018 to 2023. The study employs multivariate correlation analysis to identify the relationships among these variables, revealing significant patterns such as the strong correlation between bond yields and interest rates, as well as the inverse relationship between equity market performance and bond yields. This research highlights the influence of monetary policy, external reserves, inflation, FDI, and equity markets in shaping bond yields and interest rates, with gold and equity markets acting as safe-haven assets during times of economic uncertainty.
A key focus of this research is a detailed comparison of five regression models— Ordinary Least Squares (OLS), Heteroscedasticity-Corrected (HSC), Tobit, Logistic, and the Transformed First Difference (FD) OLS—used to analyze the relationships among these macroeconomic variables. The study demonstrates that the HSC and Logistic regressions provide the most robust and reliable insights, with the HSC model exhibiting the highest explanatory power in capturing the variance in bond yields, interest rates, and inflation. The analysis underscores the importance of selecting the right regression model to accurately capture the dynamics of financial markets, as model performance varies significantly. This comprehensive study offers a nuanced understanding of the interplay between macroeconomic indicators and financial outcomes, emphasizing the critical role of regression models in enhancing the accuracy of economic forecasting.
Keywords: *Ordinary Least Squares (OLS), Heteroscedasticity-Corrected (HSC), Tobit, Logistic, Transformed First Difference (FD) OLS, Multivariate Correlation, Interest, Inflation, and Long-Term & Short-Term Bond Yields*

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I. Introduction

This study delves into the complex relationships between inflation, interest rates, and bond yields, employing a diverse array of regression models to examine these macroeconomic variables. The models used in this research include Ordinary Least Squares (OLS), Heteroscedasticity-Corrected (HSC) regression, Tobit, Logistic, and the Transformed First Difference (FD) model. These models were chosen for their ability to address various econometric challenges. The HSC model corrects for heteroscedasticity, ensuring more accurate estimates when the variance of errors is not constant. The Tobit model addresses censored data, while the Logistic model is suitable for binary outcome analysis. The FD model, a form of transformation applied to panel data, removes individual-specific effects by differencing the data, thus improving the estimation of dynamic relationships in the context of panel datasets. By incorporating these diverse models, the study aims to provide a robust understanding of how inflation, interest rates, and bond yields are interlinked in both short-term and long-term scenarios.

Inflation is one of the most critical macroeconomic variables, with direct implications for interest rates and bond yields. According to Fisher (1930), inflation expectations have a strong influence on bond yields, as investors demand higher returns to protect against the anticipated loss of purchasing power. Interest rates are also central to monetary policy, as central banks adjust them to either stimulate or curb economic activity in response to inflationary pressures (Taylor, 1993). The relationship between these variables has long been studied, given its importance for shaping economic policies and influencing the performance of financial markets. Studies such as Blanchard and Leigh (2013) have explored how central bank actions and inflation expectations influence financial markets and asset prices, including government bonds.

In the past few years, scholars have increasingly focused on understanding the dynamic relationships between inflation, interest rates, and bond yields. Gali and Gambetti (2015) and Nakamura and Steinsson (2018) have examined how inflation expectations and monetary policy adjustments impact financial markets. The response of bond yields to shifts in inflation expectations and interest rates is of particular interest in understanding market sentiment and forecasting long-term economic trends. To capture these complexities, the HSC model offers an important tool for dealing with heteroscedasticity—allowing for more accurate model estimates where the variance of the error terms is not constant across observations (Cameron & Trivedi, 2005). The use of the FD model in this study also facilitates a clearer picture of the temporal dynamics in the data, as it controls for unobserved individual effects by differencing the data and focusing on changes over time.

The interaction between bond yields and macroeconomic variables such as inflation and interest rates are crucial to understanding financial market behaviour. Bond yields, especially on long-term government securities, often reflect expectations about future inflation and interest rates. The role of inflation expectations in shaping bond yields is widely recognized, as highlighted by Barro (2013), who emphasized the importance of understanding inflation dynamics in the context of investor decision-making. Research by Lettau and Ludvigson (2004) further supports this view, showing how both short-term interest rates and inflation expectations directly impact bond returns. The application of models like the Tobit and FD models in this study helps account for challenges such as censored data and unobserved heterogeneity, thereby providing a more nuanced understanding of the interactions between these key variables.

Beyond inflation and interest rates, other factors such as the prices of gold, foreign reserves, and stock market performance can influence bond yields and inflation dynamics. Gold, often considered a safe-haven asset, tends to have an inverse relationship with bond yields, particularly in periods of economic uncertainty (Baur & Lucey, 2010). Similarly, foreign exchange reserves play a vital role in stabilizing national economies and reducing inflationary pressures by enhancing liquidity and maintaining investor confidence. Studies by Kose et al. (2017) discuss how foreign reserves and stock market dynamics help moderate inflationary trends and influence interest rate decisions, further complicating the relationships between inflation, interest rates, and bond yields.

This study's use of multiple regression models is intended to provide a comprehensive view of the interactions between inflation, interest rates, and bond yields under varying economic conditions. By applying OLS, HSC, Tobit, Logistic, and FD models, the research aims to offer various perspectives on these relationships, from correcting for heteroscedasticity to managing censored data and analysing temporal changes in panel datasets. Each model is designed to address a different aspect of the data, thus enhancing the robustness of the study's findings. Ultimately, this research contributes to a deeper understanding of how key macroeconomic variables interact in today's rapidly evolving economic environment, offering valuable insights into economic forecasting and financial market behaviour.

II. Literature Review

The relationship between inflation, interest rates, and bond yields is central to understanding economic dynamics, financial markets, and the effectiveness of monetary policy. Over the years, numerous studies have explored these relationships from various perspectives, encompassing both theoretical frameworks and empirical investigations. This literature review will examine key studies on the interconnections between inflation, interest rates, bond yields and economic indicators, and will highlight recent contributions to the field.

Economic factors, both macroeconomic and microeconomic, significantly impact inflation dynamics. Monetary policy remains a primary driver, with interest rate adjustments influencing aggregate demand and inflation levels, as demonstrated by Taylor's (1993) rule-based approach to monetary policy. Fiscal policies also play a role, with government spending and tax adjustments creating inflationary or deflationary pressures, particularly during periods of economic expansion or contraction (Blanchard & Leigh, 2013). Exchange rate fluctuations are another critical factor, as highlighted by Dornbusch (1976), who showed how currency depreciation increases import prices, leading to higher domestic inflation. Labor market conditions, including wage growth and employment levels, directly affect inflation, with Phillips curve analyses, such as Gordon (1997), emphasizing the trade-off between unemployment and inflation. Additionally, supply chain disruptions and commodity price shocks, particularly in energy and food markets, have been linked to inflationary spikes, as discussed by Barsky and Kilian (2004). Lastly, structural factors such as productivity changes, technological advancements, and demographic shifts also influence inflation trends, with Goodhart and Pradhan (2020) arguing that aging populations and declining labour force growth may exert upward pressure on inflation in the long run. Together, these economic factors interact dynamically, shaping inflation outcomes in diverse and complex ways.

Interest rates are influenced by a myriad of factors, encompassing economic indicators, equity market performance, and broader macroeconomic conditions. Economic growth, as measured by GDP, directly impacts interest rates, with stronger growth typically leading central banks to raise rates to prevent overheating (Bernanke & Gertler, 1999). Inflation is another critical determinant, as higher inflation often prompts monetary authorities to tighten policy to anchor expectations (Woodford, 2003). Employment levels and wage growth, key labour market indicators, also play a role, as rising wages can signal inflationary pressures, necessitating rate adjustments (Blinder, 2016). Equity markets influence interest rates indirectly through the wealth effect; robust market performance may encourage spending, which in turn drives inflation and interest rate hikes (Campbell & Cochrane, 1999).

Additionally, international capital flows impact domestic interest rates, with foreign investments in government bonds affecting yields and central bank decisions (Frankel, 1993). Fiscal deficits can exert upward pressure on interest rates as governments compete with private entities for funds in the capital markets (Gale & Orszag, 2004). Market liquidity and risk premiums also contribute, particularly during periods of financial instability, as investors demand higher yields for holding riskier assets (Adrian & Shin, 2010). Finally, geopolitical tensions and uncertainties can lead to fluctuations in interest rates as central banks respond to potential economic disruptions (Borio, 2019).

Bond yields are influenced by a complex interplay of economic indicators, equity market dynamics, interest rates, inflation expectations, and other factors. Economic growth indicators, such as GDP growth, directly affect bond yields, with stronger growth often leading to higher yields due to increased borrowing demand and inflationary pressures (Litterman & Scheinkman, 1991). Inflation expectations play a pivotal role, as rising inflation erodes the purchasing power of fixed bond payments, prompting investors to demand higher yields (Ang & Piazzesi, 2003). Interest rates, primarily shaped by central bank policies, are another critical determinant, as they set the baseline for risk-free returns, influencing both short- and long-term yields (Gürkaynak et al., 2005).

Equity market performance also impacts bond yields, as stronger equity markets can shift investor preference away from bonds, raising yields, while equity downturns often result in a flight to the safety of government bonds, lowering yields (Campbell & Shiller, 1991). Risk premiums, tied to credit quality and market volatility, further contribute, with higher premiums leading to increased yields during periods of economic uncertainty (Vayanos & Vila, 2009). Fiscal policies, such as government deficits, influence bond supply and demand, affecting yields; larger deficits typically push yields higher (Laubach, 2009). Global financial conditions also play a role, as cross-border capital flows and foreign monetary policies impact domestic bond markets, particularly in interconnected economies (Borio, 2019). Additionally, market liquidity and investor sentiment can cause short-term fluctuations in yields, highlighting the multifaceted factors driving bond market dynamics (Krishnamurthy & Vissing-Jorgensen, 2011).

Recent studies highlight the varying capabilities of different regression models, such as Ordinary Least Squares (OLS), Heteroscedasticity-Corrected (HSC) models, Tobit regression, Logistic regression, and First Difference (FD) models, in providing explanatory power across diverse datasets and contexts. OLS remains a foundational tool due to its simplicity and interpretability, performing well when assumptions of linearity and homoscedasticity are met (Wooldridge, 2013). However, its performance diminishes in the presence of heteroscedasticity, prompting the use of HSC models. Studies by Cameron and Trivedi (2005) demonstrate that HSC models effectively correct for non-constant variance in residuals, leading to more reliable standard errors and improved inference. Tobit regression, as highlighted by Amemiya (1984), is particularly suited for censored datasets, ensuring unbiased estimation in cases where dependent variables are truncated or have limited ranges. Logistic regression, on the other hand, is adept at handling binary outcomes, with applications ranging from credit scoring to medical research, as noted by Hosmer et al. (2013). In scenarios involving time-series data, FD models transform variables into their first differences, addressing issues of non-stationarity and capturing short-term dynamics effectively (Greene, 2012).

The choice of regression model also depends on the complexity of the data and the research objective. For example, Meyer and Sahn (2007) found Tobit models to excel in studies of constrained consumer behaviour, while Logistic regression models are often preferred in predicting binary outcomes in financial markets (Allison, 1999). HSC models are advantageous in macroeconomic analyses, where heteroscedasticity is common due to volatile data (Bollerslev et al., 1986). FD models, as employed by Holtz-Eakin et al. (1988), have proven effective in panel data analysis, providing insights into the temporal dynamics of variables while minimizing bias. Comparative studies, such as those by Baltagi (2008), suggest that each model's explanatory power is contingent on the underlying data structure and assumptions, underscoring the importance of selecting the appropriate method for robust statistical inference.

Recent research has examined the complex interplay of economic indicators, equity markets, and other macroeconomic factors on bond yields, interest rates, and inflation while also exploring the suitability of different regression models for analysing these relationships. Studies like Hamilton et al. (2018) emphasize how inflation expectations and central bank policies directly influence bond yields, highlighting the role of forward guidance in stabilizing financial markets. Similarly, equity market volatility, as discussed by Bekaert and Engstrom (2020), has been found to significantly impact interest rates and inflation through changes in risk premiums and capital allocation. Economic indicators such as GDP growth and unemployment rates were shown by Leduc and Liu (2021) to shape inflation trends and long-term yield curves. The influence of global oil prices on inflation and interest rates has also been notable, with Kilian and Zhou (2020) demonstrating their role in driving bond yield fluctuations.

From a methodological perspective, regression models have been central to analysing these dynamics. Ordinary Least Squares (OLS) remains a primary choice for initial estimation (Wooldridge, 2020), but its limitations under heteroscedasticity have led to the adoption of Heteroscedasticity-Corrected (HSC) models, as suggested by Cameron and Trivedi (2021). Logistic regression has been increasingly applied in binary financial outcome predictions, such as the likelihood of yield curve inversions (Allison, 2019). Tobit regression, as noted by Nguyen and Sun (2022), effectively handles censored datasets, particularly in studies of restricted bond market behaviours. First Difference (FD) models are frequently employed in time-series analyses to capture short-term effects of macroeconomic changes on bond yields and inflation, as highlighted by Parker and Walker (2021). These diverse methodological approaches underscore the evolving complexity in modelling the interconnections between economic variables and financial indicators.

Recent studies have explored the dynamics of economic indicators, equity markets, and other macroeconomic factors on bond yields, interest rates, and inflation in emerging markets, alongside the effectiveness of various regression models for analysing these interconnections. Ahmed and Zlate (2020) highlighted that exchange rate volatility and foreign direct investment significantly influence bond yields in emerging economies. Similarly, Arslan and Cantú (2022) found that inflationary pressures, driven by commodity price shocks, are a critical determinant of interest rate adjustments by central banks in these regions. Equity market fluctuations and their impact on bond yields were examined by Agarwal and Moorthy (2019), who noted that equity volatility often translates into higher risk premiums in bond markets. Kim and Lim (2021) analysed the role of sovereign credit ratings in shaping bond yields, showing that market perceptions of fiscal stability strongly influence yield movements.

On the methodological front, OLS regression has been widely used for initial analysis in emerging market studies, as demonstrated by Chinn and Ito (2020), but its limitations in handling non-linear relationships and heteroscedasticity have led to the adoption of Heteroscedasticity-Corrected (HSC) models, as suggested by Gupta and Tiwari (2021). Logistic regression models, as applied by Ramos and Veiga (2019), are effective for predicting currency crises and their effects on bond markets. Tobit regression, highlighted by Mendes and Oliveira (2021), has been employed to address censored data issues in studies of government bond yields under fiscal constraints. FD models, examined by Singh and Patel (2020), have proven effective for capturing short-term impacts of economic policy changes on inflation and interest rates. Moreover, machine learning-based regression models, as explored by Zhang et al. (2022), are emerging as powerful tools for identifying complex patterns and relationships in emerging markets, reflecting the ongoing evolution of quantitative methodologies in the field.

Recent studies have explored how economic indicators, equity markets, and other macroeconomic factors impact bond yields, interest rates, and inflation in India, with several regression models being employed to analyze these dynamics. Bansal and Luthra (2020) investigated how inflation expectations and equity market movements affect bond yields in India, finding a strong linkage between inflation forecasts and long-term yields. Kumar and Ghosh (2021) examined the role of interest rates and fiscal policy in shaping bond yields, emphasizing how RBI's monetary policy adjustments directly influence market yields. Gupta et al. (2022) explored the relationship between equity market performance and interest rates, showing that equity volatility in India often leads to higher bond yield premiums, especially during times of market uncertainty. Inflationary pressures, as highlighted by Sharma and Yadav (2019), have been shown to play a pivotal role in determining interest rates and bond yields, with inflation data influencing the Reserve Bank of India's policy rate decisions.

Regarding regression models, OLS has been commonly used to estimate the relationship between inflation and bond yields, as demonstrated by Sen and Verma (2020), though limitations related to heteroscedasticity have led to the use of HSC models in more recent studies, as seen in works by Joshi and Rathi (2021). Additionally, Tobit models have been applied to capture censored data in fiscal policy studies by Mehta and Agarwal (2020), revealing how government debt affects bond market movements. The First Difference (FD) model, as employed by Rajan et al. (2022), has shown promise in capturing short-term shifts in bond yields following changes in inflation and interest rates. Logistic regression models have also been used by Sharma and Ranjan (2021) to predict bond yield movements based on fiscal and monetary indicators. Finally, machine learning techniques are increasingly being explored to enhance the predictive accuracy of bond yields in India, with Singh et al. (2023) demonstrating how these techniques outperform traditional models in forecasting bond market trends during periods of heightened volatility.

This literature review examines how economic factors such as inflation, interest rates, exchange rates, and equity markets affect bond yields and interest rates in India. It highlights the role of various regression models like OLS, HSC, Tobit, FD, and Logistic in studying these relationships. Recent studies emphasize the growing importance of inflation expectations and fiscal adjustments in determining long-term bond yields. Overall, the review shows how macroeconomic factors influence India’s bond market, inflation, interest rates and how research methods continue to evolve.

III. Methodology

This study investigates the dynamic relationships among key macroeconomic variables in India using Month-on-Month (MoM) data from January 2018 to December 2023 and data collected from Reserve Bank of India (RBI). The dataset comprises 72 observations for each variable, including 10-year Government Securities

(10Y GSec) yields, 91-day Treasury Bill (TB) rates, interest rates, inflation, exchange rates, foreign reserves, gold prices, NSE Nifty, and MoM returns. The analysis focuses on four dependent variables: 10Y GSec yields representing long-term market trends, 91-day TB rates capturing short-term monetary dynamics, interest rates as a reflection of borrowing costs, and inflation as a core economic indicator. These variables were selected for their central role in influencing financial stability and economic policy outcomes, serving as proxies for broader macroeconomic conditions.

The explanatory variables were chosen for their relevance to the dynamics of the dependent variables. Exchange rates, foreign reserves, and gold prices are key indicators of external sector strength and currency stability, which can significantly impact long-term yields and interest rates. NSE Nifty serves as a barometer for equity market performance, often linked to investor confidence and capital flows, while MoM returns capture short-term market volatilities. These diverse variables collectively provide a comprehensive framework for understanding the interplay between macroeconomic factors and financial markets, ensuring robust and multifaceted analysis.

A combination of regression models was employed to address the study's objectives, including Ordinary Least Squares (OLS), Heteroscedasticity-Corrected (HSC) regression, Tobit regression with left-censored values at 3% and right-censored values at 7%, Logistic regression for real-valued dependent variables such as interest rates and inflation, and Transformed First Difference (FD) OLS. These models were applied to accommodate data features such as censoring, non-linearity, and potential structural breaks, ensuring a nuanced exploration of the variables' relationships.

Rigorous diagnostic tests complemented the regression analyses to validate the models' reliability and stability. These included standard error evaluation, Log-Likelihood, Adjusted R-squared, and Akaike Information Criterion (AIC). Additionally, structural stability was assessed using the Chow test and QLR test for structural breaks, while the RESET test was used to verify the functional form of the models. Although the study provides a comprehensive framework for analysing macroeconomic dynamics, its limitations—such as the relatively short timeframe and inherent assumptions of some regression methods—underscore the importance of further research with extended datasets and alternative methodologies.

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.

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.

Ordinary Least Squares (OLS) 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.

Heteroscedasticity-Corrected (HSC) Regression

A Heteroscedasticity-Corrected Model adjusts regression analyses to account for non-constant variance (heteroscedasticity) in the error terms, ensuring reliable estimates and valid statistical inference. The model corrects standard errors, often using robust techniques such as White's correction. The corrected regression equation remains:

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

However, heteroscedasticity-adjusted standard errors are computed as:

$\hat{V} = (X'X)^{-1} X' \hat{\Omega} X(X'X)^{-1}$

where is $\hat{\Omega}$ a diagonal matrix of error variances. This approach ensures unbiased coefficient estimates and accurate confidence intervals in the presence of heteroscedasticity.

Tobit Regression

Tobit regression is designed for datasets where the dependent variable (Y) is censored, either at a lower threshold (L) or an upper threshold (U). The model is expressed as:

$Y_i^* = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i$, $\epsilon_i \sim N(0, \sigma^2)$

Where: Y_i^* is the dependent variable. Y_i is the observed variable:

Yi={L if $Y_i^* \leq L$, Y_i^* if $L < Y_i^* < U$, U if $Y_i^* \geq U$

- X_{ki} are the independent variables.
- β_i are the coefficients to be estimated, ϵ_i is the error term, normally distributed.

Logistic Regression

Logistic regression is used when the dependent variable is binary or categorical or real numbers, predicting the probability of an event occurring. The model is expressed as:

$P(Y=1 \mid X) = \frac{e^{\beta 0+\beta 1X1+\beta 2X2+\cdots+\beta kXk}}{1 + e^{\beta 0+\beta 1X1+\beta 2X2+\cdots+\beta kXk}}$

Where: P(Y=1|X) is the probability that the dependent variable Y equals 1 given X.

- X_k are the independent variables, β_k are the coefficients to be estimated.
- e is the base of the natural logarithm.

The model examines how independent variables influence the likelihood of specific economic outcomes, providing insights into the directional relationship between predictors and outcomes.

Transformative First Difference (FD) Method

The First Difference Method is used in regression analysis to address issues like non-stationarity and omitted variable bias by analysing changes between consecutive observations. It transforms the data by computing differences, making the model:

$\Delta Y_t = \beta \Delta X_t + \Delta \epsilon_t$

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.

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:

$VIF_i = \frac{1}{1 - R_i^2}$

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.

Adjusted R-squared

The Adjusted R-squared adjusts the R-squared value for the number of predictors in a regression model, providing a more accurate measure of goodness-of-fit, especially with multiple predictors. The formula is:

$\bar{R}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1}$

where R^2 is the R-squared value, n is the number of observations, and p*p* is the number of predictors. Unlike R-squared, the Adjusted R-squared penalizes unnecessary variables, preventing overfitting and giving a more reliable evaluation of model performance.

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:

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

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.

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:

$$AIC = 2k - 2\ln(L)$$

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.

Durbin-Watson (DW) Test

The Durbin-Watson (DW) Test checks for autocorrelation in the residuals of a regression model, particularly for first-order correlation. The test statistic is:

$$DW = \frac{\sum_{t=2}^{n} (\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{n} \hat{\varepsilon}_t^2}$$

where $\hat{\varepsilon}_t$ are the residuals at time t. The DW statistic ranges from 0 to 4; a value near 2 indicates no autocorrelation, values < 2 suggest positive autocorrelation, and values > 2 indicate negative autocorrelation. This test is critical for ensuring the validity of regression assumptions in time-series data.

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.

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.

Breusch-Pagan (BP) Test

The Breusch-Pagan (BP) Test detects heteroscedasticity in regression models by assessing whether error variances depend on independent variables. It involves regressing the squared residuals ($\hat{\varepsilon}^2$) on the predictors:

$\hat{\varepsilon}^2 = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_k X_k + u$

The test statistic is: BP = $\frac{1}{2} R^2_{aux} n$

where R^2_{aux} is the coefficient of determination from the auxiliary regression. The BP statistic follows a chi-squared distribution, with higher values indicating heteroscedasticity.

Lagrange Multiplier (LM) Test

The Lagrange Multiplier (LM) Test for autocorrelation detects serial correlation in residuals of a regression model. It involves regressing residuals ($\hat{\varepsilon}_t$) on lagged residuals and independent variables. The auxiliary regression is:

$\hat{\varepsilon}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \hat{\varepsilon}_{t-2} + \cdots + \alpha_p \hat{\varepsilon}_{t-p} + ut$

The test statistic is: LM = nR^2

where n is the sample size, and R^2 is the auxiliary regression's determination coefficient. The LM statistic follows a chi-squared distribution, with significance indicating autocorrelation.

Lagrange Multiplier (LM) Test for ARCH Effect

The Lagrange Multiplier (LM) Test for ARCH Effect identifies autoregressive conditional heteroscedasticity (ARCH) in time-series data. It involves regressing squared residuals ($\hat{\varepsilon}_t$) on their lagged values. The auxiliary regression is:

$\hat{\varepsilon}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \hat{\varepsilon}_{t-2} + \cdots + \alpha_p \hat{\varepsilon}_{t-p} + ut$

The test statistic is: LM = nR^2

where n is the sample size, and R^2 is from the auxiliary regression. A significant LM statistic indicates ARCH effects, essential for volatility modelling.

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.

Result Analysis

Table 1: Descriptive statistics of macro-economic variables.

Variable	N	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.	Skewness	Ex. kurtosis	IQ range	Jarque-Bera
10Y GSec	72	6.9268	7.0453	5.8297	8.0157	0.6083	0.0878	-0.2084	-0.9974	0.9922	3.5064 (0.1732)
91Day TB	72	5.2229	5.5964	3.0473	7.1443	1.4463	0.2769	-0.2699	-1.5833	3.0061	8.3945* (0.0150)
Foreign Reserves	72	11.11	10.532	-8.5214	30.394	8.8492	0.7965	0.0969	-0.2498	10.905	0.2999 (0.8607)
Interest Rate	72	5.5285	5.651	4.2531	6.7535	1.0353	0.1872	-0.1552	-1.6569	2.2562	8.5249* (0.0141)
Inflation	72	5.2999	5.5315	1.971	7.7912	1.5097	0.2848	-0.3206	-0.7932	2.375	3.1215 (0.2099)
Gold	72	7.366	6.2209	-9.1408	32.296	10.853	1.4734	0.3771	-0.9333	18.981	4.3195 (0.1153)
NSE NIFTY	72	11.246	9.9375	-30.156	53.571	15.231	1.3544	0.5067	1.1754	13.151	7.2259* (0.0269)
IIP	72	4.1495	3.9477	-57.312	133.52	18.939	4.5641	3.9241	30.026	5.3214	2889.5* (0.0000)
FDI	72	-7.2366	1.0125	-477.04	368.43	111.43	15.398	-0.4208	4.6886	117.48	68.074* (0.0000)
Exchange Rate	72	4.0137	3.4639	-5.7986	13.367	4.1957	1.0453	-0.0568	-0.6265	6.8366	1.2162 (0.5443)

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

Table 2: Multivariate Correlations of the macro-economic variables.

Particulars	10Y GSec	91Day TB	Foreign Reserves	Interest Rate	Inflation	Gold	NSE NIFTY	IIP	FDI	Exchange Rate
10Y GSec	1	0.8527*	-0.6796*	0.8030*	-0.3084*	-0.5230*	-0.2184	0.0151	-0.0004	0.4460*
91Day TB	0.8527*	1	-0.6232*	0.9872*	-0.4160*	-0.2830	-0.3091*	-0.0514	-0.0907	0.3540*
Foreign Reserves	-0.6796*	-0.6232*	1	-0.5531*	0.1585	0.6022*	0.0391	-0.0798	0.0556	-0.2990
Interest Rate	0.8030*	0.9872*	-0.5531*	1	-0.4512*	-0.2457	-0.3040*	-0.0461	-0.1111	0.3521*
Inflation	-0.3084*	-0.4160*	0.1585	-0.4512*	1	0.3127*	-0.0892	-0.1235	-0.0658	-0.0248
Gold	-0.5230*	-0.2830	0.6022*	-0.2457	0.3127*	1	-0.4254*	-0.3065*	-0.0659	-0.2415
NSE NIFTY	-0.2184	-0.3091*	0.0391	-0.3040*	-0.0892	-0.4254*	1	0.5277*	0.2321	-0.6109*
IIP	0.0151	-0.0514	-0.0798	-0.0461	-0.1235	-0.3065*	0.5277*	1	0.2951	-0.2832
FDI	-0.0004	-0.0907	0.0556	-0.1111	-0.0658	-0.0659	0.2321	0.2951	1	-0.2302
Exchange Rate	0.4460*	0.3540*	-0.2990	0.3521*	-0.0248	-0.2415	-0.6109*	-0.2832	-0.2302	1

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

The descriptive statistics in Table 1 provide critical insights into the behaviour of key macroeconomic variables across the study period. The 10-year Government Securities (10Y GSec) yield exhibits a relatively narrow range, with a mean of 6.9268% and a standard deviation of 0.6083, indicating low variability. Skewness (-0.2084) and excess kurtosis (-0.9974) suggest a slightly left-skewed distribution, and the Jarque-Bera test confirms normality ($p > 0.05$). In contrast, the 91-day Treasury Bill (TB) rate shows a higher standard deviation of 1.4463, reflecting greater volatility, with a significant Jarque-Bera result ($p < 0.05$), indicating non-normality in its distribution.

Foreign reserves exhibit a wide range, from -8.5214 to 30.394, with an average value of 11.11 and relatively high variability (standard deviation of 8.8492). The normal distribution assumption for these variable holds, as indicated by the Jarque-Bera test ($p > 0.05$). The Interest rate shows moderate variability (standard deviation 1.0353), with a near-normal distribution except for slight deviations, supported by a significant Jarque-Bera value ($p < 0.05$). Inflation has a mean of 5.2999% with relatively low variability (standard deviation 1.5097), and the Jarque-Bera test suggests normality ($p > 0.05$). Gold returns demonstrate substantial variability, with a high standard deviation of 10.853 and a significant skewness of 0.3771, indicating a non-normal distribution confirmed by the Jarque-Bera value.

Equity market performance, represented by NSE NIFTY, exhibits the highest volatility among the variables, with a standard deviation of 15.231 and a substantial range from -30.156 to 53.571. Skewness (0.5067) and excess kurtosis (1.1754) suggest a right-skewed and leptokurtic distribution, corroborated by a significant Jarque-Bera test ($p < 0.05$). Industrial production (IIP) displays extreme values, with a standard deviation of 18.939 and positive skewness (3.9241), indicating high variability. A significant Jarque-Bera test ($p < 0.05$) reflects severe deviations from normality. Foreign direct investment (FDI) has the most substantial dispersion, with a standard deviation of 111.43, and its non-normality is evident from significant kurtosis (4.6886) and the Jarque-Bera test ($p < 0.05$).

When analysed parameter-wise, central tendency measures like mean and median indicate that most variables, except FDI, exhibit relatively close central values, hinting at stable trends. Variability, measured through standard deviation and coefficient of variation (C.V.), is pronounced in financial market indicators like NSE NIFTY and Gold, suggesting susceptibility to external shocks. Skewness and kurtosis values reveal asymmetries and tail behaviour, with variables like IIP and FDI showing extreme departures from normality, underscoring their volatile nature.

The multivariate correlation analysis in Table 2 highlights significant relationships between key macroeconomic variables. The strong positive correlation (0.8527*) between the 10-year Government Securities (10Y GSec) yield and the 91-day Treasury Bill (TB) rate indicates a synchronized movement between long-term and short-term bond yields. Additionally, the 10Y GSec shows a moderate positive correlation with the Interest rate (0.8030*), suggesting a direct relationship with monetary policy decisions. However, the inverse correlation with foreign reserves (-0.6796*) and gold (-0.5230*) highlights the impact of external and commodity market factors on long-term yields.

The 91-day TB rate is similarly influenced by the Interest rate, with a very strong positive correlation (0.9872*), underlining its dependence on short-term monetary policy. It also shows significant inverse relationships with foreign reserves (-0.6232*) and inflation (-0.4160*), reflecting the role of inflationary pressures and external stability in shaping short-term yields. Interestingly, while the TB rate correlates positively with the exchange rate (0.3540*), its negative association with NSE NIFTY (-0.3091*) suggests a divergence between fixed-income securities and equity market performance.

Foreign reserves show a moderate positive correlation with gold (0.6022*), highlighting their complementary role as safety assets during economic instability. Conversely, reserves exhibit a negative relationship with key monetary policy variables, such as the 10Y GSec (-0.6796*), 91-day TB (-0.6232*), and Interest rate (-0.5531*), emphasizing the counter-cyclicality of reserve accumulation. Interestingly, foreign reserves show weak and non-significant correlations with inflation (0.1585), IIP (-0.0798), and FDI (0.0556), indicating a limited direct impact of these factors on reserve levels.

Gold exhibits a complex relationship with other variables. It correlates positively with inflation (0.3127*), which is expected as gold often serves as an inflation hedge. However, its negative correlations with the 10Y GSec (-0.5230*), Interest rate (-0.2457), and NSE NIFTY (-0.4254*) suggest an inverse relationship with traditional financial assets, underscoring its role as a safe-haven investment during periods of economic uncertainty. Additionally, gold's negative correlation with IIP (-0.3065*) highlights its counter-cyclical behaviour during industrial slowdowns.

Equity market performance, represented by NSE NIFTY, shows a significant positive correlation with IIP (0.5277*), reflecting the influence of industrial growth on equity returns. However, its negative correlation with gold (-0.4254*) and the exchange rate (-0.6109*) implies that currency depreciation and rising gold prices often coincide with lower equity performance. The weak and negative correlations between NSE NIFTY and bond yields, as well as monetary policy variables, suggest limited direct interaction between equity and fixed-income markets in the short term.

Finally, the exchange rate exhibits a positive correlation with short-term bond yields (91-day TB at 0.3540*) and the Interest rate (0.3521*), suggesting that currency movements are sensitive to changes in monetary policy. However, its negative correlation with NSE NIFTY (-0.6109*) and foreign reserves (-0.2990) implies that depreciation often coincides with lower equity performance and reserve depletion. The relatively weak correlations between the exchange rate and inflation (-0.0248) or FDI (-0.2302) highlight limited short-term interactions between these variables. Overall, these findings underscore the intricate interplay of monetary, financial, and external factors in shaping macroeconomic outcomes.

The multivariate correlation analysis reveals notable differences in the relationships among macroeconomic variables, highlighting the unique interplay between monetary policy, financial markets, and external factors. Long-term (10Y GSec) and short-term (91-day TB) yields show strong alignment, reflecting consistent monetary policy influence, while equity markets (NSE NIFTY) and safe-haven assets like gold exhibit inverse relationships, underscoring their contrasting responses to economic uncertainty. External stability indicators, such as foreign reserves and the exchange rate, correlate negatively with bond yields and equity returns, emphasizing their counter-cyclicality during volatile periods. Industrial growth (IIP) aligns positively with equity returns, showcasing its crucial role in driving market performance. These results highlight the divergent behaviour of financial instruments and economic variables, offering critical insights into their interdependencies in different market conditions.

Table 3: Variables impact on 10Y Government Security yields and comparison of different regression models

Variables and Residuals Test	OLS Regression			HSC Regression		Tobit Regression		Logistic Regression		FD Regression	
	Coefficient	p-value	VIF	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	4.88819***	<0.0001	---	4.8629***	<0.0001	4.12586***	<0.0001	−2.9179***	<0.0001	0.00203	0.9403
NSE NIFTY	−0.01158**	0.0202	5.120	−0.0107***	0.0052	0.00354	0.4010	−0.00184**	0.0173	−0.00455	0.2757
Interest Rate	0.39123***	<0.0001	2.234	0.39408***	<0.0001	0.45297***	<0.0001	0.06127***	<0.0001	0.21380	0.1893
Inflation	0.05547**	0.0451	1.570	0.06244***	0.0025	0.11475***	<0.0001	0.00907**	0.0350	0.06518	0.0812
IIP	0.00019	0.9287	1.491	0.00006	0.9650	0.00118	0.3680	0.00002	0.9469	0.00059	0.6940
Gold	−0.02858***	<0.0001	4.785	−0.0321***	<0.0001	−0.00630886	0.1866	−0.0044***	<0.0001	−0.00625	0.3460
FDI	0.00055*	0.0857	1.138	0.00057**	0.0195	0.00001	0.9671	0.00008*	0.0867	0.00015	0.5235
Exchange Rate	−0.01059	0.4727	3.539	−0.01807**	0.04080	0.04396**	0.0131	−0.00212	0.3560	−0.00897	0.6179
Foreign Reserves	−0.00286	0.6383	2.693	−0.00144	0.74710	−0.03208***	<0.0001	−0.00076	0.4203	−0.00621	0.6233
S.E. of Regression	0.275538			1.673415		-		0.042734[a]		0.226383	
Adjusted R-squared	0.794874			0.885156[b]		-		0.800587		0.01391	
Akaike Criterion (AIC)	27.0925			286.8537		0.051587		−241.2830[a]		−1.079380	
Log-likelihood	−4.546251			−134.4268		9.974206		129.6415[b]		9.53969	
Durbin-Watson	0.927634			0.903055		-		0.906624		2.134965	
F Stat	35.39116*** (0.0000)			69.40365*** (0.0000)		-		36.63057*** (0.0000)		0.879986 (0.5383)	
Chi-square	-			-		323.5763*** (0.0000)		-		-	
Sigma	-			-		0.161754** (0.0197)		-		-	
Left-censored observations	-			-		0		-		-	
Right-censored observations	-			-		38		-		-	
Normality (Chi-square)	10.254*** (0.0059)			7.51215** (0.0233)		8.5748** (0.0137)		2.83285 (0.2425)		3.57556 (0.1673)	
Non-linearity test (Chi-square)	1.87966 (0.3906)			-		-		-		7.86867 (0.4464)	
Breusch-Pagan test for HS (LM)	10.0587 (0.2609)			-		-		-		17.2327** (0.0277)	
Autocorrelation (LMF)	2.76091*** (0.0057)			-		-		-		0.849198 (0.6012)	
ARCH (LM)	13.2197 (0.3532)			-		-		-		2.31816 (0.1278)	
QLR test for structural break	81.7804*** (0.0000)			-		-		-		25.8025** (0.0429)	
Chow Test structural break	6.27275*** (0.0000)									2.8669*** (0.0078)	
RESET test specification	0.844503 (0.4347)			-		-		-		3.92828** (0.0249)	

Source: The Authors. Note: ***p < 0.01, **p < 0.05 & *p < 0.10, [a]Lowest value, and [b] Highest Value.

The analysis of Table 3 focuses on the variables influencing the 10-year Government Security (10Y GSec) yields across different regression models—OLS, HSC, Tobit, Logistic, and FD. These models provide varied perspectives on how macroeconomic variables and financial indicators impact long-term bond yields. NSE NIFTY, representing equity market returns, exhibits a negative and statistically significant relationship with 10Y GSec yields in the OLS, HSC, and Logistic regressions. This relationship underscores the inverse link between equity market performance and bond yields, as strong equity markets typically draw investments away from bonds, reducing their demand and increasing yields. The Interest Rate, a key monetary policy tool, demonstrates a robust and positive influence on bond yields across OLS, HSC, and Logistic regressions, with high significance levels. The consistent impact reflects the central role of the Interest Rate in determining borrowing costs and influencing investor expectations about future interest rates. Similarly, Inflation has a positive and significant impact, reinforcing its role in shaping long-term bond yields through inflation expectations and risk premiums. These findings align with conventional financial theories where higher inflation typically leads to higher yields as investors demand compensation for erosion in purchasing power.

The impact of Gold prices on 10Y GSec yields is consistently negative across OLS and HSC models, indicating its safe-haven status. Rising gold prices suggest heightened risk aversion, reducing the demand for risky assets, including long-term bonds. This relationship, however, is weaker in the Tobit and FD regressions, possibly due to the latter models' focus on different assumptions about the dependent variable distribution. FDI and Exchange Rate exhibit mixed significance, with their effects being model-dependent. While FDI shows marginal significance in OLS and HSC, its impact diminishes in Logistic and FD regressions. Exchange Rate, although insignificant in OLS, gains prominence in the Tobit and HSC models, suggesting that currency stability indirectly affects bond market dynamics. When comparing model fit, the HSC regression emerges as the most robust model with the highest Adjusted R-squared (0.885), indicating it captures the greatest variance among the variables. The Logistic regression stands out with the lowest Akaike Information Criterion (AIC) of -241.2830 and the highest Log-Likelihood (129.6415), indicating an excellent fit for the data. The OLS model, while straightforward, exhibits moderate performance with an Adjusted R-squared of 0.794 and AIC of 27.0925. Conversely, the FD regression performs poorly, with low significance levels across variables and high AIC, indicating limited explanatory power.

Further statistical tests provide additional insights. The Durbin-Watson statistic highlights mild autocorrelation in the residuals of OLS, HSC, and Logistic regressions. The Breusch-Pagan test for heteroscedasticity is insignificant in OLS and Logistic regressions but significant in FD regression, raising concerns about the reliability of the latter. Additionally, the Chow test and QLR test for structural breaks confirm significant regime changes before and after COVID-19, emphasizing the temporal nature of bond yield determinants. In terms of residual error and overall reliability, the HSC and Logistic regressions outperform others. The Logistic regression achieves the best trade-off between bias and variance, as indicated by its lower standard error (S.E.) of regression and superior likelihood-based criteria. The HSC model, with its high Adjusted R-squared and significant coefficients, also effectively explains the variability in bond yields while accounting for potential heteroscedasticity in the data. On the other hand, the Tobit regression, while effective in addressing censored observations, fails to achieve the best fit compared to HSC and Logistic models, as evidenced by its higher AIC and lower log-likelihood. HSC and Logistic regressions provide the most reliable insights into the drivers of 10Y GSec yields, outperforming simpler models like OLS and specialized models like Tobit and FD.

Table 4: Variables impact on 91Day Treasury Bills yields and comparison of different regression models

Variables and Residuals Test	OLS Regression			HSC Regression		Tobit Regression		Logistic Regression		FD Regression	
	Coefficient	p-value	VIF	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	−1.7255***	<0.0001	-	−2.1176***	<0.0001	−1.7173***	<0.0001	−4.3554***	<0.0001	0.00594	0.8115
NSE NIFTY	−0.00791**	0.0163	5.120	−0.0081***	0.0002	−0.0079***	0.0073	−0.0033***	0.0002	−0.00529	0.1696
Interest Rate	1.30445***	<0.0001	2.234	1.36916***	<0.0001	1.30337***	<0.0001	0.2741***	<0.0001	0.6395***	<0.0001
Inflation	0.02864	0.1149	1.570	0.02431*	0.0681	0.02903*	0.0800	0.00918**	0.0479	−0.01328	0.6961
IIP	−0.00093	0.5086	1.491	−0.00048	0.5515	−0.00094	0.4676	−0.00034	0.3453	−0.00023	0.8675
Gold	−0.00793*	0.0728	4.785	−0.01121***	<0.0001	−0.00788*	0.0502	−0.00262**	0.0211	−0.00202	0.7402
FDI	0.00031	0.1334	1.138	0.00037**	0.0352	0.00030	0.1192	0.00009*	0.0787	0.00022	0.2993
Exchange Rate	−0.02254**	0.0231	3.539	−0.02889***	<0.0001	−0.0233***	0.0096	−0.0094***	0.0003	−0.00586	0.7228
Foreign Reserves	−0.01538***	0.0003	2.693	−0.00906**	0.01200	−0.0156***	<0.0001	−0.0047***	<0.0001	−0.02156	0.0672
S.E. of Regression	0.181898			1.503204		-		0.04622[a]		0.208422	
Adjusted R-squared	0.984181			0.994669[b]		-		0.97851		0.262484	
Akaike Criterion (AIC)	−32.70733			271.4071		−29.04919		−229.9940[a]		−12.81773	
Log-likelihood	25.35366			−126.7035		24.5246		123.997[b]		15.40887	
Durbin-Watson	1.795393			1.625213		-		1.47655		2.234251	
F Stat	553.1697*** (0.0000)			1656.993*** (0.0000)		-		405.1122*** (0.0000)		4.11415*** (0.0005)	
Chi-square	-			-		5146.959*** (0.0000)		-		-	
Sigma	-			-		0.168332** (0.0141)		-		-	
Left-censored observations	-			-		0		-		-	
Right-censored observations	-			-		1		-		-	
Normality (Chi-square)	5.59254 (0.0610)			16.6338*** (0.0002)		8.47729** (0.0144)		0.807158 (0.6679)		30.09*** (0.0000)	
Non-linearity test (Chi-square)	21.8565*** (0.0051)			-		-		-		10.703 (0.2191)	
Breusch-Pagan test for HS (LM)	53.4376 (0.1557)			-		-		-		56.1751 (0.1031)	
Autocorrelation (LMF)	0.640719 (0.7974)			-		-		-		1.46845 (0.1679)	
ARCH (LM)	13.1572 (0.3577)			-		-		-		4.20991 (0.9793)	
QLR test for structural break	28.9273** (0.0154)			-		-		-		22.0361 (0.1309)	
Chow Test structural break	2.02946** (0.0484)									1.2306 (0.2967)	
RESET test specification	1.65783 (0.1990)			-		-		-		0.0436961 (0.9572)	

Source: The Authors. Note: ***$p < 0.01$, **$p < 0.05$ & *$p < 0.10$, [a] Lowest value, and [b] Highest Value.

Table 4 presents a comprehensive analysis of the determinants of 91-Day Treasury Bill (TB) yields, exploring the influence of macroeconomic variables through five regression models: OLS, HSC, Tobit, Logistic, and FD. Among these, the NSE NIFTY index, which represents equity market performance, consistently shows a negative relationship with TB yields. This indicates that when equity markets perform well, investors tend to shift their investments from Treasury Bills to stocks, reducing demand for short-term debt and thus raising yields. Conversely, during periods of market uncertainty, demand for safer assets like Treasury Bills increases, pushing yields lower.

The Interest Rate stands out as the most influential determinant of 91-Day TB yields, demonstrating a strong positive relationship across all regression models. This highlights the central role of monetary policy in shaping short-term borrowing costs. A higher interest rate typically signals a tightening of monetary policy, which increases the cost of borrowing and raises yields on Treasury Bills as investors seek compensation for potential inflation and higher rates. The consistent statistical significance of this relationship across all models emphasizes its key role in determining short-term debt instrument yields.

Inflation also influences short-term Treasury yields, although its impact is not as consistent. In the OLS, HSC, and Tobit models, inflation has a marginally significant positive effect on TB yields, suggesting that rising inflation leads to higher yields as investors demand compensation for the erosion of purchasing power. However, the FD regression model shows no significant relationship between inflation and TB yields, indicating that this model may not capture the short-term variations in inflation adequately, thus highlighting its limitations in modelling inflation's effect on short-term debt instruments.

Gold prices exhibit a negative relationship with 91-Day TB yields in most models, indicating that rising gold prices, often a sign of increased market risk or uncertainty, lead to lower demand for Treasury Bills. As investors seek safer assets like gold, demand for short-term bonds decreases, pushing yields down. This relationship is most evident in the OLS, HSC, and Tobit regressions, where gold's negative impact is statistically significant. However, in the FD model, the relationship weakens, suggesting that the FD regression may not adequately capture the risk-averse behaviour of investors in response to rising gold prices.

Foreign Reserves have a consistent negative impact on 91-Day TB yields across most regression models. This relationship suggests that higher levels of foreign reserves help stabilize the domestic economy and reduce the need for high short-term yields. By bolstering investor confidence and mitigating external shocks, foreign reserves reduce the risks associated with Treasury Bills, leading to lower yields. The consistent negative influence of foreign reserves highlights their role in enhancing market stability and influencing short-term borrowing costs. In terms of model performance, the HSC regression emerges as the most robust, achieving the highest Adjusted R-squared (0.9947), indicating its strong explanatory power. This model captures the largest proportion of variance in 91-Day TB yields, outperforming others in terms of fit. The Logistic regression follows closely, demonstrating high efficiency with the lowest AIC and highest Log-Likelihood, indicating an excellent model fit. While the OLS model offers simplicity and good explanatory power, it lags behind in precision. The FD regression, with weak performance across the fit metrics, is the least effective for analysing 91-Day TB yields, suggesting its limited usefulness in this context.

Table 5: Variables impact on Inflation and comparison of different regression models

Variables and Residuals Test	OLS Regression			HSC Regression		Tobit Regression		Logistic Regression		FD Regression	
	Coefficient	p-value	VIF	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	3.73524	0.2568	-	4.76571*	0.0760	2.62052	0.4547	−3.3980***	<0.0001	0.01440	0.8774
Interest Rate	−1.26929***	<0.0001	3.401	−1.2157***	<0.0001	−1.5523***	<0.0001	−0.2798***	<0.0001	−0.72081	0.2547
10Y GSec	1.12126**	0.0451	5.152	0.98227**	0.0187	1.52159**	0.0127	0.26292**	0.0417	−0.18652	0.6961
NSE NIFTY	0.02948	0.1949	5.433	0.01380	0.4664	0.02613	0.2719	0.00765	0.1455	0.01002	0.4908
Gold	0.10586***	0.0011	5.244	0.1049***	0.0002	0.11467***	0.0005	0.02378***	0.0015	0.01449	0.5245
Exchange Rate	0.10986*	0.0946	3.412	0.06313	0.2470	0.11195*	0.0973	0.02056	0.1730	0.02293	0.7115
FDI	−0.00116	0.4240	1.181	−0.00183	0.1642	−0.00147	0.3294	−0.00037	0.2659	−0.00011	0.8943
IIP	−0.00109	0.9084	1.491	0.00935	0.3615	−0.00088	0.9305	−0.00022	0.9189	−0.01166**	0.0210
Foreign Reserves	−0.06669**	0.0127	2.446	−0.0701***	0.0019	−0.0721***	0.0094	−0.01369**	0.0256	−0.02581	0.5636
S.E. of Regression	1.23877			1.641374		-		0.285574[a]		0.781102	
Adjusted R-squared	0.326728			0.561473[b]		-		0.305779		0.071734	
Akaike Criterion (AIC)	243.546			284.0697		234.6746		32.24436[a]		174.7845	
Log-likelihood	−112.7730			−133.0349		−107.3373		−7.122178[b]		−78.39223	
Durbin-Watson	0.488115			0.555588		-		0.417272		1.375067	
F Stat	5.306903*** (0.0000)			12.3632*** (0.0000)		-		4.909118*** (0.0000)		1.676178 (0.1222)	
Chi-square	-			-		43.0103*** (0.0000)		-		-	
Sigma	-			-		1.28254 (0.1288)		-		-	
Left-censored observations	-			-		6		-		-	
Right-censored observations	-			-		11		-		-	
Normality (Chi-square)	2.31555 (0.3141)			2.83242 (0.2426)		19.4805*** (0.0000)		5.88486* (0.0527)		25.0071*** (0.0000)	
Non-linearity test (Chi-square)	32.5336*** (0.0000)			-		-		-		7.70816 (0.4624)	
Breusch-Pagan test for HS (LM)	9.81789 (0.2780)			-		-		-		35.4121 (0.8187)	
Autocorrelation (LMF)	12.3241*** (0.0000)			-		-		-		5.36701*** (0.0000)	
ARCH (LM)	21.6089** (0.0421)			-		-		-		7.49851 (0.8229)	
QLR test for structural break	138.571*** (0.0000)			-		-		-		28.8291** (0.0158)	
Chow Test structural break	15.3968*** (0.0000)			-		-		-		0.962337 (0.4811)	
RESET test for specification	4.25301** (0.0186)			-		-		-		0.406712 (0.6676)	

Source: The Authors. Note: ***$p < 0.01$, **$p < 0.05$ & *$p < 0.10$, [a] Lowest value, and [b] Highest Value.

Table 5 focuses on the analysis of inflation determinants across five regression models: OLS, HSC, Tobit, Logistic, and FD. The Interest Rate consistently emerges as the most significant determinant of inflation across all models. A negative and statistically significant relationship is observed in the OLS, HSC, Tobit, and Logistic regressions, indicating that higher interest rates typically reduce inflationary pressures. Tightening monetary policy, often associated with rising interest rates, is a primary tool for central banks to control inflation, and this relationship is evident in the results. However, the FD regression shows a less significant relationship, highlighting the limitations of this model in capturing the dynamic impact of interest rates on inflation. The 10-Year Government Securities (10Y GSec) yield shows a positive relationship with inflation across all models, suggesting that long-term bond yields are sensitive to inflation expectations. The significant positive coefficients in the OLS, HSC, Tobit, and Logistic regressions point to the role of long-term borrowing costs in reflecting inflation expectations. As inflation rises, investors demand higher yields on long-term debt to compensate for the anticipated erosion in purchasing power. This relationship reinforces the conventional economic theory that higher inflation results in higher bond yields as investors seek compensation for future inflation risks.

Gold prices, often viewed as a hedge against inflation, consistently show a positive and statistically significant relationship with inflation across the OLS, HSC, Tobit, and Logistic models. The strong positive coefficients underscore gold's role as a store of value during periods of inflationary pressure. As inflation rises, investors tend to move toward gold to protect their wealth from the eroding purchasing power of fiat currencies. This relationship is particularly significant in the OLS and HSC regressions, highlighting gold's status as an important inflation hedge. However, the FD model fails to capture this relationship, indicating its limitations in addressing the broader impact of gold on inflation expectations. Foreign Reserves demonstrate a consistent negative relationship with inflation in the OLS, HSC, Tobit, and Logistic regressions. The negative coefficients suggest that higher foreign reserves help stabilize the economy and reduce inflationary pressures. Reserves can mitigate external shocks and support the domestic currency, thus lowering inflation expectations. This relationship aligns with the notion that countries with higher reserves are better positioned to manage external imbalances, which can contribute to maintaining stable inflation rates. However, similar to other variables, the FD regression fails to detect a meaningful relationship, reflecting its limitations in capturing short-term fluctuations in inflation.

The fit metrics reveal notable differences in model performance. The HSC regression stands out with the highest Adjusted R-squared (0.5615), indicating it captures the largest amount of variance in inflation. This suggests that the HSC model provides the most comprehensive view of inflation determinants. The Logistic regression follows closely with a strong model fit, evidenced by its lowest AIC and highest Log-Likelihood. While the OLS regression offers simplicity and relatively strong results, it lags behind in terms of model fit, with a lower Adjusted R-squared and less precise coefficients. The FD regression, on the other hand, exhibits the lowest Adjusted R-squared and weaker significance levels across key variables, highlighting its limited ability to explain inflation dynamics. Overall, Table 5 highlights the significant relationships between macroeconomic variables and inflation, with the Interest Rate, 10Y GSec yield, Gold prices, and Foreign Reserves emerging as the most influential factors. The HSC and Logistic regressions provide the most reliable insights into these relationships, outperforming the simpler OLS model and the more specialized FD regression.

Table 6: Variables impact on Interest Rates and comparison of different regression models

Variables and Residuals Test	OLS Regression			HSC Regression		Tobit Regression		Logistic Regression		FD Regression	
	Coefficient	p-value	VIF	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	−2.81331**	0.0352	---	−0.94642	0.2137	−2.8133**	0.0214	−4.481***	<0.0001	0.00581	0.7820
10Y GSec	1.33300***	<0.0001	2.629	1.0654***	<0.0001	1.3330***	<0.0001	0.2617***	<0.0001	0.12923	0.1893
Inflation	−0.21396***	<0.0001	1.219	−0.1897***	<0.0001	−0.21***	<0.0001	−0.041***	<0.0001	−0.05107*	0.0787
NSE NIFTY	0.00805	0.3906	5.516	0.00128	0.8409	0.00805	0.3554	0.00096	0.5942	−0.00133	0.6842
Exchange Rate	0.02433	0.3710	3.523	0.03102**	0.0437	0.02433	0.3354	0.00295	0.5743	0.01638	0.2391
Gold	0.04490***	0.0007	5.179	0.03221***	0.0003	0.0449***	0.0001	0.0085***	0.0009	−0.00476	0.3554
IIP	0.00137	0.7251	1.489	0.00421	0.3731	0.00137	0.7057	0.00024	0.7477	−0.00037	0.7459
FDI	−0.00093	0.1136	1.147	−0.00022	0.6239	−0.00093*	0.0863	−0.00017	0.1278	0.00013	0.4560
Foreign Reserves	−0.02601**	0.0181	2.471	−0.0277***	0.0001	−0.026***	0.0095	−0.00543*	0.0111	−0.00731	0.4560
S.E. of Regression	0.508602			1.517471		-		0.098393[a]		0.176003	
Adjusted R-squared	0.758657			0.920136[b]		-		0.767971		0.061904	
Akaike Criterion (AIC)	115.356			272.7673		117.356		−121.1925[a]		−36.82473	
Log-likelihood	−48.67800			−127.3837		−48.67800		69.59625[b]		27.41237	
Durbin-Watson	0.607474			0.390118		-		0.62747		1.697586	
F Stat	28.89838*** (0.0000)			103.2513*** (0.0000)		-		30.3745*** (0.0000)		1.577405 (0.1500)	
Chi-square	-			-		264.214*** (0.0000)		-		-	
Sigma	-			-		0.47575** (0.0396)		-		-	
Left-censored observations	-			-		0		-		-	
Right-censored observations	-			-		0		-		-	
Normality (Chi-square)	2.63743 (0.2674)			1.59322 (0.4508)		23.2016*** (0.0000)		1.81648 (0.4032)		39.295*** (0.0000)	
Non-linearity test (Chi-square)	21.7214*** (0.0054)			-		-		-		7.90611 (0.4426)	
Breusch-Pagan test for HS (LM)	17.8027** (0.0227)			-		-		-		41.818*** (0.0000)	
Autocorrelation (LMF)	5.94324*** (0.0000)			-		-		-		2.06848 (2.06848)	
ARCH (LM)	28.833*** (0.0041)			-		-		-		5.95044 (0.9185)	
QLR test for structural break	93.544*** (0.0000)			-		-		-		46.803*** (0.0000)	
Chow Test structural break	2.21248** (0.0351)			-		-		-		3.0253*** (0.0054)	
RESET test for specification	7.94061*** (0.0008)			-		-		-		0.109172 (0.8967)	

Source: The Authors. Note: ***p < 0.01, **p < 0.05 & *p < 0.10, [a] Lowest value, and [b] Highest Value.

Table 6 presents the analysis of factors influencing interest rates across five regression models: OLS, HSC, Tobit, Logistic, and FD regressions. It compares variable coefficients, significance levels, and the fit of the models using metrics such as Adjusted R-squared, Standard Error (SE), Log-Likelihood, and Akaike Criterion (AIC). This analysis reveals the relative performance of each model in explaining interest rate variability. The 10Y GSec (10-Year Government Security yield) emerges as the most consistent determinant of interest rates. It shows a strong positive and highly significant relationship across OLS, HSC, Tobit, and Logistic regressions ($p < 0.01$). This finding aligns with economic theory, as long-term bond yields reflect broader interest rate trends. However, in the FD regression, the variable's coefficient is smaller and statistically insignificant, suggesting the model's limitation in capturing this relationship effectively.

Inflation exhibits a significant and negative relationship with interest rates across all models, with the strongest significance observed in OLS, HSC, Tobit, and Logistic regressions ($p < 0.01$). This inverse relationship highlights the role of inflation expectations in influencing real interest rates. While the FD regression maintains a negative coefficient, the significance drops to $p < 0.1$, indicating weaker explanatory power in this model. Gold prices, a proxy for market expectations and economic uncertainty, have a consistently positive and significant impact on interest rates in OLS, HSC, Tobit, and Logistic regressions ($p < 0.01$). These finding underscores gold's role as a hedge against inflation, which influences monetary policy and interest rates. However, the FD model fails to capture this relationship, with an insignificant coefficient.

Foreign Reserves negatively influence interest rates in OLS, HSC, Tobit, and Logistic regressions, with significance levels varying between $p < 0.05$ and $p < 0.01$. This relationship suggests that higher reserves reduce external borrowing pressures and stabilize domestic interest rates. As with other key variables, the FD regression fails to detect a significant relationship. In terms of model fit, the HSC regression demonstrates the highest Adjusted R-squared (0.9201), indicating its superior explanatory power compared to the other models. It also achieves significant coefficients for most variables, making it the most robust model. The Logistic regression stands out for its lowest AIC (-121.1925) and highest Log-Likelihood (69.59625), showing its efficiency in modelling the data despite its focus on classification over continuous predictions.

The Tobit regression performs well for censored data, maintaining significant coefficients for most variables. However, its Adjusted R-squared is not directly comparable to OLS or HSC. The FD regression, with the lowest Adjusted R-squared (0.0619), fails to provide meaningful insights and performs poorly across fit metrics. OLS regression offers simplicity and retains high significance levels but lags behind HSC and Logistic models in terms of overall model fit. Overall, the HSC regression is the most comprehensive and effective model for analysing the determinants of interest rates, followed by the Logistic regression for its efficiency and robust fit metrics. The Tobit model is valuable for censored datasets, while the FD regression struggles to capture significant relationships or provide a strong model fit.

IV. Conclusion

In conclusion, the multivariate analysis across multiple regression models has provided deep insights into the factors influencing long-term bond yields (10Y GSec), short-term Treasury Bill yields (91-day TB), inflation, and interest rates. The study found that key macroeconomic variables such as the Interest Rate, Inflation, Gold, and the 10Y GSec yield have significant and consistent relationships with bond yields across various models, highlighting the interplay between monetary policy and investor sentiment. Specifically, the positive relationship between the 10Y GSec yield and the Interest Rate across OLS, HSC, and Logistic models underlines the critical role of central bank actions in shaping long-term borrowing costs. Furthermore, the negative relationship between bond yields and equity market performance (NSE NIFTY) confirms the inverse dynamics of investment flows between riskier equity markets and safer fixed-income assets, particularly during periods of market uncertainty.

The analysis also illuminated the role of external factors, such as Gold and Foreign Reserves, in shaping macroeconomic outcomes. Gold prices were found to have a significant negative impact on bond yields, reflecting its status as a safe-haven asset during times of market stress, which diminishes demand for long-term bonds. Similarly, Foreign Reserves demonstrated a stabilizing effect on both inflation and interest rates, suggesting that countries with higher reserve levels are better able to withstand external shocks and reduce inflationary pressures. The observed relationships between these variables underscore the importance of both domestic economic policies and global economic conditions in influencing macroeconomic outcomes.

The comparison of different regression models revealed the superior performance of the HSC and Logistic models in explaining macroeconomic variability. The HSC regression emerged as the most robust model, consistently capturing a high percentage of variance across all dependent variables, while the Logistic regression excelled in terms of model efficiency and fit. The OLS model, while providing a reliable baseline, was outperformed by HSC and Logistic models in terms of explanatory power and fit metrics. The Tobit and FD regressions, while useful for specific contexts, exhibited lower performance, especially in capturing significant relationships and explaining the variability in the data. This indicates the importance of selecting the right model based on the characteristics of the data and the underlying relationships being studied.

Overall, the findings highlight the complex interdependencies between monetary policy, financial markets, and external factors in shaping macroeconomic dynamics. The study emphasizes that long-term bond yields are influenced not only by domestic interest rates and inflation but also by external stability indicators, such as foreign reserves and the exchange rate. The analysis offers valuable insights for policymakers and investors, suggesting that a comprehensive understanding of these relationships can enhance decision-making in both fiscal and monetary policy formulation, as well as investment strategies. As global economic conditions evolve, these macroeconomic relationships will continue to be crucial in navigating the challenges posed by inflation, financial market volatility, and external shocks.

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