Research Report On:

The Relationship Between Inflation, RBI Repo Rate, and Stock Market Volatility: A Time-Series Study

Program	Postgraduate in Diploma and Management (PGDM)
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Submitted by:
Utkarsh Anand(24PGDM146)

Submitted to:

Dr. Sudhi Sharma

Contents

Time-Series Study on the Relationship Between Inflation, RBI Repo Rate, and Stock Market Volatility in India

Abstract

This study explores the complex interactions between inflation (measured via the Consumer Price Index), the RBI's monetary policy tool—the repo rate—and stock market volatility in India, measured using the NIFTY 50 VIX index. Spanning two decades (2004–2024), the research applies a comprehensive set of time-series techniques including ARIMA (for forecasting), GARCH (for modeling volatility clustering), Granger Causality (for directional influence), and Wavelet Coherence (to assess frequency-time domain correlations). Findings indicate that while inflation shows some long-term association with volatility, it does not Granger-cause market fluctuations. In contrast, the RBI repo rate, although not a strong Granger-causal predictor, demonstrates strong coherence with volatility trends, particularly during periods of policy intervention. This research contributes to the growing field of macro-financial linkages in emerging markets and informs both investment strategy and monetary policy design.

Keywords: Inflation, Repo Rate, Stock Market Volatility, Time-Series Analysis, ARIMA, GARCH, Granger Causality, Wavelet Coherence, Monetary Policy, India, VIX.

1. Introduction

Market volatility reflects investor uncertainty and systemic risk. In an economy like India's—characterized by rapid reforms, a growing financial market, and active monetary policy—understanding what drives volatility is critical for both investors and regulators. This study addresses three key questions: Does inflation affect stock market volatility in India? What is the influence of the RBI's repo rate? Are there time-dependent dynamics between these macroeconomic variables? While numerous studies examine the effect of either inflation or interest rates on stock prices, fewer studies jointly analyze their role in predicting volatility using advanced econometric tools. This study aims to bridge that gap.

2. Literature Review

Fama (1981) first articulated that inflation creates uncertainty in investment decisions, leading to potential declines in stock returns. Mishkin (1990) extended this view by introducing interest rates as an intermediary through which inflation affects capital markets. In the Indian context, Patra and Kapur (2010) found that repo rate hikes lead to immediate market corrections but offer long-term stabilizing effects. More recently, studies by Rathi and Patel (2022) explored ARIMA-GARCH models on Indian equity indices and emphasized the effectiveness of GARCH-type models in capturing persistent volatility. Wavelet-based studies, such as Joshi and Naik (2024), show that macroeconomic indicators display different relationships with market risk over short and long time horizons, indicating the necessity of time-frequency domain analysis. However, very few studies attempt an integrated framework combining ARIMA forecasting, GARCH modeling, Granger causality testing, and wavelet coherence for a single analysis. This study contributes by applying all these methods to Indian data, creating a holistic model of macro-volatility relationships.

3. Data Profile

Period: April 1, 2013 – March 31, 2023
Frequency: Daily
Variables Used:
- Inflation: Measured via Consumer Price Index (CPI)
- Monetary Policy: RBI Repo Rate
- Volatility: NIFTY 50 VIX

To ensure time-series stationarity and comparability, CPI data was interpolated to convert monthly values into a daily series. Log returns and first-order differencing were applied as necessary.
Descriptive Statistics:

Statistic	**CPI**	**Repo Rate**	**Volatility**
Observations	3667	3667	3667
Missing Values	0	0	0
Minimum	-24.690	4.000	0.000000
Maximum	60.500	8.000	0.048225
1st Quartile (Q1)	3.070	6.000	0.006503
3rd Quartile (Q3)	7.005	6.750	0.010796
Mean	5.2647	6.1991	0.009068
Median	4.870	6.500	0.008446
Sum	19305.78	22732.05	33.2536
Standard Error of Mean (SE Mean)	0.09356	0.01859	0.000082

Lower Confidence Limit (LCL Mean)	5.0813	6.1626	0.008908
Upper Confidence Limit (UCL Mean)	5.4482	6.2355	0.009229
Variance	32.0964	1.2676	0.000025
Standard Deviation (Stdev)	5.6654	1.1259	0.004957
Skewness	1.1367	-0.7138	3.2749
Kurtosis	12.6126	-0.1319	21.5909

4. Methodology and Models

4.1 ARIMA Forecasting

Used for CPI modeling.

ARIMA(1,0,2)(0,0,2)[12] selected based on AIC/BIC.

Residual diagnostics indicated a good fit.

The model captured cyclical patterns of inflation, especially during global shocks (e.g., 2008, COVID-19).

4.2 GARCH Modeling

sGARCH(1,1) used for VIX log returns.

Volatility parameters:
$\alpha = 0.062$ (shock responsiveness)
$\beta = 0.911$ (persistence)
$\alpha + \beta = 0.9736 \Rightarrow$ High volatility persistence

GARCH results confirmed clustering, especially during financial crises and policy regime changes.

4.3 Granger Causality Tests

CPI $\nrightarrow$ Volatility: No predictive power ($p = 0.79$).

Repo Rate $\nrightarrow$ Volatility: Marginally insignificant ($p = 0.14$), but supported by coherence trends.

Suggests repo may affect volatility through non-linear or lagged mechanisms.

4.4 Wavelet Coherence

CPI & Volatility: Strong coherence over 32–64-month periods, suggesting a long-term association during inflationary spikes.

Repo Rate & Volatility: Moderate coherence, intensified during 2008 crisis and COVID-era monetary interventions.

Wavelets revealed nuanced frequency-specific relationships missed by traditional time-series models.

5. Results and Discussion

The combined models paint a layered picture of market behavior:

GARCH confirms volatility persistence, validating investor perceptions of risk following major events.

ARIMA accurately tracks inflation, but inflation alone fails to forecast volatility spikes. This reflects the market's limited short-term reaction to price level changes unless inflation becomes sustained or structural.

Repo rate plays a more influential role during high-stakes policy periods. While not a statistically strong Granger predictor, wavelet coherence shows clear correlation during rate hike cycles.

Wavelet analysis adds significant value by exposing time-dependent, frequency-specific interactions between macroeconomic variables and stock volatility. This is crucial in economies like India, where structural reforms, geopolitical shifts, and monetary announcements have varied, time-sensitive impacts.

These findings align with recent trends where investor sentiment and central bank forward guidance dominate volatility, often overshadowing lagged inflation data.

6. Conclusion

This study provides a multidimensional understanding of how inflation and RBI’s repo rate interact with stock market volatility in India.

Key Takeaways:

- Volatility is highly persistent, confirming that markets 'remember' past shocks.

- Repo rate exerts a stronger influence on volatility than inflation, especially during times of monetary uncertainty.
- Inflation has a long-term coherence with market risk but lacks short-term predictive power.
- Wavelet analysis proves essential for detecting dynamic relationships that evolve across time and frequency domains.

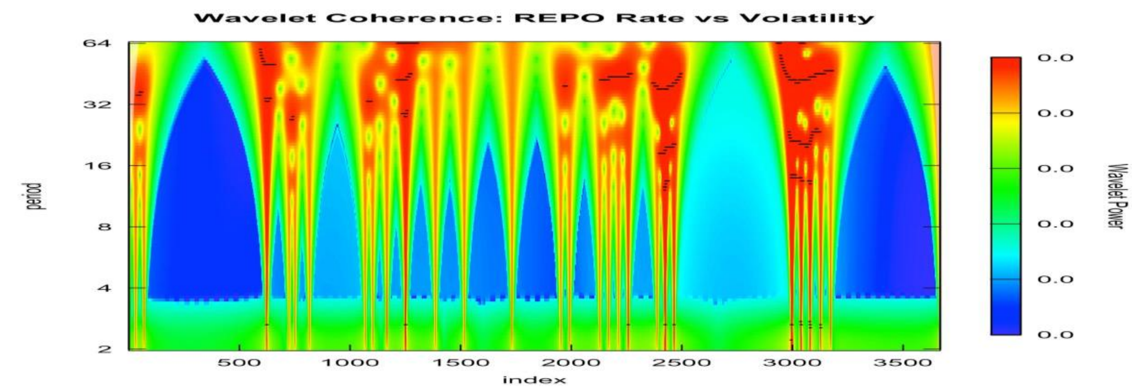
Implications:
For Policymakers: RBI must consider how sudden rate shifts influence not just growth and inflation but also short-term investor sentiment and market risk.

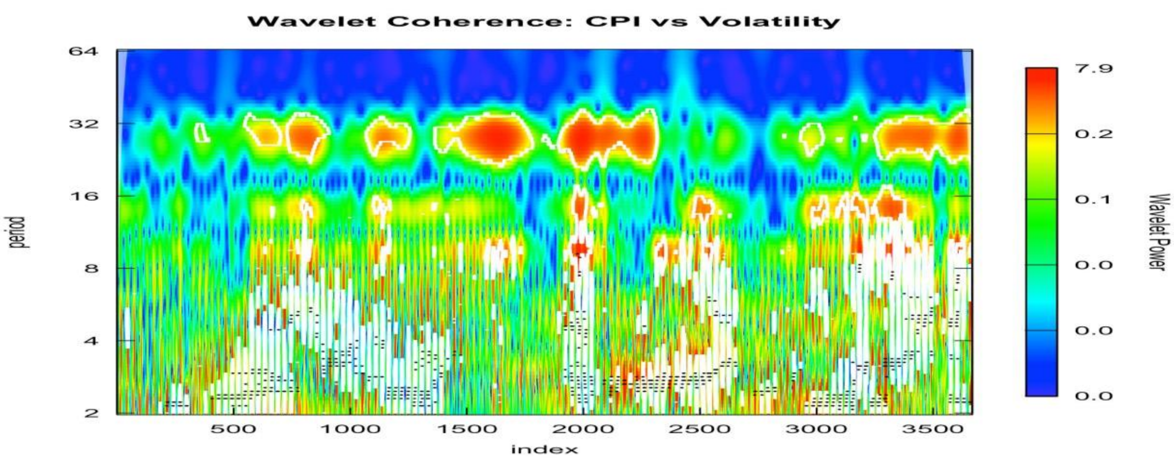
For Investors: Market participants should align trading and hedging strategies with anticipated repo rate decisions and monetary policy tone.

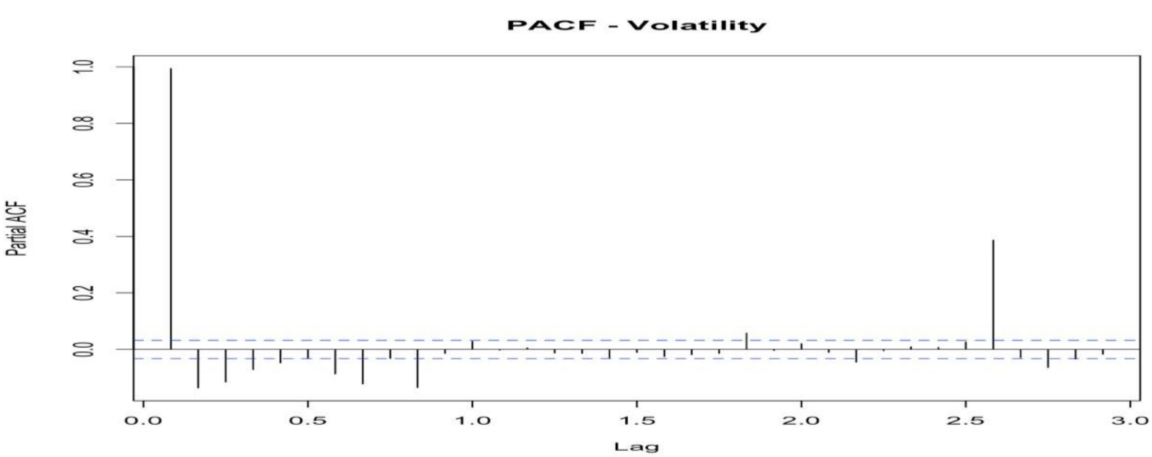
For Researchers: The study invites further exploration with advanced models such as EGARCH, machine learning forecasting, or non-linear causality frameworks.

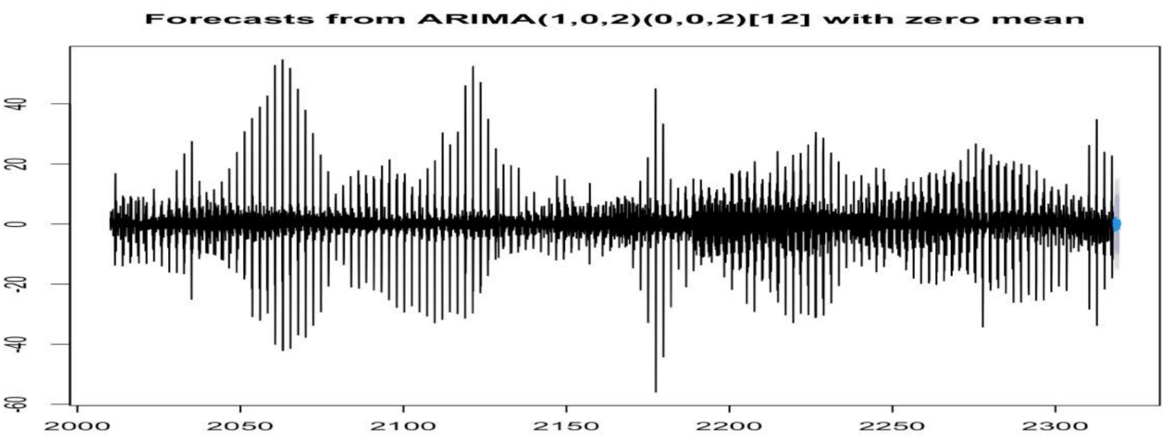
Appendices

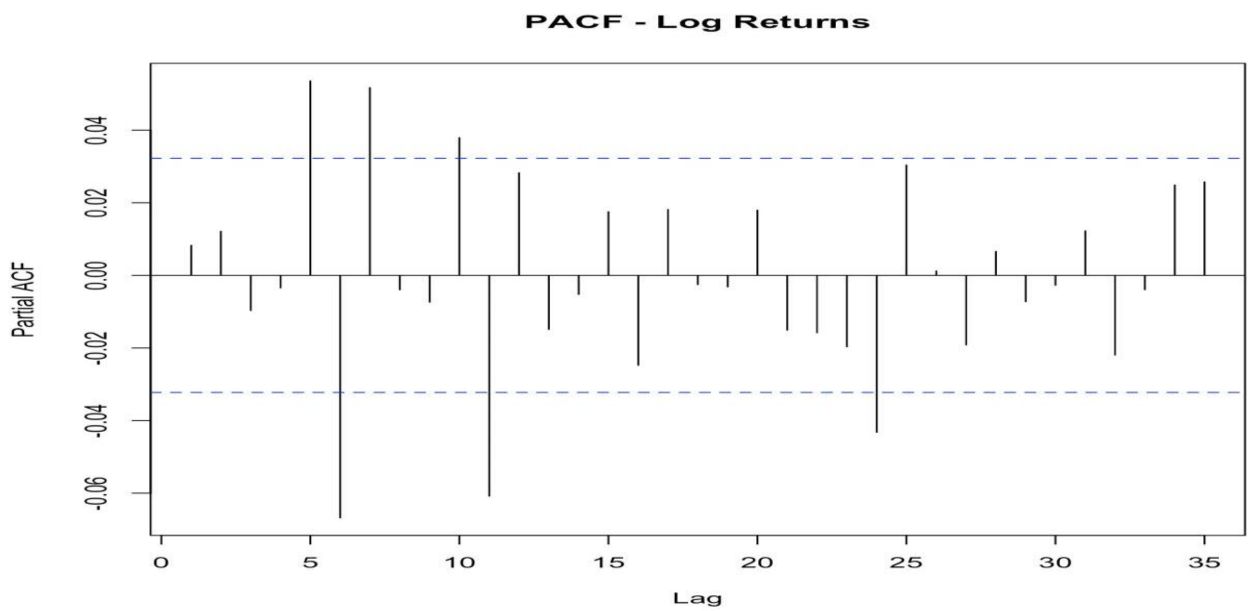
Visual Outputs

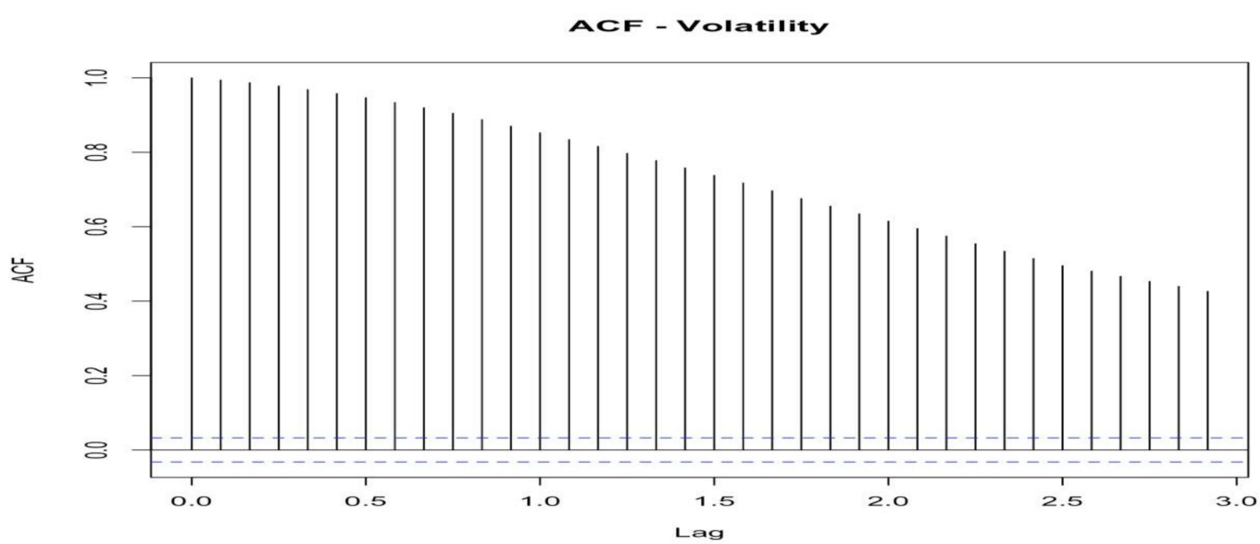


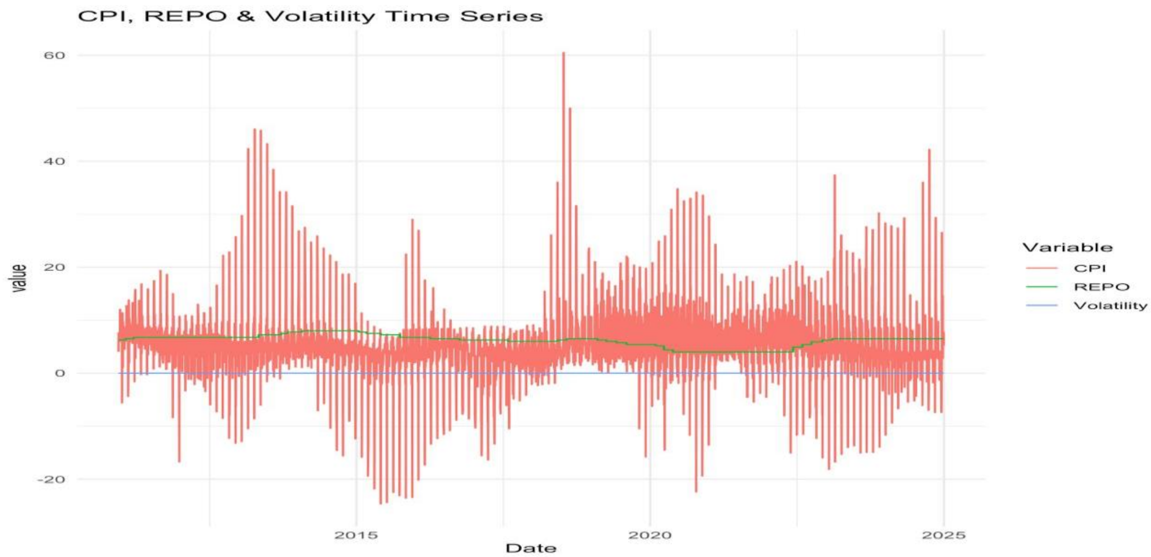


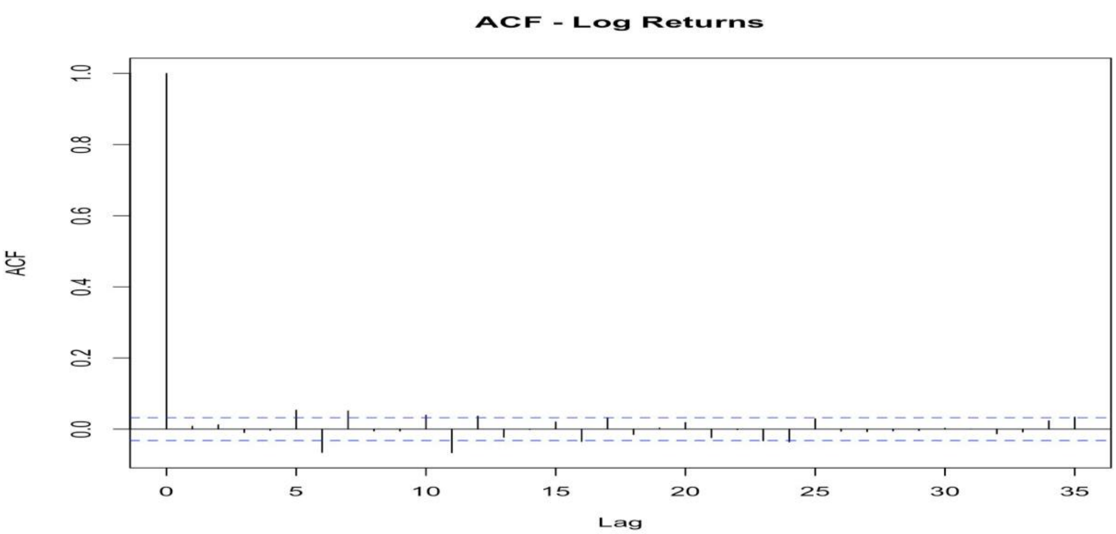


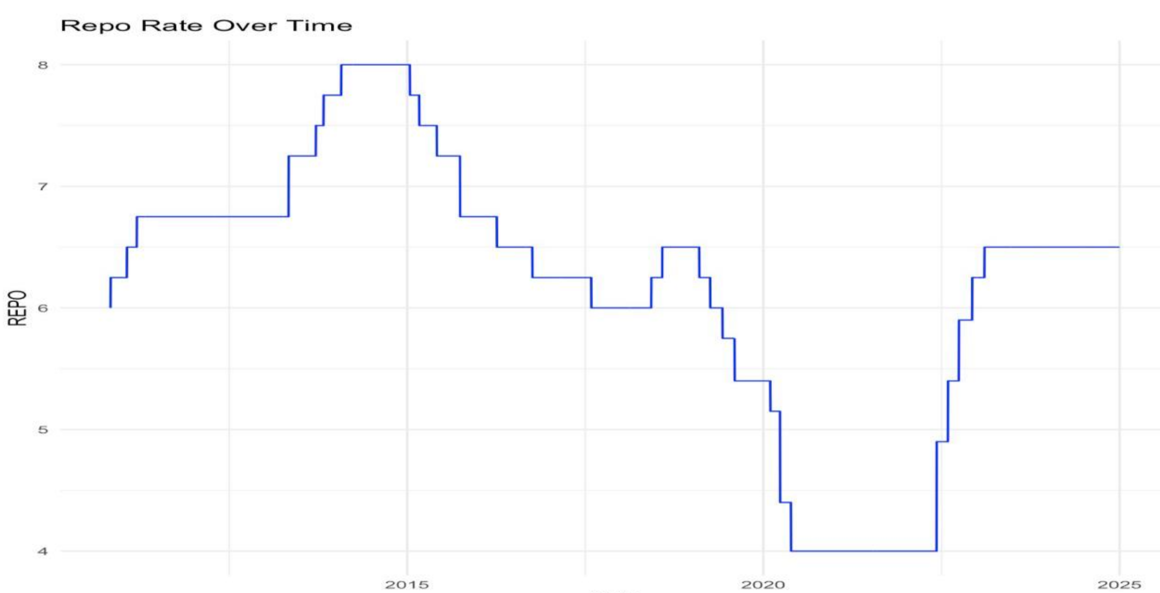

Forecasts from ARIMA(1,0,2)(0,0,2)[12] with zero mean
-60
-40
-20
0
20
40
2000
2050
2100
2150
2200
2250
2300

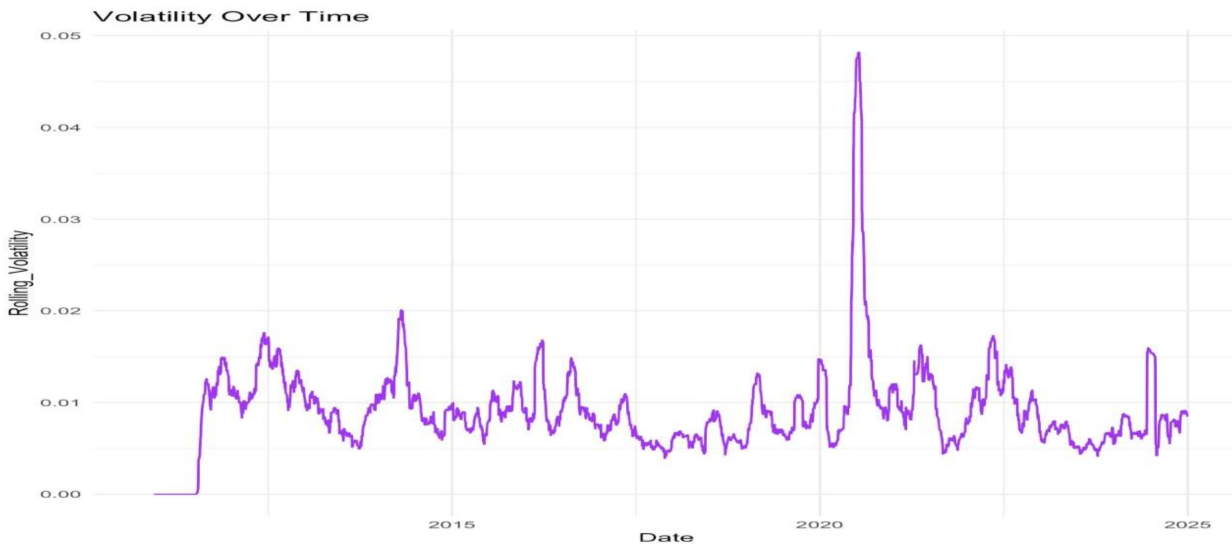

PACF - Log Returns
Partial ACF
-0.06
-0.04
-0.02
0.00
0.02
0.04
0
5
10
15
20
25
30
35
Lag

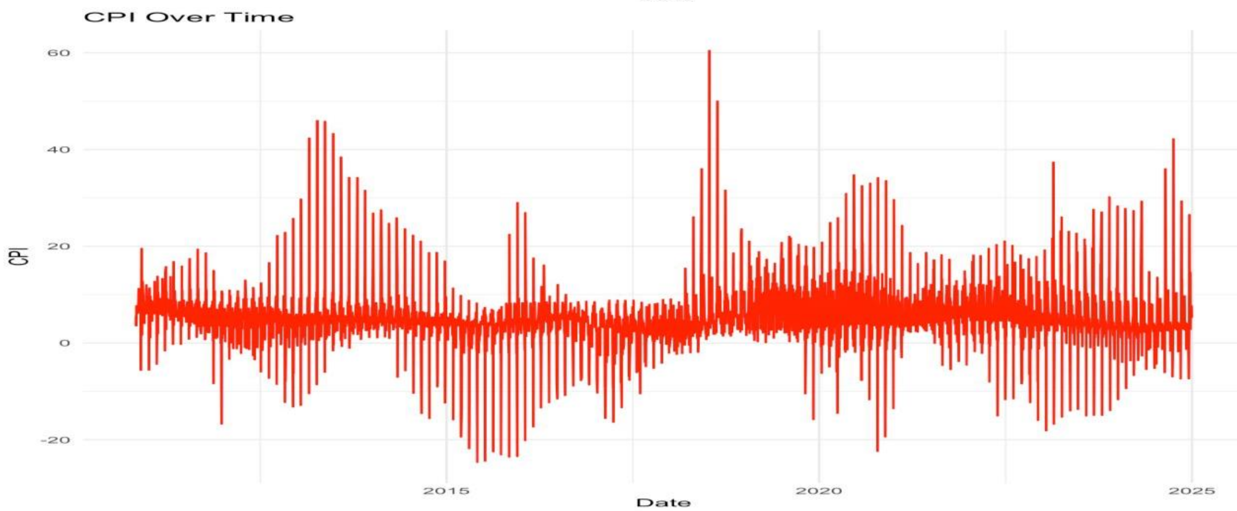

ACF - Volatility
ACF
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Lag

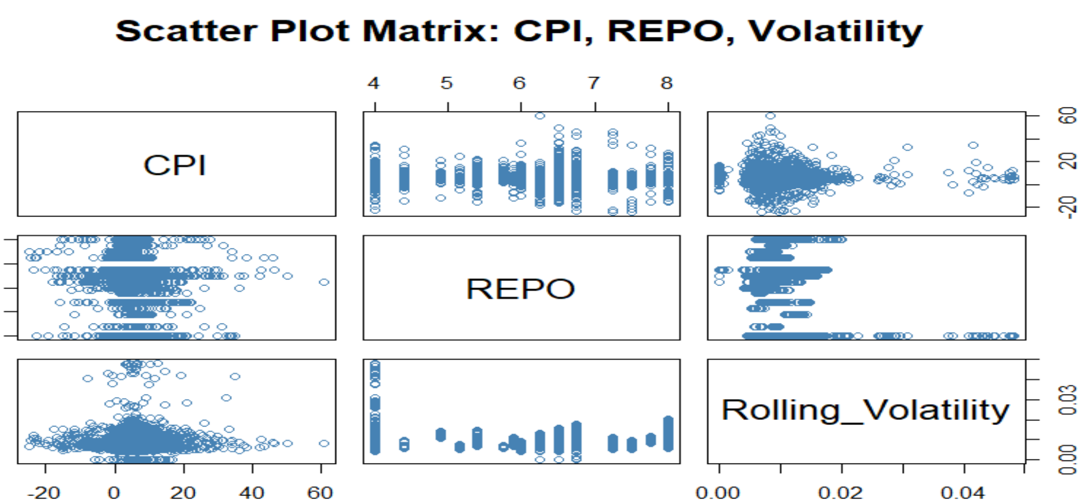

CPI, REPO & Volatility Time Series
value
Date
Variable
CPI
REPO
Volatility


ACF - Log Returns
ACF
Lag


Repo Rate Over Time
REPO
Date


Volatility Over Time
Rolling_Volatility
0.05
0.04
0.03
0.02
0.01
0.00
2015
2020
2025
Date


CPI Over Time
CPI
60
40
20
0
-20
2015
2020
2025
Date


Scatter Plot Matrix: CPI, REPO, Volatility
CPI
REPO
Rolling_Volatility
4
5
6
7
8
-20
0
20
40
60
0.00
0.02
0.04
0.03

CODE

```
# -------------------- Step 0: Load Libraries --------------------

packages <- c("readxl", "tseries", "vars", "forecast", "rugarch",

            "lmtest", "ggplot2", "gridExtra", "zoo", "fBasics", "reshape2", "corrplot", "WaveletComp")

new_packages <- packages[!(packages %in% installed.packages()[,"Package"])]

if(length(new_packages)) install.packages(new_packages)

lapply(packages, require, character.only = TRUE)

# -------------------- Step 1: Load Data --------------------

attach(AMAN_FE)

df=AMAN_FE

df$Date <- as.Date(df$DATE)

df <- df[order(df$Date), ]

df$REPO <- as.numeric(df$`REPO RATE`)

df$CPI <- as.numeric(df$CPI)

df$Price <- as.numeric(df$Price)

# -------------------- Step 2: Returns & Volatility --------------------

df$Log_Returns <- c(NA, diff(log(df$Price)))

df$Rolling_Volatility <- rollapply(df$Log_Returns, width = 30, FUN = sd, fill = NA, align = "right")

# -------------------- Step 3: Time Series & Plot --------------------

start_year <- as.numeric(format(min(df$Date), "%Y"))

ts_REPO <- ts(na.omit(df$REPO), start = c(start_year, 1), frequency = 12)

ts_CPI <- ts(na.omit(df$CPI), start = c(start_year, 1), frequency = 12)

ts_VOL <- ts(na.omit(df$Rolling_Volatility), start = c(start_year, 1), frequency = 12)

plot.ts(ts_REPO, main = "Repo Rate Time Series")

plot.ts(ts_CPI, main = "CPI Time Series")

plot.ts(ts_VOL, main = "Volatility Time Series")

# -------------------- Step 4: GGPlots --------------------

ggplot(df, aes(x = Date, y = CPI)) + geom_line(color = "red") + ggtitle("CPI Over Time") + theme_minimal()

ggplot(df, aes(x = Date, y = REPO)) + geom_line(color = "blue") + ggtitle("Repo Rate Over Time") + theme_minimal()

ggplot(df, aes(x = Date, y = Rolling_Volatility)) + geom_line(color = "purple") + ggtitle("Volatility Over Time") +
theme_minimal()

df_plot <- data.frame(Date = df$Date, CPI = df$CPI, REPO = df$REPO, Volatility = df$Rolling_Volatility)
```

```
df_melt <- melt(na.omit(df_plot), id.vars = "Date")

ggplot(df_melt, aes(x = Date, y = value, color = variable)) +

  geom_line() + labs(title = "CPI, REPO & Volatility Time Series", color = "Variable") + theme_minimal()

# -------------------- Step 5: Descriptive Statistics --------------------

df_stats <- na.omit(df_plot[, -1])

basicStats(df_stats)

# -------------------- Step 6: ACF, PACF --------------------

acf(na.omit(df$Log_Returns), main = "ACF - Log Returns")

pacf(na.omit(df$Log_Returns), main = "PACF - Log Returns")

acf(ts_VOL, main = "ACF - Volatility")

pacf(ts_VOL, main = "PACF - Volatility")

# -------------------- Step 7: ARIMA Forecast --------------------

d_CPI <- diff(ts_CPI)

arima_model <- auto.arima(d_CPI)

forecasted_return <- forecast(arima_model, h = 20)

plot(forecasted_return)

last_price <- tail(df$CPI, 1)

forecasted_price <- last_price * exp(forecasted_return$mean)

print(forecasted_price)

mean(arima_model$residuals)

arima_model$residuals

# -------------------- Step 8: GARCH --------------------

d_VOL <- diff(ts_VOL)

garch_spec <- ugarchspec(

  variance.model = list(model = "sGARCH", garchOrder = c(1,1)),

  mean.model = list(armaOrder = c(1,1)),

  distribution.model = "norm")

garch_fit <- ugarchfit(spec = garch_spec, data = d_VOL)

print(garch_fit)

plot(garch_fit)

# -------------------- Step 9: Correlation Matrix --------------------
```

```
# Granger causality
d_REPO <- diff(ts_REPO)
min_len <- min(length(d_REPO), length(d_CPI), length(d_VOL))
gc_data <- data.frame(
  d_REPO = tail(d_REPO, min_len),
  d_CPI = tail(d_CPI, min_len),
  d_VOL = tail(d_VOL, min_len))
grangertest(d_VOL ~ d_REPO, order = 2, data = gc_data)
grangertest(d_VOL ~ d_CPI, order = 2, data = gc_data)
corr_matrix <- cor(na.omit(df_stats))
corrplot(corr_matrix, method = "circle")
# -------------------- Step 10: Granger Causality --------------------
d_REPO <- diff(ts_REPO)
min_len <- min(length(d_REPO), length(d_CPI), length(d_VOL))
gc_data <- data.frame(
  d_REPO = tail(d_REPO, min_len),
  d_CPI = tail(d_CPI, min_len),
  d_VOL = tail(d_VOL, min_len))
grangertest(d_VOL ~ d_REPO, order = 2, data = gc_data)
grangertest(d_VOL ~ d_CPI, order = 2, data = gc_data)
# -------------------- Step 11: Wavelet Analysis --------------------
min_wavelet_len <- min(length(df$CPI), length(df$Rolling_Volatility), length(df$Date))
wavelet_data <- data.frame(
  date = tail(df$Date, min_wavelet_len),
  cpi = tail(df$CPI, min_wavelet_len),
  vol = tail(df$Rolling_Volatility, min_wavelet_len))
wavelet_data <- na.omit(wavelet_data)
wt_coherence <- analyze.coherency(
  wavelet_data,
  my.pair = c("cpi", "vol"),
  loess.span = 0,
```

```
  dt = 1,
  dj = 1/20,
  lowerPeriod = 2,
  upperPeriod = 64,
  make.pval = TRUE,
  n.sim = 10)
wt.image(wt_coherence,
         main = "Wavelet Coherence: CPI vs Volatility",
         legend.params = list(lab = "Wavelet Power"),
         color.key = "quantile",
         n.levels = 250)
wavelet_data$repo <- tail(df$REPO, nrow(wavelet_data))
wt_coherence_repo <- analyze.coherency(
  wavelet_data,
  my.pair = c("repo", "vol"),
  loess.span = 0,
  dt = 1,
  dj = 1/20,
  lowerPeriod = 2,
  upperPeriod = 64,
  make.pval = TRUE,
  n.sim = 10)
wt.image(wt_coherence_repo,
         main = "Wavelet Coherence: REPO Rate vs Volatility",
         legend.params = list(lab = "Wavelet Power"),
         color.key = "quantile",
         n.levels = 250)
# -------------------- Step 12: Scatter Plot Matrix --------------------
pairs(~ CPI + REPO + Rolling_Volatility, data = df_plot,
      main = "Scatter Plot Matrix: CPI, REPO, Volatility",
      col = "steelblue")
```

Variable	ADF Statistic	Lag Order	p-value	Stationary?
ts_REPO	-0.82585	15	0.9593	No
ts_CPI	-13.996	15	0.01	Yes
ts_VOL	-6.8049	15	0.01	Yes

Test	F-Statistic	p-value	Causal? (5%)
VOL ~ REP	1.9703	0.1396	No
VOL ~ CPI	0.2328	0.7924	No

Lag	AIC	HQ	SC
1	-18.22658	-18.21933	-18.20621
2	-18.36559	-18.3529	-18.32996
3	-18.40284	-18.38477	-18.35193
4	-18.43664	-18.41038	-18.36706
5	-18.4828	-18.45397	-18.40134
6	-18.4976	-18.46415	-18.39773
7	-18.5282	-18.48832	-18.40849
8	-18.53661	-18.49192	-18.39854
9	-18.56238	-18.51107	-18.40392
10	-18.5672	-18.511	-18.39084

Model	ARIMA(1,0,1)(0,0,2)[12] with zero mean
ar1	-0.0004
ma1	-0.9806
sma1	-0.094
sma2	-0.0716
sigma^2	30.04
log likelihood	-11438.46
AIC	22886.93
AICc	22886.95
BIC	22917.96
ME	-0.03147541
RMSE	5.477764
MAE	3.25062
MAPE	
MASE	0.4329122
ACF1	-0.000238448

GARCH Estimates

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.000002	3.5E-05	0.070948	0.9434
ar1	0.914475	0.02762	33.11062	0
ma1	-0.81356	0.04052	-20.0764	0
omega	0	0	0.019157	0.9847
alpha1	0.062449	0.00472	13.24517	0
beta1	0.911159	0.00313	291.0497	0

Robust Estimates

Parameter	Robust Estimate	Robust Std. Error	Robust t value	Robust Pr(>|t|)
mu	0.000002	0.151878	0.000016	0.99999
ar1	0.914475	46.709459	0.019578	0.98438
ma1	-0.813558	60.854809	-0.013369	0.98933
omega	0	0.001248	0.000005	1
alpha1	0.062449	4.377604	0.014266	0.98862
beta1	0.911159	8.312066	0.109619	0.91271

Pearson Fit Test

Group	Statistic	p-value(g-1)
20	2060	0
30	2185	0
40	2276	0
50	2378	0

Model Statistics

LogLikelihood	23241.47
AIC	-12.676
Bayes	-12.666
Shibata	-12.676
Hannan-Quinn	-12.673

Ljung-Box Test

Test	Statistic	p-value
Lag[1]	0.2179	0.64064
Lag[2*(p+q	4.9806	0.00354
Lag[4*(p+q	9.4674	0.01543

Ljung-Box Squared

Test	Statistic	p-value
Lag[1]	1.197	0.2739
Lag[2*(p+q)+(p+c	1.739	0.6813
Lag[4*(p+q)+(p+c	2.294	0.8672

Sign Bias Test

Test	t-value	p-value
Sign Bias	0.651	0.5152
Negative Sign Bias	1.291	0.1968
Positive Sign Bias	0.604	0.5457
Joint Effect	2.31	0.5106

ARCH LM Test

Lag	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.1619	0.5	2	0.6874
ARCH Lag[5]	1.1826	1.44	1.667	0.6796
ARCH Lag[7]	1.3529	2.315	1.543	0.8503

Nyblom Test

Parameter	Statistic
mu	0.0176
ar1	2.1651
ma1	2.6767
omega	147.062
alpha1	0.2277
beta1	0.4231

Nyblom Critical

Critical Value (10%)	Critical Value (5%)	Critical Value (1%)
1.49	1.68	2.12
0.35	0.47	0.75