Time Series Analysis and Volatility Modeling of SBIN.NS and INFY.NS

Srikrishna Das

MA24M025

Supervisor:- Prof. Neelesh S Upadhye



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1 Introduction

This report presents a detailed analysis of the closing prices and log returns for two prominent Indian stocks, SBIN.NS (State Bank of India) and INFY.NS (Infosys). The analysis employs various time series models including Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), GJR-GARCH, and Extreme Value Theory (EVT) with a focus on the Generalized Pareto Distribution (GPD). The objective is to model and forecast both stock prices and their associated volatilities.

The analysis relies on a suite of Python libraries for data handling, statistical modeling, and visualization, including yfinance, numpy, scipy, matplotlib.pyplot, pandas, statsmodels, pmdarima, sklearn.metrics, arch, and seaborn.

2 Data Acquisition and Initial Exploration

Closing price data for SBIN.NS and INFY.NS were downloaded from Yahoo Finance (yfinance) for the maximum available period.

2.1 Close Price Data Sample

A sample of the initial closing price data is presented below.

Table 1: Close Price of SBIN, INFY over time

Ticker Date	SBIN.NS	INFY.NS
1996-01-01	11.965004	0.511998
1996-01-02	11.584164	0.509927

2.2 Closing Price Comparison

The historical closing prices for both stocks are visualized to observe their long-term trends and fluctuations.



Figure 1: Closing Price Comparison

2.3 Classical Decomposition of Close Prices

Classical decomposition was applied to the closing prices of both SBIN.NS and INFY.NS, modeling an additive trend and seasonal components over a period of 252 observations.

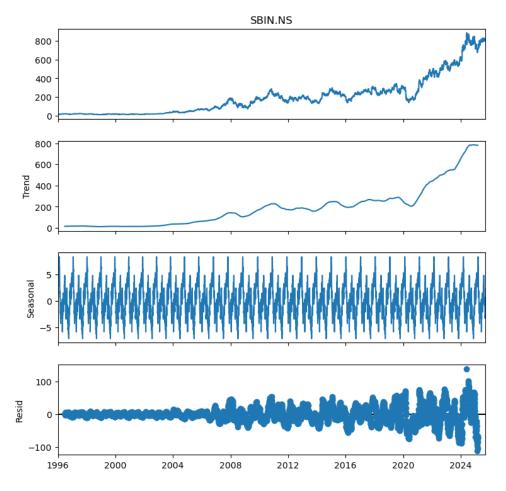


Figure 2: Classical Decomposition of SBIN.NS Close Price

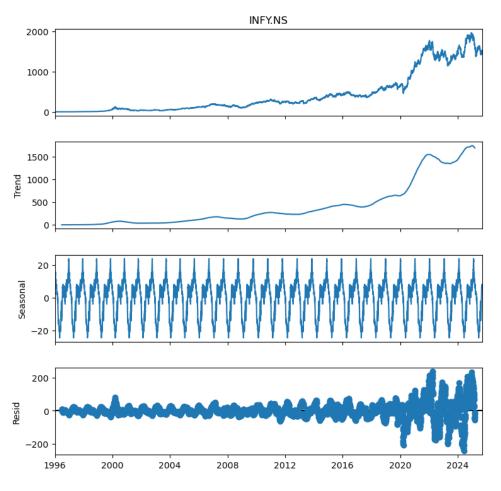


Figure 3: Classical Decomposition of INFY.NS Close Price

3 Stationarity Tests on Close Prices

To ascertain the stationarity of the closing price series, Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were performed.

3.1 Augmented Dickey-Fuller Test Results

The ADF test results for both stocks are presented below.

• SBI_Close:

- ADF Statistic: 1.2191613595661486

- p-value: 0.9961156328046668

- Lags Used: 34

- Number of Observations Used: 7423

- Conclusion: Fail to reject the null hypothesis (H0), the series is not stationary.

• INFY_Close:

- ADF Statistic: 0.2735748103194726

- p-value: 0.976099097239765

- Lags Used: 31

- Number of Observations Used: 7426

- Conclusion: Fail to reject the null hypothesis (H0), the series is not stationary.

3.2 KPSS Test Results

The KPSS test results for both stocks further confirm the non-stationarity.

• SBI_Close:

- KPSS Statistic: 10.353202593723001

- p-value: 0.01

- Number of Lags Used: 53

- Critical Values: 10%: 0.347, 5%: 0.463, 2.5%: 0.574, 1%: 0.739

- Conclusion: Reject the null hypothesis (H0), the series is not stationary.

• INFY_Close:

- KPSS Statistic: 10.268829331795486

- p-value: 0.01

- Number of Lags Used: 53

- Critical Values: 10%: 0.347, 5%: 0.463, 2.5%: 0.574, 1%: 0.739

- Conclusion: Reject the null hypothesis (H0), the series is not stationary.

Both tests consistently indicate that the close price series for both SBIN.NS and INFY.NS are not stationary.

4 Autocorrelation and Partial Autocorrelation Functions (ACF/PACF) and Differencing

ACF and PACF plots were generated for the first difference of the close prices to identify potential orders for ARIMA models. The 'ndiffs' function, utilizing the ADF test, indicated that one difference is required for both series to achieve stationarity.

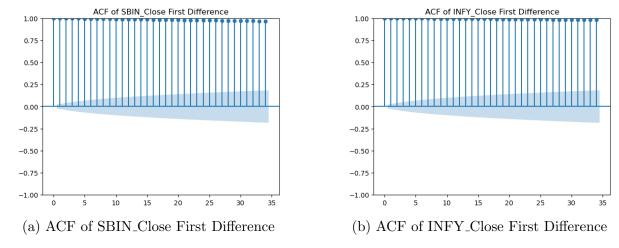


Figure 4: Autocorrelation Functions of First Differenced Close Prices

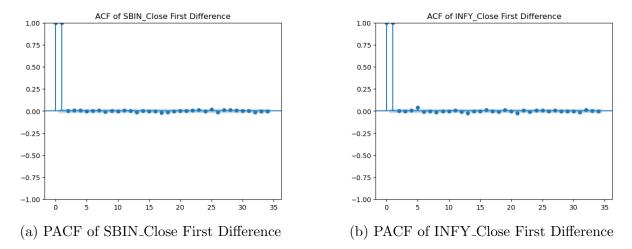


Figure 5: Partial Autocorrelation Functions of First Differenced Close Prices

- Estimated number of differences required for SBIN_Close: 1.
- Estimated number of differences required for INFY_Close: 1.

The data was then split into training (95%) and testing (5%) sets for ARIMA model development.

- Train data shape: (7085, 2).
- Test data shape: (373, 2).

5 ARIMA Model Forecasting

The **auto_arima** function was employed to automatically select the best ARIMA model order (p,d,q) by minimizing the Akaike Information Criterion (AIC).

5.1 ARIMA Model for SBIN.NS Close Price

The best ARIMA model for SBIN.NS close prices was identified as ARIMA(0,1,1)(0,0,0) with an intercept.

Table 2: SARIMAX Results for SBIN.NS ARIMA(0,1,1)

SARIMAX Results		
Dep. Variable: y	No. Observations: 7085	
Model: $SARIMAX(0, 1, 1)$	Log Likelihood: -20183.191	
Date: Fri, 12 Sep 2025	AIC: 40372.382	
Time: 23:39:43	BIC: 40392.979	
Sample: 0 - 7085	HQIC: 40379.475	
Covariance Type: opg		

The model's performance on the test set was evaluated using RMSE and MAPE.

• RMSE: 53.8107

• MAPE: 5.70%

A sample of the forecast confidence intervals is provided.

Table 3: ARIMA Forecast Confidence Interval for SBIN.NS (First 2 entries)

Date	Lower	Upper
2024-03-13	723.774175	740.157375
2024-03-14	720.211909	743.922869

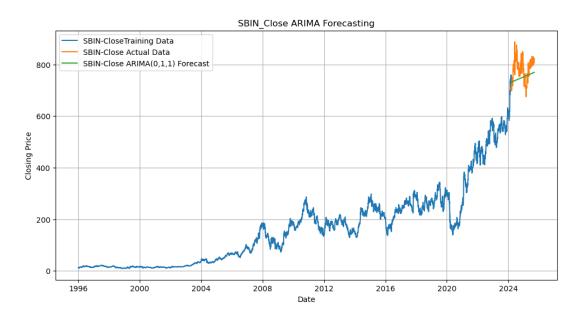


Figure 6: SBIN_Close ARIMA Forecasting

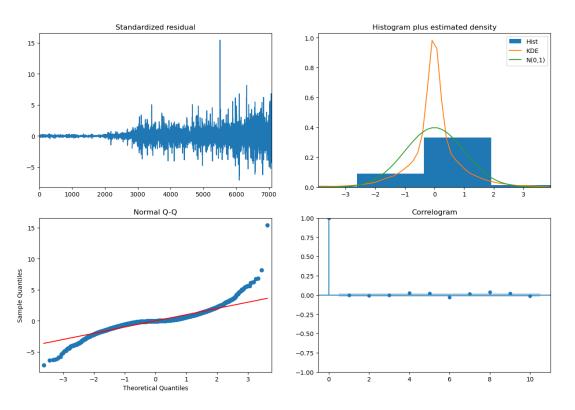


Figure 7: ARIMA Model Diagnostics for SBIN_Close

5.2 ARIMA Model for INFY.NS Close Price

The best ARIMA model for INFY.NS close prices was identified as ARIMA(1,1,1)(0,0,0) with an intercept.

Table 4: SARIMAX Results for INFY.NS ARIMA(1,1,1)

SARIMAX Results		
Dep. Variable: y No. Observations: 7085		
Model: $SARIMAX(1, 1, 1)$	Log Likelihood: -25564.854	
Date: Fri, 12 Sep 2025	AIC: 51137.707	
Time: 23:40:02	BIC: 51165.169	
Sample: 0 - 7085	HQIC: 51147.164	
Covariance Type: opg		

The model's performance on the test set was evaluated using RMSE and MAPE.

• RMSE: 193.9741

• MAPE: 9.90%

A sample of the forecast confidence intervals is provided.

Table 5: ARIMA Forecast Confidence Interval for INFY.NS (First 2 entries)

Date	Lower	Upper
2024-03-13	1533.712476	1568.734212
2024-03-14	1525.894837	1576.381621

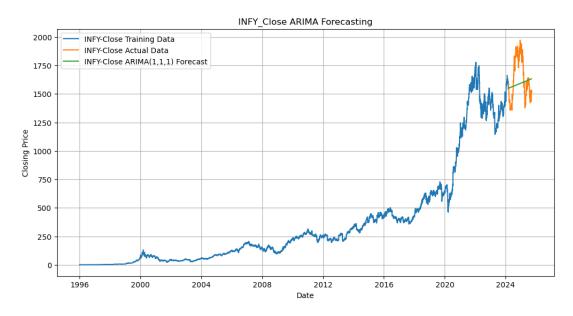


Figure 8: INFY_Close ARIMA Forecasting

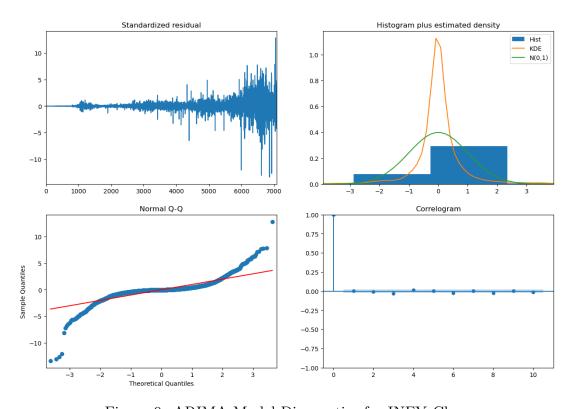


Figure 9: ARIMA Model Diagnostics for INFY_Close

6 Log Returns Analysis and Volatility Modeling

Daily log returns were computed for both stocks as a percentage, which is a common practice for financial time series analysis.

6.1 Log Returns Data Sample

A sample of the computed log returns is presented below.

Table 6: Log Returns of SBIN, INFY over time

Ticker Date	SBIN.NS	INFY.NS
1996-01-02	-3.234709	-0.405260
1996-01-03	-2.702548	0.674609

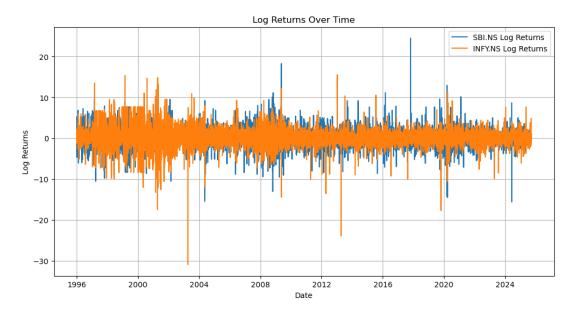


Figure 10: Log Returns Over Time

6.2 Stationarity and ARCH Effects on Log Returns

Stationarity of the log returns was tested using the ADF test, and the presence of ARCH effects was checked using the ARCH test.

6.2.1 Augmented Dickey-Fuller Test Results on Log Returns

The ADF test results for log returns indicate stationarity.

• SBI-Returns:

- ADF Statistic: -23.567715798719053

- p-value: 0.0

- Lags Used: 11
- Number of Observations Used: 7445
- Conclusion: Reject the null hypothesis (H0), the series is stationary.

• INFY-Returns:

- ADF Statistic: -14.056301415384182

- p-value: 3.112901770281877e-26

- Lags Used: 32

- Number of Observations Used: 7424

- Conclusion: Reject the null hypothesis (H0), the series is stationary.

The log return series for both stocks are found to be stationary.

6.2.2 ARCH Test Results on Log Returns

The ARCH test results for both log returns indicate significant ARCH effects.

• Arch Test for SBIN log-return:

- ARCH Test Statistic: 498.8984

- ARCH Test p-value: 0.0000

- ARCH Test F-statistic: 25.3903

- ARCH Test F-Test p-value: 0.0000

• Arch Test for INFY log-return:

- ARCH Test Statistic: 518.4929

- ARCH Test p-value: 0.0000

ARCH Test F-statistic: 26.4622

- ARCH Test F-Test p-value: 0.0000

The low p-values suggest that there are **statistically significant ARCH effects** present in both log returns, indicating the presence of volatility clustering.

The log return data was also split into training (95%) and testing (5%) sets for GARCH model development.

• Train data shape: (7084, 2).

• Test data shape: (373, 2).

6.3 GARCH Model for SBIN.NS Log Returns

A custom function **best_garch_model** was used to find the best GARCH(p,q) model with a Student's t-distribution, minimizing AIC. The best model for SBIN.NS log returns was found to be **GARCH(1, 2)** with an AIC of 30773.3989.

Table 7: Constant Mean - GARCH(1,2) Model Results for SBIN.NS Log-Returns

Constant Mean - GARCH Model Results			
Dep. Variable: SBIN.NS	R-squared: 0.000		
Mean Model: Constant Mean	Adj. R-squared: 0.000		
Vol Model: GARCH	Log-Likelihood: -15380.7		
Distribution: Standardized Student's t	AIC: 30773.4		
Method: Maximum Likelihood	BIC: 30814.6		
No. Observations: 7084	Df Residuals: 7083		
Date: Fri, Sep 12 2025	Df Model: 1		
Time: 23:40:05	Covariance estimator: robust		
Mear	Mean Model		
Term	Coefficient (Std. Error, T-stat, $P > t $)		
mu	0.0588 (0.0218, 2.693, 0.0071)		
Volatili	ity Model		
Term	Coefficient (Std. Error, T-stat, $P > t $)		
omega	0.1708 (0.0445, 3.837, 0.0001)		
alpha[1]	0.1191 (0.0154, 7.717, 1.189e-14)		

The RMSE for the SBIN.NS GARCH(1,2) forecast is ${\bf 0.4651}$.

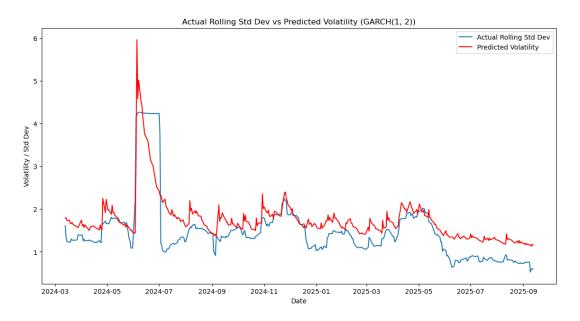


Figure 11: Actual Rolling Std Dev vs Predicted Volatility (GARCH(1,2)) for SBIN.NS

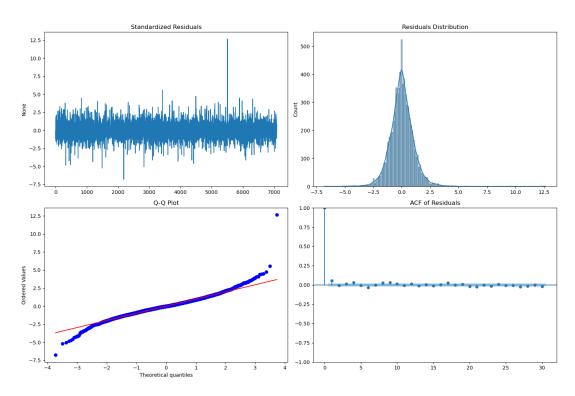


Figure 12: GARCH Model Diagnostics for SBIN.NS

6.4 GARCH Model for INFY.NS Log Returns

The best GARCH(p,q) model for INFY.NS log returns was found to be **GARCH(1, 5)** with an AIC of 29477.6792.

Table 8: Constant Mean - GARCH(1,5) Model Results for INFY.NS Log-Returns

Constant Mean - GARCH Model Results		
Dep. Variable: INFY.NS	R-squared: 0.000	
Mean Model: Constant Mean	Adj. R-squared: 0.000	
Vol Model: GARCH	Log-Likelihood: -14729.8	
Distribution: Standardized Student's t	AIC: 29477.7	
Method: Maximum Likelihood	BIC: 29539.5	
No. Observations: 7084	Df Residuals: 7083	
Date: Fri, Sep 12 2025	Df Model: 1	
Time: 23:41:02	Covariance estimator: robust	
Mean Model		
Term	Coefficient (Std. Error, T-stat, $P > t $)	
mu	0.0905 (0.0190, 4.755, 1.985e-06)	
Volatil	ity Model	
Term	$\textbf{Coefficient (Std. Error, T-stat, P}{>} t \textbf{)}$	

The RMSE for the INFY.NS GARCH(1,5) forecast is **0.3951**.

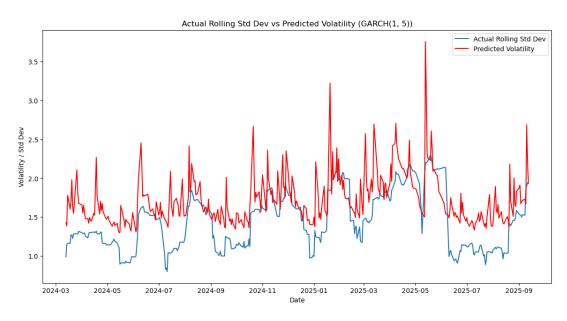


Figure 13: Actual Rolling Std Dev vs Predicted Volatility (GARCH(1,5)) for INFY.NS

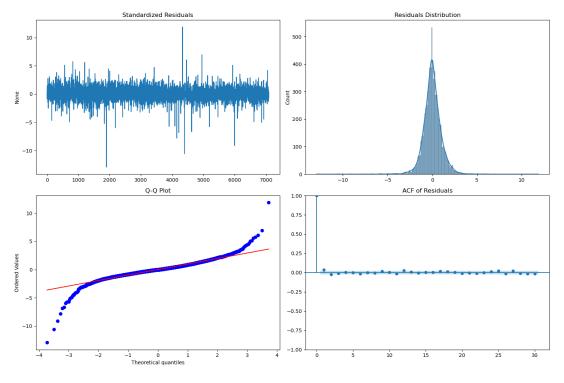


Figure 14: GARCH Model Diagnostics for INFY.NS

6.5 GJR-GARCH Model with Students-T Distribution

A GJR-GARCH(1,1,1) model with a Students-T distribution was applied to the log returns of both stocks to capture asymmetric volatility responses to positive and negative shocks.

6.5.1 GJR-GARCH(1,1,1) Model for SBIN.NS Log Returns

Table 9: Constant Mean - GJR-GARCH(1,1,1) Model Results for SBIN.NS Log-Returns

Constant Mean - GJR-GARCH Model Results		
Dep. Variable: SBIN.NS	R-squared: 0.000	
Mean Model: Constant Mean	Adj. R-squared: 0.000	
Vol Model: GJR-GARCH	Log-Likelihood: -15380.2	
Distribution: Standardized Student's t	AIC: 30772.4	
Method: Maximum Likelihood	BIC: 30813.6	
No. Observations: 7084	Df Residuals: 7083	
Date: Fri, Sep 12 2025	Df Model: 1	
Time: 23:42:29	Covariance estimator: robust	
Mear	n Model	
Term	Coefficient (Std. Error, T-stat, $P > t $)	
mu	0.0505 (0.0221, 2.291, 0.0220)	
Volatil	ity Model	
Term	Coefficient (Std. Error, T-stat, $P > t $)	
omega	0.1375 (0.0365, 3.768, 0.0002)	
alpha[1]	$0.0739 \ (0.0124, 5.930, 3.027e-09)$	
gamma[1]	$0.0353 \ (0.0125, \ 2.820, \ 0.0048)$	
beta[1]	$0.8880 \ (0.0169, \ 52.590, \ 0.000)$	
Distr	ribution	
Term	Coefficient (Std. Error, T-stat, $P > t $)	
nu	5.6788 (0.394, 14.409, 4.518e-47)	

The AIC for SBIN.NS GJR-GARCH model is 30772.4217 and BIC is 30813.6153.

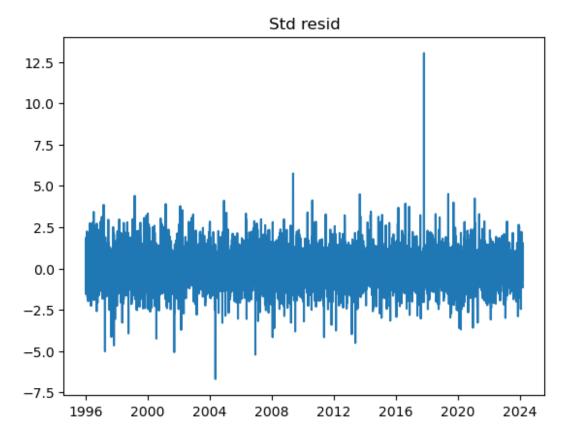


Figure 15: Standardized Residuals for SBIN.NS GJR-GARCH

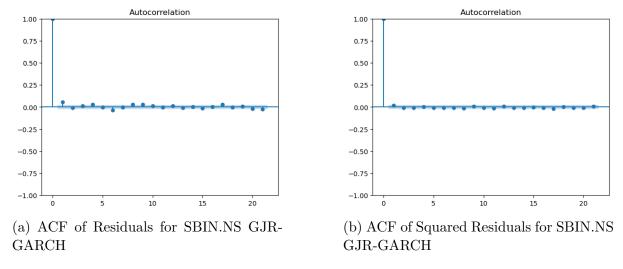


Figure 16: Autocorrelation Functions of Residuals and Squared Residuals for SBIN.NS GJR-GARCH

Table 10: Ljung-Box Test Results on Residuals for SBIN.NS

Lags	lb₋stat	lb_pvalue
10	55.102652	3.021648e-08
20	68.115410	3.687738e-07

Table 11: Ljung–Box Test Results on Squared Residuals for SBIN.NS (volatility clustering)

Lags	lb₋stat	lb₋pvalue
10	8.133868	0.615763
20	14.548234	0.801648

The ARCH LM p-value for SBIN.NS is **0.8120734381292837**. The RMSE for the SBIN.NS GJR-GARCH forecast is **0.4746**.

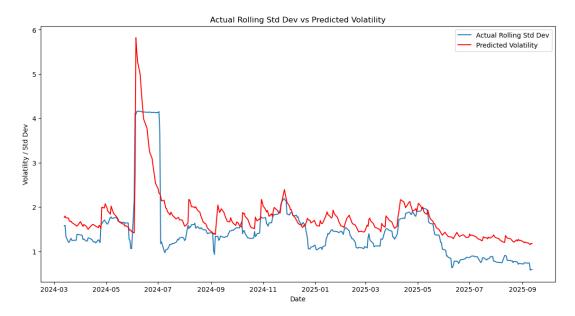


Figure 17: Actual Rolling Std Dev vs Predicted Volatility (GJR-GARCH) for SBIN.NS

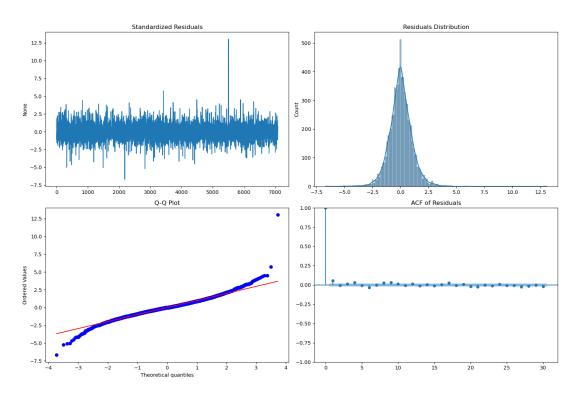


Figure 18: GJR-GARCH Model Diagnostics for SBIN.NS

6.5.2 GJR-GARCH(1,1,1) Model for INFY.NS Log Returns

Table 12: Constant Mean - GJR-GARCH(1,1,1) Model Results for INFY.NS Log-Returns

Constant Mean - GJR-GARCH Model Results			
Dep. Variable: INFY.NS	R-squared: 0.000		
Mean Model: Constant Mean	Adj. R-squared: 0.000		
Vol Model: GJR-GARCH	Log-Likelihood: -14748.3		
Distribution: Standardized Student's t	AIC: 29508.7		
Method: Maximum Likelihood	BIC: 29549.9		
No. Observations: 7084	Df Residuals: 7083		
Date: Sat, Sep 13 2025	Df Model: 1		
Time: 00:30:49	Covariance estimator: robust		
Mean Model			
Mean	n Model		
Term	$\frac{\text{n Model}}{\text{Coefficient (Std. Error, T-stat, P} > t)}$		
·			
Term mu	Coefficient (Std. Error, T-stat, $P > t $)		
Term mu	Coefficient (Std. Error, T-stat, P> $ t $) 0.0919 (0.0191, 4.814, 1.479e-06)		
Term mu Volatil	Coefficient (Std. Error, T-stat, P> t) 0.0919 (0.0191, 4.814, 1.479e-06) ity Model		
Term mu Volatil Term	Coefficient (Std. Error, T-stat, P> $ t $) 0.0919 (0.0191, 4.814, 1.479e-06) ity Model Coefficient (Std. Error, T-stat, P> $ t $)		

$\operatorname{gamma}[1]$	$0.0295 \ (0.0249, \ 1.186, \ 0.236)$		
beta[1]	$0.8153 \ (0.0398, \ 20.459, \ 4.957e-93)$		
Distribution			
Term Coefficient (Std. Error, T-stat, $P > t $)			
nu	4.0875 (0.224, 18.218, 3.744e-74)		

The AIC for INFY.NS GJR-GARCH model is 29508.6811 and BIC is 29549.8746.

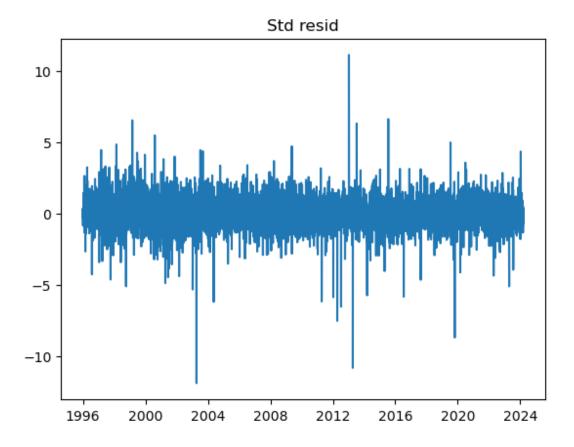
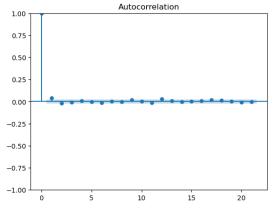
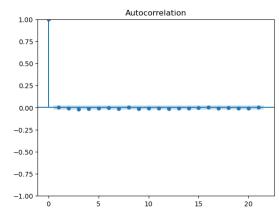


Figure 19: Standardized Residuals for INFY.NS GJR-GARCH





- (a) ACF of Residuals for INFY.NS GJR-GARCH
- (b) ACF of Squared Residuals for INFY.NS $\operatorname{GJR-GARCH}$

Figure 20: Autocorrelation Functions of Residuals and Squared Residuals for INFY.NS GJR-GARCH

Table 13: Ljung-Box Test Results on Residuals for INFY.NS

Lags	lb₋stat	lb_pvalue
10	21.215202	0.019642
20	34.055708	0.025750

Table 14: Ljung–Box Test Results on Squared Residuals for INFY.NS (volatility clustering)

Lags	lb₋stat	lb_pvalue
10	7.960256	0.632719
20	12.107908	0.912312

The ARCH LM p-value for INFY.NS is $\bf 0.8951512570675989$. The RMSE for the INFY.NS GJR-GARCH forecast is $\bf 0.4364$.

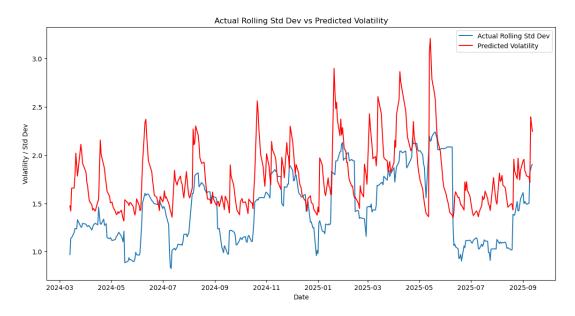


Figure 21: Actual Rolling Std Dev vs Predicted Volatility (GJR-GARCH) for INFY.NS

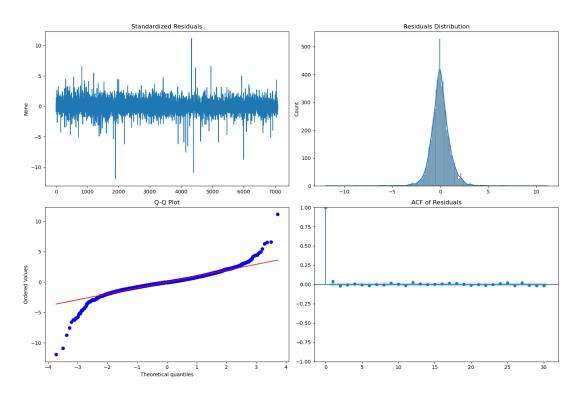


Figure 22: GJR-GARCH Model Diagnostics for INFY.NS

7 Extreme Value Theory (EVT) - Peaks Over Threshold (POT) and GPD Fit

EVT analysis using the Peaks Over Threshold (POT) method with Generalized Pareto Distribution (GPD) was performed on the log returns to model extreme events.

7.1 EVT Analysis for SBIN.NS

Log returns for SBIN.NS were selected for EVT analysis. Initial exploration included Block Maxima and POT methods for extreme value extraction, followed by Mean Residual Life and Parameter Stability plots for threshold selection.

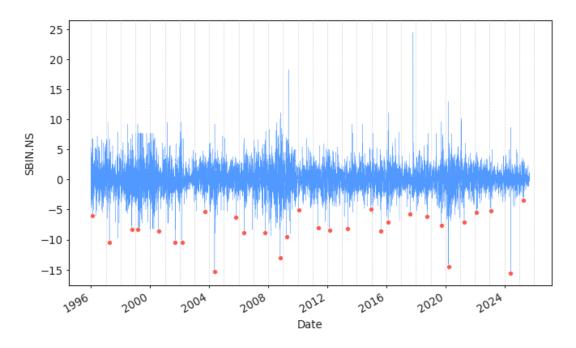


Figure 23: Extracted Extreme Values for SBIN.NS (Block Maxima - Low)

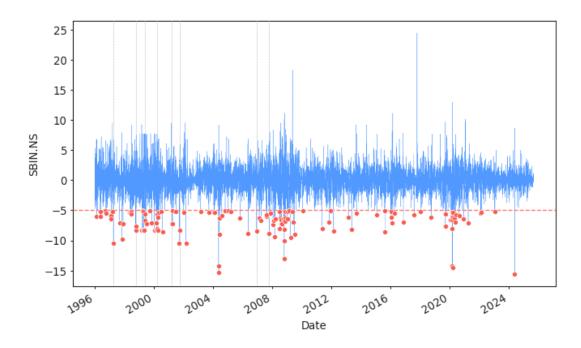
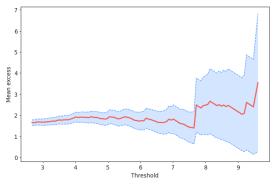
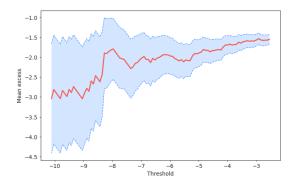


Figure 24: Extracted Extreme Values for SBIN.NS (POT - Low, Threshold -5)

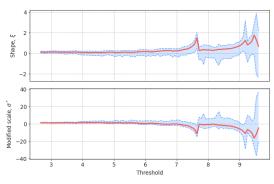


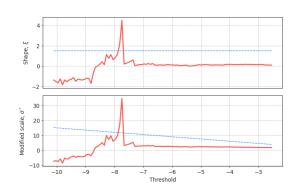


(a) Mean Residual Life Plot (High) for SBIN.NS $\,$

(b) Mean Residual Life Plot (Low) for SBIN.NS

Figure 25: Mean Residual Life Plots for SBIN.NS





- (a) Parameter Stability Plot (High) for SBIN.NS $\,$
- (b) Parameter Stability Plot (Low) for SBIN.NS $\,$

Figure 26: Parameter Stability Plots for SBIN.NS

Upper and lower thresholds for POT were set at 6.8 and -7.1, respectively.

7.1.1 Upper Tail (SBIN.NS)

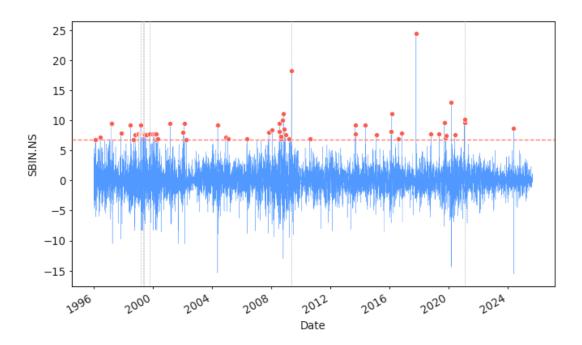


Figure 27: Extracted Extremes for SBIN.NS (POT - High, Threshold 6.8)

Number of Upper exceedances: 73.

Fitted GPD parameters: Upper: shape=0.2347, loc=0.0000, scale=1.2698.

Table 15: Return Period Summary Table (Upper Tail for SBIN.NS)

Return Period	Return Value	Lower CI	Upper CI
5.0	11.033562	9.563328	12.837318
10.0	12.808337	10.113639	16.066329
25.0	15.683417	10.747507	22.807935
50.0	18.343651	11.052627	30.303452
100.0	21.510465	11.310440	41.275181
250.0	26.640608	11.605625	63.246238
500.0	31.387388	11.784304	88.848916

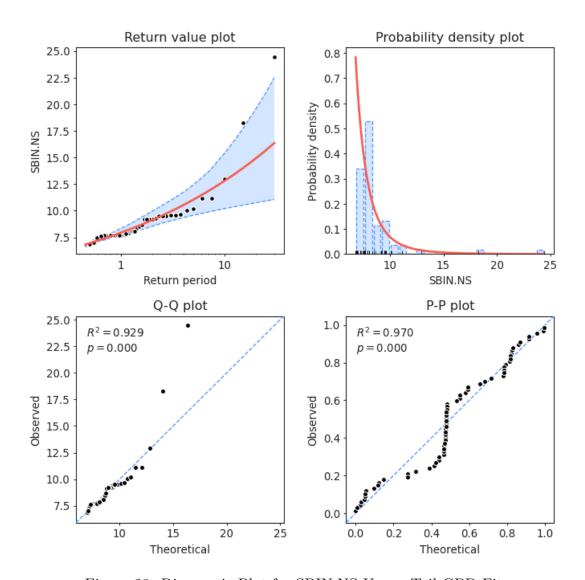


Figure 28: Diagnostic Plot for SBIN.NS Upper Tail GPD Fit

7.1.2 Lower Tail (SBIN.NS)

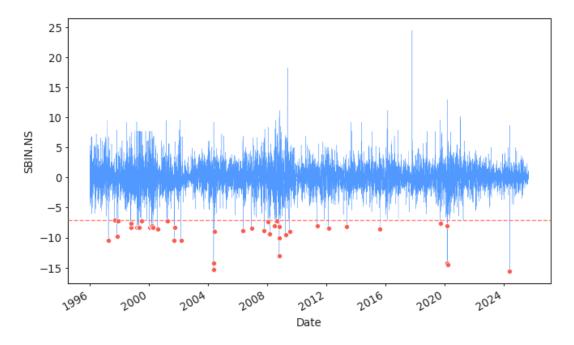


Figure 29: Extracted Extremes for SBIN.NS (POT - Low, Threshold -7.1)

Number of Lower exceedances: 45.

Fitted GPD parameters: Lower: shape=0.0930, loc=0.0000, scale=1.9219.

Table 16: Return Period Summary Table (Lower Tail for SBIN.NS)

Return Period	Return Value	Lower CI	Upper CI
5.0	-11.326967	-10.045259	-12.696948
10.0	-13.033496	-11.158379	-14.629466
25.0	-15.543824	-12.603847	-18.345814
50.0	-17.655872	-13.728093	-22.767962
100.0	-19.971028	-14.765379	-28.558467
250.0	-23.376657	-16.099475	-38.948887
500.0	-26.241960	-16.863689	-50.270198

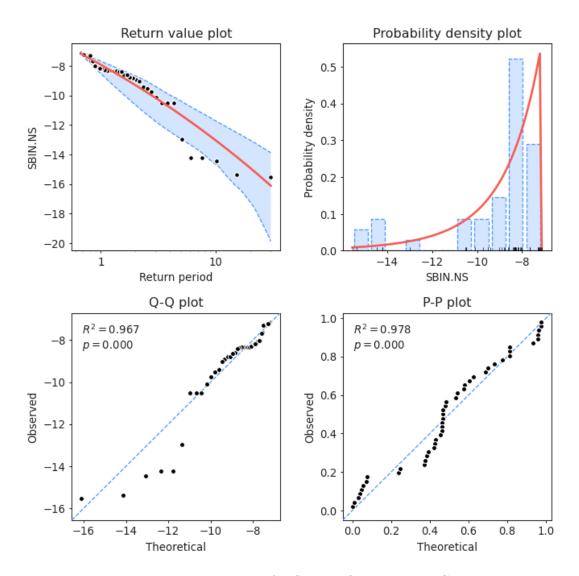


Figure 30: Diagnostic Plot for SBIN.NS Lower Tail GPD Fit

7.1.3 Goodness-of-Fit Tests (SBIN.NS)

Upper Tail Goodness-of-Fit:

- **KS test**: statistic=0.1873, p-value=0.0102
- Anderson–Darling test for GPD fit (via PIT):
 - Statistic: 2.3386
 - Critical values: [0.914 1.069 1.33 1.593 1.941]
 - Significance levels: [15. 10. 5. 2.5 1.]

Lower Tail Goodness-of-Fit:

- KS test: statistic=0.1513, p-value=0.2299
- Anderson–Darling test for GPD fit (via PIT):
 - Statistic: 0.9298

- Critical values: [0.91 1.064 1.323 1.585 1.931]

- Significance levels: [15. 10. 5. 2.5 1.]

7.1.4 Global PIT (full marginal CDF) for SBIN.NS

A smooth CDF was constructed using a t-distribution for the body and GPD tails, with a logistic splice for the transition.

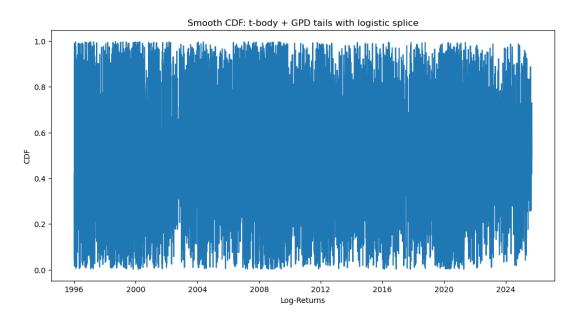


Figure 31: Smooth CDF: t-body + GPD tails with logistic splice for SBIN.NS

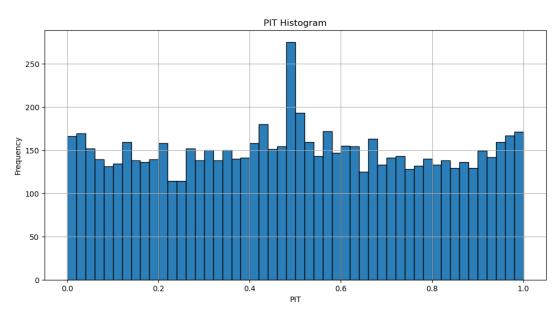


Figure 32: PIT Histogram for SBIN.NS

KS Test for Uniformity of PIT values (SBIN.NS):

• KS statistic: 0.0174, p-value: 0.0220

7.2 EVT Analysis for INFY.NS

Log returns for INFY.NS were subjected to similar EVT analysis.

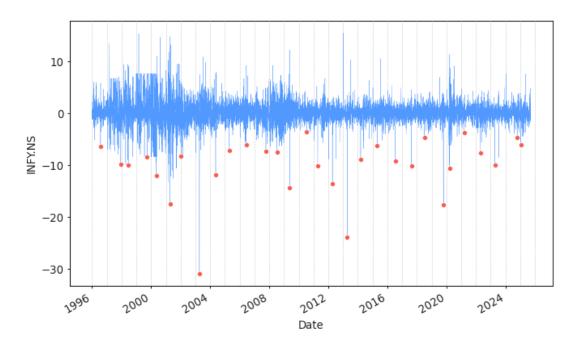


Figure 33: Extracted Extreme Values for INFY.NS (Block Maxima - Low)

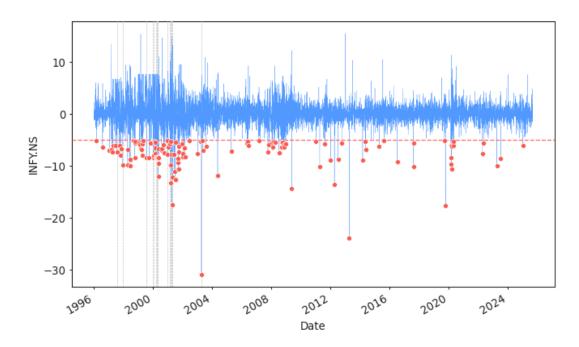
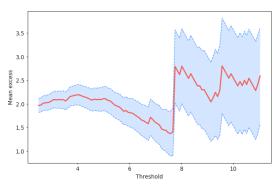
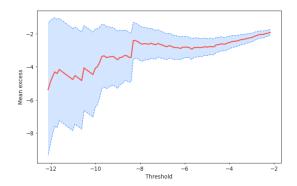


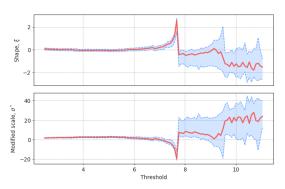
Figure 34: Extracted Extreme Values for INFY.NS (POT - Low, Threshold -5)

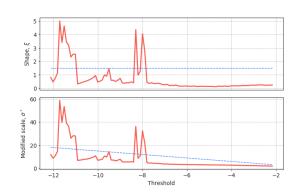




- (a) Mean Residual Life Plot (High) for $\operatorname{INFY.NS}$
- (b) Mean Residual Life Plot (Low) for INFY.NS

Figure 35: Mean Residual Life Plots for INFY.NS





- (a) Parameter Stability Plot (High) for $\operatorname{INFY.NS}$
- (b) Parameter Stability Plot (Low) for INFY.NS

Figure 36: Parameter Stability Plots for INFY.NS

Upper and lower thresholds for POT were set at 5 and -7.8, respectively.

7.2.1 Upper Tail (INFY.NS)

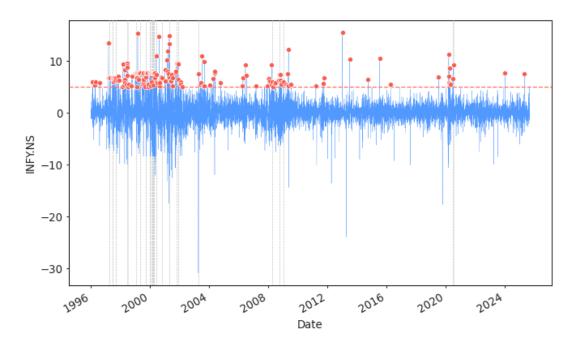


Figure 37: Extracted Extremes for INFY.NS (POT - High, Threshold 5)

Number of Upper exceedances: 210.

Fitted GPD parameters: Upper: shape=-0.0869, loc=0.0000, scale=2.2910.

Table 17: Return Period Summary Table (Upper Tail for INFY.NS)

Return Period	Return Value	Lower CI	Upper CI
5.0	12.050764	10.920361	13.153558
10.0	13.286225	11.860744	14.729138
25.0	14.826672	12.980057	16.888924
50.0	15.925628	13.715211	18.520407
100.0	16.970542	14.357779	20.339061
250.0	18.273404	15.073959	22.627256
500.0	19.202866	15.481809	24.428296

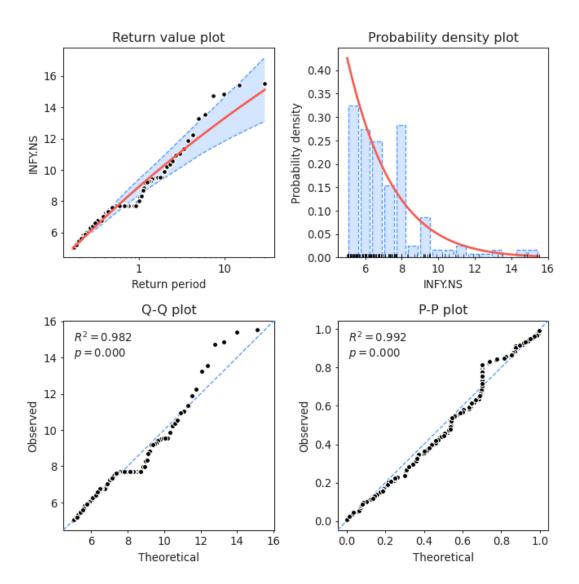


Figure 38: Diagnostic Plot for INFY.NS Upper Tail GPD Fit

7.2.2 Lower Tail (INFY.NS)

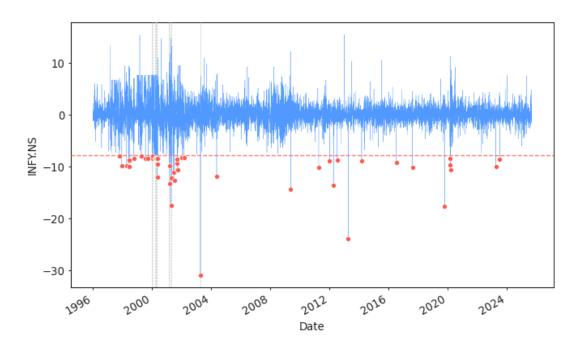


Figure 39: Extracted Extremes for INFY.NS (POT - Low, Threshold -7.8)

Number of Lower exceedances: 60.

Fitted GPD parameters: Lower: shape=0.3693, loc=0.0000, scale=1.6635.

Table 18: Return Period Summary Table (Lower Tail for INFY.NS)

Return Period	Return Value	Lower CI	Upper CI
5.0	-13.489699	-11.498241	-15.920514
10.0	-16.726617	-12.904234	-21.783638
25.0	-22.811005	-14.881361	-36.506843
50.0	-29.318953	-16.606403	-55.510045
100.0	-38.110667	-18.536147	-86.435792
250.0	-54.636328	-20.591047	-163.313953
500.0	-72.312408	-22.181420	-273.176577

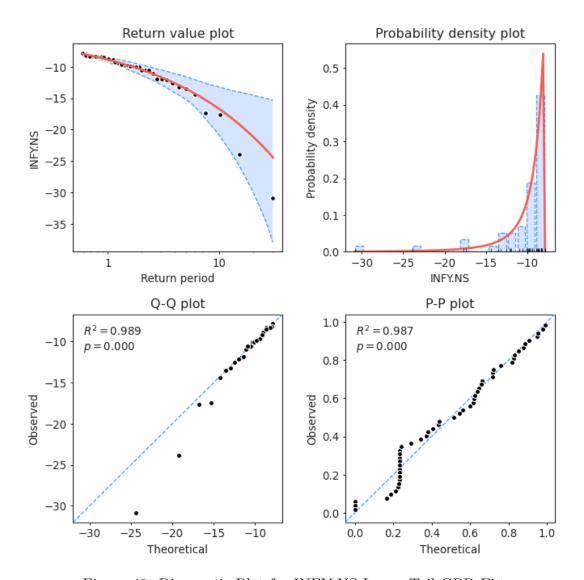


Figure 40: Diagnostic Plot for INFY.NS Lower Tail GPD Fit

7.2.3 Goodness-of-Fit Tests (INFY.NS)

Upper Tail Goodness-of-Fit:

- KS test: statistic=0.1347, p-value=0.0009
- Anderson–Darling test for GPD fit (via PIT):
 - Statistic: 2.4111
 - Critical values: [0.919 1.075 1.337 1.601 1.951]
 - Significance levels: [15. 10. 5. 2.5 1.]

Lower Tail Goodness-of-Fit:

- KS test: statistic=0.1449, p-value=0.1458
- Anderson–Darling test for GPD fit (via PIT):
 - Statistic: 1.2848

- Critical values: [0.913 1.067 1.328 1.59 1.938]

- Significance levels: [15. 10. 5. 2.5 1.]

7.2.4 Global PIT (full marginal CDF) for INFY.NS

A smooth CDF was constructed for INFY.NS using a t-distribution for the body and GPD tails with a logistic splice.

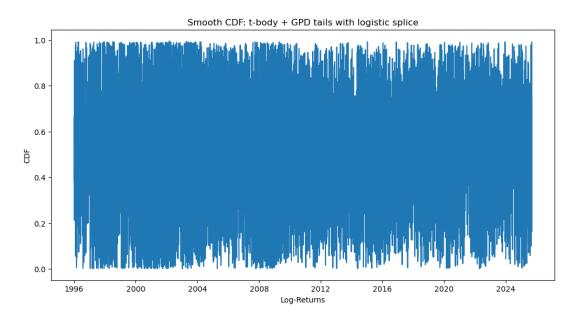


Figure 41: Smooth CDF: t-body + GPD tails with logistic splice for INFY.NS

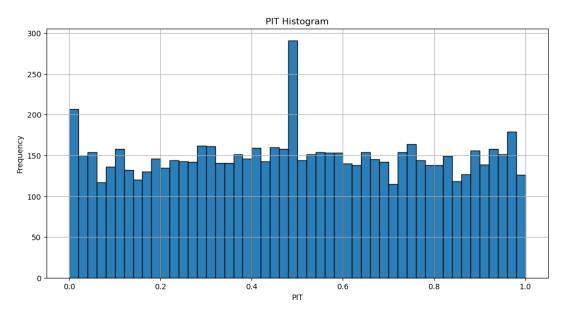


Figure 42: PIT Histogram for INFY.NS

KS Test for Uniformity of PIT values (INFY.NS):

• KS statistic: 0.0153, p-value: 0.0600