Revista de Științe Politice. Revue des Sciences Politiques • No. 91 • 2026: 138 – 157

ORIGINAL PAPER

Volatility Dynamics of Public and Private Sector Banks in India: A Comparative Study of BOI and ICICI Bank Using GARCH-Family Models

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Abstract:
The current study investigates the volatility behaviour of the leading banks in India, i.e., Bank of India (BOI) andIndustrial Credit and Investment Corporation of India (ICICI), representing the public and private banking sectors. The study analyses daily stock prices from 22nd February2016 to 20th February 2026to examine how both banks reacted to market fluctuations, economic uncertainty, and major shocks, including the COVID-19 period. To analyse volatility, the study applies different GARCH-family models, including GARCH, TGARCH, EGARCH, PARCH, and APARCH models, under alternative error distributions.

The result reflects that both BOI and ICICI Bank exhibit volatility clustering, non-normal return behaviour, and persistent market shocks. And the ARCH-LM test confirms the presence of heteroskedasticity, which braces the use of GARCH-family models for volatility gauging. The findings betray that the EGARCH model with Student's t-distribution is most suitable for BOI, while the APARCH model with Student's t-distribution provides the ideal for ICICI Bank. The study also suggests that ICICI Bank shows substantial volatility and brawny vulnerability to market shocks than BOI.

The study concludes that volatility tessellated differently between public and private-sector banks; therefore, a single model cannot elucidate the risk behaviour of all banking stocks. The edicts are useful for investors, portfolio managers, researchers, and

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policymakers in understanding risk, improving portfolio decisions, and prophesying the volatility in the Indian banking sector.
Keywords: *Indian Banking System, Bank of India, ICICI, GARCH models, Volatility*
JEL Classification Codes: G0, G1, C22, C11, C17

Introduction

BOI and ICICI are two major banks and hold a remarkable value in the Indian banking sector. They are the rescuer of the financial market, from local vendors to big corporate players. When their stock prices are volatile, it not only shows on a digital screen but also reveals whether the Indian economy is struggling or breathing easily. However, risk is always there; they presume prices are steady or fluctuate consistently, but the reality is somewhat different. The stock market is characterised by unexpected events, explosive jumps, and market crashes, driven by the COVID-19 pandemic and shifting microeconomic factors that do not fit a standard, predictable pattern.

After analysing 10 years of daily data from 2016 to 2026, this study compares the volatility patterns of ICICI and BOI, revealing their resilience and stability following significant events such as the COVID-19 pandemic. It employs advanced mathematical models, including the GARCH family, to provide insights into their risk profiles.

The finding shows that the private sector, such as ICICI, has higher kurtosis than the public sector, such as BOI. It is vital for those who are managing a portfolio or forecasting future risk. It shows that ICICI performs best with the APARCH model, and BOI performs slightly differently and captures the EGARCH model. Once understand these different patterns, it becomes much easier to see the ups and downs in the Indian banking sector.

Review of Literature

Recent studies have shown that stock prices don’t change significantly. Prices fluctuate irregularly, often in clusters. To analyse this, researchers go for advanced GARCH models to better understand and measure changes over time. Moreover, Trivedi et al. (2022) investigated the behavior of the Chinese stock market under the impact of the Covid-19 pandemic. Meher et al. (2023) have developed a research study on the FinTech industry in emerging markets. Spulbar et al. (2020) also discussed key issues regarding the dynamics of FinTech industry.

Raza et al., (2026) have conducted an empirical analysis of the volatility of the Deutscher Aktienindex (DAX) stock index using a daily dataset of 5,140 daily return observations from January 2, 2006, to March 20, 2026. The main objective of this study is to develop an econometric framework to assess the asymmetric response to market volatility shocks. The study evaluates GARCH family models—GARCH, EGARCH, GJR-GARCH, and APARCH—with error distributions like Normal, Student-t, GED, and Skewed-t. Testing shows the return series is stationary, non-normal, and has "fat tails". The GJR-GARCH model with a Skewed-t distribution is the best fit for the DAX index, based on the lowest AIC and BIC values. The findings offer valuable insights for investors and policymakers on risk gauging and strategic recommendations in the German stock market.

Shreevastava et al., (2025) the study has analysed recurrent patterns in high-frequency financial data, focusing on volatility clustering, leptokurtosis, and the asymmetric effects of news, and has conducted a thorough examination of GARCH models. The overriding goal of this study is to analyse econometric modelling and volatility conditioning in daily logarithmic returns for the MSCI index from Nov 2012 to Oct 2025.This research examines how well six GARCH models fit the data: the standard GARCH (1,1), Integrated GARCH (IGARCH), Threshold GARCH (TARCH), Exponential GARCH (EGARCH), Power ARCH (PARCH), and Asymmetric Power ARCH (APARCH). The study exploits a univariate GARCH model, concentrating exclusively on the volatility of the MSCI Mexico Index. This framework excludes potential contagion effects and interdependencies with other global markets or principal commodity prices, potentially biasing risk estimates by striking out significant exogenous factors.

Waris et al. (2026) have discussed the government's role in implementing economic reforms and addressing financial crises, particularly regarding price volatility. For this, the researcher has used data from the DataStream database on the MSCI price index for Malaysia and its trading partner from 1993 to 2021. The study used wavelet analysis, asymmetric GARCH models, and a stochastic volatility model to analyse the data. The finding shows asymmetric volatility transmission: negative shocks increase volatility more than positive ones. The author concluded that investors should invest in low-volatility stocks during a crisis. The study suggested that the government should implement effective policies to address pre- and post-crisis periods and help recover from losses.

Sharma and Vipul, (2015) argued that the objective is to compare daily conditional variance forecasts from seven GARCH models: GARCH, EGARCH, GJR-GARCH, TGARCH, AVGARCH, APARCH, and NGARCH models, using daily data for 21 stock indices from 1 January 2000 to 30 November 2013. The sample includes eight European, nine Asia-Pacific, and four American indices from Bloomberg, truncated to 3,395 trading days, and matched to the Jakarta Stock Exchange. The forecasts are tested statistically, concluding that the standard GARCH model outperforms advanced models in predicting stock index variance, providing the most accurate one-step forecasts across market conditions and is unaffected by data-snooping bias.

Lin, (2018) investigated the volatility of the SSE Composite Index using GARCH-family models, including GARCH(1,1), TARCH(1,1), and EGARCH(1,1). The researcher collected 996 daily closing prices spanning from January 3, 2011, to January 30, 2015. Analytical procedures using E-Views 8.0 and Excel included descriptive statistics, stationarity tests, and ARCH testing. The findings indicated volatility clustering, leptokurtic distribution, and significant ARCH, GARCH, and E-GARCH effects, with the E-GARCH(1,1) model demonstrating superior performance in volatility forecasting.

Chiang et al. (2001) aimed to analyse the relationship between market stock returns and volatility based on seven Asian stock exchanges: Hong Kong, Malaysia, the Philippines, Singapore, South Korea, Thailand, and Taiwan. At the same time, Japan and the United States were included for comparison of **daily, weekly, and monthly stock price index data** from January 1988 to June 1998. The authors employed the Threshold Autoregressive GARCH/TAR-GARCH (1,1)-in-mean model along with the ARIMA model. Various statistical models, such as mean return, standard deviation, skewness, excess kurtosis, autocorrelation, and the Ljung-Box Q (12) statistic for returns and squared returns, are used to forecast volatility and asymmetric effects. The findings revealed that 4 out of 7 stock exchanges have a **significant relationship between stock returns and unexpected volatility.** The study is limited because it includes only seven Asian countries, fails to address its generalizability, and relies on historical data that may not apply to the current context.

Aman et al. (2024) investigated the volatility pattern of the BUX index using advanced GARCH-family models. This study is based on quantitative, exploratory data collected from secondary sources on the BUX index, covering daily data from 2011 to 2024. This study investigates the APARCH (1,1) Student's t-distribution model to examine the volatility pattern of the BUX Index using the variance equation and finds asymmetry, volatility clustering, slower decay, and a strong influence of positive shocks, with a low response to them. The study is limited to a single data source, which is the BUX Index, which hinders the generalisability of the findings. Further research can be conducted using more advanced econometric tools, such as VARs, Copulas, and machine learning.

Gokbulut and Pekkaya, (2014) explored and forecasted the volatility of Turkish financial markets, focusing on exchange rate and interest rate returns. This study is based on secondary sources, and data are drawn from the BIST 1000 for the period 2000-2014. GARCH-family models, including ARCH, GARCH, TGARCH, EGARCH, PARCH, AGARCH, and CGARCH models, were used for the econometric analysis. CGARCH and TGARCH models have a significant, positive influence on financial market volatility among all GARCH-family models. However, this study is limited to Turkish financial markets, and the results cannot be applied to other countries. More advanced tools can be used for further research and cross-country validation to examine different financial markets and improve forecasting accuracy and broader applicability.

Lim et al. (2023) focused to estimate market volatility and the causal relationship between the markets using the historical daily prices ranging from 2008 to 2019 of the selected ASEAN stock markets, Financial Times Stock Exchange (FTSE), Bursa Malaysia Kuala Lumpur Composite Index (KLCI), the Indonesia Stock Exchange Index (LQ45), and the Stock Exchange of Thailand (SET). This study used a univariate GARCH model to capture the volatility of financial instruments, the ARIMA-GARCH model and the Granger causality test examined the causal relationships among markets.

The findings revealed volatility clustering, leverage effects, and asymmetric volatility across markets. Among the estimated models, the EGARCH(1,1) model was found to be the most effective in capturing asymmetric volatility behaviour. The main challenge of this study is that it has taken only four stock markets, which limits the generalisability of the findings for other research. Further research can be conducted across more countries and with additional advanced models to capture market volatility.

Endri et al. (2020) aimed to analyse the effect of macroeconomic variables (interest rates, exchange rate and inflation) and global stock exchange (STI, SSE, N225, DJIA, FTSE100) on the Indonesian stock exchange. The researcher has taken monthly data from secondary sources of the Indonesian stock exchange from 2012 to 2018 and applied the GARCH model, along with ADF unit root tests and AIC/SC criteria for model selection. The results show that interest rates and inflation have negative effects, while the exchange rate has a positive effect on the Indonesian stock exchange. The limitation of the study is that it utilises the GARCH (1,1) model exclusively and does not compare its performance with asymmetric models such as EGARCH, TGARCH, or APARCH models. Future research may use alternative GARCH models to obtain more robust volatility estimates and improve forecasting accuracy.

Frimpong et al. (2006) examined market volatility at the Ghana Stock Exchange over a 10-year period. The data has been collected from the period 1994-2004 of the

Ghana Stock Exchange Databank Stock Index (DSI). Random walk (RW), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) models were applied to the analysis. The results show that the symmetric GARCH (1,1) model outperformed all other models, as it had the lowest error measures. However, the analysis was limited to basic GARCH-family models and to only one stock market. The author suggested that the IGARCH and APARCH models are better suited to capture the long-memory characteristics of stock market volatility.

Research Gap

The Industrial Credit and Investment Corporation of India (ICICI) and Bank of India (BOI) are listed on the National Stock Exchange (NSE). Empirical studies have been conducted to date; however, a significant research gap remains in the advanced GARCH family for volatility forecasting. A Substantial body of existing literature has reviewed various methodologies, but it lacks a comprehensive understanding. This study analyses and understands how the stock prices of ICICI and BOI fluctuate using the GARCH Model. The study tries to analyse how much stock prices will fluctuate in future.

Objective of the studies

1. To study the price instability of BOI Bank and ICICI Bank from 22/02/2016 to 20/02/2026.
2. To examine volatility characteristics between a public sector bank, i.e. BOI, and a private sector bank, i.e. ICICI.
3. To conduct a comparative assessment of GARCH Family models (such as GARCH, EGARCH, TARCH, PARCH, APARCH) in capturing volatility dynamics of both banking entities.

Research Hypotheses

This study is Quantitative and exploratory in nature. The study adopts a stepwise modelling approach for volatility estimation and forecasting. There are 2478 data points for both banks (ICICI and BOI) spanning 22/02/2016 to 20/02/2026. The objective of the study is to estimate volatility using the GARCH Family models with Gaussian normal distribution, Student's t distribution, generalised error distribution (GED), t distribution, and GED distribution with parameters. Log returns were computed to stabilise the data series, yet volatility persistence was observed. To examine heteroskedasticity in the return series residuals, the ARCH-LM Test was used. Multiple GARCH-family models (GARCH, TGARCH, EGARCH, PARCH, and APARCH) were applied with different volatility distributions.

Significance of the study

The study holds significant value because volatility plays an important role in financial and investment decisions. The prices of these two banks' stocks have a significant impact on the Indian stock market due to their substantial market capitalisation. Volatility helps investors to make better portfolio and investment decisions because it represents the uncertainty in stock returns. A deep, detailed understanding of market fluctuations is a must for investors. This research is also important because it analyses the differences between public sector banks (BOI) and public sector banks (ICICI). Earlier studies focused only on market price indices, but this study adds new insights by examining banks. This study links statistical models to financial decisions and helps analyse risk patterns more effectively in the Indian banking sector.

Limitations of the study

1. **Restricted sample size:** This study focuses only on two banks, ICICI (Industrial Credit and Investment Corporation of India) and BOI (Bank of India). Although these are major banks in India, they cannot represent the entire banking sector.
2. **Historical data dependency:** Research is based on Historical data stock prices. It is difficult to predict the future volatility.
3. **Daily Data Limitation:** Using daily data may fail to capture intraday volatility fluctuations.
4. **Forecasting uncertainty**: Volatility forecasting is uncertain and may not estimate the extreme market events, such as policy changes, global economic crashes

Empirical analysis, estimation and results

For better clarity and systematic analysis, this section is divided into two segments: the first addresses the Bank of India, and the second focuses on ICICI Bank. Firstly, we are heading towards one of the leading public-sector banks.

Bank of India

To better understand price volatility, the Bank of India graph has been presented. The graph below shows that the index has been volatile. From the graph, it can be seen that there are irregular dips and spikes due to both systematic and non-systematic factors, such as COVID-19 and other macroeconomic effects.

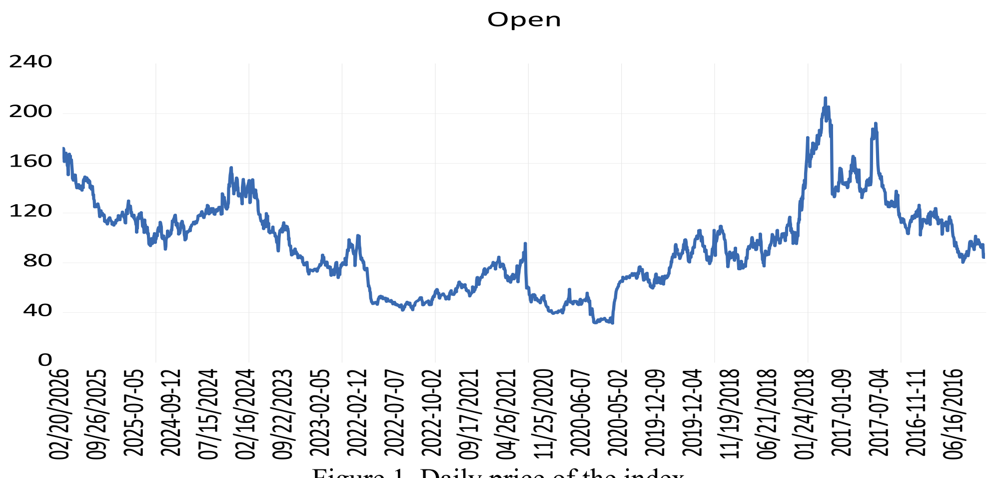

Figure 1. Daily price of the index

Source: author's Computation using EViews 12

Log returns were calculated to stabilise the data. And from the graph, it has been observed that spikes and dips occurred during the entire period. Below is the graphic representation of log returns.

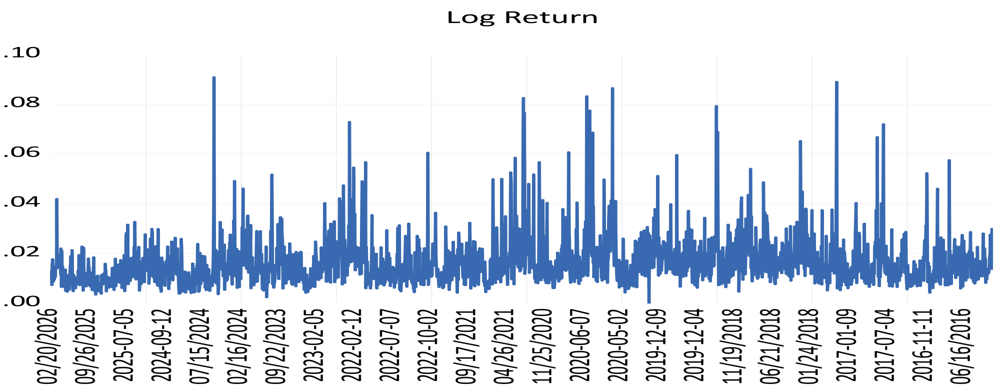

Figure 2: Log Returns Graph

Source: author's Computation using EViews 12

The log-return data exhibit clustering and patterns of shocks, which visually suggest possible heteroskedasticity; therefore, a stationarity test should be conducted first.

Test of stationarity

Table 1: Heteroscedasticity Test

Null Hypothesis: LOG RETURN has a unit root				
Exogenous: Constant				
Lag Length: 7 (Automatic - based on SIC, maxlag=26)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-11.48303	0.0000
Test critical values:	1% level		-3.432803	
	5% level		-2.862510	
	10% level		-2.567331	
*MacKinnon (1996) one-sided p-values.				

Source: author's Computation using EViews 12

The above test is the Augmented Dickey-Fuller (ADF) test. It was used to test for data stationarity. From the table, the p-value is 5%, indicating that the data pass the unit root test and are stationary. To understand the data’s nature, look at the statistical parameters below.

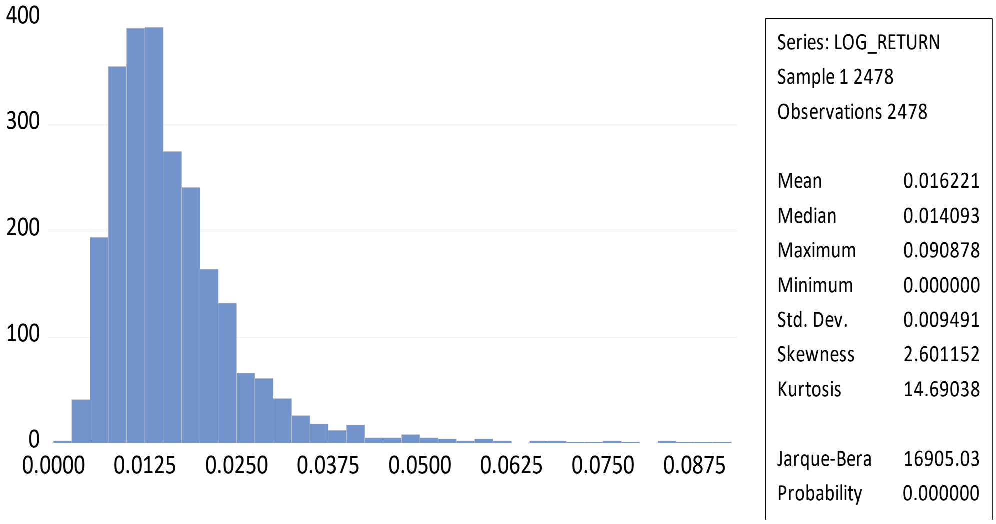

Figure 3. Log Returns Graph
Source: author's Computation using EViews 12

The histogram of 2,478 daily log returns shows that these returns don't follow a normal, bell-shaped distribution. On average, returns are positive, with a mean of 1.62% (0.016221) and a median of 1.41% (0.014093), and overall volatility remains quite low, with a standard deviation of under 1% (0.009491). However, the real story is in the shape of the graph: it has a massive spike around the 1.25% mark and a long tail stretching to the right, reaching a maximum return of about 9.09% (0.090878).

This extreme rightward skew (a skewness of 2.60) and the tall, skinny peak (a high kurtosis of 14.69) indicate the data are packed with frequent small gains and occasional massive positive jumps. In plain terms, the off-the-charts Jarque-Bera score of 16,905.03 and its 0% probability completely confirm that these returns defy standard statistical normality, leaning heavily into those big, unexpected positive outliers.

Heteroskedasticity Test

Table 2: ARCH effect test

Heteroskedasticity Test: ARCH			
F-statistic	130.0946	Prob. F (1,2474)	0.0000
Obs*R-squared	123.6953	Prob. Chi-Square (1)	0.0000

Source: author's Computation using EViews 12

Since the low probability score indicates volatility isn't constant, we reject the idea of a stable market in favour of one in which past shocks influence future risk. While the ARCH model identifies this "memory," we use the GARCH family instead because it better weights past data to predict current variance.

Table 3: Decision table for GARCH Selection

		GARCH model	TARCH model	EGARCH model	PARCH model	APARCH model
Normal Distribution	*Akaike info criterion*	4.673948	4.65937	4.64811	4.64846	4.66218
	Schwarz criterion	4.685686	4.67346	4.66220	4.66490	4.67626
	Log Likelihood	-5783.69	-5764.64	-5750.68700	-5750.12100	-5768.108
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes
Student's T	*Akaike info criterion*	4.531563	4.52218	4.51398	4.51491	4.52187
	Schwarz criterion	4.545648	4.53861	4.53041	4.53369	4.53830
	Log Likelihood	-5606.34	-5593.71	-5583.563	-5583.71	-5593.33200
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No

	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	4.537664	4.52892	4.52139	4.55342	4.52912
	Schwarz criterion	4.551749	4.54536	4.53782	4.56985	4.54555
	Log Likelihood	-5613.9	-5602.07	-5592.74	-5632.408	-5602.317
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
Generalized Error	significant coefficient	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	4.562003	4.54891	4.53982	4.54070	4.55004
	Schwarz criterion	4.57374	4.56300	4.55391	4.55714	4.56412
	Log likelihood	-5645.04	-5627.83	-5616.567	-5616.66	-5629.222
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
T distribution (Parameter)	significant coefficient	Yes	Yes	Yes	Yes	Yes
	Akaike info criterion	4.573468	4.56144	4.55244	4.55342	4.56264
	Schwarz criterion	4.585206	4.57553	4.56653	4.56985	4.57672
	Log Likelihood	-5659.24	-5643.34	-5632.197	-5632.408	-5644.826
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
Generalised Error (Parameter)	significant coefficient	Yes	Yes	Yes	Yes	Yes

Source: Author's formulation

Table 4. EGARCH (1,1) models, Student's t-distribution

Dependent Variable: OPEN				
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)				
Date: 04/10/26 Time: 22:17				
Sample (adjusted): 2 2478				
Included observations: 2477 after adjustments				
Convergence achieved after 83 iterations.				
Coefficient covariance computed using the outer product of gradients.				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C (3) + C (4) *ABS (RESID (-1)/@SQRT (GARCH (-1))) +				
C (5) *RESID (-1)/@SQRT (GARCH (-1)) + C (6) *LOG (GARCH (-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.355376	0.087787	4.048161	0.0001
OPEN (-1)	0.996035	0.001076	925.9065	0.0000
	Variance Equation			
C (3)	-0.090097	0.014316	-6.293587	0.0000
C (4)	0.171047	0.021211	8.064045	0.0000
C (5)	0.078814	0.014640	5.383404	0.0000
C (6)	0.982911	0.004354	225.7544	0.0000
T-DIST. DOF	4.142087	0.362383	11.43012	0.0000
R-squared	0.993287	Mean dependent var		94.56396
Adjusted R-squared	0.993284	S.D. dependent var		35.71354
S.E. of regression	2.926674	Akaike info criterion		4.513979
Sum squared resid	21199.42	Schwarz criterion		4.530412
Log likelihood	-5583.563	Hannan-Quinn criterion.		4.519948
Durbin-Watson stat	1.992258			

Source: Author's computation using EViews 12

To find the most accurate fit, we tested several advanced versions, including IGARCH, TARCH, EGARCH, PARCH, and APARCH, across five different statistical distributions to see which best captures the asset's specific patterns of turbulence.

From the table above, it can be concluded that the EGARCH (1,1) under the Student's t-distribution has the lowest AIC value, the lowest SC value, and the highest Log Likelihood value, making it a suitable model for the analysis. Let's proceed with the EGARCH test.

From the above model, we can see that the Bottom line is a highly accurate market model (99.3% explanatory power) that tracks a price variable called "OPEN." It proves that today's price is almost entirely driven by yesterday's price. Volatility is Sticky; the market has a long memory for drama. With a persistence score of 0.983, once the market becomes volatile or anxious, that turbulence will linger and bleed into the following days. News Matters: sudden market shocks instantly trigger higher volatility, and the direction of the news impacts the market unevenly.Expect the Unexpected: the model confirms the data has "fat tails" (a low degree of freedom of 4.14), meaning extreme, unpredictable price spikes or drops occur far more often than normal statistics would predict.

Now we are moving to the other part of the paper, which deals with the private banking sector.

The Industrial Credit and Investment Corporation of India (ICICI)

Below are the graphical representations of ICICI Bank over the decade. From these, it is clear that there are sharp dips during COVID-2019-20, but it spikes regularly after COVID-19 pandemic. This may be due to the COVID-19 pandemic and other microeconomic factors. During the entire framework, there is high volatility.

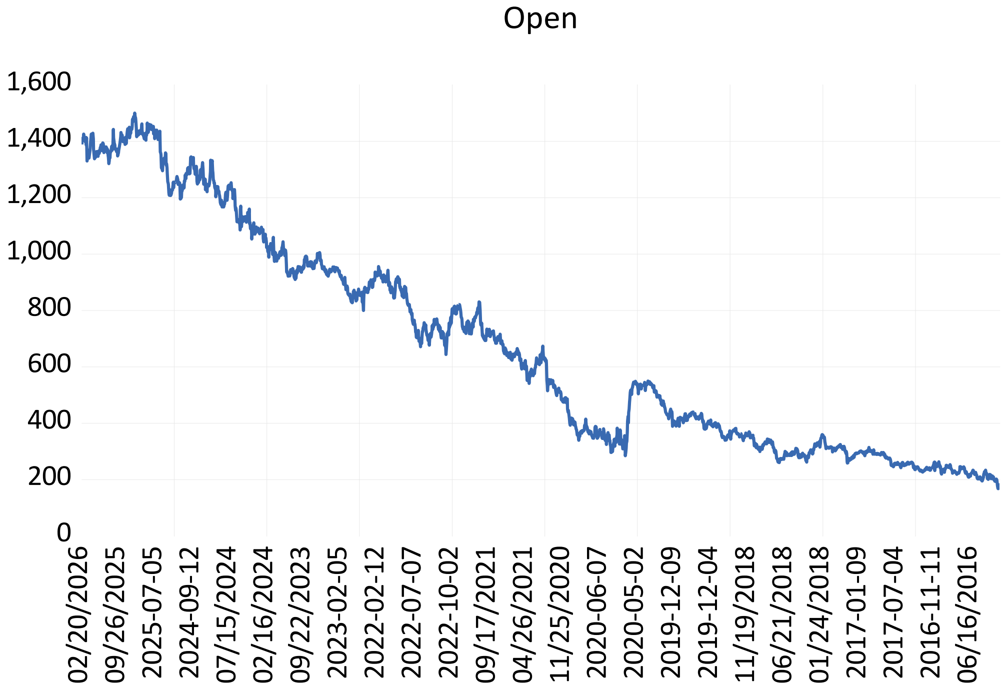

Figure 4. Daily price of the index

Source: author's Computation using EViews 12

To make returns stationary, the log return has been calculated. The following graphical representations show log returns. As discussed earlier, there is a spike in 2020, and volatility remains high throughout the period.

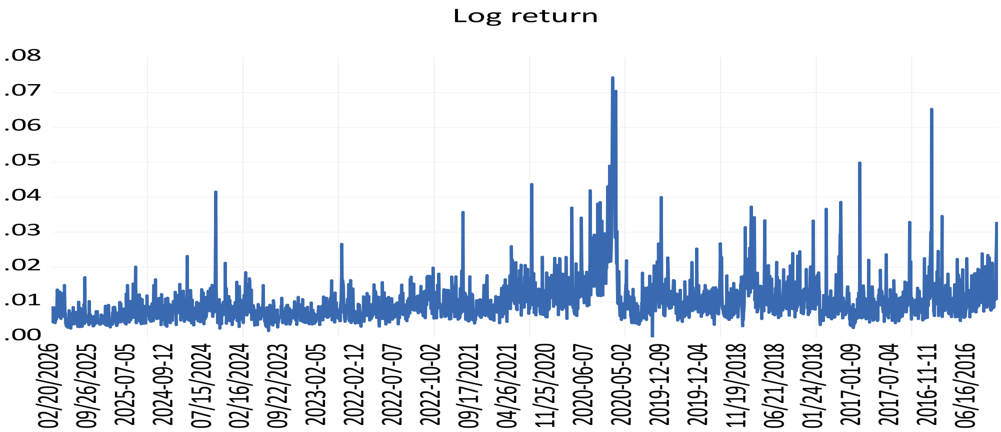

Figure 5. Log Returns Graph

Source: author's Computation using EViews 12

While a visual assessment suggests possible heteroscedasticity, it is imperative first to conduct a test for stationarity.

Table 5: Heteroscedasticity Test

Null Hypothesis: LOG_RETURN has a unit root				
Exogenous: Constant				
Lag Length: 5 (Automatic - based on SIC, maxlag=26)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-8.850059	0.0000
Test critical values:	1% level		-3.432801	
	5% level		-2.862509	
	10% level		-2.567331	

Source: Author's Computation using Eviews 12

The above test is the Augmented Dickey-Fuller (ADF) test. The probability value is less than 0.05, and the test statistic is lower than the 5% critical value; thus, we can say that the data has a unit root and is stationary.

Descriptive Statistics

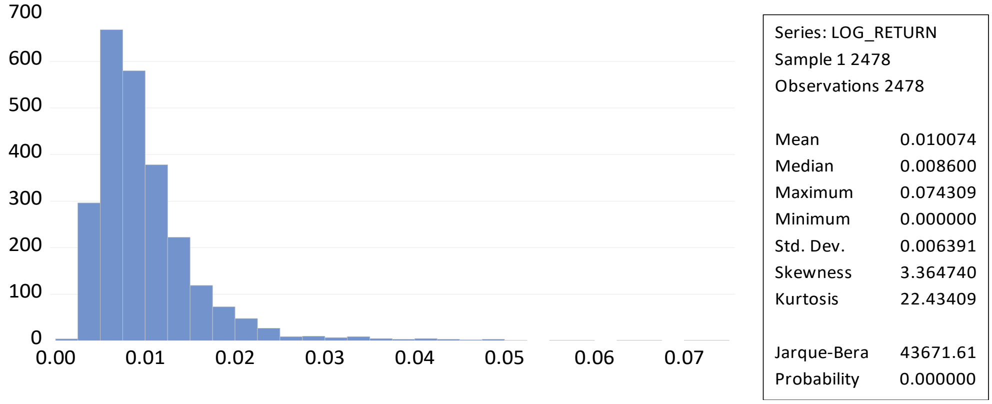

Figure 7. Test Distribution Analysis

Source: Author's Computation using Eviews 12

The histogram tracks 2,478 daily log returns and demonstrates that the data completely breaks away from a standard, normal bell curve. On average, the returns are positive, featuring a mean of 1.01% (0.010074) and a median of 0.86% (0.008600), while the overall market volatility stays relatively tight with a standard deviation of just 0.64% (0.006391). However, the defining characteristic of this dataset is its extreme shape: it features an incredibly sharp, tall peak right around the 0.5% to 1% mark and a long, drawn-out tail stretching far to the right toward a maximum return of 7.43% (0.074309), while the absolute minimum never drops below zero.

This massive rightward distortion is captured by an intense skewness of 3.36, and the sheer height of the peak is reflected in an astronomical kurtosis score of 22.43, indicating that the data is dominated by frequent small gains mixed with rare, massive positive jumps. Ultimately, the off-the-charts Jarque-Bera statistic of 43,671.61, paired with a perfect 0.000000 probability score, completely rejects any notion of standard statistical normality and proves that this market is highly prone to extreme positive outliers.

Heteroscedasticity Test

Table 6: ARCH-LM Test

Heteroskedasticity Test: ARCH			
F-statistic	63.85365	Prob. F (1,2474)	0.0000
Obs*R-squared	62.29738	Prob. Chi-Square (1)	0.0000

Source: author's computation using EViews 12

This ARCH test is a diagnostic check to see whether a dataset exhibits "volatility clustering"—meaning that periods of high market turbulence or calm tend to cluster together. Looking at the results, the F-statistic is 63.85, and the actual observations multiplied by the R-squared value yield a Chi-Square score of 62.30. The most critical takeaway here is the probability score (Prob.) for both tests, which is a perfect 0.0000; because this value is well below the standard 5% threshold, it completely rejects the idea that the data's volatility is constant and stable over time. In plain English, this test definitively proves that the dataset has significant ARCH effects, meaning the market exhibits heavy volatility clustering and absolutely requires an advanced volatility model to analyse it properly.

The decision table shows that the APARCH model with Student's t-distribution is the best model for ICICI Bank. This is because it has the lowest AIC value of 7.29695 and the lowest Schwarz Criterion value of 7.31338, which means it fits the data better than the other models. The results also show that the model exhibits significant ARCH and GARCH effects, indicating that ICICI Bank's stock returns exhibit clear volatility clustering and that past shocks continue to affect future volatility. Since there is no remaining autocorrelation and no further ARCH effect after applying the model, the APARCH model can be considered reliable. Therefore, the study selects the APARCH model with a Student's t-distribution as the most suitable model for capturing the volatility pattern of ICICI Bank.

Table 7. Decision Table

		GARCH model	TARCH model	EGARCH model	ARCH model	APARCH model
Normal Distribution	*Akaike info criterion*	7.386038	7.38222	7.37422	7.37504	7.37585
	Schwarz criterion	7.397775	7.39630	7.38831	7.39148	7.38994
	Log Likelihood	-9142.61	-9136.87	-9126.97300	-9126.99200	-9128.991
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes
Student's T	*Akaike info criterion*	7.305706	7.30421	7.29729	7.29775	7.29695
	Schwarz criterion	7.319791	7.32065	7.31372	7.31653	7.31338
	Log Likelihood	-9042.12	-9039.27	-9030.688	9030.267	79030.26200
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes
Generalized Error	*Akaike info criterion*	7.31416	7.31224	7.30615	7.30702	7.30660
	Schwarz criterion	7.328245	7.32868	7.32258	7.32580	7.32304
	Log Likelihood	-9052.59	-9049.21	-9041.667	-9041.747	-9042.228
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes
T distribution (Parameter)	*Akaike info criterion*	7.316051	7.31401	7.30659	7.30727	7.30655
	Schwarz criterion	7.327789	7.32810	7.32067	7.32370	7.32064
	Log likelihood	-9055.93	-9052.4	-9043.21	-9043.055	-9043.163
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes

	significant coefficient	Yes	Yes	Yes	Yes	Yes
Generalised Error (Parameter)	*Akaike info criterion*	7.323623	7.32115	7.56108	7.31528	7.90454
	Schwarz criterion	7.33536	7.33523	7.57517	7.33171	7.91863
	Log Likelihood	-9065.31	-9061.24	-9358.4	-9052.969	-9783.775
	ARCH significant	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes

Source: author's tabulation using MS Office

This statistical summary presents the results of an advanced PARCH (Power ARCH) model using a student's t-distribution, which analyses 2,477 adjusted observations of the price variable OPEN. The model fits the data near-perfectly with an R-squared of 99.92%, modelling both the directional movement of the price (the mean equation) and its underlying volatility (the variance equation). In the mean equation, the baseline constant C is statistically insignificant (p-value of 0.7686), but yesterday's price OPEN(-1) is an absolute powerhouse with a coefficient of 0.9994 and a p-value of 0.0000, confirming that today's price is almost entirely dictated by its immediate past value. Turning to the variance equation, which models how price swings behave, the baseline volatility constant C(3) is insignificant (p-value of 0.2351), but the market shock coefficient C(4) at 0.0519 and the volatility persistence coefficient C(5) at 0.9590 are both highly significant (p-values of 0.0000). This indicates that while immediate shocks have a minor relative impact, the market's memory for anxiety is incredibly sticky, meaning once volatility spikes, it takes a long time to decay. Furthermore, the power parameter C(6) is 0.7693 (p-value = 0.0010), indicating that the model is optimising its analysis using a fractional power of the standard deviation rather than the standard variance. Finally, the Student's t-distribution degrees of freedomis estimated at 5.33 (p-value of 0.0000), mathematically proving that the data suffers from "fat tails" where extreme price swings occur far more frequently than a standard bell curve would predict, while a Durbin-Watson statistic of 2.13 indicates the model is free of any major leftover serial correlation.

Table 8: APARCH(1,1) student's t distribution

Dependent Variable: OPEN				
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)				
Sample (adjusted): 2 2478				
Included observations: 2477 after adjustments				
Convergence achieved after 109 iterations.				
Coefficient covariance computed using the outer product of gradients.				
Presample variance: backcast (parameter = 0.7)				
@SQRT(GARCH)^C(6) = C(3) + C(4)*ABS(RESID(-1))^C(6) + C(5)				
*@SQRT(GARCH(-1))^C(6)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.073240	0.248900	0.294257	0.7686
OPEN(-1)	0.999407	0.000472	2117.675	0.0000
	Variance Equation			
C(3)	0.013070	0.011007	1.187430	0.2351
C(4)	0.051991	0.008060	6.450546	0.0000
C(5)	0.959037	0.006177	155.2693	0.0000
C(6)	0.769272	0.233539	3.293982	0.0010
T-DIST. DOF	5.333188	0.539756	9.880747	0.0000
R-squared	0.999171	Mean dependent var		675.6091
Adjusted R-squared	0.999171	S.D. dependent var		388.7595
S.E. of regression	11.19664	Akaike info criterion		7.296945
Sum squared resid	310278.0	Schwarz criterion		7.313378
Log likelihood	-9030.267	Hannan-Quinn criterion.		7.302914
Durbin-Watson stat	2.127568			

Source: author's computation using EViews 12

Conclusions

This study examined and compared the stock price volatility of Bank of India and ICICI Bank over a period of ten years. The analysis substantiates that both banks experienced irregular fluctuations, volatility clustering, and persistent shocks during the study period. This means that once volatility appears in the market, its impact does not disappear immediately; it ploughs on for some time.

The heuristic results show that BOI and ICICI Bank do not follow the same volatility pattern. For BOI, the EGARCH model with Student's t-distribution was found to be the felicitous model, while for ICICI Bank, the APARCH model with Student's t-distribution executed better. These results stipulate that the public and private banking sectors respond differently to market shocks and financial uncertainty.

The study also divulges that ICICI Bank is relatively more volatile than BOI. This may be due to its stronger market participation, higher investor response, and greater sensitivity to changing market conditions. BOI, on the other hand, shows volatility persistence, but its pattern differs from that of ICICI Bank. The presence of fat tails and non-normal distribution in both banks further shows that extreme market movements occur more frequently than expected under normal conditions.

Overall, the study concludes that advanced GARCH-family models are useful tools for understanding and forecasting stock market volatility in the Indian banking sector. The findings can help investors and portfolio managers make better investment decisions and manage financial risk more effectively. Future studies may include more public and private sector banks, intraday data, macroeconomic variables, and multivariate volatility models to provide a broader understanding of volatility transmission in the Indian financial market.

Authors' Contributions:

The authors contributed equally to this work.

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Article Info

Received: August 16 2026
Accepted: September 04 2026

How to cite this article:

Zama, M. W., Fayaz, M., Raza, S., Birau, R., Popescu, V., Shreevastava, A., Meher, B. K., Nioata (Chireac), R. M. (2026). Volatility Dynamics of Public and Private Sector Banks in India: A Comparative Study of BOI and ICICI Bank Using GARCH-Family Models. *Revista de Ştiinţe Politice. Revue des Sciences Politiques,* no. 91, pp. 137-157.