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DIVERGENT RISK ARCHITECTURES IN PUBLIC AND PRIVATE BANKING: AN ECONOMETRIC DECODING OF SBI AND HDFC RETURN SERIES

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Abstract: *This study explores the complex nature of stock market volatility within the Indian banking sector by examining two of its most significant players: The State Bank of India (SBI) and HDFC Bank. Spanning a decade from February 2016 to February 2026, the research analyses data from SBI and HDFC Bank to bridge a critical gap in accurate risk forecasting. Initial testing confirmed that both banks exhibit "volatility clustering," where periods of high instability tend to linger, and their return distributions are non-normal, characterised by extreme "fat-tail" spikes.*

By analysing a full decade of daily dataspanning 2016 to 2026, the study captured how these banks navigated major global shocks, such as the COVID-19 pandemic. The data clearly showed that market volatility has a long "memory": when a big shock hits, the turbulence doesn't just vanish overnight; it lingers in clusters. To map this out, the researchers tested a variety of specialised formulas to find the perfect "recipe" for each bank's unique personality.

In the end, we discovered that you can't treat these two the same way. SBI, a public-sector giant, behaves more explosively, and its risks are best captured by the EGARCH model. HDFC Bank, while still volatile, follows a slightly different pattern that is better tracked using a TARCH model. This research is a major step forward for anyone trying to manage a portfolio or predict future risks in the Indian banking sector, proving that each bank needs its own specific "recipe" to truly understand the danger of a market crash.

Keywords: *HDFC, SBI, GARCH models, Volatility*

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INTRODUCTION

The financial backbone of India is largely defined by two massive institutions: The State Bank of India (SBI) and HDFC Bank. Because these banks hold such significant market weight, their stock movements don't just affect individual portfolios; they act as a real-time pulse for the entire national economy. However, standard risk-measurement methods often fall short because they assume market prices move in a predictable, steady manner. In reality, the stock market is full of "wildcards"—sudden, explosive jumps or deep crashes triggered by events like the COVID-19 pandemic or shifting microeconomic factors that don't fit into a standard, predictable pattern.

By analysing ten years of daily data from 2016 to 2026, the researchers discovered that volatility in these banks has a "memory". This means that when a major shock hits, like the COVID-19 pandemic, the market doesn't just bounce back instantly; it stays shaky for a long time, creating clusters of instability. To map this out, the study tested a variety of sophisticated mathematical "recipes" known as the GARCH family.

Ultimately, this work is about moving beyond guesswork and toward much smarter financial protection. The findings show that a public-sector giant like SBI, which exhibited a staggering kurtosis, behaves much more explosively under stress than a private player like HDFC. For anyone managing a portfolio or forecasting future risk, this study provides a vital roadmap. It shows that SBI is best tracked with an EGARCH model to capture its strong reactions to shocks, while HDFC follows a slightly different rhythm, best captured by a TARCH model. Understanding these distinct patterns is the secret to navigating the unpredictable swings of the Indian banking sector.

REVIEW OF LITERATURE

Recent studies have shown that stock market data does not behave in a simple or predictable way. Prices go up and down with changing intensity, and this fluctuation (called volatility) often comes in clusters. Because of this, researchers have used advanced GARCH models to better understand and measure these changes over time.

Bollerslev explained the different types of ARCH and GARCH models clearly and in anorganised way (Bollerslev, T., 2008). His study shows that, after the basic ARCH and GARCH models, many new versions were developed to study different patterns of volatility, such as unequal responses to good and bad news, long-term volatility effects, relationships among many financial variables, and non-normal market behaviour. Thus,Bollerslev's work is useful for understanding how the GARCH family of models developed over time and how these models can be classified.

In continuation, (T Va et al., 2003) gave strong theoretical support to the GARCH model. They explained that the conditional variance in a GARCH (p, q) model depends on past squared values, which helps explain how volatility changes over time. The study also showed that the quasi-maximum likelihood estimator gives reliable results under suitable conditions. Therefore, this paper is important because it enhances the trustworthiness of GARCH models in empirical financial research.

Zhou et al. extended GARCH modelling by introducing the Network GARCH modelfor large financial datasets (Zhou et al., 2020). Their study focused on the problem that traditional multivariate GARCH models become difficult to use when many stocks are included, as the number of parameters increases rapidly. By leveraging network relationships among stocks, their model simplified the analysis, reduced complexity, and improved the application of GARCH models in large financial markets.

Volatility modelling started with the ARCH model, which explained how financial risk changes over time. Later, the GARCH model became more popular because it is easier to use and works well for stock returns, exchange rates, and other financial data. Bollerslev et al. noted that these models are useful because they capture changing volatility in financial markets (Bollerslev et al., 2023).

Mutinda et al. studied how stock prices can be predicted by combining GARCH models with Artificial Intelligence (Mutinda et al., 2024). They used Airtel stock data from June 2019 to May 2024and tested models like GARCH-LSTM, GARCH-GRU, and GARCH-Transformer. The study found that these combined models gave better results than using AI models alone. Among them, GARCH-LSTM performed the best**.** This shows that using GARCH with deep learning can improve the accuracy of financial forecasting.

Many studies have compared various GARCH models, including GARCH, EGARCH, TGARCH, and APARCH. The results show that advanced models, especially APARCH, perform better because they can capture real market behaviour more accurately. These models are particularly useful in showing that bad news (negative returns) usually increases volatility more than good news (positive returns) (Raza et al., 2024).

Research on specialised stock indices such as BSE CARBONEX and BSE GREENEX also supports this idea. These studies found that market volatility can change rapidly due to external factors such as economic conditions or policy changes. Advanced GARCH models were more effective at explaining these changes than basic models (Shreevastava et al., 2024).

Studies on international markets, such as the Nikkei 225, also show similar patterns. Volatility persists for a long time, and market returns often take extreme values (very high or very low). These studies suggest that using distributions such as Student's t rather than the normal distribution yields better results (Raza et al., 2024).

Some researchers also compared GARCH models with simpler methods, such as EWMA. While EWMA is easier to use, it cannot capture complex patterns, such as asymmetry and changing volatility. On the other hand, advanced GARCH models provide better forecasting and risk measurement (Aman et al., 2024).

Tandon et al. studied the financial performance of SBI and ICICI Bank from 2007–08 to 2011–12 using ratio analysis (Tandon et al., 2012). The study found that SBI performed better overall, especially in income, net worth, deposits, and advances. However, ICICI Bank was better in the credit-deposit ratio and net profit margin. The study concluded that customers had greater trust in public-sector banks like SBI.

Overall, these studies clearly show that financial data exhibit common features, such as volatility clustering, sudden shocks, and unequal reactions to positive and negative news. Therefore, advanced GARCH models are more suitable for analysing stock market volatility. However, most of these studies focus on indices, and very few focus on individual banking stocks, especially in India. This creates a research gap that your study on SBI and HDFC aims to fill.

RESEARCH GAP

In the context of financial modelling, the Housing Development Finance Corporation (HDFC) and the State Bank of India (SBI) are listed on the National Security Exchange (NSE) in India. Significant studies have been conducted, yet a significant research gap persists in the application of advanced GARCH models for accurate volatility forecasting. The existing literature review has explored various methodologies, but it remains substandard in its understanding. Particular research attempts to explore and understand HDFC and SBI volatility using appropriate GARCH models. The study aims to provide a specific volatility forecast.

Objective of the studies

I. To study the volatility of HDFC Bank and SBI Bank from 22/02/2016 to 20/02/2026.
II. To compare volatility behaviour between a public sector bank (SBI) and a private sector bank (HDFC Bank).
III. To estimate and compare the performance of different GARCH family models (such as GARCH, EGARCH, TGARCH) in capturing volatility patterns of both banks.

Research Hypotheses

The research is exploratory and quantitative. Study explores a multistage methodology for modelling and forecasting. There are 1791 data points from HDFC Bank and 2479 from SBI Bank, spanning 22/02/2016 to 20/02/2026. The purpose of the study is to predict volatility using GARCH-family models with Gaussian normal distribution, Student's t distribution, generalised error distribution (GED), t distribution, and GED distribution with parameters. Logarithm returns were calculated to stabilise the data, and it was observed that the data showed clustering. For this, the ARCH-LM test was applied to assess heteroskedasticity in the returns' residual series. Various GARCH models (GARCH, IGARCH, TGARCH, EGARCH, PARCH, and APARCH) are used across distributions for volatility analysis. The software package used was EViews 12.

Significance of the study

The study is significant because volatility plays a crucial role in investment decisions and financial risk management. The stock prices of HDFC Bank and SBI Bank are highly influential in the Indian stock market due to their large market capitalisations. A study helps capture time-varying volatility and forecast future risk more accurately. Volatility represents the uncertainty in stock returns, improving forecasting that enables investors to make better portfolio and hedging decisions. A deep understanding of market volatility is vital for investors. The study is also important from a comparative perspective, as it examines the differences between a private-sector bank (HDFC) and a public-sector bank (SBI). The research contributes to the literature by offering insights from the Indian banking sector, where most of the prior studies focus primarily on market indices. Also, the study bridges econometric modelling with financial decision-making and enhances understanding of risk dynamics in the Indian banking sector.

Limitations of the study

- **Limited number of banks** – The **s**tudy focuses on only HDFC and SBI. Although these banks are major banks, the results cannot represent the entire banking sector in India.
- **Use of historical data points** – Research is based on past stock data prices. Financial markets are dynamic; past performance may not always perfectly predict future volatility.
- **Daily Data Limitation** – daily closing prices are used; the study does not capture intra-day price fluctuations.
- **Forecasting uncertainty** –Volatility forecasting can never be faultless. Despite the best statistical model, it cannot predict market crashes, policy changes, or global economic shocks.

Empirical analysis, estimation and results

This part has been divided into two segments to better understand both indices.
The first section deals with the State Bank of India,and the second with HDFC Bank.

State Bank of India

To better understand price volatility, the SBI graph has been presented, and from the graph below, it is evident that the index has been volatile. From the graph, it can be seen that there is a continuous dip and spike due to both systematic and non-systematic factors, such as COVID-19 and other microeconomic effects.

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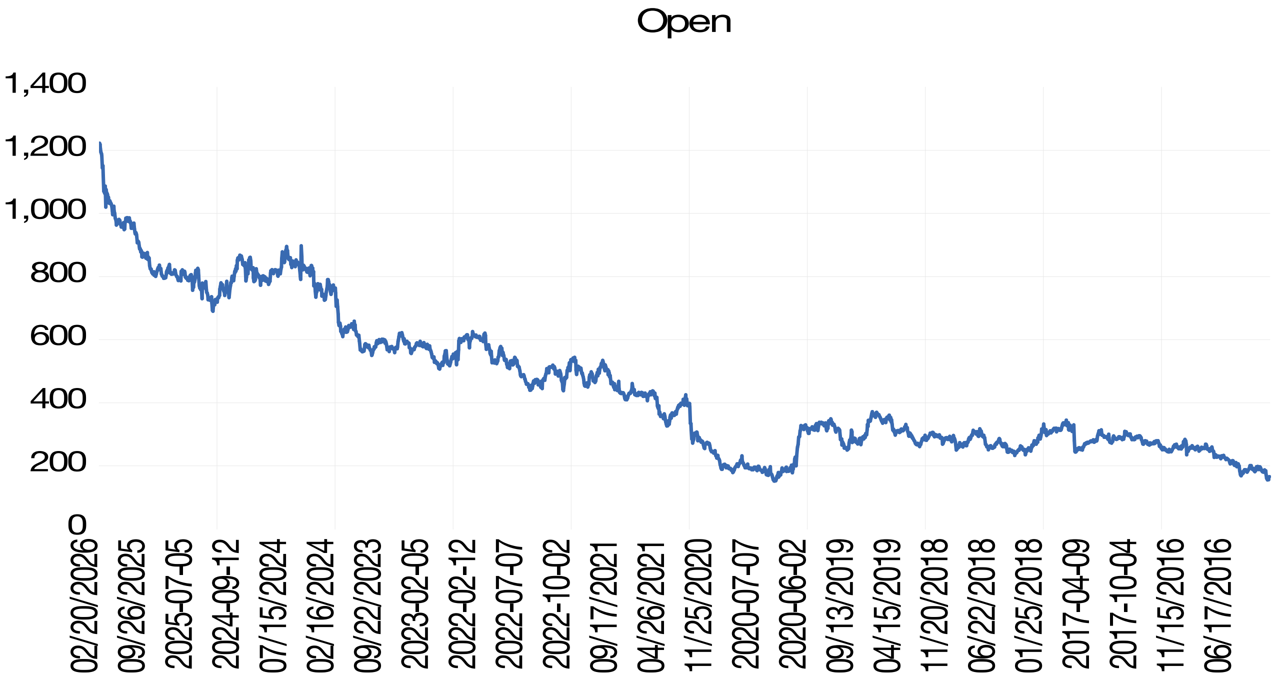

***Figure 1**. Daily price of the index*

Source: author's Computation using EViews 12

To make returns stationary, the log return has been calculated. Below is the graphical representation of log returns. As formerly discussed,there is a spike and a dip throughout the entire time span.

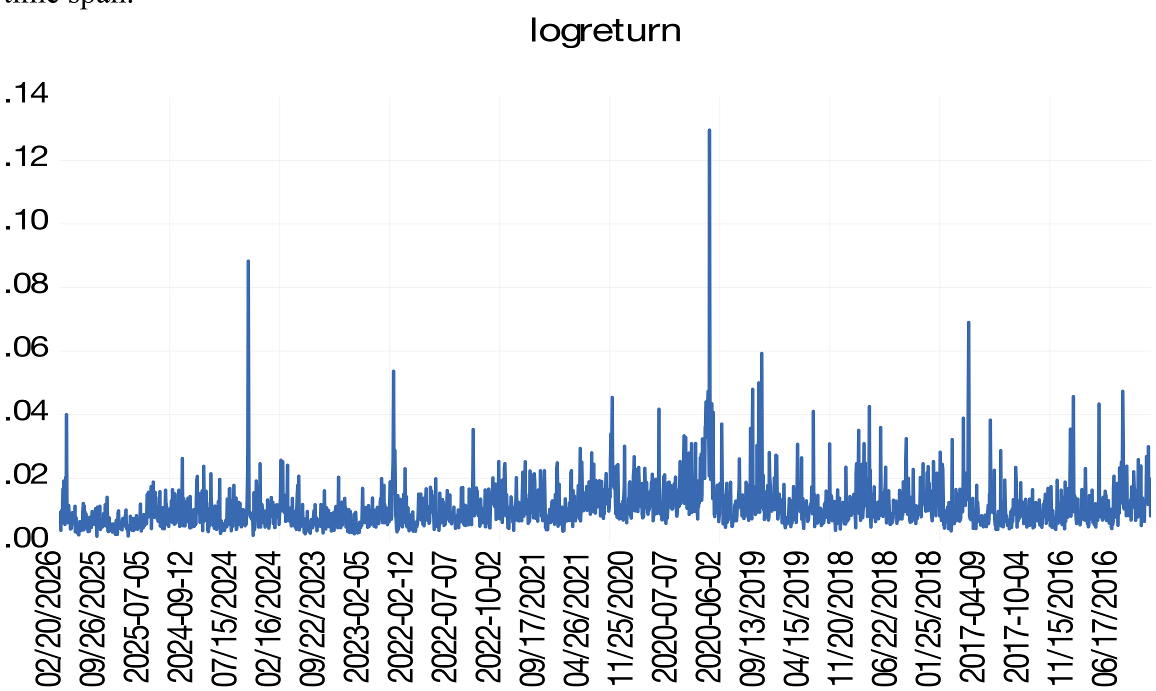

***Figure 2.** Log Returns Graph*

Source: author's Computation using EViews 12

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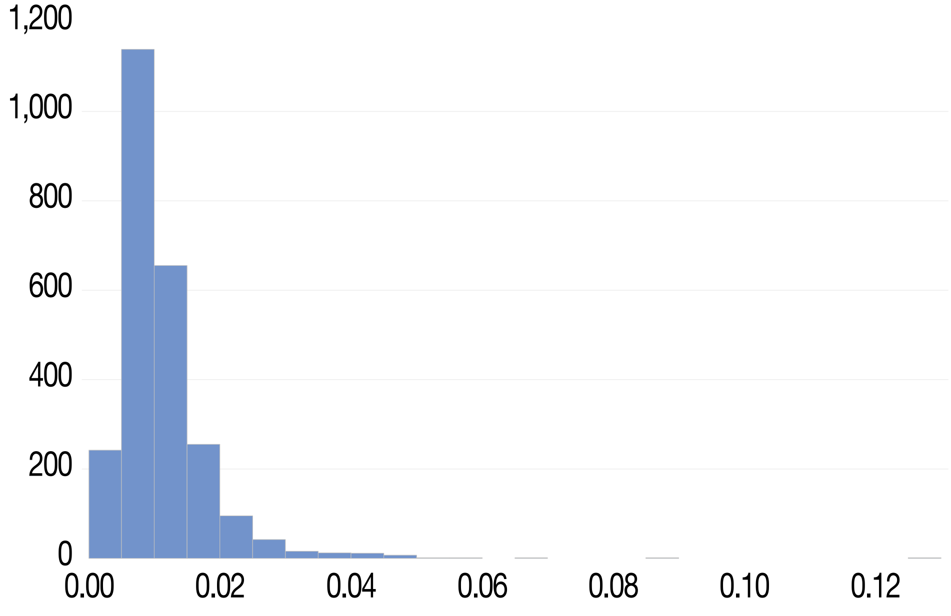
From the logarithmic data clustering of shocks and patterns, a visual representation suggests possible heteroscedasticity; it is imperative to conduct a stationarity test first.

Test of stationarity

Null Hypothesis: LOGRETURN has a unit root			
Exogenous: Constant			
Lag Length: 4 (Automatic - based on SIC, maxlag=26)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.33973	0.0000
Test critical values:	1% level	-3.432799	
	5% level	-2.862508	
	10% level	-2.567330	
*MacKinnon (1996) one-sided p-values.			

Table 1: *Heteroscedasticity Test*
Source: author's Computation using EViews 12

The above test is the Augmented Dickey-Fuller (ADF) test. It was used to test for stationarity of the data, and from the table, it can be observed that the p-value is at the 5% significance level, indicating that the data pass the unit root test and are stationary. To understand the data's nature, look at the statistical parameters below.



Series: LOGRETURN	
Sample 1 2479	
Observations 2479	
Mean	0.011008
Median	0.009380
Maximum	0.129501
Minimum	0.001721
Std. Dev.	0.007132
Skewness	4.219498
Kurtosis	45.39302
Jarque-Bera	192988.6
Probability	0.000000

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

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The data (2,479 observations) shows an average return of 1.1%, with a notable Maximum of 12.9%. Remarkably, the Minimum is 0.17%, meaning no losses were recorded in this period.

However, the high Kurtosis (45.39) and Skewness (4.22) reveal that this is not a normal "bell curve" distribution. Instead, the asset is prone to extreme, unpredictable spikes. The Jarque-Berastatistic (0.00) indicates that the data are statistically irregular and highly volatile.

Heteroscedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	78.63659	Prob. F(1,2475)	0.0000
Obs*R-squared	76.27664	Prob. Chi-Square(1)	0.0000

***Table 2**: ARCH LM Test*
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. 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.

		GARCH	TARCH	EGARCH	PARCH	APARCH
Normal Distribution	*Akaike info criterion*	6.978844	6.97677	6.96552	6.96772	6.97080
	Schwarz criterion	6.990577	6.99085	6.97960	6.98414	6.98488
	Log Likelihood	-8641.787	-8638.221	-8624.27300	-8625.99900	-8630.824
	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*	6.858457	6.85778	6.85105	6.85112	6.85177
	Schwarz criterion	6.872537	6.87421	6.86748	6.86989	6.86820
	Log Likelihood	-8491.628	-8489.80	-8481.454	-8480.534	-8482.34500
	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*	6.86655	6.86723	6.86038	6.86115	6.86057
	Schwarz criterion	6.88063	6.88365	6.87680	6.87992	6.87699
	Log Likelihood	-8501.655	-8501.494	-8493.006	-8492.964	-8493.24
	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*	6.879193	6.87876	7.04730	6.86998	6.87036
	Schwarz criterion	6.890927	6.89284	7.06138	6.88641	6.88444
	Log likelihood	-8518.321	-8516.779	-8725.604	-8504.906	-8506.373
	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*	6.890462	6.89119	6.88217	6.88352	6.88277
	Schwarz criterion	6.902195	6.90527	6.89625	6.89994	6.89685
	Log Likelihood	-8532.282	-8532.187	-8521.004	-8521.678	-8521.749
	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

***Table 3**: Decision table for GARCH Selection*
Source: Author's contribution

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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.

Dependent Variable: OPEN
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 04/08/26 Time: 00:03
Sample (adjusted): 2 2479
Included observations: 2478 after adjustments
Convergence achieved after 46 iterations
Coefficient covariance computed using 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	0.438598	0.268665	1.632511	0.1026
OPEN(-1)	0.998306	0.000615	1624.262	0.0000
	Variance Equation			
C(3)	-0.013196	0.031868	-0.414085	0.6788
C(4)	0.211886	0.026750	7.921017	0.0000
C(5)	0.027924	0.017705	1.577207	0.1147
C(6)	0.966131	0.008486	113.8540	0.0000
T-DIST. DOF	4.446877	0.405759	10.95940	0.0000

R-squared	0.998517	Mean dependent var	457.1912
Adjusted R-squared	0.998517	S.D. dependent var	230.2229
S.E. of regression	8.866496	Akaike info criterion	6.851052
Sum squared resid	194650.1	Schwarz criterion	6.867479
Log likelihood	-8481.454	Hannan-Quinn criter.	6.857019
Durbin-Watson stat	2.167143		

Table 4. *EGARCH (1,1) models, Student's t-distribution*
Source: Author's computation using EViews 12

For SBI, the data show that the opening price is almost entirely determined by the previous day's price. To track the bank's risk, the study uses a mathematical formula called LOG(GARCH), which reveals that SBI is extremely sensitive to market shocks. When a major event hits, the resulting instability in stock prices doesn't just disappear; it tends to linger and remain turbulent for a long time. Additionally, the specific statistical scores for SBI indicate that it is very prone to sudden, massive price jumps or drops that do not follow a normal, calm pattern.

Now, we are moving forward with the analysis for the rest of the paper.

Housing Development Finance Corporation (HDFC)

Below are the graphical representations of HDFC Bank over the decade. From these, it is clear that there are sharp dips and spikes throughout the time-frame; this may be due to financial problems, the COVID-19 pandemic, and other microeconomic factors. During the entire framework, there is high volatility.

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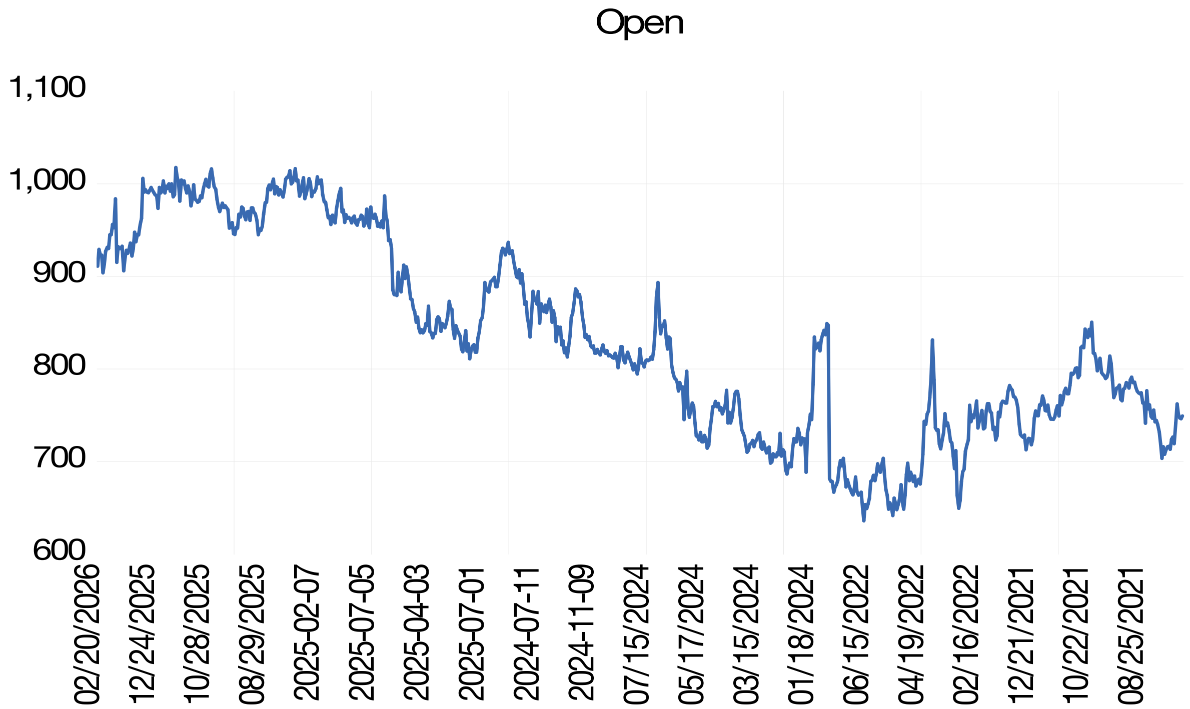

Figure 4. *Daily price of the index*
Source: author's Computation using EViews 12

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.

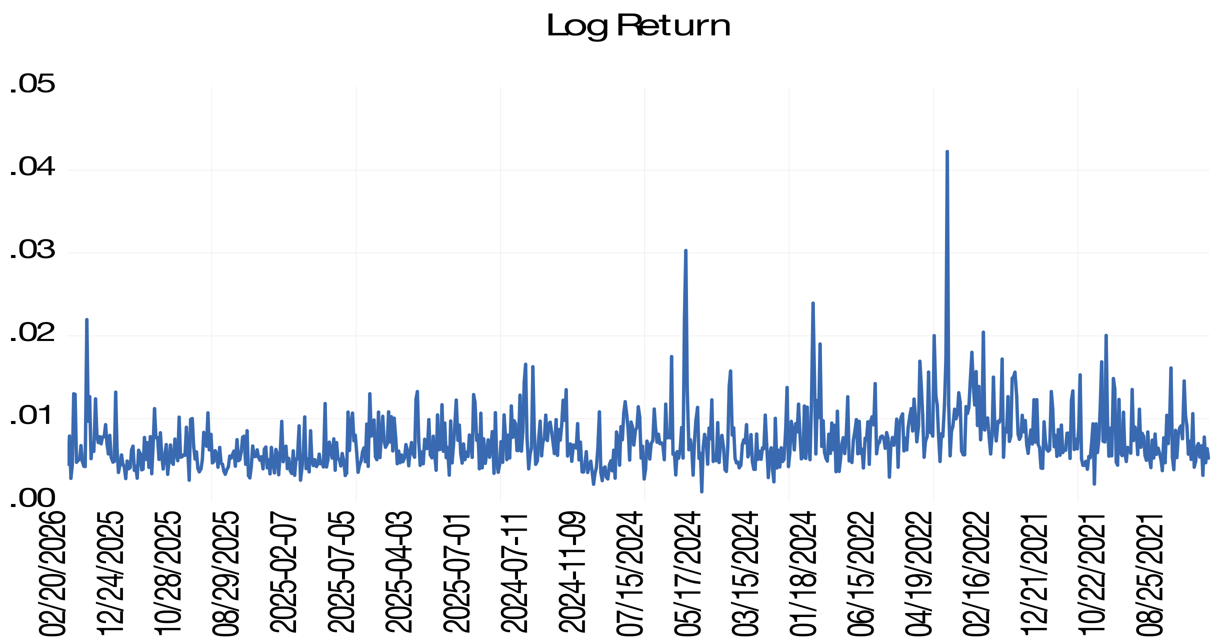

Figure 5. *Log Returns Graph*
Source: author's Computation using EViews 12

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

Null Hypothesis: LOG_RETURN has a unit root			
Exogenous: Constant			
Lag Length: 8 (Automatic - based on SIC, maxlag=20)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.296356	0.0000
Test critical values:	1% level	-3.438486	
	5% level	-2.865021	
	10% level	-2.568679	
*MacKinnon (1996) one-sided p-values.			

***Table 5**: Heteroscedasticity Test*
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

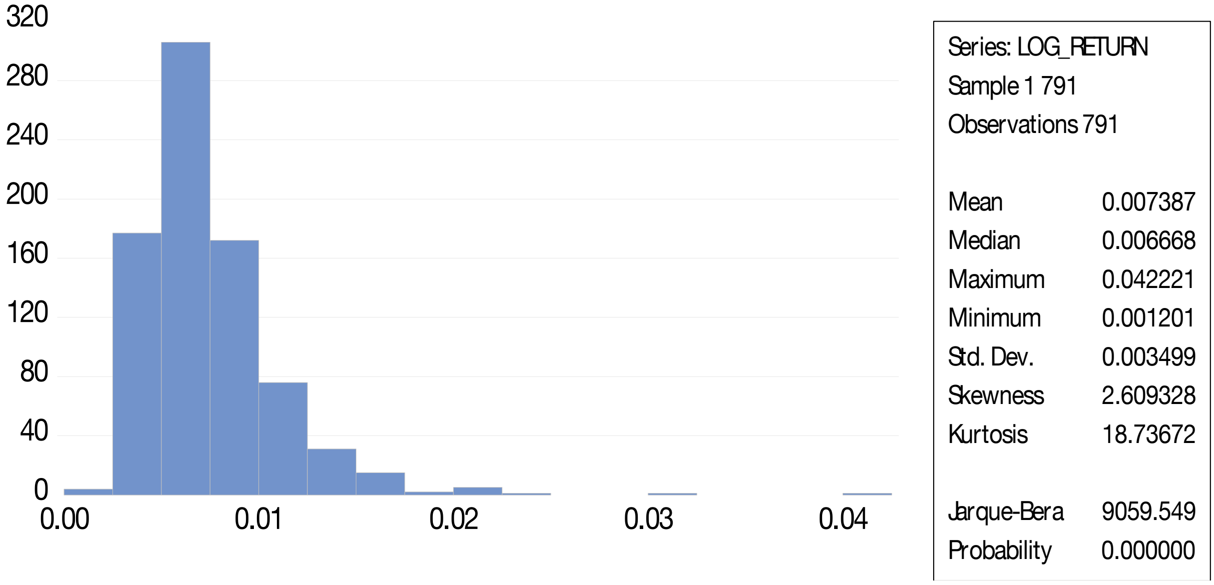

***Figure 6.** Test Distribution Analysis*
Source: Author's computation using EViews 10

Basically, while most of your gains are small, the data is "top-heavy" with some extreme spikes that a normal bell curve can't explain. With a massive Kurtosis of 18.74 and a Jarque-Bera score of zero, it's clear this isn't a steady or predictable climb; you're seeing rare but huge jumps that make the overall risk much higher than it looks at first glance.

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Heteroscedasticity Test

Null Hypothesis: LOG_RETURN has a unit root Exogenous: Constant Lag Length: 8 (Automatic - based on SIC, maxlag=20)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.296356	0.0000
Test critical values: 1% level	-3.438486	
5% level	-2.865021	
10% level	-2.568679	
*MacKinnon (1996) one-sided p-values.		

***Table 6**: ARCH effect test*
Source: Author's computation using EViews 12

The data shows that the "swinginess" or volatility of these returns isn't random—it actually depends on what happened in the recent past. Because the ARCH test rejected the idea of constant variance, we know that when the market gets bumpy, it tends to stay bumpy for a while. To capture this, we move beyond simple models to the GARCH family, which better weights past data to predict future risk. By testing various versions, like EGARCH or TARCH, across different distributions, we're essentially hunting for the specific mathematical "recipe" that best maps how volatility evolves over time.

After executing GARCH family models across the Gaussian Normal Distribution, Student's t distribution, Generalised Error Distribution (GED), t distribution with fixed parameter, and GED with fixed parameter, it can be concluded from the table below that TARCH Student's t distribution is the appropriate model for having the lowest Akaike info criterion (7.71663), lowest Schwarz criterion (7.75803), and highest log likelihood (3041.07).

		GARCH	TARCH	EGARCH	PARCH	APARCH
Normal Distribution	*Akaike info criterion*	8.009477	7.85304	7.88897	8.04724	7.96757
	Schwarz criterion	8.039047	7.88852	7.92446	8.08863	8.00305
	Log Likelihood	-3158.74	-3095.95	-3110.14400	-3171.65800	-3141.19
	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*	7.727393	7.71663	7.73088	7.76864	7.73037
	Schwarz criterion	7.762877	7.75803	7.77228	7.81595	7.77177

	Log Likelihood	-3046.32	-3041.07	-3046.698	-3060.611	-3046.49600
	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*	7.764802	7.76942	7.77121	7.80707	7.77214
	Schwarz criterion	7.800285	7.81082	7.81261	7.85438	7.81354
	Log Likelihood	-3061.1	-3061.92	-3062.628	-3075.792	-3062.994
	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*	7.791086	7.74851	7.74988	7.74924	7.77471
	Schwarz criterion	7.820656	7.78399	7.78537	7.79064	7.81020
	Log likelihood	-3072.48	-3054.66	-3055.203	-3053.951	-3065.01100
	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*	7.81851	7.77330	7.79187	7.86432	7.83131
	Schwarz criterion	7.84808	7.80878	7.82736	7.90572	7.86680
	Log Likelihood	-3083.31	-3064.45	-3071.79	-3099.405	-3087.368
	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

Table 7. *Decision Table*
Source: author's tabulation using MS Office

Dependent Variable: OPEN
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 04/08/26 Time: 00:09
Sample (adjusted): 2 791
Included observations: 790 after adjustments
Failure to improve likelihood (singular hessian) after 117 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.729984	2.658353	1.026946	0.3044
OPEN (-1)	0.996976	0.003193	312.2106	0.0000
	Variance Equation			
C	125.4806	13.47329	9.313290	0.0000
RESID (-1)^2	0.651722	0.171276	3.805106	0.0001
RESID(-1)^2*(RESID(-1)<0)	-0.593451	0.167846	-3.535695	0.0004
GARCH(-1)	-0.072103	0.032276	-2.233970	0.0255
T-DIST. DOF	4.694844	0.565376	8.303934	0.0000

R-squared	0.983579	Mean dependent var	831.3423
Adjusted R-squared	0.983558	S.D. dependent var	105.4805
S.E. of regression	13.52544	Akaike info criterion	7.716630
Sum squared resid	144154.9	Schwarz criterion	7.758028
Log likelihood	-3041.069	Hannan-Quinn criter.	7.732543
Durbin-Watson stat	2.128999		

Table 8*: Results for method: ML ARCH - Student's t distribution*
Source: Author's Computation using Eviews 12

HDFC Bank follows its own distinct pattern, where its current price is also heavily influenced by its performance from the day before. To map out its risk, the GARCH/TARCH model was used, which highlights that HDFC reacts differently depending on whether it receives "good news" or "bad news". While HDFC also experiences sharp and unexpected price spikes, the data suggests that the way these movements happen is more structured and follows a specific rhythm compared to the patterns seen in SBI. Essentially, HDFC has a unique personality under pressure that requires its own specific mathematical approach to forecast accurately

When comparing these two banking giants, the most obvious takeaway is that while both are volatile, they "behave" differently under pressure. State Bank of India (SBI), the public sector leader, showed a much more extreme profile with a staggering Kurtosis of 45.39, meaning it experiences massive, unpredictable price swings far more often than a normal market would suggest. On the other hand, HDFC Bank, representing the private sector, also displayed high volatility and "fat tails," but its Kurtosis of 18.74 indicates that while it is still risky and prone to sudden jumps, its movements are slightly less intense than SBI's. Both banks were heavily impacted by major events

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like the COVID-19 pandemic, causing their price data to "cluster", essentially meaning that when the market gets bumpy, it tends to stay bumpy for a while rather than settling down immediately.

Because their risk profiles differ, the mathematical "recipe" used to predict each bank's future volatility is unique to that bank. For SBI, the EGARCH model was the best fit, as it excels at capturing how the market reacts to past shocks. For HDFC, the TARCH model proved more accurate at mapping its specific turbulence trend. Ultimately, while both banks are stationary and passed the same technical "health checks," SBI acts as a more high-intensity representative of market swings, whereas HDFC follows a slightly different rhythm of risk that requires its own specific modelling approach to forecast accurately.

CONCLUSION

When comparing these two banking giants, the most obvious takeaway is that while both are volatile, they "behave" differently under pressure. State Bank of India (SBI), the public sector leader, showed a much more extreme profile with a staggering Kurtosis of 45.39, meaning it experiences massive, unpredictable price swings far more often than a normal market would suggest. On the other hand, HDFC Bank, representing the private sector, also displayed high volatility and "fat tails," but its Kurtosis of 18.74 indicates that while it is still risky and prone to sudden jumps, its movements are slightly less intense than SBI's. Both banks were heavily impacted by major events like the COVID-19 pandemic, causing their price data to "cluster" - essentially meaning that when the market gets bumpy, it tends to stay bumpy for a while rather than settling down immediately.

Because their risk profiles differ, the mathematical "recipe" used to predict each bank's future volatility is unique to that bank. For SBI, the EGARCH model was the best fit, as it excels at capturing how the market reacts to past shocks. For HDFC, the TARCH model proved more accurate at mapping its specific turbulence trend. Ultimately, while both banks are stationary and passed the same technical "health checks," SBI acts as a more high-intensity representative of market swings, whereas HDFC follows a slightly different rhythm of risk that requires its own specific modelling approach to forecast accurately.

For this, various models, such as Machine Learning, COPULA, AI, and VaR, can provide a broader perspective and yield additional insights that benefit society, investors, and policymakers.

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