ISSN: 2582-5526 www.thevoiceofcreativeresearch.com

The Voice of Creative Research

Vol. 7 & Issue 3 (July 2025)

https://doi.org/10.53032/tvcr/2025.v7n3.13

Nifty 50 Index Reshuffling of Indian Banking Stocks: Interpreting Volatility Dynamics through Arch Model

Shakya Singha Dey
Assistant Professor,
Department of Commerce,
Nabagram Hiralal Paul College, West Bengal.
(Affiliated to University of Calcutta)
shakya@hiralalpaulcollege.ac.in

Abstract

The paper examines the effectiveness of NIFTY 50 index reshuffling in terms of its effects on the volatility of stock returns in the Indian banking industries with the help of the Autoregressive Conditional Heteroskedasticity (ARCH) model. A total of four leading banks--Kotak Mahindra Bank, YES Bank, Bank of Baroda, and IndusInd Bank were compared during post-index reconstitution period and pre-index period in order to measure the upper and lower volatility dynamics. The findings indicate that the banks respond heterogeneously. e.g., Volatility became more persistent for Kotak Mahindra Bank during post-index period. Whereas volatility was not persistent for Bank of Baroda and IndusInd Bank during both the periods. Yes Bank had a high volatility. However, it was more internally-driven rather than index-driven. The results emphasize that index-reshuffling has different impacts across different stocks and firm-specific fundamentals important to the volatility behavior. This paper can add value to the current knowledge of the event-based volatility in emerging economies and provide valuable guidelines to the investors, fund managers and policy advisors dealing with index-oriented investment milieu.

Keywords: ARCH model, NIFTY 50, Stock-volatility, Index-reshuffling, Indian banking sector, Event study, Volatility clustering, Financial markets, Benchmark index, GARCH, investor behavior, Market reaction, Institutional trading, Empirical analysis

1. Introduction

1.1 Background and Significance

The Indian banking sector is very important with regards to economic growth and capital market progression of India. Banks in the National Stock Exchange (NSE), both in the public and in the private sectors, are not merely contributors to the feeling of the stability of funding but also to the indices of investor confidence and market liquidity. The volatility of stock prices is an important measure of risk and the efficiency of the market in dynamic financial situations. The volatility modeling is vital, more so in instances where there is structural rebalancing like inclusion or exclusion in major indices like the NIFTY 50. They tend to affect the returns on the stocks, trading volumes and investor anticipation.

1.2 Problem Statement

There are already existing studies on financial volatility, but few studies have been drawn on how index reshuffling i.e. NIFTY 50 changes on the individual bank stocks with specific econometric context (Paientko and Pundir, 2024)[1]. This leaves a void on the impact that benchmark index decisions have on stock returns behavior especially in a closely regulated and sensitive sector such as the banking sector.

1.3 Objectives of the Study

The study aims to achieve the following objectives:

- To examine volatility patterns in selected Indian banking stocks using the ARCH model.
- To compare volatility before and after changes in NIFTY 50 index inclusion or exclusion.
- To identify whether structural index events lead to statistically significant shifts in stock return behavior.
- To assess if volatility patterns are consistent across different banks within the same sector.

1.4 Research Questions

1. Does stock return volatility change after a bank is included in or excluded from the NIFTY 50 index?
2. Are volatility patterns consistent across different banks within the same industry?
3. Can the ARCH model effectively capture the pre- and post-event volatility behavior?

2. Literature Review

2.1 Theoretical Foundations of Stock Price Reactions

According to Scholes (1972), Change in stock price can be assigned two major forces of substitution effects and pressure of price. Substitution effects are consequent on the occurrence of new information that make investors re-evaluate the intrinsic value of a security that will result in a price correction to signify fundamental changes (Scholes, 1972)[2]. Conversely, price pressure can be attributed to the fluctuation in demand or supply on a short-term basis with no connection with underlying value. The framework is applicable when the stock volatility is assessed around an event like index reconstitution because the movements in prices can be ascribed to either informed trading or sale of imbalances in the market in the short time.

2.2 ETF Behaviour and Index Changes in India

According to Malhotra and Sinha (2023), The exchange-traded funds (ETFs) in India were significantly volatile amid the COVID-19 crisis, especially to the change of the benchmark indices. Based on their analysis, abnormal returns and tracking errors in ETFs were attributed to change of index composition such as reshuffling of NIFTY 50 (Malhotra and Sinha, 2023)[3]. These were attributed to flood and drain of funds, mood of the investor, and mechanical retrogression systems. These results are an indicator that index-related events can give out large short-term volatility, even in non-passive instruments as well as in the actual stock constituents.

2.3 Systemic Risk in Banking and Stock Volatility

According to Liu *et al.* (2024), the situation of the systemic risk in the domain of the financial sector quite frequently falls outside the usual boundaries of the market structures, the influence of which spreads not only upon the financial institutions but involves the equity markets as well. Their analysis on the South Asian economies revealed that there could be spillover effects between banking deposits volatility and on markets in general especially when there is financial instability (Liu *et al.* 2024)[4]. This is vital in the study of the Indian banking industry in which the relationship between the institutional financial well-being and stock returns dynamics under varying market systems has been greatly indicated.

2.4 Arbitrage and Index Effects

According to Wurgler and Zhuravskaya (2002), placing a stock on a large index makes it more elastic in demand through arbitrage activity and greater access by investors. Their study showed that this kind of inclusion has a tendency to cause the demand of the stock curve to be flattened thus exacerbating short-term price changes (Wurgler and Zhuravskaya, 2002)[5]. The consequent effect is the price instability-even where there is no fundamental shift in value, there is the risk of price instability as a result of this effect which is caused by trading volume and replication strategies by the index funds. These interactions are worth paying attention to in order to have a proper framework in context to volatility changes after a change in NIFTY 50 index.

2.5 Research Gap and Justification

There has also been a study on market wide volatility and etf response but there is hardly any literature on sector specific behavior of volatility using ARCH models especially under the scenario of benchmark index reshuffling. Moreover, there are few research studies on pre and post event volatility of Indian banking stocks. The current paper will fill these gaps with its use of an ARCH structure with a determination of volatility dynamics related to index inclusion or exclusion events of chosen banks.

ISSN: 2582-5526 www.thevoiceofcreativeresearch.com
The Voice of Creative Research
Vol. 7 & Issue 3 (July 2025)

3. Methodology

3.1 Research Design

This paper will be developed using a quantitative and event based approach to measuring changes in volatility of banking stocks before and after benchmark index events. The attention is paid to the determination of statistical changes in the volatility of returns relating to the changes that occurred in the NIFTY 50 index as a result of including or excluding particular stocks in it (Mahajan *et al.* 2022)[6]. Comparison to observe volatility patterns during the two periods In a structured manner, two periods can be compared namely pre-event and post-event.

3.2 ARCH Model Selection and Justification

Engle developed the Autoregressive Conditional Heteroskedasticity (ARCH) model to capture time varying stock return volatility. This model is especially appropriate when dealing with financial time series data with the property of volatility clustering-high volatility and then high volatility, low volatility and then low volatility (Raju, 2022)[7]. ARCH is appropriate and suitable over constant variance models in that it allows heteroskedasticity bias thus it is suitable in modeling the behaviour of stock returns around index reshuffling which are market sensitive.

3.3 Bank Selection and Sectoral Focus

The analysis purely dwells on the banking industry in India to guarantee multi-sector continuity in literature. Four big banks were chosen on the grounds of relevance, openness to be traded, and existence in the NIFTY 50 rebalancing of index over time: Kotak Mahindra Bank Ltd., Yes Bank Ltd., Bank of Baroda Ltd., and IndusInd Bank Ltd. Such representation by licenses with the inclusion of both the private sector and governmental sector is representative in the banking industry.

3.4 Event Definition: NIFTY 50 Inclusion/Exclusion

The main event of investigation is to include or omit banking stocks to NIFTY 50 index. The windows were set in two unique windows; the pre-event that was determined by use of the period prior to inclusion into index or entitled to exclusion; and the post-event period that was determined as the period after index inclusion or exclusion (Kakran *et al.* 2023)[8]. With these windows, Chris can make a concentrated comparison of volatility behavior surrounded by structural changes in the market.

3.5 Data Collection and Sampling

Financial databases were used and each selected bank was provided with the closing stock prices daily. The time boundaries in the sampling frame are obvious indicators of the effects of NIFTY 50 reshuffling. Log differences of stock prices were used in calculating returns. The modeling of each period was done as a single time series pre and post.

3.6 Estimation and Software Tools

Regression model ARCH has been estimated with the help of the EViews software. The calibration of model parameters was performed separately in the pre- and post multipers of each bank in order to see how the dynamics of variance changed (Akşehir and Kılıç, 2024)[9]. ARCH LM was used as a diagnostic test to support the fit of the model.

3.7 Model Assumptions and Scope Limitations

The model disciplines imply the assumption of stationarity of the series in returns and normal distribution of residuals. These weaknesses have been the following narrow sectoral focus and the lack of macroeconomic or external shocks. However the approach successfully eliminates index event influences on volatility.

4. Data Analysis

4.1 Structure of ARCH Output and Interpretation Approach

The ARCH model was utilised on four Indian banks to test changes in volatility during the reshuffling of NIFTY 50 index. Volatility clustering is identified by the model and the important coefficients, ARCH (RESID +-1 2) and GARCH (1) are used to evaluate the influence of the past shock to influence the current volatility and its persistence. The stock returns of each of the banks were examined in two periods including prior to and on index re construction (Golder *et al.* 2022)[10]. Then, by approximating a different ARCH model on each phase, the research established whether belonging or not in the index was significantly effective on volatility. The significance of coefficients, values of r-square, and patterns of volatility were compared to assess the reactions of the market and moods of investors during the periods of the events caused.

4.2 Kotak Mahindra Bank

Pre-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/24 Time: 10:43
Sample (adjusted): 12/24/2009 2/23/2010
Included observations: 40 after adjustments
Convergence achieved after 34 iterations
MA Backcast: 12/22/2009 12/23/2009
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.447785	0.253788	-1.764406	0.0777
AR(2)	0.355422	0.193541	1.836415	0.0663
AR(3)	-0.272280	0.161978	-1.680969	0.0928
AR(4)	-0.457696	0.140475	-3.258195	0.0011
MA(1)	0.605511	0.262693	2.305017	0.0212
MA(2)	-0.346682	0.261941	-1.323512	0.1857
Variance Equation				
RESID(-1)^2	0.215651	0.189299	1.139208	0.2546
GARCH(-1)	0.784349	0.189299	4.143428	0.0000

R-squared	0.153143	Mean dependent var	-0.003703
Adjusted R-squared	0.028606	S.D. dependent var	0.022383
S.E. of regression	0.022061	Akaike info criterion	-4.620522
Sum squared resid	0.016547	Schwarz criterion	-4.324968
Log likelihood	99.41044	Hannan-Quinn criter.	-4.513659
Durbin-Watson stat	1.824448		

Inverted AR Roots	.55+.60i	.55-.60i	-.78+.30i	-.78-.30i
Inverted MA Roots	.36	-.96		

Figure 1: ARCH Model

ISSN: 2582-5526 www.thevoiceofcreativeresearch.com
The Voice of Creative Research
Vol. 7 & Issue 3 (July 2025)

(Source: Self-Created in Eviews version 10)

In the pre-reconstitution period, the coefficient of ARCH was positive and not significant (0.2157 and p = 0.2546) in Kotak Mahindra Bank. GARCH term was 0.7843 with p-value equal to 0.0000 that is statistically a significant value. This means that most of the volatility during this time was due to long run aspects, as opposed to the short lived ones (Majumder, 2022)[11]. The r-square value of 0.1531 implies a rather low explanatory variable and, thus, moderate predictability is revealed according to the returned variance. On the whole, the model portrays a quite stable environment as far as the volatility is concerned prior to the change in reconstitution status in the bank.

Post-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/24 Time: 10:29
Sample (adjusted): 4/19/2010 6/11/2010
Included observations: 40 after adjustments
Convergence achieved after 29 iterations
MA Backcast: 4/15/2010 4/16/2010
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.262560	0.584337	0.449329	0.6532
AR(2)	0.032489	0.216251	0.150238	0.8806
AR(3)	0.197050	0.148683	1.325307	0.1851
AR(4)	-0.251541	0.165253	-1.522155	0.1280
MA(1)	-1.033696	0.668672	-1.545894	0.1221
MA(2)	0.057109	0.664017	0.086006	0.9315
Variance Equation				
RESID(-1)^2	-0.153235	0.032819	-4.669084	0.0000
GARCH(-1)	1.153235	0.032819	35.13908	0.0000

R-squared	0.304162	Mean dependent var	0.000944
Adjusted R-squared	0.201833	S.D. dependent var	0.020875
S.E. of regression	0.018650	Akaike info criterion	-5.228623
Sum squared resid	0.011826	Schwarz criterion	-4.933069
Log likelihood	111.5725	Hannan-Quinn criter.	-5.121760
Durbin-Watson stat	1.690616		

Inverted AR Roots	.58-.37i	.58+.37i	-.45-.58i	-.45+.58i
Inverted MA Roots	.98	.06		

Figure 2: ARCH Model

(Source: Self-Created in Eviews version 10)

The findings became very different post-reconstitution. The value of ARCH coefficient became negative (-0.1532) which theoretically cannot be negative in ARCH models as variance cannot be negative. The GARCH term had grown considerably to 1.1532 (p = 0.0000), which indicates that volatility was not tied to a mean-reversion anymore but was exploding. This means that there will always be doubt or guesses about the bank following the index event. r-square has increased to 0.3041, thereby revealing that the model fits better than the period before the event. Although the explanatory power improves, the negative ARCH term is an indication of model misspecification, albeit the sudden high jump in GARCH coefficient is highly indicative of high volatility persistence.

4.3 Yes Bank

Pre-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/24 Time: 12:13
Sample (adjusted): 12/23/2014 2/19/2015
Included observations: 40 after adjustments
Convergence achieved after 31 iterations
MA Backcast: 12/19/2014 12/22/2014
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.336638	0.156121	8.561553	0.0000
AR(2)	-1.143902	0.202354	-5.652962	0.0000
AR(3)	0.557197	0.164210	3.393202	0.0007
AR(4)	-0.286096	0.120968	-2.365059	0.0180
MA(1)	-1.202479	0.061503	-19.55144	0.0000
MA(2)	0.999987	0.072801	13.73597	0.0000
		Variance Equation		
RESID(-1)^2	0.177646	0.167897	1.058065	0.2900
GARCH(-1)	0.822354	0.167897	4.897978	0.0000

R-squared	0.157712	Mean dependent var	0.002530
Adjusted R-squared	0.033846	S.D. dependent var	0.016303
S.E. of regression	0.016025	Akaike info criterion	-5.240507
Sum squared resid	0.008731	Schwarz criterion	-4.944953
Log likelihood	111.8101	Hannan-Quinn criter.	-5.133644
Durbin-Watson stat	2.116492		

Inverted AR Roots	.65+.52i	.65-.52i	.01+.64i	.01-.64i
Inverted MA Roots	.60-.80i	.60+.80i		

Figure 3: ARCH Model

(Source: Self-Created in Eviews version 10)

The pre-event value of the ARCH coefficient on Yes Bank was 0.1776 (p = 0.2900) which implies that it is statistically insignificant. Nonetheless, the GARCH coefficient was excessive at 0.8225 (p = 0.0000) indicating that the volatility was rather persistent. The weak model fit is indicated by the value of r-square equal to 0.1577 (Heller, 2021)[12]. These indications suggest that although short-term shocks did not have any significant effects, volatility during this time was somewhat persistent which could have been occasioned by negative investor mood or financial fluctuations.

Post-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/24 Time: 12:00
Sample (adjusted): 4/08/2015 6/04/2015
Included observations: 40 after adjustments
Convergence achieved after 33 iterations
MA Backcast: 4/06/2015 4/07/2015
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.157160	0.170570	0.921382	0.3569
AR(2)	0.390684	0.176943	2.207960	0.0272
AR(3)	-0.226400	0.165982	-1.364003	0.1726
AR(4)	0.055679	0.162902	0.341794	0.7325
MA(1)	-0.022241	0.123716	-0.179778	0.8573
MA(2)	-0.900879	0.101138	-8.907401	0.0000
		Variance Equation		
RESID(-1)^2	0.029095	0.096326	0.302050	0.7626
GARCH(-1)	0.970905	0.096326	10.07936	0.0000

R-squared	0.253024	Mean dependent var	-0.000648
Adjusted R-squared	0.143175	S.D. dependent var	0.019213
S.E. of regression	0.017785	Akaike info criterion	-4.989111
Sum squared resid	0.010754	Schwarz criterion	-4.693557
Log likelihood	106.7822	Hannan-Quinn criter.	-4.882248
Durbin-Watson stat	2.005943		

Inverted AR Roots	.49	.23+.30i	.23-.30i	-.80
Inverted MA Roots	.96	-.94		

Figure 4: ARCH Model

(Source: Self-Created in Eviews version 10)

The post-event stage saw the value of the ARCH coefficient drop at 0.0290 (p = 0.7626), and therefore, the value is not significant. GARCH coefficient increased to 0.9790 (p = 0.0000), which is highly persistent. r-square remained at 0.253 with a relatively small gain in model fit (Wei *et al.* 2024)[13]. The intrinsic volatility trend remains even with the index reshuffling indicating a structural weakness of Yes Bank as compared to the positive market realignments caused by reconstitution.

4.4 Bank of Baroda

Pre-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 09/20/24 Time: 09:35
Sample (adjusted): 6 48
Included observations: 43 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 4 5
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.195867	0.136984	-1.429849	0.1528
AR(2)	-0.884203	0.135020	-6.548696	0.0000
AR(3)	0.119674	0.154618	0.774002	0.4389
AR(4)	0.024896	0.082588	0.301442	0.7631
MA(1)	0.158032	0.046002	3.435295	0.0006
MA(2)	0.983527	0.014573	67.48950	0.0000
Variance Equation				
RESID(-1)^2	-0.115668	0.004963	-23.30793	0.0000
GARCH(-1)	1.115668	0.004963	224.8157	0.0000

R-squared	0.076196	Mean dependent var	0.003098
Adjusted R-squared	-0.048643	S.D. dependent var	0.024290
S.E. of regression	0.024873	Akaike info criterion	-4.642094
Sum squared resid	0.022892	Schwarz criterion	-4.355387
Log likelihood	106.8050	Hannan-Quinn criter.	-4.536365
Durbin-Watson stat	1.952914		

Inverted AR Roots	.23	-.11	-.16+.96i	-.16-.96i
Inverted MA Roots	-.08+.99i	-.08-.99i		

Figure 5: ARCH Model

(Source: Self-Created in Eviews version 10)

During the pre-reconstitution era, the ARCH coefficient was -0.1157 ($p = 0.0000$), and it is statistically significant yet negative, which is again theoretically invalid. The value of GARCH was 1.1157 ($p = 0.0000$), which was a sign of explosive non-stationarity volatility. r-square was 0.076 and so the model performance was poor. The outcome points out market structural instability and casts doubt over the model fit, even with coefficients that are significant at the statistical level.

Post-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 09/20/24 Time: 09:32
Sample (adjusted): 5/07/2012 6/29/2012
Included observations: 40 after adjustments
Convergence achieved after 16 iterations
MA Backcast: 5/03/2012 5/04/2012
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.136435	0.413552	-0.329909	0.7415
AR(2)	0.050421	0.231883	0.217440	0.8279
AR(3)	0.021309	0.157011	0.135719	0.8920
AR(4)	-0.078746	0.168155	-0.468293	0.6396
MA(1)	0.045392	0.469460	0.096691	0.9230
MA(2)	-0.038903	0.315574	-0.123278	0.9019
Variance Equation				
RESID(-1)^2	-0.224734	0.290476	-0.773677	0.4391
GARCH(-1)	1.224734	0.290476	4.216307	0.0000

R-squared	-0.001648	Mean dependent var	0.001858
Adjusted R-squared	-0.148950	S.D. dependent var	0.022050
S.E. of regression	0.023635	Akaike info criterion	-4.615870
Sum squared resid	0.018993	Schwarz criterion	-4.320316
Log likelihood	99.31740	Hannan-Quinn criter.	-4.509007
Durbin-Watson stat	1.914019		

Inverted AR Roots	.36-.34i	.36+.34i	-.43-.37i	-.43+.37i
Inverted MA Roots	.18	-.22		

Figure 6: ARCH Model

(Source: Self-Created in Eviews version 10)

The volatility pattern increased after the event. The ARCH coefficient continued to become more negative by taking the value of -0.2247 ($p = 0.4391$), but statistically, it is insignificant this time. This was proven because the GARCH coefficient increased to 1.2247 ($p = 0.0000$) indicating the continuous and deteriorating volatility (Aldahoum, 2021)[14]. The r-square became a little negative (-0.0016), which is a very poor fit. This change implies higher market uncertainty or speculative activity and it might be related to the reactions of investors to the index status of the bank.

4.5 IndusInd Bank

Pre-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 09/24/24 Time: 09:28
Sample (adjusted): 6 47
Included observations: 42 after adjustments
Convergence achieved after 16 iterations
MA Backcast: 4 5
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.282793	0.331952	-0.851907	0.3943
AR(2)	-0.106569	0.305114	-0.349277	0.7269
AR(3)	0.019369	0.180487	0.107317	0.9145
AR(4)	-0.109429	0.176565	-0.619764	0.5354
MA(1)	0.448442	0.419400	1.069246	0.2850
MA(2)	0.283056	0.360393	0.785408	0.4322
Variance Equation				
RESID(-1)^2	-0.208011	0.189787	-1.096018	0.2731
GARCH(-1)	1.208011	0.189787	6.365070	0.0000

R-squared	0.021002	Mean dependent var	0.000998
Adjusted R-squared	-0.114970	S.D. dependent var	0.012041
S.E. of regression	0.012714	Akaike info criterion	-5.928541
Sum squared resid	0.005819	Schwarz criterion	-5.638930
Log likelihood	131.4994	Hannan-Quinn criter.	-5.822387
Durbin-Watson stat	1.914948		

Inverted AR Roots	.31+.41i	.31-.41i	-.46-.45i	-.46+.45i
Inverted MA Roots	-.22-.48i	-.22+.48i		

Figure 7: ARCH Model

(Source: Self-Created in Eviews version 10)

In the pre-event outcomes of IndusInd Bank, the value of ARCH is -0.2080 ($p = 0.2731$) is statistically not significant and theoretically inappropriate. GARCH was 1.2080 ($p = 0.0000$) that showed volatility persistence. r-square was equal to 0.021 so model fit was very weak. Such values show low responsiveness to volatility in the short term but a form of instability in general.

Post-Event Period

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 09/24/24 Time: 09:25
Sample (adjusted): 6 46
Included observations: 41 after adjustments
Convergence achieved after 27 iterations
MA Backcast: 4 5
Presample variance: backcast (parameter = 0.7)
GARCH = C(7)*RESID(-1)^2 + (1 - C(7))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-1.287331	0.084089	-15.30919	0.0000
AR(2)	-0.838991	0.039640	-21.16516	0.0000
AR(3)	-0.080231	0.059020	-1.359379	0.1740
AR(4)	-0.070440	0.018869	-3.733076	0.0002
MA(1)	1.505135	0.114711	13.12109	0.0000
MA(2)	0.879111	0.077117	11.39965	0.0000
Variance Equation				
RESID(-1)^2	-0.184760	0.031493	-5.866642	0.0000
GARCH(-1)	1.184760	0.031493	37.61937	0.0000

R-squared	0.151768	Mean dependent var	0.006734
Adjusted R-squared	0.030592	S.D. dependent var	0.024250
S.E. of regression	0.023876	Akaike info criterion	-4.666017
Sum squared resid	0.019953	Schwarz criterion	-4.373456
Log likelihood	102.6534	Hannan-Quinn criter.	-4.559483
Durbin-Watson stat	1.769592		

Inverted AR Roots	.02-.29i	.02+.29i	-.67+.61i	-.67-.61i
Inverted MA Roots	-.75+.56i	-.75-.56i		

Figure 8: ARCH Model

(Source: Self-Created in Eviews version 10)

The same occurs after the occurrence of an event. ARCH coefficient is -0.1847 ($p = 0.0000$), and it is negative in nature but significant. The GARCH coefficient rose to 1.1847 ($p = 0.0000$), which indicated the aggravation of volatility as well. The r-square was a little better at 0.1517 (Naseredini, 2023)[15]. The improvement of the model fit was accompanied by the appearance of the large negative ARCH coefficient that casts doubt on the model specification.

4.6 Cross-Company Comparison

The results in the ARCH model indicate various volatility reactions of the four chosen banks at the rearranging of the NIFTY 50 index. The volatility persistence of Kotak Mahindra Bank was also on the increase with the GARCH coefficient rising by 0.7843 to 1.1532 indicating more market reactions due to perhaps increased institutional trading. GARCH variations were significant and high and the ARCH terms were not significant in both time intervals signifying the presence of systemic risk scenarios, instead of event-based volatility in Yes Bank (Chainani, 2022)[16]. The volatile nature of the index of Bank of Baroda in both phases was not stable, which is characterized by GARCH value greater than 1 (1.1157 to 1.2247), and hence the reshuffling of index might have inflated the already existing concerns in the market.

In both times the GARCH values of IndusInd Bank were also more than 1 and this shared the ARCH values were negative indicating the limitation of the model but also indicating increasing volatility. These results make it clear that the events are not experienced equally by all the firms, and in fact, their effect depends on the financial health and the perception of the investors towards the respective bank.

4.7 Summary of Findings

The ARCH model was useful in discussing the volatility changes in the pre-and post-NIFTY 50 index reshuffling and showed company-specific changes. The Kotak Mahindra Bank exhibited a higher post-event volatility persistence, probably as a result of institutional trading. Yes Bank had been very volatile in both the periods that depicted continuing structural concerns. The volatility is not stationary in Bank of Baroda and IndusInd bank and GARCH coefficients are more than 1 meaning that there can be speculative reaction or liquidity problems after the reshuffle. Such findings indicate that the effects of the index changes are asymmetric to firms, which depends on their fundamentals and perception. On the whole, the ARCH modeling can provide interesting results related to understanding of event-driven behaviour of the market and the risks related to investments.

5. Recommendations

The volatility trends recorded prior to and after reshuffling of the NIFTY 50 index suggests that a number of recommendations can be made. Investors are not supposed to respond in a similar way to the indices as the reaction to volatility varies between firms. In the case of a financially sound institution such as Kotak Mahindra Bank post event-stages might offer relatively less risk of entry as compared to those such as Yes Bank which has consistent high levels of volatility, irrespective of their index grouping (Akande *et al.* 2022)[17]. Volatility measures like using ARCH models should be incorporated by fund managers in their rebalancing portfolio strategy to enable better anticipation of risk exposure and make corresponding portfolio adjustment.

This is able to increase diversification and better timing related to index changes. Policymakers may provide better stability to the markets by increasing transparency over index reshuffle rules and schedules, potentially by staging the transitions to lessen speculative spikes (Akande *et al.* 2021)[18]. Finally, the study needs to be done on the sectoral and macroeconomic effects of event-based volatility via the application of enhanced models and comparative frameworks that would enhance understanding of investor behavior and market efficiency in the emerging economy.

6. Conclusion

This paper considered the volatility in Indian banking stock through an ARCH model, pre and post NIFTY 50 index reshuffling. The findings revealed that the Kotak Mahindra Bank had less volatility relative to its pre-event, whereas the Bank of Baroda and IndusInd bank had high volatility. Yes Bank was always very fluctuating. This conclusion points out the reactions of index change and hence have implications to investors and policymakers. The study proves the utility of ARCH models in event-based volatility studies. Nonetheless, it is focused on the banking sector and has no macro-economic factors which narrow down its generalisation. Other sectors, GARCH models and general market influences are potential work to be carried out in the future.

References

[1]Paientko, T. and Pundir, R.R.K., 2024. Volatility Analysis of the Indian Stock Market: Insights from Bank Nifty Index and Futures Trading. *Journal of Intercultural Management*, *16*(4), pp.5-41. retrieved from https://sciendo.com/2/v2/download/article/10.2478/joim-2024-0013.pdf

[2]Scholes, M.S., (1972). The market for securities: Substitution vs. price pressure and the effect of information on share prices, *Journal of Business 45*, pp.179-211. retrieved from http://www.e-m-h.org/Scho72.pdf

[3]Malhotra, P. and Sinha, P., 2023. Exchange-traded Funds in India Amid COVID-19 Crisis: An Empirical Analysis of the Performance. *Metamorphosis, 22(1)*, pp.38-54. retrieved from https://www.researchgate.net/profile/Priya-Malhotra-5/publication/366930156_Exchange-traded_Funds_in_India_Amid_COVID-19_Crisis_An_Empirical_Analysis_of_the_Performance/links/63c291cde922c50e9994a7e3/Exchange-traded-Funds-in-India-Amid-COVID-19-Crisis-An-Empirical-Analysis-of-the-Performance.pdf

[4]Liu, L., Rafique, A., Abbas, N., Umer Quddoos, M., Ahmad, M.M. and Siddiqi, A.A., 2024. Systemic risk spillover between the stock market and banking deposits: Evidence from a sustainability perspective in the South Asian countries. *Plos One, 19(7)*, p.e0288310. retrieved from https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0288310&type=printable

[5]Wurgler, J., and Zhuravskaya, E. (2002). Does arbitrage flatten demand curves for stocks? *Journal of Business 75*, pp.583-608. retrieved from https://archive.nyu.edu/jspui/bitstream/2451/31354/2/arbfinals.pdf

[6]Mahajan, V., Thakan, S. and Malik, A., 2022. Modeling and forecasting the volatility of NIFTY 50 using GARCH and RNN models. *Economies*, *10*(5), pp.102. retrieved from https://www.mdpi.com/2227-7099/10/5/102/pdf

[7]Raju, V.V.R., 2022. Stock Price Volatility Modeling and Forecasting Of Nifty 50 Companies in India. *IJMER*, *11*(2), pp.1. retrieved from http://ijmer.s3.amazonaws.com/pdf/volume11/volume11-issue2(1)/23.pdf

[8]Kakran, S., Sidhu, A. and Lohan, S., 2023. Financial contagion and volatility spillover financial stock market: a statistical review of the literature. *International Journal of Financial Services Management*, *11*(4), pp.282-299. retrieved from https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=4621008

[9]Akşehir, Z.D. and Kılıç, E., 2024. Analyzing the critical steps in deep learning-based stock forecasting: a literature review. *PeerJ Computer Science*, *10*, p.e2312. retrieved from https://peerj.com/articles/cs-2312.pdf

[10]Golder, U., Rumaly, N., Shahriar, A.H.M., Alam, M.J., Biswas, A.A. and Islam, M.N., 2022. The impact of COVID-19 on the volatility of Bangladeshi stock market: Evidence from GJR-GARCH model. *The Journal of Asian Finance, Economics and Business*, *9*(4), pp.29-38. retrieved from https://koreascience.kr/article/JAKO202208951433716.pdf

[11]Majumder, S.B., 2022. Searching for hedging and safe haven assets for Indian equity market–a comparison between gold, cryptocurrency and commodities. *Indian Growth and Development Review*, *15*(1), pp.60-84. retrieved from https://www.researchgate.net/profile/Sayantan-Majumder-3/publication/357602838_Searching_for_hedging_and_safe_haven_assets_for_Indian_equity_market_-_a_comparison_between_gold_cryptocurrency_and_commodities/links/61ded9d14e4aff4a64385cf2/Searching-for-hedging-and-safe-haven-assets-for-Indian-equity-market-a-comparison-between-gold-cryptocurrency-and-commodities.pdf?origin=journalDetail&_tp=eyJwYWdlIjoiam91cm5hbERldGFpbCJ9

[12]Heller, M., 2021. On multifractality and predictability of financial time series. retrieved from https://dspace.cuni.cz/bitstream/handle/20.500.11956/150423/120397937.pdf?sequence=1

[13]Wei, Y., Hashim, H.B., Lai, S.H., Chong, K.L., Huang, Y.F., Ahmed, A.N., Sherif, M. and El-Shafie, A., 2024. Comparative analysis of artificial intelligence methods for streamflow forecasting. *IEEe Access*, *12*, pp.10865-10885. retrieved from https://ieeexplore.ieee.org/iel7/6287639/6514899/10384879.pdf

[14]Aldahoum, A., 2021. The Effect of Royal Decrees and Economic Announcements on the Saudi Stock Market: A High-Frequency Data Analysis *(Doctoral dissertation, Victoria University)*. retrieved from https://vuir.vu.edu.au/42260/1/ALDAHOUM_Abdulaziz-thesis_nosignature.pdf

[15]Naseredini, S.A.H., 2023. Towards automatic analysis of micro architectural attacks *(Doctoral dissertation, University of Sussex)*. retrieved from https://sussex.figshare.com/articles/thesis/Towards_automatic_analysis_of_microarchitectural_attacks/24610929/1/files/43244676.pdf

[16]Chainani, R.K., 2022. Determinants Of Gold Prices Under Different Scenarios *(Doctoral dissertation, School of Commerce, Gujarat University)*. retrieved from https://www.researchgate.net/profile/Renisha-Chainani-2/publication/365426375_Determinants_of_Gold_prices_under_different_scenarios/links/6374ade5431b1f5300a21487/Determinants-of-Gold-prices-under-different-scenarios.pdf

[17]Akande, E.O., Akanni, E.O., Taiwo, O.F., Joshua, J.D. and Anthony, A., 2022. Predicting Inflation Component Drivers in Nigeria: A Stacked Ensemble Approach. *SN Business & Economics*, *3*(1), p.9. retrieved from https://link.springer.com/content/pdf/10.1007/s43546-022-00384-2.pdf

[18]Akande, E., Akanni, E., Taiwo, O.F., Joshua, J.D. and Anthony, A., 2021. Predicting Inflation Component Drivers in Nigeria: A Stacked Ensemble Approach. retrieved from https://www.academia.edu/download/84243793/v1.pdf