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ASSESSING VOLATILITY IN THE BANKING STOCKS IN INDIAN STOCK MARKET DURING THE COVID-19 PANDEMIC: USING ARCH/GARCH MODELS

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ABSTRACT

The present study examines at modelling and forecasting the volatility of the Nifty, Sensex, Nifty Bank index, and five banking stocks in the Indian stock market, including HDFC Bank, ICICI Bank, Axis Bank, Kotak Bank, and SBI Bank, using regular data from January 26th, 2019 to January 25th, 2021, spanning both the period before and after the COVID-19 pandemic. The first positive case in India was recorded on January 27, 2020. The Nifty, Sensex, Nifty Bank index and five banking stocks: HDFC Bank, ICICI Bank, Axis Bank, Kotak Bank, and SBI Bank return volatility for the Indian stock market are investigated using GARCH, EGARCH, and TGARCH models. The aim of this study is to look at the Indian stock market's volatility characteristics, such as clustering volatility, leverage impact, and risk premium. Positive and negative shocks have different effects on the volatility of the Nifty, Sensex, Nifty bank index, and five bank stock returns in the TGRACH(1,1) model, which means that negative news causes more volatility than positive news. Hence, the effect of news on the Indian stock market during the Covid-19 pandemic is asymmetric.

KEYWORDS: *Leverage, GARCH, Volatility, Nifty, Covid-19*

INTRODUCTION

The banking sector is the lifeblood of the economy, keeping it afloat and going. Banks perform the majority of the functions needed to keep the country's economy running smoothly. Banks play a crucial role in providing companies with financing in the form of loans and equity investments. The black swan case of the century, Covid-19, has had a major influence on the Indian economy. Prior to the outbreak of covid-19, the Indian economy was in poor condition, and the pandemic situation has had a huge effect on India's banking sector, as well as other important sectors. The effect of COVID-19 on banking would be a significant drop in demand, lower wages, and output shutdowns. As companies scramble to deal with the effect of COVID-19 on financial services, the situation is compounded by workforce shortages, a lack of digital sophistication, and strain on existing infrastructure. In view of the novel coronavirus outbreak, banks have their hands full. As the virus spreads across the globe, borrowers and companies face job losses, slowed revenue, and decreasing earnings. Customers of banking institutions are likely to request financial assistance. Pandemics have a clear effect on financial structures because of their immense economic costs. Banks must have a strategy in place to protect staff and customers from the coronavirus in order to manage the virus's direct economic effects. Many banks are now encouraging some workers to operate remotely.

The Reserve Bank of India's (RBI) expert committee document on a resolution framework, led by former ICICI leader K.V Kamath, shows that banking debt worth Rs 23.71 lakh crore, or 45 percent of banking sector debt, was already in trouble before Covid-19 reached the economy. This essentially means that 72 percent of the banking sector's debt, valued at Rs 37.72 lakh crore, is still in jeopardy. This amounts to about 37% of the overall credit. Some analysts suggest that banks are more hesitant to limit loans this time because they have already lost a lot of money in previous attempts to do so. The banking sector, especially in India, will take a long time to recover from the pandemic's effects.

The Reserve Bank of India (RBI) has taken a number of steps to support lending institutions. The RBI has implemented credit risk assessment, in which borrowers are granted such exemptions, such as a moratorium on paying principal and interest, as well as a relaxation of their classification as a non-performing or restructured asset. This might assist the borrower in overcoming short-term financial difficulties. Banks, on the other hand, would have to locate borrowers who are experiencing some short- or long-term financial problems in order to provide the relief steps.

The RBI has reduced all banks' cash reserve ratios by 100 basis points to 3% net demand and time liability as of March 28, 2020.

As of March 28, 2020, the minimum regular CRR balance maintenance threshold has been lowered from 90% to 80%, and this one-time exemption is valid until June 26, 2020.

The RBI has allowed banks to borrow overnight at their discretion by dipping up to 2% into the Statutory Liquidity Ratio under the Marginal Standing Facility (MSF). With immediate impact, this cap has been raised to 3%. This measure will be in effect until June 30, 2020.

The current policy rate corridor has been extended by the central bank from 50 to 65 basis points. The racial divide has narrowed as a result of the current corridor.

REVIEW OF LITERATURE:

Alberg et al. [6] used daily returns data, TASE indices, the TA25 index period October 1992 to May 2005 and TA100 index period July 1997 to May 2005 and applied GARCH, EGARCH, and APARCH model Findings suggest that one can improve overall estimation by using the asymmetric GARCH model and the EGARCH model is a better predictor than the other asymmetric models.

Girard &Omran[7] examine the interaction of volatility and volume in 79 traded companies in Cairo and Alexandria Stock Exchange GARCH model. They found that information size and direction have a negligible effect on conditional volatility and, as a result, the presence of noise trading and speculative bubbles is suspected.

Joshi [8] used daily closing prices from January 2005 to May 2009 . For the purpose of ananlysis used BDS Test, ARCH-LM test, and GARCH (1,1) model Persistence of volatility is more than Indian stock market.

Wong & Cheung [9] in their paper they studied the Hong Kong stock market from 1984 to 2009 anad used GARCH family models, the EGARCH and AGARCH models can detect the asymmetric effect well in response to both good news and bad news. By comparing different

GARCH models, they find that it is the EGARCH model that best fits the Hong Kong case.

Maheshchandra[10] in his study used daily closing prices of BSE and NSE stock indices period of January 2008 to August 201, applied the ARFIMA and FIGARCH models and found that Absence of long memory in return series of the Indian stock market. Strong evidence of long memory in conditional variance of stock indices.

Purohit et al. [11] in their study used daily closing data for November 2009 to March 2013, NIFTY and NIFTY Junior indices and used the ADF Test, Johansen's co-integration test, and GARCH (1,1) model. Empirical results found that one-month futures do not bring volatility in the VIX.

Gupta et al. [12] in their paper used the daily closing prices of S&P CNX500 of National Stock Exchange for the period from January 2003 to December 2012. For the purpose of the study they used GARCH, TGARCH, and EGARCH models. The result of that volatility varies over time and constant variance assumption is inconsistent. The empirical evidence indicated the presence of time varying volatility.

Nadhem et al. [13]in their paper S&P500 market daily returns the sample period from July 1996 to May 2006. GARCH family models Results of ANN models will be compared with time series model using GARCH family models. The use of the novel model for conditional stock markets returns volatility can handle the vast amount of nonlinear data, simulate their relationship, and give a moderate solution for the hard problem**.**

Data and methodology:

The research is entirely focused on secondary data. Data on regular closing prices of the indices Nifty, Sensex, Nifty Bank index, and five banking stocks (HDFC Bank, ICICI Bank, Axis Bank, Kotak Bank, and SBI Bank) were gathered from the www.bseindia.org and www.nseindia.org websites. Data will be collected from January 26th, 2019 to January 25th, 2021, spanning both the time before and after the COVID-19 pandemic. On January 27, 2020, the first positive case in India was discovered. The Ministry of Health and Family Welfare, Government of India, provided data on COVID-19 positive cases. As a result, the research period is split into two periods for this reason.

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Firstly, returns for currency were calculated as following:

Rt = 100 * ln(St / St-1)

FOLLOWING ECONOMETRIC MODELS WERE USED FOR ANALYSIS

Augmented Dickey Fuller (ADF) test, Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests and GARCH family of models were applied for the present research. The study has employed E-views 11 package for the purpose of investigation. Volatility is estimated on daily returns of NSE Nifty, BSE Sensex, Nifty Bank index, HDFC Bank, ICICI Bank, Axis Bank Kotak Bank and SBI Bank.

UNIT ROOT TESTS

Augmented Dickey-Fuller (ADF) Test

The standard DF test is carried out by estimating the following Equation after subtracting yt-1 from both sides of the equation:

Dyt = ayt – 1 + xt ¢d + et,

Where a = r – 1. The null and alternative hypotheses may be written as,

H0: a = 0

H1: a < 0

Heteroscedasticity Test

It is extremely vital to first examine the residuals for the existence of heteroscedasticity before applying the GARCH model.

The presence of heteroscedasticity in residuals of the return is confirmed by applying the Lagrange Multiplier (LM) test.

Tools for measuring Volatility

In general, it is observed that escalating movement in the share market is followed by minor variances when compared to the downward movements with alike nature. This asymmetric moment is termed as the leverage effect. Hence, the Generalized ARCH (GARCH) methodology which is symmetrical in nature will not be suitable to evaluate the unsteadiness in time series.

To capture the asymmetrical data, Exponential GARCH (EGARCH) methodology advocated by Nelson (1991) and Threshold GARCH (TARCH) advocated by Glosten, Jaganathan, and Runkle (1993) and Zakonian (1994) are applied.

GARCH (1, 1)

The GARCH model in which the conditional variance rest on the former lags; specifies the conditional variance equation as:

Mean equation: $r_t = \mu + \varepsilon_t$ and

Variance equation: σ^2

$_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$,

Where r_t is the return of the asset at time t, μ is the average return and ε_t is the residual return and where $\omega>0$, $\alpha \geq 0$, $\beta \geq 0$. The degree of factor α and β denote the variability in time series. If $(\alpha + \beta)$ is close to unity, it states that a distress at time t will carry on for future periods.

TGARCH (1, 1)

The equation of the TGARCH for the conditional variance is:

$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \gamma\, d_{t-1}\, \varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$,

Where γ is termed as the asymmetry or leverage factor. Here, positive facts ($\varepsilon_{t-1} > 0$) and the adverse data ($\varepsilon_{t-1} < 0$) have variance outcomes. α_i connotes positive facts while $\alpha_i+\gamma_i$ connotes adverse information. Thus, in the position where γ is substantial and positive, negative information has more consequence on σ^2_t compared to the positive information.

EGARCH (1, 1)

The volatility that happens to decline when returns rise and volatility happens to rise when the returns fall is often called the leverage effect (Enders 2004). EGARCH method captures asymmetric reaction of the time changing variance where variance is constantly affirmative. It was developed by Nelson (1991) that υ is the asymmetric response parameter or leverage parameter. If it is below zero it specifies that unfavourable information boosts forthcoming fluctuation while favorable information mitigates the consequence on forthcoming doubts (Kalu 2010).

EGARCH (1, 1) is defined as,

$$\ln(\sigma_t^2)=\omega+\beta\ln(\sigma_{t-1}^2)+\gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}+\alpha\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}}-\sqrt{\frac{2}{\pi}}\right]$$

EMPIRICAL RESULTS : The daily close values and returns of India's BSE Sensex, NSE nifty, and Nifty Bank Index, as well as the top five banking stocks traded on the NSE, HDFC Bank, ICICI Bank, Axis Bank, Kotak Bank, and SBI Bank, are used in this report. Tables 1.1 and 1.2 show that the mean return, a key indicator of benefit, for Axis Bank, ICICI Bank, and SBI Bank during the Covid-19 era was negative, suggesting a stock loss. All of the indices and bank stocks that were chosen In the stock market in India, a negatively skewed return with a high kurtosis value indicates the possibility of large losses during the covid19 pandemic time.As the higher level of standard deviation than the mean for the three indices and bank stocks during the covid-19 period indicates variability. The kurtosis value of three indices and five bank stock returns during the covid-19 period indicates that they peaked earlier than usual.The higher Jarque-Bera (JB) value of three indices and five bank stocks denotes that the distribution was not normal during the Covid-19 period. Thus, the null hypothesis of normality is rejected as the probability value is less than 0.05 levels.

TABLE 1.1: DESCRIPTIVE STATISTICS OF NIFFY, SENSEX AND NIFTY 500 INDICES DAILY RETURNS FROM 2019 TO 2020

Descriptive Statistics	Nifty		Sensex		NIFTY Bank Index	
	Pre Covid-19	During Covid-19 era	Pre Covid-19	During Covid-19 era	Pre Covid-19	During Covid-19 era
Mean	0.000504	0.000477	0.000591	0.000664	0.000654	0.000219
Median	0.000445	0.002141	0.000561	0.002748	0.000336	0.003093
Std. Dev	0.008723	0.020084	0.012469	0.020498	0.012726	0.027967
SKewness	1.056864	-1.724694	1.500023	-1.682483	1.257293	-1.423299
Kurtosis	8.321474	15.24141	12.28999	15.09694	9.860648	11.52939
Jarque-Bera	329.2254	1684.901	957.0121	1642.280	540.5902	818.6766
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

TABLE 1.2:DESCRIPTIVE STATISTICS OF HDFC BANK, ICICI BANK, AXIS BANK KOTAK BANK AND SBI BANK DAILY RETURNS FROM 2019 TO 2020

Descriptive Statistics	HDFC Bank		ICICI Bank		Axis Bank		Kotak Bank		SBI Bank	
	Pre Covid-19	During Covid-19	Pre Covid-19	During Covid-19	Pre Covid-19	During Covid-19	Pre Covid-19	During Covid-19	Pre Covid-19	During Covid-19

		era		era		era		era		era
Mean	0.000691	0.000457	0.001756	-0.00012	0.000312	-0.00075	0.001134	0.00027	0.000596	-0.0073
Median	0.000306	0.000769	-0.00176	0.003745	-0.00036	0.000095	0.000468	0.00088	0.001120	0.00195
Std. Dev	0.012469	0.023130	0.01247	0.034205	0.016402	0.041210	0.014090	0.02899	0.201917	0.03073
SKewness	1.500023	-0.66076	0.750310	-0.98844	0.614314	-1.74081	0.409133	-0.3889	0.314136	-0.7143
Kurtosis	12.28999	8.423851	4.835115	8.317572	4.713853	19.74069	5.767734	7.69892	5.561415	6.94722
Jarque-Bera	957.0121	324.6312	56.42920	335.2564	44.65347	3045.544	83.64617	325.351	69.84551	183.559
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.0000	0.00000	0.0000	0.00000	0.0000

The Augmented Dickey Fuller test is used in this analysis to see whether the three indices and five bank stock time series properties are stationary. Table 2 depicts the results. The ADF test is statistically relevant at a 5% level, according to the key result of this test. This means that the returns of the three indices prior to and during the Covid-19 period are stationary, null hypothesis is rejected. All of this proves that autocorrelation does not exist. As a consequence, the null hypotheses of the ADF test are rejected, and the return series data is determined to be stationary at level.

TABLE 2: AUGMENTED DICKEY FULLER TEST (ADF) FOR NIFTY, SENSEX & NIFTY BANK INDEX HDFC BANK, ICICI BANK, AXIS BANK KOTAK BANK AND SBI BANK DURINGJANUARY,2019 TO JANUARY 2021

Indices		**Augmented Dickey Fuller Test (ADF)** Level with Intercept	
		T-Statistics	Prob. Value
Nifty	Pre Covid-19	-14.48173	0.00000*
	DuringCovid-19 era	-4.511693	0.00000*
Sensex	Pre Covid-19	-14.64799	0.00000*
	During Covid-19 era	-17.87633	0.00000*
Nifty Bank Index	Pre Covid-19	-14.34224	0.00000*
	During Covid-19 era	-15.72960	0.00000*
HDFC Bank	Pre Covid-19	-12.01499	0.00000*
	During Covid-19 era	-15.86390	0.00000*
ICICI Bank	Pre Covid-19	-15.99913	0.00000*
	During Covid-19 era	-16.98639	0.00000*
Axis Bank	Pre Covid-19	-15.43779	0.00000*
	During Covid-19 era	-15.79049	0.00000*
Kotak Bank	Pre Covid-19	-15.04113	0.00000*
	During Covid-19 era	-15.92205	0.00000*
SBI Bank	Pre Covid-19	-14.60906	0.00000*
	During Covid-19 era	-17.59105	0.00000*

*Note: ADF Test critical values: *5% level-2.88,* The ARCH test (table 3) shows that the estimation residuals are heteroscedastic in nature. Due to the existence of heteroscedasticity in residuals, ARCH family models should be used to investigate the relationship between the three selected indices and five bank stock returns over the Pre and Covid-19 periods. The ARCH-LM test results show that residuals derived from regression estimation are heteroscedasticity-free (p > 0.05). As a result, when comparing the pre-Covid-19 period to the Covid-19 pandemic period, the ARCH-LM result shows no additional ARCH impact residual.

TABLE 3: HETEROSKEDASTICITY TEST: ARCH

Nifty				
Pre Covid-19	F-Statistic	11.18948	Prob.F (1,238)	0.0010
	Obs.*R-squared	10.77684	Prob. Chi.-Square(1)	0.0010
During Covid-19 era	F-Statistic	6.157635	Prob.F(1,247)	0.0138
	Obs.*R-squared	6.056507	Prob. Chi-Square(1)	0.0139
Sensex				
Pre Covid-19	F-Statistic	10.36889	Prob. F(1,238)	0.0015
	Obs.*R-squared	10.02229	Prob. Chi-Square(1)	0.0015
During Covid-19 era	F-Statistic	6.367899	Prob. F(1,241)	0.0122
	Obs.*R-squared	6.258979	Prob.Chi-Square(1)	0.0124
Nifty Bank Index				
Pre Covid-19	F-Statistic	26.41999	Prob. F(1,238)	0.0000
	Obs.*R-squared	23.99834	Prob. Chi-Square(1)	0.0000
During Covid-19 era	F-Statistic	0.117689	Prob. F(1,241)	0.7318
	Obs.*R-squared	0.118585	Prob. Chi-Square(1)	0.7318
HDFC Bank				
Pre Covid-19	F-Statistic	12.69557	Prob. F(1,238)	0.0004
	Obs.*R-squared	12.15393	Prob. Chi-Square(1)	0.0005
During Covid-19 era	F-Statistic	0.127916	Prob. F(1,241)	0.7209
	Obs.*R-squared	0.12885	Prob. Chi-Square(1)	0.7196
ICICI Bank				
Pre Covid-19	F-Statistic	15.00079	Prob. F(1,238)	0.0001
	Obs.*R-squared	14.22995	Prob. Chi-Square(1)	0.0002
During Covid-19 era	F-Statistic	1.968587	Prob. F(1,241)	0.1619
	Obs.*R-squared	1.968835	Prob. Chi-Square(1)	0.1606
ASIX Bank				
Pre Covid-19	F-Statistic	21.13835	Prob. F(1,241)	0.0000
	Obs.*R-squared	19.57521	Prob. Chi-Square(1)	0.0000
During Covid-19 era	F-Statistic	0.002096	Prob. F(1,241)	0.9635
	Obs.*R-squared	0.002113	Prob. Chi-Square(1)	0.9633
Kotak Bank				
Pre Covid-19	F-Statistic	18.44914	Prob. F(1,241)	0.0000
	Obs.*R-squared	17.26578	Prob. Chi-Square(1)	0.0000
During Covid-19 era	F-Statistic	2.684746	Prob. F(1,241)	0.1026
	Obs.*R-squared	2.677383	Prob. Chi-Square(1)	0.1018
SBI Bank				
Pre Covid-19	F-Statistic	28.52229	Prob. F(1,241)	0.0000
	Obs.*R-squared	25.77684	Prob. Chi-Square(1)	0.0000

During Covid-19 era	F-Statistic	1.482388	Prob. F(1,241)	0.2246
	Obs.*R-squared	1.485592	Prob. Chi-Square(1)	0.2229

Table 4 shows that the sum of ARCH and GARCH coefficients in the model of Nifty pre Covid-19 is 73 percent but 95 percent during the Covid-19 period, Sensex pre Covid-19 is 63 percent but 95 percent during the Covid-19 period, and Nifty Bank Index is 90 percent and 97 percent pre and during the Covid-19 period, respectively, which is positive and statistically important during the Covid-19 period. The value of the sum of these coefficients (and) for all selected indices and bank stocks is more than 90%, which is similar to unity, indicating that volatility occurs frequently in nature. This is often seen in high-frequency financial data. The GARCH model thus showed that conditional variance exists in the Indian stock market. During the Covid-19 period of uncertainty, the GARCH(-1) concept had a major positive impact on all three indices and selected bank stocks. The fact that the GARCH coefficient is higher than the ARCH coefficient indicates that conditional variance is highly dependent on forecast variance from the previous period rather than information about prior period volatility.

TABLE 4: GARCH (1, 1) MODEL FOR VOLATILITY FORECASTING

		C ω	**ARCH(-1)** α	**GRACH(-1)** β	**AIC**	**SBC**
Nifty	**Pre Covid-19**	2.36E-02 (0.0543)	0.333325 0.0002*	0.40458 (0.0480)*	-6.697470	-6.654091
	During Covid-19 era	1.37E-05 (0.156)	0.17895 (0.0001)*	0.77259 (0.0000)*	-5.626851	-5.584594
Sensex	**Pre Covid-19**	3.21E-05 (0.0210)*	0.3725 (0.000)*	0.2567 (0.2155)	-6.669911	-6.642412
	During Covid-19 era	1.30E-05 (0.0006)*	0.16394 (0.000)*	0.79116 (0.000)*	-5.596024	-5.540002
Nifty Bank Index	**Pre Covid-19**	2.30e-05 (0.0342)*	0.22798 (0.0009)*	0.66777 (0.000)*	-6.006373	-5.948874
	During Covid-19 era	2.14E-05 (0.0044)*	0.141110 (0.0000)*	0.831125 (0.0000*	-4.730646	-4.674303
HDFC Bank	**Pre Covid-19**	6.08E-05 (0.0280)*	0.201564 (0.0724)	0.427355 (0.0444)*	-5.957444	-5.899605
	During Covid-19 era	2.47e-05 (0.0307)*	0.217188 (0.0024)*	0.759387 (0.0000)*	-4.819091	-4.76248
ICICI Bank	**Pre Covid-19**	2.66E-05 (0.1731)	0.113416 (0.0209)*	0.794479 (0.0000)*	-5.297782	-5.239943
	During Covid-19 era	2.56e-5 (0.0801)	0.114576 (0.0001)	0.838655 (0.0000)*	-4.256426	-4.200082
Axis Bank	**Pre Covid-19**	6.27e-05 (0.1266)	0.093120 (0.0630)	0.658968 (0.0005)*	-5.406071	-5.348232
	During Covid-19 era	4.48e-05 (0.0088)*	0.147248 (0.0000)*	0.838387 (0.0000)*	-3.925260	-3.868917
Kotak Bank	**Pre Covid-19**	0.00110 (0.0566)*	0.155707 (0.0222)*	0.279818 (0.3896)	-5.711450	-5.653611
	During Covid-19 era	3.77e-5 (0.0265)*	0.173290 (0.0009)*	0.787395 (0.0000)*	-4.548449	-4.492105
SBI Bank	**Pre Covid-19**	2.81e-5 (0.1273)	0.072394 (0.0397)*	0.869380 (0.0000)*	-4.841692	-4.783856
	During Covid-19 era	7.82e-54 (0.0533)	0.122072 (0.0025)*	7.82e-05 (0.0533)*	0.112072 (0.0025)*	0.787925 (0.0000)*

The TARCH (1, 1) formula is used to predict the leverage effect, and the results are shown in Tables 5. The *(RESID (-1) 2*(RESID (-1)< 0) is statistically significant in all three indices and five bank stocks before and after the covid-19 era. This backs up the claim that the model has a leverage effect, meaning that negative news causes more volatility than positive news, and that positive and negative shocks have different effects on the volatility of the Nifty, Sensex, Nifty bank index, and five bank stock returns. It also shows that the effect of news on the Indian stock market during the Covid-19 pandemic is asymmetric.

TABLE 5: TGARCH (1, 1) MODEL FOR VOLATILITY FORECASTING

		C ω	**ARCH(-1) α**	**GRACH(-1) β**	RESID(-1)^2*(RESID(-1)<0)	**AIC**	**SBC**
Nifty	**Pre Covid-19**	3.14e-6 (0.2491)	0.002717 (0.8946)	0.865373 (0.000)*	0.207899 (0.0115)*	-6.72803	-6.65573
	During Covid-19 era	6.46e-5 (0.0000)*	-0.19740 (0.0000)*	0.982264 (0.0000)*	0.314662 (0.0000)*	-5.71690	-5.64647
Sensex	**Pre Covid-19**	2.86e-05 (0.0089)*	0.161461 (0.0072)*	0.289470 (0.1009)	0.472372 (0.0030)*	-6.715874	-6.644001
	During Covid-19 era	7.12E-06 (0.0000)*	-0.17522 (0.0000)*	0.967028 (0.0000)*	0.298496 (0.0000)*	-5.681143	-5.61114
Nifty Bank Index	**Pre Covid-19**	2.33E-05 (0.0143)*	0.097599 (0.0648)*	0.352447 (0.0029)*	0.633196 (0.0000)*	-6.034652	-5.97715
	During Covid-19 era	1.90E-05 (0.0022)	0.17168 (0.6501)	0.847390 (0.0000)*	0.847390 (0.0002)*	-4.756357	-4.685928
HDFC Bank	**Pre Covid-19**	3.93E-05 (0.0252)*	0.109568 (0.0944)	0.504102 (0.0007)	0.431034 (0.0611)	-5.97275	-5.90045
	During Covid-19 era	1.66E-05 (0.0187)*	0.018139 (0.06844)	0.858202 (0.0000)*	0.204876 (0.0001)	-4.849107	-4.778677
ICICI Bank	**Pre Covid-19**	3.61E-06 (0.2823)	-0.04599 (0.0241)*	0.931639 (0.000)*	0.272142 (0.0001)*	-5.341171	-5.268873
	During Covid-19 era	2.38E-05 (0.0379)*	0.019803 (0.6272)	0.884660 (0.0000)*	0.135750 (0.0020)*	-4.270523	-4.20009
Axis Bank	**Pre Covid-19**	2.03E-05 (0.1678)	-0.02246 (0.3228)	0.850285 (0.0000)*	0.220652 (0.0144)*	-5.425416	-5.35312
	During Covid-19 era	5.20E-05 (0.0005)	-0.053221 (0.0352)	0.003187 (0.0000)*	0.209632 (0.0000)*	-4.025017	-3.95448
Kotak Bank	**Pre Covid-19**	0.000108 (0.0563)	0.138642 (0.0282)*	0.278713 (0.4009)	0.061532 (0.6936)	-5.703933	-5.631635
	During Covid-19 era	3.40E-05 (0.0040)*	0.039075 (0.5396)	0.861359 (0.0000)*	0.121395 (0.0146)*	-4.547813	-4.477384
SBI Bank	**Pre Covid-19**	1.64E-05 (0.1496)	0.031966 (0.1951)	0.916864 (0.0000)*	0.034657 (0.3519)	-4.834845	-4.762547
	During Covid-19 era	7.67E-05 (0.0557)	0.051176 (0.1525)	0.817336 (0.0000)*	0.070469 (0.1525)	-4.268512	-4.198083

If there is some degree of asymmetry and leverage impact in the price series, the EGARCH model can help understand financial market volatility. A leverage effect occurs when bad news has a greater impact on volatility than good news. The EGARCH model's findings are presented in Tables 6. We use the EGARCH model to detect the leverage effect in the financial returns of the three indices and five bank stocks in order to capture the availability of asymmetric activity and the nature of leverage effect (asymmetric). Except for HDFC bank and Axis bank pre-Covid-19 time, the sign of gamma (γ) in EGARCH model must be negative and meaningful in pre and during Covid-19 period.

TABLE 6: EGARCH (1, 1) MODEL FOR VOLATILITY FORECASTING

LOG(GARCH) = C(1) + C(2)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(3) *RESID(-1)/@SQRT(GARCH(-1)) + C(4)*LOG(GARCH(-1))							
		C ω	**ARCH(-1)** α	EGRACH	**GRACH(-1) β**	**AIC**	**SBC**
Nifty	**Pre Covid-19**	-0.5391 (0.1319	0.14754 (0.0450)	-1.1533 (0.0012)*	0.95512 (0.0000)	-6.745932	-6.688093
	During Covid-19 era	-0.2217 (0.0000)	-0.0633 (0.0001)	-0.2386 (0.0000)	-0.9665 (0.0000)	-5.722466	-5.666123
Sensex	**Pre Covid-19**	-0.38008 (0.0537)	0.06608 (0.2388)	-0.16155 (0.0001)*	0.964860 (0.0000)	-6.763997	-6.706498
	During Covid-19 era	-0.33093 (0.0000)	0.042840 (0.3826)	-0.18985 (0.0000)	0.963301 (0.0000)	-5.664178	-5.608155
Nifty Bank Index	**Pre Covid-19**	-0.42823 (0.1531)	0.130214 (0.0469)*	-0.16009 (0.0008)	0.93546 (0.0000)	-6.772257	-6.714927
	During Covid-19 era	-0.31932 (0.0001)	0.05794 (0.2305	-0.16279 (0.0000)	0.966623 (0.0000)	-5.680560	-5.62422
HDFC Bank	**Pre Covid-19**	-12.13753 (0.0000)*	0.181136 (0.0059)*	0.194931 (0.0059)*	-0.358880 (0.2739)	-5.961979	-5.90414
	During Covid-19 era	-0.45898 (0.0007)*	0.265720 (0.0017)*	-0.15719 (0.0000)*	0.966783 (0.0000)*	-4.854182	-4.79784
ICICI Bank	**Pre Covid-19**	-0.136486 (0.1510)	0.073415 (0.1131)	-0.192188 (0.0000)	0.989252 (0.0000)	-5.343777	-5.28594
	During Covid-19 era	-0.30624 (0.0045)*	0.152780 (0.0216)*	-0.12778 (0.0001)*	0.973376 (0.0000)*	-4.289318	-4.232975
Axis Bank	**Pre Covid-19**	-11.9079 (0.0000)*	0.415704 (0.0001)*	0.025884 (0.6692)	-0.39732 (0.0082)*	-5.419129	-5.361290
	During Covid-19 era	-0.29724 (0.0000)*	.0.045959 (0.2424)	-0.18778 (0.0000)*	0.961150 (0.0000)*	-4.028429	-3.973085
Kotak Bank	**Pre Covid-19**	-4.886420 (0.0620)	0.338917 (0.0013)*	-0.008383 (0.9175)	0.459087 (0.1273)	-5.700868	-5.64303

	During Covid-19 era	-0.61757 (0.0036)*	0.295924 (0.0002)*	-0.05602 (0.1142)	0.946093 (0.0000)	-4.545252	-4.488908
SBI Bank	**Pre Covid-19**	-8.404900 (0.0000)	0.351662 (0.0027)*	-0.210237 (0.0004)	-0.059737 (0.7750)	-4.819512	-4.761673
	During Covid-19 era	-0.48763 (0.0162)*	0.09634 (0.1131)	-0.08719 (0.1166)	0.941779 (0.0000)*	-4.267612	-4.211268

CONCLUSION:

The aim of this paper is to model volatility in the Nifty, Sensex, and Nifty Bank indexes, as well as five banking stocks: HDFC Bank, ICICI Bank, Axis Bank, Kotak Bank, and SBI Bank. The GARCH model shows that conditional volatility occurs in the Indian stock market. Daily data was analysed for two years prior to and during the Covid-19 pandemic era. The GARCH(-1) definition had a significant positive effect on all three indices and selected bank stocks during the Covid-19 era of uncertainty. To capture the availability of asymmetric operation and the essence of leverage, the EGARCH model was used to detect the leverage impact in the financial returns of three indices and five bank stocks. Except for HDFC bank and Axis bank pre-Covid time, the sign of gamma (γ) in EGARCH model must be negative and meaningful in pre and during Covid-19 period.

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