Section A-Research paper
ISSN 2063-5346

A STUDY ON IMPACT OF COVID-19 PANDEMIC OVERSELECTED NSE SECTORAL INDICES

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DOI: 10.48047/ecb/2023.12.si4.1775

ABSTRACT

The pandemic had an impact on human lives as well as the wealth of investors across the world. However, the impact is not uniform throughout all the sectors. The major indicator of the investors is represented by the National Stock exchanges. All the industrial sectors are not affected in the same way. The automobile industry, the banking industry, the information technology industry and the pharma industry are the major industries affected. These indices of NSE are considered for the study. The objectives of the study are to analyze data of the NSE Auto, IT, Pharma & Banking sector in the pre-covid & post-covid periods, to perform ARMA (1,1), Correlogram Q statistics & Correlogram Squared residual statistics for the selected four indices, to perform Heteroskedasticity Test and to check ARCH effect and finally to develop GARCH Family models for the volatility of selected NSE sectoral indices. For the study, secondary data from the NSE is used for the study. From the study it was found that even though all the mentioned sectors are highly volatile and move in clusters. After doing the data analysis, it was suggested that the IT and automobile sectors are more suitable for risk-averse investors and volatility will be there for longer periods of time in the pharma sector. It is concluded that all the above sectors are suitable for the investment purpose.

KEYWORDS: GARCH, EGARCH, TARCH, AUTO, BANK, IT, PHARMA

1. Introduction

The majority of the investors trading is concentrated on the National Stock Exchange, even though the major sentiment is on the Bombay Stock Exchanges. For this reason, NSE is considered for study. The pandemic created a lot of panic among the health and wealth of the investors. Volatility and the market go hand in hand. However, sometimes we come across low volatility and sometimes higher volatility. The fluctuation of stock prices within a period of time will represent volatility. If the estimation of volatility depends on the information, it becomes conditional. To analyse this conditional volatility, we can apply ARCH and GARCH models. These models will be helpful to estimate the current and future volatility depending on the previous volatility estimates.

The purpose of this paper is to study the conditional volatility of the selected industry escorts and also volatility dynamics of the same, including volatility clustering, persistence and leverage effect. It also studies the same during the pre-pandemic and post-pandemic periods. The changes in the business environment have impacted these sectors very much. Reforms in these sectors during the pre-Covid & post- Covid periods have impacted the movement of prices and volatility in prices of these sectors' indices.

2. Design of the study:

2.1 Statement of the problem:

Volatility study for the auto, IT, pharma and banking sectors will be incomplete with out studying volatility dynamics. The major components of the same include volatility clustering, leverage effect and volatility persistence through volatility modelling.

2.2Objectives

- To analyze data of NSE Auto, IT, Pharma & Banking sector in pre-covid & post-covid period
- To perform ARMA (1,1), Correlogram Q statistics & Correlogram Squared residual statisticsfor the selected four indices
- To perform Heteroskedasticity Test: To check ARCH effect
- To develop GARCH Family models for the volatility of selected NSE sectoral indices

2.3Data Collection

The study is based on the secondary data which is being collected from the National Stock Exchange official website, journals, research articles, and books.

In present study four sectoral indices like Auto, Bank, IT and Pharma have been taken. Data inform of daily closing prices of these indices have been taken from NSE website from 1st APRIL 2017 to 31st March 2020. Logged returns have been obtained from daily closing prices to use in models.

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3. Data analysis;

To study the normality of the returns, mean, standard deviation, skewness and kurtosis descriptive statistics details are given below.

Table 1: Descriptive statistics pre-covid

Pre Covid	Auto Return	Bank Return	IT Return	Pharma Return
Mean	-0.000455	0.000456	0.000469	-0.000466
Median	-0.000109	0.000673	0.000561	-0.000556
Maximum	0.094415	0.079839	0.046867	0.050830
Minimum	-0.040261	-0.035054	-0.058149	-0.044709
Std. Dev.	0.012183	0.010301	0.010344	0.012449
Skewness	0.497542	0.751320	-0.286367	-0.033907
Kurtosis	8.951366	9.189488	5.893893	3.968878
Jarque-Bera	1124.126	1252.527	268.6940	29.12509
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-0.336997	0.338186	0.347423	-0.345234
Sum Sq. Dev.	0.109834	0.078516	0.079183	0.114676
Observations	741	741	741	741

From descriptive statistics shown in above Table I. we can see that during pre-covid period average returns of 2 sectors (i.e., Bank & IT) is positive while auto & Pharma sector is showing negative returns. The risk component which can be measured through standard deviation is an important parameter. The information technology index standard deviation is highest when compared to the other indices. The skewness is also important parameter. Negative skewness is indicated for Pharma and IT indices. It is also observed that the kurosis is more than three for all the four indices. It is also observed that

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Jarque bera test P-value is also less than 0.05 indicating variability of distribution from normality.

Table 2: Descriptive statistics post-covid

Post Covid	Auto RETURN	Bank Return	IT Return	Pharma Return
Mean	0.001589	0.000754	0.001832	0.001852
Median	0.003014	0.002871	0.002291	0.001729
Maximum	0.098997	0.099951	0.086404	0.098650
Minimum	-0.149055	-0.183130	-0.100650	-0.093507
Std. Dev.	0.023674	0.028587	0.021217	0.019548
Skewness	-1.095120	-1.272567	-0.667528	-0.111749
Kurtosis	11.66488	10.73677	8.366942	8.075145
Jarque-Bera	825.3994	685.4650	316.0598	266.6728
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.394177	0.186973	0.454375	0.459308
Sum Sq. Dev.	0.138431	0.201852	0.111191	0.094382
Observations	248	248	248	248

From descriptive statistics shown in above Table II. we can see that during post covid period average returns all the sector is showing positive. Pharma sector mean return is highest followed by IT, Auto & Bank. In Std Deviation Bank is showing highest volatility followed by Auto, IT & Pharma Index. All the indices are negatively skewed. Kurtosis is also more than 3 in all indices indicating more peakedness in distribution of returns. Jarque bera test P-value is also less than 0.05 indicating variability of distribution from normality.

3.2Modelling of Mean Equation:

To study the serial correlation and ARCH effect among them, Least square method is used. At the same time return series suitability to model the vitality through GARCH Models is done. To study the serial correlation in residuals and squared residuals series Q statistics has been used. In residual series and squared residual series Q statistics have been checked up to 36 lags.

Table 3: Residual Q statistics pre covid

Pre-Covid

Auto	AC	PAC	Q-Stat	Prob
1	0.057	0.057	2.4413	0.118
2	0.048	0.045	4.1698	0.124
3	-0.043	-0.049	5.5671	0.135
4	0.041	0.044	6.8196	0.146
5	-0.072	-0.073	10.644	0.059
Bank	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.045	0.045	1.5191	0.218
2	-0.027	-0.029	2.0518	0.358
3	-0.059	-0.056	4.6315	0.201
4	0.012	0.016	4.7343	0.316
5	-0.033	-0.038	5.5573	0.352
IT	**AC**	**PAC**	**Q-Stat**	**Prob**
1	-0.016	-0.016	0.1839	0.668
2	0.001	0.001	0.1850	0.912
3	-0.037	-0.037	1.2310	0.746
4	0.002	0.001	1.2355	0.872
5	0.047	0.047	2.9045	0.715
Pharma	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.077	0.077	4.3898	0.036
2	-0.002	-0.008	4.3930	0.111
3	-0.002	-0.001	4.3951	0.222
4	0.019	0.020	4.6743	0.322
5	0.009	0.006	4.7359	0.449

Table 4: Residual Q statistics post covid

Auto	AC	PAC	Q-Stat	Prob
1	-0.053	-0.053	0.7015	0.402
2	0.071	0.068	1.9739	0.373
3	0.017	0.024	2.0432	0.563
4	-0.012	-0.015	2.0798	0.721
5	0.130	0.127	6.3792	0.271
Bank	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.020	0.020	0.1008	0.751
2	0.009	0.008	0.1190	0.942
3	0.031	0.031	0.3686	0.947
4	0.026	0.025	0.5416	0.969
5	0.156	0.155	6.7511	0.240
IT	**AC**	**PAC**	**Q-Stat**	**Prob**
1	-0.149	-0.149	5.5800	0.018
2	0.121	0.101	9.2610	0.010
3	0.118	0.154	12.773	0.005
4	-0.041	-0.017	13.211	0.010
5	0.147	0.112	18.757	0.002
Pharma	**AC**	**PAC**	**Q-Stat**	**Prob**
1	-0.046	-0.046	0.5381	0.463
2	0.166	0.164	7.4775	0.024
3	0.065	0.081	8.5494	0.036
4	0.058	0.039	9.4040	0.052
5	0.061	0.044	10.362	0.066

It is observed that in all sectoral indices residual series Q statistics is statistically insignificant because Pvalue is more than 0.05.

Table 5: Squared Residual Statistics pre-covid

Auto	AC	PAC	Q-Stat	Prob
1	0.090	0.090	6.0804	0.014
2	0.014	0.006	6.2359	0.044
3	0.220	0.220	42.445	0.000
4	0.099	0.064	49.819	0.000
5	0.035	0.023	50.750	0.000
Bank	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.294	0.294	64.106	0.000
2	0.050	-0.039	65.990	0.000
3	0.102	0.108	73.801	0.000
4	0.048	-0.012	75.553	0.000
5	0.055	0.051	77.829	0.000
IT	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.047	0.047	1.6361	0.201
2	0.064	0.062	4.7298	0.094
3	-0.004	-0.010	4.7429	0.192
4	0.024	0.020	5.1600	0.271
5	0.072	0.072	9.0895	0.106
Pharma	**AC**	**PAC**	**Q-Stat**	**Prob**
1	0.005	0.005	0.0223	0.881
2	0.069	0.069	3.5532	0.169
3	0.052	0.052	5.5696	0.135
4	0.116	0.112	15.598	0.004
5	0.005	-0.002	15.618	0.008

Table 6: Squared Residual Statistics post-covid

Auto	**AC**	**PAC**	**Q-Stat**	**Prob**
1	**0.053**	**0.053**	**0.7039**	**0.401**
2	**0.285**	**0.283**	**21.132**	**0.000**
3	**0.081**	**0.060**	**22.780**	**0.000**
4	**0.069**	**-0.018**	**23.979**	**0.000**
5	**0.197**	**0.171**	**33.913**	**0.000**
Bank	**AC**	**PAC**	**Q-Stat**	**Prob**
1	**0.015**	**0.015**	**0.0574**	**0.811**
2	**0.213**	**0.213**	**11.507**	**0.003**
3	**0.193**	**0.196**	**20.953**	**0.000**
4	**0.070**	**0.031**	**22.201**	**0.000**
5	**0.236**	**0.171**	**36.432**	**0.000**
IT	**AC**	**PAC**	**Q-Stat**	**Prob**
1	**0.333**	**0.333**	**27.877**	**0.000**
2	**0.383**	**0.306**	**64.932**	**0.000**
3	**0.071**	**-0.149**	**66.197**	**0.000**
4	**0.196**	**0.121**	**75.986**	**0.000**
5	**0.225**	**0.226**	**88.915**	**0.000**
Pharma	**AC**	**PAC**	**Q-Stat**	**Prob**
1	**0.224**	**0.224**	**12.628**	**0.000**
2	**0.167**	**0.123**	**19.660**	**0.000**
3	**0.092**	**0.033**	**21.784**	**0.000**
4	**0.039**	**-0.006**	**22.165**	**0.000**
5	**0.016**	**-0.007**	**22.231**	**0.000**

In the squared residual series Q- statistics then we can find that all p values are less than 0.05 except Pharma sector in pre covid period. It means there is a serial correlation in squared residual series.

Table 7: Heteroskedasticity Test: ARCH (pre-covid)

PRE COVID	Lags	F-statistics	P-value	obs R-squared	Prob-chi square 2	Inference
NSE Auto	1	6.168590	0.0132	6.134036	0.0133	ARCH
	2	3.080937	0.0465	6.135622	0.0465	ARCH
NSE Bank	1	71.11043	0.0000	65.03651	0.0000	ARCH
	2	36.19151	0.0000	66.17044	0.0000	ARCH
NSE IT	1	2.225481	0.1362	2.224803	0.1358	NO ARCH
	2	3.053704	0.0478	6.081834	0.0478	ARCH
NSE Pharma	1	0.022956	0.8796	0.023018	0.8794	NO ARCH
	2	1.831103	0.1610	3.658927	0.1605	NO ARCH

Table 8: Heteroskedasticity Test: ARCH (post-covid)

During Covid	**Lags**	**F-statistics**	**P-value**	**obs R-squared**	**Prob-chi square 2**	**Inference**
NSE Auto	1	0.689269	0.4072	0.692946	0.4052	NO ARCH
	2	10.93345	0.0000	20.30928	0.0000	ARCH
NSE Bank	1	0.056202	0.8128	0.056648	0.8119	NO ARCH
	2	5.816015	0.0034	11.23770	0.0036	ARCH
NSE IT	1	30.61445	0.0000	27.43604	0.0000	ARCH
	2	29.35165	0.0000	47.86495	0.0000	ARCH
NSE Pharma	1	13.18226	0.0003	12.61131	0.0004	ARCH
	2	8.622424	0.0002	16.30093	0.0003	ARCH

From the above table it is observed that the p values at lag 2 are less than 0.05 in the four sectors except pharma index. Thus there is ARCH effect on Auto, Banking and IT sector indices during pre covid period. The precondition for the volatility model including no auto correlation in resirdual series, serial correlation in squared residual series or ARCH effect in residual series have been met for the above said three sector. Now it is time to fit GARCH family models to the model the volatility in the three sectors. With respect to pharma sector pre covid period can not be used as there is no ARCH effect found.

Table 9: GARCH FAMILY MODEL (pre-covid)

	PRE COVID	MEAN	Variance Equation					
	Sector	α	α0	α1 (ARCH Term)	β1 (GARCH Term)	α1+β1 of Variance Equation	γ (leverage effect)	Durbin Watson Stat.
GARCH (1,1)	AUTO	0.000114	3.87E-06	0.108651	0.872853	.981504	-	1.867644
	P-value	0.7653	0.0016	0.0000	0.0000			
	BANK	0.000845	4.40E-06	0.090798	0.871151	0.961949	-	1.889257
	P-value	0.0131	0.0037	0.0000	0.0000			
	IT	0.000654	6.28E-06	0.050344	0.893912	0.944256	-	1.987398
	P-value	0.0858	0.0016	0.0010	0.0000			
EGARCH (1,1)	AUTO	-0.000353	-0.282680	0.125938	0.979042	1.104	-0.098608	1.871595
	P-value	0.3378	0.0000	0.0000	0.0000		0.0000	
	BANK	0.000474	-0.420584	0.128646	0.965183	1.093	-0.092928	1.891942
	P-value	0.1517	0.0001	0.0000	0.0000		0.0000	
	IT	0.000564	-0.844134	0.135476	0.918732	1.054	-0.037790	1.987865
	P-value	0.1337	0.0001	0.0001	0.0000		0.0255	

	PRE COV ID	MEAN	Variance Equation					
TARCH	**Sector**	**α**	**α0**	**α1 (ARCH Term)**	**β1 (GARCH Term)**	**α1+β1 of Variance Equation**	**γ (leverage effect)**	**Durbin Watson Stat.**
	AUTO	-0.000283	2.90E-06	-0.000495	0.917642	0.9171	0.135729	1.871355
	P-value	0.4479	0.0000	0.9598	0.0000		0.0000	
	BANK	0.000562	5.76E-06	0.021367	0.845250	1.058	0.167464	1.891748
	P-value	0.0962	0.0008	0.0868	0.0000		0.0000	
	IT	0.000606	6.99E-06	0.035068	0.885567	0.9206	0.033460	1.987682
	P-value	0.1118	0.0011	0.0410	0.0000		0.0583	

Pre-Covid

The impact of previous period volatility on current period return can be observed with positive Coeffeicients of variance equation. The same is observed in GARCT(1.1). volatility clustering and whether conditional variance is significantly affected by previous period volatility is observed the help of GARCH (β1) coefficients. In this the this value is also positive and statistically significant at 5%. The is observed that the combined value of α1+β1values in it are close to 1 in all indices indicating volatility persistencemeans it takes time to decay volatility shocks. More are less the results are observed in EGARCH(1,1) model coefficients of variance equation are positive and previous period volatility is significantly impacting current period volatility.

β1values can be seen for volatility persistence valuesclose to 1 indicates higher persistence and α1+β1values are slightly more than 1 in all sectors indicatingvolatility increases with time and conditional variance is explosive, all γ values are negative so this slightly more than 1 value is not making model estimation incorrect. Leverage effect is shown by γ all values of γ are negative and statistically significant.

However, interesting obseratatin can be made from TGARCH (1, 1) model. Arch term (α1) coefficients of variance equation are negative in auto while positive in Bank, IT but insignificant in Auto & Bank at 5% indicating news about previous period volatility is not impacting current period volatility so arch term unable to predict volatility. In IT sector arch term is significantly predicting volatility. All GARCH term (β1) Coefficients are positive and statistically significant indicating conditional variance of current period is significantly affected by previous period volatility. α1+β1values are close to 1 in Auto & IT indicating higher persistence of volatility shocks as compared to Bank because these 2 sectors are showing low persistence with their low values. Leverage effect is shown by γ all values of γ are positive and statistically significant.

Table 10: GARCH FAMILY MODEL (post-covid)

	POST COVID	**MEAN**	**Variance Equation**					
	Sector	**α**	**α0**	**α1 (ARCH Term)**	**β1 (GARCH Term)**	**α1+β1 of Variance Equation**	**γ (leverage effect)**	**Durbin Watson Stat.**
GARCH (1,1)	**AUTO**	0.002601	1.40E-05	0.081541	0.876988	0.958529	-	2.091735
	P-value	0.0310	0.0125	0.0001	0.0000		-	
	BANK	0.002669	1.58E-05	0.082282	0.887578	0.96986	-	1.938477
	P-value	0.0440	0.0119	0.0005	0.0000		-	
	IT	0.002492	1.61E-05	0.090664	0.851054	0.9416	-	2.287686
	P-value	0.0144	0.0279	0.0139	0.0000		-	
	PHARMA	0.001289	1.26E-05	0.026421	0.918572	0.9449	-	2.062353
	P-value	0.2180	0.0029	0.1358	0.0000		-	

EGARCH(1, 1)	**AUTO**	0.001950	-0.273244	0.061781	0.971903	1.033	-0.154043	2.095084
	P-value	0.0894	0.0002	0.0757	0.0000		0.0000	
	BANK	0.001852	-0.317755	0.084761	0.967252	1.052	-0.129605	1.944331
	P-value	0.1721	0.0012	0.0758	0.0000		0.0000	
	IT	0.002230	-0.540328	0.193372	0.951511	1.144	-0.076634	2.289099
	P-value	0.0303	0.0147	0.0078	0.0000		0.0863	
	PHARMA	0.001245	-0.319120	0.084965	0.969422	1.054	-0.016147	2.062073
	P-value	0.2329	0.0026	0.0399	0.0000		0.6629	

ISSN 2063-5346

	POST COVID	MEAN	Variance Equation					
TARCH (1,1)	**Sector**	**A**	**α0**	**α1 (ARCH Term)**	**β1 (GARCH Term)**	**α1+β1 of Variance Equation**	**γ (leverage effect)**	**Durbin Watson Stat.**
	AUTO	0.001621	1.19E-05	-0.040929	0.921928	0.880	0.150036	2.095569
	P-value	0.1483	0.0003	0.1113	0.0000		0.0000	
	BANK	0.001956	2.06E-05	-0.008099	0.897213	0.896	0.124332	1.943761
	P-value	0.1442	0.0028	0.7415	0.0000		0.0004	
	IT	0.002267	1.76E-05	0.024474	0.867060	0.8915	0.088641	2.288941
	P-value	0.0276	0.0156	0.4858	0.0000		0.0967	
	PHARMA	0.001225	1.22E-05	-0.009231	0.937784	0.9285	0.040470	2.061936
	P-value	0.2340	0.0026	0.5623	0.0000		0.1732	

GARCH(1,1) models in post-covid period :

We can see that the arch term (α1) coefficients of variance equation in the GARCH (1, 1) model are positive and statistically significant at 5% level, indicating news about previous period volatility is significantly impacting current period returns. All GARCH term (β1) Coefficients are also positive and statistically significant at 5%, indicating volatility clustering and conditional variance is significantly affected by previous period volatility. α1+β1values in it are close to 1 in all indices indicating volatility persistence, means it takes time to decay volatility shocks.

EGARCH (1, 1) model we can also see that arch term (α1) coefficients of variance equation are positive and statistically significant at 5% indicating news about previous period volatility is significantly impacting current period volatility, except Auto & Bank statistically significant at 10%. All GARCH term (β1) Coefficients are positive and statistically significant, indicating volatility clustering and that conditional variance, of the current period is significantly affected by previous period, volatility. β1values can be seen for volatility persistence values close to 1 indicate higher persistence and α1+β1values are slightly more than 1 in all sectors indicating volatility increases with time, and conditional variance is explosive, all γ values are negative so this slightly more than 1 value is not making model estimation incorrect. Leverage effect is shown by γ all values of γ are negative and statistically significant. Leverage effect γ in the post-covid IT sector is significant at 10% but in the post-covid Pharma sector it is insignificant, indicating less effect of shocks on volatility.

TGARCH (1, 1) model we can see that arch term (α1) coefficients of variance equation are negative in auto, Bank & Pharma while positive in IT but insignificant in all four index at 5% indicating news about previous period volatility is not impacting current period volatility so arch term unable to predict volatility. All GARCH term (β1) Coefficients are positive and statistically significant, indicating the conditional variance of the current period is significantly affected by previous period volatility. α1+β1values are close to 1 in all the four indices, indicating higher persistence of volatility shocks. Leverage effect is shown by γ all values of γ are positive and statistically significant except IT and Pharma indicating negative shocks have greater impact on volatility than positive shocks.

4.Conclusion:

From the above data analysis it can be concluded that all the four sector indices are showing volatility clustering. However, only three sector indices are found suitable to implement GARCT family models in precovid. The left out one is the pharma sector index, which is not found suitable to implement GARCH models . The GARCH (1, 1) model and EGARCH (1, 1) are found best fit as compared to TGARCH (1, 1) to capture the volatility dynamics as volatility clustering and persistence. As we have two types of investors, risk-averse investors and risk-taking investors. From the study it can be suggested that the auto, banking and IT sectors are suitable for risk-aversive investors. For risk-taking investors, they can plan in the pharma sector as the volatility will persist for a longer duration. There are more chances of highly volatile stocks generating more returns.

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