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MODELLING VOLATILITY OF SIZE INDICES THROUGH GARCH AND TGARCH MODELS: EVIDENCE FROM INDIA

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ABSTRACT

Purpose: The objective of this study was to select the best model for modelling the volatility of log return series of four size indices taken from the Indian stock markets.

Theoretical framework: Stock markets throughout the world have been designing various kinds of indices depending upon the requirements of the investors. Accordingly, BSE launched some indices, categorized as size indices, depending upon the market capitalization of the stocks listed on their exchange. Such categorization helps the investors in appropriate decision making. Research on these specific indices is scarce and therefore the aim of the present study.

Design/methodology/approach: We analyzed the log return series of four indices, namely S&P BSE Sensex, S&P BSE Large cap index, S&P BSE Mid cap Select index and the S&P BSE Small cap index, by fitting the GARCH (1,1) and the TGARCH (1,1) models for the period from 1 Januray 2018 to 31 December 2022.

Findings: The research on modelling volatility is voluminous with varied results as per the various assets and datasets utilized for the purpose. Present study confirms the results from previous study that to model the volatility of size indices a GARCH (1,1) model should suffice and there is no betterment achieved by implementing a TAGARCH (1,1) model.

Research, Practical & Social implications: We suggest the implementation of a simple GARCH (1,1) model for all those investors who want to invest in Indian size indices in order to model volatility of these indices.

Originality/value: Present study is one of its kinds, investigating size indices specifically, through the two of the most popular GARCH-family models in the Indian context.

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MODELANDO A VOLATILIDADE DOS ÍNDICES DE TAMANHO ATRAVÉS DOS MODELOS GARCH E TGARCH: EVIDÊNCIAS DA ÍNDIA

RESUMO

Objetivo: Objetivo: O objetivo deste estudo foi selecionar o melhor modelo para modelar a volatilidade da série de retorno logarítmico de quatro índices de tamanho retirados dos mercados acionários indianos.

Quadro teórico: Os mercados de ações em todo o mundo têm vindo a conceber vários tipos de índices, dependendo das necessidades dos investidores. Assim, a BSE lançou alguns índices, categorizados como índices de tamanho, dependendo da capitalização de mercado das ações listadas em sua bolsa. Tal categorização ajuda os investidores na tomada de decisão apropriada. Pesquisas sobre esses índices específicos são escassas e, portanto, o objetivo do presente estudo.

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Desenho/metodologia/abordagem: Analisamos a série de retornos logarítmicos de quatro índices, a saber, S&P BSE Sensex, S&P BSE Large cap index, s&p bse Mid cap Select index e S&P BSE Small cap index, ajustando os modelos GARCH (1,1) e TGARCH (1,1) para o período de 1º de janeiro de 2018 a 31 de dezembro de 2022.
Resultados: A pesquisa sobre modelagem de volatilidade é volumosa, com resultados variados de acordo com os vários ativos e conjuntos de dados utilizados para o propósito. O presente estudo confirma os resultados de estudos anteriores de que para modelar a volatilidade dos índices de tamanho um modelo GARCH (1,1) deve ser suficiente e não há melhora alcançada com a implementação de um modelo TAGARCH (1,1).
Implicações Práticas, de Pesquisa, Práticas e Sociais: Sugerimos a implementação de um modelo GARCH simples (1,1) para todos os investidores que desejam investir em índices de tamanho indianos, a fim de modelar a volatilidade desses índices.
Originalidade/valor: O presente estudo é um de seus tipos, investigando índices de tamanho especificamente, através dos dois dos modelos mais populares da família GARCH no contexto indiano.

Palavras-chave: Volatilidade, GARCH, TGARCH, Índice, Mercado de Ações.

MODELIZACIÓN DE LA VOLATILIDAD DE LOS ÍNDICES DE TAMAÑO A TRAVÉS DE LOS MODELOS GARCH Y TGARCH: EVIDENCIA DE LA INDIA

RESUMEN
Objetivo: El objetivo de este estudio fue seleccionar el mejor modelo para modelar la volatilidad de las series de rendimiento logarítmico de cuatro índices de tamaño tomados de los mercados de valores indios.
Marco teórico: Los mercados de valores de todo el mundo han estado diseñando varios tipos de índices dependiendo de los requisitos de los inversores. En consecuencia, BSE lanzó algunos índices, categorizados como índices de tamaño, dependiendo de la capitalización de mercado de las acciones que cotizan en su bolsa. Tal categorización ayuda a los inversores en la toma de decisiones adecuadas. La investigación sobre estos índices específicos es escasa y, por lo tanto, el objetivo del presente estudio.
Diseño/metodología/enfoque: Analizamos la serie log return de cuatro índices, a saber, S&P BSE Sensex, S&P BSE Large cap index, S&P BSE Mid cap Select index y el índice S&P BSE Small cap, ajustando los modelos GARCH (1,1) y TGARCH (1,1) para el período comprendido entre el 1 de enero de 2018 y el 31 de diciembre de 2022.
Hallazgos: La investigación sobre la modelización de la volatilidad es voluminosa con resultados variados según los diversos activos y conjuntos de datos utilizados para este propósito. El presente estudio confirma los resultados de un estudio anterior de que para modelar la volatilidad de los índices de tamaño un modelo GARCH (1,1) debería ser suficiente y no se logra ninguna mejora mediante la implementación de un modelo TAGARCH (1,1).
Implicaciones de investigación, prácticas y sociales: Sugerimos la implementación de un modelo GARCH simple (1,1) para todos aquellos inversores que quieran invertir en índices de tamaño indio para modelar la volatilidad de estos índices.
Originalidad/valor: El presente estudio es uno de su tipo, investigando específicamente los índices de tamaño, a través de los dos modelos más populares de la familia GARCH en el contexto indio.

Palabras clave: Volatilidad, GARCH, TGARCH, Índice, Mercado de valores.

INTRODUCTION

An asset's variation in the returns is often termed as volatility. Modelling the distribution of log return series of any asset is pivotal in quantitative finance. It has resulted in copious volatility prediction models available for the members of the investment fraternity. These models have been tested plenty number of times with one over-performing the other depending upon factors like assets, markets or evaluation metrics utilized. Indian stock markets have been flourishing especially in the past few decenniums, but how these volatility models perform on Indian data has not been researched much. Bombay Stock Exchange (BSE) is one of the leading stock exchanges in India which has intermittently introduced various indices which can cater to different aspects of investment strategies of the investors. Present study considers four indices of BSE, namely the most popular Sensex, the Large cap index, the mid cap select index and the small cap select index.

Sensex is the throb of the Indian stock markets and is the oldest index broadcasted by BSE since 1986. It consists of most liquid thirty stocks on the exchange. BSE came with the S&P BSE Largecap index (LCAP) in 2015 which consist of 90 stocks. It serves as a representative of the top seventy percent of the total market capitalization of the S&P BSE Allcap index. The S&P BSE Mid cap (MCAPSI) Select index was launched in 2015 so as to represent thirty most liquid stocks from within BSE Midcap. And lastly, the BSE Small cap Select index (SCAPSI) launched in 2015 was launched with the aim of representing sixty most liquid stocks of the BSE Small cap index. All these indices are together known as size indices since the categorization of these indices is based on market capitalization concept. They are categorized based on companies of a particular size that is large-, mid- and small-cap companies, cap meaning thereby market capitalization of these companies. This categorization has been quite popular amongst the investors as it clearly aggregates companies with a particular size. Large cap companies being more mature, has lower growth prospects and volatility, especially in rough markets. Whereas, Small cap stocks have lower value leading to more affordability and more volatility, especially in unstable markets. Recovery after a major fall, of Mid cap and Large cap stocks is also slower than small cap stocks. Modelling these varied behavior patterns in the volatility forecasting process, thus becomes crucial for the investor. Volatility domain has gained more attention, therefore there is a necessity for future research to model predictive accuracy to match the rising volatility and uncertainty environment ((Hoong et al., 2023). Moreover, Sensex being the popular index has always been the consideration for researchers and not much attention has been given for the purpose of those investors who are interested in investing in the size indices.

The present study tries to fill this gap. The objective of the present study is to investigate the daily closing prices of Sensex and compare that with BSE LCAP, MCAPSI and SCAPSI indices for volatility modelling through GARCH (1,1) and TGARCH (1,1) models.

The study is further designed as follows: first section is about literature review, second section describes the data and methodology, third presents the results and discussions and last section concludes the study.

LITERATURE REVIEW

Alberg, Shalit and Yosef (Alberg et al., 2008) tested GARCH, EGARCH and APARCH models on TA25 and TA100 indices. Their study favored asymmetric GARCH models. In this category also the authors concluded that the EGARCH is better performer than its counterparts. Sabiruzzaman with others (Sabiruzzaman et al., 2010) modelled the trading volume index of the Hongkong Stock Exchange through the GARCH (1,1) and the TGARCH (1,1) models. The authors found the TGARCH model to be superior as compared to the GARCH model for the period of study. Tripathy and Gil-Alana (Tripathy and Gil-Alana, 2010) tested Nifty daily open, high, low and close price returns and found that amongst various models evaluated, GARCH model seemed to perform better. In one study (Liu & Hung, 2010) it was found that EGARCH model to be the best performer amongst the six models tested from the GARCH family on Taiwanese stock index future daily price returns. Gupta, Jindal and Gupta (Gupta, Jindal and Gupta, 2014) evaluated three GARCH models from the GARCH family, that is GARCH, EGARCH and TGARCH models. The daily close returns of CNX 500 Index from the National Stock Exchange were picked for evaluating the performance of the models. The authors confirmed the presence of asymmetric volatility in the Nifty return series.

Some authors found PGARCH model to best fit the data from Indian stock market amongst all the models evaluated from the GARCH family (Dixit & Agrawal, 2019). Akigray (Akgiray, 1989) found GARCH(1,1) to be most suitable for modelling daily returns on CRSP indices. Awartani and Corradi (Awartani & Corradi, 2005) investigated the predictive abilities of GARCH models and found asymmetric GARCH models beer performers. Naimy and Hayek (Naimy & Hayek, 2018) found EGARCH model's ability to forecast volatility is superior to EWMA and simple GARCH model when implemented on Bitcoin/USD exchange rate.

METHODOLOGY

Present study concentrates on daily closing prices of BSE Sensex, S&P BSE Large cap index, S&P BSE Mid cap Select index and the S&P BSE Small cap index for the period from 1 January 2018 to 31 December 2022. The daily closing prices for all the indices are collected from the BSE website. Following previous research ((Krishnan & Periasamy, 2022) the daily closing prices are converted to log return series through the formula:

R(t)=log(t)-log(t-1) ……………………….[1]

Where log(t) and log(t-1) are the logarithm of prices at time t and t-1 respectively. The actual volatilities are taken to be $\sigma_t^2 = r_t^2$, since the mean return of all indices are near zero. The simple GARCH model, (given by (Bollerslev, 1986)), is stated as:

$$X_t = \mu_t + \sigma_t \epsilon_t \qquad \ldots\ldots\ldots\ldots\ldots\ldots..[2]$$

$$\sigma_t^2 = \omega + \alpha\epsilon_t^2 + \beta\sigma_{t-1}^2 \qquad \ldots\ldots\ldots\ldots\ldots[3]$$

which is built on the idea that the conditional variance at time t depends not only on the squared error term in the past time period, but also on its conditional variance in the past time period. TGARCH (Zakoian, 1990) and (Glosten et al., 1993) specifications for the conditional variance are:

$$\sigma_t = \omega + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots.[4]$$

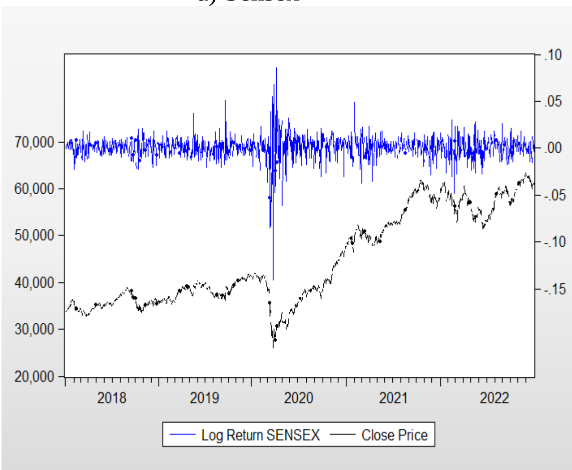
where $d_{t-1} = 1$ if $\epsilon_{t-1} \leq 0$ and $d_{t-1} = 0$, if $\epsilon_{t-1} > 0$. TGARCH model resonance the asymmetric behavior of investors. γ designate an asymmetry parameter. A positive shock will enhance volatility by γ, whereas a negative shock will contract it by $\alpha + \gamma$.

RESULTS AND DISCUSSIONS

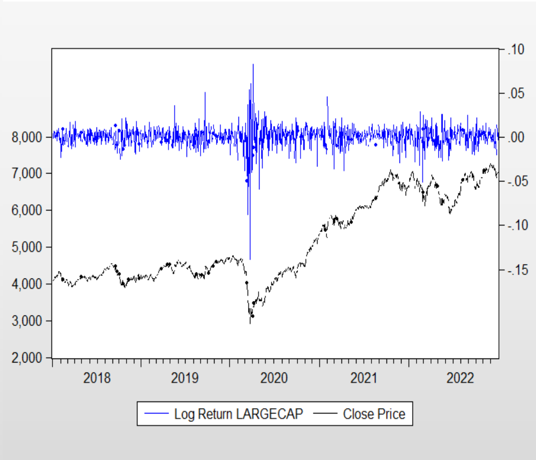
Figure 1 shows the closing price levels and the log returns over the period 2018 to 2022. As can be seen from the figure, Sensex moved upward from around 35000 to 60000 in the period of five years with touching the downside level of 25000 during the 2019 pandemic. Si milar is the case with other indices with BSE LCAP moving from 4200 to around 6500, BSE MCAPSI moving from 8000 to around 9000 and lastly BSE SCAPSI moving from 3000 to 4500 approximately in these years. In the whole period of five years, the impact of pandemic can be easily seen in all the return series with one major fall in second half of 2019. If percentage downfall is compared in relation to the respective minimum of the four indices, then it comes to around 32%, 28%, 46% and 46% for Sensex, LCAP, MCAPSI and SCAPSI respectively. The percentages indicate that the highest fall was seen in mid cap and small cap indices at BSE during the pandemic.

Figure 1: Price and log return graph

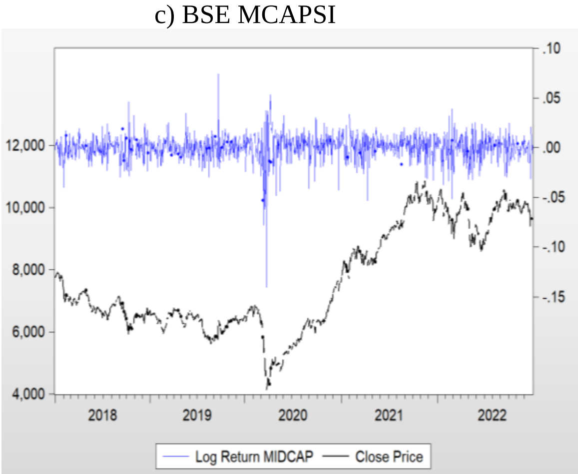
a) Sensex



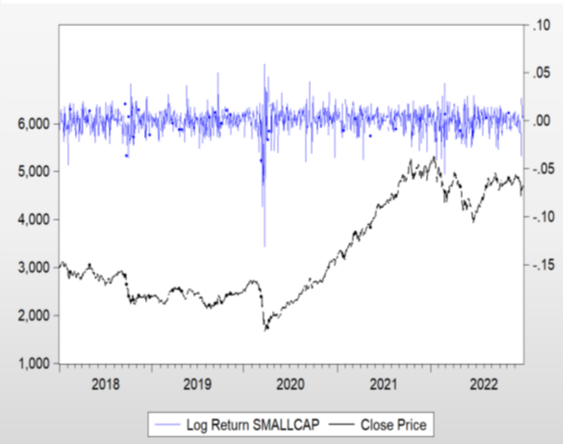
b) BSE LCAP



c) BSE MCAPSI



d) BSE SCAPSI

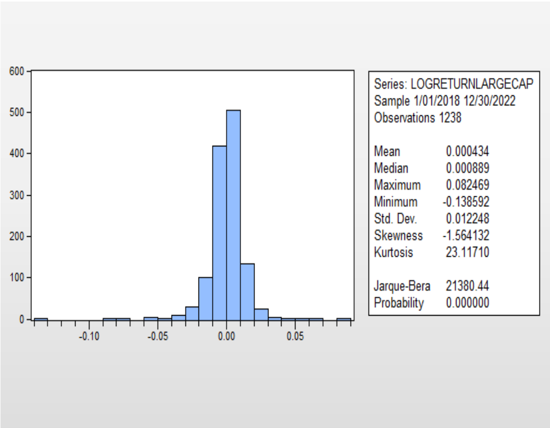


Source: prepared by the author (2023)

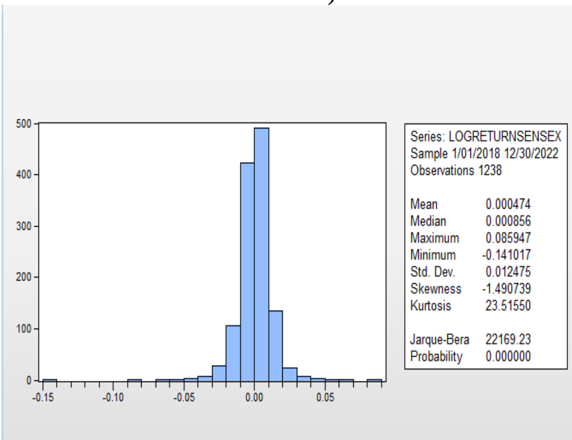
The descriptive statistics for all the return series is shown in table 1 along with the respective histograms. As indicated in previous research (the mean returns of all series is very close to zero. All return series are negatively skewed with high kurtosis identifying themselves with leptokurtosis. The p-value for JB test statistic for all series is zero thereby rejecting the hypothesis of normality.

Table 1: Descriptive statistics and histogram

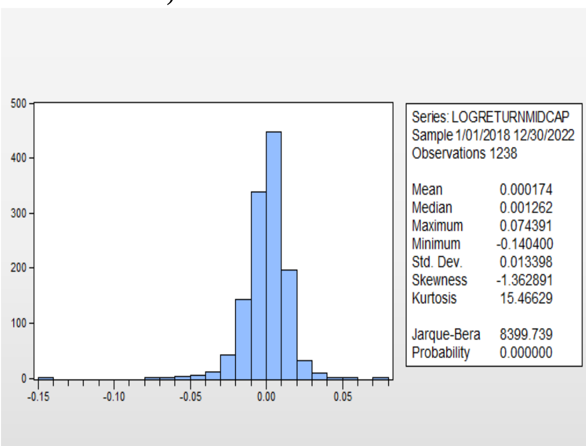
a) Sensex



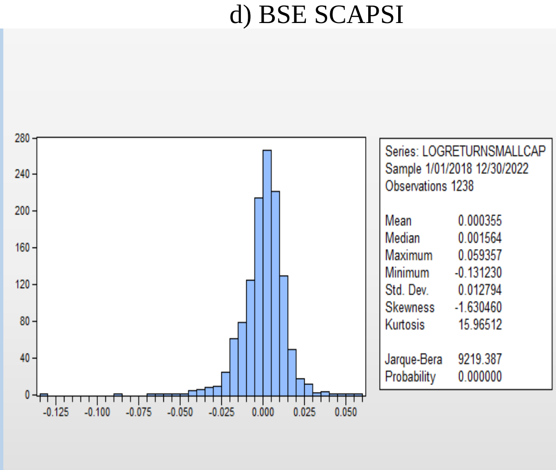
b) BSE LCAP



c) BSE MCAPSI



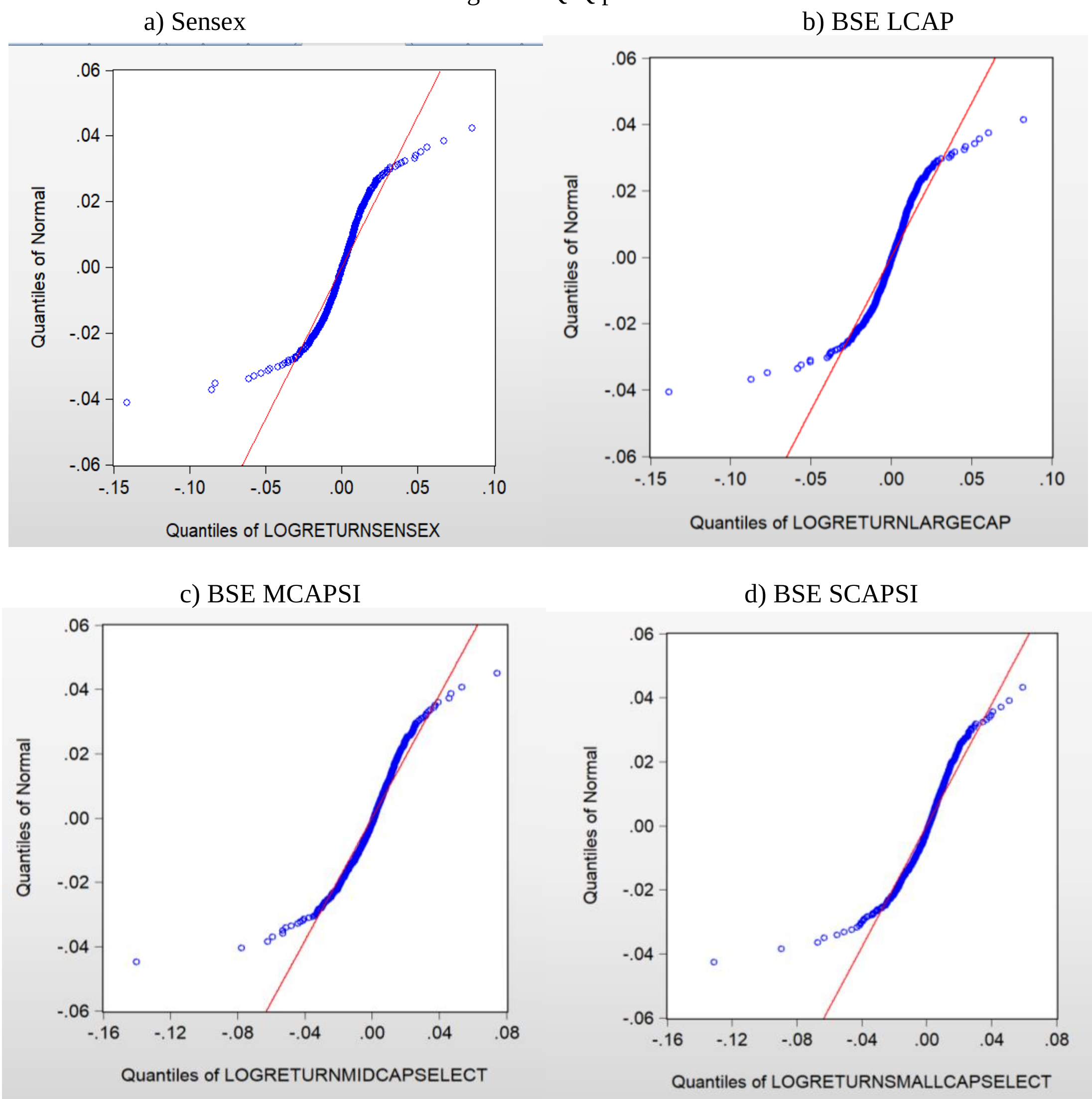
d) BSE SCAPSI



Source: prepared by the author (2023)

The Quantile-Quantile (Q-Q) plots, presented in figure 2, are graphical presentation to be cognizant about whether two sets of quantiles comes from the same distribution or not. The pattern created from plotting the points can be utilized for investigating whether they come from same distribution or not. The figure reveals that they both share similar distributions and this is true for all the four indices.

Figure 2: Q-Q plots



Source: prepared by the author (2023)

The log return series of all four indices have been tested for stationarity through the Augmented Dickey Fuller test the results of which are stated in table 2. As can be seen from the table, the probability values are all zero which implies that the null hypothesis of unit root presence is rejected. Moreover, the calculated t-statistics is higher than the critical values at one, five and ten percent. Thus all series were stationary. The autocorrelation (ACF) and the partial autocorrelations (PACF) were also checked. All of them indicated presence of serial correlation and dependency on past returns. These are reported in the four sections of table 3. It can be evidenced from table 3 that both the ACFs and PACFs in the initial lags were found to be out of bounds for all four series.

Table 2: ADF test results for the four return series

Index	Augmented Dickey Fuller Test				
	t-stats	Prob.	Critical value at 1%	Critical value at 5%	Critical value at 10%
Sensex	-12.15324	0.000	-3.4354	-2.8636	-2.5679
LCAP	-12.02066	0.000	-3.4354	-2.8636	-2.5679
MCAPSI	-34.30126	0.000	-3.4354	-2.8636	-2.5679
SCAPSI	-32.22284	0.000	-3.4354	-2.8636	-2.5679

Source: prepared by the author (2023)

Table 3: Autocorrelation functions of the four return series

a) Sensex

	AC	PAC	Q-Stat	Prob
1	-0.049	-0.049	2.9512	0.086
2	0.018	0.015	3.3415	0.188
3	0.004	0.005	3.3584	0.340
4	0.019	0.020	3.8285	0.430
5	0.136	0.138	26.695	0.000
6	-0.133	-0.123	48.813	0.000
7	0.090	0.078	58.942	0.000
8	0.011	0.020	59.094	0.000
9	-0.022	-0.030	59.685	0.000
10	0.073	0.062	66.284	0.000
11	-0.100	-0.070	78.908	0.000
12	0.071	0.028	85.236	0.000
13	-0.013	0.011	85.454	0.000
14	-0.035	-0.040	86.961	0.000
15	0.038	0.019	88.775	0.000
16	-0.059	-0.021	93.110	0.000
17	0.061	0.017	97.827	0.000
18	-0.055	-0.028	101.70	0.000
19	-0.014	-0.015	101.95	0.000
20	0.040	0.022	103.98	0.000
21	0.001	0.034	103.98	0.000
22	0.010	-0.023	104.09	0.000
23	-0.043	-0.013	106.46	0.000
24	-0.052	-0.067	109.89	0.000
25	0.065	0.050	115.27	0.000
26	-0.032	-0.009	116.57	0.000
27	0.019	0.005	117.02	0.000
28	0.021	0.044	117.58	0.000
29	-0.010	-0.013	117.71	0.000
30	-0.007	-0.034	117.78	0.000
31	-0.020	0.015	118.31	0.000
32	-0.026	-0.054	119.15	0.000
33	-0.033	-0.035	120.57	0.000

b) LCAP

	AC	PAC	Q-Stat	Prob
1	-0.045	-0.045	2.5668	0.109
2	0.028	0.026	3.5173	0.172
3	0.008	0.010	3.5938	0.309
4	0.018	0.018	3.9866	0.408
5	0.134	0.135	26.210	0.000
6	-0.128	-0.120	46.772	0.000
7	0.097	0.083	58.419	0.000
8	0.014	0.024	58.672	0.000
9	-0.024	-0.033	59.396	0.000
10	0.079	0.067	67.158	0.000
11	-0.088	-0.058	76.772	0.000
12	0.069	0.026	82.777	0.000
13	-0.027	-0.003	83.676	0.000
14	-0.039	-0.045	85.547	0.000
15	0.045	0.024	88.117	0.000
16	-0.051	-0.014	91.386	0.000
17	0.054	0.013	95.025	0.000
18	-0.055	-0.026	98.804	0.000
19	-0.001	-0.002	98.805	0.000
20	0.040	0.021	100.86	0.000
21	-0.008	0.026	100.95	0.000
22	0.013	-0.016	101.16	0.000
23	-0.047	-0.021	103.92	0.000
24	-0.048	-0.065	106.86	0.000
25	0.052	0.042	110.34	0.000
26	-0.033	-0.010	111.69	0.000
27	0.022	0.005	112.30	0.000
28	0.021	0.045	112.84	0.000
29	-0.011	-0.015	113.00	0.000
30	-0.016	-0.038	113.35	0.000
31	-0.017	0.015	113.69	0.000
32	-0.018	-0.045	114.10	0.000
33	-0.035	-0.033	115.68	0.000

c) MCAPSI

	AC	PAC	Q-Stat	Prob
1	0.024	0.024	0.7281	0.394
2	0.040	0.039	2.7080	0.258
3	0.003	0.001	2.7159	0.438
4	0.041	0.040	4.8162	0.307
5	0.089	0.088	14.723	0.012
6	-0.081	-0.089	22.881	0.001
7	0.070	0.069	29.046	0.000
8	0.023	0.024	29.692	0.000
9	0.024	0.009	30.382	0.000
10	0.069	0.068	36.358	0.000
11	-0.025	-0.021	37.141	0.000
12	0.035	0.011	38.719	0.000
13	-0.051	-0.044	41.939	0.000
14	-0.064	-0.075	47.064	0.000
15	0.001	-0.001	47.064	0.000
16	-0.022	-0.008	47.670	0.000
17	0.030	0.017	48.813	0.000
18	-0.016	0.002	49.140	0.000
19	0.007	0.005	49.209	0.000
20	0.034	0.027	50.697	0.000
21	-0.042	-0.032	52.910	0.000
22	-0.008	-0.013	52.988	0.000
23	-0.052	-0.032	56.345	0.000
24	-0.024	-0.023	57.059	0.000
25	0.014	0.019	57.321	0.000
26	-0.005	0.009	57.358	0.000
27	0.007	-0.009	57.427	0.001
28	0.030	0.041	58.578	0.001
29	-0.011	-0.021	58.733	0.001
30	-0.053	-0.060	62.293	0.000
31	-0.002	0.019	62.299	0.001
32	0.003	0.001	62.312	0.001
33	-0.013	-0.007	62.515	0.001

d) SCAPSI

	AC	PAC	Q-Stat	Prob
1	0.087	0.087	9.3332	0.002
2	0.071	0.064	15.666	0.000
3	0.045	0.034	18.210	0.000
4	0.031	0.020	19.389	0.001
5	0.099	0.091	31.673	0.000
6	-0.082	-0.104	40.038	0.000
7	0.080	0.084	47.926	0.000
8	0.028	0.018	48.896	0.000
9	-0.001	-0.013	48.898	0.000
10	0.084	0.075	57.689	0.000
11	-0.003	-0.004	57.701	0.000
12	0.080	0.048	65.641	0.000
13	-0.051	-0.058	68.880	0.000
14	-0.066	-0.070	74.305	0.000
15	0.011	0.007	74.469	0.000
16	-0.012	0.011	74.643	0.000
17	0.046	0.029	77.255	0.000
18	0.003	0.020	77.263	0.000
19	-0.001	-0.014	77.264	0.000
20	0.044	0.028	79.676	0.000
21	-0.043	-0.038	82.027	0.000
22	0.016	0.003	82.349	0.000
23	-0.035	-0.022	83.858	0.000
24	-0.038	-0.032	85.723	0.000
25	0.012	0.020	85.907	0.000
26	-0.028	-0.005	86.884	0.000
27	0.010	-0.013	87.009	0.000
28	0.038	0.050	88.815	0.000
29	-0.018	-0.030	89.247	0.000
30	-0.032	-0.043	90.555	0.000
31	-0.003	0.031	90.565	0.000
32	-0.031	-0.045	91.776	0.000
33	-0.030	-0.015	92.900	0.000

Source: prepared by the author (2023)

Next, the two GARCH models are applied on the four indices. The estimation results of GARCH (1,1) for Sensex, LCAP, MCAPSI and SCAPSI all are presented in table 4 for the period from 2018 to 2022. The first part of the table explains the mean equation and the middle part explains the variance equation details. The last part is about the diagnostic tests performed on the standardized residuals and the standardized squared residuals in order to check for presence of ARCH effects. The probability values indicate that the constant terms in mean equation were insignificant (significant) for the return series of Sensex and LCAP (MCAPSI and SCAPSI), whereas the constant terms were all significant for all the series in the variance equation. The ARCH and GARCH terms for all four series were statistically significant as indicated by a zero p-value.

Table 4: GARCH (1,1) estimation results for the four log return series

	Sensex	LCAP	MCAPSI	SCAPSI
		Mean Equation		
C (constant)	0.000953	0.000824	0.000440	0.000759
SE	0.000249	0.000256	0.000312	0.000304
Probability	0.0001	0.0013	0.1582	0.0125
μ	0.048494	0.056259	0.085422	0.180140
SE	0.030544	0.030715	0.030972	0.031033
Probability	0.1124	0.0670	0.00058	0.000
		Variance Equation		
B (constant)	3.22E-06	3.69E-06	1.05E-05	1.24E-05
SE	8.11E-07	8.52E-07	1.77E-06	2.14E-06
Probability	0.0001	0.000	0.000	0.000
α **(Arch term)**	0.124153	0.123547	0.125952	0.153019
SE	0.014587	0.014708	0.015739	0.018160
Probability	0.0000	0.000	0.0000	0.000
β**(Garchterm)**	0.854299	0.849971	0.813489	0.763088
SE	0.017210	0.017954	0.020793	0.026795
Probability	0.0000	0.000	0.0000	0.000
$\alpha+\beta$	0.978452	0.973518	0.939441	0.916107
Loglikelihood	3962.872	3966.835	3722.681	3815.273
AIC	-6.399147	-6.405554	-6.010803	-6.160506
BIC	-6.378450	-6.384857	-5.990105	-6.139809
DW-stat	2.191411	2.202520	2.127240	2.202957
		Diagnostic		
ARCH-LM	0.016071 (p=0.8991)	0.000412 (P=0.9838)	0.246602 (P=0.6196)	0.096290 (P=0.7564)
Q-Stats for residuals:Q(6)	7.6807 (p=0.262)	7.8718 (P=0.248)	4.0231 (P=0.674)	4.5166 (P=0.607)
Q(12)	9.4532 (p=0.664)	10.314 (P=0.588)	11.498 (P=0.487)	14.674 (P=0.260)
Q-Stats for sqd residuals: Q(6)	1.1744 (p=0.978)	0.9689 (P=0.987)	1.2098 (P=0.976)	0.6727 (P=0.995)
Q(12)	7.0277 (p=0.856)	6.4480 (P=0.892)	4.7377 (P=0.966)	6.5070 (P=0.888)

Source: prepared by the author (2023)

The sum of the ARCH and GARCH terms were 0.978452, 0.973518, 0.939441 and 0.916107 for Sensex, LCAP, MCAPSI and SCAPSI respectively, which were all very near to one thereby highlighting the presence of mean reverting variance process. The diagnostics in last part of the table indicate rejection of null hypothesis of significant autocorrelation in the standardized residuals and the squared residuals as all p-values are more than 0.05, indicating that the model was able to remove the ARCH effects from the data series quite satisfactorily.

Table 5: TGARCH (1,1) estimation results for Sensex, LCAP, MCAPSI and SCAPSI return series

	Sensex	LCAP	MCAPSI	SCAPSI
		Mean Equation		
C(constant)	0.000487	0.000372	5.52E-05	0.000216
SE	0.000241	0.000248	0.000320	0.000312
Probability	0.0432	0.1324	0.8631	0.4892
μ	0.080457	0.090241	0.104783	0.227878
SE	0.027384	0.027374	0.028882	0.029025
Probability	0.0033	0.0010	0.0003	0.0000
		Variance Equation		
C (constant)	3.62E-06	3.90E-06	1.01E-05	1.24E-05
SE	5.24E-07	5.12E-07	1.27E-06	1.47E-06
Probability	0.000	0.000	0.000	0.000
α	-0.020659	-0.021090	-0.002725	-0.019752
SE	0.00943	0.009085	0.013591	0.014244
Probability	0.0285	0.0203	0.8411	0.1655
γ	0.217143	0.220581	0.178174	0.245967
SE	0.023384	0.023274	0.023371	0.029936
Probability	0.000	0.000	0.000	0.000
β	0.877744	0.873121	0.844016	0.797838
SE	0.011279	0.011352	0.015952	0.021184
Probability	0.000	0.000	0.000	0.000
Loglikelihood	3999.14	4003.255	3743.930	3842.511
AIC	-6.456169	-6.462821	-6.043541	-6.20292
BIC	-6.431332	-6.437984	-6.018704	-6.17809
DW-stat	2.258013	2.272524	2.167526	2.30112
		Diagnostics		
ARCH-LM	0.094692 (p=0.7583)	0.129280 (P=0.7192)	0.546596 (P=0.4599)	0.016997 (P=0.8963)
Q-Stats for residuals:Q(6)	6.0099 (p=0.422)	6.8192 (P=0.338)	4.1581 (P=0.655)	4.1756 (p=0.653)
Q(12)	7.6297 (p=0.813)	8.8556 (p=0.715)	11.833 (p=0.459)	12.988 (p=0.370)
Q-Stats for sqd residuals: Q(6)	3.2178 (p=0.781)	4.1274 (p=0.659)	2.5723 (p=0.860)	1.3320 (p=0.970)
Q(12)	5.4556 (p=0.941)	6.2350 (p=0.904)	6.5546 (p=0.886)	5.0881 (p=0.955)

Source: prepared by the author (2023)

The estimation results of Sensex, LCAP, MCAPSI and SCAPSI for the TGARCH (1,1) model are reported in table 5. The probability values indicate that the constant terms in the mean equation were insignificant for all the return series, whereas the constant terms were all significant for all the series in the variance equation. The asymmetric parameter gamma value was more than zero for all the return series exhibiting existence of leverage effect. Thus, variations in negative innovations were more pronounced than those in positive innovations for all the return series. The last part of the table 4 shows all p-values to be more than 0.05, thereby suggesting all null hypothesis to be rejected, namely presence of ARCH effects, and also the presence of autocorrelations and partial autocorrelations in both the standardized residuals as well as squared residuals for all the return series.

Comparing the results in table 4 and table 5, epitomize that according to both the Akaike info criterion (AIC) and the Schwarz criterion (BIC) GARCH (1,1) model is a better fit for all series since both the AIC and BIC values are minimized for GARCH (1,1) model as compared to the TGARCH (1,1) model. Thus, the study supports the evidence from literature that, generally GARCH (1,1) suffice for fitting most of the financial time series. Moreover, GARCH (1,1) shows consistent results for all the return series suggesting that whatever the cap size of an index, there is no need to go beyond a simple GARCH (1,1) model.

CONCLUSIONS

Volatility is tough to predict and is required for almost every investment decision. To deal with the issue there are innumerous models prevalent in the investment field that can be used by an investor. India is a growing economy, with its stock markets becoming one of the most sought-after investment destinations. Not many studies have tried to model the volatility of size indices in India. The objective of the present study is to model the volatility of the size indices in India through GARCH-family models. Present study considers GARCH (1,1) and the TGARCH (1,1) models in order to model four Indian indices, namely BSE's Sensex, Large cap index, Mid cap Select index and the Small cap Select index log return series. Dataset consists of daily closing prices for these indices for the period 1 January 2018 to 31 December 2022. The results of the present study indicated that the AIC and BIC criterion were minimized for the GARCH (1,1) model. Thus, it can be suggested that GARCH (1,1) model is sufficient to model the different size index return series and there is no need to implement more complex models in order to model volatility in Indian markets. The limitation of the present study is that it tried to model the stock market indices data from only India and no international comparison to judge the modelling capabilities across markets was made. This fosters the area for future research where Indian data can be compared with other international markets with respect to modelling volatility through the GARCH-family models.

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