“Predictive modeling of return volatility in sustainable investments: An in-depth analysis of ARIMA, GARCH, and ARCH techniques”

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PREDICTIVE MODELING OF RETURN VOLATILITY IN SUSTAINABLE INVESTMENTS: AN IN-DEPTH ANALYSIS OF ARIMA, GARCH, AND ARCH TECHNIQUES

Abstract

This paper aims to forecast the stock price and analyze the return volatility of India's top three socially responsible companies. This study used ARIMA and GARCH models to forecast the stock price and analyze return volatility. For the analysis, the required time series data are collected from Yahoo Finance from 01-08-2012 to 29-07-2022 of the companies' Monthly and daily closing stock prices. The socially responsible companies are selected based on India's sustainability indices. The findings of the study show that the ARIMA (9,1,9) model for HDFC Ltd, ARIMA (10,1,7) for Reliance Industries Ltd, and ARIMA (2,1,2) are suitable models to forecast the stock price. Also, the study's findings forecasted stock prices from August 2022 to July 2023. The forecasted stock price for July 2023 of HDFC Ltd is INR 2,613.78, Reliance industries Ltd is INR 3,073.75, and ICICI Bank Ltd is INR 857.73. Reliance Industries Ltd ($\sigma 2t$ = 0.9270586) is less volatile, and HDFC Ltd ($\sigma 2t$ = 0.9665041) is more volatile among the three companies, ICICI Bank Ltd ($\sigma 2t$ = 0.9507527) is the second high volatile company. The present study is limited to the top three companies that were selected from the three sustainability indices of BSE. The study is also limited to analysis of past volatility of stock price returns.

Keywords socially responsible companies, forecasting, sustainability indices, stock price

JEL Classification G11, G17

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INTRODUCTION

The idea of "socially responsible investing (SRI)," or investment based on ESG criteria, has gained widespread acceptance over the past ten years. Sustainable stocks are becoming increasingly popular as an alternative to traditional profit-maximizing equities due to their emphasis on pursuing societal goals, including environmental conservation, social equity, and economic advancement (Sharma et al., 2022). Companies are contributing to United Nation's sustainable development goals (SDG's) through these practices.

Within the tight constraints of financial analysis, SRI considers both beneficial and detrimental impacts on society and the environment of investments. It can also be described as the increasingly popular process of choosing and investing in a business that complies with certain requirements for corporate social responsibility (CSR) (Tripathi & Bhandari, 2015). In India, four sustainability indices represent companies following sustainable practices viz S&P BSE GREENEX, S&P BSE CARBONEX, S&P BSE 100ESG, and Nifty 100 ESG (Seth & Singh, 2022).

Stocks are regarded as a very popular kind of investment. Financial management is often done by individuals, while strategic investment is done by businesses. Stock forecasting is therefore extremely important in all sectors (Huang, 2022). It is more imperative to study and forecast the stock price and volatility of returns of those companies who fall under the sustainability indices. It is crucial for the economy that the companies remain longer and set the benchmark for the rest of the companies to adopt sustainable practices in their business.

Predicting the trend in stock price movement is widely regarded to be a challenging financial challenge. Earnings for stockholders can be maximized through improved price prediction abilities. (Zhao & Chen, 2022). Economic and industrial time series are frequently predicted using ARIMA models, which can help investors make better investment decisions (Kusuma & Kumar, 2018). To analyze the volatility of time series data in practice, there is GARCH modelling, which considers variance of residuals as well and replaces ARCH models.

1. LITERATURE REVIEW

It is important to review the available literature on time series modeling and forecasting with the ARIMA model. In this review of literature, more emphasis is given on the literature made for the identification of ARIMA and GARCH time series models. Few studies are identified and reviewed relating to stock price prediction using ARIMA models. The present literature is also evident for forecasting rice price, gold price, GDP, and Net assets value using the ARIMA model.

Adebiyi et al. (2014) reported that, based on the experimental results obtained using the top ARIMA model, it can be concluded that ARIMA models are effective in short-term forecasting of stock prices. Possible use for assisting those looking to invest in the stock market to pick winners. The findings of Reddy (2019) are in support of the findings of the above study, the best fitted model supports the ability of the ARIMA model to accurately anticipate the BSE CLOSE and NSE CLOSE on a short-term basis, and they will help people choose profitable investment options. Kumar et al. (2021) compared two different models for predicting stock market performance. The study's findings demonstrated that, in the short term, anticipating future time series, ARIMA performed better than the RNN-LSTM model.

Mustapa and Ismail (2019) also find the same results with the ARIMA modeling with a little different angle. According to the experimental findings, there was an improvement in prediction quality between the static forecast and the dynamic forecast. However, this study could only provide forecasts for the near future. Challa et al. (2020) interpreted the same findings in the different way. They discovered that there is more uncertainty when the period is long and less uncertainty when the time is short. Utilizing time series data, ARIMA was applied to validate quick and accurate prediction.

The study by Kolte et al. (2020) adopted GARCH modeling to find out the volatility of BSE BANKEX indices. The paper finds the GARCH model predicts volatility with very less error. The authors conclude that investors can decide what they want to invest in the banking industry. The banking industry is profitable for investments in the future since the findings of volatility predictions indicate an increase in returns.

In the study by Wang et al. (2020), the GARCH-MIDAS model developed by Engle et al. (2013) is proposed to be extended in 15 different ways in this work so that it can take into account the impact of asymmetry and the effect of excessive volatility caused by shocks to the short-term and/or long-term volatility elements. Malik and Yadav (2020) compared the volatility of sustainability indices using ARIMA and GARCH models. Firstly, it bolsters the case for using univariate time series analysis, and secondly, it offers additional practical evidence in support of recording the auto-regressive nature of time series data and then managing the volatility of residuals.

The stock price volatility of three airline companies is studied by Deb (2021). The study used the

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GARCH model to analyze volatility. They suggested the methodology offers a fresh method for gathering pertinent data from online user behavior to create practical predictors for predicting stock return volatility. A study on the impact of COVID-19 on stock volatility by Sharma et al. (2022) found that COVID-19 has the greatest significant impact on the volatility of the large-cap index, according to the asymmetric power ARCH model, whereas COVID-19 has the greatest significant impact on the volatility of the mid-cap index, according to the exponential GARCH model. The recent study by Huang (2022) reported, the time series analysis approach is used to confirm the benefits and drawbacks of the prior model by comparing the historical value of the stock open price with the fitting value in addition to a number of other basic preparations for building the best model. And it is proved that ARIMA and GARCH are the best fitted models for analyzing and predicting time series data.

There are few other studies conducted using time series data apart from stock price. Setiyowati et al. (2013) reported that a strength of this work is the efficient combination of two models, ARCH(1) and ARCH(2). For a non-stationary forecast of rice prices, either model is preferable to the GARCH(1,1) model. Kusuma and Kumar (2018) using ARIMA reported, the results of the best fitted model confirm the accuracy of the ARIMA model in predicting the short-term NAV values of mutual funds, which will aid individual investors in making well-informed investment choices. Ma et al. (2018) studied time series data of yearly GDP using ARIMA. It is their opinion that the ARIMA model forecast is a more advanced method for time series prediction. In the context of time series, it can be used for statistical analysis and prediction. The model works best for making predictions in the near future. Big fluctuations occur when the time frame for making predictions is stretched out. Monthly gold prices are studied by using ARIMA model by R. K. Sharma and A. Sharma (2019), and they interpreted that the ARIMA model shows a little difference between real and anticipated gold prices, and the percentage variance is likewise under 2%, confirming the accuracy and usefulness of the existing model. Determining the extent to which basic food prices fluctuate, the ARCH model with the order 1-0 is the appropriate model for analyzing the price volatility of staple goods in Kebumen Regency, as per analysis using the ARCH GARCH method (Setiawati et al., 2021).

The present study reviewed several other studies. They used other models for predicting volatility of price and returns apart from ARIMA and GARCH. Few of them are DEA-TOPSIS, Descriptive statistics, TVP-VAR, ADF Test. OLS Regression model Granger Causlity Test, Panel regression estimation technique, Event Study, Sharpe ratio, Treynor ratio, Jensen's α, Information ratio, and Fama's decomposition measure and dummy regression model. Tabular representation of the summary of literature review has been given in Table 1 (see Appendix A).

Industrial operations use a lot of energy and emit a lot of pollutants; this would be reduced by socially conscious business practices to reduce industrial pollution and so lessen the effects of climate change, socially responsible companies follow local pollution standards and energy efficiency guidelines (Bhuvaneskumar et al., 2022). These companies are considered as Socially responsible companies in the present study.

Based on the relevant literature review, there is a lack of research on the prediction and fluctuation of returns for companies included in sustainability indices. This paper seeks to examine and predict the stock price of the three leading socially responsible companies, as well as analyze the volatility of their stock price returns.

2. DATA AND METHODOLOGY

The paper analyzes three companies' stock prices, such as Reliance industries Ltd, ICICI Bank Ltd, and Housing Development Finance Corp (HDFC). For the ARIMA model (Stock price forecast), monthly closing stock price from 01-08-2012 to 01-07-2022 time series data is analyzed. For the GARCH model (Stock price volatility), daily closing stock price from 01-08-2012 to 29-07-2022 time series data are analyzed. All the relevant data are extracted from Yahoo finance (https://finance.yahoo.com).

The three companies (Table 1) for analysis are selected from the Indian Sustainability indices viz., BSE 100 ESG, BSE Greenex and BSE Carbonex.

The selected companies fall under the top 10 constituents in all three sustainability indices. The fact sheet of the sustainability indices is taken from S&P Global (www.spglobal.com).

Table 1. Top three companies falling under all the sustainability indices

Company	Symbol	Sector
Reliance Industries Ltd	500325	Energy
ICICI Bank Ltd	532174	Financials
HDFC	500010	Financials

To achieve the proposed objectives, ARIMA and GARCH analyses are undertaken to analyze the time series data. The data are analyzed using EViews software for both models.

One of the most advanced methods for time series forecasting is the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA). The Box-Jenkins method of time series modeling is so widely used in econometrics that it is referred to as time series analysis (R. K. Sharma & A. Sharma, 2019).

The model consists of AR, I, and MA. AR refers to the Autoregressive model, I to the Integration model (where I represents the order of a single integer), and MA to the Moving Average model. To determine whether the sequence is stationary, the Unit root test is applied. A non-stationary sequence should be changed using the difference operation to become stationary. In essence, differential operation and the ARMA (p, q) model are combined to create the ARIMA (p, d, q) model (Ma et al., 2018).

A popular time series model and the highly accurate short-term forecasting model is the ARIMA model. Even though some time series is merely a collection of time-dependent random variables, the model's central idea is that the overall changes in the time series adhere to a set of laws that can be approximatively described by the corresponding mathematical model. (Ma et al., 2018).

Bollerslelv first introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in 1986, which is an expanded version of the ARCH model. GARCH methods allow conditional variance to be described as an ARMA process. In the heteroskedastic variance, they include auto regressive and moving average components.

The change in variance over a lengthy period of time in a time series is modelled by the Autoregressive Conditional Heteroskedasticity (ARCH). The conditional variance may fluctuate over time as a function of previous errors since the model understands the distinction between unconditional and conditional variance (Wing-Yi Chio et al., 2021). GARCH models are used as replacement for high order ARCH models. GARCH models give more parsimonious models compared to ARCH.

For calculating volatility of stock price returns, the GARCH model conditional variance equation is utilized. The equation is as follows in a GARCH(1,1) model,

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \quad (1)$$

where $\alpha_0 > 0,\ \alpha_1 > 0,\ \beta_1 > 0,$ and $\alpha_1 + \beta_1 < 1$ (Costa, 2017).

3. RESULTS

Before attempting to estimate the ARIMA model, it is necessary to ensure that the data are stationary. The stationarity of the time series data has been tested using the Augmented Dickey-Fuller (ADF) unit root test. When a data set's mean and covariance are independent of time, and the distribution's form does not vary over time, the data set is said to be stationary. ADF test results shown in Table 2 says that the original time series data of stock prices of three different SRCs are non-stationary.

The probability value of all three companies is more than the 0.05 desired level, which says that the data are non-stationary. A similar test has been run for the data set at the first difference to make the time series data stationary. Table 3 shows that the data becomes stationary after taking the first difference.

From the ADF test results at the first difference, it is clear that the data becomes stationary. The same can be confirmed through the probability value of

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Table 2. ADF test results of observed data

SRC	Type of test and critical values		t- statistic	Prob*
HDFC Ltd.	Augmented Dickey-Fuller test statistics		– 1.26091	0.646
	Test critical values	1% level	– 3.48606	
		5% level	– 2.88586	
		10% level	– 2.57982	
Reliance Industries Ltd.	Augmented Dickey-Fuller test statistics		1.792977	0.9997
	Test critical values	1% level	– 3.48806	
		5% level	– 2.88673	
		10% level	– 2.58028	
ICICI Bank Ltd.	Augmented Dickey-Fuller test statistics		0.758121	0.9929
	Test critical values	1% level	– 3.48655	
		5% level	– 2.88607	
		10% level	– 2.57993	

Table 3. ADF test results of data at first difference

SRC	Type of test and critical values		t- statistic	Prob*
HDFC Ltd.	Augmented Dickey-Fuller test statistics		– 11.7675	0.0000
	Test critical values:	1% level	– 3.48655	
		5% level	– 2.88607	
		10% level	– 2.57993	
Reliance Industries Ltd.	Augmented Dickey-Fuller test statistics		– 8.36533	0.0000
	Test critical values:	1% level	– 3.48806	
		5% level	– 2.88673	
		10% level	– 2.58028	
ICICI Bank Ltd.	Augmented Dickey-Fuller test statistics		– 12.8213	0.0000
	Test critical values	1% level	– 3.48655	
		5% level	– 2.88607	
		10% level	– 2.57993	

0.0000 for all the three companies. The graphical representation of original data series and first difference data series if shown in Figure 1.

For the potential ARIMA model, the identification correlogram that has ACF and PACF values of first difference of data series has been employed. After observing the patterns of ACF and PACF values, p and q for the ARIMA model are calculated. With the help of spikes or lags in the correlogram, the values for AR(p) and MA(q) are selected. Figure 2 shows the correlogram at first difference of the three companies.

To identify the best ARIMA model, the correlogram was first analyzed. To increase the robustness of the identification process, Automatic ARIMASel Add-in was used, which is available in EViews software. Further, to identify the best ARIMA parameters, the following criteria were considered:

1. Smaller Akaike information criterion (AIC) and Schwarz information criterion (SIC).
2. Relatively high R^2 and Adjusted R^2.
3. Significant F-Statistics.

After going through the above-mentioned process and employing the criteria for ARIMA(p,d,q) parameter estimation, the best goodness of fit model has been found for HDFC Ltd ARIMA (9,1,9), Reliance Industries Ltd ARIMA (10,1,7), and ICICI bank Ltd ARIMA (2,1,2). Table 4 shows ARIMA(p,d,q) model estimations for all the three companies.

The above mentioned ARIMA models were found to be significant to forecast the future stock prices of the selected companies. After comparing all the possible models with the selected criteria, the models with smaller AIC and SIC, Higher R-squared and adjusted R-squared and Prob(F-statistic) are less than 0.05 for all the selected ARIMA models. Durbin-Watson stat was also significant with values near 2 for all the three models, indicating no autocorrelation. Since all the values are significant enough, now with the help of fit stock price has been forecasted for the future period till July 2023.

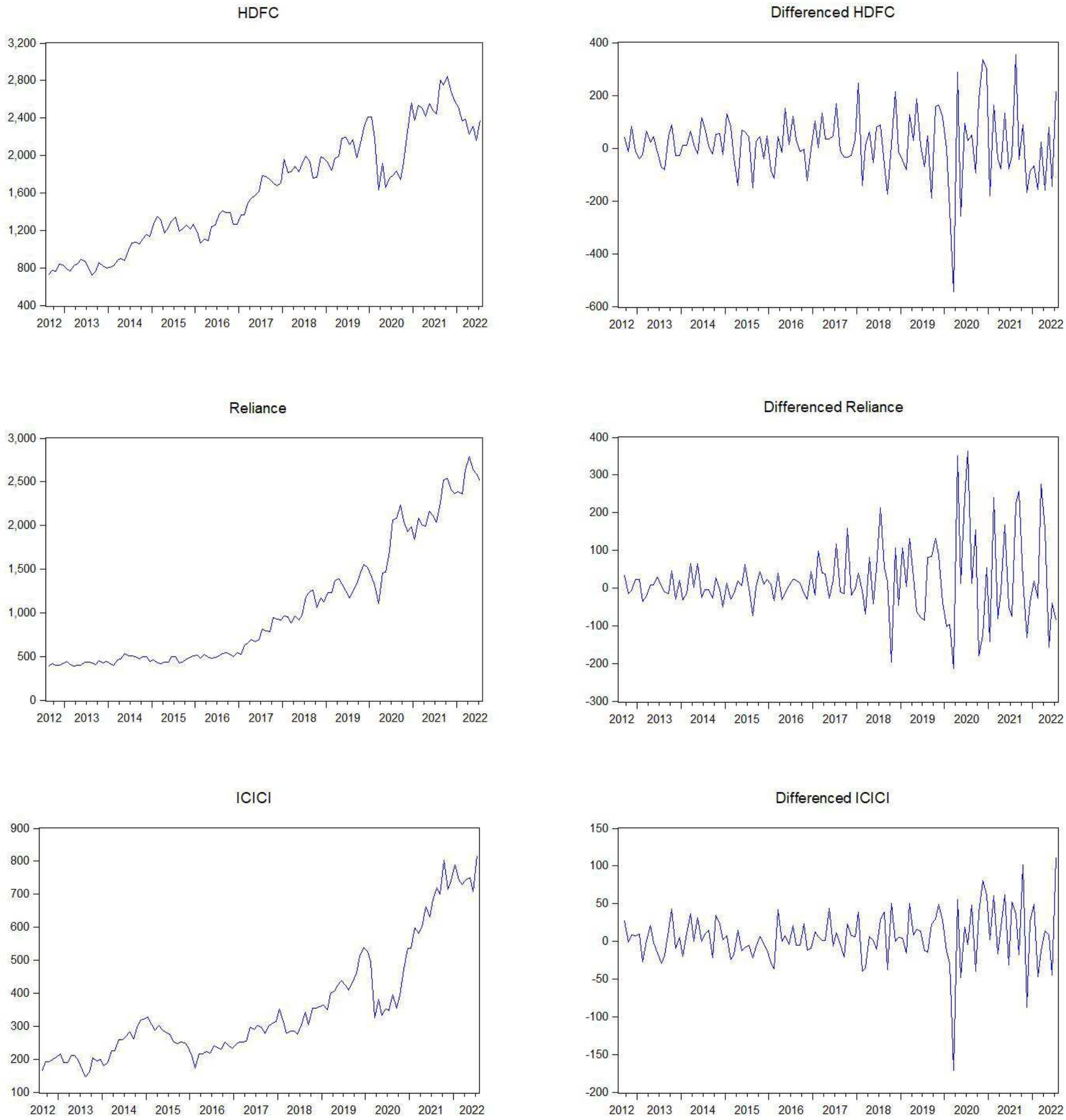

Figure 1. Non-stationarity and stationarity of observed data series

Table 4. Selected ARIMA (p,d,q) model parameter estimations

SRC	Criteria	Coefficient	Criteria	Coefficient
HDFC Ltd ARIMA (9,1,9)	R-Squared	0.336748	Akaike Information Criterion	12.48284
	Adjusted R-Squared	0.209457	Schwarz Information Criterion	12.94992
	F-Statistic	2.645497	Durbin-Watson stat	2.030278
	Prob(F-Statistic)	0.000955		
Reliance Industries Ltd ARIMA (10,1,7)	R-Squared	0.447829	Akaike Information Criterion	11.83346
	Adjusted R-Squared	0.348438	Schwarz Information Criterion	12.27718
	F-Statistic	4.505736	Durbin-Watson stat	2.065998
	Prob(F-Statistic)	0.00000		
ICICI Bank Ltd ARIMA (2,1,2)	R-Squared	0.150083	Akaike Information Criterion	9.859556
	Adjusted R-Squared	0.112477	Schwarz Information Criterion	9.99968
	F-Statistic	3.990846	Durbin-Watson stat	1.928214
	Prob(F-Statistic)	0.002267		

Note: Full model estimations are given in appendices.

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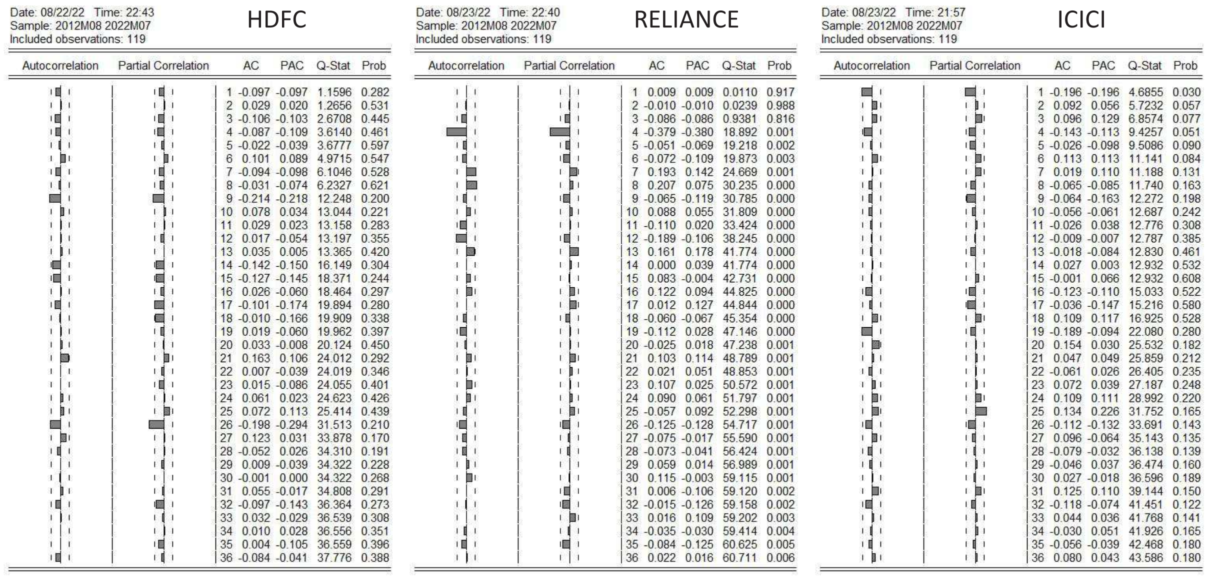

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Sample: 2012M08 2022M07
Included observations: 119

HDFC

Lag	AC	PAC	Q-Stat	Prob
1	-0.097	-0.097	1.1596	0.282
2	0.029	0.020	1.2656	0.531
3	-0.106	-0.103	2.6708	0.445
4	-0.087	-0.109	3.6140	0.461
5	-0.022	-0.039	3.6777	0.597
6	0.101	0.089	4.9715	0.547
7	-0.094	-0.098	6.1046	0.528
8	-0.031	-0.074	6.2327	0.621
9	-0.214	-0.218	12.248	0.200
10	0.078	0.034	13.044	0.221
11	0.029	0.023	13.158	0.283
12	0.017	-0.054	13.197	0.355
13	0.035	0.005	13.365	0.420
14	-0.142	-0.150	16.149	0.304
15	-0.127	-0.145	18.371	0.244
16	0.026	-0.060	18.464	0.297
17	-0.101	-0.174	19.894	0.280
18	-0.010	-0.166	19.909	0.338
19	0.019	-0.060	19.962	0.397
20	0.033	-0.008	20.124	0.450
21	0.163	0.106	24.012	0.292
22	0.007	-0.039	24.019	0.346
23	0.015	-0.086	24.055	0.401
24	0.061	0.023	24.623	0.426
25	0.072	0.113	25.414	0.439
26	-0.198	-0.294	31.513	0.210
27	0.123	0.031	33.878	0.170
28	-0.052	0.026	34.310	0.191
29	0.009	-0.039	34.322	0.228
30	-0.001	0.000	34.322	0.268
31	0.055	-0.017	34.808	0.291
32	-0.097	-0.143	36.364	0.273
33	0.032	-0.029	36.539	0.308
34	0.010	0.028	36.556	0.351
35	0.004	-0.105	36.559	0.396
36	-0.084	-0.041	37.776	0.388

Date: 08/23/22 Time: 22:40
Sample: 2012M08 2022M07
Included observations: 119

RELIANCE

Lag	AC	PAC	Q-Stat	Prob
1	0.009	0.009	0.0110	0.917
2	-0.010	-0.010	0.0239	0.988
3	-0.086	-0.086	0.9381	0.816
4	-0.379	-0.380	18.892	0.001
5	-0.051	-0.069	19.218	0.002
6	-0.072	-0.109	19.873	0.003
7	0.193	0.142	24.669	0.001
8	0.207	0.075	30.235	0.000
9	-0.065	-0.119	30.785	0.000
10	0.088	0.055	31.809	0.000
11	-0.110	0.020	33.424	0.000
12	-0.189	-0.106	38.245	0.000
13	0.161	0.178	41.774	0.000
14	0.000	0.039	41.774	0.000
15	0.083	-0.004	42.731	0.000
16	0.122	0.094	44.825	0.000
17	0.012	0.127	44.844	0.000
18	-0.060	-0.067	45.354	0.000
19	-0.112	0.028	47.146	0.000
20	-0.025	0.018	47.238	0.001
21	0.103	0.114	48.789	0.001
22	0.021	0.051	48.853	0.001
23	0.107	0.025	50.572	0.001
24	0.090	0.061	51.797	0.001
25	-0.057	0.092	52.298	0.001
26	-0.125	-0.128	54.717	0.001
27	-0.075	-0.017	55.590	0.001
28	-0.073	-0.041	56.424	0.001
29	0.059	0.014	56.989	0.001
30	0.115	-0.003	59.115	0.001
31	0.006	-0.106	59.120	0.002
32	-0.015	-0.126	59.158	0.002
33	0.016	0.109	59.202	0.003
34	-0.035	-0.030	59.414	0.004
35	-0.084	-0.125	60.625	0.005
36	0.022	0.016	60.711	0.006

Date: 08/23/22 Time: 21:57
Sample: 2012M08 2022M07
Included observations: 119

ICICI

Lag	AC	PAC	Q-Stat	Prob
1	-0.196	-0.196	4.6855	0.030
2	0.092	0.056	5.7232	0.057
3	0.096	0.129	6.8574	0.077
4	-0.143	-0.113	9.4257	0.051
5	-0.026	-0.098	9.5086	0.090
6	0.113	0.113	11.141	0.084
7	0.019	0.110	11.188	0.131
8	-0.065	-0.085	11.740	0.163
9	-0.064	-0.163	12.272	0.198
10	-0.056	-0.061	12.687	0.242
11	-0.026	0.038	12.776	0.308
12	-0.009	-0.007	12.787	0.385
13	-0.018	-0.084	12.830	0.461
14	0.027	0.003	12.932	0.532
15	-0.001	0.066	12.932	0.608
16	-0.123	-0.110	15.033	0.522
17	-0.036	-0.147	15.216	0.580
18	0.109	0.117	16.925	0.528
19	-0.189	-0.094	22.080	0.280
20	0.154	0.030	25.532	0.182
21	0.047	0.049	25.859	0.212
22	-0.061	0.026	26.405	0.235
23	0.072	0.039	27.187	0.248
24	0.109	0.111	28.992	0.220
25	0.134	0.226	31.752	0.165
26	-0.112	-0.132	33.691	0.143
27	0.096	-0.064	35.143	0.135
28	-0.079	-0.032	36.138	0.139
29	-0.046	0.037	36.474	0.160
30	0.027	-0.018	36.596	0.189
31	0.125	0.110	39.144	0.150
32	-0.118	-0.074	41.451	0.122
33	0.044	0.036	41.768	0.141
34	-0.030	0.051	41.926	0.165
35	-0.056	-0.039	42.468	0.180
36	0.080	0.043	43.586	0.180

Figure 2. Correlogram of observed data at first difference of three companies

Table 5. HDFC Ltd, Forecast results

Forecasted Month	Forecasted Stock Price
01-08-2022	2423.34
01-09-2022	2538.94
01-10-2022	2529.73
01-11-2022	2598.50
01-12-2022	2532.99
01-01-2023	2547.88
01-02-2023	2444.20
01-03-2023	2451.32
01-04-2023	2496.08
01-05-2023	2489.07
01-06-2023	2613.29
01-07-2023	2613.78

Table 6. Reliance Industries Ltd, Forecast results

Forecasted Month	Forecasted Stock Price
01-08-2022	2711.87
01-09-2022	3084.84
01-10-2022	2983.01
01-11-2022	2863.99
01-12-2022	2948.88
01-01-2023	2920.32
01-02-2023	2849.64
01-03-2023	2884.07
01-04-2023	3063.25
01-05-2023	3149.47
01-06-2023	3050.38
01-07-2023	3073.75

The forecasted stock prices of HDFC Ltd (Table 5) shows that there is an increase in the stock price till the month of January 2023. The stock prices started decreasing from the month of February 2023 till May 2023. Again, there is an increase in the stock price from June 2023.

The above forecasted stock prices show that the Reliance industries Ltd stock prices (Table 6) will be volatile. There is a significant increase in the month of September 2022 and a decrease in October and November 2022. They increased again in December 2022 but decreased in the next

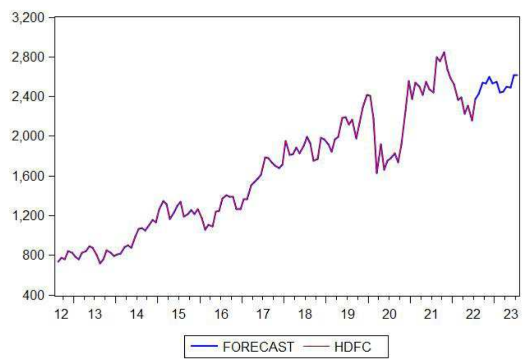

Figure 3. Past and forecasted stock price of HDFC Ltd

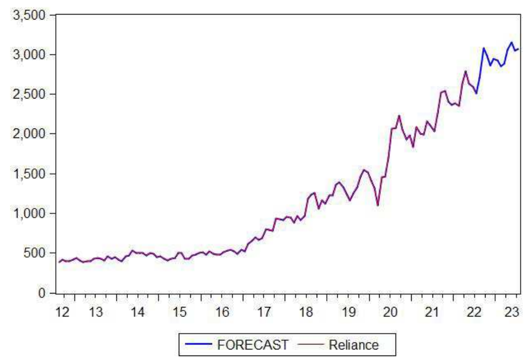

Figure 4. Past and forecasted stock price of Reliance Industries Ltd

month. As per the forecasted results, it is going to meet the stock price of Rs. 3073.75 in July 2023.

Table 7. ICICI Bank Ltd, Forecast results

Forecasted Month	Forecasted Stock Price
01-08-2022	792.47
01-09-2022	797.58
01-10-2022	825.85
01-11-2022	822.34
01-12-2022	814.14
01-01-2023	831.05
01-02-2023	841.69
01-03-2023	836.34
01-04-2023	841.78
01-05-2023	854.76
01-06-2023	856.92
01-07-2023	857.73

The forecasted stock prices of ICICI Bank Ltd (Table 7) rise until February 2023, fell in March 2023 and started rising again. Till the last forecasted month of July 2023, the stock price is increasing.

To know the volatility of the stock returns, daily closing stock price has been employed. The command used to generate the returns is "returns=d(log(data series))". Figure 6 shows the graphical representation of returns of three companies.

The first step to GARCH model estimation is the identification of the ARMA model. ARMA (p,q) parameters are identified using the correlogram ACF and PACF values, as well as using automatic ARIMASel Add-in. The same criteria have been followed, which is mentioned in the ARIMA model analysis. But, as the returns data series of all the three companies are found stationary, no further difference has been made.

To find out the presence of heteroskedasticity or ARCH effect, the Heteroskedasticity test was performed with ARCH 1 lag. The results accepted the Alternative hypothesis of the presence of heteroskedasticity. Further, the best-fitted number of ARCH effects or lags are determined using correlogram squared residuals. Figure 7 shows the correlogram of squared residuals of the three companies.

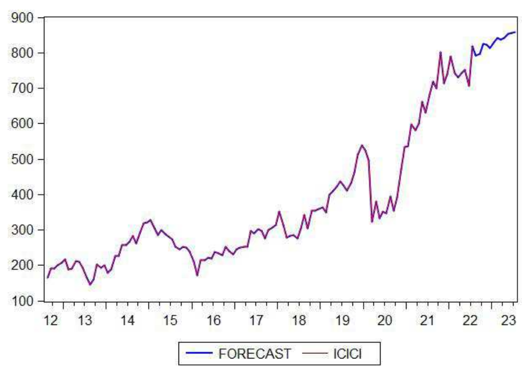

Figure 5. Past and forecasted stock price of ICICI Bank Ltd

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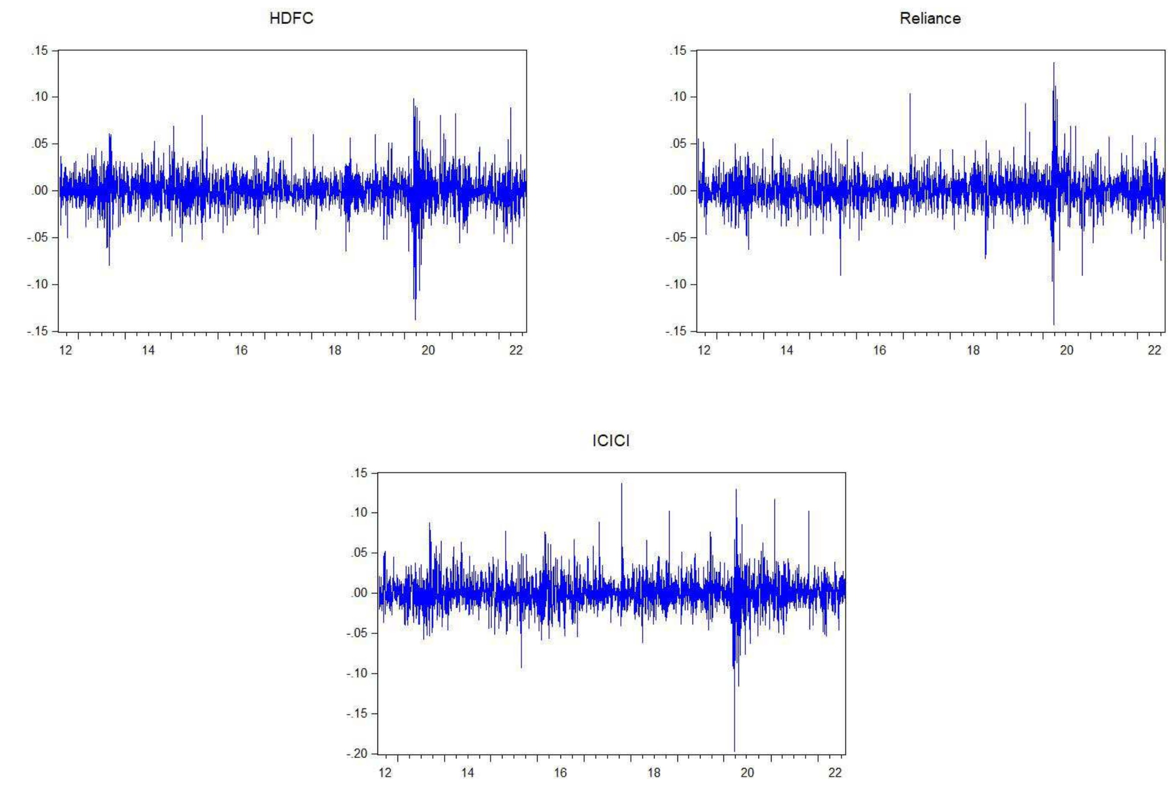

Figure 6. Stock price returns of three companies

HDFC

Date: 08/28/22 Time: 22:27
Sample: 8/16/2012 7/28/2022
Included observations: 2452

	AC	PAC	Q-Stat	Prob
1	0.244	0.244	146.02	0.000
2	0.279	0.234	337.78	0.000
3	0.209	0.112	444.78	0.000
4	0.099	-0.025	468.78	0.000
5	0.283	0.222	665.29	0.000
6	0.173	0.066	739.17	0.000
7	0.198	0.060	835.44	0.000
8	0.162	0.021	900.35	0.000
9	0.160	0.070	963.15	0.000
10	0.139	-0.002	1010.6	0.000

Reliance

Date: 08/28/22 Time: 22:34
Sample: 8/01/2012 7/29/2022
Included observations: 2462

	AC	PAC	Q-Stat	Prob
1	0.213	0.213	111.83	0.000
2	0.289	0.255	317.33	0.000
3	0.186	0.096	402.38	0.000
4	0.109	-0.007	431.53	0.000
5	0.145	0.067	483.75	0.000
6	0.136	0.075	529.28	0.000
7	0.306	0.250	759.97	0.000
8	0.130	-0.007	801.89	0.000
9	0.226	0.073	927.67	0.000
10	0.131	0.002	969.92	0.000

ICICI

Date: 08/28/22 Time: 22:30
Sample: 8/16/2012 7/29/2022
Included observations: 2453

	AC	PAC	Q-Stat	Prob
1	0.101	0.101	25.021	0.000
2	0.107	0.097	52.909	0.000
3	0.074	0.056	66.467	0.000
4	0.134	0.115	110.91	0.000
5	0.124	0.094	148.90	0.000
6	0.084	0.043	166.14	0.000
7	0.145	0.108	217.64	0.000
8	0.137	0.091	264.11	0.000
9	0.210	0.158	372.43	0.000
10	0.097	0.035	395.85	0.000

Figure 7. Correlogram of observed data squared residuals of three companies

The number of ARCH effects or lags for the ARCH model is determined using correlogram squared residuals. The HDFC Ltd and Reliance Industries Ltd ARCH 3 models have been selected, and the ICICI bank Ltd ARCH 5 model has been chosen. For all the selected ARCH models, the heteroskedasticity test was run, and it showed no heteroskedasticity with a significance value of 0.0000. To maintain the parsimony in the models, the GARCH (1,1) model was replaced with all the ARCH models where the GARCH (1,1) model is significant enough in the place of ARCH(3) and ARCH(5) models. Again, to select the best model between ARCH and GARCH, Log-likelihood, AIC, SIC, and Hannan-Quinn criteria are compared and chosen.

The criteria followed in selecting the best model between ARCH and GARCH:

1. Minimum AIC
2. Minimum SIC
3. Minimum Hannon-Quinn
4. Maximum Log-likelihood.

The model compares and selects all the coefficients of the criteria mentioned above. The coefficients of the requirements are given in Table 8.

Selecting the best model based on the criteria for the three companies: GARCH (1,1) model was estimated, and all the necessary coefficients were obtained to estimate the volatility of stock price returns. Table 9 represents necessary coefficients of GARCH estimation.

Table 9. GARCH model estimation coefficients of three companies

SRC	Variable	Coefficient	Prob.
HDFC	C	0.0000101	0.0000
	RESID(–1)^2	0.070654	0.0000
	GARCH(–1)	0.89584	0.0000
Reliance Industries Ltd	C	0.0000216	0.0000
	RESID(–1)^2	0.081848	0.0000
	GARCH(–1)	0.845189	0.0000
ICICI Bank Ltd	C	0.0000215	0.0000
	RESID(–1)^2	0.086954	0.0000
	GARCH(–1)	0.863777	0.0000

From coefficients estimated through GARCH modeling, the volatility of a company's stock price return is calculated using the GARCH Conditional variance equation.

$$HDFC = 0.0000101 + 0.070654$$
$$+0.89584 = 0.9665041.$$

$$Reliance\ Industries\ Ltd = 0.0000216$$
$$+0.81848 + 0.845189 = 0.9270586.$$

$$ICICI\ Bank\ Ltd = 0.0000215$$
$$+0.086954 + 0.863777 = 0.9507525.$$

Calculation results of conditional variance equation of all the three companies are close to 1, which shows that stock returns of all the three compa-

Table 8. Comparing ARCH and GARCH models

SRC	Criteria	Model		Best Model
		Model A	Model B	
HDFC Ltd		**ARCH (3)**	**GARCH (1,1)**	
	Log likelihood	6554.652	6589.75	B
	Akaike	–5.32679	–5.35624	B
	Schwarz	–5.26998	–5.30179	B
	Hannan-Quinn	–5.30614	–5.33645	B
Reliance Industries Ltd		**ARCH (3)**	**GARCH (1,1)**	
	Log likelihood	6539.91	6562.668	B
	Akaike	–5.330809	–5.350219	B
	Schwarz	–5.295251	–5.317032	B
	Hannan-Quinn	–5.317886	–5.338157	B
ICICI Bank Ltd		**ARCH (5)**	**GARCH (1,1)**	
	Log likelihood	6149.746	6173.133	B
	Akaike	–4.99857	–5.020084	B
	Schwarz	–4.953606	–4.98222	B
	Hannan-Quinn	–4.98223	–5.006324	B

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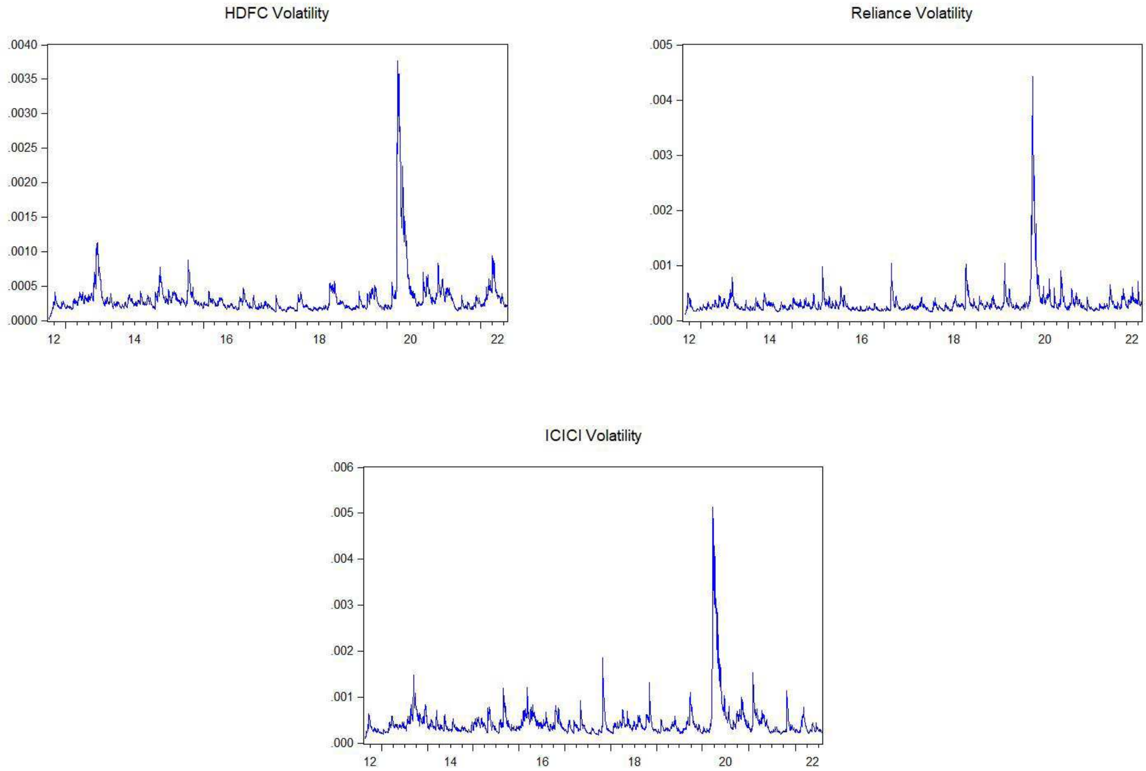

Figure 8. Stock price return volatility of three companies

nies are highly volatile. Figure 8 shows the stock price return volatility of all the three companies over the time period taken for the study.

4. DISCUSSION

ARIMA models provide a framework for understanding the time series behavior of returns, while GARCH and ARCH models offer insights into the conditional volatility dynamics, capturing the clustering and persistence of volatility shocks (Kusuma & Kumar, 2018). ARIMA, GARCH, and ARCH models offer sophisticated tools for forecasting volatility in financial time series data (Koreisha & Pukkila, 1993). It has been compared how well the ARIMA, GARCH, and ARCH models can forecast stock prices. The results imply that when it comes to stock price forecasting, the GARCH (1,1) model outperforms ARIMA models (A.A et al., 2023; Novita Sari., Achmad Hizazi., 2021). The present study also supports that the GARCH (1,1) model best estimates the forecasting and volatility. The combination of ARIMA (1,1,1)-GARCH (1,1) has been found to yield the best results in forecasting stock prices (Yang, 2023). The AR-ARCH model has also been identified as a suitable model for forecasting volatility and return in stock prices (Zili et al., 2022). In order to determine the order in which the ARIMA and GARCH models should be used, it has been suggested that the least information criterion, such as AIC and BIC, be given priority (HR & V, 2023). Additionally, it has been discovered that the GARCH model is superior to the ARIMA model in terms of its ability to anticipate stock values in situations when there are outliers.

Regarding the validity of GARCH models in terms of their ability to forecast volatility, there is a significant consensus. The findings of this research lend credence to the conclusion that GARCH models, and more specifically GARCH (1,1), offer improved estimates for volatility forecasting. Prior research has shown that GARCH models perform better than ARIMA models when it comes to forecasting stock prices, particularly when it comes to capturing volatility dynamics. This is consistent with the findings of that research. Furthermore, findings are consistent with the proposal made by earlier research, which is to prioritise information criteria such as AIC and BIC when deciding the order in which ARIMA and GARCH models should be examined.

CONCLUSION AND IMPLICATIONS

This paper aimed to forecast the stock prices of three socially responsible companies (SRCs) until July 2023 and analyze the stock price return volatility among them. By incorporating ARIMA and GARCH models into the time series data of these SRCs, This study provided forecasts for their stock prices from August 2022 to July 2023. Additionally, examined the stock price return volatility of the three companies over the period from 01-08-2012 to 29-07-2022.

The findings of this study suggest that Reliance Industries Ltd. exhibits the lowest volatility among the selected SRCs, with a sigma squared value of 0.9270586, indicating a relatively stable stock price performance. Conversely, Housing Development Finance Corporation Ltd. (HDFC Ltd.) demonstrates higher volatility, with a sigma squared value of 0.9665041, making it the most volatile among the analyzed companies. ICICI Bank Ltd. falls in between, with a sigma squared value of 0.9507527, positioning it as moderately volatile.

Our forecasts indicate that by July 2023, the stock price of HDFC Ltd. is anticipated to reach INR 2,613.78, while Reliance Industries Ltd. is expected to have a stock price of INR 3,073.75. ICICI Bank Ltd. is projected to have a stock price of INR 857.73 during the same period.

In conclusion, this study provides valuable insights into the future stock price trends of socially responsible companies, emphasizing their varying volatility levels. Investors can utilize these findings to make informed decisions regarding their investment strategies, considering factors such as risk tolerance and expected returns. Additionally, policymakers and stakeholders in the financial industry can use this information to better understand the dynamics of socially responsible investments and their implications for market stability.

The study will identify benchmark companies for all the other companies in following sustainable practices. These findings have significant repercussions for the nation's finances and economy. Starting with the top three socially conscious corporations in India that are included in sustainable indices, it aids portfolio managers as well as investors in developing portfolio strategies for a deeper comprehension of the dynamic fluctuations and stock price movements of these companies. As a consequence of this, it may be helpful in making better judgments regarding allocation and risk management. Second, the findings have substantial repercussions for ethical and faith-based investors, as they provide insight into the future of the companies' stock prices, both in terms of their direction and their magnitude.

The study contributes to the related literature by analyzing the return volatility of socially responsible companies in India contributing to the United Nations' SDGs.

AUTHOR CONTRIBUTIONS

Conceptualization: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
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Formal analysis: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Investigation: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Methodology: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Project administration: Srihari G., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Software: Srihari G., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Supervision: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Validation: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Visualization: Srihari G., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Writing – original draft: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.
Writing – review & editing: Srihari G., Kusuma T., Chetanraj D. B., Senthil Kumar J. P., Ravi Aluvala.

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APPENDIX A

Table A1. Summary of literature review

Author and Year	Objective	Variable	Model used	Results	Country
Setiyowati et al., 2013	Non-stationarity forecasting model	Daily Rice Price	ARIMA and GARCH	Non-stationarity models are better served by ARCH(1) and ARCH(2) than GARCH(1,1)	Indonesia
Adebiyi et al., 2014	Stock price prediction model construction utilizing the ARIMA model.	Daily Stock Price	ARIMA	ARIMA are the best models to predict stock prices for short-term period	Nigeria, South Africa
Tripathi & Bhandari, 2015	Compare the performance of portfolios of general firms and socially conscious stocks on the Indian stock market.	Monthly closing value of company stock prices	Sharpe ratio, Treynor ratio, Jensen's α, etc.	Net selectivity returns for ESG and Greenex are positive. While taking net selectivity into account, GREENEX and ESG still performed better than NIFTY and SENSEX	India
Joshi et al., 2017	Empirically investigates how investors react to corporate sustainability initiatives	S&P 500 Index	Event Study	Since inclusion implies that sustainability activities are expensive without corresponding financial rewards, it is perceived negatively	US and India
Kusuma & Kumar, 2018	Evaluate the accuracy of the ARIMA model's predictions	Daily Closing value of NAV of Axis Mutul Fund	ARIMA	The best-fitted model's results validate the ARIMA model's ability to predict the near-term NAV rates of mutual funds	India
Ma et al., 2018	The forecasting process using the ARIMA model is demonstrated in this work using the EViews program	GDP (Yearly)	ARIMA	The ARIMA model forecast is a more advanced method of predicting time series. The model works best for making predictions in the near future. Large variations emerge when the time horizon across which predictions are made is quite long	China
Mehta et al., 2019	Ranking Indian business for using methods to reduce carbon emissions	Operating Profit	DEA-TOPSIS	Tata Consultancy Services Ltd. has been named one of the top 25 GREENEX index components by both TOPSIS and DEA results, demonstrating both a high ranking and consistency in their efficiency score	India
R. K. Sharma & A. Sharma, 2019	Creation of model for predicting gold prices in India	Monthly gold price	ARIMA	The ARIMA model shows little difference between real and anticipated gold prices, and the percentage variance is likewise under 2%, confirming the accuracy and usefulness of the existing model	India
Mustapa & Ismail, 2019	Creation of adequate ARIMA model	Monthly stock price of S&P 500	ARIMA	The experimental results showed that the dynamic forecast was superior to the static forecast. However, this research could only make interim projections	Malaysia
Reddy, 2019	Determining whether time series data were stationary and to forecast using time series ARIMA modeling	Weekly closing prices of BSE and NSE	ARIMA	The findings of the best fitted model support the ability of the ARIMA model to accurately anticipate the BSE CLOSE and NSE CLOSE on a short-term basis	India
Challa et al., 2020	Predicting about the return and volatility characteristics	Daily stock returns of S&P BSE Sensex and S&P BSE IT	ARIMA	More uncertainty predicting long period and less in short period. Utilizing time series data, ARIMA was applied to validate quick and accurate prediction	India
Kolte et al., 2020	Predicting the volatility of the BSE BANKEX indexes	Monthly close values	GARCH	The banking industry is profitable for investments in the future since the findings of volatility predictions indicate an increase in returns	India

Table A1 (cont.). Summary of literature review

Author and Year	Objective	Variable	Model used	Results	Country
Wang et al., 2020	Aiming to improve stock volatility simulation and prediction by enhancements to the GARCH-MIDAS model	Daily stock price of S&P 500	GARCH-MIDAS	To account for the asymmetry effect and the extreme fluctuation effect brought about by severe shocks in the smaller long-term volatility components, it is recommended to adapt the GARCH-MIDAS model in 15 distinct ways	China
Malik & Yadav, 2020	Look at how time-varying volatility affects India's sustainability indexes differently at different points in time	S&P BSE Carbonex, S&P BSE ESG, S&P BSE Greenex	ARIMA and GARCH	This study demonstrates the value of time series with univariate analysis and provides more empirical support for the importance of recording the time series data's inherent autoregressive behavior	India
Tasnia et al., 2020	This study looks into how CSR affects the volatility of US bank stock prices	CSR, ESG, Stock price volatility data of 37 US banks	Panel regression estimation technique	The US banking authorities should review and update its CSR disclosure policy to cut down on wasteful spending and put more of an emphasis on enhancing social and environmental conditions for society	Malaysia
Deb, 2021	Analysing Stock price changes of 3 airlines	Daily closing stock price	GARCH	The suggested methodology offers a fresh method for gathering pertinent data from online user behaviour to create practical predictors for predicting stock return volatility	India
Kathiravan et al., 2021	Looks into effect of temperature on returns of stock	Daily closing values BSE Greenex	ADF Test. OLS Regression model Granger Causality Test	The current study unequivocally shown that a meteorological variable, specifically temperature, did influence investors' decisions regarding their investments in the carbon emission index, formerly known as BSE GREENEX	India
Kumar et al., 2021	Stock market forecast comparison of ARIMA and RNN-LSTM	Monthly closing values of SENSEX and NIFTY	ARIMA and RNN-LSTM	The study's findings demonstrated that, in the short term, anticipating future time series, ARIMA performed better than the RNN-LSTM model	India
Setiawati et al., 2021	To find the most effective model to use as an alternate price-volatility forecasting model.	Weekly prices of staple food	ARCH-GARCH	According to ARCH GARCH analysis, the proposed system for evaluating the price fluctuations of staple goods in Kebumen Regency is the ARCH model with the order 1-0	Indonesia
Almansour et al., 2022	Examining the relationships between dynamic return volatility	Daily data for 10 S&P and DJ indices	Descriptive statistics, TVP-VAR	The findings show a strong correlation between the relative sustainability indices for the S&P and DJ indices across the whole sample, both before and after the COVID-19 epidemic	Jordon, Abu Dhabi, UAE
Sharma et al., 2022	Checking to see if green and sustainable stock investments can provide some stability during the current uncertain period	Daily returns from Greenex, Carbonex, Large-Cap, Mid-Cap and Small-Cap index	ARCH-GARCH	The COVID-19 has the greatest significant impact on the volatility of the large-cap index, according to the asymmetric power ARCH model, whereas the COVID-19 has the greatest significant impact on the volatility of the mid-cap index, according to the exponential GARCH model	India
Huang, 2022	Predicting stock price using ARMA and ARIMA	Daily open price of Shanghai securities composite index	ARIMA-GARCH	Time series analysis approach is used to confirm the benefits and drawbacks of the prior model by comparing the historical value of the stock open price with the fitting value in addition to a number of other basic preparations for building the best model	China

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