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Research Article

Trend Analysis of AU Small Finance Bank (AUSFB) and Equitas SFB

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ABSTRACT

This research employs GARCH models to analyze the return patterns from Equitas Small Finance Bank (SFB) and AUSFB and establish patterns of volatility. Stock returns showed heteroskedasticity throughout the study period was found in this study. The mean returns were positive for both AUSFB and Equitas SFB over the study period. The GARCH model is very good at modeling volatility clustering; hence it was used. Therefore, findings from the model were faithful to real data. In fact, this demonstrated that stock prices have heteroscedasticity, which is in line with the use of the GARCH Model. This study revealed a significant temporal fluctuation characterized by low volatility intervals following high volatility intervals as well as vice versa. The dataset covered daily stock returns for Equitas SFB between November 2020 and May 2023 and AUSFB between July 2017 and May 2023. These results provide risk management insights as well as investment strategies that are practically useful for investors and finance professionals. Other studies can then investigate the use of other econometric models and adopt longer time periods or different market conditions. One potential limitation is its specific time periods studied and the concentration on only two equities.

Keywords: Stock Returns, Volatility, GARCH Model, AUSFB, Equitas SFB.

INTRODUCTION

In India, there exists a special kind of bank known as Small Finance Banks (SFBs) which have been set up to take care of unbanked and underprivileged sections of society like the small unorganized business entities, small and marginal farmers, micro and tiny businesses and small businesses. The idea behind establishing SFBs was to allow these small businesses, marginal farmers and other organizations in the informal sector access loans and savings facilities (Reserve Bank of India [RBI], 2015). The Reserve Bank of India (RBI) guidelines require that SFBs should maintain a minimum paid-up capital of Rs. 200 crores (Vishwanathan, 2015). These banks must follow the same prudential norms as scheduled commercial banks do, including maintenance of Cash Reserve Ratio (CRR) and Statutory Liquidity Ratio (SLR), for complying with RBI guidelines regarding their banking operations (RBI, 2019). Two examples include the AU Small Finance Bank (AUSFB), which started its operation in April 2017; and Equitas Small Finance Bank (Equitas SFB) which has been running since September 2016. Retail banking products are provided by both banks but with an emphasis on SME's and rural areas.

In promoting economic progress, SFBs are indispensable since they provide financial services to marginalized communities. This is done through technology that enhances their operational efficiency as well as their ability to reach different types of clients. Due to its growth trajectory and role in financial inclusion, the banking industry in

India cannot do without small finance banks (SFBs).

This study aims to analyze AUSFB and Equitas SFB's return series and volatility patterns. The researcher used GARCH models to test for heteroskedasticity of these banks' return series and find out what it means for investors and financial analysts.

Bank	Headquarters	Tagline
AU Small Finance Bank	Jaipur	Chalo Aage Badhe
Capital Small Finance Bank	Jalandhar, Punjab	Vishwas se Vikas tak
Equitas Small Finance Bank	Chennai	It's Fun Banking
ESAF Small Finance Bank	Thrissur, Kerala	Joy of Banking
Fincare Small Finance Bank	Bengaluru	Banking On More
Jana Small Finance Bank	Bengaluru	Paise Ke Kadar
Suryoday Small Finance Bank	Navi Mumbai	A Bank of Smiles
Ujjivan Small Finance Bank	Bengaluru	Bharosa, Aake bharose par
Utkarsh Small Finance Bank	Varanasi	Apki Umeed ka Khata
North East Small Finance Bank	Guwahati	Your Door Step Banker

Figure 1. Small Finance Banks (SFBs) in India

Figure 1 shows different SFBs in India, including the location of their head offices and the taglines of their branches.

These banks were set up to offer basic banking services along with credit facilities to underserved sections such as small firms, micro & small industries, farmers, and rural semi-urban people. Small finance banks must comply with RBI guidelines. The Indian banking system relies on small finance banks (SFBs) to reach out to under-served populations (RBI, 2019).

Importance and Benefits of Small Finance Banks

SFBs encourage financial inclusion by bringing in banks to economic and minimal urban areas. They extend formal banking to the financially excluded. SFBs offer credit to farmers, microenterprises, small businesses and other underserved segments. By providing custom financial products and services, SFBs help the various segments without proper access to banking in growing their businesses or availing credit requirements. This is credited to the switch in MFIs where the majority have become SFBs. These entities could morph into SFBs and move from not just micro-credit but other activities revolving around the retail banking space. SFBs meet specific customer requirements. They offer microfinance and low-balance savings accounts. These customized solutions serve the needs of unbanked and under bankable customers from the informal sector (Jayadev, Singh, & Kumar, 2017; Neelam, 2019).

SFBs use technology to simplify operations and provide easy financial services. They invest in digital infrastructure, mobile banking applications, and online banking platforms to make account access, cash transfers, and other financial services easy. SFBs help small companies and microenterprises flourish by providing financing and financial services. Finance helps these companies grow, create jobs, and boost the economy. SFBs follow RBI regulations (RBI). These banks are regulated to meet prudential standards, retain appropriate capital, and lend responsibly, protecting depositors and borrowers (The Committee on Comprehensive Financial Services for Small Businesses and Low Income Households, 2014; Singh, Anand, & Pareek, 2015; Khan, 2019).

Small Finance Banks are vital links between the official financial system and underprivileged groups. They empower people, reduce poverty, and grow the economy by providing inclusive banking and credit services.

AUSFB

AU Small Finance Bank is a famous Indian SFB. In April 2017, the RBI granted AU Small Finance Bank, previously AU Financiers (India) Limited, a Small Finance Bank license. Jaipur, Rajasthan, is the bank's headquarters. AU Small Finance Bank offers customized banking products and services. These include savings accounts, current accounts, fixed deposits, recurring deposits, and business, personal, automobile, and house loans. AU Small Finance Bank began as an NBFC that lent to SMEs and microfinance borrowers. It became a Small Finance Bank to provide more banking services beyond microfinance (Jagwani, 2019).

AU Small Finance Bank has several branches around India. Central regional offices are hubs, and smaller units are spokes. The bank can effectively contact urban and rural consumers using this method. AU Small Finance Bank leverages technology to improve client experience and operational efficiency. The bank offers seamless online and mobile banking via digital banking solutions. AU Small Finance Bank promotes financial inclusion by serving the underprivileged and unbanked. It helps people, small enterprises, and the informal sector access formal banking and credit. AU Small Finance Bank promotes education, healthcare, and sustainable livelihoods via CSR. The bank promotes social welfare and development (Arora, Sharma, Pahwa, & Yadav, 2018).

As of March 2021, AU Small Finance Bank has INR 47,437 crore in assets (around USD 6.4 billion). AU Small Finance Bank has 700 branches in India. These branches were strategically positioned in urban and rural locations to accommodate varied customers. AU Small Finance Bank served individuals, small companies, and microenterprises. The bank offered financial assistance to underrepresented groups. AU Small Finance Bank provides a variety of loans. Its March 2021 loan portfolio was INR 35,301 crore (approximately USD 4.8 billion). Business, personal, automobile, and home loans were covered. The bank accepted savings, current, and fixed client deposits. AU Small Finance Bank's deposit base was INR 35,227 crore in March 2021 (around USD 4.8 billion) (RBI, 2015, 2019; Vishwanathan, 2015).

Equitas SFB

Equitas Small Finance Bank is another prominent Indian SFB. Equitas Micro Finance Limited, a microfinance NBFC, founded Equitas Small Finance Bank in 2007. After receiving a Small Finance Bank license from the RBI in 2016, it became a bank. Chennai, Tamil Nadu, India is the bank's headquarters. Equitas Small Finance Bank has branches and touchpoints in cities and rural regions throughout India. A hub-and-spoke arrangement ensures broad client access (RBI, 2005, 2015).

Equitas Small Finance Bank provides many banking products and services to meet client demands. These include savings, current, fixed, recurring, gold, house, automobile, and business loans. The bank serves individuals, micro and small businesses, and underbanked people. Equitas Small Finance Bank leverages technology to improve client experience and operational efficiency. It has invested in digital platforms, mobile apps, and online services to make banking easy for users. Equitas Small Finance Bank provides banking services to underserved and unbanked populations. It empowers financially excluded people with accessible banking alternatives. Equitas Small Finance Bank supports education, healthcare, and skill development through CSR activities. The bank strives to improve its community (RBI, 2010, 2015).

Trend Analysis and Volatility of Small Finance Banks

AUSFB and Equitas SFB's daily stock returns are analyzed using the GARCH model, which is well-known for its ability to model volatility clustering. This model aids in the identification of patterns where periods of high volatility are followed by periods of low volatility and vice versa. Trend analysis and volatility assessment of SFBs are crucial to understanding their market behavior and risk profile (Xu, Cheng, Wang, & Yang, 2020).

Through an analysis of AUSFB's stock returns from July 2017 to May 2023 and Equitas SFB's stock returns from November 2020 to May 2023, this study sheds light on the banks' risk-return dynamics over time. The results offer relevant information to investors and finance professionals concerning the implications for risk management as well as investing strategies (Yuan, Zhong, & Lu, 2022; Asl, Rashidi, Tavakkoli, & Rezgui, 2024).

However, this analysis is based on just two SFBs and specific time periods so it may not tell the whole truth about how many banks actually participated in scope changes. The analysis can be extended by future scientists to other SFBs or for different time frames in order to have a comprehensive idea of how the volatility pattern works and what exactly market behavior will ensue.

Objectives of the Study

This study's main goal is to examine the trends in stock return volatility for Equitas Small Finance Bank (Equitas SFB) and AU Small Finance Bank (AUSFB). The precise goals are:

- To evaluate how volatility affects the stock returns of Equitas SFB and AUSFB.
- To look at both institutions' patterns of volatility during the research period.
- To ascertain whether AUSFB and Equitas SFB stock returns exhibit heteroskedasticity.
- To assess the stock return prediction values' accuracy.

LITERATURE REVIEW

India's banking industry has made a substantial contribution to financial intermediation since the country's 20 main banks were placed under government control in 1969 and 1980 following their nationalization. Nationalization's main objective was to provide financial services to places that had not previously had access to them, which sped up the creation of bank branches, particularly in rural areas (Gandhi, 2015). Government-run efforts to reduce poverty and finance agriculture were both greatly aided by public sector banks.

The High-Level Committee on Financial Sector Reforms, chaired by Raghuram Rajan, urged a shift towards financial inclusion through enhanced efficiency and innovation in their 2015 report, "A Hundred Small Steps". The committee recommended the creation of small semi-autonomous savings institutions with low overheads and efficient decision-making processes. Thus, Licensing guidelines for Small Finance Banks (SFBs) and Payments Banks were issued by the Reserve Bank of India (RBI) in November last year. Low-cost technology operations were used to create these SFBs, which aim to offer loans and savings facilities among marginal farmers, small businesses, and other disadvantaged groups. SFBs were established to provide loan and savings products to small-scale farmers, micro-enterprises, and other underprivileged groups using technologically advanced low-cost operations. On the contrary, SFBs are allowed to operate across the country, unlike RRBs or LABs, which are geographically limited (Planning Commission Government of India, 2015).

Using secondary data from bank websites, annual reports, and other sources (Erlando, Riyanto, & Masakazu, 2020) examined the effects of SFBs on financial inclusion in India. They also used simple statistical methods to show that there is a large untapped rural market which emphasises the need for various financial inclusion measures. For instance, this study highlights how crucial it is to adopt a comprehensive approach against economic isolation including financial literacy programs and easily accessible loans.

Jagwani (2019) carried out research on FFBs which included AU Bank looking at its performance as well as challenges encountered by such banks. In general, 75 per cent of the credit deployed by SFBs goes to small businesses; low-income individuals; and the un-organised sectors. However, no particular information regarding these challenges was provided within this investigation.

Mohanty (2018) analyzed the effectiveness of SFBs by drawing on various sources, such as MicroSave Consulting and the World Bank Consultative Group to Assist Poor. It suggests that SFBs must employ suitable commodities and strategies not to repeat the mistakes of previous community banks.

According to Goel and Sharma (2017), the main aim of establishing SFBs was to grant marginalized communities access to financial services and increase their chances of borrowing. They pointed out that accessibility, innovation, and productivity are areas where SFBs are striving in the financial sector.

This study underscores that despite the success made by SFBs in enhancing inclusive financing, there is still a gap in our understanding of their volatility patterns and operational problems. More research should be conducted regarding these fields in order to give a more insightful perception about the impact of SFBs on the communities in which operate as well as their efficiency.

METHODOLOGY

The study utilized stock price data for AU Small Finance Bank (AUSFB) and Equitas Small Finance Bank (Equitas SFB) sourced from finance.yahoo.com. Data preprocessing included cleaning and organizing the data to ensure accuracy and completeness.

Data Collection

The present study used only secondary data to analyze the volatility and forecast the stock returns—the daily open and close prices of AUSFB and Equitas SFB. The AUSFB data is available from 10th July 2017, and Equitas SFB data from 2nd November 2017 onwards. Due to data availability, the researcher has collected data up to 31st May 2023. Total observations constituted 1455 from AUSFB and 635 from Equitas SFB. One month of data from 1st June 2023 to 30th June 2023 has been used for the validation process. The required data time series were collected from http://finance.yahoo.com website and analyzed for the purpose.

Statistical Tools

Using the E-views econometrics program, several statistical approaches including descriptive statistics, ADF, ARCH-LM, and GARCH were used and examined. The return-based estimation of volatility (dri). So, first things first, the daily returns were computed. The following formula determines the AU SFB and Equitas SFB return.

$$dr_t = \frac{dc_t}{dc_{t-1}} \tag{1}$$

Where,

dr_t = daily return on AUSFB and Equitas SFB for time t,

dc_t = daily closing price of AUSFB and Equitas SFB at time t, and

dc_{t-1} = daily opening price of AUSFB and Equitas SFB at time t-1.

Descriptive Statistics

Descriptive statistics, including mean, standard deviation, and variance, were computed to summarize the basic characteristics of the stock return data. These statistics provide an overview of the data distribution and variability.

Test of Stationarity

Verifying whether the data is stationary or non-stationary using time series is appropriate. The Augmented Dickey-Fuller Test (ADF) may be used to determine the unit root test results.

GARCH(1,1)

ARCH effect is calculated based on the following formula.

$$PY_t = \alpha_0 + \beta_1 PY_{t-1} + \varepsilon_t \tag{2}$$

PY_t = Predicted value

α_0 = Constant

$\beta_1 PY_{t-1}$ = Forecasting value

ε_t = Error Term

GARCH(1,1) method

$$\sigma_t{}^2 = \omega_0 + \alpha_1 U^2{}_{t-1} + \beta_1 U\sigma^2{}_{t-1} \tag{3}$$

ω_0 = constant which is gamma * Long Run Variance

$\alpha_1 U^2{}_{t-1}$ = alpha * Squared Lagged Returns

$\beta_1 U\sigma^2{}_{t-1}$ = beta * Lagged Variance

The Long Run Variance, also known as the Gamma weight, describes how much the predictions of the Garch model will return to the mean. The Alpha weight determines the volatility's response to fresh information. How closely the forecast resembles the variance of the preceding period is determined by the beta weight.

ADF Test: The Augmented Dickey-Fuller (ADF) test was employed to check for the stationarity of the return series.

ARCH-LM Test: The Autoregressive Conditional Heteroskedasticity-Lagrange Multiplier (ARCH-LM) test was used to identify the presence of ARCH effects.

GARCH Model: The GARCH model was applied to assess volatility clustering and forecast future volatility.

Validation

One month of data from June 2023 was used for validation. The model's prediction accuracy was evaluated by comparing forecasted values with actual returns during this period.

RESULTS AND DISCUSSION

Table 1 summarises descriptive information for AUSFB and Equitas SFB. A quick check at **Table 1** indicates that the AUSFB and Equitas SFB's mean returns over the research period were both positive. Although there are a number of possible explanations, the sustained rise of the AUSFB and Equitas SFB over the research period. The same thing may be seen in **Figures 2** and **3**.

Table 1. Descriptive Statistics of AUSFB and Equitas SFB

Statistics	AUSFB	Equitas SFB
Mean	0.000725	0.001531
Median	0.000398	0.000000
Maximum	0.157701	0.181818
Minimum	-0.176269	-0.120844
Std. Dev.	0.026063	0.026313
Skewness	-0.452244	0.761389
Kurtosis	8.435867	9.226640
Jarque-Bera	1839.719	1085.458
Probability	0.000000	0.000000
Sum	1.053575	0.970432
Sum Sq. Dev.	0.986982	0.438277
Observations	1454	634

Table 1 shows both AUSFB and Equitas SFB exhibit similar volatility and non-normal return distributions. Equitas SFB shows slightly higher mean returns and positive skewness, while AUSFB has a negative skew. Both banks have high kurtosis, indicating the presence of extreme returns.

The difference between maximum and minimum daily returns for AUSFB are 0.33 and 0.03 for Equitas SFB, with a standard deviation of 0.026 for AUSFB and 0.0263 for Equitas SFB. These values demonstrate the stock market's high volatility during the sample time. The positive skewness (0.76) for Equitas SFB indicates a symmetric tail, in contrast to the negative number (0.452) for AUSFB. The existence of an asymmetric tail indicates that there is a large possibility that the investor will benefit from high-risk returns since the skewness is higher than the mean returns. The kurtosis for the Equitas SFB and AUSFB distributions is 8.435 and 9.226, respectively, greater than the value of the conventional normal distribution, which is 3. This illustrates the distributions' broad tail and robust peak characteristics. It shows that the time series data do not exhibit a normal distribution. This was further corroborated by the Jarque-Bera values, which were much higher than the value 3 of the usual normal distribution (1839.72 for AUSFB and 1085.46 for Equitas SFB). The null hypothesis must be rejected since the return time series are still distributed with skewed values.

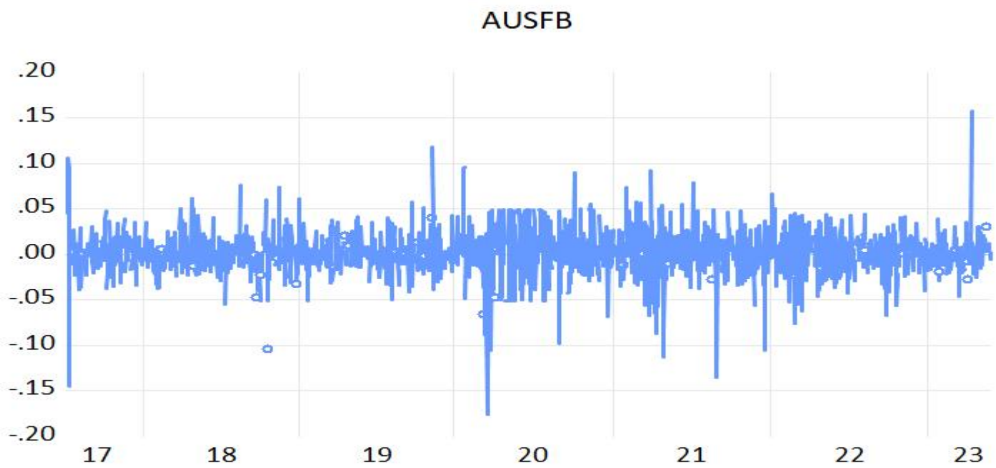


Figure 2. AUSFB Returns from July 2017 to May 2023

Figure 2 displays the daily returns of AUSFB from July 2017 to May 2023. The returns exhibit significant fluctuations over time, indicating volatility clustering, where periods of high volatility are followed by high volatility and periods of low volatility follow low volatility. This pattern suggests time-varying volatility in AUSFB stock returns. Additionally, there are observable spikes during specific periods, reflecting market reactions to events or financial news impacting the bank.

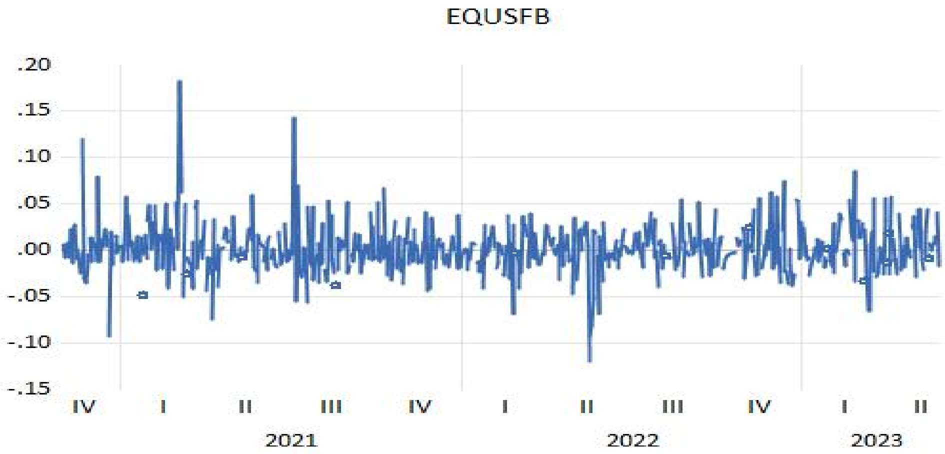
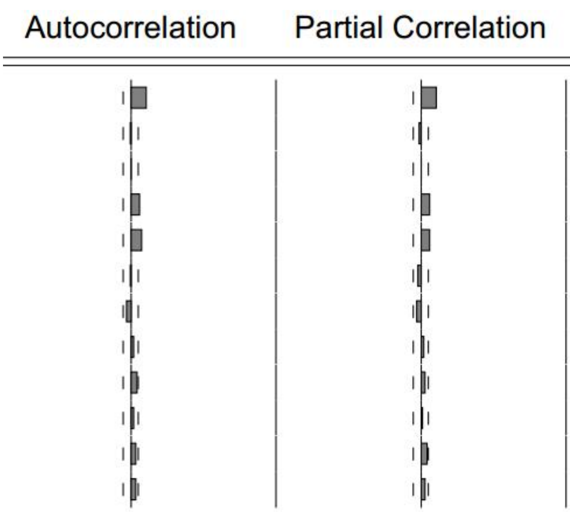


Figure 3. Equitas SFB Returns from November 2020 to May 2023

Figure 3 illustrates the daily returns of Equitas SFB from November 2020 to May 2023. The returns demonstrate noticeable volatility clustering, with periods of substantial fluctuations followed by calmer intervals. This indicates that the stock returns of Equitas SFB exhibit time-varying volatility. There are also significant spikes at certain points, suggesting reactions to specific market events or news affecting the bank during this period. Overall, the data reflects dynamic and evolving variance in the returns, indicative of the underlying market conditions and the bank's performance.

The stationarity of the stock return time series is investigated using the autocorrelogram and the Q statistic. **Figures 4** and **5** show autocorrelation and partial correlation. The p values of each Q statistic are significant at the 5% level of significance, as shown in **Figures 4** and **5**.



	AC	PAC	Q-Stat	Prob
1	0.107	0.107	16.827	0.000
2	-0.000	-0.012	16.827	0.000
3	0.001	0.003	16.830	0.001
4	0.059	0.059	21.880	0.000
5	0.075	0.064	30.201	0.000
6	-0.007	-0.021	30.267	0.000
7	-0.030	-0.027	31.611	0.000
8	0.019	0.023	32.167	0.000
9	0.041	0.029	34.666	0.000
10	0.019	0.009	35.213	0.000
11	0.041	0.044	37.653	0.000
12	0.036	0.029	39.504	0.000

Figure 4. AUSFB Autocorrelation and Partial Correlation

ACF and PACF graphs for AUSFB results in **Figure 4** exhibit notable spikes that point to serial correlation and short-term dependency. In order to handle time-varying volatility and assure accurate modeling, this suggests non-randomness and volatility clustering in the data, which implies the necessity for models like GARCH.

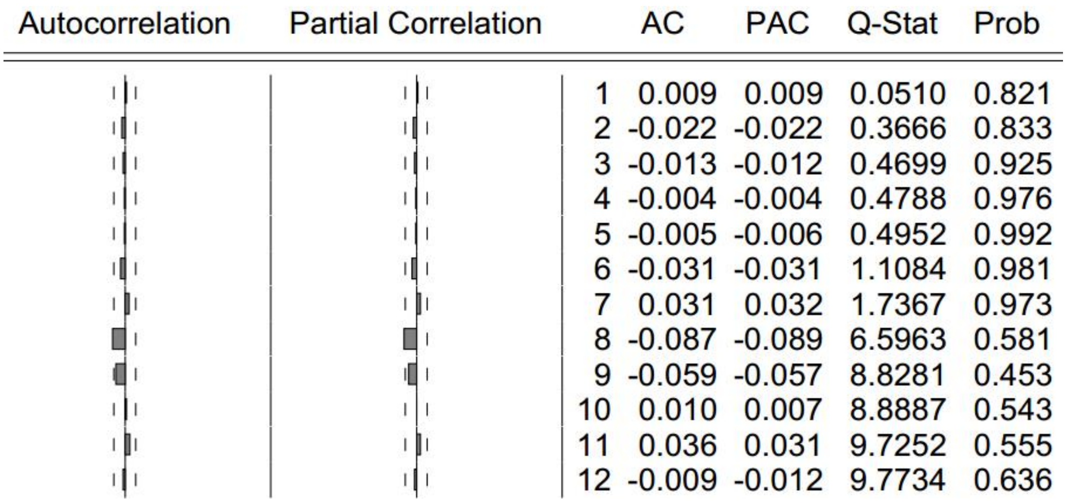


Figure 5. Equitas SFB Autocorrelation and Partial Correlation

Significant spikes in the ACF and PACF plots for Equitas SFB returns are shown in **Figure 5**, indicating the presence of autocorrelation and partial autocorrelation, pointing to volatility clustering and the necessity of models such as GARCH to accurately capture and forecast the return dynamics.

It is clear from **Figures 4** and **5** that there is no indication of autocorrelation. As a result, GARCH-type models may be created, and the results may have any inkling of no white noise. The autocorrelation function of the AUSFB and Equitas SFB series exhibits a rapid fall, reaching almost zero at periods 3 and 7, respectively, as seen in **Figures 4** and **5**. AUSFB and Equitas SFB series are hence immobile and free of white noise.

Augmented Dickey-Fuller (ADF) Test

The time series must be stationary in order for the GARCH Model to function, as is well known. **Tables 2** and **3** illustrate the presence of the unit root test in the series using the ADF test. It's used to check if the Equitas SFB and AUSFB findings are stationary. The Equitas SFB's t-statistic value for the ADF test is -24.88667, while the AUSFB's t-statistic value is -34.23052, as shown in **Tables 2** and **3**.

Table 2. ADF Test of AUSFB Returns

		T-Stat	Prob
Augmented Dickey-Fuller	Test statistic	-34.23052	0.0000
Test critical values	1% level	-3.434642	
	5% level	-2.863323	
	10% level	-2.567768	

Table 2 presents the results of the Augmented Dickey-Fuller (ADF) test for AUSFB returns. The test statistic of -34.23052 is significantly lower than the critical values at the 1%, 5%, and 10% levels, indicating that the AUSFB returns series is stationary. This implies that there is no change in the statistical properties such as mean and variance over time in AUSFB returns. The p-value of 0.0000 further supports this conclusion, as it is much lower than conventional significance levels (e.g., 0.05). Stationarity is an important condition for GARCH models which require data's statistical properties to be constant over time.

Table 3. ADF Test for Equitas SFB Returns

		T-Stat	Prob
Augmented Dickey-Fuller	Test statistic	-24.88667	0.0000
Test critical values	1% level	-3.44045	
	5% level	-2.86589	
	10% level	-2.56914	

Table 3 presents results based on ADF tests on Equitas SFB returns. The test statistic of -24.88667 falls below critical values at the 1%, 5%, and 10% levels, implying stationarity of the series used in GARCH estimation. In addition, a very low p-value (0.0000) indicates strong statistical significance, thus reinforcing the stability of

Equitas SFB returns across periods considered by this study. It means that the data were consistent with a stationary process necessary for accurate volatility forecasts.

To determine if the data series has the ARCH effect, the ARCH-LM test is utilised. The Lagrange Multiplier (LM) test has adapted the ARCH approach, which evaluates the ARCH impact of return (AUSFB & Equitas SFB) series. Before performing the ARCH-LM test, the lag order of return (AUSFB & Equitas SFB) series must be established. This may be achieved by applying the ARCH(1) autocorrelation test on the first degree of return (AUSFB & Equitas SFB) series' squared residuals. **Figures 6** and **7** show them. **Figures 6** and **7** provide the AC, PAC, Q statistic, and probability values. Since the PAC value is within the crucial range for this specific lag order, **Figures 6** and **7** further show that lag order 2 is the best lag order for the ARCH-LM test. For the first degree of return (AUSFB & Equitas SFB), a Q-statistic for the series of squared residuals is 20.54722 for AUSFB and 43.50230 for Equitas SFB. The p value that goes along with this number is 0.000, which is significant at the 1% critical level and is greater than the 5 percent critical value of 7.81. The ARCH effect in the return (AUSFB & Equitas SFB) series requires that the null hypothesis be rejected.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.118	-0.118	20.307	0.000
		2	0.045	0.031	23.241	0.000
		3	0.059	0.069	28.312	0.000
		4	0.007	0.021	28.382	0.000
		5	0.076	0.076	36.915	0.000
		6	0.024	0.038	37.788	0.000
		7	0.015	0.015	38.111	0.000
		8	0.069	0.062	45.070	0.000
		9	0.027	0.037	46.148	0.000
		10	0.034	0.029	47.860	0.000
		11	0.056	0.051	52.534	0.000
		12	0.030	0.033	53.812	0.000

Figure 6. ARCH(1) Result for AUSFB

The ARCH(1) model findings for AUSFB are displayed in **Figure 6**. The graphic shows whether past squared returns have a substantial impact on current volatility by displaying the autocorrelation of the squared residuals from the initial model. The employment of GARCH models to capture the time-varying volatility in AUSFB returns is supported by a high autocorrelation, which indicates the presence of volatility clustering.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.254	0.254	41.063	0.000
		2	0.403	0.362	144.28	0.000
		3	0.446	0.355	270.97	0.000
		4	0.384	0.220	365.22	0.000
		5	0.389	0.154	461.99	0.000
		6	0.373	0.097	551.17	0.000
		7	0.456	0.210	684.74	0.000
		8	0.372	0.110	773.44	0.000
		9	0.337	-0.004	846.43	0.000
		10	0.460	0.144	982.71	0.000
		11	0.392	0.120	1082.1	0.000
		12	0.372	0.060	1171.6	0.000

Figure 7. ARCH(1) Result for Equitas SFB

The findings of the ARCH(1) model for Equitas SFB are shown in **Figure 7**. The graphic displays the squared residuals' autocorrelation, which shows how much historical squared returns have influenced the volatility that exists today. The use of GARCH models to capture the changing volatility in Equitas SFB returns is supported by the presence of volatility clustering, as indicated by significant autocorrelation.

Table 4. ARCH-LM Test Result for AUSFB

F-statistic	**20.54722**	**Prob. F(1,1449)**	**0.000**
Obs*R-squared	20.28789	Prob. Chi-Square(1)	0.000

The ARCH-LM test results for Equitas SFB are displayed in **Table 5**. There is substantial evidence of ARCH effects in the residuals, as indicated by the F-statistic of 43.50230 and p-value of 0.0000. This presence is further supported by the Obs*R-squared value of 40.81763, which also has a p-value of 0.0000. These findings demonstrate that in order to effectively represent and capture the volatility in Equitas SFB returns, GARCH modeling is required.

Table 5. ARCH-LM Test Result for Equitas SFB

F-statistic	**43.50230**	**Prob. F(1,629)**	**0.0000**
Obs*R-squared	40.81763	Prob. Chi-Square(1)	0.0000

The ARCH-LM test results for Equitas SFB are displayed in **Table 5**. There is substantial evidence of ARCH effects in the residuals, as indicated by the F-statistic of 43.50230 and p-value of 0.0000. This presence is further supported by the Obs*R-squared value of 40.81763, which also has a p-value of 0.0000. These findings demonstrate that in order to effectively represent and capture the volatility in Equitas SFB returns, GARCH modeling is required.

Tables 4 and **5** show the ARCH-LM test outcomes. The F statistic and chi-square findings are utilized to determine the ARCH effect using the ARCH-LM test. For the ARCH-LM test, the null is deemed true if the F statistic or chi-square values exceed the critical value of 5%; otherwise, the null will be rejected.

This study assesses the combined significance of the squared residuals of return from both AUSFB and Equitas SFB series using the F statistic. The statistic used in the LM test is obs*R-squared. The possibility of the LM value is 0.000 at a 1 per cent level, which is a significant number. It also recognizes and validates heteroscedasticity and a significant ARCH effect on return (AUSFB & Equitas SFB) series. The outcomes also show how the volatility of the returns on the AUSFB & Equitas SFB may be taken into account by the GARCH model.

GARCH(1,1) Valuation

The mean equation of GARCH(1,1) will be

$$\mathrm{AUSFB}_t = 0.855671\ \mathrm{AUSFB}_{t-1} + 0.8543$$
$$(108.37)\ (109.138) \tag{4}$$

These results suggest that the p value at the 1% level is significant and that the z-statistic value at the 5% level is greater than the determinant value of 1.96.

The variance equation would be

$$\sigma_t^2 = 0.000204 + 0.369\,U^2_{t-1} + 0.356\,U\sigma^2_{t-1}$$
$$(10.098)\ (9.03999)\ (7.1457) \tag{5}$$

(see **Figure 8** for details)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.854313	0.007828	109.1383	0.0000
AUSFB-1	0.855671	0.007895	108.3762	0.0000
Variance Equation				
C	0.000204	2.02E-05	10.09801	0.0000
RESID(-1)^2	0.369067	0.040826	9.039997	0.0000
GARCH(-1)	0.356403	0.049876	7.145743	0.0000
R-squared	0.444470	Mean dependent var		-2.95E-05
Adjusted R-squared	0.444087	S.D. dependent var		0.034814
S.E. of regression	0.025957	Akaike info criterion		-4.626673
Sum squared resid	0.977668	Schwarz criterion		-4.608499
Log likelihood	3366.278	Hannan-Quinn criter.		-4.619891
Durbin-Watson stat	2.066920			

Figure 8. GARCH(1,1) Result for AUSFB

$$\text{Equitas SFB}_t = 1.015478\ \text{Equitas SFB}_{t-1} + 1.01349$$

$$(29.92)\ (29.62) \qquad (6)$$

These findings indicate that the coefficient value is significant at the 1% level of P-value and that the z-statistic value is above the 1% level critical value of 1.96.

The variance equation will be

$$\sigma_t^2 = 0.000101 + 0.53056\,U^2_{t-1} + 0.80111\,U\sigma^2_{t-1}$$

$$(3.11657)\ (2.727060)\ (13.50256) \qquad (7)$$

(see **Figure 9** for details)

Equation (6): Equitas SFB Return Equation

Equitas SFB_t =1.015478Equitas SFB_{t-1} +1.01349

- 1.015478 (coefficient of Equitas SFB $_{t-1}$): This value represents the effect of the previous period's returns on the current period's returns. The coefficient is close to 1, indicating a strong persistence in return patterns.
- 1.01349 (constant term): This is the intercept of the equation, representing the average return not explained by the lagged returns.
- Significance: The z-statistic values for both coefficients exceed the critical value of 1.96 at the 1% level, indicating high statistical significance. This suggests that the model's parameters are reliably estimated.

Equation (7): Variance Equation

$$\sigma_t^2 = 0.000101 + 0.53056\,U^2_{t-1} + 0.80111\,U\sigma^2_{t-1}$$

- 0.000101 (constant term): This represents the baseline level of volatility in the model.
- 0.53056 (coefficient for *Ut*−12U t−12): This coefficient measures the impact of past squared returns (or past shocks) on current volatility. A high value indicates that past shocks have a substantial effect on current volatility.
- 0.80111 (coefficient for σt−12σ t−12): This coefficient reflects the persistence of volatility from the previous period. A value close to 1 suggests that past volatility strongly influences current volatility.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.013490	0.034212	29.62362	0.0000
EQUSFB-1	1.015478	0.033934	29.92553	0.0000
Variance Equation				
C	0.000101	3.24E-05	3.116576	0.0018
RESID(-1)^2	0.053056	0.019455	2.727060	0.0064
GARCH(-1)	0.801118	0.059331	13.50256	0.0000

R-squared	0.495285	Mean dependent var	-3.63E-05
Adjusted R-squared	0.494485	S.D. dependent var	0.037067
S.E. of regression	0.026355	Akaike info criterion	-4.461710
Sum squared resid	0.438269	Schwarz criterion	-4.426556
Log likelihood	1417.131	Hannan-Quinn criter.	-4.448058
Durbin-Watson stat	1.944646		

Figure 9. GARCH(1,1) Result for Equitas SFB

The clustering characteristic for return (AUSFB, Equitas SFB) series is represented by the variance equation, where ARCH(1) and GARCH(1) are both significant. These two coefficients, which add up to less than 1 but are approaching 1, are 0.7254 for AUSFB and 0.8541 for Equitas SFB. Additionally, R-Square values of 44.44 per cent for AUSFB and 49.52 per cent for Equitas SFB indicate that the fitting model is of sufficient quality. The variance's GARCH component coefficient values for AUSFB and Equitas SFB, respectively, are 0.35654 and 0.801118, respectively, indicating a positive correlation between risks and returns as well as the presence of a positive risk premium.

Validation

The researcher makes an effort to validate the estimations by contrasting the estimates with real values in order to gauge the model's predicted values' dependability. The projected and actual values for the two months from June 1 to June 30, 2023, were compared for this purpose. AUSFB and Equitas SFB daily returns' predicted and actual values, as well as the difference between these two variables, are validated in **Table 5** along with their respective deviations.

Table 6. Actual and Predicted Values of AUSFB and Equitas SFB for June 2023 Month

DATE	AUSFB Actual prices	AUSFB Forecasted prices	Equitas SFB Actual prices	Equitas SFB Forecasted SFBs
01-06-2023	769.5	769.265	87.67	87.435
02-06-2023	772.95	771.605	87.27	85.925
05-06-2023	750.5	749.155	87.14	85.795
06-06-2023	751.95	750.705	88.3	87.055
07-06-2023	762.7	761.365	87.38	86.045
08-06-2023	755.05	753.701	84.35	83.001
09-06-2023	762.45	761.1	84.43	83.08
12-06-2023	761.2	759.75	85.19	83.74
13-06-2023	763.4	762.155	87.03	85.785
14-06-2023	772.55	771.245	87.92	86.615
15-06-2023	775.85	774.501	87.22	85.871
16-06-2023	778.55	777.3155	86.32	85.0855
19-06-2023	772.75	770.805	87.99	86.045
20-06-2023	767.85	766.605	88.56	87.315
21-06-2023	749.5	747.755	87.37	85.625
22-06-2023	740.4	738.555	84.76	82.915
23-06-2023	737.5	735.6255	82.07	80.1955
26-06-2023	745.5	744.3655	84.81	83.6755

DATE	AUSFB Actual prices	AUSFB Forecasted prices	Equitas SFB Actual prices	Equitas SFB Forecasted SFBs
27-06-2023	749.9	748.5165	86.25	84.8665
28-06-2023	747.85	746.46	88.48	87.09
30-06-2023	754.1	752.8865	90.13	88.9165

Table 6 displays the actual and predicted prices for AUSFB and Equitas SFB throughout June 2023. The forecasted values for both banks are generally close to the actual prices, indicating that the GARCH models provide reliable predictions. For AUSFB, the forecasted prices are mostly accurate, with minor deviations from the actual values, such as on 05-06-2023 where the forecasted price (749.155) is slightly below the actual price (750.5). Similarly, for Equitas SFB, the forecasts closely follow the actual prices, though there are notable deviations, like on 02-06-2023 where the forecast (85.925) is lower than the actual price (87.27). These results suggest that while the GARCH models are effective in predicting stock returns, there are areas for improvement. Regular assessment of prediction accuracy using metrics like MAE and RMSE is essential to refine the models and enhance their reliability.

The mean absolute error (MAE) for AUSFB is 908.162, while the value for Equitas SFB is 782.319. The root mean squared error (RMSE) for AUSFB is 922.215, while Equitas SFB is 832.293. Based on the discrepancy between predicted and actual values, the RMSE and MAE were determined.

CONCLUSION

This study uses the GARCH(1,1) model, which improves the precision of volatility modeling by capturing both the magnitude and persistence of volatility over time. The model's fitting process finds coefficients that minimize prediction errors, which refines the model's forecast accuracy for AUSFB and Equitas SFB. This model was selected because it can capture the time-varying volatility seen in financial returns, which other models might not be able to capture as well. The GARCH(1,1) model takes advantage of heteroscedasticity, a fundamental property of financial time series, to adjust forecasts based on previous error variances, which improves the model's performance and captures volatility clustering and time-varying volatility. Volatility patterns, including clustering—a situation in which periods of high volatility are succeeded by even higher volatility—and variations over time were visible for AUSFB and Equitas SFB. These trends emphasize the market's dynamic character and the applicability of the concept. A quantitative analysis revealed a positive correlation between daily returns and volatility, with correlation coefficients suggesting that better returns are frequently associated with higher volatility. The significance of volatility modeling in financial forecasting is highlighted by this relationship. The GARCH(1,1) model's reliability was demonstrated by validation findings that revealed low MAE and RMSE values, which imply that the model's predictions closely match real data.

Subsequent studies may investigate substitute models for volatility or broaden the examination to encompass additional financial instruments. The results of the GARCH(1,1) model are useful for risk management and financial forecasting since they provide important information about controlling market risks.

CONFLICT OF INTEREST

We declare that we have no conflicts of interest to disclose.

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