Comparative Investment decisions in emerging textile and FinTech industries in India using GARCH models with high-frequency data

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ABSTRACT – REZUMAT

Comparative Investment decisions in emerging textile and FinTech industries in India using GARCH models with high-frequency data

The domestic textiles and apparel industry stood at $152 billion in 2021, growing at a CAGR of 12% to reach $225 billion by 2025. The textiles and apparel industry in India has strengths across the entire value chain from fibre, yarn, and fabric to apparel. On the other hand, many FinTech companies gained enough importance and attention during the Demonetization and COVID-19 pandemic situation where most people are dependent and prefer cashless payments and receipts over hard cash payments and receipts. Due to the growth of FinTech companies in India, consumer lending FinTech companies in India make up 17% of total FinTech enterprises. Many angel investors are coming forward to invest in such FinTech companies as this industry has much potential to grow in future. As there is enough scope for the expansion of FinTech companies in India, retail investors come forward to invest in the stocks of listed FinTech companies. As retail investors always look forward to returns either in the form of dividends or appreciation of stock prices, it is also necessary to analyse and model the stock price volatility of FinTech companies in India before investing. Hence, this research study is an attempt to use high-frequency data i.e. 1-minute closing prices, to formulate suitable GARCH (Generalised Autoregressive Conditional Heteroscedasticity) models for stock price volatility of listed textiles and FinTech companies that could also capture the asymmetric volatility if it exists due to third phase of COVID-19 pandemic and Russia-Ukraine war. The results concluded that there is a presence of positive shocks which might be due to the third wave of the COVID-19 pandemic that might have again shot the demand for financial products and services of these FinTech companies namely Paytm and PolicyBazaar and there is no negative shock of Russia-Ukraine war.

Keywords: *textile industry of India, FinTech companies, asymmetric volatility, high-frequency data, Indian Stock Market, GARCH models*

Deciziile de investiții comparative în industriile emergente din domeniile textil și FinTech din India folosind modele GARCH cu date de înaltă frecvență

Industria internă din domeniul textil și cel de îmbrăcăminte s-a situat la 152 de miliarde de dolari în anul 2021, crescând cu un CAGR (rata de creştere anuală compusă) de 12% pentru a ajunge la 225 de miliarde de dolari până în 2025. Industria textilă și de îmbrăcăminte din India are puncte forte de-a lungul întregului lanț valoric, de la fibre, fire, materiale textile până la îmbrăcăminte. Pe de altă parte, multe companii FinTech au câștigat suficientă importanță și atenție în timpul situației generate de procesul de demonetizare și de pandemia COVID-19, în care majoritatea persoanelor au depins de conjunctură și au preferat plățile și încasările fără numerar în detrimentul plăților și încasărilor în numerar. Datorită creșterii companiilor FinTech în India, companiile de creditare FinTech din India reprezintă până la 17% din totalul întreprinderilor FinTech. Mulți așa-numiți investitori ”îngeri” se preocupă să investească în astfel de companii FinTech, deoarece această industrie are mult potențial de dezvoltare în viitor. Întrucât există suficientă sferă de extindere a companiilor FinTech în India, investitorii de retail se vor prezenta pentru a investi în acțiunile companiilor FinTech listate. Deoarece investitorii din zona de retail așteaptă întotdeauna cu nerăbdare obținerea de profituri, fie sub formă de dividende, fie sub formă de apreciere a prețurilor acțiunilor, este, de asemenea, necesar să se analizeze și să modeleze volatilitatea prețului acțiunilor companiilor FinTech din India înainte de a se investi. Prin urmare, acest studiu de cercetare este o încercare de a utiliza date de înaltă frecvență, adică prețuri de închidere la intervale de 1 minut, pentru a aplica modele GARCH (adică modelul generalizat autoregresiv condiţional heteroscedastic) adecvate pentru volatilitatea prețului acțiunilor la companiile din domeniul textil și FinTech listate, care ar putea capta și volatilitatea asimetrică dacă aceasta există datorită celei de-a treia faze a pandemiei COVID-19 și războiului dintre Rusia și Ucraina. Rezultatele empirice au condus la concluzia că există o prezență de șocuri pozitive care s-ar putea datora celui de-al treilea val al pandemiei COVID-19, care ar fi putut afecta din nou cererea de produse și servicii financiare ale acestor companii FinTech și anume Paytm și PolicyBazaar și nu există un șoc negativ cauzat de războiul dintre Rusia și Ucraina.

Cuvinte-cheie: *industria textilă din India, companii FinTech, volatilitate asimetrică, date de înaltă frecvență, piața bursieră din India, modele GARCH*

INTRODUCTION

The domestic textiles and apparel industry stood at $152 billion in 2021, growing at a CAGR of 12% to reach $225 billion by 2025. The textiles and apparel industry in India has strengths across the entire value chain from fibre, yarn, and fabric to apparel. The organized textile industry in India is characterized by the use of capital-intensive technology for the mass production of textile products and includes spinning, weaving, processing, and apparel manufacturing. On the other hand, technological advances are not new to finance, digital innovation has brought major improvements in the connectivity of systems, in computing power and cost, and in newly created and usable data. These improvements have alleviated transaction costs and given rise to new business models and new entrants [1]. These new entrants are termed as FinTechs. In this digital era, many FinTech start-ups have been started and flourished in India. FinTech, as the name suggests, is the amalgamation of finance and technology. FinTech experienced the most remarkable expansion only after the global financial crisis in 2008. Therefore, it is a rather new area that is growing very fast and has not been fully explored yet [2]. A lot of players in the market are using technology to simplify financial services like lending, insurance, investment, trading, budgeting, and a lot more. This leads to the smooth and efficient functioning of financial services provided by traditional banks and insurance companies. Many FinTech companies gained enough importance and attention during the Demonetization and COVID situation where most people are dependent and prefer cashless payments and receipts over hard cash payments and receipts. Paytm is one the emerging examples of it. As the FinTech sector expands, many players in India are focusing on niche sectors. Consumer lending FinTech companies in India make up 17% of total FinTech enterprises. From business loans to consumer loans, the demand for credit in India is ever-increasing. Moreover, the banks are also tying up with such FinTech companies to provide better facilities, like Paytm which helps in achieving frictionless payments by reducing manual intervention by customers for cards and net banking transactions. Many angel investors are coming forward to invest in such FinTech companies as this industry has much potential to grow in future. Few FinTech companies have reached a certain height by expanding their operations and registering themselves in stock exchanges. Now the point of discussion is that there is enough scope for expansion of FinTech companies in India, should the retail investors come forward to invest in the stocks of listed FinTech companies.

For investing in the stocks of FinTech, it is necessary to analyse the stock price volatility of listed Textile Companies and FinTechs. Again, in recent years, there has been a significant increase in both high-frequency trading (HFT) and algorithmic trading (AT) activity in financial markets. Most of the transaction volume in developed markets is created by HFT [3]. The question arises, to facilitate high-frequency trading (HFT) and algorithmic trading (AT), can the high-frequency data be used to frame suitable volatility models for FinTech companies so the retail investors could forecast the volatility of stock prices of FinTechs for investment? This paper is an attempt to use high-frequency data to formulate suitable GARCH (Generalised Autoregressive Conditional Heteroscedasticity) models for listed textiles and FinTech companies that could capture the asymmetric volatility if any and forecast volatility accordingly if the companies have adequate time series data points.

REVIEW OF LITERATURE

Many studies have already been done in the area of FinTech Companies. This review of literature is divided into 4 sections. The first section deals with a few important different studies on Textile Industry. The next section deals with the growth of FinTech. The third section specifically deals with the studies related to FinTechs and the stock market. The last section deals with the investment using GARCH models.

Present scenario, prospects and determinants of textile industry growth

A study attempted to measure the changes and instabilities in employment and the number of apparel factories in Bangladesh after the MFA phase-out based on secondary data from 1998 to 2011 using different statistical techniques [4]. Moreover, a study from India where the authors discussed the impacts of cotton yarn price volatility on handloom weavers and the public and private interventions that have been employed to address them [5].

Present scenario, prospects and determinants of fintech growth

A study explores the current state and prospects of FinTech in the Middle East and North Africa (MENA) region whose financial systems are not deepening, by applying descriptive, inductive and analytical methodologies [6]. Again a review paper consists of burgeoning literature on FinTech and FinTech-enabled services, focusing on the opportunities and risks for banks by using high-quality bank-level data from 115 countries around the world for the past 16 years and computing statistical moments of some key indicators of the changing banking landscape in the FinTech era and found that FinTech lenders will replace banks, perhaps because banks are developing their own FinTech platforms or working with FinTech start-ups [7]. Similarly, a paper aims to find out the main factors that determine the change in the number of FinTech companies in Lithuania and predict the future development of this sector and found that 8 out of 17 factors indicate economic conditions, 4 out of 9 factors indicating business environment and 7 out of 14 other factors are major factors [2]. Likewise, a study covers the development, opportunities, and challenges of financial sectors because of new technologies in India. This chapter throws light on opportunities that emerged because of demographic dividend, high penetration, and access to the latest and affordable technology, affordable cost of smartphones, and government policies such as Digital India, Startup India, and Make in India. Lastly, this chapter portrays the untapped potential of FinTech in India [8]. Apart from that, a paper describes the key role of FinTech regulation to manage the risks, and keep the balance and stability of the FinTech ecosystem from the highest impact of risks' in this industry by taking 3 variables i.e. namely Risk Construct, Financial Regulation Construct and FinTech Ecosystem Constructs by taking interview from 150 FinTech industry Stakeholders in Indonesia using purposive sampling and found that COVID-19 pandemic has a positive influence on startups FinTech companies [9]. Besides that research showed that FinTechs are bringing about economically meaningful changes in the production of financial services, with implications for the industrial structure of finance. Regulatory and supervisory policy tools will have to adapt. Existing regulatory perimeters may not adequately cover emerging providers of financial services, and new players may pose challenges to day-to-day financial supervision [1]. Furthermore, a study attempts to determine whether FinTech is a threat to global banking and found that the average cost of sending remittances and the role of banks in sending remittances have been declining [10]. Likewise, a paper has presented the main risk concerns that arise with the development of the most important financial technologies, and has suggested research directions in risk measurement models, appropriate to manage and mitigate the involved risks like a strict collaboration and open discussion between academics, FinTech experts, and regulators can help move us ahead in this direction, developing FinTech risk management models that, while limiting the negative impact of disrupting technologies, encourage their development [11, 12].

FinTech and stock market

Now some of the important studies related to FinTech and Stock market. A paper analyses two indices of public FinTech firms i.e. one for the United States and another for Europe by computing the ΔCoVaR of the FinTech firms against the financial system to measure their impact on systemic risk and found that FinTech firms do not contribute greatly to systemic risk [13]. Again, a study tries to find out the effect of FinTech funding frequency and value on retail banks' stock returns listed on the Indonesia Stock Exchange and found that FinTech funding frequency does not affect retail banks' stock returns [14]. Similarly, a study examines the effects of high-frequency trading (HFT) and algorithmic trading (AT) activities, which represent important technological developments in financial markets in the past two decades, on Borsa Istanbul in terms of volatility by using GJR-GARCH-in-Mean and I-GARCH models during pre and post period of implementation of BISTECH project, a technology transformation program, which is a stock market transaction system that was put into operation in 2015, along with Genium INET software and other technological components [3]. Furthermore, a study analyses the impact of the COVID-19 pandemic on the dynamics of volatility spillovers in financial markets, focusing on innovative assets, such as a FinTech index and Bitcoin, and traditional assets, such as gold, oil, global equities, and the USD and found that bursts of volatility spillovers between the FinTech index, Bitcoin, and traditional assets are associated with the outbreak of this global pandemic [15].

Retail investment and GARCH models

The research applied the E-GARCH model approach to data from 2015 to 2018, to explore the influence of investor sentiment on the return rate of the Shanghai Composite Index [16]. Again, a paper investigates whether changes in a firm's investor following can influence volatility in the French stock market. By defining a novel proxy of investor following, the paper contributes to the emerging literature on the impact of information technology on financial markets [17, 18]. Many research questions have been raised while studying the existing literature of various researches related to textiles, FinTech, the stock market and FinTech and GARCH model – there are very few studies related to FinTech and the stock market. Moreover, there is not enough research on the stock price volatility of Textiles and FinTech Companies in India. Can it be possible to use the High-frequency data to formulate a suitable GARCH model for listed textiles and FinTech companies in India? Can these formulated GARCH models also grasp the leverage effect of events that took place from December 2021 to July 2022? Hence related stocks Whether COVID-19 affected the stock price volatility of Indian Banks? Now it will be interesting to find out the answers to this research questions through this study. As high-frequency data are not available for textiles, investment in FinTech could be a wise decision; hence, the objectives are made accordingly.

OBJECTIVES OF THE STUDY

- To analyze the volatility of the stock price of listed FinTech Companies in India namely One 97 Communications Ltd (Paytm), PB FinTech Ltd. (Policy Bazar) and Niyogin FinTech Ltd.
- To formulate a suitable GARCH Model for each listed FinTech Company that could grasp their volatility.

HYPOTHESES OF THE STUDY

- H_{0A}: The high-frequency data i.e. 1-minute closing price data of three listed FinTech companies under BSE, from 1st December 2021 to 31st July 2022 are stationary in nature.
- H_{0B}: There is no ARCH effect on the stock price volatility of 3 listed FinTech Companies under BSE from December 2021 to July 2022.

- H_{0C}: There is no leverage effect on the stock price volatility of each 3 listed FinTech Companies under BSE from December 2021 to July 2022.

MATERIALS AND METHODS

The study is Empirical in nature. The study is based on High-frequency secondary data. The secondary data involves the 1-minute closing prices of listed FinTech companies on BSE.

There are only three listed companies on BSE namely One 97 Communications Ltd (Paytm), PB FinTech Ltd. (PolicyBazaar) and Niyogin FinTech Ltd. The 1-minute data is for 8 months which ranges from 1st December 2021 to 31st July 2022 that have been extracted and downloaded from www.moneycontrol.com. Wherever required, an attempt has been made to make the unbalanced data into balanced data i.e. 5 days a week. There are only 3companies listed on BSE which is specifically recognised as FinTech Industry which are considered for this study. The total sample size is 1,95,144 i.e. 3 FinTech companies of 65,048 observations each [19]. For the application of GARCH, Log Returns have been calculated to make the data stationary and Augmented Dickey Fuller Test (ADF) has been employed to check whether the data is stationarity in nature. Different GARCH models have been trailed and tested based on various statistical parameters to find a suitable GARCH model for each FinTech company. After formulating the models, the models have been used to predict the volatility for the period last 15 trading days of the selected trading period i.e. 16thJuly, 2022 to 31st July, 2022. To formulate models and forecast the volatility of selected FinTech stocks, E-Views 10 has been used.

SIGNIFICANCE OF THE STUDY

The affairs of the study could provide a feasible volatility model for each selected textiles and FinTech stocks that can assist the investors having basic knowledge on algorithms, to run the developed models to study and forecast the volatility of these stocks. This may enable them to take a calculated risk. Through this study the price volatility of listed textiles and FinTechs could be judged by taking into consideration the positive or negative news or leverage effect of different important events on the price volatility which could help the scholars and researchers to go through a proper study to develop suitable volatility predicted models in future as well. In addition to that, the research could highlight the impact of important events on the price volatility of commodities under the energy sector, to the policymakers as well, which may help them to formulate relevant counter policies to avoid inflation.

DATA ANALYSIS, RESULTS AND DISCUSSION

The reason for selecting GARCH models over ARCH is because the major limitations of the ARCH Model suppose that the variance or heteroscedastic of tomorrow's return is an equally weighted average of the residuals squared from the last 22 days. The assumption of equal weights looks ill-favoured, as one may think that the more recent events would be more significant and therefore should have more weight [20]. To the contrary GARCH has diminishing weights that now decline to zero. It provides parsimonious models that are soft to estimate and, even in its simplest form, has proven astonishingly successful in forecasting conditional variances [7]. The simple GARCH model i.e. GARCH (1,1) is depicted below:

$$h_t = \varphi + \theta_1 h_{t-1} + b_1 u_{t-1}^2 \tag{1}$$

where h_t is variance or returns, φ – Constant, θ – GARCH effects, h_{t-1} – past values of itself, u_{t-1}^2 – past values of the shocks captured by the lagged spared error terms.

The EGARCH model is distinct from the GARCH variance structure because of the log of the variance [21]. In addition to that, the advantage of using EGARCH is that the positivity of the parameters is assured as it will be working with the log of the variance [22]. The following formula is for the EGARCH model:

$$\log(h_t) = \varphi + \sum_{i=1}^{q} \eta_i \left| \frac{u_t - i}{\sqrt{h_t - i}} \right| + \sum_{i=1}^{q} \lambda_i \frac{u_t - i}{\sqrt{h_t - i}} + \\ + \sum_{k=1} \theta_k \log(h_{t-k}) \tag{2}$$

where $\log(h_t)$ is a log of variance or log returns, φ – Constant, η_i – ARCH Effects, λ_i – Asymmetric effects, θ – GARCH effects.

The threshold GARCH (TGARCH) is similar to the GJR model, different only because of the standard deviation, instead of the variance, in the specification [23]. The following formula is for TGARCH(1,1) model:

$$h_t = \varphi + \theta_1 h_{t-1} + b_1 u_{t-1}^2 + \gamma_1 u_{t-1}^2 D_{t-1} \tag{3}$$

where h_t is variance or returns, φ – Constant, θ – GARCH effects, D_t – value of 1 (bad news) for $u_t < 0$, γ – Asymmetric effects or leverage term, b_1 – good news (positive shock) has an impact of b_1, $b_{1+}\gamma_1$ – Impact of Bad news.

To choose an appropriate model, the results of the formulated models with three different distributions need to be analysed. The standard way to select a model is the coefficients, ARCH and GARCH should be significant and there should not be the existence of Heteroscedasticity and autocorrelation after framing the model. In addition to that, the model with lesser AIC (Akaike Information Criterion) and SIC (Schwartz Information Criterion) is better and a model with higher Log Likelihood statistics, R squared and Adjusted R Squared is better [24]. The following section deals with a brief description of three FinTech companies under BSE as of 31st March 2022 and the tables representing the results of different models. The major obstacle in predicting the volatility of textile companies is the unavailability of high-frequency data due to which only FinTechs are considered feasible investments.

About three listed FinTech companies in India

One 97 Communications Ltd (Paytm)

One 97 Communications Ltd (Paytm) is India's leading digital ecosystem for consumers and merchants, according to RedSeer. It offers payment services, commerce and cloud services, and financial services to 337 million consumers and over 21.8 million merchants registered with it, as of June 30, 2021. Paytm was launched in 2009, as a "mobile-first" digital payments platform to enable cashless payments for Indians, giving them the power to make payments from their mobile phones. Starting with bill payments and mobile top-ups as the first use cases, and Paytm Wallet as the first Paytm Payment Instrument, the company has built the largest payment platform in India based on the number of consumers, number of merchants, number of transactions and revenue as of March 31, 2021, according to RedSeer. As per the Kantar BrandZ India 2020 Report, the "Paytm" brand is India's most valuable payments brand, with a brand value of US$ 6.3 billion, and Paytm remains the easiest way to transact across multiple methods.

PB FinTech Ltd. (Policybazar)

PB FinTech Ltd. launched Policybazaar, its flagship platform, in 2008 to respond to Consumers' need for more awareness, choice and transparency and create a consumer-pull-based, provider-neutral model for insurance distribution. In 2014, PB FinTech Ltd. launched Paisabazaar to transform how Indians access personal credit by accentuating ease, convenience and transparency in selecting a variety of personal loans and credit cards. According to Frost & Sullivan, Paisabazaar was India's largest digital consumer credit marketplace with a 53.7% market share, based on disbursals in Fiscal 2021. In Fiscal 2020, Policybazaar was India's largest digital insurance marketplace among all online insurance distributors with a 93.4% market share based on the number of policies sold.

Furthermore, in Fiscal 2020, Policybazaar constituted 65.3% of all digital insurance sales in India by number of policies sold (including online sales done directly by insurance companies and by insurance distributors).

Niyogin FinTech Ltd.

Niyogin FinTech Limited operates as a non-banking finance company. The Company offers loans, finance, and investment, as well as lending and allied activities to micro, small, and medium enterprises. Niyogin FinTech serves customers in India. Niyogin believes in superior execution leveraging cutting-edge technology, innovative risk management and strong on-ground connections. To give small businesses access to a holistic support system that is cost-efficient through innovative technology and a committed network of partners with a vision to be the country's best small business-centric organization, empowering customers through an ecosystem of

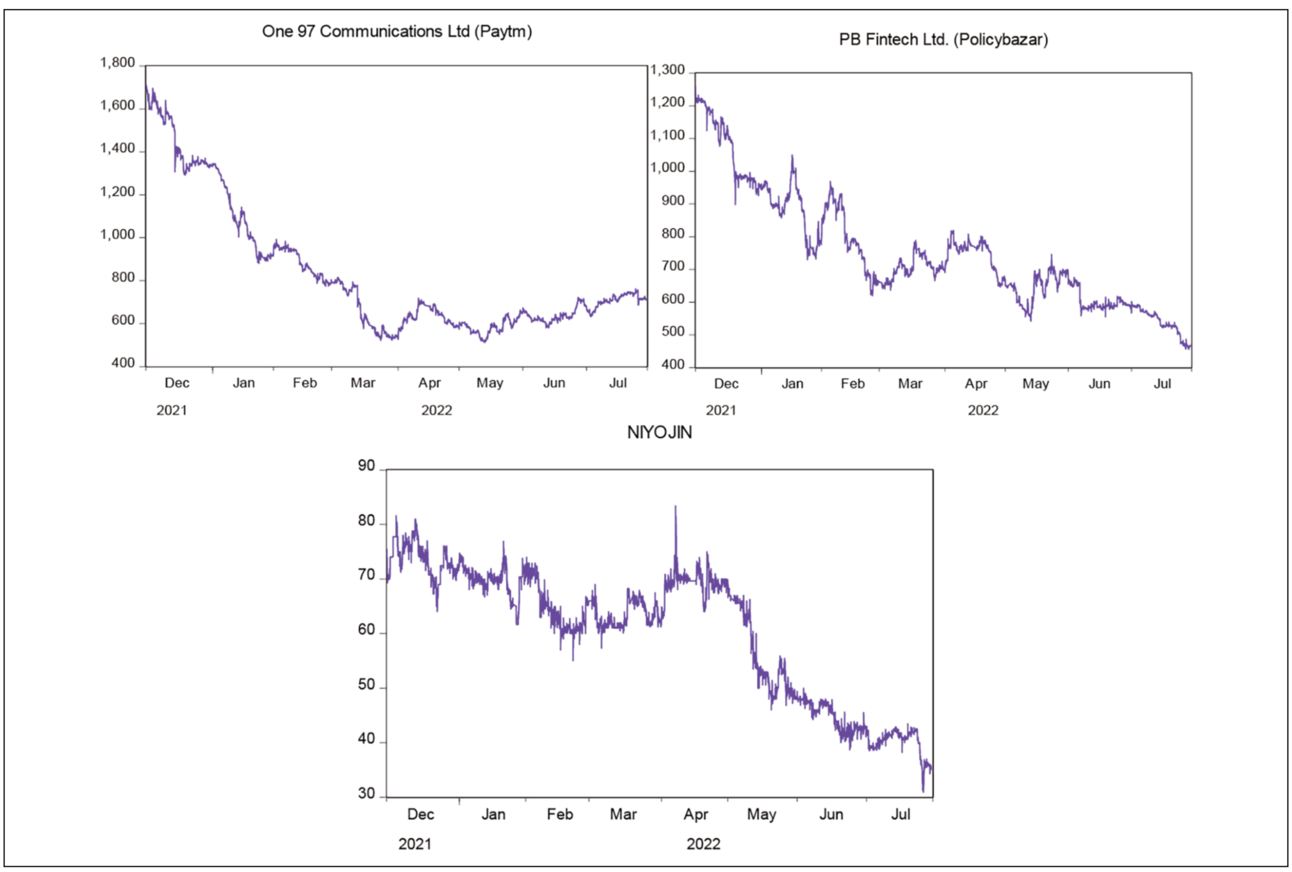

Fig. 1. Graphs Representing Stock Prices of Paytm, PolicyBazaar and Niyojin FinTech Companies from 1st December 2021 to 31st July 2022 (*Source: Authors' Formulation using EVIEWS 10*)

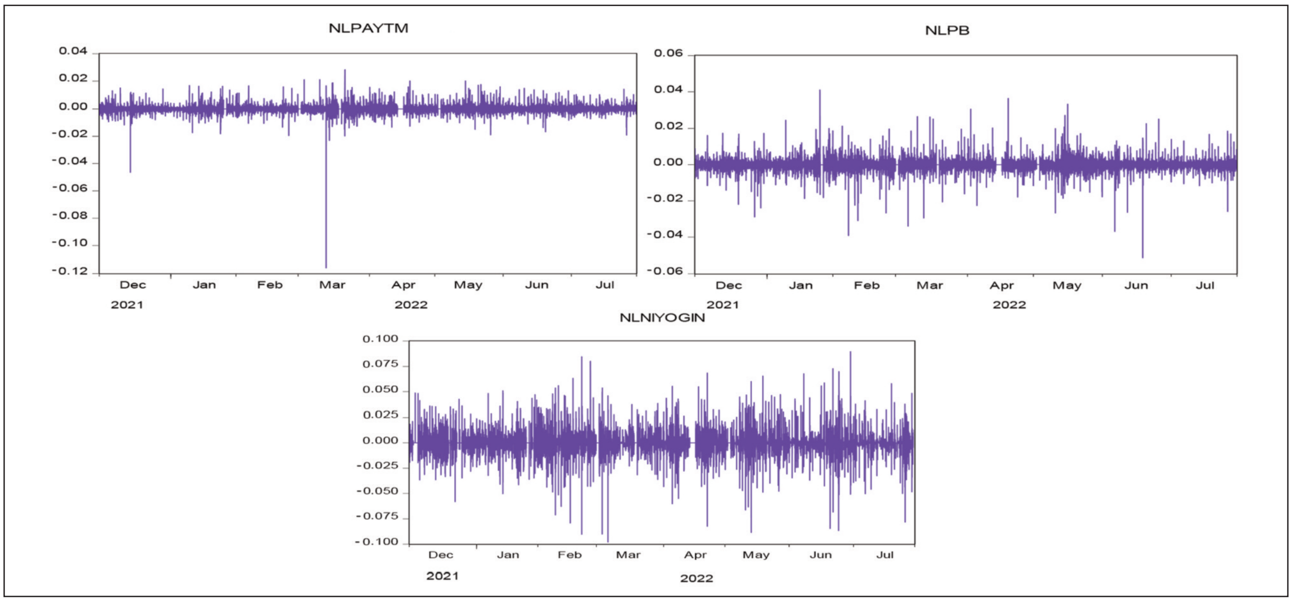

Fig. 2. Graphs Representing Log Returns of Paytm, PolicyBazaar and Niyojin FinTech Companies from 1st December 2021 to 31st July 2022 (*Source: Authors' Formulation using EVIEWS 10*)

products, partnerships, technology and exceptional customer experience.

For the application of GARCH, Log Daily Returns have been calculated to make the data stationary. Again the graphs of log returns have been plotted for visualization. Augmented Dickey Fuller Test (ADF) will be applied to check whether the data is stationarity in nature.

The stationarity of log returns series of the above FinTech companies have been examined with the help of a unit root test named Augmented Dickey Fuller Test with the inclusion of test equations as Intercept, Trend and Intercept and None and found stationary. After visualising the above graphs of log returns of all the FinTech companies, it can be said that there is the existence of volatility clustering in the data of all companies i.e. huge variations in log returns followed by huge variations in log returns and small variations in log returns followed small variations in log returns. Moreover, it can also be observed there were certain abnormal variations in the returns of the stocks of the selected companies. These variations indicate that there might be the existence of asymmetricities which should be statistically checked while framing a suitable GARCH model. Moreover, the data of all selected companies are leptokurtic or highly peaked which have been checked with the values of the coefficients of Skewness, Kurtosis and Jarque-Bera Statistics.

Testing ARCH effect

To apply any GARCH Model it is also mandatory to inspect the presence of the ARCH effect within the data i.e. price volatility of three listed FinTechs. The following table is based on testing the presence of ARCH effects in data related to the price volatility of the 3 FinTechs taken into study.

Table 1 reveals the results of the Heteroscedasticity Test of Paytm, PolicyBazaar and Niyogin which could show the presence of ARCH effect in the data. The ARCH effect can be judged from lag range multiplier (LM) statistics which is shown in the form of

Table 1

RESULTS OF HETEROSKEDASTICITY TEST TO EXAMINE ARCH EFFECTS ONE 97 COMMUNICATIONS LTD. (PAYTM)			
Heteroskedasticity Test: ARCH			
F-statistic	114.7372	Prob. F(1,65042)	0.0000
Obs*R-squared	114.5387	Prob. Chi-Square(1)	0.0000
PB FinTech Ltd.			
Heteroskedasticity Test: ARCH			
F-statistic	1271.304	Prob. F(1,65043)	0.0000
Obs*R-squared	1246.971	Prob. Chi-Square(1)	0.0000
Niyogin FinTech Ltd.			
Heteroskedasticity Test: ARCH			
F-statistic	3710.881	Prob. F(1,65043)	0.0000
Obs*R-squared	3510.700	Prob. Chi-Square(1)	0.0000

Table 2

DECISION TABLE FOR SELECTING SUITABLE GARCH (1,1), TGARCH (1,1) & EGARCH (1,1) MODEL FOR ONE 97 COMMUNICATIONS LTD (PAYTM)									
Statistics	**GARCH (1,1)**			**TGARCH**			**EGARCH**		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	340071.0	359204.3	358891.0	340331.3	NA	358534.2	339582.0	359291.9	358237.6
AIC	–10.45633	–11.04461	–11.03498	–10.46430	NA	–11.02397	–10.44126	–11.04727	–11.01486
Schwartz IC	–10.45563	–11.04377	–11.03414	–10.46346	NA	–11.02300	–10.44042	–11.04629	–11.01388
Heteroscedas-ticity (ARCH LM-Test)	No	No	No	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No	No	No	No

Observed R Squared. The Observed R-squared statistics of all these three companies are considered significant as their probability value is less than 0.05. Moreover, the F statistics are also significant as its significant value is less than 0.05. This proves that there is an existence of ARCH effect in the stock price volatility of all these 3 companies which indicates GARCH models are suitable for the data.

The table 2 reveals that Coefficients, ARCH Effect and GARCH are significant in all three GARCH (1,1), all the three EGARCH (1,1) and all the three TGARCH (1,1) models with Normal Distribution Error Construct, with Student t's Distribution Error Construct and with Generalised Error Distribution Construct. After framing the above models, there is no Heteroscedasticity (which has been checked with the help of the ARCH LM Test) and no Autocorrelation (which has been checked with the help of a correlogram of residuals and squared residuals) in any of the nine models. While comparing the AIC and SIC of all the above nine models, it has been found that EGARCH with Student t's distribution has the lowest AIC (–11.04727) and SIC (–11.04629) as compared to the other eight models. This model also has the highest Log-Likelihood (359291.9). Hence, this is considered as the most suitable model. The result of the selected EGARCH (1,1) Model for One 97 Communications Ltd (Paytm) is mentioned in the table given below.

Table 3

RESULTS OF EGARCH (1,1) MODEL WITH STUDENT'S T DISTRIBUTION CONSTRUCT FOR ONE 97 COMMUNICATIONS LTD (PAYTM)

Dependent Variable: NLPAYTM
Method: ML ARCH - Student's t distribution
Date: 09/11/22 Time: 16:43
Sample (adjusted): 12/01/2021 09:17 7/29/2022 15:29
Included observations: 65045 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(–1)/@SQRT(GARCH(–1))) + C(5)*RESID(–1)/@SQRT(GARCH(–1)) + C(6)*LOG(GARCH(–1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	–1.67E-05	1.17E-07	–143.1913	0.0000
NLPAYTM(–1)	–0.127766	0.003290	–38.83038	0.0000
Variance Equation				
C(3)	–0.360869	0.006121	–58.95468	0.0000
C(4)	0.215254	0.003599	59.81152	0.0000
C(5)	0.059267	0.001967	30.13622	0.0000
C(6)	0.983256	0.000329	2989.062	0.0000
T-DIST. DOF	2.934953	0.036506	80.39625	0.0000
R-squared	–0.019382	Mean dependent var		–1.37E-05
Adjusted R-squared	–0.019397	S.D. dependent var		0.001663
S.E. of regression	0.001679	Akaike info criterion		–11.04727
Sum squared resid	0.183283	Schwarz criterion		–11.04629
Log likelihood	359291.9	Hannan-Quinn criterion		–11.04697
Durbin-Watson stat	1.731277			

The above table shows the results of the selected EGARCH(1,1) model with Student t's distribution Construct for One 97 Communications Ltd (Paytm). The results are classified into two parts. The upper part shows the mean equation and the lower part represents the variance equation. In the mean equation, the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of the first lag [NLPAYTM(–1)] is also significant as it is probability value is also less than 0.05.

In the case of the variance equation, C(3) is the constant, C(4) is the GARCH Coefficient, C(5) is the Asymmetric Coefficient, and C(6) is the GARCH Coefficient. All the coefficients of the variance equation are significant as their probability values are less than 0.05. The coefficient of an asymmetric term is positive, i.e. 0.06 approx. and it is also statistically significant even at the 1% level, which indicates that for this stock there are asymmetries. Hence, this model seems fit to the stock price data of Paytm and would be suitable for forecasting the stock price volatility of the company.

Table 4 reveals that Coefficients, ARCH Effect and GARCH are significant in two out of three GARCH (1,1), all three EGARCH (1,1) and all the three TGARCH (1,1) models with Normal Distribution Error Construct, with Student t's Distribution Error Construct and with Generalised Error Distribution Construct. After framing the above models, there is no Heteroscedasticity (which has been checked with the help of the ARCH LM Test) and no Autocorrelation (which has been checked with the help of a correlogram of residuals and squared residuals) in any of the nine models. While comparing the AIC and SIC of all the above nine models, it has been found that EGARCH with Generalised Error Distribution has the lowest AIC (–11.05742) and SIC (–11.05644) as compared to the other eight models. This model also has the highest Log-Likelihood (359627.4). Hence, this is considered as the most suitable model. The result of the selected EGARCH (1,1) Model for PB FinTech Ltd is mentioned in the table 5.

Table 5 shows the results of the EGARCH(1,1) model with a Generalized error distribution Construct for PB FinTech Ltd. The results are classified into two parts. The upper part shows the mean equation and the lower part represents the variance equation. In the mean equation, the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of the first lag [NLPB(–1)] is also significant as it is probability value is also less than 0.05.

In the case of the variance equation, C(3) is the constant, C(4) is the ARCH Coefficient, C(5) is the Asymmetric Coefficient, and C(6) is the GARCH Coefficient. All the coefficients of the variance equation are significant as their probability values are less than 0.05. The coefficient of an asymmetric term is positive, i.e. 0.0675 approx. and it is also statistically significant even at the 1% level, which indicates that for this stock there are asymmetries. Hence, this model seems fit to the stock price data of PB FinTech Ltd. and would be suitable for forecasting the stock price volatility of the company.

Table 6 reveals that Coefficients, ARCH Effect and GARCH are significant in one out of the three GARCH (1,1), two out of the three EGARCH (1,1) and one out of the three TGARCH (1,1)models with Normal Distribution Error Construct, with Student t's Distribution Error Construct and with Generalised Error Distribution Construct. After framing the above models, there is no Heteroscedasticity (which has

Table 4

DECISION TABLE FOR SELECTING SUITABLE GARCH (1,1), TGARCH (1,1) & EGARCH (1,1) MODEL FOR PB FINTECH LTD

Statistics	GARCH (1,1)			TGARCH (1,1)			EGARCH (1,1)		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	335904.6	353381.1	357740.5	335915.4	352922.1	NA	336670.6	356756.2	359627.4
AIC	–10.32806	–10.86539	–10.99943	–10.32836	–10.85125	NA	–10.35158	–10.96913	–11.05742
Schwartz IC	–10.32737	–10.86455	–10.99859	–10.32753	–10.85027	NA	–10.35075	–10.96816	–11.05644
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No	No	No	No

been checked with the help of thve ARCH LM Test) and no Autocorrelation (which has been checked with the help of a correlogram of residuals and squared residuals) in any of the nine models. While comparing the AIC and SIC of all the above nine models, it has been found that GARCH with Student t's distribution has the lowest AIC (–15.53218) and SIC (–15.53134) as compared to the other five models. This model also has the highest Log-Likelihood (505159.1). Hence, this is considered as the most suitable model. The result of the selected GARCH (1,1) Model for Niyogin Ltd. is mentioned in the table 7.

Table 7 shows the results of the GARCH(1,1) model with Student t's distribution Construct for Niyogin FinTech Ltd. The results are classified into two parts. The upper part shows the mean equation and the lower part represents the variance equation. In the mean equation, the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of the first lag [NLNIYOGIN(–1)] is also significant as its probability value is also less than 0.05.

In the case of variance equation, C is the Constant, RESID(–1)^2 is the ARCH co-efficient, RESID(–1)^2*(RESID(–1)<0) is the asymmetric co-efficient, and GARCH(–1) is the GARCH co-efficient. Only the ARCH and GARCH coefficients are significant in the variance equation as their probability values are less than 0.05. The coefficient of an

Table 5

RESULTS OF EGARCH (1,1) MODEL WITH GENERALIZED ERROR DISTRIBUTION CONSTRUCT FOR PB FINTECH LTD.

Dependent Variable: NLPB
Method: ML ARCH - Generalized error distribution (GED)
Date: 09/11/22 Time: 17:25
Sample (adjusted): 12/01/2021 09:17 7/29/2022 15:30
Included observations: 65046 after adjustments
Convergence achieved after 65 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(–1)/@SQRT(GARCH(–1))) + C(5)*RESID(–1)/@SQRT(GARCH(–1)) + C(6)*LOG(GARCH(–1))

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	–1.88E-05	3.53E-08	–532.8613	0.0000
NLPB(–1)	–0.082177	0.002025	–40.59007	0.0000
Variance Equation				
C(3)	–0.256660	0.003214	–79.85324	0.0000
C(4)	0.231130	0.002641	87.50845	0.0000
C(5)	0.067419	0.001663	40.54481	0.0000
C(6)	0.991904	0.000128	7750.765	0.0000
GED PARAMETER	0.703055	0.002162	325.1633	0.0000
R-squared	–0.002960	Mean dependent var		–1.51E-05
Adjusted R-squared	–0.002975	S.D. dependent var		0.001810
S.E. of regression	0.001812	Akaike info criterion		–11.05742
Sum squared resid	0.213656	Schwarz criterion		–11.05644
Log likelihood	359627.4	Hannan-Quinn criterion		–11.05711
Durbin-Watson stat	1.883933			

Table 6

DECISION TABLE FOR SELECTING SUITABLE GARCH (1,1), TGARCH (1,1) & EGARCH (1,1) MODEL FOR NIYOGIN FINTECH LTD

Statistics	**GARCH (1,1)**			**TGARCH (1,1)**			**EGARCH (1,1)**		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	No	Yes	No	Yes	Yes	No	Yes	No	No
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	279704.6	505159.1	331723.2	279804.3	468946.4	313122.6	280159.9	427838.1	304919.6
AIC	–8.600056	–15.53218	–10.19946	–8.603091	–14.41870	–9.627512	–8.614025	–13.15472	–9.375291
Schwartz IC	–8.599358	–15.53134	–10.19863	–8.602253	–14.41772	–9.626535	–8.613187	–13.15375	–9.374314
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No	No	No	No

Table 7

RESULTS OF GARCH (1,1) MODEL WITH STUDENT'S T DISTRIBUTION CONSTRUCT FOR NIYOGIN LTD.				
Dependent Variable: NLNIYOGIN Method: ML ARCH - Student's t distribution Date: 09/11/22 Time: 22:22 Sample (adjusted): 12/01/2021 09:17 7/29/2022 15:30 Included observations: 65046 after adjustments Failure to improve Likelihood after 66 iterations Presample variance: backcast (parameter = 0.7) GARCH = C(3) + C(4)*RESID(–1)^2 + C(5)*GARCH(–1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	8.14E-09	1.61E-09	5.056414	0.0000
NLNIYOGIN(–1)	0.412086	0.002888	142.6697	0.0000
Variance Equation				
C	1.85E-15	9.87E-17	18.74773	0.0000
RESID(–1)^2	0.604497	0.006569	92.01715	0.0000
GARCH(–1)	0.276554	0.000526	525.6451	0.0000
T-DIST. DOF	2.780253	0.005127	542.3203	0.0000
R-squared	–0.237692	Mean dependent var		–1.11E-05
Adjusted R-squared	–0.237711	S.D. dependent var		0.004582
S.E. of regression	0.005098	Akaike info criterion		–15.53218
Sum squared resid	1.690554	Schwarz criterion		–15.53134
Log likelihood	505159.1	Hannan-Quinn criterion		–15.53192
Durbin-Watson stat	2.774798			

asymmetric term is negative, i.e. –0.0082 and it is not statistically significant even at the 5% level, which indicates that for this stock there are no asymmetries due to the pandemic COVID-19. Hence, this model seems fit to the stock price data of Niyogin FinTech Ltd. and would be suitable for forecasting the stock price volatility of the company.

Forecasting of stock price volatility and returns of three listed companies

The suitable GARCH model that has been formulated for each listed FinTech company has been used to forecast stock price volatility and returns. A selected GARCH Model has been formulated taking into consideration the data for 7 months 15 days (01/12/2021 to 15/07/2022) and then forecasting has been done for the remaining 15 days (16/07/2022 to 31/07/2022. The forecasting graphs are mentioned in figure 3. In figure 3, the forecasting graph of Paytm shows that there were negligible fluctuations in the returns but so far as the volatility is concerned high fluctuations can be seen during the 25^{th} to 29^{th} moderate levels of fluctuations on other days and the possibility to continue in future as well. Similar case with the returns and stock price volatility of Niyogin Ltd. – no fluctuations in returns but high volatility throughout the forecasting period which may continue in the future too. Hence, these two stocks i.e. Paytm and Niyogin should not be considered for retail investment. On the contrary, the forecasting graphs of PB FinTech Ltd. seem much more stable as its returns have no fluctuations and even the volatility has been slowed down to a little towards the end

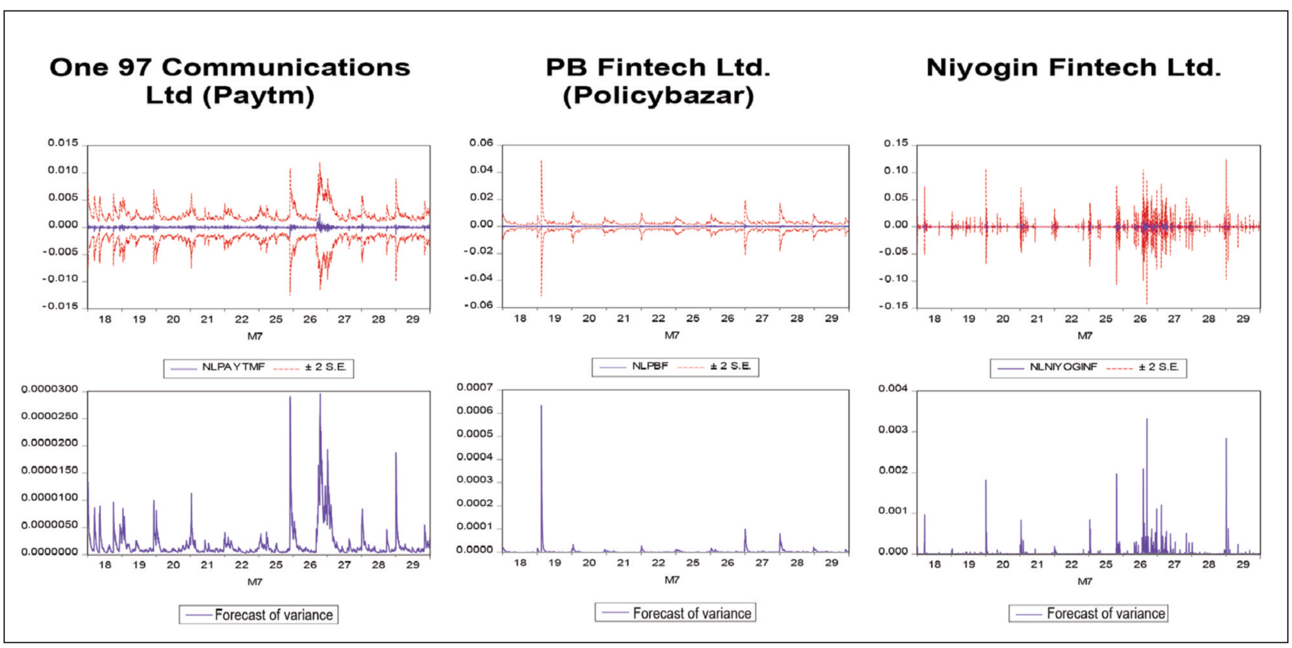

Fig. 3. Forecasting Graphs of Stock Price Volatility and Returns of One 97 Communications Ltd (Paytm), PB FinTech Ltd. (Policybazar) &Niyogin FinTech Ltd. (*Source: Authors' Formulation using EVIEWS 10*)

of the forecasting period and hence can be considered by retail investors.

CONCLUSIONS

From the above results and discussion, it can be observed that EGARCH (1,1) with Student t's Distribution Model is the suitable volatility model for One 97 Communications Ltd (Paytm)to grasp the volatility along with the leverage effect during those eight months i.e. 1st December 2021 to 31st July 2022, as it has highest log likelihood and lowest AIC and Schwartz IC with all significant coefficients. Similarly, EGARCH (1,1) with a Generalised Error Distribution Model is the suitable volatility model for PB FinTech Ltd. (Policy Bazar) to grasp the volatility along with the leverage effect during those eight months, i.e. 1st December 2021 to 31st July 2022 as the model has highest log likelihood and lowest AIC and Schwartz IC with all significant coefficients. This implies that there is an existence of asymmetricity in the stock price volatility of Paytm and Policy Bazar. The point of discussion is the asymmetricity coefficient in the models. The asymmetricity coefficient (λ) is positive and also statistically significant in both the above EGARCH models which implies that the good news (positive shocks) generates larger volatility than the bad news (negative shocks). The presence of positive shocks might be due to the third wave of COVID-19 which might have again shot the demand for financial products and services of these FinTech companies. Paytm might get more demand for cashless receipts and payments while PolicyBazaar might be able to provide many insurance via digital mode. On the other hand, for Niyogin FinTech Ltd., the simple GARCH model i.e. GARCH (1,1) is suitable to grasp the volatility during those eight months. There is no existence of any leverage effect or any effect of positive and negative news on the stock price volatility of Niyogin FinTech Ltd. The non-existence of asymmetricity in the stock price volatility of Niyogin, even during the third wave might be due non exposure of any positive or negative news to the nature of services provided by them during that period. Moreover, the positive asymmetricity coefficient of both the EGARCH models for Paytm and PolicyBazaar and the absence of leverage effect in the stock price volatility of Niyogin also inferred that the war between Ukraine and Russia did not adversely affect the stock price volatility of these listed FinTech companies. Hence, it could be concluded that investment in FinTechs is more feasible than textiles in India at present. These statistical models with the use of high-frequency data can also lead future researchers to develop different models for forecasting using the high-frequency data that can be used even for Algo Trading. Moreover, further research can also be done on removing the noise from the high-frequency data to make the short-term forecasting models more accurate.

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