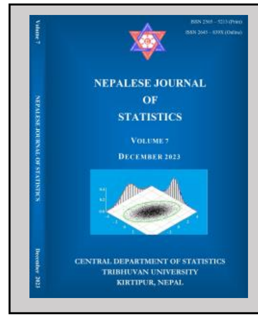
Comparative Study of Risk in General-Finance and Production-Service Categories of NEPSE Market



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ABSTRACT

Background: The study of risk in investment in the stock market has become a popular area of research since last few decades. The inherent nature of risk that is associated with volatile behavior of stock prices as well as of returns of investment makes investors to think more than once before investing in stock markets. In this regard, this research is focused on comparison of risk associated with investment in General-Finance and Production-Service groups of the NEPSE market.

Objective: Primary objective of this research is to assess and compare risk present in the 'General-Finance' group and the 'Production-Service' group of the NEPSE market.

Materials and Methods: Different companies enlisted in the NEPSE stock market are categorized into ten groups. Some of the groups are related to direct financial activities and they are placed in the 'General-Finance' group. Other groups which are related to production and service activities are placed in the 'Production-Service' group. Daily means of NEPSE indices for these groups, available from official website of NEPSE are used to fit ARIMA model to the indices of 'General-Finance' and to 'Production-Service' groups. It is attempted to compare risks in these two groups with respect to the variance of error terms of the fitted models. Moreover, GARCH models are employed to describe conditional heteroscedasticity present in observations.

Results: It is observed that ARIMA (1, 1, 3) is the optimal model for daily indices of 'General-Finance' group with variance of errors terms observed to be 4636.1933. For the 'Production-Service' group the optimal model resulted is ARIMA (1, 1, 1) with variance of error terms being 1335.0058. Conditional heteroscedasticity and volatility clustering are observed to have GARCH (1, 1) model for both the groups.

Conclusion: After observing variance of error terms of optimal ARIMA models for 'General-Finance' and 'Production-Service' group and coefficients of GARCH models, it is concluded that 'General-Finance' group owes more risk in investment than that in 'Production-Service' group.

Keywords: ADF-test, ARIMA model, GARCH, Ljung-Box test, stationarity, volatility clustering.

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INTRODUCTION

Financial risk arises mainly due to instabilities, losses in the financial market or movements in stock prices, currencies exchange rates, interest rates, etc. and it refers to business' ability to fulfill financial obligations. It is any uncertainty with respect to investments that has the potential to negatively impact financial welfare. It is considered that in a country where financial development is still ongoing we should not expect the stock market to behave in line with the theory of efficient markets (Girardin & Joyeux, 2013). According to Guillemette and Finke (2014) accurate risk tolerance assessments can help financial planners make portfolio recommendations that clients are comfortable with during times of economic expansion and, perhaps more importantly, during economic downturns. Nepal Stock Exchange Ltd. (NEPSE) is the only stock exchange of Nepal that provides a platform for investors to buy and sell shares of publicly traded companies in various sectors in Nepal. It was established under the Companies Act-2006 and operates under Securities Act-2007. In this research, different companies enlisted in NEPSE market are categorized into two groups, namely 'General-Finance' group and 'Production-Service' group and it is attempted to compare risk prevailing in these two groups.

In current research, the risk in 'General-Finance' and 'Production-Service' groups are assessed using historical data with the help of standard deviation as well as value-at-risk (VaR). Standard deviation measures the dispersion of data from its expected value. A stock that has high standard deviation experiences higher volatility and is therefore considered riskier. VaR measures maximum potential loss with a degree of confidence for a specified period and it is expressed in terms of confidence interval. Moreover, it is attempted to describe risk in these two groups fitting Autoregressive Integrated Moving Average (ARIMA) models to historical values of NEPSE indices. The assumption of homoscedasticity of ARIMA model is tested to observe and detect volatility clustering and is described using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The primary objective of this research is to assess and compare risk present in the 'General-Finance' group and the 'Production-Service' group of the NEPSE market.

Maskey (2022) used ARIMA model to predict NEPSE index. Similarly, Dhyani et al. (2020) used ARIMA method to predict the movement of Nifty-50 index, the index on the National Stock Exchange (NSE) of India Ltd. Khan and Alghulaiakh (2020) applied ARIMA model to get accurate stock forecasting on Netflix stock value using historical data for five years and identified that ARIMA

(1, 1, 33) is the best model. To predict the share prices of some selected pharmaceutical companies in India, listed under NIFTY100, Meher et al. (2021) used ARIMA model and suggested efficient models for them. Research by Dadhich et al. (2021), outlined the best-fitted equation using ARIMA as well as GARCH model for stock prices of the two major indices of India, i.e., BSE (Bombay Stock Exchange) and NSE. It highlighted the strength of the models to forecast the daily closing price of the time series data. Singh et al. (2021) stress the need for reliable, cost-effective, and accurate forecasting models significantly arises to reduce risk and uncertainty in stock market investment. They tried to resolve the issue by adopting a short-time Fourier transform by using wavelet functions. In a paper entitled "ARIMA Model in Predicting Banking Stock Market Data", Almasarweh and Alwadi (2018) present the advantages of the ARIMA model forecasting accuracy. Banking data from Amman Stock Market (ASE) in Jordan was selected as a tool to show the ability of ARIMA in forecasting banking data.

Published stock data obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) are used by Ariyo et al. (2014) to develop stock price predictive model using ARIMA technique. Mondal et al. (2014) conducted a study on the effectiveness of ARIMA model, on fifty-six Indian stocks from different sectors by using ARIMA model. They selected fifty-six companies from seven sectors, eight companies in each sector from the official website of NSE of India. In article entitled "An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50", Devi et al. (2013) explained that the stock market some time fails to attract new investor because people don't want to come forward to fall in to the risk. They applied machine learning approaches for analysis purposes.

METHODOLOGY

Data source and description of data

Data required for analysis purposes are obtained online from the official website of NEPSE, named www.nepalstock.com. Different companies enlisted in the NEPSE market are categorized into ten groups. The names of these groups are: (i) Banking (ii) Trading (iii) Hotel and tourism (iv) Development Bank (v) Hydropower (vi) Finance (vii) Microfinance (viii) Non-life Insurance (ix) Life Insurance (x) Manufacturing and Production. The daily indices of these ten groups, available online, are used as data source for the analysis purpose. 2109 number of data points on NEPSE indices of different groups starting from 2014-02-02 to 2023-05-08 are utilized for the study. For the research purpose, these ten groups are categorized into two groups- 'General-Finance' group and 'Production-Service' group on the basis of the notion whether they are directly involved in financial activities or in production and service activities. Accordingly, the groups 'Banking', 'Development Bank', 'Finance', 'Microfinance', 'Life Insurance' and 'Non-Life Insurance' groups are categorized as 'General-Finance' group. In the same way, 'Trading', 'Hotel and Tourism', 'Hydropower' and 'Manufacturing and Production' groups are categorized as 'Production-Service' group. The daily means of indices of these two categories are considered as the main data for analysis. Table 1 exhibits few recent daily mean values of ‘General-Finance’ and ‘Production-Service’ categories. Fig.1 is the plot of daily means of indices of ‘General-Finance’ and ‘Production-Service’ groups.

Table 1. Glimpse of few recent mean indices of two groups.

Date	General-Finance	Production-Service
2023-05-08	4495.79	2999.35
2023-05-07	4544.77	3042.08
2023-05-04	4585.82	3074.06
2023-05-03	4543.42	3049.78
2023-05-02	4563.08	3071.03
2023-04-30	4569.78	3078.93
2023-04-27	4609.64	3116.18
2023-04-26	4618.93	3115.97
2023-04-25	4649.78	3143.41
2023-04-24	4606.91	3100.40
2023-04-23	4590.51	3107.45
2023-04-20	4634.24	3123.12
2023-04-19	4672.44	3146.79
2023-04-18	4632.74	3126.97
2023-04-17	4640.26	3134.54

Fig. 1. Plot of mean indices.

Using historical data to assess risk

Traditionally, risk is assessed by observing volatility, i.e., the standard deviation of observations. Sometimes to account for mean of observations for assessing variability, coefficient of variation is also used. Alternatively, historical VaR (Value at Risk), which is a non-parametric method of calculating value at risk, is also used. The VaR considers quantiles of specified level corresponding to change in values of historical data without considering the form of probabilistic distribution of data. Historical method is based on the notion that data values are uncorrelated and independent. But financial data are usually correlated with one another and there is some form of dependencies among these data. These correlations among data, usually called autocorrelation or sometimes serial correlation is captured by a special form of statistical regression modeling method, known as ARIMA model.

Using ARIMA model to assess risk

Different values in time series data are usually correlated values on one or more past values. In the same way, time series observations are serially correlated with one or more past errors. This type of serial correlation in time series data is best explained by the ARIMA model. ARIMA is different from traditional regression models in the sense that in this model past values as well as past errors are considered as regressor variables. If past observations of p lags and past errors of q lags are considered for describing autocorrelations, then such a model is denoted as ARMA (p, q) model and it is described mathematically by:

$$y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \qquad (1)$$

where y_t is value at time t; $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ are lagged values at times $t-1, t-2, \dots, t-p$. Similarly, ϵ_t is error at time t and $\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_{t-q}$ are past errors up to lag q. Moreover, $\alpha, \phi's$ and $\theta's$ are constants. As ARMA (p, q) model can describe dependencies among observations only if they are stationary and financial data are rarely stationary, so in ARIMA (p, d, q) model is deployed. Here 'd' represents the order of differencing, i.e., order of successive differences that are required to attain a stationary time series. Stationarity can be revealed in a number of ways- such as observing plots of actual observations, plots of autocorrelations of different lags, plot of partial autocorrelation of different lags, etc. The auto-correlation plot and partial auto-correlation plot are also used to determine the order 'p' and 'q' of ARIMA model.

The formal and the most common method of testing stationarity of data is Augmented Dickey-Fuller test (ADF-test). In this test it is observed whether at the least one of the auto-regressive coefficients of the ARMA model is equal in magnitude to unity. The unit root is a measure of stationarity of a time series process. It is based on the null hypothesis that there is a unit root in the process, i.e., the process is non-stationary. Moreover, the ARIMA model assumes that the error components or residuals of the model are uncorrelated variables with 0 mean and some finite variance. For fitting of ARIMA model Hyndman-Khandakar algorithm, Hyndman and Khandakar (2008) which combines unit root tests, minimization of the AICc and MLE, is used. An optimal ARIMA model that can be considered as the best one for a set of observations is selected on the basis of different measures. Some commonly used measures are AIC (Akaike Information

Criterion), AICc (Corrected Akaike Information Criterion), BIC (Bayesian Information Criterion), etc. The process used in this research fits several ARIMA models to data values and selects the optimal one with minimum value of AIC, AICc as well as BIC. For validation of the ARIMA model developed, it is observed whether the error components are uncorrelated random variables having zero mean and finite variance. The common method used for this purpose is Ljung-Box test. The statistic concerned with Ljung-Box test is:

$$Q(h) = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \qquad (2)$$

where n is the sample size, $\hat{\rho}_k$ is the sample autocorrelation at lag k, and h is the number of lags being used. The ARIMA models thus identified are used to predict values of mean indices of the two groups for subsequent 25 trading periods. Finally, risks present in the two groups considered are compared by observing variances of residuals of the models developed.

Using GARCH model to describe volatility clustering

ARIMA model assumes that the residuals are uncorrelated random variables with zero mean and constant variance. If variance of time-series data varies over time, then this heteroscedastic nature causes trailing of variance over time. This concept is referred to as volatility clustering. The presence of volatility clustering is studied in terms of conditional variance by using the GARCH model. Volatility clustering is observed graphically by using different plots of residuals of the ARIMA model as well as by using Engle's ARCH test. Engle (1982) detects whether there is auto-regressive conditional heteroscedasticity in data. GARCH (p, q) model uses 'p' number of lag variance terms and 'q' number of lag residuals from the ARIMA model. It is specified by equation

$$y_t = \sigma_t . \epsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i\, y_{t-i} + \sum_{j=1}^{q}\beta_i\, \sigma_{t-i}^2 \qquad (3)$$

where σ_t^2 is the variance at time t, $\sigma_{t-i}^2; i = 1,2,\ldots,q$ are variances at lagged times and ϵ_t is residual at time t and it is assumed to be white noise process with mean 0 and variance 1. Moreover, $\omega, \alpha's$ and $\beta's$ are constants. Finally, the values of orders 'p' and 'q' of GARCH (p, q) model is determined by observing several models and selecting optimal one with minimum AICc value and then GARCH model is fitted to explain the conditional variance that is associated with observations of 'General-Finance' and 'Production-Service' groups.

Tools used for analysis

In current research, NEPSE indices of different groups available online in '.csv' format are used for study periods. For data analysis purposes, **RStudio** R Core Team (2022), the statistical analysis programming language, is used. For visual presentation of data **ggplot2** package Wickham (2016) of RStudio is used. For data manipulation purpose **dplyr** Wickham et al. (2023), **readr**

Wickham, Hester and Bryan (2023), **tidyr** Wickham, Vaughan, and Girlich (2023) packages are used. Similarly, for tabular presentation of results **knitr** Xie (2023), **kableExtra** packages are used. For time-series analysis, modeling as well as for forecasting purpose **tseries** Trapletti and Hornik (2020), **forecast** R. Hyndman et al. (2023) and **fpp3** are used.

RESULTS

The result of assessing risk in terms of standard deviation and coefficient of variation based on observations of day-wise means of 'General-Finance' and 'Production-Service' groups are presented in Table 2. Describing risk in terms of VaR, it is observed that the 95% confidence intervals of daily fluctuations in means of the General-Finance group is (1261.83, 7609.23). Similarly, for the 'Production-Service' group the corresponding confidence interval is found to be (1263.14, 4228.78).

Table 2. Summarized values of mean indices.

Group	Mean	Standard Deviation	Coefficient of Variation
General-Finance	3439.395	1814.0160	52.7423
Production-Service	2065.648	925.3508	44.7971

Table 3 shows the results of applying ADF test to observe stationarity of actual mean indices and of differenced mean indices of the two study groups. It is observed that actual mean indices of both groups are non-stationary while differenced mean indices are stationary for both groups. After observing several ARIMA models with different values of autoregressive order, moving average order and difference order, ARIMA (1, 1, 3) is identified as the optimum model for 'General-Finance' category.

Table 3. Result of test of stationarity.

Group	p-value of actual means	p-value of differenced means
General-Finance	0.4497	0.01
Production-Service	0.6009	0.01

The selected model ARIMA (1, 1, 3) for 'General-Finance' category is observed to have AICc value of 23783.4 and estimated coefficients of the model are ϕ_1= 0.8321, θ_1= -0.704 , θ_2= -0.2006 and $\theta_3 = 0.1466$ with no drift. Hence, fitted model for 'General-Finance' group is:

$$y_t - y_{t-1} = 0.8321(y_{t-1} - y_{t-2}) - 0.704(\epsilon_{t-1} - \epsilon_{t-2}) - 0.2006(\epsilon_{t-2} - \epsilon_{t-3}) + 0.1466(\epsilon_{t-3} - \epsilon_{t-4}) + \epsilon_t \qquad (4)$$

Similarly, for the 'Production-Service' category after observing several ARIMA models with different values of autoregressive order, moving average order and difference order ARIMA (1, 1,

1) is identified as the optimum one. The model ARIMA (1, 1, 1) identified for the 'Production-Service' group is found to have AICc value of 21156.9. The estimated model coefficients for this model are: ϕ_1= -0.5278 and θ_1= 0.6486 with no drift. The mathematical description of the model selected for 'Production-Service' group is:

$$y_t - y_{t-1} = -0.5278(y_{t-1} - y_{t-2}) + 0.6486(\epsilon_{t-1} - \epsilon_{t-2}) + \epsilon_t \qquad (5)$$

The graphical display of forecasts of mean indices for 'General-Finance' and 'Production-Service' groups for next 25 trading days based on the best model considered are shown in Fig. 2 and in Fig. 3, respectively.

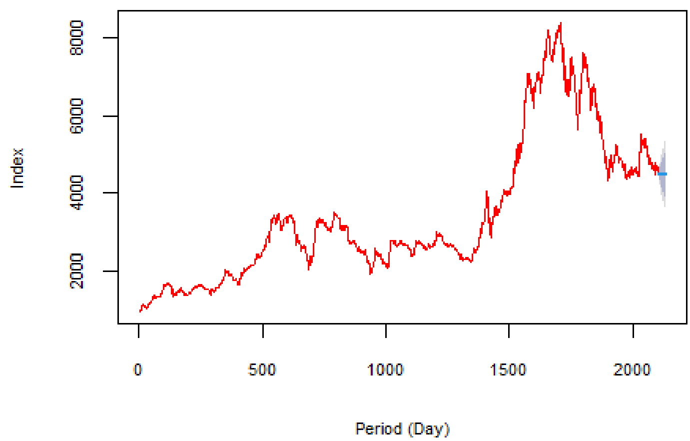

Fig. 2. General-finance group indices with forecasts for next 25 periods.

Validation of the fitted models

On observing whether the residuals of error components ϵ_t are uncorrelated random variables by using Ljung-Box test to the two models, it is found that p-values of Ljung-Box test for 'General-Finance' group is 0.8749324 and for 'Production-Service' group it is 0.5308698. Thus it is resulted that there is no reason to reject the assumption that the error components are uncorrelated.

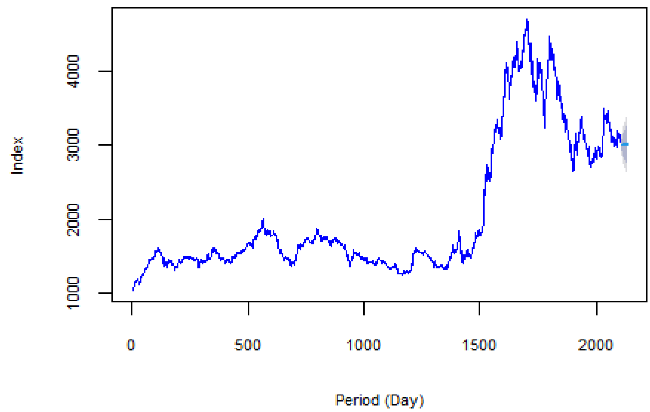

Fig. 3. Production-service group indices with forecasts for next 25 periods.

Using variance of errors to assess risk

From the fitted model, the variance of errors for the 'General-Finance' group is observed to be 4636.1933 and for the 'Production-Service' group it is observed to be 1335.0058.

Observing volatility clustering and fitting GARCH models

On observing plots of residuals of ARIMA models for the two groups, as shown in Fig. 4 and Fig. 5 it can be revealed that it is not plausible to ignore the effect of volatility clustering present in observations.

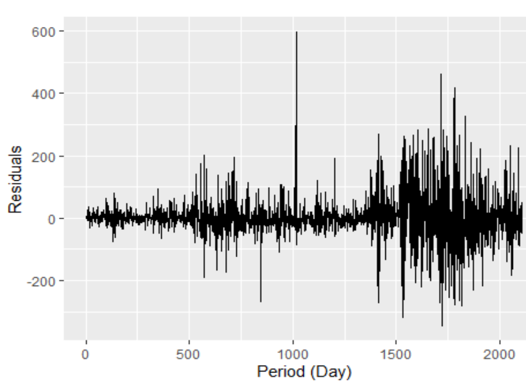

Fig. 4. Residual plot of model for general-finance group.

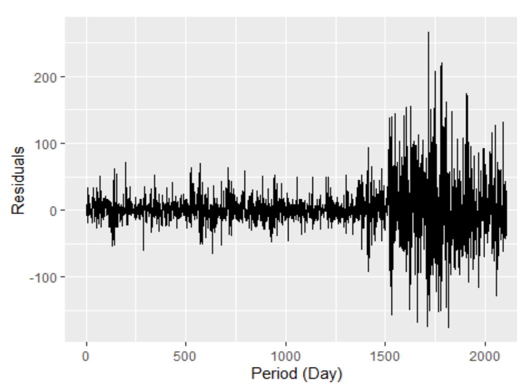

Fig. 5. Residual plot of model for production-service group.

The auto-correlation function (ACF) plots of squared residuals of ARIMA models for 'General-Finance' and 'Production-Service' groups shown in Fig. 6 and in Fig. 7. Similarly, Fig. 8 and Fig. 9 are the partial auto-correlation function (PACF) plots of squared residuals of ARIMA models for the two groups.

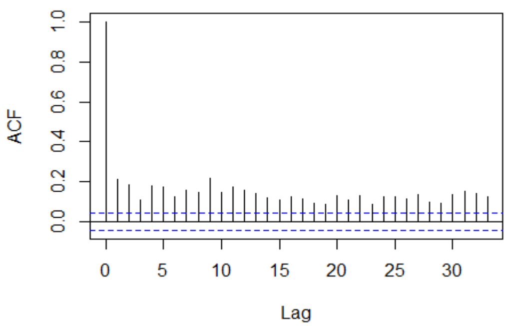

Fig. 6. ACF-plot of squared residuals of model for general-finance group.

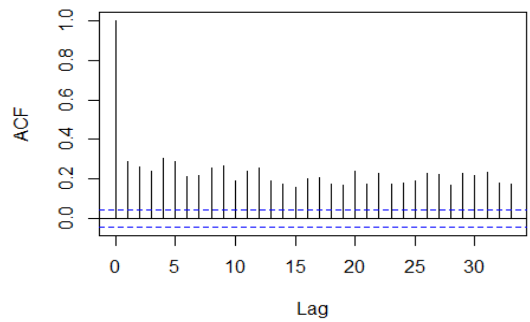

Fig. 7. ACF-plot of squared residuals of model for production-service group.

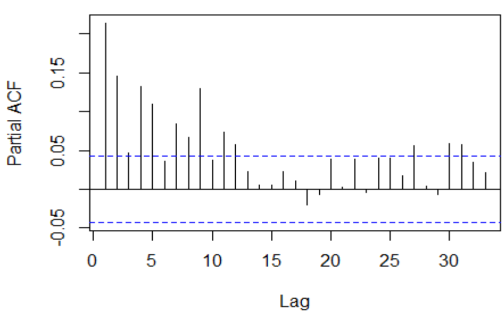

Fig. 8. PACF-plot of square of residuals of model for general-finance group.

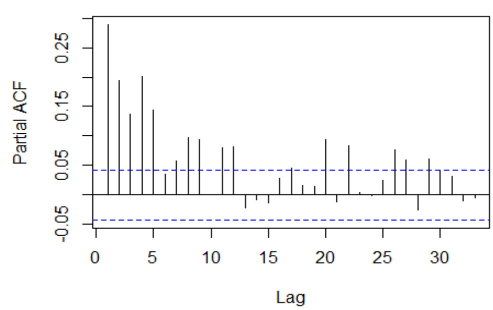

Fig. 9. PACF-plot of square of residuals of model for production-service group.

The ACF-plots and PACF-plots of squared residuals of models indicate that it is not plausible to accept the assumption of homoscedasticity, i. e., constant variance of error terms over time for both the groups. Tests for presence of heteroscedasticity of daily fluctuations by using Engle's ARCH test for both 'General-Finance' group as well as for 'Production-Service' group are observed to have very small p-value indicating that there is volatility clustering in daily fluctuations for both groups and so it is required to model data taking conditional heteroscedasticity into consideration.

After experimenting with several GARCH models and comparing values of AIC, AICc, BIC, etc. GARCH (1, 1) is found to be the optimum model for 'General-Finance' as well as for 'Production-Service' groups. The optimum ARIMA-GARCH model identified for 'General-Finance' group is given by Equation (3.2).

$$y_t - y_{t-1} = -1.92 + 0.85(y_{t-1} - y_{t-2}) - 0.73(\epsilon_{t-1} - \epsilon_{t-2}) - 0.17(\epsilon_{t-2} - \epsilon_{t-3}) + 0.12(\epsilon_{t-3} - \epsilon_{t-4}) + \sigma_t \epsilon_t$$
$$\epsilon_t \sim WN(0, \sigma^2)$$
$$\sigma_t^2 = 8.96 + 0.12(y_{t-1} - y_{t-2}) + 0.88\sigma_{t-1|t-2}^2 + \eta_t$$
$$\eta_t \sim WN(0,1) \qquad (6)$$

Moreover, all the coefficients in the model are observed to be significant. Equation (3.3) represents the optimum ARIMA-GARCH model identified for 'Production-Service' group with all the coefficients observed to be significant.

$$y_t - y_{t-1} = -0.79 - 0.66(y_{t-1} - y_{t-2}) + 0.73(\epsilon_{t-1} - \epsilon_{t-2}) + \sigma_t \epsilon_t$$
$$\epsilon_t \sim WN(0, \sigma^2)$$
$$\sigma_t^2 = 9.79 + 0.15(y_{t-1} - y_{t-2}) + 0.84\sigma_{t-1|t-2}^2 + \eta_t$$
$$\eta_t \sim WN(0,1) \qquad (7)$$

DISCUSSION

In this research, it is attempted to compare risk in the 'General-Finance' and 'Production-Service' groups of the NEPSE market using some standard methods. Firstly, risk is assessed by observing standard deviation of day-wise means of indices of two groups. Secondly, value-at-risk is used in terms of widths of confidence intervals of day-wise fluctuations of means of the two groups using historical observations. Similarly, ARIMA models are fitted to daily mean indices of two groups and variance of residuals are observed for comparison purposes. Moreover, conditional variances are used to describe volatility clustering present in observational data by using the GARCH model. Since volatility, i.e., standard deviation as well as coefficient of variation of historical data for 'General-Finance' group are both greater than that for 'Production-Service', it is observed that there is higher risk in investment in 'General-Finance' group than in 'Production-Service' group. Similarly, the width of confidence intervals for fluctuations in means of daily indices of 'General-Finance' group is higher with value of 6347.4 compared to that of 'Production-Service' group with value 2965.65, so risk in 'General-Finance' group is greater than in 'Production-Service' group.

By observing variances of residuals of the ARIMA models fitted for the two groups, it is concluded that the 'General-Finance' group has greater risk with variance of residuals being 4636.1933 compared to the variance 1335.0058 for 'Production-Service' group. By observing GARCH models developed for two groups, it is found that the coefficient of past conditional variance terms for 'General-Finance' group is found to be slightly greater with value of 0.88 than that for 'Production-Service' with value of 0.84. Since the coefficient of conditional variance term of GARCH model for 'General-Finance' group is greater than that of 'Production-Service' group, it is inferred that risk owed by 'General-Finance' group is greater in comparison to 'Production-Service' group.

In majority of research articles related to describe behavior of stock values, viz., Maskey (2022), Dhyani et al. (2020), Khan and Alghulaiakh (2020), etc. information on either individual price or individual index of share market is used to describe distribution of data. In current research work, it is attempted to compare risk present in 'General-Finance' and 'Production-Service' groups of Nepal Stock Exchange (NEPSE) market. In fact, each investment is associated with some amount of risk. If these risks are managed properly, the investors will be able to meet expected financial returns. Understanding the basic ideas and concepts behind the risk and return strategy associated with investments is important because that is the only way of managing investment risk or minimizing them. While investing in share markets people are usually concerned only on more profit, i.e., higher returns and normally does not consider the amount of risk present in investment. Increased risk does not only signify increased possibility of loss in investment, it equally signifies increased possibility of gain in investment. It depends on the attitude of investors to bear risk to choose the group for investment.

CONCLUSION

After observing volatility in means of indices as well as their day-wise fluctuations of the 'General-Finance' and 'Production-Service' groups, it is found that the 'General-Finance' group possesses greater risk than the 'Production-Service' group. Similarly, for the two groups considered, after observing conditional means treating variances constant, it is observed that ARIMA (1, 1, 3) is the optimum model for the 'General-Finance' group and ARIMA (1, 1, 1) is the optimum model for the 'Production-Service' group. Next in terms of conditional variance it is observed that GARCH (1, 1) is the optimum model for both the groups considered. Comparing variances of residuals of ARIMA model as well as coefficients of variance components of GARCH models of the two groups, it is found that the 'General-Finance' group possesses more risk than the 'Production-Service' group.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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