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STOCK RETURNS VOLATILITY IN NEPAL: EVIDENCE DURING COVID-19

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ABSTRACT

This study scrutinizes the stock returns volatility pattern in Nepal during the COVID-19 period from March 3, 2020 to February 27, 2022. By examining GARCH family models with Generalized Error Distribution specification, the results of symmetric GARCH models show that there is persistent volatility in daily stock returns in Nepal over the study period. The observed persistent volatility in daily stock returns indicate that the current shocks in daily stock returns exist in forecasting variance for longer period in future. The results of asymmetric TGARCH (1, 1) model show that there is the leverage effects on the volatility of daily stock returns in Nepal during the study period. The observed leverage effects implies that uncomplimentary news have larger effects on the volatility than the complimentary news of the same intensity. Finally, results establish the GARCH (1, 1) model as the best fitted symmetric model to explain the volatility persistence and the TGARCH (1,1) model as the best fitted asymmetric models to predict the leverage effects on the time varying conditional volatility of daily stock in Nepal. The main implication of findings from this study is that it offers an additional insight to form sound investment strategy to address risk structure of Nepali stock market.

Keywords: Conditional volatility, GARCH, TGARCH.

INTRODUCTION

Modelling stock market volatility has been one of the interesting areas of study in financial economics over the past few decades. Understanding volatility pattern of stock returns has been necessary for stock market participants to assess the risk of investment. Investors are risk-averse because they prefer higher return and lower risk. Therefore, by examining the stock return volatility pattern carefully, investors may obtain important insight to hedge against investment risk in stock market.

Stock returns volatility refers to the unpredictable fluctuations in stock returns over a period of time. Generally, the pattern of volatility in daily stock returns varies from times to time, which is known as time varying volatility in stock returns. As Engle (2001) argues, financial time series are affected by their own past values (autoregressive). They are dependent on past information (conditional), and have non-constant variance (heteroscedasticity). Moreover, Miron and Tudor (2010) argue that financial time series generally exhibit the clustering in volatility. It implies that larger fluctuations in financial time series are usually followed by further larger fluctuations and smaller fluctuations are followed by further smaller fluctuations over a period of time. In addition, Black (1976) suggests that financial time series may also contain the leverage effect, which implies that uncomplimentary shocks have larger effects on stock price than the complimentary shocks of equal magnitude. Besides, financial time series also reveals persistent volatility, which indicates the pattern of long memory.

Several models have been developed since past to deal with time varying conditional volatility in stock returns. Autoregressive Conditional Heteroscedasticity (ARCH) model developed by Engle (1982) and its extension, the Generalized Autoregressive Heteroscedasticity (GARCH) model proposed by Bollerslev (1986), are popular ones. The GARCH model is more popular than the ARCH model because the GARCH model makes use of few parameters to provide parsimonious estimates. On the other hand, the ARCH model provides over-parameterized estimates. However, one limitation of the basic GARCH model is that it does not take into account the asymmetricity in financial time series to capture the leverage effects. Therefore, the extensions of GARCH model such as GARCH-M model, E-GARCH model (Nelson, 1991), and T-GARCH model (Glosten, Jagannathan, & Runkle, 1993) have been popularly used in studies to explain the asymmetric volatility pattern of stock returns.

The stock market in Nepal has demonstrated considerable ups and downs over its history of about three decades. Earlier before Covid-19 pandemic, NEPSE index reached its all-time high of 1888 points on July 27, 2016, which afterward moved down to 1188 points two year later in 2018. Even after the detection of first Covid -19 case in January 23, 2020, NEPSE reached to maximum 1509 points in March 3, 2020. However, due to the nationwide lockdown announced by Government of Nepal from March 24, 2020, the stock market trading also became affected and remained closed. NEPSE trading then resumed online only form June 29, 2020. Since the reopening of NEPSE trading, it started taking momentum and ultimately reached its history making all-time high of 3198 points as on August 18, 2021. However, the renewed vigor in the economy brought about by government change also caused the stock market to create negative shocks. Particularly, increased liquidity crunch in the economy along with market unfriendly monetary policy affected stock market adversely in the later period. Since then, NEPSE is experiencing a continuous downward trend.

Higher fluctuations in NEPSE index have created both risk and opportunities for investors. The notable fluctuations observed over the periods in stock market of Nepal demand a need for appropriate modelling of stock market volatility to understand its volatility pattern and behavior. Several studies on stock market volatility in the past in case of Nepal have demonstrated varying degree of volatility pattern from time to time. For example, in a more recent study conducted by Rana (2020) in case of Nepal over the period 2011-2020 using 2059 observations on daily returns of NEPSE index series, the author showed that there is volatility persistence in daily returns on composite NEPSE index series over the sampled period. However, the estimated results also showed that there is no significant risk premium offered by stock returns to hedge against investment risk in stock market of Nepal and asymmetric models do not capture the leverage effects on the stock returns volatility.

The properties of stock returns volatility might have changed in recent period due to Covid-19 pandemic and other vulnerable in the economy. Therefore, this study makes an attempt to update the evidence on the stock returns patterns in the context of Nepal by using the GARCH family models. The study particularly seeks to investigate the volatility pattern of daily stock returns in Nepal over Covid-19 pandemic period covering a more recent data set from March 3, 2020 to February 27, 2022 consisting of 419 daily observations of NEPSE return series. Using both symmetric and asymmetric volatility models, the study basically attempts to uncover whether the stock returns in Nepal offer significant risk premium and exhibit leverage effect on the conditional variance of stock returns during Covid-19 pandemic in Nepal or the scenario remains the same as observed in Rana’s (2020) study. The findings from this study offers an additional insight to understand the volatility pattern of daily stock returns and to form sound investment strategy to address the risk structure of Nepali stock market.

The rest of this paper describes the following: next section presents a brief review of related studies; third section deals with data and methodology of the study; fourth section provides empirical results and discussion; and final section concludes the study.

LITERATURE REVIEW

Many empirical attempts have been made in past to examine the significance of GARCH family models in capturing volatility properties of stock returns in the context of developed capital markets. Some of those studies, in the context of developed stock market, include Akgiray (1989), Pagan and Schwert (1990), and Episcopos (1996), among others. These studies have documented that one or other of the GARCH family model is efficient in explaining time varying volatility in stock returns. In later period, studies such as Bekaert and Wu (2000), Kaur (2004), Karanasos and Kim (2005), Alberola (2007), Basher, Hasan and Islam (2007), Alam, Siddikee, and Masukujjaman (2013), Hasan and Hady (2014), Banumathy and Azhagaiah (2015), and Boako, Agyemang-Badu and Frimpong (2015), among others have demonstrated some stylized characteristics of stock returns such as volatility clustering and leverage effect consistent to those found in the case of developed stock markets.

Studies after 2015 until recent past have also established the significance of GARCH family models. For example, Maqsood et al. (2017) used GARCH family models to estimate volatility of the daily returns of the Kenyan stock market using the data from March 2013 to February 2016. Using both symmetric and asymmetric models to capture the leverage effect and volatility clustering, the results showed that the volatility process is highly persistent with existence of risk premium and exhibited the presence of leverage effect in the stock return series. Similarly, Aliyev, Ajayi and Gasim (2020) using univariate symmetric and asymmetric GARCH models in the context of Nasdaq 100 data over the period January 4, 2000 through March 19, 2019, revealed that the volatility shocks on the index returns are quite persistent and study evidence showed that the index has leverage effect, and the impact of shocks is asymmetric.

Thus, literatures generally provide mixed evidences on the presence of conditional volatility, persistent volatility, risk premium and the leverage effects on stock return series. Most of the evidences are associated with the stock markets of developed and emerging economies and little is known about the developing stock markets like in Nepal in the context of recent period of Covid-19 pandemic. Therefore, this study attempts to update the evidences on the presence of symmetric and asymmetric volatility in daily stock returns in Nepal during Covid-19 pandemic.

RESEARCH METHODOLOGY

Data sources

This study makes use of NEPSE daily index return series in Nepal over March 3, 2020 to February 27, 2022 periods consisting of 419 daily observations. Although Covid-19 pandemic started showing its effects in Nepal during the later periods of the March 2020, the date March 3, 2020 has been selected as the starting data point of the study. The basic motivation to cover data point from this date is that stock market actually started to show down trend although the first Covid-19 case was detected in January 23, 2020. For the purpose of investigating daily stock return volatility pattern over the study period, daily stock returns have been estimated as natural logarithm of the fraction of current day NEPSE index on previous day index.

The model

This study uses several specifications of GARCH models to examine the volatility patterns of daily returns on NEPSE index series during Covid 19 period. Before estimating GARCH models, the presence of possible ARCH (q) effects in the residuals have been confirmed using GARCH representation of the squared residuals shown in Equation (1).

$$\hat{\varepsilon}_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \hat{\varepsilon}_{t-i}^2 + e_t \quad \text{... (1)}$$

In Equation (1), the ARCH effect is confirmed if the parameter 'β_i' is significant. Then, the GARCH family models can be estimated. The basic GARCH model includes lagged conditional variance terms as autoregressive terms and it is based on few parameters to capture long lagged effects, which makes GARCH model parsimonious. The basic GARCH (1, 1,) model has been presented in Equation (2).

$$\sigma_t^2 = \alpha + \theta_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \quad \text{... (2)}$$

In Equation (2), 'α' represents the constant, $'\theta_1'$ denotes to the GARCH coefficient, and $'\beta_1'$ denotes to the ARCH coefficient. This basic GARCH (1, 1) model is easier to estimate and performs well because there are only three parameters ($\alpha, \theta_1,\ and\ \beta_1$) to estimate. The coefficients of ARCH term (β_i) and GARCH term (θ_k) must be greater than zero to ensure that the conditional variance is always positive.

According to investment theory, all investors are risk-averse and hence they demand risk premium against risky investment. To detect whether there is significant risk premium, GARCH-M (p,q) model has been used, which allows the conditional mean to depend on variance. This model, as represented in Equation (3) primarily includes time varying risk premium to explain stock returns.

$$r_t = \mu + \delta\sigma_t^2 + \varepsilon_t \qquad \text{... (3)}$$

In Equation (3), 'δ' is the coefficient of conditional variance which represents the risk premium against risky assets. The basic GARCH-M (p, q) model is presented as in *Equation (4)*,

$$\sigma_t^2 = \alpha + \sum_{k=1}^{p} \theta_k \sigma_{t-k}^2 + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}^2 \qquad \text{...(4)}$$

According to symmetrical GARCH model, the bad news and good news having intensity have same degree of impact on asset volatility. However, in the context of financial markets, good and bad news have asymmetric impact on stock returns. Generally, good news forces an asset to enter into the equability resulting into decline in volatility and bad news forces it to enter into disorder resulting into increase in volatility. In this study, TGARCH model proposed by Zakoian (1994) has been used to account for the asymmetric impact of good and bad news. This model uses a dummy variable into the variance equation to account for negative and positive shocks of bad and good news, respectively. The conditional variance specification of the model is specified in Equation (5).

$$\sigma_t^2 = \alpha + \sum_{k=1}^{p} \theta_k \sigma_{t-k}^2 + \sum_{i=1}^{q} (\beta_i + \gamma_i D_{t-i}) \varepsilon_{t-i}^2 \qquad \text{...(5)}$$

In Equation (5), D_t takes the value of 1 for bad news and 0 otherwise; β_i explains the impact of good news and $\beta_i + \gamma_i$ explains the impact of bad news; $\gamma > 0$ denotes the asymmetry and $\gamma = 0$ represents the symmetry. If γ is significant and positive, it means that the effect of negative shocks is larger on conditional variance than that of the equivalent positive shocks.

The study also uses Exponential GARCH (EGARCH) model developed by Nelson (1991), which is similar to TGARCH model that captures the leverage effects of shocks on the financial markets. This model uses log of the variance series to test for asymmetries. The EGARCH specification for conditional variance is given by Equation (6).

$$log\ (\sigma_t^2) = \alpha + \sum_{i=1}^{q} \beta_i \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \sum_{i=1}^{q} \gamma_i \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \sum_{k=1}^{p} \theta_k log\ (\sigma_{t-k}^2) \quad \ldots(6)$$

In *Equation (6)*, $\log(\sigma_t^2)$ is the log of variance series, which shows exponential leverage effect; α is the constant; β_i denotes to the ARCH effects; γ_i is the asymmetric effects, and θ_k is the GARCH effects. The model is symmetric if $\gamma_1 = \gamma_2 = \ldots = 0$. Conversely, volatility created by bad news is larger than that of good news if $\gamma_i < 0$.

After estimating several GARCH family models, a diagnostic checking of the model has been carried out to determine the best fitted symmetric and asymmetric GARCH model. The best fitted model should have least number of parameters, significant ARCH and GARCH coefficients, high adjusted R-square, high log-likelihood ratio, lowest AIC and SIC, no heteroscedasticity and no autocorrelation under generalised error distribution (GED) construct.

RESULTS AND DISCUSSION

Distributional properties of the daily returns on NEPSE index series

Table 1 shows the distributional properties of the daily returns on NEPSE return series over the study period using descriptive statistics. The mean return on daily NEPSE index series over the study period is positive 0.0014, which implies that daily NEPSE index series has increased over the study period.

Table 1: Descriptive statistics of daily returns on NEPSE index series, March 3, 2022-February 27, 2022

Mean	0.0014	Kurtosis	4.8091
Median	0.0011	Jarque-Bera	57.1528
S.D.	0.0177	p-value	0.0000
Skewness	-0.0133	N	419

The daily return on NEPSE index series has negative value of skewness, which implies that the returns data are negatively skewed and have flatter tail to the left of distribution. Negative skewness contained on the data indicates that it does not follow normal distribution. Moreover, the value of kurtosis is greater than 3, which indicates that the distribution is leptokurtic. Kurtosis greater than 3 indicates that there are high probabilities of extremely large and small returns. The Jarque-Bera (JB) test statistic for normality is significant at 1 percent level. It implies that daily returns on NEPSE index are not normally distributed.

Results of volatility clustering

Since the level series of daily NEPSE index over the study period is not stationary, the daily returns on NEPSE index series have been generated using natural logarithmic transformation. The plot of daily returns on NEPSE index in *Figure 1* shows a pure shape of volatility clustering. It implies that larger changes in returns on daily NEPSE index are followed by further larger changes and smaller changes in returns are followed by further smaller changes. This evidences that small volatilities are clustering together and large volatilities are also clustering together. Particularly, this shows that the variance of daily return series changes over time but varies around the constant mean. Thus, there exists a clear time varying volatility of daily return series on NEPSE index.

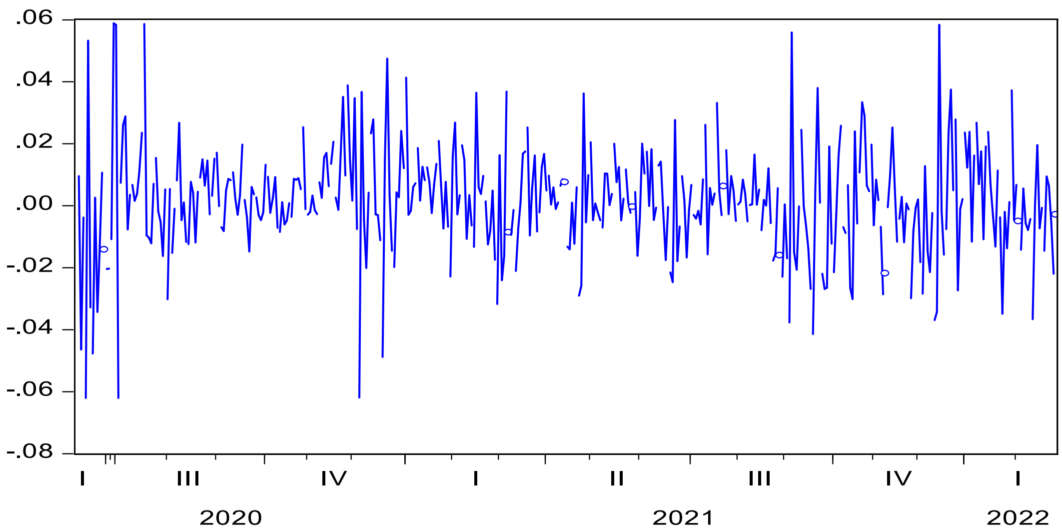

Figure 2: Volatility clustering of daily returns on NEPSE index, March 3, 2022-February 27, 2022

Results of unit root test

The stationarity in daily return series has been confirmed by unit root test such as ADF and PP tests. Table 2 shows the results of unit root tests.

Table 2: Results of unit root test of daily returns on NEPSE index series

		ADF Test	PP Test
t-Statistic		-11.193*	-19.357*
Test critical values:	1% level	-3.446	
	5% level	-2.868	
	10% level	-2.570	

Note: '' sign indicates that results are significant at 1% level.*

As reported in Table 2, both ADF and PP test statistics are significant at 1 percent level. Therefore, test results show that daily NEPSE return series is stationary.

Results of ARCH effects Test

Before running the GARCH family models, it is necessary to confirm the presence of ARCH effects. So, Table 3 reports the results of ARCH- LM test.

Table 3: The result of ARCH - LM test on residuals

F-statistic	36.017	Prob. F(1,415)	0.000
Obs*R-squared	33.301	Prob. Chi-Square(1)	0.000

The ARCH – LM test statistic (33.301) is significant at 1 percent level. It implies that there is the presence of ARCH effect. Hence it provides sufficient reason for applying GARCH models as daily stock returns in Nepal exhibit the presence of conditional volatility over the study period.

Results of symmetric and asymmetric GARCH models

Table 4 shows the estimated results of GARCH family models, namely GARCH (1,1), GARCH-M (1,1), TGARCH (1,1) and EGARCH (1.1) models. As the results indicate, the GARCH model parameters across all specifications of GARCH family models are statistically significant. Particularly, the constant (α), the coefficients of ARCH terms (β) and the coefficients of GARCH terms (θ) are all significant at least at 5 percent level. The results of conditional variance equation reported in Panel B of Table 4 indicate that coefficients of GARCH terms (θ) are considerably larger than the coefficients of ARCH terms (β) across all the specifications. It implies that daily returns on NEPSE index have a long memory than one period and volatility to daily stock returns is more sensitive to the lagged values of stock returns than to the surprises and innovations in the market. These findings clearly establish the presence of time varying conditional volatility of daily returns on NEPSE index over the study period. The result also indicates that the persistence of volatility shocks, as represented by the sum of the coefficients of ARCH and GARCH terms ($\beta + \theta$), is large. The sum of these coefficients, except in EGARCH (1,1) model, is less than but nearer to 1. It implies that the effect of today's shock will remain in the forecasts of variance for many periods to come in the future. This finding is consistent to the hypothesis that daily stock returns in Nepal demonstrate the volatility persistence.

Table 4: Estimated results of symmetric and asymmetric GARCH Models

	GARCH (1,1)	GARCH-M (1,1)	TGARCH (1,1)	EGARCH (1,1)
Panel A: Mean Equation				
Constant (Mean,μ)	0.0020*	0.0030*	0.0016**	0.0016**
Risk Premium (δ)	-	-4.5602	-	-
Panel B: Variance Equation				
Constant (α)	1.19E-05**	1.25E-05**	1.38E-05**	-0.8539*
ARCH Effect (β)	0.1483*	0.1517*	0.0708**	0.3025*
GARCH Effect (θ)	0.8092*	0.8040*	0.8021*	0.9256*
Leverage Effect (γ)	-	-	0.1598**	-0.0937**
$\beta + \theta$	0.9575	0.9557	0.8729	1.2281
Adj. R^2	0.0536	0.0357	0.0521	0.0317
Log Likelihood	1147.53	1146.11	1149.26	1147.98
AIC	-5.4523	-5.4500	-5.4654	-5.4592
SIC	-5.3944	-5.3827	-5.3978	-5.3916
LM test statistic	0.0665 (0.797)	0.0794 (0.778)	0.2058 (0.650)	0.0345 (0.853)
LB $Q^2(36)$	30.819 (0.713)	31.747 (0.671)	37.431 (0.403)	40.589 (0.275)

Note.'' sign indicates that results are significant at 1% level and '**' sign indicates that results are significant at 5% level. p-value are in parentheses.*

The estimated results of GARCH-M (1, 1) model, in mean equation indicate that the coefficients of conditional variance (δ) is not significant. It implies that there is no significant impact of volatility on expected return and there is lack of risk-return trade-off over the period. The estimated results of GARCH-M (1,1) model suggest that the risk premium is not significant to hold the risky stocks. This finding suggests that daily stock returns in Nepal do not offer significant risk premium to hedge against the level of risk associated with investment.

In TGARCH (1, 1) estimates, the coefficient of leverage effect (γ) is positive and significant at 5 percent level. It indicates that there is significant leverage effect meaning that negative shocks have larger effects than positive shocks on the conditional variance. Similarly, in EGARCH (1, 1) estimates, the leverage coefficients (γ) across all the specifications are negative and significant implying that there is negative correlation between past returns and future returns with significant leverage effect. Moreover, in EGARCH (1,1) models, the sum of ARCH and GARCH coefficient ($\beta + \theta$) is greater than 1 and is significant at 1 percent level. It shows the explosive nature of conditional variance.

Table 4 also shows the result of residual diagnostic check. The ARCH-LM test for heteroscedasticity indicates that residuals of all the estimated models are homoscedastic. Similarly, Ljung-Box Q-statistic of standardized squared residuals ($LB\ Q^2$) for serial correlation reveals no any problem of serial correlation in residuals up to 36 lags. Finally, the best fitted models among symmetric GARCH (1, 1) and GARCH-M (1,1) models and asymmetric TGARCH (1,1) and EGARCH (1,1) models are selected based on log likelihood, AIC and SIC criteria. Among these models estimated in *Table 4*, the symmetric GARCH (1, 1) model and asymmetric TGARCG (1,1) model have the highest log likelihood, and the lowest AIC and SIC among their respective counterpart models. So, the result of GARCH (1,1) model explains best the time varying volatility associated with daily returns on NEPSE index over the study period. Though, both the asymmetric models capture the leverage effect, on the basis of log likelihood, AIC and SIC criteria, TGARCH (1,1) model fits best to capture the leverage effects. Overall, the results support the hypothesis that there is significant leverage effect on the conditional volatility of daily stock returns in Nepal, and symmetric GARCH (1, 1) and asymmetric TGARCH (1,1) models fit the best to capture the properties of time varying conditional volatility of daily returns on NEPSE index series over the study period.

This study's findings associated with the presence of time varying conditional volatility and the volatility persistence of daily stock returns are consistent to Akgiray (1989), Pagan and Schwert (1990), Alberola (2007), and Rana (2020), among others. With respect to the presence of leverage effects, the study results confirm to the findings of Pagan and Schwert (1990), Kaur (2004), Miron and Tudor (2010), Hasan and Hady (2014), and Boako, Agyemang-Badu, and Frimpong (2015), among others. In contradiction with Rana (2020), the result of this study gives new evidence of containing leverage effects specially during Covid-19 period in case of Nepal.

CONCLUSION AND IMPLICATION

This study scrutinized the properties of daily stock returns volatility in Nepal during COVID-19 period from March 3, 2020 to February 27, 2022. The study examined several

GARCH family models using Generalized Error Distribution (GED) specification. The results of symmetric GARCH models detect the presence of persistent volatility in daily returns on NEPSE series over the study period. This implies that the observed current shocks in daily returns of NEPSE index series exist longer in the variance forecasts for future periods as well. The estimated results for GARCH-M (1, 1) models showed that the stock returns in Nepal offer no significant risk premium to hedge against holding risky stocks. The study also demonstrated that asymmetric TGARCH (1, 1) model captures the leverage effects on the volatility. It implies that unfavorable news affects significantly on the volatility of daily stock returns than the equivalent favorable news. Finally, study results showed that GARCH (1, 1) and TGARCH (1,1) models are the best fitted symmetric and asymmetric models respectively to capture the volatility persistence and leverage effects on conditional time varying volatility of daily returns on NEPSE index series over the sampled period.

The basic implication of this study's findings is that it suggests a new intuition in understanding the volatility pattern of daily stock returns in Nepal for the most recent Covid-19 period. This study offers a good model to forecast volatility in the stock returns in the context of Nepal over the study period. It serves as the starting point for risk assessment and also contributes for pricing and risk management of investment in stocks in stock market of Nepal. This provides an opportunity for investors to formulate sound investment strategy to address the risk pattern of investing in stock market of Nepal thereby maintaining a proper risk-return trade-off.

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