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Predicting NEPSE Index: An ARIMA-Based Model

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Abstract

Purpose: *This research aims to employ the Auto Regressive Integrated Moving Average (ARIMA) approach to forecast the Nepal Stock Exchange (NEPSE) index.*

Methods: *Daily univariate time series data were taken from the NEPSE website and other sources for 27 years for a total 6143 daily time series data starting in 1997. The presence of unit roots was identified through an Augmented Dickey-Fuller (ADF) test, which ensures stationarity in data. Thereafter, estimation and evaluation of AR (autoregressive), MA (moving average), and ARIMA models were carried out.*

Results: *The study reveals that the ARIMA (2,1,1) model is well fitted in predicting the NEPSE index, indicating its ability to capture temporal dependence and trends that exist within the data.*

Conclusion: *It concludes the temporal dynamics of series highlighting both the short-term impacts of past shocks and longer-term adjustment towards equilibrium. The research work supports the efficacy of model in capturing and predicting the behaviour of NEPSE index, thereby adding in informed decision making and future projections based on proposed statistical foundations.*

Keywords: NEPSE, ARIMA, time series, financial forecasting

I. Introduction

The securities market in Nepal traces its origins to 1937, when Biratnagar Jute Mills Ltd. and Nepal Bank Ltd. became the first entities to issue shares. A pivotal moment occurred in 1964 with the enactment of the Companies Act, which laid the foundation for the issuance of the first government bond. Further development of the financial markets was facilitated by the establishment of the Securities Exchange Centre Ltd. in 1976, marking a significant milestone in the evolution of Nepal's securities market (Nepal Stock Exchange, 2024).

NEPSE commenced its trading operations on January 13, 1994, marking a significant

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advancement in the development of capital market of Nepal. The stock market in Nepal is now seeing modest improvement. In comparison, numerous favorable developments are evident in the current stock market. At that time, share trading was notably challenging and troubled with difficulties. The lengthy queues for IPO subscriptions, the necessity of visiting broking offices for share transactions, and the trips to banks for monetary transfers have rendered trading and investing in the stock market unwieldly, hence diminishing interest among prospective investors and traders.

As of now, there are 6.2867 million DMAT account holders and 5.33728 million Meroshare users (My Republica, 2024). These individuals possess significant nervousness over the capital markets and its fluctuations. The capital market index reflects several socio-economic elements of the economy, resulting in trends and seasonality in its movement. There may be potential inefficiencies in the market. This study purposes to develop, assess, and compare the forecasting capabilities of several ARIMA models for Nepal's Stock Market (NEPSE) index. This study aims to determine the optimal univariate model for forecasting the NEPSE index in the Nepalese capital market.

Predictive modelling in financial market

Predictive models are imperative in financial markets for decision-making, risk management, and better investment strategies (Neri, 2012). Using historical data combined with powerful algorithms, their predictive models can accurately predict shifts in the market dynamics (Kim, 2003). Analysts and investors use these models to predict the behavior of stock prices, interest rates, and currency rates, among other asset prices. In addition, predictive modeling helps to inform strategic portfolio management based on the optimal distribution of assets in order to achieve specific risk-return profiles in different economic conditions (Cavanillas et al., 2016). If changes in price are predictable, this predictive modeling allows financial professionals to accept uncertainty and rapidly take advantage of changes in their many forms while protecting their assets in a dynamic and modern market.

ARIMA models are particularly suitable for analyzing time series data that display temporal dependencies and patterns, which are often found in financial markets (Seddik et al., 2023). The NEPSE Index, like other stock market indexes, exhibits patterns that are impacted by historical values and external influences over a period. ARIMA models excel in capturing these autocorrelations and integrating them into predictions, therefore offering valuable insights into future price fluctuations and market dynamics (Huang, 2024). ARIMA models are very beneficial in financial time series research because they can effectively capture both short-term and long-term relationships (Bandara et al., 2020).

ARIMA models provide a strong foundation for modeling the NEPSE Index by accurately capturing the temporal relationships, trends, and volatility that are inherent in financial time series data (Simpson, 2018). Due to their adaptability and capacity to respond to different market situations, they are highly favored for predicting and assessing stock market indices such as the NEPSE. This, in turn, helps in making strategic decisions and managing risks in the context of the Nepalese financial market.

Nevertheless, little effort has focused on the scientific study and forecasting of indexes of the stock market and corporate valuations, particularly within the context of Nepal. Consequently, it is imperative to develop and evaluate scientific models and instruments to anticipate and forecast stock market indices and corporate valuations. The primary issues in the Nepal stock market are inadequate information and the absence of validated forecasting algorithms.

This research seeks to identify an appropriate univariate forecasting model to evaluate the autoregressive integrated moving average of the NEPSE index. This would assist in predicting the daily index value of the Nepali stock market. The current project is expected to yield tested and validated predictive models, which will benefit the Nepali stock market and its stakeholders. The study's findings will serve as a reference for developing investment and trading methods, particularly for investors. Furthermore, empirical study would contribute to the body of literature in financial economics broadly and specifically to the capital market of Nepal.

The research paper is substantially based on the secondary data. The researcher tried to cover the census; however, only the data from 1997 AD were found in public sources, though the NEPSE started its trading in 1994 AD. The time series data should be in an equal interval. However, the NEPSE trading floor opens only 5 days a week and remains closed on public holidays. So, the data are not in an equal interval.

The research paper is substantially based on the secondary data. The researcher tried to cover the census; however, only the data from 1997 AD were found in public sources, though the NEPSE started its trading in 1994 AD. The time series data should be in an equal interval. However, the NEPSE trading floor opens only 5 days a week and remains closed on public holidays. So, the data are not in an equal interval. This paper has used only the NEPSE index for preparing the model; application of the fitted model for the individual company analysis is not suggested to the investors.

II. Reviews

A stock index quantifies the worth of a specific stock market (Kevin, 2024). It is derived from the price of the publicly traded shares. The weighted average approach is typically employed to construct the index of a specific exchange. An index is a mathematical construct that cannot be directly created (Wong et al., 2020). Mutual funds and specialised financial institutions endeavour to replicate stock indexes to create specialised investment vehicles, such index funds (IFs) and exchange-traded funds (ETFs) (Gaire, 2017). Nonetheless, these funds and investment vehicles cannot be evaluated in relation to the broader market. A stock index serves as a metric that delineates market performance, utilised by investors and financial managers for estimate and forecasting objectives (Fama, 1991). It is utilised to evaluate the performance of individual stocks in relation to the market's performance. From a macroeconomic perspective, stock indices serve as a barometer for assessing the overall economic performance (Levine & Zervos, 1998).

Theoretical Linkage

In an efficient market, prices do not retain any past information and hence do not provide any chances for investors to earn higher returns than what is commensurate with the amount of risk involved (Fama, 1970). The existence of long memory in a series defies the principles of the Efficient Market Hypothesis (EMH) and suggests that a market is inefficient. In a market with inefficiencies and long memory features, prices are influenced by previous values, allowing for the prediction of returns and the potential for generating excess returns.

Empirical Review

Time series methodologies have become the leading approach for short- and medium-term forecasting in practice (Box & Jenkins, 1976). The Auto-Regressive Integrated Moving Average (ARIMA) models have been applied in stock markets to model and predict daily index values and stock prices with favorable results. Adebiyi et al. (2014) developed a comprehensive methodology for constructing a predictive stock price model using the ARIMA framework. Their model utilized data from the New York Stock Exchange (NYSE) and the Nigerian Stock Exchange (NSE), demonstrating that the ARIMA model holds significant potential for predicting short-term fluctuations in stock prices.

Preliminary data obtained using the optimal ARIMA model suggest that stock prices can be forecasted with a satisfactory level of accuracy, providing valuable guidance for stock market investors in making profitable decisions. Hou and Li (2015) applied the GARCH model using high-frequency data from the China Shanghai Stock Index (CSI 300), revealing a unidirectional volatility transfer from CSI 300 index futures to spot returns. Their findings further indicate that the index futures market leads the spot market, offering new insights into the informational efficiency of the CSI 300 index futures market compared to previous studies.

Various studies utilizing different sampling intervals, asset classes, and performance evaluation criteria have demonstrated that the ARIMA model exhibits superior predictive performance in the stock market. The model's high parameterization allows it to effectively capture elements of volatility (Hou & Li, 2015). However, while a better in-sample fit is often achieved, this does not necessarily translate into improved out-of-sample predictive performance, where simpler models may outperform more complex ones.

Jarrett and Kyper (2011), in their study of the Japanese Stock Market Index, demonstrated the importance of classifying time series elements as either permanent or transitory, essential for long-term financial modeling. They highlighted the role of intervention analysis in understanding the dynamics of economic instability and price fluctuations. Jarrett (2017) applied ARIMA intervention analysis to model the Chinese stock market price index, discovering autoregressive patterns in daily stock prices.

In 2013, Darçın and Aslam investigated the influence of macroeconomic factors on stock market indices in Pakistan, including the real effective exchange rate, consumer price index, per capita income, and interest rate. Their findings, using NLS and ARMA techniques, showed that the discount rate and inflation negatively impact the Karachi stock market index, while the real exchange rate and per capita income have positive effects. The discount rate was identified as the most influential factor on the stock index, underscoring the importance of effective macroeconomic management in boosting stock market performance (Kavkler&Festić, 2011).

G.C. (2008) examined daily return volatility in the Nepalese stock market from 2003 to 2009, using the GARCH (1,1) model due to the condition of variable variance. The study found that daily returns in the Nepal stock market exhibited lexical anomalies and significant temporal dependency. A range of models, including the random walk, non-linear GARCH (1,1), and three asymmetric models (GJR, EGARCH, and PARCH), were employed to highlight the constrained volatility of the NEPSE series, demonstrating the presence of stylized characteristics such as variability subgroups and time-varying variance.

Maskey (2022) conducted analytical research using ARIMA for stock index prediction, concluding that the ARIMA model holds significant promise for forecasting short-term market fluctuations, particularly for the NEPSE index, where historical values and stochastic errors play a critical role. Econometric models such as ARIMA have also been used to forecast stock fluctuations in other exchanges, including the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), demonstrating their efficacy for short-term profit forecasting and portfolio strategy development (Dadhich et al., 2022).

Zhao (2021) proposed that linear SVM and XGBoost models are highly effective in predicting stock market movements in Nepal, while Alotaibi (2022) supported the proficiency of the ARIMA model for forecasting stock market trends. Khanderwal and Mohanty (2021) argued that ARIMA models perform competitively against other forecasting methods, making them suitable for further evaluation in trading.

Overall, the literature reflects a growing body of research on the Nepalese stock market, where a variety of financial and statistical techniques have been employed to assess stock performance and pricing. Many scholars emphasize the critical role of a robust stock market in driving economic growth, highlighting the positive correlation between stock market development and national economic progress.

III. Research Methodology

Research Design

To achieve the objectives set for this investigation, an analytical study design was selected. This approach allows for a more structured and systematic process of gathering, analyzing, and interpreting secondary data relevant to the research. By employing this design, the study aims to ensure that conclusions drawn are both accurate and reliable. The analytical framework facilitates a comprehensive examination of the data, enabling a clearer understanding of patterns and trends, while also supporting the development of informed insights that align with the research goals. This method enhances the robustness of the findings and contributes to a more precise interpretation of the secondary data sources used in the study.

Data

The study focuses on Nepal's secondary market and aims to model the daily NEPSE index to analyze historical trends and forecast future movements. A total of 6,143 time series data points were collected, representing the daily final statistics of the NEPSE index from July 20, 1997, to March 4, 2024. The data was sourced from various annual and monthly reports published by the Nepal Stock Exchange Ltd. (NEPSE). By utilizing this extensive dataset, the study seeks to provide valuable insights into the historical behavior of the NEPSE index and its potential future performance, offering a solid foundation for predictive modeling.

Forecasting technique

The present study depends on time series data; it is essential to ascertain the stationarity of a series before employing it in a model. A series is deemed stationary when its mean and auto-covariance are invariant over time (Metzler et al., 2014). A series that exhibits non-stationarity is identified by the existence of a unit root problem (Nelson &Plosser, 1982). A unit root is a property of time-dependent processes that can complicate statistical inference in time series models (Lindgren et al., 2011).

Unit Root Test

Shiller (2003) and Bernardi et al. (2020) observed that many economic and financial time series exhibit trending behaviors or are classified as non-stationary in terms of their mean. Reinhart and Rogoff (2008) highlighted that this non-stationarity applies not only to macroeconomic aggregates such as real GDP but also to asset prices like stocks, gold, and exchange rates. One of the primary challenges in econometrics is accurately identifying the appropriate form of trend within the data. As De Oliveira and Oliveira (2018) noted, for effective modeling using Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) methods, it is essential to first convert the data into a stationary form. This transformation ensures that the time series is suitable for analysis.

The unit root test serves as a formal statistical method to determine whether a time series is stationary or non-stationary. Dickey and Fuller (1979) provided a comprehensive framework for unit root testing, offering a widely accepted approach for assessing stationarity. This procedure has since become a fundamental tool in time series analysis, as it allows researchers to identify the presence of a unit root and apply appropriate transformations, such as differencing, to make the series stationary. Without addressing the issue of non-stationarity, the reliability and validity of forecasting models like ARMA and ARIMA would be compromised.

$$Y_t = \phi Y_{t-1} + \theta X_t + \varepsilon_t$$

Where x_t is an optional exogenous regressor, which may consist of a constant or a constant and trend, ϕ and θ are parameters to be estimated, and εt is assumed to be white noise.

A series is a non-stationary series if ϕ >= 1, and the variance of y increases with time and approaches infinity. Series Y has a (trend) stationary process if ϕ <1. Thus, the hypothesis of (trend) stationarity can be evaluated by testing whether the absolute value of is strictly less than one or not.

Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average, ARIMA, is often referred to as the Box-Jenkins technique. Box and Jenkins asserted that non-stationary data may be transformed into a stationary form by applying differencing to the series, Y_t. The mathematical representation for Y_t is expressed as,

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} \ldots\ldots\ldots \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots\ldots\ldots + \theta_q \epsilon_{t-q} + \epsilon_t$$

The value of Y_t is obtained by taking the difference of the time series. The parameters ϕ and θ are unknown, and the error terms ϵ are independent and identically distributed with a mean of zero. Y_t is represented as a function of its previous values and the current and previous values of error terms.

The ARIMA model integrates three fundamental methodologies:

- Auto Regression (AR) is a statistical model that represents the relationship between a variable and its past values. Auto-regression involves regressing the values of time series data on their own lagged values, denoted by the "p" value in the ARIMA model. An autoregressive (AR) model is mathematically represented as:
- Differencing (I for Integrated): This process entails differencing the time series data to eliminate the trend and transform a non-stationary time series into a stationary one. The "d" number in the ARIMA model signifies this. If d = 1, it examines the difference between two time series entries; if d = 2, it analyses the differences of the differences acquired at d = 1, and so on.
- Moving Average (MA): The moving average nature of the ARIMA model is represented by the "q" value, which is the number of lagged values of the error term.

This model is called Autoregressive Integrated Moving Average or ARIMA(p,d,q) of Y_t. A basic non-seasonal ARIMA model is identified as an ARIMA (p, d, q) model.

Where:

- p is the number of autoregressive (AR) term
- d is the number of non-seasonal differences (Trend Difference) needed for making the series stationary, and
- q is the number of lagged forecast errors in the prediction equation (MA) term

IV. Results and Discussions

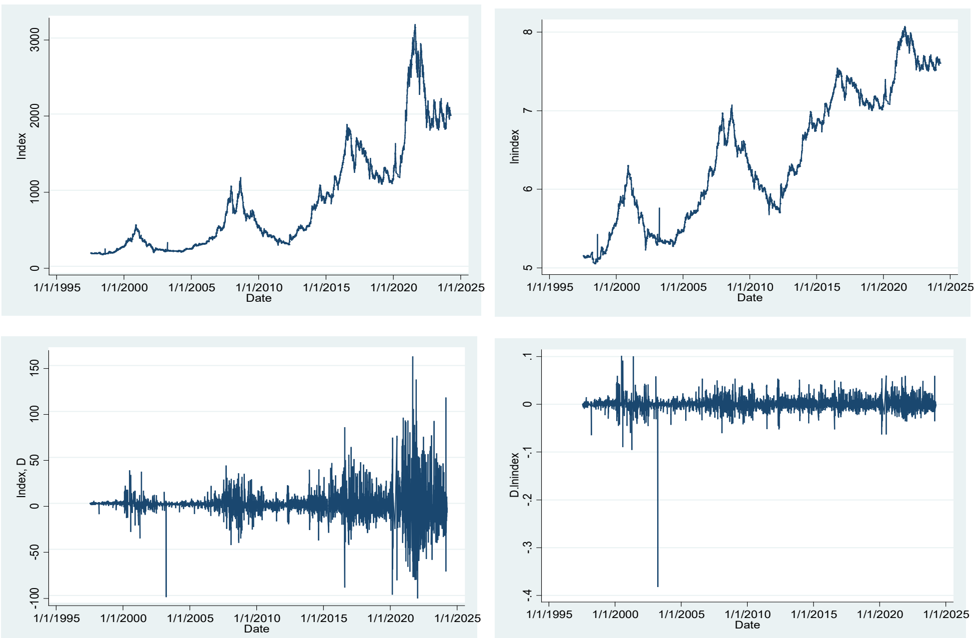
The objective of this chapter is to estimate univariate ARIMA models for numerical forecasting based on historical behavior. Specifically, the aim is to identify the self-healing, seasonal, and cyclical components of the NEPSE index. By applying ARIMA modeling techniques, this chapter seeks to uncover the underlying patterns within the data, allowing for a more precise understanding of the index's trends and fluctuations. This approach will help in predicting future movements in the NEPSE index, providing valuable insights into its inherent dynamics over time.

Test of Stationarity

The fundamental premise of the ARIMA model is the stationarity of the data. To assess the stationarity of the data, the absolute index is graphed in the time series, indicating non-stationarity. Additionally, the index is represented on a logarithmic scale, which illustrates the trend in the chart.

Figure 1

Daily Closing Index and Log of Index (y-axis) with First Difference of the Series Studied Versus Time in Working Days (x-axis), Starting from July-20, 1997, to May 12,2022.



From figure no. 1, it is possible to understand the behavior of the prices of the time series daily collected during the period. The index shows the pattern in the figure. Which means the data are not stationary. So, to make the data stationary, the log of index was plotted in the figure, which also depicted the non-stationary pattern in the figure. But after taking the first difference, both absolute index and log index show the variance around zero, which means data are stationary at the first difference.

Figure 2

Autocorrelation for Absolute Index, lnindex, Index(1) and Logindex(1)

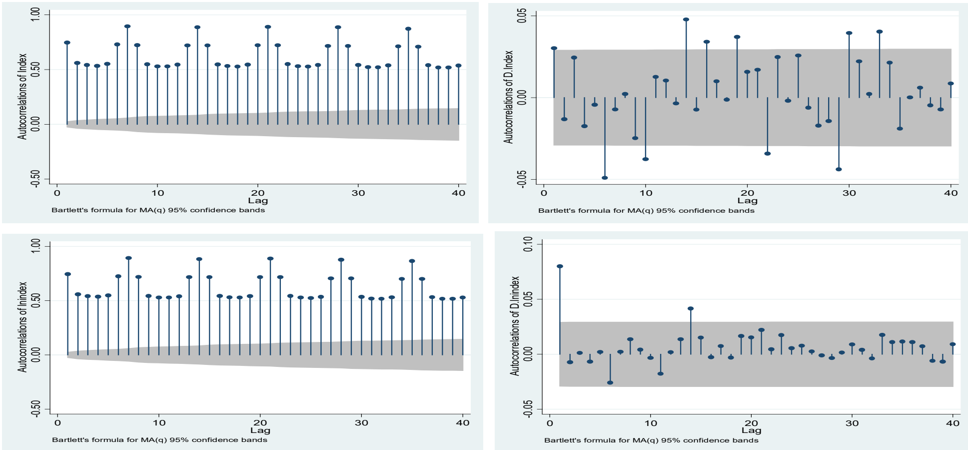


Figure 2 demonstrates the plot of the autocorrelation function (ACF), and Figure No. 3 shows the plot of the partial autocorrelation function (PACF). From the figures, the absolute index and logindex show the autocorrelation. However, while taking the first difference, both dindex and dlnindex show stationary in the figure. But dlnindex seems more accurate in the picture. This result is also confirmed with the statistical tools. Augmented Dickey Fuller (ADF) test.

Figure 3

Partial Autocorrelation for Absolute Index, Logindex, Index(1) and Logindex(1)

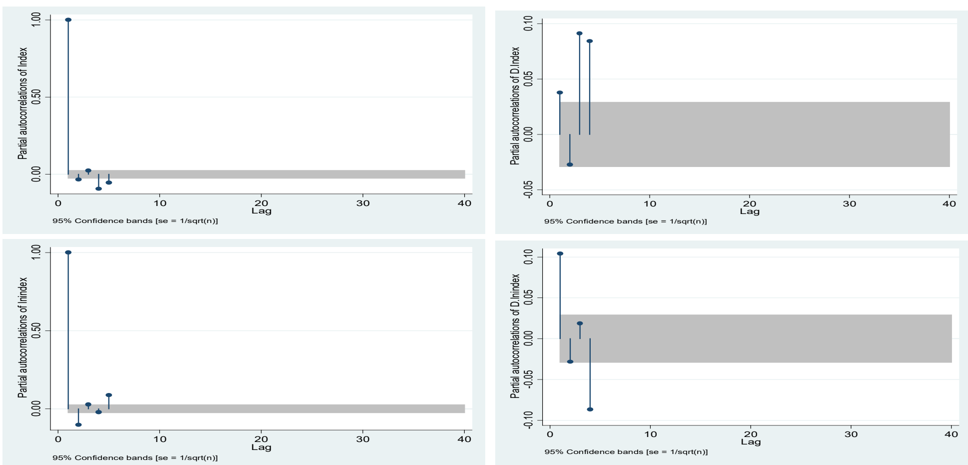


Table 1

Result of Augmented Dickey Fuller Test (ADF) of NEPSE index

Predictor Variables	Coefficient	Std. Error	t	p-value	95% Confidence Interval
Li	-0.005	0.005	-0.95	0.363	-0.0166, 0.0066
Lb	-0.175	0.149	1.18	0.262	-0.1491, 0.4994
L2D	-0.099	0.202	-0.49	0.635	-0.5393, 0.3422
L3D	-0.171	0.216	0.79	0.445	-0.3006, 0.6419
L4D	-0.054	0.189	0.28	0.781	-0.3581, 0.4656
Constant	-0.526	7.821	0.07	0.947	-16.5139, 17.5662

Note. Z(t) statistic = -0.946, p-value = 0.1814.

Critical Values: 1% = -2.681, 5% = -1.782, 10% = -1.356.

Table 1 presents the result of ADF test of time series NEPSE index. The test results suggest that the time series is non-stationary. The test statistic value of -0.946 is not sufficiently negative to reject the null hypothesis of a unit root, as it is higher than the critical values at the 1%, 5%, and 10% significance levels (-2.681, -1.782, and -1.356, respectively). Additionally, the p-value of 0.1814 is above the common significance threshold of 0.05, indicating that there is not enough evidence to reject the null hypothesis of a unit root. Therefore, we conclude that the series likely has a unit root and is non-stationary.

Table 2

Result of Augmented Dickey Fuller Test (ADF) of NEPSE lnindex

Predictor Variables	Coefficient	Std. Error	t	p-value	95% Confidence Interval
L1	-0.001	0.0004	-2.35	0.019	-0.00187, -0.00017
LD	0.0739	0.0331	2.23	0.026	0.00889, 0.13887
L2D	-0.0722	0.0324	-2.23	0.026	-0.1359, -0.00854
L3D	0.0210	0.0207	1.01	0.311	-0.01966, 0.06166
Constant	0.00785	0.0028	2.80	0.005	0.00235, 0.01336

Note. Z(t) statistic = -2.350, p-value = 0.0095. *Critical Values: 1% = -2.330, 5% = -1.647, 10% = -1.282.*

The above table 2 illustrates ADF test results of the log of the NEPSE index (lnindex), which indicate that the time series is stationary. The test statistic value of -2.350 is more negative than the critical values at the 1%, 5%, and 10% significance levels (-2.330, -1.647, and -1.282, respectively). This indicates that we can reject the null hypothesis of a unit root. Additionally, the p-value of 0.0095 is below the significance threshold of 0.05, further confirming that the series does not have a unit root and is stationary. Hence, it is concluded that the time series of the NEPSE index is stationary while taking log value and 3 lags.

ARIMA Parameters

The ARIMA model treats each component as a parameter and employs a standard notation for its operation. When referring to ARIMA models, the standard nomenclature is ARIMA (p, d, q), where p, d, and q are integer values that represent the parameters that indicate the type of ARIMA model that is being utilised. The parameters can be stated in a specific manner as follows:

p: the quantity of lag observations used in the model; often referred to as the lag order. The Partial Autocorrelation Function (PACF) indicates that the value of p is equal to 1 and 4 as seen in Figure 3.

d: is the number of times the raw observations are differenced, which is sometimes referred to as the degree of differencing. Since the data becomes steady after taking the first difference, we assign a value of 1 to 'd' based on the stationarity test of lnindex.

q: The value of q is obtained by analyzing the Autocorrelation Function (ACF) plot, which indicates a value of 1.

So possible ARIMA (p,d,q) are ARIMA (1,1,1), ARIMA (4,1,1). However, doing multiple iteration is it found ARIMA (2,1,1) is more significant, and results are presented below.

Table 3

Results of ARIMA (2,1,1)

Predictor Variables (D.lnindex)	Coefficient	Std. Error	z	p-value	95% Confidence Interval
Constant (lnindex)	-0.0006184	0.0002277	2.72	0.007	[0.000172, 0.0010648]
ARMA					
AR (L1)	-0.607577	0.173864	-3.49	0.000	[-0.94834, -0.26681]
AR(L2)	-0.065326	0.0305272	2.14	0.032	[0.005493, 0.125158]
MA(L1)	0.749589	0.1737625	4.31	0.000	[0.409021, 1.090157]
/sigma	-0.012808	0.0000249	513.62	0.000	[-0.012759, -0.012857]

Note: ARIMA regression with sample size = 4560, Wald $\chi^2(3) = 323.57$, $p < 0.001$. Log-likelihood = 13,383.34, Sample Range: 7/21/1997 to 4/3/2024

Log-likelihood: The log-likelihood component of the ARIMA model should be high, like in the present case. The value of log-likelihood is 13383.34. This is sufficiently high. Comparing with other ARIMA models ARIMA (2,1,1) gives higher log-likelihood so, this model is selected.

Coefficient of AR (p): AR(1): The first lag of the autoregressive term has a significant negative effect, suggesting that an increase in the previous value is associated with a decrease in the current value. Similarly, AR(2), the second lag of the autoregressive term has a significant positive effect, suggesting that an increase in the value from two periods ago is associated with an increase in the current value.

Coefficient of MA(q): The first lag of the moving average term has a significant positive effect, indicating that past shocks have a direct positive effect on the current value.

Forecasted model

$$Y_t = 0.0006184 - 0.607577Y_{t-1} + 0.0653256Y_{t-2} + 0.7495889\epsilon_{t-1} + \epsilon_t$$

The application of ARIMA models has proven effective in capturing and forecasting the daily NEPSE index, which exhibits self-healing and cyclical (moving average) characteristics. In this study, the univariate AR (2), I (1), and MA (1) model—commonly referred to as ARIMA (2, 1, 1)—emerged as a strong candidate for accurately predicting daily movements in the NEPSE index. The ARIMA (2, 1, 1) model's structure allows it to account for both the autoregressive and moving average components, making it a robust tool for forecasting the index's short-term fluctuations.

Maskey (2022) identified the ARIMA (0, 1, 1) model as the most suitable for predicting short-term changes in the NEPSE index, concluding that the ARIMA framework efficiently captures the impact of past values and random errors on daily index movements. These findings align with the results of Dadhich et al. (2022), Hou and Li (2015), and Jarrett and Kyper (2011), who also highlighted the efficacy of ARIMA models in forecasting stock market indices across various contexts.

A key takeaway from this research is the significance of the ARIMA model in establishing a relationship between the current NEPSE index and its historical values. The results demonstrate a statistically significant relationship between today's NEPSE index and its historical data, reinforcing the model's ability to capture the underlying dynamics of the stock market. This finding underscores the ARIMA model's utility in financial forecasting, particularly for short-term predictions in stock markets like NEPSE, where historical trends and random disturbances play a critical role in shaping daily price movements.

V. Conclusion and Implication

This study studied the attributes and behaviors of the Nepalese stock market. Especially, consider the daily closing stock index of NEPSE. The ARIMA (2, 1, 1) model provides a robust framework for forecasting lnindex, incorporating significant autoregressive and moving average effects observed in the data. The model's coefficients offer insights into the temporal dynamics of the series, highlighting both the short-term impacts of past shocks and the longer-term adjustments towards equilibrium. These findings support the model's efficacy in capturing and predicting the behavior of lnindex, thereby aiding in informed decision-making and future projections based on reliable statistical foundations.

Investment professionals, securities experts, and legislators would all benefit from the approach that has been offered when it comes to projecting the daily NEPSE index and putting into action necessary improvements. The publication makes it clear that the daily NEPSE index will be affected by its historical values and previous random errors. This information is intended to be of particular interest to investors and analysts. Both observable and random factors from the past will have an impact on the value of the NEPSE index in the future. One of the most significant benefits of this study is that it has been able to successfully trade NEPSE-listed stocks. Self-healing, moving averages, and seasonal impacts with specified predictors and related indications are the three components that need to be taken into consideration. In spite of this, it is possible that the valuation of a particular firm will not follow the same path as the NEPSE index.

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