

ARIMA Modeling and Forecasting of National Consumer Price Index in Nepal

¹Omkar Poudel, ²Khom Raj Kharel (Corresponding author), ³Pradeep Acharya, ⁴Daya Simkhada, ⁵Sarad Chandra Kafle

¹ Assistant Professor of Economics, Birendra Multiple Campus, Tribhuvan University, Nepal
[(Email: omkar60475@gmail.com) ORCID: <https://orcid.org/0009-0008-7873-0237>]

²Associate Professor of Economics, Saraswati Multiple Campus, Tribhuvan University, Nepal
[(Email: kharelkhom@yahoo.com) ORCID: <https://orcid.org/0000-0002-9806-7224>]

³Freelance Researcher, MBA, Tribhuvan University, Kathmandu, Nepal
[(Email: pradeep.acharya197@gmail.com) ORCID: <https://orcid.org/0000-0001-8055-8757>]

⁴James Madison University, (Scholar: M. Ed leading PhD, Mathematics Education, USA
[(Email: dayasimkhada@gmail.com) ORCID: <https://orcid.org/0009-0008-7873-0237>]

⁵Assistant Professor of Statistics, Birendra Multiple Campus, Tribhuvan University, Nepal
[(Email: sarad.kafle49@gmail.com) ORCID: <https://orcid.org/0009-0003-6346-2878>]

Received 23 Oct. 2023; Reviewed 12 Nov. 2023; Revised 20 Dec. 2023; Accepted 3 Jan. 2024.

Copyright: Poudel, Kharel, Acharya, Simkhada & Kafle (2024)



This work is licensed under a Creative Commons Attribution-Non Commercial 4.0 International License.

Abstract

This research aims to determine an Auto-Regressive Integrated Moving Average (ARIMA) model and forecasting the National Consumer Price Index (NCPI) in Nepal, using annual data from the fiscal year 1972/73 to 2022/23. The research utilized secondary data collected from the online bulletin published by Nepal Rastra Bank, aiming to enhance understanding of NCPI patterns and contribute to predictive modelling techniques for economic indicators. Adopting the Box-Jenkins technique and using E-Views statistical software, this study identifies ARIMA (1, 2, 8) as the most suitable model for NCPI forecasting. This selection is validated through meticulous diagnostic tests, affirming the appropriateness of the model, as evidenced by residuals exhibiting white noise characteristics. The research findings suggest a rapid increase in the National Consumer Price Index for the coming years. Implications of this research extend to both academic and policy-oriented audiences. A successful ARIMA model development holds significant potential for providing accurate predictions of future price trends in Nepal. This, in turn, can assist policymakers in making informed decisions regarding economic strategies, monetary policies, and inflation control measures. Moreover, the study's outcomes offer a foundational framework for future research endeavours in the domain of economic forecasting and modelling, contributing to the broader field of economic analysis and policy formulation.

Keywords: Box–Jenkins methodology, autocorrelation function, partial autocorrelation function, time series data, Augmented Dickey-Fuller test

JEL Classification: E470, E310

Introduction

Modeling a time series data is crucial to forecast the value for the future. Short run forecast can be done by applying Box-Jenkins technique. However, the random nature of time series values is very hard to understand. The Box-Jenkins technique provides a very good way of forecasting called Auto-Regressive Integrated Moving Average (ARIMA). This technique is considered the best method for short-reforecasts to their flexibility, ability to capture seasonal patterns, and robustness in handling noisy data (Singh et al., 2020). This research utilizes Consumer Price Index data which has a random time series nature. Therefore, ARIMA can be considered a suitable method for modelling and short-run forecasting.

The Consumer Price Index (CPI) is a very important way to look at inflation in a country. According to Landén (2023) and STATISTICS (2023), the CPI shows how prices change for a normal group of goods and services. This gives a clear picture of inflation and how it affects different types of goods and services. To fully grasp how inflation impacts people living in cities (Nguyen et al., 2023; Purba, 2023), this is especially crucial. The NCPI is an important measure in Nepal because it shows the average change in costs and helps with planning the economy (Gupta et al., 2021). It takes into account many economic factors and is affected by both inside and outside factors, such as the Indian Consumer Price Index because Nepal is closely connected to India (Joshi & Acharya, 2019).

The utilization of the Auto-Regressive Integrated Moving Average (ARIMA) model emerges as a valuable statistical tool for the anticipation of random values like Nepal's National Consumer Price Index. With its autoregressive, integrated, and moving average components, this approach facilitates predictions based on historical data and prevailing trends (Wikipedia, 2023; Silva et al., 2021). However, the efficacy of ARIMA in forecasting Nepal's National Consumer Price Index (NCPI) is contingent upon the data quality, economic stability, and the appropriateness of the model configuration (Singh et al., 2020; Yunus et al., 2015). Consequently, these pivotal factors significantly influence the effectiveness of ARIMA modelling in projecting forthcoming price trends and contributing to the formulation of sound economic policies.

The study aims to develop an ARIMA model that optimally fits the observed data series of NCPI of Nepal. By doing so, the research intends to enhance our understanding of the underlying patterns and dynamics within the NCPI, contributing to the advancement of predictive modelling techniques for economic indicators.

Literature Review

In this study, previously available online research studies were searched and reviewed to determine the methodology for the current study and identify research gaps.

Consumer Price Index (CPI)

The Consumer Price Index (CPI) serves as a crucial measure for assessing inflation by tracking the price changes of a standard set of goods and services over time (Landén, 2023). Here, inflation refers to a sustained and significant increase in the overall price level within an economy over the study period. Also, CPI is a valuable resource for anyone who wants to understand the current state of inflation and it provides clear and concise information about changes in prices over time and across different categories of goods and services (STATISTICS, 2023). According to Nguyen et al. (2023), CPI is a vital macroeconomic indicator used to measure inflation and it represents the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. So, this index is key for understanding the economic conditions affecting urban consumers (Purba, 2023). These studies collectively underscore the importance of CPI in economic analysis and policy formulation. The studies have shown that CPI is used as a scale for adjusting wages, and pensions, and as a guide for monetary policy. It serves as an essential tool for the government and policymakers in decision-making processes related to inflation control and economic stability (Cieslak et al., 2021). It is an essential tool for economic planning and policy formulation, continuous evaluation and adaptation of its methodology are necessary to ensure its relevance and accuracy (Graf, 2020).

National Consumer Price Index (NCPI) in Nepal

The National Consumer Price Index NCPI represents the Nepalese Consumer Price Index, which is an important metric for understanding inflation in Nepal (Khatri, 2023). The NCPI remains a fundamental economic indicator in Nepal, providing insights into inflation and cost-of-living changes. Previous studies showed that NCPI in Nepal is an important economic indicator that reflects the average change in prices of a basket of goods and services over time. In the context of the study, the NCPI is used in an econometric model to analyze various economic factors. This model also includes other variables such as broad money supply (M2), budget deficit (BD), real gross domestic product (RGDP), nominal effective exchange rate (NEER), and the Indian Consumer Price Index (ICPI). The study by Shrestha (2023), focusing on the relationship between public debt and economic growth in Nepal offers a significant context to understand the broader economic environment in which the NCPI operates. The NCPI data from the Nepal Rastra Bank is used to reflect current economic conditions in Nepal, crucial for accurately assessing the status (Joshi & Acharya, 2019). External factors such as the Indian Consumer Price Index also play a role due to the close economic ties between Nepal and India (Gupta et al., 2021). The history of Nepal's National Consumer Price Index (NCPI) shows big changes over time and these changes are important for understanding things like how wages are set, making government policies, and controlling inflation (Shrestha, 2023).

ARIMA Modelling in Economic Forecasting

ARIMA modelling in economic forecasting is a statistical technique used for analyzing and predicting time series data where ARIMA stands for Auto-Regressive Integrated Moving Average (Wikipedia, 2023). It combines three key components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR part involves using past data points to predict future ones, the I component includes differentiating the data to achieve stationarity, and the MA aspect uses past forecast errors in the prediction model. This model is particularly effective in applications offering a cost-effective tool for

planning and decision-making (Silva et al., 2021). The components of ARIMA are described as follows:

Autoregressive (AR): This component accounts for the influence of past values of the time series on the current value. It uses a linear regression model to predict the current value based on a set number of past values (p).

Integrated (I): This component deals with non-stationarity in the time series. It uses differencing to eliminate trends and seasonality, transforming the data into a stationary form. The degree of differencing required is denoted by d.

Moving Average (MA): This component incorporates the impact of past random errors (shocks) on the current value. It uses a linear regression model to predict the current value based on a set number of past errors (q).

An ARIMA model is typically denoted as ARIMA (p, d, q) where: p: Order of the autoregressive component (number of past values used), d: Degree of differencing and q: Order of the moving average component (number of past errors used) (Singh et al., 2020). For example, an ARIMA (1, 1, 1) model uses one past value (p=1), one differencing step (d=1), and one past error (q=1). When two out of the three terms are zeros, the model may be referred to as the non-zero parameter, dropping "AR", "I" or "MA" from the acronym describing the model. For example, ARIMA (0,0,1) is AR (1), ARIMA (0, 1, 0) is I (1) and ARIMA (0, 0, 1) is MA (1) (Wikipedia, 2023). This method shows potential for accurately capturing the time correlation and probability distribution which is crucial for reliability and planning (Yunus et al., 2015).

ARIMA Modeling and Forecasting of National Consumer Price Index (NCPI) in Nepal

ARIMA modelling for forecasting the National Consumer Price Index (NCPI) in Nepal is a powerful instrument for deciphering and projecting inflationary patterns (Yunus et al., 2015). Despite its complexity and the need for meticulous consideration of multiple factors, this method plays a crucial role in aiding economic planning and policy development (Silva et al., 2021). The efficacy of the ARIMA model is contingent upon the precision of the data used, the stability of the economic environment, and the correctness in the specification of the model parameters (Singh et al., 2020). Thus the studies show that ARIMA modeling is a key tool in the economic analysis of Nepal, offering valuable insights into future inflation trends through the NCPI. However, the effectiveness of ARIMA models in forecasting the NCPI is contingent on several factors: the quality and timeliness of data, the stability of the economic environment, and the accuracy of model specification (Singh et al., 2020). In essence, ARIMA modelling is an invaluable tool in Nepal's economic analysis, offering insights into future inflation trends via the NCPI, but its success relies on quality data, economic stability, and precise model configuration.

Research Gap

Previous studies have shown that although many research studies in other countries have modeled NCPI, there hasn't been any such model developed for Nepalese data. Therefore, the forecast model of NCPI using an ARIMA method is a novel study for Nepal. To put it simply, ARIMA analysis is a new and unexplored area of study when it comes to Nepalese NCPI data.

Research Methodology

Research Design

The descriptive and analytical method was used in this research, which was designed for a quantitative study (Poudel & Sapkota, 2022). In order to interpret the data, the collected data was analyzed using E-views statistical package version 10.

Nature and Sources of Data

This study used secondary data, specifically time series data, comprising annual datasets of the National Consumer Price Index (NCPI) in Nepal spanning from the fiscal year 1972/73 to 2022/23. Data of this study were derived from the Quarterly Economic Bulletin, a publication by the Nepal Rastra Bank, which is accessible at www.nrb.org.np.

Data Analysis Method

This research is based on the Box–Jenkins technique (Box and Jenkins, 1976) which is a suitable technique for short-run forecasting. To analyse the data E-Views statistical software is used for modeling the data by the mean of Box-Jenkins technique. The ARIMA model is determined for the data which stands for Autoregressive Integrated Moving Average. It is an extension of the ARMA model that includes an additional component called differencing. Differencing is used to make non-stationary time series stationary. Box-Jenkins Methodology has been employed to study the time series nature of the data of national consumer price index of Nepal.

Box and Jenkins developed a four-step method for selecting and estimating ARIMA models: identification, estimation, diagnostic checking and forecasting.

Identification

The identification step involves analyzing the time series data to determine whether it is stationary and to identify the orders of the AR, I, and MA components. The first step in the Box and Jenkins method is to identify the orders of the AR, I, and MA components. This could be done by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series data.

The ACF shows the correlation between the time series and its lagged values. The PACF shows the correlation between the time series and its lagged values after removing the effect of the previous lags. The orders of the AR, I, and MA components can be identified by looking for patterns in the ACF and PACF. For example, if the ACF dies off slowly, then the time series may be non-stationary and require differencing. If the PACF has significant spikes at certain lags, then the AR component may be of a certain order.

A non-seasonal ARIMA model is expressed as $ARIMA(p,d,q)$, where p is the number of autoregressive terms, d is the number of non-seasonal differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation.

Estimation

This step involves estimating the parameters of the ARIMA model. Once the orders of the AR, I, and MA components have been identified, the next step is to estimate the parameters of the ARIMA model. This could be done by applying a variety of statistical methods. Before starting an ARIMA model fit, stationary test is required, for that unit root test is used. Augmented Dickey-Fuller (ADF) test is used for unit root test which helps determine whether the variables satisfy the condition of stationarity (Poudel, 2022, Poudel, 2023). Correlogram could be used to identify patterns in time series data, such as seasonality or trends. Cross-correlation is the correlation between two different variables at different time lags, which could be used to identify relationships between variables, such as lead-lag relationships or causal relationships. Spikes of ACF and PACF help to determine the parameters p and q respectively for an ARIMA model (Kafle & Hooda, 2023).

Diagnostic checking

Once the ARIMA model has been estimated, it is important to check the model to ensure that it is well-fitting and that the residuals are white noise. This could be done by examining the residuals of the model and by performing various statistical tests.

Forecasting

Once the ARIMA model has been estimated and checked, it can be used to forecast future values of the time series. This is done by substituting the estimated parameters into the ARIMA model and predicting for the future.

Subsequently, the ARIMA model is employed to predict the forthcoming values of the National Consumer Price Index (NCPI) in Nepal. The quantity of forecasts generated is contingent upon the preferred forecast horizon. Given that the data originates from the reputable institution of Nepal, namely the Nepal Rastra Bank, the predicted values obtained through the ARIMA model are deemed reliable.

Results and Discussions

Data analysis starts with graphical representation. Model development uses Box-Jenkins technique to develop ARIMA models.

Trend of NCPI

Trend line is used to observe the trend of NCPI change over the time from the fiscal year 1972/73 to 2022/23. The NCPI trend has been increasing since the fiscal year 1972/73 (see Figure 1).

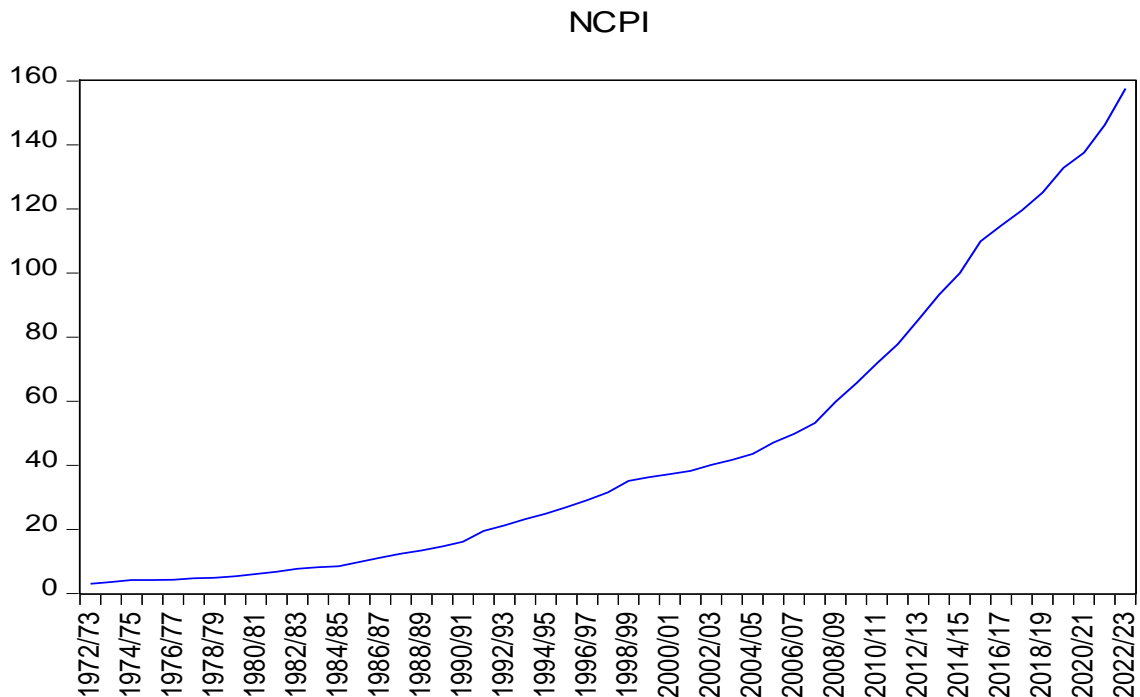


Figure 1: Trend of National Consumer Price Index of Nepal

(Source: Authors calculations performed using E-Views)

The trend analysis of national consumer price index of Nepal from 1972 to 2022 exhibits a presence of trend i.e. increases in national consumer price index of Nepal with time which is an indication of non-stationary time series. In such a series, mean and variance change with respect to time (see Figure 1).

Stationary Test

The ADF test is used to test whether the time series data of NCPI is stationary or not, the results show that the data series of NCPI is stationary on second difference (p-value < 0.05) (see Table 1).

Table 1: Result of ADF Test on NCPI Series

Series	On Level		On First Difference		On Second Difference	
	t-Stat	P-Value	t-Stat	P-Value	t-Stat	P-Value
NCPI	5.109243	1.0000	1.748411	0.9996	-3.230492	0.0254

Source: Authors calculations performed using E-Views

Results of an ADF test for a unit root in the NCPI data series with the null hypothesis of the variable has a unit root that is it is non-stationary, show that NCPI has a unit root at the level and first difference but not at the second difference (P-value < 0.05). This means that the variable is non-stationary at the level and first difference but stationary at the second difference. Hence to find a best ARIMA model we have to difference two times. This shows the value of parameter ‘d’ in ARIMA model is 2 (see Table 1).

Identification of Parameters of ARIMA

The identification step involves the determination of the parameters p, d and q. As the ADF test declared that value of d is one. ACF and PACF help to determine the value of p and q respectively. The ACF and PACF plot along with their p value is plotted (see Table 4).



























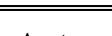
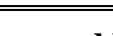

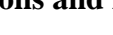


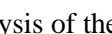
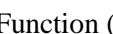

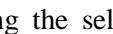
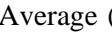
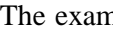
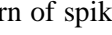
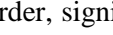
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.337	-0.337	5.9093	0.015
		2	-0.038	-0.171	5.9879	0.050
		3	0.064	-0.010	6.2103	0.102
		4	0.151	0.193	7.4708	0.113
		5	-0.260	-0.150	11.318	0.045
		6	-0.075	-0.245	11.645	0.070
		7	0.279	0.152	16.260	0.023
		8	-0.276	-0.166	20.890	0.007
		9	-0.073	-0.165	21.219	0.012
		10	0.123	-0.004	22.195	0.014
		11	0.046	-0.018	22.334	0.022
		12	-0.140	0.007	23.662	0.023
		13	0.048	-0.025	23.819	0.033
		14	0.147	-0.013	25.370	0.031
		15	-0.073	0.080	25.763	0.041
		16	-0.082	-0.065	26.270	0.050
		17	0.297	0.224	33.178	0.011
		18	-0.096	0.065	33.914	0.013
		19	-0.003	0.099	33.915	0.019
		20	-0.047	-0.007	34.109	0.025

Table 4: Autocorrelation functions and Partial autocorrelation functions

Source: Authors calculations performed using E-Views

The analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots yielded insightful findings regarding the selection of parameters for the Autoregressive Integrated Moving Average (ARIMA) model. The examination of the ACF plot indicates a notable alteration in the pattern of spikes after the first order, signifying an appropriate choice for the Autoregressive (AR) parameter 'p' as 1. Subsequently, the PACF plot suggests potential values for the Moving Average (MA) parameter 'q,' specifically, 1, 5, 7, or 8. This inference is drawn based on the observed significant spike after the first order and visible alterations in pattern occurring at lags 4, 6, and 7 in the PACF plot (see Table 4). Thus the ACF and PACF plot suggests possible ARIMA models are ARIMA (1,2,1), ARIMA (1,2,5), ARIMA (1,2,7) and ARIMA (1,2,8). The best ARIMA model will be identified after comparison of models (see Table 4).

Parameters Estimation for an ARIMA

To determine which of the above mentioned ARIMA models are the best model for forecasting the NCPI value, comparison of these models with respect to different criteria: Significant Coefficient, SIGMASQ, Adjusted R-squared, AIC, Schwarz criterion and Hannan-Quinn criterion are used.

Table 5: Models' Comparison

Comparison criteria	Models			
	ARIMA(1,2,1)	ARIMA(1,2,5)	ARIMA(1,2,7)	ARIMA(1,2,8)
Significant Coefficient	3	3	2	4
SIGMASQ	1.80	1.70	1.72	1.52
Adjusted R-squared	0.11	0.16	0.15	0.25
AIC	3.60	3.55	3.56	3.47
Schwarz criterion	3.75	3.70	3.72	3.63
Hannan-Quinn criterion	3.66	3.60	3.62	3.53




















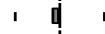












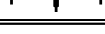







Source: Authors calculations performed using E-Views

In the evaluation of ARIMA models: ARIMA(1,2,1), ARIMA(1,2,5), ARIMA(1,2,7), and ARIMA(1,2,8), the findings reveals that ARIMA(1,2,8) stands out as the optimal model, supported by its superior performance across critical metrics. With the highest count of significant coefficients (4) and adjusted R-squared value (0.25) and, lowest SIGMASQ value (1.52), SIGMASQ value (1.52, AIC value (3.47), Schwarz criterion value (3.63) and Hannan-Quinn criterion value (3.53) signaling its superior goodness of fit and parsimony signifying enhanced model fit and reduced variability in residuals. This meticulous assessment collectively underscores ARIMA(1,2,8) as the preferred among the other three models (see Table 5).

4.6 Model Diagnosis

This can be done by examining the residuals of the model and by performing various statistical tests.

Table 6: Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.065	-0.065	0.2225	
		2 -0.136	-0.141	1.2109	
		3 0.156	0.140	2.5387	0.111
		4 0.007	0.007	2.5411	0.281
		5 -0.311	-0.283	8.0272	0.045
		6 -0.017	-0.078	8.0435	0.090
		7 0.212	0.160	10.715	0.057
		8 -0.146	-0.063	12.014	0.062
		9 -0.007	0.019	12.017	0.100
		10 0.108	-0.041	12.763	0.120
		11 0.018	0.032	12.785	0.173
		12 -0.142	-0.045	14.141	0.167
		13 0.075	0.024	14.527	0.205
		14 0.109	0.072	15.374	0.222
		15 -0.103	-0.017	16.155	0.241
		16 0.061	0.066	16.437	0.287
		17 0.304	0.280	23.631	0.072
		18 -0.059	0.007	23.910	0.091
		19 -0.081	0.017	24.452	0.108
		20 -0.001	-0.137	24.452	0.141

Source: Authors calculations performed using E-Views

Subsequent to the identification of ARIMA(1,2,8) as the most optimal model, the investigation endeavors to scrutinize its goodness of fit through an examination of Q-statistic probabilities adjusted for 2 Autoregressive Moving Average (ARMA) terms. The Q-statistic, an indispensable diagnostic tool, is employed to assess the conformity of the model's residuals to white noise characteristics. Findings show the white noise pattern because the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are anticipated to exhibit a rapid decay. A swift decline in residuals underscores the model's proficiency in accounting for autocorrelation, fortifying the reliability of the chosen ARIMA(1,2,8) model (see Table 6).

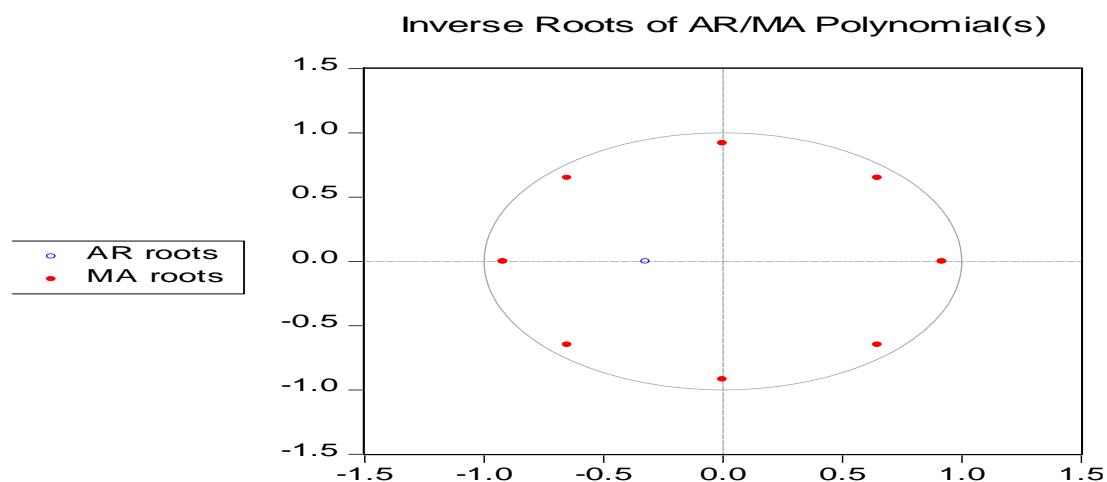


Figure 2: Unit Circle (Source: Authors calculations performed using E-Views)

Visualizing the stability of the proposed model ARIMA(1, 2, 8) is done by plotting the inverses of the roots of the characteristic equation on the complex plane. The inverse root of AR/MA plot shows that AR roots as well as MA roots lies inside the unit circle. This shows the stability of AR and MA models. With this, we have completed the model diagnostics and verified the ARIMA(1,2,8) model is an appropriate (see Figure 2).

Forecasting NCPI for Short-run

A primary aim in the establishment of time series models is the accurate anticipation of future values predicated upon the estimated model. Specifically designed for short-run forecasting, the ARIMA model assumes particular significance in this context. Consequently, the ARIMA(1, 2, 8) model, identified as the most suitable for forecasting the NCPI, is employed to forecast values up to the year 2030. Preceding the projection of future values, an evaluation of the model's performance is undertaken through the utilization of the Root Mean Squared Error (RMSE) and Theil Inequality Coefficient. These metrics serve to assess the efficacy of the ARIMA(1, 2, 8) model in accurately estimating NCPI values based on historical data, thereby contributing to the validation and reliability of the forecasting outcomes.

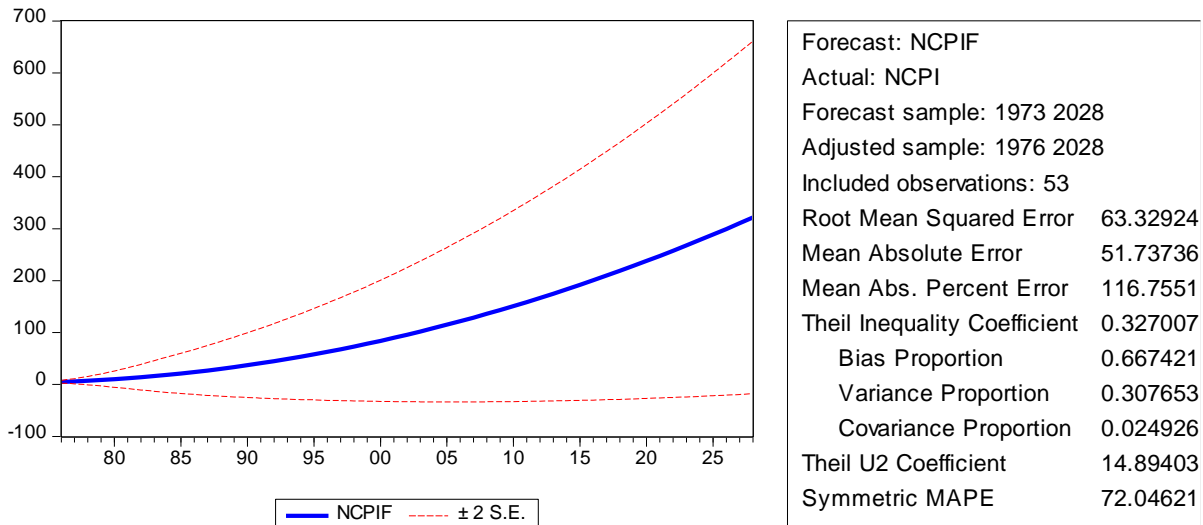


Figure 3: Root Mean Squared Error (RMSE) and the Theil inequality coefficient (Source: Authors calculations performed using E-Views)

Together with the plot of actual and forecast value of NCIP, the graph provides statistical measures in its right side a number of statistical measures like RMSE and the Theil inequality coefficient. Specifically, the RMSE, with a value of 63329.24, signifies a comparatively low level, indicative of the model's capability to yield accurate predictions on average. Similarly, the Theil inequality coefficient, with a value of 0.327, is also relatively low, underscoring the model's proficiency in accurately predicting the NCPI. These measures collectively affirm the strength and precision of the forecasting model, providing confidence in its ability to appropriately capture and replicate the underlying patterns within the NCPI dataset (see Figure 3).

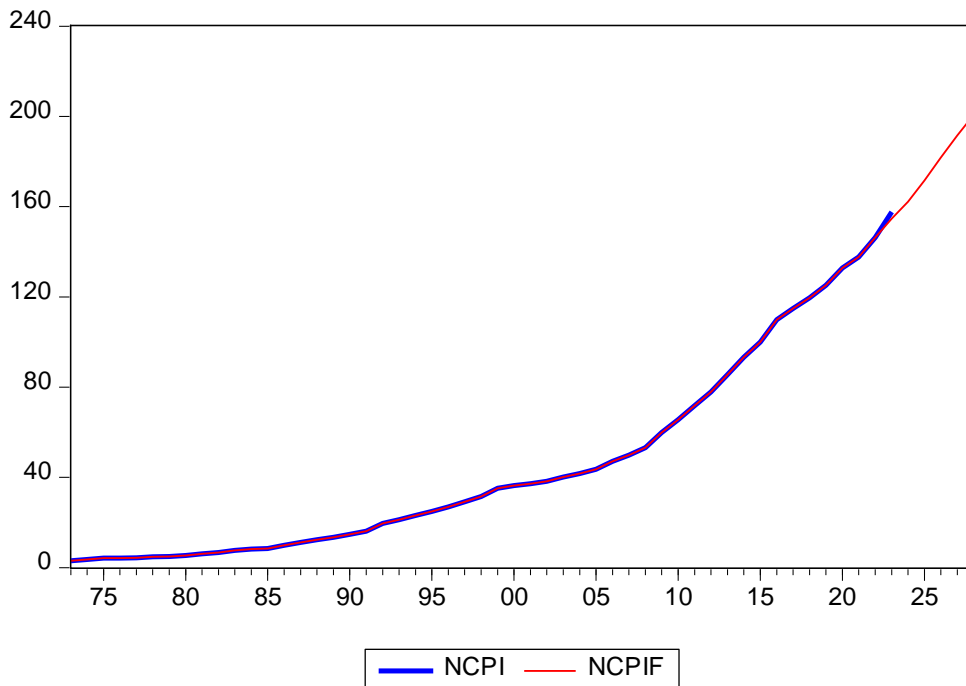


Figure 4: Actual and Forecast trend line of NCPI in Nepal (Source: Authors calculations performed using E-Views)

The trend lines for actual and forecasted National Consumer Price Index (NCPI) values closely align and overlap, affirming the model's appropriateness. The analysis indicates a consistent upward trend in NCPI, with projections reaching around 200 by 2028 (see Figure 4).

The National Consumer Price Index (NCPI) in Nepal is a crucial gauge of inflation, reflecting changes in the prices of consumer goods and services. Inflation, indicated by a rising NCPI, can lead to reduced purchasing power, increased uncertainty, and social unrest. The Nepalese government implements monetary, fiscal, and supply-side policies to control inflation, effectiveness of which depends on the economic context.

Discussion

This study employed the Box-Jenkins methodology, a well-established statistical technique, to ascertain the most appropriate Auto-Regressive Integrated Moving Average (ARIMA) model for forecasting the annual values of the NCPI. Notably, the investigation identified ARIMA(1,2,8) as yielding the most favorable outcomes among the considered ARIMA models. This finding aligns with the broader research landscape, where scholars, such as Ibrahim et al. (2022) in the context of Nigerian Consumer Price Index (CPI) forecasting and Imron et al. (2022) for Probolinggo City's CPI, have similarly engaged ARIMA models, albeit with distinct parameter specifications tailored to the specific economic characteristics of their respective regions. The diversity in optimal ARIMA model across countries underscores the unique nature of economic changes and necessitates the development of context-specific models. This observation emphasizes the importance of tailoring forecasting models to the unique economic dynamics of each country. Therefore, the utilization of ARIMA(1,2,8) for NCPI forecasting in Nepal not only contributes to the refinement of predictive modeling within the country but also underscores the need for a nuanced approach in selecting appropriate models tailored to the idiosyncrasies of individual economies.

Conclusion

This research leveraged ARIMA modeling and forecasting techniques, specifically focusing on the NCPI in Nepal using annual data from the fiscal year 1972/73 to 2022/23. The study, employing the Box-Jenkins methodology and E-Views statistical software, identified ARIMA(1, 2, 8) as the most suitable model for NCPI forecasting. Diagnostic tests affirmed the model's appropriateness, with residuals demonstrating white noise characteristics. Forecast analysis, including Root Mean Squared Error (RMSE) and Theil inequality coefficient, underscored the model's accuracy in predicting the NCPI's upward trajectory. The result of this research show that the ARIMA(1,2,8) is the best ARIMA model for prediction of NCPI in short-run. Furthermore, the prediction of NCPI shows the trend of NCPI will increase as same as in recent fiscal year and will be nearly 200 points in 2028. The NCPI has a crucial role for inflation. Also it has potential economic implications for governmental bodies for the adoption of monetary, fiscal, and supply-side policies to manage inflation. Thus the model that

appropriately predicts NCIP in Nepal has implication in many fields. This research contributes valuable insights for policymakers and stakeholders, aiding in informed decision-making for sustaining economic stability in Nepal amidst evolving inflationary trends.

References

- Cieslak, A., Hansen, S., McMahon, M., & Xiao, S. (2023). *Policymakers' Uncertainty* (No. w31849). National Bureau of Economic Research. SSRN. <https://doi.org/10.2139/ssrn.3936999>
- Graf, B. (2020). Consumer Price Index Manual, 2020: Concepts and Methods. In *Consumer Price Index Manual, 2020*. International Monetary Fund. https://www.ilo.org/global/statistics-and-databases/publications/WCMS_761444/lang--en/index.htm
- Gupta, D., Fischer, H., Shrestha, S., Ali, S. S., Chhatre, A., Devkota, K., ... & Rana, P. (2021). Dark and bright spots in the shadow of the pandemic: Rural livelihoods, social vulnerability, and local governance in India and Nepal. *World Development, 141*, 105370. <https://doi.org/10.1016/j.worlddev.2020.105370>
- Ibrahim, A., Sani, U. M., & Olokojo, V. O. (2022). Forecasting Consumer Price Index and Exchange Rate using ARIMA Models: Empirical Evidence from Nigeria. *FUDMA Journal of Sciences, 6*(6), 114-124. <https://doi.org/10.33003/fjs-2022-0606-1136>
- Imron, M., Utami, W. D., Khaulasari, H., & Armunanto, F. (2022). ARIMA Model of Outlier Detection for Forecasting Consumer Price Index(CPI). *BAREKENG: Jurnal Ilmu Matematika Dan Terapan, 16*(4), 1259-1270. <https://doi.org/10.30598/barekengvol16iss4pp1259-1270>
- Joshi, S. K., & Acharya, K. (2019). Modification of Kuppuswamy's socioeconomic status scale in the context of Nepal, 2019. *Kathmandu Univ Med J, 17*(65), 1-2. <https://pubmed.ncbi.nlm.nih.gov/31734669/>
- Kafle, S. C., & Hooda, E. (2023). ARIMA and Exponential Smoothing Model to Forecast Average Annual Precipitation in Bharatpur, Nepal. *BMC Journal of Scientific Research, 6*(1), 113-125. <https://doi.org/10.3126/bmcjsr.v6i1.60959>
- iLandén, J. (2023). A "new" Consumer Price Index (CPI) for monetary policy decisions in Sweden: How does a "new" technological CPI compare to the traditional CPI in measuring inflation and influencing monetary policy decisions?. <https://www.diva-portal.org/smash/get/diva2:1764447/FULLTEXT01.pdf>
- Nguyen, T. T., Nguyen, H. G., Lee, J. Y., Wang, Y. L., & Tsai, C. S. (2023). The consumer price index prediction using machine learning approaches: Evidence from the United States. *Heliyon, 9*(10). <https://doi.org/10.1016/j.heliyon.2023.e20730>
- Poudel, O. (2022). Impacts of Foreign Direct Investment on Economic Growth of Nepal: A Johansen Co-integration Analysis. *Journal of Balkumari College, 11*(1), 50. <https://doi.org/10.3126/jbkc.v11i1.53023>
- Poudel, O. (2023). Relationship between Defense Expenditure and Economic Growth in Nepal. *Unity Journal, 4*(1), 208-226. <https://doi.org/10.3126/unityj.v4i01.52242>

Interdisciplinary Journal of Management and Social Sciences (IJMSS)

Vol. 5, No. 1, January 2024. Pages: 105-118

ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)

DOI: 10.3126/ijmss.v5i1.62666

- Poudel, O., & Sapkota, M. P. (2022). Consumer Perception toward Digital Payment System. *Management Dynamics*, 25(1), 39–50. <https://doi.org/10.3126/md.v25i1.53286>
- Purba, J. O. (2023). Consumer Price Index Analysis as Teaching Material for Accounting Students. *Reflection: Education and Pedagogical Insights*, 1(2), 62-68. <https://firstcierapublisher.com/index.php/reflection/article/view/29>
- Shrestha, P. (2023). Public Debt and Economic Growth in Nepal. *Khwopa Journal*, 25-36. <https://doi.org/10.3126/kjour.v5i1.53317>
- Silva, A. B. D. S., Araújo, A. C. D. M., Frias, P. G. D., Vilela, M. B. R., & Bonfim, C. V. D. (2021). Auto-Regressive Integrated Moving Average Model (ARIMA): conceptual and methodological aspects and applicability in infant mortality. *Revista Brasileira de Saúde Materno Infantil*, 21, 647-656. <https://doi.org/10.1590/1806-93042021000200016>
- Singh, R. K., Rani, M., Bhagavathula, A. S., Sah, R., Rodriguez-Morales, A. J., Kalita, H., & Kumar, P. (2020). The Prediction of COVID-19 Pandemic for top-15 Affected Countries using advance ARIMA model. *JMIR Public Health and Surveillance*, 6, 1–10.
- STATISTICS, U. B. O. L. (2023). *Consumer price index summary*. <https://www.bls.gov/news.release/cpi.nr0.htm>
- Wikipedia contributors. (2023, December 9). *Autoregressive integrated moving average*. Wikipedia. <https://en.wikipedia.org/?title=ARIMA&redirect=no>
- Yunus, K., Thiringer, T., & Chen, P. (2015). ARIMA-based frequency-decomposed modeling of wind speed time series. *IEEE Transactions on Power Systems*, 31(4), 2546-2556. <https://doi.org/10.1109/TPWRS.2015.2468586>