Forecasting Canada's Inflation: A Time Series Analysis with focus on Exchange Rates and Unemployment Dynamics

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***Abstract*—This paper focuses on forecasting the inflation rate in Canada using various time series models, including the ARIMA model, Neural Network Auto Regression model, Standard Regression, and Dynamic Regression model. We also proposed a hybrid model that combines the strengths of dynamic regression and neural networks, harnessing the explanatory power of regression models and the adaptability of neural networks. The project utilizes unemployment rate and exchange rates as predictors in the models. The primary objective is to compare the performance and accuracy of these models to identify the best-fit model for forecasting inflation in Canada. The initial phase involves employing ARIMA models to capture the temporal patterns inherent in the inflation data and Neural network model to capture complex structures. Subsequently, standard regression models provide insights into the linear relationships between these variables. Simultaneously, dynamic regression models account for potential external influences, offering a more nuanced understanding of inflation's intricate dynamics. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are employed to assess the models. The hybrid model outperformed all models in forecasting Canada's inflation. The findings highlight the strengths and limitations of each approach, informing the development of an integrated forecasting model. The project will delve into the intricate relationships between predictors and inflation, providing insights into the economic factors influencing inflationary trends in Canada.**

I. Introduction

Inflation rate means a rise in the price and it reflects the cost of living in a country. One major factor influencing a nation's rate of inflation is foreign exchange prices. There exists a negative correlation between the inflation rate and the exchange rate(1). Additionally, inflation has an inverse relationship with unemployment rate(2). This means that when inflation rises, unemployment drops. The relationship between inflation, unemployment, and exchange rates is intricate and dynamic. However, it's crucial to recognize that the exchange rate and unemployment rate are just one of several factors contributing to a country's inflation.

The objective of this project is to forecast the inflation of Canada using time series models such as the ARIMA model, neural network auto regression model, standard time series and dynamic regression model, and proposed hybrid model to improve the performance. By analyzing the historical data of these variables through time series methods, we intend to unravel patterns, correlations, and trends that can inform accurate predictions of future inflation rates. The findings are expected to assist policymakers, economists, and financial analysts in making informed decisions and predictions regarding inflationary trends in the Canadian economy. A robust understanding of the relationships between inflation, unemployment, and exchange rates can guide strategic decision-making, enabling stakeholders to formulate effective policies, manage risks, and navigate the complexities of the economic landscape with greater confidence.

II. Data

While numerous factors contribute to the inflation rate, our analysis focuses exclusively on two factors: the unemployment rate and the exchange rate, aiming to forecast the inflation rate. For this research, the unemployment rate, exchange rate, and inflation rate data are downloaded from the FRED (Federal Reserve Economic Data) website https://fred.stlouisfed.org/series/. FRED is an online database consisting of a vast collection of economic and financial data series. We extracted the required data and consolidated it for forecasting the inflation rate using time series models. The dataset is split into a training set with data less than or equal to August 31, 2022; and a test set with greater than August 31, 2022, till August 31, 2023.

III. Methods

This section will explain the methods we implemented on the time series data of Canadian inflation. This analysis includes several steps. Our dataset consists of the CPI index, exchange rate, and unemployment rate. All unit is the same for all variables i.e percent change from a year ago. It is calculated using the formula $PercentChange = ((NewValue - oldvalue)/OldValue) * 100$. First, we fitted the ARIMA model, and neural network model on the CPI index time-series, and then to consider the impact of external factors like the exchange rate and unemployment rate on Canada's inflation; we deployed a time-series regression and dynamic regression model and a hybrid model.

A. Sign Correlation

Sign correlation is a helpful tool for understanding the distribution of data(3). By utilizing sign correlation, we've assessed the distribution of the Consumer Price Index (CPI) time series data.

B. ARIMA Models

ARIMA is short for 'Auto-Regressive Integrated Moving Average' and is used to forecast future values on the basis of past values i.e its own lags and lagged forecast errors. The assumption of this model is that the data should be stationary. It is denoted by $ARIMA(p, d, q)$ where p is the order of the autoregressive model, d is the degree of differencing and q is the order of the moving average model. We deployed this model on the CPI index series to forecast the future inflation rate. We have checked for different combinations of (p, d, q) and selected the best model by considering the least AICc(Akaike Information Criteria)(4). And then checked for error assumptions by residual diagnostic tests and plots.

C. NNAR Model

This is the Neural Network Autoregression model which combines autoregressive (AR) components with neural network structures. It has only one hidden layer and lagged values are used as input to the neural network. In the $NNAR(p, P, k)$ model, the notation (p, P, k) refers to the number of lagged observations used as input (p), seasonal autoregressive terms (P), and number of neurons in the single hidden layer (k). To deal with the non-linearity and complexity of the inflation data we have fitted the NNAR model on the CPI index series.

D. Standard Timeseries Model

Standard Regression incorporates linear relationships between the predictor's unemployment rate, exchange rate, and inflation rate. The linear time series model is built on the training set with the inflation rate as the response and the unemployment rate and exchange rate as predictors. Standard regression assumes the residuals are white noise and uncorrelated but this is not the case always. For considering the correlated information in the errors, dynamic regression is used.

E. Dynamic Linear Regression

When there are external factors that might influence the time series and are not fully captured by the ARIMA model, dynamic regression becomes a valuable tool. The dynamic regression model is formulated by integrating the ARIMA structure with predictors. The lagged effects of the predictors are included in the model as covariates impact the inflation rate. By incorporating dynamic regression into the ARIMA framework, the model becomes more adaptive to the impact of external variables, such as the unemployment rate and exchange rate, leading to a more comprehensive and accurate forecast of the inflation rate. The dynamic regression model has a form

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + ... \beta_2 x_{2,t} + ... + \eta_t \quad (1)$$

where η_t is assumed to follow an ARIMA model.

F. Hybrid Model

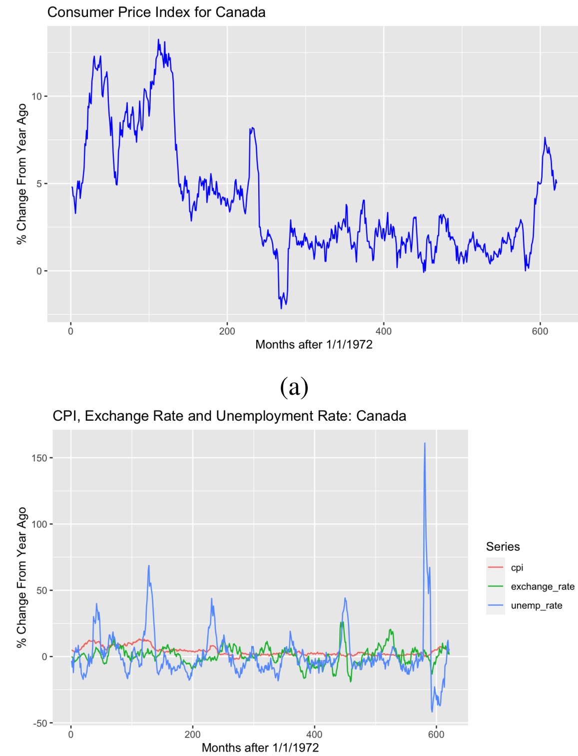
The hybrid model is a combination of the dynamic regression model and neural network model. The GitHub Link: https://github.com/Ankita918/Canada-Inflation-Forecasting

IV. Result

This study uses monthly historical data spanning from 1972 to 2023. The research investigates the relationship between the exchange rate and unemployment with the inflation rate of Canada. Our objective involves forecasting the inflation rate for the upcoming 12 months. In the analysis of Canada's CPI summary using R, the inflation rates showcase remarkable variability, climbing to a peak of 13.25 and dipping to the lowest point of -2.17, indicating a period of deflation. The exploratory data analysis shows the historical trend of CPI time series data and the findings are visually represented in figure 1a which shows the overview from Jan 1972 till Aug 2023. After a pandemic period, inflation worsened and it is reflected in the same figure 1a as well. Another graph 1b shows the historic trend of CPI, Exchange rate, and unemployment. Negative correlations have been observed between CPI and Exchange rate as well as CPI and unemployment.

To get a more accurate prediction, we identified and replaced outliers with suggested numbers from the exchange rate and unemployment rate data sets. The CPI series, however, showed no outliers. We analyzed the data by splitting it as a training data set (from Jan 1972 till Aug 2022) and a testing data set (from Sept 2022 till Aug 2023). This helped us to train our models on historical data and evaluate their performance on unseen future data. To forecast the inflation, we deployed time-series models including ARIMA, NNAR, Time series, and Dynamic regression model. Additionally, we have introduced a hybrid model that combines the strength of a Dynamic regression model and a neural network model. This model considers past observations as well as external factors and provides more precise forecasts. We have assessed these models against benchmark methods and this comparative analysis helps us to understand how well our advanced model performs in comparison to simpler methods.

The initial phase was to fit the model and verify the forecasting model by examining residual assumptions. A good forecasting model will produce uncorrelated errors suggesting that the model adequately captures the information from the data. If deviations from white noise are observed, then there is scope to improve the model. To assess the autocorrelation of the data, we conducted the Ljung-Box test. This formal test considers the null hypothesis as residuals come from white noise series. If $pvalue$ is greater than .05, leads to a failure to reject the null hypothesis. The next crucial step involves evaluating forecast accuracy. The model that produces minimum RMSE is considered the optimal model for forecasting as it suggests the closest alignment between predicted and observed values.



(a)

(b)

Fig. 1: Consumer Price Index since 1972

In our analysis, first, we checked for the distribution of the inflation rate(CPI) using sign correlation (ρ). The value of ρ is .82 which suggests that the CPI series has normal distribution. Then, we employed benchmark methods as reference points for evaluating the performance of more complex models on the CPI time series data. The naive method and Drift method gave better forecasts than the Mean method.

To fit the ARIMA model, we used the ARIMA() function which automatically selected the ARIMA(0,1,0) model. ARIMA(0,1,0) suggests that the time series has undergone one round of non-seasonal differencing to make it stationary. In this case, the ARIMA model does not use any lagged value or lagged forecast errors. The errors from this model are not white noise. Additionally, we deployed a neural network model to capture the underlying structure of the CPI time series. The NNETAR function selected the NNAR(25,13) model which can be interpreted as the model utilizing 25 of the most recent observations with a hidden layer containing 13 nodes to capture the complex nature of the CPI series. The residuals of this model are white noise.

Moreover, we aimed to find out the correlation between the exchange rate and CPI, as well as between unemployment and CPI. To achieve this, we employed a time series regression model and dynamic regression model and forecasted CPI by assuming the exchange rate and the unemployment rate will be 2.8% and -10% respectively constant over the test set duration. The time series regression model revealed the presence of auto-correlation, indicating that there is some information left in the residual and the model did not fully explain the data. Subsequently, we deployed a dynamic regression model which used correlated errors in the regression equation. The dynamic model considers the external factors and the time series dynamics. The findings showed that the CPI and exchange rate are inversely proportional means when the exchange rises CPI tends to fall and vice versa. Similarly, the study illuminated an inverse relationship between unemployment and CPI. Finally, we deployed the hybrid model which is a combination of dynamic regression and neural network model which helped us to capture the complex data and include external factors resulting in a more accurate representation of underlying relationships.

A comparative analysis of forecast accuracy, presented in table I, showcased that our hybrid model yielded the lowest Root Mean Squared Error (RMSE). The forecast results, visualized in 2, illustrated the forecasts of all fitted models.

TABLE I: RMSEs and MAEs of the Forecast Model

Model	RMSE	MAE
Mean Method	2.18	2.01
Naive Method	1.49	1.23
Drift Method	1.52	1.26
ARIMA model	1.49	1.23
NNAR model	.60	.49
Time series Regression model	2.84	2.71
Dynamic Regression model	1.63	1.40
Combined model	.39	.30

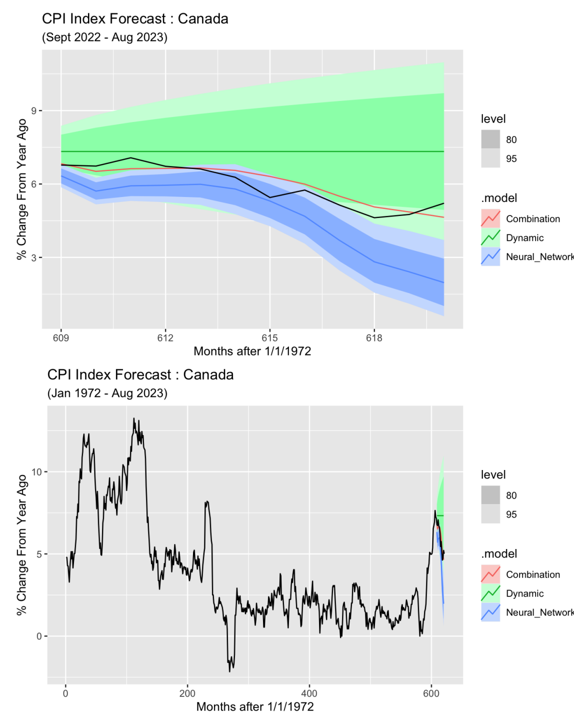


Fig. 2: Forecast of Dynamic, NNAR(25,23) and Combine model

V. Conclusion

To conclude the paper, we deployed various models including ARIMA, NNAR, time series regression, dynamic regression, and a hybrid model(a combination of NNAR and dynamic). The hybrid model outperformed the other models in forecasting the inflation rate of Canada. The study findings indicated that the inflation rate of Canada has a negative relationship with the exchange rate as well as with the unemployment rate. These insights hold particular significance for the Bank of Canada, as policymakers closely monitor inflation forecasts to guide decisions on interest rates. The central goal of maintaining inflation at 2% underscores the relevance of accurate forecasts for effective monetary policy.

Due to time limitations, We could not examine important factors influencing inflation, such as oil prices, GDP rates, and global considerations. We also propose the consideration of advanced models like the VAR model in future research, as it efficiently captures dynamic interactions among multiple time series variables. This will help us understand more about what causes inflation in different countries.

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