AFRICAN CENTRE OF EXCELLENCE IN DATA SCIENCE

COLLEGE OF BUSINESS & ECONOMICS

FORECASTING INFLATION OF RWANDA USING MACROECONOMICS VARIABLES(2006Q1-2019Q4)

By

HAKIZIMANA Celestin

Registration Number: 219013768

A dissertation submitted in partial fulfilment of the requirements for the degree ofMaster of Data Science in Econometrics

University of Rwanda, College of Business and Economics

Supervisor: Dr. Richard Kabanda

September 2022

Declaration

I declare that this dissertation entitled **Forecasting inflation of Rwanda using macroeconomics Variables (2006Q1-2019Q4)** is the result of my own work and has not been submitted for any other degree at the University of Rwanda or any other institution.

Names: HAKIZIMANA Celestin

Signature:

Approval sheet

This dissertation entitled **Forecasting inflation of Rwanda using macroeconomics Variables** written and submitted by **HAKIZIMANA Celestin** in partial fulfilment of the requirements for the degree of Master of Science in Data Science majoring in **Econometrics** is hereby accepted and approved. The rate of plagiarism tested using Turnitin is **17** % which is less than 20% accepted by the African Centre of Excellence in Data Science (ACE-DS).

____

Supervisor

____

Head of Training

DEDICATION

To

My Parents

my brother and sisters

my colleagues.

ACKNOWLEDGMENT

This study should not be possible without the support and assistance of many people whom I am grateful. I wish to express my gratitude to my supervisor Dr. Richard KABANDA for his comparable support, suggestions, optimism and guidance for the success of my thesis. I am grateful to my lecturers, Africa center of Excellence in Data Science leaders for their guidance and support. I also wish to express my gratitude to my classmates in master's cohort 2 especially students that measure in econometrics. God bless you all.

ABSTRACT

This study was intended to forecast the inflation of Rwanda using macroeconomics variables, the variables that used were money supply, interbank rate, exchange rate, international oil price and lending rate. The change in consumer price index was treated as inflation. The objectives of the study were to forecast inflation of Rwanda and compare the performance of machine learning algorithms with the existing methods used. The study used quarterly time series data from National Bank of Rwanda from 2006 Q1 to 2019 Q4. The data were analyzed using various methods such as ARMA model used to model dependent variable when the predictors are the past values of that variable with specified number of lags. VAR model which uses its previous values and the previous values of other variables was also used with specified number of lags. Machine learning techniques Random Forest, Ridge Regression, LASSO Regression and K Nearest Neighbor (KNN) were used to forecast inflation and evaluation were made on RMSE. The results of different techniques gave different RMSE for the ARMA model the resulted RMSE was 1.176938, for VAR model the RMSE was 1.17868, for K Nearest Neighbor the resulted RMSE was 1.2382, for Random Forest the resulted RMSE was 0.5111, for Ridge regression RMSE was 1.2148 and for LASSO Regression, the resulted RMSE was 1.2868. so, Random Forest model was the first model to have small root mean squared error and is the best model that work well in forecasting inflation followed by existing models ARMA and VAR model due to the small RMSE compared to the others. Based on results, implementing machine learning techniques for forecasting Rwandan inflation is a promising endeavor. So, first line of work could be the improvement in the application of methods that underperformed in the study, as well as the potential to extend the work to include other machine learning techniques such as Neural networks methods.

Key words: Inflation, Forecasting, Machine learning, Root Mean Squared error.

Table of content

List of tables

List of figures

LIST OF ABBREVIATIONS

ADF: Augmented Dicker Fuller test

AIC: AKAIKE information criterion

AR: Autoregressive

ARMA: Autoregressive moving average

CPI: Consumer Price index

ECM: Error correction model

HQ: Hannan-Queen

KNN: K Nearest Neighbor

MAE: Mean Absolute Error

NBR: National Bank of Rwanda

RMSE: Root Mean Squared Error

SBIC: Schwarz Information criteria

VAR: Vector Autoregressive

CHAP 1: INTRODUCTION

1.1. Background

Forecasting inflation is a difficult job. Irrespective of the difficulty of predicting inflation, having correct forecasts make an economic environment more stable. Expecting inflation through forecasting plays a crucial role for economic agents in making decisions (Özgür & Akkoç, 2021) In the future, the direction that the price level will follow would have an impact for the choice made by the investment companies because the profit on investment is highly dependent on the rate of inflation. The inflation level is also essential for families in making their decisions regarding the supply of labor. They may modify their decision based on the impact of inflation on their real wages. In other words, all market participants would change their decision to the inflation forecasts (Medeiros, 2017).

It is hard to underestimate the role of forecasting inflation in making economic decisions. different contracts regarding sales, employment and debts are settled in nominal terms. so, forecasting inflation plays an important role to investors, policymakers and households. In addition, national banks depend on forecasted inflation not only to give information on monetary policy but also to deal with inflation expectations and thus increase policy efficacy. Indeed, as a way of improvement of economic decision-making, most of the national banks release their inflation forecasts regularly.

Inflation can be defined as an increase of the quantity of money in circulation or defined as persistent decreases of the money value. As result, inflation lowers the purchasing power of the people as it requires more money to afford one unit of good or service (Ruzima, 2018).

Inflation is a worldwide scenario. It exists in all countries either large or small, underdeveloped or developed, socialist and capitalist, in the north and south, and the east and west. Furthermore, inflation existed in the previous centuries as well as during the 20th century. Some countries experienced higher price increases than others. The inflation rate in particular countries has changed gradually over time (Cause et al., 2014).

Inflation plays a crucial role in stabilizing an economy and is considered key part of macroeconomic policies. Lower inflation affects economic growth negatively while higher inflation impacts negatively the poor more than it does for the rich. After 1973, when Pakistan suffered the highest inflation rate (38 percent), in 2008-09 severity again has been experienced when the inflation has an increase of 17 percent and economic growth has a decrease of 0.4 percent(Asghar & Naveed, 2015).

Until now, no agreement on the exact causes of inflation. A popular understanding is that expanding money supply by the government is considered as the principal cause, with combination of negative shocks in domestic food supply (Durevall & Sjö, 2012). Another idea is that increases in world food price increases prices of domestic food. Increasing the price of food led to devaluations and negative effects on consumer prices in general(Durevall & Sjö, 2012).

It is widely known that inflation is related to increase in supply of money. The principal cause is that country prints more money to avoid its deficiency, it increases amount of money in circulation to encourage demand, and anticipation of future inflation forces the government to experience price increases. However, many countries in Africa especially Sub-sahara, it is a challenge for monetary leaders to control inflation even if there is a political interest, due to weak institutional frameworks, small financial markets and lack of perfect competition among banks. In that environment, central banks lack the effective tools to regularize supply of money. Exogenous shocks, like poor harvests or energy-price hikes, might set off expectations and cause continuing inflation due to an insufficient monetary policy that break prices down(Durevall & Sjö, 2012).

However, to reduce the barrier of inflation in the economy, many central banks in developed and less developed countries set the objective to maintain inflation at a minimum rate for achieving and sustaining high economic growth. In the same way, the National Bank of Rwanda (N.B.R) aims to keep prices stable towards sustainable economic development. Considering this, to achieve a low inflation rate, the National Bank of Rwanda monetary policy works under two monetary targeting tools, reserve money used to increase or decrease money in the banking system and Broad money (M3) used to control the money supply with the targeted inflation and economic growth. Inflation creates doubt in investment for both domestic and foreign investors. Also, it negatively affects the terms of trade in the country by increasing the domestic prices of goods and services more than the region and the world market price. Thus, domestic trade becomes less competitive globally. Accordingly, the less competitive trade leads to the deficit in the current account.

1.2. Statement of the problem

The principal responsibility of any National bank is to keep price stable. Stability of price can mainly be violated by inflation which increases the level of prices. Increases in the level of price reduce the purchasing power such that a consumer is unable to maximize his/her utility.

Forecasting accurately future inflation should be a good way to help in price stability. National Bank of Rwanda which is in charge of price stability usually forecasts future inflation. Gicondo Ananias and Kimenyi (Bank, 2010) forecasted inflation covered data from January 2004 to December 2009 on monthly basis. They used ARMA model to forecast future inflation and RMSE and MAE as evaluation tool to their model. Their study used small time interval, and this may result in obtaining poor quality results. The result of their study showed RMSE of 1.29 and MAE of 1.04 and this is a large value compared to results obtained using machine learning techniques, OnderOzgur and UgurAkkoç on "Inflation forecasting turkey economy as a case study they practicing the exercises to test the ability of machine learning algorithms. They used sample data from March 2007 to 2017. He found that inflation forecasting using Ridge, LASSO Regression as machine learning techniques has more forecasting power than that existing method such as the ARMA model due to lower Root Mean Square Error which is small for Ridge Regression (1.099), 0.834 for LASSO regression compared to 1.237 of ARMA model (Özgür& Akkoç, 2021). The higher RMSE in Rwanda should be the reason why the consumer price index keeps increasing. This study applies machine learning techniques to forecasting inflation in Rwanda and models' evaluation are based on their respective root mean squared errors and model with low root mean square error is the best forecaster.

1.3. Objectives

1.3.1. General objective

1. To forecast inflation of Rwanda

1.3.2. Specific objectives

1. Forecasting inflation using machine learning methods
2. Forecasting inflation using existing methods
3. Comparison of machine learning techniques and existing methods in forecasting inflation of Rwanda.

1.4. Hypotheses

1. Machine learning models perform better than existing methods in inflation forecasting

1.5. Significance of the study

Policy makers who are in charges of maintaining the price stability will use the results of this study to take appropriate decisions regarding price stability by applying different monetary policy or other inflation targeting techniques to keep inflation as low as possible to maintain the growth of the economy of the country. The investors both national and international will use the results of this study to help them make appropriate plan about investing their money.

CHAP 2: LITERATURE REVIEW

2.1 THEORETICAL LITERATURE

2.1.1. Monetary theory of inflation

Monetarism refers to Mr. Friedman's (1912-2006) theory "only money matters" and that monetary policy is a more important tool to stabilize the economy than fiscal policy. Monetarists believe that the supply of money is the first predictor of production levels and price levels in the short run, and it affects only the level of price in long run. According to Milton Friedman's Modern Quantity Theory, "Inflation is always and everywhere a monetary phenomenon that arises from more rapid increase in the quantity of money than total output". Its explanation is in the simple equation of quantity theory of money.

$P = \frac{Mv}{y}$ Where P: level of Price, M: Supply of money, v: Velocity of money, and y: income The above formula shows that the price P has positively relationship to the money supply M. The price level is a measure of inflation. In the case of forecasting inflation, according to the monetary theory of inflation, the money supply is directly related to the price, and the change in the price is inflation. This means that we use money supply variables to predict future inflation.

2.1.2. The Quantity Theory of Money

The quantity theory of money is the oldest existing economic theory. It assumes that changes in the general price level are due primarily to changes in the quantity of money in circulation. The quantity theory of money created the core of classical nineteenth-century monetary analysis, provided the main conceptual framework for the interpretation of contemporary financial events, and formed the intellectual basis for orthodox policy prescription designed to preserve the gold standard. David Hume (1711-1776) provided the first dynamic process analysis of how the impact of a monetary change spreading from one sector of the economy to another affects the level of prices and quantities in the process. He brought considerable refinement, elaboration, and extension to the quantity theory of money (Totonchi, 2011). The quantity theory of money highlights the impact of the money supply in determining inflation in an economy.

2.1.3. Theory of inflation and exchange rate

Dornbusch (1987) was the first to show the relationship of exchange rates and inflation. According to him, he presented model and assessed impact of exchange rates on prices. His research became the starting point for the work of other researchers (Kasapoğlu, 2007; Brooks, 2002). In assessing this "exchange rate-domestic price relationship", it takes into account market size, quantity of import, domestic production channels and import substitution. Agenor and Montiel (1996) provide important information on how changes in exchange rates affects inflation:

• For an open economy covering import and export of goods and services, it can directly affects the price level of exported and imported goods.

• They said changes in the exchange rate indirectly increase price of final goods through prices of inputs imported from abroad.

• Uncertainty in outside currency prices, due to changes in exchange rates, can affect domestic price makers and raise prices of domestic goods and services.

According to Svensson (2000) one of the roles of exchange rate in monetary transmission mechanism. Therefore, he said that changes in exchange rates can affect inflation in three different ways:

• Exchange rate changes observed in an open economy affect the relative prices of domestic and foreign goods, thereby shifting demand from domestic to domestic goods. As a result, aggregate demand and indirect inflation are affected by net exports.

• On the other hand, exchange rate changes directly affect the price level of imported goods in local currency. Therefore, it directly affects the consumer price index. Ultimately, the inflation rate is affected by the price of imported final products, the effect of which is mainly observed over a shorter period of time compared to the indirect effect produced by net exports.

• Finally, exchange rate movements affect nominal wages through the impact of import prices in local currency on the consumer price index. When these two effects are combined, the inflation rate is influenced by the cost of household products. A second point about the role of exchange rates in inflation targeting strategies is that, as an asset price, exchange rates are a future and expected variable. As such, it has an impact on expectations that it has an important place in monetary policy. Thus, according to these researchers, it is clear that the exchange rate has a significant impact on inflation forecasts.

2.2. Empirical review

2.2.1. Machine learning forecasting methods

LASSO technique was used to forecast the inflation and their results were compared with that of benchmark techniques of forecasting inflation (ARMA). Onder Ozgur and Ugur Akkoç in their study "Inflation forecasting in an emerging economy: selecting variables with machine learning algorithms" with an application to turkey economy, they used sample data from March 2007 to 2017. Using LASSO machine learning technique and RMSE to measure the performance, they found that LASSO has high forecasting power compared with RMSE (0.834) for LASSO regression compared to 1.237 of ARMA model (Özgür & Akkoç, 2021), they also found that Ridge regression outperform existing method with lower root mean squared error of 1.099 compared to 1.237 of ARMA model.

In forecasting Brazilian inflation, in the study "Real-time inflation forecasting with high-dimensional models", "Márcio G.P. Garcia, Marcelo C. Medeiros a,∗ , Gabriel F.R. Vasconcelos" found that the LASSO perform well in forecasting inflation when it applies to short time horizon. Among all the methods used, LASSO regression outperforms others with its small RMSE and MAE which are 0.95 and 0.74 respectively. In their study their further showcase that autoregressive (AR) model perform poorly in forecasting with RMSE of 2.3 and MAE of 1.93 (Garcia et al., 2017).

Random forest model which combines the prediction of different trees and predicts the average of the trees was nominated among the top three models for forecasting the Brazilian inflation for the study "Machine learning methods for inflation forecasting in Brazil: new contenders versus classical models" by "Gustavo Silva Araujo & Wagner Piazza Gaglianone". They found that random forest forecasts have lower mean squared error of 0.07 compared to other forecasting methods. They conclude that machine learning techniques especially random forest perform better than existing used methods in term of root mean squared error(Araujo, 2020).

Ivan Baybuza**,** in his study "Inflation Forecasting Using Machine Learning Methods" in 2018 in Russia, using sample consists of 92 main macroeconomics variables consisting of industrial production, business activity, employment rate, balance of payment, financial market and the prices of the main export goods of the Russian economy. He used changes in CPI as measure of inflation; the sample period was from 2002 to 2016, he concluded that forecasting inflation using machine learning techniques can perform well in terms of quality of forecasting of inflation of Russian compared to reference models (benchmarks, ARMA model and Random walk model) that use only their previous values of inflation as predictors. Especially, random forest outperforms all other methods of forecasting. However contrary to other scholars, he concluded that regularization methods (LASSO, Ridge) perform poorly compared to the benchmark models(Baybuza, 2018).

K Nearest Neighbor (KNN), Random forest and Ridge regression methods were used to forecast UK Inflation, in the study entitled "Machine learning at central banks", Chiranjit Chakraborty and Andreas Joseph, they used data from 1988Q1 to 2015Q4 on quarterly basis, their conclusion is that all these machine learning techniques outperform the benchmarks methods of forecasting inflation due to smaller mean absolute error 0.26 for KNN, 0.28 for random forest, 0.44 for Ridge regression compared to 0.48 of VAR model(Chakraborty & Joseph, 2017).

In his study of "Forecasting Costa Rican inflation with machine learning methods", Adolfo Rodríguez-Vargas used Data cover the period January-2003 to February-2019, he found that the KNN model and random forecast outperform existing methods used in inflation forecasting of Costa Rica(Rodríguez-Vargas, 2020)

In the past days, existing methods namely ARMA model and VAR model were mainly used in forecasting inflation. ARMA model was used in many studies from different countries, in Rwanda, Gicondo Ananias and Kimenyi (Bank, 2010) forecasted inflation of Rwanda and RMSE was 1.29. in Gambia, the study entitled"modeling and forecasting the Gambia inflation using ARMA Approach", "Nyoni, Thabani and Mutongi" used ARMA model to forecast using data covering 11960 to 2016, they found that ARMA has high forecasting power(Nyoni & Mutongi, 2019).

In existing methods, some studies reported that VAR model outperform ARMA model while others not, the study "time series modeling and forecasting inflation: evidence from Nigeria" conducted by "Ikechukwu Kelikume" used ARMA model and VAR model in forecasting Nigeria inflation, he used monthly data from 2003-2012. He used supply of money and change of CPI as variables to forecast inflation. The results of his study shows that VAR model has high predicting power due to small error compared to ARMA model(Kelikume & Salami, 2008).

In forecasting Jamaica Inflation of Jamaica, “Wayne Robinson” studied the performance of VAR model against ARMA, he used variables money supply, exchange rate, interest rate was used to forecast inflation, their results of VAR and ARMA model were evaluated using the root mean squared error. The results show VAR model provides high predictive power with RMSE (0.004) compared to ARMA model with RMSE 0.008) (Robinson, 1998).

The study “Forecasting inflation in Bosnia and Herzegovina”, “Elma Hasanovi” evaluate the performance of each model between ARMA and VAR model, he revealed that in his research the ARMA model outperforms VAR model when compared to the RMSE, similar results was obtained by Fritzer et al. (2002) for inflation of Austria, he found that univariate models ARMA model performs better than VAR models at short horizons(Paper et al., 2020).

Many studies on forecasting inflation have shown a high forecasting power when machine learning techniques are applied over forecasting using existing methods, ARMA model and VAR model, and VAR model mostly outperform ARMA model. Machine learning methods such as KNN, Random Forest, LASSO perform well in forecasting inflation for different studies in different countries; this study applies machine learning techniques to forecast inflation of Rwanda mostly most of the study on inflation was done to find the variables affecting inflation in Rwanda. On his study “Determinants of Inflation in Rwanda from 1970-2013”, (Ruzima, 2018) shows that inflation in Rwanda is mainly accelerated by the supply side, and import of goods and services.

On her study” evaluation of The relationship between inflation and its Determinants In Rwanda” Esperance, use the determinants such as supply of money, exchange rate as the main drivers of inflation in Rwanda(Esperance & Fuling, 2020). This study uses the selected determinants of inflation in to forecast inflation used machine learning methods.

2.3. Exchange rate and Inflation

Numerous studies have been conducted to assess the relationship between inflation and exchange rates, in his study "The Relationship Between Exchange Rates and Inflation: The Case of Iran", "Sanam Shojaeipour Monfared", use data from 1976 to 2012, by Hendry General Specific Modeling method, he found direct association between exchange rates and inflation. Therefore, rising in exchange rate drives inflation (Monfared & Akın, 2017).

In the study "The Impact of Exchange Rates on Inflation and Economic Growth in Vietnam", "Thanh Tung Hoang" used data from 2005 to 2018. He applied vector autoregressive model with six endogenous variables namely real exchange rate, supply of money, Exports, imports, GDP at comparable prices in 2010, CPI and international prices, and the Fed's interest rate are two exogenous variables, and their results show that increase in exchange rate cause the consumer price index to increase immediately in the first quarter(Hoang et al., 2020).

In study "The Relationship Between Exchange Rates and Inflation: The Case of the Western Balkans", "Besnik Fetai" assessed this relationship using data from 1996 to 2014 on quarterly basis, using fixed-effects and random-effects as panel method models. and "Hausman-Taylor Instrumental Variables IV" model, their findings suggest that exchange rates remain the principle driver of inflationary in the Western Balkans (Koku et al., 2016).

In study “The Relationship between Exchange Rate and Inflation: An Empirical Study of Turkey”,” Abderezak Ali Abdurehman, Samet Hacilar” they used data from January 2005 up to December 2014, they applied Generalized autoregressive conditional heteroskedasticity (GARCH) and his result show direct relationship between exchange rate and inflation(Abdurehman & Hacilar, 2016). So, considering many studies in different countries that were done to show relationship of exchange rate and inflation using various methods, they all came up with the same conclusion of significant impact of exchange rate on inflation. So based on these studies, we will use exchange rate as explanatory variable to forecast inflation using Machine learning techniques.

2.4. Money supply and inflation

There are various empirical studies evaluating the association between supply of money and inflation, "Amedeo Strano" his study titled "How and to what extent does the money supply affect the rate of inflation?" research conducted in Iceland to test the association between inflation and monetary growth took 11 countries as samples over the same period from 1972 to 2002 for testing the quantitative theory of the relationship between money and inflation. By analyzing all countries in the sample, its study results showed an association between long-term inflation and monetary growth. There is a strong positive correlation implies strong relationship between inflation and monetary growth in all countries, whether high or low inflation (less than 10% per year on average)(Strano, 2009).

Suna Korkmaz in her study "The Relationship between Money Supply, Inflation and Economic Growth in Mediterranean Countries", the dataset covers 7 years from 2008 to 2014, the average annual growth rate of money was used as supply of money and change in CPI was used as measure of inflation. From his results, there is a direct and one-way relationship between the money supply and inflation (Korkmaz, 2017).

In the study "Interrelationships between Money Supply, Inflation, Government Expenditure and Economic Growth", "Muhammad Ijaz Hussain1*, Tasneem Zafar", they did research to assess the relationship among supply of money, government expenditures, inflation and economic growth from 1972-2015 for Pakistan economy. Data used was from World Development Indicators, their findings show a significant association between supply of money and inflation(Hussain & Zafar, 2018)**.**

The study “The nature of the relationship between the money supply and inflation in the Jordanian economy”, to assess the relationship “Atif Batarseh” used data from the period 1980 to 2019. Using the Granger-Causality results, he found a one-way relationship of supply of money and inflation in short run, implies that supply of money leads to inflation, but inflation doesn’t lead to money supply; therefore changes in supply of money can lead to changes in CPI in the Jordanian economy, he recommended that Jordanian monetary authority strengthen its monetary policy control especially for the money supply because of its effects for the stability of the general price level in the way to prevent a repetition of devaluation of the dinar during the 1989 crisis that raise inflation rate for that year to 25.6% (Batarseh, 2021).

The study "The Relationship Between Money Supply and Inflation: A Causal Approach to the Study of the Jamaican Economy", "Samuel P. Indalmanie" used data for the period 1961-2006 from the Bank Jamaica Statistical Digest and International Finance Statistics, the study results revealed the direct effect of supply of money on inflation implies that there is a significant direct correlation between money supply and inflation (Indalmanie, 2015).

the study entitled “Dynamic Impact of Money Supply on Inflation: Evidence from ECOWAS Member States”, “Obi, Kenneth O. Ph.D 1, Uzodigwe, Anthony Ajana”, using data from the 1980 up to 2012. As a conclusion in their study, their results revealed an association between supply of money and inflation in ECOWAS members(Ajana, 2015)**.**

In the study "The Effect of Money Supply on Inflation in Nepal", "Uttam Lal Joshi" using data from 1964/65 to 2018/19, the model includes inflation the dependent variable, supply of money and ICPI as independent variables. Then, applying ARDL Bounds test and ECM test, the results show a long-run cointegration relationship between supply of money and inflation, which means that supply of money effects significantly inflation in Nepal (Joshi, 2021). Therefore, all studies looking for the relationship between supply of money and inflation in different countries have come to the same conclusion that supply of money has a significant impact on inflation in each country. This allows us to use the money supply as an explanatory variable to predict inflation in Rwanda.

2.5. Oil price and inflation

Changes in price of oil affects each economy worldwide. The oil price is essential in assessing the economies of countries especially underdeveloped because they are financially unstable and are severely affected by outside shocks. the main impacts resulting from the change in oil price is its effect on the inflation. inflation changes lead the economy to change and ultimately affect the overall performance of the whole economy.

Various studies report the price of oil has a significant influence in determining inflation, oil is basic factor of production for most production and it is used as a basic factor input for almost everything we consume. In their study "Comparative Study of the Impact of Changes in Oil Prices on Inflation" by Siok Kun Sek*, Xue Qi Teo and Yen Nee Wong, they focused on comparing effects of changes in oil prices of domestic market Inflation between low and high dependency groups. Their findings suggest that there is a long-run relationship between changes in oil prices and inflation and changes in price of oil have a significant impact on determining domestic inflation. Furthermore, they find that changes in oil prices have a direct effect on domestic inflation in the low oil dependence group, but an indirect effect on domestic inflation in the high oil dependence group (Sek et al., 2015).

On the study of "How do oil price changes affect inflation in Central and Eastern European countries?"," Dejan Živkov, Jasmina Đurašković & Slavica Manić" used monthly time series data covering the period from january 1996 to june, 2018 from Brent oil and CPI of eleven CEECs – the Czech Republic, Poland, Hungary, Slovakia, Lithuania, Latvia, Estonia, Romania, Bulgaria, Slovenia and croatia. Their results show a relatively low impact of change in oil price in these selected European countries, they revealed that a 100% change increase in oil price in these countries change an inflation from 1 up to 6 percent but the impact is significant(Živkov et al., 2019). On the study" Oil Prices and Inflation Dynamics: Evidence from Advanced and Developing Economies", "Sangyup Choi, Davide Furceri", used data of the period from 1970-2015. Their finding shows that a 10 percent increase in global oil inflation, on average, increases domestic inflation at the peak impact by about 0.4 percentage point, with the effect becoming statistically insignificant two years after the shock(Choi et al., 2018).

In the study “The Impact of Oil Prices on Inflation: The Case of Azerbaijan”, “Shahriyar Mukhtarov, Jeyhun Mammadov, Fariz Ahmadov” used data covering the period starting in 1995 to 2017, result of cointegration test shows a long run relationship among the variables and estimation results of vector error correction model show that the oil prices have positive and statistically significant impact on inflation in the long-run. This implies that 1% increase in oil prices and exchange rate increases inflation by 0.58% and furthermore, the results of their study also reveal that inflation is observed during the periods of both high and low oil prices(Mukhtarov et al., 2019).

in study “Oil Price Shock and its Impact on the Macroeconomic Variables of Pakistan: A Structural Vector Autoregressive Approach”, “Kashif Zaheer Malik, Haram Ajmal, Muhammad Umer Zahid” examines the dynamic effects of the oil price shocks on the key macroeconomic variables of Pakistan using structural vector autoregressive model and time series data from 1960 to 2014. Their results show that inflation rate rise as a result of increase in oil price.

The study done by “TANVEER AHMED NAVEED” titled “Pass-Through of World Oil Prices to Inflation: A Time Series Analysis Of Pakistan”, the primary objective of their study was to investigate long-run pass through of world oil prices to domestic inflation in Pakistan using monthly data from January 2000 to December 2014, The results of the study clearly explain that in the long-run international oil prices significantly affect the inflation rate in Pakistan and oil price has positive relationship with inflation and their findings using Granger causality test reveal that there is unidirectional causality that runs from world oil prices to inflation rate, that is world oil prices causes inflation but not vice versa(Asghar & Naveed, 2015). Several studies that had done to find the impact of international oil price change on inflation revealed that change in oil prices has an impact on inflation as shown by different studies done in different countries, based on this evidence from the studies, we will use change in international oil prices as independent variables to forecasting inflation in Rwanda

2.6. Lending rate and inflation

Studies found negative correlation between economic growth and lending rate, study conducted in Nigeria to assess the relationship between bank lending rate and economic growth, Akinwale used data from 1980 to 2016, he found a negative relationship between bank lending rate and economic growth, the findings proved that a unit percent decrease in bank lending rate will bring about 118% increase in economic growth (S. O., 2018). This shows relationship between lending rate and inflation, hence lending rate affects economic growth, and this means that increase in lending rate discourage the investors from borrowing money and expand their businesses, hence lower the production of goods and service. This is followed by an increase in general prices for the small available quantity produced and results in inflation.

CHAP 3: RESEARCH METHODOLOGY

3.1. Study design

The study aims at build machine learning model that attempts to forecast Rwanda inflation from main macroeconomics variables, different machine learning methods were attempted to find model that best forecast inflation.

3.2. Source of data

The study uses secondary time series data from the National Bank of Rwanda (NBR). The dataset contains variables from 2006 up to 2019 will be used.

3.3. Sample size

Time series data used for this study is quarterly data. Based on time interval from 2006 up to 2019, it is a period of 14 years and each year account for 4 quarters. So, a total of 56 observations from 2006 quarter one up to 2019 quarter four will be used in this study.

3.4. Data analysis

Python software used to build machine learning models: models such as Ridge Regression, LASSO Regression, KNN and Random Forest will be used to find model that best forecast inflation. Eviews software also was used to run existing models ARMA, and VAR used in this study.

3.5. Data Preprocessing

To model time series data, we first check whether the variables are stationary or not. If they are not stationary their mean and variance are changing overtime. So, time series data need to be stationary such that the forecasting results become accurate. the variables used in this study were tested for Stationarity using ADF (Augmented Dicker Fuller) test. The variables which are stationary at level are used as they are while those which are not stationary were making stationary by differentiating them.

3.6. Description of Methods used

3.6.1. Autoregressive Moving Average (ARMA)

To build an ARMA model, the variables need to be stationary; we first tested the Stationarity of variables used. We used ADF test to test the Stationarity of the variables, variables in whose P-value of ADF test is smaller than 0.05 are stationary at level while variables which are not stationary at level are differentiated to make them stationary. After differentiating, we determine the number of past lags (p) and number of previous error term (q) to include in the model.

To determine number of past lags (p) and (q), we used AKAIKE criterion (AIC), Hannan-Queen (HQ) and Schwarz Information criteria (SBIC) run using Eviews software, for all those ways, it is recommended to choose a method which produces small number of p and q.

3.6.1.1. Estimation

After determining number of previous lags p and previous error term q to use in model. The model is estimated by least squares method and past values of lags p and error q becomes the independent variables to determine dependent variable.

To measures the quality of forecast, which are based on the errors of forecasts ($Y_{t+h} - Y_{t+h} / t$). RMSE which is the square root of MSE and MAE, are defined as:

$$MSE = \frac{1}{T-(T_1-1)} \sum_{i=T_1}^{T} (Y_{t+s} - f_{t,s})^2$$

$$MAE = \frac{1}{T-(T_1-1)} \sum_{i=T_1}^{T} \left| Y_{t+s} - f_{t,s} \right|$$

3.6.2. Vector Autoregressive (VAR)

VAR model is a set of statistical equations where the past values of variable and past values of other variables are used to predict the dependent variable. All variables in the VAR model are endogenous. They can be on either side on the left or the right.

The vector autoregressive model (VAR), proposed in 1980 by Sims, is the most powerful, flexible, and easy-to-use model for multivariate data analysis. It is used to capture the interaction between multiple time series. VAR models is an extension of AR models to multivariate time series by allowing multiple variables to evolve. All variables in a VAR model are treated symmetrically in a structural sense; each variable has an equation, the equation explains its evolution in terms of its own lags and the lags of other variables in the model.

The VAR model is expressed as in a set of equations:

$$Infl_t = \mu_1 + A_1\sum Infl_{t-i} + A_2\sum M_{t-i} + A_3\sum Oil_{t-i} + A_4\sum Interbank_{t-i} + A_5\sum Lending_{t-i} + \varepsilon_t$$

$$M_t = \mu_2 + B_1\sum Infl_{t-i} + B_2\sum M_{t-i} + B_3\sum Oil_{t-i} + B_4\sum Interbank_{t-i} + B_5\sum Lending_{t-i} + \varepsilon_t$$

$$Oil_t = \mu_3 + C_1\sum Infl_{t-i} + C_2\sum M_{t-i} + C_3\sum Oil_{t-i} + C_4\sum Interbank_{t-i} + C_5\sum Lending_{t-i} + \varepsilon_t$$

$$Interbank_t = \mu_4 + D_1\sum Infl_{t-i} + D_2\sum M_{t-i} + D_3\sum Oil_{t-i} + D_4\sum Interbank_{t-i} + D_5\sum Lending_{t-i} + \varepsilon_t$$

$$lending_t = \mu_4 + E_1\sum Infl_{t-i} + E_2\sum M_{t-i} + E_3\sum Oil_{t-i} + E_4\sum Interbank_{t-i} + E_5\sum Lending_{t-i} + \varepsilon_t$$

Where i: number of previous lags

3.6.3. RANDOM FOREST

The random forest model was proposed by Breiman (2001) to reduce the variance of regression trees by constructing regression trees randomly. Regression tree is a nonparametric model that assumes an unknown nonlinear function with local predictions through recursive partitioning of the space of the covariates (Breiman 1996).

RF is a collection of regression trees, created from bootstrapping of the original data. In regression, bootstrap samples $h_j(x)$ are formed randomly from original data and each gives its own prediction. Then random forest averages the prediction from many bootstraps to give the final prediction f(x).

$$f(x) = \frac{1}{J}\sum_{J=1}^{J} h_j(x)$$

Where: h_j denotes different bootstrap sample that is formed from random variables.

3.6.4. K NEAREST NEIGHBOR (KNN)

The supervised machine learning algorithm K Nearest Neighbor assumes that the closer observations are going to be similar or closer each other. We determined the number K of nearest neighbors and the new observation is obtained by averaging the observations of K nearest neighbors. There is no method to determine the exact value of K, the accuracy of the model is tested for various values of K. K that gives best accuracy for both training and testing data is chosen. Larger K: There is under fittin, the model is unable to perform well on training data. Smaller K**:** There is overfitting. The model capture all the data including noise of the training data. The model do poorly for the test data.

3.6.5. MODEL WITH REGULARIZATION

Regularization improves the performance of model which was overfitted through introducing extra term to the loss function.

3.6.5.1. Ridge Regression

Ridge regression improves the model performance through shrinking the regression coefficients by imposing penalty or extra term in their size. Its coefficients minimize the penalized residual sum of square. Ridge adds lambda times squared weight term to the loss function.

$$\beta^{ridge} = \operatorname{argmin}\left\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \beta_j^2\right\}$$

$\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2$: is the loss function

$\lambda \sum_{j=1}^{p} \beta_j^2$: is the penalty

Wherey_i: is the dependent variable (Inflation)

x_i: are independent variables (Money Supply, Oil Price, Exchange rate, lending rate and interbank rate)

β_j: Is a set of parameters.

λ: Lambda or learning rate ($\lambda \geq 0$)

the choice of λ is depends on small root mean squared error.

3.6.5.2. LASSO Regression

Tibshirani introduced LASSO Regression in (1996), it is similar to Ridge regression but LASSO regression add lambda times the absolute weight term to the loss function.

$$\beta^{lasso} = \text{argmin}\left\{\frac{1}{2}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right\}$$

$\frac{1}{2}\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2$: Loss function

$\lambda\sum_{j=1}^{p}|\beta_j|$:Penalty

CHAP 4: DATA ANALYSIS

4.1. Stationarity of Data

Before performing any task on time series data, we first examine stationarity because without it, the interpretation of these results is misleading and the problem is compounded by applying nonlinear methods to time series (Manuca & Savit, 1996). Stationarity means constant mean and constant variance. we often use the Augmented Dicker Fuller (ADF) test in testing stationarity with the null hypothesis of non-stationarity. Therefore, by performing an ADF test, we do not reject the null hypothesis and confirm the non-stationarity of the CPI.

The Stationarity of all variables after first difference (except Lending rate and change in international Oil price which are Stationary at levels) is confirmed by ADF unit root test. CPI at level has Probability (0.367) and becomes stationary at first difference with probability (0.00) which is less than (0.05), Exchange rate has probability (0.997) at level and becomes stationary at first difference with probability (0.022) which is less than (0.05), lending rate is stationary at level because its probability at level (0.03) is less than (0.05), Money supply has probability (0.374) at level and becomes stationary at first difference with probability (0.00) which is less than (0.05), Oil price is stationary at level with probability (0.00) which is smaller than (0.05). Therefore, the null hypothesis that all variables have a unit root is not be rejected because their p-values are above the 5% significance level, except that the variables mentioned are fixed in level, which means that they are not a stationary at level, while the null hypothesis are rejected after the first-difference as all p-values have a significance level of less than 5%.

.

4.2.VAR MODEL

4.2.1. Introduction

Before we start using VAR model, we first test whether there is no serial correlation and long run relationship in the variables by Johansen cointegration techniques.

4.2.2. Determining the optimum lag length

We find optimal lag length using SC, HQ and AIC as lag order selection criteria (Helmut, 1980). the minimum lags among those provided with these selection criteria is selected as the optimal lags. The maximum number of lags was 6 and the optimum number of lags selected is 1 as indicated by the below results in table

VAR Lag Order Selection Criteria
Endogenous variables: CHANGE_CPI CHANGE_EXCHANGE_RATE CHANGE_INTERBANK_RATE CHANGE_M3 CIOP LENDING_RATE
Exogenous variables: C
Date: 09/07/21 Time: 00:03
Sample: 2006Q1 2019Q4
Included observations: 49

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-777.3516	NA	3098126.	31.97354	32.20519	32.06142
1	-701.5523	129.9417	617613.1	30.34907	31.97063*	30.96429*
2	-680.6250	30.75033	1220831.	30.96429	33.97575	32.10683
3	-651.9877	35.06605	1971574.	31.26480	35.66618	32.93468
4	-581.5201	69.02950*	703849.1	29.85796	35.64925	32.05517
5	-519.9142	45.26145	510760.4*	28.81283	35.99402	31.53736
6	-459.7445	29.47088	770244.7	27.82631*	36.39741	31.07817

* indicates lag order selected by the criterion

Table 1: Optimal lag length result

4.2.3. Testing Residual Serial Correlation

After selecting, the optimal lag length, we test whether there is a residual serial correlation with LM test by using EVIEWS software, the results show that multivariate errors are white noise as the VAR residual Serial Correlation LM Tests do not reject the Null Hypothesis of No serial correlation as all P-Values are greater than 0.05, we confirm no residual serial correlation.

VAR Residual Serial Correlation LM Tests
Date: 09/07/21 Time: 00:10
Sample: 2006Q1 2019Q4
Included observations: 53

Null hypothesis: No serial correlation at lag h						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.61165	36	0.5346	0.958692	(36, 130.1)	0.5425
2	48.11795	36	0.0853	1.398408	(36, 130.1)	0.0895
3	39.06585	36	0.3337	1.099267	(36, 130.1)	0.3418
4	36.47563	36	0.4465	1.017002	(36, 130.1)	0.4548
5	41.97399	36	0.2278	1.193372	(36, 130.1)	0.2349
6	34.75295	36	0.5278	0.963087	(36, 130.1)	0.5358

Table 2:Testing residual correlation results

4.2.4. Testing The Long Run Relationship

4.2.4.1. Johansen Cointegration Test Results

We used Johansen cointegration technique to test the long-term relationship among the variables. Trace and Max-Eigen rejected the null hypothesis of no cointegration because their statistics were above the critical value and the corresponding probability was below the 5% significant Dependability level.

On the other hand, a simple cointegration equation is not rejected by the Trace and Max – Eigenvalue tests because its statistic is below the critical value at the 5% significance level. This suggests the existence of a cointegration equation and implies a long run relationship among the variables.

4.2.5. Forecast with VAR Model

Vector autoregressive model involves forecasting the value of time series data where the current values are predicted from its previous values and the previous values of other variables at a specified lag. The number of lags to use using the lag structure, both the AIC, SC and HQ as resulted above is lag of 1, the resulted RMSE for the VAR model is 1.1786 and its mean absolute error is 0.9411.

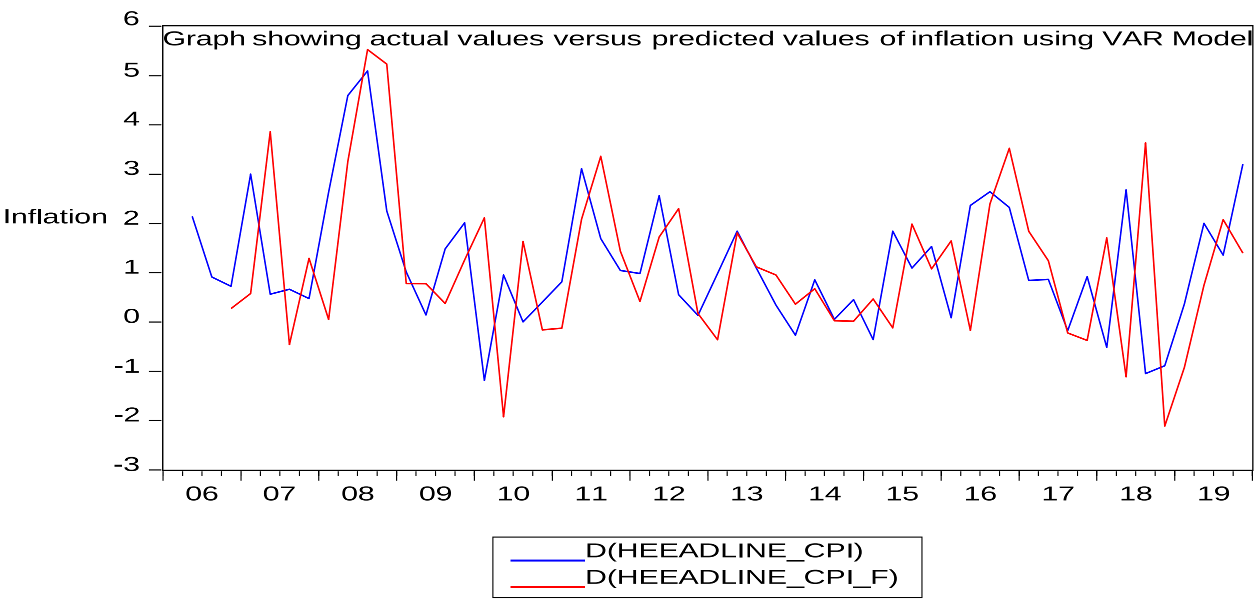


Figure 1: Prediction with VAR model

The figure above shows the actual value in blue color and the forecasted values using the VAR model, the graph were designed using Eviews software and the resulted root mean squared error is 1.17868 and means absolute error is 0.9411.

4.3. Forecasting with ARMA Model

The Autoregressive moving average model involves that the past values of the variable are used in predicting the current value of the variable, to perform an ARMA model, it involves determining the number of lags of past values(p) and number of previous error to include in the model (q), so the results of AIK (Akaike Information Criterion) and Schwarz Information criteria (SBIC) are (p=2) and (q=1), the ARMA model is regressed on two past values of inflation and one past value of previous error. The RMSE for ARMA model is 1.176938.

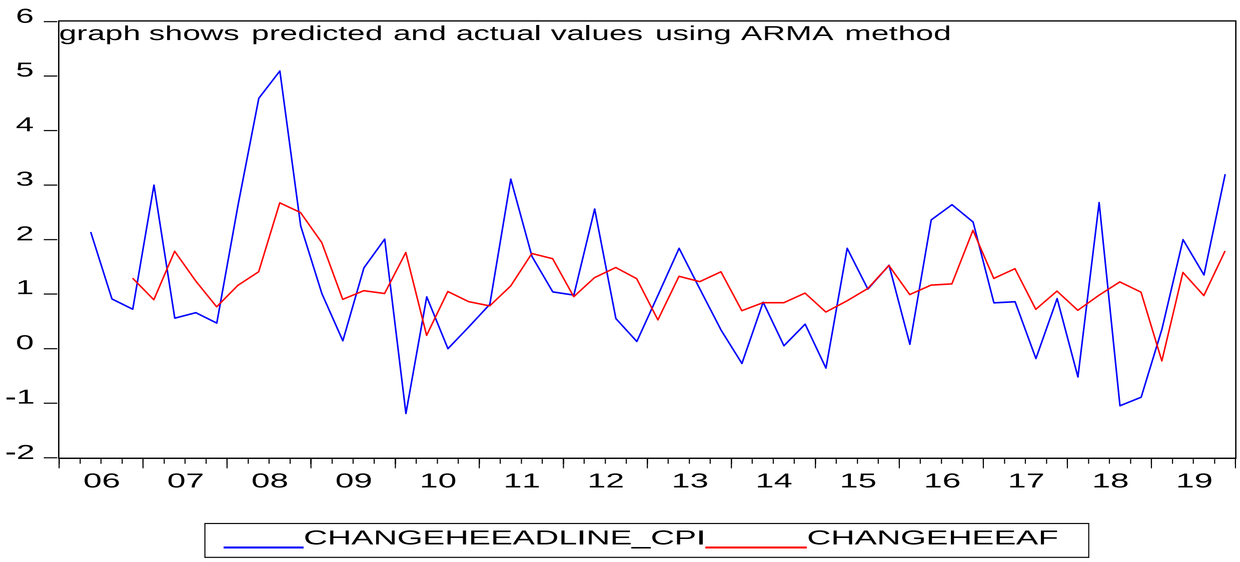


Figure 2: Prediction with ARMA model

The figure above shows the actual value in blue color and the forecasted values using the ARMA model, the graph was designed using Eviews software and the resulted RMSE is 1.176938 and MAE is 0.9204.

4.4. FORECASTING WITH MACHINE LEARNING METHODS

Table 3: RMSE for training and testing data using ML techniques

Model	RMSE for Training	RMSE for testing
KNN	1.2382	1.2681
Random forest	0.5111	1.1687
Ridge	1.2148	1.3313
LASSO	1.2868	1.2504

The table above show the different values of root mean squared RMSE obtained using different machine learning methods, to get these results different K neighbors for KNN model were tried and the best that provided the small RMSE for both the training and testing data was K=8, where the RMSE for training is (1.2382) and RMSE for testing is (1.2681), Random forest model which is an ensemble of decision trees also was performed using different n_estimators, the n_estimators that provides the best results are n_estimators (also known as number of decision trees) is equal to 30. The RMSE for training is (0.5111) and the RMSE for testing is (1.1687). Ridge regression and LASSO regression which applies penalty for OLS methods both produced good results at alpha of 1.0, the RMSE of training for Ridge regression is (1.2148) and it is (1.3313) for testing data. LASSO regression has RMSE for training data of (1.2868) and (1.2504). Among all models, random forest model performs well in both training (RMSE=0.5111) and testing data (RMSE=1.1687) while LASSO do poorly in training data (RMSE=1.2868) and Ridge do poorly in testing data (RMSE=1.3313).

To do machine learning methods, our dataset is divided into two parts, the first part is 67 percent of the data starting from the first observation and the remaining 33 percent were used for testing. The figures in appendix show that some of the methods try to capture the trends of the data on training and testing. Random forest model which is an ensemble or aggregation of decision trees perform well in training data, looking at its figure, we see that almost all the predicted data follows the trends of actual data making it the best model to perform well on training and looking at the testing side, the data follows the trend of the data but some slightly deviation making root mean square error for testing be greater than root mean square error for training. Considering the figures for KNN model, the predicted values follows the trend of actual values except for an outlier that occurred in 2008 where the value of inflation went up. Its figure of testing also shows that the predicted values follow the trend of actual values. Ridge regression which applies penalties to reduce variance, their predicted values on training data follows the trend of the actual values and the figure of testing data shows also that the predicted values follow the trends of the actual values with slight deviation. The LASSO method shows a poor performance in predicting the inflation, its figures both for the training and testing data shows that the predicted values have no trend towards the actual values. So, based on the figures and above RMSE, Random forest model perform better in predicting inflation that other methods.

SUMMARY RESULTS OF FORECASTING

Table 4: Summary of results of RMSEs

Model	RMSE
KNN	1.2382
Random forest	0.5111
Ridge	1.2148
LASSO	1.2868
ARMA	1.176938
VAR	1.17868

Based on the results of the table above, forecasting with Random forest model is the best approach that provides the best result due to its small root mean squared error, followed by ARMA model and VAR model. Random forest is the best model due to its capability of averaging the values of different decision trees that used to build it. This is because averaging different values of these trees reduces the effect of an outlier which mainly affects the root mean squared error. ARMA Model also performs fairly better because it depends on the previous values of inflation.

CHAP 5: DISCUSSION OF THE RESULTS AND CONCLUSION

5.1. Discussion of findings

The first objective of our study was to introduce the machine learning techniques in forecasting the inflation in Rwanda, in this study different supervised machine learning techniques including Random Forest, K nearest neighbor, LASSO regression, and Ridge regression were run and provided different results. Because this study is supervised learning with regression, the results of these methods were evaluated with respect to their RMSE. the best model, is the one with small root mean squared compared to the remaining ones. Comparing the RMSE of our models, Random Forest model perform best over the others, it has RMSE of 0.5111 at training and 1.1687 at testing data, and it was followed by K nearest neighbor, ridge regression and lastly the LASSO regression. This results confirm the results of Ivan Baybuza(Baybuza, 2018) who concluded that ensemble methods (RF and Boosting) showed better results while regularization models forecast poorly.

The second objective was to forecast inflation using existing methods, ARMA model and VAR model were used, RMSE evaluated the performance of each method, their results showed that these methods provided the closer RMSE 1.176938 for ARMA and 1.1786 for VAR model`

The third objective was to compare the performance of machine learning in forecasting inflation with existing methods used, the existing methods discussed in this study were ARMA where dependent variable uses its own past values to forecast the present or future value. Another method used is Vector Autoregressive (VAR) model where the dependent variable uses its previous values and the previous values of the other variables, their results were evaluated using their root mean squared error and compared with that of the machine learning techniques used in forecasting the inflation. In the overall models including machine learning models and existing models, the Random forest model still the best performer among all others due to its small root mean squared 0.5111 at training and 0.1687 at testing. However, ARMA model outperform all the remaining models in forecasting due to its small RMSE (1.176938) compared to the remaining models and VAR perform thirdly with the RMSE of 1.1786. the results are in line with that of Babyuza (Baybuza, 2018) who concluded that ensemble methods showed results comparable to the existing models in predicting monthly inflation.

5.2. Conclusion

This study has aimed to introduce the machine learning techniques in forecasting Rwandan inflation compared to existing existing methods. Four machine learning methods were used: KNN, random forests, Ridge and LASSO regression however, not all methods performed equally well in forecasting inflation when compared to existing methods. The results show that the best performer method was ensemble method (Random forest) which showed low RMSE when compared to existing methods that currently used by the central bank to forecast inflation, however the regularization methods (Ridge and LASSO) show a poor performance in forecasting inflation. Our results are similar with other studies that used machine learning to forecast inflation in other countries, (Baybuza, 2018) in his study of forecasting Russian inflation using machine learning techniques, he concluded that forecasting inflation using random forest model showed promise however the regularization (Ridge and LASSO regression) models forecast poorly compared to existing models, (Rodríguez-Vargas, 2020) in forecasting Costa Rica inflation using machine learning techniques also found that random forest, LSTM model, univariate KNN all showed performance in forecasting Costa Rica inflation. Based on results, implementing machine learning techniques for forecasting Rwandan inflation is a promising endeavor. So, first line of work could be the improvement in the application of methods that underperformed in the study, as well as the potential to extend the work to include other machine learning techniques such as Neural networks methods.

6. REFERENCE

Abdurehman, A. A., & Hacilar, S. (2016). The relationship between exchange rate and inflation: An empirical study of Turkey. *International Journal of Economics and Financial Issues*, *6*(4), 1454–1459.

Ajana, A. (2015). Dynamic Impact of Money Supply on Inflation: Evidence from ECOWAS Member States. *IOSR Journal of Economics and Finance Ver. III*, *6*(3), 2321–5933. https://doi.org/10.9790/5933-06331017

Araujo, G. S. (2020). *Machine learning methods for in ‡ ation forecasting in Brazil : new contenders versus classical models*. 1–39.

Asghar, N., & Naveed, T. (2015). Pass-Through of World Oil Prices to Inflation: A Time Series Analysis of Pakistan. *Pakistan Economic and Social Review*, *53*(2), 269.

Bank, N. (2010). June, 2010. *The Lancet Neurology*, *9*(9), 853. https://doi.org/10.1016/S1474-4422(10)70202-7

Batarseh, A. (2021). The nature of the relationship between the money supply and inflation in the Jordanian economy (1980–2019). *Banks and Bank Systems*, *16*(2), 38–46. https://doi.org/10.21511/bbs.16(2).2021.04

Baybuza, I. (2018). Inflation Forecasting Using Machine Learning Methods. *Russian Journal of Money and Finance*, *December*, 42–59. https://doi.org/10.31477/rjmf.201804.42

Cause, I., Author, C., Source, B. W. S., Journal, F. A., & Url, S. (2014). *CAUSE*. *27*(3), 11–16.

Chakraborty, C., & Joseph, A. (2017). Machine Learning at Central Banks. *SSRN Electronic Journal*, *674*. https://doi.org/10.2139/ssrn.3031796

Choi, S., Furceri, D., Loungani, P., Mishra, S., & Poplawski-Ribeiro, M. (2018). Oil prices and inflation dynamics: Evidence from advanced and developing economies. *Journal of International Money and Finance*, *82*, 71–96. https://doi.org/10.1016/j.jimonfin.2017.12.004

Durevall, D., & Sjö, B. (2012). *The Dynamics of Inflation in Ethiopia and Kenya*. *August*.

Esperance, N., & Fuling, H. (2020). Evaluation of Economic relationship between inflation and its determinants in Rwanda. *European Journal of Economic and Financial Research*, *3*(6), 137–149. https://doi.org/10.5281/zenodo.3714179

Garcia, M. G. P., Medeiros, M. C., & Vasconcelos, G. F. R. (2017). Real-time inflation forecasting with high-dimensional models: The case of Brazil. *International Journal of Forecasting*, *33*(3), 679–693. https://doi.org/10.1016/j.ijforecast.2017.02.002

Hoang, T. T., Thi, V. A. N., & Minh, H. D. (2020). The impact of exchange rate on inflation and economic growth in Vietnam. *Management Science Letters*, *10*(5), 1051–1060. https://doi.org/10.5267/j.msl.2019.11.004

Hussain, M. I., & Zafar, T. (2018). The Interrelationship between Money Supply, Inflation, Public Expenditure and Economic Growth. *European Online Journal of Natural and Social Sciences*, *7*(1), 1–24. http://www.european-science.com

Indalmanie, S. P. (2015). The Relationship between Money Supply and the Rate of Inflation: A Causality Approach to the Study of the Jamaican Economy, 1961-2006. *SSRN Electronic Journal*, 1–20. https://doi.org/10.2139/ssrn.2586254

Joshi, U. L. (2021). Effect of Money Supply on Inflation in Nepal: Empirical Evidence from ARDL Bounds Test. *International Research Journal of MMC*, *2*(1), 84–98. https://doi.org/10.3126/irjmmc.v2i1.35134

Kelikume, I., & Salami, A. (2008). *Time Series Modeling and Forecasting*. *8*(2), 115–138. https://doi.org/10.1007/978-0-387-77827-3_5

Koku, P. S., Caushi, A., Fetai, A., & Fetai, B. (2016). The relationship between exchange rate and inflation: the case of Western Balkans Countries. *Pressacademia*, *5*(4), 360–364. https://doi.org/10.17261/pressacademia.2017.358

Korkmaz, S. (2017). *The Relationship between Money Supply, Inflation, and Economic Growth in Mediterranean Countries*. *November 2017*.

Manuca, R., & Savit, R. (1996). Stationarity and nonstationarity in time series analysis. *Physica*

D: Nonlinear Phenomena, *99*(2–3), 134–161. https://doi.org/10.1016/S0167-2789(96)00139-X

Medeiros, M. C. (2017). *FORECASTING INFLATION IN A DATA-RICH ENVIRONMENT: THE BENEFITS OF MACHINE LEARNING METHODS Marcelo C. Medeiros*.

Monfared, S. S., & Akın, F. (2017). the Relationship Between Exchage Rates and Inflation: the Case of Iran. *European Journal of Sustainable Development*, *6*(4), 329–340. https://doi.org/10.14207/ejsd.2017.v6n4p329

Mukhtarov, S., Mammadov, J., & Ahmadov, F. (2019). The impact of oil prices on inflation: The case of Azerbaija. *International Journal of Energy Economics and Policy*, *9*(4), 97–102. https://doi.org/10.32479/ijeep.7712

Nyoni, T., & Mutongi, C. (2019). Munich Personal RePEc Archive Modeling and forecasting inflation in Burundi using ARIMA models. *Munich Personal RePEc Archive*, *92444*. https://mpra.ub.uni-muenchen.de/93984/%0D

Özgür, Ö., & Akkoç, U. (2021). Inflation forecasting in an emerging economy: selecting variables with machine learning algorithms. *International Journal of Emerging Markets*, *February*. https://doi.org/10.1108/IJOEM-05-2020-0577

Paper, W., Studies, D., Paper, W., Section, I. E., Studies, D., Paper, W., & Studies, D. (2020). *www.econstor.eu*.

Robinson, W. (1998). Forecasting Inflation Using VAR Analysis by Wayne Robinson Bank of Jamaica 1. *Bank of Jamaica*, *October*, 1–22.

Rodríguez-Vargas, A. (2020). Forecasting Costa Rican inflation with machine learning methods. *Latin American Journal of Central Banking*, *1*(1–4), 100012. https://doi.org/10.1016/j.latcb.2020.100012

Ruzima, M. (2018). *A Study on Determinants of Inflation in Rwanda from 1970-2013 A Study on Determinants of Inflation in Rwanda from 1970-2013*. *April*.

S. O., A. (2018). Bank Lending Rate and Economic Growth: Evidence from Nigeria. *International Journal of Academic Research in Economics and Management Sciences*, *7*(3), 111–122. https://doi.org/10.6007/ijarems/v7-i3/4440

Sek, S. K., Teo, X. Q., & Wong, Y. N. (2015). A Comparative Study on the Effects of Oil Price Changes on Inflation. *Procedia Economics and Finance*, *26*(15), 630–636. https://doi.org/10.1016/s2212-5671(15)00800-x

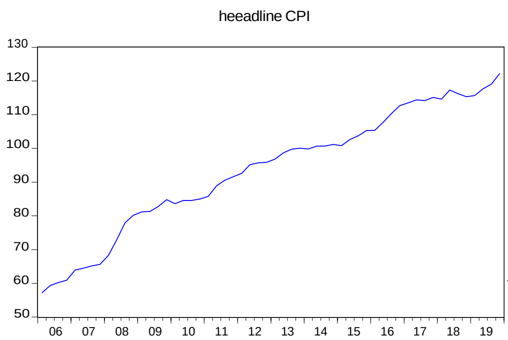
Strano, A. (2009). How and how much can the Money Supply affect the Inflation Rate ? *Economic and Social Data Services*, *2009*, 1–15. https://www.ukdataservice.ac.uk/media/263125/strano-paper.pdf

Totonchi, J. (2011). Macroeconomic Theories of Inflation. *International Conference on Economics and Finance Research*, *4*(July), 459–462.

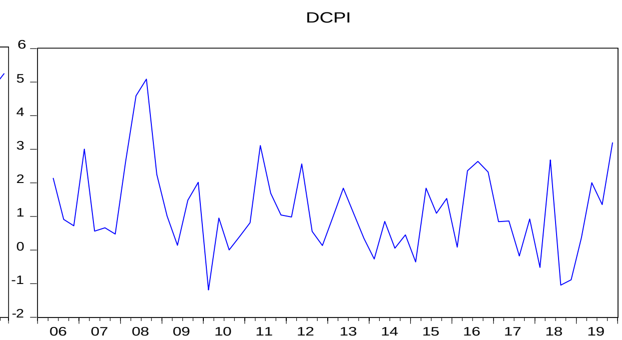
Živkov, D., Durašković, J., & Manić, S. (2019). How do oil price changes affect inflation in Central and Eastern European countries? A wavelet-based Markov switching approach. *Baltic Journal of Economics*, *19*(1), 84–104. https://doi.org/10.1080/1406099X.2018.1562011

7. APPENDIX

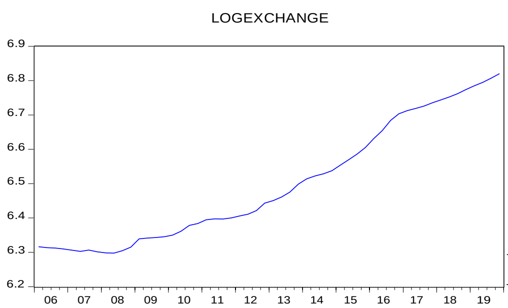
7.1. Figures of Stationarity and Non-Stationarity Of Variables



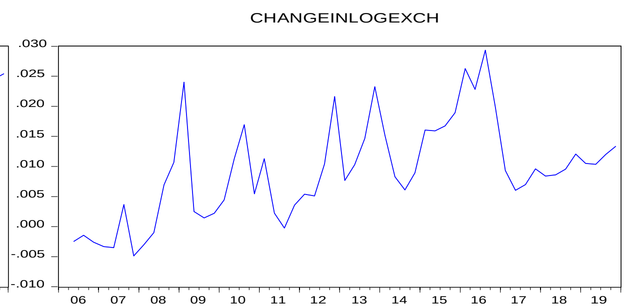
Time plot of heedline CPI at level



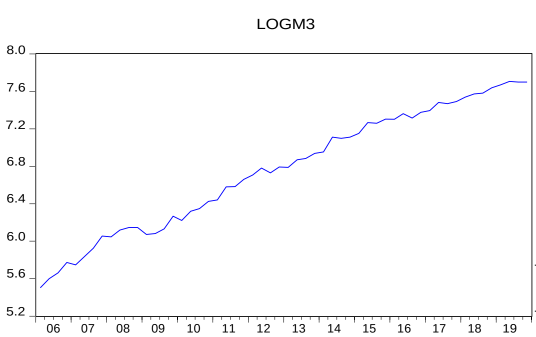
Time plot of heedline CPI at first difference



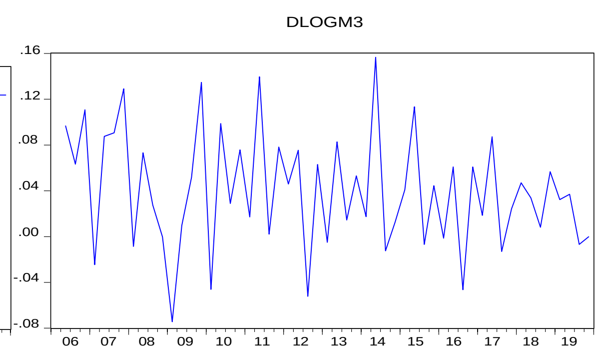
Time plot of LogExchange rate at level



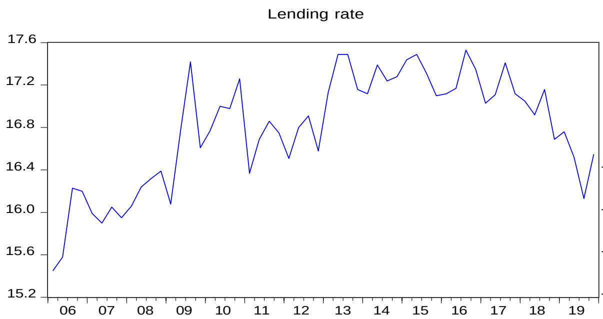
Time plot of LogExchange rate at first difference

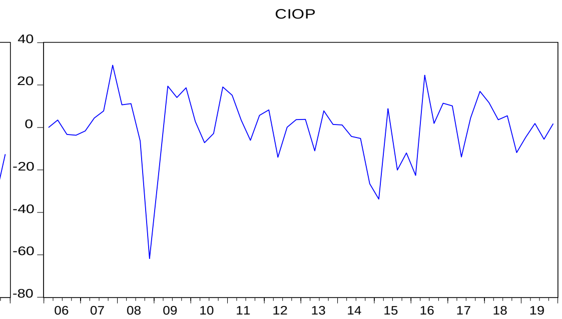


Time plot of Log Money supply at level



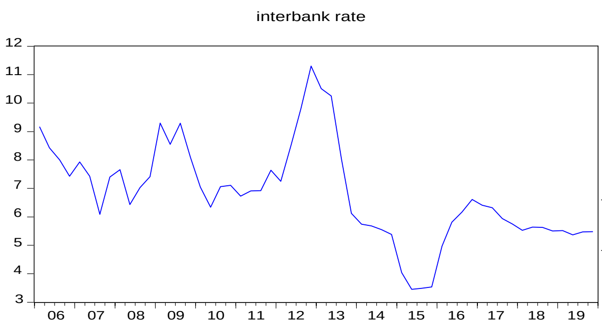
Time plot of Log Money supply at first difference

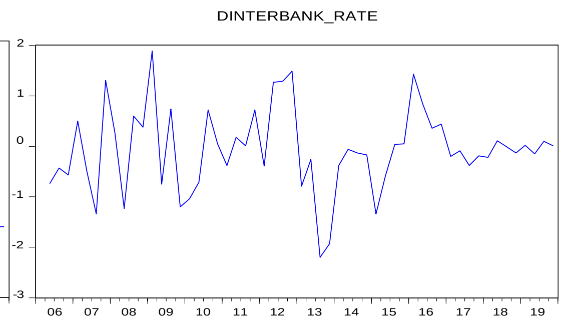




Time plot of Lending rate at level (Stationary)

Time plot of Change in oil price at level





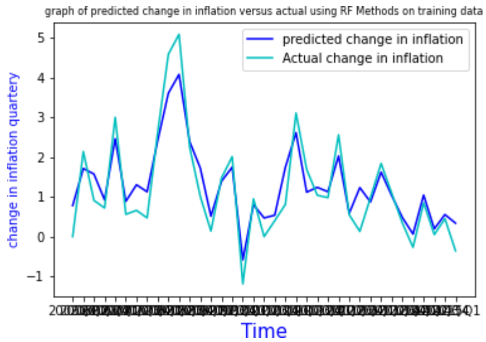
Time plot of Interbank rate at level

Time plot of Interbank rate at first difference

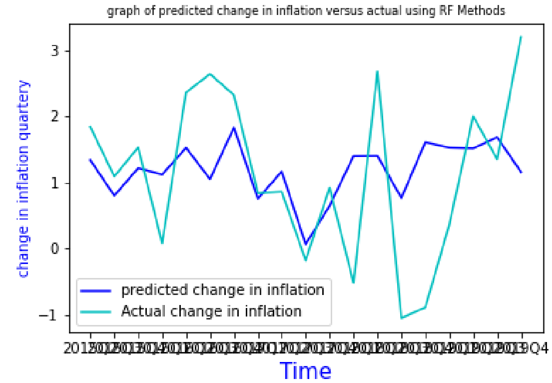
7.2. Table of Results of ADF test of unit root for all variables

Variables	A level				At first c fference			
	t-s at	critical values 5%	10%	Prob	t-stat	critical values 5%	10%	Prob
Headline cpi	-1 819	-2.915	-2.595	0.367	-5.177	-2.916	-2.59	0.00
log(Exchange rate)	1. 55	-2.916	-2.596	0.997	-3.254	-2.916	-2.59	0.022
Lending rate	-3 125	-2.915	-2.595	0.030				
logM3	-1 804	-2.921	-2.598	0.374	-11.007	-2.919	-2.597	0.000
CIOP	-5 494	-2.915	-2.595	0.000				
Interbank rate	-2 238	-2.918	-2.597	0.195	-4.201	-2.918	-2.597	0.001

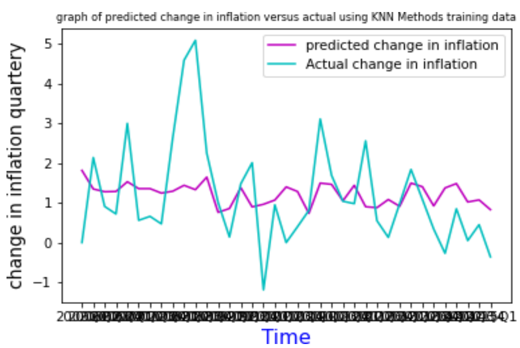
7.3. Forecasting Figures with Machine Learning



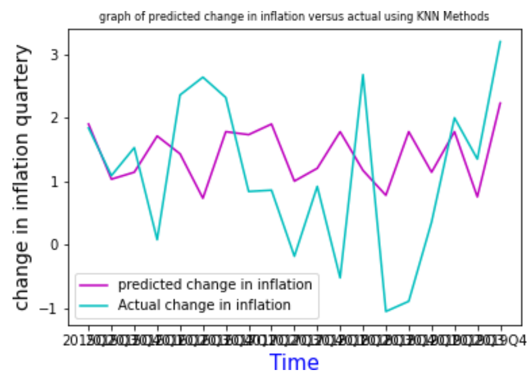
Prediction on training data using RF



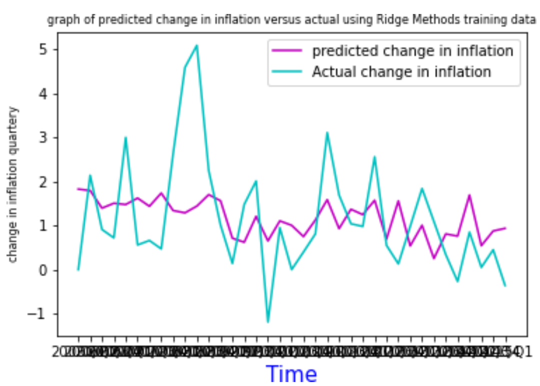
Prediction on testing using RF



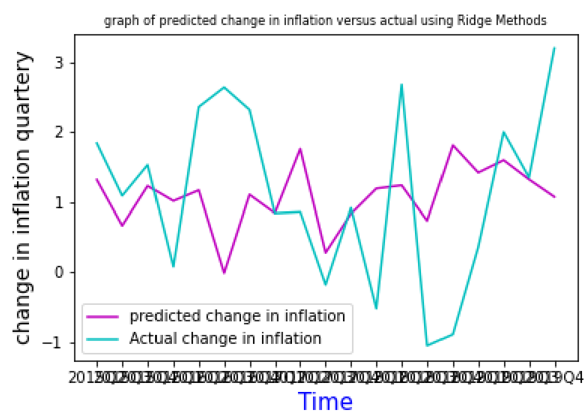
Prediction on training data using KNN



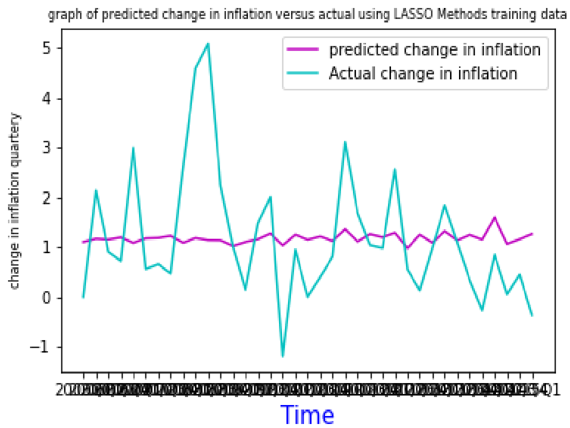
Prediction on testing using KNN

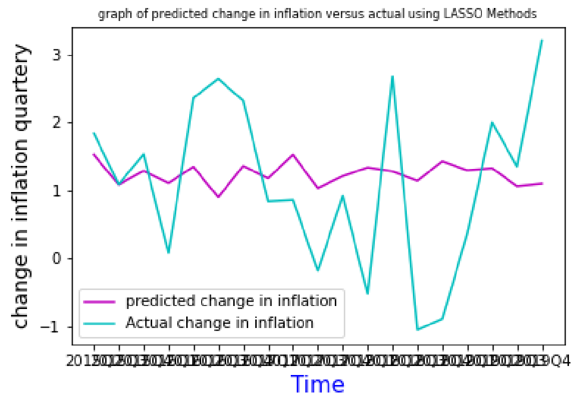


Prediction on training data using Ridge



Prediction on testing using Ridge





Prediction on training data using LASSO

Prediction on testing using LASSO

7.4. Cointegration results for both Trace test and Max eigen values test

Date: 09/07/21 Time: 00:21

Sample (adjusted): 2006Q4 2019Q4

Included observations: 53 after adjustments

Trend assumption: Linear deterministic trend

Series: CHANGE_CPI CHANGE_EXCHANGE_RATE
CHANGE_INTERBANK_RATE CHANGE_M3 CIOP LENDING_RATE

Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.545528	143.7462	95.75366	0.0000
At most 1 *	0.486433	101.9493	69.81889	0.0000
At most 2 *	0.461635	66.63140	47.85613	0.0004
At most 3 *	0.335651	33.81279	29.79707	0.0163
At most 4	0.142578	12.13860	15.49471	0.1504

At most 5 *	0.072447	3.985865	3.841466	0.0459

Trace test indicates 4 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.545528	41.79686	40.07757	0.0317
At most 1 *	0.486433	35.31789	33.87687	0.0334
At most 2 *	0.461635	32.81861	27.58434	0.0097
At most 3 *	0.335651	21.67419	21.13162	0.0419
At most 4	0.142578	8.152730	14.26460	0.3634
At most 5 *	0.072447	3.985865	3.841466	0.0459

Max-eigenvalue test indicates 4 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

ORIGINALITY REPORT

17%	13%	9%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Sanam Shojaeipour Monfared, Fetullah Akın. "THE RELATIONSHIP BETWEEN EXCHAGE RATES AND INFLATION: THE CASE OF IRAN", European Journal of Sustainable Development, 2017 Publication	1%
2	journals.pu.edu.pk Internet Source	1%
3	Submitted to Caleb University Student Paper	1%
4	www.econjournals.com Internet Source	1%
5	Adolfo Rodríguez-Vargas. "Forecasting Costa Rican inflation with machine learning methods", Latin American Journal of Central Banking, 2020 Publication	1%
6	www.tandfonline.com Internet Source	1%
7	Submitted to Strayer University	

	Student Paper	1%
8	Submitted to Heriot-Watt University Student Paper	<1%
9	Submitted to University of Sheffield Student Paper	<1%
10	www.imf.org Internet Source	<1%
11	dergipark.org.tr Internet Source	<1%
12	www.jacksoncommunityreview.org Internet Source	<1%
13	hrmars.com Internet Source	<1%
14	Submitted to ESC Rennes Student Paper	<1%
15	Submitted to Nexford University Student Paper	<1%
16	www.cbr.ru Internet Source	<1%
17	Submitted to University of Ghana Student Paper	<1%
18	Dejan Živkov, Jasmina Đurašković, Slavica Manić. "How do oil price changes affect	<1%

inflation in Central and Eastern European countries? A wavelet-based Markov switching approach", Baltic Journal of Economics, 2018
Publication

19	Submitted to Queen Mary and Westfield College Student Paper	<1%
20	Uttam Lal Joshi. "Effect of Money Supply on Inflation in Nepal: Empirical Evidence from ARDL Bounds Test", International Research Journal of MMC, 2021 Publication	<1%
21	econpapers.repec.org Internet Source	<1%
22	www.researchgate.net Internet Source	<1%
23	Submitted to University Der Es Salaam Student Paper	<1%
24	mpra.ub.uni-muenchen.de Internet Source	<1%
25	www.businessperspectives.org Internet Source	<1%
26	Submitted to University of Glasgow Student Paper	<1%
27	Submitted to Middlesex University Student Paper	<1%

28	citeseerx.ist.psu.edu Internet Source	<1%
29	visir.maxwell.vrac.puc-rio.br Internet Source	<1%
30	Submitted to Mzumbe University Student Paper	<1%
31	Submitted to University of Sydney Student Paper	<1%
32	econjournals.com Internet Source	<1%
33	hal.archives-ouvertes.fr Internet Source	<1%
34	Submitted to Indian Institute of Management, Bangalore Student Paper	<1%
35	Submitted to Universidad Carlos III de Madrid Student Paper	<1%
36	Submitted to Copperbelt University Student Paper	<1%
37	Submitted to Taylor's Education Group Student Paper	<1%
38	Submitted to University of Warwick Student Paper	<1%
39	oapub.org Internet Source	

		<1%
40	www.i-scholar.in Internet Source	<1%
41	www.iprjb.org Internet Source	<1%
42	etd.uum.edu.my Internet Source	<1%
43	jultika.oulu.fi Internet Source	<1%
44	rfh.org.pk Internet Source	<1%
45	www.SciRP.org Internet Source	<1%
46	www.conscientiabeam.com Internet Source	<1%
47	www.slideshare.net Internet Source	<1%
48	medium.com Internet Source	<1%
49	pureportal.coventry.ac.uk Internet Source	<1%
50	www.sci-int.com Internet Source	<1%

51	www.ukessays.com Internet Source	<1 %
52	Salah A. Nusair. "Oil price and inflation dynamics in the Gulf Cooperation Council countries", Energy, 2019 Publication	<1 %
53	arfjournals.com Internet Source	<1 %
54	casopisi.junis.ni.ac.rs Internet Source	<1 %
55	edoc.pub Internet Source	<1 %
56	fbf.utar.edu.my Internet Source	<1 %
57	hdl.handle.net Internet Source	<1 %
58	iosrjournals.org Internet Source	<1 %
59	jurcon.ums.edu.my Internet Source	<1 %
60	koreascience.or.kr Internet Source	<1 %
61	m.scirp.org Internet Source	<1 %

62 www.athensjournals.gr
Internet Source
<1%

63 www.iosrjournals.org
Internet Source
<1%

64 zbw.eu
Internet Source
<1%

65 ANTHONY IMOISI. "Fiscal Policy and Sustainability of Public Debt: The Nigerian Experience", Research Square Platform LLC, 2021
Publication
<1%

66 Atif Batarseh. "The nature of the relationship between the money supply and inflation in the Jordanian economy (1980–2019)", Banks and Bank Systems, 2021
Publication
<1%

67 Malayaranjan Sahoo, Narayan Sethi. "The Dynamic Relationship between Export, Import and Inflation: Empirical Evidence from India", The Indian Economic Journal, 2020
Publication
<1%

68 Siok Kun Sek, Xue Qi Teo, Yen Nee Wong. "A Comparative Study on the Effects of Oil Price Changes on Inflation", Procedia Economics and Finance, 2015
Publication
<1%

69	Tilak Singh Mahara. "An Empirical Investigation Between Money Supply, Inflation, Capital Expenditure and Economic Growth in Nepal", Quest Journal of Management and Social Sciences, 2021 Publication	<1%
70	Submitted to University of North Florida Student Paper	<1%
71	european-science.com Internet Source	<1%
72	www.ipedr.com Internet Source	<1%
73	Submitted to University of Huddersfield Student Paper	<1%
74	papers.ssrn.com Internet Source	<1%

Exclude quotes	On	Exclude matches	Off
Exclude bibliography	On		