Does Expectations Affect Inflation Forecasting Abilities of Machine Learning Techniques: Case of Ukraine

Nataliia Dziubanovska[1], Viktor Koziuk[1], Dmytro Hural[1] and Iryna Danyliuk[1]

[1] *Western Ukrainian National University, 11 Lvivska Str., Ternopil, 46009, Ukraine*

Abstract

By improving forecast accuracy, the study aims to address the issues of unstable inflation levels and the dependence of macroeconomic stability on exchange rate fluctuations during the transition to inflation targeting. The study utilized the XGBoost machine learning (ML) algorithm for inflation forecasting in Ukraine. To assess the adequacy and stability of forecasting models, a systematic approach based on sequential expansion of the time period for modeling was applied. In order to enhance the accuracy of forecasts, the model parameters were refined by considering additional factors (inflation and exchange rate expectations) and increasing the level of model detail. This modification contributed to improving the model's sensitivity to economic changes and enhancing its ability to align forecasted values with real data. The findings of the study could be of significant importance for understanding and forecasting inflation trends in the Ukrainian economy.

Keywords

Inflation, expectations, forecasting, machine learning, XGBoost, Ukraine.

1. Introduction

ML technologies are actively being implemented in the forecasting practices of central banks. It is premature to say that they are beginning to replace traditional forecasting methods based on semi-structural, structural, or DSGE models. However, interest in their ability to forecast trajectories of macroeconomic variables is growing. The post-COVID surge in inflation demonstrated the weakness of traditional forecasting tools of central banks. Focus on linear relationships and failure to account for a range of self-reinforcing effects on the inflation level (BIS (2022) [1], Michele Lenza, Inés Moutachaker, and Joan Paredes (2023) [2]) resulted in significant forecast errors during 2021-2022 in most monetary institutions.

Criticism of the application of ML techniques is based on assumptions about its atheoretical nature. The lack of predetermined assumptions about the nature and form of the relationship between variables, which would find broad academic recognition, complicates the correct interpretation of forecast results. The role of shocks also takes a back seat. While the nature of macroeconomic shocks is significant for central banks.

Nevertheless, the application of ML for inflation forecasting is already demonstrating promising results (Wagner Piazza Gaglianone (2020) [3], Michele Lenza, Inés Moutachaker, and Joan Paredes (2023) [2]). In the future, the number of studies on the use of ML in central bank forecasting will only increase.

Ukraine, as a typical emerging market country, faces the challenge of volatile inflation levels and macroeconomic stability dependence on exchange rate fluctuations. When transitioning to inflation targeting in 2015-2016 and thereafter, the sensitivity of inflation to pass-through effects

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n.dziubanovska@wunu.edu.ua (N. Dziubanovska); viktorkoziuk@wunu.edu.ua (V. Koziuk); deemahural@gmail.com (D. Hural); irunkadanyliuk@gmail.com (I. Danyliuk)

0000-0002-8441-5216 (N. Dziubanovska); 0000-0002-5715-2983 (V. Koziuk); 0009-0004-2697-1355 (D. Hural); 0009-0005-8724-5338 (I. Danyliuk)

was considered a significant obstacle to achieving reliable and predictable transmission of NBU policy rate changes to macroeconomic variables, particularly inflation. A forward-looking design of inflation targeting entails a significant role for economic agents' expectations. Changes in inflation expectations are seen as a key prerequisite for changing the policy rate, enhancing the central bank's ability to maintain inflation close to the target. The role of inflation expectations in determining inflation levels in many countries is considered significant (Rudolfs Bems, Francesca Caselli, Francesco Grigoli, Bertrand Gruss, and Weichen Lian (2018) [4], IMF (2023) [5]). Considering the significant role of pass-through effects in inflation behavior, it is worth noting that exchange rate expectations, along with inflation expectations, may play an equally important role in influencing consumer prices. Furthermore, inflation expectations may be shaped by exchange rate expectations in economies sensitive to exchange rate fluctuations, with a high level of dollarization and an informal sector. It is possible that exchange rate expectations may have a stronger impact on inflation processes even despite the formal focus on monitoring inflation expectations within inflation targeting frameworks. Such specificity of monetary transmission is well known from the literature (Airaudo M., Buffie E., Zanna L.-F. (2016) [6], Lubik A., Schorheide F. (2007) [7]).

This article applies ML technology to construct inflation forecasts based on lagged values of the Consumer Price Index (CPI). After the model underwent training, external variables of inflation expectations, exchange rate expectations, and combined inflation and exchange rate expectations were added to it. The predictive properties of the baseline model with lagged CPI values demonstrated promising results. Deviations from the actual trajectory may be explained by strong unforeseen exogenous shocks in each respective case, naturally deflecting inflation from the trajectory consistent with the forecast. The addition of external variables in all three cases enhances the predictive properties of the model. However, the model with variable exchange rate expectations yields the lowest forecast error. The overall research findings align with theoretical insights into the role of the exchange rate factor in inflation behavior. Additionally, the results of this study confirm the potential for more active application of ML in the forecasting activities of the National Bank of Ukraine.

This research contributes to the field of macroeconomic forecasting by integrating ML techniques into the prediction of inflation trajectories, particularly focusing on the context of emerging market economies like Ukraine. While previous studies have explored the application of ML in central bank forecasting, this research specifically addresses the challenges associated with volatile inflation levels and the dependence of macroeconomic stability on exchange rate fluctuations in countries transitioning to inflation targeting frameworks.

The primary goal of this study is to evaluate the effectiveness of ML technology in enhancing inflation forecasting accuracy, with a specific focus on incorporating external variables such as inflation expectations and exchange rate expectations. Building upon existing literature that highlights the significance of these factors in shaping inflation behavior, this research aims to develop a predictive model that can provide reliable inflation forecasts for policy-making purposes. By leveraging ML algorithms and incorporating relevant economic indicators, this study seeks to improve upon traditional forecasting methods that may overlook complex relationships and nonlinear dynamics inherent in macroeconomic variables.

2. Literature review

The role of forecast quality under inflation targeting regimes is highlighted in several works (Heenan G., Peter M., Roger Sc. (2006) [8], Ismailov Sh., Kakinaka M., Miyamoto H. (2016) [9]). Most forecast models of inflation-targeting central banks rely either on quarterly forecast models (QPMs), which are structural or semi-structural, or on DSGE models based on rigid theoretical equations (Malin Adolfson Michael K. Andersson Jesper Linde Mattias Villani and Anders Vredin (2007) [10], John C. Robertson (2000) [11], Sergii Kiiashko (2018) [12]). The application of ML methods in central bank forecasting activities is only beginning to spread. The advantages and disadvantages of different approaches, as well as their impact on the accuracy of inflation forecasts, are noted in several studies.

For instance, in the work by Gustavo Silva Araujo & Wagner Piazza Gaglianone (2020) "Machine learning methods for inflation forecasting in Brazil: new contenders versus classical models" [13], the combination of various ML methods and traditional econometric models is described to build accurate inflation forecasts in Brazil. The research findings confirm the effectiveness of using nonlinear automated procedures, indicating that ML algorithms (particularly random forests) can outperform traditional forecasting methods in terms of mean square error metric. These conclusions represent a valuable contribution to the field of macroeconomic forecasting and provide alternative methods to conventional statistical models, which often rely on linear statistical relationships.

Emanuel Kohlscheen in the study "What does machine learning say about the drivers of inflation?" (2021) [14] applies ML algorithms to identify the factors driving changes in the Consumer Price Index. The researcher forecasts inflation in 20 developed countries from 2000 to 2021 using 1000 regression trees constructed based on six key macroeconomic variables. The findings underscore the significance of expectations in determining inflation trends in developed economies, although their role has slightly diminished over the past decade.

Nishant Singh and Binod B. Bhoi in their work "Inflation Forecasting in India: Are Machine Learning Techniques Useful?" (2022) [15], exploring the impact of the COVID-19 pandemic and associated supply chain disruptions on inflation dynamics, employ ML algorithms (ML) for forecasting and compare the effectiveness of their application with some popular traditional time series models for both pre-crisis and post-crisis periods. The empirical results confirm the utility of ML methods and their superiority over traditional forecasting approaches for inflation prediction in India over different time periods.

Michele Lenza, Inés Moutachaker, and Joan Paredes in their study "Forecasting euro area inflation with machine learning models" (2023) [16], drawing on the findings of a strategic review completed in 2021, generalize that most models used by the Eurosystem for inflation forecasting are linear. Linear models assume that changes, such as in wages, always have the same fixed proportional impact on inflation. A new ML model recently developed at the European Central Bank (ECB) accounts for broad spectrums of nonlinearity, such as changes in the sensitivity of inflation dynamics to prevailing economic conditions. Forecasts obtained using these models accurately replicate the expected inflation values proposed by Eurosystem staff, indicating their consideration of weak instability in dynamics and adherence to contemporary econometric methodologies.

Miguel Faria e Castro and Fernando Leibovici in their research on "Artificial Intelligence and Inflation Forecasts" (2023) [17] describe the capabilities of large language models (LLMs) to generate conditional inflation forecasts within the sample period from 2019 to 2023. The LLM (PaLM from Google AI) is utilized to create distributions of conditional forecasts at various horizons for comparison with the forecasted values from a leading source – the Survey of Professional Forecasters (SPF). The results reveal that LLM forecasts are generally characterized by smaller mean squared errors in most years and across almost all horizons. LLM forecasts exhibit a slower return speed to the established 2% inflation level.

3. Methodology

Among a wide array of ML methods that can be applied in inflation forecasting, this article focuses on time series analysis methods. The model undergoes a training stage, during which ML algorithms are used to obtain retrospective forecast data, which are then compared with retrospective actual data. The primary method chosen is the XGBoost library (Extreme Gradient Boosting), which enables the implementation of optimized ML algorithms using gradient boosting. XGBoost demonstrates high forecasting accuracy due to its efficiency and robustness. It efficiently handles large volumes of data and various types of features. Moreover, the model based on XGBoost algorithms has built-in regularization support, which helps prevent overfitting and enhances its overall accessibility.

Furthermore, the application of XGBoost allows improving the accuracy of time series forecasting by considering the values of additional indicators that may influence the target variable, reducing the impact of noise, and enhancing the model's resilience to unforeseen changes. This is particularly important in cases where the main variables may be subjective or unstable. The use of external factors expands the model's capabilities and enhances its overall balance between simplicity and complexity.

To assess the adequacy and stability of the forecasting models, a systematic approach based on sequential expansion of the time period for modeling was applied. At the initial stage, data for the training set were selected for the years 2007–2018, and for the testing set, the year 2019 was chosen. Subsequent research involved increasing the volume of data for training the model up to the year 2019 inclusive, with testing conducted for the values of the target variable throughout 2020, and so on (see Figure 1). The final model was built on the complete set of statistical data for the period from 2007 to 2021, allowing for forecasting for the year 2022. This approach allowed for systematically verifying and confirming the adequacy of the forecasting model, as well as examining its stability to changes in time series, which is an important aspect in determining the reliability of predictive properties.

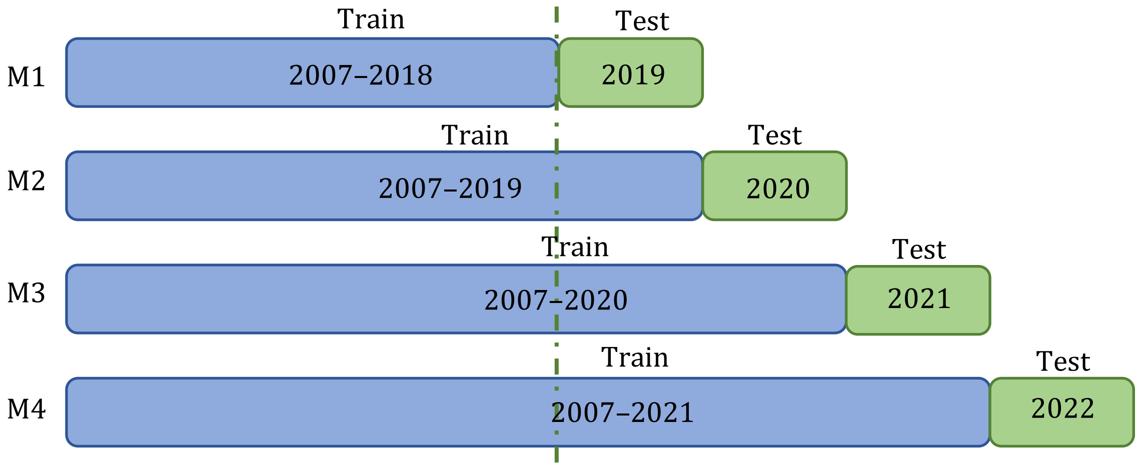

Figure 1: Stages of building predictive models

During the study, the target variable chosen was the Consumer Price Index (Y), with additional variables including inflation expectations (exog1) and exchange rate expectations (exog2).

The source of statistical data included data from enterprises, financial analysts, banks (based on surveys conducted by the NBU), and households (surveys conducted by "INFO SAPIENS" LLC, calculations by the NBU) [18].

4. Results

Let's examine the dynamics of the Consumer Price Index in Ukraine from 2007 to 2023 (Figure 2).

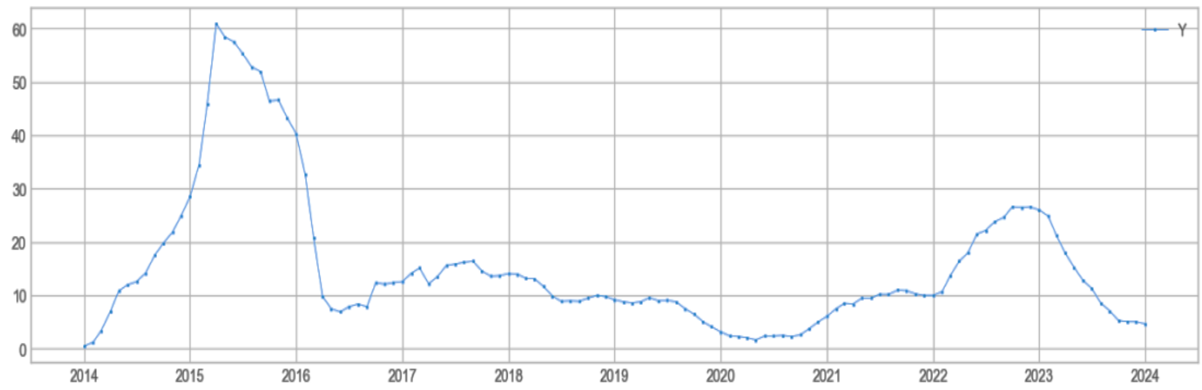

Figure 2: CPI Dynamics in Ukraine

The graph depicting the dynamics of the Consumer Price Index in Ukraine from 2007 to 2023 reveals certain trends and fluctuations during the period under consideration. There are periods of stability as well as moments when anomalies are observed.

For a better understanding of the mechanics of the inflationary process, let's decompose the time series using an additive model (Figure 3). Decomposing the time series will allow us to break it down into components such as trend, seasonality, and residual components. This will help us understand to what extent homogeneous factors influence inflation dynamics and to what extent such dynamics are determined by the stochastic influence of external factors. The additive model simplifies data analysis by distributing it into separate parts and facilitates the identification and analysis of trends, cycles, and seasonality. This approach enhances forecast accuracy by carefully considering the characteristics of time series dynamics.

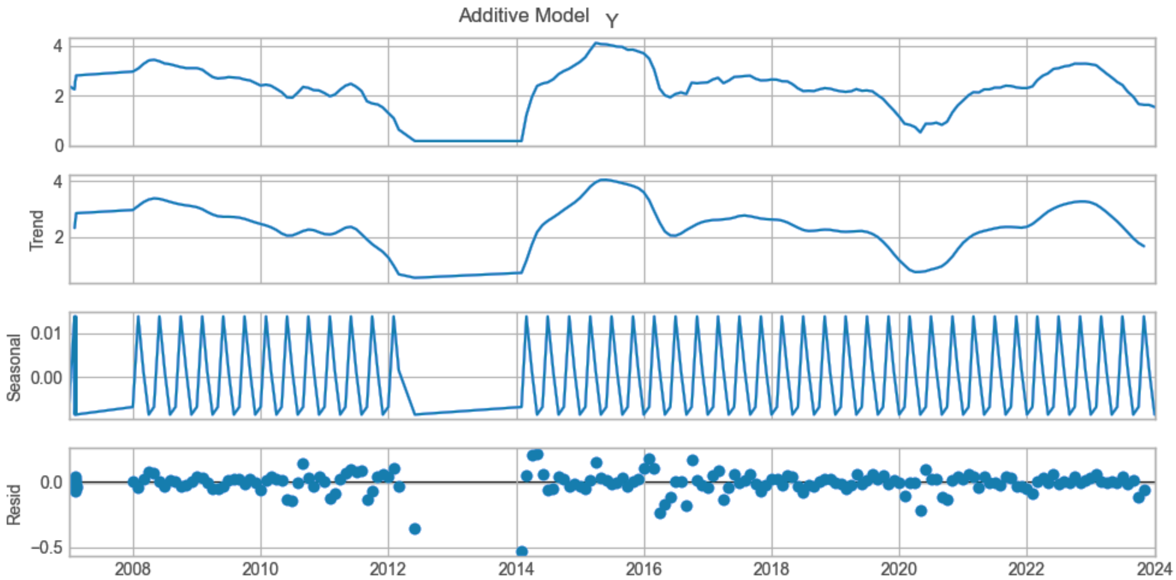

Figure 3: Additive Model

From the graphs, we observe the absence of a trend, the presence of seasonality, and a gap in the residual component graph. This may indicate inadequate adaptation of the model to the internal structure of the data or unpredictable changes in external factors. To improve the accuracy of the modeling in the final stage of the study, we will enhance the model by considering additional factors that may affect the dynamics of the series. It is worth noting that the additive model confirmed that the inflationary process in Ukraine was influenced by a range of external factors, the predictability of which corresponds to the tail effects of the probability distribution. The crisis events of 2014-2015, the change in the monetary regime in 2015-2016, the COVID-19 crisis in 2020, post-COVID recovery, and the wide-scale aggression from the Russian Federation since 2022 are examples of strong external shocks that significantly impacted the changes in the internal structure of the time series data.

Having a statistical series of monthly Consumer Price Index data from January 1, 2007, to January 1, 2024, we will use it to build forecasting models for various time ranges using ML algorithms to automate the forecasting process, identify complex relationships in the time series, and formulate forecasts based on them.

For the first time interval to build the forecasting model (Figure 1), we divided the time series into two datasets: the training set (from 2007-01-01 to 2018-12-01) and the testing set (from 2019-01-01 to 2019-12-01). We built the model on the training set and evaluated its quality on the testing set. During the study, we attempted to apply various neural networks, including feedforward networks and recurrent neural networks, but did not achieve the expected results due to the complexity and peculiarities of the data. However, after testing the XGBoost model, we obtained the best results (Table 1).

Table 1
Results of Prognostic Model (M1)

Time Period	Predicted Values	Real Data
2019-01-01	9.744	9.2
2019-02-01	9.605	8.8
2019-03-01	9.819	8.6
2019-04-01	10.728	8.8
2019-05-01	10.423	9.6
2019-06-01	10.044	9.0
2019-07-01	9.959	9.1
2019-08-01	9.983	8.8
2019-09-01	10.157	7.5
2019-10-01	10.364	6.5
2019-11-01	10.426	5.1
2019-12-01	10.426	4.1

The model's accuracy and its forecast are determined using the MPE (Mean Percentage Error) = -0.373, MAPE (Mean Absolute Percentage Error) = 0.373.

MPE indicates that, on average, the forecasted values deviate from the actual values by approximately 37.3%, while MAPE indicates the average absolute deviation at the level of 37.3%. Although these estimates demonstrate a certain level of discrepancy between the forecasted and actual values, they also suggest that the forecasts obtained from the modeling are quite close to the real values.

It should be noted that an upward bias in the forecast results should not be considered an example of inadequacy of the modeling scenario chosen during ML. On the contrary, retrospective forecast values of the model moved almost parallel to the historical actual trajectory until August 2019, after which they began to diverge. The reason for this should be recognized as the significant strengthening of the hryvnia exchange rate, which was unexpected for many economic agents. The insufficient consideration of the strength of the exchange rate pass-through effect on disinflation was also noted by the NBU.

Similarly, we construct forecasting models, gradually changing the training and testing datasets (Table 2).

Table 2
Results of Prognostic Models

Time Period	Predicted Values	Real Data
M2; MAPE = 0.034; MPE = -0.024		
2020-01-01	3.433	3.2

2020-02-01	3.570	2.4
2020-03-01	4.492	2.3
2020-04-01	5.250	2.1
2020-05-01	5.497	1.7
2020-06-01	5.970	2.4
2020-07-01	6.154	2.4
2020-08-01	6.095	2.5
2020-09-01	6.603	2.3
2020-10-01	6.928	2.6
2020-11-01	7.530	3.8
2020-12-01	8.293	5.0
M3; MAPE = 1.242; MPE = -1.242		
2021-01-01	6.093	6.1
2021-02-01	7.204	7.5
2021-03-01	8.485	8.5
2021-04-01	9.420	8.4
2021-05-01	10.062	9.5
2021-06-01	10.023	9.5
2021-07-01	10.263	10.2
2021-08-01	10.164	10.2
2021-09-01	10.852	11.0
2021-10-01	10.977	10.9
2021-11-01	10.739	10.3
2021-12-01	10.606	10.0
M4; MAPE = 0.437; MPE = 0.437		
2022-01-01	9.744	10.0
2022-02-01	9.605	10.7
2022-03-01	9.819	13.7
2022-04-01	10.728	16.4
2022-05-01	10.423	18.0
2022-06-01	10.379	21.5
2022-07-01	10.044	22.2
2022-08-01	9.959	23.8
2022-09-01	9.983	24.6
2022-10-01	10.157	26.6
2022-11-01	10.364	26.5
2022-12-01	10.426	26.6

The difference between the forecasted and actual Consumer Price Index (CPI) values in 2020 and 2022 is attributed to the influence of economic, social, or political conditions that led to changes in the predicted dynamics of the indicator. The selected time period also significantly affects the forecast quality. Moreover, if the time series contains many random anomalies or seasonal variations, the model may provide inaccurate or unreliable forecasts. Additionally, the model does not account for the influence of external factors on the variable under study, which is also a reason for deviations in forecasting. The deviations of retrospective forecast values from historical actuals for 2020 indicate unforeseen deflationary effects of the COVID crisis, which necessitated social distancing measures. In 2022, the divergence of data is due to the inflationary consequences of the onset of Russia’s wide-scale aggression against Ukraine. However, the retrospective forecast values of our model are close to the retrospective forecast values of the NBU published in January 2022. The absence of significant stochastic shocks throughout 2021 resulted in a significant improvement in the forecast quality of the model.

To ensure a more accurate forecast, we will improve the model parameters by considering additional factors. We will choose the time period from 2014 to 2021 for the training dataset and 2022 for the testing dataset. Additionally, we will introduce external variables such as "Inflation expectations" and "Exchange rate expectations." Before constructing the forecasting model, we will examine the dynamic series of the main variable (CPI) and the two external factors (Figure 4).

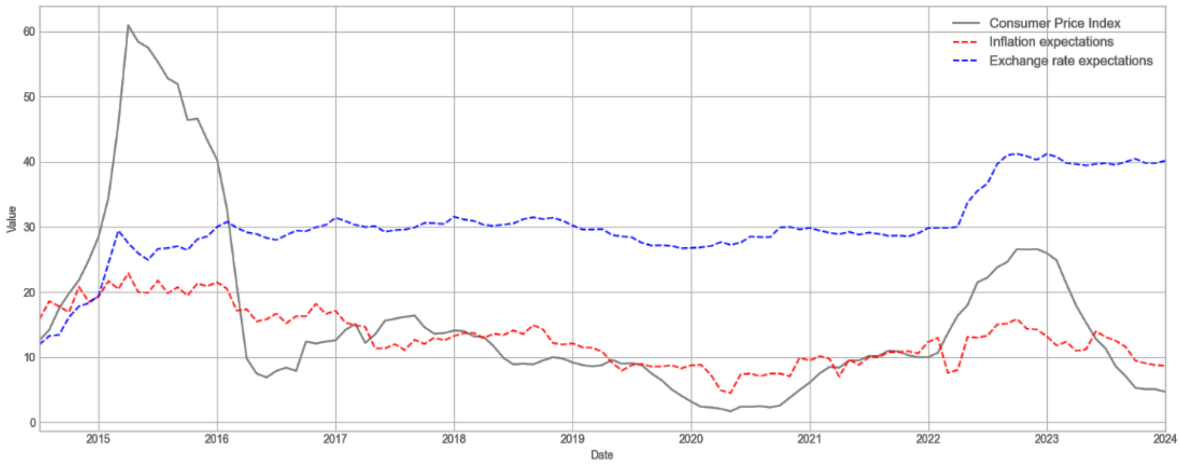

Figure 4: CPI, Inflation expectations and Exchange rate expectations Dynamics in Ukraine

From Figure 4, we observe fluctuations in the dynamic series of these three indicators relative to stable values in certain periods, indicating the influence of various economic or political factors on these indicators. In particular, the Covid-19 pandemic and the full-scale Russian-Ukrainian war.

Using XGBoost, we will construct three forecasting models: considering the impact of one factor on the change in CPI (Inflation expectations), then another (Exchange rate expectations), and finally their combined effect. The modeling results will be presented in Table 3.

Table 3

The Evaluation of Modeling Results Considering External Factors

Prognostic Model with External Factors	MPE	MAPE
Inflation expectations	0.2135	0.2135
Exchange rate expectations	0.1750	0.1750
Inflation expectations& Exchange rate expectations	0.2289	0.2289

As an example of visualizing the modeling results, we present the forecasting model with the lowest error (Forecasting model of the consumer price index taking into account exchange rate expectations) (Figure 5).

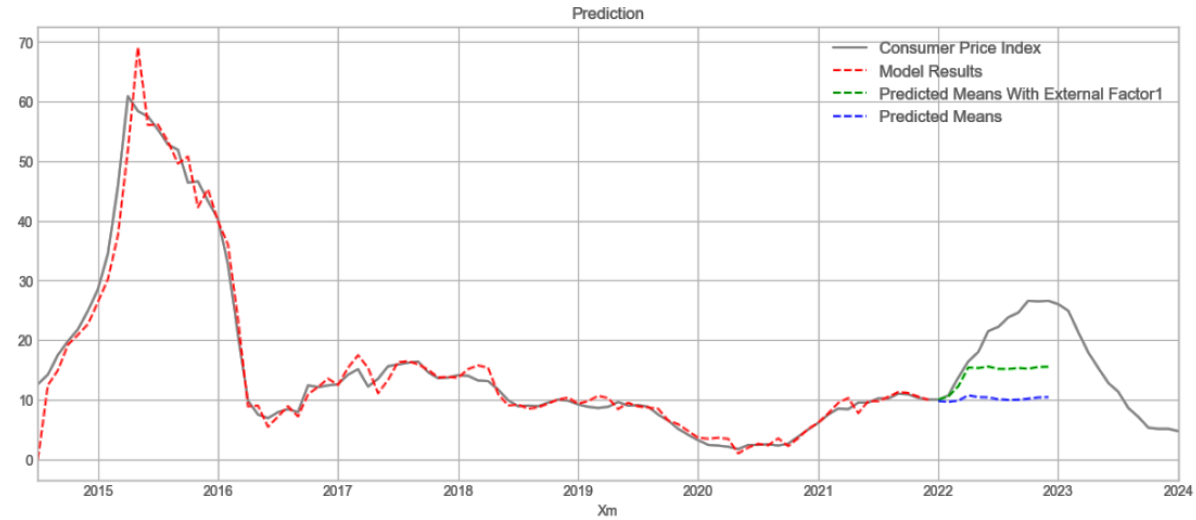

Figure 5: Results of Prognostic Model with External Factor (Exchange rate expectations)

Analyzing the forecasting results of the consumer price index using XGBoost ML models with and without considering external factors, we note that incorporating additional variables into the model contributes to improving the accuracy of the forecasts. In this case, the model reacts more quickly to changes in the economic environment, enhancing its adaptability to real data and making the forecasts more reliable. The results indicate that the model considering exchange rate expectations demonstrates better ability to predict fluctuations in the consumer price index in the future compared to the model without considering this factor. This could be beneficial for forecasting and making informed economic decisions in real-time. It is also important to note that the accuracy of forecasting may vary depending on the chosen model, selected parameters, and the quality of the input data. On one hand, the improvement in the predictive properties of the model due to the external variable of exchange rate expectations confirms theoretical assumptions about the characteristics of the macroeconomic structure in emerging market economies. On the other hand, it should be noted that exchange rate expectations are often influenced by behavioral shifts that need to be considered in forecasting work. The non-linearity in the behavior of exchange rate expectations also poses a challenge to the unequivocal recognition of their key role in the accuracy of the predictive model. Therefore, the inclusion of variables characterizing expectations in the structure of the forecasting model requires initial study of their nature and tracking their consistency with theoretical assumptions about the sources of expectation formation.

For further research, it is recommended to consider other external factors that may influence the dynamics of the consumer price index and to expand the model to incorporate them for even more accurate forecasts.

Conclusions

The increasing utilization of ML technologies in central bank forecasting efforts offers both advantages and challenges. ML excels in analyzing a wide range of data types and identifying complex nonlinear relationships, yet interpreting results can be complex, and its detachment from the nature of shocks poses theoretical challenges. Experience with ML underscores the need for a nuanced approach that capitalizes on modern technological capabilities.

The transition to inflation targeting in Ukraine has elevated the importance of macroeconomic forecasts in monetary policy decision-making, particularly regarding the policy rate. ML, notably through the XGBoost library, has shown promise in retrospective inflation forecasting for Ukraine, with initial models demonstrating reasonable predictive accuracy. Deviations between forecasts and actual data were primarily attributed to unforeseen external shocks.

Considering the forward-looking nature of NBU's monetary policy and the significance of exchange rate effects in Ukraine's economy, the baseline forecasting model was enhanced with inflation and exchange rate expectations. While all enhancements improved forecasting results, the model incorporating exchange rate expectations exhibited superior predictive performance, aligning with theoretical expectations for emerging market economies' macroeconomic structures.

Furthermore, augmenting the model with additional variables and analyzing their impact enhances understanding of how inflation and exchange rate expectations influence inflation processes in Ukraine. The integration of machine learning into inflation forecasting presents an opportunity for the National Bank of Ukraine to effectively manage inflation levels and ensure macroeconomic stability.

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