Machine Learning for French Inflation Forecasting: A Comparative Approach

Gabriel B.
Simon D.
Enzo N.

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Introduction

Inflation is an essential macroeconomic indicator, measuring changes in the general price level of goods and services in an economy over a given period. Anticipating inflation is crucial for economic players such as central banks, investors and companies, as it is directly influencing decisions linked to monetary policy, interest rates and even economic risk management. Accurate inflation forecasting thus enables better planning and helps maintain global financial and economic stability, by facilitating the adaptation of the various players to changes in the economic context.

1. Objectives

The main objective of this report is to develop a machine learning model capable of accurately and reliably predicting inflation from a diverse set of macroeconomic and financial data. More specifically, we aim to:

- Identify and collect relevant data, such as monetary indicators, interest rates, commodity prices and stock market indices, which are likely to significantly influence inflation.

- Explore and analyze these data to understand the dynamics and interconnections between different economic variables.

- Apply advanced modeling methods to extract underlying relationships between these variables and future inflation trends.

- Evaluate the performance of the models developed in order to select the one with the best predictive capacity and which could be used effectively by economic decision-makers.

2. Data extraction and cleaning

2.1 Data presentation

The data used in this study come mainly from Bloomberg and cover a period up to December 2023 for macroeconomic and financial indicators. To improve the relevance of the predictive models, we also have inflation data updated to February 2025. This recent extension enables us to assess model performance on very recent trends, making our forecasts useful for economic decision-makers.

The main data categories selected include :

- **Market data:** Major stock market indices (CAC 40, Dow Jones) and key commodity prices (Brent, wheat, sugar, natural gas, cotton).

- **Interest rates and monetary aggregates:** US sovereign rates (US 2-year, US 10-year), European swap rates (EU 10Y Swap), European monetary aggregates (M1, M2, M3) and ECB main policy rate (Refinancing Rate).

- **Economic indicators:** French unemployment rate, trade balance, industrial production and wage indices.

- **Monetary and exchange rate data:** EUR/USD exchange rate and ESTER rate (European short-term financing rate).

- **Inflation data:** Monthly time series representing the global inflation rate up to February 2025, which is the target variable for predictive models.

2.2 Data pre-processing

To ensure the quality and consistency of the results obtained by our machine learning models, several pre-processing steps have been implemented:

- **Handling missing values :** Some variables had missing data, notably for natural gas (TTF Gas), European swap rates (EUR 10Y SWAP, EUR SWAP 2Y) and the ESTER rate. Where necessary, we performed imputation by linear interpolation or deleted the observations concerned.

- **Data conversion and normalization :** The "Date" column was converted to datetime format, and all explanatory variables were transformed into numerical format. Normalization (z-score) was applied to exogenous data to ensure consistency between variables.

- **Data cleaning and standardization :** Columns were renamed with a clear and homogeneous nomenclature to facilitate exploratory analysis and interpretation of results.

3. Review of literature

Inflation forecasting is essential for economic decision-makers, central banks and investors, as it influences monetary policy, interest rates and overall economic stability. Traditionally, linear econometric models such as autoregressive (AR) and vector autoregressive (VAR) models have been used to forecast inflation. However, these models have limitations, including their inability to capture complex non-linear relationships between macroeconomic variables. With the advent of Big Data and advances in artificial intelligence, machine learning (ML) techniques have emerged as adaptable tools for improving the accuracy of inflation forecasts.

3.1 Machine learning techniques applied to inflation forecasting

Several studies have explored the application of various ML methods to forecast inflation :

- **Artificial neural networks (ANNs):** These models are capable of capturing complex non-linear relationships. For example, one study used recurrent neural networks to forecast the components of the U.S. Consumer Price Index (CPI), demonstrating a significant improvement over traditional models.
- **Random Forest:** This ensemble method based on decision trees was used to forecast inflation in Brazil, showing superior performance to conventional econometric models.
- **Support Vector Machines (SVM):** SVMs have been applied to forecast the CPI in the USA, demonstrating their ability to handle non-linear data and deliver accurate forecasts.
- **Boosting models (XGBoost, LightGBM):** These boosting algorithms have proved highly effective in various forecasting tasks, including inflation, due to their ability to improve predictive performance by combining several weak models.

3.2 Model performance comparison

Studies comparing ML models with traditional approaches have generally found that ML models offer better predictive accuracy. For example, a study of inflation forecasting in Brazil showed that ML methods outperformed conventional econometric models, particularly decision tree-based methods such as random forests and XGBoost. Similarly, a recent bibliometric analysis highlighted the growing impact of ML techniques in inflation forecasting, reflecting their increasing adoption in economic research.

3.3 Challenges and considerations in the application of machine learning

Despite the potential benefits, applying ML to inflation forecasting presents challenges :

- **Data quality and availability:** ML models require large quantities of high-quality data. However, macroeconomic data are often limited in frequency and availability, which can affect model performance.
- **Interpretability:** ML models, in particular deep neural networks, are often regarded as “black boxes”, making it difficult to interpret the relationships between variables. This opacity can limit their adoption in areas requiring a clear understanding of the underlying mechanisms.
- **Overfitting:** Because of their ability to model complex relationships, ML models are likely to overfit training data, which can impair their ability to generalize to unseen data.

3.4 Future prospects

Integrating machine learning techniques into inflation forecasting is promising but requires a cautious approach. Future research could focus on combining models by utilizing hybrid approaches that merge traditional methods with ML techniques to leverage the strengths of each for improved predictive accuracy. Additionally, efforts could be directed towards enhancing interpretability, making ML models more accessible and acceptable to policy-makers and economists by clarifying the relationships between variables.

Further potential lies in the exploitation of real-time data sources, such as social media or online search data, which could provide timely and novel insights for forecasting inflation. In conclusion, machine learning techniques offer powerful tools for forecasting inflation, potentially significantly outperforming traditional methods. However, careful attention must be given to the inherent challenges associated with data quality, interpretability, and model generalization. A balanced approach that integrates traditional economic expertise with advancements in ML technology is crucial to fully realize the benefits of these methods in forecasting inflation.

4. Model Implementation

4.1 Inflation trend analysis and modeling

The aim of this sub-part is to analyze the evolution of inflation, identify its main components (trend, seasonality and residuals) and check the stationarity of the time series before moving on to predictive modeling. This first step is essential for choosing the most suitable models for forecasting inflation.

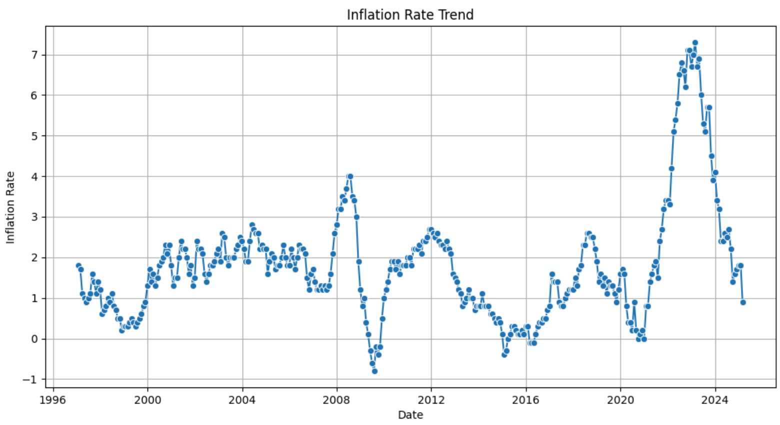


Chart 1: Evolution of the inflation rate between 1996 and 2025.

The first graph above shows the evolution of the inflation rate over the period studied. We can see that inflation follows a fluctuating trajectory, with phases of stability followed by periods of sharp increase. In particular, there is a clear acceleration between 2020 and 2023, corresponding to the post-pandemic economic disruptions and supply crises that marked this period. At other times, inflation falls significantly, reflecting phases of economic slowdown or monetary intervention aimed at controlling price rises. This visualization highlights the need for a model capable of capturing both these abrupt variations and the underlying trends in inflation.

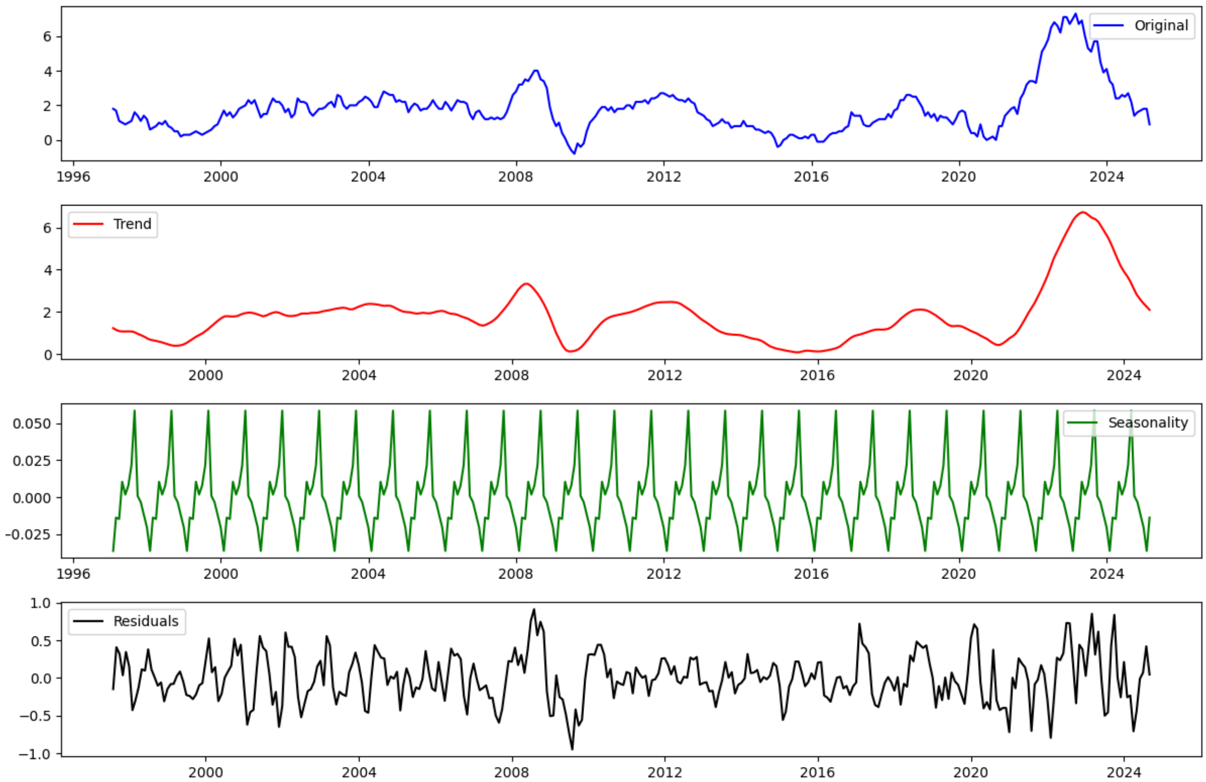


Chart 2: Evolution between 1996 and 2025 of the inflation rate (1st), showing its trends (2nd), its seasonality (3rd) and its residuals (4th).

The second chart breaks down the inflation series into three distinct components: trend, seasonality and residuals. The trend line shows a general rise in inflation, with periods of prolonged increases followed by corrections. Seasonality reveals a repetitive pattern in price evolution, suggesting recurring fluctuations on an annual or sub-annual basis. Finally, the residual component contains unpredictable variations that are not explained by trend or seasonality. These elements confirm that inflation is influenced by both long-term structural forces and shorter cycles, which must be taken into account when choosing a predictive model.

4.2 ARIMA

Before using an ARIMA model, it is essential to check whether the series is stationary, using the Augmented Dickey-Fuller (ADF) test. Stationarity implies that the statistical properties of the series remain constant over time, a necessary condition for the application of an ARIMA model. As our initial inflation series proved to be non-stationary (p-value > 0.05), we carried out a first differentiation, calculating the difference between each observation and the previous one. After this transformation, the series became stationary (p-value < 0.05). To select the optimum parameters for the ARIMA model, we analyzed the autocorrelation (ACF) and partial autocorrelation (PACF) graphs.

These suggested potential orders for the autoregressive and moving-average components of the model. Based on these analyses, we tested two specific configurations: ARIMA(1,1,1) and ARIMA(2,1,2).

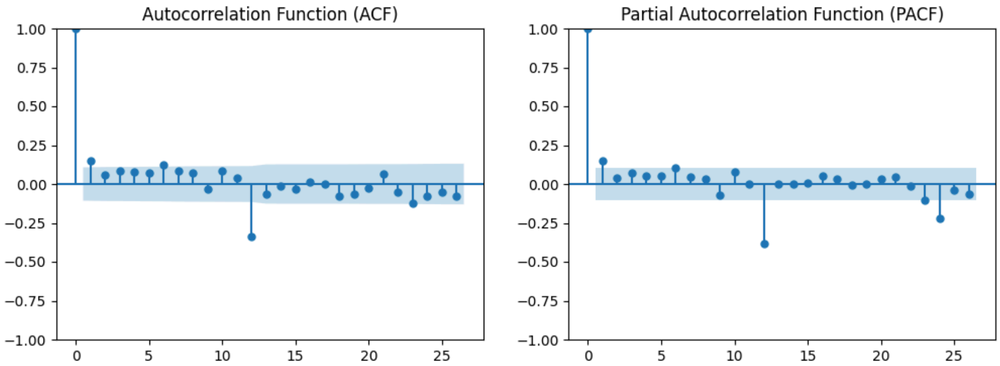


Chart 3: Analysis of time dependencies via ACF (left) and PACF (right).

The ARIMA models were evaluated by calculating the mean absolute error (MAE), an indicator measuring the average deviation between forecasts and actual inflation values. The ARIMA(1,1,1) model produced an **MAE of 0.0450**, reflecting good forecast accuracy. In comparison, the ARIMA(2,1,2) model obtained a slightly **higher MAE of 0.0467,** confirming that the ARIMA(1,1,1) model was better suited to our data.

```
==============================================================================
Dep. Variable:              Inflation   No. Observations:                  338
Model:                 ARIMA(1, 1, 1)   Log Likelihood                 -92.683
Date:                Sat, 22 Mar 2025   AIC                            191.367
Time:                        11:50:49   BIC                            202.827
Sample:                             0   HQIC                           195.935
                                - 338
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.8169      0.107      7.663      0.000       0.608       1.026
ma.L1         -0.7070      0.133     -5.313      0.000      -0.968      -0.446
sigma2         0.1015      0.007     14.845      0.000       0.088       0.115
===================================================================================
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):                 9.71
Prob(Q):                              0.75   Prob(JB):                         0.01
Heteroskedasticity (H):               0.52   Skew:                             0.12
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.79
===================================================================================
```

Chart 4: Analysis of the ARIMA (1, 1, 1) model linked to inflation.

After selecting the ARIMA(1,1,1) model, we fitted it and estimated its parameters. The results show a strong time dependence of inflation, represented by an AR(1) **autoregressive coefficient of 0.8169**, accompanied by a negative MA(1) moving average structure of -0.7070. The information criteria obtained **(AIC = 191.367 and BIC = 202.827)** indicate a good compromise between good fit and model simplicity. The Ljung-Box test (Q-statistic = 0.10, p-value = 0.75) confirmed the absence of significant correlation between residuals, validating the model's relevance. However, the Jarque-Bera test (p-value = 0.01) shows that the residuals do not perfectly follow a normal distribution. Overall, these results confirm that the ARIMA(1,1,1) model effectively captures past inflation dynamics and fits historical data well.

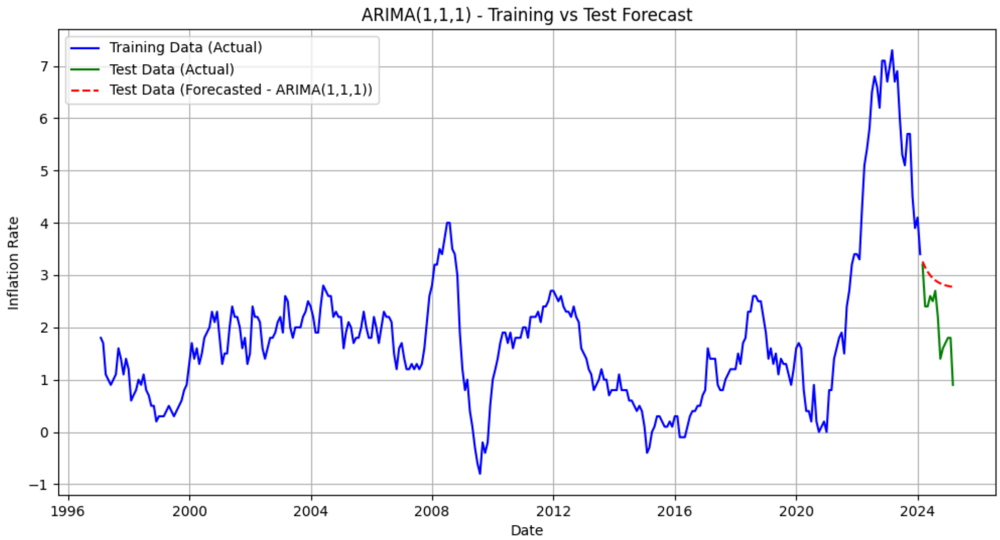


Chart 5: Inflation Forecast with ARIMA(1, 1, 1): test vs. predicted data.

```
Training Performance Metrics (ARIMA(1,1,1)):
Mean Squared Error (MSE): 0.1078
Mean Absolute Error (MAE): 0.2404
R-squared (R²): 0.9487

Testing Performance Metrics (ARIMA(1,1,1)):
Mean Squared Error (MSE): 0.9291
Mean Absolute Error (MAE): 0.8296
R-squared (R²): -1.5758
```

Chart 6: Analysis of the performance of the ARIMA (1, 1, 1) model.

After fitting the ARIMA(1,1,1) model, we evaluated its performance by splitting the data into a training set (up to January 2024) and a test set (February 2024 to February 2025). In the training set, the model performs well **(MSE = 0.1078, MAE = 0.2404, R^2 = 0.9487)**, demonstrating its ability to capture historical inflation trends. On the other hand, its performance decreased significantly over the test period **(MSE = 0.9291, MAE = 0.8296, R^2 = -1.5758)**, indicating a difficulty in predicting recent variations. This limitation can be attributed to the linear nature of the ARIMA model, which is unable to capture non-linear economic dynamics, sudden shocks or the effects of significant exogenous variables (energy prices, monetary policies, geopolitical tensions), as well as the absence of a seasonal component.

4.3 OLS Regression

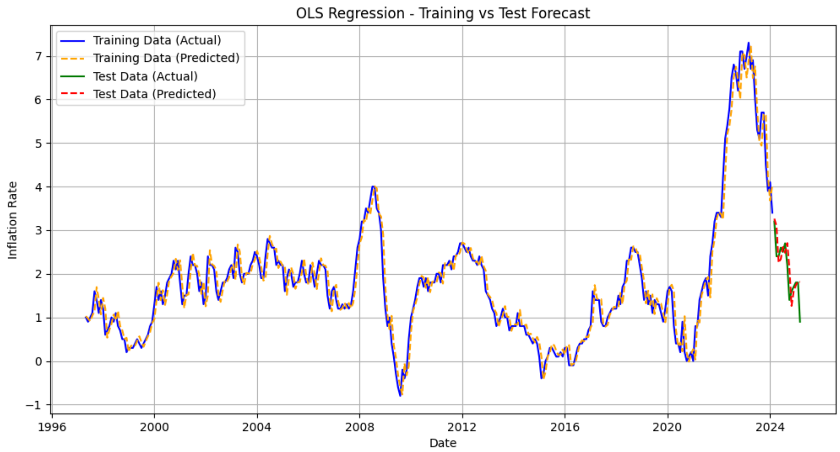
After noting the limitations of the ARIMA(1,1,1) model, which captured historical trends well but failed to generalise to recent data, we explored an alternative approach using ordinary linear regression (OLS). This model incorporates lagged variables to take better account of the temporal dynamics of inflation while remaining explainable. The results show a very good performance on the training set **(MSE = 0.0969, R^2 = 0.9543)**, demonstrating a strong ability to explain historical variations. Over the test period (February 2024 - February 2025), performance remains satisfactory **(MSE = 0.1829, R^2 = 0.4928)** and clearly superior to that of the ARIMA model previously tested.

```
Training Performance Metrics (OLS Regression):
Mean Squared Error (MSE): 0.0969
Mean Absolute Error (MAE): 0.2315
R-squared (R²): 0.9543

Testing Performance Metrics (OLS Regression):
Mean Squared Error (MSE): 0.1829
Mean Absolute Error (MAE): 0.3210
R-squared (R²): 0.4928
```

<u>Chart 7:</u> Analysis of the performance of the OLS Regression model.

The following graph illustrates the comparison between the actual values and the predictions of the OLS model, both on the training set and on the test set. We will now analyse these results and determine whether this approach is a better alternative to traditional time series models.

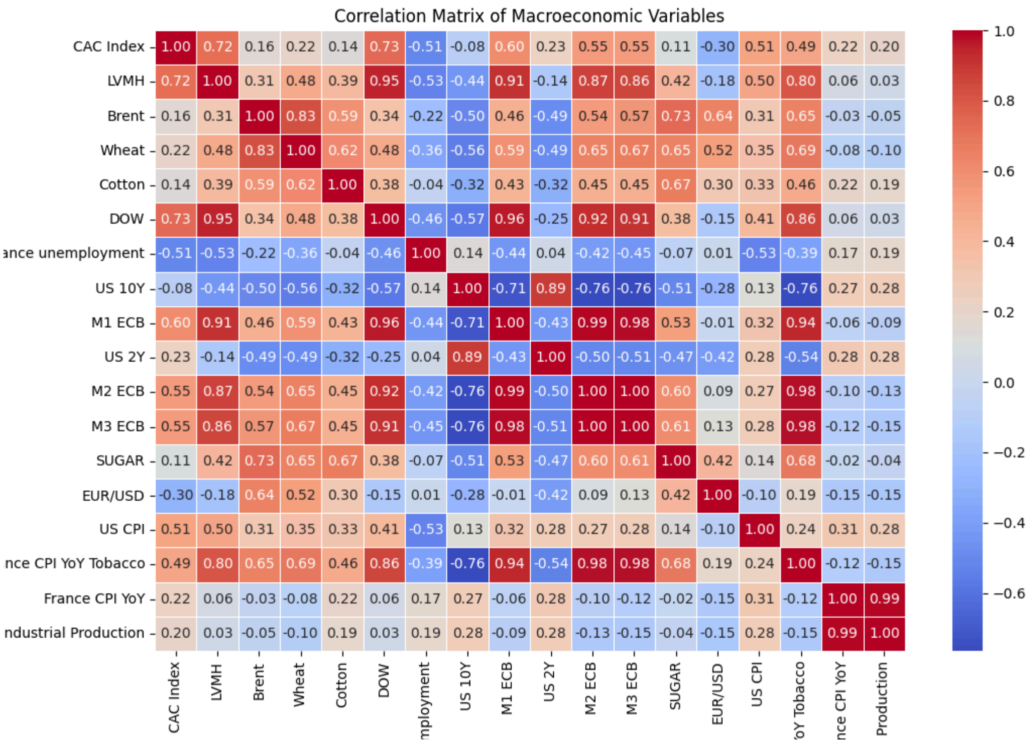


<u>Chart 8:</u> Inflation Forecast with OLS Regression: test vs. predicted data.

Over the training period, the predictions of the OLS model closely follow the actual values, with a **high R^2 of 0.9543** and a **low MSE of 0.0969**, confirming its ability to capture the historical dynamics of inflation. Over the test period (February 2024 - February 2025), the forecasts remain broadly in line with the actual trend, although there are some deviations. An **R^2 of 0.4928** indicates that the model maintains an acceptable performance, but lower than on the training set, suggesting a difficulty in anticipating more sudden fluctuations. In conclusion, OLS regression provides relatively reliable forecasts that are superior to those of the ARIMA model, but remains limited by its linearity assumption and the absence of certain potentially influential exogenous variables.

4.4 XGBoost

Before training an XGBoost Regressor model to predict inflation, it is essential to analyse the relationships between macroeconomic variables in order to optimise the quality of the model. A correlation matrix helps to identify variables that are highly correlated with each other, which is crucial because XGBoost is not specifically designed to handle variable redundancy. When several variables have a high correlation (>0.8), they run the risk of introducing unnecessary noise and increasing the training time of the model without providing any additional information. By eliminating these redundant variables, we improve the efficiency of the model while strengthening its robustness and generalisability. The aim of this analysis is therefore to visualise the correlation matrix, identify the strong relationships between the variables and select only the most relevant ones before training XGBoost. This step is essential to avoid overfitting and ensure more reliable predictions.



<u>Chart 9:</u> Correlations matrix of macroeconomic variables.

Analysis of the correlation matrix revealed several pairs of highly correlated variables (coefficient greater than 0.8), indicating information redundancy. To improve the efficiency of the XGBoost model, certain redundant variables were removed. Among these, the monetary aggregates **M1 ECB, M2 ECB and M3 ECB** (correlations greater than 0.9) were simplified by keeping only **M3 ECB**. Similarly, between the **DOW** and **LVMH** indices, which are highly correlated (0.95), only LVMH has been retained for its more sectoral dimension. Finally, the variables **France CPI YoY Tobacco** and **France CPI YoY**, which are very similar (0.98), have been reduced to **France CPI YoY**, providing a more general measure of French inflation. These adjustments make it possible to limit noise and avoid the biases associated with data redundancy.

We therefore trained an XGBoost model to predict inflation from macroeconomic variables. To optimise its performance, we used GridSearchCV, which tests several combinations of hyperparameters via cross-validation in order to minimise the mean square error (MSE). The optimised hyperparameters include the number of trees (n_estimators), the learning rate (learning_rate), the tree depth (max_depth) and the sampling fractions for the data and variables.

```
XGBoost Model Performance:
RMSE : 2.0708
MAE  : 1.4451
R²   : 0.2034
```

<u>Chart 10:</u> Analysis of the performance of the XGBoost model.

Once the model was trained, we evaluated its performance using several metrics. The RMSE (2.0708) and MAE (1.4451) indicate a moderate level of error. However, the R^2 (0.2034) suggests that the model has a limited ability to explain the variance in the data.

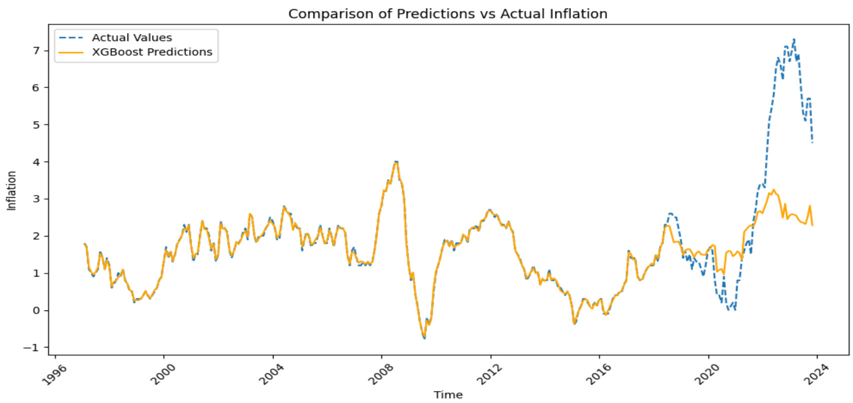


Chart 11: Inflation Forecast with XGBoost: test vs. predicted data.

Looking at the graph, we see that the predictions (orange line) follow the general trends in inflation (blue dotted line), but struggle to capture the abrupt fluctuations. In addition, the predictions appear to be time-lagged, suggesting the model does not take sufficient account of the data temporal dynamics.

5. Critical Analysis of results

This project provided a comprehensive evaluation of several predictive models for inflation forecasting, highlighting distinct strengths and limitations in each approach. While the ARIMA(1,1,1) model demonstrated considerable effectiveness in capturing historical inflation dynamics, its forecasting capability deteriorated significantly on recent, more volatile data, likely due to its inherent linearity and inability to accommodate non-linear economic events or even shocks.

Conversely, the Ordinary Least Squares (OLS) regression approach provided improvements by adding lagged variables, which enhances its predictive accuracy, particularly in the medium term. The OLS model, however, remains constrained by linearity assumptions and the exclusion of potentially influential exogenous factors, suggesting scope for further improvement through the integration of additional variables or hybrid modeling approaches.

The XGBoost model exhibited potential due to its ability to handle complex, non-linear relationships among macroeconomic variables. Nevertheless, it faced significant limitations in effectively capturing temporal dynamics, as evidenced by lagged responses to abrupt inflation fluctuations. This outcome indicates that although powerful, XGBoost requires additional methodological adjustments, such as incorporating derived time-series features or combining it with other techniques to achieve better predictive performance at the end.

Ultimately, the comparative analysis identifies OLS regression as the most balanced and effective model among those evaluated. However, the critical insights obtained show the necessity for future research to adopt hybrid models that integrate linear and non-linear methods, thus leveraging the strengths of traditional econometric models and advanced machine learning techniques. Additionally, addressing interpretability and managing data quality concerns will be essential for the successful practical application of machine learning in the inflation forecasting.

Model comparison table			
Model	**RMSE**	**MAE**	**R^2**
ARIMA(1,1,1)	0.9291	0.8296	-1.5758
OLS regression	0.1829	0.2404	0.4928
XGBoost	2.0708	1.4451	0.2034

Table 1: Performance comparison between ARIMA (1, 1, 1), OLS Regression and XGBoost models.