Will Japan's "Lost Three Decades" Come to an End?

Kuon Ito

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Abstract

This paper addresses two research questions: First, which model among the autoregressive model, the principal components regression model(PCR), and the factor-augmented autoregressive model (FAAR) demonstrates the best forecasting performance? Second, will Japan's inflation rate remain above 2% based on the forecast by FAAR model? The results can be summarized as follows: The FAAR model outperformed the other two models in terms of forecasting accuracy. Based on forecasts using the FAAR model, Japan's inflation rate is predicted to fall below 2% by December 2024. Focusing on the inflation rate, it can be concluded that Japan's Lost Three Decades have not yet come to an end.

1 Introduction

Figure 1 illustrates the inflation rate in Japan from 1974 to 2022. Since the collapse of Japan's bubble economy in the 1990s, the country has experienced prolonged economic stagnation, commonly referred to as the "Lost Three Decades." Specifically, from 1990 to 2020, Japan remained in a state of low inflation, with the inflation rate consistently below 2%. Initially, some scholars predicted that the economy would recover within about 10 years, but the expected improvement never materialized, and the stagnation has now persisted for over 30 years. This has even led to the pessimistic expression "Lost 10 Decades" within Japan. However, starting with the introduction of "Abenomics" in 2012, which addressed demand-side issues, and compounded by the supply shocks from the COVID-19 pandemic and the Ukraine crisis, Japan's inflation rate has recently surpassed 2%. The motivation behind this analysis is the fact that not only Japan, but the entire world is closely watching to see whether the inflation rate exceeding 2% will continue in the future.

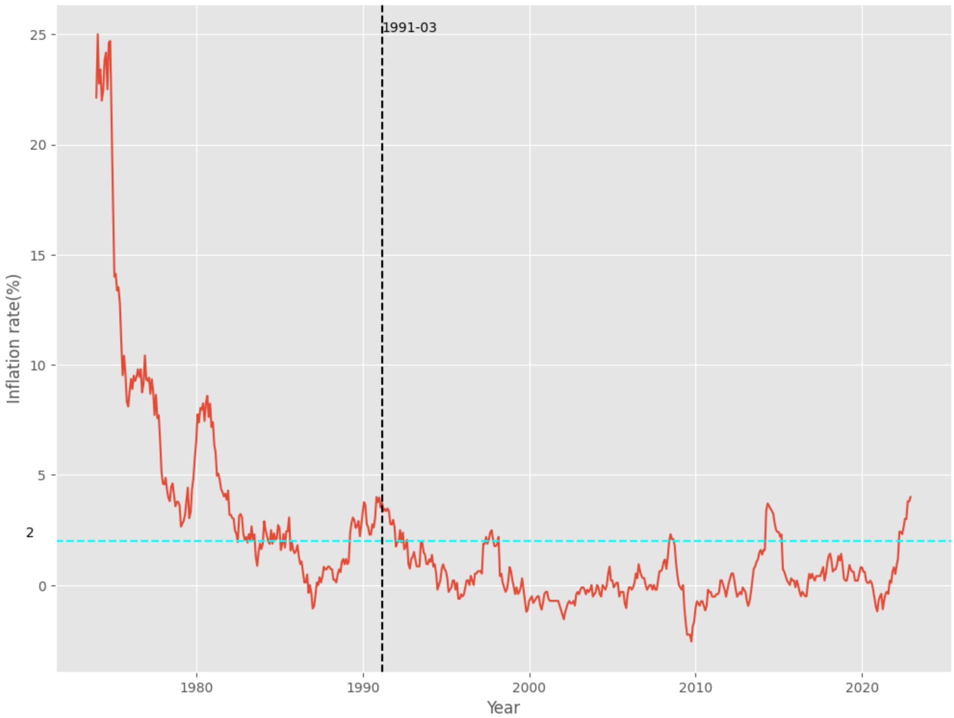

Figure 1: Inflation rate in Japan (1974-2022)

The reason for setting 2% as the target value is that, like other countries, Japan's central bank, the Bank of Japan, has set 2% as its inflation target, based on the annual rate of change in the Consumer Price Index (CPI). The bank of Japan's official website clearly states that maintaining a 2% inflation rate is their goal, and in this analysis, the inflation rate is defined accordingly.

$$\text{Year-over-Year Change (\%)} = \left(\frac{\text{CPI}_{\text{Current Year}} - \text{CPI}_{\text{Last Year}}}{\text{CPI}_{\text{Last Year}}} \right) \times 100 \tag{1}$$

I used autoregressive model and dynamic factor models to forecast the inflation rate. Dynamic factor models are based on the idea that macroeconomic variables often move together over both the short and long term due to shared underlying factors, and these models capture this co-movement by utilizing a small number of common factors to explain the behavior of multiple time series variables. The paper by Stock and Watson (2002) titled "Macroeconomic Forecasting Using Diffusion Indexes" [4] analyzed the prediction of eight U.S. macroeconomic time series, including the CPI and personal income, for 6, 12, and 24 months ahead using 215 variables from 1970 to 1998. In their paper, it is stated that for the 24-step-ahead CPI forecast using the full dataset, the models in order of decreasing mean squared error (MSE) are: DI-AR, lag model(a model where the principal components, their lags, and the dependent variable lags are used as independent variables), followed by the AR model, and lastly, the DI model (a model using principal components as independent variables).

In the paper by Maehashi and Shintani (2020) [3], they construct a forecasting model that incorporates machine learning, including neural networks, in addition to the dynamic factor model. Regarding the CPI forecast using the dynamic factor model, it was shown that the AR model had the highest accuracy for the 24-step-ahead forecast compared with the factor models.

One of the forecast methods used in my paper follows the two-stage forecasting model in the paper by Dwight B. Crane and James R. Crotty (1967) [2]. In their paper, the exponentially smoothed moving average model was used not only for predicting the dependent variable but also for selecting the independent variables. The predicted independent variables were then used as inputs for multiple regression analysis. Specifically, in the two-stage forecast of demand deposits, the first stage involved predicting demand deposits using exponentially weighted moving average (EWMA), and in the second stage, the predicted values, along with lags of variables such as the volume of business loans and corporate AAA bond yields, were used as independent variables in the multiple regression analysis.

My research design differs from those studies in the following three points. First, the inflation rate predicted in this analysis is calculated using the same formula that the Bank of Japan (BOJ) uses to compute inflation, aiming to forecast whether the BOJ's 2% inflation target will be met. In contrast, the CPI values in the paper by Maehashi and Shintani were transformed into the "year-on-year change of the original series," which diverges from the intent of this study. Second, this analysis forecasts the inflation rate up to December 2024, while Maehashi and Shintani's paper only extended their predictions until 2021. This extended forecast horizon offers a more forward-looking perspective on Japan's economic trajectory. Third, this paper adopts a two-stage forecasting method, where, in the first stage, the independent variables are predicted using LSTM (Long Short-Term Memory) instead of the exponentially weighted moving average (EWMA) employed in Dwight and James's paper.

Based on the above considerations, the aim is to not only evaluate the forecasting accuracy of different models but also assess whether Japan's inflation rate is expected to stay above the 2% threshold over the forecast horizon (2023-2024).

The main results can be summarized as follows. First, the forecast performance of factor augmented autoregressive (FAAR) model is better than that of principal component regression (PCR) model and autoregressive model. Second, the forecasted inflation rate will fall below 2% in June 2023 and continue to fall until December 2024

The remainder of the paper is as follows. Section 2 introduces the econometric framework and explains how to evaluate the model and forecast. In Section 3, I describe the overviews of the data. In Section 4, the empirical results are shown. Section 5 describes the conclusion.

2 Econometric framework

2.1 Autoregressive model

The AR forecast is generated by performing a linear regression of y_{t+h} on the current and lagged values of y_t, with the number of lags p chosen based on the minimization of the Bayesian Information Criterion (BIC) with the maximum lag length set at 12.

$$y_{t+h} = \phi(L)y_t + \epsilon_{t+h} \tag{2}$$

where $\phi(L)$ is the lag polynomial with a lag operator L and ϵ_{t+h} is the forecast error.

2.2 Principal components regression (PCR)

In Stock and Watson's 2002 paper, this model referred to as diffusion indexes (DI) model. In this paper, following Maehashi and Shintani, I will refer to this model as principal components regression model. To build this model, two computational steps are necessary. The first step involves calculating the common factors $F_t^k = (f_{1t}, f_{2t}, ..., f_{kt})'$ as the principal component of all independent variables by minimizing equation (3) below.

$$\sum_{i=1}^{N}\sum_{t=1}^{T}\left(x_{it} - \lambda_i' F_t^k\right)^2 \tag{3}$$

where N is the number of the predictors, T is the length of the time series, x_{it} is a potential candidate predictor, λ_i' is a $k \times 1$ vector of factor loading and e_{it} is the idiosyncratic disturbance.

The second step is constructing the h-period ahead forecast by running a principal components regression (PCR) as follows:

$$y_{t+h} = \beta_F' F_t^k + \epsilon_{t+h} \tag{4}$$

where β_F is a $k \times 1$ vector of coefficients.

For the selection of the number of factors (denoted as k), I use the value of k that minimizes the information criterion proposed by Bai and Ng (2002) [1]. However, the number of factors must be sufficiently fewer than the number of independent variables. As in the paper by Maehashi and Shintani, I set the maximum number of factors to 20.

$$IC(k) = \ln V(k) + k\left(\frac{N+T}{NT}\right)\ln C_{NT}^2, \tag{5}$$

where $V(k) = \min_{\lambda_i, F_t^k} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(x_{it} - \lambda_i' F_t^k\right)^2$
and $C_{NT} = \min\left\{\sqrt{N}, \sqrt{T}\right\}$.

2.3 Factor augmented autoregression (FAAR)

In Stock and Watson's paper, this model was referred to as the DI-AR, lag model. It is an extension of the PCR model, with the addition of lags of the factors and the dependent variable. According to (6), the lags of the factors F_t^k and inflation rate y_t can differ. The optimal lag lengths were determined using the Bayesian Information Criterion (BIC). Following Maehashi and Shintani's paper, the maximum number of lags was set to 12. Because the maximum lag for both the factor and inflation rate is 12, a total of 169 BIC values were calculated for all combinations of lags between 0 and 12.

$$y_{t+h} = \beta_F'(L) F_t^k + \phi(L) y_t + \epsilon_{t+h}, \tag{6}$$

where $\beta_F(L) = \sum_{j=1}^{r} \beta_{Fj} L^{j-1}$
and $\phi(L) = \sum_{j=1}^{p} \phi_j L^{j-1}$ are the lag polynomials.

2.4 Evaluation method

This section describes the method for comparing the three models (AR model, PCR model, and FAAR model). Ultimately, the goal is to forecast the inflation rate from January 2023 to December 2024, using the available data up to 2022. Therefore, the forecast horizon will be 24 steps ahead.

To compare the accuracy of the 24-step-ahead forecasts, the dataset from January 1974 to December 2022 was divided into training and test periods. The training period spans from January 1974 to December 2020, while the test period is set from January 2021 to December 2022.

The forecast accuracy during the test period is assessed using the Mean Squared Forecast Errors (MSFEs), calculated to measure the difference between the predicted and actual values, as described by the following equation.

$$\sum_{t=01.2021}^{12.2022} (y_{t+h} - \hat{y}_{t+h})^2 / 24 \tag{7}$$

where $\hat{y}_{t+h}$ is the forecast value for horizon h by a forecast model.

During the test period, forecasts were made recursively. To improve the reliability of the forecasts by using more data over time, an expanding window approach was employed, progressively increasing the forecast horizon as more data became available.

2.5 Forecast

This section describes the method used to forecast the inflation rate from January 2023 to December 2024 using the FAAR model, based on the original dataset of variables up to December 2022.

The full dataset of 219 variables available from January 1974 to December 2022 was used to extract factors based on the number of factors selected by Bai and Ng's information criterion. The lags of the factors and the lags of the inflation rate were then determined using the Bayesian Information Criterion (BIC). Using these factors, their lags, and the lags of the inflation rate, an FAAR model was constructed to forecast inflation rate. However, as the dataset used in this paper only to December 2022, an approach similar to that in Dwight and James's paper, which used a two-stage forecast for demand deposits, was applied to forecast inflation in two stages.

In the first stage, the independent variables were forecast using LSTM to obtain values for the period from January 2023 to December 2024. In the second stage, these predicted independent variables were used to forecast the inflation rate for the period from January 2023 to December 2024 as independent variables for FAAR model.

In contrast to Dwight and James's approach, where the independent variables were forecast using the exponentially weighted moving average (EWMA) in the first stage, this paper utilizes LSTM for the prediction. The reasons for this include LSTM's ability to capture long-term dependencies. While EWMA places more weight on recent data and struggles to capture long-term fluctuations, LSTM has memory cells that allow it to retain information over longer periods. Additionally, LSTM can process multivariate time series data. Since the optimal number of factors was 10 and this first stage of the forecast involves forecasting 21 variables, including factors, their lags and lagged inflation rate, LSTM is capable of capturing the interactions between these variables. EWMA, on the other hand, processes each variable independently, lacking the ability to model such interactions.

In my implementation of the LSTM model, I employed a structure with 50 hidden units in each LSTM layer. The model consists of two LSTM layers followed by a Dense layer. The LSTM layers use the following activation functions: For the gates (input, forget, and output gates), I use the sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$, which is standard for controlling the flow of information in and out of the memory cells. This ensures that the model can regulate the addition and removal of information effectively over time. For the cell state and output activation, I apply the hyperbolic tangent (tanh) function $tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, which allows the model to output values in a range between -1 and 1, providing a smoother gradient and better handling of long-term dependencies in the data.

The model is trained to minimize the mean squared error (MSE) loss, which measures the difference between the predicted values and the actual values. The final Dense layer produces predictions for each time step, matching the number of independent variables in the dataset.

3 Data

The data are monthly observations of 219 Japanese macroeconomic time series from January 1974 to December 2022. The total number of predictors was 128772 (219 predictors x 588 periods).These predictors include variables from the fields of real output, inventories, investments, employment, consumption, firms, money, stock prices, interest rates, price indexes, and trade. This data and the full list of the variables are available on the Shintani's web site

The dependent variable is the inflation rate. I got the CPI data from January 1973 to December 2022 from e-Stat, which is the Japanese government official data site. I used the CPI of all items. Since the CPI transformation method was year-on-year change of the original series in Maehashi and Shinntani's paper and it differs from the purpose of this study, the inflation rate was calculated independently using the formula (1), in order to match the Bank of Japan's inflation rate.

4 Empirical results

According to the Figure 2, the optimal lag length of AR model is 12 based on BIC.

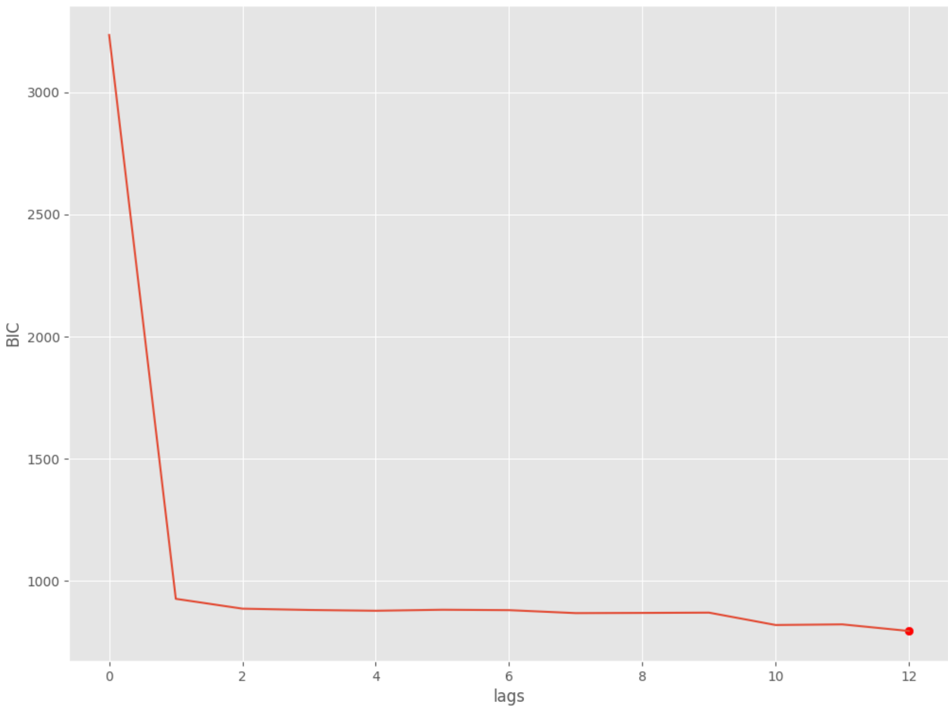

Figure 2: The optimal lag length of AR model

According to the Figure 3, the selected number of factors for PCR and FAAR model was 10 based on the information criterion of Bai and Ng.

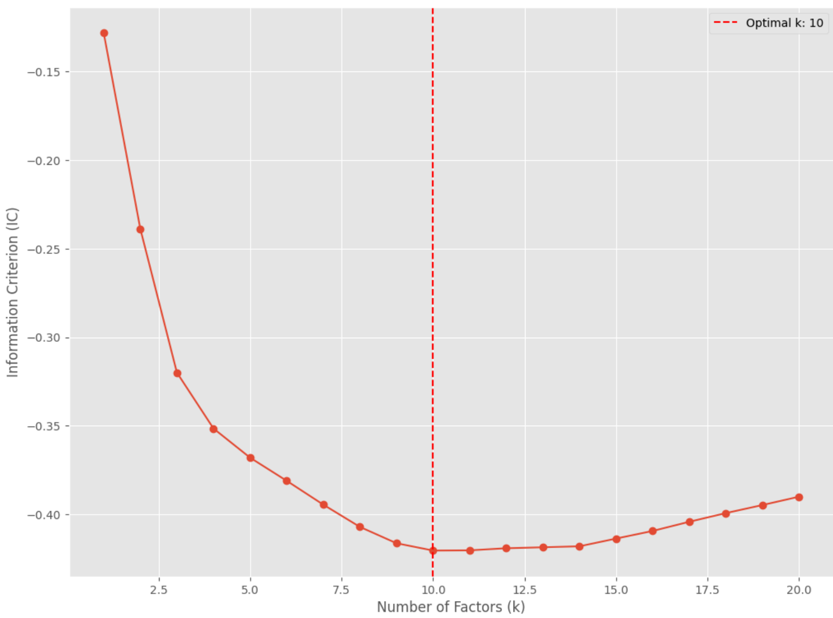

Figure 3: The optimal number of factors for PCR and FAAR model

To create the FAAR model, it was necessary to select the optimal lags for both the AR model part and the factor part. By exploring different combinations of lags for the

AR model part and the factor part, I identified the point where the BIC was minimized. According to Figure 4, the optimal lag for the AR model part is 12, while the optimal lag for the factor part is 11.

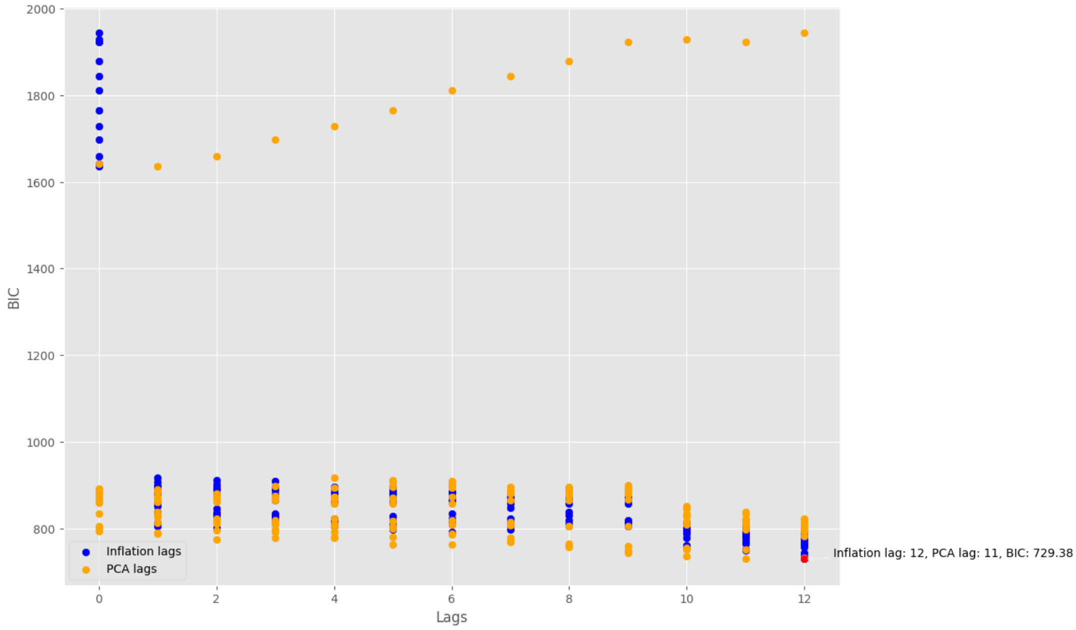

Figure 4: The optimal lag length of AR part and factors part for FAAR model

Examination of Table 1, Figure 5 and Figure 6 addresses some of my research questions.

	mean squared forecast errors
AR model	3.593
PCR model	3.441
FAAR model	2.443

Table 1: Comparison of model's performances

According to Table 1, the MSFEs of the FAAR model are the smallest. Using data from January 1974 to December 2020, we recursively predicted the inflation rate for the period from January 2021 to December 2022 by progressively expanding the forecast window. The results indicate that the FAAR model performed the best, followed by the PCR model, and finally the AR model. This outcome differs from the findings of Stock and Watson, as well as from the results of Maehashi and Shintani's paper.

According to Figure 5 and Figure 6, it is evident that by the end of 2024, the inflation rate falls below 2%. This observation provides insight into the research question posed by the title of this paper: "Will Japan's Lost Three Decades Come to an End?" Based on the inflation rate trends, the answer seems to be no, as the inflation rate does not sustain a level above 2%.

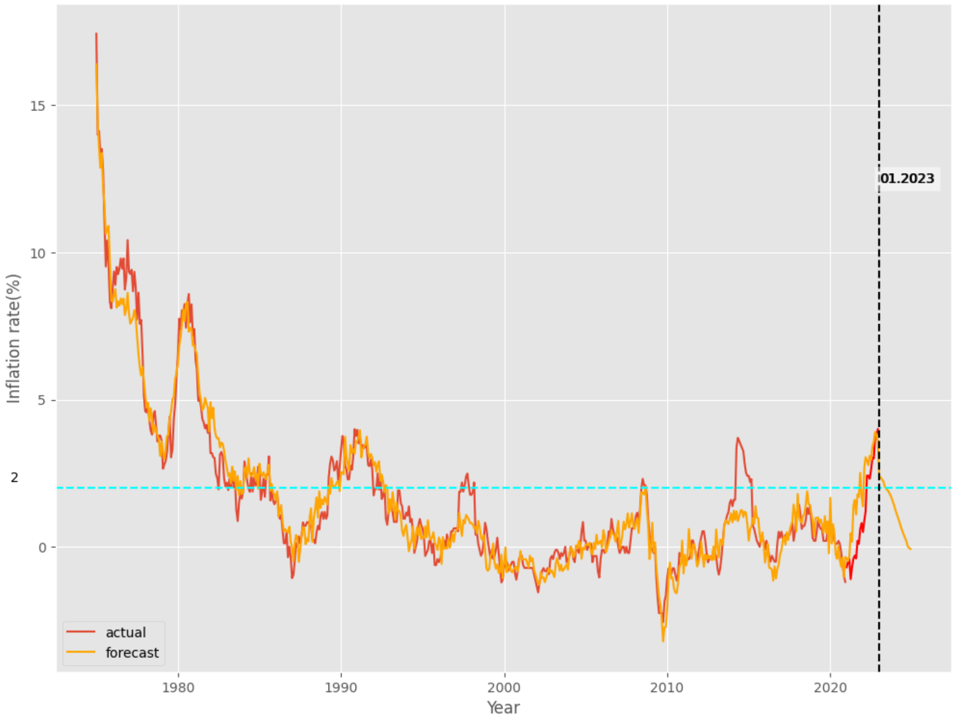

Figure 5: Forecast of inflation rate in Japan (1974-2024)

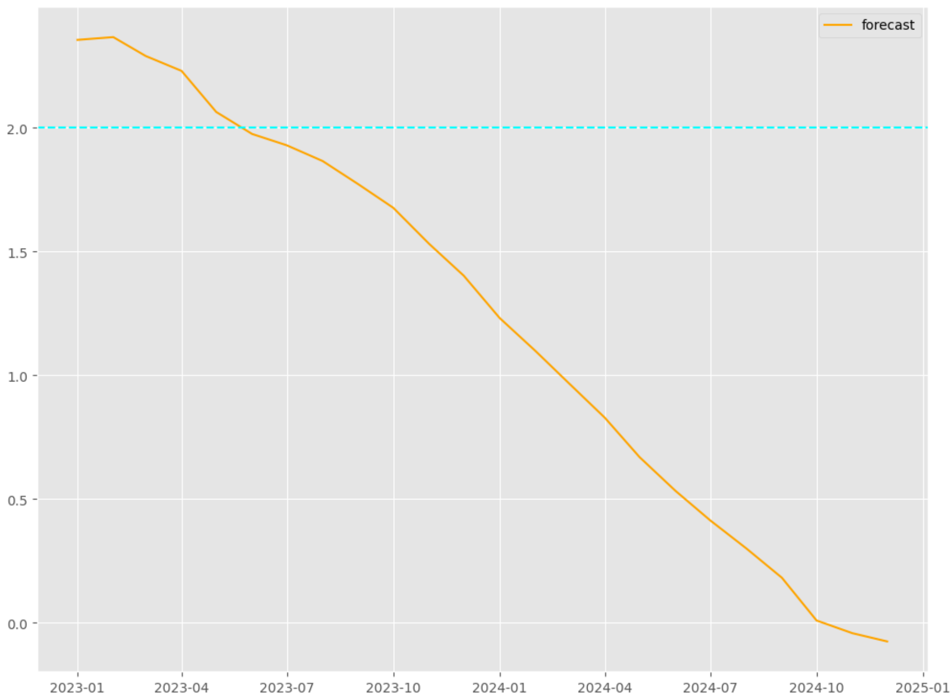

Figure 6: Forecast of inflation rate in Japan (2023-2024)

5 Conclusion

In this paper, the AR model, PCR model, and FAAR model were employed to forecast Japan's inflation rate. Among these, the FAAR model demonstrated superior forecasting performance compared to both the PCR and AR models. According to future forecasts using the FAAR model, it was forecasted that the inflation rate would fall below 2%. Based on the inflation rate, "Japan's Lost Three Decades" have not yet come to an end.

However, there is still room for improving the quality of forecasts by using more recent data. Additionally, as indicated by Maehashi and Shintani's paper, models utilizing boosting techniques outperformed the FAAR model in terms of prediction accuracy for 24-step-ahead CPI forecasts, suggesting that other methods may further enhance forecasting precision.

A Appendix

e-Stat: the data of the CPI in Japan is available

Kuon Ito: this github page has the computations of this paper

Mototsugu Shintani: the data of the 219 variables and the full list of them are available on the his web site.

The bank of Japan's official website

References

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[4] James H Stock and Mark W Watson. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2):147–162, 2002.