Predicting future inflation in Indonesia using Dynamic Model Averaging (DMA)

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Abstract.
The features of Indonesia's inflation data, which make it extremely susceptible to shocks like those felt in 2005 and 2008, as well as extensive potential influencing factors, lead to problems in forecasting inflation. These problems include time variation in coefficients, models that can change over time, and many predictors to consider. Dynamic Model Averaging (DMA) solves these problems since it has evolved coefficients and models that change over time. This study uses DMA to predict future inflation by involving eight macroeconomic indicators as exogenous variables. The results of the in-sample analysis show that six predictors are significant in forecasting inflation, with posterior inclusion probability (PIP) being above 40%. Although the remaining predictors have PIP means below 40%, they can still be considered important. The out-of-sample results suggest that DMA performs better than dynamic model selection and models that don't include exogenous variables, such as autoregressive models. The forecast results indicate a consistent pattern over the 12 months studied. The attempt to control inflation can be achieved by prioritizing the money supply factor, which has the highest PIP value, indicating that it is the most important factor.

Keywords: *Dynamic Model Averaging, Forecasting, Inflation*

JEL Classification: C53, E31, E52.

INTRODUCTION

According to the IMF's World Economic Outlook 2022 report (IMF, 2022), Indonesia's yearly inflation rate in 2022 is 5.5%, which is higher than the government's target of 3% and stands out compared to neighboring ASEAN countries like Malaysia and Thailand, where it is only 2.8%. This disparity underscores the unique challenges Indonesia faces in managing inflation volatility. High and volatile inflation adversely affects a nation's socioeconomic aspects (BI, 2023). Forecasting inflation is vital for the Indonesian government and the Bank of Indonesia in formulating monetary policy to control inflation. Predicting inflation is challenging due to Indonesia's inflation volatility and susceptibility to shocks. As Figure 1 illustrates, inflation spiked in 2005 and 2008, driven by increased world crude oil prices that impacted fuel prices in Indonesia.

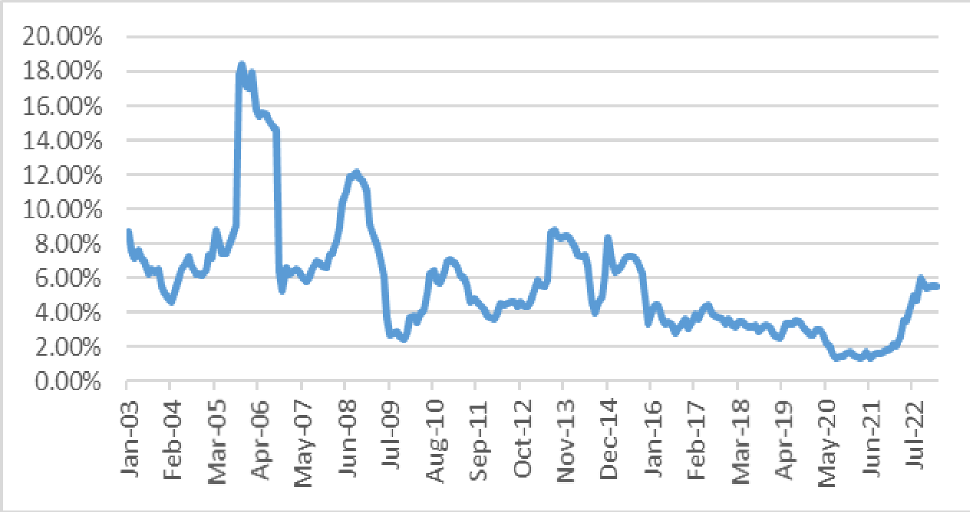

Figure 1. Yearly inflation rate in Indonesia.

Adding economic indicator variables to forecast inflation can reduce errors in the results (Arisanti et al., 2023). Factors impacting inflation include demand-supply interactions, the external environment (exchange rates, international commodity prices, and inflation rates of trading partners), and inflation expectations among traders and consumers (BI, 2023). While numerous economic indicators potentially influence inflation, this study focuses on eight key macroeconomic variables: the M2 index of money supply, the Jakarta composite stock price index, the exchange rate from US Dollar to Indonesian Rupiah, the one-month BI Rate, the industrial production index, the global price of food index, the global price of gold, and the global price of crude oil. Money supply and the industrial production index can affect inflation from the perspective of demand-supply interactions (Christianingrum & Syafri, 2019). The theory of interest rates, proposed by Irving Fisher, explains the relationship between interest rates and inflation expectations. Furthermore, it suggests that stock market prices have the potential to impact inflation expectations (Fisher, 1930). Additionally, three commodities can be considered when forecasting inflation: global food prices (Juhro & Iyke, 2019), global crude oil prices (Juhro & Iyke, 2019), and gold prices (Christianingrum & Syafri, 2019).

Predicting inflation presents numerous challenges, including structural changes that may cause time variations in the underlying relationship between inflation and its predictors (Juhro & Iyke, 2019). The optimal inflation forecasting model can change over time, and many predictors must be considered. Selecting the optimal set of predictors can be challenging, and models with many variables can suffer from overfitting. Stock & Watson (2008) confirmed the existence of a time-varying relationship problem when forecasting US inflation using the ARDL model. There are changes in the coefficients due to changes in economic policy, the economy's structure, increasingly complex financial markets, and economic shocks. Stock & Watson (2008) also confirmed the model instability problem, where the optimal forecasting model can vary depending on the economic environment. Forecasting models change over time; the Phillips curve model works well in some periods, while a simpler univariate model is more effective in others. Such problems make the

Autoregressive Distributed Lag (ARDL) and transfer function models unsuitable, as neither can solve the time-varying relationships and model instability problems.

Dynamic Model Averaging (DMA) offers a solution for inflation forecasting, overcoming the limitations of traditional models with time-varying coefficients, the capability of handling numerous predictors, and model selection flexibility. DMA utilizes dynamic linear models, where coefficients can adapt to evolving economic conditions, capturing time-varying relationships (Juhro & Iyke, 2019). DMA incorporates multiple models with various combinations of predictors, mitigating the issue of overfitting and potentially improving accuracy (Juhro & Iyke, 2019). Additionally, DMA doesn't rely on a single model but dynamically averages forecasts from different models, adapting to changing economic environments (Koop & Krobilis, 2012). Previous studies in forecasting inflation involving factors that can influence inflation as exogenous variables use DMA, such as the research of Juhro & Iyke (2019), Koop & Krobilis (2012), Styrin (2018), and Ferreira & Palma (2015). These studies utilized DMA to overcome the issues of predictor coefficients that may change over time, the large number of involved predictors, and relevant forecasting models that can change over time. Juhro & Iyke's study (2019) on inflation prediction in Indonesia found that, with a PIP mean cut-off above 40%, 87% of all predictors are important in forecasting inflation. Furthermore, models with many predictors had better forecasting results over a long period than simple inflation forecasting models, as confirmed by the out-of-sample results.

This study aims to enhance the accuracy of inflation forecasting in Indonesia by utilizing DMA with eight macroeconomic indicators as exogenous variables. By addressing the limitations of traditional models, we hope to provide more reliable forecasts that can inform more effective monetary policy decisions by the Bank of Indonesia, ultimately contributing to greater macroeconomic stability. The results from in-sample analysis can be used to determine which exogenous variables are most important. In contrast, the results from out-of-sample analysis can determine if DMA provides better results than dynamic model selection and autoregressive models.

METHODS

This study uses secondary data obtained from the Indonesian Central Bureau of Statistics (Badan Pusat Statistik Indonesia) (BPS, 2023) for monthly inflation data from the Special Data Dissemination Standard (SDDS) of Bank Indonesia (SDDS BI, 2023) for the money supply, stock price index, exchange rate, one-month BI rate, and industrial production index; and from the World Bank (World Bank, 2023) for the global commodity price index. Each data series consists of 306 monthly data points from January 1998 to June 2023. The variables used in this study are listed in Table 1.

The response variable used in this study is the monthly inflation rate in Indonesia, representing an increase in the consumer price index from the previous month. Monthly interest rates can provide more up-to-date information than yearly interest rates, representing an increase in the consumer price index from the same month in the previous year (Art & Artlova, 2015). The exogenous variables are the M2 index of money supply, the Jakarta composite stock price index, the exchange rate from the US Dollar to the Indonesian Rupiah, the one-month BI Rate, the industrial production index, the global price of food index, the global price of gold, and the global price of crude oil.

Table 1. Variables and source of data

Variable	Description	Period	Data Sources
INF	Monthly inflation rate in Indonesia	Jan 1998 – June 2023	Indonesian Central Bureau of Statistics
M2	Money supply (M2 index)	Jan 1998 – June 2023	Bank Indonesia
IHSG	Jakarta composite stock price index	Jan 1998 – June 2023	Bank Indonesia
EXCH	Exchange rate from US Dollar to Indonesian Rupiah	Jan 1998 – June 2023	Bank Indonesia
SB1	One-month BI Rate	Jan 1998 – June 2023	Bank Indonesia
IPI	Industrial Production Index	Jan 1998 – June 2023	Bank Indonesia
FOOD	Global Price of Food Index	Jan 1998 – June 2023	World Bank
GLD	Global Price of Gold	Jan 1998 – June 2023	World Bank
OIL	Global Price of Crude Oil	Jan 1998 – June 2023	World Bank

While numerous economic indicators potentially influence inflation, this study focuses on these eight key macroeconomic variables. The M2 money supply index reflects the total money supply in circulation, potentially impacting inflation through increased aggregate demand (Christianingrum & Syafri, 2019). A strong-performing stock market can signal economic optimism and potential future growth. This optimism can translate into expectations of higher future prices and wages, ultimately feeding into inflation expectations. Fluctuations in the exchange rate can affect import prices, impacting inflation (BI, 2023). Changes in production levels, reflected by the industrial production index, can influence both supply and price levels (Christianingrum & Syafri, 2019). The one-month BI Rate is the central bank's benchmark interest rate, influencing borrowing costs and economic activity, potentially impacting inflation (BI, 2023). Global food price fluctuations can affect domestic food prices in Indonesia (Juhro & Iyke, 2019). Similarly, global oil price volatility can impact domestic fuel costs and contribute to inflation. While less directly linked, gold prices can influence inflation expectations as a safe-haven asset (Christianingrum & Syafri, 2019). These eight variables are selected based on established theoretical frameworks (quantity theory of money, theory of interest rates) and their demonstrated influence on inflation in previous studies (Juhro & Iyke, 2019; Christianingrum & Syafri, 2019).

Several potentially relevant variables were considered but ultimately excluded due to limitations or redundancy concerns. For instance, the unemployment rate and per capita income lacked the necessary monthly data granularity. Interpolating these values to achieve monthly data was avoided due to potential information loss and the risk of introducing unreliable predictions. Business and consumer confidence data were also excluded due to data limitations that could compromise the analysis. Additionally, export and import prices were not included to avoid potential multicollinearity issues. The chosen indicators, exchange rates and commodity prices, already capture the influence of international trade without introducing redundancy.

Inflation in Indonesia has a dynamic relationship with its predictors, especially during economic shocks. Various methods can be utilized to forecast inflation involving exogenous variables, such as the Autoregressive Distributed Lag (ARDL) or Transfer Function model. Unfortunately, neither model can explain such dynamic relationships. Dynamic Model Averaging (DMA) can overcome these problems because it has model coefficients that vary over time and models that can change over time (Koop &

Krobilis, 2012). DMA offers a flexible approach to forecasting by combining the predictions from multiple models. Unlike traditional methods that rely on a single chosen model, DMA creates a weighted average forecast. These weights are strategically assigned based on each model's past performance, influencing models that have performed well in predicting past data points. This approach helps capture potential shifts in the underlying relationships over time and can lead to more accurate forecasts than relying on a single model.

Log transformation

Inflation and some of the exogenous variables have vastly different ranges, which can lead to problems with estimation. Log transformation is needed to bring their scales closer. If we denote the observation as x_t, the log-transformed observation can be denoted as $w_t = \log(x_t)$ (Kutner et al., 2005). Therefore, some exogenous variables, such as the M2 index of money supply, the Jakarta composite stock price index, the exchange rate from US Dollar to Indonesian Rupiah, the industrial production index, the global price of food index, the global price of gold, and the global price of crude oil, will enter the model in logarithm form.

Dynamic Model Averaging (DMA)

Dynamic model averaging (DMA) involves averaging the forecast results of multiple dynamic linear models built based on various possible combinations of exogenous variables by applying weights based on the model's past forecast performance. The number of models that can be built based on a combination of n possible exogenous variables is $k=2^n$. The i-th dynamic linear model of the k number of possible models can be written in equations (1) and (2) (Catania & Nojedad, 2018):

$$y_t = \boldsymbol{f}_t^{(i)T}\boldsymbol{\theta}_t^{(i)} + \varepsilon_t^{(i)} \quad , \quad \varepsilon_t^{(i)} \sim N(0, V_t^{(i)}) \text{ ....(1)}$$

$$\boldsymbol{\theta}_t^{(i)} = \boldsymbol{\theta}_{t-1}^{(i)} + \boldsymbol{\eta}_t^{(i)} \quad , \quad \boldsymbol{\eta}_t^{(i)} \sim N(0, \boldsymbol{W}_t^{(i)}) \text{ ....(2)}$$

Where $\boldsymbol{f}_t^{(i)T} = (y_{t-1}, y_{t-2}, \ldots, x_{1,t-1}, x_{2,t-1}, \ldots)$ is a vector containing the combination of all predictors of size $p\times1$ with y denoting response variable and x denoting exogenous variables, $\boldsymbol{\theta}_t^{(i)}$ is a regression coefficient vector that changes over time according to Equation (2), $\varepsilon_t^{(i)}$ and $\boldsymbol{\eta}_t^{(i)}$ is error with conditional variance $V_t^{(i)}$ and $\boldsymbol{W}_t^{(i)}$ respectively. DMA's estimation and prediction process uses a Kalman filter recursion process with the approach Raftery et al. (2010) suggested involving forgetting factors, namely α and δ.

To explain the recursive process, we first consider a one-model case of the dynamic linear model from Equation (1) and (2), with $\mathcal{F}_t = y_t, y_{t-1}, \ldots, y_1$ denote the information up to t time. Kalman filter process of estimation is divided into 2 phases: prediction and correction. We first assume that the coefficient follows the Equation (3) distribution.

$$\boldsymbol{\theta}_{t-1}|\mathcal{F}_{t-1} \sim N(\widehat{\boldsymbol{\theta}}_{t-1}, \boldsymbol{\Sigma}_{t-1}) \text{ ....(3)}$$

At the prediction phase in the estimation process, the calculation of the estimated prior state ($\widehat{\boldsymbol{\theta}}_t$) and the prediction covariance matrix ($\mathbf{R}_t$) can be written in equations (4) and (5). So the prediction equation can be expressed in Equation (6).

$\widehat{\boldsymbol{\theta}}_t = \widehat{\boldsymbol{\theta}}_{t-1}$ ……………………………………………………………………………(4)

$\mathbf{R}_t = \boldsymbol{\Sigma}_{t-1} + \mathbf{W}_t$ …………………………………………………………………...………(5)

$\boldsymbol{\theta}_t|\mathcal{F}_{t-1} \sim N(\widehat{\boldsymbol{\theta}}_{t-1}, \mathbf{R}_t)$ ……………………………………………………………..(6)

To simplify the calculation of $\mathbf{W}_t$, Raftery et al.(2010) propose an approach using forgetting factor $0 < \delta \leq 1$ by replacing $\mathbf{R}_t = \frac{1}{\delta}\boldsymbol{\Sigma}_{t-1}$. The relationship of δ and $\mathbf{W}_t$ can be expressed in Equation (7). This forgetting factor implies that observation u periods in the past have weight δ^u (Koop & Krobilis, 2012).

$\mathbf{W}_t = \frac{1}{\delta}(1-\delta)\,\boldsymbol{\Sigma}_{t-1}$ ……………………………………………………………..(7)

During the correction phase of the estimation process, the Kalman gain matrix ($\boldsymbol{G}_t$) is initially computed. This matrix is subsequently employed in Equation (8) to modify the state estimate ($\widehat{\boldsymbol{\theta}}_t$) and the udating covariance matrix ($\boldsymbol{\Sigma}_t$), in Equation (9) and (10), respectively.

$\mathbf{G}_t = \mathbf{R}_t\, \boldsymbol{f}_t^{\,T}(\mathrm{V}_t + \boldsymbol{f}_t \boldsymbol{R}_t \boldsymbol{f}_t^{\,T})^{-1}$ ……………………………………………………...(8)

$\widehat{\boldsymbol{\theta}}_t = \widehat{\boldsymbol{\theta}}_{t-1} + \boldsymbol{G}_t(y_t - \boldsymbol{f}_t^{\,T}\widehat{\boldsymbol{\theta}}_{t-1})$ …………………………………………………….(9)

$\boldsymbol{\Sigma}_t = (\mathbf{I} + \boldsymbol{G}_t \boldsymbol{f}_t)\mathbf{R}_t$ ……………………………………………………………...(10)

The updating equation can, therefore, be formulated in Equation (11). This process is performed recursively as new information is added. The recursive prediction of y_t follows the distribution in Equation (12).

$\boldsymbol{\theta}_t|\mathcal{F}_t \sim N(\widehat{\boldsymbol{\theta}}_t, \boldsymbol{\Sigma}_t)$ ………………………………………………………………......(11)

$y_t|\mathcal{F}_{t-1} \sim N(\boldsymbol{f}_t^{\,T}\widehat{\boldsymbol{\theta}}_{t-1}, \mathrm{V}_t + \boldsymbol{f}_t \boldsymbol{R}_t \boldsymbol{f}_t^{\,T})$ ……………………………………………....(12)

Suppose we have k models (M_1, M_2, …, M_i) based on different predictor combinations, and $\boldsymbol{\Theta}_t = \boldsymbol{\theta}_t^{(1)}, \boldsymbol{\theta}_t^{(1)}, \ldots., \boldsymbol{\theta}_t^{(k)}$ can be formed. In the case of multi-model estimation, which depends on the i-th model (M_i), the process is analogous to a single model where equations (3), (6), and (11) can be expressed as equations (13), (14), and (15).

$\boldsymbol{\Theta}_{t-1}|M_{i,t-1}, \mathcal{F}_{t-1} \sim N\left(\widehat{\boldsymbol{\theta}}_{t-1}^{\,(i)}, \boldsymbol{\Sigma}_{t-1}^{\,(i)}\right)$ ……………………………………….(13)

$\boldsymbol{\Theta}_t|M_{i,t}, \mathcal{F}_{t-1} \sim N(\widehat{\boldsymbol{\theta}}_{t-1}^{\,(i)}, \mathbf{R}_t^{\,(i)})$ …………………………………………….....(14)

$\boldsymbol{\Theta}_t|M_{i,t}, \mathcal{F}_t \sim N(\widehat{\boldsymbol{\theta}}_t^{\,(i)}, \boldsymbol{\Sigma}_t^{\,(i)})$ …………………………………………………...(15)

Where the state estimate for the i–th model, denoted as $\widehat{\boldsymbol{\theta}}_t^{\,(i)}$, can be obtained from Equation (9), the prediction covariance matrix for the i–th model, denoted as $\mathbf{R}_t^{(i)}$, obtained from Equation (5) and the updating covariance matrix for the i–th model, denoted as $\boldsymbol{\Sigma}_t^{(i)}$, can be obtained via Equation (10).

Based on the distribution in Equation (15), the probability density of $\boldsymbol{\Theta}_{t-1}$, unconditional on M_i can be obtained by averaging density probability $\widehat{\boldsymbol{\theta}}_{t-1}^{(i)}$ and adding weight of $\Pr(M_{i,t-1}|\mathcal{F}_{t-1})$ and written in Equation (16). DMA mechanism involves averaging process across models. One way to make an unconditional prediction is by using an unrestricted matrix of transition probabilities $\Pr(M_{i,t}|M_{j,t-1})$. The prediction equation of models can be written in Equation (17).

$$p(\boldsymbol{\Theta}_{t-1}|\mathcal{F}_{t-1}) = \sum_{i=1}^{k} p(\hat{\boldsymbol{\theta}}_{t-1}^{(i)}|M_{i,t-1}, \mathcal{F}_{t-1}) \Pr(M_{i,t-1}|\mathcal{F}_{t-1}) \quad \text{...(16)}$$

$$\Pr(M_{i,t}|\mathcal{F}_{t-1}) = \sum_{j=1}^{k} \Pr(M_{j,t-1}|\mathcal{F}_{t-1}) \Pr(M_{i,t}|M_{j,t-1}) \quad \text{...(17)}$$

Raftery et al. (2010) suggest a simplification using forgetting factor $0 \leq \alpha \leq 1$ as written in Equation (18). This forgetting factor implies that forecast performance u periods in the past have weight α^u (Koop & Krobilis, 2012).

$$\Pr(M_{i,t}|\mathcal{F}_{t-1}) = \frac{\Pr(M_{i,t-1}|\mathcal{F}_{t-1})^{\alpha}}{\sum_{j=1}^{k} \Pr(M_{j,t-1}|\mathcal{F}_{t-1})^{\alpha}} \quad \text{...(18)}$$

Finally, the updating equation of the model can be written in Equation (19), where $p_i(y_t|\mathcal{F}_{t-1})$ the predictive density of Mi follows the distribution in Equation (12). The point forecast of DMA can be written in Equation (20).

$$\Pr(M_{i,t}|\mathcal{F}_t) = \frac{\Pr(M_{i,t}|\mathcal{F}_{t-1}) p_i(y_t|\mathcal{F}_{t-1})}{\sum_{j=1}^{k} \Pr(M_{j,t}|\mathcal{F}_{t-1}) p_j(y_t|\mathcal{F}_{t-1})} \quad \text{...(19)}$$

$$\mathrm{E}(y_t|\mathcal{F}_{t-1}) = \sum_{i=1}^{k} \Pr(M_{i,t}|\mathcal{F}_{t-1}) \boldsymbol{f}_t^{(i)T} \hat{\boldsymbol{\theta}}_{t-1}^{(i)} \quad \text{...(20)}$$

The graphical representation of the DMA process from data preparation to obtaining point prediction is illustrated in Figure 2. The forgetting factor plays a critical role in DMA, but there is currently no optimal method for determining its value. Previous studies, such as those by Koop & Krobilis (2012) and Ferreira & Palma (2015), used forgetting values $\delta = \{0{,}95; 0{,}99\}$ and $\alpha = \{0{,}95; 0{,}99\}$. In this study, we apply DMA using the eDMA Package version 1.5-3 (Catania & Nojedad, 2018) on R version 4.2.2 (R Core Team, 2022). We divide the data into training and testing sets with a ratio of 80:20, then perform in-sample analysis based on the training data and out-of-sample analysis based on the testing data. The exogenous variables are predicted individually and then used to forecast inflation, as in the study by Arisanti & Puspita (2022).

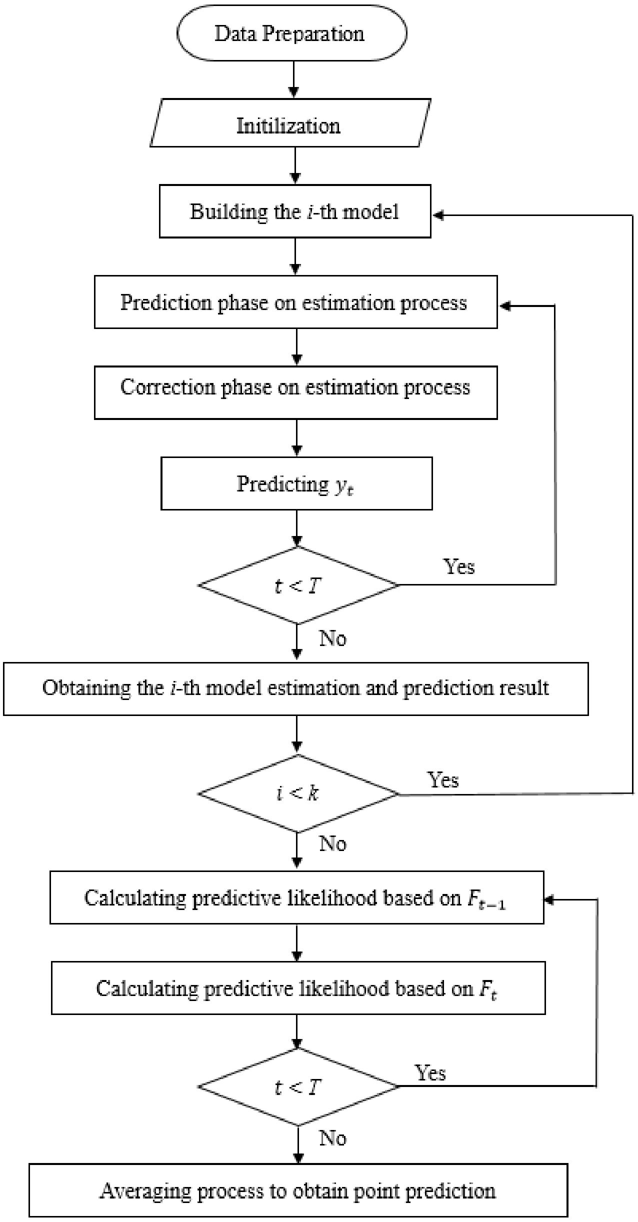

Figure 2. Flowchart of DMA process to obtain point prediction.

Forecast performance analysis

Forecasting performance is evaluated by comparing forecasts from DMA with dynamic model selection (DMS) and benchmarking the autoregressive model. While DMA is averaging forecast across models, DMS involves selecting a single model with the highest probability value of $\Pr(M_{i,t}|\mathcal{F}_{t-1})$ and using this to perform forecast. In this case, Mean Absolute Percentage Error (MAPE) can't be used to evaluate the model since monthly inflation data has extreme cases where the error produced can be relatively larger than the actual value. We compare these three models based on Mean Square Error (MSE), Mean Absolute Deviation (MAD), and log-predictive likelihood (logPL) as forecast accuracy metrics to determine which model can forecast better.

Mean Squared Error (MSE) is calculated by averaging the square difference between the predicted and actual values. At the same time, Mean Absolute Deviation

(MAD) is determined by averaging the absolute value of the predicted and actual differences (Makidakris et al., 2008). A lower MSE and MAD indicate that the forecast is closer to the actual values, meaning the model is more accurate and reliable. Both MSE and MAD can be written in Equation (21) and (22) from *n* total of data testing (Hidayat et al., 2021).

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \quad \text{...(21)}$$

$$\text{MAD} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad \text{...(22)}$$

Log-predictive likelihood (logPL) can be used as forecast metrics involving the entire predictive distribution. A higher value of logPL indicates that the model predicts the data with a higher probability, meaning the model is more confident in its predictions. In other words, it's better to say how likely something will happen. The predictive likelihood can be calculated by the sum of the predictive density of $p_i(y_t|\mathcal{F}_{t-1})$. (Koop & Krobilis, 2012)

Dynamic Model Averaging (DMA) offers a powerful forecasting tool with limitations. Our study acknowledges two key challenges. First, choosing the right predictor variables is crucial, as irrelevant ones can lead to inaccurate forecasts, while missing important ones can limit the model's ability to capture inflation's complexity. Second, unforeseen economic shocks like global oil price fluctuations or policy shifts can disrupt historical trends and render forecasts less accurate. By acknowledging these limitations, we aim to utilize DMA responsibly and effectively within the broader context of the Indonesian economy.

RESULTS AND DISCUSSION

Data exploration

Table 2 provides a descriptive statistics summary of all variables used in this study. The average monthly inflation rate from January 1998 to June 2023 is 0.6568, with a standard deviation 1.3076. The highest inflation rate occurred in February 1998 at 12.76, and the lowest occurred in August 1999 at -1.05. The highest one-month BI rate was in August 1998 at 69.51, while the lowest was from February 2021 to July 2022 at 3.50.

Table 2. Descriptive statistics of variables

Variables	Mean	Minimum	Maximum	Standard Deviation
INF	0.6568	-0.105	12.7600	1.307565
M2	6.348	5.634	6.931	0.375029
IHSG	3.336	2.441	3.859	0.446353
EXCH	4.032	3.826	4.212	0.094239
SB1	9.864	3.500	69.510	9.155858
IPI	2.081	1.852	2.201	0.060343
FOOD	2.914	2.408	3.301	0.298561
GLD	1.918	1.648	2.202	0.146938
OIL	1.714	1.017	2.123	0.256621

Forecasting inflation using DMA

The inflation rate will be forecasted using DMA by involving predictors that include the inflation rate in the previous lag and exogenous variables in one lag before. The number of lags for inflation to be included in the model can be done using the Partial Autocorrelation Function (PACF) plot, which follows the same process as determining the number of lags in an Autoregressive (AR) model.

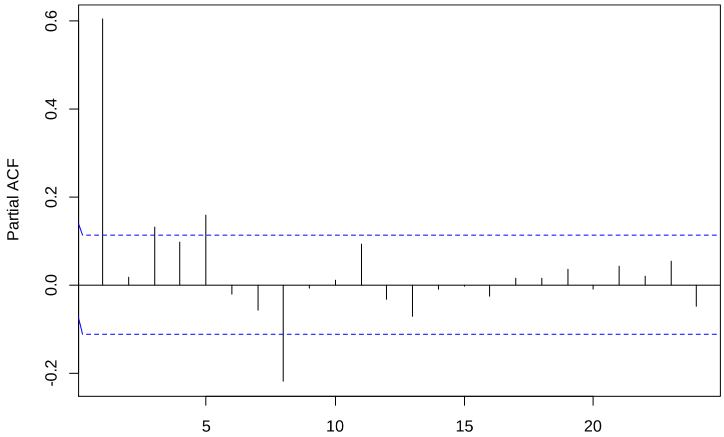

Figure 3. PACF Plot of Monthly Inflation Rate

Based on the results from Figure 3, a cut-off occurs after the first lag, indicating that the number of inflation lags that can be included in the model is one. This result is consistent with the findings of Juhro & Iyke (2019), where only the first lag of inflation is significant in forecasting inflation. The list of predictors to be included to forecast inflation are the first lag of inflation, the first lag of the logarithm of the M2 index of money supply, the first lag of the logarithm of the Jakarta composite stock price index, the first lag of the logarithm of the exchange rate from the US Dollar to the Indonesian Rupiah, the first lag of the one-month BI Rate, the first lag of the logarithm of the industrial production index, the first lag of the logarithm of the global price of food index, the first lag of the logarithm of the global price of gold, and the first lag of the logarithm of the global price of crude oil.

In sample analysis

There are $2^9 = 512$ different combinations of models that can be created from 9 predictors. Dynamic Model Averaging (DMA) involves averaging the forecasts of 512 individual models, where each model is assigned a weight based on a forgetting factor. The forgetting factor determines the extent to which past performance is considered when assigning weights. Models with better past performance are given higher weights, while models with poorer performance are given lower weights. This helps ensure that any one model does not overly influence the DMA forecast. The study utilized a forgetting factor of $\delta = 0.99$ and $\alpha = 0.99$. These values mean that observations from one year prior will receive 88.36% as much weight as last month's observation, and forecast performances from a year earlier will receive 88.36% as much weight as last month's forecast performance. Model analysis for training data was carried out using the mean value of the posterior inclusion probability (PIP). The PIP value measures the probability that a particular predictor is included in the best model. A higher PIP value indicates a greater influence of the predictor on the dependent variable (Koop & Krobilis, 2012). According to Juhro's research, predictors are deemed significant in forecasting inflation when the mean posterior inclusion probability is more than 40%.

Table 3. Summary of coefficient's means and standard deviation as well as posterior inclusion probability's means and standard deviations for each of the predictors

Variables	E[θ]	SD[θ]	E[PIP]	SD[PIP]
Intercept	-1.11	1.13	1	0
INF_{t-1}	0.26	0.12	0.8	0.24
$M2_{t-1}$	-0.93	0.57	0.46	0.05
$IHSG_{t-1}$	0.09	0.38	0.37	0.04
$EXCH_{t-1}$	1.42	0.84	0.5	0.05
$SB1_{t-1}$	0	0.01	0.21	0.14
IPI_{t-1}	0.63	0.34	0.44	0.02
$FOOD_{t-1}$	0.29	0.38	0.41	0.05
GLD_{t-1}	-0.25	0.3	0.41	0.04
OIL_{t-1}	0.19	0.42	0.36	0.05

According to the findings in Table 3, there are six predictors with PIP values exceeding 40%. These include the first lag of inflation, the money supply, the logarithm of the M2 index of money supply, the logarithm of the exchange rate from the US Dollar to the Indonesian Rupiah, the logarithm of the industrial production index, the logarithm of the global price of food index, and the logarithm of the global price of gold. The intercept has a constant PIP value of one, as it remains a part of every model. Figure 4 depicts the importance of each predictor in forecasting inflation at each point in time through posterior inclusion probability.

During the inflation surge in 2005, starting from the 94th observation, the Posterior Inclusion Probability (PIP) values for the predictors of money supply, exchange rate, interest rate, and world oil price experienced significant changes. This indicates an increase in the influence of these four predictors on inflation, meaning that they played a more significant role in explaining the inflation surge of 2005. The PIP value for money supply increased from 0.44055 to 0.49749, the exchange rate changed from 0.485687 to 0.566945, the interest rate from 0.107733 to 0.184679, and the world oil price from 0.255185 to 0.384804. Further investigation is warranted to understand the underlying factors driving these pronounced rises.

One of the primary causes of the inflation surge in 2005 was the increase in world oil prices, which led to a subsequent increase in fuel prices. The increase in fuel oil prices had a particularly strong impact on inflation, as fuel oil is a major input cost for many businesses and households. The government's response to the inflation surge included measures to increase food and fuel supply and provide subsidies to low-income households. A potential rise in money supply could have contributed to inflationary pressures. Fluctuations in the exchange rate in 2005 likely played a more significant role in determining import costs and impacting inflation. Interest rates' influence on inflation might have grown as policymakers attempted to raise them to combat rising prices. These factors likely didn't operate in isolation. For example, increased money supply and a depreciating Rupiah could exacerbate imported inflation. Similarly, rising world oil prices could magnify the impact of higher interest rates aimed at curbing inflation. Understanding the interplay of these factors is crucial for explaining the 2005 inflation surge.

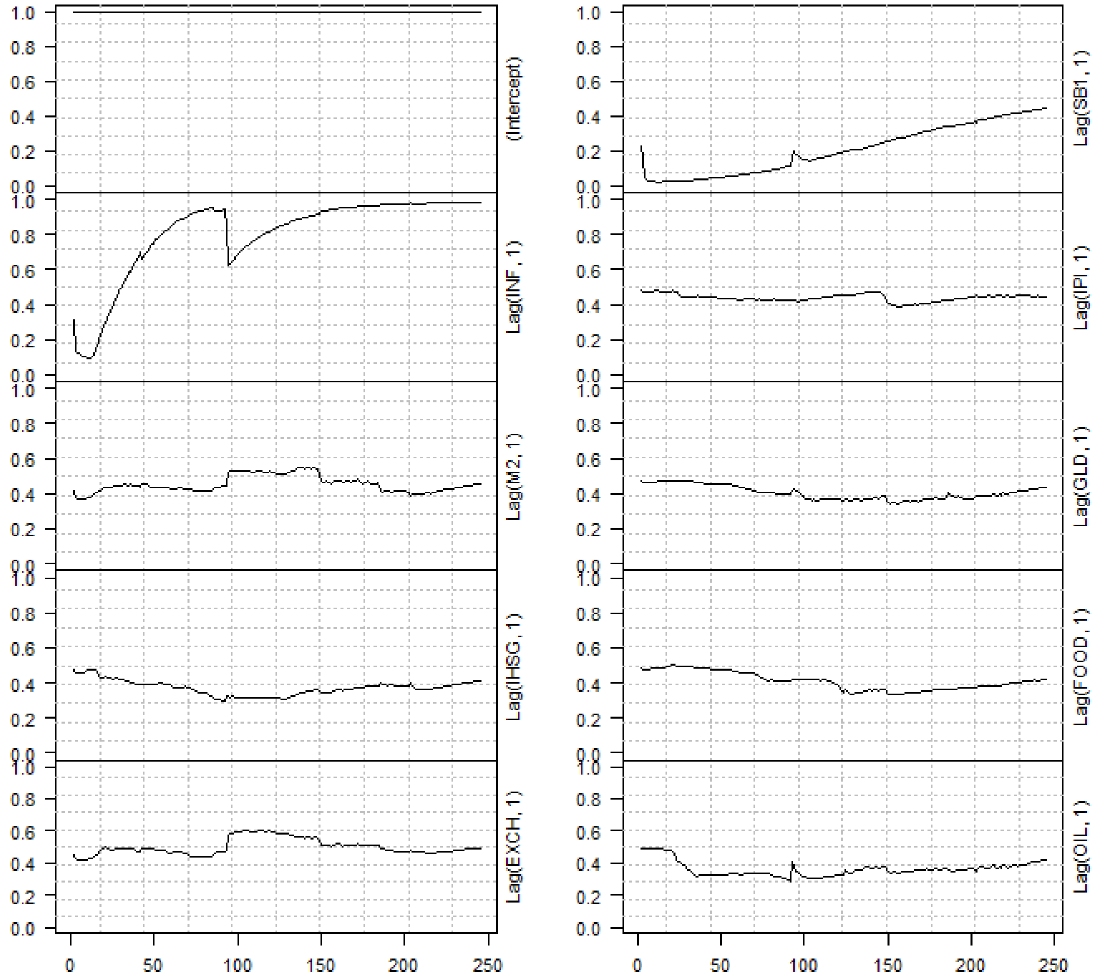

Figure 4. Posterior inclusion probability plot for each predictor.

According to Figure 4, the first lag of inflation, the money supply, the logarithm of the M2 index of money supply, the logarithm of the exchange rate from the US Dollar to the Indonesian Rupiah, the logarithm of the industrial production index, the logarithm of the global price of food index, and the logarithm of the global price of gold have PIP values above 40% most of the time. Despite the PIP means of the logarithm of the Jakarta composite stock price index and the logarithm of world crude oil prices being below 40%, there are certain times when the PIP value exceeds the 40% limit. Therefore, one can assume these variables hold significant importance in forecasting inflation. Interestingly, the PIP of the one-month interest rate has steadily risen above the 40% limit over time. So, it can be said that future interest rates will be important in forecasting inflation.

Out-of-sample analysis

We will compare the models' MSE and MAD values during out-of-sample analysis to determine the best model. We performed this forecasting evaluation on testing data from July 2018 to June 2023, totaling 60 data points. Table 4 summarizes the MSE, MAD, and LogPL values from DMA, DMS, and AR(1). AR(1) is not a Bayesian method, so no LogPL is presented.

Models that include exogenous variables, namely DMA and DMS, have smaller MSE and MAD values than simple models that do not include exogenous variables, namely AR(1). This indicates that adding exogenous variables in forecasting inflation can provide better forecast performance, as confirmed in previous research by Juhro & Iyke (2019) and Koop & Krobilis (2012). DMA outperforms DMS in terms of MSE and MAD, which aligns with the results from previous research by Juhro & Iyke (2019) and Koop & Krobilis (2012). This indicates that averaging multiple models yields superior outcomes compared to selecting the model with the highest predictive performance in forecasting inflation.

Table 4. Summary of MSE, MAD, and LogPL for each model.

Model	MSE	MAD	LogPL
DMA	0.081	0.210	-63.743
DMS	0.095	0.235	-63.612
AR(1)	0.109	0.265	-

Although MSE and MAD values indicate that DMA performs better than DMS, the result from LogPL says the opposite. DMS has a higher value of LogPL than DMA, which means that in terms of predictive likelihood, DMS performs better than DMA. Koop & Krobilis (2012) explain that this happens because DMS only puts weight on the best model and considers the weight of the other models as zero. MSE and MAD are calculated using point forecasts; therefore, we refer to both values in this study to determine the best model. The plot of actual and forecasted inflation values using DMA is illustrated in Figure 5.

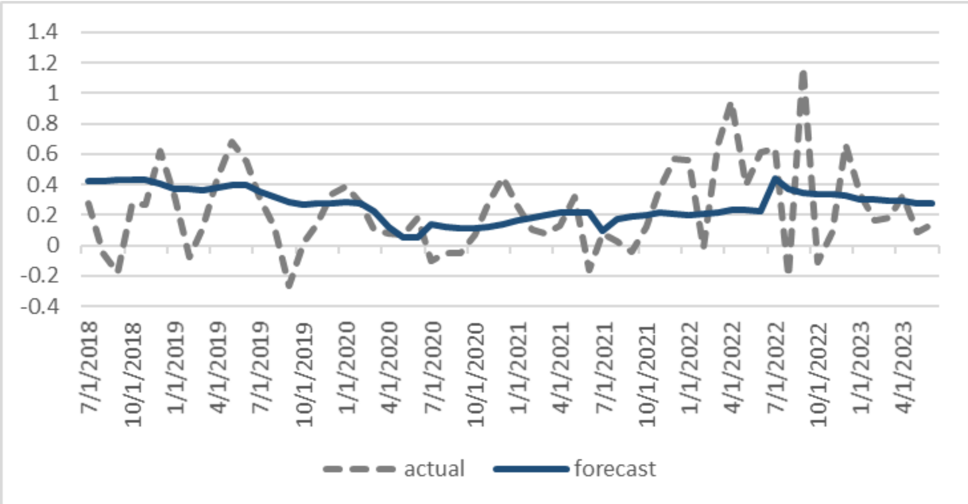

Figure 5. Plot of actual vs forecast using DMA.

The out-of-sample analysis highlights the importance of incorporating relevant economic factors into inflation forecasting models. By including variables like the exchange rate and global oil prices, which can significantly impact production costs and consumer prices, DMA captures a more comprehensive picture of inflationary dynamics in Indonesia. This economic rationale aligns with the observed lower MSE and MAD for DMA, suggesting its forecasts are closer to actual inflation on average.

The discrepancy between LogPL and MSE/MAD highlights the complexities involved in model selection. While LogPL emphasizes the model's fit to the historical data, MSE and MAD directly assess the accuracy of point forecasts. In this context, prioritizing lower MSE and MAD might be more relevant for inflation forecasting with practical implications. However, acknowledging the trade-offs and potential limitations is crucial.

Forecast result

DMA provides a recursive one-step-ahead prediction of response variables and requires the exogenous variables to be forecasted ahead of time for long-period forecasting. In this study, exogenous variables such as the logarithm of the M2 index of money supply, the logarithm of the Jakarta composite stock price index, the logarithm of the exchange rate from the US Dollar to the Indonesian Rupiah, the logarithm of the industrial production index, the logarithm of the global price of food index, the logarithm of the global price of gold, and the logarithm of the global price of crude oil are forecasted with auto arima (Hyndman & Khandakar, 2008) in R. Since the one-month BI rate is a policy set by the Bank of Indonesia, the value used to forecast inflation remains constant, consistent with the previous period's value. The forecast results for the next 12 months for inflation are listed in Table 5 and plotted in Figure 6.

Table 5. Forecast result of the monthly inflation rate from July 2023 until June 2024

Date	INF	Date	INF
July 2023	0.2328742	January 2024	0.2420444
August 2023	0.2504239	February 2024	0.2406261
September 2023	0.2503788	March 2024	0.2385067
October 2023	0.2479908	April 2024	0.236336
November 2023	0.2467738	May 2024	0.2345745
December 2023	0.2444976	June 2024	0.2327651

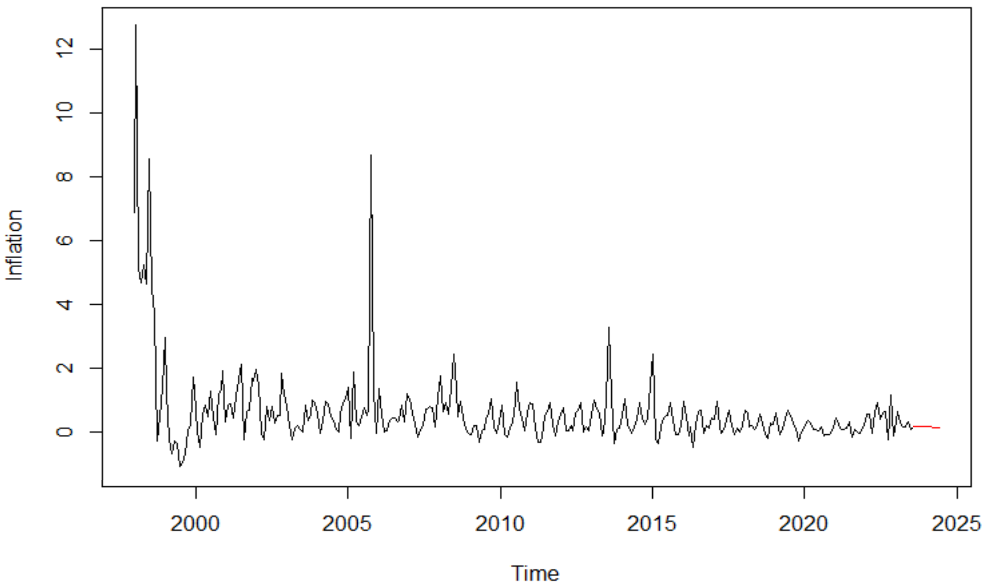

Figure 6. The plot of monthly inflation from January 1998 until June 2023 with forecast value of the next 12 months in the red line.

According to the results in Table 5, these forecasts suggest a relatively stable inflation environment over the next twelve months. This projected inflation range indicates a continuation of the current trend of moderate price increases. This could provide some stability for businesses and households regarding planning and budgeting. If the forecasts hold true, policymakers at Bank Indonesia (BI) could potentially maintain a cautious monetary policy stance. This might involve keeping interest rates steady or raising them slightly to ensure inflation remains within the target range. A stable inflation environment can support economic growth by encouraging investment and consumer spending. However, policymakers need to balance inflation control with promoting economic activity.

While our forecasts suggest a relatively stable inflation environment, it's crucial to acknowledge inherent uncertainties and limitations. Unforeseen global events like oil price spikes, supply chain disruptions, or geopolitical tensions can significantly impact Indonesia's inflation trajectory. Similarly, domestic factors like changes in government policies, natural disasters, or unexpected food price fluctuations can also cause deviations from the forecast. Additionally, all forecasting models have limitations. The accuracy of this DMA forecast depends on the underlying assumptions and the historical data used to train the models. These external shocks, domestic developments, and model limitations highlight the importance of continuous monitoring and potential forecast adjustments as new information emerges.

CONCLUSION AND RECOMMENDATIONS

Conclusion

Forecasting inflation in Indonesia poses a significant challenge due to the dynamic nature of the factors influencing it. Traditional forecasting methods often struggle to capture these complexities, as their underlying relationships may change. This study addresses this limitation by employing Dynamic Model Averaging (DMA). DMA offers a unique advantage by incorporating models with varying coefficient structures, allowing it to adapt to these time-varying relationships and potentially deliver more accurate forecasts.

The in-sample analysis results suggest that the first lag of inflation, money supply, the logarithm of the M2 index of money supply, the logarithm of the exchange rate from the US Dollar to the Indonesian Rupiah, the logarithm of the industrial production index, the logarithm of the global price of food index, and the logarithm of the global price of gold have significant importance in predicting inflation. The logarithm of the Jakarta composite stock price index and world crude oil prices also hold significant importance as their PIP values rise above the 40% limit at certain times. It also reveals that future interest rates will be important in forecasting inflation, as the PIP has steadily risen above the 40% limit over time.

Overall, the out-of-sample analysis shows that DMA outperforms DMS and autoregressive models. This highlights the advantage of incorporating multiple models with time-varying coefficients for improved inflation forecasting accuracy. The forecast results indicate consistent patterns over the 12 months studied.

The strong performance of DMA directly relates to its ability to adapt to changing relationships between inflation and its determinants. The PIP metric from the in-sample analysis provided robust statistical evidence for identifying the key macroeconomic indicators influencing inflation dynamics in Indonesia. These findings informed the selection of variables used in the DMA models, ultimately contributing to the accurate out-of-sample forecasts.

Recommendations

Using Dynamic Model Averaging (DMA), this study identified the money supply (M2) as the most significant variable impacting inflation in Indonesia based on PIP means. The importance of exchange rates, the industrial production index, global food prices, and global gold prices was highlighted. By focusing on money supply management through targeted monetary policies and collaborating with the government to address external influences and domestic supply chain issues, Bank Indonesia (BI) can leverage the insights gained from this study to develop a comprehensive strategy for inflation control in Indonesia. Here are some specific policy measures that the Indonesian government and BI could consider based on these findings:

1. BI can increase reserve requirements for commercial banks. This would force banks to hold a higher proportion of deposits as reserves, effectively reducing the amount of money available for lending and credit creation. This strategy will slow down money supply growth and potentially curb inflationary pressures.
2. BI can increase benchmark interest rates (e.g., the BI Rate). Higher interest rates make borrowing more expensive for businesses and individuals, potentially decreasing investment and consumer spending. This reduced demand can help dampen inflationary pressures.
3. BI can engage in open market operations by selling government bonds. This absorbs money from circulation, reducing the money supply and potentially mitigating inflation.
4. In extreme circumstances, BI could intervene in the foreign exchange market by selling US dollars if the Rupiah weakens significantly. This can help stabilize the exchange rate and prevent imported inflation, where rising import costs translate to higher domestic prices. However, frequent interventions are generally discouraged due to potential market distortions.
5. Closely monitoring global food and gold price trends allows policymakers to anticipate potential inflationary pressures from external sources. This can inform strategic decisions on managing domestic food reserves or implementing targeted subsidies for essential goods.

There are a few limitations that need to be addressed in this study. First, forecasting involving exogenous variables could lead to a double-counting error problem, resulting in less accurate inflation forecasting. Second, there is an indication that inflation might contain a seasonal component that was not added to this study. Based on these limitations, further research can be conducted to determine the optimal model for predicting exogenous variables to minimize double-counting error. A seasonal component can be added to provide better forecast results. Additionally, future studies need to identify significant factors and potential policy measures within Indonesia's current economic environment, including global trends and the interplay of domestic and international economic policies.

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