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Trend, Cycle, and Forecasting Analysis of Monthly Inflation in Indonesia Using the Hodrick–Prescott Filter and ARIMA

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Abstract:

This study aims to analyze the structure of inflation and forecast monthly inflation in Indonesia using a time series approach. The method used is the Hodrick–Prescott Filter to decompose data into trend and cycle components, and the ARIMA model to forecast inflation. The data used is monthly inflation data for the period 2010–2025. The decomposition results show that inflation has a relatively stable long-term trend with short-term fluctuations reflecting the presence of economic shocks. Based on model identification, the best model is ARIMA(2,0,1)(1,0,1)[12] which is able to capture past influences, seasonal components, and short-term shocks. The evaluation results show that the model meets the white noise assumption and is suitable for use in forecasting. The forecasting results show that inflation tends to be stable with a moderate increasing tendency, although uncertainty increases over longer periods. This study shows that the combination of structural analysis and time series modeling provides a more comprehensive understanding of inflation dynamics and produces relevant predictions to support decision making.

1. Introduction

Inflation is one of the most important macroeconomic indicators in determining monetary policy in Indonesia. According to Bank Indonesia, inflation refers to a continuous and general increase in the prices of goods and services over a certain period. Bank Indonesia sets an inflation target of 2.5±1% to maintain financial system stability and support sustainable economic growth (Bank Indonesia, 2020). Understanding inflation dynamics has important implications for economic policy because high inflation can reduce purchasing power, weaken a country's economic competitiveness in the global market, and create uncertainty for economic agents, including businesses, investors, and households (Widyaningsih, 2024).

In time series analysis, inflation data generally consist of several main components, namely long-term trends and short-term fluctuations. The trend reflects the long-term movement of inflation, while short-term fluctuations indicate temporary economic shocks. To separate these two components, the Hodrick–Prescott Filter is employed because it can decompose data into trend and cycle components. Although the HP Filter is effective in identifying the structure of the data, it cannot be directly used for forecasting. Therefore, another approach is needed to model the data dynamics and predict future values. In this regard, the ARIMA model is utilized due to its ability to capture autocorrelation patterns, both in terms of past influences (autoregressive) and short-term shocks (moving average) (Saputra & Febrianti, 2025).

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By combining the HP Filter and ARIMA in a single study, a comprehensive approach can be achieved, where the HP Filter is used to understand the underlying structure of inflation, while ARIMA is used to model and forecast inflation dynamics. Consequently, the decomposition results showing trends and fluctuations can be linked with ARIMA modeling results that capture historical influences and shocks in the data.

However, previous studies still tend to use only one approach, either decomposition or forecasting, without systematically integrating both. Therefore, this study aims to combine structural analysis using the HP Filter with predictive modeling using ARIMA to obtain a more comprehensive understanding of monthly inflation dynamics in Indonesia.

2. Literature Review

2.1. Hodrick-Prescott Filter

The Hodrick–Prescott (HP) Filter is a time series decomposition method that separates trend and cyclical components. This method was first introduced by Hodrick and Prescott (1997). In macroeconomic studies, the filter is often used to measure output gaps or inflation gaps by assuming that a time series y_t consists of trend g_t and cyclical components c_t. Formally, the HP Filter decomposes the series into:

$$y_t = g_t + c_t$$

where y_t, g_t, and c_t represent the time series (in logarithmic form), the trend component, and the cyclical component, respectively. This method essentially estimates the stochastic series g_t d by minimizing the sum of squared differences between the original time series y_t and the trend component g_t, hich represents the goodness of fit, subject to the constraint that the sum of squared dynamic differences of the permanent component (which measures the degree of smoothness) is not excessively large.

Thus, the optimization problem to be solved is as follows:

$$\min_{g_t} \sum_{t=1}^{T} (y_t - g_t)^2$$

with constraints:

$$\sum_{t=1}^{T} (\Delta^2 g_t)^2 = \sum_{t=1}^{T} [(g_{t+2} - g_{t+1}) - (g_{t+1} - g_t)]^2 = v$$

where Δ^2 epresents the second-order differencing of the trend component and v is a constant parameter.
In practice, this optimization problem is solved using the Lagrange multiplier method, resulting in:

$$\min_{g_t} \left[\sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=1}^{T} [(g_{t+2} - g_{t+1}) - (g_{t+1} - g_t)]^2 \right]$$

In this formulation, there is a trade-off between the goodness of fit and the smoothness of the trend component, which is controlled by the parameter λ. This parameter represents the variance ratio between the cyclical component and the growth changes of the trend component.

In the application of the Hodrick–Prescott Filter, the selection of the smoothing parameter λ is an important aspect that influences the decomposition results of the trend and cyclical components (Hodrick & Prescott, 1997). In general, the larger the value of λ, the smoother the trend component becomes, while more short-term fluctuations are captured in the cyclical component. Conversely, a smaller value of λ produces a trend that follows the movement of the original data more closely, resulting in a relatively smaller cyclical component (Enders, 2014).

The determination of the value of $\lambda$is not arbitrary, but rather adjusted according to the frequency of the data used. Hodrick and Prescott (1997) initially recommended $\lambda = 1600$for quarterly data. Subsequently, Ravn dan Uhlig (2002) eveloped a scaling rule for adjusting the value of λbased on data frequency using a frequency-scaling approach. They demonstrated that the value of $\lambda$is proportional to the fourth power of the data frequency ratio (Ravn & Uhlig, 2002).

Based on these findings, the commonly used values are $\lambda = 100$for annual data, $\lambda = 1600$ for quarterly data, and $\lambda = 14400$ for monthly data. The use of $\lambda = 14400$ for monthly data aims to produce a sufficiently smooth trend capable of representing long-term movements without being distorted by temporary short-term fluctuations (Ravn & Uhlig, 2002). herefore, this study employs $\lambda = 14400$ because the analyzed data consist of monthly observations. This choice is expected to provide an optimal separation between the long-term inflation trend and short-term fluctuations caused by economic shocks (Monahov, 2023).

2.2. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is one of the methods used in time series analysis to model and forecast data based on historical patterns (Box & Jenkins, 1976). his model was introduced by Box and Jenkins (1976) and is widely known as the Box–Jenkins approach, which consists of systematic stages of model identification, parameter estimation, diagnostic checking, and forecasting. In general, the ARIMA model is expressed in the form ARIMA(p, d, q), with each component model described in Table 1 below.

Table 1. AR, MA, and ARMA Time Series Models

Model	Equation
AR (p)	$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p}$
MA (q)	$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots + \theta_q a_{t-q}$
ARMA (p, q)	$\phi_p(B) Y_t = \theta_q(B) a_t$

where,

ϕ_p : parameter of the AR model of order p

θ_q : parameter of the MA model of order q

a_t : error term at time t

B : *backshift* operator

The integrated component indicates that differencing is required to achieve stationarity in the data. The differencing process is performed as follows:

$$y'_t = y_t - y_{t-1}$$

If the data are already stationary at the level form, then $d = 0$ (Hamilton, 1994)

2.2.1. Stationary

A time series is said to be stationary if it has a constant mean and variance over time. To test stationarity, the Augmented Dickey–Fuller (ADF) test can be used. If the p-value of the ADF Test is less than $\alpha = 0.05$, then the data are considered stationary in the mean (Enders, 2014)

2.2.2. Model Identification (ACF and PACF)

The determination of the values of $p$and $q$is carried out through the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF is used to identify the MA component, while the PACF is used to identify the AR component. The general characteristics of ACF and PACF plots are described in Table 2 below.

Table 2**.** Characteristics of ACF and PACF Plots

Model	**ACF**	**PACF**
AR (p)	Dies down	Cuts off after lag p
MA (q)	Cuts off after lag p	Dies down
ARMA (p, q)	Dies down	Dies down

2.2.3. Seasonal Autoregressive Integrated Moving Average (SARIMA)

For data exhibiting seasonal patterns, the Seasonal ARIMA (SARIMA) model is used, which is expressed as:

$$ARIMA(p,d,q)(P,D,Q)_s$$

where P, D, and Q represent the seasonal components, and $s$denotes the seasonal period (for example, $s = 12$ for monthly data). This model is capable of capturing recurring patterns in the data, such as annual inflation patterns (Hyndman & Athanasopoulos, 2018).

2.2.4. Estimation and Evaluation Model

After the model has been identified, the parameters are estimated and the model is evaluated. The best model is the one with the smallest AIC value and residuals that satisfy the white noise assumption and do not contain autocorrelation (Box et al., 2008)

2.3. Inflation

Inflation is defined as an increase in the money supply or an increase in liquidity within an economy. This definition refers to the general phenomenon caused by an increase in the money supply, which is believed to result in rising prices. In a broader sense, inflation can be briefly defined as a continuous and general tendency for the prices of goods and services to increase over time.

The general increase in the prices of goods and services from one period to another is referred to as the inflation rate. The inflation rate is generally expressed as a percentage (%). Inflation may occur at mild, moderate, severe, or hyperinflation levels.

The inflation rate is calculated based on an index number compiled from the prices of goods and services consumed by the public, known as the Consumer Price Index (CPI). The calculation is performed by comparing the CPI in the base year with the CPI in the observation period. In Indonesia, the CPI is calculated using a modified Laspeyres formula as follows *(Badan Pusat Statistik, 2022).*

$$CPI_n = \frac{\sum_{i=1}^{k} \frac{P_{ni}}{P_{(n-1)i}} P_{(n-1)i} \cdot Q_{Oi}}{\sum_{i=1}^{k} P_{Oi} \cdot Q_{Oi}} \times 100$$

Dengan,

CPI_n : Consumer Price Index in month n

P_{ni} : Price of goods/service type $i$in month n

$P_{(n-1)i}$: Price of goods/service type $i$in month $n-1$

$P_{(n-1)i} \cdot Q_{Oi}$: Consumption Value (CV) of goods/service type $i$in month $n-1$

$\frac{P_{ni}}{P_{(n-1)i}}$: Relative price (RP) of goods/service type $i$in month n

$P_{Oi} \cdot Q_{Oi}$: Consumption Value (CV) of goods/service type $i$in the base year

k : Number of goods/service types included in the CPI commodity basket

The percentage change in the index, or the monthly inflation/deflation rate, is obtained by subtracting the index of the previous month from the index of the current month, then dividing the result by the index of the previous month and multiplying by 100. The inflation or deflation rate can also be calculated by dividing the index of the current month by the index of the previous month, subtracting 1, and multiplying by 100. The calculation is expressed by the following formulas (Badan Pusat Statistik, 2022)

$$Inf_n = \frac{CPI_n - CPI_{(n-1)}}{CPI_{(n-1)}} \times 100$$

or

$$Inf_n = \left(\frac{CPI_n}{CPI_{(n-1)}} - 1 \right) \times 100$$

where,

Inf_n : Inflation/deflation rate in month n
CPI_n : Consumer Price Index in month n
$CPI_{(n-1)}$: Consumer Price Index in month $n-1$

3. Research Methodology

The data used in this study are secondary data obtained from Badan Pusat Statistik (BPS), namely monthly inflation data from 2010 to 2025. The collected data were processed using RStudio software. The data analysis was conducted through the following stages::

1) HP Filter
   a. Data Decomposition
   Inflation data were analyzed using the HP Filter with a smoothing parameter of $\lambda = 14400$(for monthly data) to obtain the trend and cyclical components.
   b. Descriptive Analysis
   The decomposition results were analyzed through graphical visualization and statistical calculations to identify long-term inflation patterns and short-term fluctuations.
2) ARIMA
   a. Stationarity Test
   The Augmented Dickey–Fuller (ADF) test was used to determine whether the data were stationary.
   b. ARIMA Model Identification
   Model identification was conducted using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
   c. Model Estimation
   The ARIMA model was estimated based on the identified parameters $(p, d, q)$and seasonal components.
   d. Model Evaluation
   The model was evaluated using the Akaike Information Criterion (AIC) and residual diagnostic tests (Ljung–Box test) to ensure that the residuals satisfied the white noise assumption.
   e. Peramalan (Forecasting)
   Model terbaik digunakan untuk memprediksi inflasi dalam beberapa periode ke depan.

4. Results and Discussion

4.1. Inflation Decomposition Analysis Using the HP Filter

The decomposition results of monthly inflation data using the Hodrick–Prescott Filter indicate that Indonesian inflation can be separated into two main components, namely the long-term trend and the short-term cycle.

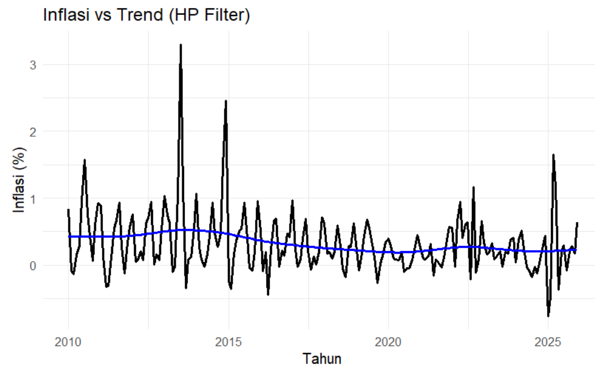

Figure 1. Inflation Trend in Indonesia from HP Filter Decomposition

Based on Figure 1, the trend component shows a relatively stable long-term pattern. During the initial observation period (2010–2014), the inflation trend tended to increase, indicating relatively high price pressures. Subsequently, the trend gradually declined during the 2015–2020 period, suggesting inflation stabilization. During the COVID-19 pandemic period, the inflation trend remained at a low and relatively flat level, reflecting weakened aggregate demand. After 2023, the trend began to increase again, indicating economic recovery.

In addition to the trend component, the cyclical component was also obtained, showing short-term fluctuations in inflation.

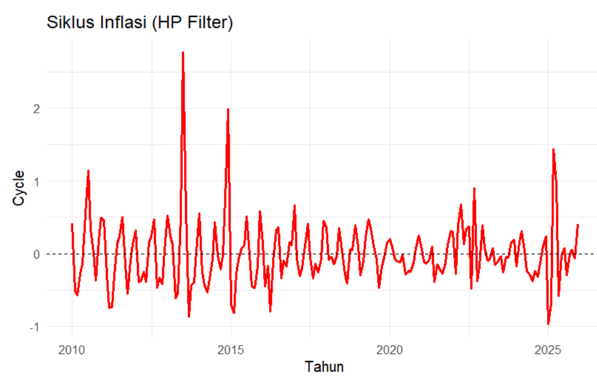

Figure 2. Inflation Cyclical Component from HP Filter Results

Based on Figure 2, the cyclical component shows fairly significant fluctuations around zero. Positive cyclical values indicate that inflation is above the trend, while negative values indicate that inflation is below the trend. High fluctuations were observed during the 2013–2015 period, reflecting strong inflation shocks. During the pandemic period, the cyclical component tended to be negative, indicating deflationary pressure due to declining economic activity. After 2023, fluctuations increased again, indicating the emergence of new shocks in the economy.

Based on Figures 1 and 2, it can be concluded that although the inflation trend is relatively stable, inflation remains vulnerable to short-term shocks that may cause deviations from the trend.

4.2. ARIMA

4.2.1. Stationarity Test

The results of the Augmented Dickey–Fuller (ADF) test indicate that the inflation data are stationary at the level form, with a p-value of 0.01 (<0.05). This indicates that the data do not contain a unit root, and therefore differencing is not required. Consequently, the ARIMA model uses $d = 0$.

4.2.2. ARIMA Model Identification

Model identification was carried out through the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.

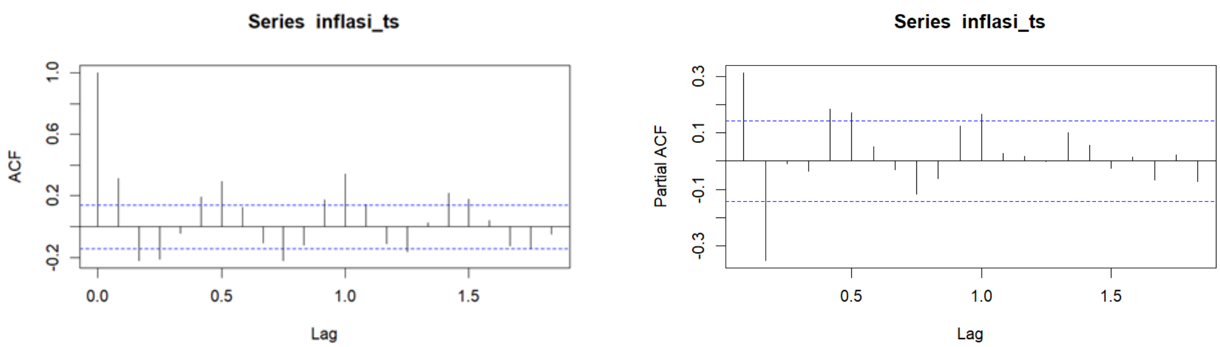

Figure 3. ACF and PACF of Inflation Data

Based on Figure 3, the ACF plot exhibits a tailing-off pattern, where the autocorrelation values gradually decrease as the lag increases. Meanwhile, the PACF plot shows a cut-off pattern at lag 2, indicating the presence of a second-order autoregressive component (AR(2)). In addition, there is an indication of a seasonal pattern at lag 12, suggesting the presence of annual seasonal effects. This is consistent with the characteristics of inflation, which is often influenced by seasonal factors such as religious holiday periods and year-end effects (Komara Rifai & Zhahirulhaq, 2024). Based on these observations, several candidate models were tested to obtain the best model. From the initial identification results using the ACF and PACF plots, several non-seasonal model alternatives were obtained, including ARIMA(2,0,0), ARIMA(2,0,1), and ARIMA(1,0,1). Furthermore, considering the indication of seasonal patterns at lag 12, a seasonal model, namely ARIMA(2,0,1)(1,0,1)[12], was also tested.

Each proposed candidate model was then estimated and compared based on the AIC value and the results of residual diagnostic tests. The comparison results are presented in the following table:

Table 3. AIC Values of Candidate Models

Model	**AIC**
ARIMA(2,0,0)	213,9908
ARIMA(2,0,1)	215,9803
ARIMA(1,0,1)	221,5939
ARIMA(2,0,0)(1,0,0)[12].	202,9572
ARIMA(2,0,1)(1,0,1)[12].	**199,425**

Based on Table 3, the results show that the ARIMA(2,0,0) model is the best non-seasonal model because it has the smallest AIC value compared to the other non-seasonal candidate models. However, when compared with the seasonal models, the ARIMA(2,0,1)(1,0,1)[12] model produced the smallest AIC value, indicating that this model is better at capturing the data pattern, particularly in accommodating the seasonal component present in the monthly inflation data.

Therefore, the ARIMA(2,0,1)(1,0,1)[12] model was selected as the final model because it not only has better statistical criteria but is also able to represent the characteristics of the data more comprehensively. After obtaining the smallest AIC value, residual diagnostic checking was conducted to ensure that the residuals satisfied the white noise assumption. The results of the Ljung–Box test on the residuals produced a p-value of 0.3705 (> 0.05), indicating that the residuals satisfy the white noise assumption.

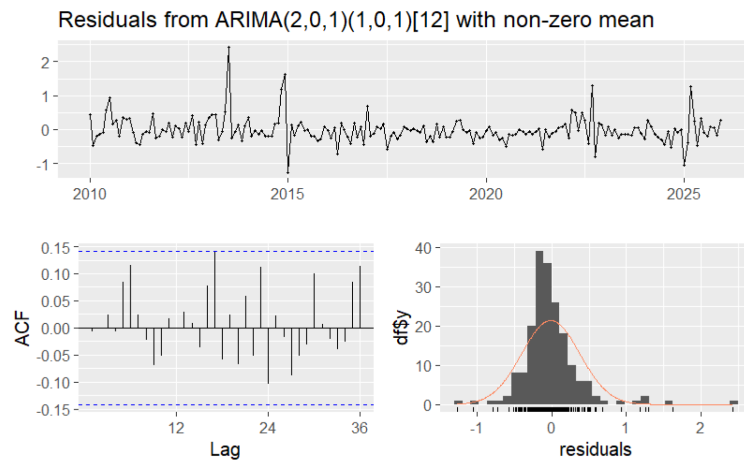

Figure 4. Residual Diagnostics

Based on Figure 4 above, the residual diagnostic results indicate that the residuals fluctuate randomly around zero without any specific pattern. The residual ACF plot shows no significant autocorrelation because all bars remain within the significance limits. This result is also supported by the Ljung–Box test, which produced a p-value of 0.3705 (> 0.05). In addition, the residual distribution appears to be approximately normal, as reflected by the bell-shaped curve. These findings indicate that the model satisfies the white noise assumption and is appropriate for forecasting purposes.

4.2.3. Forecasting

The inflation forecasting results using the ARIMA(2,0,1)(1,0,1)[12] model are presented visually in Figure 5, while the numerical forecasting results are presented in Table 4.

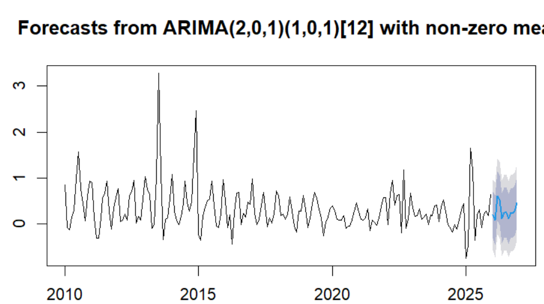

Figure 5. ARIMA Forecasting Results

ased on Figure 5 above, the ARIMA forecasting results indicate that inflation is expected to move relatively stable with a moderate upward tendency. No significant spikes are observed in the forecasting results, indicating that inflation is expected to remain under control. In addition, the prediction intervals become wider over longer forecasting horizons, indicating that the level of uncertainty increases over time. This relatively smooth forecasting pattern also reflects that the model has successfully captured inflation dynamics effectively.

Furthermore, the numerical forecasting results are presented in Table 4 below:

Table 4. ARIMA Forecasting Results

Month	Point Forecast	Lo 95	Hi 95
January	0,18761374	-0,5866969	0,9619244
February	0,07661416	-0,7411333	0,8943617
March	0,59653599	-0,2312162	1,4242881
April	0,51863049	-0,3130823	1,3503433
May	0,11483332	-0,7170111	0,9466778
June	0,23248706	-0,5996156	1,0645897
July	0,24551591	-0,5865868	1,0776186
August	0,10255904	-0,7295564	0,9346745
September	0,23827154	-0,5938443	1,0703874
October	0,22422197	-0,6078944	1,0563383
November	0,27988993	-0,5522265	1,1120063
December	0,45949911	-0,3726173	1,2916155

Based on Table 4, the inflation forecasting results indicate that the forecast values for future periods remain relatively stable across periods. The 95% confidence intervals show the possible range of actual inflation values, where both the lower and upper bounds widen over time. This confirms that although inflation is expected to remain stable, there is still potential variation due to external factors that cannot be predicted with certainty.

Overall, these forecasting results are consistent with the previous analysis using the HP Filter, which indicated a gradually increasing inflation trend with controlled short-term fluctuations. Therefore, the ARIMA model used is not only capable of capturing historical patterns but also produces realistic predictions of future inflation conditions.

5. Conclution

This study aims to analyze the structure of inflation and forecast monthly inflation in Indonesia. The analysis results indicate that inflation exhibits a relatively stable long-term trend pattern, while also experiencing short-term fluctuations that reflect responses to various economic shocks. An important finding of this study is that inflation is not entirely random; rather, it follows patterns that can be systematically explained and modeled. Inflation contains seasonal components and past influences that create recurring characteristics, making it predictable within certain limits.

The forecasting results indicate that future inflation tends to follow its historical pattern with a relatively stable tendency. Although uncertainty continues to increase over time, inflation remains under relatively controlled conditions while still being sensitive to changes in economic circumstances. Therefore, this study confirms that structural analysis and time series modeling provide a more comprehensive understanding of inflation dynamics. This combination is capable of generating relevant predictions to support appropriate decision-making in addressing inflation in Indonesia.

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