

# Forecast of Polish Inflation Rate

Erste Group CEE Research Interview Task

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# Task Overview

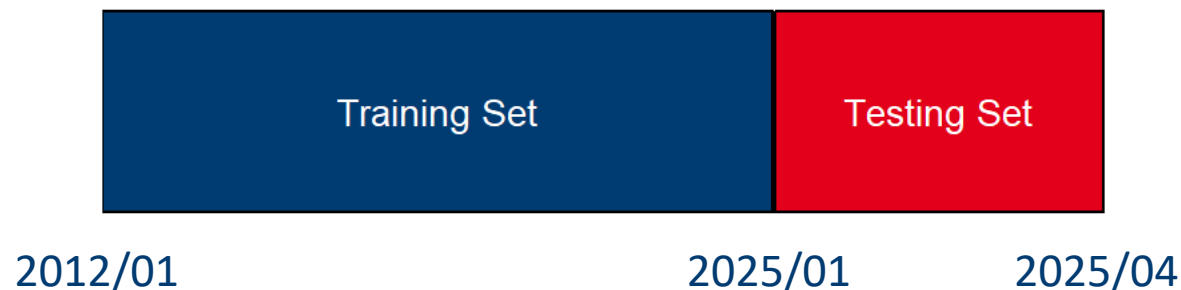
- The task is to analyze the historical dynamics of Polish inflation and **forecast the HICP for the first four months of 2025**
- My approach begins with **a diagnosis of the time series** and observation of the key characteristics of time series **like stationarity, seasonality, trend and autocorrelation**
- I then build and compare **3 models**:
  - A **basic AR(1)** model
  - A **univariate Auto ARIMA** model selected by AIC minimizing
  - A **multivariate ARIMAX** model with **external macroeconomic variables**
- **Goals** of this task:
  - Create **a both technically and economically meaningful forecast**
  - Show that **my AIC** with Erste's CEE Research team is **approximately 0** :)

# Data Overview & Libraries Used

## Data description:

- Original [data set](#) is downloaded from Eurostat
- Represents percentage change in Polish HICP
- Monthly frequency
- Spans between January 1997 and April 2025
- Last accessed on the 21<sup>st</sup> of May

For the sake of this task I have split the data in the following 2 data subsets:

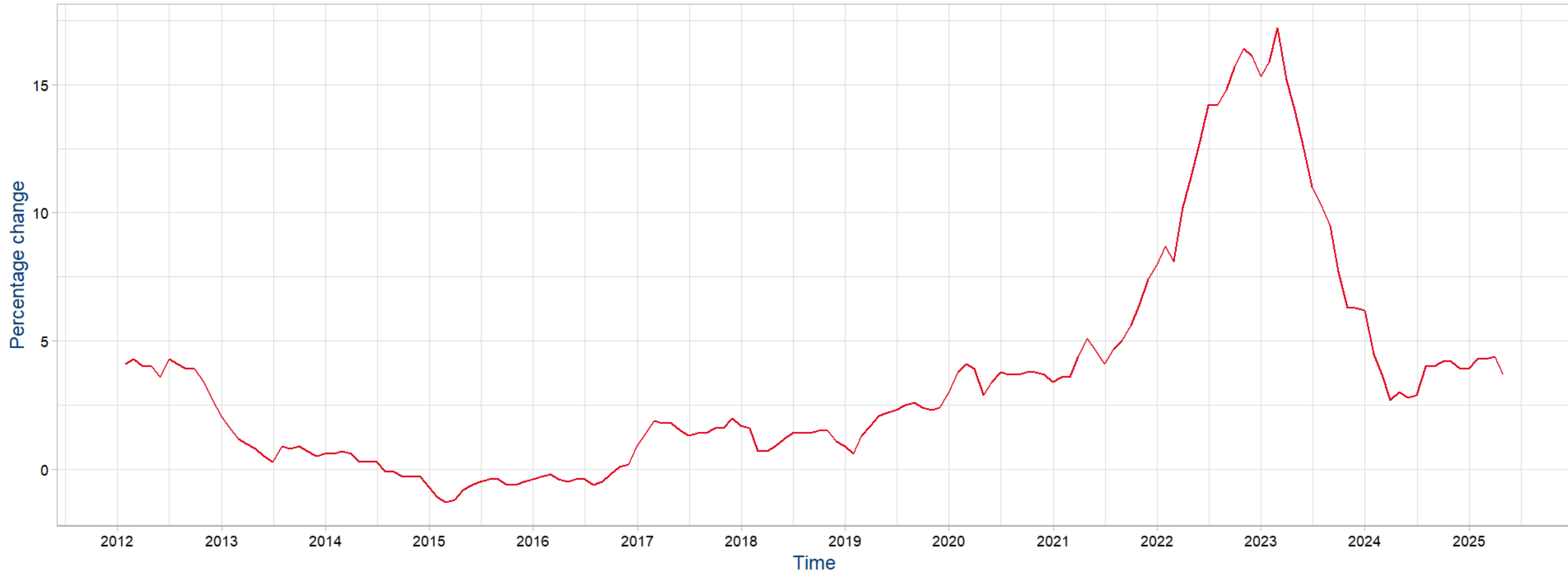


## During the project I have used the following libraries:

- lubridate
- ggplot2
- tseries
- forecast
- quantmod
- dplyr
- tidyr

# Data Overview & Libraries Used

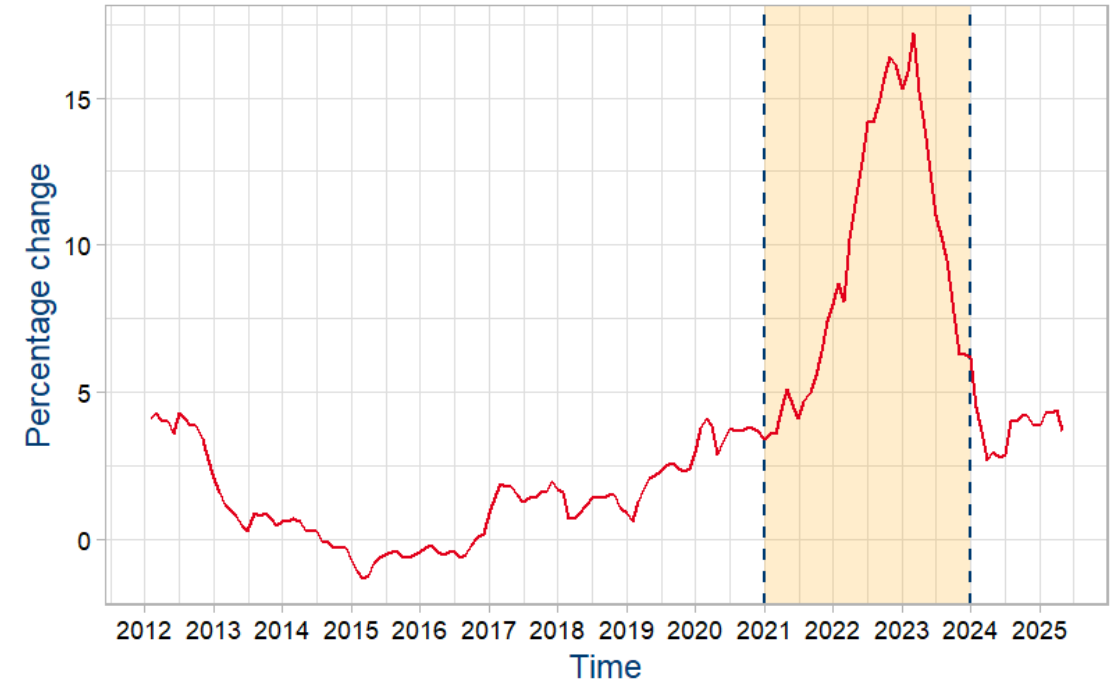
HICP Poland (Monthly)



# TS Diagnostics (Stationarity)

- Stationarity implies **constant mean, variance and autocovariance** over time
- Most time series models (like ARIMA) **require stationarity** to perform well
- Due to the COVID spike in inflation one can't visually decide if the time series is stationary
- Use **Augmented Dickey-Fuller Test**:
  - At  $\alpha = 0.05$
  - $H_0$ : there is unit root (non-stationary)
  - $H_A$ : there is no unit root (stationary)
- **Conclusion:** Reject  $H_0 \Rightarrow$  the series **is stationary** at 5% level

HICP Poland (Monthly)



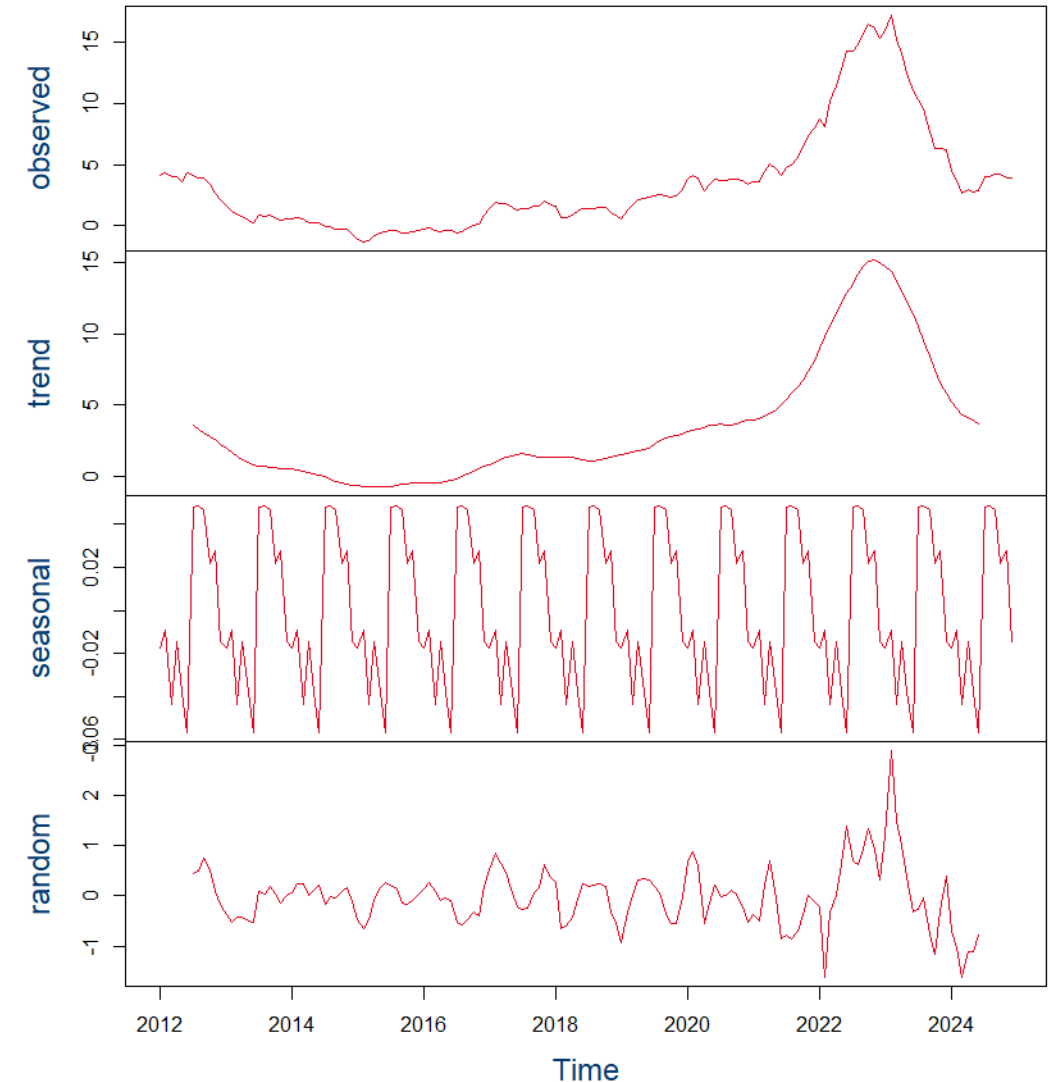
```
##  
## Augmented Dickey-Fuller Test  
##  
## data: train_ts  
## Dickey-Fuller = -3.5707, Lag order = 5, p-value = 0.03827  
## alternative hypothesis: stationary
```

# TS Diagnostics (Decomposition)

A time series can be decomposed into **Trend**, **Seasonality** and **Noise**:

- **Trend** - not permanent
  - No clear trend before 2021
  - Strong upward movement between 2021 and 2023 due to COVID
  - Fast decline after 2023
- **Seasonality** - regular pattern detected, but variation is small ( $\approx 0.08$ )
  - Seasonality is statistically visible but economically minor
  - If seasonality is not impactful, SARIMA model will drop it
- **Noise** - what's left after removing trend and seasonality
  - Stable before 2020 and more volatile around 2021–2023
  - Indicates that external factors likely play a role

Decomposition of additive time series

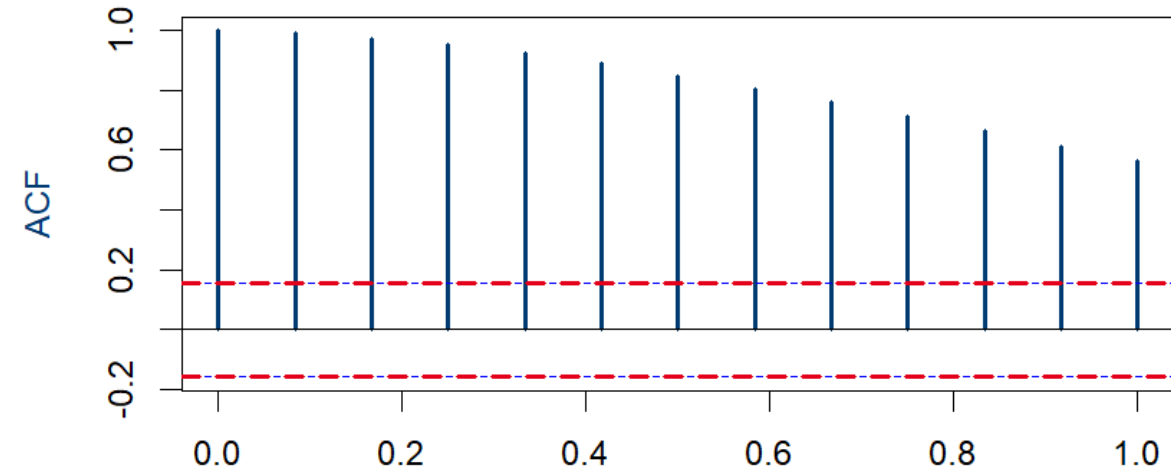


# TS Diagnostics (Autocorrelation)

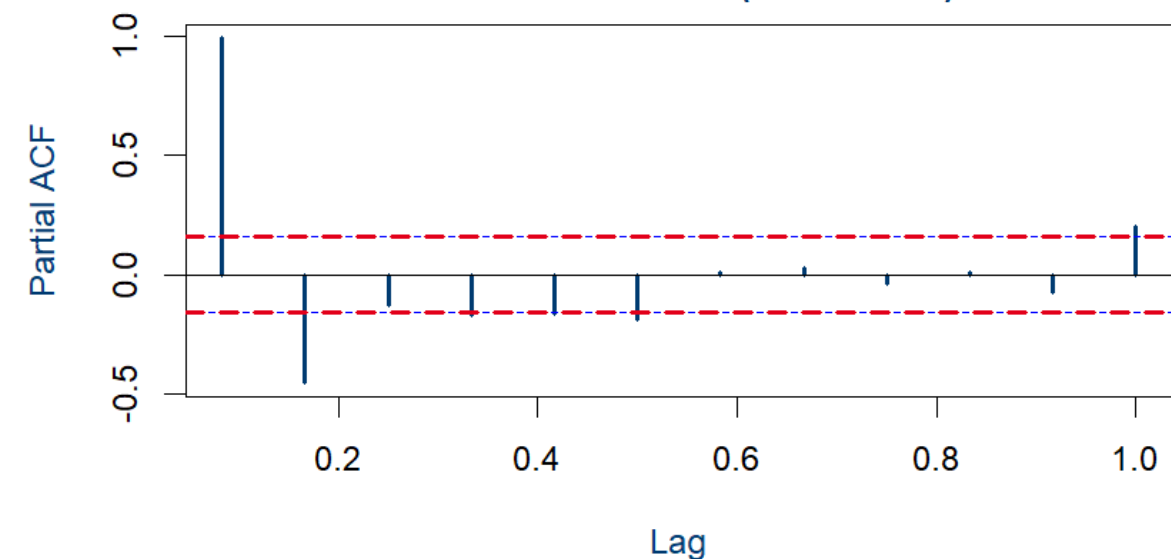
**Autocorrelation** measures how current values are related to past values

- **ACF (Autocorrelation Function)**
  - Captures correlation between current and past values (past errors in MA process)
  - **Strong correlation at lag 1 ( $\approx 1$ )**
  - No clear cut-off
- **PACF (Partial ACF)**
  - shows the pure correlation between a value and its lag (isolates true AR influence)
  - **Huge value at lag 1, then drops significantly**
- This pattern suggests the time series is driven by an **AR(1) process**

ACF of Inflation (2012–2024)



PACF of Inflation (2012–2024)



# Univariate Model - AR(1)

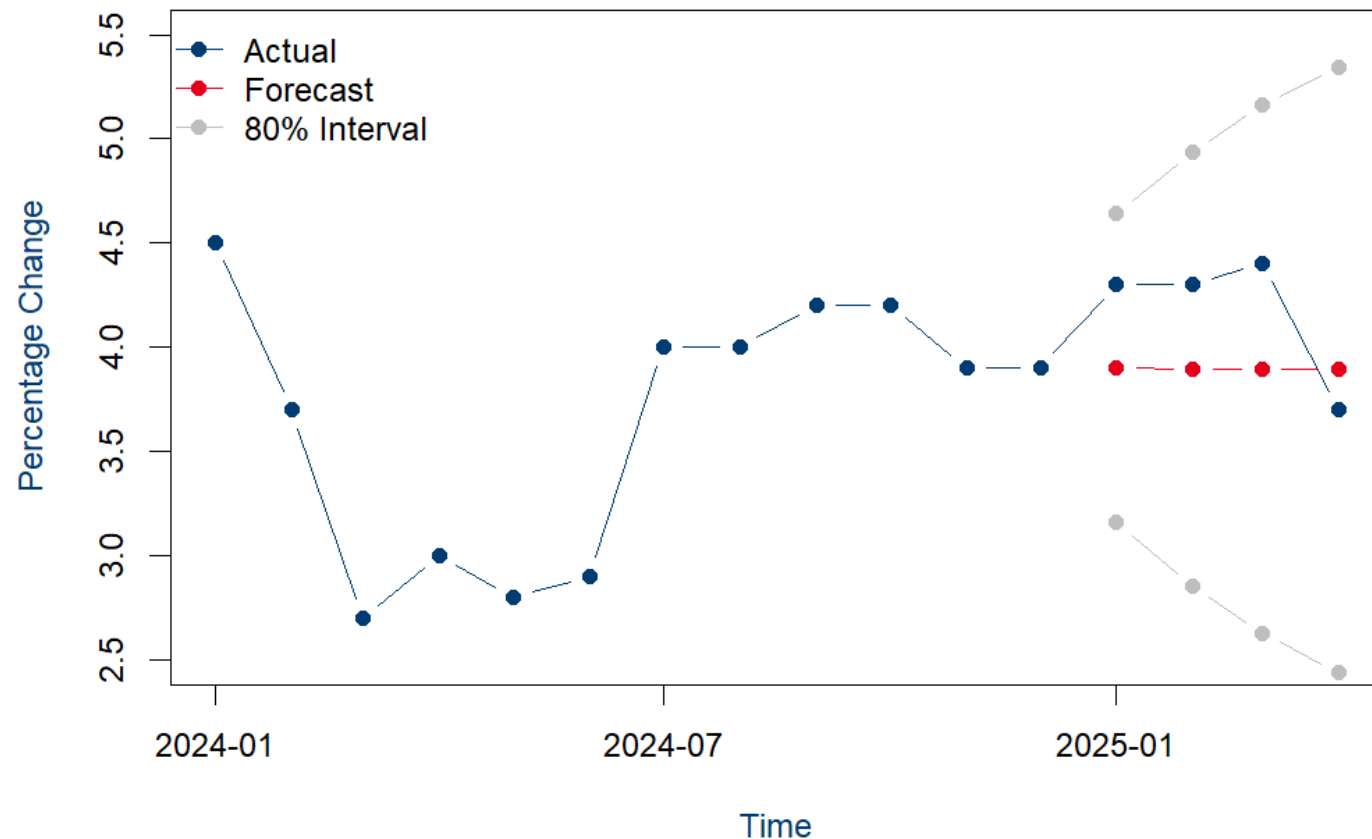
- **ARIMA(1,0,0) based on diagnostics:**
  - PACF showed a strong lag-1 spike => use  $p = 1$
  - ADF test confirmed stationarity => use  $d = 0$
  - ACF decays gradually => no need for MA terms ( $q = 0$ )

- **Model output:**
  - AR(1) coefficient  $\approx 0.99$  => strong persistence
  - Residual variance  $\sigma^2 \approx 0.34$
  - AIC  $\approx 281.8$

- **Forecast:**

##	Observed	Forecast
## 2025 Jan	4.3	3.897829
## 2025 Feb	4.3	3.895688
## 2025 Mar	4.4	3.893575
## 2025 Apr	3.7	3.891490

**HICP Poland – AR(1) Forecasted vs Observed**





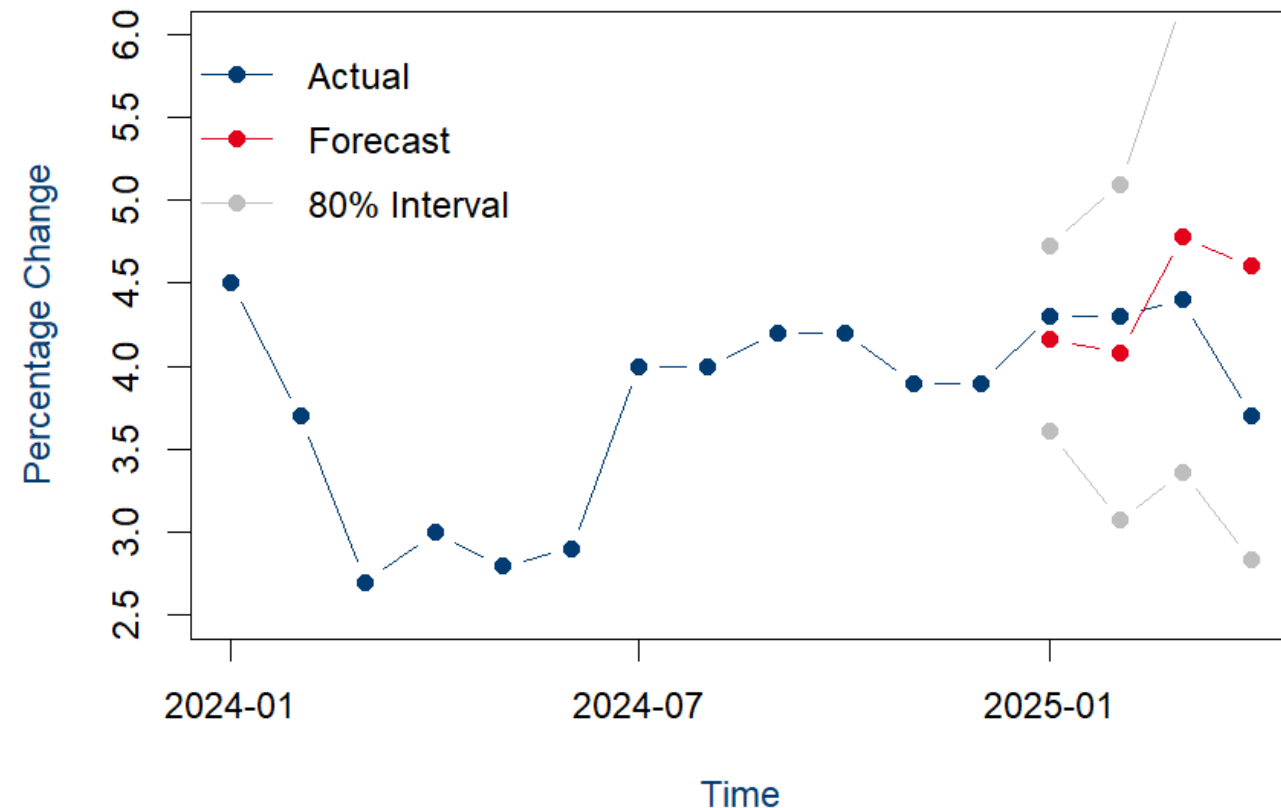
# Univariate Model - Auto ARIMA

- ***auto.arima()*** to let R choose the best (p,d,q) based on AIC minimization
- Allows seasonality detection (if present uses SARIMA)
- **Selected Model - ARIMA(1,1,0)(0,0,1)[12]:**
  - 1 AR term, 1 order of differencing, 1 seasonal MA term
  - Residual variance  $\sigma^2 \approx 0.19$  (better than AR(1))
  - AIC  $\approx 198.2$  (better than AR(1))

- **Forecast:**

##	Observed	Forecast
## 2025 Jan	4.3	4.165496
## 2025 Feb	4.3	4.084557
## 2025 Mar	4.4	4.777414
## 2025 Apr	3.7	4.605298

**HICP Poland – Auto ARIMA Forecasted vs Observed**



# Expanding the Model I

## Unemployment Rate

- Captures domestic labour market pressure
- According to the Phillips Curve there is inverse relationship between inflation and unemployment
- Lag of 1 month performs best (inflation reacts with a short delay to labour shifts)
- [Data](#) from Eurostat, monthly % of population

## EUR/PLN Exchange Rate (YoY log diff)

- Poland's largest trade partners (Germany, France) operate in EUR
- EUR/PLN affects prices of cars, industrial equipment and other euro-denominated imports
- Used log return over 12 months + 1-month lag to reflect pricing contract delays
- Data from Yahoo Finance (*quantmod*)

## Oil Price (in PLN)

- Oil is a key input for transportation, heating and production costs
- Oil shocks are historically linked to inflation spikes
- Measured in PLN to reflect true domestic cost (USD price \* USD/PLN rate)
- Lag of 9 months best captures delayed cost pass-through
- [Data](#) from FRED and Yahoo Finance (*quantmod*)

## USD/PLN Exchange Rate (YoY log diff)

- Many key commodities (especially oil and food) are priced in USD
- Depreciation of the PLN makes imports more expensive (inflationary pressure)
- Used 12-month log return to smooth volatility and capture trend
- Data from Yahoo Finance (*quantmod*)

# Expanding the Model II

## Global Food Price Index

- Food makes up a large share of Poland's consumer basket
- Index reflects global agricultural prices (wheat, oils, dairy, meat)
- Captures import-driven food inflation (e.g. droughts, trade restrictions, supply chain distortions, wars)
- [Data](#) from FAO

## Average Nominal Gross Wage

- Wages reflect domestic demand strength and cost-push inflation
- As wages increase, consumption increases and firms pass labour costs to prices
- Lag of 2 months chosen based on test performance
- [Data](#) from Statistics Poland (GUS)

## 10-Year Government Bond Yield

- Long-term yield reflects market expectations of future inflation and monetary policy
- Yields increase when a higher inflation or tighter monetary stance is expected
- Used 6-month lag based on test performance
- [Data](#) from FRED

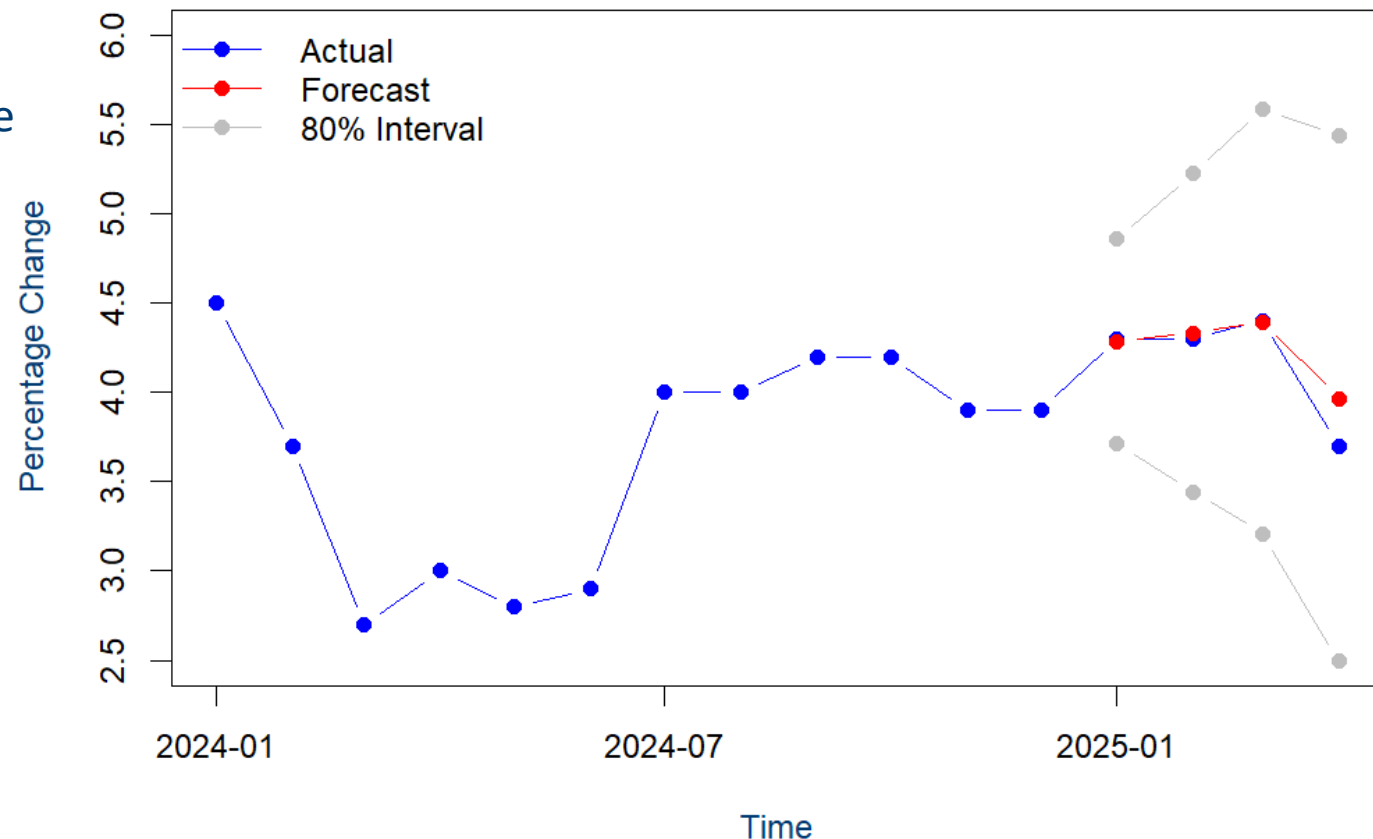
# Multivariate Model - ARIMAX

- Trained using **auto.arima()** with exogenous variables
- **Selected Model - ARIMA(2,0,1)(1,0,0)[12] + 11 regressors:**
  - 2 AR terms, 1 MA term and 1 seasonal AR term (12 months)
  - Residual variance  $\sigma^2 \approx 0.199$
  - AIC  $\approx 211.1$  (slightly worse than the univariate model)

- **Forecast:**

##	Observed	Forecast
## 2025 Jan	4.3	4.284120
## 2025 Feb	4.3	4.332600
## 2025 Mar	4.4	4.394824
## 2025 Apr	3.7	3.965498

**HICP Poland - ARIMAX Forecasted vs Observed**



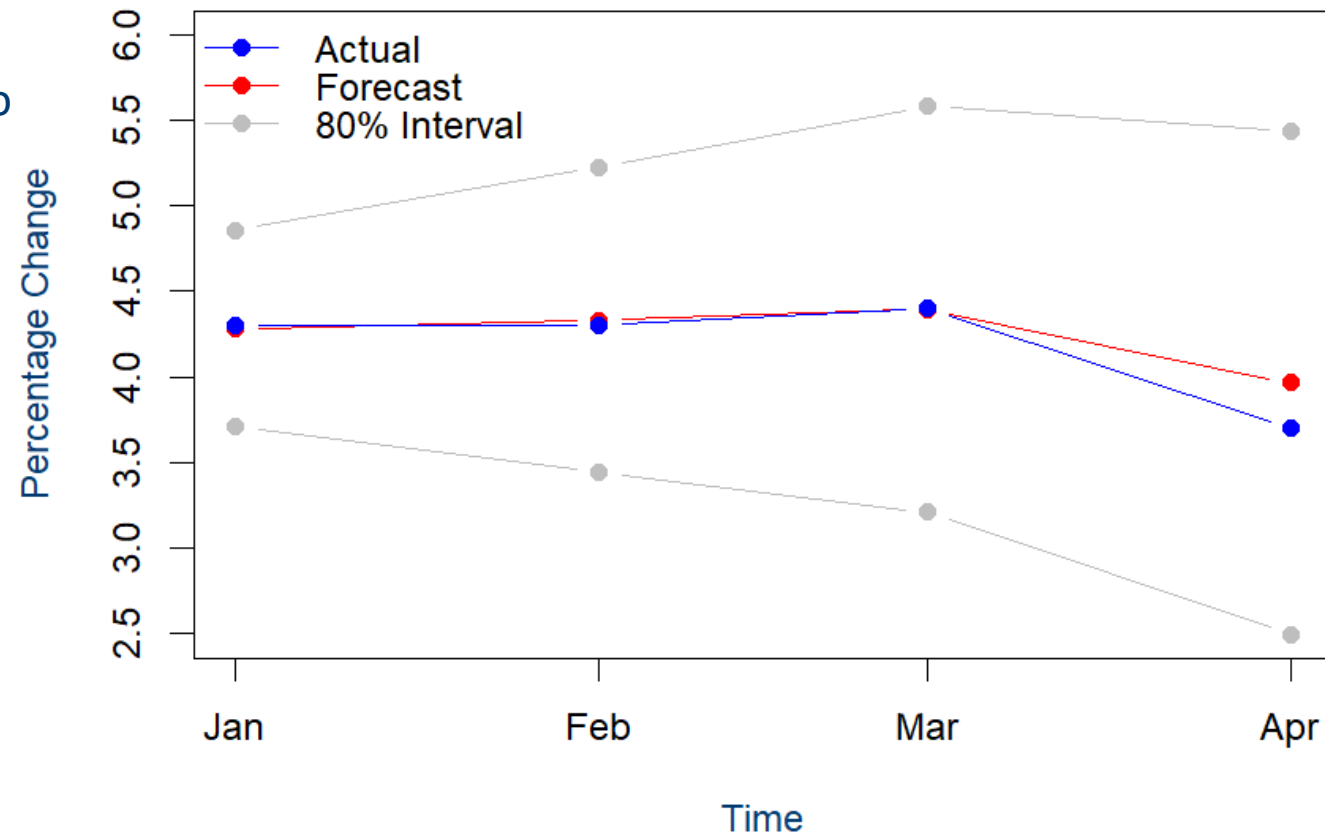
# Multivariate Model - ARIMAX

- Forecast:

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- AIC measures in-sample fit and penalizes model complexity => Slightly higher AIC in ARIMAX is due to more parameters (external variables)
- ARIMAX achieved better forecast accuracy for the forecasting period (2025/01 – 2025/04)
- External variables helped capture real-world shocks
- This improved out-of-sample generalization, even with a slight AIC trade-off

HICP Poland 2025 - ARIMAX Forecasted vs Observed



Thank you!