# TsA in Finance: group project

Swiss National Bank Policy Rates and Inflation

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# Chapter 1

# Introduction

## 1.1 About the authors

This is the project report by Dongyuan Gao and Daniel Huber, master students at the HSLU University, in the module “Time Series Analysis in Finance” in spring 2025.

## 1.2 Contextual Background

Monetary policy in Switzerland is under the management of the Swiss National Bank(SNB). Its main objective is to maintain price stability and control inflation in Switzerland. During the recent history, Switzerland has maintained a low and stable inflation rate, “from 1960 to 2024, the average inflation rate was 2.4% per year. Overall, the price increase was 346.12%. For 2024, an inflation rate of 1.3% was calculated”[Infl00].

## 1.3 Problem Statement

Our team was eager to understand the efficacy of SNB’s monetary policy on inflation in Switzerland: does it significantly influence the inflation development or vice versa? If so, we would like to determine if changes in one can predict the other. These are engaging questions for us, especially in recent economic environment of uncertainty. We aim to provide solid analysis and perspectives for researchers and financial professionals.

# Chapter 2

# Motivation and Objective

## 2.1 Project Objectives

The project aims to

- investigate the dynamic relationship between SNB's policy interest rates and Swiss core inflation.
- determine if there is causality between these two variables.
- analyze the impact and timing of policy rate adjustments on inflation.
- help team members learn about Time Series Analysis by doing, including models, theory, tools that we explored in class

## 2.2 Motivation

Personal/team motivation:

We share a strong academic interest in exploring the world of financial analysis and were motivated by the opportunity to apply our skills to a real-world scenario with practical relevance in the Swiss context. This project also aligns with our professional aspirations, for example, finance, market research, and trading. That makes the project both intellectually engaging and career-relevant.

Real-world relevance: In today's volatile economic landscape, it is beneficial for individuals and institutions to understand inflation dynamics. Such insights can contribute to better financial or policy decisions. It is relevant for policymakers, investors, researchers and private individuals.

## 2.3 Research Questions

- Does SNB policy rate significantly influence core inflation, Or vice versa?
- For policy rate and core inflation, can changes in one predict the other?.
- How quickly and how strongly do core inflation rates respond to policy changes?
- Exploring any extra findings In the relationship between inflation rates and the SNB's policy Interest rates, during the project implementation.

# Chapter 3

# Theory, literature and methodology

To answer our research questions, we first needed to clarify what the basis for modern monetary policy is. Why do central banks raise and lower interest rates according to inflation? For that, a benchmark for monetary policy theory is Taylor's rule, in which he defined the formula for the targeted rate of central banks. "Put simply, the Taylor rule says that the Federal Reserve should raise the interest rate when inflation increases and lower the interest rate when gross domestic product (GDP) declines. The desired interest rate is one-and-a-half times the inflation rate, plus one-half times the gap between GDP and its potential, plus one." [Mark23]

Then the next clarification is: how does Switzerland evaluate and implement monetary policy to foster economic prosperity? After trying out some datasets, we discovered the following statements: "Since the beginning of 2000, the Swiss National Bank (SNB) has used a range for the three-month Swiss franc Libor as its announced target for monetary policy." "Before 2000, the Swiss National Bank officially targeted monetary aggregates, using a medium-term target for the seasonally-adjusted monetary base."[Schi00]

Then for the analysis, we have adopted the theory and practice what we have learned in TSA classes. For example, VAR modeling, stationarity testing, Granger causality, lag-lead effect, and ARIMA.

# Chapter 4

# Data selection process

First, after some research, we started the analysis with a dataset from SNB, “Interest rates and threshold factor” [Inte00a], afterwards is called Dataset 1. It includes policy rate (for a short period), interest rate on sight deposits above threshold, special rate, SARON fix etc. For inflation data, we used core inflation, trimmed mean from “Consumer prices – SNB and SFSO core inflation rates” [Cons00b].

In Dataset 1, the threshold is more suitable to use as the interest rate policy target. However, since threshold data is not available before 2009, we used the special rate for earlier years. From 13 June 2019, the special rate was based on the current SNB policy rate plus a surcharge of 50 basis points.

Additionally, we determined that the SARON fix rate is the market reaction to the policy target, so it shouldn’t be used as the policy rate to be analyzed.

The trial analysis has been successful; we were able to draw some findings and conclusions applying ARIMA, VAR, and linear regression. However, we were not fully satisfied with the different rate types. It was puzzling that we had to convert and “compromise” to the complicated data structure. Therefore, we continued our research and found a second Dataset (referred to as Dataset 2), which contains only two types of official interest rate data. This made it more consistent and more suitable to use as the policy rate.

In this Dataset, “From 13 June 2019, the SNB policy rate is applied. From 3 January 2000 until 13 June 2019, the SNB set a target range for the three-month Swiss franc Libor” [Snbd00].

With it, we’ve also done a VAR to check causality between policy rate/target to inflation, or vice versa. As with Dataset 1, no causality was proven. The result also gives us more confidence that both Datasets reflect the economic reality, although Dataset 2 appeared more consistent overall.

In the end, we chose Dataset 2 for the final analysis. Still, the data selection process was an important learning experience and worth sharing with readers.

# Chapter 5

# Team collaboration and tool set

## 5.1 Team organization and meetings

Team structure: For our team of 2, we both shared responsibility for all aspects of the project; however, with a focus on different aspects. For example, Daniel presented the initial idea, Dongyuan focused more on methodology and research, Daniel focused more on coding diverse models, and Dongyuan dived into finding more data options during the project. We reached team consensus through weekly meetings and follow-ups. The tasks were also interest-based according to both team members. Meeting schedule: weekly meetings were set up on Monday/Tuesday at 14:00, and frequent follow-ups took place.

## 5.2 Collaborative tools

### 5.2.1 Brainstorming and ideation:

Miro Board - Initial concept visualization, real-time collaboration on ideas and analysis structure, organizing literature and conceptual mapping

### 5.2.2 Task Distribution and Project Management

Excel - Task assignment tracking, deadlines and progress monitoring, visualization of milestones and status

### 5.2.3 Coding, Version Control

RStudio GitHub - coding environment, collaborative script development, version control, merging and conflict resolution workflow, documentation of code changes and version tracking.

### 5.2.4 Documentation and Presentation

Quarto - Unified document format (code, analysis, interpretation) - Integration of R code and results - Final report preparation (paper and presentation) - Consistent style and format across deliverables.

## 5.3 Reflection on tool set effectiveness

- Miro is a great tool for visualization and brainstorming. With downside that it can be information-intensive for new users.
- RStudio code collaboration has its learning curve. It was challenging for the first 2 weeks for us to get used to save, commit, pull and push. But in the end, after getting used to it, we think it is a great tool for R collaboration in team. Although it does not allow to work at the same document at the same time.

- Recommendations for future projects: collaboration tool like rstudio-git and team structure take time to form. For short projects, it takes time to getting used to them. However, we are happy that we tried out these tools: It gave us a chance to learn some essential and popular options in the data science world.

# Chapter 6

# Analysis of SNB policy rates and Swiss inflation rates

## 6.1 Data evaluation & preparation

### 6.1.1 libraries

```
library(tidyverse)
library(lubridate)
library(readxl)
library(zoo)
library(tseries)
library(forecast)
library(lmtest)
library(stats)
library(quantmod)
library(vars)
library(car)
```

### 6.1.2 Load data

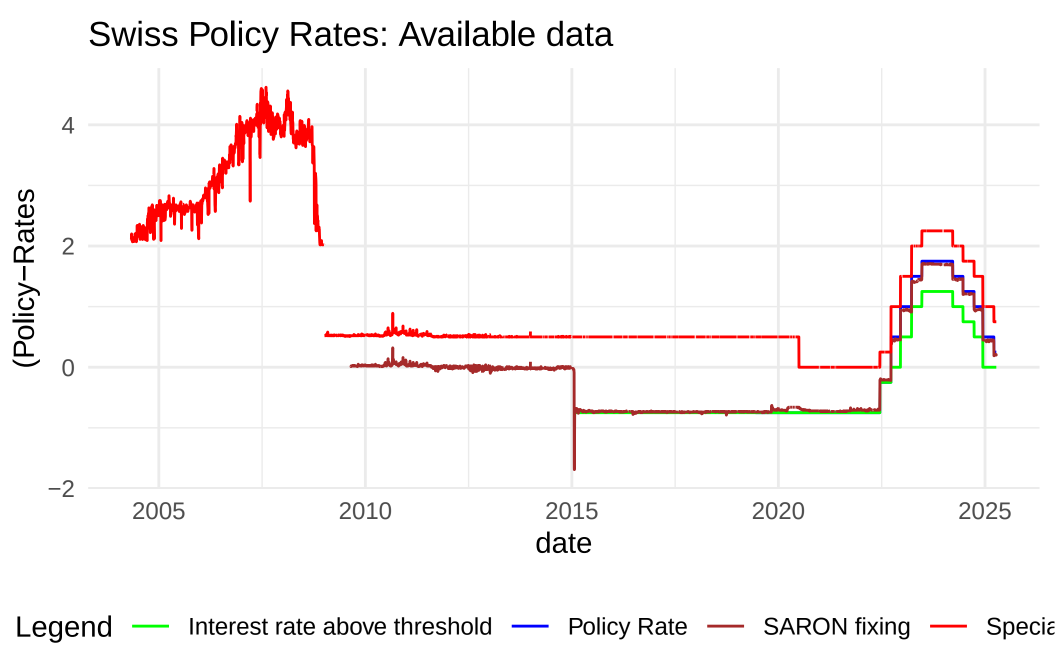
```
policy_rate_data <- read_excel("../data/snb-data-snbgwdzid-en-all-20250414_1000.xlsx",
                               col_types = c("text", "numeric", "numeric", "numeric", "numeric", "numeric"
                               skip = 21)

inflation_data <- read_excel("../data/snb-data-plkoprinfla-en-all-20250422_0900.xlsx",
                             skip = 14) #skipping the first 14 rows
```

### 6.1.3 First trial analysis using dataset 1

various data types are available in several time windows, initial analysis using dataset 1, as described in section 4. Data selection process

```
pr_full <- policy_rate_data %>%
  as_tibble() %>%
  dplyr::select(date = "Overview",
         policy = "SNB policy rate",
         ir_above = "Interest rate on sight deposits above threshold",
         sar_fix = "SARON fixing at the close of the trading day",
```

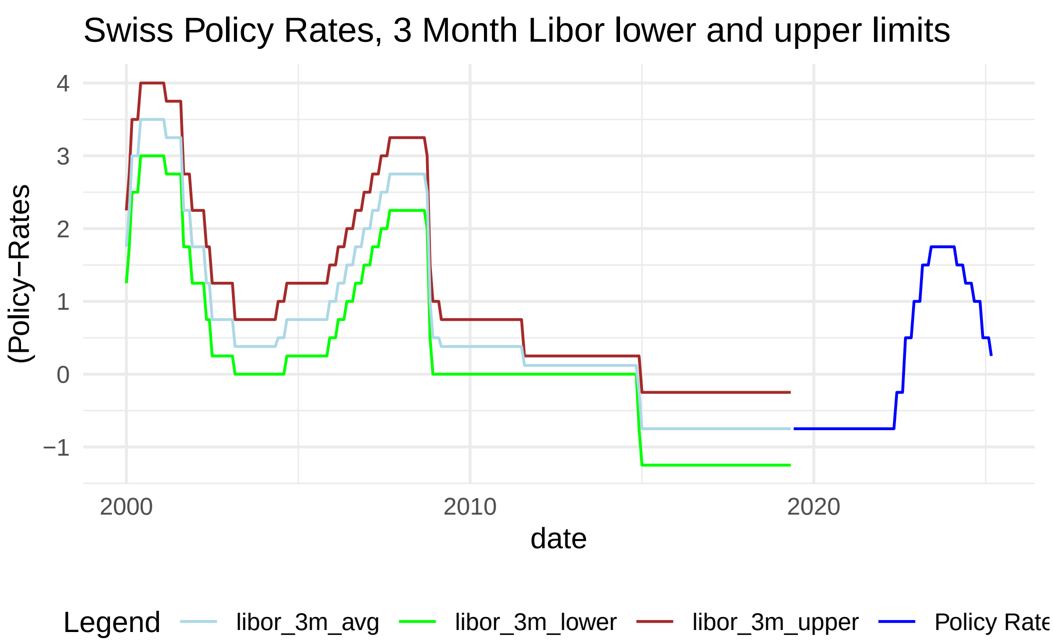
```r
         special = "Special rate  (Liquidity-shortage financing facility)") %>%
  mutate(date = ymd(date),
         (across(c(policy, ir_above, sar_fix, special),
                 ~ round(as.numeric(.), 2)))
  )

ggplot(pr_full, aes(x = date)) +
  geom_line(aes(y = policy, color = "Policy Rate")) +
  geom_line(aes(y = ir_above, color = "Interest rate above threshold")) +
  geom_line(aes(y = sar_fix, color = "SARON fixing")) +
  geom_line(aes(y = special, color = "Special rate")) +
  scale_color_manual(values = c("Policy Rate" = "blue",
                                "Interest rate above threshold" = "green",
                                "SARON fixing" = "brown",
                                "Special rate" = "red")) +
  labs(title = "Swiss Policy Rates: Available data",
       color = "Legend",
       y = "(Policy-Rates") +
  theme_minimal() +
  theme(legend.position = "bottom", legend.direction = "horizontal")
```




### 6.1.4 Average of 3 month Libor upper/lower limits as proxy for missing SNB policy rate data before 2020.

```r
libor_data <- suppressWarnings(
  read_excel("../data/snb-target rate-policy rate-2000-2025.xlsx",
                             range = cell_limits(c(18, 1), c(NA, 4)),
                             col_names = c("date", "policy_rate", "libor_3m_low", "libor_3m_high"),
                             col_types = c("text", "numeric", "numeric", "numeric")) %>%
  mutate(date = ymd(str_c(date, "-01")),
         (across(c(policy_rate, libor_3m_low, libor_3m_high),
                 ~ round(as.numeric(.), 2))),
         libor_3m_avg = (libor_3m_low + libor_3m_high) / 2) %>%
```

```
  mutate(libor_3m_avg = round(libor_3m_avg, 2))
)

ggplot(libor_data, aes(x = date)) +
  geom_line(aes(y = policy_rate, color = "Policy Rate")) +
  geom_line(aes(y = libor_3m_low, color = "libor_3m_lower")) +
  geom_line(aes(y = libor_3m_high, color = "libor_3m_upper")) +
  geom_line(aes(y = libor_3m_avg, color = "libor_3m_avg")) +
  scale_color_manual(values = c("Policy Rate" = "blue",
                                "libor_3m_lower" = "green",
                                "libor_3m_upper" = "brown",
                                "libor_3m_avg" = "lightblue")) +
  labs(title = "Swiss Policy Rates, 3 Month Libor lower and upper limits",
       color = "Legend",
       y = "(Policy-Rates") +
  theme_minimal() +
  theme(legend.position = "bottom", legend.direction = "horizontal")
```



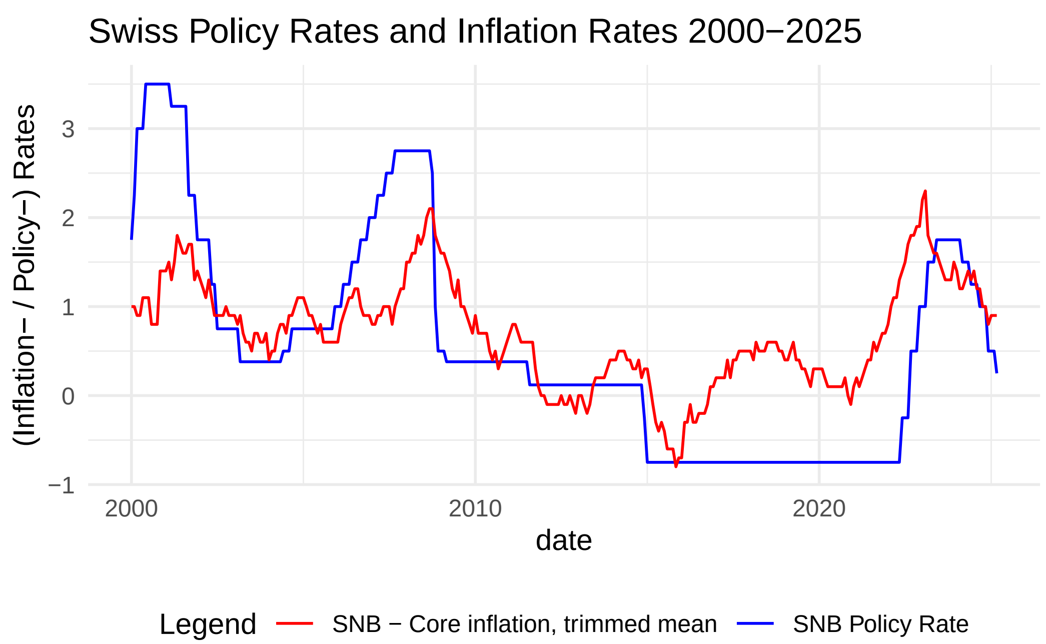

### 6.1.5 Further data preparation, data merge and timeseries object

```
pr <- libor_data %>%
  mutate(
  policy_rate = if_else(
    date < as.Date("2019-06-01"),
    libor_3m_avg,
    policy_rate)) %>%
    dplyr::select(date, policy_rate)

infl <- inflation_data %>%
  as_tibble() %>%
  dplyr::select(date = Overview, infl = `SNB - Core inflation, trimmed mean`) %>%
  mutate(date = ymd(str_c(date, "-01")),   # add a '-01' to the date string before making it a date
         infl = as.numeric(infl),
```

```
        infl = round(infl, 1))


# merge data

df <- inner_join(pr, infl, by = "date")  # merge the two tibbles


# convert df to a zoo time series object

df_ts <- zoo(
  df %>% dplyr::select(-date),
  order.by = df$date
)
```

### 6.1.6 Final look at the data we use for analysis

```
ggplot(df, aes(x = date)) +
  geom_line(aes(y = policy_rate, color = "SNB Policy Rate")) +
  geom_line(aes(y = infl, color = "SNB - Core inflation, trimmed mean")) +
  scale_color_manual(values = c("SNB Policy Rate" = "blue",
                                "SNB - Core inflation, trimmed mean" = "red")) +
  labs(title = "Swiss Policy Rates and Inflation Rates 2000-2025",
       color = "Legend",
       y = "(Inflation- / Policy-) Rates") +
  theme_minimal() +
  theme(legend.position = "bottom", legend.direction = "horizontal")
```



## 6.2 Stationarity & linear regression models

### 6.2.1 Stationarity

Both series are not stationary.

```
adf.test(na.omit(df_ts$policy_rate))
```

```

	Augmented Dickey-Fuller Test

data:  na.omit(df_ts$policy_rate)
Dickey-Fuller = -3.0722, Lag order = 6, p-value = 0.1244
alternative hypothesis: stationary
```

```
adf.test(na.omit(df_ts$infl))
```

```

	Augmented Dickey-Fuller Test

data:  na.omit(df_ts$infl)
Dickey-Fuller = -2.8432, Lag order = 6, p-value = 0.2209
alternative hypothesis: stationary
```

Take first differences of the series and check again

```
df_differenced <- diff(df_ts)
adf.test(na.omit(df_differenced$policy_rate))
```

```

	Augmented Dickey-Fuller Test

data:  na.omit(df_differenced$policy_rate)
Dickey-Fuller = -5.1719, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary
```

```
adf.test(na.omit(df_differenced$infl))
```

```

	Augmented Dickey-Fuller Test

data:  na.omit(df_differenced$infl)
Dickey-Fuller = -4.9773, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary
```

Both series are stationary now.

### 6.2.2 Correlations

p value is merely bigger than 0.05, it shows very week positive correlation.

```
cor(df_differenced$policy_rate, df_differenced$infl, use = "pairwise.complete.obs")
```

```
[1] 0.0635118
```

### 6.2.3 Basic Linear regression model

Linear regression of policy_rate on inflation shows no significant coefficients and R squared is very low.

```
lin_reg <- lm(infl ~ policy_rate, data = df_differenced)
summary(lin_reg)
```

```
Call:
lm(formula = infl ~ policy_rate, data = df_differenced)

Residuals:
     Min       1Q   Median       3Q      Max
-0.52421 -0.09991  0.00009  0.10009  0.60009

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -8.974e-05  7.395e-03  -0.012    0.990
policy_rate  4.860e-02  4.409e-02   1.102    0.271

Residual standard error: 0.1285 on 300 degrees of freedom
Multiple R-squared:  0.004034,	Adjusted R-squared:  0.0007139
F-statistic: 1.215 on 1 and 300 DF,  p-value: 0.2712
```

### 6.2.4 Residual analysis

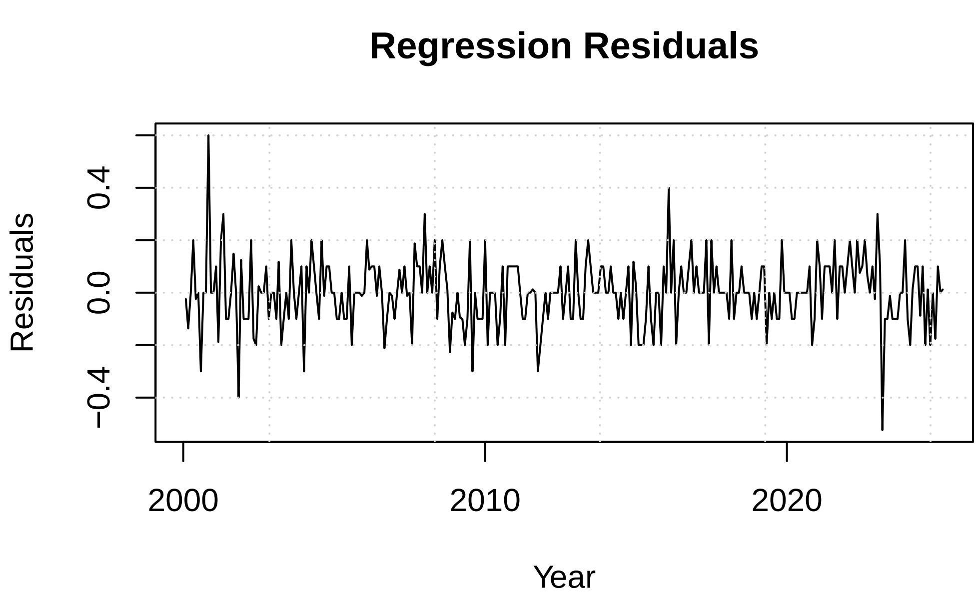
#### 6.2.4.1 Range of Residuals

- Most residuals are between **-0.2 and 0.2** → This suggests **moderate prediction error**.
- **2 outliers** (±0.5) are present → These are **not necessarily problematic** unless they're influential (we check later for Cook's distance).

#### 6.2.4.2 Wavelike Pattern

- the residual plot shows a **wave or sinusoidal pattern**, that suggests **non-linearity** or **autocorrelation** in the data.
- In a good linear model, residuals should be **randomly scattered** around zero (no pattern).

```r
resid <- lin_reg$residuals
plot(y=resid, x=as.Date(time(df_differenced)), ylab="Residuals", xlab="Year", type="l", main="Regression Re
grid()
```



#### 6.2.4.3 Breusch-Pagan test

- Tests for: Heteroskedasticity (i.e., changing variance of residuals).
- Null hypothesis: Residuals have constant variance.
- Interpretation: If $p > 0.05$, fails to reject the null → residuals are homoscedastic → Good. This **does not mean** the linear model is good. It simply means the **residuals are homoscedastic.**

  If $p<0.05$, rejects the null→ residuals are heteroskedastic → Bad.

```
bptest(lin_reg)
```

```

	studentized Breusch-Pagan test

data:  lin_reg
BP = 0.20106, df = 1, p-value = 0.6539
```

#### 6.2.4.4 Shapiro test for normality

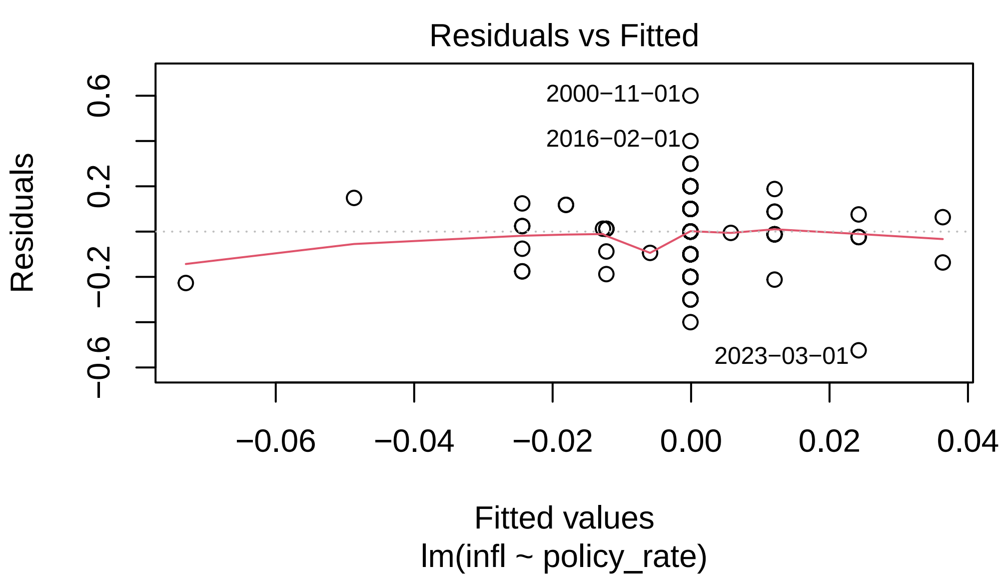
Shapiro test for normality with null hypothesis that Residuals are normally distributed shows a strong rejection of the null hypothesis: The residuals of the model are NOT normally distributed. With n = 302 we might disregard non-normality.

```
shapiro.test(resid)
```

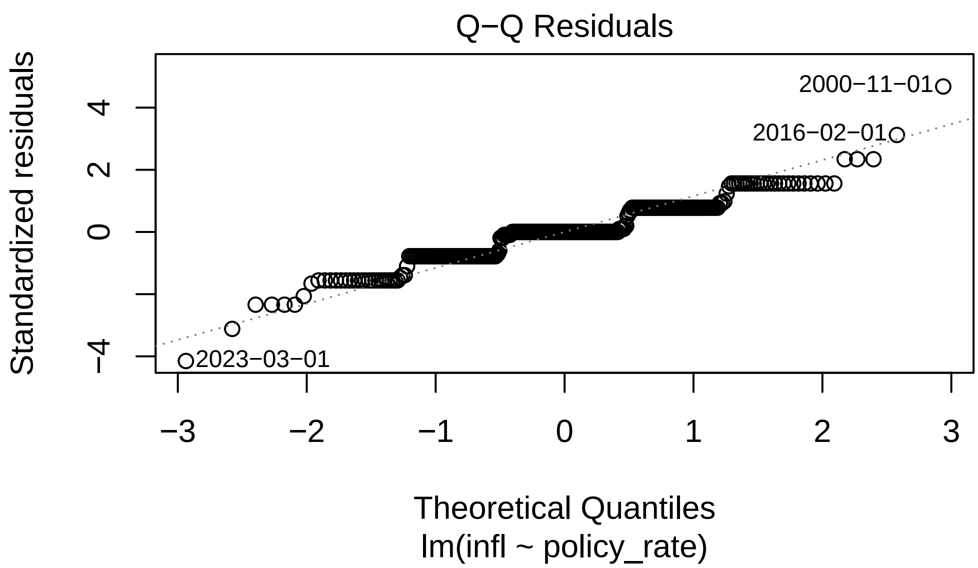
```

	Shapiro-Wilk normality test

data:  resid
W = 0.93868, p-value = 7.332e-10
```

#### 6.2.4.5 Visual check for outliers and influencial points

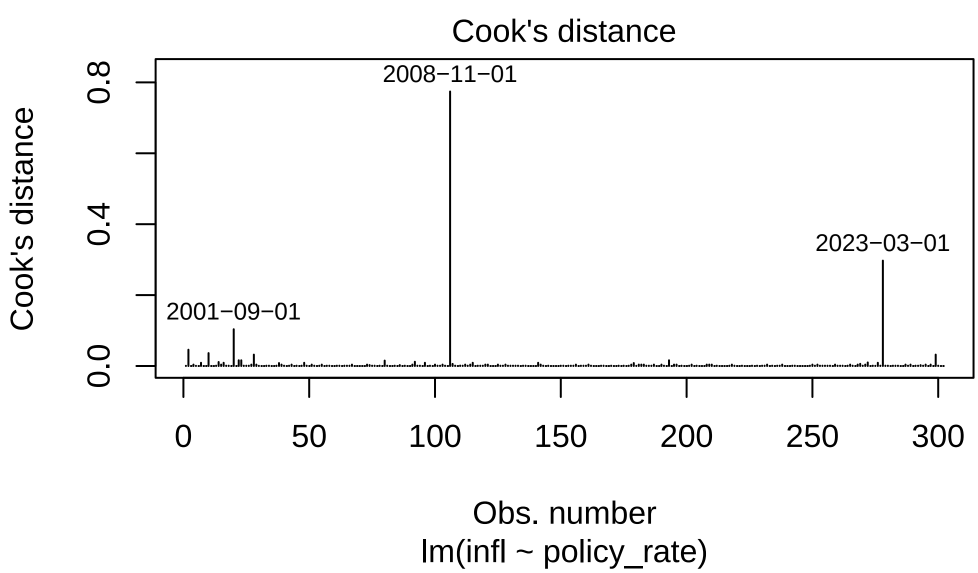
```
plot(lin_reg, which = 1)  # Residuals vs Fitted
```



```r
plot(lin_reg, which = 2)  # Q-Q plot
```




```r
plot(lin_reg, which = 4)  # Cook's distance
```




#### 6.2.4.6 Durbin-Watson test for serial correlation

Durbin-Watson test for serial correlation with null hypothesis that Residuals are not autocorrelated results in a test statistic that is very close to 2, which is the expected value under the null hypothesis of no autocorrelation: p > 0.05: There is no statistically significant evidence of positive autocorrelation in the residuals.

```r
dwtest(lin_reg)
```

```
	Durbin-Watson test

data:  lin_reg
DW = 2.0417, p-value = 0.6373
alternative hypothesis: true autocorrelation is greater than 0
```

### 6.2.5 Alternatives to the basic linear model

#### 6.2.5.1 Alternative 1: Lead-lag relation: infl(t) = a + b * policy_rate(t-1) + e(t)

Create lagged variables

```r
df_differenced$policy_rate_lag1 <- stats::lag(df_differenced$policy_rate, k = 1)
df_differenced$policy_rate_lag2 <- stats::lag(df_differenced$policy_rate, k = 2)
df_differenced$policy_rate_lag3 <- stats::lag(df_differenced$policy_rate, k = 3)
df_differenced$policy_rate_lag4 <- stats::lag(df_differenced$policy_rate, k = 4)
df_differenced$policy_rate_lag5 <- stats::lag(df_differenced$policy_rate, k = 5)
df_differenced$policy_rate_lag6 <- stats::lag(df_differenced$policy_rate, k = 6)
df_differenced$policy_rate_lag7 <- stats::lag(df_differenced$policy_rate, k = 7)
df_differenced$policy_rate_lag8 <- stats::lag(df_differenced$policy_rate, k = 8)
df_differenced$policy_rate_lag9 <- stats::lag(df_differenced$policy_rate, k = 9)
df_differenced$policy_rate_lag10 <- stats::lag(df_differenced$policy_rate, k = 10)
df_differenced$policy_rate_lag11 <- stats::lag(df_differenced$policy_rate, k = 11)
df_differenced$policy_rate_lag12 <- stats::lag(df_differenced$policy_rate, k = 12)
```

Fit the linear model, removing rows with NA due to lagging.

```r
lin_reg_lagged <- lm(infl ~ policy_rate_lag1 + policy_rate_lag2 + policy_rate_lag3 +
                       policy_rate_lag4 + policy_rate_lag5 + policy_rate_lag6 +
                       policy_rate_lag7 + policy_rate_lag8 + policy_rate_lag9 +
                       policy_rate_lag10 + policy_rate_lag11 + policy_rate_lag12,
                     data = na.omit(df_differenced))
summary(lin_reg_lagged)
```

```

Call:
lm(formula = infl ~ policy_rate_lag1 + policy_rate_lag2 + policy_rate_lag3 +
    policy_rate_lag4 + policy_rate_lag5 + policy_rate_lag6 +
    policy_rate_lag7 + policy_rate_lag8 + policy_rate_lag9 +
    policy_rate_lag10 + policy_rate_lag11 + policy_rate_lag12,
    data = na.omit(df_differenced))

Residuals:
     Min       1Q   Median       3Q      Max
-0.48931 -0.09963 -0.00025  0.08991  0.48523

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.0002487  0.0075422   0.033   0.9737
policy_rate_lag1   0.1118330  0.0505080   2.214   0.0276 *
policy_rate_lag2   0.0617822  0.0527645   1.171   0.2426
policy_rate_lag3  -0.1021098  0.0524807  -1.946   0.0527 .
policy_rate_lag4   0.0095258  0.0554855   0.172   0.8638
policy_rate_lag5  -0.0091973  0.0558748  -0.165   0.8694
policy_rate_lag6   0.0851385  0.0557948   1.526   0.1282
policy_rate_lag7   0.0284712  0.0556422   0.512   0.6093
policy_rate_lag8  -0.0275253  0.0558752  -0.493   0.6227
policy_rate_lag9   0.0230595  0.0553549   0.417   0.6773
```

```
policy_rate_lag10 -0.1169032  0.0526436  -2.221   0.0272 *
policy_rate_lag11  0.0447757  0.0528974   0.846   0.3980
policy_rate_lag12 -0.0583718  0.0520051  -1.122   0.2627
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1275 on 277 degrees of freedom
Multiple R-squared:  0.06249,   Adjusted R-squared:  0.02187
F-statistic: 1.539 on 12 and 277 DF,  p-value: 0.11
```

Lag 1 and lag 10 are significant (p-value < 0.05), this could imply **some short- and delayed reaction** of inflation to past policy decisions. But R squared (0.06249, adjusted 002187) is very low, **only 6% of the variance(fluctuations)** in inflation can be accounted to the model.

Lag 1 would make sense and the model shows that it is statistically significant.

But the direction of lag 1 is not as expected: higher policy rate goes with higher inflation.

As interest rate would normally between 10-18 months to have a noticeable impact on inflation, and the coefficient for policy_rate_lag_10 is negative, we can say an increase in the policy rate 10 months ago is maybe associated with lower inflation today. But as only 6% is explained by the model,

Overall we are not convinced by this model, there is no strong predictive power.

#### 6.2.5.2 Alternative 2: Treat SNB actions as events

```r
df_differenced$event_2008_10 <- ifelse(index(df_differenced) >= as.Date("2008-10-01"), 1, 0)
df_differenced$event_2014_11 <- ifelse(index(df_differenced) >= as.Date("2014-11-01"), 1, 0)
df_differenced$event_2020_01 <- ifelse(index(df_differenced) >= as.Date("2020-07-01"), 1, 0)
df_differenced$event_2022_05 <- ifelse(index(df_differenced) >= as.Date("2022-05-01"), 1, 0)
df_differenced$event_2022_10 <- ifelse(index(df_differenced) >= as.Date("2022-10-01"), 1, 0)

lin_reg_events <- lm(infl ~ event_2008_10 + event_2014_11 + event_2020_01 + event_2022_05 + event_2022_10,
summary(lin_reg_events)
```

```
Call:
lm(formula = infl ~ event_2008_10 + event_2014_11 + event_2020_01 +
    event_2022_05 + event_2022_10, data = na.omit(df_differenced))

Residuals:
     Min       1Q   Median       3Q      Max
-0.46667 -0.07671  0.00441  0.08942  0.58942

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.01058    0.01246   0.849  0.39659
event_2008_10 -0.03386    0.01940  -1.746  0.08194 .
event_2014_11  0.01888    0.02141   0.882  0.37876
event_2020_01  0.04987    0.03116   1.600  0.11065
event_2022_05  0.09455    0.06294   1.502  0.13419
event_2022_10 -0.17333    0.06423  -2.699  0.00738 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.127 on 284 degrees of freedom
Multiple R-squared:  0.04497,   Adjusted R-squared:  0.02816
F-statistic: 2.675 on 5 and 284 DF,  p-value: 0.02213
```

The last event 2022_10 is significant. This was a month after the SNB had increased their policy rate from negative (-0.25) to positive (+0.50). But again R squared is very low.

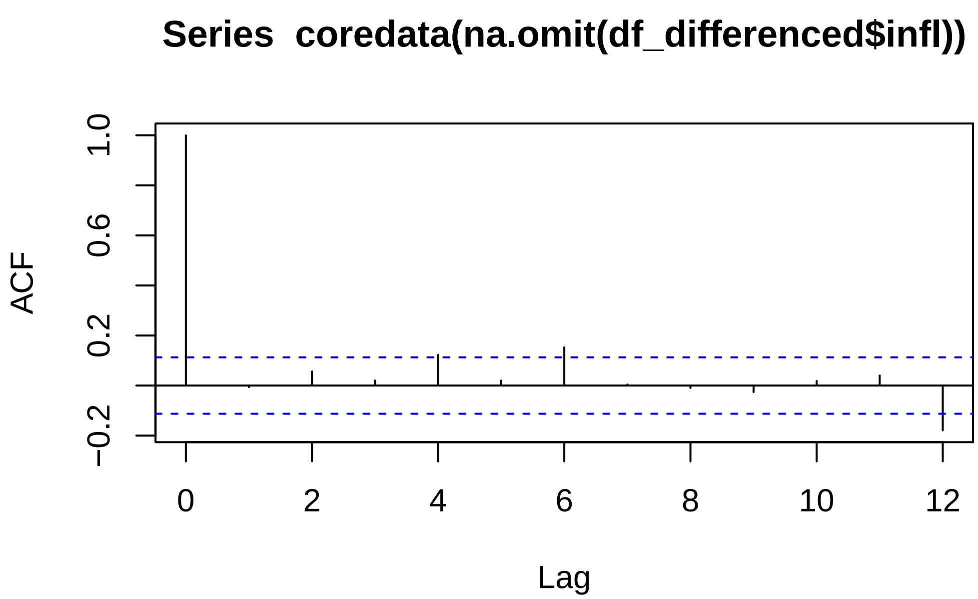
## 6.3 Excursus: Closer look at inflation only (auto/direct correlations and an ARIMA model)

### 6.3.1 Correlations

#### 6.3.1.1 Autocorrelations

The series shows weak to moderate positive autocorrelation at lags 4 and 6, and a negative autocorrelation at lag 12. The inflation changes (infl) today are somewhat positively related to those 4, and 6 months ago. But inflation 12 months ago tends to move in the opposite direction from today's.

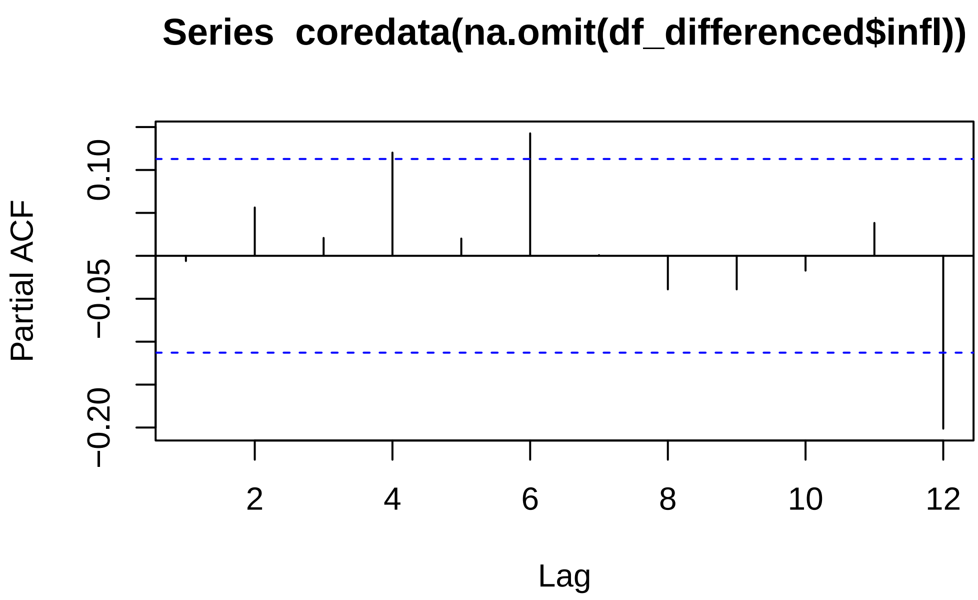
```
acf(coredata(na.omit(df_differenced$infl)), lag.max = 12)
```




#### 6.3.1.2 Direct correlations

Direct correlation between a time series and lag k, controlling for all shorter lags (1 to k−1).

```
pacf(coredata(na.omit(df_differenced$infl)), lag.max = 12)
```




#### 6.3.1.3 Rule of thumb regarding ARIMA parameters q and p

Use acf() to choose the q in MA(q) models. -> q = 4 or 6 Use pacf() to choose the p in AR(p) models. -> p = 4 or 6

The ACF and PACF plots suggest that the series may be modeled as an ARMA(4,4) or AR(6,6).

## 6.4 Akaike information criterion: AIC

Identifying the orders p and q of the ARIMA(p,1,q)-model by testing different model specifications. We only allow a maximum of six AR- and MA-terms and set the order of integration d to 1.

```
max.order <- 6
d <- 1
```

Defining the matrix in which the values of the AICs for different model specifications are stored. Then calculating and storing the AICs for different model specifications.

```
arima_aic <- matrix(NA, ncol=max.order+1, nrow=max.order+1)
row.names(arima_aic) <- c(0:max.order) # Order of AR(p) in rows
colnames(arima_aic) <- c(0:max.order) # Order of MA(q) in columns

for(i in 0:max.order){
  for(j in 0:max.order){
    arima_aic[i+1,j+1]<-Arima(y=df_differenced$infl, order=c(i,d,j), include.constant =  FALSE)$aic
  }
}
arima_aic
```

```
          0         1         2         3         4         5         6
0 -168.6189 -371.3014 -369.3014 -367.3014 -365.3014 -363.3014 -361.3014
1 -247.5208 -369.3014 -367.3014 -365.3014 -363.3014 -361.3014 -359.3014
2 -359.4566 -368.0223 -365.3015 -363.3014 -361.3014 -359.3014 -357.3014
3 -365.0392 -365.8290 -363.2961 -361.3014 -359.3013 -357.3014 -355.3014
4 -358.5969 -364.3533 -361.7275 -359.6208 -357.3013 -355.3014 -353.3016
5 -348.3162 -366.2311 -359.6077 -357.3880 -355.4800 -353.3025 -351.4714
6 -403.2342 -390.8695 -362.8963 -355.4723 -353.3884 -351.3918 -349.3954
```

```
index <- which(arima_aic == min(arima_aic), arr.ind = TRUE)
ar <- as.numeric(rownames(arima_aic)[index[1]])
ma <- as.numeric(colnames(arima_aic)[index[2]])
c(ar, ma)
```

```
[1] 6 0
```

```
arima_aic[ar+1, ma+1]
```

```
[1] -403.2342
```

**Interpretation**: The optimal ARMA-model is ARMA(6,0) with an AIC of -398.5921. (d according to order of integration.

## 6.5 ARIMA model

Convert to ts object from zoo and estimate the optimal ARIMA-model (incl. testing for significance of the coefficients)

```
infl_diff_ts <- ts(coredata(df_differenced$infl), frequency = 12)
arima <- Arima(y=infl_diff_ts, order=c(ar,d,ma), include.constant = FALSE)
print(arima)
```

```
Series: infl_diff_ts
ARIMA(6,1,0)

Coefficients:
          ar1      ar2      ar3      ar4      ar5      ar6
      -0.9255  -0.7922  -0.6760  -0.4535  -0.3323  -0.0867
s.e.   0.0574   0.0761   0.0851   0.0854   0.0766   0.0581

sigma^2 = 0.01758:  log likelihood = 183.41
AIC=-352.81   AICc=-352.43   BIC=-326.86
```

```
coeftest(arima)
```

```

z test of coefficients:

     Estimate Std. Error  z value  Pr(>|z|)
ar1 -0.925475   0.057449 -16.1095 < 2.2e-16 ***
ar2 -0.792221   0.076102 -10.4100 < 2.2e-16 ***
ar3 -0.675997   0.085097  -7.9438 1.960e-15 ***
ar4 -0.453496   0.085392  -5.3107 1.092e-07 ***
ar5 -0.332307   0.076583  -4.3392 1.430e-05 ***
ar6 -0.086676   0.058142  -1.4908     0.136
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Interpretation:

**ARIMA(6,1,0)**: This means the model includes: 6 autoregressive (AR) terms, 1 difference (change in inflation), 0 moving average (MA) terms.

All AR coefficients (ar1 to ar6) are **negative**, meaning **reverting behavior** (past increases in inflation are followed by decreases).

**ar1 to ar5** are **significant** (p-values almost 0), indicating strong predictive power. Inflation show **strong autoregressive behavior** and **tendency to revert.**

```
arima_5_1_0 <- Arima(infl_diff_ts, order=c(5,1,0))
print(arima_5_1_0)
```

```
Series: infl_diff_ts
ARIMA(5,1,0)

Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -0.9034  -0.7592  -0.6229  -0.3871  -0.2539
s.e.   0.0557   0.0731   0.0775   0.0731   0.0559

sigma^2 = 0.01765:  log likelihood = 182.3
AIC=-352.6   AICc=-352.31   BIC=-330.35
```

```
coeftest(arima_5_1_0)
```

```
z test of coefficients:

     Estimate Std. Error  z value  Pr(>|z|)
ar1 -0.903417   0.055721 -16.2131 < 2.2e-16 ***
ar2 -0.759246   0.073087 -10.3882 < 2.2e-16 ***
ar3 -0.622855   0.077532  -8.0335 9.472e-16 ***
ar4 -0.387099   0.073149  -5.2919 1.210e-07 ***
ar5 -0.253930   0.055930  -4.5401 5.622e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The **ARIMA(5,1,0)** is superior with one coefficient less. So we proceed with this.

As this is just an Excursus, not helping to identify the relations between policy rates and inflation, we skip here the evaluation of residuals. But we do a forecasting of inflation just based on this ARIMA model anyway.

### 6.5.1 Forecast the next 12 months of inflation

```
forecast_arima <- forecast(arima_5_1_0, h = 12)
print(forecast_arima)
```

```
       Point Forecast      Lo 80      Hi 80      Lo 95     Hi 95
Mar 26   -0.084298236 -0.2545725 0.08597602 -0.3447102 0.1761138
Apr 26   -0.011199785 -0.1822664 0.15986681 -0.2728236 0.2504240
May 26   -0.050704287 -0.2237561 0.12234749 -0.3153641 0.2139556
Jun 26    0.007383639 -0.1679378 0.18270509 -0.2607474 0.2755147
Jul 26   -0.027998335 -0.2100036 0.15400694 -0.3063514 0.2503547
Aug 26   -0.022421557 -0.2085356 0.16369249 -0.3070584 0.2622153
Sep 26   -0.040046216 -0.2375923 0.15749983 -0.3421668 0.2620744
Oct 26   -0.018774470 -0.2190504 0.18150149 -0.3250701 0.2875212
Nov 26   -0.029137767 -0.2333571 0.17508154 -0.3414642 0.2831887
Dec 26   -0.018122481 -0.2263109 0.19006591 -0.3365192 0.3002742
Jan 27   -0.028048428 -0.2415563 0.18545943 -0.3545805 0.2984837
Feb 27   -0.024748471 -0.2424099 0.19291293 -0.3576329 0.3081359
```

```
forecast_arima$mean        # Point forecasts
```

```
            Jan          Feb          Mar          Apr          May
26                           -0.084298236 -0.011199785 -0.050704287
27 -0.028048428 -0.024748471
            Jun          Jul          Aug          Sep          Oct
26  0.007383639 -0.027998335 -0.022421557 -0.040046216 -0.018774470
27
```

```
            Nov          Dec
26 -0.029137767 -0.018122481
27
```

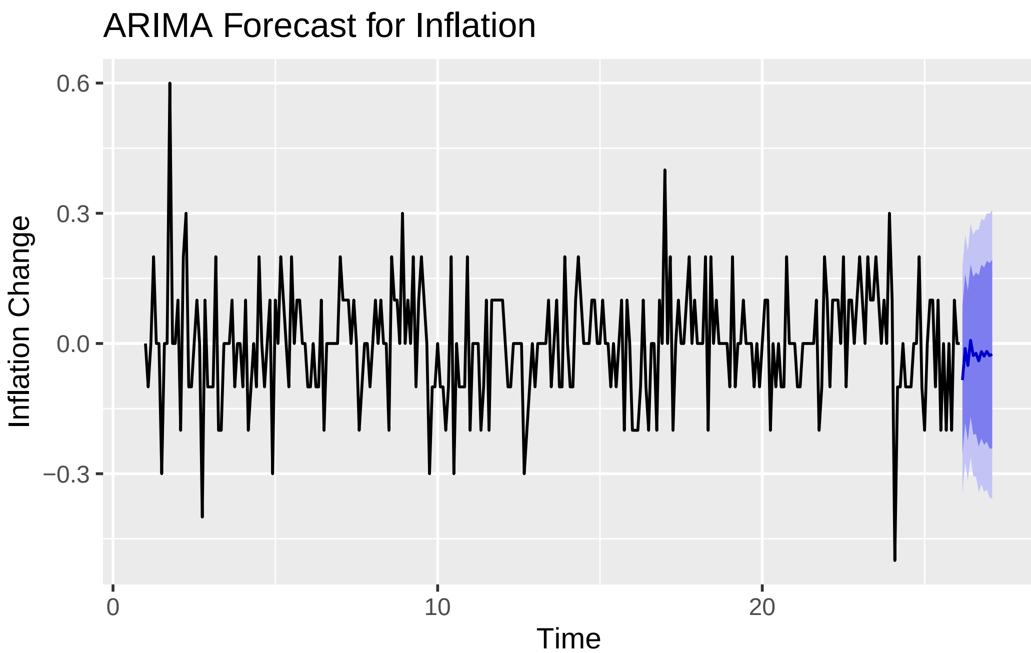
```r
forecast_arima$lower       # Lower bounds (80% and 95%)
```

```
              80%        95%
Mar 26 -0.2545725 -0.3447102
Apr 26 -0.1822664 -0.2728236
May 26 -0.2237561 -0.3153641
Jun 26 -0.1679378 -0.2607474
Jul 26 -0.2100036 -0.3063514
Aug 26 -0.2085356 -0.3070584
Sep 26 -0.2375923 -0.3421668
Oct 26 -0.2190504 -0.3250701
Nov 26 -0.2333571 -0.3414642
Dec 26 -0.2263109 -0.3365192
Jan 27 -0.2415563 -0.3545805
Feb 27 -0.2424099 -0.3576329
```

```r
forecast_arima$upper       # Upper bounds (80% and 95%)
```

```
              80%       95%
Mar 26 0.08597602 0.1761138
Apr 26 0.15986681 0.2504240
May 26 0.12234749 0.2139556
Jun 26 0.18270509 0.2755147
Jul 26 0.15400694 0.2503547
Aug 26 0.16369249 0.2622153
Sep 26 0.15749983 0.2620744
Oct 26 0.18150149 0.2875212
Nov 26 0.17508154 0.2831887
Dec 26 0.19006591 0.3002742
Jan 27 0.18545943 0.2984837
Feb 27 0.19291293 0.3081359
```

```r
autoplot(forecast_arima) +
  ggtitle("ARIMA Forecast for Inflation") +
  xlab("Time") + ylab("Inflation Change")
```




#### 6.5.1.1 Last known and forecasted inflation levels

```
last_infl <- tail(na.omit(df$infl), 1)
forecast_changes <- forecast_arima$mean
forecast_inflation <- cumsum(forecast_changes) + last_infl
forecast_upper <- cumsum(forecast_arima$upper[,2]) + last_infl
forecast_lower <- cumsum(forecast_arima$lower[,2]) + last_infl
```

Get the last date from indexed too object and generate 12 monthly forecast dates

```
last_date <- tail(index(df_differenced), 1)
forecast_dates <- seq(from = as.Date(last_date) %m+% months(1), by = "month", length.out = 12)
```

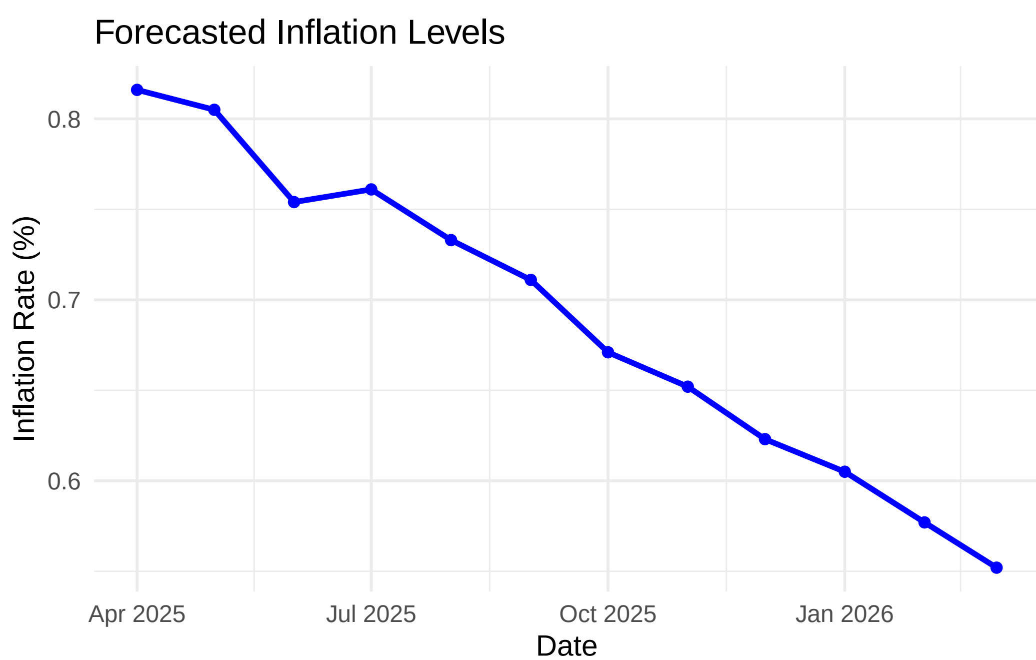
Forecast table and plot.

```
forecast_table <- data.frame(
  Date = forecast_dates,
  Forecast_Inflation = round(as.numeric(forecast_inflation), 3),
  Forecast_Change = round(as.numeric(forecast_arima$mean), 3),
  Lower_95 = round(forecast_arima$lower[,2], 3),
  Upper_95 = round(forecast_arima$upper[,2], 3)
)

print(forecast_table)
```

```
         Date Forecast_Inflation Forecast_Change Lower_95 Upper_95
1  2025-04-01              0.816          -0.084   -0.345    0.176
2  2025-05-01              0.805          -0.011   -0.273    0.250
3  2025-06-01              0.754          -0.051   -0.315    0.214
4  2025-07-01              0.761           0.007   -0.261    0.276
5  2025-08-01              0.733          -0.028   -0.306    0.250
6  2025-09-01              0.711          -0.022   -0.307    0.262
7  2025-10-01              0.671          -0.040   -0.342    0.262
8  2025-11-01              0.652          -0.019   -0.325    0.288
9  2025-12-01              0.623          -0.029   -0.341    0.283
```

```
10 2026-01-01                  0.605          -0.018    -0.337    0.300
11 2026-02-01                  0.577          -0.028    -0.355    0.298
12 2026-03-01                  0.552          -0.025    -0.358    0.308
```

```
ggplot(forecast_table, aes(x = Date, y = Forecast_Inflation)) +
  geom_line(color = "blue", linewidth = 1) +
  geom_point(color = "blue") +
  labs(
    title = "Forecasted Inflation Levels",
    x = "Date",
    y = "Inflation Rate (%)"
  ) +
  theme_minimal()
```




After this extensive **Excursus** we now go **back our main topic**, explaining interactions between SNB policy rates and inflation rates in Switzerland.

## 6.6 Vector autoregression and Granger causality

### 6.6.1 Do policy rates explain inflation rates?

```
VAR_model <- VAR(cbind(df_differenced$policy_rate, df_differenced$infl) , ic="AIC", lag.max = 12)
# coeftest(VAR_model)
# summary(VAR_model)
causality(VAR_model, cause="df_differenced.policy_rate")["Granger"]
```

```
$Granger

    Granger causality H0: df_differenced.policy_rate do not Granger-cause
    df_differenced.infl

data:  VAR object VAR_model
F-Test = 2.8265, df1 = 4, df2 = 578, p-value = 0.02424
```

The Granger Causality Test (VAR) examines whether past policy rates help predict current values of inflation beyond what's already explained by past values of inflation itself.

There is **statistically significant evidence that past policy rates Granger-cause inflation**, i.e., policy rates have predictive power for inflation in our model. But **remember: Granger causality** is **not proof** of true causation, it **only indicates predictive** helpfulness.

### 6.6.2 Do inflation rates explain policy rates?

```
causality(VAR_model, cause="df_differenced.infl")["Granger"]
```

```
$Granger

	Granger causality H0: df_differenced.infl do not Granger-cause
	df_differenced.policy_rate

data:  VAR object VAR_model
F-Test = 1.2403, df1 = 4, df2 = 578, p-value = 0.2926
```

**No: Inflation rates do not Granger-cause the policy rates.**

### 6.6.3 Does the "SNB event in September 2022" explain inflation rates.

```
VAR_df <- na.omit(cbind(df_differenced$event_2022_10, df_differenced$infl))
colnames(VAR_df) <- c("event_2022_10", "infl")
VAR_model <- VAR(VAR_df , ic="AIC", lag.max = 12)
coeftest(VAR_model)
```

```
t test of coefficients:

                                Estimate Std. Error t value  Pr(>|t|)    
event_2022_10:(Intercept)      0.0034847  0.0035938  0.9696 0.3330589    
event_2022_10:event_2022_10.l1  0.9835028  0.0594264 16.5499 < 2.2e-16 ***
event_2022_10:infl.l1          0.0166767  0.0271886  0.6134 0.5401252    
event_2022_10:event_2022_10.l2  0.0020321  0.0832146  0.0244 0.9805350    
event_2022_10:infl.l2          0.0421153  0.0271638  1.5504 0.1221586    
event_2022_10:event_2022_10.l3 -0.0024969  0.0832247 -0.0300 0.9760864    
event_2022_10:infl.l3          0.0192806  0.0267348  0.7212 0.4713950    
event_2022_10:event_2022_10.l4  0.0035873  0.0836355  0.0429 0.9658179    
event_2022_10:infl.l4          0.0198585  0.0268170  0.7405 0.4596005    
event_2022_10:event_2022_10.l5 -0.0059441  0.0837218 -0.0710 0.9434495    
event_2022_10:infl.l5          0.0386697  0.0269170  1.4366 0.1519277    
event_2022_10:event_2022_10.l6  0.0218920  0.0609708  0.3591 0.7198196    
event_2022_10:infl.l6         -0.0045400  0.0270938 -0.1676 0.8670456    
infl:(Intercept)               0.0022383  0.0075788  0.2953 0.7679574    
infl:event_2022_10.l1          0.0503928  0.1253204  0.4021 0.6879055    
infl:infl.l1                  -0.0126927  0.0573363 -0.2214 0.8249624    
infl:event_2022_10.l2         -0.0897124  0.1754857 -0.5112 0.6095930    
infl:infl.l2                   0.0554753  0.0572840  0.9684 0.3336588    
infl:event_2022_10.l3          0.3052153  0.1755070  1.7390 0.0831136 .  
infl:infl.l3                   0.0087977  0.0563792  0.1560 0.8761085    
infl:event_2022_10.l4         -0.1937597  0.1763734 -1.0986 0.2728864    
infl:infl.l4                   0.1150805  0.0565527  2.0349 0.0427903 *  
infl:event_2022_10.l5         -0.6153546  0.1765553 -3.4853 0.0005695 ***
infl:infl.l5                   0.0035575  0.0567634  0.0627 0.9500713    
infl:event_2022_10.l6          0.5141070  0.1285772  3.9984 8.143e-05 ***
infl:infl.l6                   0.1409905  0.0571364  2.4676 0.0141935 *  
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

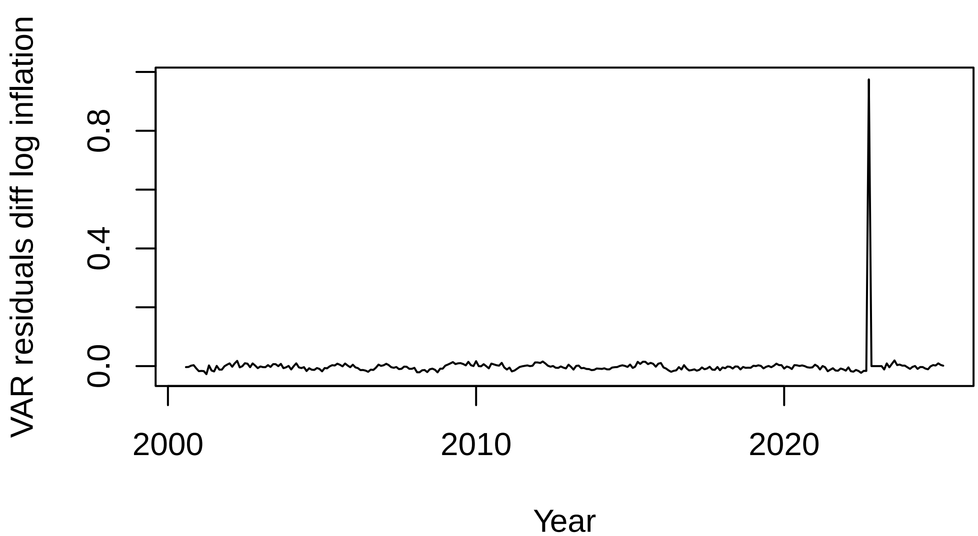
```r
causality(VAR_model, cause="event_2022_10")["Granger"]
```

```
$Granger

    Granger causality H0: event_2022_10 do not Granger-cause infl

data:  VAR object VAR_model
F-Test = 4.232, df1 = 6, df2 = 566, p-value = 0.0003524
```

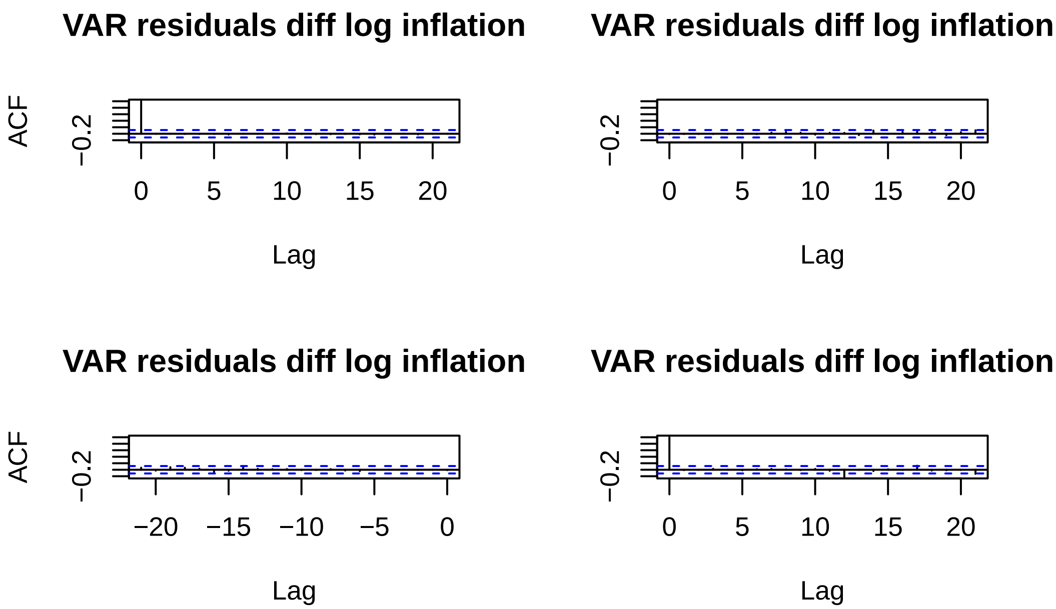
There is **strong evidence that event_2022_10 Granger-cause inflation** (at lag 5 and lag6). This means, that the SNB policy rate change in autumn 2022 influenced the Swiss inflation rates.

We now do a **residual analysis** based on the last VAR model with Event_2022_10 to check the quality of the model.

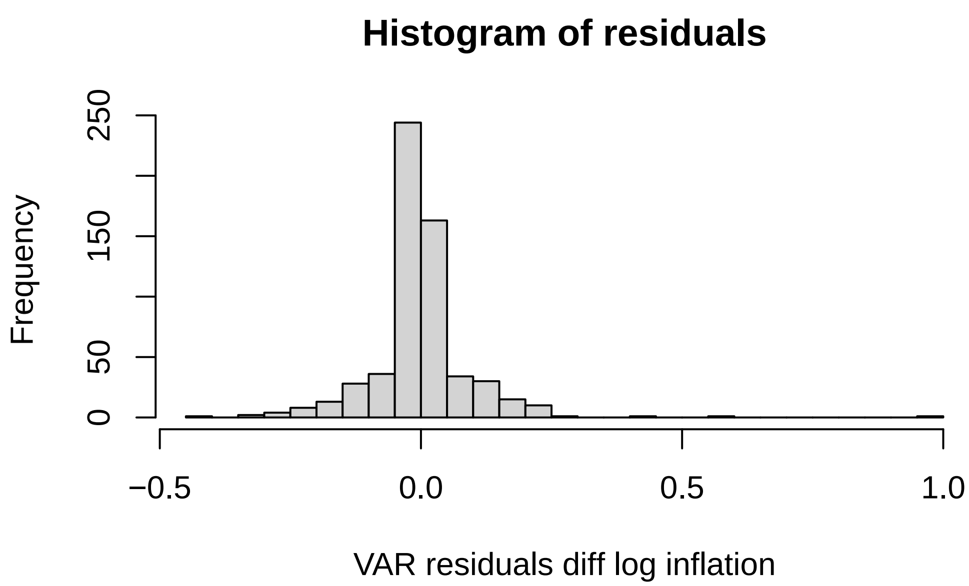
```r
Resid_VAR <- resid(VAR_model)
p <- VAR_model$p
residual_dates <- tail(index(df_differenced), -p) # Remove first p dates
plot(x = residual_dates,
     y = Resid_VAR[,1],  # First equation's residuals
     type = "l",
     ylab = "VAR residuals diff log inflation",
     xlab = "Year")
```



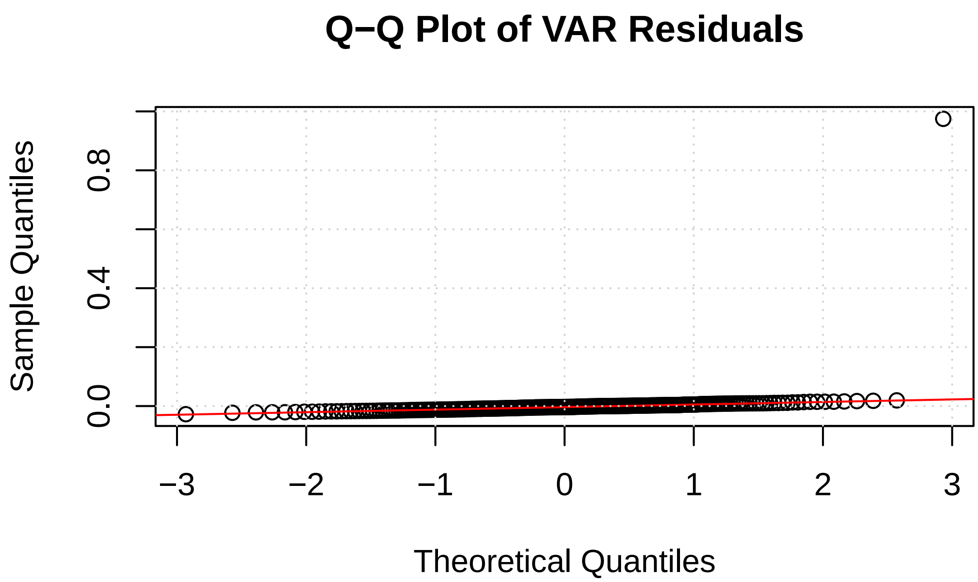

```r
# Plotting ACF, histogram, and Q-Q-plot of residuals
acf(data.frame(Resid_VAR), main="VAR residuals diff log inflation") # ACF of residuals
```




```
hist(Resid_VAR, breaks=25, main="Histogram of residuals", xlab="VAR residuals diff log inflation") # Histog
```




```
# For a single equation's residuals (e.g., first variable)
residuals_to_plot <- Resid_VAR[,1]  # Select first column

# 1. Q-Q plot with grid
qqnorm(residuals_to_plot, main = "Q-Q Plot of VAR Residuals")
qqline(residuals_to_plot, col = "red")
grid()
```




```r
# Residual tests
arch.test(VAR_model) # ARCH-LM test for constant variance, null hypothesis = Residuals are homoscedastic
```

```
    ARCH (multivariate)

data:  Residuals of VAR object VAR_model
Chi-squared = 53.988, df = 45, p-value = 0.1685
```

```r
normality.test(VAR_model) # Jarque-Bera test for normality, null hypothesis = Residuals are normally distr
```

```
$JB

    JB-Test (multivariate)

data:  Residuals of VAR object VAR_model
Chi-squared = 968505, df = 4, p-value < 2.2e-16


$Skewness

    Skewness only (multivariate)

data:  Residuals of VAR object VAR_model
Chi-squared = 13520, df = 2, p-value < 2.2e-16


$Kurtosis

    Kurtosis only (multivariate)

data:  Residuals of VAR object VAR_model
Chi-squared = 954985, df = 2, p-value < 2.2e-16
```

```
serial.test(VAR_model) # Portmanteau test (default) for serial correlation, null hypothesis = Residuals are
```

```
    Portmanteau Test (asymptotic)

data:  Residuals of VAR object VAR_model
Chi-squared = 30.849, df = 40, p-value = 0.8502
```

The ARCH-LM test for constant variance with the null hypothesis that residuals are homoscedastic shows with a p-value of 0.1685, that **residuals are homoscedastic**.

The Jarque-Bera test for normality with the null hypothesis that residuals are normally distributed shows with a p-value close to zero, that **residuals are not normally distributed**.

The Portmanteau test for serial correlation with the null hypothesis that residuals are not autocorrelated shows with a p-value of 0.8502, that the **residuals are not autocorrelated**.

**Overall interpretation of residual analysis**:

The non-normality remains an issue. It **might** be neglected as we have 302 observations (large n tends towards normality).

The **peak of the residuals** around (see plot above) is another issue, that needs to be further investigated. Is it related to the significant Granger-causality of the event_2022_10 on inflation?

# Chapter 7

# Findings, discussion and limitations

## 7.1 Key findings

1. **Stationarity and Correlation**
   Both the policy rate and core inflation series were non-stationary but became stationary after differencing. After differencing, the correlation between the two was very weak ($\approx 0.06$).
2. **Linear Regression and Lag Effects**
   A basic linear regression showed no significant relationship between policy rates and inflation ($p > 0.05$; $R^2 \approx 0.004$). Even when including lags of up to 12 months, only lag 1 and lag 10 were statistically significant. Overall explainability was low (adjusted $R^2 \approx 0.02$). It suggests weak evidence of delayed effects.
3. **Event-based Models**
   After treating major SNB policy changes as events, October 2022 had a statistically significant effect on inflation (p almost 0). This suggests a large policy major change (from negative to positive rates in 2022) could have delayed effect on inflation. However, overall explainability was still low ($R^2 \approx 0.04$).
4. **Granger Causality (VAR Model)**
   The Granger causality test showed that policy rates Granger-cause inflation ($p \approx 0.024$). It suggested that past policy rate changes help predict inflation, but remember, no causality can be determined. On the other hand, inflation did not Granger-cause policy rates ($p \approx 0.29$). This suggests that the SNB reacts independently of recent inflation trends, which is conterintuitive, but the data suggests such story might be the reality .
5. **ARIMA Forecasting**
   The ARIMA(5,1,0) model was selected as optimal for inflation. Most AR were statistically significant. Forecasts suggest a auto-reverting inflation trend that once it rises, autoregression tend to happen. We have done a forecast, no significant changes of inflation was predicted.

## 7.2 Limitations

- **Limited Prediction Power**: Most models (especially linear regression) show very low $R^2$ values, indicating weak predictive power.
- **Two Variables**: The models only consider two variables: policy rate and core inflation. Other factors like global energy prices, pandemic and trade wars were not included.

Despite these limitations, the analysis contributes to understanding how SNB policy rates and inflation interact. It offers a foundation for more complex modeling in future studies.

# Chapter 8

# Discussion

Why combining ARIMA and Granger causality test is more comprehensive : **ARIMA**: Univariate model: It uses only past values of inflation to forecast future inflation. It does not include other variables (e.g., policy events).

**Granger Causality Test**: Multivariate test: It checks if a variable (like our events or interest rate change) helps predict inflation.

Are the results consistent?

**The results are actually consistent, without contradiction**:

Granger shows: policy interest rate dosen't help predict inflation. ARIMA shows inflation doesn't change much, its own past doesn't predict much either.

So, both point to a weakly moving inflation series, not driven by recent shocks or clear autocorrelation.

## 8.1 Conclusion

Our team analyzed the relationship between SNB policy rates and inflation rate in Switzerland. We applied time series models for the analysis. Weak connections between the two variables were found, lacking strong correlation or deterministic evidence. Even though Granger causality indicates that past policy rate changes have some predictive value for inflation, and event-based analysis suggest a connection between higher policy rate and lower inflation with delayed effect, the overall predictive power of models is still low.

The findings suggest that inflation in Switzerland could be influenced by a broader set of factors, including monetary policy, but not limited to it.

Future research could expand on this work by including more variables, testing other models, analyzing specific events' effect on inflation rate, and their relationship with policy decisions.

# Chapter 9

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