TsA in Finance - Group project

Swiss National Bank Policy Rates and Inflation Dynamics

Daniel Huber / Dongyuan Gao

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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 by controlling 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

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.

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, lead-lag effects, 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 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 2, “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, and in Dataset 2, one direction causality was proven, it shows that the dats sets actually produced different results.

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 with a GitHub repository has its learning curve. It was challenging for the first 2 weeks for us to get used to save, commit, push and pull. 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

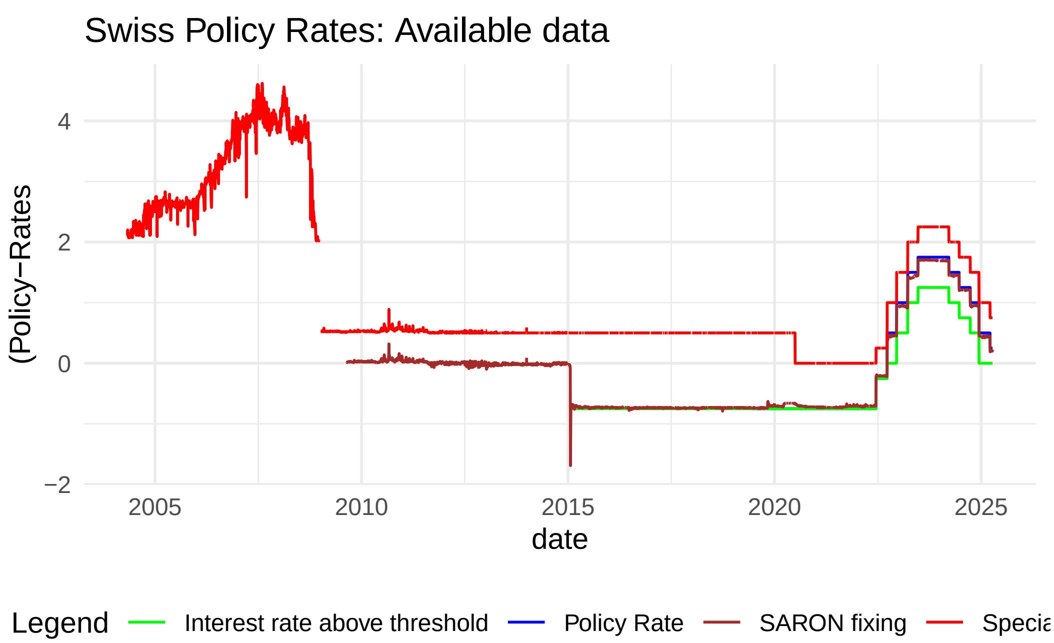
```
policy_rate_data <- read_excel("../data/snb-data-snbgwdzid-en-all-20250414_1000.xlsx",
                               col_types = c("text", "numeric", "numeric", "numeric", "numeric", "numeric"
                               skip = 21)

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

Our first dataset (Dataset 1) for the SNB policy rates provides several columns that could be used as **SNB policy rate**. But they are all **only available for specific time windows**, in particular the column labeled 'SNB policy rate' is only **available since June 2019**. So we have to decide which (or which combination) would be best for our analysis.

```
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",
        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")
```

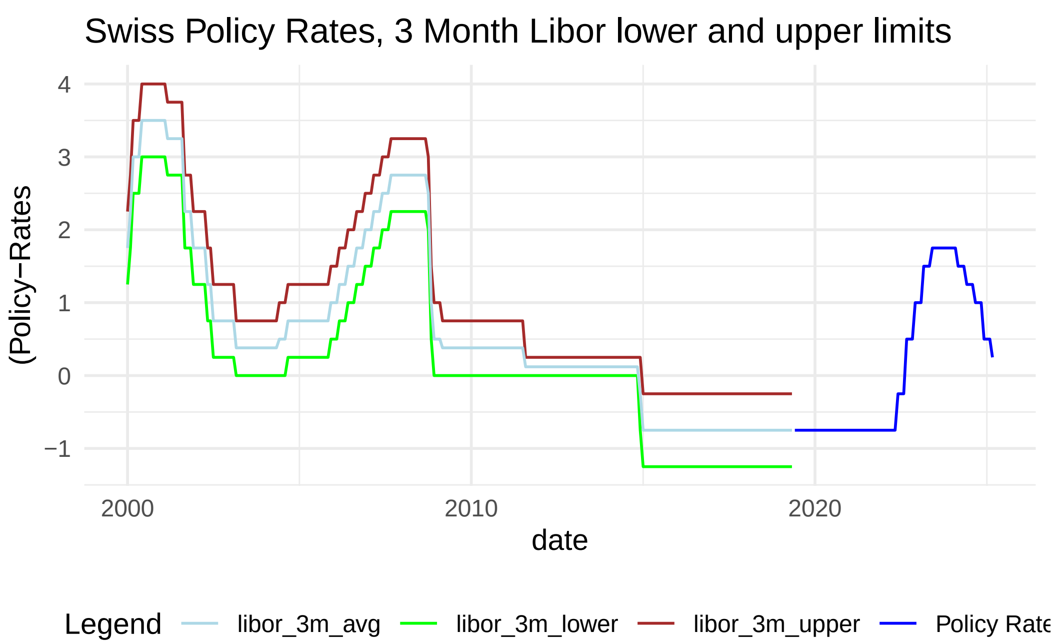


6.1.4 Average of 3 months Libor upper/lower limits as proxy for missing SNB policy rate data before 2020.

After we have learned that the SNB's policy rate before 2020 was actually a range, namely the **upper and lower limits** of the 3 months Libor, we found another dataset (Dataset 2) with this data. Visual inspection shows that the average of the upper and lower limits indeed fits perfectly well to the policy rates afterwards.

```
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

We calculated the **average of the limits** of the 3 months Libor and used it as policy rate until June 2019 and switch to the official SNB policy rate after June 2019.

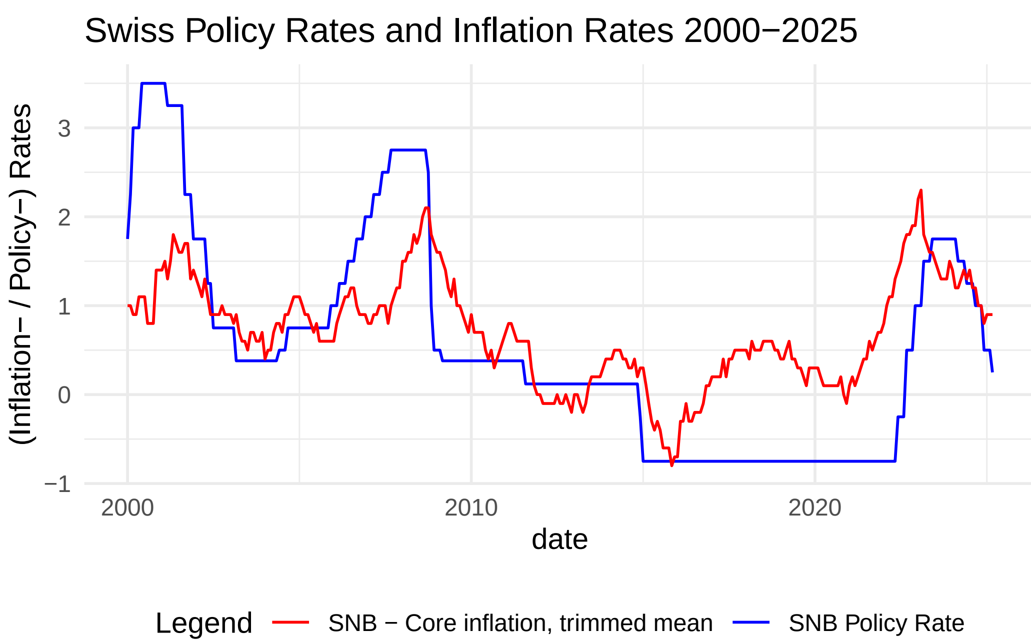
```
pr <- libor_data %>%
  mutate(
  policy_rate = if_else(
    date < as.Date("2019-06-01"),
    libor_3m_avg,
    policy_rate)) %>%
    dplyr::select(date, policy_rate)

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

A look at the data we use for our time series analysis suggests that there is a **relation** between SNB **policy rates** and Swiss **inflation rates**, although it is not obvious which one is triggering the other. Furthermore it shows very different behavior regarding fluctuation: **Inflation rates change monthly** (actually daily), whereas **policy rates** are **sometimes constant** for longer time periods.

```
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

Initially both data series are **not stationary** (p-values > 0.05). **After calculating the differences** from one month to the next, the Augmented Dickey-Fuller Test shows that **both series are stationary** now with p-values = 0.01 each.

```
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
```

```
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
```

6.2.2 Correlations

The p-value is 0.06. It shows a very **week positive correlation** between policy rates and inflation rates.

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

```
[1] 0.0635118
```

6.2.3 Basic Linear regression model

A linear regression model of policy_rate and inflation rates 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 (as an exercise)

6.2.4.1 Visual inspection

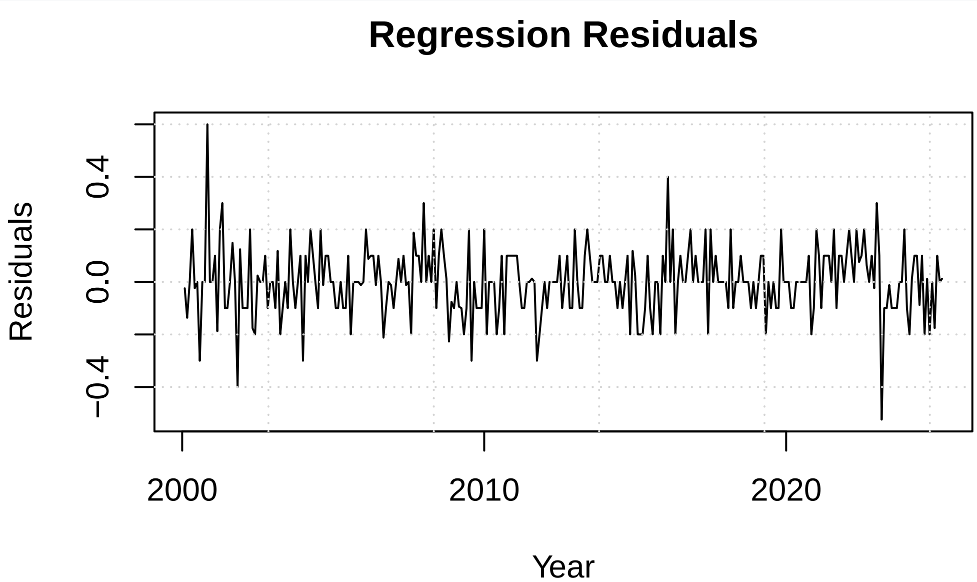
Range of Residuals

- Most residuals are between **-0.2 and 0.2** → This suggests a **moderate prediction error**. There is information left that is not used in the current model.
- **2 outliers** (±0.5) are present → These are **not necessarily problematic** unless they're influential (we check later for Cook's distance).

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).

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



6.2.4.2 Breusch-Pagan test

- **Test** for **heteroskedasticit**y (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, the **residuals are homoscedastic.**
- p<0.05 rejects the null hypothesis → residuals would be heteroskedastic

```
bptest(lin_reg)
```

```

	studentized Breusch-Pagan test

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

6.2.4.3 Shapiro test

- Test for **residual**'s normality
- Null hypothesis that residuals are **normally distributed**.
- Test 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
```

6.2.4.4 Outliers and influencial points

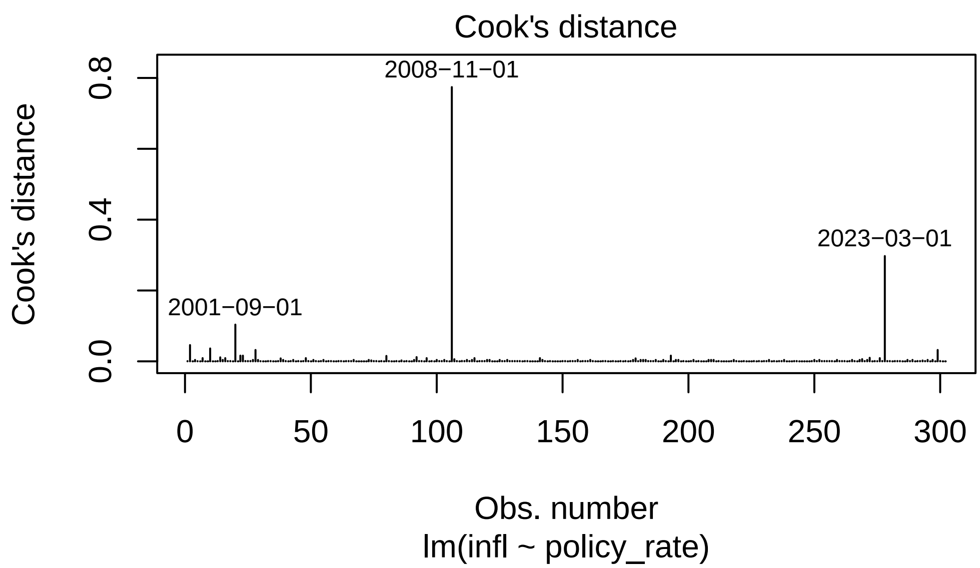
There are two large values of Cook's distance on **2008-11-01**, **2023-03-01 and 2001-09-01**. The first with Cook's distance >0.6 is **highly influential**, the other with Cook's distance around 0.3 is **moderately influential**. High Cook's distance values indicate impact on the model's coefficient, but it requires **further inspections** (e.g. is it an outlier or a data error), then a decision on how this data point should be treated (transformed or removed) should be made.

After checking the dates in the data, we did find major policy rate changes:

- 2001_09_01 was a full 1% step down from 2.75% to 1.25%, starting a continuous decrease to 0%.
- 2008_11-01 was the last 0.5% step of a continuous decrease of the policy rate from 2.25 to 0.
- 2023-03-01 the policy rate was the last 0.5% step in a continuous interest rate hike from -0.75%.

These 3 events are reflection of substantial economic interventions by the SNB, so we tend towards **accepting these residuals as facts**.

```
# plot(lin_reg, which = 1)  # Residuals vs Fitted
# plot(lin_reg, which = 2)  # Q-Q plot
plot(lin_reg, which = 4)  # Cook's distance
```



6.2.4.5 Durbin-Watson test

- Test for serial correlation
- Null hypothesis that residuals are not autocorrelated
- Test statistic 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.

```
dwtest(lin_reg)
```

```

	Durbin-Watson test

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

6.2.4.6 Summary and Interpretation of our residual tests:

- **Breusch-pagan** test for Heteroskedasticity: showed residual with constant variance (**homoskedasticity**)
- **Shapiro** test: **rejects** the null hypothesis of **normally** distributed residuals, however with sample size n=302, the non-normality may **not have great impact**.
- **Cook's distance**: several events that had great influence on the coefficient are **in fact substantial events**, so they are not errors.
- **Durbin Watson** test: **no significant autocorrelation** in residuals.

All residual tests prove that our linear model is valid and has no data quality issues.

So **why** the small R-squared? It doesn't necessarily mean that the model is wrong, the **reasons** could be that:

- Inflation is affected by **many more factors**.
- Time series data in economic events and shocks can be **noisy.**
- Linear relationship is **weak but statistically significant** and economically justifiable.

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

```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)

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
```

Interpretation:

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 0.02187) is very low, **only 6% of the variance (fluctuations)** in inflation can be explained by the model.

Lag 1 could make sense regarding the time frame and the model shows that it is statistically significant. But the direction of lag 1 is not as expected: a higher policy rate goes with higher inflation.

Lag_10 could make sense as the estimate is negative. Though it is **common** that a change in the policy rate has a **quite delayed effect** on inflation rates, but we wonder **why only Lag_10** shows this effect and nearby months don't? The overall credibility of the lag effect is **questionable**.

Our conclusion: As only 6% of variation is explained by the model and the two significant lags are against theory or questionable, we are **not convinced** by this model.

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
```

Our conclusion: 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). This is plausible. But again R squared is very low.

6.3 Excursus:

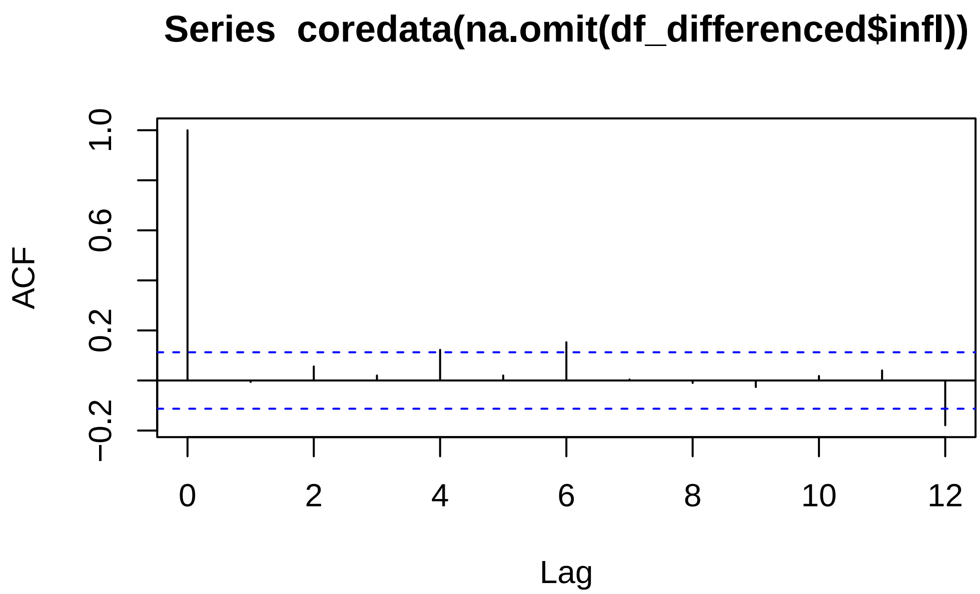
Closer look at inflation only (auto/direct correlations and an ARIMA model)

6.3.1 Correlations

Autocorrelations

The series show **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.

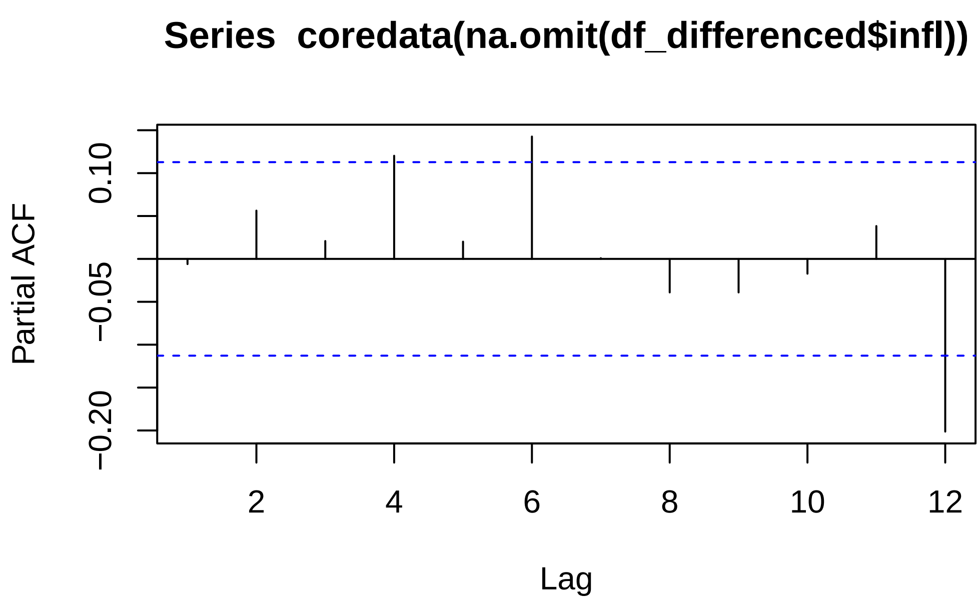
```
acf(coredata(na.omit(df_differenced$infl)), lag.max = 12)
```



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)
```



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.

```r
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.

```r
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 -398.5921 -391.1260 -362.9382 -355.4723 -353.3884 -351.3918 -349.3954
```

```r
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
```

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

```
[1] -398.5921
```

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

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

```r
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
```

```r
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.**

```r
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
```

```r
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 much helping to identify the relations between policy rates and inflation, we skip here the evaluation of residuals. But - as another exercise - we do a forecasting of inflation based on this ARIMA model.

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
```

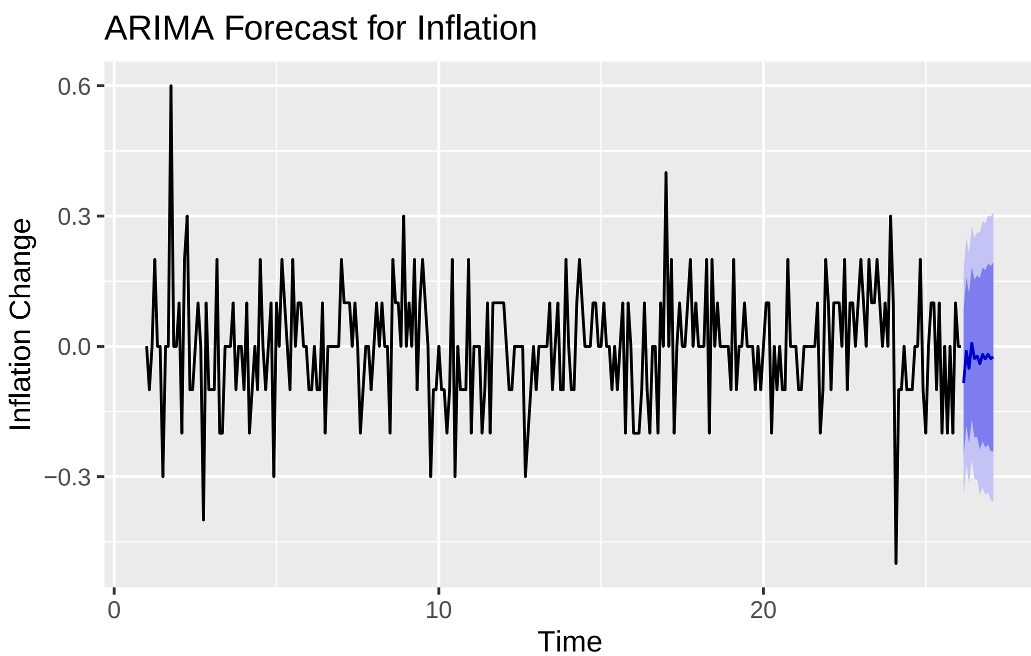
```
forecast_arima$lower       # Lower bounds (80% and 95%)
```

```
              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
```

```
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
```

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



Last known and forecasted inflation levels

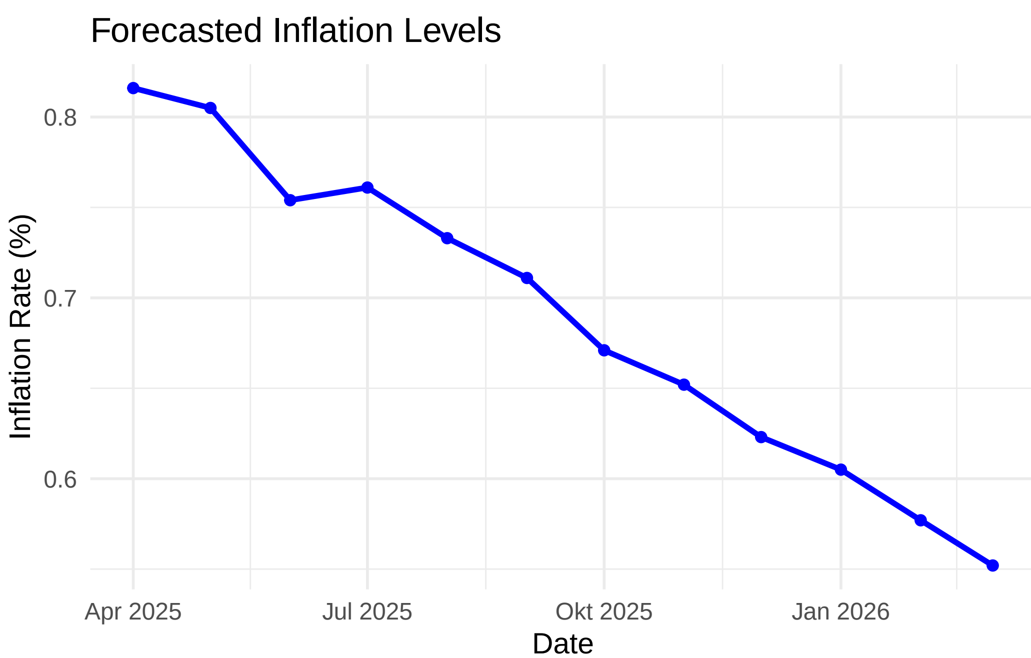
We get the last date from indexed too object, generate 12 monthly forecast dates and produce forecast table and plot.

```
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

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 <- 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),
```

```r
  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
```

```r
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 to 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.

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?

No: Inflation rates do not Granger-cause the 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
```

6.6.3 Do major SNB changes in policy rates ('events') explain inflation rates.

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

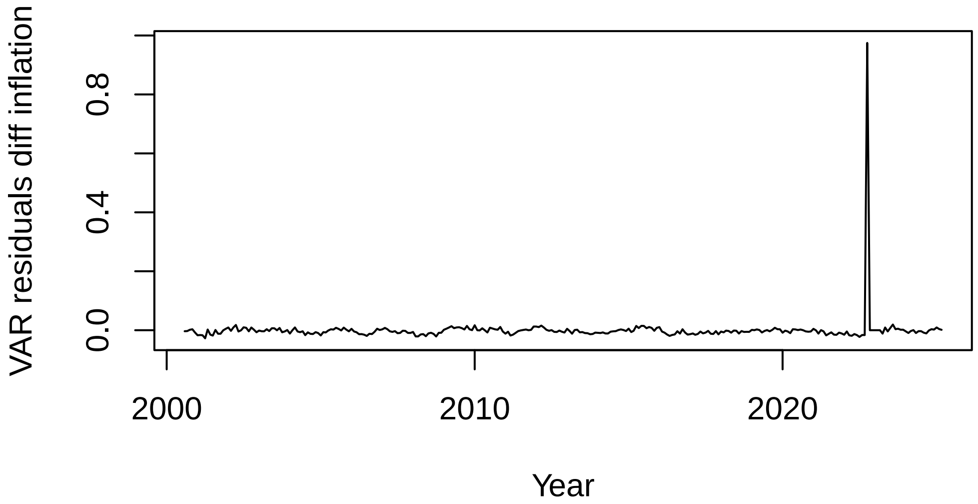
```
event_2022_10:infl.l3           0.0192806  0.0267348  0.7212 0.4713950
event_2022_10:event_2022_10.l4  0.0035873  0.0836355  0.0429 0.9658179
event_2022_10:infl.l4           0.0198585  0.0268170  0.7405 0.4596005
event_2022_10:event_2022_10.l5 -0.0059441  0.0837218 -0.0710 0.9434495
event_2022_10:infl.l5           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"]
```

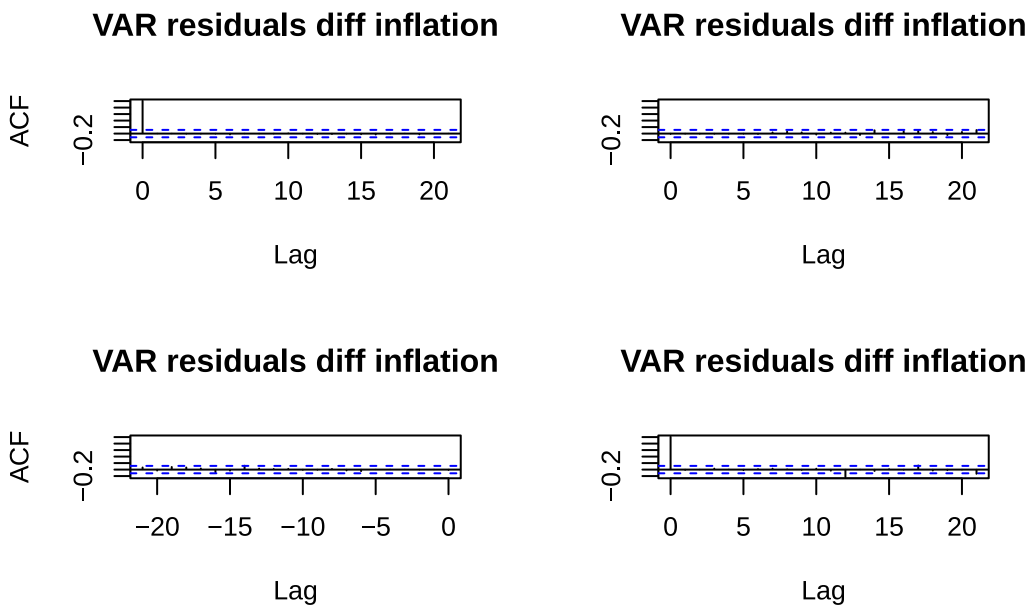
```
$Granger

    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
```

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

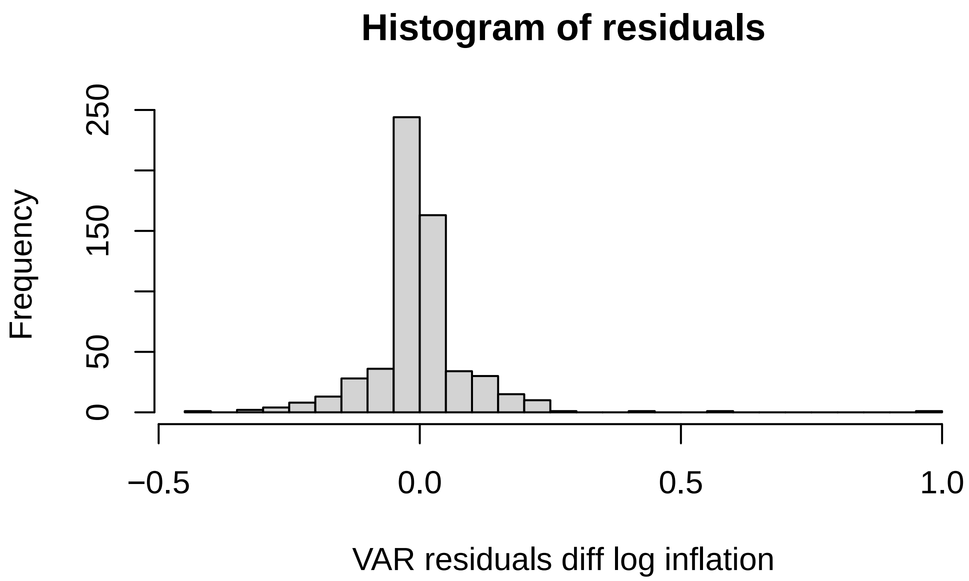
```r
Resid_VAR <- resid(VAR_model)
p <- VAR_model$p
residual_dates <- tail(index(df_differenced), -p) # Remove first p dates
plot(x = residual_dates,
     y = Resid_VAR[,1],  # First equation's residuals
     type = "l",
     ylab = "VAR residuals diff inflation",
     xlab = "Year")
```



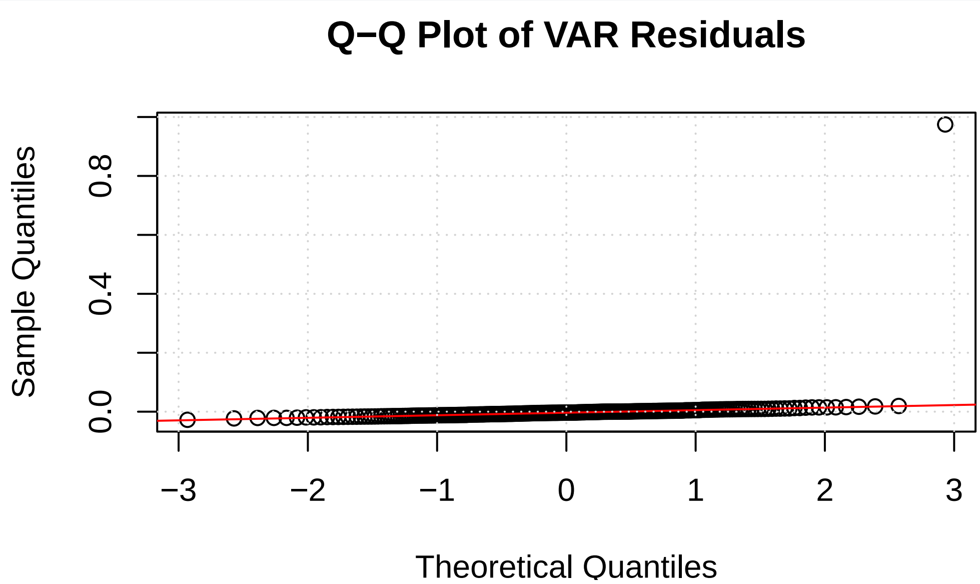

```
# Plotting ACF, histogram, and Q-Q-plot of residuals
acf(data.frame(Resid_VAR), main="VAR residuals diff inflation") # ACF of residuals
```




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




```
# 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()
```




```
# 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
```

```
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
```

Summary of residual tests:

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 auto-correlated shows with a p-value of 0.8502, that the **residuals are not auto-correlated**.

The peak in residuals around the **October 2022** event: may reflect the **impact of a major policy intervention**, aligning with the significant Granger causality result. After checking the dates, 2022 October was exactly where SNB was continuously **lowering rates** for months, due to economic slow down in Europe, global **energy crisis**, and a **25% draw back** of global **stock markets**.

Overall interpretation of residual analysis:

Residuals are not **heteroskedastic or auto_correlated,** but the non-normality remains an issue. It **might** be neglected as we have 302 observations (large n tends towards normality). The model is overall valid, though incorporating other factors or considering nonlinear models in futures studies could be beneficial.

Chapter 7

Findings, limitations and discussion

7.1 Key findings

1. **Linear Regression model with Lag Effects shows weak relations**
   A basic linear regression showed no significant relationship between policy rates and inflation ($p > 0.05$; $R^2 \approx 0.004$). When including lags of up to 12 months, lag 1 and lag 10 were statistically significant. While in this context a lag of 10 months might be feasible, we still have doubts. Overall explanatory power was low (adjusted $R^2 \approx 0.02$). It suggests only weak evidence of delayed effects.

2. **Linear Regression model with SNB events shows evidence of one event in 2022**
   After treating major SNB policy changes as events, October 2022 had a statistically significant effect on inflation (p close to 0). This suggests that a major policy change (from negative to positive rates in 2022) might have had an effect on inflation. However, overall explanatory power was still very low ($R^2 \approx 0.04$).

3. **Granger Causality (VAR Model) but not deterministic**
   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 ($p \approx 0.29$). Either the SNB really acts independently of recent inflation trends, which is against theory, or we just did not find an appropriate model to prove that SNB policy reacts to inflation rates.

4. **ARIMA forecasting suggests reverting behavior**
   An ARIMA(5,1,0) model on inflation rates shows significant auto-regressive effects of lags 1-5 on inflation rates. The negative estimates in all lags suggest an auto-reverting effect: a rise in inflation is followed by an decrease. We have also done forecast, but no significant changes of inflation were predicted.

7.2 Limitations

- **Limited Prediction Power**: Most models (especially linear regression) show very low R^2 values, indicating weak predictive power.
- **Only two Variables**: The models only consider two variables: policy rate and core inflation. Other factors like global energy prices, the pandemic or global trade conflicts 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.

7.3 Discussion

Are the results from linear regression (SNB event), ARIMA (5,1,0) and Granger causality test consistent?

Linear regression: There is an effect of a major SNB change in policy rate, but the model only explains a small portion of variance in inflation rates.

ARIMA: It uses past values of inflation to forecast future inflation so it is a univariate model, not taking into account other variables (e.g., policy events).

Granger Causality Test: Multivariate test: It checks if variables (like our events or interest rate changes) help to explain each other better then they are explained by themselves.

The results are actually consistent, without contradiction:

Based on the linear regression model a major change in SNB policy rates explains inflation rates variance, but only a very small portion of it. ARIMA shows an auto-regressive reverting effect, inflation can be in parts be explained by itself. But , without further checking the quality of the ARIMA model, the respective forecast based on this model was not convincing. Finally, the Granger causality test shows an effect of policy rates on inflation, suggesting that it can help explaining inflation. The other way round, there is no effect of inflation rates on policy rate.

So, our analysis **suggests an effect of SNB policy rates on inflation**, which is itself auto-correlated. But all relationships and model are rather to very weak. Meaning our results were **consistent** without contradiction but only show **weak effects**.

Chapter 8

Conclusion

Our team analyzed the relationship between SNB policy rates and inflation rate in Switzerland. We applied several time series models for the analysis.

Weak connections between the two variables were found, lacking strong correlation or deterministic evidence.

However, some non-deterministic effects were observed:

- Granger causality indicates that past policy rate changes have some predictive value for inflation.
- Event-based regression suggests a mild relation between a major change in SNB policy on inflation.
- ARIMA suggests an auto-regressive and reverting behavior of the inflation rates.

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

Bibliography

[Infl00] *Inflation rates in Switzerland*. URL: https://www.worlddata.info/europe/switzerland/inflation-rates.php - retrieved: 2025-05-18. —Worlddata.info

[Inte00] Interest rates and threshold factor. URL: https://data.snb.ch/en/topics/snb/cube/snbgwdzid - retrieved: 2025-05-14. — Interest rates and threshold factor

[Mark23] Marking 30 years of the Taylor rule | Stanford Institute for Economic Policy Research (SIEPR). URL: https://siepr.stanford.edu/news/marking-30-years-taylor-rule - retrieved: 2025-05-14

[Schi00] SCHINDLER, JOHN: The Swiss National Bank's Three-month Libor Target (2000)

[Snbd00] SNB data portal. URL: https://data.snb.ch/en/topics/snb/cube/snbgwdzid - retrieved: 2025-05-15. — SNB data portal