SNB_policy_rate_and_inflation

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Table of contents

Chapter 1

Project: Time series analysis in Finance

Chapter 2

How do the policy rates of the Swiss National Bank and the Swiss inflation rates interact?

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.

Chapter 3

Introduction

3.1 Contextual Background

Brief overview of monetary policy and inflation dynamics in Switzerland. Importance of understanding policy rate interactions with core inflation. Brief introduction to the role of the Swiss National Bank (SNB).

3.2 Problem Statement

Explanation of the specific problem: understanding how SNB policy rates and Swiss core inflation rates interact dynamically. Brief justifiction why this relationship is economically relevant or timely.

Chapter 4

Motivation and Objective

4.1 Project Objectives

For example: Investigate the dynamic relationship between SNB's policy interest rates and Swiss core inflation. Determine directional causality between these two variables. Analyze the impact and timing of policy rate adjustments on inflation.

4.2 Motivation

Personal/team motivation: We share an academic interest in exploring the world of financial analysis, and it is also great that we can add practical relevance in a Swiss context. Additionally, it is applicable to career interests (finance/trading). 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, and researchers.

4.3 Research Questions

For example: Does SNB policy rate significantly influence core inflation? Is there evidence of bidirectional causality between policy rates and core inflation? How quickly and how strongly do core inflation rates respond to policy changes?

Chapter 5

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 6

Data selection

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, interest rate on sight deposits above threshold, special rate, SARON fix etc. For inflation data, we have used core inflation, trimmed mean from “Consumer prices – SNB and SFSO core inflation rates” [Cons00b]. In Dataset 1, the threshold is optimal to be used as the interest rate policy target, and because before 2009 there is no threshold data in Dataset 1, we have used the special rate. From 13 June 2019, the special rate was based on the current SNB policy rate plus a surcharge of 50 basis points. The special rate always amounted to at least 0.5 percent”[Inte00]. 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 could give certain findings and conclusions applying ARIMA, VAR, and linear regression. However, we were not satisfied with the different rate types; it seemed puzzling that we had to convert and “compromise” to the seemingly complicated data. So, we researched more, and we did find a second dataset (afterwards called Dataset 2). It only contains 2 types of data to be considered official interest rate, which is more consistent and more appropriate to take as the policy rate. “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 the second dataset, we’ve also done a VAR to evaluate if there is causality between policy rate/target to inflation, or inflation to the policy decisions, which with both datasets, no causality was proven. This also gives us more confidence that both datasets represent the reality well, even though the dataset 2 seemed more consistent.

Chapter 7

Team collaboration and tool set

7.1 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 delved 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.

7.2 Collaborative tools

7.2.1 Brainstorming and ideation:

Miro Board - Initial concept visualization - Real-time collaboration on ideas and analysis structure - Organizing literature and conceptual mapping

7.2.2 Task Distribution and Project Management

Excel - Task assignment tracking - Deadlines and progress monitoring - Visualization of milestones and status

7.2.3 Coding and Version Control

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

7.2.4 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.

7.3 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 set 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 8

SNB_policy_rate_and_inflation

Chapter 9

Analysis of SNB policy rates and Swiss inflation rates

9.1 Data evaluation & preparation

9.1.1 libraries

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

9.1.2 Load data

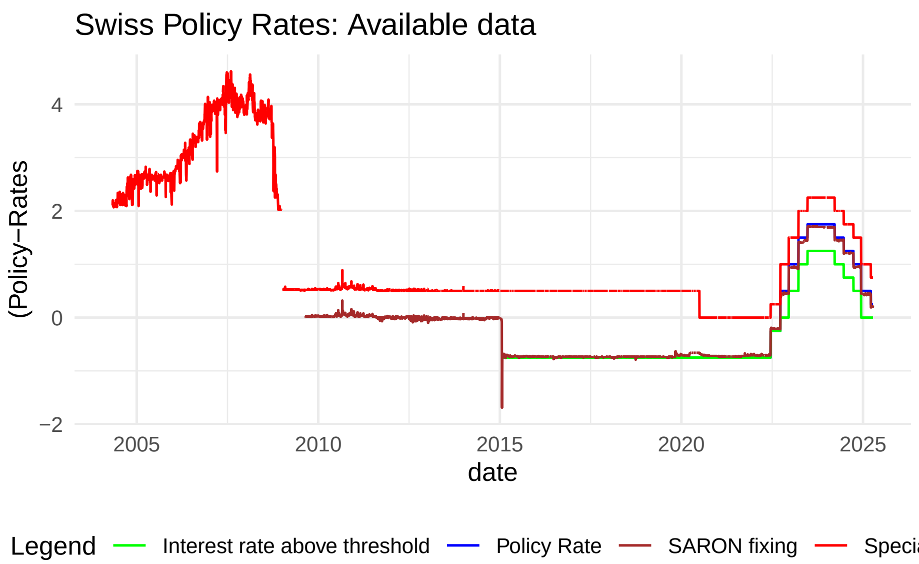
```
policy_rate_data <- read_excel("../data/snb-data-snbgwdzid-en-all-20250414_1000.xlsx",
                               col_types = c("text", "numeric", "numeric", "numeric", "numer
                               skip = 21)

inflation_data <- read_excel("../data/snb-data-plkoprinfla-en-all-20250422_0900.xlsx",
```

```
                              skip = 14) #skipping the first 14 rows
```

9.1.3 Evaluation of appropriate policy rate data

Looking at different available columns in the policy rate data from SNB website.

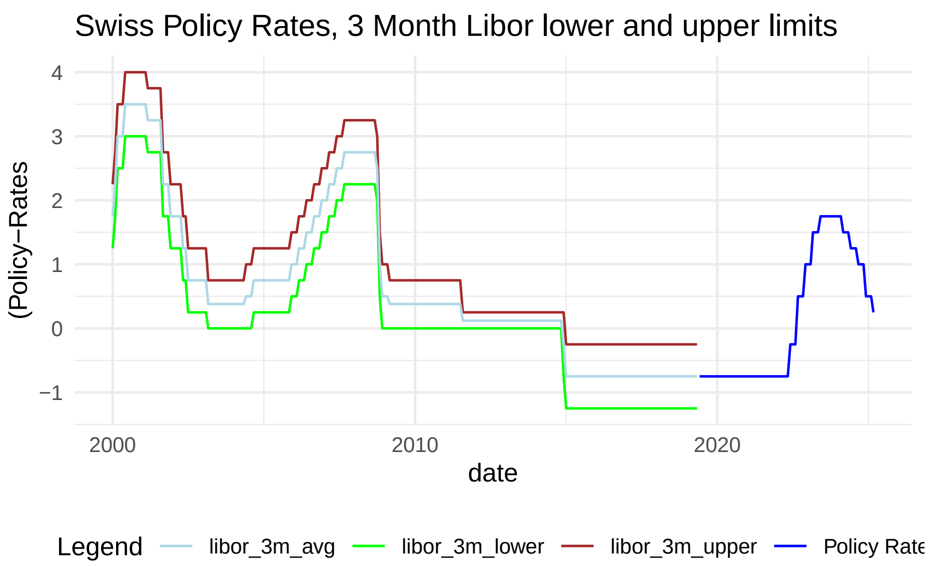
```
pr_full <- policy_rate_data %>%
  as_tibble() %>%
  dplyr::select(date = "Overview",
         policy = "SNB policy rate",
         ir_above = "Interest rate on sight deposits above threshold",
         sar_fix = "SARON fixing at the close of the trading day",
         special = "Special rate  (Liquidity-shortage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



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

```
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")
```



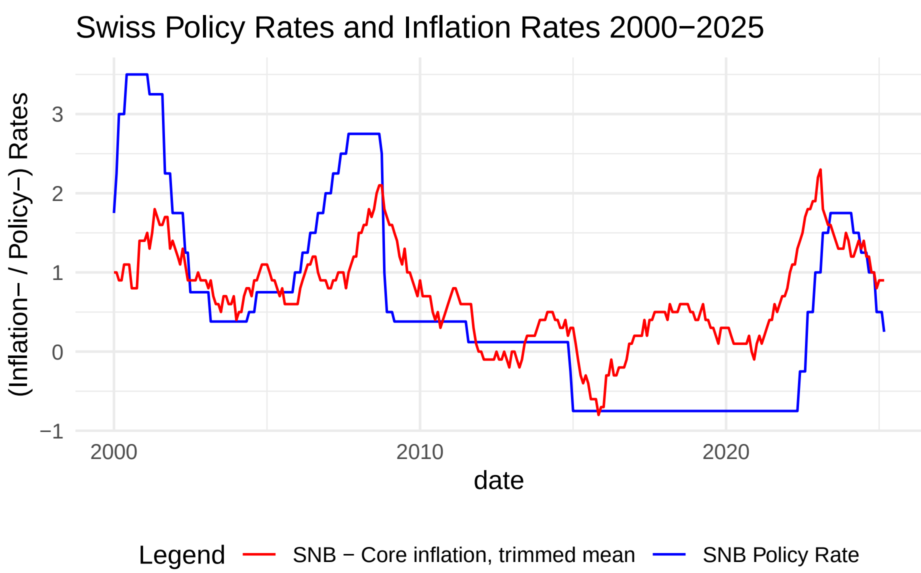
9.1.5 Further data preparation, data merge and timeseries object

```
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
         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
)
```

9.1.6 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")
```



9.2 Stationarity & linear regression models

9.2.1 Stationarity

Both series are not stationary.

```r
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
```

```r
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

```r
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
```

```r
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.

9.2.2 Correlations

Very week positive correlation.

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

```
[1] 0.0635118
```

9.2.3 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)
```

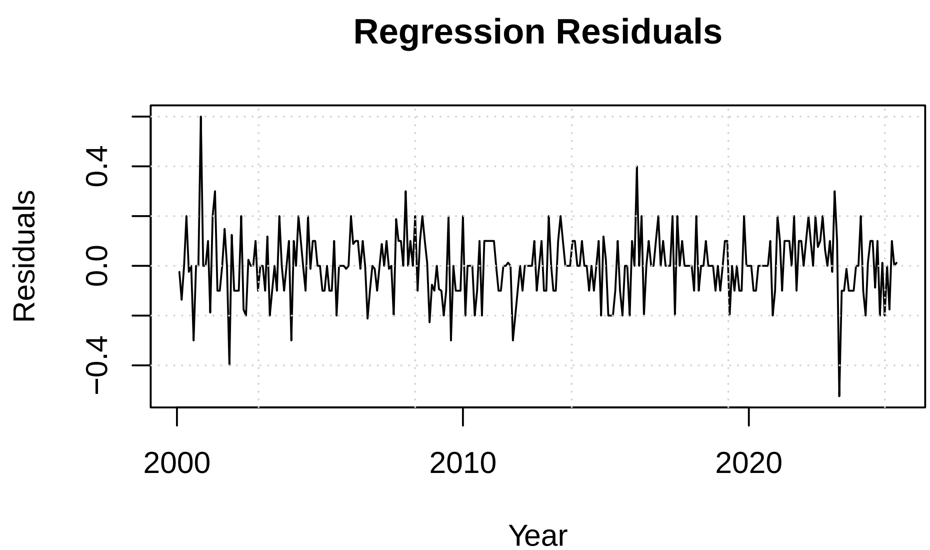
```
Call:
lm(formula = infl ~ policy_rate, data = df_differenced)

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
```

9.2.4 Residual analysis

9.2.4.1 Residual plot

The plot shows large residuals, confirming the low R squared.

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



9.2.4.2 Breusch-Pagan test

Breusch-Pagan test for Constant variance, with null hypothesis that Residuals are homoscedastic shows, that there is no significant evidence of heteroskedasticity in the linear regression model.

```
bptest(lin_reg)
```

```

	studentized Breusch-Pagan test

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

9.2.4.3 Shapiro test for normality

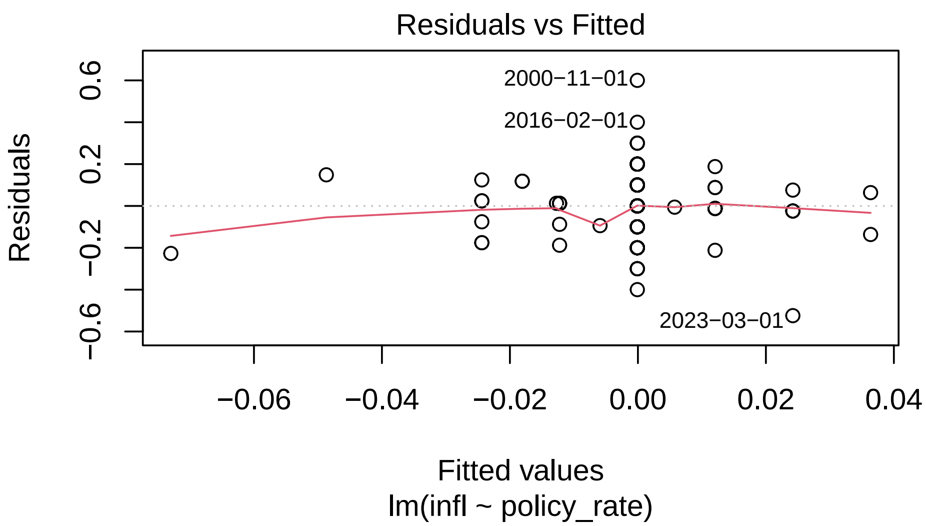
Shapiro test for normality with null hypothesis that Residuals are normally distributed shows a strong rejection of the null hypothesis: The residuals of the model are NOT normally distributed. With n = 302 we might disregard non-normality.

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

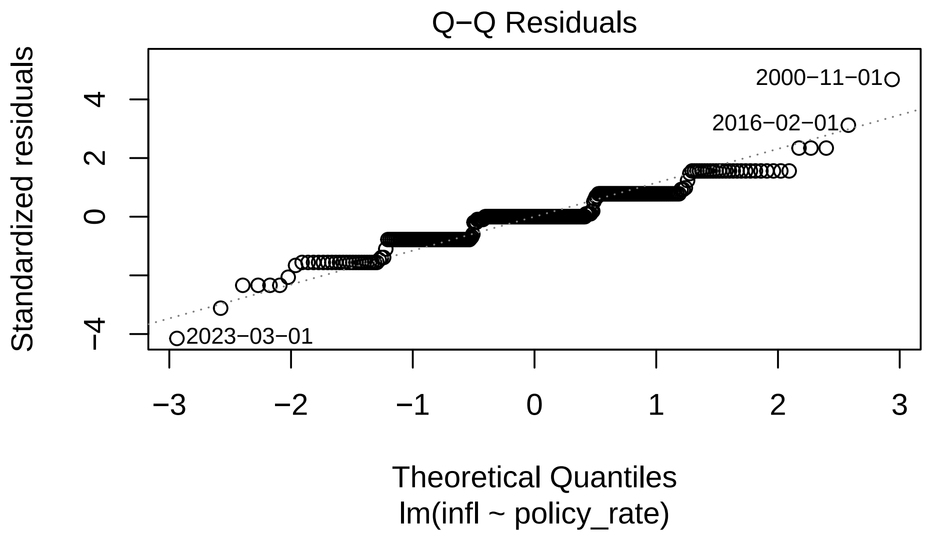
```

	Shapiro-Wilk normality test

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

9.2.4.4 Visual check for outliers and influencial points

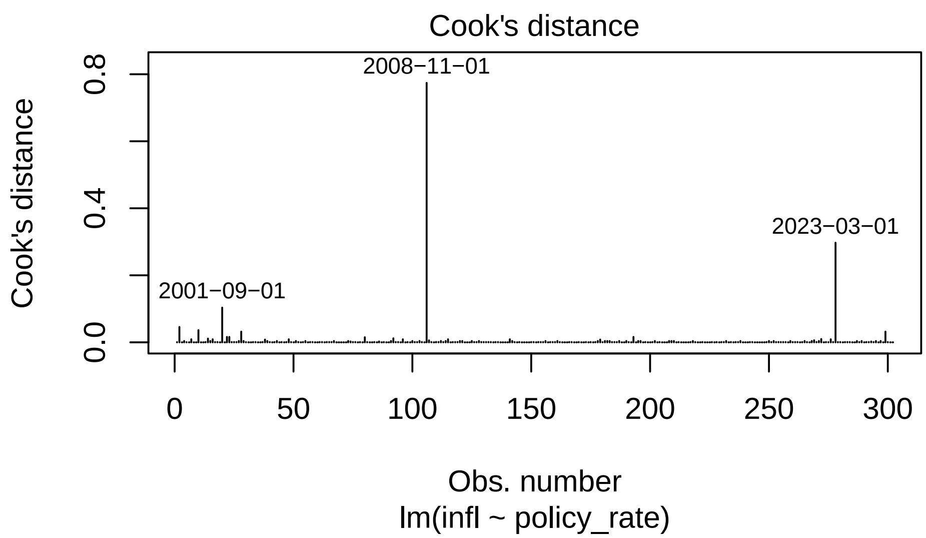
```r
plot(lin_reg, which = 1)  # Residuals vs Fitted
```




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




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



9.2.4.5 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.

```
dwtest(lin_reg)
```

```

	Durbin-Watson test

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

9.2.5 Alternatives to the basic linear model

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

Create lagged variables

```
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)
```

```r
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), but R squared (0.06249, adjusted 002187) is very low.

We are not sure if a lag of 10 months makes sense from a logical point of view.

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.

Overall we are not convinced by this model.

9.2.5.2 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 +
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 R squared is very low.

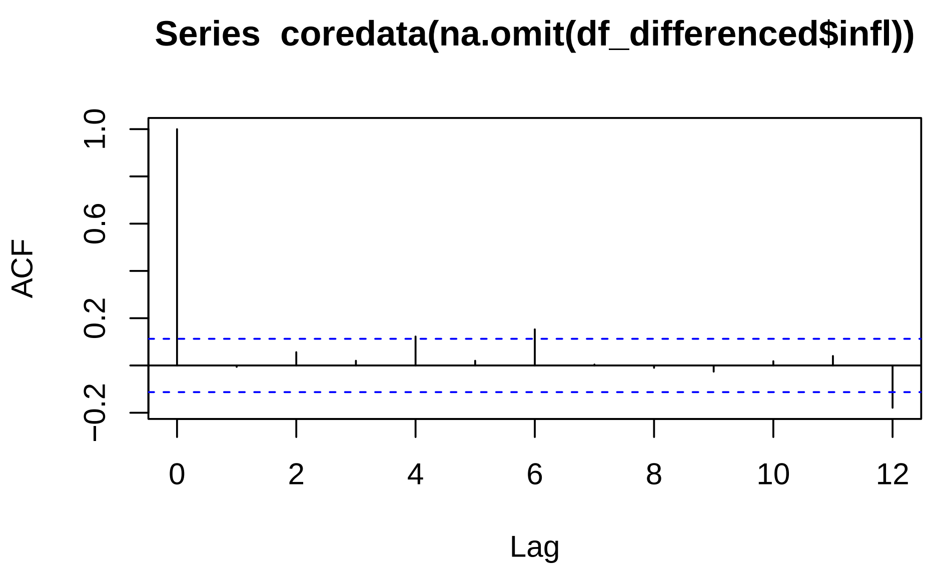
9.3 Excursus: Closer look at inflation only (auto/direct correlations and an ARIMA model)

9.3.1 Correlations

9.3.1.1 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.

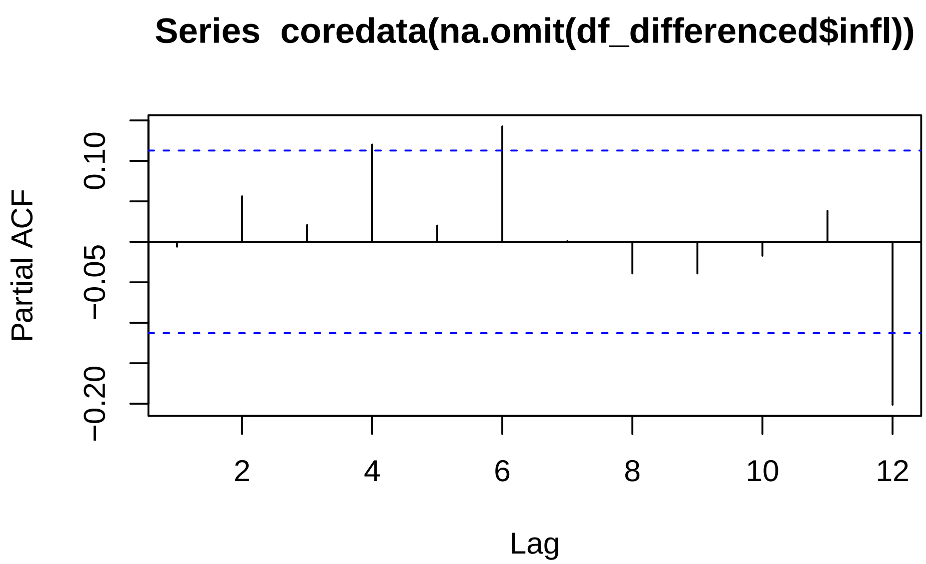
```
acf(coredata(na.omit(df_differenced$infl)), lag.max = 12)
```



9.3.1.2 Direct correlations

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

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



9.3.1.3 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).

9.4 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 =  FAI
  }
}
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
```

```
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] -398.5921
```

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

9.5 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
```

```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: ar1 to ar5 are highly significant at the 95% confidence interval. The negative values of the coefficients reveals that a positive change in the time series in the previous period leads to a negative change in the subsequent period.

```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 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.

9.5.1 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%)
```

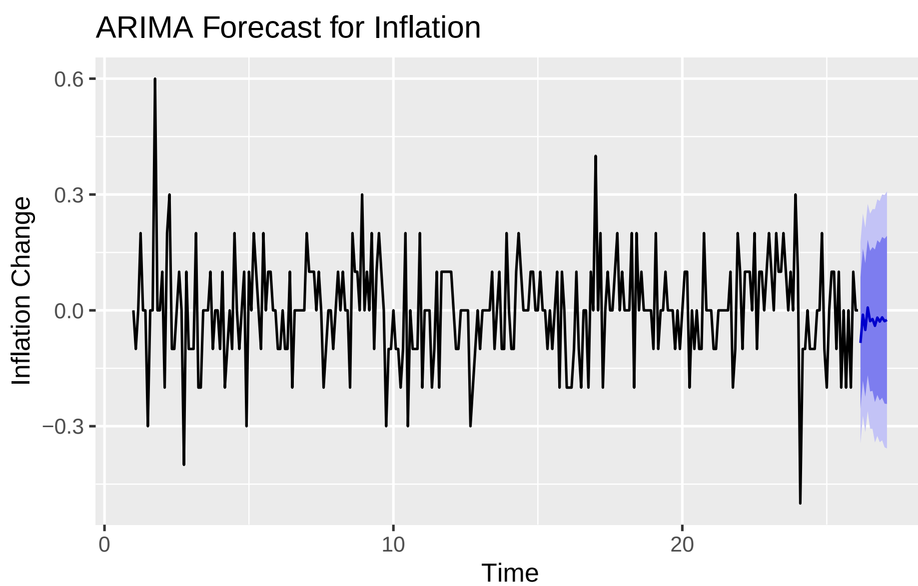
```
              80%        95%
Mar 26 -0.2545725 -0.3447102
Apr 26 -0.1822664 -0.2728236
May 26 -0.2237561 -0.3153641
Jun 26 -0.1679378 -0.2607474
Jul 26 -0.2100036 -0.3063514
Aug 26 -0.2085356 -0.3070584
Sep 26 -0.2375923 -0.3421668
Oct 26 -0.2190504 -0.3250701
```

```
Nov 26 -0.2333571 -0.3414642
Dec 26 -0.2263109 -0.3365192
Jan 27 -0.2415563 -0.3545805
Feb 27 -0.2424099 -0.3576329
```

```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")
```



9.5.1.1 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 = 1
```

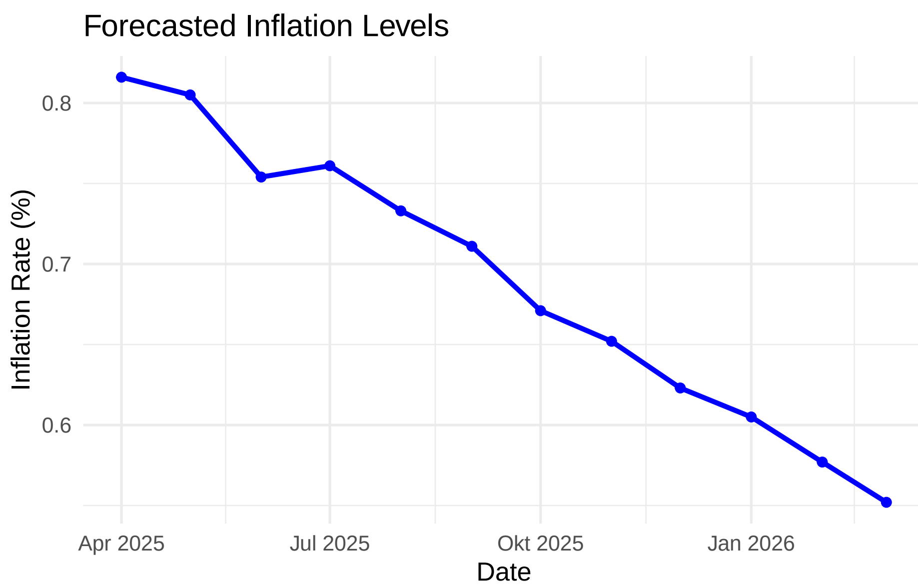
Forecast table and plot.

```
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.

9.6 Vector autoregression and Granger causality

9.6.1 Do policy rates explain inflation rates?

```
VAR_model <- VAR(cbind(df_differenced$policy_rate, df_differenced$infl) , ic="AIC", lag.max
# 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 ability.

9.6.2 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.

9.6.3 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
```

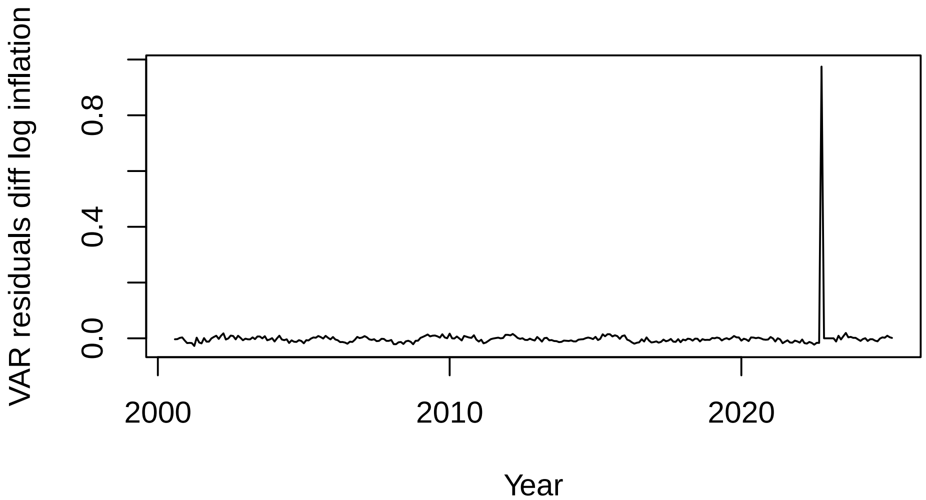
```r
causality(VAR_model, cause="event_2022_10")["Granger"]
```

```
$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
```

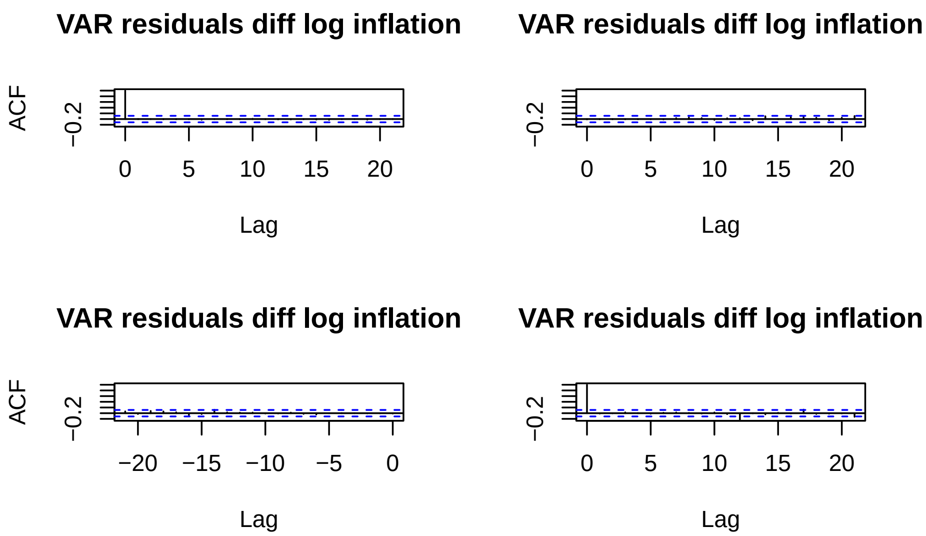
There is **strong evidence that event_2022_10 Granger-cause inflation** (at lag 5 and lag6). This means, that the SNB policy rate change in autumn 2022 influenced the Swiss inflation rates.

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

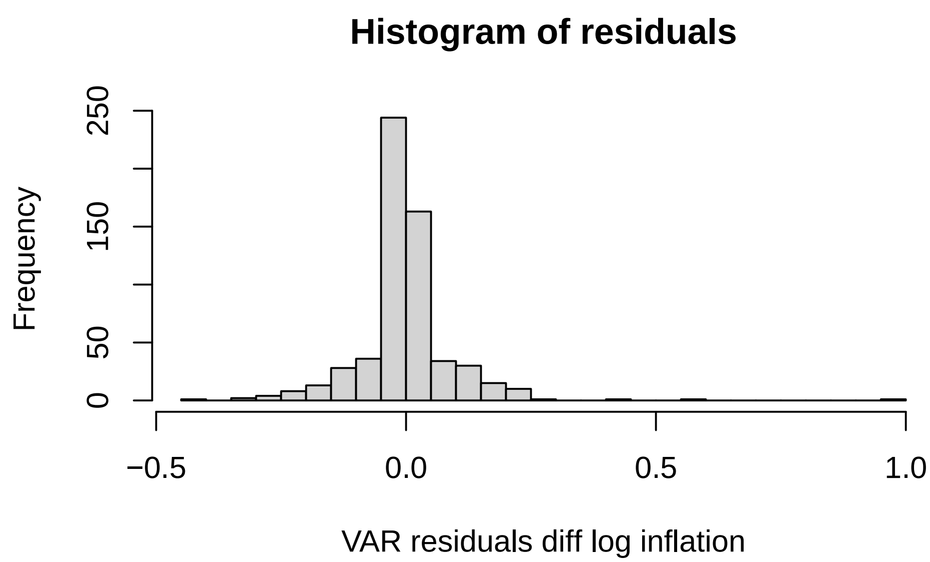
```r
Resid_VAR <- resid(VAR_model)
p <- VAR_model$p
residual_dates <- tail(index(df_differenced), -p) # Remove first p dates
plot(x = residual_dates,
     y = Resid_VAR[,1],  # First equation's residuals
     type = "l",
     ylab = "VAR residuals diff log inflation",
     xlab = "Year")
```



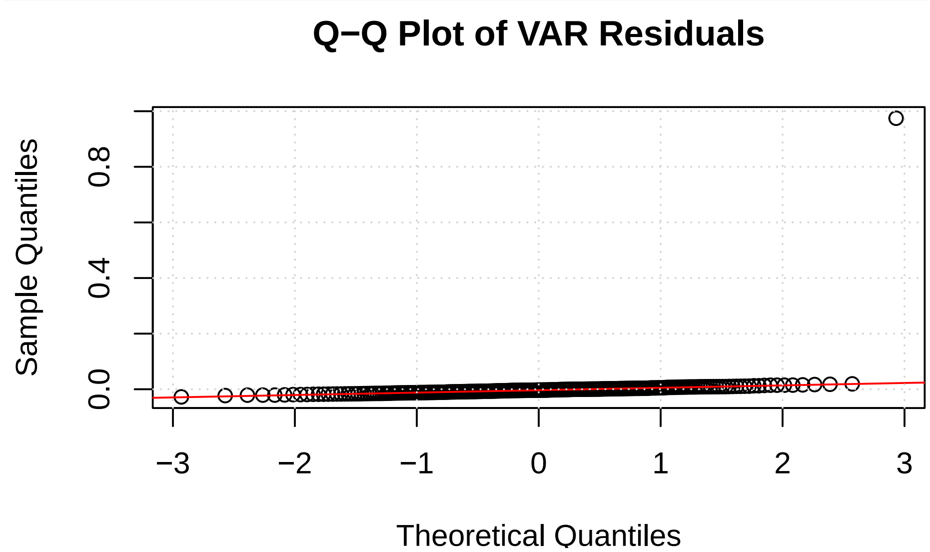

```
# Plotting ACF, histogram, and Q-Q-plot of residuals
acf(data.frame(Resid_VAR), main="VAR residuals diff log inflation") # ACF of residuals
```




```
hist(Resid_VAR, breaks=25, main="Histogram of residuals", xlab="VAR residuals diff log infla
```




```
# 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 h
```

```
    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
```

```
$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
```

```
    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 10

Findings, discussion and limitations

10.1 Lead-lag effect and VAR

Lead-lag models shows that special_lag11 (11 months ago) has a statistically significant and positive effect on current inflation.This suggests a delayed association: changes in the special variable may be linked to inflation nearly a year later. However, the overall model fit is modest (Adjusted R^2 ~8.4%), and no other lags were significant. The Granger causality test (VAR) found that past values of special (lags 1 to 12 as a group) do not significantly improve forecasts of inflation. In other words, knowing the past values of special does not help predict future inflation beyond what past values of inflation already tell us. We have tested this with both datasets and got the same result, which also gives the result more credibility. Overall, there is weak evidence of a specific delayed effect (lag 11) of special on inflation, but no broader or systematic predictive relationship. The effect might be real but isolated, or due to noise in the data. The Granger test confirms that special is not a reliable predictor of inflation when considering its full lag history.

10.2 ARIMA

ar2, ar4, ma2, and ma4 are significant at the 95% confidence level because their p-values ($Pr(>|t|)$) are less than 0.05. ar2 and ar4: The 2nd and 4th past inflation changes (lags) have a statistically significant effect on today's change in inflation. ma2 and ma4: The forecast errors from 2 and 4 months ago are also significant predictors. Inflation today is significantly influenced by the change in inflation 2 and 4 months ago, and by past prediction errors from 2 and 4 months ago.

ARIMA prediction

Date	Forecast_Inflation	Forecast_Change	Lower_95	Upper_95

1 2025-04-01 0.900 0 -0.237 0.238 2 2025-05-01 0.901 0 -0.237 0.238 3 2025-06-01 0.901 0 -0.237 0.238 4 2025-07-01 0.902 0 -0.237 0.238 5 2025-08-01 0.902 0 -0.237 0.238 6 2025-09-01 0.902 0 -0.237 0.238 7 2025-10-01 0.903 0 -0.237 0.238 8 2025-11-01 0.903 0 -0.237 0.238 9 2025-12-01 0.904 0 -0.237 0.238 10 2026-01-01 0.904 0 -0.237 0.238 11 2026-02-01 0.904 0 -0.237 0.238 12 2026-03-01 0.905 0 -0.237 0.238

Predicted change each month is 0.04. This is very close to zero, suggesting that your model expects almost no change in inflation month-to-month during the forecast horizon. These symmetric intervals around zero mean the model has low confidence in predicting a strong directional trend. Inflation might: - Increase slightly - Decrease slightly - Or stay flat The forecast suggests inflation will remain stable over the next 12 months, hovering around 0.90%–0.91%. Forecast Change = 0 each month → the model expects no significant monthly change in inflation. The 95% confidence interval ranges from -0.237% to $+0.238\%$, showing moderate uncertainty around a flat trend. **Overall**: Inflation is forecasted to stay steady, with small possible fluctuations up or down.

Chapter 11

Discussion

Are the results consistent?

ARIMA Result: Univariate model: It uses only past values of inflation to forecast future inflation. The ARIMA (4,1,4) model shows inflation is nearly constant going forward, with very small changes predicted. It does not include other variables (e.g., policy events).

Granger Causality Result: Multivariate test: It checks if another variable (like an event or interest rate change) helps predict inflation. You found no Granger causality, meaning those events do not add predictive power beyond inflation's own past.

The results are actually consistent, without contradiction:

Granger says: "Other variables don't help predict inflation." ARIMA says: "Inflation doesn't change much — its own past barely predicts anything new either."

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

Chapter 12

Conclusion

Chapter 13

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