Homework1

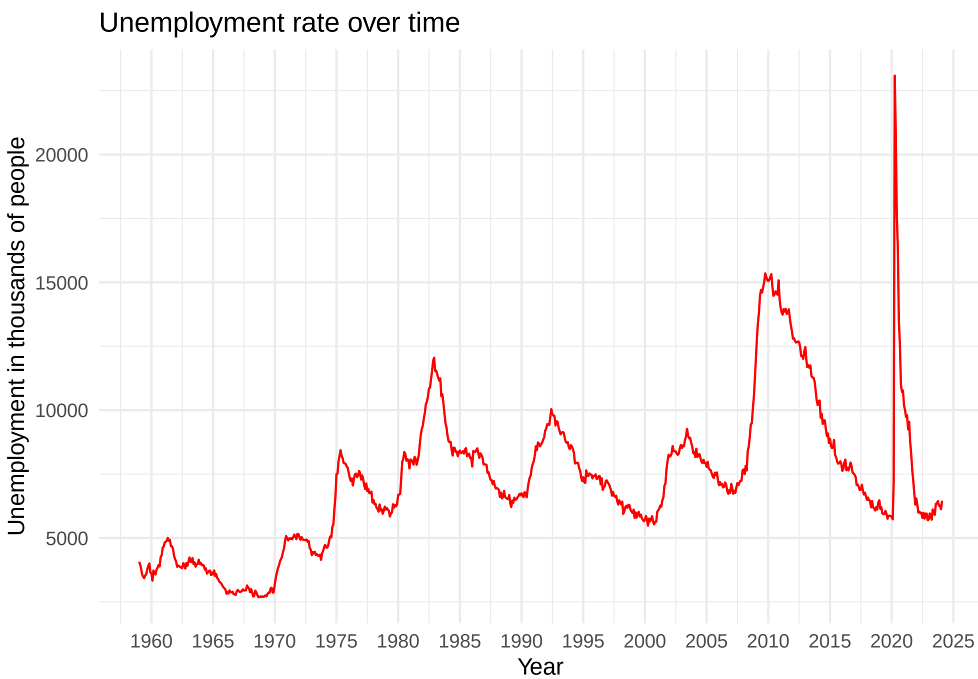
Erdan Beka, Cyril Scheuermann, Roman Krass, Keijo Nierula

2024-04-14

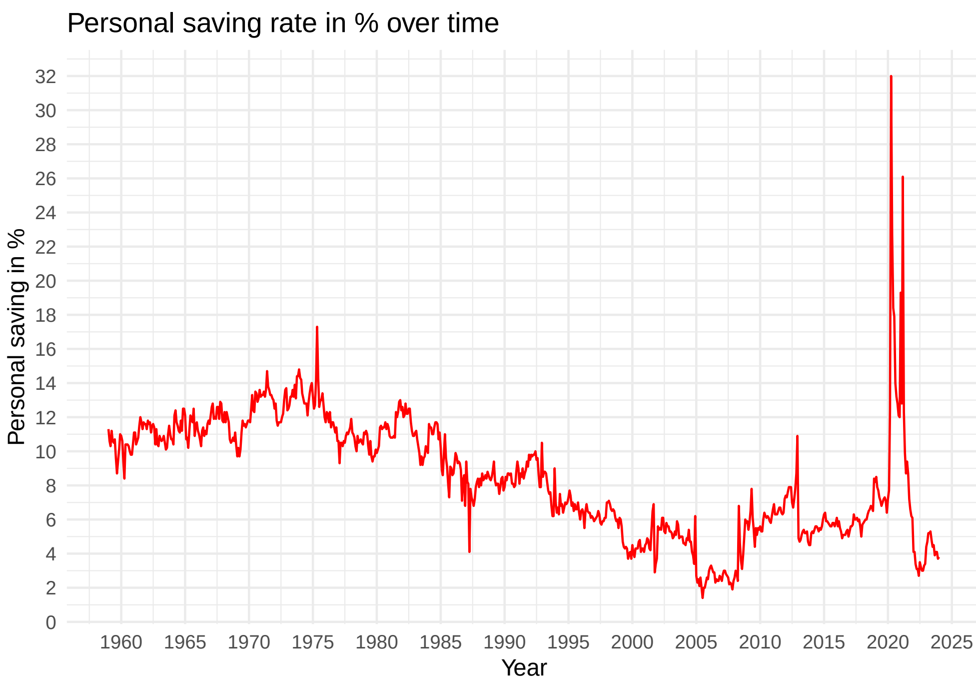
Part 1

```
##         DATE UNEMPLOY       DATE    POP       DATE PSAVERT
## 1 1948-01-01     2034 1952-01-01 156309 1959-01-01    11.3
## 2 1948-02-01     2328 1952-02-01 156527 1959-02-01    10.6
## 3 1948-03-01     2399 1952-03-01 156731 1959-03-01    10.3
```

When looking into the different datasets, we can see that the data doesn't have the same time period. Because of that when combining the three datasets there would be some NAs if we just would join the data. We can solve this by using the smallest common date range of the three datasets.



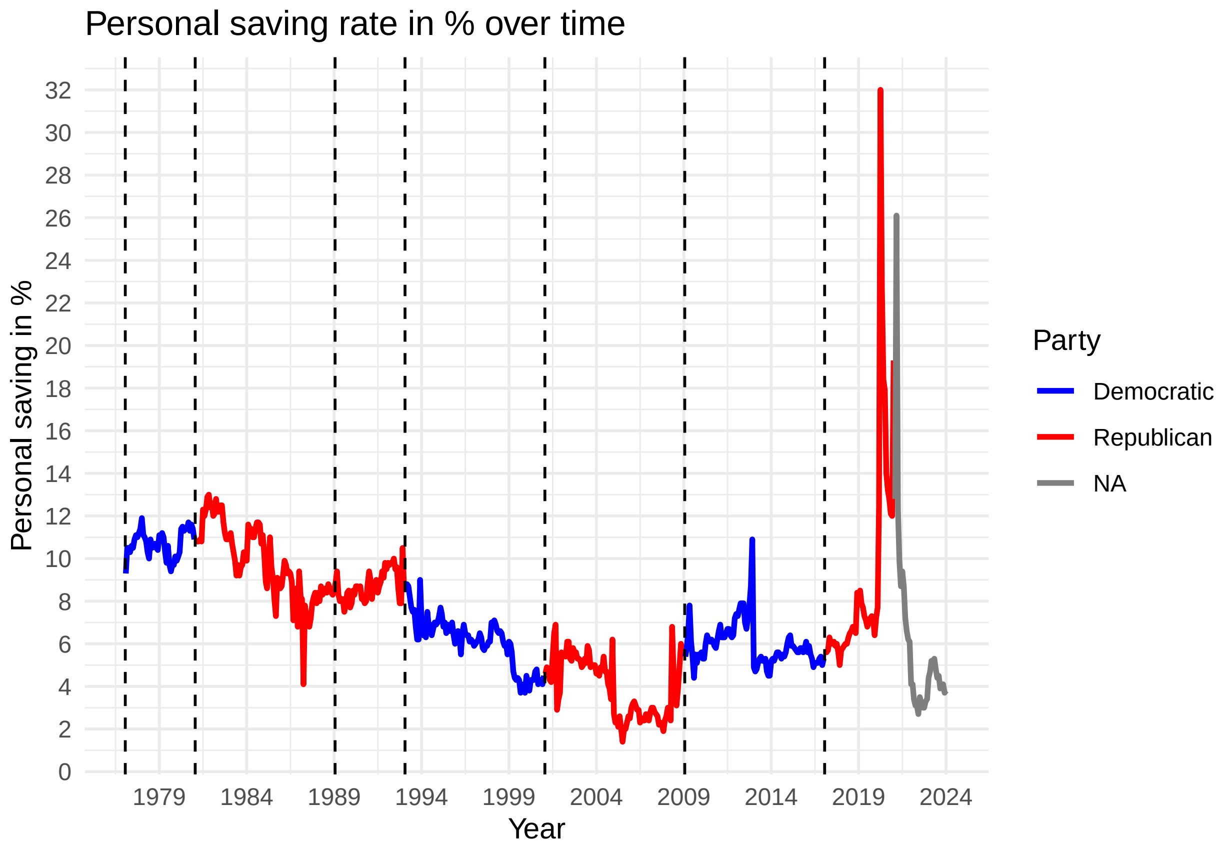
In the plot we can see that the number of unemployed people has a lot of variation over time. But in this plot we just see the number of people that are unemployed. It would be interesting to see the unemployment rate in percent. What also can be seen very clearly is the COVID-19 pandemic in 2020. The number of unemployed people increased a lot in this year. In the plot we can also see an increase in the number of unemployed people in the years 2008 and 2009. This is the financial crisis that happened in these years.



In the plot we can see that the personal saving rate decreased from about 1976 to 2007 from about 13% to 2%. After that the saving rate increased again to about 7% in 2020. Something extreme in the plot is the increase of the saving rate during the COVID-19 pandemic from 2019 to 2022. The saving rate increased from about 7% to 32% in 2020. This is a huge increase in the saving rate. After that the saving rate had a big de and increase. After the pandemic the saving rate dropped to about 3%. This makes sense because the people saved a lot of money during the pandemic and after the pandemic they started to spend the money again.

Part 2

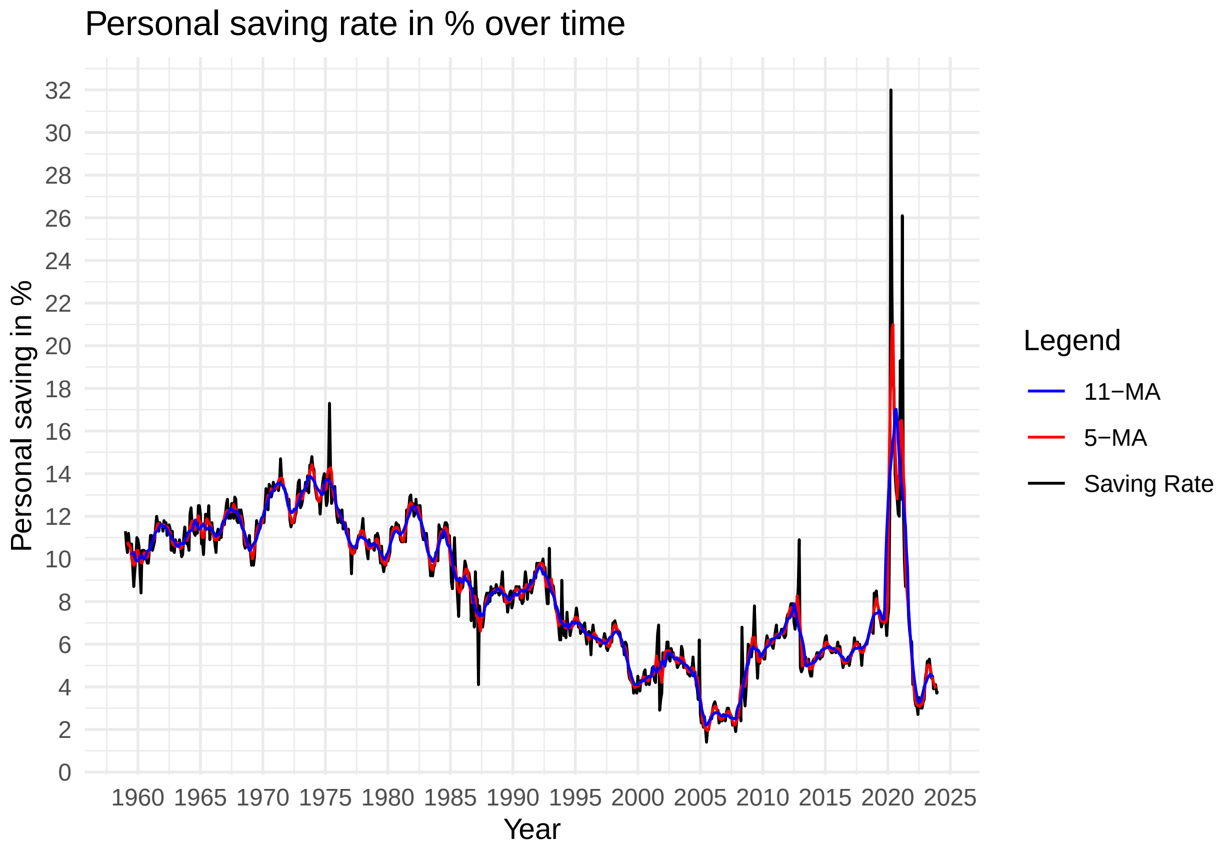
We would like to visualize how the ruling party and the election year affect unemployment and personal saving rate. Recreate the timeplots with the ruling parties shown by their color. Indicate also the election years on your plots. Start from Carter's presidency.



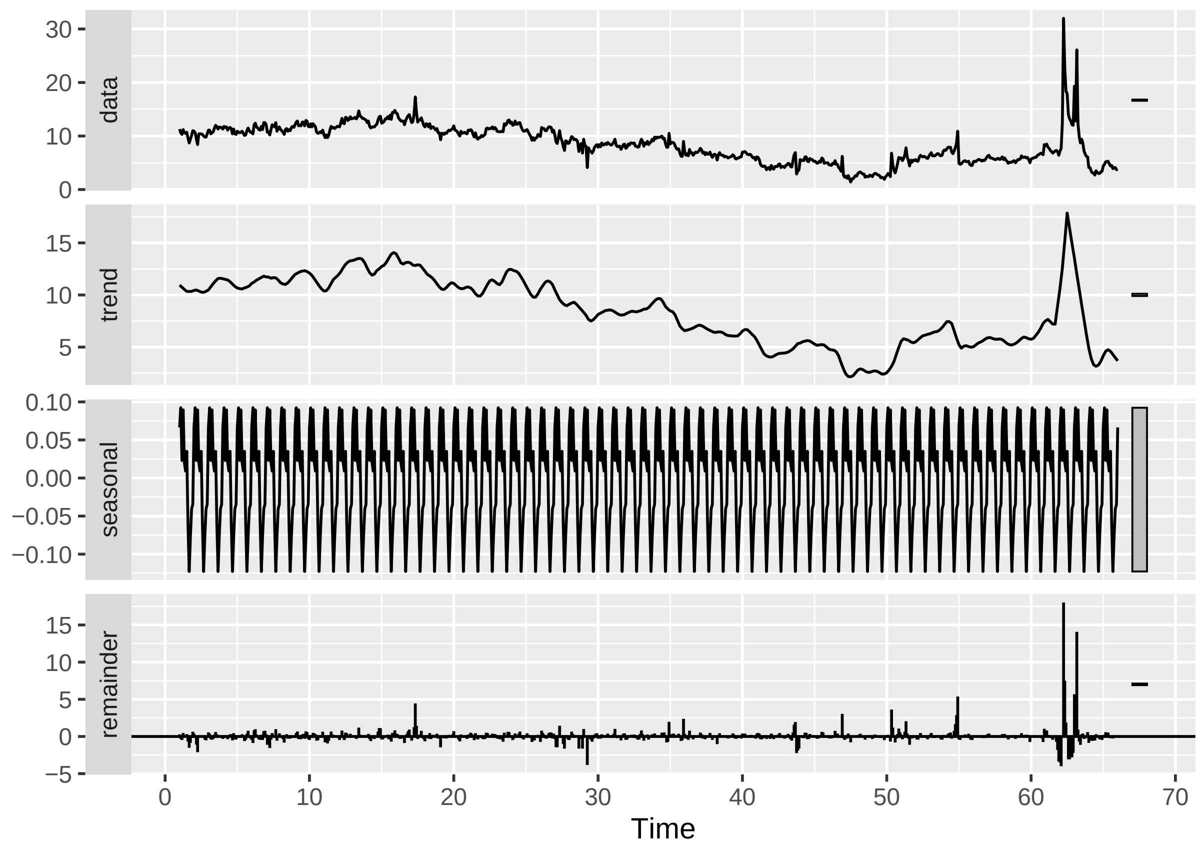
In the plot we can see that the personal saving rate decreased from about 1976 to 2007 from about 12% to 3%. After that the saving rate increased again to about 7% in 2020. We can also see that there is no obvious difference between the two parties. The saving rate increased and decreased for both parties in the same way. The big increase in the personal saving rate during the COVID-19 pandemic is also visible in this plot but has nothing to do with the party that is in power. Because the dataset presidential only contains data until 2021 there is a NA part in the graph. The vertical lines in the plot are the elections. Because the dataset contains only the president some elections are missing in the plot when the president was re-elected.

Part 3

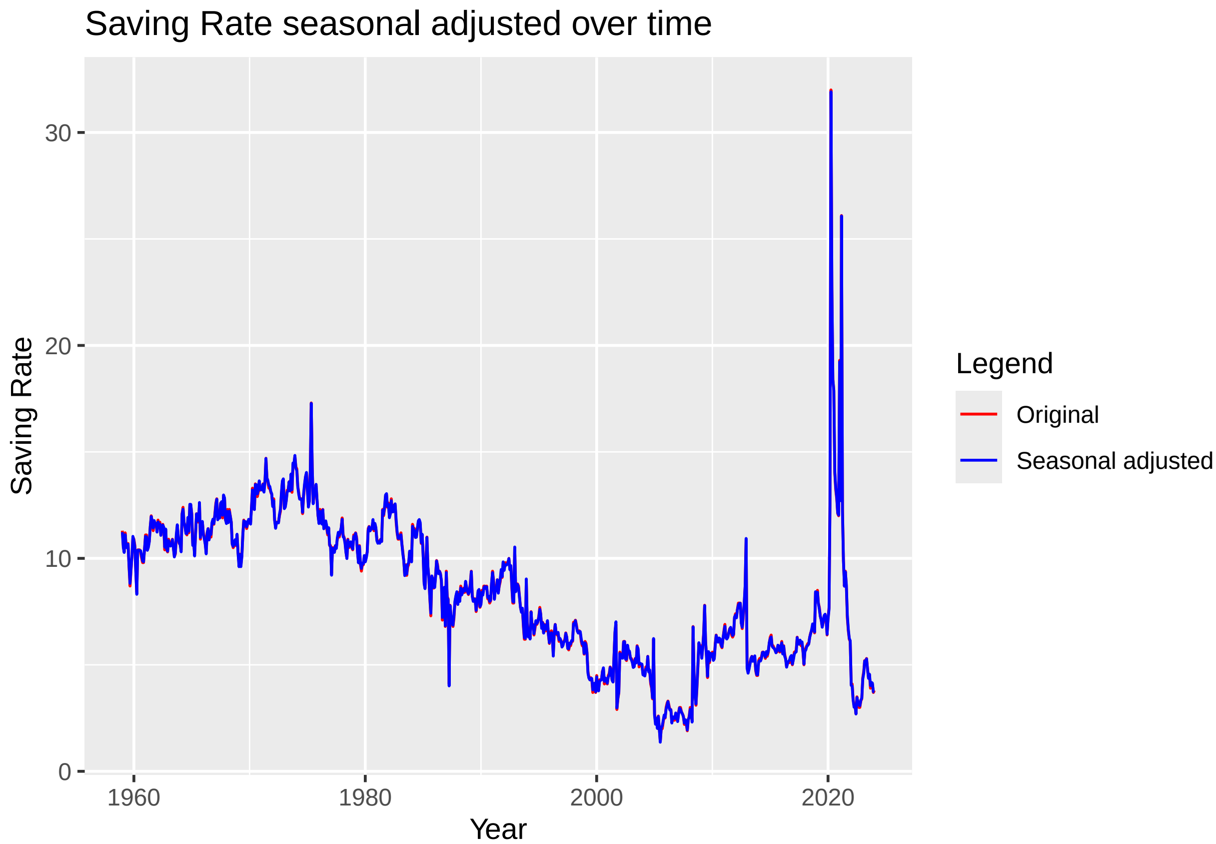
Because the dataset we needed to use only contains seasonally adjusted data we can't decompose the seasonally part again because it is already removed. We can still decompose the data into trend and remainder. We can also calculate the moving average of the data.



When we look at the moving average we can see that the moving average is a lot smoother than the original data. The moving average is a lot smoother because it is the average of the data in a specific time frame. The 5-MA is the average of the data in a time frame of 5 months. The 11-MA is the average of the data in a time frame of 11 months. The 11-MA is smoother than the 5-MA because it is the average of a longer time frame. We can also see that the random variation in the data is removed in the graph.



When we look at the STL decomposition we can see that the seasonal part is very low because it was already removed in the data. We can also see that there is a negative trend in most of the time series. This means that the saving rate decreased over time. The remainder is the part that is left after removing the seasonal and trend part. This part is the part that is not explained by the trend and the seasonal part. We can see that the remainder is white noise because it doesn't have any trend or pattern to it. But when we look at the results from our other plots we can explain the last extreme variation in the remainder. This is the COVID-19 pandemic.



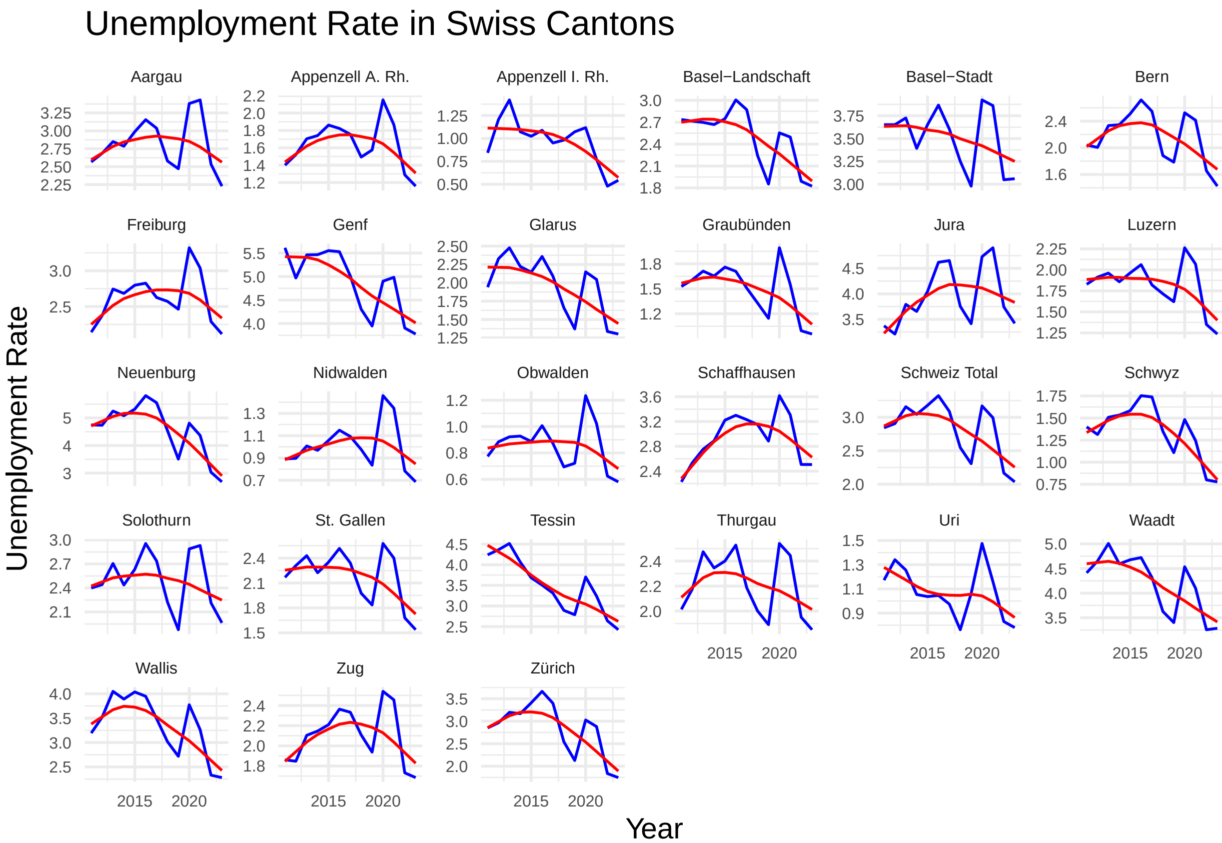
As already mentioned, the seasonal part is already removed in the data. Because of that we can see nearly no difference between the original and the adjusted saving rate.

Part 4

Data Sources we used:

- Unemployment per canton: https://www.bfs.admin.ch/bfs/de/home/statistiken/arbeit-erwerb/erwerbslosigkeit-unterbeschaeftigung/registrierte-arbeitslose-seco.assetdetail.30245369.html
- Population statistics: https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung/stand-entwicklung.assetdetail.26565154.html

Both sheets have been manipulated manually to make the parsing in R easier, e.g. we removed unnecessary columns and rows and for the population dataset we merged all the values from the years into one sheet. Population data for 2023 was not yet available, which is why the combined tsibble has some NA values.



The plot shows the seasonal and trend components of the unemployment rate in Switzerland by canton. The blue line represents the seasonal component, while the red line represents the trend component. With the seasonal line, peaks in unemployment, like the Covid-19 Pandemic can be seen clearly. Also from the Task Description it was not clear for us whether the additional data (population data) also has to be displayed in the plot. We decided not do it, as it would have made the plot unreadable.

Part 5

Purpose of the unemployment forecast in Switzerland

The purpose of the unemployment forecast in Switzerland is multifaceted. It serves to inform political decision-makers, economists and companies about the future development of the labor market. For political decision-makers, forecasts help to mitigate fluctuations in unemployment and ensure stable economic growth. Economists use forecasts to understand underlying trends in the labor market, assess the impact of economic factors on unemployment rates and develop models for economic analysis. Businesses rely on unemployment forecasts to anticipate labor market conditions.

Availability of information for the unemployment forecast in Switzerland

The accuracy of unemployment forecasts in Switzerland depends on the availability of relevant data and timely information. Key factors influencing unemployment, such as GDP growth, inflation rate, labor force participation and demographic trends, need to be closely monitored. Access to up-to-date statistical data from government agencies such as the Federal Statistical Office is essential for the creation of reliable forecasting models. This is why we also use these data files from the federal government. Timely access to labor market indicators, surveys and economic reports ensures that forecasters have the necessary information to make informed predictions about future unemployment rates in Switzerland.

Assessing the value of unemployment forecasts in Switzerland

This prediction is arguably more valuable to businesses and the federal government than to ordinary citizens. Accurate forecasts help policy makers to develop effective labor market policies that can contribute to social stability, economic growth and improved prosperity. For businesses, unemployment forecasts serve as a basis for workforce planning, hiring strategies and investment decisions, which can optimize resource allocation and minimize labor market risks. In addition, financial institutions, investors and international organizations rely on unemployment forecasts to assess Switzerland's economic performance and evaluate the country's attractiveness for investment.