Advanced Programming 2025

Effectiveness of monetary policy according to the macroeconomic regime in place in Switzerland

Final Project Report

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Abstract

This paper aims to understand how a small country like Switzerland can combat inflation through its key interest rate, its exchange rate, or its labor market. The data retrieved for this project comprises a series of monthly macroeconomic data covering the period from February 1991 to December 2024, representing 407 observations. The K-Means algorithm was used to segment observations in order to obtain macroeconomic regimes. The Elbow method was also used to optimize our optimal KK. We observe non-linearity in monetary policy through short-term interest rates and note, as Thomas Jordan said, that the exchange rate channel is now becoming the SNB's main channel, combining data science for clustering and econometrics for analyzing these regimes, which could prove more appropriate in a constantly changing economy.

Keywords: Data science, K-Means, PCA, Econometrics, Monetary policy, Negative interest rates, Swiss economy

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1 Introduction

Central banks have undergone many phases since their creation. Initially designed to meet monetary needs or finance wars, over time, and particularly during the 20th century, they have evolved towards a role of price stabilization[1]. To this end, they mainly use monetary policy, adjusting the economy through the key interest rate in order to influence the economic situation.

However, since the 1990s, interest rates have fallen steadily as a result of demographic changes, economic crises and a lack of investment opportunities[2]. This gradual decline has led central banks to set extremely low, even negative, interest rates, calling into question the traditional principle of the zero lower bound. This raises the question: once the conventional limit of 0% has been exceeded, is monetary policy still the same? Understanding this development is crucial, both for central banks, which need to adjust future monetary policies, and for economists and financial institutions, which need to assess the intensity of the transmission of these policies to the real economy.

This project therefore attempts to address the following question: does monetary policy lose its effectiveness when interest rates become very low or negative, and if so, how does monetary policy influence inflation at present? The aim is to understand how a small country like Switzerland can combat inflation through its key interest rate, its exchange rate, or its labor market. Switzerland is an interesting case because it has a strong currency and is very open economically to the international market, particularly in terms of exports, making the analysis different from that of some large countries or economic zones.

To study this question, we will divide the project into several parts. First, we will determine the different macroeconomic regimes based on macroeconomic data. We will do this using an unsupervised clustering algorithm for variables that are known to all, such as short-term interest rates, bond yields, inflation, unemployment, GDP, and SMI index growth. Second, we will analyze whether or not conventional monetary policy has declined for each cluster. This will be done through empirical analysis based on linear regressions including the macro data cited for clustering.

This report is organized into several sections. Section 2 will focus on the literature review. Section 3 will present the data and methodology. Section 4 of the report will present empirical results and graphical visualization. Section 5 will focus on the discussion of our results, limitations, and possible future research directions. Finally, Section 6 will conclude with a few lines summarizing the key elements of this project.

2 Literature Review / Related Work

Today, monetary policy plays a central role in economies around the world. In order to ensure price stability, the Swiss National Bank sets an inflation target of below 2% but above 0%[1]. It uses various tools to achieve this, the most common being conventional monetary policy. This method uses the key interest rate, which directly influences economic rates and the foreign exchange market. The literature highlights several possible relationships between the key interest rate and inflation depending on the economic regimes in place. Indeed, there is no uniform reaction, and the effectiveness of this channel tends to diminish when rates become very low. This persistent decline is the result of efforts to combat growing deflation in global economies[2].

[1] In accordance with its official mandate (SNB, Tasks and Objectives, accessed in 2025)

Several articles show that negative rates create a certain amount of financial friction, particularly among banks and investors. According to economists Borio and Hofmann in their paper "Is monetary policy less effective when interest rates are persistently low? " (2017)[4], who analyzed several scientific economic journals, banks see their profitability directly impacted in the long term, and investors find themselves caught between security and return, sometimes leading to a reallocation of their assets. These problems have led central banks to innovate by implementing unconventional monetary policies with the aim of ensuring price stability. These include forward guidance, intervention in the foreign exchange market, and quantitative easing[3]. The use of new unconventional tools would therefore indicate that traditional methods are no longer sufficient. Indeed, according to Borio and Hofmann, interest rates would reach a point where transmission becomes non-linear and where they would no longer be sufficient to guarantee price stability.

In addtion, for small economies such as Switzerland, the foreign exchange market remains today the main channel for monetary policy transmission, as Thomas Jordan, former director of the Swiss National Bank, stated in his speech (2016)[5]. Lower interest rates lead to a “loss of interest” in the Swiss franc compared to other currencies. The transmission of monetary policy through short-term interest rates is therefore weaker than in the eurozone, which is an important point to note, especially in our research work.

At the same time, identifying economic regimes is becoming difficult. Indeed, a multitude of macroeconomic variables must be taken into account. Throughout history, several methods have been used to determine macroeconomic regimes. Early approaches relied on indicators such as recessions (slowing GDP growth) or monetary policy changes. Other tools, such as the Keynesian model or the Phillips curve, have also been used to illustrate these changes. Then, more quantitative models emerged, such as the Markov Switching model, as well as threshold models, and the use of data science and clustering[6,7]. These tools have reduced human deliberation in defining regimes. Statistical algorithms such as K-Means can be used to identify these regimes. One example is the work of Qinmeng Luan and James Hamp (2023)[7], who use K-Means in their finance research to identify different regimes.

In short, the effectiveness of conventional monetary policy is being called into question. Over the years, numerous articles have discussed the significant decline in central banks' room for maneuver, leading to the emergence of new monetary policies. This is due to the decline in nominal interest rates since the 1990s. Theoretical limits seem to have been reached, opening the door to new research. This project is part of this trend, aiming to explore and quantify this decline through a two-part approach, namely data science and statistics.

3 Methodology

3.1 Data Description

The data retrieved for this project comprises a series of monthly macroeconomic data covering the period from February 1991 to December 2024, representing 407 observations. Most of the data was collected from the internationally recognized Swiss National Bank portal[8], a monthly series on the SMI from the Federal Reserve Bank[9], a series of data from The KOF Swiss Economic Institute[10], and a final partial series from the fxtop website[11], notably to complete the EUR/CHF exchange rates. The data was collected manually from the various websites in CSV format and then entered into an XLSX file. We note that automation with API would have been possible if certain data had been available on the portal. However, for practical reasons, the manual option was chosen, avoiding a mix of the two options. The data table is available in the appendix [A.1].

Some clarifications regarding certain data:

- The euro was only introduced in 1999, consequently, the preceding months have been completed on the basis of the Deutsche Mark (was chosen because it was the most influential currency in Europe at the time) in relation to the Swiss franc. We justify this choice by the fact that the data must reflect the economic situations as they were, ceteris paribus, we will therefore not take into account the adjustment of the DEM to an equivalent in EUR.
- With regard to Swiss GDP growth, no reliable database provides a monthly series. We will use the KOF, an indicator that anticipates the evolution of real Swiss GDP. This has been converted into growth in order to obtain a comparable variable.
- The Swiss Market Index (SMI) reflects the monthly variation in the Swiss stock market.

3.2 Approach

This project will be divided into two parts: the first part will focus on data science, with the aim of identifying macroeconomic regimes. The second part will focus on econometrics, which will enable us to determine the loss in monetary policy effectiveness.

3.2.1 Data Science

The Data Science section will serve as the basis for our analysis. This approach will enable us to segment our data into different groups, with the aim of achieving distinct macroeconomic regimes. This segmentation will be performed using the K-Means clustering algorithm, which assigns each observation to a group whose other members have similar properties, based on Euclidean distance. Indeed, this algorithm performs particularly well for the segmentation of macroeconomic data[7]. For segmentation, values are standardized beforehand to ensure a scale of comparison between variables. Subsequently, the number of groups k is defined according to the Elbow Method, a method for representing intra-cluster variance as a function of the number of clusters. Formally, K-means solves the following optimization problem :

$$WCSS(k) = \min_{S_1,\dots,S_k} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2$$

where $S_1, \dots, S_k$ denote the clusters and μ_i represents the centroid of cluster S_i.

For each value of k, the Within-Cluster Sum of Squares (WCSS) is computed, which corresponds to the total squared distance between the points and their respective centroids. As k increases, the WCSS decreases, since the clusters become more compact. However, beyond a certain point, adding an additional cluster no longer significantly improves the clustering structure. This is precisely what the Elbow Method aims to identify. The choice therefore remains human, but based on an algorithmic result. Nevertheless, even visually, the elbow test can sometimes be difficult to interpret. Other tests may be necessary. For simplicity's sake, we will focus on the visual aspect and notify the possible consequences of this choice through analysis and discussion.

Once the clustering has been carried out, we will use two more tests to understand the key variables and the quality of the clusters :

- **ANOVA test.** This test evaluates whether the mean values of the variables differ significantly across clusters, helping to identify which variables contribute most to cluster separation. It does not validate the clustering itself but provides insights into the drivers of segmentation [A.2].
- **Silhouette coefficient.** This index measures the interna consistency and separation of clusters. Values close to 1 indicate well-separated clusters, values around 0 suggest overlapping groups, and negative values point to poor clustering quality [A.3].

3.2.2 Econometrics

In this section, we will focus on the relationship between variables. We will therefore perform multiple linear regressions on each cluster. The objective will be to understand the possible links between variables by analyzing the overall quality of the models (R^2) and the betas (including significance). The choice of variables is thus based exclusively on statistical tests.

$$Inf_t = \alpha + \beta_1 \cdot 3Mth_t + \beta_2 \cdot Unmp_t + \beta_3 \cdot CHF_t + \varepsilon_t$$

Inflation will be the value dependent variable in accordance with the main objective of monetary policy. As we saw earlier, central banks adjust their interest rates to ensure price stability. We can add to this the exchange rate, which according to the Swiss National Bank is an relevant metric[5], and the unemployment rate, which provides insight into production dynamics.

In addition to regression, we will also perform two additional diagnostic tests:

- **Variance Inflation Factor (VIF).** We will perform a multicollinearity test, called VIF, for which we expect a score below 5 for each variable, indicating that there is no severe collinearity between the variables and that they evolve independently of each other[A.4].
- **Breusch–Pagan test.** Finally, a heteroscedasticity test will be performed. We will use the Breusch–Pagan test and will serve as a starting point for understanding whether the residuals are evenly distributed and whether there is a dispersion problem in our models [A.5].

3.3 Implementation

For this project, we used Python 3.11.9, released in April 2024. Various libraries were used to extract data science algorithms, econometric models, and data management functions. The full code, provided in Python format, is available on GitHub and includes all intermediate steps and implementations used in the project. Here is a summary of the different stages of the code leading to our results. All libraries required for the project are available in `requirement.txt` on GitHub. The code also contains all the results presented in this work.

Here are the different steps of the code :

```
# 1.  Load data
# 2.  Data visualization and modification
# 3.  Standardize variables
# 4.  Run K-Means for k = 1...10
# 5.  Plot WCSS and choose k*
# 6.  Run ANOVA and silhouette analysis
# 7.  Remove low-informative variables
# 8.  Re-run K-Means on the reduced variable set
# 9.  Visualize clusters (PCA, time chart)
# 10. For each cluster, fit an OLS model
# 11. Check VIF and BreuschPagan (BP) tests, and use robust SE
```

Listing 1: Analysis pipeline used in the project

4 Results

4.1 Experimental Setup

As seen in the methodology, we apply K-Means clustering to our entire dataset to begin with, and observe the Elbow method in order to optimize our optimal k. We then note that $k_{\text{optimal0}} = 3$, based on figure 3 . However, we note that the choice between 3 and 4 groups is not entirely clear: even though the curve seems to flatten out from level 3 onwards, assigning 4 groups might not be a mistake. We then apply the ANOVA test and the silhouette test.

Table 1: Comparison of ANOVA p-values and Silhouette Test Results

Variable	**p-value Set 1**	**p-value Set 2**
3Mth	0.0000	0.0000
10Yd	0.0000	0.0000
Inf	0.0000	0.0000
Unmp	0.0000	0.0000
CHF	0.0000	0.0000
GDP	0.7473	–
SMI	0.1023	–
Silhouette Test	0.3026	0.4129

Through this initial analysis, we observe that the p-values of the ANOVA test for GDP and SMI do not seem to indicate a significant difference between clusters. This indicates that these variables do not significantly differentiate the clusters (p-value > 0.05). The rest of the variables, however, remain highly significant, indicating significative difference between clusters. The silhouette test stands at 0.30, indicating that the different groups are distinct, but not completely separate.

Based on this initial experiment using ANOVA and the silhouette test, we decided to remove GDP and SMI for a new experiment. As with the first test, we note $k_{\text{optimal1}} = 3$, based on figure 3, with the same observation as before regarding the choice. We also apply the ANOVA test and the silhouette test.

We observe that the p-values are close to zero, indicating that each variable is significantly important in determining clustering. Furthermore, we find that excluding GDP and SMI significantly improves our silhouette test to 0.41, indicating that the clusters are better formed when these variables are omitted. This result prompts us to set aside these two variables for the remainder of the analysis.

In line with this, we verify that clustering has indeed given us macro regimes. To perform this information, we plot the observations over time for each cluster on a graph. We find that the clusters are indeed assigned to a continuous macroeconomic regime. We can confirm this by observing the distribution of points, which follow each other almost perfectly. We do note a slight, mixed transition between regimes in the 2012s, but this does not materially affect the analysis.

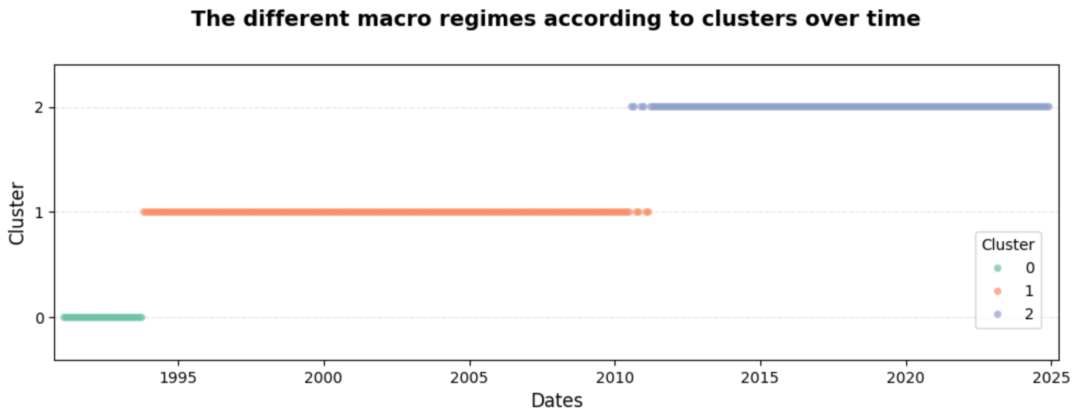


Figure 1: Macroeconomic regimes identified by K-means clustering over time. Source: SNB, FRED, KOF and FXTOP.

Thsu, we have now defined our clusters according to three groups. We then calculate the averages for each variable per cluster, with the aim of obtaining an overall view of the representation of each cluster.

Table 2: Cluster Means for Key Variables

Cluster	3Mth	10Yd	Inf	Unmp	CHF	Obs
0	7.1193	5.8310	4.4911	2.6293	1.1252	33
1	1.7800	3.2121	0.9062	3.4673	1.4332	205
2	-0.1818	0.3200	0.3854	2.7967	1.1084	169

As we can see, the average of the variables are relatively different between clusters, giving us an overview of what the macroeconomic regimes in place look like on average. As we mentioned in Part 2 of this report during the literature review, we can see rates falling throughout the regimes until they become negative. In addition, inflation is also very low, indicating persistent deflationary pressure. We also note that the population of cluster 0 is relatively smaller than the other groups. We will take this into account when discussing and interpreting the results. However, in theory, this should not pose a problem; according to the rules of the central limit theorem, a sample of more than 30 individuals is large enough to be considered satisfactory.

4.2 Performance Evaluation

4.2.1 Multicollinearity (VIF test)

Before starting the multiple regression, and as previously announced in the methodology, we carry out an analysis of multicollinearity (VIF test) between variables. Indeed, we suspect a strong link between 3Mth and 10Yd, which could potentially affect the stability and interpretability of the estimated coefficients of the models. The VIF test yields the following results.

Table 3: Comparison of VIF Before and After Variable Reduction

Variable	VIF Before	VIF After
Const	95.27	48.56
3Mth	11.18	1.02
Unmp	2.04	1.01
CHF	1.74	1.01
10Yd	11.58	–

The test indicates a pronounced degree of collinearity (VIF > 5) between 3Mth and 10Yd, leading us to exclude 10Yd from the regression specification. In fact, we would prefer to maintain short-term rates that best reflect monetary policy. After this adjustment, the VIF diagnostics, computed on a model that omits Swiss bond yields, suggest that multicollinearity has been effectively eliminated from the model. This is naturally due to the strong correlation between rates. Indeed, long-term rates are based on short-term rates.

4.2.2 Linear Regression

We assess the effectiveness of monetary policy across macroeconomic regimes using linear regressions. Specifically, we analyze how inflation relates to interest rates, labor market conditions, and the EUR/CHF exchange rate, estimating three separate specifications with distinct empirical outcomes.

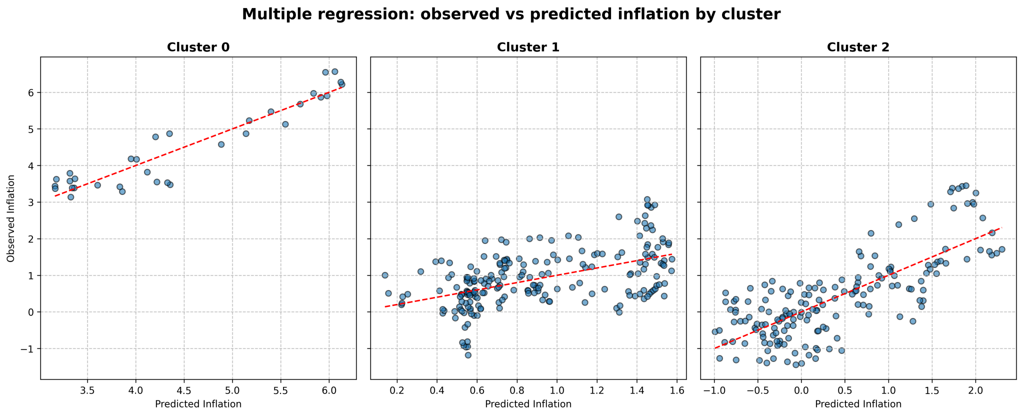


Figure 2: Linear regression results by cluster. Source: SNB, FRED, KOF and FXTOP.

Table 4: Unified Regression Summary by Cluster

Variable	Cluster 0	Cluster 1	Cluster 2
Intercept	4.34	-1.89	6.64
β (3Mth)	-0.32^{**}	0.34^{***}	0.09
β (Unmp)	-1.00^{***}	0.04	-1.54^{***}
β (CHF)	4.49	1.42^{***}	-1.74^{**}
R^2	0.88	0.27	0.58
BP p-value	0.90	0.02	0.00
N obs	33	205	169

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The regressions thus reveal a clear change in monetary transmission across different macroeconomic regimes. Indeed, when rates are high, as in cluster 0 (3Mth = 7.11%), inflation depends significantly on monetary policy ($\beta = -0.32^{**}$), while the exchange rate has no significant impact. We therefore observe in this regime a transmission of monetary policy mainly through interest rates with the aim of combating inflation. The exchange rate does not seem to play a major role.

When rates fall and become moderate, as in cluster 1 (3Mth = 1.78%), short-term rates remain very significant ($\beta = 0.34^{***}$). In addition, the exchange rate also begins to become significantly relevant ($\beta = 1.42^{***}$). We therefore assume that we are entering a regime in which monetary policy is losing its power, changing from negative to positive, indicating that an increase in rates no longer lowers inflation, with a reduction in the power of β, which nevertheless remains statistically very significant, and an increased importance of the exchange rate on inflation.

In a very low interest rate environment, such as in cluster 2 (3Mth = -0.18%), conventional transmission becomes ineffective ($\beta = 0.09$, not significant with a p-value = 0.3345). In contrast to interest rates, the exchange rate becomes a key factor in the fight against inflation ($\beta = -1.74^{**}$). These results would therefore indicate that the closer rates get to the zero lower bound, the less sensitive inflation becomes to them, which does not seem to be the case for the foreign exchange market.

The unemployment rate appears to be very significant at the extremes, clusters 0 and 2 of our model, but less relevant in cluster 1. This indicates that in times of economic stress, this variable tends to be more valuable than in what we would cautiously describe as an "intermediate" period, when macroeconomic data tends to be more stable.

Regarding the quality of the models, the three regressions demonstrate different levels of reliability. Cluster 0 obtains a very high R^2 (0.88), indicating that the model explains inflation very well in this regime. It also does not present heteroscedasticity (BP p-value = 0.90). Cluster 1, on the other hand, demonstrates a less satisfactory explanation of the results R^2 (0.27), indicating a less precise interpretation of this macroeconomic regime. We note the presence of heteroscedasticity (BP p-value = 0.02). For the last model, the R^2 (0.58) is good overall, suggesting an average interpretation of the regime. However, unlike the other two models, it shows a strong presence of heteroscedasticity (BP p-value = 0.00). The data do not reveal any multicollinearity between the variables in the multiple regression, reinforcing the interpretation of the coefficient estimates and their significance. In conclusion, the statistical results should not call into question the outcome of the analyses, but they should be interpreted with caution or suggest further testing to improve the models.

To do this, we perform a final robustness test on our regressions in order to limit the impact of heteroscedasticity on the degrees and improve the significance of our variables[2]. Indeed, using the robustness test increases certain the p-value and increases also the significance of one of them, namely the β of the CHF in Cluster 2 (p-value: $0.0134 \rightarrow 0.0085$), which become highly significant. The robustness test therefore strengthens the interpretation of our previous results by showing that the main conclusions remain valid when standard errors are replaced with heteroscedasticity-robust standard errors.

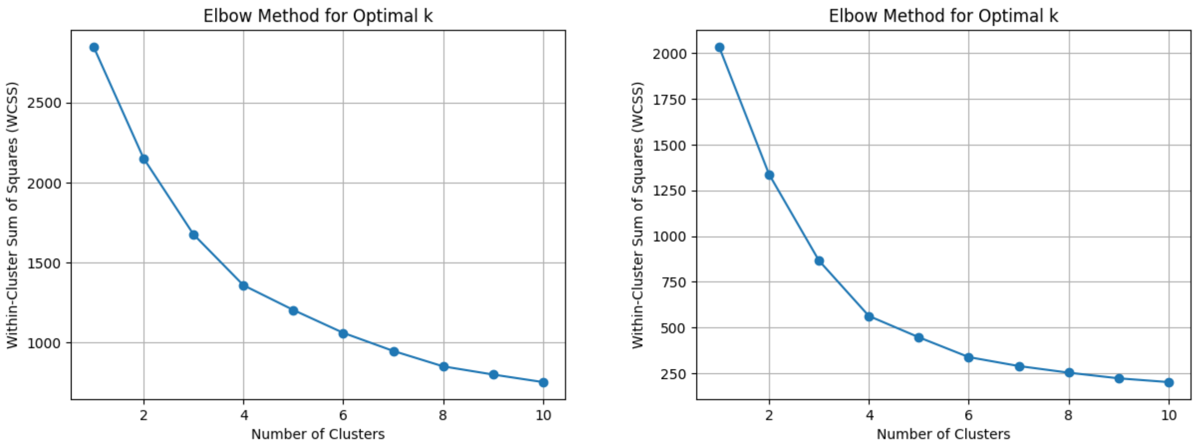
[2] We use the HC3 test. This test is widely used in academic research, as it is considered to provide reliable inference. It is also well suited for small samples (33 observations in cluster 0)[12].

Table 5: OLS p-values before and after heteroscedasticity-robust correction (HC3)

Variable	Initial p-values			HC3 robust p-values		
	C0	**C1**	**C2**	**C0**	**C1**	**C2**
β (3Mth)	0.0211 **	0.0000 ***	0.3345	0.0110 **	0.0000 ***	0.3573
β (Unmp)	0.0000 ***	0.5257	0.0000 ***	0.0000 ***	0.4377	0.0000 ***
β (CHF)	0.3059	0.0014 ***	0.0134 **	0.1841	0.0017 ***	0.0085 ***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.3 Visualizations



(a) Elbow Method (Full Variable Set) (b) Elbow Method (Reduced Variable Set)

Figure 3: Elbow method used to determine the optimal number of clusters. Source : SNB, FRED, KOF and FXTOP

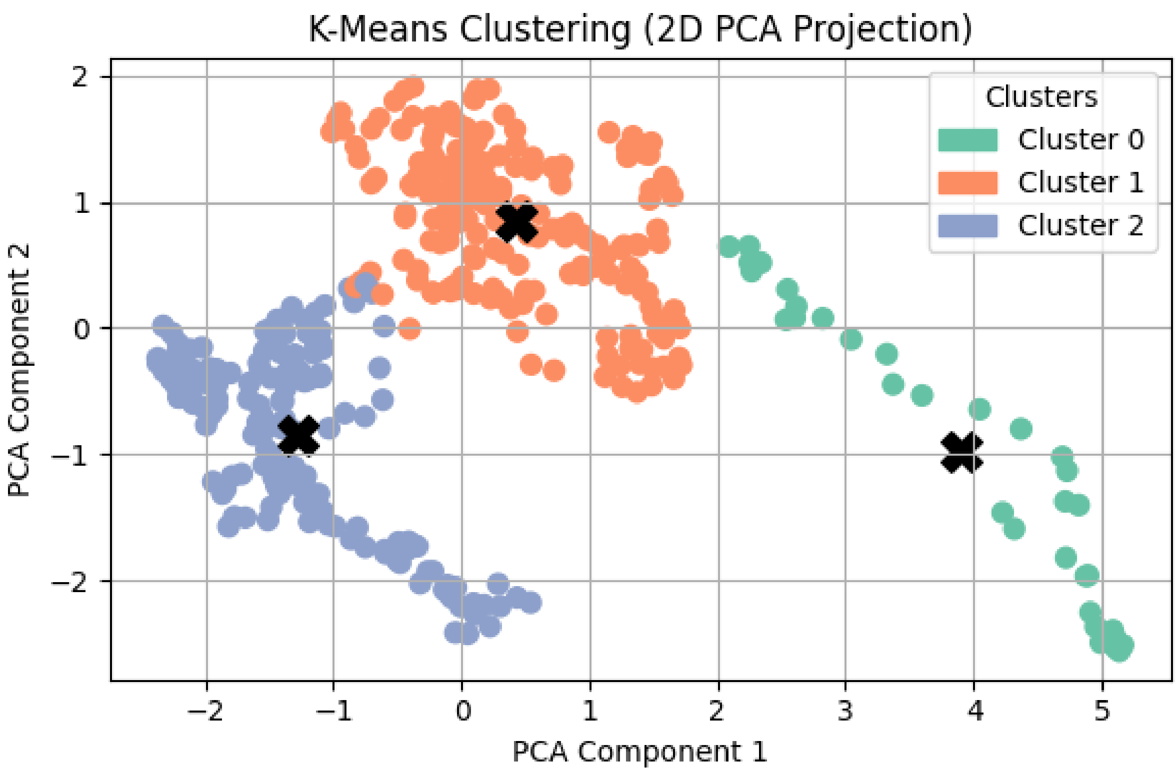


Figure 4: This figure shows the two-dimensional projection of the observations using the PCA method. Three distinct groups can be clearly identified, corresponding to the clusters identified by the K-means algorithm. Each cluster forms a coherent structure, which visually confirms the relevance of the segmentation. Source : SNB, FRED, KOF and FXTOP

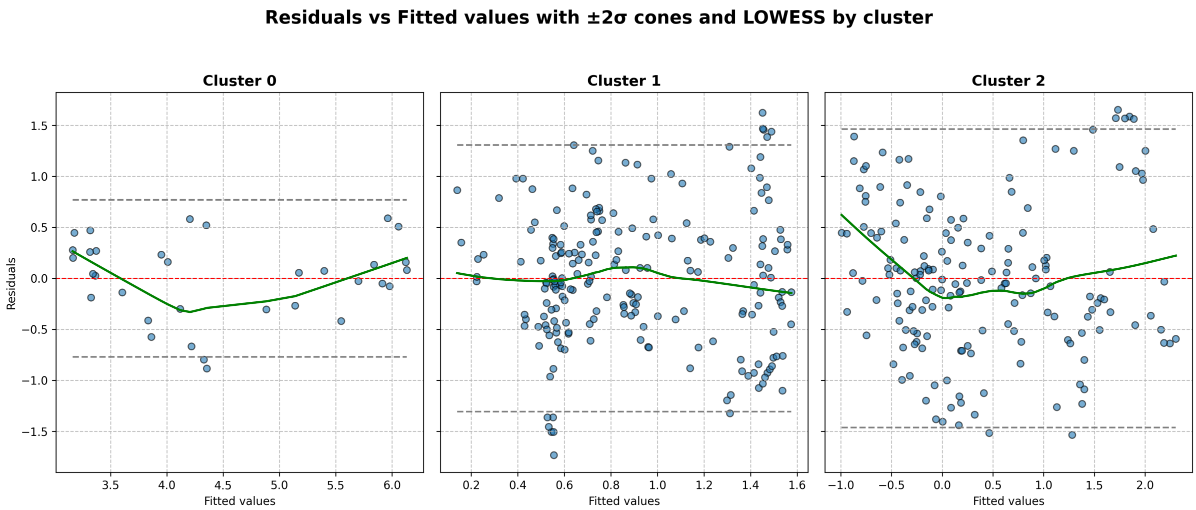


Figure 5: Residuals versus fitted values with LOWESS curves for each cluster, illustrating the dispersion of residuals across clusters. The residual plots reveal heteroscedasticity in regimes, particulary in regimes 1 and 2. Since the residual dispersion shows no clear structure and appears random, the Breusch–Pagan test is the primary tool for detection. The test will partially correct this problem, making a detailed graphical analysis unnecessary. A visual check of the residuals is sufficient to demonstrate and confirm heteroscedasticity. Source: SNB, FRED, KOF and FXTOP

5 Discussion

We can highlight several elements that worked well in this project. First, clustering, based on the K-Means algorithm, suggests that we successfully identified macroeconomic regimes since 1991. Indeed, it did not simply separate the data into groups but provided a true chronology of the economic situation. This confirms that clustering captured real macroeconomic structures for Switzerland.

Secondly, linear regressions provided us with stable and interpretable results. We were able to successfully observe the findings of modern literature. Indeed, we noted a loss of effectiveness in short-term rates across clusters, with a less impactful beta between clusters 0 and 1, then becoming insignificant in cluster 2. Conversely, we observed increased transmission through the exchange rate across clusters, to the point where it became the most important transmission channel, as Thomas Jordan stated in his 2016 speech [5]. Furthermore, the robustness test reinforced these interpretations by taking heteroscedasticity into account and consolidating the significance of the variables.

However, there were a few difficulties. Selecting variables was not always straightforward. We would have liked to import a better variable for production. The KOF index ultimately proved to be of little use in this analysis, as did the monthly growth of the SMI. In the end, they did not provide additional explanatory power. Other data might have been welcome, particularly data more closely related to monetary policy. We are thinking in particular of quantitative easing, which is now a major asset for central banks but was not taken into account in the analysis.

We also note the difficulty in determining the correct number of clusters using the Elbow method. The addition of an extra group might have improved this analysis. Indeed, cluster 1 covers several periods of crisis (2000 and 2008). The algorithm might have split cluster 1, refining the interpretations. Nevertheless, this did not prevent us from obtaining results. However, we take into consideration that the imbalance in the number of observations can make the comparability of models more difficult, particularly for cluster 0, which is just above the theoretical limit set at 30.

We note that unemployment data was not very significant in cluster 1, perhaps due to the stability of the Swiss labor market. This may plausibly explain why, in times of stress, as in clusters 0 and 2, unemployment has a greater impact on inflation. Another explanation could be due to the presence of two major crises in this regime, rendering the unemployment rate unusable in this defined regime. A segmentation into four regimes may be necessary to verify this.

Limitations apparent in this project. We have already mentioned the choice of variables and the number of clusters. We also note the idea of possibly using nonlinear models in regressions, which could prove more appropriate in a constantly changing economy. We are thinking in particular of a logarithmic formula, which could cap certain aspects of monetary policy and demonstrate more clearly the limitations of the tools available to central banks today. Finally, other statistical tests could prove useful in improving and better understanding these regressions, and could be explored in future work. At the start of this project, the results are consistent with the initial expectations and with the findings of the modern literature. Similarly, we noted the growing importance of the exchange rate channel for Switzerland over time.

6 Conclusion

This project analyzes monetary policy transmission since 1991. To do so, the K-Means algorithm was used to segment observations in order to obtain macroeconomic regimes. Econometrics then demonstrated that conventional monetary policy becomes less effective as it approaches the zero lower bound. Conversely, the exchange rate becomes one of the main transmission channels. Unemployment explained inflation in periods of stress, but less so during stable periods.

In short, the results confirm the scientific literature. We observe non-linearity in monetary policy through short-term interest rates and note, as Thomas Jordan said, that the exchange rate channel is now becoming the SNB's main channel, combining data science for clustering macroeconomic regimes and econometrics for analyzing these regimes.

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A Additional Figures

A.1 Data

Table 6: Description of the macroeconomic variables used

Variable	**Description**	**Source**	**Unit / Format**
3Mth	Policy rate set by the SNB (Libor/Saron, 3 months)	SNB	Percentage
10Yd	Yield on 10-year Swiss government bonds	SNB	Percentage
Inf	Monthly change in the consumer price index	SNB	Percentage
Unmp	Monthly unemployment rate	SNB	Percentage
CHF	Monthly evolution of the DEM-EUR/CHF exchange rate	SNB / FXTOP	Level
GDP	Leading indicator of Swiss real GDP growth	KOF	Percentage
SMI	Monthly variation of the Swiss Market Index	FRED	Percentage

A.2 ANOVA test

To test the usefulness of variables in clustering, we perform the ANOVA test, which is defined as follows:

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}}, \qquad MS = \frac{SS}{df}.$$

MS_{between} measures the variation between cluster means, while MS_{within} captures the dispersion of observations within clusters. The null hypothesis assumes equality of group means (H_0), and statistical significance is evaluated using the associated p-value ($p < 0.05$).

A.3 Silhouette coefficient

The silhouette coefficient measures how well an observation is assigned to its cluster relative to other clusters. It is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i),\, b(i)\}},$$

where $a(i)$ denotes the average distance between observation i and points within the same cluster, and $b(i)$ the lowest average distance to observations in any other cluster. Higher values indicate better cluster separation.

A.4 Variance Inflation Factor (VIF)

The Variance Inflation Factor (VIF) is used to detect multicollinearity between variables. It is defined as:

$$VIF_j = \frac{1}{1 - R_j^2},$$

where R_j^2 is obtained by regressing variable j on all other explanatory variables. Higher values indicate stronger linear dependence with the remaining regressors. In practice, values above 5 are commonly interpreted as evidence of problematic multicollinearity.

A.5 Breusch–Pagan Test

The Breusch–Pagan test is used to assess the presence of heteroscedasticity in regression residuals. The test statistic is defined as:

$$BP = n \cdot R^2_{\text{aux}},$$

where R^2_{aux} is obtained from an auxiliary regression of squared residuals on the explanatory variables. The null hypothesis assumes homoscedasticity, and rejection of H_0 (typically at the 5% level) indicates heteroscedasticity.

B Code Repository

GitHub Repository: `https://github.com/Stefan704S/Data-Science`

Provide information about:

- Repository structure
- Installation instructions
- How to reproduce results