THE EVOLUTION OF THE NOMINAL EFFECTIVE EXCHANGE RATE

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Abstract

This study develops a direct forecasting model to predict Switzerland's nominal effective exchange rate (NEER). Using a theoretical framework based on the Taylor rule and the uncovered interest parity (UIP) condition, we assess the impact of inflation and output gap differentials on bilateral exchange rates with major trading partners (United States, Eurozone, China, and United Kingdom), weighted by trade importance. Our findings indicate that the Swiss NEER will appreciate by 1.06% in March 2025 and 3.43% by March 2026, driven by low inflation, easing global monetary policies, the franc's safe-haven role, and Switzerland's modest growth amid euro area challenges.

Keywords: Switzerland, NEER, Taylor rule, UIP, Inflation, Output Gap

1. Introduction

Switzerland's economy depends heavily on the stability of its currency. The Swiss franc (CHF) is known as a safe-haven asset because of the country's political neutrality, strong fiscal policies, and stable economy (Auer, 2015). The Nominal Effective Exchange Rate (NEER) measures the CHF's value against a basket of currencies weighted by trade volumes. Fluctuations in the NEER affect Switzerland's export competitiveness and import costs, which have a direct impact on the economy. In recent years, the CHF has appreciated significantly, especially against the euro. This has created challenges for Swiss exporters, as their goods have become more expensive in foreign markets (Müller, 2017).

This study develops a forecasting model for Switzerland's NEER using the Taylor rule and the Uncovered Interest Parity (UIP) condition. By looking at inflation and output gap differences with key trading partners such as the United States, Eurozone, China, and the United Kingdom, this research explores the main factors influencing Switzerland's exchange rate. The findings aim to support better decision-making and guide economic policy.

2. Data

This study uses monthly data spanning from January 1999, the creation of the Eurozone (European Central Bank, 2009), to September 2024. The analysis incorporates key macroeconomic variables including the NEER, output gap, inflation, and trade shares.

2.1 Construction of the NEER

The NEER measures the value of the Swiss franc relative to a basket of currencies, weighted by trade shares to reflect each partner's importance in Swiss trade. Nominal exchange rate data were collected from Investing.com, while trade shares were obtained from the Swiss Federal Statistical Office (OFS).

2.2 Inflation, Output gap and Trade shares

To approximate the output gap, industrial production data were used as a proxy for GDP, a method widely supported in the literature (Molodtsova & Papell, 2009; Chang & Chien, 2008; Kim & Ryu, 2013; Wesche, 2003). For Switzerland, the data were sourced from both FRED and the Swiss Federal Statistical Office (OFS), while data for trading partners were obtained exclusively from FRED. The Swiss industrial production series was interpolated into a monthly series using the Denton-Cholette method with a monthly indicator from the OFS (Appendix A), following the approach outlined by Di Fonzo and Marini (2012).

Afterward, following Kim & Ryu (2013) the HP filter was applied to the industrial production series of all countries to derive the output gaps. This approach leverages monthly industrial production figures to ensure higher temporal granularity compared to quarterly GDP data. All series were normalized to a base index of 100 in March 2021 for comparability across countries.

Inflation data, reported as the year-over-year percent change in the Consumer Price Index (CPI), were collected from FRED and the European Central Bank (ECB). These data provide consistent measures of price level changes across countries.

Trade shares, used to weight the NEER and other variables, were obtained from the OFS. For the forecasting horizon, trade shares were assumed to follow a random walk, being constant over time.

3. Methodology

3.1 The forecasting model

The model in this study builds on extensive literature leveraging the Taylor rule, developed by Taylor (1993). This rule states that central banks set short-term interest rates based on

changes in inflation, output gap, the equilibrium real interest rate, and the inflation target (Wesche, 2003). Assuming central banks share the same reaction function and Taylor rule coefficients for inflation and the output gap, we construct a homogeneous model. This model uses relative (domestic minus foreign) inflation, relative output gap, and a constant to determine interest rate differentials between economies (Molodtsova & Papell, 2009).

By linking interest rate differentials to exchange rate movements through the UIP condition and assuming this relationship holds, we develop a forecasting model for nominal exchange rates based on macroeconomic fundamentals of the domestic economy and its trading partners.

According to Chang & Chien (2016), models incorporating the Taylor rule for the US dollar outperform other macroeconomic fundamentals in explaining exchange rate movements. Although macroeconomic fundamentals may be limited in their predictive power for exchange rates in the short run, they offer stronger explanatory potential over the long term (Killian & Taylor, 2003; Kim, 2009).

This results in a model adapted to the NEER, incorporating trade shares as weights:

$$\Delta S_{t+1} = \alpha + \psi \sum_{j=1}^{n} w_j(\pi_t - \tilde{\pi}_t^j) + \gamma \sum_{j=1}^{n} w_j(y_t - \tilde{y}_t^j) + \eta_{t+1} \tag{1}$$

Where: ΔS_{t+1}: Change in the exchange rate at time $t + 1$; α: Constant; ψ: Weight on the inflation differential; w_j: Trade share for each foreign economy j; $\pi_t - \tilde{\pi}_t^j$: Inflation differential between Switzerland and foreign economy j; γ: Weight on the output gap differential; $y_t - \tilde{y}_t^j$: Output gap differential between Switzerland and foreign economy j; η_{t+1}: Error term.

Ultimately, the model demonstrates how differences in inflation and output gaps between economies determine interest rate differentials, which influence capital flows and drive exchange rate movements.

3.2 Model estimation

Firstly, all variables except inflation were first-differenced because they were not stationary according to the Augmented Dickey-Fuller (ADF) test. Then, Ordinary Least Squares (OLS) models were estimated for each forecast horizon (1, 6, 12, and 18 months) using a direct forecasting approach. The coefficients of interest (constant, weight on inflation differentials, and weight on output gap differentials) were estimated with a rolling window of 120 months. This rolling estimation scheme accounts for the changing relationships between predictors and the NEER over time. Detailed results and key diagnostics concerning the significance and evolution of coefficients are provided in Appendix B.

In the forecasting process, the most recent set of rolling coefficients was applied to reflect the current dynamics between macroeconomic predictors and the NEER.

4. Results

4.1 Point and density forecast evaluation

Horizon	Unbiasedness	Efficiency	MSFE Ratio	DM Test
1 Month	Tau: -0.00022, p = 0.86	p = 0.78	0.55	DM: -2.07, p = 0.98
6 Months	Tau: -0.00123, p = 0.69	p = 0.31	0.57	DM: -1.83, p = 0.97
12 Months	Tau: -0.00315, p = 0.50	p = 0.18	0.69	DM: -1.16, p = 0.88
18 Months	Tau: -0.00326, p = 0.59	p = 0.47	0.62	DM: -1.23, p = 0.89

Table 1: Summary of Point Forecast Results

Table 1 summarizes the evaluation of point forecasts for all horizons. The point forecasts are unbiased, as indicated by the unbiasedness test (H_0 : Forecast errors have zero mean, $p > 0.05$), and efficient, as the efficiency test (H_0 : No systematic forecast errors) fails to reject the null hypothesis at the 5% level. The null hypothesis (H_0) of the Diebold-Mariano test states that our model performs better than the random walk benchmark, and it is a one-sided test, while the MSFE ratio evaluates whether the model outperforms the benchmark random walk (MSFE Ratio < 1). The MSFE ratios confirm that the model outperforms the benchmark random walk across all horizons, although the Diebold-Mariano test reveals no statistically significant evidence that our model performs better ($p > 0.05$). These results demonstrate the model's ability to produce accurate and reliable point forecasts.

The spaghetti graph (Appendix C) illustrates the consistency of forecasted NEER levels across all horizons for the model, closely following the actual NEER trajectory, validating the robustness of the point forecasts.

The density forecast evaluation assesses the model's ability to produce well-calibrated prediction intervals. For instance, the high concentration of PIT values around 0.5 in the histogram shows that the model is predicting values close to the middle of the distribution most of the time, which suggests that the forecast intervals might not be capturing enough of the variability in the data. Violation rates and LR tests further support acceptable calibration at higher confidence levels (90% and 95%), demonstrating the model's robustness in capturing forecast uncertainty. All detailed results of the density forecasts, including PITs and additional tests, are presented in Appendix D.

4.2 Point and density forecast at the forecast horizon

According to Figure 1, from September 2024, the model predicts a NEER appreciation of 0.23% in October 2024, 1.06% in March 2025, 2.24% in September 2025, and 3.43% in March 2026. The confidence intervals around this gradual appreciation widen over time, reflecting greater uncertainty in forecasting longer horizons.
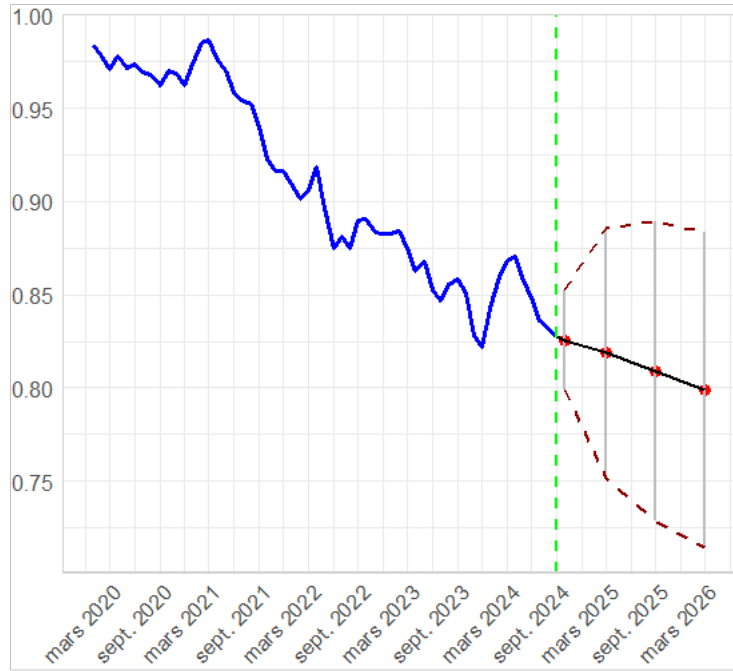
Figure 1: Forecasted NEER levels at 1, 6, 12, and 18 months (95% confidence intervals)

This expected appreciation is consistent with the anticipated reductions in interest rates among Switzerland's major trading partners, combined with the smaller decrease in Switzerland, which puts upward pressure on the Swiss franc (UBS Switzerland AG, 2024).

5. Conclusion

The primary objective of this study was to develop a reliable model to forecast Switzerland's NEER based on macroeconomic fundamentals. The results demonstrate both the absolute and relative performance of the model, establishing it as an unbiased and efficient tool for forecasting Switzerland's NEER at horizons ranging from one month to 18 months.

However, this model relies on several critical assumptions that may undermine its performance. Clearly, there is a need to better capture the short-term determinants of exchange rate dynamics, which are more closely linked to financial markets and less to the fundamentals of an economy.Future work could explore more complex models, allowing modifications of the original Taylor rule to provide a more realistic representation of monetary policy, especially in economies approaching the zero lower bound of interest rates. Additional regressors, such as financial market data, could also be incorporated to capture the short-term volatility of exchange rates.

As a conclusion, this report represents a solid foundation for exchange rate forecasting, leveraging macroeconomic theory and applying it to an empirical case. Ultimately, it provides a reliable base for developing more sophisticated forecasting models in the future.

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Appendix A: Swiss Industrial Production Disaggregation via Denton-Cholette

We interpolate the quarterly production indexes into monthly values because we have an original quarterly series for 1999-2024 and a monthly series from October 2010 to June 2024. Both series are in index with the same base. To achieve this, we use the Denton-Cholette method, which minimizes changes in the proportionate differences between the interpolated series and the indicator series. The optimization problem is:

$$
\min_{\{x_t\}_{t=1}^{T}} \sum_{t=2}^{T} \left(\frac{x_t}{X_t} - \frac{x_{t-1}}{X_{t-1}} \right)^2 \quad \text{st.} \quad \frac{1}{3} \sum_{m=1}^{3} x_{q,m} = Q_q, \ \forall q
$$

where X_t is the monthly indicator (2010–2024), x_t is the interpolated series, Q_q is the original quarterly series (1999–2023), and $X_{q,m}$ are the monthly values in quarter q.

The constraint ensures that the monthly averages within each quarter match the corresponding quarterly value in the original data.
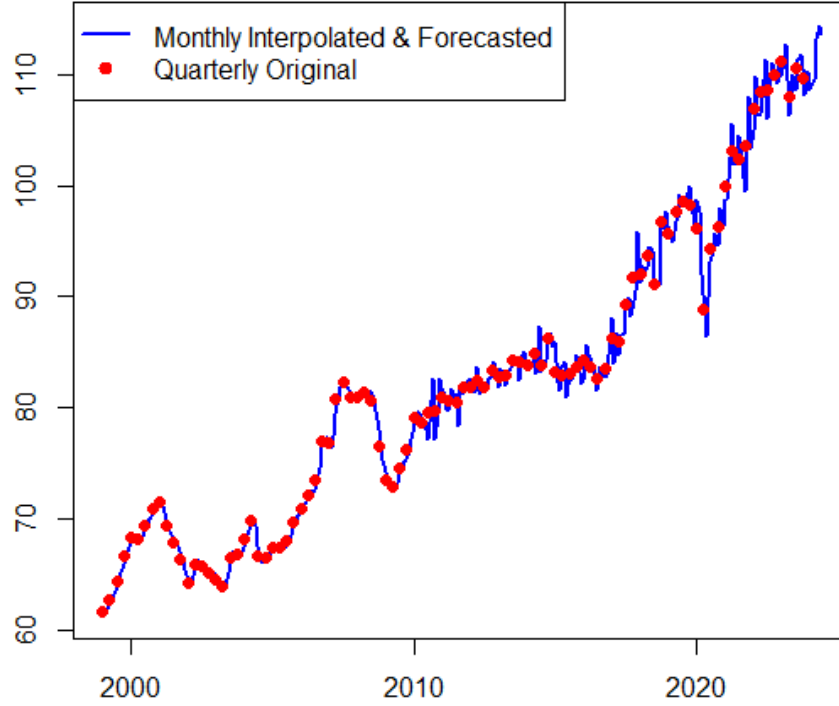

Figure 2: Interpolated monthly series of Switzerland's industrial production index (Denton-Cholette method), from January 1999 to September 2024.

Appendix B: Diagnostic tests for the model

Horizon	Parameter	Final Value (95% CI)
1-month	Beta Intercept	**-0.0021** (95% CI: -0.0064, 0.0022)
	Beta Inflation	**-0.0001** (95% CI: -0.0021, 0.0019)
	Beta Output Gap	**-0.0002** (95% CI: -0.0011, 0.0007)
6-month	Beta Intercept	**-0.0077** (95% CI: -0.0184, 0.0030)
	Beta Inflation	**0.0015** (95% CI: -0.0035, 0.0066)
	Beta Output Gap	**-0.0006** (95% CI: -0.0028, 0.0016)
12-month	Beta Intercept	**-0.0163** (95% CI: -0.0291, -0.0034)
	Beta Inflation	**0.0029** (95% CI: -0.0031, 0.0089)
	Beta Output Gap	**-0.0006** (95% CI: -0.0033, 0.0020)
18-month	Beta Intercept	**-0.0256** (95% CI: -0.0391, -0.0121)
	Beta Inflation	**0.0036** (95% CI: -0.0029, 0.0100)
	Beta Output Gap	**-0.0007** (95% CI: -0.0037, 0.0022)

Table 2: Final coefficients and their confidence intervals used for point forecasts across the different horizons.

Focusing on the final coefficient values, the negative intercept indicates a tendency for the Swiss franc to appreciate over time across all horizons. Inflation initially has a positive effect on short-term appreciation (one month) but turns negative for longer horizons, signaling depreciation. The output gap shows a consistently growing appreciation effect across all horizons. However, in the last rolling window, neither the inflation nor the output gap coefficients are statistically different from zero at any horizon.
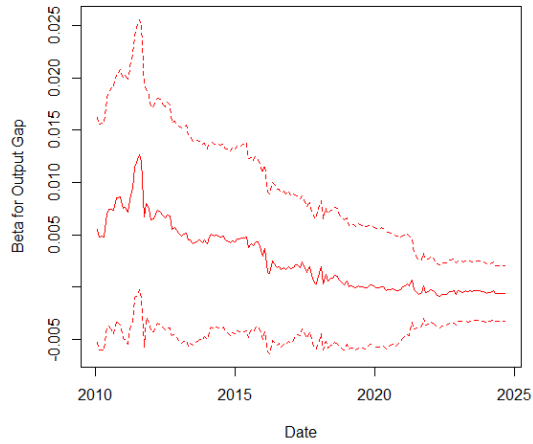
Figure 3: Evolution of beta output gap
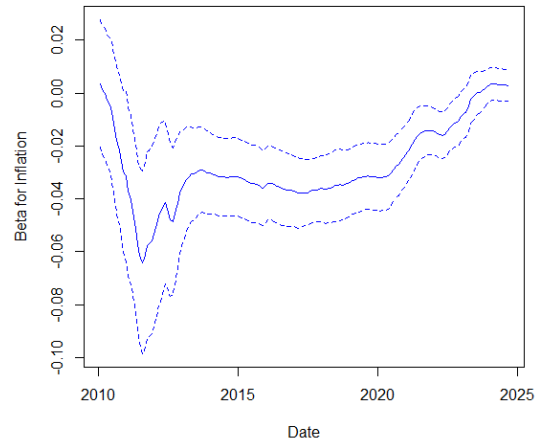for the 12-month horizon

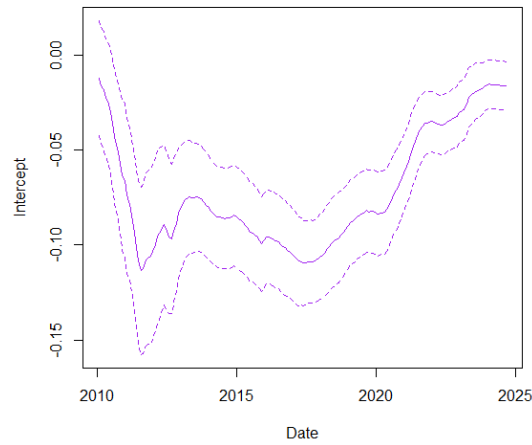Figure 4: Evolution of beta Inflation for
the 12-month horizon

Figure 5: Evolution of the intercept for
the 12-month horizon

These three graphs represent the evolution of coefficients through the rolling estimation
scheme. Similar patterns are observed for the 1-month, 6-month, and 18-month horizon
models. We observe for all betas after 2009 the effects of the global financial crisis and the
European sovereign debt crisis, periods during which the Swiss franc appreciated signifi-
cantly, increasing the relationship between the predictors and NEER. The coefficients then
become less pronounced as the effects of these crises gradually disappear from the data.

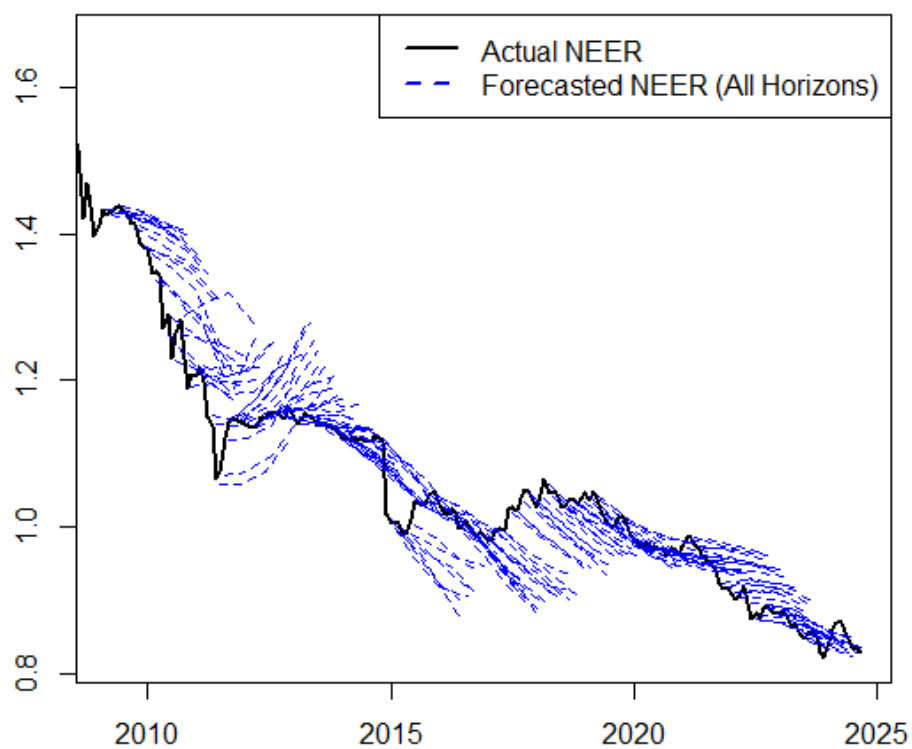**Appendix C: Visualization of the point forecasts: the spaghetti plot**

Figure 6: Spaghetti plot of point forecasts, showing the evolution of predictions over a horizon of 1 to 18 months, generated using a rolling estimation scheme.

According to Figure 6, the model starts to produce more accurate forecasts around 2020. This coincides with a period of consistent NEER appreciation without significant shocks, highlighting the model's difficulty in generating accurate forecasts during periods of high volatility.
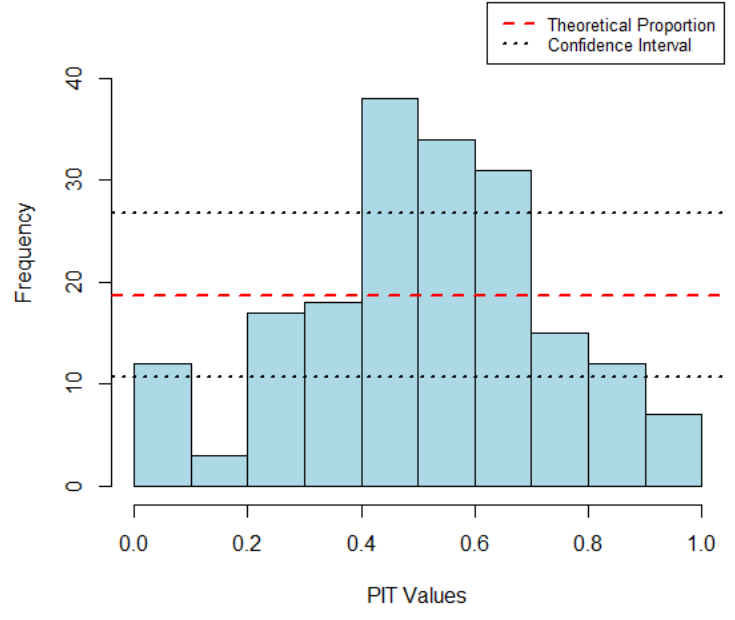
Appendix D: Density forecast evaluation

Figure 7: Histogram of PIT (Probability Integral Transform) values, testing the uniformity of the forecasted prediction intervals at 1 month.

A perfectly calibrated model is translated by a uniform distribution of the bins. Meaning that each single bins fall in its expected frequency. Here, we reject the null hypothesis of uniformity. The PIT values are also not serially correlated according to the Ljung-Box test, confirming the independence of forecast errors and the model's validity.

Confidence Level	Observed Violation Rate	LR Statistic	p-Value	H0	Test Result
80% CI	0.1016	13.24	0.00027	H0: Rate = 20%	Reject H0
90% CI	0.0642	3.02	0.0824	H0: Rate = 10%	Fail to Reject H0
95% CI	0.0481	0.014	0.906	H0: Rate = 5%	Fail to Reject H0

Table 3: Summary of violation rates and likelihood ratio tests for different confidence intervals.