Smooth Sailing? A Finite Gaussian Mixture Factor Model of What Makes Safe Haven Currencies

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Executive Summary

In this study we analyzed what variables define safe haven periods. In particular, we explored how the Swiss franc is affected and differs from other safe haven currencies such as the Japanese yen and across different base currencies. Furthermore, we analyzed if patterns persist over time and if there exist early warning indicators to predict a regime switch. To characterize states, we use a Gaussian Mixture model with factor models on the partitioned data. We find that the Swiss franc exhibits safe haven properties relative to various currencies, both on average and during crisis. Especially an increase in risk factors such as the VSTOXX, Gold, and Global FX Volatility lead to an appreciation of the franc. The effects are non-linear in crisis and non-crisis periods, with a stronger effect in crisis periods. While the Japanese yen appears to be a safer currency with increasing FX volatility and increasing yields on sub-investment grade US corporate bonds, the franc has a strong link to gold. Moreover, we find that the safe haven status of the franc has changed since the SNB removed the CHF/EUR floor in early 2015. We observe more noise which makes it harder to classify whether an appreciation of the Swiss franc is a result of safe haven refuge. Switzerland's safe haven status has ramifications for the SNB in that the appreciation causes downward pressure on prices and dampens the business cycle due to Switzerland's high export dependency. A particular cause for concern would be uncertainty in Europe due to the particular sensitivity of the CHF/EUR spot rate to increases in risk and Europe being Switzerland's largest trading partner. The interventions of the SNB may have reduced the reverse peso problem as the franc no longer provides an attractive insurance against crises.

1 Introduction

With the effects of the COVID-19 pandemic still present in the financial markets, the discussion about flight to safety was remarkably pronounced in March 2020. With heightened uncertainty, investors were scrambling to shift their assets into less affected, better-performing assets, to shelter their funds from these adverse effects. Among others, assets such as US government bonds, the Swiss franc, and even paintings are usually considered safe haven assets. Safe haven assets tend to provide hedging benefits both on average and during crisis. This phenomenon is not new, however. Certain assets such as the Swiss franc have provided shelter in past recessions and market turmoils. Report after report of the Swiss National Bank's (SNB) quarterly monetary policy assessment mentions the upward pressure on the Swiss franc in light of uncertainty and their willingness to intervene in the foreign exchange market. This has led to Switzerland being branded a currency manipulator in 2020 by the US Treasury Department, only to be removed the following year. Thus, the question naturally arises, what makes an asset a safe haven and why is it important that the Swiss franc is one?

In this study, we set out to explore safe haven currencies with a particular focus on the Swiss franc. We analyze the franc vis-à-vis various currencies and compare it to other safe haven currencies such as the Japanese yen. While numerous characteristics of safe haven currencies have been discussed in the FX literature, less focus has been placed on the distinction between crisis and non-crisis periods. We contribute to the safe haven literature in several ways. We identify factors that define safe haven periods and show that a differential effect exists between the Swiss franc and other safe haven currencies. Furthermore, we show that the results are not stable over time with particular focus on how the SNB FX interventions from early 2015 changed the safe haven characteristics of the Swiss franc. We also provide new evidence on early warning indicators for a switch to the safe haven regime by analysing the threshold values on which the mixture classifies an observation in the crisis regime. In terms of methodology, to the best of our knowledge, we are the first to apply a Mixture model to analyze safe haven currencies, providing evidence for future studies.

The remainder of the paper is structured as follows. First, the literature on safe haven currencies is examined, with special focus on the Swiss franc. Second, we present our methodology to identify FX regimes. Third, the data is described and all adjustments are explained. In the final sections, we provide the results and give actionable policy recommendations for central bankers and other FX practitioners.

2 Literature Review

The literature on safe haven currencies gives a clearer idea of what constitutes a safe haven asset and which properties it should possess. Intuitively, a safe haven asset should have a low correlation with traditional risk factors and not be too sensitive to volatility in markets or liquidity squeezes. Safe haven assets should also provide hedging benefits against a reference asset, both in times of stress and on average (Ranaldo & Söderlind, 2010).

Traditionally, currencies such as the US dollar, the British pound sterling and the Euro have been mentioned as safe haven currencies. The Swiss franc also exhibits safe haven characteristics, both on average and in times of crisis. On average, the Swiss franc is negatively correlated with world equity markets. In times of distress, Ranaldo & Söderlind (2010) show that these effects are magnified, making the hedging characteristics visible within minutes of catastrophic events happening (e.g., 9/11). Jäggi, Schlegel, & Zanetti (2019) also use high-frequency data to show that the Swiss franc and Japanese yen react more strongly to macroeconomic surprises than other currencies, showing that these surprises drive risk aversion and uncertainty. This is also consistent with Lee (2017), who shows that the yen and franc qualify as strong safe haven currencies, while the British pound, Euro, Canadian dollar, Norwegian krone can be considered risky currencies. More precisely, Lee (2017) shows that the franc does not covary with the global stock market at all, while the yen provides positive returns in times of crisis.

However, as Grisse & Nitschka (2015) note, the Swiss franc does not show the above properties against all currencies. More specifically, it does not show safe haven traits against the US dollar or Japanese yen, while it does against the Euro. This is best exemplified by the massive appreciation of the Swiss franc following the European debt crisis, prompting the SNB to take unconventional monetary policy measures such as Forex (FX) intervention. In financial crises, Fatum & Yamamoto (2016) find that both the Swiss franc and US dollar depreciate against the Japanese yen, implying that the yen is a safer currency than the franc.

The low risk of the Swiss franc is also shown by its relatively low-interest rates, making the franc a popular funding currency for carry trades. According to Uncovered Interest Parity, carry trades should not be profitable, as the interest rate differential would create arbitrage opportunities for investors. Hence, high-interest rate currencies should depreciate, and low-interest rate currencies should appreciate. However, the empirics show the opposite, leading to the "forward premium puzzle" (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012, p. 682). Menkhoff et al. (2012) show that part of the excess returns from carry trades can be thought of as compensation for time-varying risk. More precisely, high-interest rate currencies perform poorly in times of heightened global FX volatility, while low-interest rate or safe haven currencies provide better returns in high-volatility periods.

The Swiss franc is a peculiar case of UIP violation, as it has provided lower returns than comparable currencies, leading to Switzerland being called the "Swiss Interest Rate Island" (Kugler & Weder, 2002, p. 1). Historically, its origins can be traced to World War I, when its low-interest rates began to reflect its economic, monetary and political stability (Baltensperger et al., 2016). Kugler & Weder (2002) put forward the hypothesis that Switzerland suffers from a reverse peso problem, arguing that the interest rate puzzle has more to do with its currency than structural features of the banking system. Instead of constant depreciation expectations such as with the Mexican peso, investors have constant appreciation expectations in the event of a catastrophic event happening. Therefore, investors are willing to accept a lower interest rate in return for an insurance premium against certain unlikely events.

Further determinants of safe haven currency status are laid out by Habib & Stracca (2012), who find that a strong net foreign asset position (NFA) is robustly associated with safe haven currency status and to a lesser extent the size of the stock market. From these findings they put forward three possible explanations currency as to what investors look for in a safe haven currency country. First, as the NFA can indicate country risk, investors naturally prefer countries with lower intrinsic risk in times of crisis. Second, since the size of the stock market can show the degree of development and liquidity of a country's financial markets, investors would tend to countries with a solid financial system in times of heightened volatility and low liquidity. Lastly, investors would prefer a country that is less integrated with the global financial system, making it less susceptible to contagion in times of financial crises.

Looking to the future of safe haven assets, the advent of cryptocurrencies has generated a discussion around stablecoins, whose price is pegged to other assets such as fiat currencies or commodities. As their price is backed by other assets they could provide investors with a hedge against the extreme volatility of traditional cryptocurrencies such as Bitcoin and

Ethereum. Baumöhl & Vyrost (2020) find that while stablecoins do not show reliable and stable behavior they can still provide hedging benefits due to their negative dependence on nonstable coins.

3 Methodology

To capture non-linearities in safe haven characteristics, i.e., if there exists a differential effect of risk factors in crisis and non-crisis periods, we propose a finite Gaussian Mixture model with factor models on the partitioned data. The Gaussian Mixture model allows us to investigate if two different exchange rate return regimes can be detected, crisis and non-crisis periods, by probabilistically separating states based on unobserved factors. Hence, the advantage is that we can actually test the hypothesis if all exchange rate returns are drawn from a single underlying distribution. Interesting applications of mixture models include Conway & Deb (2005), Caudill, Gropper, & Hartarska (2009), Pérez-Rodríguez, Gómez-Déniz, & Sosvilla-Rivero (2021).

Following the methodology laid out by Dempster, Laird, & Rubin (1977), we use the two-step expectation-maximizing (EM) algorithm for a parametric mixture. This is an iterative method for maximum likelihood estimates in models which depend on unobserved (so-called latent) variables. It is convenient because the maximum likelihood strictly increases with the iterations, which guarantees a solution and avoids non-convergence. McLachlan et al. (2019) argues that virtually all mixture models post-1977 follow the EM approach with the maximum likelihood estimation as the key computation. The model has two types of parameters, the component weights and component means and variances. For $K = 2$ components, the states we are identifying, component one and two have means and variances of μ_1, μ_2, σ_1, σ_2 for the univariate case. The one dimensional model is given by:

$$p(x) = \sum_{i=1}^{K} \phi_i \mathcal{N}(x \mid \mu_i, \sigma_i) \tag{1}$$

$$\mathcal{N}(x \mid \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right) \tag{2}$$

$$\sum_{i=1}^{K} \phi_i = 1 \tag{3}$$

where $p(x)$ is the a-priori posterior probability, the probability that an observed x is generated by component K, and ϕ_i are the component weights constrained to 1 in order for the probability distribution to not exceed 1. x are the spot returns, μ_i and σ_i the mean and standard deviation of spot returns, respectively.

The EM algorithm starts with an initialization step. Samples without replacement from the data $X = (x_1, ..., x_N)$, the spot rate returns, are randomly assigned to the component mean estimates. For instance, for $K = 2$ and N we get $\hat{\mu}_1 = x_{i+15}$, $\hat{\mu}_2 = x_{i+261}$. The component variances are set to the sample variances and mixture weights are uniformly distributed. With parameters ϕ_k, μ_k, and σ_k, the EM algorithm proceeds in two steps. In the E step, we estimate the expected values of the latent variables, i.e., the probability weights, also referred to as membership probabilities or component assignments, by means of Bayes' theorem. We calculate $\forall i, k$:

$$\hat{\gamma}_{ik} = \frac{\hat{\phi}_k \mathcal{N}(x_i \mid \hat{\mu}_k, \hat{\sigma}_k)}{\sum_{j=1}^{K} \hat{\phi}_j \mathcal{N}(x_i \mid \hat{\mu}_j, \hat{\sigma}_j)} \tag{4}$$

where $\hat{\gamma}_{ik}$ gives the probability that x_i belongs to component K, i.e., $\hat{\gamma}_{ik} = p(C_k \mid x_i, \hat{\phi}, \hat{\sigma})$.

Using the $\hat{\gamma}_{ik}$ from the E-step, we calculate $\forall k$ in the M-step:

$$\hat{\phi}_k = \sum_{i=1}^{N} \frac{\hat{\gamma}_{ik}}{N} \tag{5}$$

$$\hat{\mu}_k = \frac{\sum_{i=1}^{N} \hat{\gamma}_{ik} x_i}{\sum_{i=1}^{N} \hat{\gamma}_{ik}} \tag{6}$$

$$\hat{\sigma}_k^2 = \frac{\sum_{i=1}^{N} \hat{\gamma}_{ik} (x_i - \hat{\mu}_k)^2}{\sum_{i=1}^{N} \hat{\gamma}_{ik}} \tag{7}$$

E- and M-steps are then iteratively changed and repeated until the difference for parameters θ_t at iteration $t \mid \theta_t - \theta_{t-1} \mid \leq \epsilon$ is arbitrarily small and does not change anymore.

We then use the partitioned data from the Gaussian Mixture to run regressions on each state to obtain coefficients, standard errors, and significance levels. This allows us to explore if heterogeneous effects exist in the states, i.e., if safe haven characteristics are non-linear and the effect of risk factors is stronger in crisis periods. Furthermore, we find threshold values of the independent variables on which the mixture splits the data in order to identify possible switches into safe have regimes:

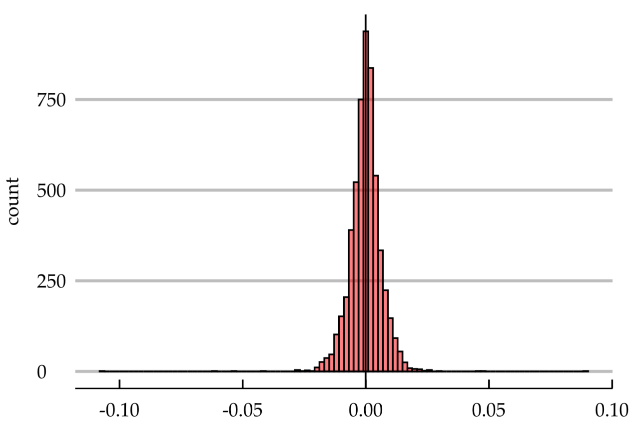
$$x_i = \begin{cases} \varphi, & \text{if } \gamma > 0.5 \\ x_i, & \text{otherwise} \end{cases} \tag{8}$$

where φ indicates the threshold value computed separately for the mean of the positive and negative data points belonging to the crisis component and γ the posterior probability of each observation. It is important to note here that we do not split the data based on the risk factor returns but assume that threshold values of the risk factor lead to the spot rate return being characterized as belonging to the crisis component.

4 Data

We obtained data from Bloomberg, Eikon, and the Federal Reserve Bank of St. Louis. For the independent variables, we opted for a broad range of daily risk factors used in previous papers such as the TED spread (difference between 3M Libor and T-bills), the VIX (and VSTOXX) and measures of equity markets such as the MSCI World. Additionally, we considered variables we have not seen in previous papers such as the CBOE Put/Call ratio to capture investor sentiment. In choosing the currency pairs, we included G10 and emerging market currencies but chose to focus our analysis on currencies typically considered safer currencies such as the British pound, the US dollar, the Japanese yen, the Euro and the Swiss franc. This allows us to investigate if certain variables are significant for all safer currencies or whether some are more idiosyncratic to the Swiss franc. To avoid confusion, spot rates are reported as CHF/EUR, i.e., Swiss franc per Euro. Lastly, we chose a daily measure of FX liquidity, namely the Bid-Ask spread at 1700 EST as this has the highest mean correlation with the effective cost of liquidity per Karnaukh, Ranaldo, & Söderlind (2015).

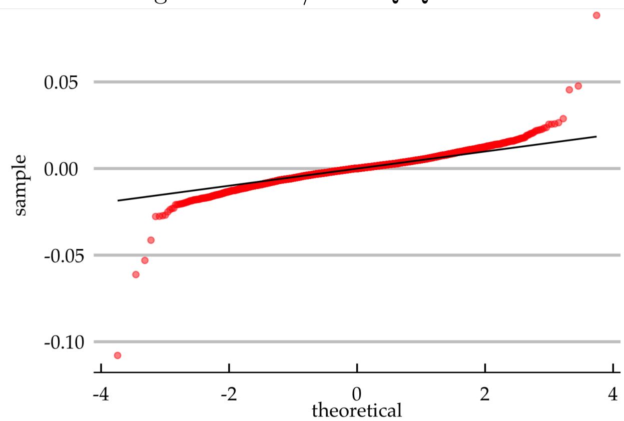
Figure 1: CHF/USD Spot Rate Return Histogram



Notes: This figure shows a histogram for the CHF/USD spot returns. The data covers the period 20-03-2000 until 18-03-2000.

Most of the variables cover the period of 17-03-2000 until 18-03-2021. As some of the variables did not have data on certain dates, we explicitly took dates where the spot rates and independent variables matched. We calculated crossrates for the currency pairs CHF/JPY, CHF/NOK, CHF/BRL, CHF/IDR via the US dollar to extend the available data. For missing data, we checked the number of consecutive missing values and disregarded variables with more than five missing values in a row, imputing the others with the previous period's value.

Figure 2: CHF/USD Q-Q Plot



Notes: This figure shows the Q-Q Plot for CHF/USD spot returns. The data covers the period 20-03-2000 until 18-03-2000.

For our model specification, we use daily simple spot returns as the dependent variable and calculate simple returns for the independent variables to avoid spurious relationships from non-stationary time series. Table 1 provides summary statistics for selected dependent and independent variables. As is typical with financial time series, the distribution of returns looks fairly normal but has significantly fatter tails, as can be seen in figures 1 and 2 taking the CHF/USD rate as an example. In figure 3 we plotted the CHF/EUR spot rate to visualise the impact of times of heightened volatility on the Swiss franc vis-à-vis the Euro.

Table 1: Descriptive Statistics

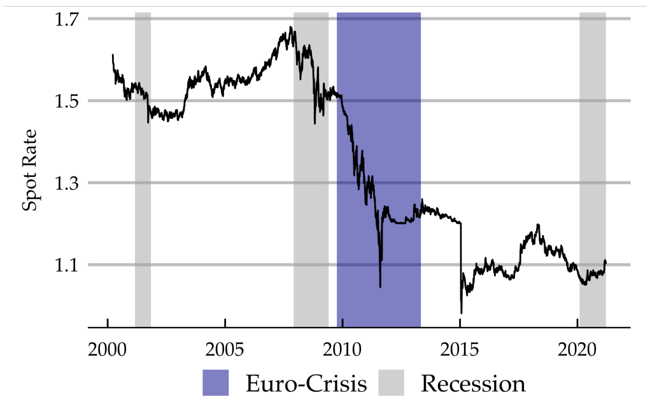
	min	mean	max	count
CHF/USD	-10.79	-0.01	8.84	5,479
CHF/GBP	-11.06	-0.01	8.17	5,479
CHF/EUR	-14.40	-0.01	8.32	5,479
CHF/JPY	-10.76	-0.01	8.64	5,479
Put-Call	-55.55	1.42	146.87	5,480
FX Vola	-21.17	0.02	30.89	5,480
VSTOXX	-35.233	0.184	60.106	5,480
MSCI	-9.915	0.018	9.523	5,480

Notes: This table shows descriptive statistics for selected spot rate and risk factor returns. The data for the spot rate returns covers the period of 20-03-2000 until 18-03-2021 while risk factor returns cover until 19-03-2021. The figures are in percentage.

5 Results

Our model splits the spot returns into two components – one which we coin the "crisis" component due to the significantly higher daily volatility and another component which we term "non-crisis" with lower daily volatility. The component weights, daily volatility, and regression coefficients for the crisis and non-crisis components are presented in table 2 and 3, respectively. We plot the results of the mixture model of the CHF/EUR return series in figures 4 and 5 against recessions and significant European events. We can clearly see that the mixture splits the spot rate returns well, with good identification around recessions. Furthermore, it detects significant events such as the SNB floor removal in early 2015, flash crashes, and terrorist attacks. In particular, it underscores the impact the London Bombings in July 2005 had on the British pound, leading to an appreciation of the franc.

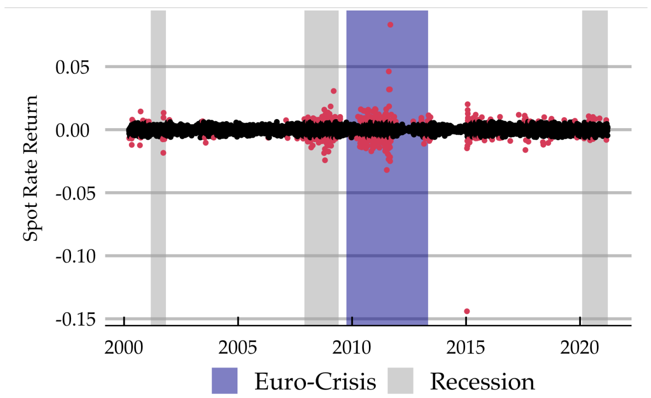
Figure 3: CHF/EUR spot rate



Notes: This figure shows the CHF/USD spot rate. The data covers the period 17-03-2000 until 18-03-2021. Dates of US Recessions and the European Sovereign Debt Crisis are shown in grey and blue, respectively. The dates for the US Recessions are from the Federal Reserve in St. Louis and the European Sovereign Debt Crisis dates from the European Central Bank.

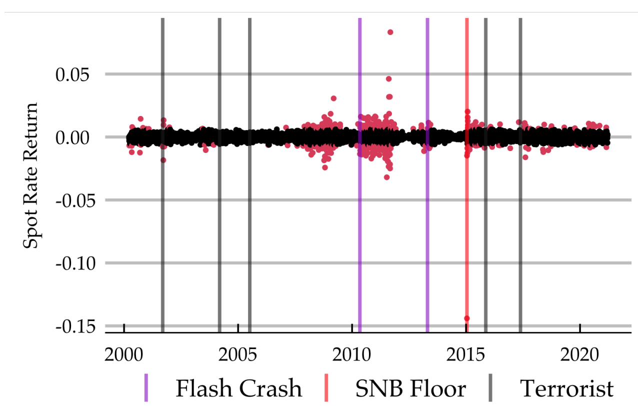
Overall, we see clear evidence that the Swiss franc exhibits safe haven properties and that the effects are non-linear in the components. The results are robust vis-à-vis most currencies. Diving deeper, we find evidence that the CHF/EUR exchange rate is particularly sensitive to increases in risk and market uncertainty. The franc tends to appreciate against the Euro in response to increases in credit risk, market uncertainty in the European area as well as increases in FX market volatility. Interestingly, the results are more pronounced for the VSTOXX (European risk) than the VIX (US risk), underscoring the fact that the Swiss franc is more responsive to local market conditions. Furthermore, FX market volatility is insignificant against the US dollar and significantly negative for the Japanese yen. This underscores that the Japanese yen is a safer currency when risks are idiosyncratic to the FX market. The result is similar for the equity market (MSCI) and fixed income risks (high yield index). Unsurprisingly, the Brazilian real appreciates with an increasing MSCI. This is a result of its use in the long end in carry trades, in which high-interest currencies benefit from accommodating market conditions. Across most currencies, we also find that the put-call ratio explains spot rate returns. An increasing put-call ratio, which indicates bearish market sentiment, leads to an appreciation of the franc.

Figure 4: Two Regimes in the CHF/EUR Return Series



Notes: This figure shows the crisis and non-crisis components of the spot rate returns in red and black, respectively. The data is divided according to the Gaussian Mixture model. The data covers the period 20-03-2000 until 18-03-2021. Dates of US Recessions and the European Sovereign Debt Crisis in grey and blue, respectively. The dates for the US Recessions are from the Federal Reserve in St. Louis and the European Sovereign Debt Crisis dates from the European Central Bank.

Figure 5: Two Regimes in the CHF/EUR Return Series



Notes: This figure shows the crisis and non-crisis components of the spot rate returns in red and black, respectively. The data is divided according to the Gaussian Mixture model. The data covers the period 20-03-2000 until 18-03-2021. Dates of significant risk events are highlighted with vertical lines.

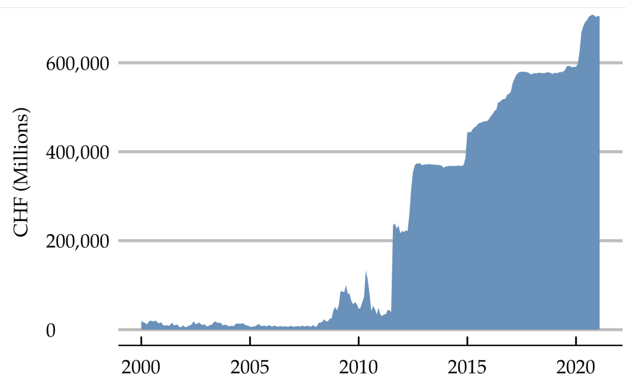
The order of magnitude of the appreciation is larger during crisis periods, indicating non-linearities. For instance, the effect of Global FX Volatility on the Swiss franc vis-à-vis the Euro is more than ten times larger in a crisis period than non-crisis period. This indicates that the Swiss franc exhibits safe haven properties on average and during crisis, but that the effects are more pronounced in crises. Although we find a weaker link between spot returns and risk factors in the crisis state as a whole, we conjecture that this is due to the limited sample size of the crisis component, which by construction is small when looking at tail risk periods such as the Great Recession. The sample size for the CHF/EUR in the crisis component is 326 compared to 5,153 in the non-crisis component.

A key result which further underscores the franc's status as a safe haven currency is its positive association with gold prices. Except for the Norwegian krone, which may be a result of its strong link to international commodity prices, an increase in gold prices is associated with an appreciation of the franc against all currencies in our sample. Gold is widely considered a safe haven asset by investors due to its weak correlation with other asset classes and for being able to store its value in times of crisis, acting as an inflation hedge and diversification vehicle. Hence, gold prices tend to increase in times of rising market uncertainty, analogously to the Swiss franc. We argue that the franc's positive correlation with gold prices is further compounded by Switzerland's strong ties to gold. Switzerland is the largest exporter of gold and while the formal link between the Swiss franc and gold was legislatively severed at the end of the 20th century, the Swiss constitution[1] still mandates that the SNB keep part of its currency reserves in the form of gold.

While the safe haven status of the Swiss franc is clear, it has changed over time. Our mixture model identifies less extreme swings in spot returns but a rather consistently higher volatility level post-SNB removal of the Swiss franc floor. This is shown by the stark appreciation of the franc in early 2015 in figure 5. Letting the Swiss franc float freely and given that the the SNB is extremely active in FX market (evidenced by weekly sight deposits in figure 6), introduces more noise to the Swiss franc returns. This makes classification more difficult and we argue that the safe haven status is less clear because it is not possible to disentangle actual safe haven appreciation from noise.

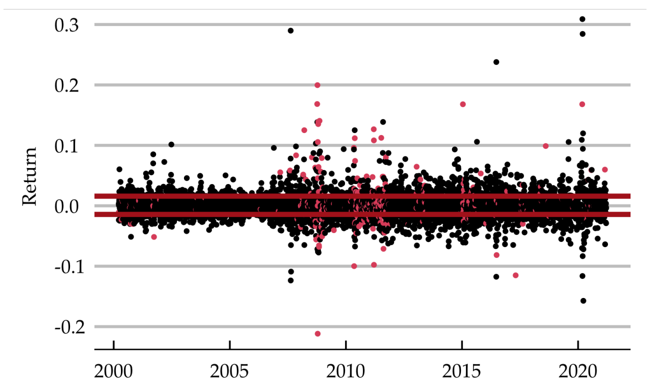
[1] Art. 99 para. 3

Figure 6: Monthly Sight Deposits of the SNB



Notes: This figure shows the aggregate SNB sight deposits on a monthly basis. The data covers the period 01-2000 until 02-2021. Source: SNB

Figure 7: Distribution Global FX Volatility with Mixture Thresholds



Notes: This figure shows crisis and non-crisis returns of the JPM Global FX Volatility Index in red and black, respectively. The data covers the period 20-03-2000 until 19-03-2021. The horizontal lines indicate the positive and negative threshold values computed as the mean of the positive and negative data in the crisis component. The classification is done based on the respective spot rate return, i.e., if a spot rate return is classified as crisis, the FX volatility point on that same day is characterized as crisis, too.

To further characterize the two states, we analyze the independent variables to determine whether there are threshold values between the two, which would act as potential early warning indicators. We characterize a positive and a negative threshold value by calculating the mean of the data attached to a spot rate return data point classified as crisis. The threshold values can be found in table 4. Furthermore, we calculate the proportion of data points of each state, crisis and non-crisis, outside of the thresholds to check for potential predictability. If more crisis than non-crisis data points are outside of the thresholds, we argue that there is indeed the potential to act as early warning indicators. We plot the Global FX Volatility returns in figure 7 with horizontal thresholds. The mean threshold is an arguably crude estimate, yet we find compelling evidence in the proportions. For instance, the proportion of VSTOXX returns above/below the threshold for the crisis component is more than 45%, compared to only 37% for the non-crisis component. We find similar results for other risk factors. Although the difference may not seem striking at first, it is important to note that the partition is not done on the risk factor returns but on the spot rate returns.

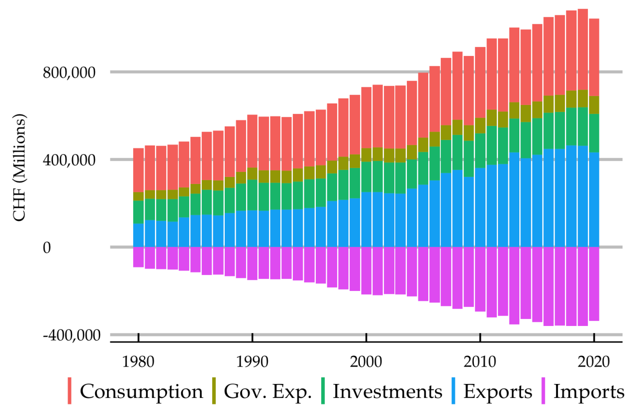
6 Policy Implications

Given that the dynamics we show above are not driven by fundamental factors such as productivity or terms of trade but rather by risk aversion and market uncertainty, the (transitory) appreciation of the franc can be seen as unjustified. Typically, a central bank in a country with free capital flows and an independent monetary policy does not have an explicit goal for exchange rates. However, looking at Switzerland's GDP from the expenditure side in figure 8 shows that it is inextricably linked to developments abroad, with over 50% of GDP coming from exports in the past years. Therefore, the exchange rate has a decisive impact on prices and real activity.

As we have shown, the appreciation of the Swiss franc is pro-cyclical and hence dampens real activity and creates downward pressure on prices when risk aversion increases. The combination of an appreciating franc, a recession, declining exports and Switzerland's typically low inflation rate harbors the potential to significantly damage the economy. The attractiveness of the franc during times of uncertainty has been exacerbated by the compression of interest rate differentials post the Great Financial Crisis, with record-low interest rates making expansionary monetary policy even more difficult to implement. This has at least partially been alleviated via the introduction of a negative policy rate on sight deposits at the SNB.

Our results suggest that increases in different risk factors affect the franc and other currencies heterogeneously. A key variable for the Swiss franc is the gold price. Given that increases in the gold price are strongly associated with an appreciation of the franc, the SNB should closely monitor developments in the gold market. A further cause for concern would be an increase in European risk factors such as the VSTOXX, while risk factors such as the VIX or MOVE index appear to be less important for the franc and may have a larger effect on the US dollar or Japanese yen. Our threshold values for the VSTOXX could provide a very rough estimate for identifying a switch into a safe haven regime and allow the SNB to act accordingly.

Figure 8: Swiss GDP (Expenditure Side)



Notes: This figure shows the composition of Swiss GDP from the expenditure side. The data covers the period from 1980 until 2020 in yearly intervals. Source: SECO

Furthermore, Switzerland's safe haven status does not call for intervening across all currency pairs. While our results show that the franc appreciates against most currencies in times of crisis, not all currency pairs are material for the development of the Swiss economy. For example, an emerging market crisis in Brazil would most likely lead to an appreciation of the Swiss franc against the Brazilian real but given that Brazil is not a top trading partner it would not exert significant downward pressure on prices. The most significant scenario would be heightened uncertainty or a recession in the European Union. Given that the franc reacts strongly vis-à-vis the Euro in response to increases in risk and that Europe is Switzerland's largest trading partner, the deflationary risks would be substantial.

According to our model, the SNB interventions in the FX market post-2015 have led to more noise through a consistently higher level of volatility but less extreme swings in the CHF/EUR exchange rate. This is beneficial for exporters as they enjoy more exchange rate stability. Furthermore, the interventions may alleviate the reverse peso problem mentioned in the literature since the SNB no longer tolerates an excessive appreciation of the franc during crisis times. Therefore, investors can not earn as large of an insurance premium on the franc in the case of black swan events and adjust their expectations accordingly.

Lastly, the capital flows generated by the switch into and out of safe haven currencies raise questions around financial stability, another part of the SNB's mandate. These inflows can create additional exposure in the banking system if they lead to an expansion in credit by banks. A sudden outflow of these funds could then cause liquidity issues depending on the maturity of the financial instrument in which banks invest these additional funds. While we do not expect sudden stops such as in the Mexican peso crisis or other emerging markets, we do believe it is important to monitor these flows. Our threshold values computed above could provide a rough estimate for predicting such flows. Another indirect effect could come from the interest rate normalization after capital flows back out of the franc, which depending on the size of the increase could cause substantial write-downs on mortgages and a deterioration in net interest income for banks.

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Appendix

Table 2: Results Gaussian Mixture and Regression Crisis Component

	Dependent variable:								
	CHF/EUR	CHF/GBP	CHF/USD	CHF/JPY	CHF/BRL	CHF/INR	CHF/NOK	JPY/USD	BRL/USD
ϕ_1	0.094	0.036	0.065	0.105	0.126	0.036	0.149	0.206	0.204
σ_1	0.011	0.019	0.017	0.015	0.014	0.020	0.023	0.010	0.019
MSCI	0.129*	0.183	0.066	−0.358***	0.162	0.210	0.259***	0.015	−0.348***
	(0.068)	(0.112)	(0.333)	(0.123)	(0.116)	(0.263)	(0.067)	(0.051)	(0.081)
Put-Call Ratio	−0.004	−0.012	−0.013	0.004	−0.018**	−0.005	−0.006	−0.012***	0.011**
	(0.005)	(0.009)	(0.016)	(0.009)	(0.008)	(0.021)	(0.006)	(0.003)	(0.006)
MOVE 3-months	0.018	0.064	0.057	−0.007	0.088**	−0.069	0.011	0.046***	−0.024
	(0.021)	(0.046)	(0.090)	(0.036)	(0.043)	(0.095)	(0.022)	(0.014)	(0.026)
VIX	0.013	0.040**	0.005	−0.038*	0.029	0.019	0.026**	0.009	−0.042***
	(0.011)	(0.020)	(0.047)	(0.021)	(0.021)	(0.045)	(0.012)	(0.008)	(0.014)
VSTOXX	−0.018	−0.033	−0.020	0.031	−0.094***	−0.061	−0.042***	−0.041***	0.051***
	(0.012)	(0.025)	(0.054)	(0.021)	(0.020)	(0.054)	(0.012)	(0.008)	(0.014)
TED Spread	0.019*	0.025	0.018	0.008	0.003	0.045	0.015	−0.006	−0.001
	(0.011)	(0.018)	(0.030)	(0.015)	(0.011)	(0.035)	(0.010)	(0.005)	(0.007)
Gold	−0.101**	−0.244***	−0.748***	−0.183**	−0.241***	−0.720***	0.025	−0.352***	−0.180***
	(0.051)	(0.086)	(0.170)	(0.080)	(0.087)	(0.188)	(0.056)	(0.033)	(0.055)
Global FX Vola	−0.124***	−0.199***	−0.147*	0.047	−0.192***	−0.197**	−0.047*	−0.105***	0.139***
	(0.024)	(0.046)	(0.084)	(0.037)	(0.041)	(0.089)	(0.024)	(0.017)	(0.030)
10-year Breakeven Inflation	−0.003	0.009	0.008	−0.009	0.004	−0.016	0.003	0.007	−0.007**
	(0.010)	(0.011)	(0.014)	(0.013)	(0.004)	(0.022)	(0.002)	(0.005)	(0.003)
US 10-year HY Index	0.005	−0.019	0.143	−0.013	−0.110*	0.203	−0.065*	−0.015	0.075*
	(0.034)	(0.064)	(0.160)	(0.061)	(0.057)	(0.143)	(0.033)	(0.024)	(0.041)
Bid-Ask Spread	−0.978	−2.712	−5.672*	0.901	0.673	−0.038	−0.035		
	(0.752)	(1.943)	(3.145)	(1.141)	(0.446)	(0.084)	(0.031)		
Constant	0.001	0.001	0.005	−0.002	−0.0005	0.002	−0.001	0.0003	0.001
	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)
Observations	326	165	71	246	374	67	341	479	573
R^2	0.241	0.391	0.449	0.213	0.362	0.443	0.355	0.444	0.330
Adjusted R^2	0.214	0.348	0.346	0.176	0.342	0.331	0.333	0.432	0.318
Residual Std. Error	0.013	0.019	0.023	0.020	0.026	0.025	0.015	0.011	0.021
F Statistic	9.047***	8.942***	4.367***	5.751***	18.658***	3.969***	16.449***	37.352***	27.644***

Notes: This table shows the results for Gaussian Mixture model and regression for the crisis component. The data covers the period of 20-03-2000 until 18-03-2021. The figures are in percentage. Statistical significance is given by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. ϕ_1 indicates the mixture proportion for the crisis component while σ_1 indicates the daily volatility of the spot rate returns. Spot rates are reported as CHF/EUR, i.e., Swiss franc per Euro.

Table 3: Results Gaussian Mixture and Regression Non-Crisis Component

	Dependent variable:								
	CHF/EUR	CHF/GBP	CHF/USD	CHF/JPY	CHF/BRL	CHF/INR	CHF/NOK	JPY/USD	BRL/USD
ϕ_2	0.906	0.964	0.935	0.895	0.874	0.964	0.851	0.794	0.796
σ_2	0.002	0.006	0.005	0.005	0.004	0.006	0.008	0.004	0.006
MSCI	0.023***	0.011	−0.149***	−0.065***	0.027	−0.096***	0.069***	−0.058***	−0.180***
	(0.005)	(0.010)	(0.010)	(0.011)	(0.018)	(0.012)	(0.009)	(0.009)	(0.015)
Put-Call Ratio	0.0001	−0.001*	−0.002***	−0.001**	−0.003***	−0.001***	−0.001	−0.001***	0.0002
	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.001)	(0.0005)	(0.0003)	(0.0004)	(0.001)
MOVE 3-months	0.001	0.003	0.002	−0.013***	0.0005	0.007**	0.001	0.012***	0.003
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
VIX	0.002***	0.0003	−0.008***	−0.003**	0.003	−0.004***	0.005***	−0.004***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
VSTOXX	−0.003***	−0.009***	−0.014***	−0.0002	−0.026***	−0.018***	−0.009***	−0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
TED Spread	−0.001**	−0.001	−0.001	−0.0002	−0.003**	−0.001	−0.001	−0.001	0.0004
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gold	−0.006*	−0.061***	−0.195***	−0.044***	−0.068***	−0.147***	0.003	−0.092***	−0.072***
	(0.003)	(0.006)	(0.007)	(0.007)	(0.011)	(0.008)	(0.006)	(0.006)	(0.009)
Global FX Vola	−0.012***	−0.019***	−0.001	0.039***	−0.044***	−0.023***	−0.033***	−0.023***	0.032***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.005)
10-year Breakeven Inflation	−0.001***	−0.001	−0.002***	−0.001*	0.004	−0.001	0.002	−0.0003	0.001
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.003)
US 10-year HY Index	−0.004**	−0.016***	−0.021***	0.017***	−0.028***	−0.040***	−0.026***	−0.031***	0.008
	(0.002)	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)	(0.004)	(0.003)	(0.005)
Bid-Ask Spread	−0.027	−0.084	−0.096	0.041	−0.004	−0.00004	−0.002		
	(0.047)	(0.082)	(0.085)	(0.105)	(0.007)	(0.001)	(0.004)		
Constant	−0.00002	0.0001	0.0002**	−0.0001	−0.0001	−0.00001	0.0001*	0.0003***	0.00004
	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	5,153	5,314	5,408	5,233	5,105	5,412	5,138	5,000	4,906
R^2	0.054	0.066	0.195	0.064	0.117	0.141	0.130	0.131	0.132
Adjusted R^2	0.052	0.064	0.193	0.062	0.115	0.139	0.128	0.129	0.130
Residual Std. Error	0.002	0.005	0.005	0.005	0.007	0.006	0.004	0.004	0.006
F Statistic	26.484***	34.141***	118.857***	32.676***	61.456***	80.251***	69.790***	74.999***	74.400***

Notes: This table shows the results for Gaussian Mixture model and regression for the non-crisis component. The data covers the period of 20-03-2000 until 18-03-2021. The figures are in percentage. Statistical significance is given by *p<0.1; **p<0.05; ***p<0.01. ϕ_2 indicates the mixture proportion for the non-crisis component while σ_2 indicates the daily volatility of the spot rate returns. Spot rates are reported as CHF/EUR, i.e., Swiss franc per Euro.

Table 4: Results Threshold Values Risk Factors

	CHF/EUR	CHF/GBP	CHF/USD	CHF/JPY	CHF/BRL	CHF/INR	CHF/NOK	JPY/USD	BRL/USD
Put-Call Ratio	15.333	15.377	15.294	15.325	15.320	15.330	15.322	15.222	15.339
	-12.412	-12.379	-12.358	-12.419	-12.287	-12.377	-12.475	-12.443	-12.391
VIX	5.664	5.668	5.753	5.661	5.560	5.743	5.467	5.549	5.483
	-4.430	-4.427	-4.460	-4.425	-4.363	-4.461	-4.405	-4.435	-4.391
VSTOXX	5.122	5.106	5.194	5.104	4.997	5.185	4.848	4.947	4.927
	-4.019	-4.024	-4.056	-4.039	-3.961	-4.059	-3.977	-4.033	-3.982
TED Spread	6.824	6.769	6.766	6.745	6.692	6.753	6.790	6.727	6.620
	-8.266	-8.287	-8.226	-8.251	-7.965	-8.241	-8.243	-8.217	-7.937
Gold	0.739	0.737	0.736	0.727	0.730	0.744	0.725	0.708	0.714
	-0.734	-0.738	-0.747	-0.733	-0.725	-0.747	-0.729	-0.705	-0.703
Global FX Vola	1.592	1.604	1.660	1.554	1.556	1.651	1.493	1.461	1.507
	-1.428	-1.436	-1.457	-1.439	-1.414	-1.453	-1.411	-1.414	-1.410
US 10-year HY Index	1.528	1.538	1.565	1.531	1.508	1.551	1.449	1.488	1.491
	-1.420	-1.422	-1.432	-1.426	-1.413	-1.434	-1.401	-1.406	-1.405

Notes: This table shows the positive and negative threshold values of the risk factors. The data covers the period of 20-03-2000 until 18-03-2021. We characterize the positive and a negative threshold value by calculating the mean of the data attached to a spot rate return data point classified as crisis.