QF621 Sample Report - Group 1

Introduction

The objective of this project is to develop and validate an FX factor investing strategy that applies risk-factor models—well established in equities—to foreign exchange markets. The project will investigate whether factors can explain FX return dynamics, improve risk management, and guide currency portfolio construction.

While factor investing is well researched in equities, its application in FX markets remains relatively underexplored. Recent studies by Baku et al. (2019) and Li et al. (2023) indicate that traditional FX risk factors (carry, value, and momentum) as well as new factor constructs can meaningfully capture currency comovements. Moreover, integrated approaches (e.g., Ranganathan et al. 2024) and optimization methods (Maurer et al. 2017) suggest potential for improved portfolio performance and hedging effectiveness. Testing these models in FX could yield novel insights and practical benefits for international investors.

As such, we would be using FX factors such as carry, value, momentum, commodity and volatility components as well as mean-variance and long-term cointegrated portfolio optimization to build an integrated, multi-factor model that not only explains FX return dynamics but also informs active management strategies. This integrated approach is highlighted in Ranganathan et al. (2024) and offers a fresh perspective compared to traditional FX models.

Datasets

Our dataset integrates financial and commodity index data from two primary sources: World Bank Commodity Index and St. Louis Federal Reserve Economic Data (FRED).

Our datasets from World Bank Commodity Index comprising 66.6% energy-related commodities and 33.3% other commodities, these indices track price movements in global commodity markets. The remaining dataset is sourced from FRED, which provides real effective exchange rate, exchange rates, bond yields and financial market data.

Besides, our dataset consists of 312 monthly records covering a range of economic indicators, including exchange rates, commodity indices, and macroeconomic indicators. The exchange rates include USD-based rates against major global currencies (e.g., USDEUR, USDJPY, USDCAD, USDGBP, etc.). The commodity indices cover various categories such as energy (oil and gas prices), agricultural products (grains, oils and meals, other food), raw materials (timber, other raw materials), and metals and minerals (base metals, precious metals, fertilizers). Additionally, the dataset includes macroeconomic indicators, such as inflation-adjusted pricing and indexed values for economic analysis.

Since the dataset integrates information from different sources with varying frequencies, several transformations were applied to ensure a consistent monthly format. Daily or weekly reported data from sources like FRED were resampled to a monthly frequency using start-of-month values, while commodity indices from world Bank, reported at the end of the month, were retained in their original form. All data were aligned to the first day of each month to maintain consistency across features, and missing values were addressed through forward-filling where necessary. However, we would use a daily exchange rate for some of our feature engineering in the next section.

Feature Engineering

Features that we need to feature engineer are volatility, interest rate differential, real effective exchange rate (REER), momentum factor and our target.

Volatility : The first step in our dataset was getting the monthly volatility with a lookback period of 22 days, for each currency pair, which we calculated with the standard deviation formula of their returns.

$$return = X = \frac{Price_T - Price_{t-1}}{Price_{t-1}}$$

$$annualized\ volatility = \frac{\sum(X-\overline{X})^2}{n-1} \times \sqrt{252}$$

where,

- X is the return
- $\overline{X}$ is the average of return
- n is the number of observations

For unchanged annualized volatility, the columns are as such : **USDxxx_vol22**
For percentage change of annualized volatility, the columns are as such **USDxxx_vol22_pct_change**

Interest rate differential : It is calculated by subtracting the 10y yield of the country from the benchmark US 10y yield. This will be our carry factor in our fx factor model. Ex : **ird_us_xx**

$$Interest\ Rate\ Differential = US\ 10y - xx\ 10y$$

REER : We did not have to calculate it because it was provided in the data. REER is useful for currency trading because it adjusts nominal exchange rates for inflation and trade weights, providing a truer measure of currency valuation. This will be our value factor in our fx factor model. Ex : **xxx_REER**

REER percentage change : *Ex :* **xxx_REER_pct_change**

$$REER\ Percentage\ Change = \frac{REER_t - REER_{t-1}}{REER_{t-1}}$$

Momentum: We ranked the past monthly returns of each currency pair, into 4 different quartiles and simple ranking.
For quartiles, the columns are as such : **USDxxx_mo_quartile**
For the normal rankings, the columns are as such **USDxxx_mo_rank**

Commodity: We will just use the World Bank Commodity Index of 66.6% energy-related commodity and 33.3% other commodities.

Target: We calculated the monthly returns of each currency pair and we will predict one month ahead.

$$return = \frac{Price_t - Price_{t-1}}{Price_{t-1}}$$

Feature Selection

As we have multiple variables for some of the same category, we decided to use R squared to decide which variables should be used after running linear regression on them.

Model	Volatility	Carry	Value	Commodity	Momentum
Model 1	Volatility of the past 22 days	Interest rate differential	Real Effective Exchange Rate Percentage Change	Commodity Index	Rank by quartile
Model 2	Volatility of the past 22 days	Interest rate differential	Real Effective Exchange Rate Percentage Change	Commodity Index	Rank by number
Model 3	Volatility of the past 22 days Monthly	Interest rate differential	Real Effective Exchange Rate	Commodity Index	Rank by number

	Percentage Change		Percentage Change		
Model 4	Volatility of the past 22 days Monthly Percentage Change	Interest rate differential	Real Effective Exchange Rate Percentage Change	Commodity Index	Rank by quartile

Table 1: *The possible permutations of our 5 factors.*

From table 1, we will introduce 4 different models for each individual currency. Those models are the permutations of all the possible factors that we have.

Currency	Model 1	Model 2	Model 3	**Model 4**
USDEUR	0.00024512	0.00078718	**0.00096573**	0.00037048
USDJPY	**0.00044022**	0.00000900	0.00001876	0.00033014
USDCAD	0.00154349	**0.00185282**	0.00117347	0.00096300
USDGBP	0.00161310	0.00132818	0.00221355	**0.00262798**
USDAUD	0.00813869	**0.00814717**	0.00349062	0.00313134
USDCHF	0.00847182	0.00501894	0.00619373	**0.01008517**
USDNOR	0.00038265	0.00014310	0.00028681	**0.00056685**
USDSEK	**0.00218214**	0.00171552	0.00131395	0.00163822
USDNZD	0.00001037	0.00000014	**0.00121050**	0.00085915

Table 2: *The R squared of each of the models and currency pair.*

Next, we ran regression on those factors, obtained their R squared, which are shown in table 2. The best R squared of each currency are bolded. We can see that model 4 has the most number of highest R squared, so we will be using model 4.

Lesson Learnt: In our initial regression, we discover a lookahead bias, which results in a high R squared. We managed to fixed it and this fix produces the current R squared.

Portfolio Optimization

Mean-Variance Optimization (MVO)

Mean-variance optimization portfolio is a way to minimize risk for a given expected returns for the weights of the assets. This portfolio is a long only portfolio.

It is formulated as:

$min_w \frac{1}{2} w' \sum w$ – subject to $w'\mu = \mu_k$ and $w'1 = 1$

Where,

- $\sum$ is the covariance matrix of the currency pairs.
- w is the weight matrix for the currencies.
- μ is the average predicted returns of the past 36 months
- μ_k is the average predicted returns up to the current point in time to prevent lookahead bias (Haugh, 2016).

We used the predicted returns from our factor model from the previous section as the expected returns in the mean-variance optimizer with 36 months lookback. This optimizer will give us the optimal weights of the currency pairs.

Stable Portfolio By VECM (Vector Error Correction Model)

We will be using VECM (Vector Error Correction Model) to design our stable portfolio with a long-term cointegrated relationship between currencies.

First, we used a rolling vector autoregression (VAR) model with a 36 months lookback on differencing variables to find the optimal lag based on the lowest Bayesian Information criterion (BIC), which given us 0 lagged order for all periods, however, statsmodels' VECM requires at least 1 lagged order, so we will enforce it.

Next, the VECM equation:

$$\Delta X_t = \Pi X_{t-1} + \sum \Gamma_i \Delta X_{t-1} + \varepsilon_i$$

Where,

- X_t is the vector of currency pair prices.
- $\Pi = \alpha\beta^T$ is the long-run impact matrix.
- β contains the information on the long term relationships between the variables in levels.
- α is the information that corrects the deviation from the long term relationships.
- Γ is the coefficient for the lagged terms of variables (Mohr, 2019).

So, we will be utilizing the β matrix to determine the assets weightage for our stationary portfolio as this long term relationships between currency pairs act as the stabilizer in this portfolio. This rolling VECM model has a lookback of 36 months.

Combined Stable Portfolio and MVO Together

This portfolio is a combination of the previous two subsections (Mean-variance Optimization and VECM Stable Portfolio). We still have it based on mean-variance optimization formulation and added an additional constraint which uses β matrix from VECM Stable Portfolio. This portfolio is a long only portfolio.

This portfolio ideas mainly come from optimal mean reverting equity portfolio, which they used $w's_t$ as constraint in the portfolio, where $s_t = \beta' y$ and β is the beta matrix from VECM but is assumed to be identify matrix due to stationary condition and y is the spread of the two stocks (Zhao et al., 2018).

We formulated it as

$min_w \frac{1}{2} w' \sum w$ – subject to $w'\mu = \mu_k$, $w'1 = 1$ and $\beta' w = 0$

Where,

- $\sum$ is the covariance matrix of the currency pairs.

- w is the weight matrix for the currencies.
- μ is the average predicted returns of the past 36 months
- μ_k is the average predicted returns up to the current point in time to prevent lookahead bias (Haugh, 2016).
- β which is from VECM, contains the information on the long term relationships between the variables in levels.

This additional constraint of $\beta' w = 0$ provides a long term stable relationship between currency pairs, as such the optimizer is forced to find the weights to ensure that the sum of $\beta_i w_i$ is 0. This helps to stabilise the portfolio.

Backtest Performance

For our backtest, we used the weights provided by the 3 optimizers and ran from 2002 May to 2025 March for Stable portfolio and from 2005 April to 2025 March for both MVO portfolio and combination of both MVO and stable portfolio, as the MVO method requires a total of 72 months lookback. This backtest performance is before transaction cost and other costs. The free interest rate parameter used in this backtest is 3%

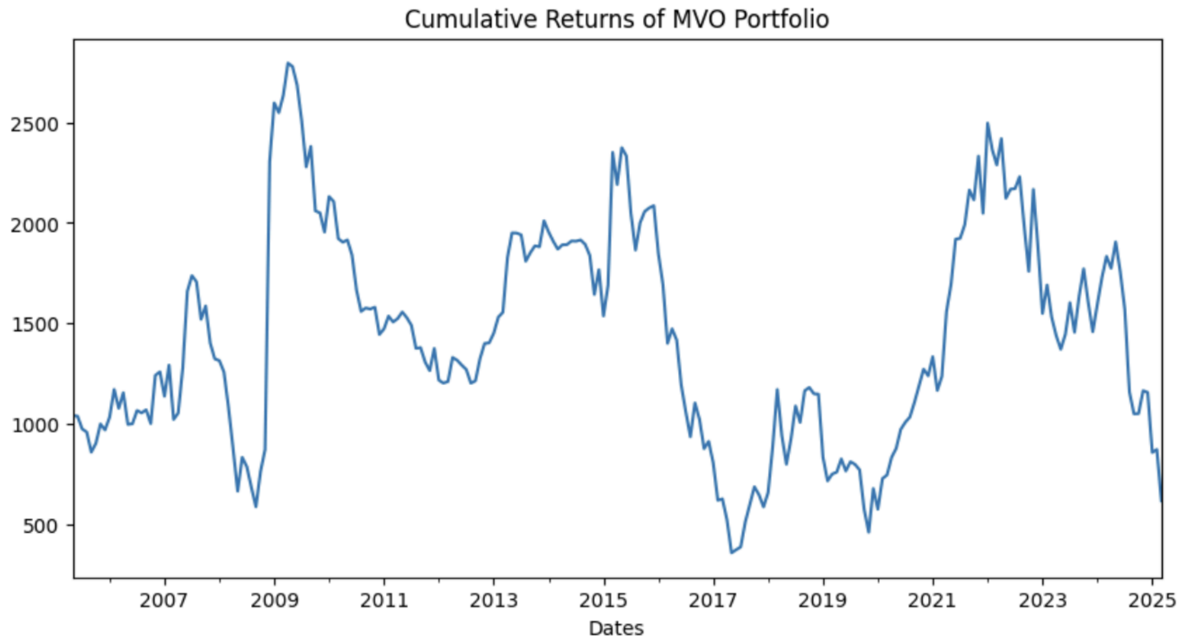

Figure 1: *The cumulative returns of a mean-variance optimized portfolio with initial value of $1000.*

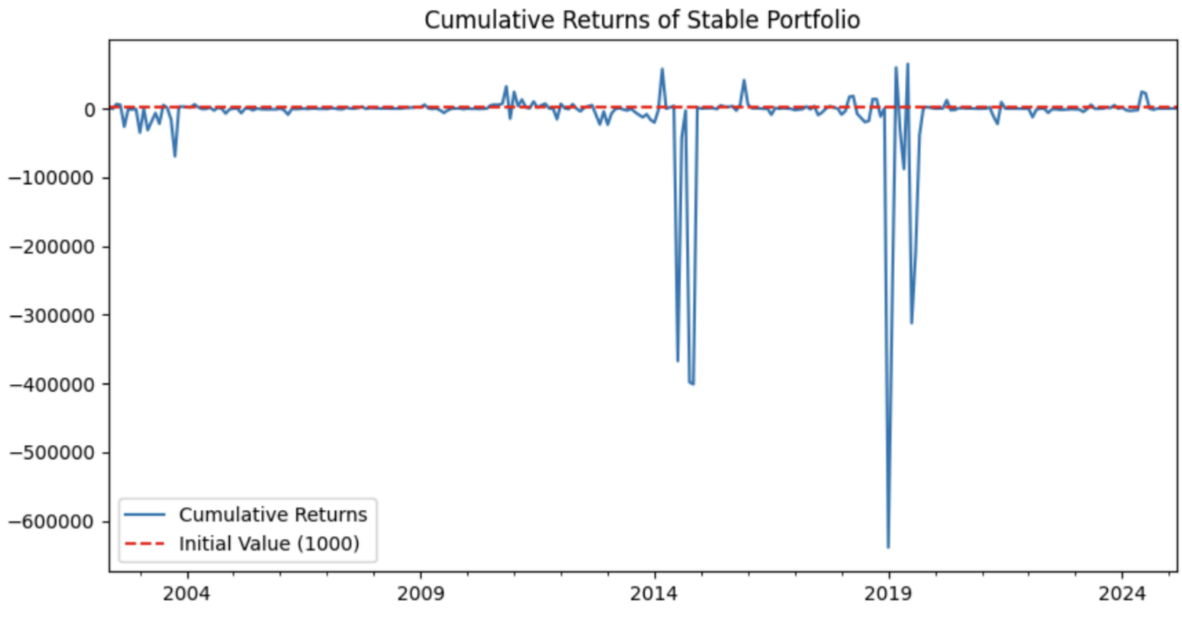

Figure 2: *The cumulative returns of a stable optimized portfolio by Vector Error Correction Model (VECM) with the dotted line with initial value of $1000.*

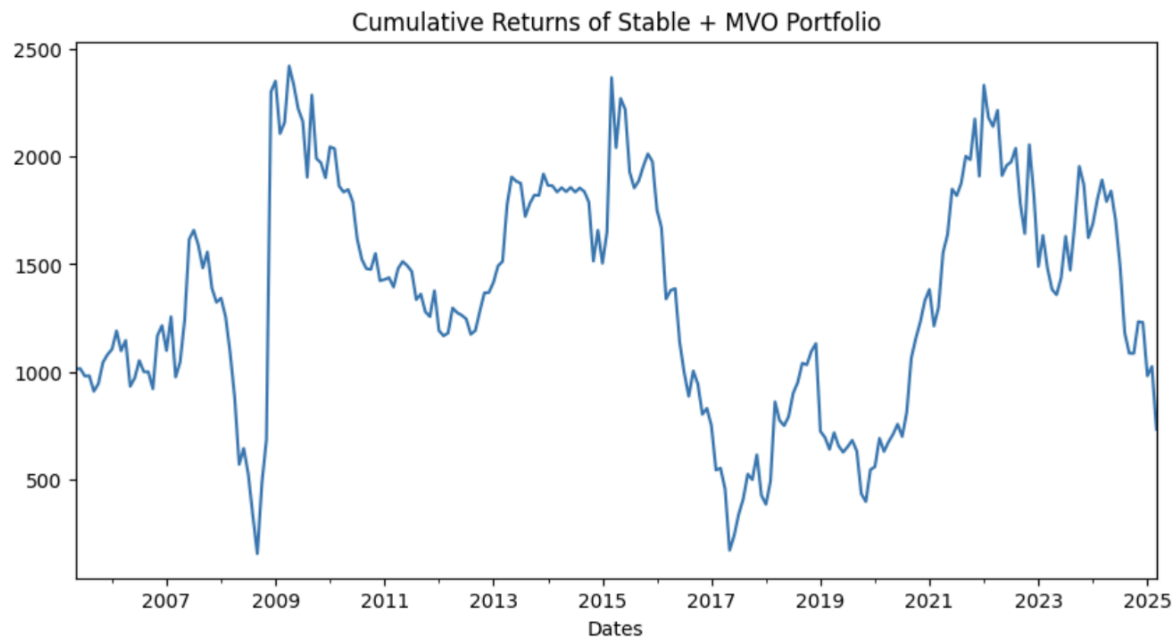

Figure 3: *The cumulative returns of a both mean-variance and stable optimized portfolio with initial value of $1000.*

From figure 1 and 3, we can see that MVO+Stable portfolio and MVO portfolio are largely similar. As for figure 2, we can see that the Stable portfolio has been quite stable, staying around the initial capital of $1000. However, there are still some shocks that could result in big losses.

Portfolio	Sharpe Ratio	Max Drawdown	Average Turnover
MVO	0.11	-87.23%	7.11%
Stable	-0.22	-1210.43%	0.99%
MVO + Stable	0.22	-92.79%	6.75%

Table 3: *The portfolio performance of all 3 kinds of portfolio (MVO, Stable, MVO + Stable).*

From the above table 3, It can be seen that the MVO+Stable portfolio has the highest sharpe ratio. It has a lower average turnover rate of 6.75% than MVO portfolio of 7.11%. However, it has the highest max drawdown of -92.79%. The Stable portfolio from VECM did a good job of having the most stable portfolio with an average turnover of 0.99%, however, the sharpe ratio and max drawdown performance is not the best. The MVO portfolio has the lowest max drawdown of -87.23% but with a slightly lower sharpe ratio of 0.11 compared to MVO+Stable.

Decomposing Optimal Currency Weights Into Factor Contribution

MVO Portfolio

The MVO is used to construct an optimal FX portfolio by allocation weights to different currencies based on expected returns and risk. The expected return is determined by the rolling linear regression model that we apply on the 5 key factors, volatility, carry, value, commodity and momentum. We will analyze 2 of the 9 currencies below to showcase how we can interpret the model results. We will be using USDEUR and USDJPY as the currency pairs of interest.

Here is the factor contribution to the currency pair for USDEUR under the MVO model.

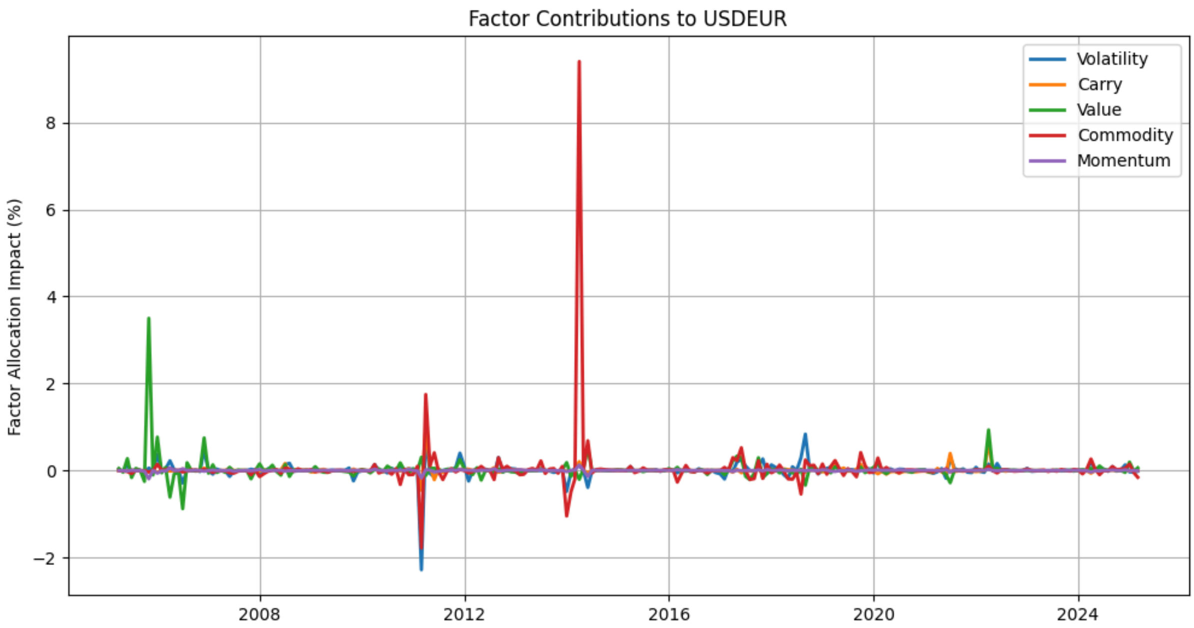

Figure 4: *The factor contribution to USDEUR in the MVO portfolio.*

Over the long-term we see value, volatility and momentum explain the large majority of the movement in the currency pair. We see a few brief periods where 1 particular factor dominates the others and hence drives most of the currency movement in that period. For example from 2010-2011, we can see commodity and volatility having a big contribution to USDEUR in the midst of the European Debt Crisis and in 2013-2015, commodities had a big factor contribution in the midst of the Greek Debt Crisis. Beyond that we generally see factors like carry and momentum playing a very minor role in the factor contributions to USDEUR. This could be because both USD and EUR are developed countries with similar interest rate regimes, thus these factors are unlikely to be a major cause of price movements.

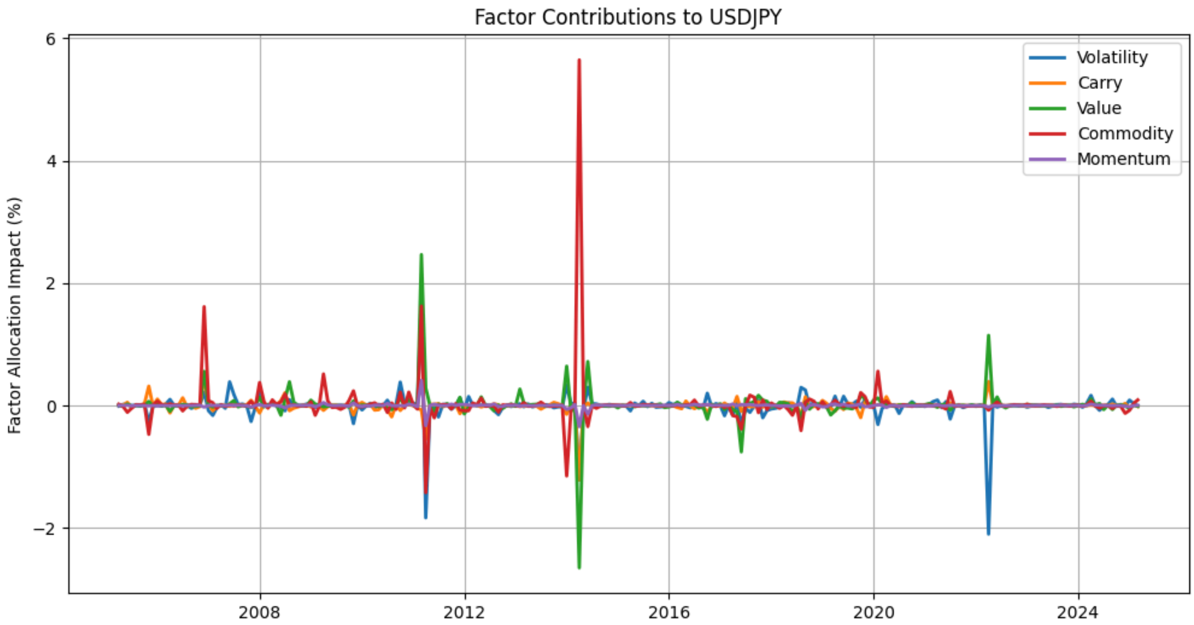

Figure 5: *The factor contribution to USDJPY in the MVO portfolio.*

Under the MVO model, USDJPY has a different story. Value plays a bigger role during one-off events such as in the 2011 during the Fukushima earthquake. In general, while we can see commodity continuing to play an important role in the factor contributions, other factors such as volatility and carry do have periods of outsized contribution. This shows that the USDJPY currency pair is more idiosyncratic compared to USDEUR as it is more likely to be affected by different factors at different times. Thus, this provides an interesting opportunity to balance out our portfolio by having diversified currency pairs.

Combination of Stable (VECM) and MVO (Stable+MVO) Portfolio

The aim of this combined portfolio is to achieve stability by holding a basket of currency pairs that would minimise volatility and exposure to general FX risk. Our model in this instant has certain positive elements while one area for improvement. Our model thus achieves our objective of minimizing the impact of the various factors on each country on our overall portfolio, generally the factor contributions are near zero. However, there are still specific periods where our model is not able to mitigate the outsized impact of specific factors.

In the USDEUR pair, the main bout of volatility where the factor exposure stability was broken was in 2011, which coincides with 'Draghi' whatever it takes moment which coincided with the Eurozone crisis. Thus, this showcases that our model has a weakness is working effectively for idiosyncratic events.

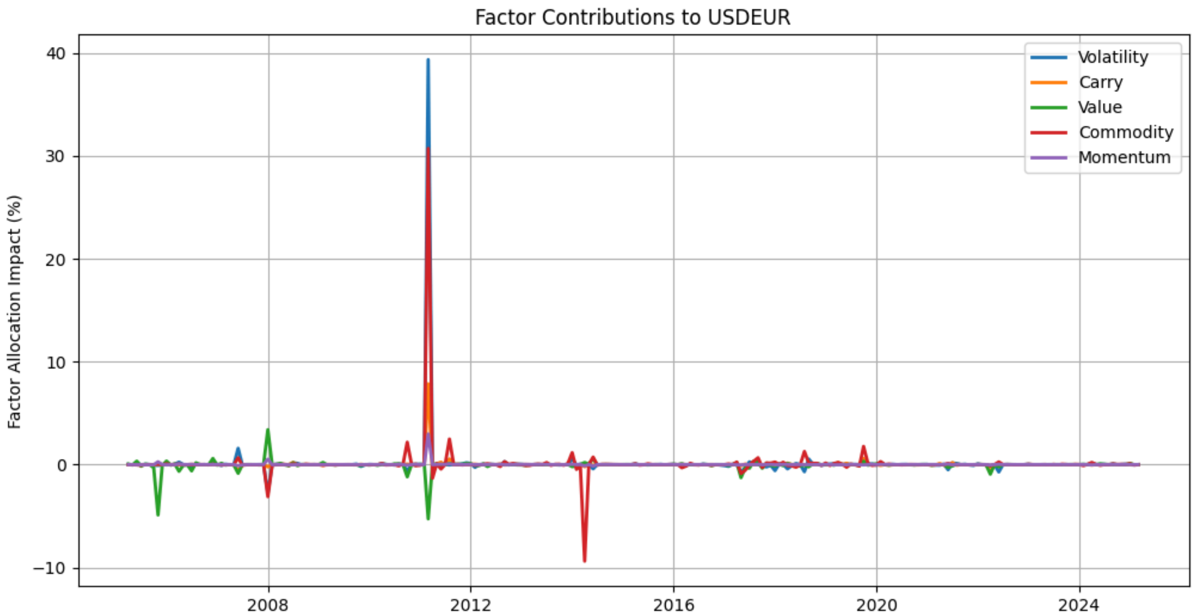

Figure 6: *The factor contribution to USDEUR in the Stable+MVO portfolio.*

In USDJPY, the main period of volatility comes in 2011 on the wake of the Fukushima earthquakes which was a major black swan event where the central banks had to intervene in the market and factors that were properly modelled were not able to explain the movements in the currency pair. Hence highlighting the weaknesses of our model which was to work well in black swan event scenarios, which is where we can potentially consider other options such as adding risk limits or hard stop-loss criteria to limit the damage and review our trading systems in times of excess volatility.

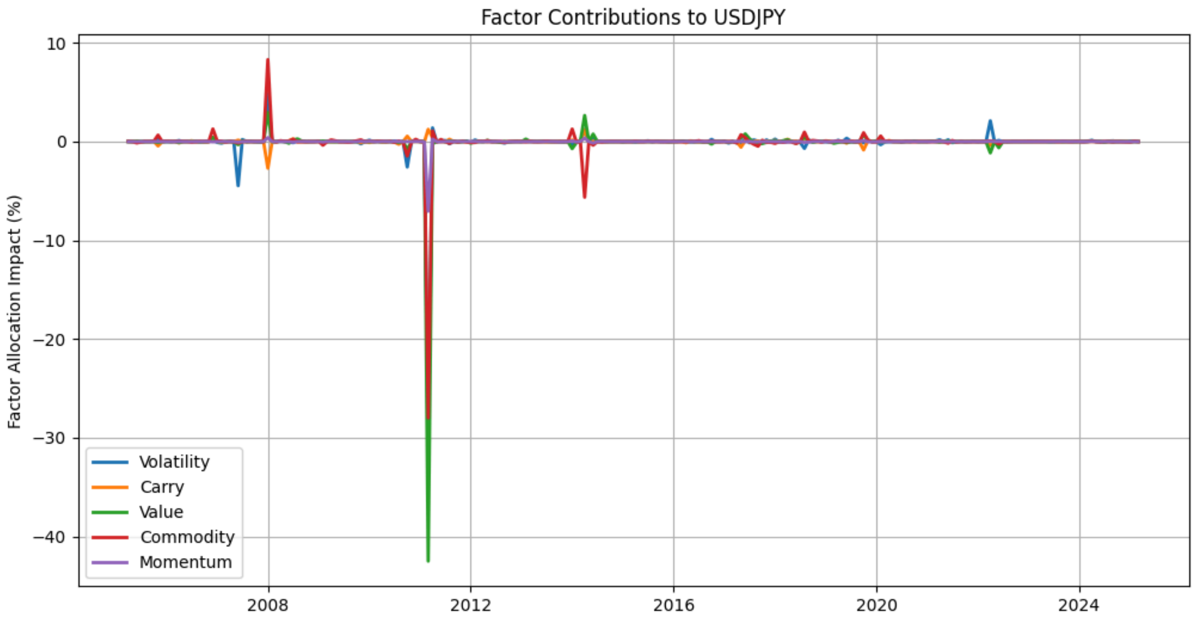

Figure 7: *The factor contribution to USDJPY in the Stable+MVO portfolio.*

The remaining factor contributions to currency figures will be presented in the appendix.

Conclusion

In conclusion, this project has demonstrated that an integrated strategy combining FX factors and portfolio optimization can achieve a positive Sharpe ratio in monthly datasets. Our stable portfolio, constructed using FX factors, has successfully met its objective of maintaining the lowest average turnover rate. Additionally, a combination of the stable portfolio and the mean-variance optimization (MVO) portfolio, incorporating FX factors, can produce double the Sharpe ratio of the MVO portfolio alone.

Furthermore, our investigation into factor contributions revealed that the combination stable and MVO portfolio is more stable than the MVO portfolio on its own. By analyzing factor contributions, we gained insights into risk allocation within our portfolios and the significant events that influenced them.

References

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Appendix

Appendix A - Factor contributions to currency in Mean-Variance Optimization (MVO) Portfolio

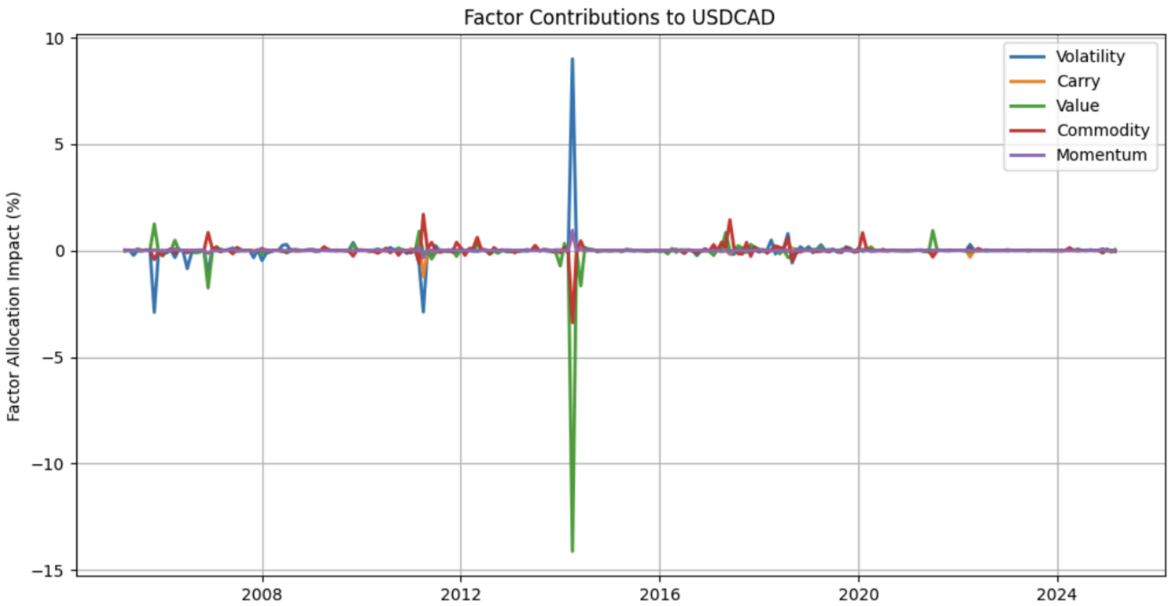

Figure A1: *The factor contribution to USDCAD in the MVO portfolio.*

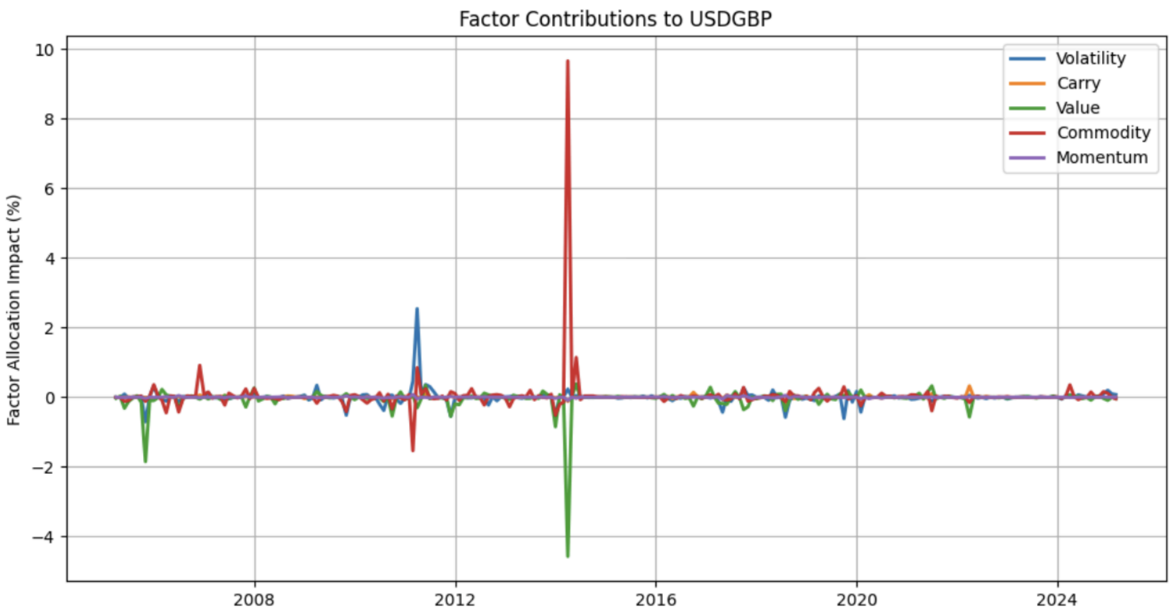

Figure A2: *The factor contribution to USDGBP in the MVO portfolio.*

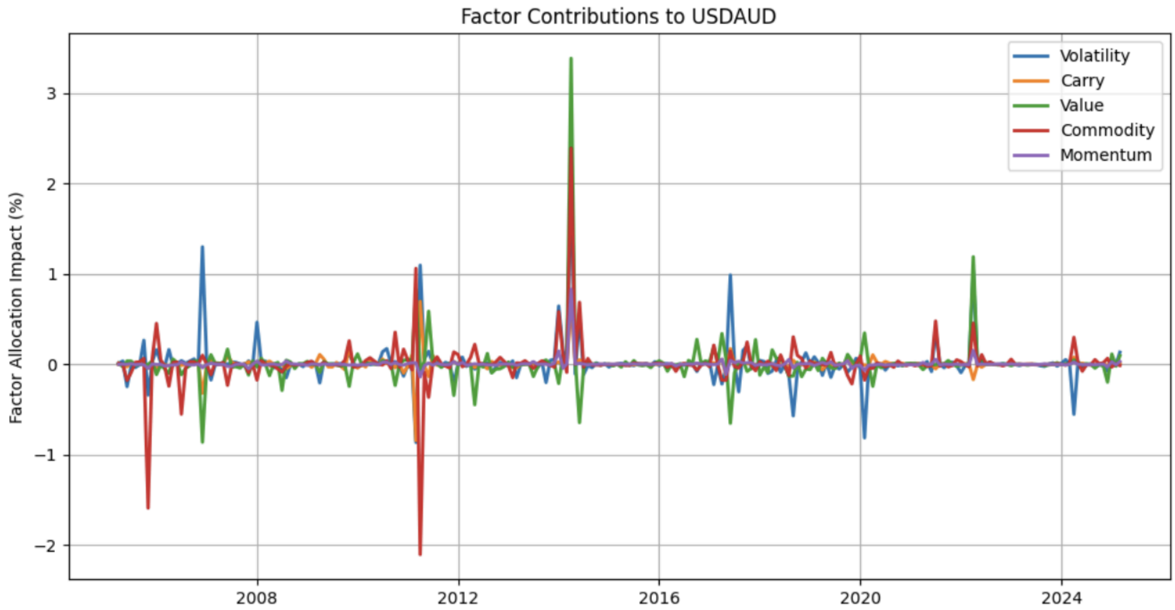

Figure A3: *The factor contribution to USDAUD in the MVO portfolio.*

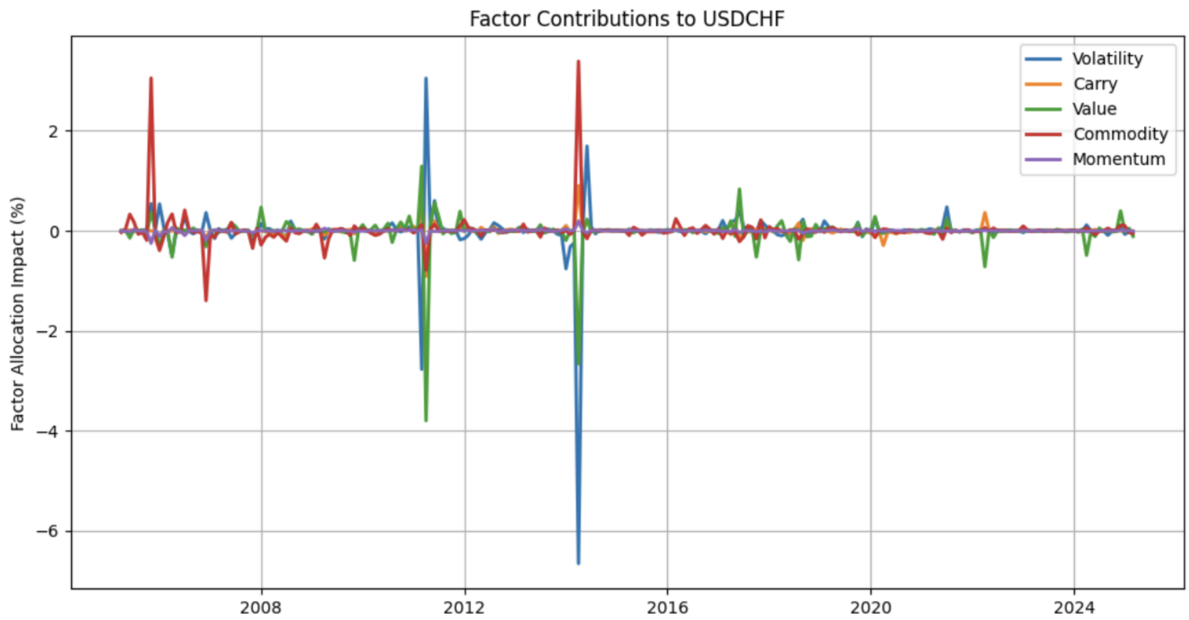

Figure A4: *The factor contribution to USDCHF in the MVO portfolio.*

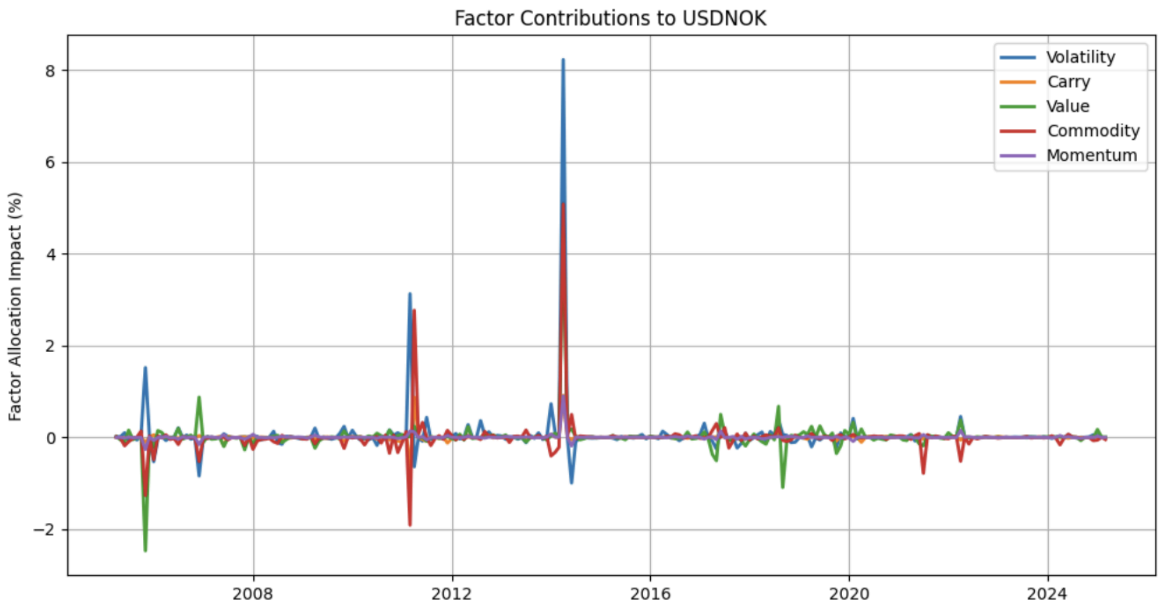

Figure A5: *The factor contribution to USDNOK in the MVO portfolio.*

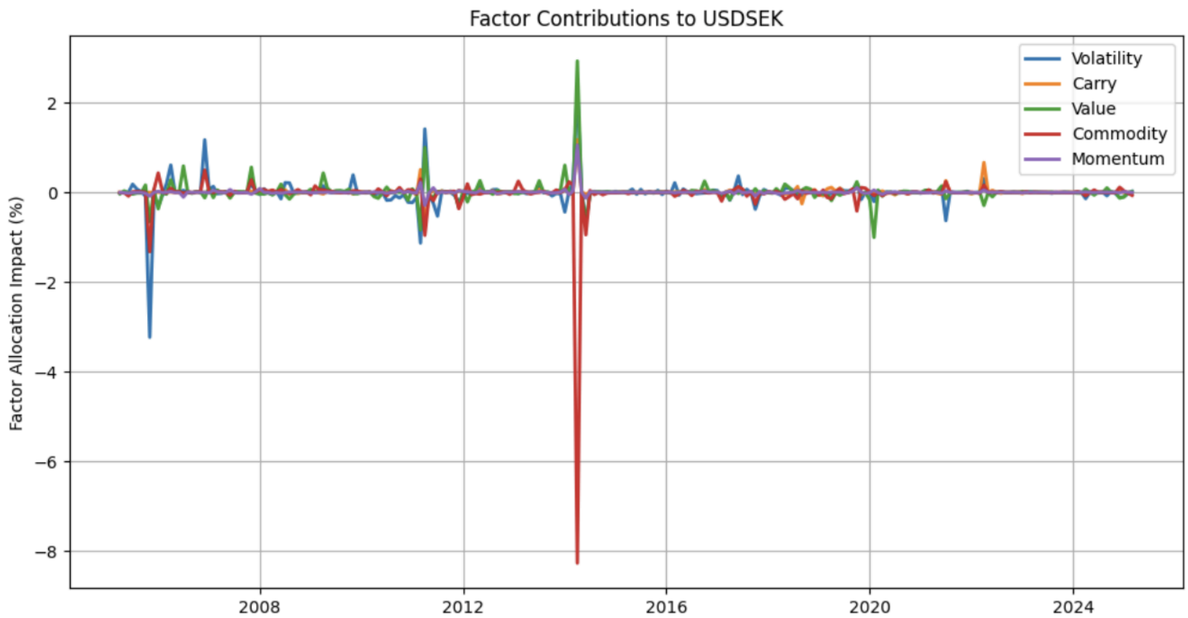

Figure A6: *The factor contribution to USDSEK in the MVO portfolio.*

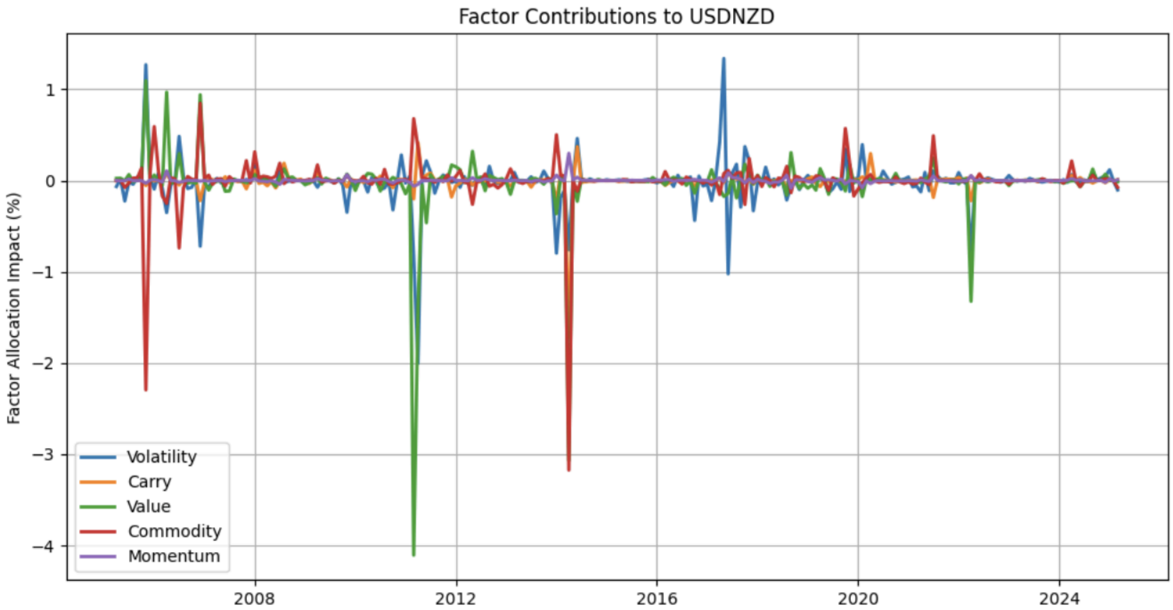

Figure A7: *The factor contribution to USDNZD in the MVO portfolio.*

Appendix B - Factor contributions to currency in combination of Stable (Vector Error Correction Model) and Mean-Variance Optimization (Stable+MVO) Portfolio

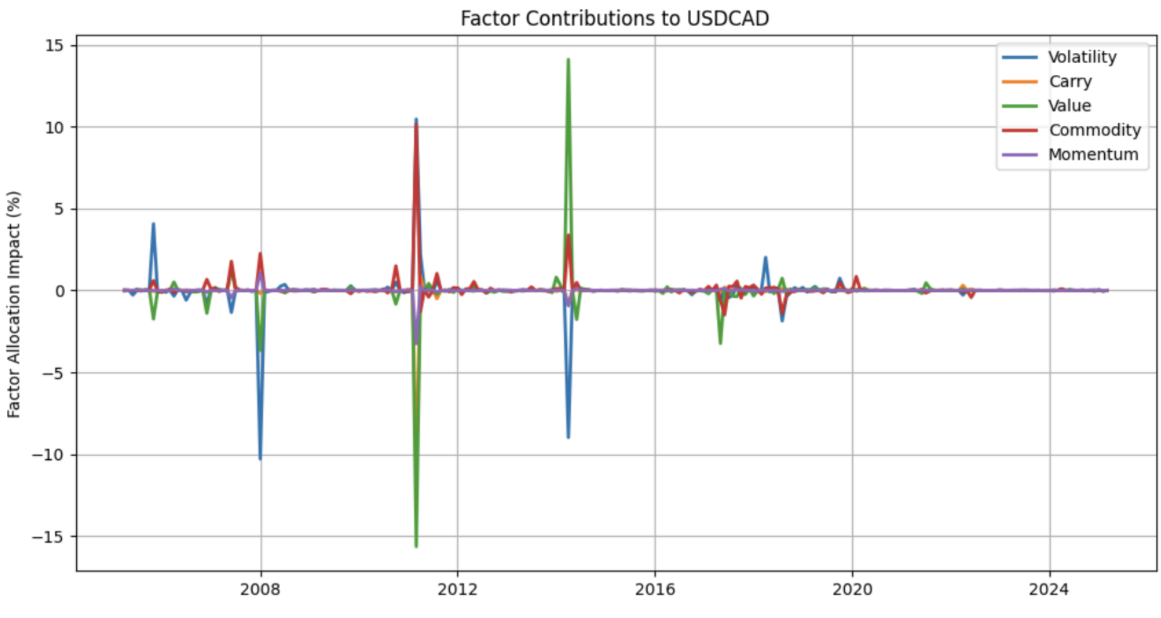

Figure B1: *The factor contribution to USDCAD in the Stable+MVO portfolio.*

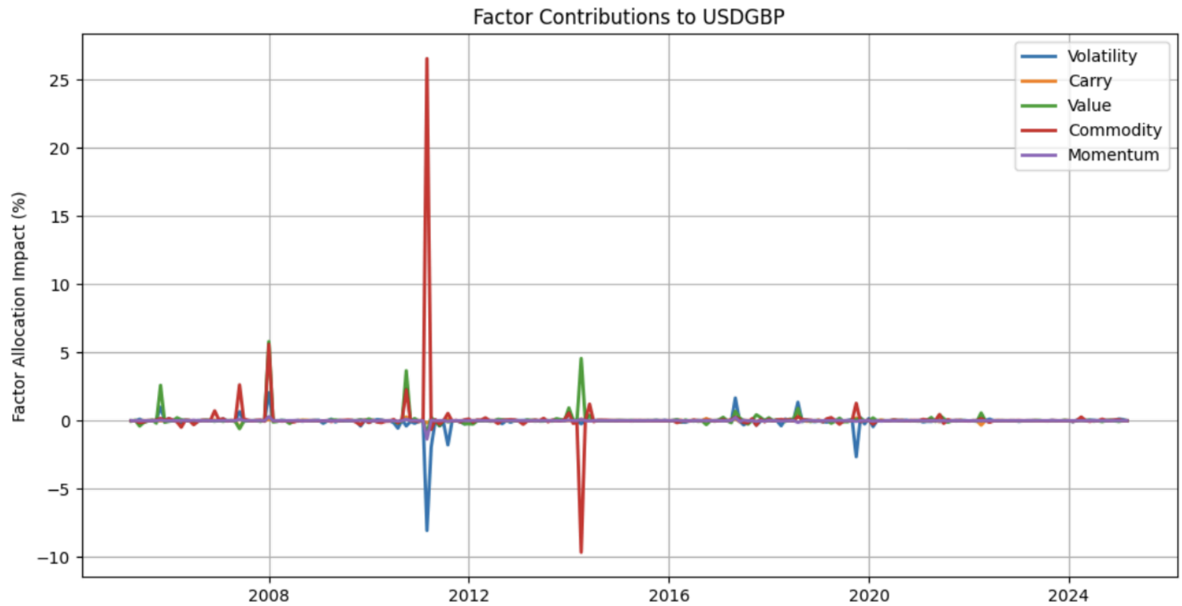

Figure B2: *The factor contribution to USDGBP in the Stable+MVO portfolio.*

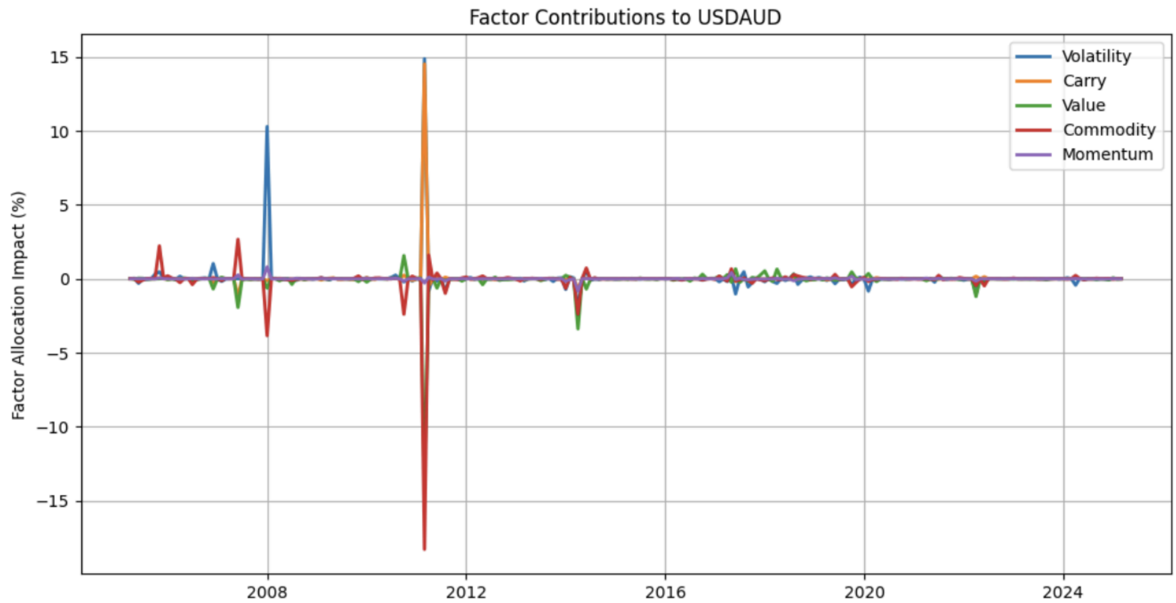

Figure B3: *The factor contribution to USDAUD in the Stable+MVO portfolio.*

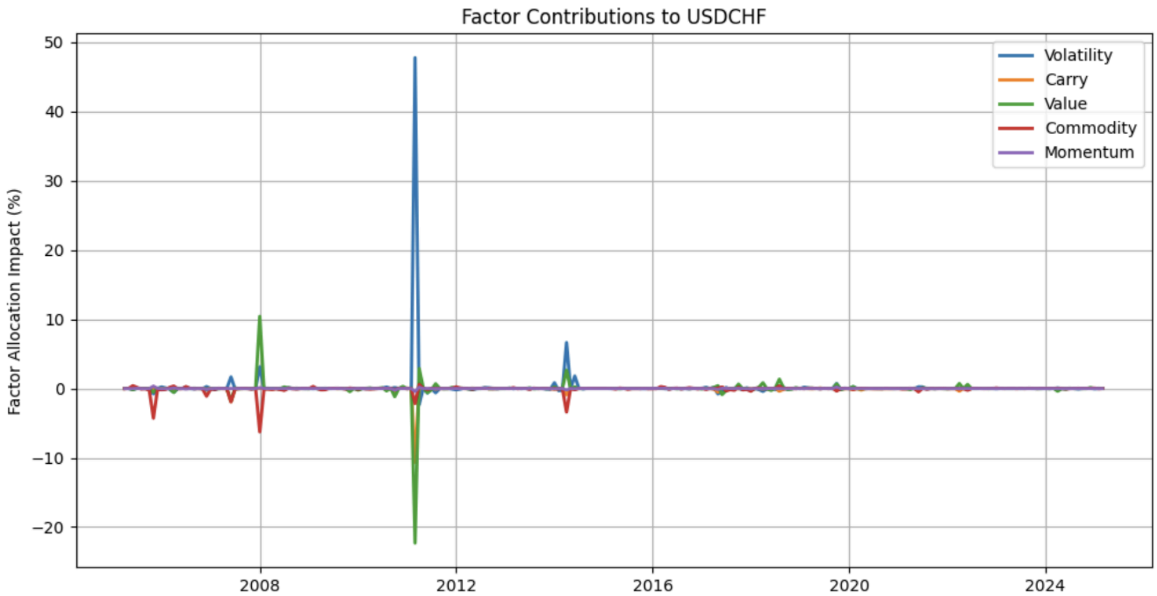

Figure B4: *The factor contribution to USDCHF in the Stable+MVO portfolio.*

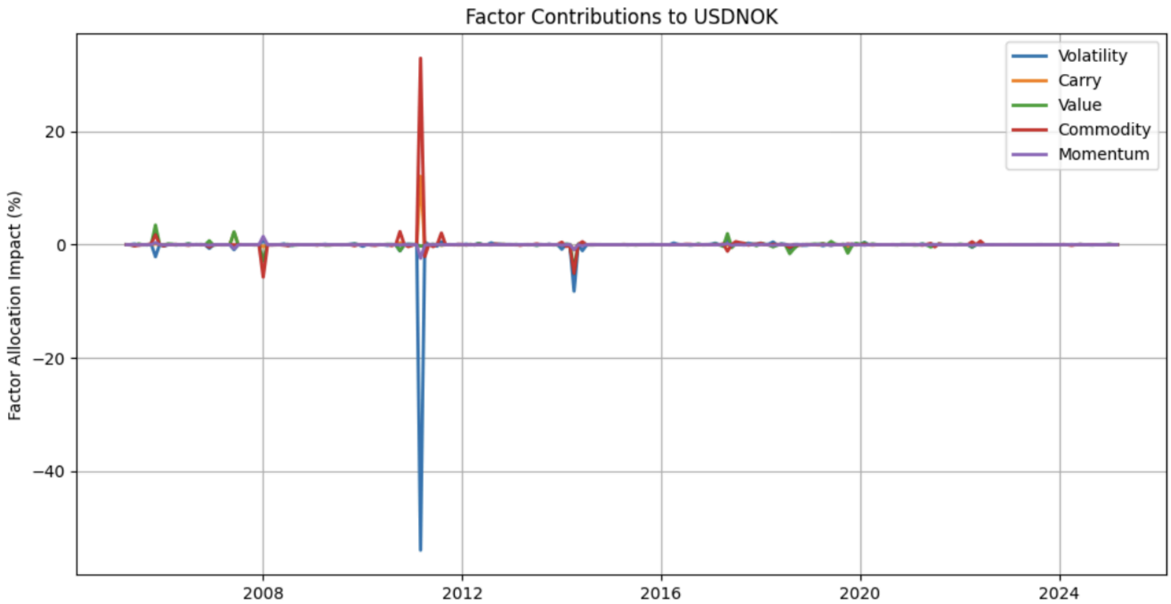

Figure B5: *The factor contribution to USDNOK in the Stable+MVO portfolio.*

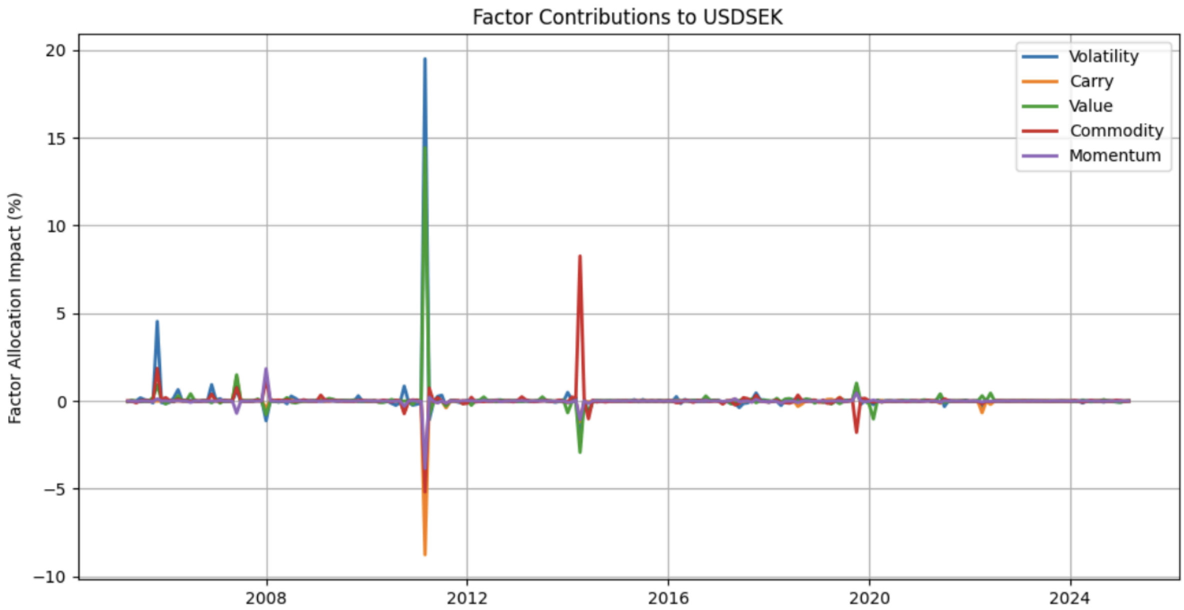

Figure B6: *The factor contribution to USDSEK in the Stable+MVO portfolio.*

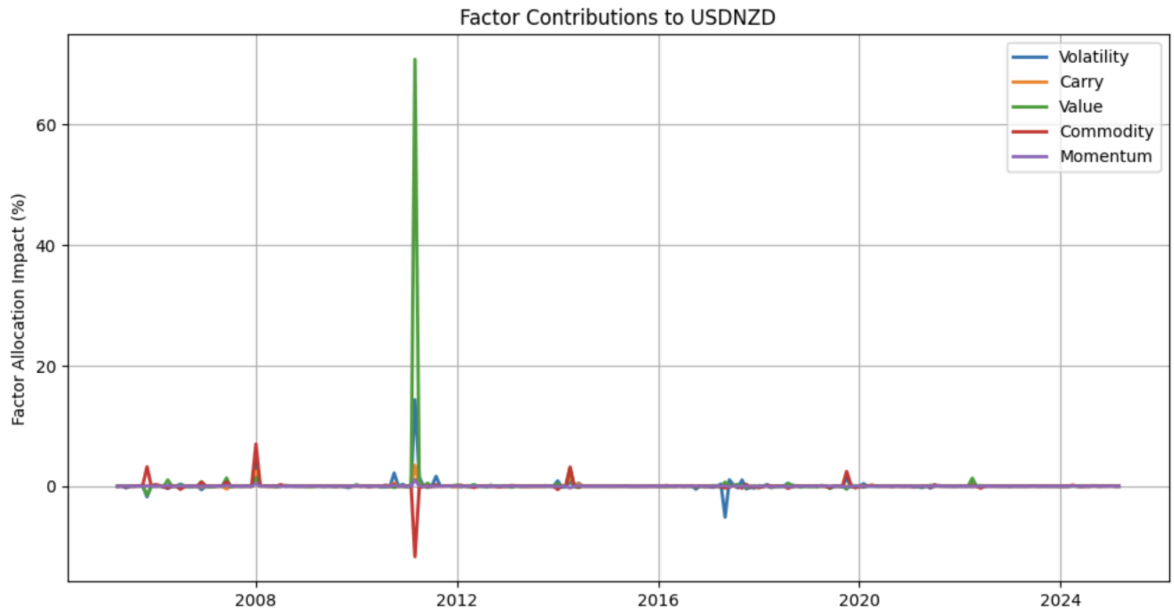

Figure B7: *The factor contribution to USDNZD in the Stable+MVO portfolio.*