Constructing Trading Strategies for the USD/GBP Market:

Implementing Methods of Difference on Comparative National Inflation, Unemployment, and Central Bank Interest Rates to Construct a Profitable Market Profile; a Project Overview

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Introduction

“L'arbitrage est une combinaison que l’on fait de plusieurs changes, pour connoitre [sic] quelle place est plus avantageuse pour tirer et remettre.”

“Arbitration is a combination of several changes, to find out which place is more advantageous to shoot and put back.”

- Mathie de la Porte, *La Science des Négociants et Teneurs de Livres* (*The Science of Traders and Bookkeepers*) (1704)

Exchange rate forecasting represents a critical component of effectively managing assets. At times when markets are volatile, knowing which currencies are depreciating relative to other currencies is essential to building sound investment strategies - and being able to predict these changes in advance provides one with a large edge over other investors. Central to these forecasts is the selection of variables that act as quality predictors of exchange rates over time, in addition to the selection of quality methods to analyze these predictors - including a strategy and appropriate hyperparameters.

In this project, we seek the most effective strategy to estimate the DEXUSUK (U.S. dollars to UK pound sterling exchange rate) over time. To that end, we examined different forecasting strategies using three economic fundamentals - interest rates, inflation rates, and unemployment rates between the United States and the United Kingdom. After calculating the differentials for each fundamental over time, we chose the Kalman Filter as our forecasting method, laid out a strategy, and determined necessary hyperparameters to act upon our strategy using cross-validation. With our long and short positions decided, we were able to calculate returns - in addition to a variety of metrics used to assess strategy efficacy - for the three strategies. Ultimately, we determined that the strategy with the most success predicting exchange rates - established by examining returns and metrics such as the Sharpe Ratio - was the inflation rate differential, which yielded majority positive returns over the time frame examined. This report details our strategy, hyperparameter selection, and returns/strategy metrics for using the US-UK inflation rate differential to predict exchange rates from 2015 to 2022.

Description of Forecast and Strategy

To decide long and short positions for our forecast strategy, we fitted a Kalman Filter on the inflation differential. The aim is to use the Kalman Filter to estimate the inflation differential (using monthly data) by reducing the 'noise' and use the estimation to determine positions to take in the market. The Kalman Filter is set up in the following way:

$$i_t^{diff} = i_t^{us} - i_t^{uk}$$

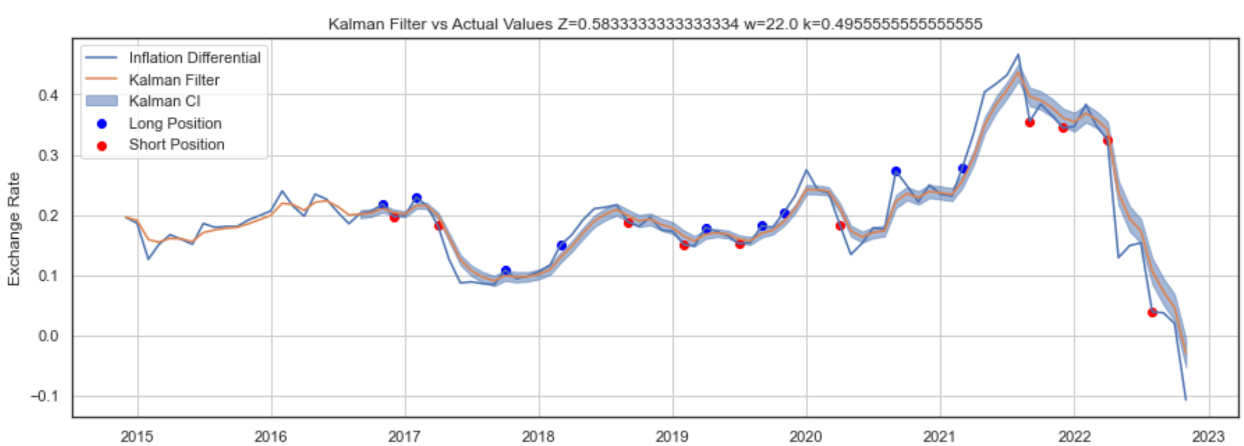
$$\hat{\imath}_t^{diff} = (1-k)\hat{\imath}_{t-1}^{diff} + k\hat{\imath}_1^{diff}$$

$$s_t = \begin{cases} -1 & i_t^{diff} > \hat{\imath}_t^{diff} + z \cdot \sigma_{w,t} \\ 1 & i_t^{diff} < \hat{\imath}_t^{diff} - z \cdot \sigma_{w,t} \\ 0 & otherwise \end{cases}$$

where i_t^{diff} represents the inflation differential between the US and the UK, $\hat{i}_t^{diff}$ represents the estimated inflation differential for the previous period, k is the Kalman gain (or the weight on how much the market cares about current data versus the past), z represents the number of standard deviations needed to determine positions, $\sigma_{w,t}$ is the standard deviation of the Filter Error, and *w* is the number of lags used to calculate the Filter.

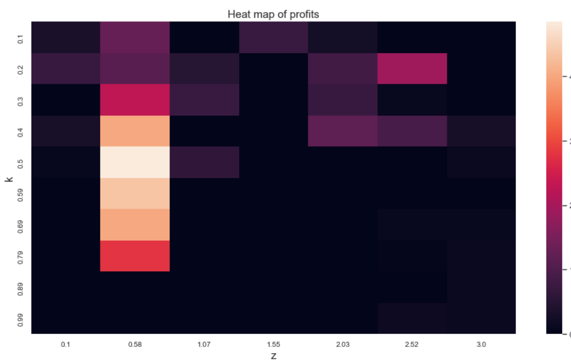
With the Filter defined, we then determined our long positions to be where the inflation differential fell below the filter plus z standard deviations and short positions to be where the inflation differential rose above z standard deviations from the filter. Additionally, we are using a holding period, h, where we will hold our position for h months or until a new signal is created (where we will take a new position). For our strategy, the hyperparameters - k, z, w, h - that we fine-tuned using cross-validation.

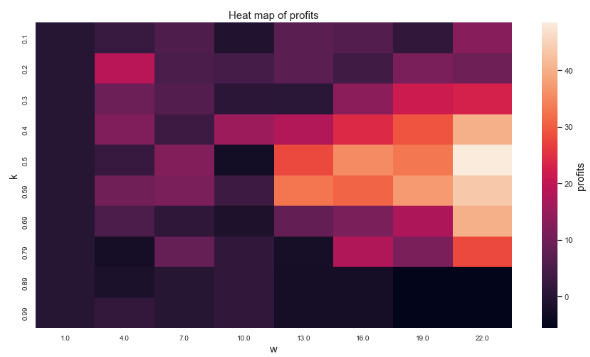
Figure 1: *Kalman Filter and Long/Short Positions by Inflation Rate Differential*

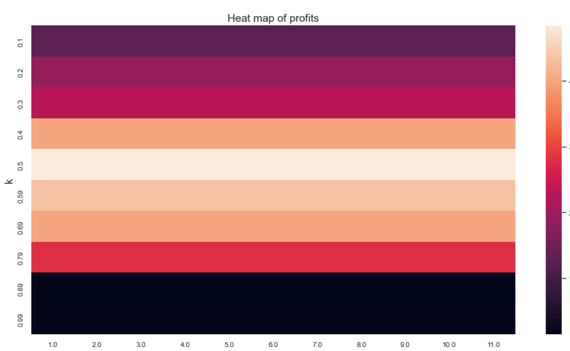


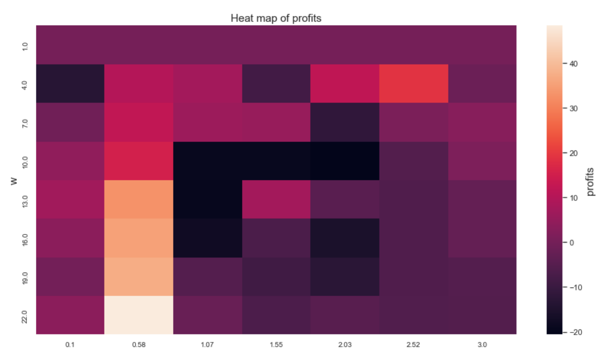
Optimization of Hyperparameters

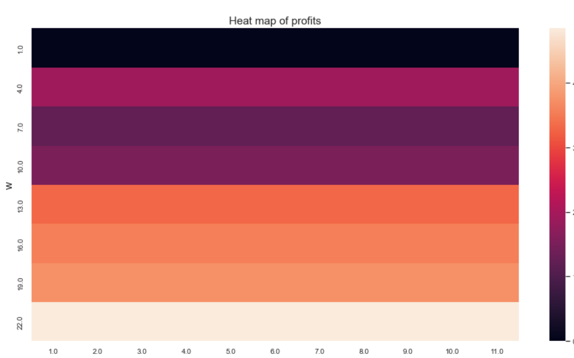
After determining our forecast strategy, it was necessary to select the optimal hyperparameters to make this strategy actionable. As discussed above, the parameters we measured were length of holding period (h), the Kalman gain (k), the number of standard deviations needed to determine positions (z), and the number of lags used in calculating the filter (w). Using grid-search, it was possible to create a grid of potential values for each of these parameters and search through them to find the most optimal value of each. To begin, we established a search range for each parameter - k from 0.1 to 0.99, z from 0.1 to 3, w from 1 to 24, and h from 1 to 12, with set intervals between each potential value. We stored these ranges in a grid and iterated through to find the profits produced by each possible set. From there, we were able to select the parameters that yielded the highest profits. Profits produced by sets of hyperparameters are visualized in the heatmaps below - each heatmap visualizes profits for 2 sets of hyperparameters at a time.

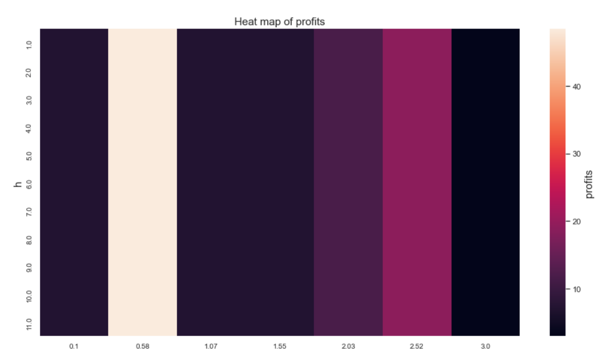












Based on the above, we determined that the optimal hyperparameters were as follows:

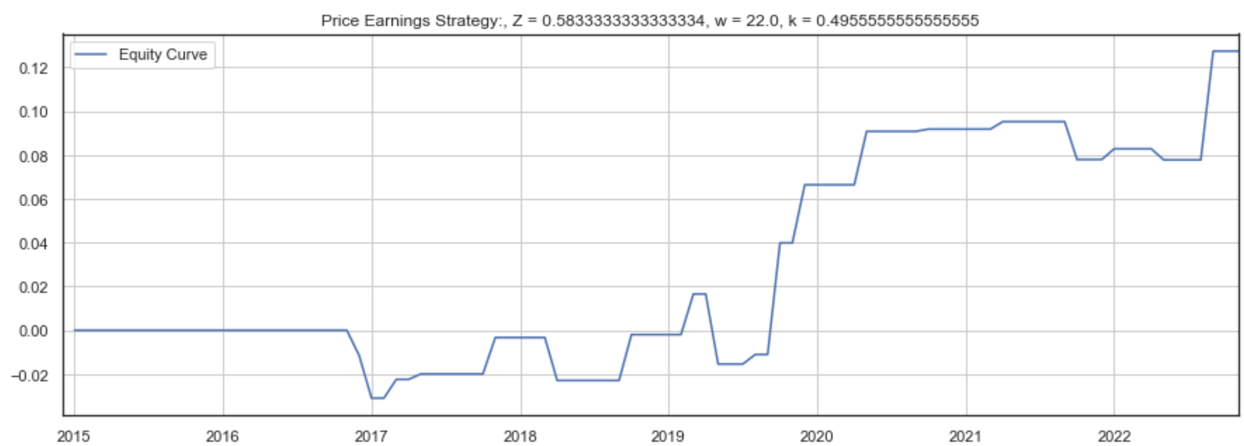
- k = 0.1
- z = 1.067
- w = 10
- h = 2

Equity Curve and Performance Tables

Equity Curve Visualizations

Using the optimal hyperparameters, we can apply the Kalman Filter strategy to our data to produce a trading strategy, as described above. Using the long and short positions, we calculated the strategy returns as well as the cumulative returns. The equity curve, seen below in Figure 3, plots the cumulative returns of our trading strategy overtime. The cumulative returns begin at 0% and rise and fall overtime based on our trading strategy's performance. The lowest point of our equity curve occurs in 2017 at approximately -2% cumulative return. Lastly, our equity curve ends, and is the highest point, with a cumulative return of approximately 12%.

Figure 3: *Equity Curve for Strategy using Inflation Rate Differential*



Performance Table with Comparisons to HFRI Metrics

Risk and return Table

For a more detailed overview of the risk and return tables — as well as metric and sub-metric values for non-optimal strategies — please refer to **Table 3** in the appendix. Comparisons between the inflation rate difference strategy and the HFRI Macro (Total) Index are as follows:

Metric	Sub-Metric	Inflation Differential	HFRI
Standard deviation of returns	*Base*	1.088398	1.99

	Annualized	0.144527	6.90
Geometric mean of returns	—	0.128073	0.75
Months	*High*	5.024032	7.88
	Low	-3.197153	-6.40
	% wins	12.50000	62.03
Annualized returns	—	1.618581	9.35
Risk free rate	—	2.177790	2.17779
Sharpe Ratio	—	0.104246	0.96
% Max drawdown	—	4.320972	10.7

From the table above, there are a couple interesting metric comparisons of note in favor of the inflation rate difference strategy. First, its standard deviation of returns is much lower relative to the HFRI. Second, the percent max drawdown and lowest month value experienced in the strategy is over half of that seen in the HFRI. Unfortunately, the HFRI outperforms the strategy in every other metric: percent wins and the Sharpe Ratio are two metrics of note at approximately five and nine times that of our strategy.

Regression Table

For a more detailed overview of the regression results table — as well as metric and sub-metric values for non-optimal strategies — please refer to **Table 4** in the appendix. Regression results for the inflation rate difference strategy are as follows:

Metric	**Sub-Metric**	**Inflation Differential**
Alpha	*General*	0.144527
	Up	0.001918
	Down	-0.001411
Beta	*General*	-0.042747
	Up	-0.043427
	Down	-0.095729
R-squared	*General*	0.032413
	Up	0.013947
	Down	0.068426
Correlation	—	-0.180037

For a more detailed overview of the regression results table, please refer to **Table 4** in the appendix. Our strategy generally sees positive excess returns to the market, but appears to falter slightly when market returns turn negative. Meanwhile, all betas indicate that our strategy moves counter to the market; this spikes even further when market returns are negative. In terms of variance in the market explained by our strategy, the use of inflation rate differential as a market forecasting tool is relatively poor across the board. However, there is a curiously large relationship present between the strategy and the movement of the market. The relationship's sign is not particularly surprising (large increases in inflation rate differentials would likely indicate a turbulent economy), but its magnitude relative to other regression results might nonetheless require further research.

Binomial Test

The Binomial Test is a statistical test that is used to test that our directional forecasts are uncorrelated with the realized directional changes (H_0: $cov(D_{t,\ t+h}, R_{t,\ t+h}) = 0$). The alternative hypothesis of the Binomial test is that the directional forecasts are positively correlated with the realized directional changes (H_1: $cov(D_{t,\ t+h}, R_{t,\ t+h}) > 0$). To implement the Binomial Test on our forecast, we first converted the monthly returns into daily returns. Using this new dataframe, we were able to calculate our test statistic to be -0.128. At 5% significance level and critical value is 1.64, our test statistic is less than the critical value therefore causing us to fail to reject the null hypothesis. Therefore, our direction forecast failed to capture the realized appreciation or depreciation of exchange rates. Similarly, we can implement the Weighted Binomial Test that tests whether the expected value of our directional forecast is zero (H_0: $E[D_{t,\ t+h}(s_{t+h} - s_t)] = 0$), while having an alternative hypothesis that the expected value is positive (H_1: $E[D_{t,\ t+h}(s_{t+h} - s_t)]$

> *0*). Using the results of our strategy, we calculated the Weighted Binomial test statistic to be -0.363. At 5% significance level and critical value is 1.64, our test statistic is less than the critical value therefore causing us to fail to reject the null hypothesis. Therefore, our direction forecast failed to capture the big movements of the realized appreciation or depreciation of exchange rates.

Conclusion

Fitting a Kalman Filter on the differential of the three economic fundamentals - interest rates, inflation rates, and unemployment rates - we were able to develop three different trading strategies that resulted in very different results. For each fundament, we optimized the four hyperparameters - k (Kalman gain), z (number of standard deviations), w (number of lags), and h (holding period), using a grid-search, selecting the optimal hyperparameters that resulted in the highest profits. Additionally, we confirmed our optimal parameters through the use of heatmap visualizations. Using these optimal parameters, we were able to calculate our long and short positions that ultimately determined our strategy and cumulative returns. Using these returns, we visualized an equity curve and calculated various metrics to compare to HFRI metrics.

While our strategy resulted in positive total returns, a Sharpe Ratio of 0.104246, an alpha of 0.144527, and a beta of -0.042747 help to conclude that the overall performance of our strategy is not successful. This is further confirmed by the failure to pass the Binomial and Weighted Binomial tests.

Appendix