FX Fair Value Model

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"There is no sphere of human thought in which it is easier to show superficial cleverness and the appearance of superior wisdom than in discussing questions of currency and exchange.", Winston Churchill, 1925.

Contents

1 An Introduction to FX Fair Value Models

1.1 Introduction

FX fair value models are built to identify discrepancies between market exchange rates and their theoretical *fair value*. Historically, defining the true equilibrium value of exchange rates and determining how to model it has been a topic of ongoing academic debate. Several approaches have emerged in this area, ranging from traditional methods like Purchasing Power Parity (PPP) to more nuanced models such as the Behavioral Equilibrium Exchange Rate (BEER) and the Fundamental Equilibrium Exchange Rate (FEER). PPP, for example, suggests that exchange rates should adjust to reflect relative price levels between two economies, based on the *Law of One Price*. More advanced models like FEER (or FERM), on the other hand, take into account not only internal economic balance but also external macroeconomic factors, offering a more dynamic understanding of exchange rate movements. BEER (or BERM) models estimate the fair values of real exchange rates based on empirical long-term cycles in fundamental economic factors.

The challenge, however, is that no single model provides a definitive answer. Different models can yield varying results depending on their assumptions about economic conditions and which drivers are considered as relevant for the models. Figure 1 shows an example of USDEUR spot plotted vs. different measures of fair value going back to 2000:

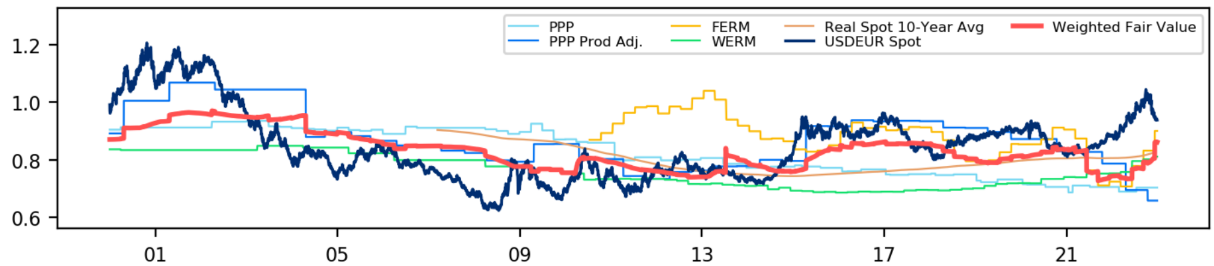

Figure 1: USDEUR Spot vs Fair Value Estimates - *Citi Research*

One common way market participants use these models is through systematic FX trading. Value-based strategies are grounded in the idea that currencies will eventually converge to their fair value levels. As a result, profits can potentially be generated by systematically buying undervalued currencies and selling overvalued ones. Those strategies have demonstrated historical profitability, with systematic trading strategies potentially offering an edge in volatile markets.

1.2 Building the model

In this analysis, we will focus on the practical application of a fair value model for FX trading. Our first step will involve understanding which features "drive" FX rates. This means we will test the significance of each potential driver on FX rate changes. Once the drivers are identified, we will be able to understand the sensitivity of exchange rates to these drivers and draw conclusions about their effects. Finally, we will perform an out-of-sample analysis to compare the "fair value" model with the market rate and identify any potential misevaluation.

1.2.1 Selecting Inputs

This research is based on the G10 Currencies market: USD, EUR, CHF, GBP, CAD, AUD, NZD, JPY, NOK, SEK, with data retrieved from a student version of *Bloomberg* (which provides limited access to data).

We built a model relying on a basket of independent variables that have been chosen discretionarily, using textbook knowledge and commonly used parameters. Since our main interest is statistical inference (we want to understand which features have historically explained movements in currencies), we begin by modeling **weekly changes** in exchange rates relative to the USD. We prefer a weekly frequency over daily and monthly frequencies because daily data can be noisy and sensitive to closing times, while monthly data can result in a lower number of data points relative to the number of features. Our dependent variable is given by the **log change in currency vs USD in percentage points** for the week ending at time t:

$$\mathbf{\Delta ccyusd_t} = \log\left(\frac{ccyusd_t}{ccyusd_{t-1}}\right) \times 100 \tag{1}$$

We use log changes because exchange rates cannot take zero or negative values. The selected features are listed below:

- **Rates Factor** - The rates factor is defined as the spread between the 10-year government yield of a currency and the corresponding USD yield. The theoretical justification for this factor comes from the *Uncovered Interest Rate Parity* (UIP), which suggests that interest rate differentials drive expected exchange rate changes. Although UIP is not empirically verified, it provides a strong theoretical link.

The intuition is that a higher yield spread ($yield_{ccy} - yield_{usd}$) leads to greater demand for the CCY currency, resulting in an appreciation of the $CCYUSD$ exchange rate (positive relationship). Using the spread rather than separate yields helps avoid potential multicollinearity. The input for this factor is the change in the yield spread:

$$\mathbf{rate_t} = \mathbf{\Delta(y_{ccy} - y_{usd})} \tag{2}$$

- **Equity Factor** - This factor is based on the performance of major equity indices, including those for each currency and the S&P 500 Index. Since equity market performance often reflects the economic health of a country, these indices are considered important drivers of FX rates. The selected equity factors are the returns of the equity indices, measured in percentage terms, using **total return indices** in order to accurately capture performance. The intuition is that stronger local equity market performance tends to lead to currency appreciation, while a stronger performance of the USD's S&P 500 Index would indicate a weaker USD. Therefore, we expect a positive beta for local equity indices and a negative beta for the USD S&P 500 Index. The input for these factors is given by:

$$\mathbf{ccy\_equ_t} = \log\left(\frac{index\_ccy_t}{index\_ccy_{t-1}}\right) \times 100 \qquad \mathbf{usd\_equ_t} = \log\left(\frac{SPXT_t}{SPXT_{t-1}}\right) \times 100 \tag{3}$$

- **Terms of Trade** - The *Terms of Trade* (ToT) refers to the ratio of a country's export prices to its import prices. Changes in the terms of trade directly impact the exchange rate: when a country's export prices increase relative to its import prices, its currency tends to appreciate. This relationship is especially relevant for economies that are highly reliant on exports. The intuition is that the larger the spread between the terms of trade ($tot_{ccy} - tot_{usd}$), the stronger the foreign exchange rate (CCYUSD), leading us to expect a positive beta. The input for this factor is given by:

$$\mathbf{tot_t} = \mathbf{\Delta(tot_{ccy} - tot_{usd})} \tag{4}$$

- **Economic Surprise Index** - The Economic Surprise Index (*ESI*) measures how economic data compares to market expectations, tracking whether economic indicators outperform or underperform expectations. When actual data surpasses expectations, it typically boosts investor sentiment and can lead to currency appreciation. Conversely, if the data falls short of expectations, it can weaken the currency. The ESI is constructed using weighted historical standard deviations of surprises (the difference between actual releases and *Bloomberg* surveys) for various macroeconomic indicators. A positive ESI indicates that economic performance generally exceeds market expectations, while a negative ESI suggests that economic conditions are worse than expected. ESI readings tend to rise as the economy recovers and decline sharply during economic downturns. The intuition is that the higher the spread between the ESI of the currency and the USD ($esi_{ccy} - esi_{usd}$), the stronger the foreign exchange rate (CCYUSD), which leads us to expect a positive beta. The input for this factor is given by:

$$\mathbf{esi_t} = \mathbf{\Delta(esi_{ccy} - esi_{usd})} \tag{5}$$

- **Inflation Factor** - In line with *Purchasing Power Parity* (PPP), the inflation factor is included to account for the relationship between purchasing power and exchange rates. In our model, we consider the 1-year expected inflation rates, derived from Zero-Coupon Swaps. The intuition behind this factor is that the higher the inflation spread ($inflation_{ccy} - inflation_{usd}$), the greater the upward pressure on the foreign exchange rate relative to the USD. Therefore, we expect a positive beta for this factor. The input for this factor is given by:

$$\mathbf{inflation_t} = \mathbf{\Delta(inflation_{ccy} - inflation_{usd})} \tag{6}$$

We now summarize the variables used in our model. Table 1 presents all the information necessary for our analysis. Note that we use linear differences to measure changes for all variables, except for equities and the FX rate (negative values problem).

Table 1: Summary of the Model Inputs

Inputs	Assets	Model Name	Formula	Unit
FX	FX Rate	y	$log(\frac{ccyusd_t}{ccyusd_{t-1}}) \times 100$	%
Rates	10Y Govern. Bond Yield	$rate$	$\Delta(y_{ccy} - y_{usd})_t$	%
CCY Equity	Total Return Index (local)	ccy_equ	$log(\frac{index\_ccy_t}{index\_ccy_{t-1}}) \times 100$	%
USD Equity	S&P 500 Total Return	usd_equ	$log(\frac{SPXT_t}{SPXT_{t-1}}) \times 100$	%
Terms of Trade	Citi Commodities Terms of Trade (local)	tot	$\Delta(tot_{ccy} - tot_{usd})_t$	%
Econ. Surp. Index	Citi Economic Surprise Index (local)	esi	$\Delta(esi_{ccy} - esi_{usd})_t$	pts

1.2.2 Statistical Rationale

From a technical perspective, we want to see if there's any statistical justification for the effectiveness of the fair value model. Essentially, we're trying to explain FX rate changes using factors that should, in theory, have strong explanatory power. This implies there should be a long-term relationship between the FX rate and the fair value model, which is the concept of *cointegration*.

To test this, we first ran *Augmented Dickey-Fuller* (ADF) tests for stationarity on each variable which - as expected - were all non-stationary (see Figure 2). After differencing them, however, all variables became stationary and were integrated of order 1 - I(1). We then performed a *Johansen* cointegration test on each of the currencies' features. The results of these tests exhibited the presence of cointegration relationships between the model inputs for every currency. The EURUSD for instance, showed 6 cointegrating relationships. This suggests that the exchange rate and the factors move together in the long run, supporting the idea that the model captures real long-term dynamics.

```
EUR
                       y    rate ccy_equ usd_equ     tot     esi
Stationary I(0)    False   False   False   False   False   False
Pvalues I(0)      67.25%  23.01%   6.13%  64.04%  12.46%  29.07%
Integrated I(1)     True    True    True    True    True    True
Pvalues I(1)        0.0%    0.0%    0.0%    0.0%   0.01%    0.0%
Cointegration detected! 6 cointegrating relationships found
```

Figure 2: Results of Augmented Dickey-Fuller and Johansen's Tests on EURUSD

Now that the statistical assumptions are verified, we may have more confidence in the capacity of our models to display strong relationships with exchange rates change.

2 Identifying FX Drivers

2.1 Significance Analysis

Now that we have presented the model, its inputs, and the potential relationships between the variables, we aim to identify which of the presented factors affect the FX rate. Using the previously defined inputs, we perform multiple OLS regressions for each FX pair *CCYUSD* and their corresponding factors, with windows ranging from 3 months to 24 months. Figure 3 shows the results of these regressions for a 1-year window. Note that significance levels are indicated by ∗/∗∗, and OLS assumptions are also checked.

Global Regression Results

	const	rate	ccy_equ	usd_equ	tot	esi	inflation	Homos.	No autoc.	Normal.	R2 Adj.
EUR	−0.0878	7.1564**	0.2164*	−0.0741	0.4302	−0.0003		true	true	true	53.7%
CHF	0.0811	7.1224**	0.1019	−0.1673	0.1322	−0.0082		true	true	true	45.2%
GBP	−0.1502	6.0552*	0.0575	0.2568*	1.602*	0.0092	−0.1268	true	true	true	41.14%
NOK	−0.2349	6.0344**	0.0905	0.2653*	0.1293	−0.005		true	true	true	40.57%
SEK	−0.2141	8.5811**	0.0181	0.2292	0.4306	−0.0205*		true	true	true	46.75%
JPY	0.0829	12.518**	−0.2103**	−0.01	0.0464	−0.0054	−1.5334	true	true	true	80.06%
AUD	−0.2745		0.093	0.2827*	0.2404*	−0.0105	1.6094	true	true	true	50.88%
NZD	−0.2232	6.408**	−0.2459	0.2951**	0.2516	0.0078		true	true	true	42.33%
CAD	−0.1375	4.2569*	0.0447	0.0728	−0.0078	−0.0096		true	true	true	22.59%

Figure 3: OLS Regression Results on a 6M window. ∗ indicates significance at the 5% level, and ∗∗ indicates significance at the 1% level. Blank cells represent missing values.

Some interesting facts can be drawn from Figure 3:

- As expected, the rate spread is strongly significant in the regression models (at the 1% level for most currencies) and proves to be a strong driver of FX rate changes.
- The JPYUSD pair exhibits the strongest sensitivity to the interest rate differential, with a beta of 12.518. This aligns with the well-known *Carry Trade* driving the JPYUSD. Furthermore, this is the currency pair with the highest Adjusted R^2 at 80.06%, indicating that its significant factors (the rate differential and the JPY equity index) have strong explanatory power.
- Both the GBPUSD and AUDUSD show significant sensitivity to the Commodity Terms of Trade. This is consistent with the fact that these economies are highly reliant on exports (for Australia, commodities) and imports (for the United Kingdom, gas and cars).
- We observe that, globally, the sensitivity of CCYUSD pairs to S&P 500 returns is positive. This may seem counterintuitive, given our initial expectation of negative betas. One possible explanation for the signs of these coefficients lies in one specificity of the US dollar, known as the *Dollar Smile*. According to this theory, when the US economy is strong and experiencing robust GDP growth, investors tend to allocate heavily to US assets, driving up the value of the US dollar. Conversely, during risk-off periods (such as crises), investors seek safe-haven assets like the US dollar, which also increases its value. However, in the intermediate phase between these two extremes, the US dollar generally underperforms relative to other currencies. Thus, theoretically, both strong growth and downturns in the US economy (as reflected in S&P 500 index returns) can lead to an appreciation of the USD relative to other currencies.

2.2 Rolling Regressions Analysis

The results of running the regression model over a longer period show similarities with those obtained so far. However, we may wonder whether the significance of our factors has evolved over time. For instance, we might ask if the rate spread has always had the strong explanatory power that it has today. To investigate this, we perform rolling regressions on our data and analyze the rolling betas estimated by our models.

Figure 4 presents the significance ratios of each parameter over the past 10 years. For example, the *rate* factor for the EURUSD pair has been significant *63.38%* of the time over the past decade. This allows us to identify which factors have remained consistently significant over time. The main findings align with our previous results: rates generally exhibit strong predictive power, while terms of trade are mostly significant for economies that heavily rely on imports and exports (such as Australia and Canada).

Ratio of Significant Periods: 6M window

	EUR	CHF	GBP	NOK	SEK	JPY	AUD	NZD	CAD
const	6.84%	9.05%	9.05%	9.86%	6.44%	4.83%	7.04%	5.23%	2.01%
rate	63.38%	61.57%	45.27%	60.16%	62.98%	67.0%		42.05%	46.68%
ccy_equ	24.75%	21.93%	40.85%	24.95%	22.74%	52.52%	8.05%	20.32%	16.9%
usd_equ	28.57%	16.5%	49.9%	56.14%	39.64%	9.26%	56.34%	40.24%	32.39%
tot	12.88%	11.07%	13.88%	33.6%	13.28%	7.04%	32.8%	11.07%	31.39%
esi	5.23%	6.64%	11.47%	16.1%	12.27%	13.68%	11.67%	6.24%	10.46%
inflation			19.11%			1.41%	15.09%		

Figure 4: Significance ratios for each coefficient over the past 10 years, using a 6-month rolling window.

We also present the rolling betas per currency and per factor below. Although we do not show results for each currency or factor individually, some interesting observations can be made:

- On average, the rate factor has the highest beta: a 1% change in the JPYUSD rate spread induces a change in the FX rate between 5% and 10%, holding all other factors constant (see Figure 5).
- There is a point in time where the *rate* factor loses its predictive power. This can be seen in Figure 6, specifically the period from Q3 2020 to Q2 2021. During this period, no significant currency changes were explained by the rate factor. Intuitively, this could be attributed to the market panic during the COVID-19 crisis, which led to a sharp decline in yield rates in response to the uncertainty.

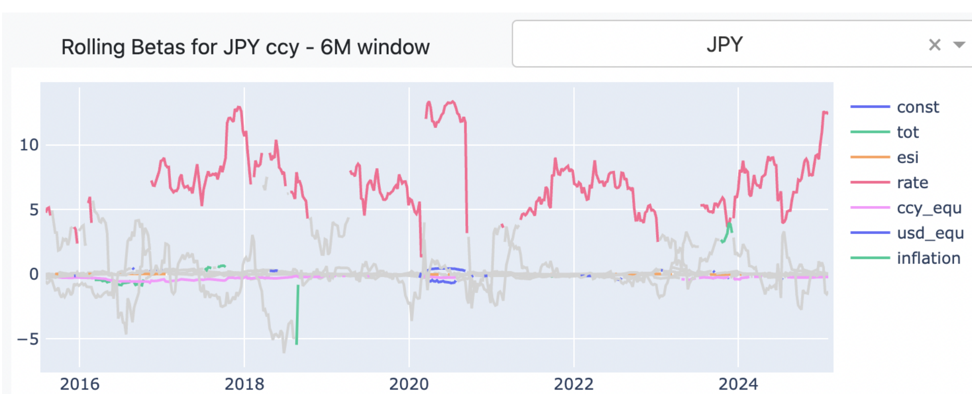

Figure 5: Rolling betas for JPYUSD over the past 10 years, using a 6-month rolling window.

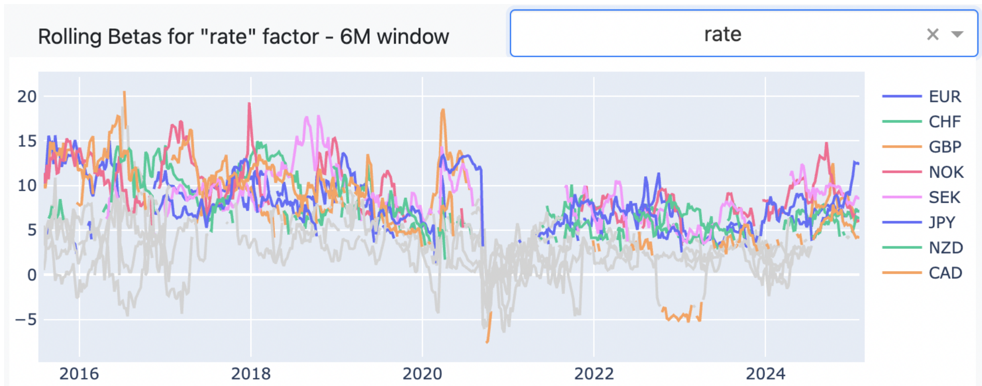

Figure 6: Rolling betas for *rate* factor over the past 10 years, using a 6-month rolling window.

3 Trading Analysis

3.1 Drivers Regression

In the previous section, we identified the driver factors corresponding to each of the G10 currencies. We may now ask whether building a model solely on the relevant drivers would be more effective, and if so, what conclusions we can draw from our analysis to generate potential trade ideas. To explore this, we run another OLS regression, but this time, the inputs of our model consist only of the drivers that were statistically significant in our previous regression models. For example, as we observed for the EURUSD pair, the rate and the EUR Index (SX5E Total Return Index) were the only significant drivers. How would the regression betas, p-values, and goodness of fit (adjusted R-squared) change when we use only these factors? Figure 7 provides some answers to these questions:

Drivers Regression Results

	const	rate	ccy_equ	usd_equ	tot	esi	inflation	R2 Adj.
EUR		7.7767**	0.1507**					55.13%
CHF		7.3785**						45.42%
GBP		5.697**		0.2551**	1.7703**			45.21%
NOK		4.8077*		0.2774**				35.4%
SEK		6.9436**				-0.0127		27.08%
JPY		11.7436**	-0.1995**					82.11%
AUD				0.2921**	0.2341*			47.18%
NZD		7.1158**		0.2551**				37.7%
CAD		2.8698*						9.87%

Figure 7: OLS Regression Results on drivers only, using a 6-month rolling window. $*$ indicates significance at the 5% level, and $**$ indicates significance at the 1% level. Blank cells represent missing values.

As expected, most of the factors that were significant in the global regression remain significant in the drivers-only regression (except for the SEKUSD Economic Surprise Index). We use the adjusted R-squared as a measure of goodness of fit because, by removing variables from the model, we tend to increase the residual sum of squares (which would lower the classical R-squared). However, we also increase the number of degrees of freedom in the model, creating a trade-off between these two effects. The adjusted R-squared accounts for this trade-off, whereas the classical R-squared does not. We can conclude that, for certain currencies (EUR, CHF, GBP, JPY), running the regressions on the drivers instead of on all the features leads to a better-fitting model.

3.2 Trading Signal

Our regression on the drivers allowed us to quantify the impact of each relevant feature on exchange rates. From a practical perspective, a trader could use these results to form expectations about the future path of exchange rates. For instance, let us consider a simple example to illustrate this: if the European economy has entered a tightening cycle while the US economy is expected to begin cutting rates soon, the trader might anticipate that the spread between European yields and US yields will widen. Based on this expectation, the trader could consult the drivers regression to confirm the following: has the yield spread historically driven EURUSD changes ? And, if so, based on the anticipated change in the yield spread, how much does he expect EURUSD to move ?

On the other hand, these models also allowed us to create a kind of *Fair Values* for exchange rates. Assuming that the drivers represent the true or equilibrium change that should occur in the FX market, we may want to compare these results with the actual changes observed in the market. Hence, we can formulate the following question: given that yesterday my fair value model predicted a change of X% for today, how much did the FX rate actually change on the market? More generally, given my fair value model, has the FX market rate been overvalued or undervalued over the past M months? And if so, by how much?

In order to answer these questions, we build a rolling regression on our drivers and perform an out-of-sample analysis. For each data point, we build a model based on the drivers of the FX rate and make a forecast for the following date. This forecast is then compared with the actual change that occurred in the market on the following date, and the error is calculated. We repeat this regression and process for each date, allowing us to build cumulative errors for different periods. The results of this analysis are presented in Figure 8.

Cumulative Errors Tables per ccy

	1W	2W	1M	3M	6M	9M	12M	18M	24M	48M	60M
EUR	0.1061	−0.5416	1.258	3.6826	3.1766	4.2823	4.9415	4.6472	2.8226	26.298	26.6076
CHF	0.5853	−0.2778	0.9076	2.711	−1.1499	−2.9584	0.2273	−2.4202	−11.8918	−9.9747	−11.235
GBP	−0.6432	−1.5802	0.6407	4.1095	5.9963	6.3609	9.4286	9.051	6.309	26.4974	42.0532
NOK	−0.4862	−0.4141	−0.2937	2.5551	7.1669	11.1438	14.8346	20.1989	23.5001	40.8232	57.5895
SEK	0.0154	−1.8303	−0.2756	3.4501	0.5318	0.0228	1.1792	−1.8732	−5.233	21.1389	8.3755
JPY	0.1802	0.9833	0.1908	0.446	−3.7595	−0.8468	0.6626	2.3747	3.7731	12.6045	20.5205
AUD	−0.0584	−0.3308	−0.5637	4.6009	7.2053	9.825	12.1257	17.8672	27.2165	40.4809	42.2084
NZD	−0.5072	0.2227	0.1046	5.6667	5.194	7.9881	12.4397	16.0487	24.8831	40.5211	44.1045
CAD	0.4889	−0.2462	−0.0631	2.0241	1.4944	2.8097	3.5736	4.2515	3.6176	7.603	6.4953

Figure 8: Cumulative Errors (in %) for each currency

For instance, we can see that EURUSD was overvalued by 0.1061% over the past week but undervalued by -0.5416% over the last two weeks. On average, currency pairs tend to be undervalued for short observation periods (the last 1-2 weeks or the last month), but as the observation periods increase, they tend to be overvalued (over the last 2-4 years). Given this information, an FX trader relying on his model can now form an idea of both the direction and magnitude of the misvaluation of an exchange rate. Figure 9 presents the graph of the cumulative trading errors over the past year:

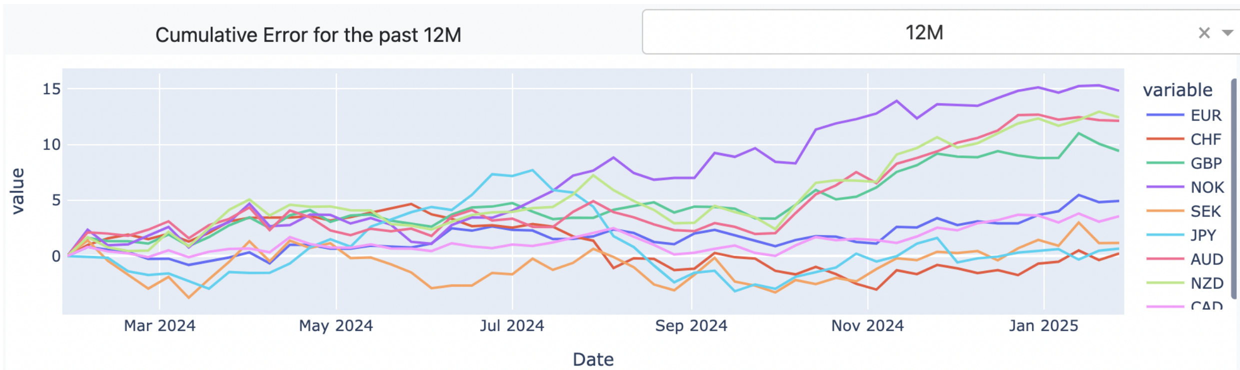

Figure 9: Cumulative Errors (in %) for each currency over the past 12 months.

4 Conclusion

Throughout this project, we were able to build an FX fair value model from scratch. This model quantifies the relationship between different macroeconomic drivers and exchange rate movements, providing insights into how certain factors, such as interest rate differentials, equity performance, and terms of trade, influence FX rates. In my case, the goal was not to develop a fully automated systematic trading tool. Instead, the aim was to create a simple model that a discretionary trader could use to confirm their signals. By relying on the fair value model, the trader can gain insights into the direction and expected magnitude of exchange rate movements for a given currency pair.
However, we can formulate several criticisms and potential improvements for our model:

- The universe of currency pairs considered (G10) might be too restrictive. Expanding the basket to include emerging market currencies, for instance, could lead to better explanatory power for certain factors. For example, emerging market countries may experience very high inflation rates (e.g., Turkey) or have economies that rely heavily on trade (e.g., Brazil, Mexico).

- Fair Value models are subjective in nature, particularly in the choice of drivers, which are often selected based on subjective judgment. While there are no definitive "right" or "wrong" choices for which drivers are best for these models, we could have considered other relevant factors that had theoretical reasons to be included, such as the Volatility Index (VIX Index), different interest rate tenors, Macro Risk Index,...

- Our model does not account for the fact that market regimes can vary over time. We build our model using the most recent available data within a selected window. One way to improve the model's performance could be to first cluster the variables into distinct "market regimes" and then build separate models for each regime.

- An interesting further step could be to calibrate an Ornstein-Uhlenbeck process on the errors, as they tend to mean revert: $dX_t = \theta(\mu - X_t)dt + \sigma dW_t$. This would allow us to deduce useful parameters for prediction, such as long-term means (μ), mean reversion rates (θ), volatility (σ) and half-life (half of the time it takes to revert to the long-term value).

- In terms of practical improvements for the Dashboard, the main one would be to use a *Bloomberg* API with Python to retrieve data continuously. Additionally, to enhance the trading analysis, we could incorporate Bid and Ask prices for the time series. Finally, we could explore deploying the application on an online server for easier access and scalability.

Thank you very much!

5 Appendix

5.1 Dashboard Presentation

We will now briefly present the Dashboard linked to this paper. The goal was to create a user-friendly tool that summarizes all the results discussed above. The Dashboard can be split into two main sections (rows):

- The drivers identification section (the first row of the dashboard)
- The drivers analysis and trading section (the second row of the dashboard)

At the top of the page, there is a slider that allows the user to select a *window*. This selection is crucial for the analysis, as all subsequent results depend on the choice of this parameter. The window defines the period for which the user wants to derive the regression models. For example, if the user selects a *6M* window, the OLS regression will be computed on the past 6 months of available data, and each rolling regression will use a *6M* rolling window.

The drivers identification section (first row) contains the results of the regression models for each currency on every feature (*Global Regression Results*), the significance ratios for each factor over a 10-year period (*Ratio of Significant Periods: 6M window*), and the graphs of the rolling betas for each currency and factor (*Rolling Betas for EUR ccy - 6M window* and *Rolling Betas for EUR ccy - 6M window*).

On the other hand, the drivers analysis and trading section is split into two parts: first, we present the results of the regression on the identified drivers only (*Drivers Regression Results*), and second, we provide the table and graphs for cumulative errors per trading period (*Cumulative Errors Tables per ccy* and *Cumulative Error for the past 12M*).

5.2 Python Packages

We present a list of all the Python modules used in this project. One should ensure that all the required packages are installed before running the program.

```python
import dash
import numpy as np
import pandas as pd
import plotly.express as px
import statsmodels.api as sm
from flask_caching import Cache
import plotly.graph_objects as go
import dash_bootstrap_components as dbc
from dateutil.relativedelta import relativedelta
from statsmodels.stats.stattools import jarque_bera
from statsmodels.regression.rolling import RollingOLS
from dash import html, dcc, Input, Output, dash_table
from statsmodels.stats.diagnostic import het_white, acorr_breusch_godfrey
```

Figure 10: Required Python modules

6 Bibliography

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[3] ECB Monthly Bulletin (Nov. 2000), *Determinants of the Equilibrium Value of a Currency*, `https://www.ecb.europa.eu/pub/pdf/other/mb200011_focus03.en.pdf`