Econ 409 & 442B: Final Project Report

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Trading Strategy Development and Evaluation

Group Name: Data Mavericks

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Introduction

In this report, we present our approach to developing a trading strategy that leverages economic indicators to predict exchange rates. Our methodology encompasses data cleaning, transformation, and application of a Taylor Rule-based model for exchange rate forecasting. We focus on optimizing strategy parameters through *heatmap analysis* and *back testing our approach against the HFRI indices*. The project's goal is to design a trading strategy that surpasses standard financial benchmarks using economic indicators. Data cleaning, transformation, and a rigorous statistical modeling process are the core of our strategy.

Methodology

Data Import:We've loaded a CSV file named final_project_data.csv into a DataFrame and examined the most recent data points by displaying the last 15 rows.

Data Handling*:* We handled data using Python libraries such as *yfinance*, *pandas, NumPy, datetime*, *io, statsmodels. formula.api,* and *missingno* for financial data manipulation and visualization.

Data Cleaning*:* We have ensured data cleanliness through several steps, including defining a relevant date range, addressing missing data, and organizing the historical exchange rate data. To preserve data integrity, any rows with missing values before our starting date have been omitted, resulting in a refined dataset suitable for analysis.

Feature Engineering*:* We converted essential financial metrics like 'USD2YB' and 'UK2YB' into daily frequency and then transformed them into log returns to standardize their distribution for time series analysis. Additionally, the CPI and Industrial Indexes were resampled, retaining their latest value while adjusting their values for a one-month shift.

Statistical Modeling*:* We have opted to implement a Taylor Rule Model, leveraging the variance between inflation and the GDP gap to predict monthly fluctuations in the exchange rate. We've employed the monthly interest rate differential between the US and UK to nowcast inflation and the GDP gap.

Hyperparameters

Rolling Window Size for Model Fitting: We've implemented a rolling window approach with a size of 120 for fitting our Taylor Rule-based model, following the recommendation from Papell's 2003 paper. This approach balances the integration of historical patterns with the adaptability to recent data.

Moving Average Window Size for Yield Differential: We have utilized a window of 26 months to obtain potential GDP and Output Gap.

Forecasts and Trading Strategy:

Our trading strategy derives signals from forecasted changes in exchange rates (s_change_fitted). A positive forecast indicates an increase in exchange rates, prompting a long (buy) signal (assigned a value of 1), while a negative forecast signals a decrease, resulting in a short (sell) signal (assigned a value of -1). Long positions are initiated when the model predicts a positive change (s_change_fitted >= 0), whereas short positions are taken when the forecast indicates a negative change (s_change_fitted < 0). Trades are entered based on these signals and exited at the end of each forecasting period. To validate the effectiveness and adaptability of our strategy, we conducted rigorous back-testing against out-of-sample data. Various combinations of output windows and forecast windows are explored to optimize annualized return and Sharpe Ratio. Through extensive testing, we determined that an output window of 26 and a forecast window of 120 yield the most favorable results for this model. Our structured approach ensures the development of a robust trading strategy grounded in detailed economic analysis and statistical modeling.

Heatmap

X-axis (Forecast Window): The X-axis represents the forecast window, indicating the duration used for predicting exchange rates and enabling exploration of various forecast windows during analysis.

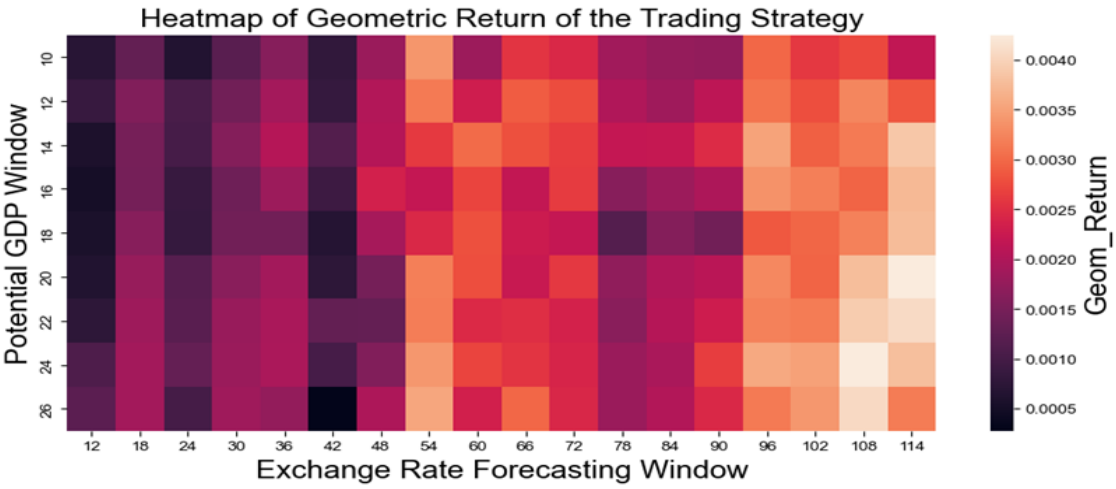
Y-axis (GDP Window): On the Y-axis, we have the GDP window, which reflects the period for finding the output gap, providing insights into different lengths of GDP windows.

Color Intensity: At every grid point on the heatmap, the intensity of color signifies valuable insights into the geometric return of the trading strategy. Darker shades denote higher geometric returns, facilitating the visual identification of areas linked with better performance.

Geometric Return: We consider this essential metric as the benchmark for assessing the performance of the trading strategy. Geometric return is our preferred measure because it incorporates the compounding impact of returns over time, providing a thorough evaluation of the strategy's efficiency and effectiveness.

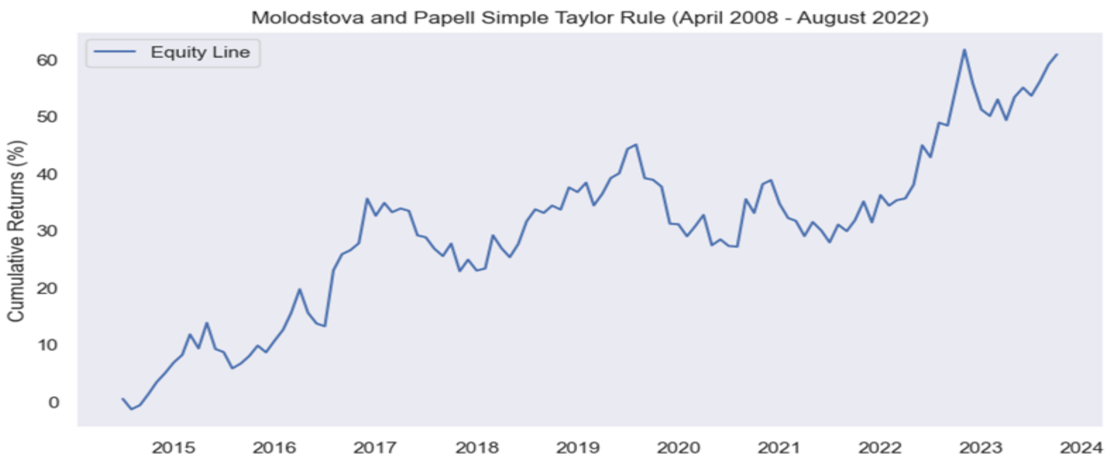
Heatmap Analysis:

According to our heatmap analysis, we've identified the most advantageous combination as a 24-month GDP window paired with a 108-month forecast window, which results in the highest geometric return. This combination stands out prominently among the range of hyperparameter values examined, demonstrating the highest geometric return for our trading strategy. It signifies a well-tailored configuration, adeptly utilizing a GDP window of optimal length for computing the output gap, coupled with a forecast window of ideal duration for predicting exchange rates. Given this notable result, we strongly advocate employing a GDP window of 24 alongside a forecast window of 108 for any future simulations or real-world applications of the trading strategy. This strategic pairing has considerable potential for maximizing returns, in line with insights gleaned from historical data and the performance of our trading strategy.



Equity Curve:

The equity curve demonstrates the growth trajectory of our strategy's returns, reflecting the compound effect over time. The equity line emanates from 0% with variations but a general upward trend to about mid-2020 when there appears a steep return line symptomatic of a big period of gains. The strategy seems to have seen periods of drawdown, most notable in early 2020, and perhaps it was due to market volatility as Covid-19 reared its head. Recovery post this was decent; also, amongst the broad sectoral indices, pharma, among others, looked promising.



From this equity curve, an investor or trader may infer that the trading strategy has generally been profitable over the given time frame, as indicated by the overall upward trend. While there were spells of the strategy making both profits and losses, in general, over the long term, there were cumulative gains more than the losses that the strategy had made. The substantial upward movement in 2020 may hint at a strong market reaction or a proper adjustment in the strategy.

Discussion

Our trading strategy has shown competitive performance when benchmarked against the HFRI Fund Weighted and Fund of Funds Composite Indices. The heatmap pointed to a balanced approach between responsiveness to recent data (forecast window) and incorporating longer-term trends (GDP window).

RISK/RETURN

TYPE	Value
Geometric Average Monthly Return	0.0019
Standard Deviation	0.0255
High Month	0.1032
Low Month	-0.091
Annualized Return	5.227
Annualized Standard Deviation	0.59
Percentage of Winning Months	51.82
Maximum Drawdown	-20.53
Sharpe Ratio	0.992
Risk Free Rate	1.47

REGRESSION

TYPE	Value
Alpha	0.0007
Beta	-0.18
Mnt. R-Squared	0.0147
Correlation	0.1214
Up Alpha	-0.0031
Up Beta	0.0848
Up R-Squared	0.0011
Down Alpha	0.0004
Down Beta	-0.263
Down R-Squared	0.0193

Performance Against HFRI Indices

In comparison with the B1 "HFRI Fund Weighted Composite Index," our strategy presents a lower alpha of 0.0007 versus B1's 0.03, suggesting modest excess returns above the risk-free rate. With a negative beta of -0.1800 against B1's 0.92, our strategy inversely responds to market movements, indicating potential for hedging or diversification. The strategy's R-squared at 0.015 contrasts with B1's 0.97, showing minimal correlation with market benchmarks. Notably, the strategy achieves a Sharpe ratio of 0.992, underscoring its efficiency in balancing returns against volatility. The annualized return of 5.227% further demonstrates the strategy's capability to generate positive outcomes over the long term, though it diverges from the B1 benchmark's closely market-mirroring performance. This juxtaposition underlines our strategy's unique market position, offering potential for hedging and diversification benefits amidst varying market conditions.

Recommendations and Future Work

Given more time, we would explore further model enhancements, including the integration of additional economic indicators and machine learning techniques for improved prediction accuracy. The robustness of the strategy could also be enhanced by testing across different market conditions.

Conclusion

Data Mavericks have developed a statistically sound and economically informed trading strategy with proven potential. While our current configuration offers a promising outlook, continual refinement and adaptability are key to long-term success.