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Skewness Trading Strategy for Currencies

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A) Background

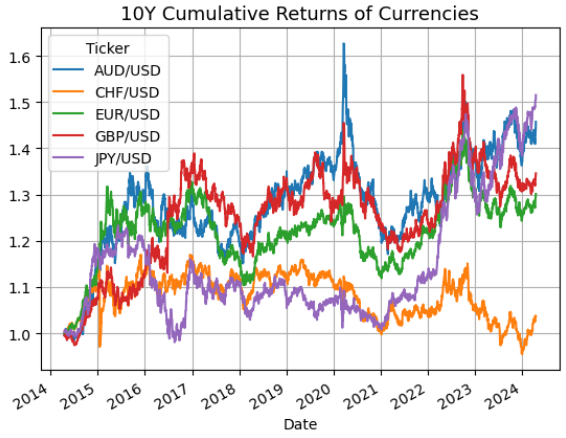
The strategy aims to implement the idea from the QuantConnect blog. This blog post runs a risk premia strategy that enters long-short positions in the Forex market based on signals from a skewness indicator. The strategy is derived from the paper "Risk Premia: Asymmetric Tail Risks and Excess Returns" by Lemperiere, Deremble, Nguyen, Seager, Potters, and Bouchaud.

B) Implementation

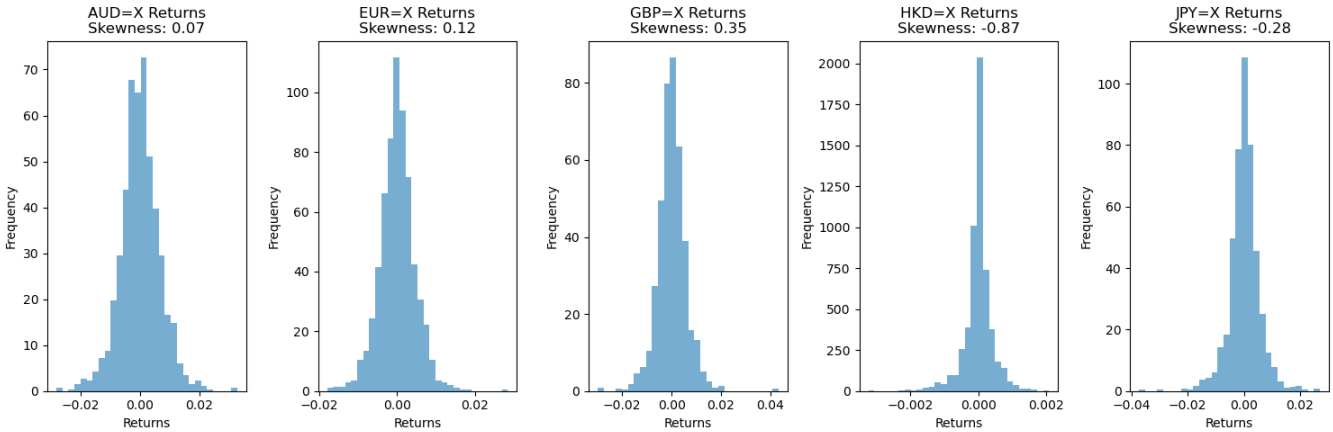
Data

The dataset consists of daily currency prices data from Yahoo Finance. Specifically, the strategy trades currency crosses of USD vs. EUR, JPY, GBP, CHF and AUD, so a total of 5 currency crosses. I then split the data into training (first 7 years) and test (last 3 years) datasets based on the total number of trading days. The data will be pulled with the `get_currencies()` function.

Before doing any work, I am curious to look at the behavior of each currency cross I have selected. Below we can see the cumulative returns and some summary statistics of each currency vs. USD. All except CHF have appreciated in the past 10Y, but did not yield large enough annual returns to end up with a positive Sharpe. HKD and JPY exhibit negative skewness while EUR and GBP are on the positive side. Although the HKD skewness seems to present a trading opportunity given the strategy we are testing, the small returns over the years really take away from that opportunity.



Ticker	Std	Ann. Vol	Ann. Ret	Cum. Ret	Sharpe
AUD/USD	0.64%	10.11%	0.17%	46.23%	-0.44
CHF/USD	0.58%	9.17%	0.02%	3.60%	-0.50
EUR/USD	0.50%	7.93%	0.12%	30.28%	-0.57
GBP/USD	0.59%	9.35%	0.14%	35.24%	-0.48
JPY/USD	0.55%	8.65%	0.19%	51.05%	-0.51



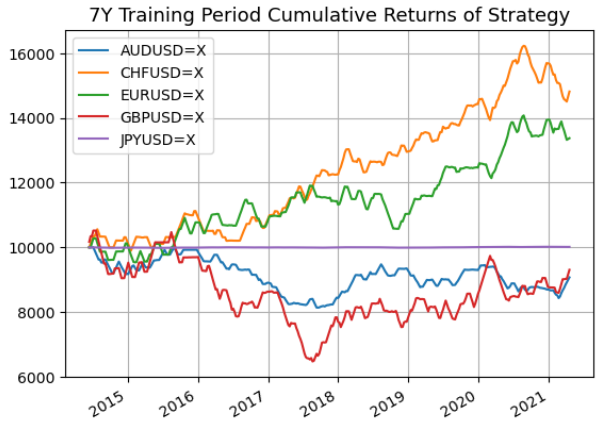
Trading Signal
I calculate a skewness signal over a rolling window of 42 days (6 weeks). `trading_signal` generates buy (1), sell (-1), or hold (0) signals based on skewness threshold, which is defined by the use.

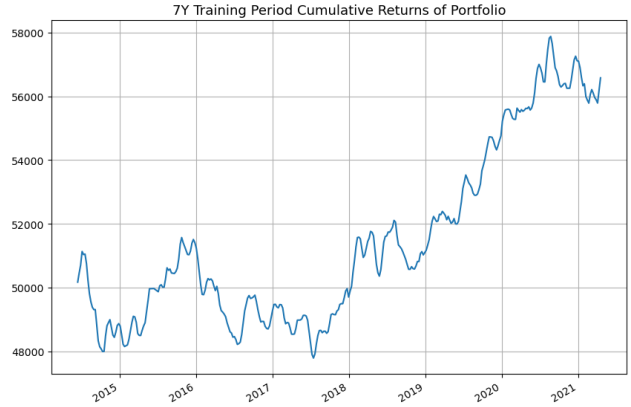
Strategy Simulation
The function `run_strategy` attempts to simulate trading actions based on the generated signals. I then simulate a portfolio across various currencies by buying or selling 100 positions in the currency given the weekly position of the trading signal. I then create a "Total" portfolio that sums over all trades in each currency. I rebalance my positions every week.

Parameter Evaluation
Lastly, I was curious about how changing the skewness cutoff would impact the results. So I evaluate performance using a step-increase in the skewness cutoff. This iterative testing can help me find an optimal parameter. I tried changing the cutoff point from 0.1 to 0.8 for the skewness calculation. So our indicator would sell short if skewness is < -0.6 and buy long if > 0.6.

C) Results

Backtest
The backtest yielded mixed results for the currency crosses.
For GBP, AUD and EUR crosses, despite a positive cumulative return for the period, the Sharpe ratios are negative, which implies the strategy might have been taking on excessive risk relative to the returns achieved, potentially capturing small, frequent gains but suffering from infrequent, significant losses. The CHF cross performed the best, which might be explained by its large negative skewness we noted in the exploratory analysis. The JPY cross barely moved, which I'm attributing now to the fact that USD/JPY cross is quoted in terms of how many Yen represent one unit of USD. Whereas with the other currency pairs, the quote represents how many U.S. dollars you can buy with one unit of the other currency. There needs to be an adjustment to the USD/JPY returns so we can assess the performance of the strategy better.

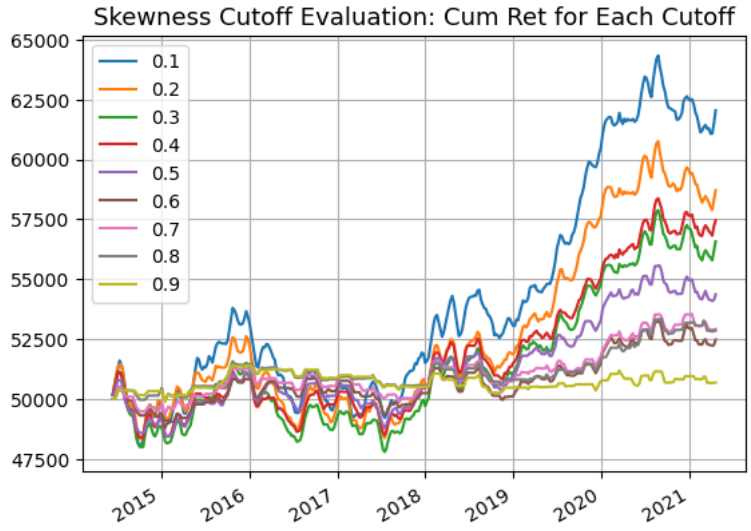




	Std	Ann. Vol	Ann. Ret	Cum. Ret	Sharpe
AUDUSD=X	0.58%	4.19%	-1.33%	-9.27%	-1.419790
CHFUSD=X	0.65%	4.71%	5.84%	48.15%	0.258883
EURUSD=X	0.75%	5.44%	4.38%	33.73%	-0.043469
GBPUSD=X	1.18%	8.52%	-0.93%	-8.51%	-0.651713
JPYUSD=X	0.01%	0.05%	0.02%	0.15%	-92.009217
total	0.39%	2.80%	1.79%	12.78%	-1.01083

Skewness indicator cutoff point

Below we see the cumulative return given a skewness cutoff point for the total portfolio. Given these results, 0.7 is a good cutoff point, though the reactions of positive vs. negative news could also be studied. (ie, returns react more aggressively to rolling negative skewness than rolling positive skewness so we might want to try -0.7 and 0.5 as the cutoff points etc.) We can also try different cutoff points for each currency vs. just the total portfolio and see how the strategy performs.



D) Next Steps

- **Larger universe:** The fixed universe I chose of five currencies is likely not large enough to properly diversify market risk. I would also prefer looking at different crosses vs. only USD to assess their historical volatility and price appreciation while factoring in macroeconomic news to decide on a better set of currencies to trade.
- **T-costs and slippage:** I do not account for trading costs or slippage in my analysis. If we know the approximate trading cost of each asset in our exchange, this can easily be incorporated. For slippage, we might want to use something like slippage adjustment factor that adjusts the price we get from the market. We can also try limit orders vs. market orders to mitigate the slippage problem. Although this analysis assumes a systematic execution, a discretionary execution will surely mitigate slippage.
- **Lack of intraday data:** This strategy assumes a medium-term holding strategy with weekly rebalancing, and therefore might miss out on intraday opportunities or big macroeconomic news.
- **FX options:** I'd be interested in exploring this effect more so on FX options vs. just currency crosses.
- **Rebalance period:** Different rebalance periods can be tested. This period may be adjusted to be more frequent or less frequent given market volatility.
- **Position sizing:** Dynamic adjustment of position sizes based on market volatility can be helpful. I might want to reduce position sizes during high market volatility.
- **Testing:** Lastly, I did not have the time to test using the last 3 years of my 10 year sample, but this would create an out-of-sample backtest to see if how our strategy works with data outside of what it's been trained on.