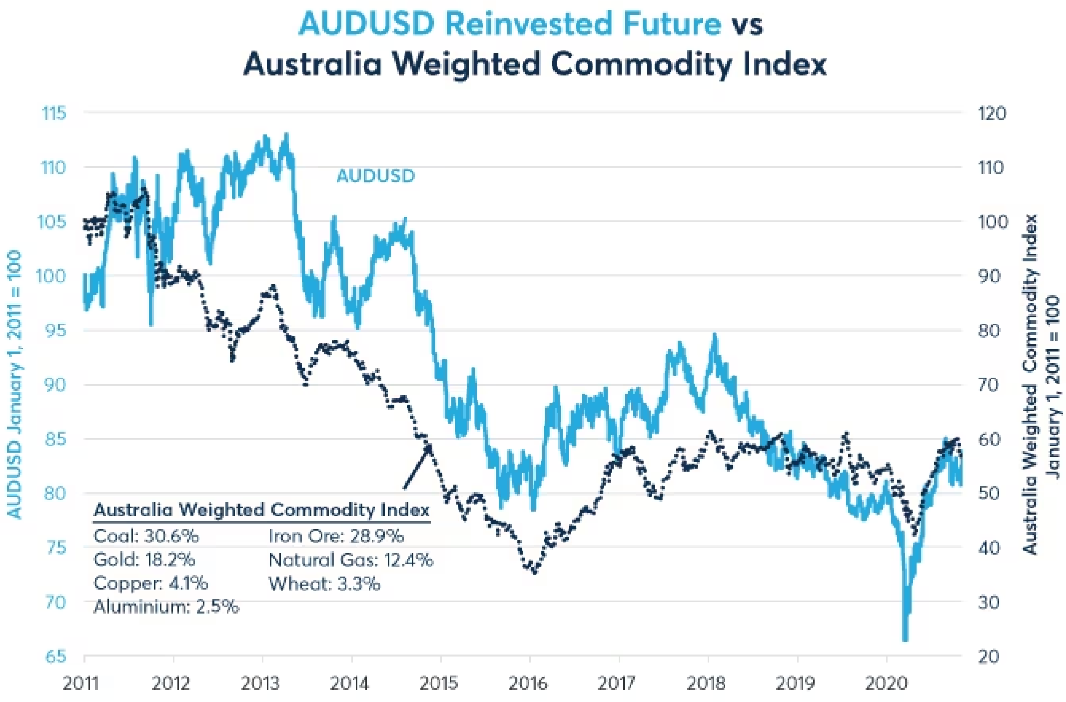
1. Introduction

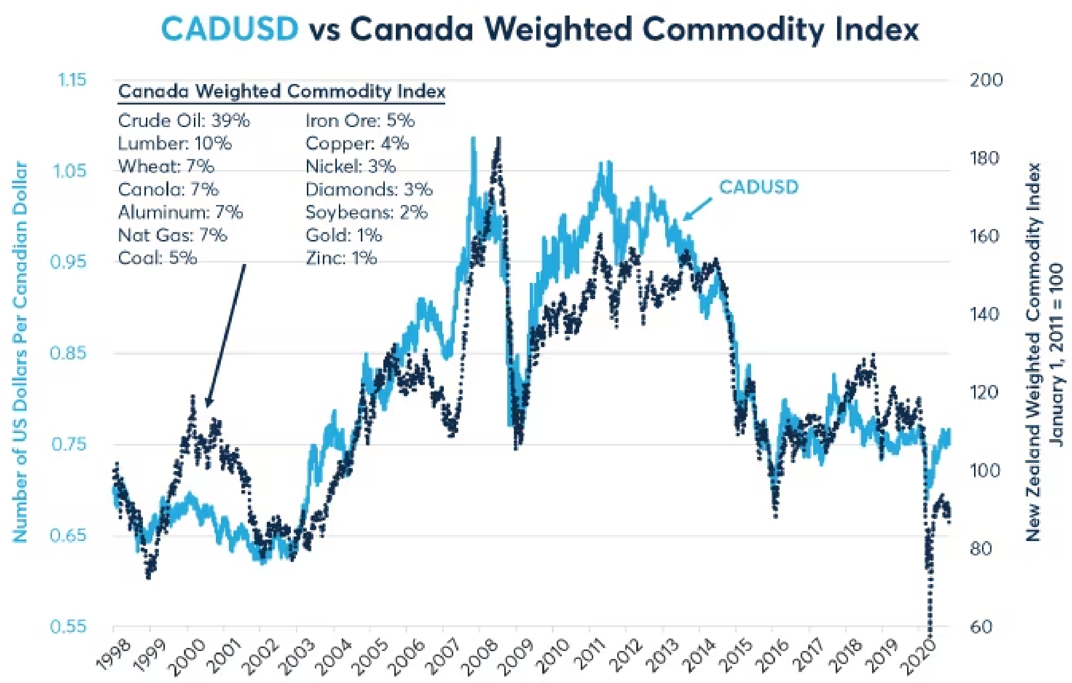
1.1 Economic Intuition

Currecies of major commodity exporters are heavily influenced by the prices of their various raw materials exports that are of economic importance. A basket of commodities that share a significant weight in the total export of such country can track closely the performance of that country's currency. For example, a commodity basket with the following trade weights has had similar performance as AUD over the past 10+ years:



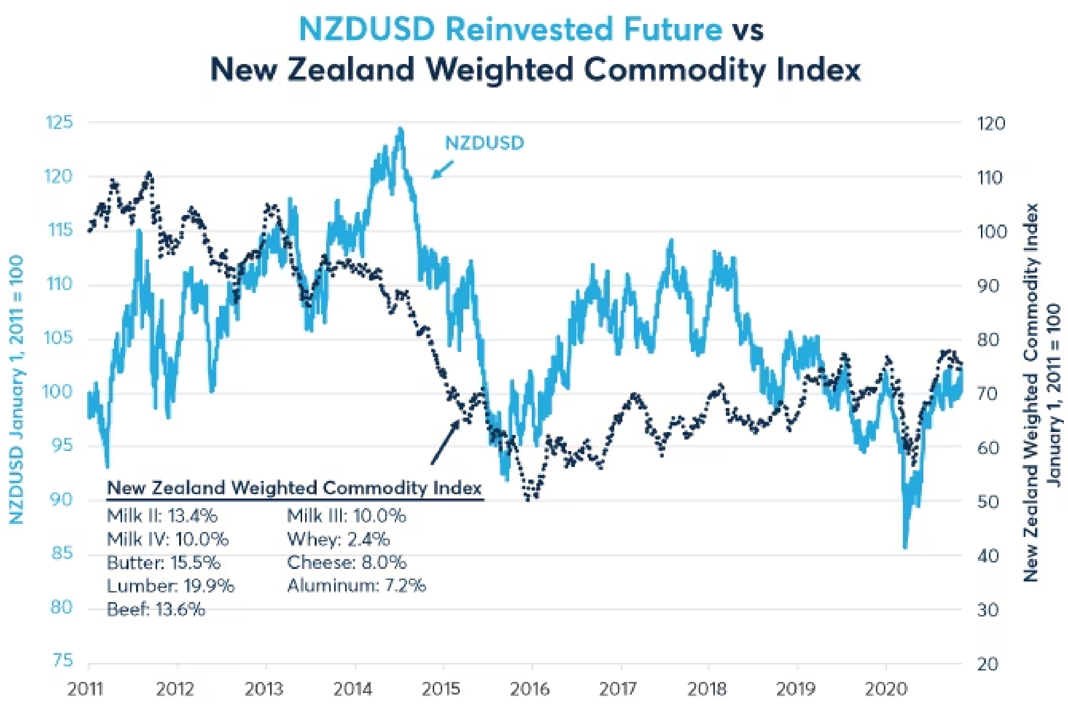
Source: Bloomberg Professional (AD1, TIO1, MFE1, GC1, CO1, NG1, HG1, LA1, OEC Australia)

Similarly, a trade weighted commodity basket that has a large portfolio in crude oil also tracks the performance of CAD quite well:



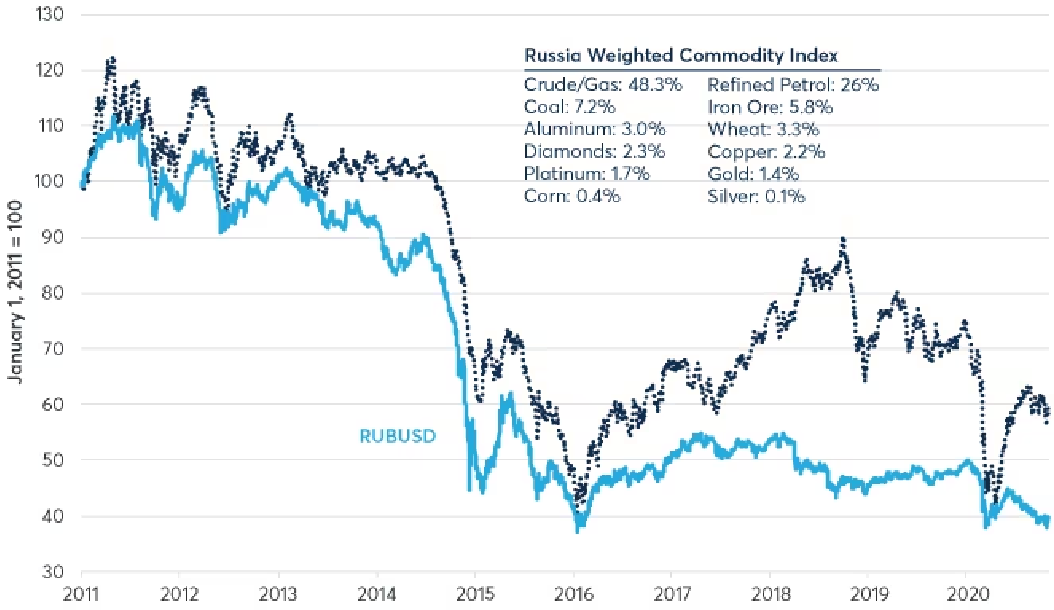
Source: Bloomberg Professional (CADUSD, TIO1, MFE1, QZ1, API31MON, GC1, CO1, NG1, HG1, LA1, LN1, LX1, LB1, DIAM1CRT, S 1, RS1), (Weigths OEC, Canada Net Exports) CME Economic Research Calculations

This is by no means a unique phenomenon for the above two countries. Around the world, we have more examples to look at[1]:



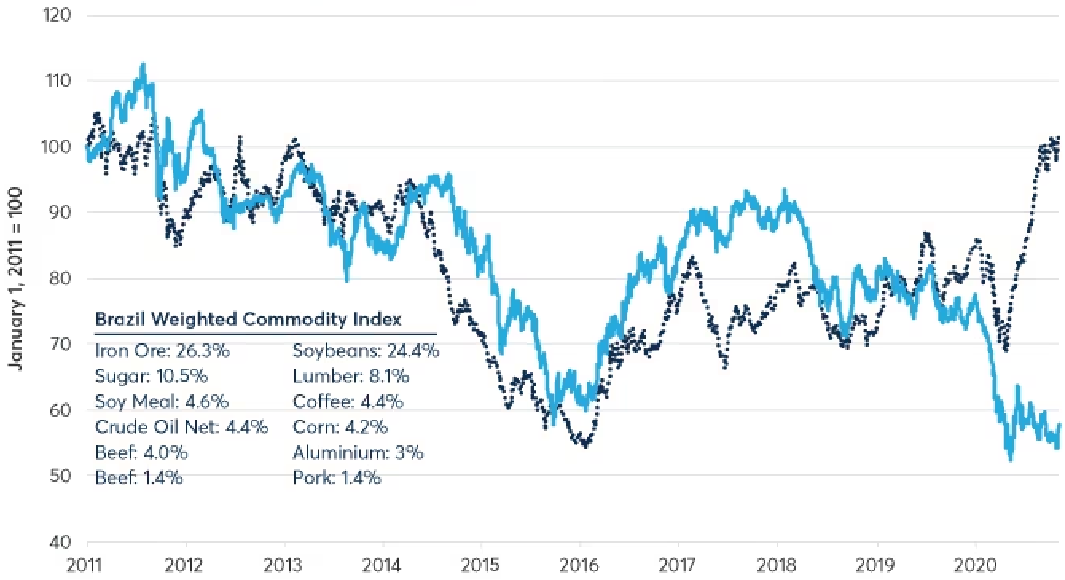
Source: Bloomberg Professional (NV1, KV1, LE1, DRW1, V61, CHE1, LB1, LA1, LC1 OEC New Zealand)

RUBUSD vs Russia Weighted Commodity Index



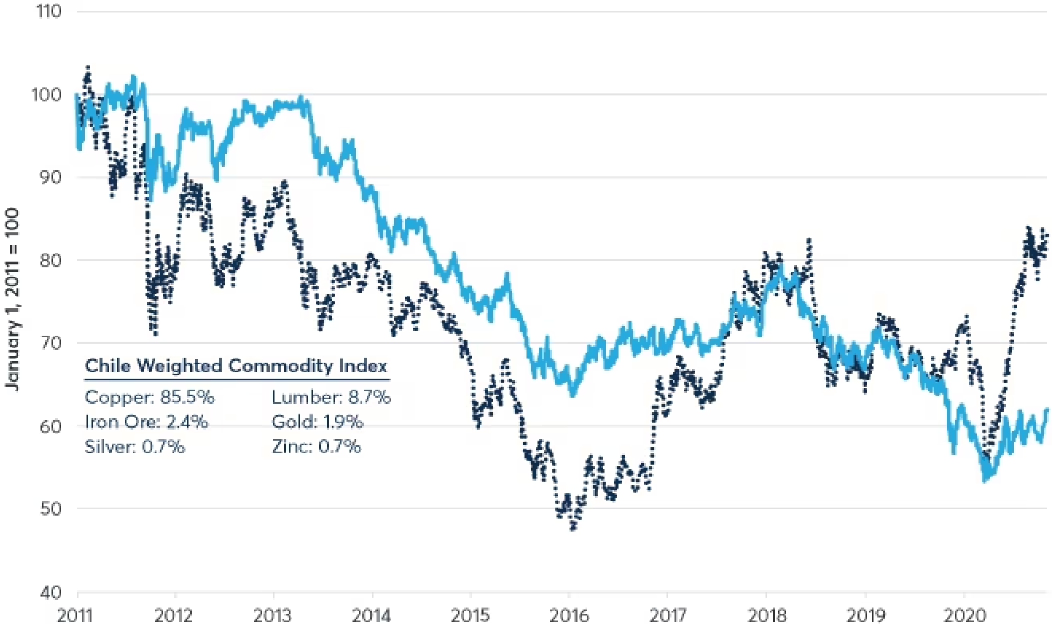
Source: Bloomberg Professional (RU1 Rolled 10 Days Prior to Expiry, BZA1, HO1, XB1, MFE1, TIO1, ALE1, W 1, DIAM1CRT, HG1, PL1, GC1, C 1, SI1, Observatory of Economic Complexity (OEC Russia Exports))

BRLUSD Reinvested Future vs Brazil Weighted Commodity Index



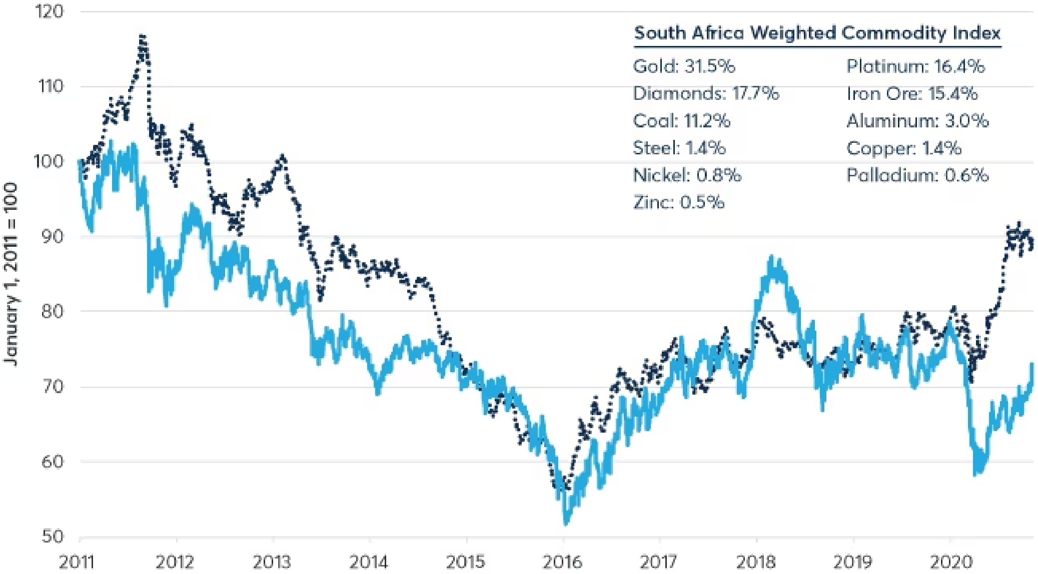
Source: Bloomberg Professional (BR1 Rolled 10 Days Prior to Expiry, TIO1, S 1, SB1, LB1, SM1, KC1, CL1, C 1, LC1, LA1, HG1, LH1, Observatory of Economic Complexity (OEC Brazil))

CLPUSD vs Chile Weighted Commodity Index

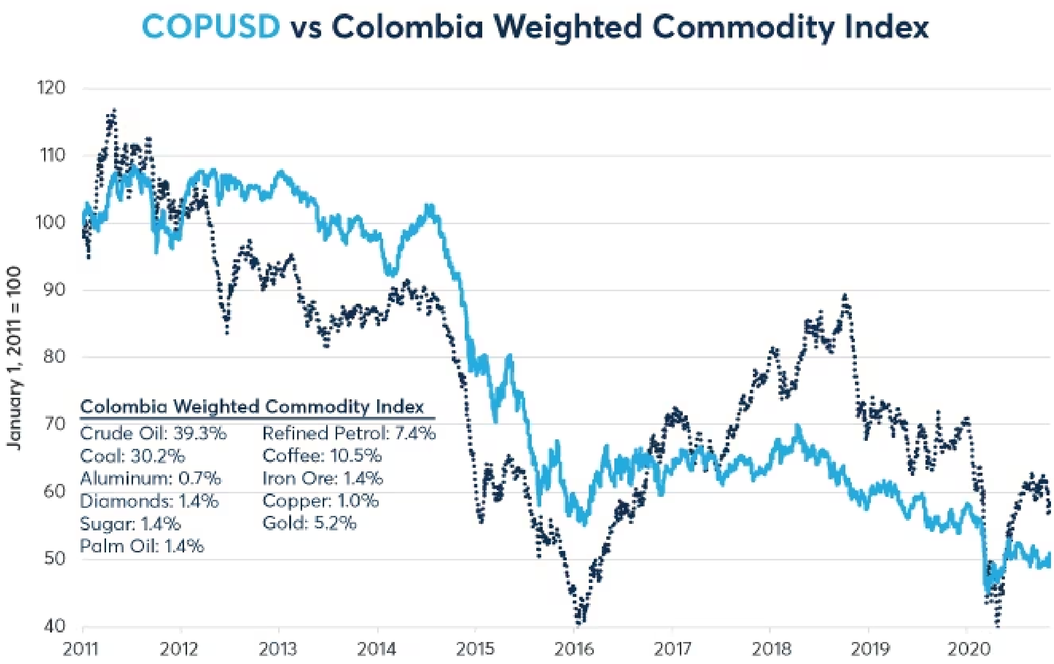


Source: Bloomberg Professional (CLPUSD, TIO1, GC1, SI1, LB1, HG1, LX1, Observatory of Economic Complexity (OEC Chile))

ZARUSD Reinvested Future vs South Africa Weighted Commodity Index



Source: Bloomberg Professional (RA1 Rolled 10 Days Prior to Expiry, MFE1, TIO1, ALE1, LX1, LN1, HRC1, HG1, DIAM1CRT, HG1, PL1, GC1, Observatory of Economic Complexity (OEC South Africa Exports))



Source: Bloomberg Professional (COPUSD, CL1, HO1, XB1, MFE1, TIO1, ALE1, SB1, DIAM1CRT, HG1, KC1, GC1, SI1, Observatory of Economic Complexity (OEC Colombia Exports)), CME Economic Research Calculations

All these currencies have demonstrated high correlations with their commodity baskets over the past 10 years up until COVID-19. After COVID, there's a temporary divergence in currencies like BRL, CLP, ZAR. Part of this can be explained by the supply chain disruptions that were quite common during covid when miners and producers were forced to shutdown and curtail production. But hopefully, as COVID becomes history, we should see more stable correlations going forward.

With this tightly linked economic relationship in mind, the strategy tries to capitalize by trading the dynamic spread between the "commodity currency" and the hypothetical trade weighted commodity basket.

1.2 Kalman Filter

We use Kalman Filters to model the relationship between the currency and the commodity basket. We assume a linear form of relationship as we can hardly trade nonlinear ones. Let y_t be the currency price, x_t be the commodity basket price. We try to model the spread between the two as a residual process ϵ_t by the following:

$$y_t = \beta_t x_t + \epsilon_t \tag{1}$$

where β_t is the hedge ratio. As can be seen from the above charts, β_t is likely to change over time. We overlay a simple state transition model on it by having:

$$\beta_t = a_t \beta_{t-1} + g_t w_t \tag{2}$$

where w_t is a noise process inherent in the state estimation. For simplicity, we assume the state estimation noise is uncorrelated with the spread:

$$\epsilon_t \sim F_1(\mu_1, \sigma_1^2) \tag{3}$$

$$w_t \sim F_2(\mu_2, \sigma_2^2) \tag{4}$$

$$\mathbb{E}(\epsilon_t w_t) = 0 \tag{5}$$

$$\mathbb{E}(\epsilon_t \epsilon_s) = \delta(t-s) \tag{6}$$

$$\mathbb{E}(w_t w_s) = \delta(t-s) \tag{7}$$

where $\delta(\cdot)$ is the Dirac delta function.

Equations (1) - (7) give us a simple one dimensional Kalman filter, where β_t is the hidden state and y_t the measurement. Given a series of observations and measurements (x_t, y_t), the goal is to find an optimal state estimation despite the inherent noises (ϵ_t, w_t):

$$\min_{\hat{\beta}_t} J = \mathbb{E}[(\hat{\beta}_t - \beta_t)^T (\hat{\beta}_t - \beta_t)] \tag{8}$$

with state estimate transition and output equations:

$$\hat{\beta}_{t|t-1} = \mathbb{E}[a_t \hat{\beta}_{t-1} + g_t w_t] = a_t \hat{\beta}_{t-1} \tag{9}$$

$$\hat{y}_t = \mathbb{E}[x_t \hat{\beta}_{t|t-1} + \epsilon_t] = x_t \hat{\beta}_{t|t-1} \tag{10}$$

estimation correction based on the new measurement y_t:

$$\hat{\beta}_t = \hat{\beta}_{t|t-1} + k_t (y_t - \hat{y}_t) \tag{11}$$

where k_t is the one dimensional Kalman gain matrix.

The solution to problem (8) - (11) can be found by differentiating the error function w.r.t the Kalman gain matrix. This is given by the following:

$$k_t = \frac{x_t p_{t|t-1}}{x_t^2 p_{t|t-1} + \sigma_1^2} \tag{12}$$

$$p_t = (1 - k_t x_t) p_{t|t-1} \tag{13}$$

$$p_{t+1|t} = a_t^2 p_t + g_t^2 \sigma_2^2 \tag{14}$$

where $p_{t|t-1} = \mathbb{E}[(\hat{\beta}_{t|t-1} - \beta_t)(\hat{\beta}_{t|t-1} - \beta_t)^T]$ the error variance of the prior state estimation and $p_t = \mathbb{E}[(\hat{\beta}_t - \beta_t)(\hat{\beta}_t - \beta_t)^T]$ the posterior variance.

In a nutshell, equations (12) - (14) give the update rules to recursively compute the optimal state estimation as more data come in.

1.3 Preliminary Analysis

All data used in the following analysis come from yahoo.finance. As high quality data are available only on certain commodity futures, we focus on a few selected currencies from above: BRL, CAD, CLP, COP, RUB and ZAR. We also exclude certain commodities due to data issues[2].

We start by building the commodity baskets that track each of the currencies. Note that we have used the "truncated" baskets due to liquidity and data availability issues.

Currency	Selected Commodities
BRL	Iron Ore (26.3%), Soybeans (24.4%), Sugar (10.5%), Soy Meal (4.6%), Coffee (4.4%)
CAD	Crude Oil (39%), Natural Gas (7%), Wheat (7%), (7%), Iron Ore (5%)
CLP	Copper (85.5%), Iron Ore (2.4%), Gold (1.9%), Silver (0.7%)
COP	Crude Oil (39.3%), Coffe (10.5%), Gold (5.2%), Iron Ore (1.4%), Sugar (1.4%)
RUB	Crude Oil (26%), Natural Gas (12%), Iron Ore (5.8%), Wheat (3.3%)
ZAR	Gold (31.5%), Platinum (16.4%), Iron Ore (15.4%), Copper (1.4%)

Fig. 1 Commodity Basket Composition

The following charts display the volatility adjusted currency prices against the corresponding baskets. Note that the spread was relatively tight during the years from 2010 to 2020. After COVID-19, commodities seem to have gained a lot more volatility due to the supply side constraints and the spread started to widen.

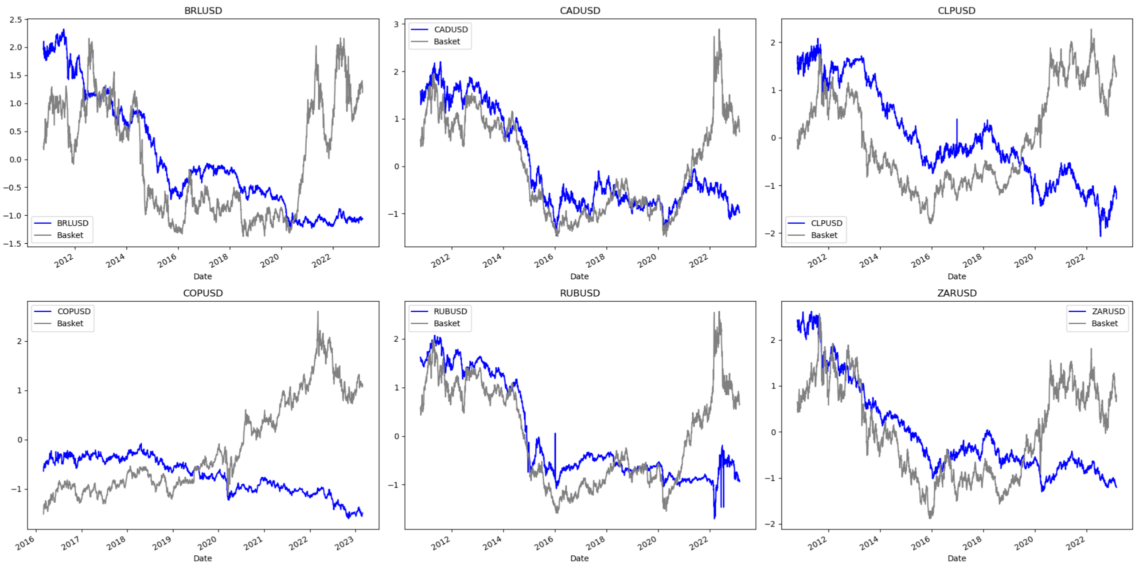


Fig. 2 Currencies and Commodity Baskets

Next we fit the Kalman Filters to the above time series. The following charts show the fitted parameters as well as the predicted measurements. The fit result looks quite decent. Long term R^2 is above 90% across all currencies and short term (since 2022) R^2 is above 80% with the exceptions of CAD and RUB[3].

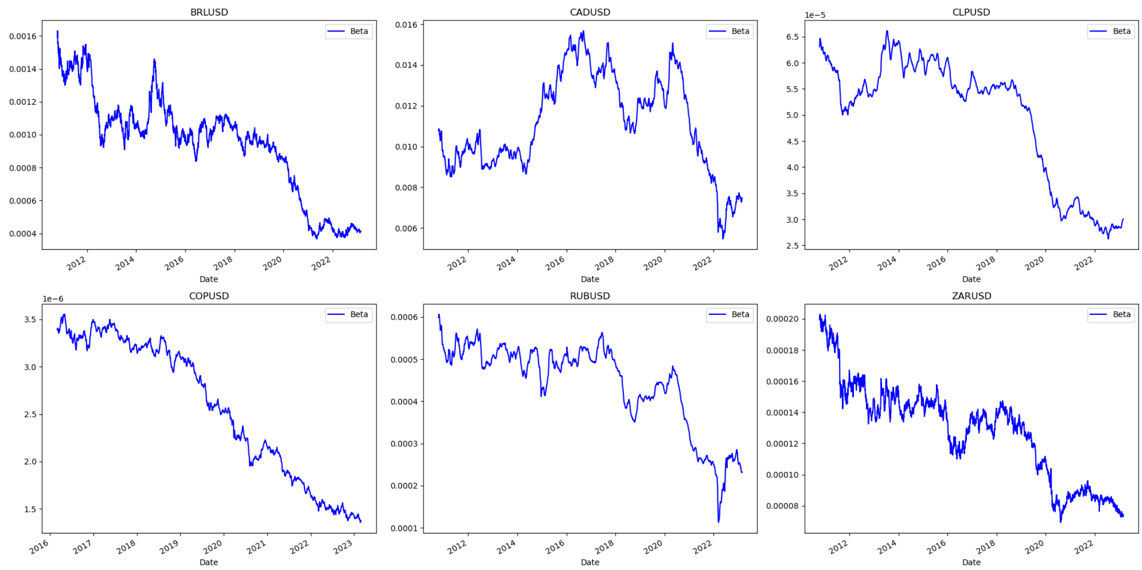


Fig. 3 Fitted Kalman Filters Beta

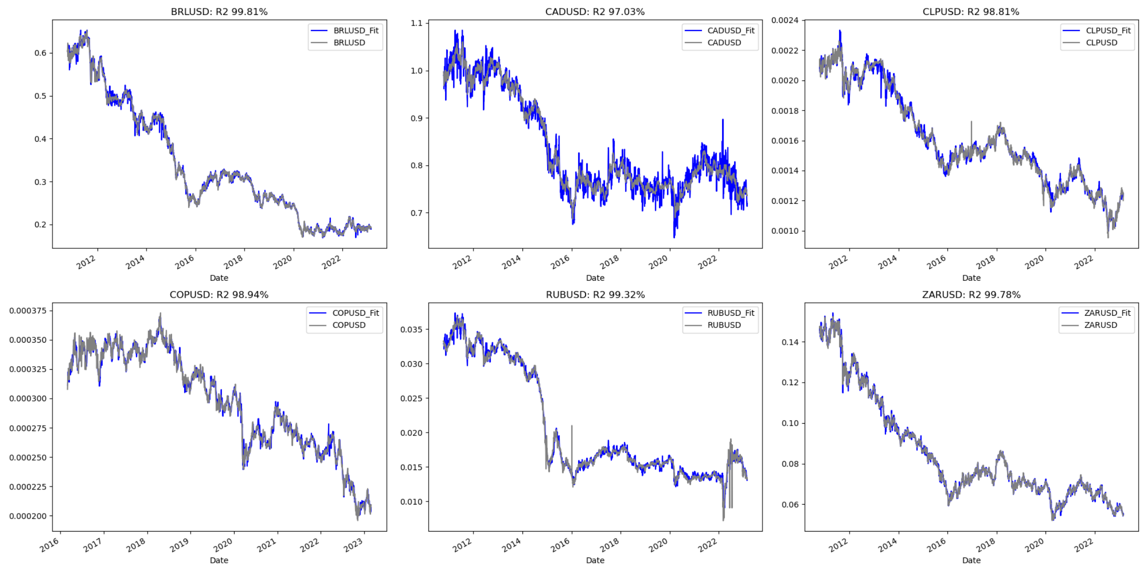


Fig. 4 Fitted Measurements

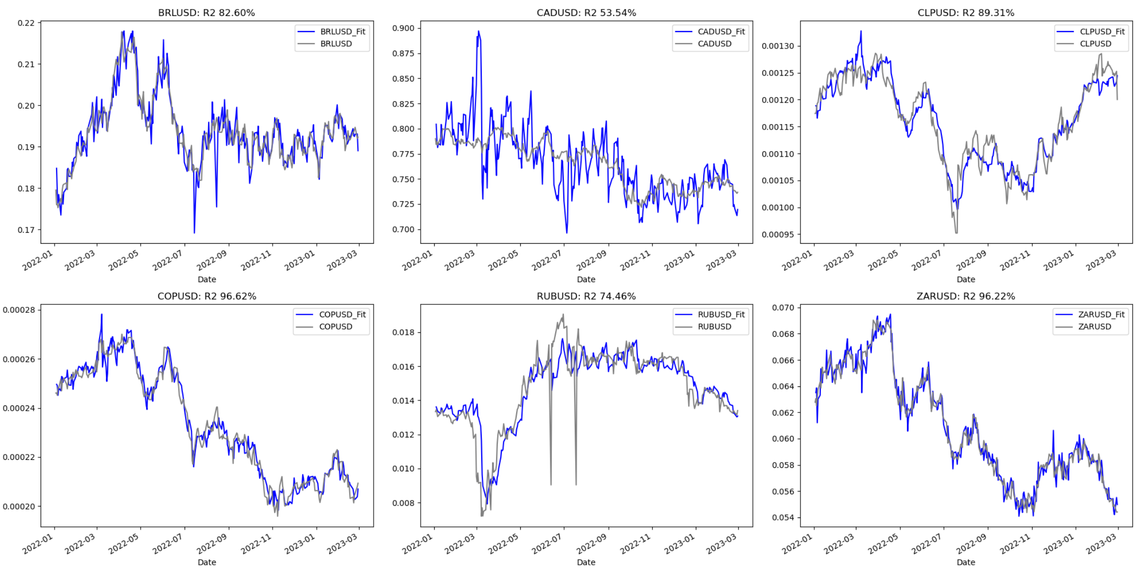


Fig. 5 Fitted Measurements Since 2022

We then extract the residual time series and run ADF test on it to check whether it is stationary / mean reverting. As can be seen from below, test results are highly statistical significant with pvalues almost equal to zero. This suggests the fitted dynamic linear relation is stable over time.

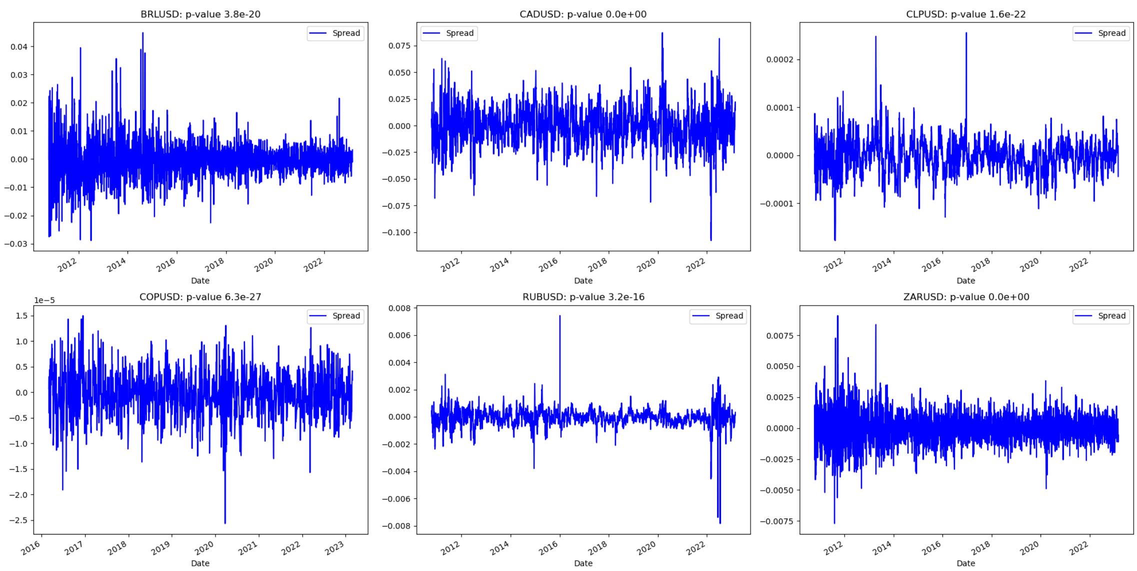


Fig. 6 Residual and ADF Test

2. Backtest

2.1 Parameters

From the above stationary residual / spread we then formulate a trading strategy by going long / short the spread when it deviates too much from the mean and closing the trade when it comes back. Specifically, assume the underlying currency is BRL:

$$z = BRL - \hat{\beta} * (0.263 * TIO + 0.244 * ZS + 0.105 * SB + 0.046 * ZM + 0.044 * K$$

To long 1 unit of z means to long 1 unit of Brazilian Real and short $\hat{\beta} * 0.263$ unit of Iron Ore futures, $\hat{\beta} * 0.244$ unit of Soybean futures, $\hat{\beta} * 0.105$ unit of Sugar futures, $\hat{\beta} * 0.046$ unit of Soy Meal futures, and $\hat{\beta} * 0.044$ unit of Coffee futures.

Furthermore, we define "deviates too much from the mean" by the spread deviating n_1 standard deviation from its m day moving average and "comes back" by it falling back into its m day n_2 standard deviation envelope.

This leaves three hyperparameters to tune for strategy performance: m, n_1, n_2. Ideally, we should pick a parameter set that sits in the center of a "plateau", a region where nearby parameter set also gives similar high sharpe ratio. In this case, it's a bit difficult to visualize a four dimensional dataset. We just picked the parameter set that maximizes in-sample sharpe ratio.

We split the sample data into in-sample and out-sample portions. The in-sample dataset covers data from 2010 to 2022. Out-sample dataset covers the rest from 2022 onwards to 2023-05-01. The following table summarizes the optimal in sample parameters to use for different currencies:

	m	n1	n2
BRL	40	1.25	1.25
CAD	15	1.7	1.7
CLP	35	1	1
COP	55	1.1	1.1
RUB	30	0.9	0.9
ZAR	55	0.8	0.8

Fig. 7 Optimal In-Sample Parameters

2.2 Performances

We apply the above optimal parameters to backtest the entire sample history. The following charts summarize performances across all currencies[4]. The blue line portion is the out-sample period. We have adjusted leverages for all strategies to target 10% annual volatility. The extreme volatility for RUB performance around 2022 is likely due to data issue or disruptive effects from the war.

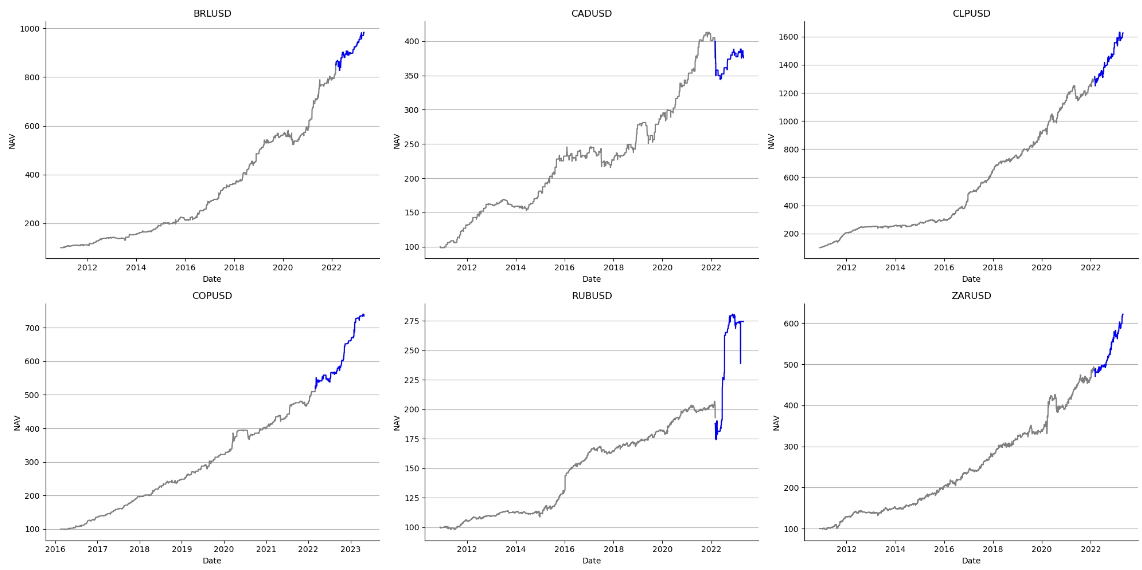


Fig. 8 Full History NAV

Currency	Annual Return	Annual Volatility	Max Drawdown	Sharpe Ratio	Calmar Ratio
BRL	19.05%	10.00%	10.06%	1.91	1.89
CAD	11.36%	10.00%	16.70%	1.14	0.68
CLP	23.14%	10.00%	8.64%	2.31	2.68
COP	28.39%	10.00%	7.13%	2.84	3.98
RUB	8.77%	10.00%	15.71%	0.88	0.56
ZAR	15.42%	10.00%	10.15%	1.54	1.52

Fig. 9 Full History Performance Stats

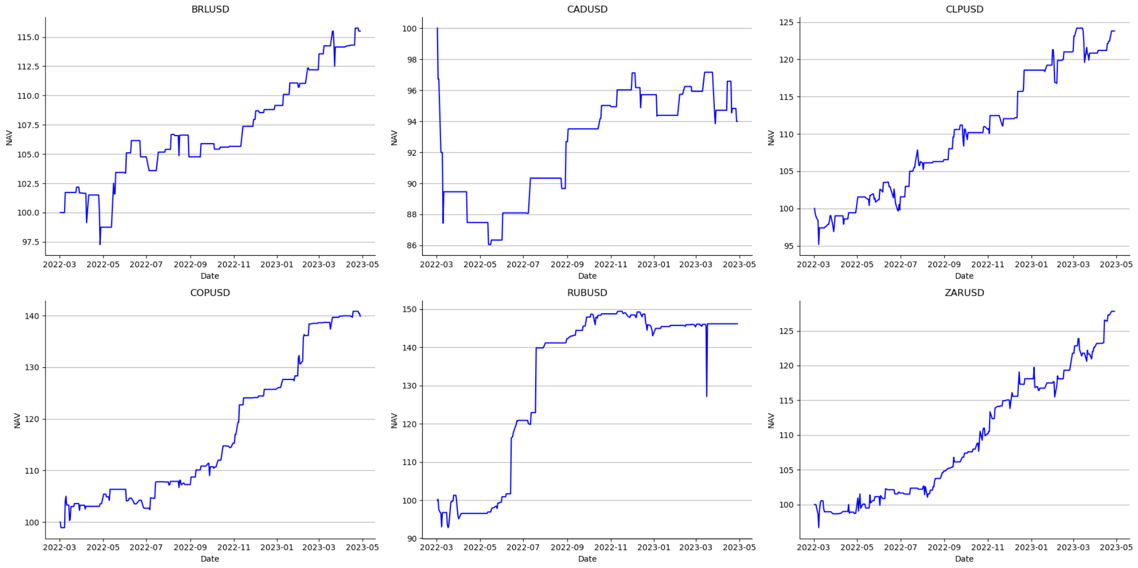


Fig. 10 Out Sample NAV

Currency	Annual Return	Annual Volatility	Max Drawdown	Sharpe Ratio	Calmar Ratio
BRL	12.84%	8.49%	4.80%	1.51	2.68
CAD	-4.81%	10.51%	13.94%	-	-
CLP	19.07%	10.67%	4.84%	1.79	3.94
COP	29.72%	11.30%	4.48%	2.63	6.63
RUB	36.72%	28.37%	14.91%	1.29	2.46
ZAR	21.78%	10.28%	3.56%	2.12	6.12

Fig. 11 Out Sample Performance Stats

2.3 Equal Weight Portfolio

In this section, we combine the above single currency strategies into a equal weight porfolio and check if there's any diversification benefit. First, we examine the inter-currency correlations:

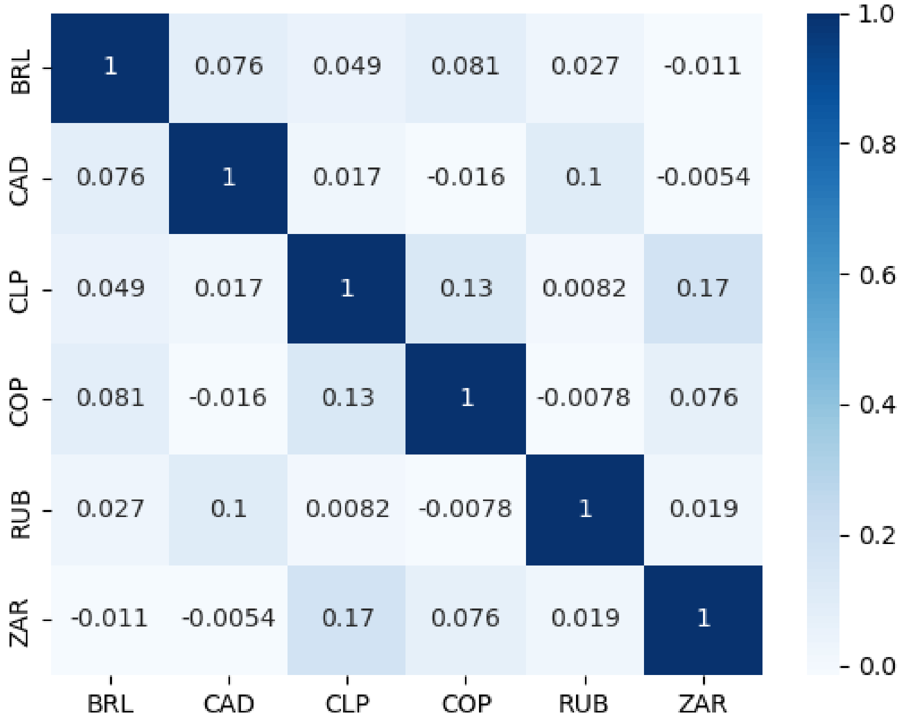


Fig. 12 Inter-Currency Correlations

Overall, correlations are close to zero indicating there's potential benefit combining them into a single portfolio. But please also note that some currency pairs like CLP/ZAR, RUB/CAD exhibit higher correlations above 10%. This may be caused by the fact that these currencies share a common economic driver. For example, both Russia and Canada are large crude oil exporters.

In the next few charts we exhibit the performance of the equal weight currency portfolio.

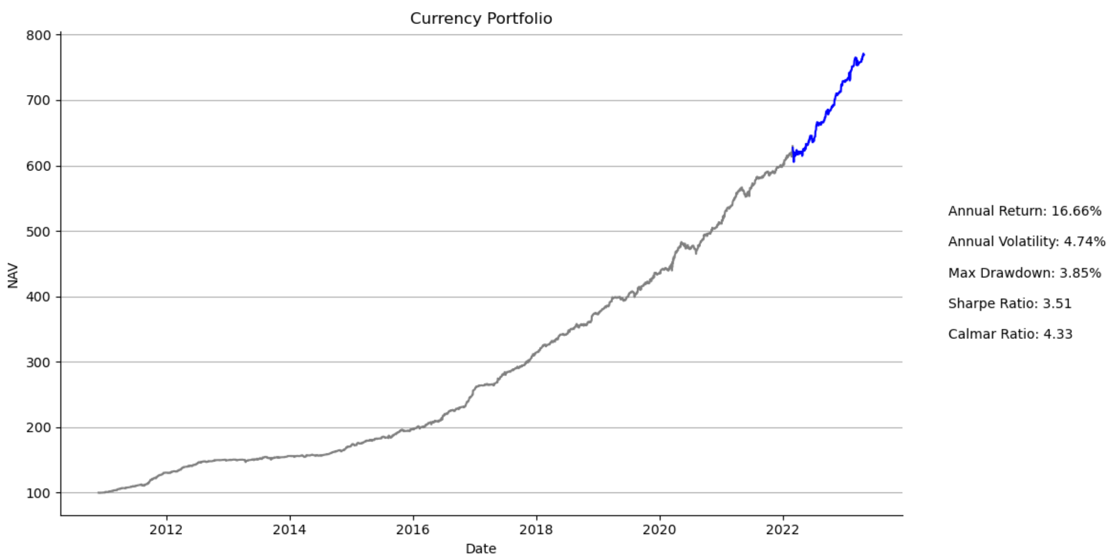


Fig. 13 Currency Portfolio Full History NAV

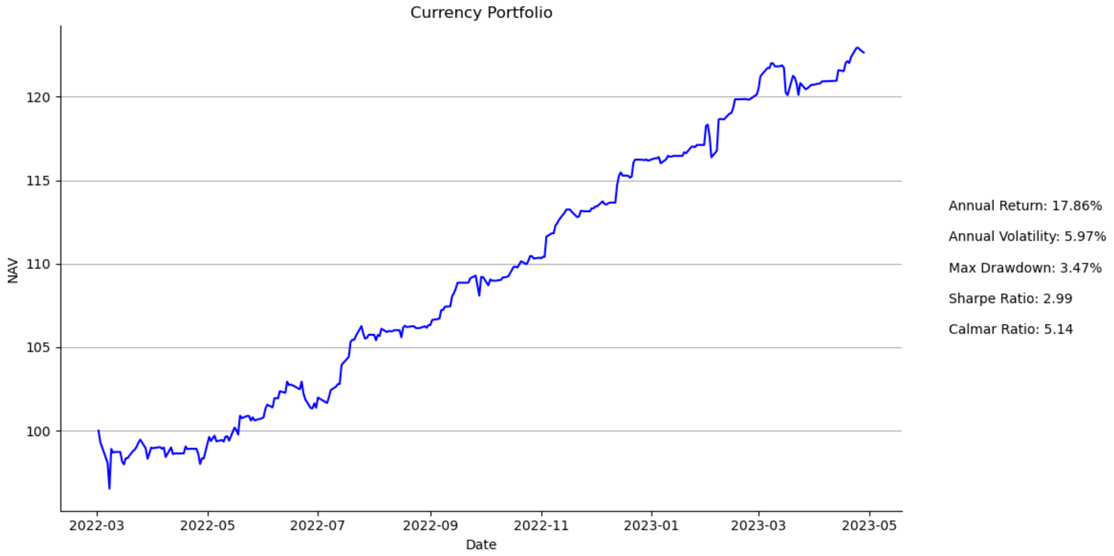


Fig. 14 Currency Portfolio Out Sample NAV

Each individual strategy targets 10% annual volatility. The portfolio volatility is around 5%, which has been reduced by half.

3. Conclusion

In this article we investigated a potential systematic trading strategy that is based on the spread between a "commodity currency" and a hypothetical trade weighted commodity basket. We used Kalman Filters to help establish the spread / linear relations between the two economic variables. Trading signals originate from the occassions when the spread deviates too much from the mean.

We looked at performances of currencies across six major commodity exporters: Brazil (BRL), Canada (CAD), Chile (CLP), Colombia (COP), Russia (RUB) and South Africa (ZAR). Most of the currencies performed strongly in the backtests, with Sharpe Ratios ranging from 1.5+ to 2.5+. Correlations across individual currency strategies are also low, hence bringing diversification benefits to the combined currency portfolio.

The strategy also has low correlations with common asset classes like SPX and TY. It can serve as a diversification source for a traditional 60/40 portfolio.

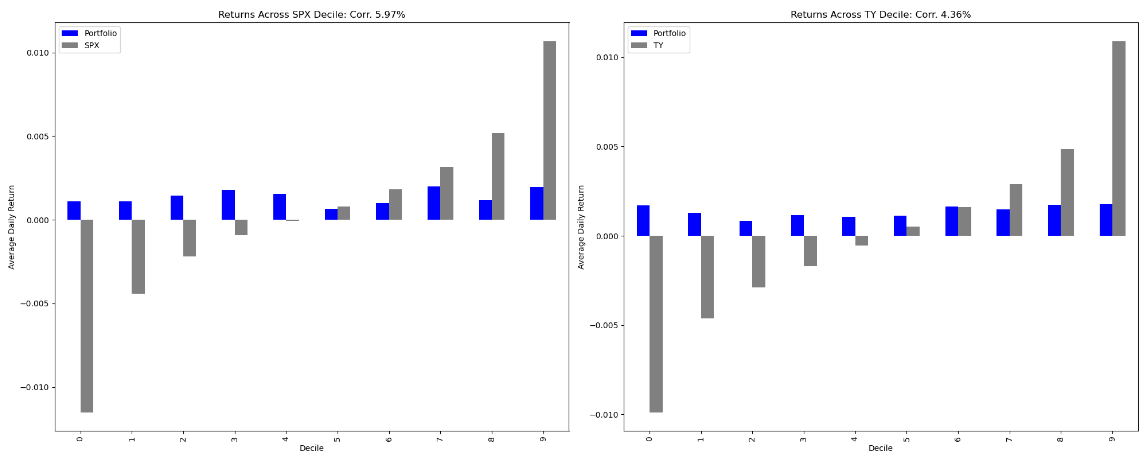


Fig. 15 Correlations with SPX and TY

1. Charts are sourced from https://www.cmegroup.com/education/featured-reports/how-commodity-currencies-performed-amid-covid-19.html and since currencies are less volatile than commodities, the above prices have been adjusted by volatility.

2. There are discontinuities / gaps in certain commodities that can last months or even years. We believe this is a data quality issue and exclude these from the samples. We also replaced outliers that are 100x or more larger than the usual levels with their sample averages.

3. We used β on a 1-day lag basis to produce the predicted measurement.

4. We assume 100% margin for futures trading and performance numbers are before cost.