Pairs Trading LatAm Currencies vs Commodities

Capstone Report: Mean Reversion Strategies of LatAm currencies and their main exports

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Abstract

This Capstone Report is written to fulfill the requirements for graduation of the Master of Science in Financial Engineering for New York University Tandon School of Engineering. For this Capstone experience, the two special topic courses taken during our studies were: Fixed Income Quantitative Trading (FRE-GY 6971) and Real Time Trading Risk Management (FRE-GY 7801). The idea was to combine the knowledge learned from these two courses, in order to develop a personal project. The course lectures, teachings and techniques were used as inspiration, as well as a guide in terms of the statistics, mathematics and trading strategies implemented. This project would gather some of the theories, techniques and implementations for these two courses, into one project. Other techniques and theories learned throughout the Masters Program will also be used to obtain the best results.

For this specific project, a pairs trading strategy was chosen, which seeks to find mean reverting spread of pairs, in order to obtain profits from those spreads. In this case our pairs will be futures of currencies (specific to Latin America) and specific commodities. The idea here, is that LatAm economies such as Mexico, Brazil, Chile, Argentina, Peru and Colombia, are very dependent on certain commodities in terms of their GDP and strength of their currencies. This means that their currencies are sometimes linked to fluctuations in prices of certain commodities. This relationships and correlations between these currencies and their man commodities, is what will be analyzed, to see if there is any potential in this strategy and any upward returns. The strategy, results and figures were obtained using python, and the data obtained was through the use of Bloomberg.

The main purpose is to use these implementation and theories learned from these two courses, to find any potential returns with these relationships, with a quantitative/fundamental approach to them. The dataset used were LatAm/usd currency generic first year futures and commodity/usd generic first year futures dating from October 2013 till October 2018.The following introduction, implementation, results and conclusion will be explained throughout this report. The hypothesis is that in order for this pairs trading strategy to work the chosen country has to have a significant percentage of exports of a certain commodity, for its currency to work as am optimal pair for that commodity. This paper will attempt to either prove or dismiss that hypothesis.

Introduction

The chosen topic was pairs trading with a mean reversion strategy. Pairs trading is defined as a strategy that monitors the performance of two historically correlated securities. Pairs trading takes advantage of those market inefficiencies. When the correlation weakens a spread is created, meaning the pairs trade would short the outperforming stock and long the underperforming one. It is expected that the price of those two pairs will converge to the mean at some point. This trading style is set to be profitable in any market condition including periods of high or low volatility. The idea is to define this spread or residual for two stocks (a and b) and beta as the hedge ratio as:

$$Residual = Y_a - \beta Y_b + \alpha$$

The idea is to find two securities or financial assets that behave the same, so for the purposes of this project the chosen area was LATAM currencies and Commodities. Historically economies in Latin America depend immensely in commodities being a big part of their GDP as shown in this Table 1 in the following table for Chile:

Sector	GDP %
Mining	15.2
Business services	13
Manufacturing industry	10.9
Personal services	10.6
Retail	7.9
Construction	7.4
Real estate services	5
Public administration	4.3
Financial services	4.2
Transportation	4.1
Agriculture and forestry	2.8
Electricity, gas and water	2.4
Communications	1.9
Restaurants and hotels	1.6
Fishing	0.4

Table 1

In this case the specific currencies to be filtered and tested were Chilean Peso, Brazilian Real, Mexican Peso, Argentinian Peso, Peruvian Sol and Colombian Peso. These currencies were paired with future commodities of Copper, Aluminium, Meat, Soy Beans, Crude oil, Iron Ore, Corn, Sugar, Coffee Beans, Wheat, Gold and Silver. These economies also have a big part of their revenue from these exports, being a huge percentage of the exports of LatAM economies are those commodities. Table 2 shows the list of specific economies and how much they export these commodities.

Commodity/Currency	BRL/USD	CLP/USD	ARS/USD	MXN/USD	COP/USD	PEN/USD
Copper/usd	1%	45%	1%	0%	1%	28%
Alum/usd	1%	0%	1%	0%	1%	2%
meat/usd	6%	0%	3%	0%	0%	3%
soybean/usd	13%	0%	23%	0%	0%	0%
crudeoil/usd	6%	0%	3%	5%	31%	6%
ironore/usd	7%	1%	1%	0%	1%	2%
corn/usd	2%	0%	7%	0%	0%	0%
sugar/usd	6%	0%	0%	0%	1%	0%
coffee/usd	3%	0%	0%	0%	9%	2%
wheat/usd	0%	1%	0%	1%	0%	0%
gold/usd	2%	2%	4%	1%	4%	17%
silver/usd	1%	0%	1%	5%	0%	2%

Table 2

As we can see countries such as Chile (CLP) have 45% of their exports being copper, Colombia (COP) have 31% of their exports being crude oil, Argentina (ARS) have 23% of their exports being soy beans, etc. This leads to the hypothesis that if commodity prices change, so will the linked currencies with respect to the dollar.

Another example of how the currency follows the commodity price with CLP (blue) and Copper (orange) futures. Figure 1 shows a graph of this heavily correlated relationship. They movement in a very similar way and this happens to many of the currencies vs commodities relationships shown above.

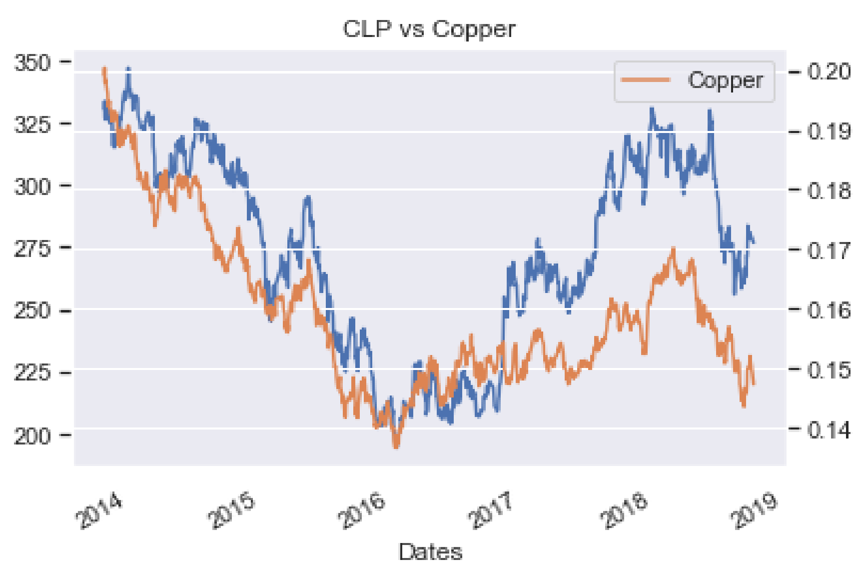

Figure 1

Technical Analysis - Filtering and Pair Selection

This hypothesis was tested to select the optimal pairs using two main statistical techniques, correlation and Co-integration (using an augment dickey fuller test). These currencies were paired with each commodity to create a ranking systems that consisted in certain filters to generate possible profitable pairs with their correlations, co-integrations and percent exports. The idea here is to grab pairs that are highly correlated, their residuals are stationary (co-integration less than 90% confidence interval), and ideally, the commodity is actually exported by the said country.

First, the correlation between the currency and the commodity was calculated. This was performed to measure the relationship between the two stocks and if their price follows the same trends. Using the following equation for asset A and B, the correlation is defined as:

$$\rho = \frac{\sum(A_i - \overline{A})(B_i - \overline{B})}{[\sum(A_i - \overline{A})^2 \sum(B_i - \overline{B})^2]^{\frac{1}{2}}}$$
$$\overline{A} = \frac{1}{N}\sum A_i$$
$$\overline{B} = \frac{1}{N}\sum B_i$$

The correlation was calculated for every currency/commodity pair and the following heat map shows the distribution. For example CLP/Copper, COP/CrudeOil and BRL/Soy Beans are highly correlated but ARS/Aluminium and MXN/Aluminium isn't. This is the first filter for selected a pair, where it is necessary that the currency and commodity pairs be highly correlated (at least 60% or above).

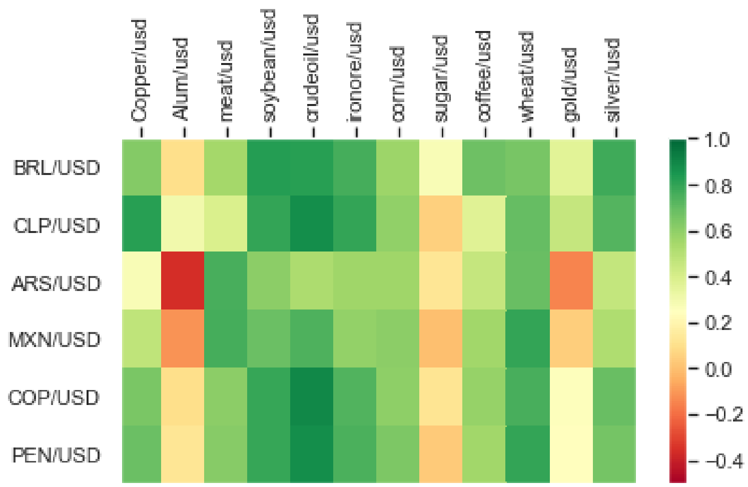

Figure 2

Then the co-integration between currency/commodity pair was calculated. In this case the co-integration identify pairs that tend to have mean-reverting properties relative to its prices. Co-integration states that given two non-stationary time series, there can be a linear combination of the two time series that is in fact stationary. This just shows that the two assets move together in the same way. This is defined as the price of asset A and B, there exists a parameter γ (which is defined as then co-integration coefficient) such that the following equation follows a stationary process:

$$Y_A - \gamma Y_B = \mu + \epsilon_t$$

A popular stationary test for co-integration is the Augment Dickey Fuller Test (ADF), which in this particular case was used to test for stationarity of the residuals (Dickey and Fuller, 1979). First, the ADF test is used to obtain the unit root of the residuals seen in the following equation:

$$z_t = y_t - \gamma x_t \tag{1}$$

$$\Delta z_t = \alpha + \beta + \gamma z_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta Z_{t-i} + \mu_t \tag{2}$$

Where (1) z_t is the simplification of the residuals from above and (2) is the residuals regressed with α being the constant, β the coefficient of the pairs, p the lag order and u_t the error term. In order to estimate all the parameters an OLS regression was used. As we simplify the terms the unit root test for the residuals ϵ_t using ADF becomes:

$$ADF = \frac{\gamma^*}{SE(\gamma^*)}$$

$$where$$

$$SE(\gamma^*) = \sqrt{\frac{\sum_{i=1}^{n}(\Delta z_{ti} - \Delta z_t)^2)}{(n-2)\sum_{i=1}^{n}(z_{(t-1)i} - z_{t-1})^2}}$$

reference: George J. Miao

The ADF test result is then compared to the critical value of the ADF test, if the test is lower than the critical value, the null hypothesis is rejected meaning there is stationarity in the pair, meaning the pair is co-integrated. SE refers to the standard errors from the OLS estimate.

In this case, a 90% confidence interval for the critical value was used. This is the threshold used for the rankings filter, where if the co-integration coefficient was equal or less than that number it would be considered a profitable pair. Due to them being different type of securities, it was determined that a lower confidence interval would be used (90 percent). Once again the co-integration was calculated for every pair of currency/commodity and the following heat map (which in this case the more red the relationship is, the better the co-integration value), Figure 3 shows the results between the pairs. For this specific case the more red the relationship the more co-integrated are the pairs (as opposed to the correlation being a good one if the color is green). For example CLP/Copper are highly co-integrated, as well as ARS/meat and BRL/Coffee, on the other hand ARS/Iron Ore and MXN/Iron Ore are definitely not co-integrated and not stationary.

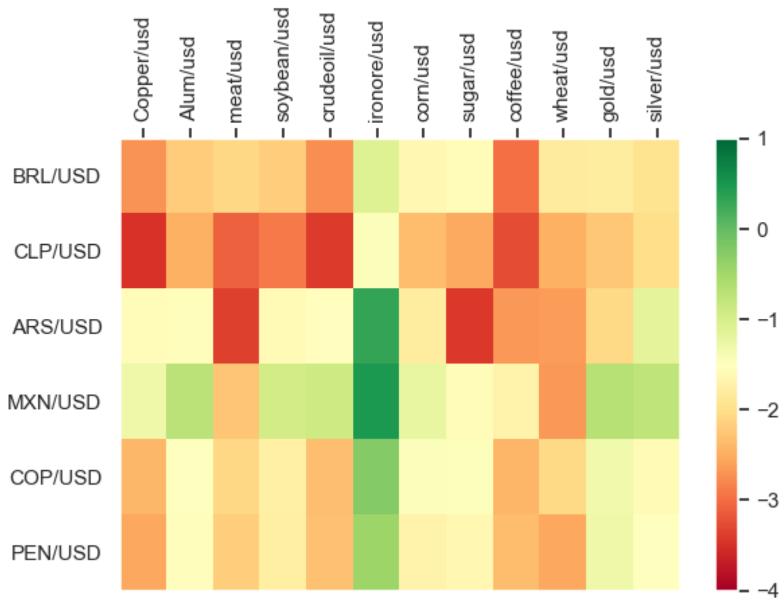

Figure 3

The final filter was the percent exports that country had for that specific commodities. The hypothesis here is that if the country has a higher percent of exports of that commodity, it would increase the probability of it being an actual profitable pair. The greener the relationship, the better the pair is for the strategy, being CLP/Copper the pair that has the highest percent of exports. Figure 4 shows that relationship.

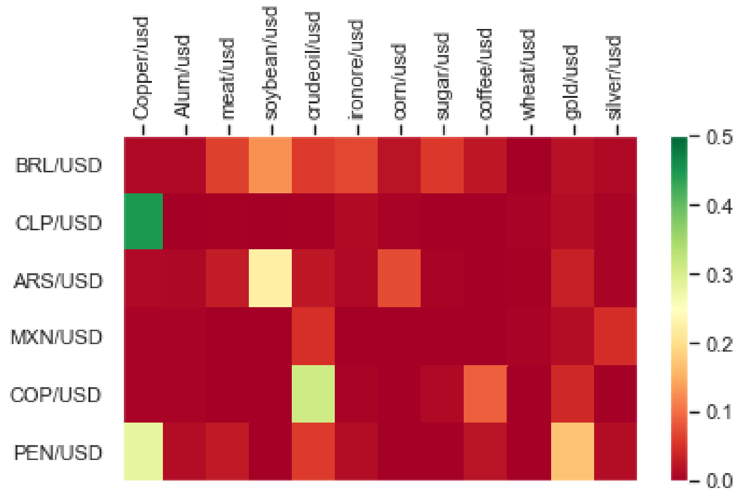

Figure 4

Once these three filters were created, the ranking portion of the project began. The rankings were obtained using a training data set which was about 70% of the data set (Oct 2013 - Mar 2017). The idea was to rank these pairs between these three variables (correlations, co-integrations and exports) meaning that basically if they had values above a certain threshold, the pair would be a possible profitable pair for the strategy. In this case, the correlation was lower than normal equity pairs (usually these pairs have above 90% correlation) this was done due to the fact that is practically impossible that the currency of a country is that correlated to the commodity. The same thing happens with the cointegration and that's why the critical value chosen for stationarity was only 90% instead of a usual 99% or 95% confidence interval. Once the pairs were all ranked, nine pairs were chosen profitable. Out of those nine pairs, seven of them had exports and were stationarity, while the other two (highlighted red) either were not stationary (barely not stationary) or did no have any significant exports of that commodity. This was done with the intention of proving the hypothesis that percent exports and stationarity have an actual impact on the possible profits of the pair strategy. Table 3 shows the pairs chosen to perform the pairs trading strategy:

Pairs	Correlation	Cointegration	Stationarity	% Exports
CLP/USDCopper/usd	0.93	-3.49	1	44.8%
CLP/USDcrudeoil/usd	0.92	-3.40	1	0.3%
ARS/USDmeat/usd	0.62	-3.36	1	3.0%
BRL/USDcoffee/usd	0.60	-2.97	1	2.7%
CLP/USDsoybean/usd	0.82	-2.89	1	0.0%
BRL/USDcrudeoil/usd	0.95	-2.75	1	6.0%
BRL/USDCopper/usd	0.91	-2.70	1	1.0%
MXN/USDwheat/usd	0.84	-2.67	1	0.5%
COP/USDcrudeoil/usd	0.96	-2.32	0	30.9%

Table 3

The first approach was to find the betas in the linear relationship or the "hedge ratios" by using OLS explained above. After the betas were calculated, the residuals ϵ_t were calculated for each pair in order to be used in the pairs trading strategy. Figure 5 below shows the residuals for the relationship between the top pair CLP/Copper. As seen in the graph the blue line represent the residuals, the black line the mean, the red line one standard deviation from the mean and the green line two standard deviations from the mean. This was done for every selected pairs, as the residuals are fundamental in order to apply the strategy and find long/short relationships.

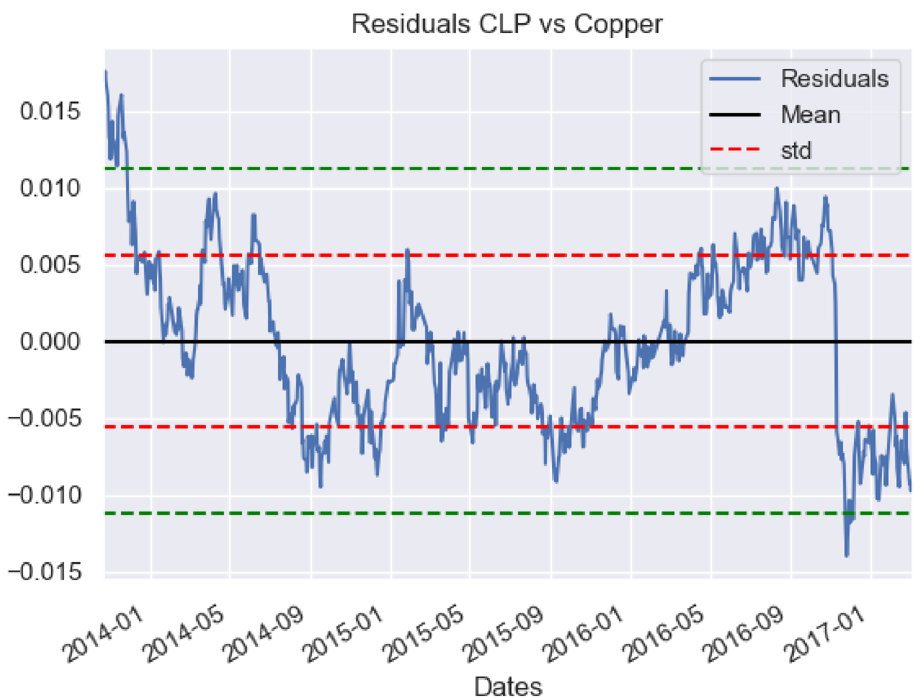

Figure 5

The idea here is that if the residual would be between the mean and minus one standard deviation from the mean (the lower bound), this would execute a long signal. If the residual would be between the mean and plus one standard deviation from the mean (the upper bound), this would execute a short signal. In this case as seen from the graph, one standard deviation was chosen instead of two because it would embrace a more consistent and executable strategy.

The rolling window used for the rules was the half-life of the pairs. This is used to calculate the average time that the process will mean revert. It follows a Ornstein - Uhlenbeck Process which is a mean reverting process defined as :

$$dX_t = \lambda(\mu - X_t)dt + \sigma dW_t$$

Where $\lambda > 0$ and W_t is a Wiener Process. Solving explicitly we have:

$$X_t = e^{-\lambda t}X_0 + \mu(1 - e^{\lambda t}) + \int_0^t \sigma e^{\lambda(s-t)}dW_s$$

This gives the following expectation:

$$E[X_t] = e^{-\lambda t}X_0 + \mu(1 - e^{-\lambda t})$$

The parameter λ refers to the speed of the mean reversion and $t_{1/2}$ the half-life. Solving the equation above we have that:

$$\begin{aligned} X_t =& e^{-\lambda t}(X_0 - \mu) + \mu \\ X_{t_{1/2}} - \mu =& \frac{x_0 - \mu}{2} \\ t_{1/2} =& \frac{log(2)}{\lambda} \end{aligned}$$

reference: Alexandre d'Aspremont

This half-life was calculated for every chosen pair. The idea is that this window (half-life) would be the average time that the residuals would mean revert, which is the strategy we are trying to implement. Each pair had a specific optimal half-life, which was calculated using the formula above.

Once the parameters were set due to a risk neutral strategy once a currency was long, the commodity was short and vice versa. The output of the strategy would give percent returns, Sharpe Ratio (annualized with square root of 252), Maximum Drawdown, Number of Trades and VaR. The percent return was a cumulative returns for the specific time period of the set (either training or test). In terms of the sharpe ratio, the annualized sharpe ratio was calculated using the following equation:

$$Sharpe = \frac{r_p - r_f}{\sigma_p} \cdot \sqrt{252}$$

In this case for simplicity, transaction costs were disregarded, as well as the risk free rate. The other components of the Sharpe Ratio is r_p which are the returns for the pair, σ_p the volatility of the pair, and it's multiplied by the $\sqrt{252}$ due to it being annualized. For Maximum drawdown, this refers to the maximum loss from a peak (maximum) before a new peak is reached. This is calculated through-out the whole period and for each of the chosen pairs. The number of trades is through-out the whole period as well.

For the Value at Risk (VaR) refers to the maximum amount of loss in an investment with a certain confidence interval. It estimates how much of the investment is it possible to loose, given normal market conditions, in any given day. VaR in this case is given by the following equation:

$$VaR = -\,\Delta S[\mu\delta t - \sigma\sqrt{\delta t}N^{-1}(1-c)]$$

Where ΔS refers as the change in residuals through-out the period, μ the mean, σ the standard deviation, δt the time horizon and finally $N^{-1}(1-c)$ is the inverse cumulative distribution function for the standard Normal distribution. We calculate the VaR parameter for each pair to understand the risk of each trade. In this case a standard 1 million dollars was used as the invested capital, as a way to state if one million dollars was invested in this strategy, the amount shown would be the maximum amount of capital lost in a certain confidence interval.

In terms of other risk measures the strategy had certain risk controls. First of all the stop loss, is defined as a closing position, and it will be executed once the residual reaches two standard deviations from the mean, in either direction. This was done, due to two standard deviations creating very high potential losses, which would be detrimental to the strategy and as a way to close the position if the pairs become not stationary. The maximum holding period for a position is about 50 days, which is the average half-life of the pairs. The primary risk control is the fact that this strategy is risk neutral, meaning once a position is entered, one of them is a long position and the other is a short one. This serves as a standard hedging to manage convexity. As explained above, the VaR was calculated in order to see potential losses on a pair with one million investment. This is also a very important risk measure to have, as it is necessary to know potential losses for the investors' risk aversion. The same thing happens with the maximum drawdown and the sharpe ratio which were added as performance measures in the strategy to see the potential upsides and downsides of the strategy.

After the performance and risk measures were established, the strategy was ready to be implemented. First the training set was performed with the hedge ratios for 2014-2017, which were then implemented with the corresponding windows (half-life). The idea was to run the strategy for the chosen 9 pairs and determine after running the strategy, which pairs had optimal results. This would create a second filter from the first rankings system implemented above, which would provide the pairs with potential real upside. These potential pairs would then be used to run the test set. The idea here is to determine which pairs provide good results and determine if the hypothesis, that percent exports have an actual real importance in the returns of the strategy. Below are the results for the training set, as well as the test set.

Implementation - Training Set Results

Once the final pairs were selected and the performance and risk measures were selected, the strategy was implemented for the training set. The residuals and half-life calculated with the OLS regressions were used, as well as the rules explained above. All the calculations and filtering from above was performed using python for the training and test sets. Below are the results:

Pairs	Total Returns	Sharpe Ratio	Maximum Drawdown	Number of Trades	VaR
CLP/USDCopper/usd	88.41	1.23	17.27	108	$ 35,513.29
CLP/USDcrudeoil/usd	22.29	0.62	10.95	71	$ 18,160.98
ARS/USDmeat/usd	59.42	0.24	56.39	27	$ 127,214.22
BRL/USDcoffee/usd	-87.62	-0.37	92.01	37	$ 121,675.72
BRL/USDcrudeoil/usd	69.96	0.68	37.36	79	$ 51,841.60
BRL/USDCopper/usd	3242.76	0.18	544.20	63	$ 9,249,652.84
MXN/USDwheat/usd	-253.16	-0.43	452.99	66	$ 300,368.54
COP/USDcrudeoil/usd	45.94	0.50	42.50	63	$ 46,248.14
CLP/USDsoybean/usd	-8.37	-0.12	47.35	61	$ 36,537.67

Table 4

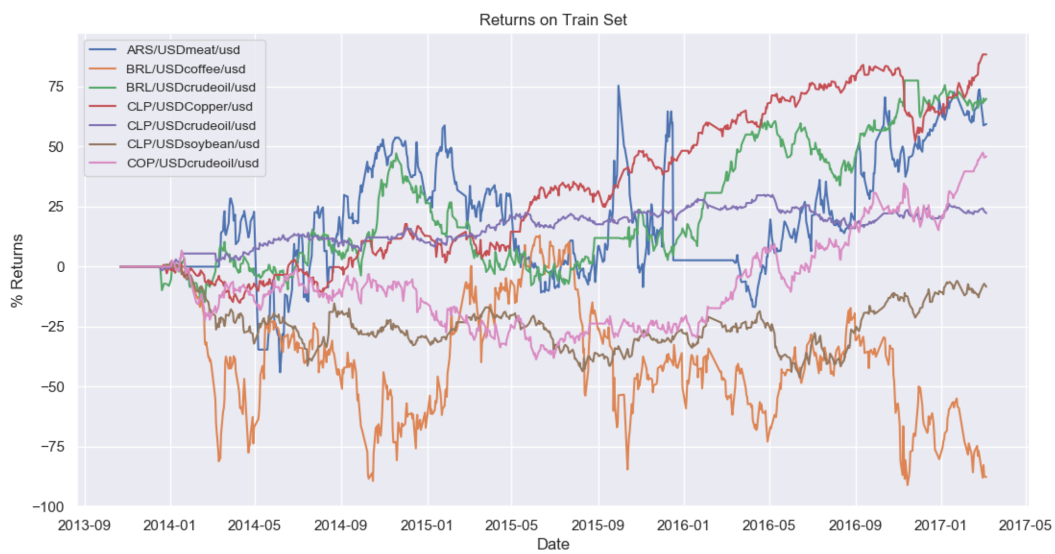

Figure 6

As seen from the table and graphs the pairs varied a lot in terms of performance. The best performing pair was CLP/Copper which ranked first in the rankings filter performed above. As seen above this pair has great correlation and co-integration but more important almost 50% of Chile's exports are copper which had a clear impact in the strategy. It also has a solid sharpe ratio and a decent maximum drawdown which are very good performance indicators. CLP/CrudeOil and BRL/CrudeOil, also had positive results although their sharpe ratio are below 1. These three pairs were determined to be the top three pairs of the set and are highlighted green.The other pairs were ignored due to them having very unusual returns and performance statistics, specially having very high VaRs. The three pairs highlighted red had negative returns and sharpe ratios and very hight maximum drawdowns. The other pairs although they had positive returns, their maximum drawdowns were very high and there sharpe ratios very low, meaning they are very risky pairs to invest in. Due to this, it was decided to perform the test portion of the results only using the three green pairs, in order to test the actual hypothesis (CLP/Copper and BRL/CrudeOil have solid exports, but CLP/CrudeOil doesn't) and get a strategy with the highest potential returns.

Figure 6 shows the returns of 7 out of the 9 pairs (the other two results were unreasonable for the set). As seen from the graph of the returns , CLP/Copper (colored red) has a very constant slope going upwards and so does BRL/Crude Oil (colored green) but a bit more volatile. The other pairs show a very volatile behavior and negative trends. That is the main reason why these pairs are disregarded in the test set. There is no point in determining if they will be actual good pairs to trade, if in the training set they perform poorly or in with a very risky behavior. After reviewing the results, the next steps was to show how the three chosen pairs (highlighted green) will perform in the test set. Below are the results of those three pairs in the test environment.

Implementation - Test Strategy and Final Results

The test strategy with the remaining of the data set (Mar. 2017 - Oct. 2018) was a portfolio constructed of the pairs mentioned above these pairs are CLP/Copper, CLP/Crude Oil, BRL/Crude Oil. The idea here is to use the same beta coefficient from OLS calculated from the training set in order to calculate residuals and the performance statistics through that test period. The same thing happens with the half-life, where the half-life (windows) calculated from the training set above were used for the test set. Table 5 shows the details from the three chosen pairs in terms of correlation, co-integration, stationarity and percent exports.

Pairs	Correlation	Cointegration	Stationary	% Exports
CLP/USDCopper/usd	0.93	-3.49	yes	45%
BRL/USDcrudeoil/usd	0.95	-2.75	yes	6%
CLP/USDcrudeoil/usd	0.92	-3.40	yes	0%

Table 5

As seen from the table all three pairs have a strong correlation and co-integration. The only clear difference comes from the exports where CLP/Copper has 45%, BRL/Crude Oil 6% and finally CLP/Crude Oil has 0% exports. This difference should also be shown in the results. The strategy was then performed with the coefficients obtained from the training set into the test, these are the following results.

Pairs	Total Returns %	Sharpe Ratio	Maximum Drawdown	Number of Trades	VaR
CLP/USDCopper/usd	29.71	0.72	25.51	39.00	$ 42,928.03
CLP/USDcrudeoil/usd	-6.15	-0.31	18.40	30.00	$ 21,172.50
BRL/USDcrudeoil/usd	-25.02	-0.30	63.43	24.00	$ 87,697.88

Table 6

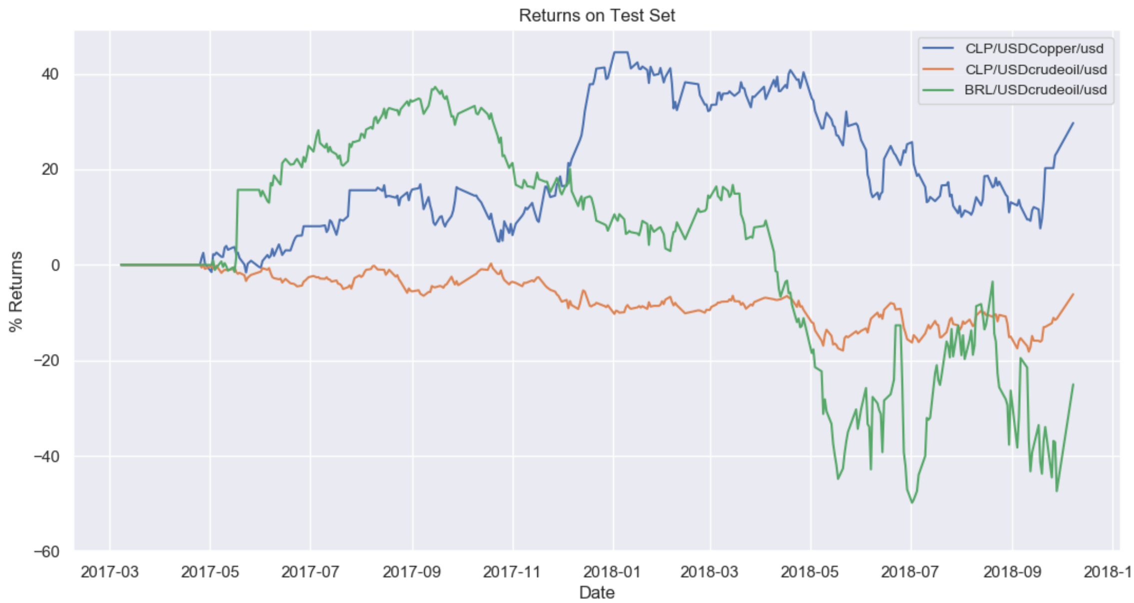

Figure 7

As seen from Table 6 and Figure 7, the only pair who had positive returns was CLP/Copper. BRL/Crude Oil had a positive trend until end of 2017 where there was a clear downward trend. For CLP/Crude Oil the returns are slightly negative but never seem to become positive. In terms of Sharpe Ratios all three of them are below 1, which is an indication that this strategy may not be the best to trade. Maximum drawdown are standard and number of trades are significant. Finally the value at risk seems to be an acceptable number as well. In terms of overall performance the only pair with potential is CLP/Copper as it is the best performing pair. As seen from Table 5, the only pair with strong correlation, co-integration and percent exports is CLP/Copper which follows the hypothesis explained at the beginning; percent exports have an actual impact on the potential for returns for the strategy. Although BRL/Crude Oil has significant correlation and actual exports, it is not as co-integrated as it could be. The same thing happens with CLP/Crude Oil, the pair has strong correlation and co-integration but no exports whatsoever .Once again the best performing pair in the portfolio was CLP/Copper, helping the hypothesis that high exports have a high influence on profits of the pair.

Finally, Figure 8 graph shows how the residuals change between the training and test set for CLP/Copper from the example from before. As seen, the test sets values of the residual decrease compared to the training set, which could be an explanation on the decrease in returns and less returns on the strategy from training to test period for CLP/Copper.

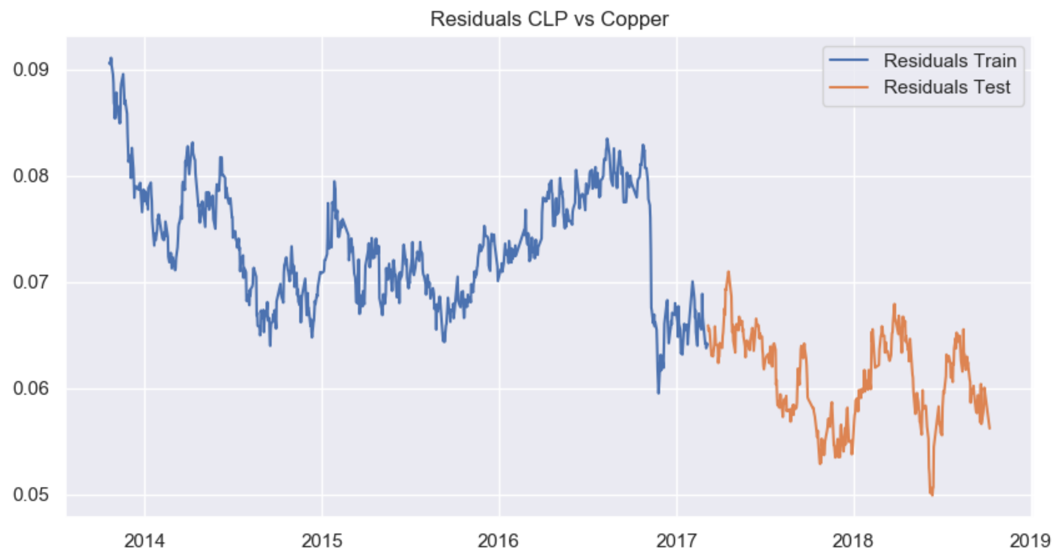

Figure 8

This change in residuals between training and test data sets, is fundamental in understanding the change in returns and performance statistics. For the training set the three selected pairs had positive returns and good performance statistics. As soon as the same hedge ratios and half life was applied to the training set, the returns decreases drastically, as well as having worse performance throughout the period. This is a clear indication that using the same OLS coefficients from the training set into the test, might not be the best decision for a strategy like this. The coefficients should be updated regularly for them to gather the behavior of the time series in a more precise manner. The hedge ratio and half-life could be optimized in a rolling manner that would capture the behavior of the residuals with more precision. This could help improving the timing in taking a position and would increase the returns.

Conclusions

The only pair from the chosen pairs that had solid returns and performance statistics was CLP/Copper, which was the pair that had 45% of exports. The pairs that had no exports were the pairs that performed the worse from the nine chosen pairs.The pairs that had exports between 1 and 10% performed below average and had below average performance statistics and the pairs who's co-integration wasn't significant enough, also had poor returns. The strategy performed with lower returns after 2017, this could be due to the emerging markets turmoil that has been going on through 2018. As mention before there is a clear decrease in the values of the residuals from 2017 till Oct. 2018 which could have had a clear influence in the final results of the portfolio. Overall it is clear that the only profitable pair with solid performance statistics is CLP/Copper and the fact that the percent exports of copper in Chile are very high, it could have a clear influence in the profits of the strategy, which is a very good indication that the hypothesis stated at the beginning was possibly correct. It should also be considered that in this case transaction costs were neglected but many of the pair had around 30 trades per year. This could be significant in terms of limiting the returns of each pair and could be an important obstacle in a strategy like this one.

In order to improve the strategy there are many factors that could be incorporated. First, select different windows for moving mean and standard deviation (use solver to find the best window for every pair) or a rolling shifting beta that is updated regularly. Also, changing the rankings approach to incorporate a higher weight on exports (use pairs that have exports higher than 20 percent). This means that pairs that have high exports of that commodity should definitely be incorporated as profitable pairs. This could also include an increase of the confidence in the co-integration test value to 95 percent. The strategy could also incorporate intra-day prices instead of end of the day and using log prices instead of actual prices but for the case of this study, actual prices were used. Expanding to this, use different generic futures for currencies (not only 1 year futures). Finally, a new approach could be use in the data set where a different training strategy such as slicing per year the inputs and where the rolling window moves depending on the year could be incorporated. In this scenario also the implementation of a Kalman filter to have a shifting window and a moving beta could be an essential implementation to obtain more precise performance statistics and strategy. Using a beta and half-life obtained from 3 years data into a different year and climate doesn't seem to be the most optimal approach.

As mentioned before the hypothesis makes sense, exports have a clear influence in the profitability of the strategy. In this case with a high correlation, high co-integration and high percent exports, this could be a profitable strategy. From the pairs chosen only one specific pair had all those three components, this means that if other countries (not only LatAm) and commodities are included such as Indian Ruppe vs Steel, there could be more profitable pairs in the strategy. This strategy for currencies and commodities seem to be a profitable one, specially in the emerging markets Latin American spectrum. Optimizing this strategy could lead to a very profitable margin, if the pairs chosen are the most effective. The idea is to keep working on this strategy in order to find a great overall final strategy that incorporates changes in an effective matter for the future.

References

A mix of the following articles and websites was used to develop the strategy from the filtering, till the implementation.

1) "Better Hedge Ratios for Spread Trading" by Paul Teetor
2) "Pairs Trading, Convergence Trading, Cointegration" by Daniel Hermont
3) "High Frequency and Dynamic Pairs Trading Based on Statistical Arbitrage Using a Two-Stage Correlation and Cointegration Approach" by George J.Miao
4) "Identifying Small Mean Reverting Portfolios" by Alexandre d'Aspremont