PAIRS TRADING STRATEGY ON ETFS

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ABSTRACT

This paper presents the application of pairs trading strategy on ETFs which are in the energy sector and are heavily commodity driven. I use R programming language for analysis and all other necessary computations. The results showed that pairs trading strategy works very well on ETFs but we note that the strategy gives very low returns at relatively low risk. Risk averse investors would prefer this strategy since it gives consistent profits at very low risk. All performance indicators did justify this notion. Increasing number of pairs in the strategy and integrating the strategy with other models will definitely increase returns and considerable risk thereby improving our strategy.

* *Pairs Trading Strategy on ETFs*

1 INTRODUCTION

Rapid advancements in technology from the late 20^{th} century and their continuous improvements are real game changers in the way financial markets work and financial assets are traded. The use of computer by investors in automating almost all trading processes and markets has made markets go electronic as opposed to manual book keeping and perusals. The electronic status of markets has accelerated the speed and quality of trading.

A pairs trade or pairs trading is a market neutral trading strategy enabling traders to profit from virtually any market conditions: up-trend, downtrend, or sideways movement. This strategy is categorized as a statistical arbitrage and convergence trading strategy. Pair trading was pioneered by Gerry Bamberger and later led by Nunzio Tartaglia's quantitative group at Morgan Stanley in the 1980s. The strategy monitors performance of two historically correlated securities. When the correlation between the two securities temporarily weakens, that is, one stock moves up while the other moves down, the pairs trade would be to short the outperforming stock and to long the under-performing one, betting that the "spread" between the two would eventually converge. The divergence within a pair can be caused by temporary supply/demand changes, large buy/sell orders for one security, reaction for important news about one of the companies, and so on. Pairs trading strategy demands good position sizing, market timing, and decision making skills. Although the strategy does not have much downside risk, there is a scarcity of opportunities, and, for profiting, the trader must be one of the first to capitalize on the opportunity.

We apply the pairs trading strategy on Exchange-traded Funds (ETFs). An ETF is an investment fund traded on stock exchanges, much like stocks. An ETF holds assets such as stocks, commodities, or bonds and generally operates with an arbitrage mechanism designed to keep it trading close to its net asset value, although deviations can occasionally occur. Most ETFs track an index, such as a stock index or bond index. ETFs may be attractive as investments because of their low costs, tax efficiency, and stock-like features. ETF distributors only buy or sell ETFs directly from or to authorized participants, which are large broker-dealers with whom they have entered into agreements—and then, only in creation units, which are large blocks of tens of thousands of ETF shares, usually exchanged in-kind with baskets of the underlying securities. An ETF combines the valuation feature of a mutual fund or unit investment trust, which can be bought or sold at the end of each trading day for its net asset value, with the tradability feature of a closed-end fund, which trades throughout the trading day at prices that may be more or less than its net asset value.

In this report, we design a pairs trading strategy as applied on ETFs. We provide a walk through on every step of the algorithm and summarize the results. In the next section we discuss on related work on pairs trading strategy, then after that we provide a strategy overview followed with the implementation of the strategy, and the last sections provide results from in sample and out of sample analysis. Finally we provide ways which can further improve our strategy and we conclude on our findings.

2 RELATED WORK

Pairs trading, on the other hand, exploits short term mis-pricing (sometimes heuristically called arbitrage), present in a pair of securities. It often takes the form of either statistical arbitrage or risk arbitrage [1].

The success of pairs trading, especially statistical arbitrage strategies, depends heavily on the modeling and forecasting of the spread time series although fundamental insights can aid in the pre-selection step. Pairs trading needs not be market neutral although some say it is a particular implementation of market neutral investing [2].

This strategy is comprised of two stages. In the first stage (the formation period) the method applied to form pairs; and second (the trading period), the criteria for opening and closing positions. If the two prices of a pair of stocks move together in the past, they are likely to continue in the future. So when the prices diverge, a trader can simply take a short position with the over-priced stock and a long position with the under-priced one, and as effect of mean reversion, wait for the prices to converge in the future. When they do, the trader clears the positions and makes a profit [3].

An extensive empirical analysis of performance of pairs trading, a popular relative-value arbitrage strategy, based on four different selection methods—the Minimum Distance, Augmented Dickey Fuller Test and Granger Causality test, Linear Regression, and Correlated Remaining methods across different asset classes including the Tehran Stock Exchange (TSE) shares, and components of S&P500 as well as commodities from February 2013 to May 2015. Results of the empirical test of four methods demonstrate that using different asset classes yields an excess return more than market. In addition, Minimum Distance can be considered the best method for application of the pairs trading strategy with an average annualized excess return of about 22%. [4].

The study conducted by [5] found that results indicate green ETFs exhibit an overall negative to zero (approximately) monthly mean returns. When he compared the pre-GFC and post-GFC sample periods, he observed that GFC impacted the performance of green ETFs. Also the broad ETFs performed slightly better than the thematic ETFs on average based on mean and median returns as well as standard deviation during all sample periods. In addition he found that thematic ETFs exhibit high volatility relative to broad ETFs in all sample periods. Further, some funds delivered high positive returns despite the poor average in both groups which was also observed by [6].

3 STRATEGY OVERVIEW

Our procedure

1. Load ETF closing price data from yahoo
2. Divide data for in sample and out of sample analysis
3. Run a for loop to detect co-integrated pairs
4. Choose only one pair for analysis
5. Conduct preliminary analysis on the pairs (graph on prices and a scatter plot)
6. Conduct regression analysis
7. Conduct ADF test to cross check and confirm co-integration of the two series
8. Compute z-scores from the residuals
9. Apply strategy
10. Performance Analysis (In sample and out of sample analysis)

Strategy

- When z-score touches +1.5 we short the pair that is, short EWA and long EWC, and close the positions when it reverts back to 0.5.
- When z-score touches -1.5 we long the pair meaning, long EWA and short EWC, and close the positions when it reverts back to 0.5.
- More than one position is held at a single instance of time.

4 STRATEGY IMPLEMENTATION

In this section I try to implement our strategy using R. Initial data consist of four ETFs (EWA, EWC, XOP, UNG). EWA and EWC, ETFs are baskets of equities for Australia and Canada respectively, both countries are heavily commodity driven therefore possibilities of high correlation. XOP and UNG, ETFs are both in the energy sector. Firstly, we loop around these ETFs with a goal to get those pairs that are co-integrated instead of just correlation.

We attach all necessary libraries and initialise dates for in sample and out of sample analysis. We get the ETFs data from yahoo finance using the **quantmod** library function, **getSymbols()**.

```r
library(quantmod)
library(tseries)
library(foreach)
library(PerformanceAnalytics)

#fetch ETFs daily data from yahoo.

etf_symbols <- c('EWA', 'EWC', 'XOP', 'UNG')

#set start and end dates (training: 6 years, Test: 2 years)
in_sd <- "2011-01-01"
in_ed <- "2017-12-31"
out_sd <- "2018-01-01"
out_ed <- "2019-10-01"

getSymbols(etf_symbols ,src="yahoo")
```

Listing 1: Get data from yahoo

Next we loop on a list of all four ETFs so as to easily find the co-integrated ETFs. The loop also tries to find the suitable ETF to be the dependent variable of our regression model. We subset by closing prices and the in sample dates from January 2011 to December 2017. All the combinations are fitted and the one with the most negative critical value and that satisfy the condition that p-value should be less than 0.05 is chosen and appended to the empty **pair** vector. Finally we print the pairs accordingly (dependent and independent successively).

```
#preparing data for looping so to detect pairs that are cointegrated/ stationary
dfs <- list(EWA, EWC, XOP, UNG)
foreach(x=1:4,.combine=cbind)%do%
  {
    dfs[[x]]
  }

names(dfs) <- etf_symbols
pair <- c()
n = length(dfs)

#Looping to find cointegrated pairs
for (i in seq_along(n)) {
  for (j in seq_along(i+1:n)) {


    y = unclass(dfs[[i]][index(EWA)>=in_sd &index(EWA)<=in_ed,4])
    x = unclass(dfs[[j]][index(EWA)>=in_sd &index(EWA)<=in_ed,4])
    yname = names(dfs[i])
    xname = names(dfs[j])

    #choose the dependent by applying regression on both combinations
    comb1 = lm(y ~ x)
    comb2 = lm(x ~ y)

    #computing adf test on residuals of the linear combinations
    t1 = adf.test(comb1$residuals, k=1)
    t2 = adf.test(comb2$residuals, k=1)

    #critical value
    t1_cvalue = t1[[1]]
    t2_cvalue = t2[[1]]

    #pvalue
    t1_p = t1[[4]]
    t2_p = t1[[4]]

```

```
    #select the combination with a critical value that is more negative and pvalue
    less than 0.05
    if (t1_p<0.05 && t1_cvalue<t2_cvalue) {
      #save the pair to the vector pair
      pair = c(pair, c(yname, xname))

    } else if (t2_p<0.05 && t2_cvalue<t1_cvalue){

      #save the pair to the vector pair
      pair = c(pair, c(xname, yname))
    } else{

      #if no cointegration exist between the pairs print:
      print('no matching pair')
    }

  }
}

print(pair)
```

Listing 2: Detecting Co-integrated ETF Pairs

This gives the following list:

```
> print(pair)
[1] "EWA" "EWC" "EWA" "XOP"
```

Fore the sake of simplicity and to explain the strategy. We will focus on the first detected ETF pair which is EWA and EWC. We first visualize closing price trends for both ETFs.

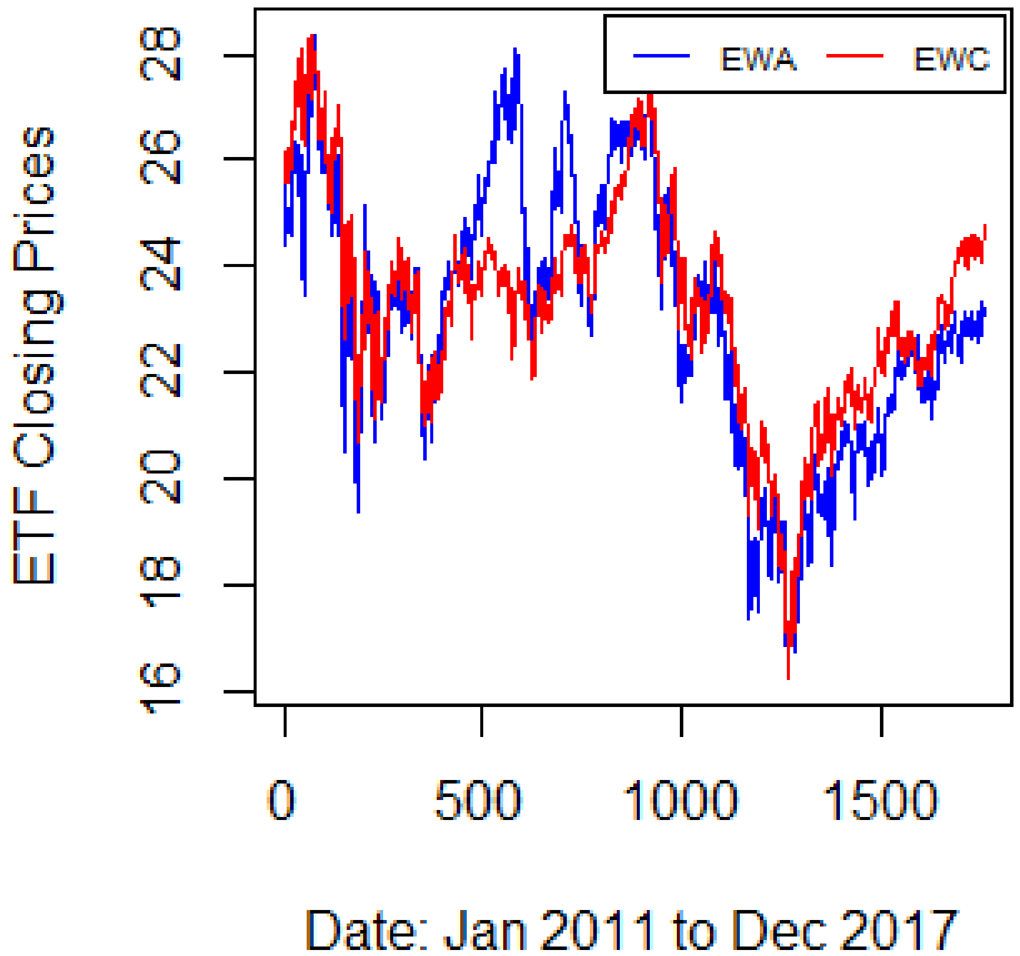

Figure 1: Closing prices of the pair from the year 2011 to 2017

From figure 1 we can clearly see the trends are almost the same and the price movements are also similar. Scatter plot in figure 2 also confirms a linear relationship between the ETFs for the 6 years under analysis.

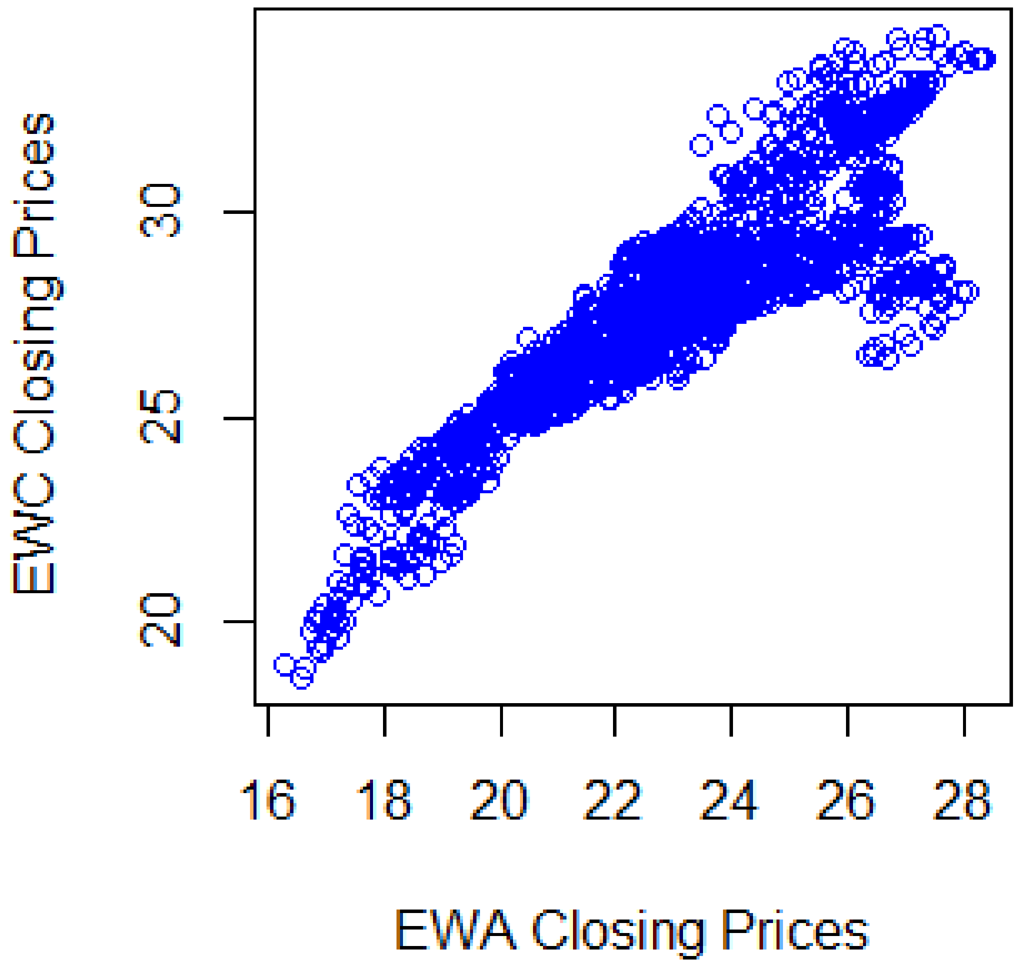

Figure 2: Scatter plot for the closing prices of the ETFs

We then run our regression model. EWA closing prices as the dependent variable and EWC as the independent variable as detected from the for loop.

```
> ewaewc_lm <- lm(ewaAdj ~ ewcAdj)
> ewaewc_lm
```

```

\textbf{Call:}
lm(formula = ewaAdj ~ ewcAdj)

Coefficients:
(Intercept)       ewcAdj
    0.07634      0.82911
```

Listing 3: Fitting regression model

We can now plot the residuals to check for stationarity visually. We can see that the residuals which shall be called spread for the rest of the document. Figure 3 shows that there is no unit root in the relationship between the ETFs and therefore there is possibility of mean reversion between the two series.

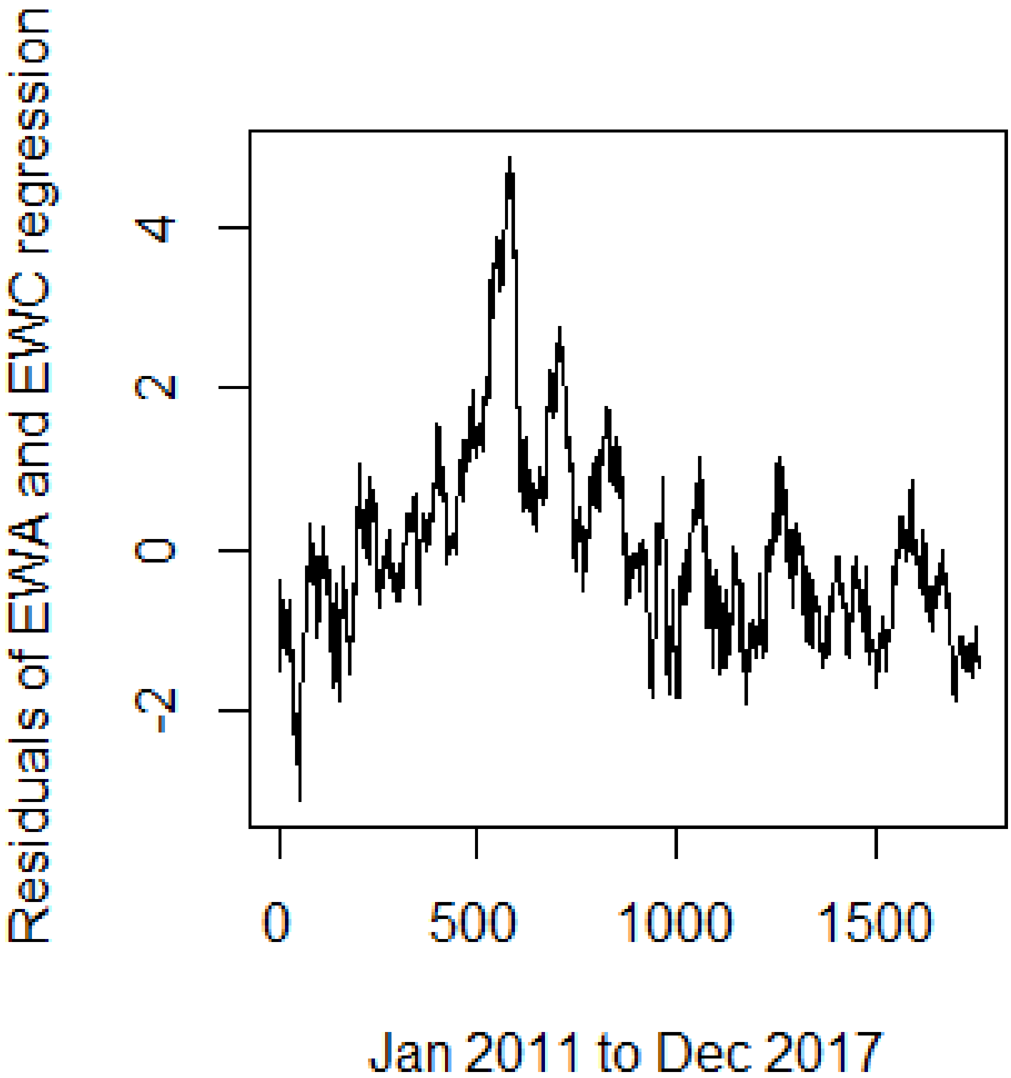

Figure 3: Residual/ Spread plot from the regression model

To explain fully our strategy we then conduct ADF test on the spread again, so as to confirm co-integration between the two series. From the results displayed below, the critical value of -3.4847 is more negative than the standard -2.86 and p value is less than 0.05. Therefore, we reject the null hypothesis and confirm that the series are mean reverting.

```
> #ADF test for co-integration
> cadf_test <- adf.test(ewaewc_lm$residuals, k=1)
> cadf_test

  Augmented Dickey-Fuller Test

data:  ewaewc_lm$residuals
Dickey-Fuller = -3.4847, Lag order = 1, p-value = 0.04376
alternative hypothesis: stationary
```

Listing 4: Run ADF test to confirm co-integration

We then calculate the z-scores, which is just the normalized spread. We use a 10 day window period to calculate the moving average and the standard deviation to normalize the spread. The strategy also uses the z-score of -1.5 and 1.5 as the thresholds. The listing also shows the head of the z-cores.

```
> spread = ewaewc_lm$residuals
> df1 <- cbind(in_ewa_return, in_ewc_return, spread)
> n_period <- 10
> z_up <- 1.5
> z_low <- -1.5
 #10 day moving average of the residuals
> ma_10 <- rollapply(df1$spread, n_period, mean)
#10 day rolling standard deviation of the residuals
> sd_10 <- rollapply(df1$spread, n_period, sd)
> zscore <- (df1$spread - ma_10)/sd_10       #zscore
> head(na.omit(zscore))
               spread
2011-01-14 -0.2166933
2011-01-18  0.3317246
2011-01-19  1.7212913
2011-01-20  0.7907030
2011-01-21  0.3779468
2011-01-24  1.4812021
```

Listing 5: Calculate Z-scores

Figure 4 shows the plot of the z-scores along with the thresholds.

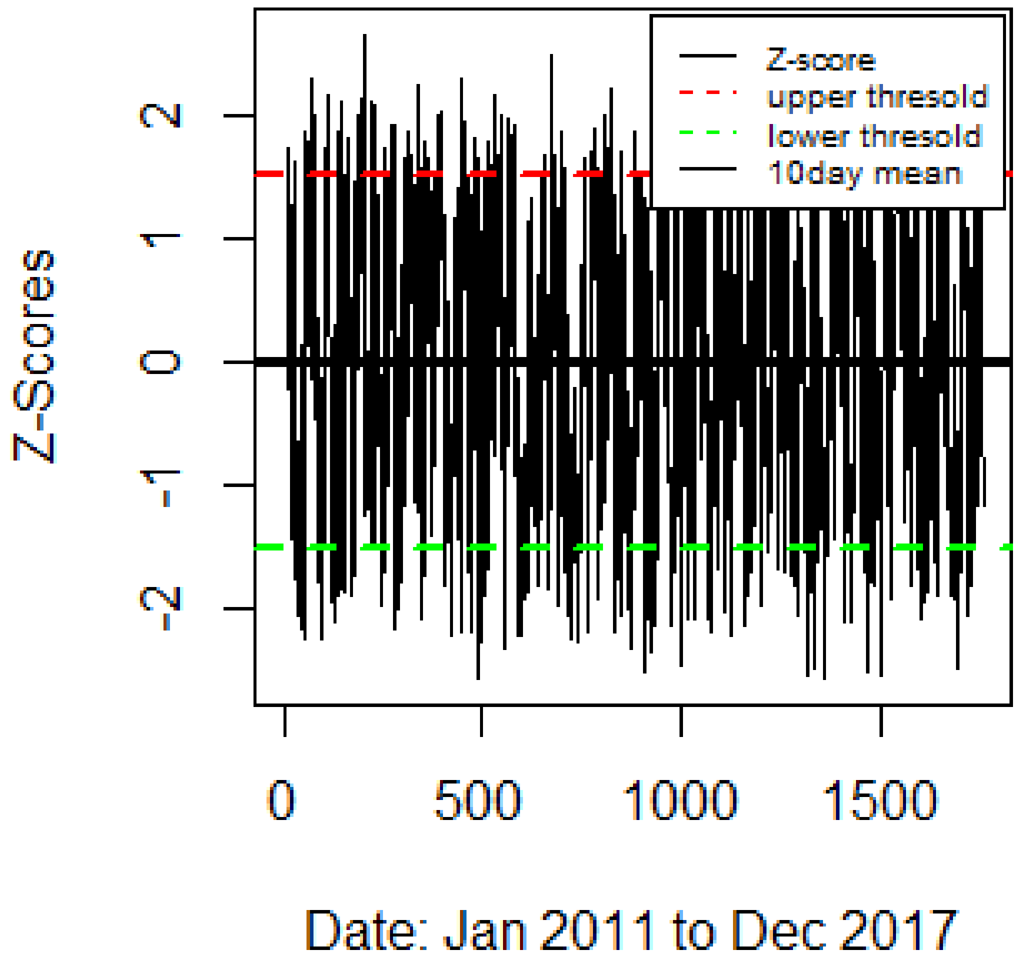

Figure 4: Z-score plot with the upper and lower thresholds

We also create a data frame combining the daily returns of the two series, the spread and the z-score. The list below shows the head of our new data frame. We also create a new object called hedge ratio which is the coefficient of EWC series from the regression analysis. The strategy uses hedge ratio to determine the units of EWC to buy or sell when there is a signal.

```
> in_ewa_return <- dailyReturn(ewa_etf) #in sample daily returns
> in_ewc_return <- dailyReturn(ewc_etf)
> #append/ bind zscores data with the prices and residuals.
> df2 <- cbind(df1, zscore)
> df_ewaewc <- na.omit(df2)   #clean data to remove rowns with NAs
> colnames(df_ewaewc)<- c("EWA_return","EWC_return", "spread", "zscore") #change
   column names
> head(df_ewaewc)
              EWA_return   EWC_return     spread     zscore
2011-01-14  0.0004019293  0.002560819 -1.1541823 -0.2166933
2011-01-18  0.0084371639  0.005427842 -1.0851306  0.3317246
2011-01-19 -0.0007968127 -0.011432232 -0.8066488  1.7212913
2011-01-20 -0.0167464115 -0.008994507 -0.9944978  0.7907030
2011-01-21 -0.0008110706  0.002269044 -1.0725368  0.3779468
2011-01-24  0.0158280039  0.002587322 -0.7488639  1.4812021

> #defining hedge ratio
> hedge_ratio <- ewaewc_lm$coefficients[2]
```

Listing 6: Daily returns and creating a data frame

5 IN SAMPLE BACK-TESTING RESULTS

Firstly we create signals. Figure 5 show the plot of the signal. It indicates that there are enough signals to make trades from. We then compute returns per each trade made from the signals. When z-score touches +1.5 we short the pair that is short EWA and long hedge ratio times EWC, and close the positions when it reverts back to 0.5. When z-score touches -1.5 we long the pair meaning, buy EWA and short hedge ratio times EWC, and close the positions when it reverts back to 0.5.

```
> #Building our Strategy
> #genarating signals
> hedge_ratio <- ewaewc_lm$coefficients[2]
> signal = NULL
> signal <- ifelse(df_ewaewc$zscore < z_low,1,
+                  ifelse(df_ewaewc$zscore > z_up,-1,0))
> #default lag perid
> signal <- lag(signal)
```

```
> plot(signal)
```

Listing 7: Compute signals

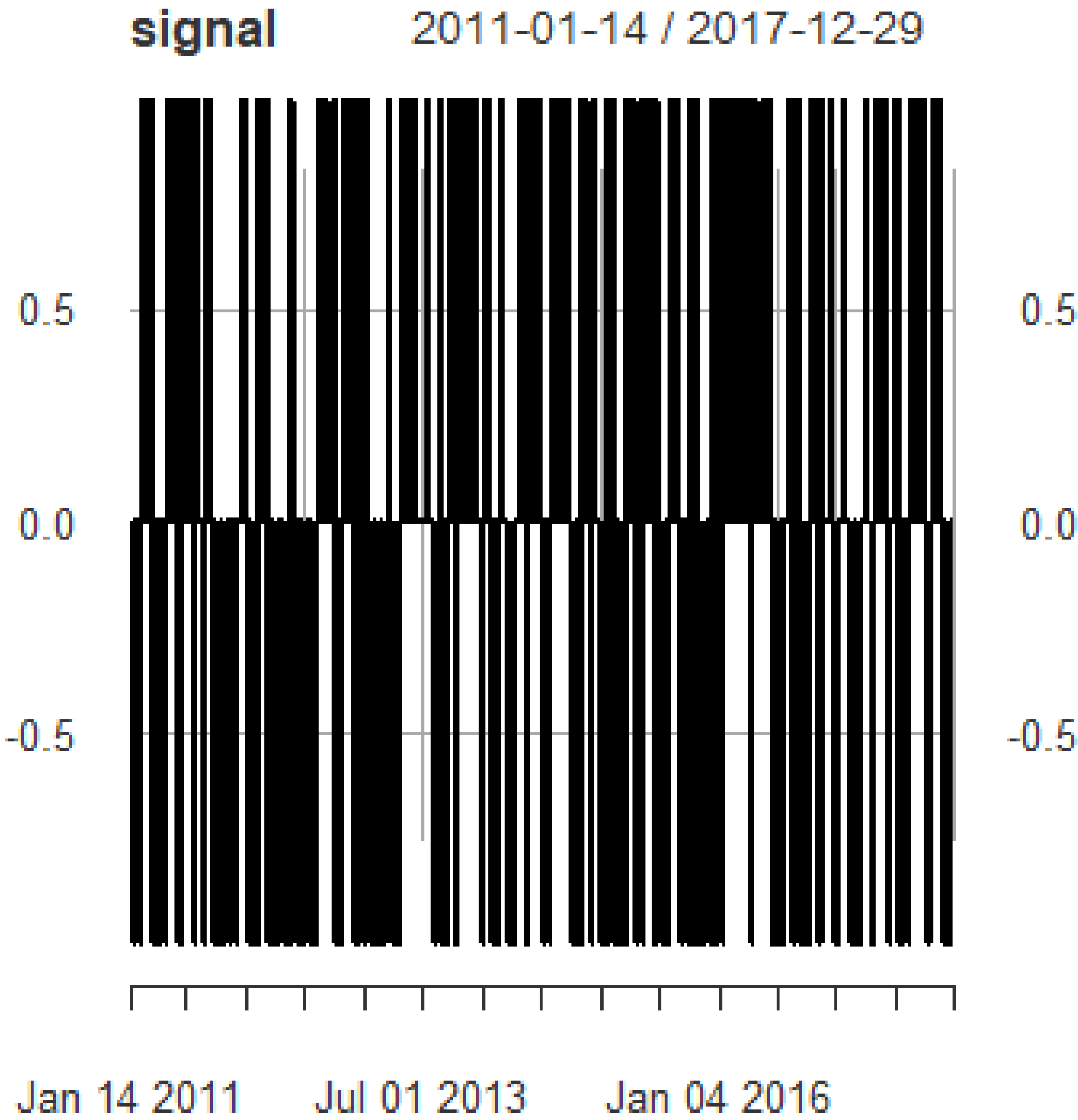

Figure 5: Signal plot

```
> #calculate trade return
> trade_return <- in_ewa_return*signal + in_ewc_return*hedge_ratio*-signal
> head(trade_return)
           daily.returns
2011-01-14            NA
2011-01-18   0.000000000
2011-01-19   0.000000000
2011-01-20   0.009288943
2011-01-21   0.000000000
2011-01-24   0.000000000
```

Listing 8: Compute trade returns

5.1 Performance Analysis

For only the two ETFs, over 6 years, the strategy produces a small cumulative return of 46.9% and a small annual return of 5.7%. Figure 6 shows the chart for daily trade returns and the drawdown. We can observe the maximum drawdown of 17.89% from the analysis results, which indicates that the losses from the investments were relatively small. Several other performance indicators can also be observed. One of the vital ones is the VaR, which is defined as the predicted worst case loss at a specific confidence level, say 95%. For our case, at 95% confidence level our VaR is very small and negative, and implies that the portfolio has a high probability of making a profit. We also observe the volatility (Standard deviation) of trade return of 0.45%, which indicates that the risk is very low. We also observe the Sharpe ratio which measures the risk adjusted return of the portfolio. It describes how much excess return an investor receives for the extra volatility they endure for holding a riskier asset. A preferred Sharpe ratio for any investment is greater than 1. For our case, the ratio is 0.8 and is smaller than the preferred.

```
> #Performance Analysis
> cumm_return <- Return.cumulative(trade_return)
> print(cumm_return)
                  daily.returns
Cumulative Return      0.468732
> annual_return <- Return.annualized(trade_return)
> print(annual_return)
                  daily.returns
Annualized Return    0.05688078
> charts.PerformanceSummary(trade_return)
```

Listing 9: Cumulative and Annual returns computation

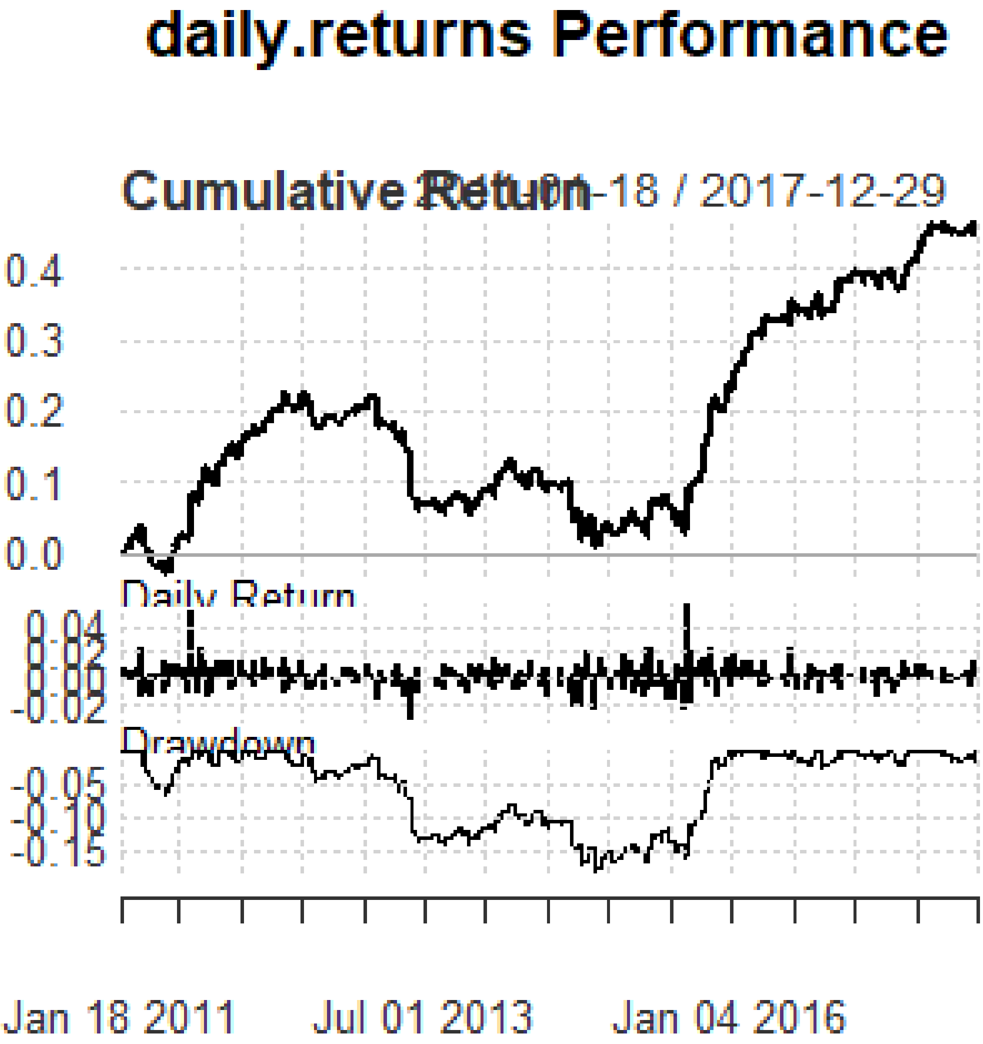

Figure 6: Performance summary chart

```
> summary(as.ts(trade_return))
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.       NA's
-0.0329731  0.0000000  0.0000000  0.0002295  0.0000000  0.0568379          1
> maxDrawdown(trade_return)
```

```
[1] 0.178941
> StdDev(trade_return)
              [,1]
StdDev 0.004473322
> VaR(trade_return, p=0.95)
    daily.returns
VaR -0.0007968736
> SharpeRatio(as.ts(trade_return), Rf=0, p=0.95)
                                    [,1]
StdDev Sharpe (Rf=0%, p=95%): 0.05130132
VaR Sharpe (Rf=0%, p=95%):    0.28798462
ES Sharpe (Rf=0%, p=95%):     0.28798462
> SharpeRatio.annualized(trade_return, Rf=0)
                                daily.returns
Annualized Sharpe Ratio (Rf=0%)     0.8010047
```

Listing 10: Computation of further performance indicators

6 OUT OF SAMPLE BACK-TESTING RESULTS

Figure 7 shows the chart for the signals from the year January 2018 to October 2019. Enough signals were generated.

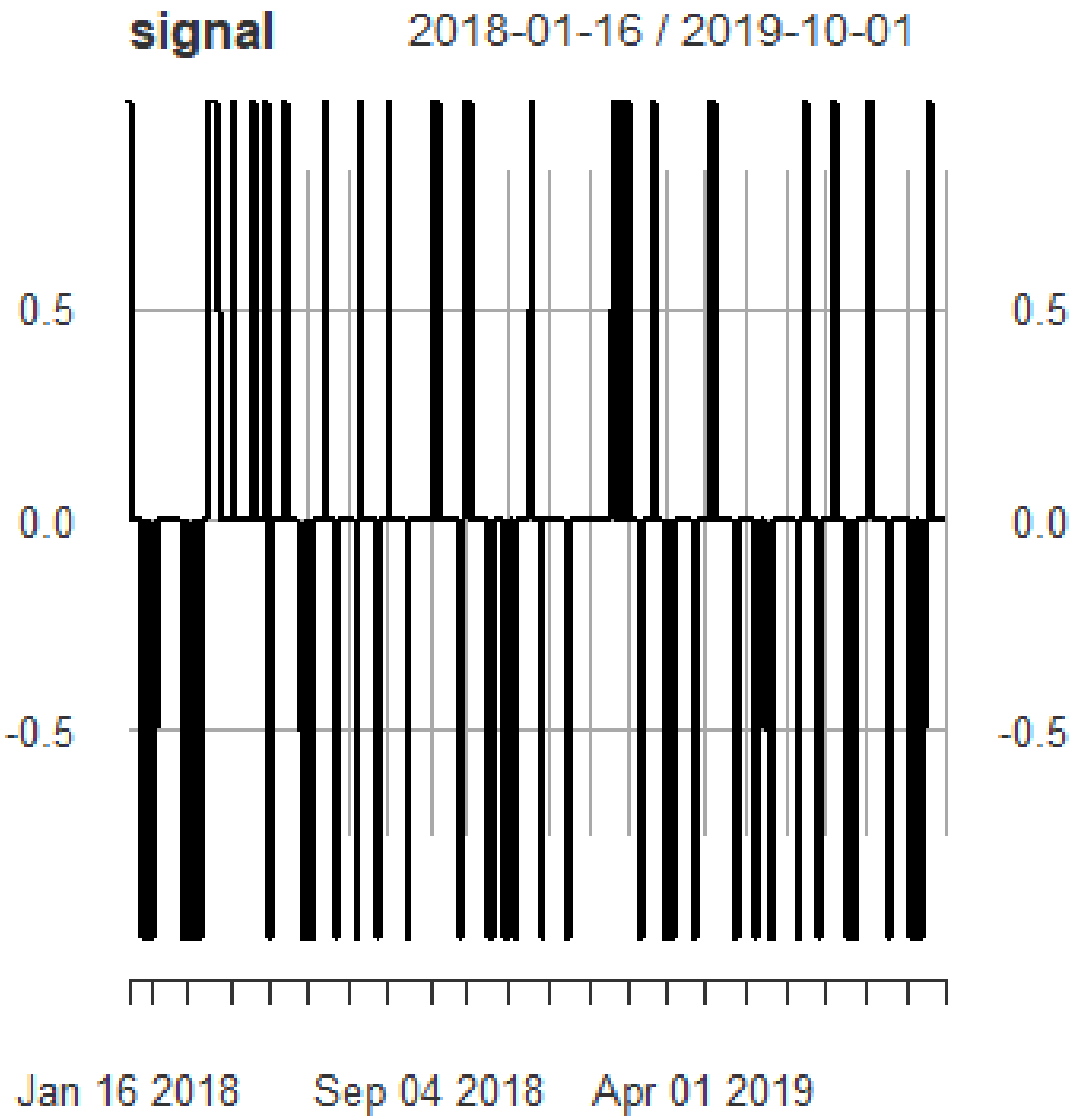

Figure 7: Signals from the out of sample test

For out of sample test, over 2 years, the strategy produces a cumulative return of 11.4% and an annual return of 6.5%. Figure 8 shows an upward trend for daily trade returns and the drawdown chart. We can observe the maximum drawdown of 3.2% from the analysis results, which indicates that the losses from the investments were relatively smaller than for the in sample. We can observe the VaR of -0.2%, which implies that at 95% confidence level the portfolio has a high probability of making a profit. We also observe the volatility (Standard deviation) of trade return of 0.3%, which indicates that the risk is very low. We can also observe the Sharpe ratio of 1.32 which is greater than the preferred of more than 1.

```
> #Performance Analysis
> cumm_return <- Return.cumulative(trade_return)
> print(cumm_return)
                  EWA/EWC_out_return
Cumulative Return           0.114025
> annual_return <- Return.annualized(trade_return)
> print(annual_return)
                  EWA/EWC_out_return
Annualized Return         0.06532621
> charts.PerformanceSummary(trade_return)
```

Listing 11: Cumulative and Annual returns computation for out of sample test

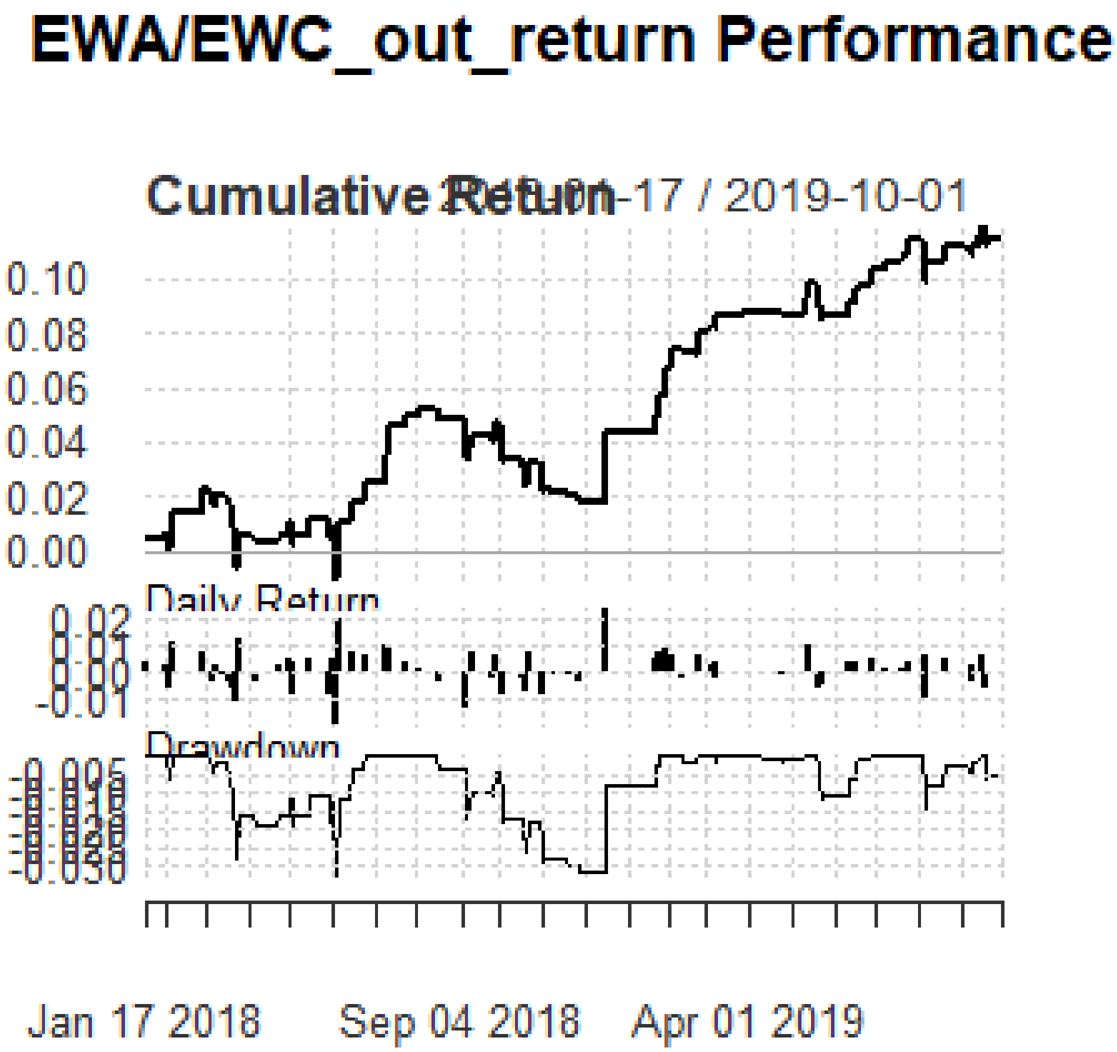

Figure 8: Out of sample performance summary chart

```
> summary(as.ts(trade_return))
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.       NA's
-0.019869  0.000000  0.000000  0.000256  0.000000  0.024449          1
> maxDrawdown(trade_return)
```

```
[1] 0.03209174
> StdDev(trade_return)
              [,1]
StdDev 0.00310874
> VaR(trade_return, p=0.95)
    EWA/EWC_out_return
VaR       -0.002222247
> SharpeRatio(as.ts(trade_return), Rf=0, p=0.95)
                                    [,1]
StdDev Sharpe (Rf=0%, p=95%): 0.08233321
VaR Sharpe (Rf=0%, p=95%):    0.11517737
ES Sharpe (Rf=0%, p=95%):     0.11517737
> SharpeRatio.annualized(trade_return, Rf=0)
                                EWA/EWC_out_return
Annualized Sharpe Ratio (Rf=0%)            1.32374
```

Listing 12: Performance indicators for out of sample test

NB Note that the analysis does not consider transaction costs such as slippage and commissions which can have a high impact on the performance of our strategy.

7 FURTHER IMPROVEMENTS

Pairs trading strategy can be improved by incorporating stop orders like stop loss and take profit limits so as to avoid big losses from trades. We can also play around with parameters like the looking back window period when calculating the mean and standard deviation of the spread. Also parameters like the upper and lower z-score thresholds can be played with to improve our strategy. We can also integrate the strategy with other models especially on predicting the movement of trends. Volatility models like GARCH models can be incorporated. lastly but not least, is to increase the number of ETFs to trade on. Just two ETFs is not enough for pairs trading since the strategy only relies on small profits emanating from very short-term arbitrage opportunities.

8 CONCLUSION

From our in sample and out of sample analysis we can conclude that the pairs trading strategy works very well on ETFs but we have to put in mind that the strategy gives very low returns for very low risk. Risk averse investors would prefer this strategy since it gives small consistent profits at very low risk. All performance indicators did justify this notion. Increasing a number of pairs in the strategy and integrating the strategy with other models will definitely increase returns and considerable risk thereby improving our strategy. This explains why pairs trading strategy is widely used by hedge funds.

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