

# Design Report

-By Team 04

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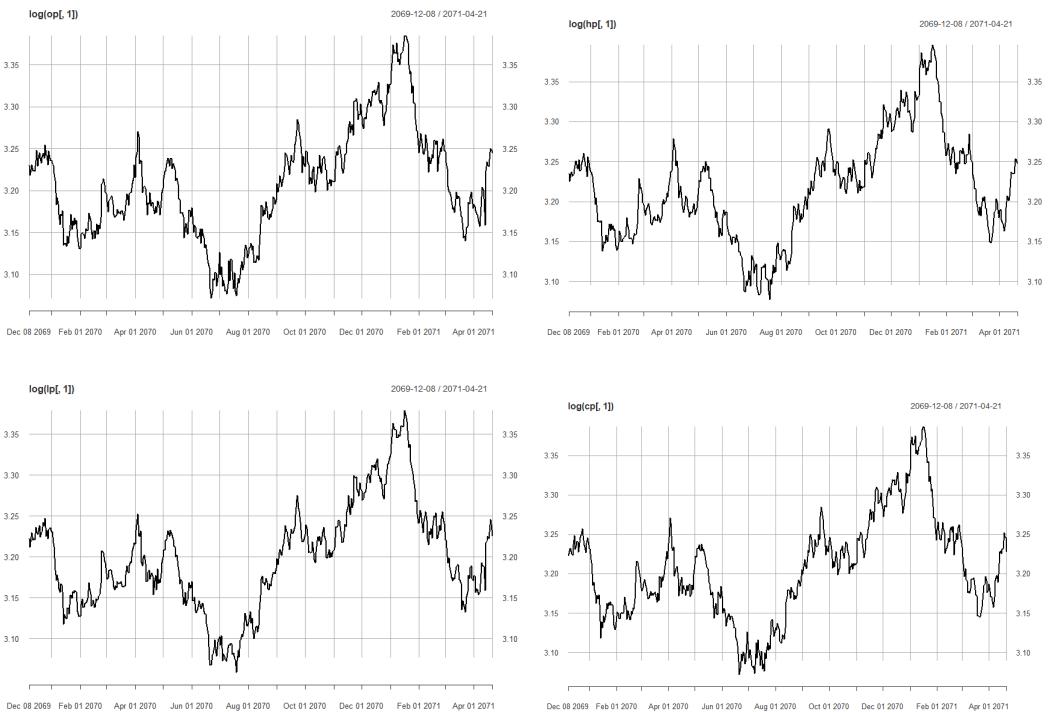
# 1 Analysis of time series

## 1.1 Basics Exploration

The OHLCV need to be explored at the beginning of designing any trading strategy. In this part, the first 500 days as in-sample data of Part 1 will be explored.

Firstly, the data needs to be logged before analysis, because logging reduces noise and makes the distribution smoother, which is better for observing changes in trends. Secondly, it is not only necessary to observe the trend and fluctuation of each individual series, but also to check whether there is a correlation or cointegration between different series.

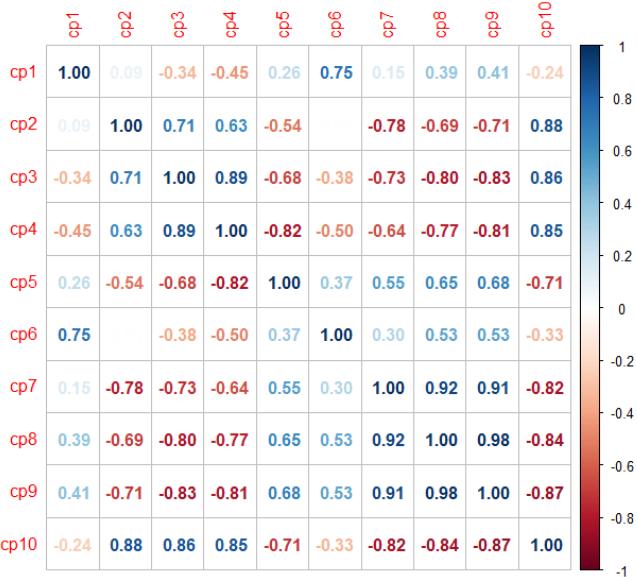
Series 1 OHLC data will be posted below as an example, all other OHLCV data are in the appendix A:



Graph 1. Series 1 OHLC price

From graph 1, as can be seen, trends and changes in volatility are nearly identical and therefore only one of the OHLC will be selected for further analysis in the next steps. And the close price will be chosen because it is the up-to-date data of the day and reduces the bias of using historical data to predict tomorrow's trends.

Based on the log close price graph, it can be concluded that series 2, 3, 4 and 10 are in downtrend, series 7, 8 and 9 are in uptrend and these three series are very similar, while series 1, 5 and 6 have no clear trend and are more volatile over time.



Graph 2. Close price correlation map

According to the rule of thumb of correlation, when the correlation between two series is greater than 0.8 or less than -0.8, it is considered to have a strong positive or negative correlation.

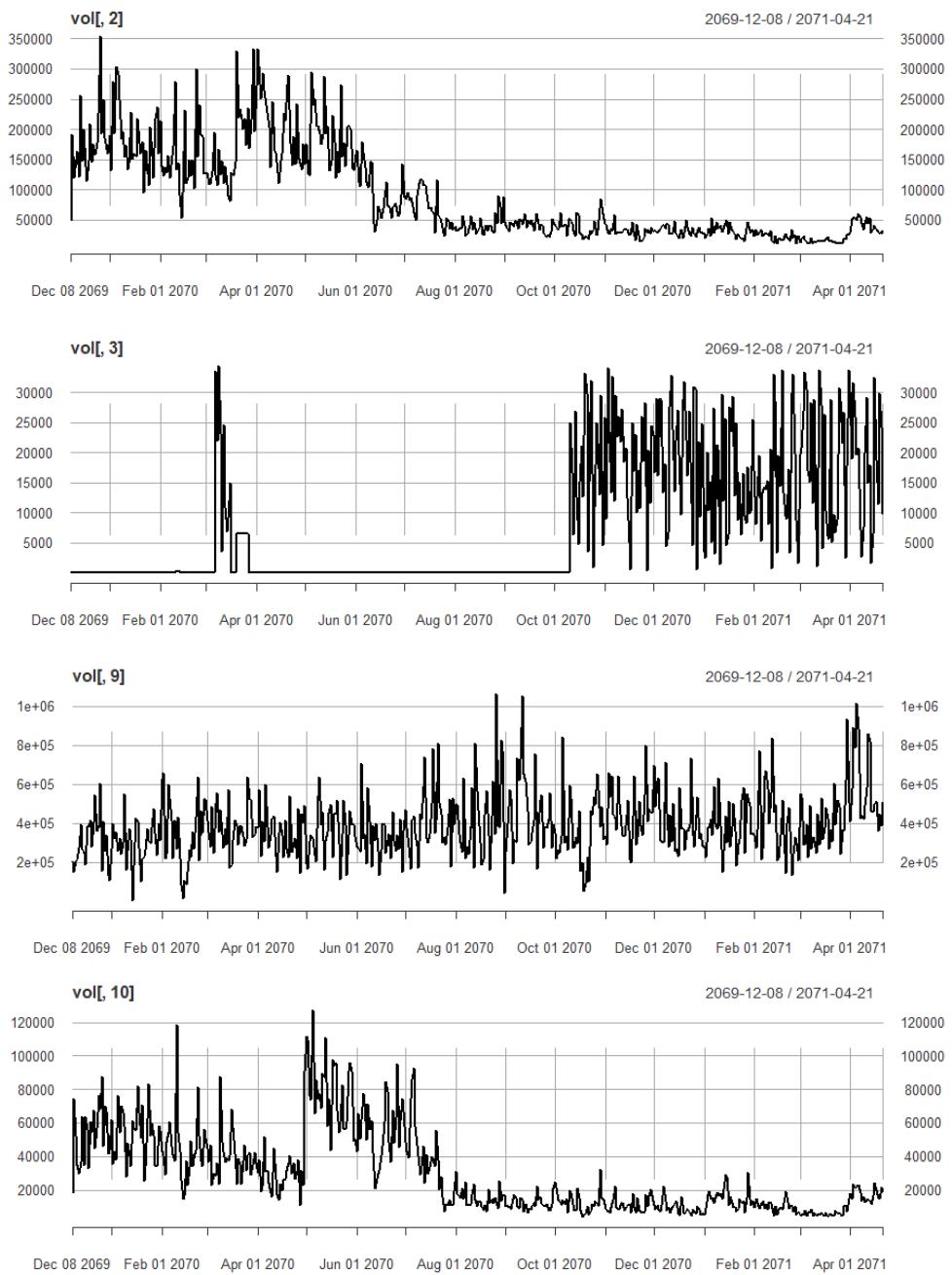
According to graph 2, we can conclude that series 10 has a strong positive correlation with series 2,3,4 and a strong negative correlation with series 7, 8 and 9; series 4 has a strong negative correlation with series 5.

Based on this conclusion, we conjecture that the price trend of series 10 may precede the arrival of the price trend of 6 series, series 2,3,4,7,8 and 9. If this precedence is proven to exist, then we can design trend strategies to use price of series 10 as reinforcing signals to judge the rise and fall of series 2,3,4 and series 7,8,9. To prove this hypothesis, we calculated the number of ups and downs for six series after each time series 10 had gone up or down respectively.

Table 1. up and down movements of series 2,3,4/7,8,9 after series 10 up and down

up&down times/Series	10	2	3	4	7	8	9
up/up	225	105	100	102	97	111	109
up/down		114	122	120	120	106	104
down/up	258	105	119	125	134	125	131
down/down		144	129	124	114	123	116

Table 1 shows that after series 10 up or down, the prices of the other 6 series did not follow the up/down trend of series 10 and would not lead the other 6 series to show significant price movements, so it cannot be used as a leading indicator for the two pairs of series 2,3,4 and series 7,8,9.

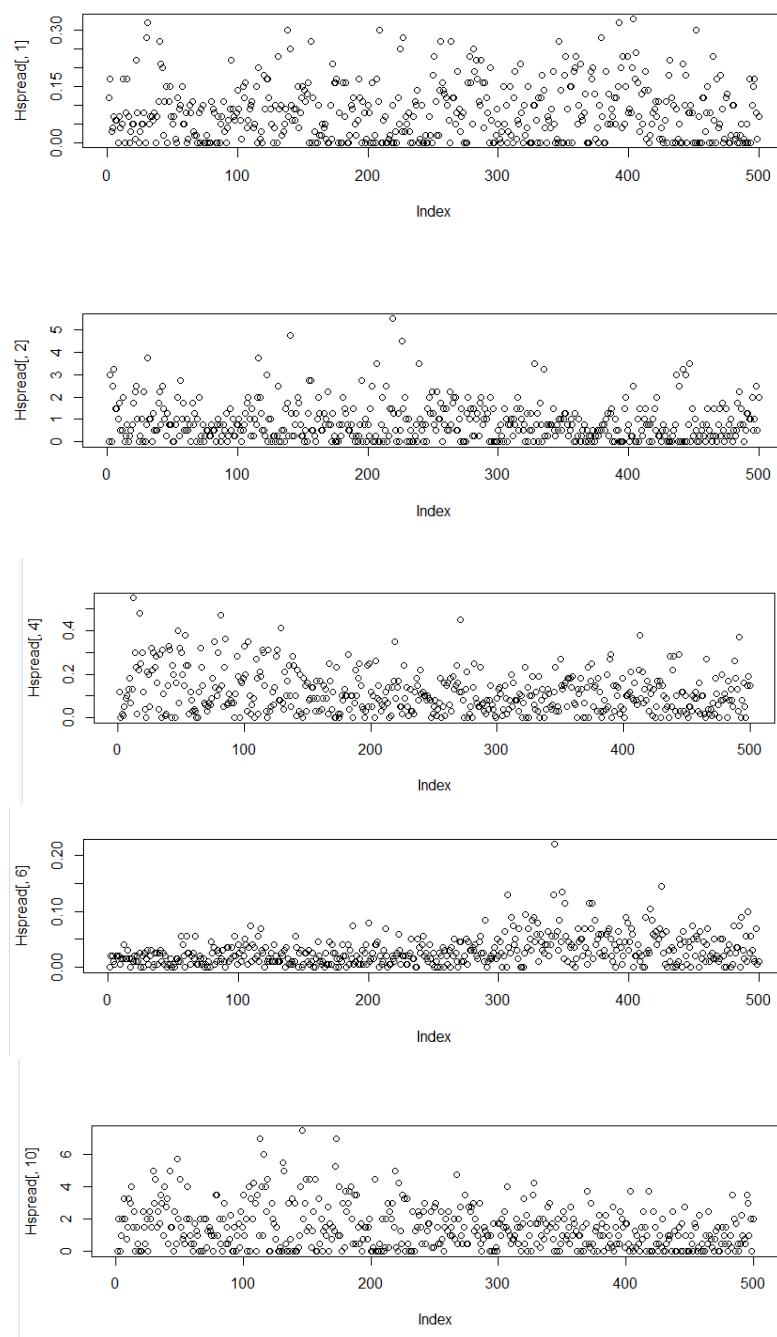


Graph 3. Volume for series 2, 3, 9, 10

Based on graph 3, some anomalies have been found that series 2, 3 and 9 all show very uncommon volumes at different periods thus signal filtering will be needed to prevent trading strategies from falling into false signal traps or suffering extreme risks (e.g., sudden delisting or suspension).

Series 2 and 10 also have a very strong positive correlation in terms of volume (0.72), with a high probability of homogeneity. They may be very similar in nature, such as the relationship between Google's parent company alphabet and Google. None of the other series show a particularly significant correlation in terms of volume.

From descriptive statistics, in terms of daily spread, the series 1 is very high and where its highest is 0.3. the average spread is about 0.1, which means that market marking strategy can be used and set the volatility of 0.1 bilateral limit order to make profit from this series.

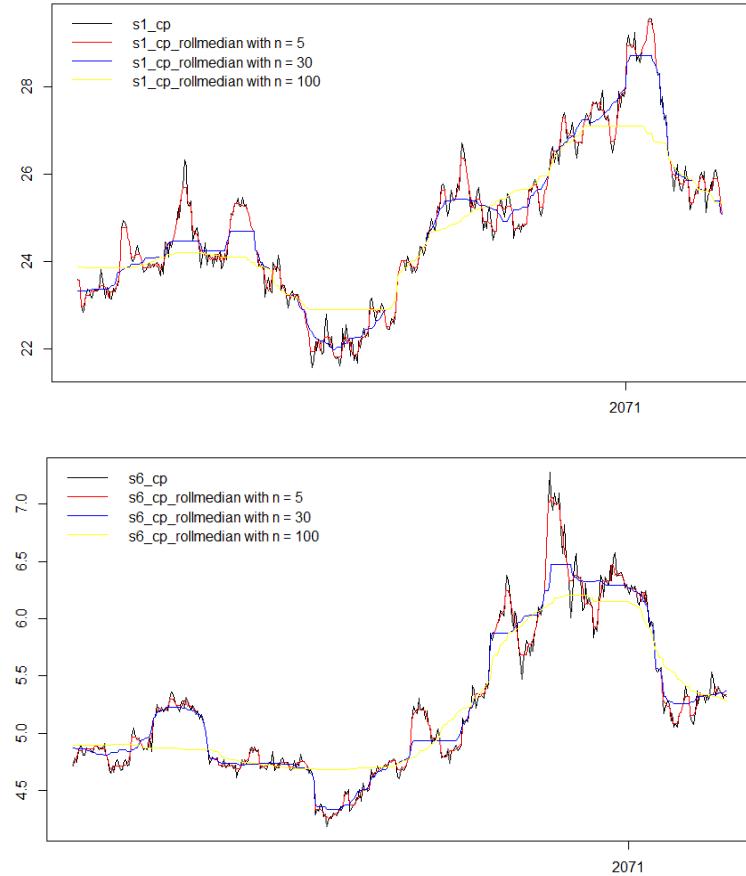


Graph 4. Daily spread for series 1, 2, 4, 6, 10

From graph 4, it is obvious that series 1,2,4,6,10 can be arbitrage with spread trading or market marking strategy by taking advantage of the bilateral limit order. In addition, series 2 and 10 are more volatile and have a higher volatility range and frequency.

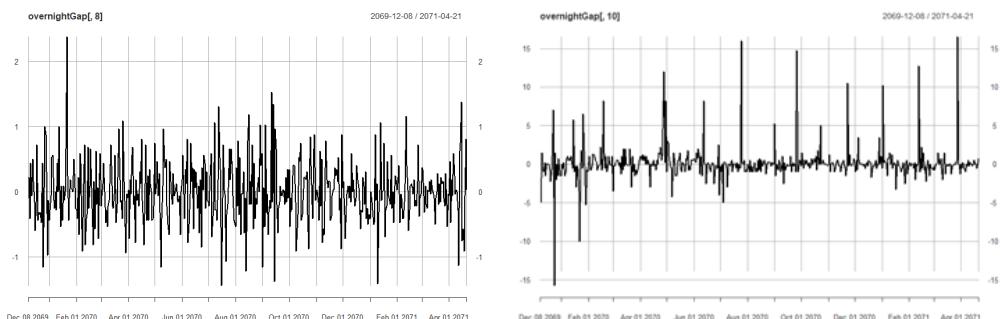
According to Appendix A Graph A.20, it was found that the trending of VWAP is more foreseeable in direction than OHLC. For stationary series, it would be easier and more frequent to trigger trend signals if we use VWAP to construct factors, while too much entry into positions in oscillating market would lead us to lose slippage frequently.

In accordance with Graph 5, rolling medians for series 1 and 6 always fall off a cliff after rising to new high, resulting in high volatility for both. Hence this pattern may be tried in part 2 with trend strategy to test if this idea is solid.



Graph 5. Close price and rolling medians for series 1, 6

Based on graph 6, the overnight gap of series 8 and 10 are highly volatile across the first 500 days.



Graph 6. Overnight gap for series 8, 10

## 1.2 Basics Statistics Testing

The Dickey-Fuller test can observe whether the data is stationary or not.

Table 2. Dickey-Fuller test results for close price for 10 series

series	tau1 statistic	tau1 95% critical value	stationary
1	-0.1195607	1.95	stationary
2	-1.742317	1.95	stationary
3	-1.547832	1.95	stationary
4	-0.9461022	1.95	stationary
5	0.8367743	1.95	stationary
6	-0.2815926	1.95	stationary
7	1.018251	1.95	stationary
8	1.339446	1.95	stationary
9	1.339882	1.95	stationary
10	-1.825916	1.95	stationary

According to table 2, it can be concluded that all the close prices are stationary.

It is also important to test whether the time series is lagged, and this can be done by using the Ljung-Box test to determine whether the series is stochastic.

Table 3. Ljung-Box test results for close price for 10 series

series	CP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

The table 3 shows that the close price of each series is non-white noise, which means that the patterns we concluded from close price can be trusted.

The cointegration test showed whether there is a cointegration relationship between the two sets of data, and thus determines whether a pair trading strategy can be devised.

```

#####
# Johansen-Procedure #
#####

Test type: maximal eigenvalue statistic (lambda max) , with linear trend
Eigenvalues (lambda):
[1] 0.3721529598 0.0929146426 0.0855103747 0.0606051996 0.0412756301 0.0396997391 0.0315908840 0.0242244536 0.0069764818 0.0001996895

values of teststatistic and critical values of test:
      test 10pct 5pct 3pct
r <= 9 | 0.10 6.50 8.18 11.65
r <= 8 | 3.49 12.91 14.90 19.19
r <= 7 | 12.21 18.90 21.07 25.75
r <= 6 | 20.09 25.30 28.32 34.14
r <= 5 | 20.17 30.84 33.32 36.88
r <= 4 | 20.99 36.25 39.43 44.59
r <= 3 | 31.13 42.05 44.91 51.30
r <= 2 | 44.13 48.43 51.40 57.07
r <= 1 | 48.36 53.00 59.00 67.07
r = 0 | 231.80 59.00 62.42 66.61

Eigenvectors, normalised to first column:
(These are the cointegration relations)

a.12   b.12   c.12   d.12   e.12   f.12   g.12   h.12   i.12   j.12
a.12  1.0000000  1.0000000  1.0000000  1.0000000  1.0000000  1.0000000  1.0000000  1.0000000  1.0000000  1.000000e+00
b.12 -0.04131573  0.298269  1.0664889  2.388202  0.09104709 -0.01049434 -0.2650312 -0.043880459 -0.07478396  3.766011e-03
c.12  30.9862990 -32.6161050 20.6602055 105.9900000 -29.5000000 -1.5230000  53.0000000  1.72021685 -1.53399492  8.592145e-01
d.12 -2.10631440  14.6602061  0.98141235 -67.075829 -0.56383160  0.19681388 -0.50967021  0.172021685 -1.53399492  8.592145e-01
e.12 -0.33969687  4.2830188  2.4243507 -26.993416 -0.69115792  0.24710021  0.30644764  0.091944633  1.26388978 -8.712495e-01
f.12  1.27324770 -8.7419186 -2.7094368 -286.163670  2.26623206 -2.19502460  3.35987788 -0.567718632  11.8000609  2.036341e-02
g.12  37.74253449 -47.0657944  49.0315047 -202.90182  3.6949526  1.5311976  5.57979096 -0.026777902 -12.81803575  3.213670e+00
h.12  2.40920500 -1.2045518  2.3150041 -2.1620003  0.09104709  0.4211010  0.4211010 -1.2045518  0.09104709 -1.2045518  0.09104709
i.12  14.21716803  5.8645202 -7.0533324  33.762908 -0.99274923 -0.35590655 -1.64809007  0.1431350010  3.27672217 -5.889195e-01
j.12  0.19789308 -0.8371368 -0.5241784 -2.452442 -0.16223992  0.02178916  0.06291508  0.030266933  0.12745798 -4.279355e-02

weights w:
(This is the loading matrix)

a.12   b.12   c.12   d.12   e.12   f.12   g.12   h.12   i.12   j.12
a.d  1.513102e-04 -1.023121e-03 1.186732e-03 -1.762842e-04 -6.464035e-03 -2.285756e-02 2.590636e-03 -1.451913e-03 4.709336e-05 -6.115699e-05
b.d  1.299862e-04 -1.023121e-03 1.186732e-03 -1.762842e-04 -6.464035e-03 -2.285756e-02 2.590636e-03 -1.451913e-03 4.709336e-05 -6.115699e-05
c.d  9.582957e-07 -1.053833e-05 -1.704281e-05 5.029176e-06 -8.168832e-06 -9.933816e-05 2.420302e-06 8.728690e-06 -7.043663e-06 5.558594e-06
d.d -1.423802e-03 -4.485158e-03 -3.182559e-03 4.005977e-04 -4.170203e-03 6.510740e-03 2.132033e-03 -5.992552e-03 -1.045906e-04 1.303023e-04
e.d -7.730412e-04 7.723812e-04 -6.925601e-03 2.288711e-03 8.213636e-03 -4.697756e-02 -4.121759e-03 1.459899e-02 -9.237127e-04 -3.308723e-04
f.d  1.740495e-04 9.038573e-05 4.976602e-04 2.711819e-05 -3.607412e-03 4.181241e-03 -4.421101e-03 3.677799e-04 -1.932959e-04 -2.793264e-05
g.d  1.323589e-02 3.738812e-04 -1.383268e-03 -2.117336e-05 3.254386e-04 5.154927e-03 9.086909e-04 -3.945933e-03 -2.217727e-05 -1.568900e-04
i.d  4.234682e-03 1.998524e-03 -3.237798e-03 -8.490236e-03 5.863858e-03 2.159282e-02 7.092334e-03 -1.630812e-02 -5.608793e-04 -1.190437e-03
j.d  6.255989e-03 1.005277e-02 2.225365e-03 9.002399e-03 2.234911e-03 -2.82251e-01 -1.011754e-02 6.620518e-03

> slotnames(cotest)
[1] "X"    "Z0"   "Z1"   "Zk"   "type" "model" "ecdet" "lag"   "P"    "season" "dumvar" "cval"
[13] "teststat" "lambda" "vorg"  "v"    "w"    "pi"    "delta" "gamma" "R0"   "RK"    "bp"    "spec"
[25] "call"   "test.name"

```

Table 4. Cointegration test results for close price for 10 series

According to table 4, there are 9 cointegration vectors which means pair trading is viable in 10 series.

Other statistical test was carried out on all the basics to exclude some basics or a few series-basics combinations that were not suitable for signal processing or different strategies. (See Appendix B)

### 1.3 Technical Indicator Data Analysis

The data analysis and statistical tests allow the conclusions of technical indicator to have been drawn. (See Appendix C)

Indicator	Conclusion
Conclusion	<ol style="list-style-type: none"> <li>1. Series 2, 8, 9 are quite stationary</li> <li>2. Series 1, 3, 4, 5, 6, 10 are highly volatile</li> <li>3. Highly related to the up-down direction</li> <li>4. The scales of momentum for different series are different, we need to change it to percentage if needed</li> </ol>
Stochastic Oscillator / Stochastic Momentum Index	<ol style="list-style-type: none"> <li>1. Series 1, 5, 6, 7, 8, 9 are more often overbought</li> <li>2. Series 2, 3, 10 are more often oversold</li> <li>3. Series 3, 4 have frequent crossover breakouts above and below 50, indicating that its buy-sell signals are less credible</li> </ol>
SMI	<ol style="list-style-type: none"> <li>1. For Series 1, 3, 4, 6, 7, 10 trends and OHLC trends are basically synchronized</li> <li>2. Series 2, 8 downtrends does not fit OHLC trend, but uptrend fits well</li> <li>3. Series 5, 9 uptrends does not fit OHLC trend, but downtrend fits well</li> <li>4. All non-stationary for 10 series which means we can't use it for trend prediction</li> </ol>
ADX	<ol style="list-style-type: none"> <li>1. For Series 1, 3, 4, 6, 7, 10 trends and OHLC trends are basically synchronized</li> <li>2. Series 2, 8 downtrends do not fit OHLC trend, but uptrend fits well</li> <li>3. Series 5, 9 uptrends do not fit OHLC trend, but downtrend fits well</li> <li>4. All non-stationary for 10 series which means we can't use it for trend prediction</li> </ol>
RSI	<ol style="list-style-type: none"> <li>1. The RSI values of Series 1, 2, 3, 9, 10 are not above 80, which means there are no selling points, so these series are not applicable to RSI</li> <li>2. Series 4, 6 are found to be mostly concentrated in the range 20-50, and there are few opportunities for sell points, so the market characteristics are extremely weak, and the use of RSI is not recommended</li> <li>3. Series 5, 7, 8 have the most sell points and most of them are concentrated in the 50-80 buy range, so they have strong market characteristics</li> <li>4. All series pass stationary test, meaning mean-reversion strategy might work using this indicator.</li> </ol>
OBV	<ol style="list-style-type: none"> <li>1. For series1, OBV trend is irrelevant to OHLC trend</li> <li>2. For series 9 uptrend is relevant to OHLC trend, but downtrend is obviously irrelevant</li> <li>3. Except series 7, all series pass stationary test, meaning mean-reversion strategy might work using this indicator</li> </ol>
MACD	<ol style="list-style-type: none"> <li>1. For series1, OBV trend is irrelevant to OHLC trend</li> <li>2. For series 9 uptrend is relevant to OHLC trend, but downtrend is obviously irrelevant</li> <li>3. Except series 7, all series pass stationary test, meaning mean-reversion strategy might work using this indicator</li> </ol>
Aroon	<ol style="list-style-type: none"> <li>1. Aroon has long entered too many times in ten series and is not suitable for Trend trading</li> <li>2. ALL series are non-stationary, meaning mean-reversion strategy might not work using this indicator</li> </ol>
BBands	<ol style="list-style-type: none"> <li>1. All series pass stationary test, meaning mean-reversion strategy might work using this indicator</li> </ol>
ATR	<ol style="list-style-type: none"> <li>1. All series pass stationary test, meaning mean-reversion strategy might work using this indicator</li> </ol>
TR	<ol style="list-style-type: none"> <li>1. ALL series are non-stationary, meaning mean-reversion strategy might not work using this indicator</li> </ol>
MFI	<ol style="list-style-type: none"> <li>1. All series pass stationary test, meaning mean-reversion strategy might work using this indicator</li> <li>2. No obvious relationship with OHLC trend</li> </ol>
KDJ	<ol style="list-style-type: none"> <li>1. By the rule of if the number of K values greater than 80 and the number of K values less than 20 are many indicates that 10 series are suitable for KDJ, series 1, 3, 5, 6, 7, 8, 9 are suitable, series 2, 4, 10 are not</li> </ol>

## **2 Trading Strategies**

### **2.1 Hierarchical Design**

Some investment philosophy will be obeyed in our strategy:

1. Never put eggs in one basket

A FOF like strategy management system will be implemented in our project. Because diversifying our investments in different strategies can gain us more profit by allocation funds to different strategies depending on data. Also, diversification of strategy and series can effectively reduce systematic risk instead of putting money heavily in minority bets.

2. Using leverage can bring more profit

Cases may happen at period when a strategy generally holds short positions which give us more money temporarily and such that we can invest more in other long viable strategies temporarily to exploit the maximum profit. In our project, 200% leverage that can be used at maximum should be considered in our strategy level and series level allocating strategy. But proper leverage level will be testing via position sizing and risk management exploration in Part 2.

3. Never risk losing all in one bet

In order to not lose all money in one bet, we plan to implement not only risk management measures but also a long-term effective position sizing strategy. Furthermore, some anomalies in data have been found about huge drop in volume at suspicious periods should be considered. In order to prevent extreme risk like the black swan, we will add market condition filters to stop trading at hazardous periods or extreme patterns depending on further data exploration and testing in Part 2.

4. All strategies are wrong, but some are useful

We found that all our strategies cannot make money from all series the whole time and this is expected. Thus, trading timing filters and market condition filters will be added to avoid those bad trading decisions. For example, we might want to classify our strategy as long-like and short-like strategy depending on their performance or characteristics. Likewise, some strategy might perform better in bear market which is a hard to define terminology which we need to explore market condition quantitatively using combination of basics or indicators depending on further data analysis in Part 2.

One idea in mind is to use multiple signals to double confirm instead of one single signal or one plain triggering point. Also, we can define enter and exit points in different strategies with different ideas, so we will test each of them to find the best one. Last

but not least is to choose the right parameters or technical indicators depending on the conclusion derived from our Part 1 data analysis.

## 2.2 Trading Ideas

### 2.2.1 Triple Moving Average Strategy

According to Singh, D. (quantinsti blog, 2017), by using three moving averages of different lookback periods, the trader can confirm whether the market has actually witnessed a change in trend or whether it is only resting momentarily before continuing in its previous state. The buy signal is generated early in the development of a trend and a sell signal is generated early when a trend ends.

In a nutshell, following trading rules will be implemented:

Long signal: short > medium > long

Short signal: short < medium < long

```
1 # main strategy
2 getOrders.tma<- function(store, newRowList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newRowList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newRowList,params$series)}else{
9       store <- updateStore(store, newRowList, params$series)
10    }
11
12  # init today's enter positions on each series
13  pos <- allzero
14
15  # default exit yesterday's overall positions
16  marketOrders <- -currentPos
17
18  # we need to wait until day 101 so that we have ma100 signal
19  if(store$iter > params$lookback){
20    for(i in params$series){
21      # everyday re-calculate today's ma5/ma30/ma100
22      sma5 <- last(SMA(store$op[1:store$iter,i],5))
23      sma30 <- last(SMA(store$op[1:store$iter,i],30))
24      sma100 <- last(SMA(store$op[1:store$iter,i],100))
25
26      # enter conditions
27
28      # Long enter when ma5 > ma30 > ma100
29      if((sma5 > sma30) & (sma30 > sma100)){
30        pos[i] <- params$posSizes[i]
31      # short enter when ma5 < ma30 < ma100
32      }else if((sma5 < sma30) & (sma30 < sma100)){
33        pos[i] <- -params$posSizes[i]
34      }
```

```

36      # exit conditions
37
38      if(currentPos[i] > 0){ # when in long position
39          # Long exit when new close is no longer the new highest close
40          if (store$c1[store$iter, i] < store$c1[store$iter-1, i]){
41              pos[params$series[i]] <- 0
42          }
43
44      }else if (currentPos[i] < 0){ # when in short position
45          # short exit when new close is no longer the new lowest close
46          if (store$c1[store$iter, i] > store$c1[store$iter-1, i]){
47              pos[params$series[i]] <- 0
48          }
49      }
50  }
51 }
52 marketOrders <- marketOrders + pos
53 return(list(store=store,marketOrders=marketOrders,
54             limitOrders1=allzero,limitPrices1=allzero,
55             limitOrders2=allzero,limitPrices2=allzero))
56 }
```

## 2.2.2 Relative Strength Strategy

From Faber, M. (CAMBRIA INVESTMENT MANAGEMENT, 2010), a strategy idea and example has been introduced as followed.

According to this trading idea, we designed a similar version which has long 3 series with strongest 12-month momentum and short 3 series with weakest 12-month momentum into our portfolio and weights them equally. Rebalance once every month.

```

1 # main strategy
2 getOrders.rs<- function(store, newRowList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newRowList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newRowList,params$series)}else{
9     store <- updateStore(store, newRowList, params$series)
10    }
11
12   # init today's enter positions on each series
13   pos <- allzero
14
15   # default exit yesterday's overall positions
16   marketOrders <- allzero
17
18   # we need to wait until day 366 so that we have open price 1 yr earlier
19   # and the day must be 30 days after last trading day
20   # (the first trading day should be day 366)
21   if((store$iter > params$lookback) & ((store$iter-365) %% 30 == 1)){
22     # default exit yesterday's overall positions
23     marketOrders <- -currentPos
24
25     # init mtm/max 3 mtm series/min 3 mtm series
26     mtm <- allzero
27     max3mtm_series <- allzero
28     min3mtm_series <- allzero
29
30     for(i in params$series1){
31       # re-calculate today's pricechange = today's open - open 1 year earlier
32       # we use change in percentage to represent pricechange
33       # to eliminate the differences in price measurement
34       mtm[i] <- (store$op[store$iter,i]-store$op[store$iter-365,i]) /
35         (store$op[store$iter-365,i])
36     }
37
38     # the best 3 momentum series
39     max3mtm_series <- order(mtm,decreasing=TRUE)[1:3]
40     # the worst 3 momentum series
41     min3mtm_series <- order(mtm,decreasing=FALSE)[1:3]
42
43     for(i in params$series){
44       # long enter
45       if(i %in% max3mtm_series){
46         pos[i] <- params$posSizes*1000000/store$cl[store$iter,i]
47       }
48       # short enter
49       else if(i %in% min3mtm_series){
50         pos[i] <- - params$posSizes*1000000/store$cl[store$iter,i]
51       }
52     }
53   }
54   marketOrders <- marketOrders + pos
55   return(list(store=store,marketOrders=marketOrders,
56             limitOrders1=allzero,limitPrices1=allzero,
57             limitOrders2=allzero,limitPrices2=allzero))
58 }
```

### 2.2.3 Market Making Strategy

Market Making strategy will be implemented in high volatility series.

The trading mechanism is quite simple:

Like arbitrage, ordering two sides (long and short) limit orders at the same position but with different prices depending on daily spread. If two trades executed, then profit gains.

In our trading idea, we trade every day and set the limit price to be daily (high-low)/2 +/- (spread in percentage) \* open and when accumulated positions reach a high level which we set as twice betting sizes as each bet will trigger our exit condition to clear out all positions in one series.

```
1 # main strategy
2 getOrders.mm<- function(store, newList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newList))
5
6   # init today's enter positions on each series
7   pos <- allzero
8
9   # if our positions reach 2 times betting Level then exit yesterday's overall positions
10  marketOrders<- ifelse(abs(currentPos)>2*params$posSizes, -currentPos, 0)
11
12  # init store
13  if (is.null(store)) {
14    store <- initStore(newList,params$series)}else{
15    store <- updateStore(store, newList, params$series)
16  }
17
18  # init limitPrices1/limitPrices2/LimitOrders1/LimitOrders2
19  limitPrices1<- allzero; limitOrders1<- allzero
20  limitPrices2<- allzero; limitOrders2<- allzero
22  if(store$iter > params$lookback){
23    for(i in params$series){
24      # market making - betting on both sides
25      limitOrders1[i]<- params$posSizes[i]
26      limitPrices1[i]<- (store$hi[store$iter,i]+store$lo[store$iter,i])/2-params
27      $spread*store$cl[store$iter,i]
27      limitOrders2[i]<- -params$posSizes[i]
28      limitPrices2[i]<- (store$hi[store$iter,i]+store$lo[store$iter,i])/2+params
28      $spread*store$cl[store$iter,i]
29    }
30  }
31  marketOrders <- marketOrders + pos
32  return(list(store=store,marketOrders=marketOrders,
33             limitOrders1=limitOrders1,limitPrices1=limitPrices1,
34             limitOrders2=limitOrders2,limitPrices2=limitPrices2))
35 }
```

## 2.2.4 The Jump Trading Strategy

The Jump Trading System is using in a downtrend where prices fluctuate around the lower end of the box range for 5 to 10 days, then open sharply lower below the trend line with extreme selling sentiment, and if it then rebounds to yesterday's lows, it indicates a reversal of market energy, and another bullish upward move is ready to take place. Trading rules are as follow:

1. Close 4% below the five-day average price to ensure the signal occurs on a down trend
2. Open price of 1% below yesterday's low
3. Close price rally above yesterday's minimum price

However, when testing this strategy with Part 1 data, we found that this strategy never triggered with no matter what indicator or parameter we tried so we will drop it.

```
1 # main strategy
2 getOrders.jt<- function(store, newList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newList,params$series)}else{
9     store <- updateStore(store, newList, params$series)
10    }
11
12  # init today's enter positions on each series
13  pos <- allzero
14
15  # default exit yesterday's overall positions
16  marketOrders <- -currentPos
17
18  # we need to wait until day 101 so that we have ema100 signal
19  if(store$iter > params$lookback){
20    for(i in params$series){
21      # everyday re-calculate today's emas
22      ema5 <- last(EMA(store$c1[1:store$iter,i],5))
23
24      # Long enter
25      if(((store$c1[store$iter,i] - ema5) / ema5 <= -0.04) &
26          ((store$op[store$iter,i] - store$lo[store$iter-1,i]) / store$lo[store$it
er-1,i] <= -0.01) &
27          (store$c1[store$iter,i] > store$lo[store$iter-1,i])){
28        pos[i] <- params$posSizes[i]
29
30      # exit when direction turned again
31      }else if(((currentPos[i] != 0) &
32                  (store$c1[store$iter,i] < store$c1[store$iter-1,i]))){
33        pos[i] <- 0
34
35      # hold when still in the trend
36      }else if(((currentPos[i] != 0) &
37                  (store$c1[store$iter,i] >= store$c1[store$iter-1,i]))){
38        pos[i] <- currentPos[i]
39      }
40    }
41  }
42  marketOrders <- marketOrders + pos
43  return(list(store=store,marketOrders=marketOrders,
44             limitOrders1=allzero,limitPrices1=allzero,
45             limitOrders2=allzero,limitPrices2=allzero))
46 }
```

## 2.2.5 Lawrence Macmillan Volatility Trading System

Lawrence Macmillan Volatility Trading System is using volatility as the rate at which stock prices change and can be calculated using the standard deviation formula and by comparing historical volatility over different lengths of time, such as 10, 20 and 50 days, and 100 days. However, the exit signals are not clear yet which we will explore in Part 2.

Trading rules are as follow:

1. Historical volatility is short aligned, i.e., the range of volatility is getting narrower, suggesting the calm before the storm.
2. Calculate historical volatility at 5, 10, 20, 30 and 100 days and find its standard deviation.
3. AC and AO indicators fall for 5 consecutive days. (This is not added to Part 1 code yet).

```
1 # main strategy
2 getOrders.lmv<- function(store, newList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newList,params$series)}else{
9     store <- updateStore(store, newList, params$series)
10    }
11
12  # init today's enter positions on each series
13 pos <- allzero
14
15  # default exit yesterday's overall positions
16 marketOrders <- -currentPos
17
18  # we need to wait until day 101 so that we have ema100 signal
19  if(store$iter > params$lookback){
20    for(i in params$series){
21      # everyday re-calculate today's ema5/ema10/ema20/ema30/ema100
22      ema5 <- last(EMA(store$c1[1:store$iter,i],5))
23      ema10 <- last(EMA(store$c1[1:store$iter,i],10))
24      ema20 <- last(EMA(store$c1[1:store$iter,i],20))
25      ema30 <- last(EMA(store$c1[1:store$iter,i],30))
26      ema100 <- last(EMA(store$c1[1:store$iter,i],100))
27
28      # everyday re-calculate today's std5/std10/std20/std30/std100
29      std5 <- store$c1[store$iter,i] - ema5
30      std10 <- store$c1[store$iter,i] - ema10
31      std20 <- store$c1[store$iter,i] - ema20
32      std30 <- store$c1[store$iter,i] - ema30
33      std100 <- store$c1[store$iter,i] - ema100
34
35      # Long enter when the volatility is getting smaller and in the down trend
36      if((std5<std10) &
37          (std10<std20) &
38          (std20<std30) &
39          (std30<std100) &
40          (std5 < 0)){
41        pos[i] <- params$posSizes[i]
42
43        # Long exit when direction turned up
44        if((currentPos[i] > 0)
45           & (ema5 >= 0)){
46          pos[i] <- 0
47        }
48      }
49    }
50    marketOrders <- marketOrders + pos
51    return(list(store=store,marketOrders=marketOrders,
52               limitOrders1=allzero,limitPrices1=allzero,
53               limitOrders2=allzero,limitPrices2=allzero))
54 }
```

## 2.2.6 BBands based Strategy (Mean-reversion)

BBands will be used as the basic signal to decide long (short) on contract whenever the close is below (above) the lower (upper) Bollinger Band of the close due to the statistical facts of data distribution given different confidence levels. Meanwhile, after breakthroughs the 'reasonable' range, returning to a short-term average price is expected in this idea which is different from the sample strategy.

```
1 # main strategy
2 getOrders.bb<- function(store, newList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newList,params$series)}else{
9     store <- updateStore(store, newList, params$series)
10   }
11
12   # init today's enter positions on each series
13   pos <- allzero
14
15   # default exit yesterday's overall positions
16   marketOrders <- -currentPos
17
18   # we need to wait until Lookback to get the bbands signal
19   if (store$iter > params$lookback){
20     for (i in params$series){
21       # calculate everyday bbands upper/Lower bounds
22       up <- last(BBands(store$cl[1:store$iter,i], sd=params$sdParam)[,3])
23       dn <- last(BBands(store$cl[1:store$iter,i], sd=params$sdParam)[,1])
24
25       # everyday re-calculate today's ma30
26       sma30 <- last(SMA(store$op[1:store$iter,i],30))
27
28       # Long enter when cross the upper bound
29       if(store$cl[store$iter, i] > up){
30         pos[params$series[i]] <- -params$posSizes[i]
31
32         # short enter when cross the Lower bound
33       } else if(store$cl[store$iter, i] < dn){
34         pos[params$series[i]] <- params$posSizes[i]
35       }
36
37       if(currentPos[i] > 0){ # when in Long position
38         # Long hold when not reach MA
39         if ((pos[params$series[i]] > 0) |
40             (store$cl[store$iter, i] > sma30)){
41           pos[params$series[i]] <- currentPos[i]
42           next
43         }
44
45       }else if (currentPos[i] < 0){ # when in short position
46         # short hold when not reach MA
47         if ((pos[params$series[i]] < 0) |
48             (store$cl[store$iter, i] < sma30)){
49           pos[params$series[i]] <- currentPos[i]
50           next
51         }
52       }
53     }
54   }
55   marketOrders <- marketOrders + pos
56   return(list(store=store,marketOrders=marketOrders,
57             limitOrders1=allzero,limitPrices1=allzero,
58             limitOrders2=allzero,limitPrices2=allzero))
59 }
```

## 2.2.7 BBands based Strategy (Trend-following)

BBands will be used in trend following strategy to decide short(long) on contract whenever the close is below(above) the lower(upper) Bollinger Band of the close due to the belief that small probability cases happen with reason. When price breakthrough their 'reasonable' ranges, this trend will be continued. But unlike sample strategy, we set an exit condition where new close price is no longer the new highest/lowest then we will exit our positions.

```
1 # main strategy
2 getOrders.bb<- function(store, newRowList, currentPos, info, params){
3   # used for initializing vectors
4   allzero <- rep(0,length(newRowList))
5
6   # init store
7   if (is.null(store)) {
8     store <- initStore(newRowList,params$series)}else{
9     store <- updateStore(store, newRowList, params$series)
10   }
11
12   # init today's enter positions on each series
13   pos <- allzero
14
15   # default exit yesterday's overall positions
16   marketOrders <- -currentPos
17
18   # we need to wait until Lookback to get the bbands signal
19   if (store$iter > params$lookback){
20     for (i in params$series){
21       # calculate everyday bbands upper/lower bounds
22       up <- last(BBands(store$cl[1:store$iter,i], sd=params$sdParam)[,3])
23       dn <- last(BBands(store$cl[1:store$iter,i], sd=params$sdParam)[,1])
24
25       # Long enter when cross the upper bound
26       if(store$c1[store$iter, i] > up){
27         pos[params$series[i]] <- params$posSizes[i]
28
29       # short enter when cross the lower bound
30       } else if(store$c1[store$iter, i] < dn){
31         pos[params$series[i]] <- -params$posSizes[i]
32       }
33
34       if(currentPos[i] > 0){ # when in long position
35         # hold when still in the long trend
36         if ((pos[params$series[i]] > 0) |
37             (store$c1[store$iter, i] > store$c1[store$iter-1, i])){
38           pos[params$series[i]] <- currentPos[i]
39           next
40         }
41
42       }else if (currentPos[i] < 0){ # when in short position
43         # hold when still in the short trend
44         if ((pos[params$series[i]] < 0) |
45             (store$c1[store$iter, i] < store$c1[store$iter-1, i])){
46           pos[params$series[i]] <- currentPos[i]
47           next
48         }
49       }
50     }
51   }
52   marketOrders <- marketOrders + pos
53   return(list(store=store,marketOrders=marketOrders,
54             limitOrders1=allzero,limitPrices1=allzero,
55             limitOrders2=allzero,limitPrices2=allzero))
56 }
```

## 2.3 Preliminary Strategy Performance

In the following analysis, we aim to find the best indicators and strategies.

No parameter optimization techniques will be used in the following analysis because we solely want to see if our plain trading ideas work in the easiest way.

### 2.3.1 Indicator Analysis

Different alternative indicators will be tested in the following steps.

#### 2.3.1.1 Triple Moving Average Strategy

Part 1 day 1-500 with 0.2 slippage

Indicator/Slippage	PD ratio	PnL	Activeness
SMA	-29037.53	-29037.53	77%
VWAP	-41863.15	-41863.15	78%
EMA	-86263.66	-86263.66	79%
Rolling Median	-62488.88	-62488.88	76%

Part 1 day 1-500 without slippage

Indicator/Slippage	PD ratio	PnL	Activeness
SMA	1.23	53237.92	77%
VWAP	0.97	40088.46	78%
EMA	0.09	7343.56	79%
Rolling Median	-15972.56	-15972.56	76%

#### 2.3.1.2 Relative Strength Strategy

Part 1 day 1-500 with 0.2 slippage

Indicator/Slippage	PD ratio	PnL	Activeness
Stochastic Oscillator	-83609.15	-83609.15	27%
SMI30	0.71	51440.48	27%
SMI100	1.1	97236.07	27%
ADX30	-42865.13	-42865.13	27%
ADX100	-63516.43	-63516.43	27%
Momentum	-36916.8	-36916.8	27%
Triple Exponential Moving Average30	0.37	51218.15	27%
Triple Exponential Moving Average40	0.66	83840.37	27%
RSI30	-64204.87	-64204.87	27%
RSI100	0.69	107325.94	27%

### Part 1 day 1-500 without slippage

Indicator/Slippage	PD ratio	PnL	Activeness
Stochastic Oscillator	-83609.15	-83609.15	27%
SMI30	0.71	51440.48	27%
SMI100	1.1	97236.07	27%
ADX30	-42865.13	-42865.13	27%
ADX100	-63516.43	-63516.43	27%
Momentum	-34969.65	-34969.65	27%
Triple Exponential Moving Average30	0.37	51218.15	27%
Triple Exponential Moving Average40	0.66	83840.37	27%
RSI30	-64204.87	-64204.87	27%
RSI100	0.69	107325.94	27%

#### **2.3.1.3 Market Making Strategy**

No alternative indicators for this strategy yet.

#### **2.3.1.4 The Jump Trading Strategy**

This strategy does not trigger any transactions.

#### **2.3.1.5 Lawrence Macmillan Volatility Trading System**

Using EMA, ATR and Spread to represent volatility are completely different in nature. Thus, their performance cannot simply compare. We will explore it with different enter logic further in Part 2. (See Appendix E)

#### **2.3.1.6 BBands based Strategy (Mean-reversion)**

### Part 1 day 1-500 with 0.2 slippage

Indicator/Slippage	PD ratio	PnL	Activeness
SMA	-58218.8	-58218.8	28%
VWAP	-45318.14	-45318.14	51%
EMA	-58218.8	-58218.8	28%
Rolling Median	-18312.19	-18312.19	89%

### Part 1 day 1-500 without slippage

Indicator/Slippage	PD ratio	PnL	Activeness
SMA	-43300.78	-43300.78	28%
VWAP	-30351.83	-30351.83	51%
EMA	-43300.78	-43300.78	28%
Rolling Median	-9254.32	-9254.32	89%

### 2.3.1.7 BBands based Strategy (Trend-following)

No alternative indicators for this strategy yet.

### 2.3.2 Strategy Comparable Analysis

In order to test our strategy objectively, comparable analysis will be implemented among strategies and benchmark which have been given in Lecture 226 as sample strategies.

Because parameters in the sample strategies have been optimized, in the following comparable analysis, wager for each strategy, each series and each enter point will be re-adjusted to the same as 1 unit of series per time. Also, all strategies (11 sample and 7 ours) trading with 10 series over time. (See Appendix F)

Part 1 day 1-500 with 0.2 slippage and 1 unit fixed wager

Strategy/Performance Measurement	PD Ratio	PnL	Activeness
Bankrupt	-1184169.61	-1184169.61	2%
BBands contrarian	-24.12	-24.12	75%
BBands holding period	-28.22	-28.22	86%
BBands trend following	-7.1	-7.1	78%
Big spender	-58873.53	-58873.53	100%
Copycat	-194.39	-194.39	100%
Extreme limit	-7539.21	-7539.21	0
Fixed (buy & hold)	-275.63	-275.63	100%
Random	3.64	138229.89	100%
Rsi contrarian	-3.94	-3.94	3%
Simple limit	-1188.76	-1188.76	100%
Triple moving average Strategy (with SMA5/30/100)	-66.72	-66.72	77%
Relative strength Strategy (with MTM365)	-70.22	-70.22	27%
Market making Strategy (no indicator)	4.47	18.29	67%
The Jump Trading Strategy (with EMA5)	0	0	0
Lawrence Macmillan Volatility Trading System (with SD5/10/20/30/100)	-99.21	-99.21	34%
BBands based Strategy (Mean-reversion) (with SMA30)	-18.9	-18.9	27%
BBands based Strategy (Trend-following) (with no indicator)	-40.4	-40.4	32%

Part 1 day 1-500 without slippage and 1 unit fixed wager

Strategy/Performance Measurement	PD Ratio	PnL	Activeness
Bankrupt	-1626623.2	-1626623.2	2%
BBands contrarian	-22.81	-22.81	92%
BBands holding period	0.29	14.94	86%
BBands trend following	0.07	3.68	86%

Big spender	-58483.06	-58483.06	100%
Copycat	0.35	68.71	100%
Extreme limit	-7539.21	-7539.21	0
Fixed (buy & hold)	-267.59	-267.59	100%
Random	-125498.86	-125498.86	100%
RSI contrarian	-2.63	-2.63	3%
Simple limit	-1182.18	-1182.18	100%
Triple moving average Strategy (with SMA5/30/100)	0.14	19.57	77%
Relative strength Strategy (with MTM365)	-70.16	-70.16	27%
Market making Strategy (no indicator)	4.52	18.36	67%
The Jump Trading Strategy (with EMA5)	0	0	0
Lawrence Macmillan Volatility Trading System (with SD5/10/20/30/100)	-58.26	-58.26	34%
BBands based Strategy (Mean-reversion) (with SMA30)	0.3	6.45	27%
BBands based Strategy (Trend-following) (with no indicator)	-17.23	-17.23	32%

In part 2, we will also explore the winning rate, losing rate, winning times, losing times, triggering times and odds for each strategy for each series further due to the complexity of coding.

```

1 # example parameters setting in our benchmark strategies
2 example_params <- list(
3   "fixed"=list(sizes=rep(1,10)),
4   "big_spender"=list(sizes=rep(1,10)),
5   "bankrupt"=list(leverage=40000000),
6   "copycat"=NULL,
7   "random"=list(maxLots=100),
8   "rsi_contrarian"=list(lookback=10,threshold=25,series=1:10),
9   "bbands_contrarian"=list(lookback=20,sdParam=1.5,series=1:10, poss
  izes=rep(1,10)),
10  "bbands_trend_following"=list(lookback=50, sdParam=1.5, series=1:1
  0, posSizes=rep(1,10)),
11  "bbands_holding_period"=list(lookback=50, sdParam=1.5, series=1:10,
  posSizes=rep(1,10),holdPeriod=6),
12  "simple_limit"=list(spreadPercentage=0.001,inventoryLimits=rep(10,
  10)),
13  "extreme_limit"=list(spreadPercentage=0.001,inventoryLimits=rep(1
  0,10)))
14 )

```

## **3 Risk management**

### **3.1 Position sizing**

#### **3.1.1 Wager strategy**

##### **3.1.1.1 Fixed Size wager (benchmark)**

By assigning fixed size wager for each series for each bet, we can get a fair performance benchmark in the simplest way.

##### **3.1.1.2 Performance based weighted average size wager (benchmark)**

Similar to 3.1.1.1, we can re-allocate our money depending on the PD ratio or PnL of our strategy on each series.

For instance, we have 2 series and first time we allocate 50/50 wager equally in them. After a month, we observed that 1 series make \$500 profit in total, but the other one only makes \$30 so that we can re-allocate  $500 / (500+30) = 94.33\%$  of our balance in the first series and put the rest in the other series.

##### **3.1.1.3 Volatility based weighted average size wager (benchmark)**

The idea of volatility-based wager strategy solely introduce volatility into consideration. From data analysis, there is huge volatility in several series in OHLCV which related to the profitability of volatility-based trading strategies. Besides, more volatility often means more price changes in short-term which is in nature beneficial to almost all trading ideas.

##### **3.1.1.4 Kelly formula (Optimal Position)**

In short, here are the pros and cons about the implementation of this formula in reality:

Pros:

1. Maximizing profit in the long term.
2. Without bankruptcy concerns.

Cons:

1. Need to re-balance on a regular basis which will cost slippage.
2. Optimal positions may not meet in the real world due to the equation assumes that money and gambling are infinitely divisible.
3. Hard to decide on the frequency of re-balance.

This strategy will be tried in our cross-strategy and cross-series level wager strategies. Firstly, Part 1 in-sample data will be used to find respective winning and losing probability and the expected amount gained with a win and a loss at each series.

Secondly, the optimal positions derived from the formula will be put in the strategies in the Part 1 out-of-sample data.

Thirdly, optimal weights in each series and each strategy will be re-calculated per 30 days. If the next optimal positions change more than 10% than its previous positions, then positions will be re-assigned at cross-strategy and cross-series level. 10% rule is introduced by industry to avoid over frequently changing positions might lose more trading cost.

### **3.1.1.5 Martingale**

By setting fairly small wager for each trade in the beginning, we are able to use Martingale strategy. For example, when triggering enter point, we put in \$1. If we lose, we double our wager to \$2 in the next triggering enter point until winning. After winning once, our wager return to the initial amount.

Here are the pros and cons of the implementation of this strategy:

Pros:

When one wins (each time is considered a 100% win/loss of the bet), not only will he recover the previous loss, but he will also gain the total amount of the first bet. Assuming that one has an infinite amount of money, the strategy must be able to achieve its purpose.

Cons:

1. The average trading cost after the second entry will be higher than the current market price.
2. Small short-term profits will be followed by the possibility of large losses
3. Potentially unlimited loss.
4. No stop-loss positions, account losses and then re-enter the positions.
5. Floating losses can cause problems with allocating funds throughout the portfolio.

### **3.1.1.6 Reversed Martingale**

In contrast to martingale, Reversed Martingale is to double the wager every time you win until you return the wager to the initial unit when there is a loss. In theory this strategy is more suitable for use in trend strategy, as trading with the trend has a high winning rate.

Here are the pros and cons of the implementation of this strategy:

Pros:

1. The average trading cost after the second entry will be lower than the current market price.
2. Small short-term losses will be followed by the possibility of large profits.
3. Potential unlimited profit.
4. Have a stop-loss position and will not add to it after a loss.

Cons:

The floating profit will help the whole portfolio allocate funds loosely.

### **3.1.2 Capital Utilization Rate**

By calculating the time spent by the strategy on each series position, we can get the strategy's capital utilization rate on each series.

In part 2, capital utilization analysis will implement to measure the performance of strategy.

### **3.1.3 Leverage rate**

As mentioned in 2.1, leverage can bring more profit or more risks into our portfolio, so further exploration on leverage effect is needed in part 2.

Here are the pros and cons of leverage:

Pros:

1. Leveraged investments allow investors to invest high amounts of money in the market with less capital, which greatly saves on transaction costs and especially improves capital utilization rate
2. With the use of leverage, the profit result will increase exponentially if they make a profit

Cons:

1. The greater the leverage used, the greater the percentage of position, and the greater the probability that the portfolio will experience losses and bankruptcy if judgment is faulty.

Therefore, different levels of leverage rate will be tested in Part 2 to utilize this tool but with the minimal probability of brokerage.

## 3.2 Risk Control

### 3.2.1 Stop Gain

The 5 most common take-profit strategies will be tested in Part 2 as listed:

1. Valuation Take Profit Strategy
2. Annualised Return Take Profit Strategy
3. Enhanced Annualised Return Stop Out Method
4. Split Take Profit Strategy
5. Retracement/peak-right take-profit

### 3.2.2 Stop Loss

Like stop gain, there are also 11 most common ways of setting stop loss triggering points listed and will be tested:

1. Chandelier stop loss
2. YOYO Stops
3. ATR indicator in the application of stop loss
4. Time Stops
5. Time + Spread Ladder Stops
6. Capital preservation
7. Support/pressure levels
8. Trailing Stops
9. Ladder Stops
10. Spread Stop Loss
11. Limit Stops/Stop Losses

### 3.2.3 VaR

Historical method of VaR will be tested in Part 2, which looks at previous earnings history and ranks them in order from greatest loss to greatest gain.

```
1 # VaR control to prevent extreme cases happen
2 # Calculate returns
3 rtn<- diff(log(store$cl[1:store$iter,which(params$series==i)]))
4 if(VaR(rtn,p=0.99)>0.05){
5   marketOrders[i] <- marketOrders[i]
6   next
7 }
```

### 3.2.3 ES (Expected Shortfall)

ES is a more practical method than VaR across investment industry, so it will also be tried in Part 2.

### **3.2.4 Holding Period**

Like 3.1.2, a holding period limit can prevent one strategy having a low capital utilization rate but taking up most of positions. In addition, the average profitable periods can be calculated in each trade, so a reasonable holding period can be calculated like the concept of duration.

### **3.3 Strategy Exit Mechanism**

A real-time monitor for the performance of our strategies by setting strategy exit mechanism is needed. For example, limit the maximum drawdown to less than 20%, if this limit has been broken, then stop trading. However, this kind of mechanism may also affect the activity level of strategy which need to be further analyzed in Part 2.

### **3.4 Liquidity Assessment**

Due to investment duration constraints, there may be days when all trades cannot be satisfied at the same time, and it is necessary to evaluate the priority of all trades on the same day as which ones should be satisfied more and which ones can be cancelled. What's more, due to the existence of leverage, to prevent the occurrence of extreme risk, it is necessary to keep a certain amount of cash. But keeping too much cash will not enable us to maximize profits. In Part 2 we will explore the relationship between cash, profit and risk.

## **4 Plan**

1. With part 1 of the data, the performance of strategy on the in-sample data will be utilized to optimize parameters, parameter approximation and find the best performance indicators
2. Using the out-of-sample data to test and optimize our indicators, trading mechanisms and parameters
3. Rolling window method will be implemented to check strategy performance across time to check if performance of portfolio swings rapidly
4. Meanwhile, other methods like simulation that randomizing different factors will also be tried. The most stable, robust and superior parameter, series for each strategy and indicator will be chosen eventually.
5. Part 2 data will be used to verify the out-of-distribution performance and robustness of mix portfolio. If performance finally goes bad, trading ideas will be back to factory and do root cause analysis part by part.

## 4.1 Parameter Optimization

### 4.1.1 Grid Search

Grid Search is solely using violent search for every possibility of parameter set that we put in like an example code below.

```
1 # grid search with cross validation -----
2
3 # insample series
4 # the first 500 rows of data in dataList
5 insample<- lapply(dataList, function(x) x[1:500,])
6
7 # RSI trading parameters Optimization
8 # (n & lev)
9 sMult <- 0.2 # slippage multiplier
10 nSeq<- c(12,14,16,18,20,22,24,26,28)
11 levSeq <- c(10,15,20,25,30,35,40)
12 paramsList<- list(nSeq, levSeq)
13 numberComb <- prod(sapply(paramsList,length))
14
15 resultsMatrixRSI <- matrix(nrow=numberComb,ncol=3)
16 colnames(resultsMatrixRSI) <- c("n","lev","PD Ratio")
17 pfolioPnLlist <- vector(mode="list",length=numberComb)
18
19 count <- 1
20 for (n in nSeq) {
21   for (lev in levSeq) {
22     INparams.rsi<- list(lookback=33, series=1:10,posSizes=rep(0.01,10),n=n,lev=le
v ) # tbd
23     results <- backtest(insample, getOrders.RSI, INparams.rsi, sMult)
24     pfolioPnL <- plotResults(insample,results)
25     resultsMatrixRSI[count,] <- c(n,lev,pfolioPnL$fitAgg)
26     pfolioPnLlist[[count]]<- pfolioPnL
27     cat("Just completed",count,"out of",numberComb,"\n")
28     print(resultsMatrixRSI[count,])
29     count <- count + 1
30   }
31 }
32 INn<- resultsMatrixRSI[order(resultsMatrixRSI[, "PD Ratio"] ),][nrow(resultsMatrixR
SI),1]
33 INlev<- resultsMatrixRSI[order(resultsMatrixRSI[, "PD Ratio"] ),][nrow(resultsMatri
xRSI),2]
```

### 4.1.2 Evolutionary Algorithms

By setting a target like PD Ratio of our portfolio and running simulations with different random combinations of parameter. In each epoch, we drop the combination with the worst performance valued by our pre-set target. After several epochs, the algorithm will be stopped and select the Top-K combinations. But the result of the best combination is highly sensitive to the functions we selected.

### 4.1.3 Rolling Window Method

This is a process for testing a trading strategy by finding its optimal trading parameters in the in-sample time period and checking the performance of those parameters across the out-of-sample time period.

```
1 # rolling window method
2 window <- 200
3 int1 <- 50
4 i = 0
5 resagg <- NULL
6 outdta <- outSample
7 while((i+window) < nrow(outdta[[1]])){
8   ddata <- lapply(outdta, function(x) x[(i+1):(i + window),])
9   test <- backtest(ddata, getOrders.bb, params.bb, sMult=0.2)
10  pfolioPnL <- plotResults(ddata, test, plotType='ggplot2')
11  perf <- pfolioPnL$fitAgg
12  resagg<- c(resagg, perf)
13  i <- i+int1
14 }
15 plot(resagg,type="l")
16 title(c('pd ratio of cumulative pnl over period'))
```

## 4.2 Parameter Approximation

### 4.2.1 Bisection Method

Bisection method will be implemented to find the reasonable range of parameters. First, 2 numbers of one parameter will be selected and test the strategy performance. Afterwards, a new greater/smaller number than the previous one that has better performance which is in our favor. And iterate this process many times until the performances are relatively stable so that we can know the proper range of that parameter.

### 4.2.2 Newton-Raphson Method

Like Bisection Method, but Newton-Raphson Method is solely much quicker. So, if our computation power is not enough, we will try this method.

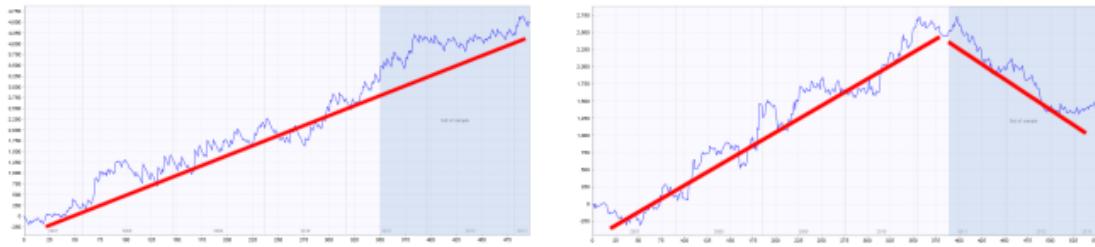
## 4.3 Market Condition Identification and Signal Filtering

There are many anomalies in OHLCV and indicators as graph 3 showed. For preventing uncertain market conditions, a proper range of OHLCV need to be established. Secondly, strategies only work in certain periods. Strategy can perform completely differently in such as bull and bear market. Thus, in part 2, we will further analyze data about the basics and indicators to find their mutual patterns or common behaviors to identify different market conditions.

## 4.4 Robustness Testing

### 4.4.1 Make use of In Sample and Out of Sample periods

The most basic test for robustness is testing the strategy on out-of-sample data. If we run genetic evolution, the strategy is evolved only on the In-sample part of data. The out-of-sample part is “unknown” to the strategy, so it can be used to determine if the strategy performs also on unknown part of data.



The blue part of each chart is the Out of Sample (unknown) data., We can see that the strategy on the left performs well also on this part, while strategy on the right fails on the unknown data – it is almost certain to be over-fitted.

### 4.4.2 Test strategy on multiple symbols

Second test for robustness is very tough – it means testing the same strategy on different symbol(s). Robust strategy should ideally work on multiple symbols.

In reality, because each market has its own characteristics, daily volatility, etc., it will be not easy to find a strategy that has the same perfect performance on multiple symbols using just one set of settings.

We can be satisfied if the strategy performs on other markets with at least some degree of profitability, or just slightly losing.

### 4.4.3 Monte-Carlo method

This simply repeatedly tests the strategy with different random changes in the input parameters and data performing Monte Carlo simulation.

The idea behind this robustness testing is to verify how well the strategy performs when there are small changes in inputs, history data or other components of the strategy.

For instance, we can randomize several factors that might affect the performance of our strategy:

1. Randomize Trades Order
2. Randomly Skip Trades

3. Randomize Trades Type (market order/limit order)
4. Randomize Starting trade day
5. Randomize Strategy Parameters
6. Randomize History Data (by adding noise)

#### **4.4.4 Use Rolling-Window Matrix as a robustness test**

As mentioned in section 4.1.3, if the strategy passes this test, it means that with the help of parameter re-optimization it is adaptable to a wide range of market conditions.

## **5 Breakdown of teamwork**

*Shuying Zhai*

1. Consulted relevant information on statistical tests and indicators;
2. Analysed the trend and volatility of the high and low prices of each series;
3. Conducted preliminary analysis using rolling median and open to open difference methods;
4. Analysed each indicator in momentum and mean reversion;
5. Designed the relative strength strategy, Bbands based Strategy, Jump Trading Strategy and Market Making Strategy;
6. Prepared design reports.

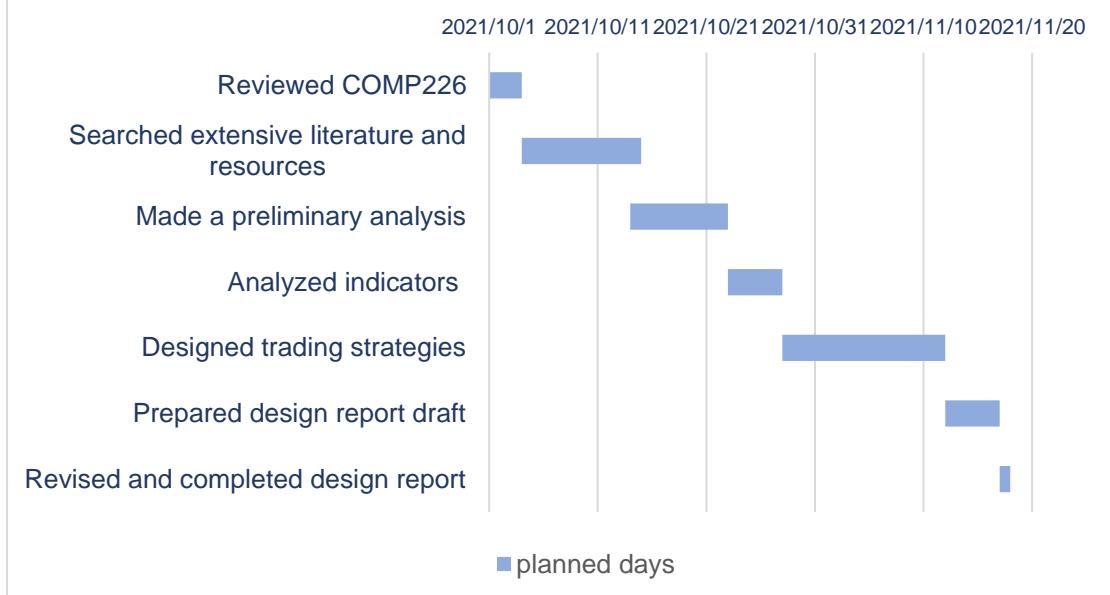
*Yushan Zhang*

1. Reviewed relevant information on trading strategies and indicators;
2. Analyzed the trend and volatility of the opening price and volume of each series;
3. Conducted preliminary analysis using overnight gap, VWAP and other methods;
4. Analysed the indicators in trend trading;
5. Designed the relative strength strategy, Bbands based Strategy, The Jump Trading Strategy and Market Making Strategy;
6. Prepared design reports.

*Chia-Wei Liu*

1. Reviewed relevant information on parameter optimization and risk control;
2. Analyzed the trend and volatility of the closing price of each series;
3. Conducted preliminary analysis using EMA, SMA, daily spread, and other methods;
4. Analysed each indicator in volatility;
5. Designed the Triple moving average Strategy, Lawrence Macmillan Volatility Trading System and Market Making Strategy;
6. Prepared design reports.

## Design Report Schedule



(Count: 4660 words)

## 6 References

- Zach, V., 2021. *Augmented Dickey-Fuller Test in R (With Example)*. [online] Statology. Available at: <<https://www.statology.org/dickey-fuller-test-in-r/>> [Accessed 15 November 2021].
- Quantstart.com. *Johansen Test for Cointegrating Time Series Analysis in R | QuantStart*. [online] Available at: <<https://www.quantstart.com/articles/Johansen-Test-for-Cointegrating-Time-Series-Analysis-in-R/>> [Accessed 15 November 2021].
- Otexts.com. 2018. *Chapter 8 ARIMA models | Forecasting: Principles and Practice (2nd ed)*. [online] Available at: <<https://otexts.com/fpp2/arima.html>> [Accessed 15 November 2021].
- School.stockcharts.com. *Technical Indicators and Overlays [ChartSchool]*. [online] Available at: <[https://school.stockcharts.com/doku.php?id=technical\\_indicators](https://school.stockcharts.com/doku.php?id=technical_indicators)> [Accessed 15 November 2021].
- Trading Technologies. *List of Technical Indicators | Trading Technologies*. [online] Available at: <<https://www.tradingtechnologies.com/xtrader-help/x-study/technical-indicator-definitions/list-of-technical-indicators/>> [Accessed 15 November 2021].
- Tradingsim. 2021. *How to Day Trade with the Triple Exponential Moving Average (TEMA)*. [online] Available at: <<https://tradingsim.com/blog/triple-exponential-moving-average/>> [Accessed 15 November 2021].
- Faber, M., 2010. *Relative Strength Strategies for Investing*. [online] Cambriainvestments.com. Available at: <<https://www.cambriainvestments.com/wp-content/uploads/2018/01/Relative-Strength-Strategies-for-Investing.pdf>> [Accessed 15 November 2021].
- Singh, D., 2017. *Moving Average Trading Strategies*. [online] Blog.quantinsti.com. Available at: <<https://blog.quantinsti.com/moving-average-trading-strategies/>> [Accessed 15 November 2021].
- Xiong, Y., Yamada, T. and Terano, T., 2015. *COMPARISON OF DIFFERENT MARKET MAKING STRATEGIES FOR HIGH FREQUENCY TRADERS*. [online] Informs-sim.org. Available at: <<https://www.informs-sim.org/wsc15papers/027.pdf>> [Accessed 15 November 2021].
- McMillan, L., 2013. *Mcmillan on options*. Hoboken, N.J.: Wiley.
- Yoder, N., 2021. *The Kelly Criterion - Quantitative Trading*. [online] Nick Yoder. Available at: <<https://nickyoder.com/kelly-criterion/>> [Accessed 15 November 2021].

Forex Training Group. *Martingale and Anti-Martingale Trading Strategies - Forex Training Group*. [online] Available at: <<https://forextraininggroup.com/martingale-and-anti-martingale-trading-strategies/>> [Accessed 15 November 2021].

Engineering Education (EngEd) Program | Section. 2021. *Using Grid Search to Optimize Hyperparameters*. [online] Available at: <<https://www.section.io/engineering-education/grid-search/>> [Accessed 15 November 2021].

BRIE, L., GENEST, B. and ARSAC, M., 2021. [online] Chappuishalder.com. Available at: <[https://chappuishalder.com/wp-content/uploads/2020/02/Whitepaper-ES-BT\\_GRA\\_Vdef\\_20180402\\_LON\\_.pdf](https://chappuishalder.com/wp-content/uploads/2020/02/Whitepaper-ES-BT_GRA_Vdef_20180402_LON_.pdf)> [Accessed 15 November 2021].

Dawson, T., 2017. Top Gambling Strategies That Could Help You Win More Often. [online] Legitgamblingsites.com. Available at: <<https://www.legitgamblingsites.com/blog/betting-strategies-that-work-at-least-some-of-the-time/>> [Accessed 15 November 2021].

## Appendix A



Graph A.1: Open price graph

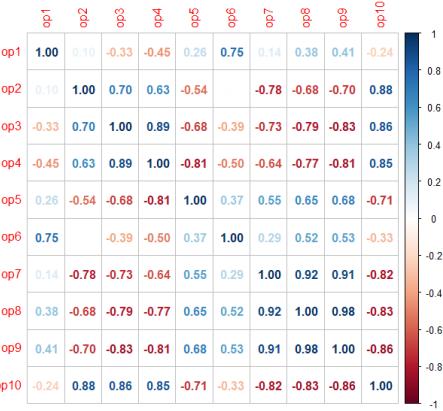


Graph A.2: Log open price graph

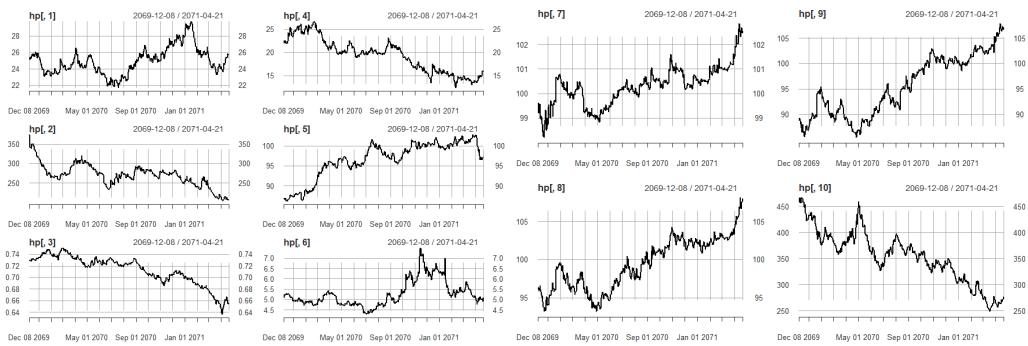
```
> basicstats(op)
   nobs      op1      op2      op3      op4      op5      op6      op7      op8
 500.000000 5.000000e+02 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
  NAS      0.000000 0.00000000
  Minimum 21.580000 1.982500e+02
  Maximum 29.650000 2.820000e+02
  1. Quartile 23.693000 2.519375e+02
  3. Quartile 25.625000 2.820000e+02
  Mean 24.650000 2.734900e+02
  Median 24.650000 2.695000e+02
  Sum 12391.370000 1.337423e+03
  SE Mean 24.639407 2.649907e+02
  LCL Mean 24.621557 2.649907e+02
  UCL Mean 24.647250 2.649907e+02
  Variance 8.75938 8.689889e+02
  StdDev 2.954380 2.954380e+01
  Skewness -0.493210 0.920215
  Kurtosis 0.223414 7.374890e-01
  op9      op10
 500.000000 500.000000
  NAS      0.000000 0.00000000
  Minimum 85.317500 246.750000
  Maximum 120.500000 357.500000
  1. Quartile 89.585975 321.250000
  3. Quartile 100.257800 383.250000
  Mean 94.609400 357.500000
  Median 94.609400 357.500000
  Sum 47500.624800 175432.750000
  SE Mean 94.621557 346.536033
  LCL Mean 94.621557 346.536033
  UCL Mean 94.621557 346.536033
  Variance 34.179913 247.985165
  StdDev 5.846359 49.729118
  Skewness -0.104917 -0.872998
  Kurtosis -1.324605 -0.443109
```

```
> scale_op<-scale(op)
> basicstats(scale(op))
   nobs      op1      op2      op3      op4      op5      op6      op7      op8      op9      op10
 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
  NAS      0.000000 0.00000000
  Minimum -1.958114 -2.438866e-3 -3.147382 -2.032201 -2.311638 -1.687492 -2.807477 -2.023404 -1.680428
  Maximum 2.388437 3.787313 1.547381 2.082673 1.416174 3.370769 3.044084 2.585163 2.120208
  1. Quartile 0.512438 0.511300 0.734139 0.629349 0.781002 0.566215 0.879266 0.876193
  3. Quartile 0.512438 0.511300 0.734139 0.629349 0.781002 0.566215 0.879266 0.876193
  Mean 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
  Median 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
  Sum 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
  SE Mean 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721
  LCL Mean 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721
  UCL Mean 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865 0.087865
  Variance 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
  StdDev 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
  Skewness 0.565977 0.100550 -0.872998 0.042221 1.047088 0.067581 -0.00606 0.061656
  Kurtosis 0.223414 0.737489 0.126498 -1.002581 -0.224933 0.555945 0.428475 -0.997450 -1.324050
  op9      op10
 500.000000 500.000000
  NAS      0.000000 0.00000000
  Minimum -2.034427
  Maximum 2.314429
  1. Quartile -0.6501368
  3. Quartile 0.512354
  Mean 0.000000
  Median 0.000000
  Sum 0.000000
  SE Mean 0.044721
  LCL Mean -0.044721
  UCL Mean 0.087865
  Variance 1.000000
  StdDev 1.000000
  Skewness -0.104917
  Kurtosis -0.443109
```

Figure A.3: Basic statistical data of open price



Graph A.4: Correlation graph of open price



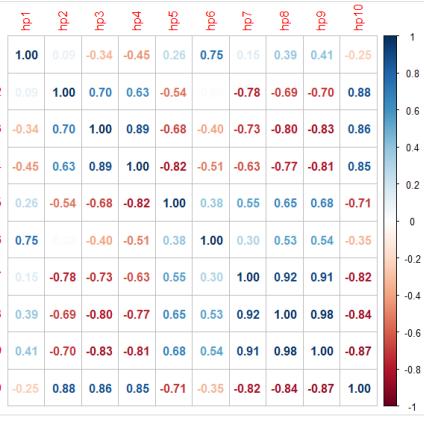
Graph A.5: High price graph



Graph A.6: Log high price graph

> basicStats(hp)										> Loghp<-log(hp)									
nobs	500,000000	5,000000e+02	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000	nobs	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000	500,000000
NAs	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	NAs	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000
Minimum	21,700000	2,037500e+02	0,618300	12,350000	86,139000	4,285000	98,201102	93,218803	102,190000	Minimum	3,198300	3,750000e+02	0,751200	26,740000	102,867203	108,156197	5,395515	5,926926	-0,286083
Maximum	29,830000	3,750000e+02	0,751200	26,740000	7,500000	100,700000	100,700000	100,700000	100,700000	Maximum	3,198300	3,750000e+02	0,751200	26,740000	102,867203	108,156197	5,395515	5,926926	-0,286083
1. Quartile	23,295000	2,847500e+02	0,731423	21,573000	100,250000	5,476250	100,742203	102,312500	102,312500	1. Quartile	3,171784	5,543711	-0,358713	2,760010	4,534561	1,573811	4,603568	4,688915	4,683176
3. Quartile	25,822500	2,847500e+02	0,731423	21,573000	100,250000	5,476250	100,742203	102,312500	102,312500	3. Quartile	3,216165	5,593076	-0,339065	2,944199	4,569636	1,650758	4,607942	4,598681	4,598681
Mean	24,985920	2,700775e+02	0,712883	19,345320	96,617820	5,276810	100,286011	99,409866	99,409866	Mean	3,213440	5,606721	-0,326908	2,988429	4,580075	1,631550	4,608524	4,598601	4,598601
Median	24,985920	2,700775e+02	0,712883	19,345320	96,617820	5,276810	100,286011	99,409866	99,409866	Median	3,213440	5,606721	-0,326908	2,988429	4,580075	1,631550	4,608524	4,598601	4,598601
Sum	124492,960000	1,350384e+03	356,443440	987,660000	48308,310000	2638,405000	50140,305702	49704,392949	16080,310000	16080,310000	279,860000	-18,000000	140,300000	210,300000	239,000000	229,000000	229,000000	229,000000	
SE Mean	0,074008	1,274189e+00	0,001117	0,163128	0,202098	0,027984	0,049195	0,149338	0,149338	st. Mean	0,002921	0,004078	0,001593	0,008625	0,002142	0,005049	0,003348	0,001503	
LCL Mean	0,074008	1,274189e+00	0,001117	0,163128	0,202098	0,027984	0,049195	0,149338	0,149338	LCL Mean	3,210426	5,583889	-0,342195	2,972733	4,565427	1,646883	4,607258	4,595728	4,595728
UCL Mean	25,131326	2,723809e+02	0,715078	19,665822	97,014887	5,331271	100,349250	99,702395	99,702395	UCL Mean	3,210426	5,583889	-0,342195	2,972733	4,565427	1,646883	4,607258	4,595728	4,595728
Variance	2,738616	3,137787e+02	0,000624	13,305338	20,421732	0,391553	0,610234	11,150935	11,150935	Variance	0,004266	0,011414	0,001269	0,037199	0,022995	0,017247	0,000068	0,001129	0,001129
StdDev	1,660000	1,772700e+01	0,000624	3,614221	4,462154	0,278562	0,770078	3,352104	3,352104	StdDev	0,065316	0,106836	0,036262	0,192872	0,047903	0,117901	0,007785	0,033606	0,033606
Skewness	0,579777	8,540200e-02	-0,849850	0,057444	-0,327626	0,108783	0,170078	0,028698	0,028698	Skewness	0,112000	0,351220	-0,153120	0,351220	0,101470	0,131263	0,579100	-0,993146	-0,993146
Kurtosis	0,214213	7,074170e-01	-0,039982	-1,012181	-0,212090	0,670524	0,616340	-0,954463	-0,954463	Kurtosis	-0,022356	0,554222	-0,198445	-1,049664	-0,101470	0,131263	0,579100	-0,993146	-0,993146
nobs	500,000000	500,000000								nobs	500,000000	500,000000							
NAs	0,000000	0,000000								NAs	0,000000	0,000000							
Minimum	0,000000	0,000000								Minimum	4,446648	4,446648							
Maximum	107,937500	2,723809e+02								Maximum	4,446648	4,446648							
1. Quartile	89,968800	325,300000								1. Quartile	4,499463	5,785359							
3. Quartile	104,980000	325,300000								3. Quartile	4,801621	5,806431							
Mean	95,489313	354,552100								Mean	4,553548	5,878492							
Median	94,968800	364,500000								Median	4,553548	5,878492							
Sum	477,600,0000	177,272,0000								Sum	2,988429	2,988429							
SE Mean	0,262748	2,448837								SE Mean	0,002753	0,006528							
LCL Mean	94,97085	350,134337								LCL Mean	4,551716	5,847825							
UCL Mean	107,937500	325,300000								UCL Mean	4,551716	5,847825							
Variance	34,518273	2528,184488								Variance	0,003788	0,021307							
StdDev	5,875725	50,281055								StdDev	0,061550	0,145968							
Skewness	0,067722	-0,109804								Skewness	0,058484	-0,424549							
Kurtosis	-1,307702	-0,469369								Kurtosis	-1,397028	-0,469660							

Figure A.7: Basic statistical data of high price



Graph A.8: Correlation graph of high price



Graph A.9: Low price graph



Graph A.10: Log low price graph

Figure A.11: Basic statistical data of low price



Graph A.12: Correlation graph of low price



Graph A.13: Close price graph



Graph A.14: Log close price graph

```
> basicStats(cp)
> basicStats(cp1)
> basicStats(cp2)
> basicStats(cp3)
> basicStats(cp4)
> basicStats(cp5)
> basicStats(cp6)
> basicStats(cp7)
> basicStats(cp8)
> basicStats(cp9)
> basicStats(cp10)

nobs      500.000000 5.00000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
NAS       0.000000 0.00000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Minimum   21.580000 3.675000e+02 634900 11.560000 4.185000 98.156197 92.843888
Maximum   29.560000 3.675000e+02 751100 26.560000 102.780000 102.623000 107.687500
1. Quartile 23.450000 3.675000e+02 751100 26.560000 102.780000 102.623000 107.687500
3. Quartile 25.830000 2.823125e+02 730900 21.382500 99.830000 5.397500 100.658173 102.156288
Mean      24.768600 2.674700e+02 712032 19.040280 96.346580 5.207682 100.217579 99.192940
Median    24.768600 2.674700e+02 712032 19.040280 96.346580 5.207682 100.217579 99.192940
Sum      12384.300000 1.337350e+05 396.015800 95.020000 4805.730000 5.397500 100.658173 102.156288
SE Mean   0.072221 1.265914e+00 0.001124 0.163148 0.020347 0.028644 0.034558 0.148977
LCL Mean  24.627412 2.469282e+02 0.001124 0.163148 0.020347 0.028644 0.034558 0.148977
UCL Mean  24.877750 2.469282e+02 0.001124 0.163148 0.020347 0.028644 0.034558 0.148977
variance  2.680643 8.012689e+02 0.000632 13.308329 0.360350 0.597121 0.1107962
Stdev     1.637267 2.830669e+01 0.021319 3.648050 4.479899 0.600254 0.777236 3.313225
skewness  -0.869750 24.664949 0.884899 -0.913974 1.018193 0.079111 0.0318187
kurtosis  0.225808 6.723150e-01 0.090137 -0.892365 0.545878 0.477747 -1.000527
cp9
cp10

nobs      500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
NAS       0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Minimum   85.125000 246.750000
Maximum   107.687500 246.750000
1. Quartile 95.164370 350.390000
3. Quartile 100.437500 382.250000
Mean      95.164370 350.390000
Median    94.537070 349.770000
Sum      47582.218700 171519.000000
SE Mean   0.262503 2.221103
LCL Mean  94.606049 348.111313
UCL Mean  95.680185 354.73867
Variance  34.453969 2466.649950
Stdev     5.869750 49.665380
skewness  -0.869750 24.664949
kurtosis  -1.321241 -0.450592

> scale_cp<-scale(cp)
> basicStats(scale_cp)
> basicStats(cp1)
> basicStats(cp2)
> basicStats(cp3)
> basicStats(cp4)
> basicStats(cp5)
> basicStats(cp6)
> basicStats(cp7)
> basicStats(cp8)
> basicStats(cp9)
> basicStats(cp10)

nobs      500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
NAS       0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Minimum   -1.947314 -2.401199 -3.068197 -2.050483 -2.291699 -1.703748 -2.667642 -1.905947 -1.710369
Maximum   2.307644 2.047211 1.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721
1. Quartile 0.664489 -0.548722 -0.560148 -0.964288 -0.354155 -0.729161 -0.549485 -0.920964 -0.934412
3. Quartile 0.526121 0.524346 0.750561 0.642046 0.777567 0.316229 0.570173 0.889540 0.898345
Mean      0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Median    0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Sum      0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
SE Mean   0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721 0.044721
LCL Mean  -0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863
UCL Mean  0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863 0.087863
Variance  1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
Stdev     1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
skewness  0.390000 0.000000 0.000000 -0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
kurtosis  0.225808 0.672315 0.090137 -0.892365 0.545878 0.477747 -1.000527 1.321241 -0.008583 0.542348

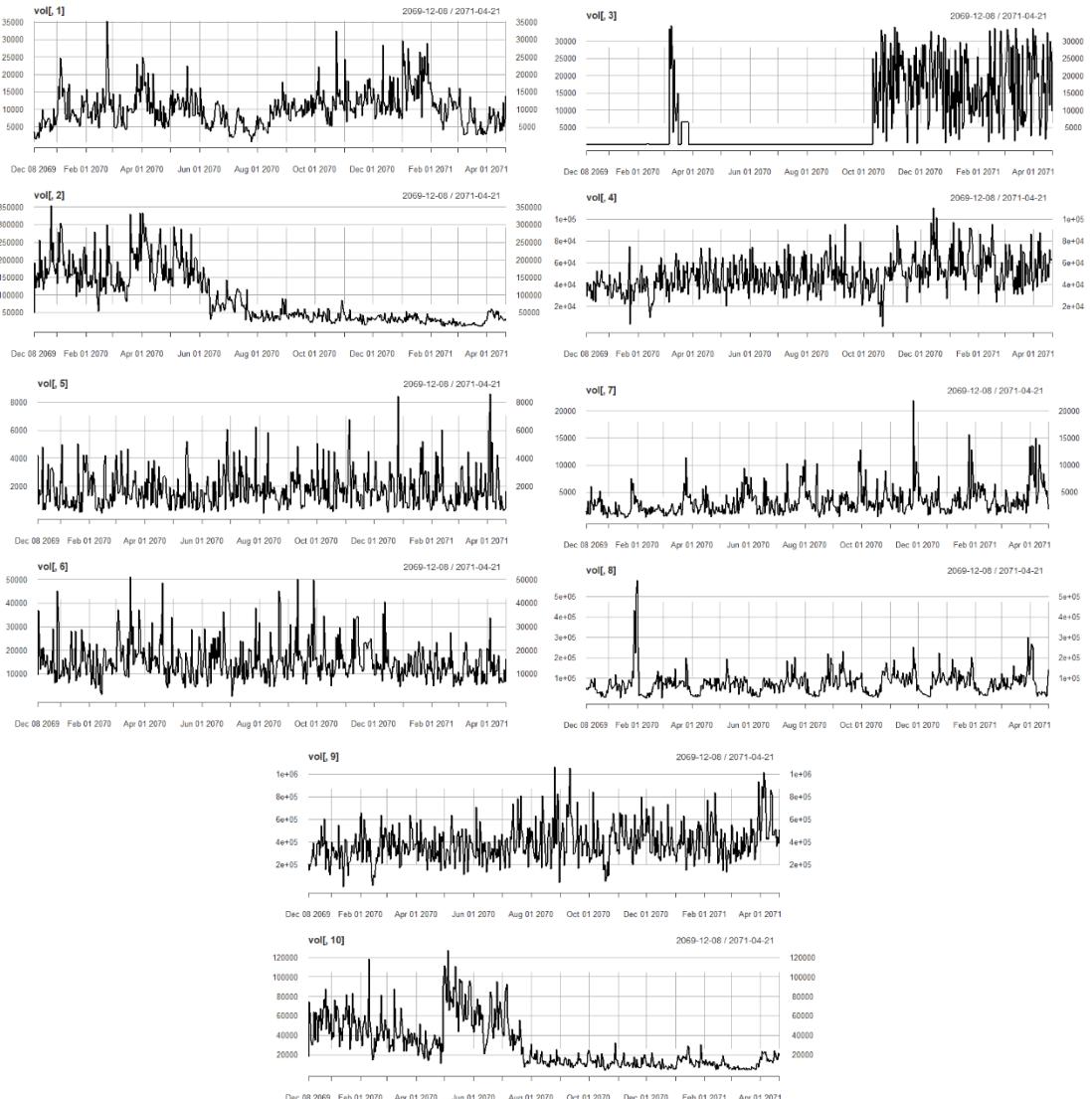
> scale_cp<-scale(log(cp))
> basicStats(log(cp))
> basicStats(cp1)
> basicStats(cp2)
> basicStats(cp3)
> basicStats(cp4)
> basicStats(cp5)
> basicStats(cp6)
> basicStats(cp7)
> basicStats(cp8)
> basicStats(cp9)
> basicStats(cp10)

nobs      500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000 500.000000
NAS       0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
Minimum   4.444121 5.508376
Maximum   5.386422 5.906723 -0.286216 3.281663 4.630448 1.985131 4.611082 4.679734
1. Quartile 3.186431 5.529179 -0.359608 2.742289 4.551147 1.562346 4.603098 4.565649
3. Quartile 5.152374 5.645288 2.447551 3.552709 4.865160 1.505000 4.606637 4.593511
Mean      3.207436 5.583328 -0.340269 2.927674 4.566839 1.643900 4.607314 4.596504
Median    3.207436 5.583328 -0.340269 2.927674 4.576565 1.623144 4.608018 4.597012
Sum      1602.218700 271.804000 170.000000 146.000000 229.000000 146.000000 229.000000 146.000000 229.000000 146.000000
SE Mean   0.002912 0.004800 0.008779 0.002123 0.004927 0.000345 0.002152 0.004927 0.000345 0.002152
LCL Mean  4.022912 5.008400 0.001006 0.000892 0.001006 0.000892 0.000892 0.000892 0.000892 0.000892
UCL Mean  4.562636 5.738797 2.910426 4.562636 1.634220 4.606637 4.593511 4.679734 4.593511 4.679734
Variance  0.002760 0.005652 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766
Stdev     0.002760 0.005652 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766 0.002766
skewness  0.000808 0.012188 0.002188 0.000808 0.012188 0.000808 0.012188 0.000808 0.012188 0.000808
kurtosis  -1.340497 -0.398918
cp10
```

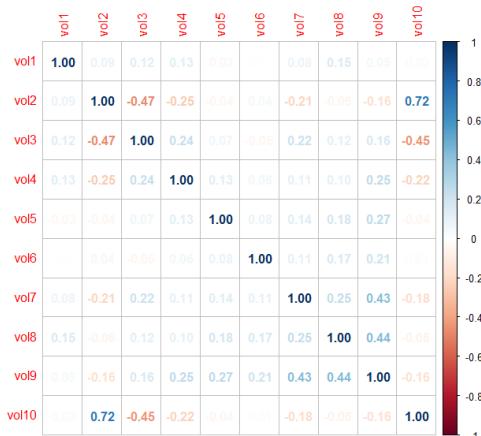
Figure A.15: Basic statistical data of close price



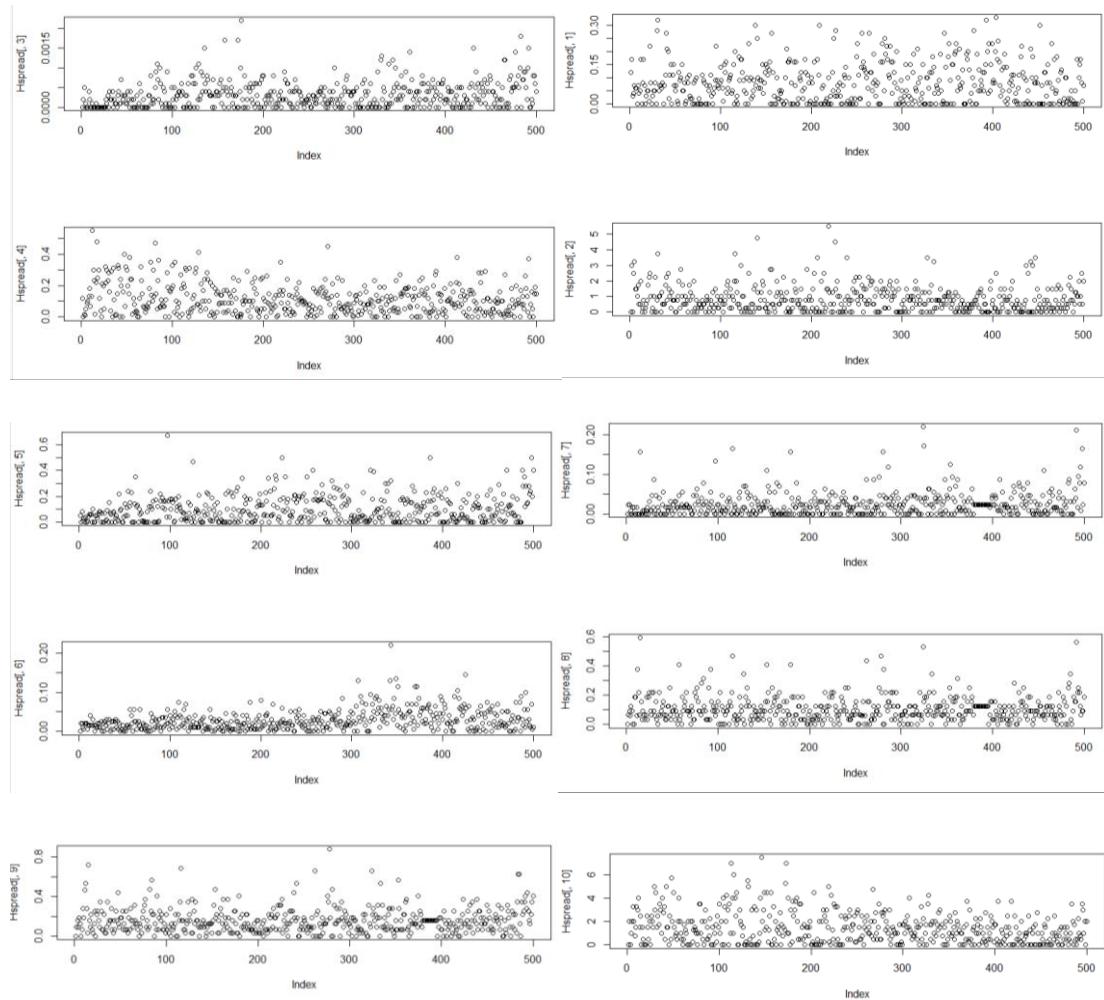
Graph A.16: Correlation graph of close price



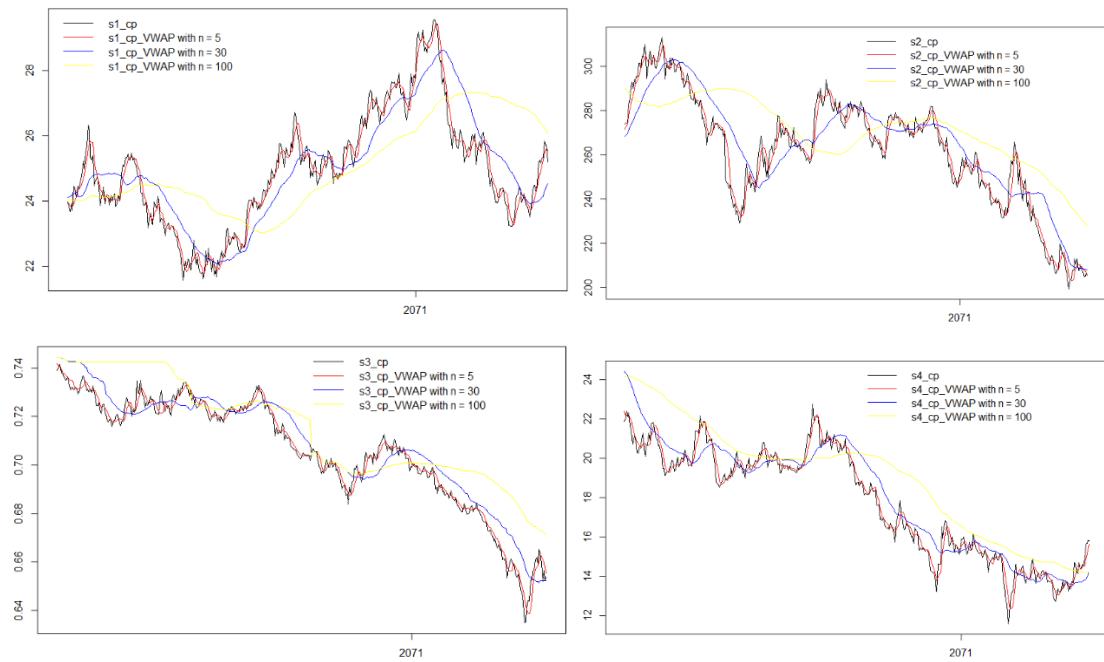
Graph A.17: Volume

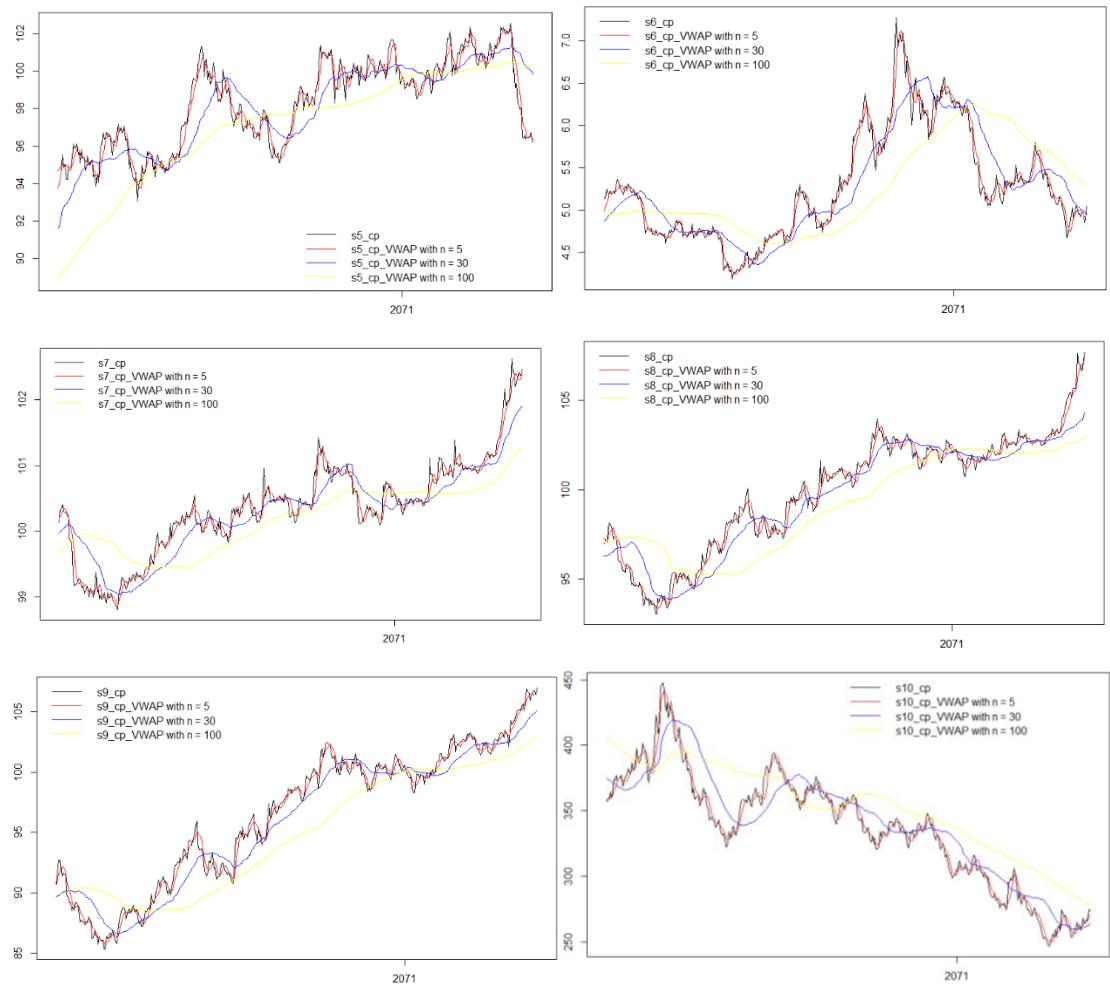


Graph A.18: Correlation graph of volume

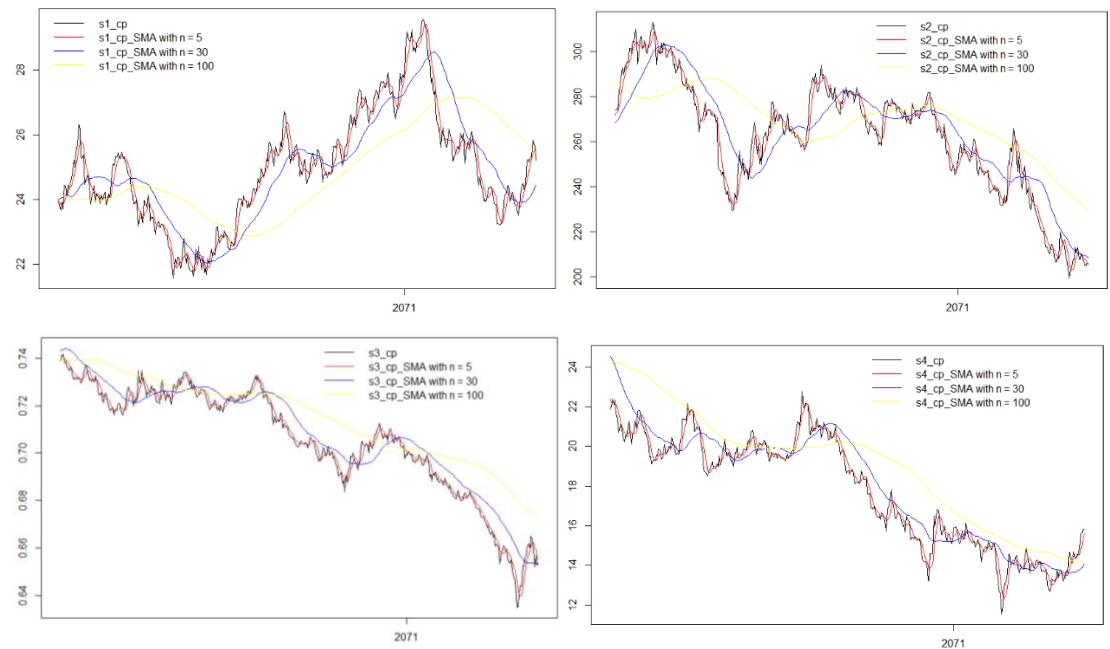


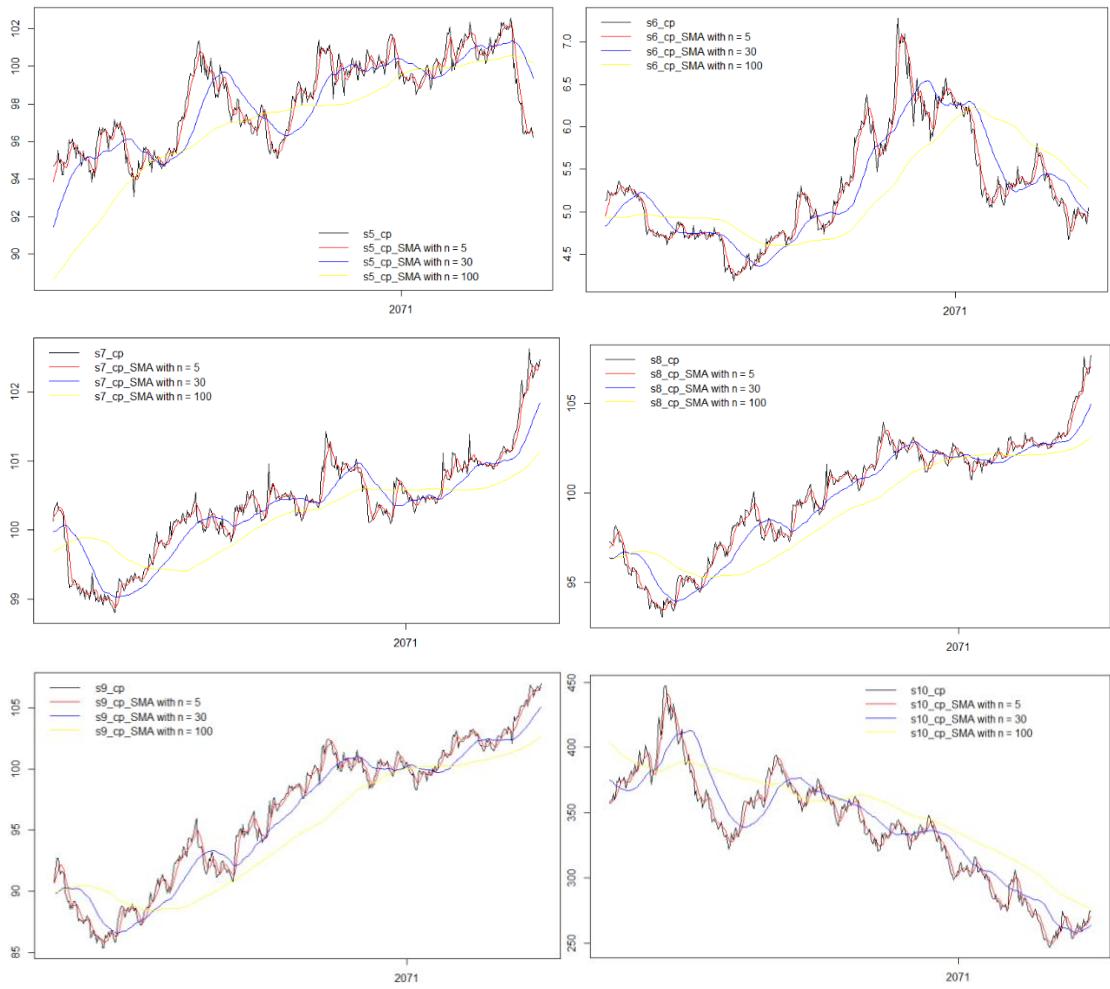
Graph A.19: Daily spread of each series



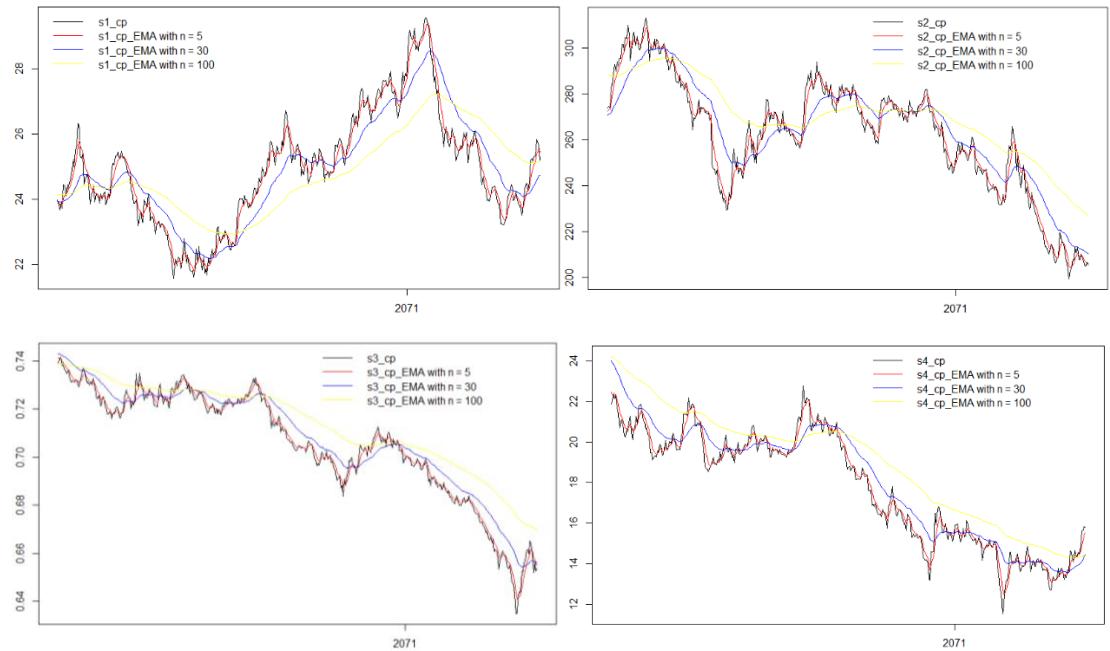


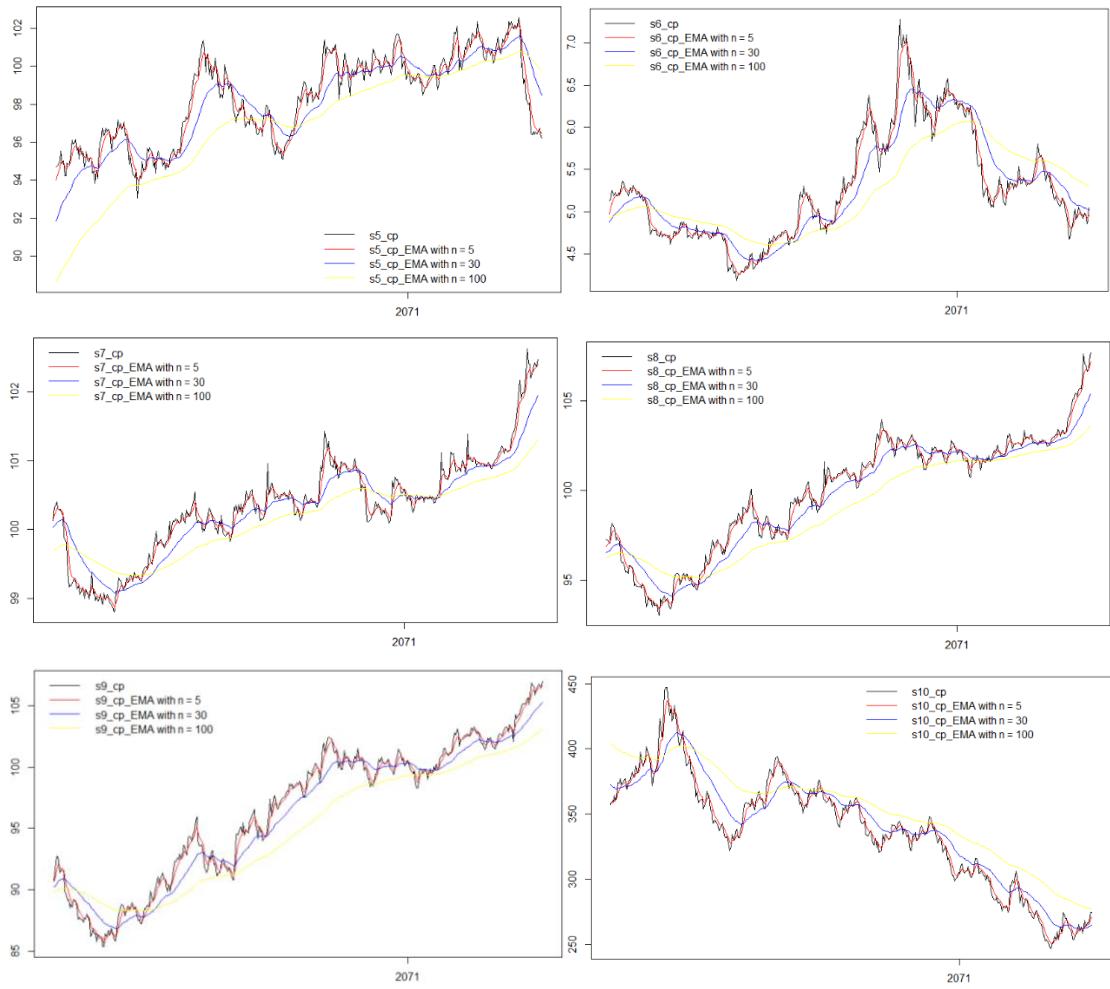
Graph A.20: VWAP of each series



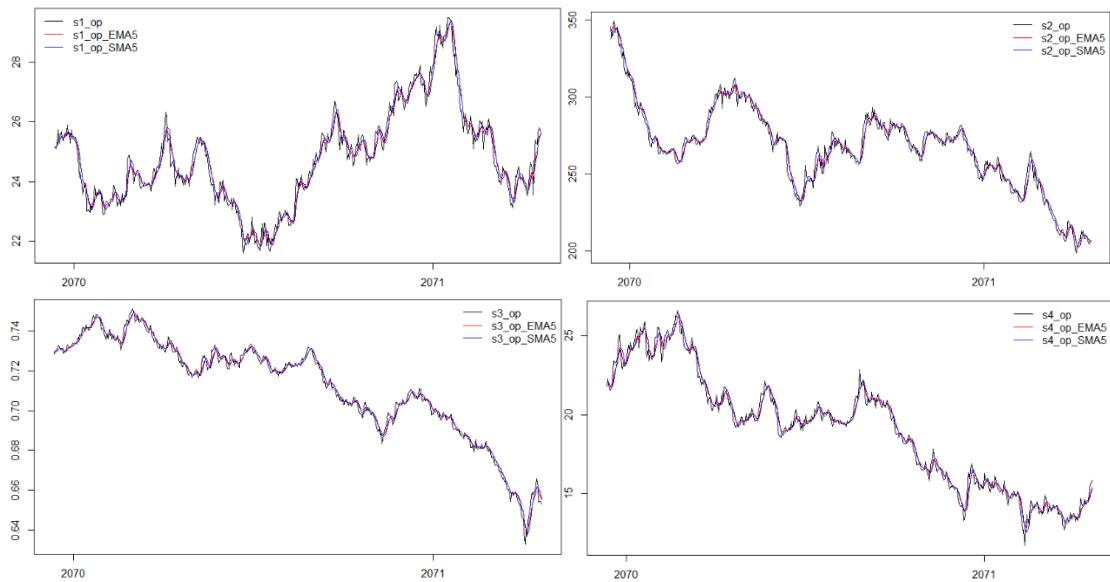


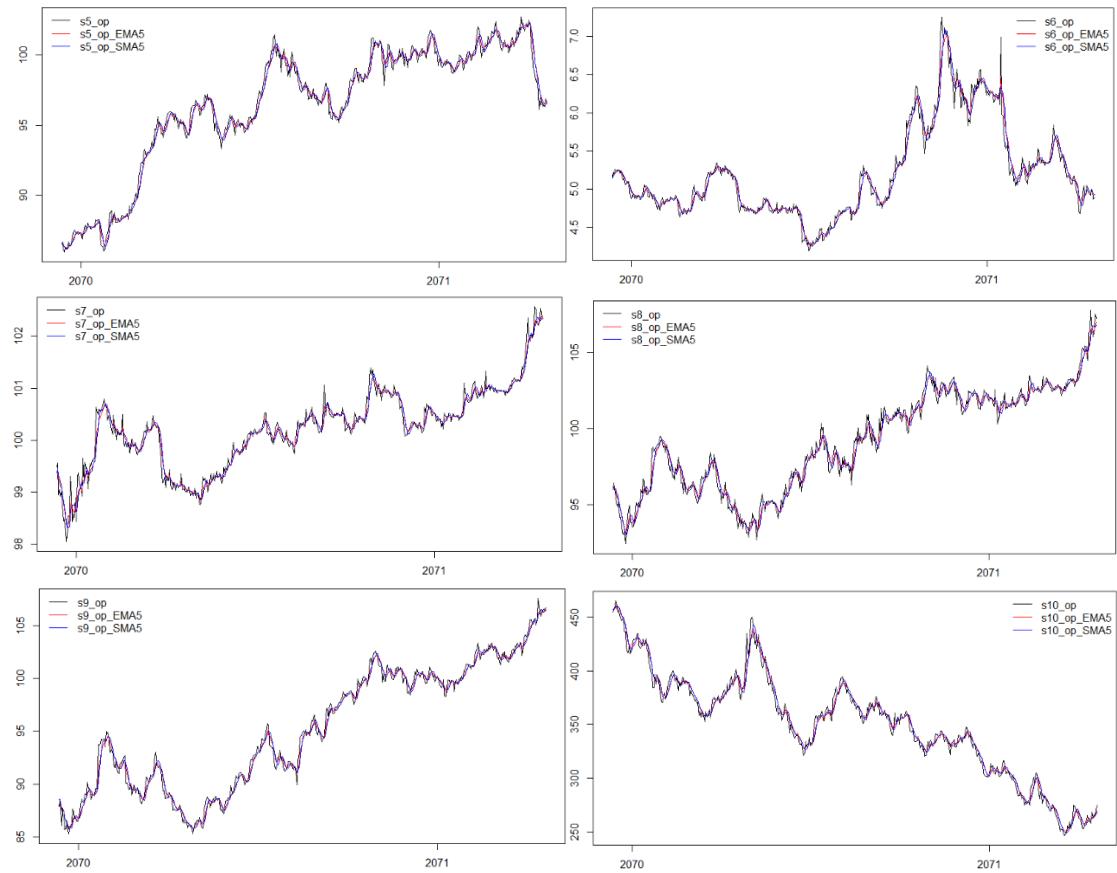
Graph A.21: SMA of close price of each series



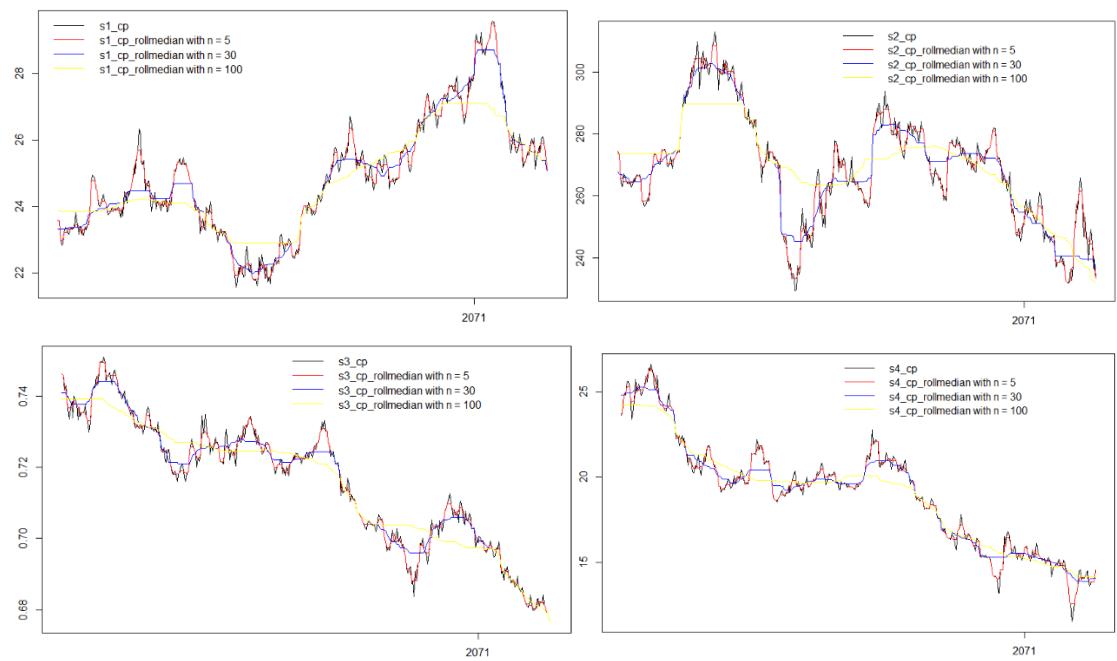


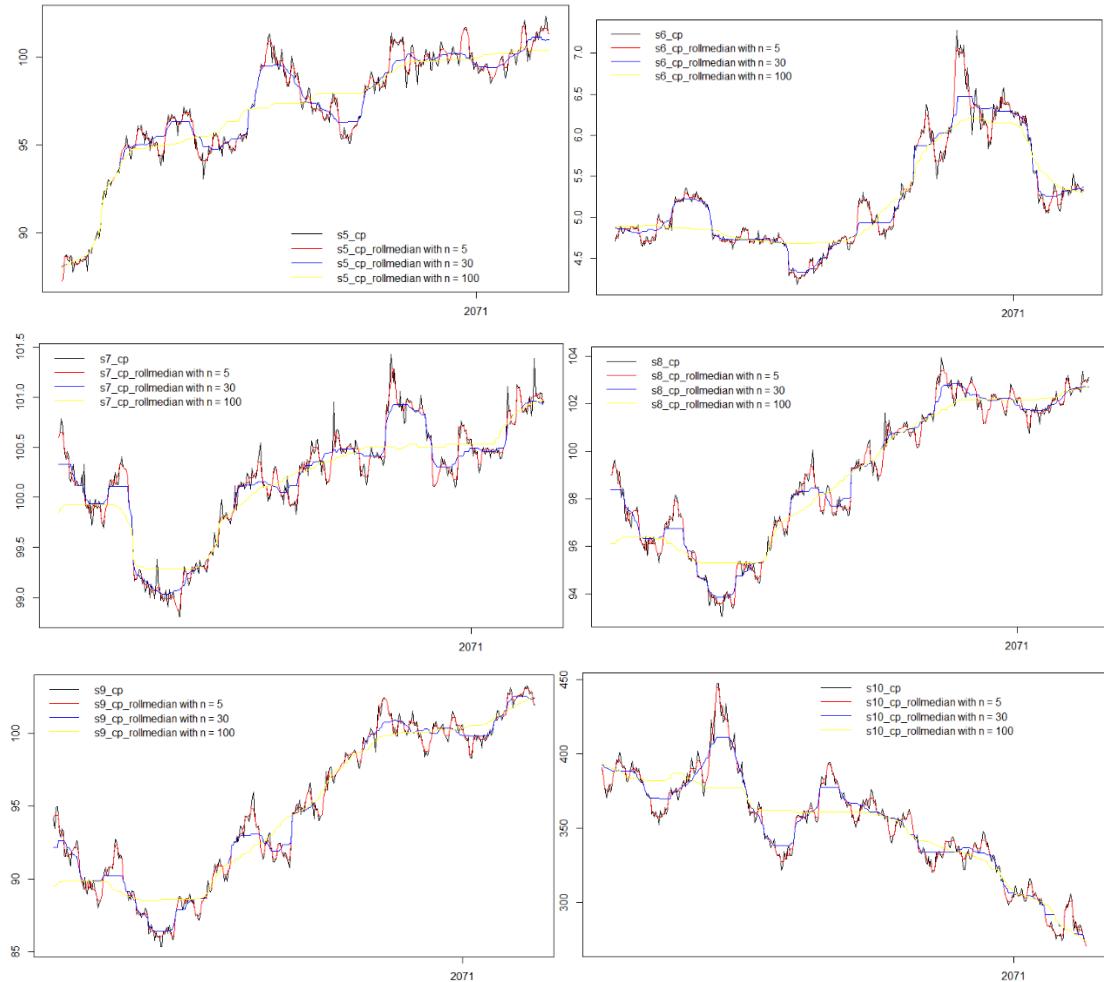
Graph A.22: EMA of close price of each series



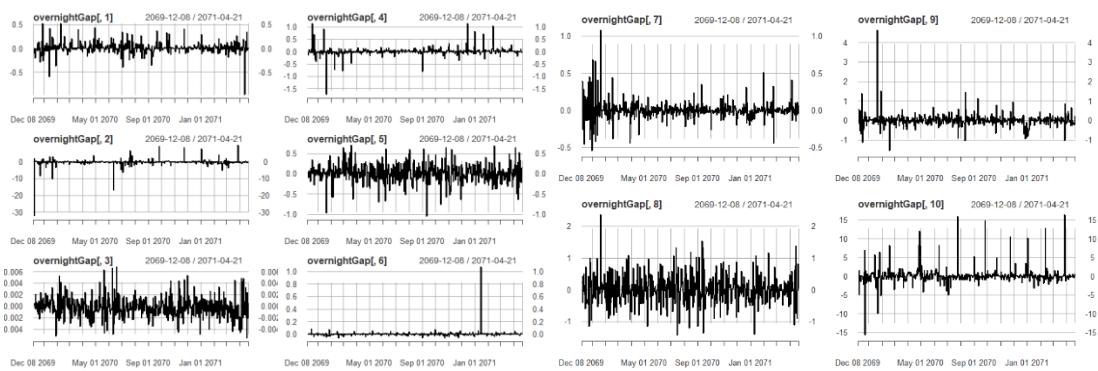


Graph A.23: Compare open price, EMA and SMA of close price of each series

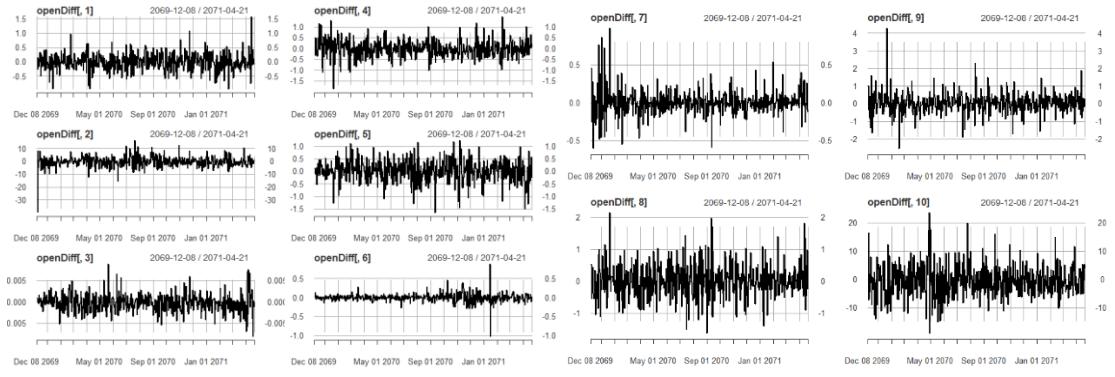




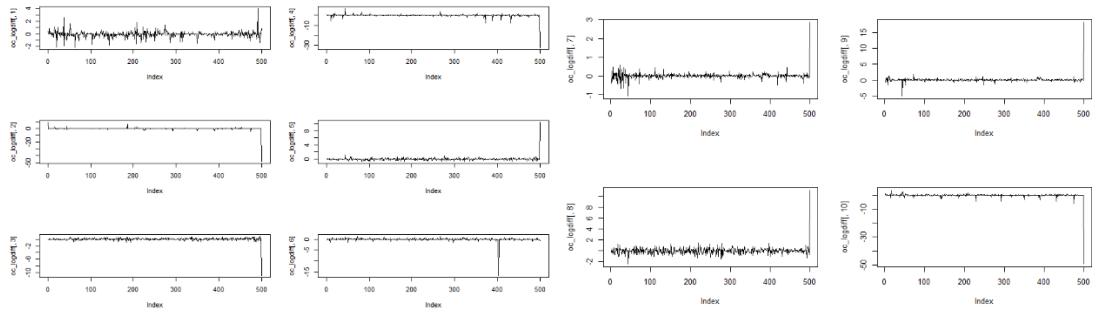
Graph A.24: Rolling Median of each series



Graph A.25: Overnight gap of each series



Graph A.26: Open to open difference of each series



Graph A.27: Log return of each series

## Appendix B

```

> ht <- ur.df(cp[,1])      > ht <- ur.df(cp[,2])      > ht <- ur.df(cp[,3])      > ht <- ur.df(cp[,4])      > ht <- ur.df(cp[,5])
> attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -0.1195607          statistic -1.742317          statistic -1.547832          statistic -0.9461022         statistic 0.8367743
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62
> ht <- ur.df(cp[,6])      > ht <- ur.df(cp[,7])      > ht <- ur.df(cp[,8])      > ht <- ur.df(cp[,9])      > ht <- ur.df(cp[,10])
> attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -0.2815926          statistic 1.018251          statistic 1.339446          statistic 1.339882          statistic -1.825916
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62

```

Figures B.1: Dickey-Fuller Test of close price

```

> ht <- ur.df(vol[,1])     > ht <- ur.df(vol[,2])     > ht <- ur.df(vol[,3])     > ht <- ur.df(vol[,5])     > ht <- ur.df(vol[,4])
> attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat  > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -3.049012          statistic -2.488921          statistic -4.932752          statistic -6.213791          statistic -2.460282
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62
> ht <- ur.df(vol[,6])     > ht <- ur.df(vol[,7])     > ht <- ur.df(vol[,9])     > ht <- ur.df(vol[,10])    > ht <- ur.df(vol[,8])
> attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -4.334623          statistic -4.878953          statistic -4.698547          statistic -3.528123          statistic -3.188845
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62

```

Figures B.2: Dickey-Fuller Test of volume

Table B.1: Dickey-Fuller Test of volume

series	tau1 statistic	tau1 95% critical value	stationary
1	-3.049012	-1.95	non-stationary
2	-2.488921	-1.95	non-stationary
3	-4.932752	-1.95	non-stationary
4	-2.460282	-1.95	non-stationary
5	-6.213791	-1.95	non-stationary
6	-4.334623	-1.95	non-stationary
7	-4.878953	-1.95	non-stationary
8	-4.698547	-1.95	non-stationary
9	-3.528123	-1.95	non-stationary
10	-3.188845	-1.95	non-stationary

```

> ht <- ur.df(Hspread[,1])  > ht <- ur.df(Hspread[,2])  > ht <- ur.df(Hspread[,3])  > ht <- ur.df(Hspread[,4])  > ht <- ur.df(Hspread[,5])
> attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -10.25218           statistic -10.31087          statistic -10.357            statistic -8.938003          statistic -10.5956
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62
> ht <- ur.df(Hspread[,6])  > ht <- ur.df(Hspread[,7])  > ht <- ur.df(Hspread[,8])  > ht <- ur.df(Hspread[,9])  > ht <- ur.df(Hspread[,10])
> attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat   > attributes(ht)$teststat
tau1                           tau1                           tau1                           tau1                           tau1
statistic -8.745409          statistic -10.55195          statistic -8.839029          statistic -7.790467          statistic -9.447146
> attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval        > attributes(ht)$cval
  ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct            ipct 5pct 10pct
tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62       tau1 -2.58 -1.95 -1.62

```

Figures B.3: Dickey-Fuller Test of daily spread

Table B.2: Dickey-Fuller Test of daily spread

series	tau1 statistic	tau1 95% critical value	stationary
1	-10.25218	-1.95	non-stationary
2	-10.31097	-1.95	non-stationary

3	-10.357	-1,95	non-stationary
4	-8.938003	-1.95	non-stationary
5	-10.5956	-1.95	non-stationary
6	-8.745409	-1.95	non-stationary
7	-10.55195	-1.95	non-stationary
8	-8.839029	-1.95	non-stationary
9	-7.790467	-1.95	non-stationary
10	-9.447146	-1.95	non-stationary

```

> ht <- ur.df(overnightGap_S1) > ht <- ur.df(overnightGap_S2) > ht <- ur.df(overnightGap_S3) > ht <- ur.df(overnightGap_S4) > ht <- ur.df(overnightGap_S5)
> attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat
> attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1
statistic -15.93029 statistic -17.85881 statistic -15.57334 statistic -15.22881 statistic -16.13264
> attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval
1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62
> ht <- ur.df(overnightGap_S6) > ht <- ur.df(overnightGap_S7) > ht <- ur.df(overnightGap_S8) > ht <- ur.df(overnightGap_S9) > ht <- ur.df(overnightGap_S10)
> attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat
> attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1
statistic -15.54861 statistic -19.68034 statistic -16.33168 statistic -16.65716 statistic -14.85384
> attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval
1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62

```

Figures B.4: Dickey-Fuller Test of overnight gap

Table B.3: Dickey-Fuller Test of overnight gap

series	tau1 statistic	tau1 95% critical value	stationary
1	-15.93029	-1.95	non-stationary
2	-17.85881	-1.95	non-stationary
3	-15.57334	-1.95	non-stationary
4	-15.22881	-1.95	non-stationary
5	-16.13264	-1.95	non-stationary
6	-15.54861	-1.95	non-stationary
7	-19.68034	-1.95	non-stationary
8	-16.33168	-1.95	non-stationary
9	-16.65716	-1.95	non-stationary
10	-14.85384	-1.95	non-stationary

```

> ht <- ur.df(openDiff_S1) > ht <- ur.df(openDiff_S2) > ht <- ur.df(openDiff_S3) > ht <- ur.df(openDiff_S4) > ht <- ur.df(openDiff_S5)
> attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat
> attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1
statistic -15.98474 statistic -15.21893 statistic -15.42344 statistic -16.89176 statistic -15.29016
> attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval
1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62
> ht <- ur.df(openDiff_S6) > ht <- ur.df(openDiff_S7) > ht <- ur.df(openDiff_S8) > ht <- ur.df(openDiff_S9) > ht <- ur.df(openDiff_S10)
> attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat > attributes(ht)$teststat
> attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1 > attributes(ht)$tau1
statistic -16.35839 statistic -16.29278 statistic -13.80379 statistic -16.88328 statistic -15.94599
> attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval > attributes(ht)$scval
1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct 1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62 tau1 -2.58 -1.95 -1.62

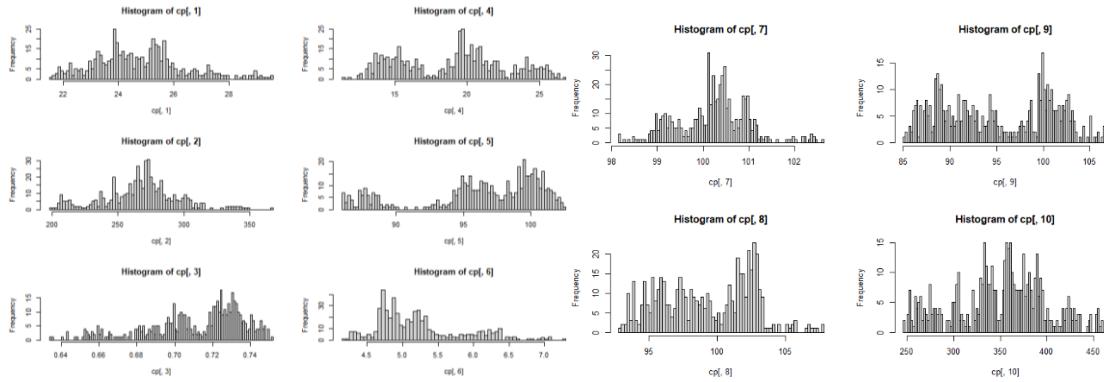
```

Figures B.5: Dickey-Fuller Test of open-to-open difference

Table B.4: Dickey-Fuller Test of open-to-open difference

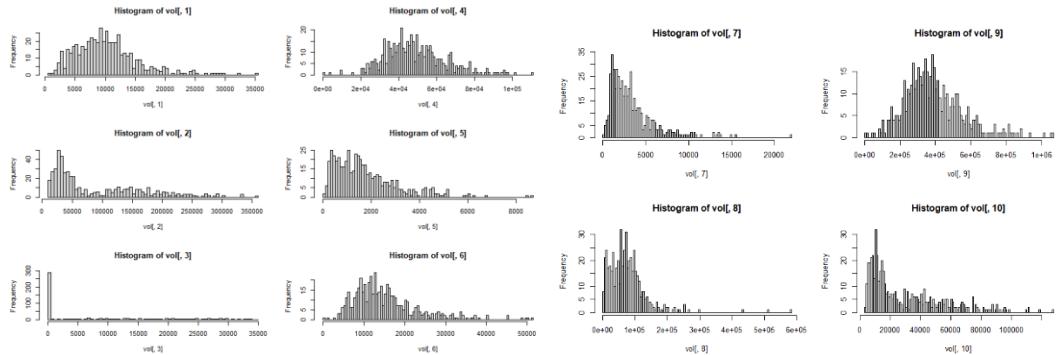
series	tau1 statistic	tau1 95% critical value	stationary
1	-15.98474	-1.95	non-stationary
2	-15.21893	-1.95	non-stationary
3	-15.42344	-1.95	non-stationary

4	-16.89176	-1.95	non-stationary
5	-15.29016	-1.95	non-stationary
6	-16.35839	-1.95	non-stationary
7	-18.29278	-1.95	non-stationary
8	-13.80379	-1.95	non-stationary
9	-16.88328	-1.95	non-stationary
10	-15.94599	-1.95	non-stationary



Graph B.6: Ljung-Box test of close price

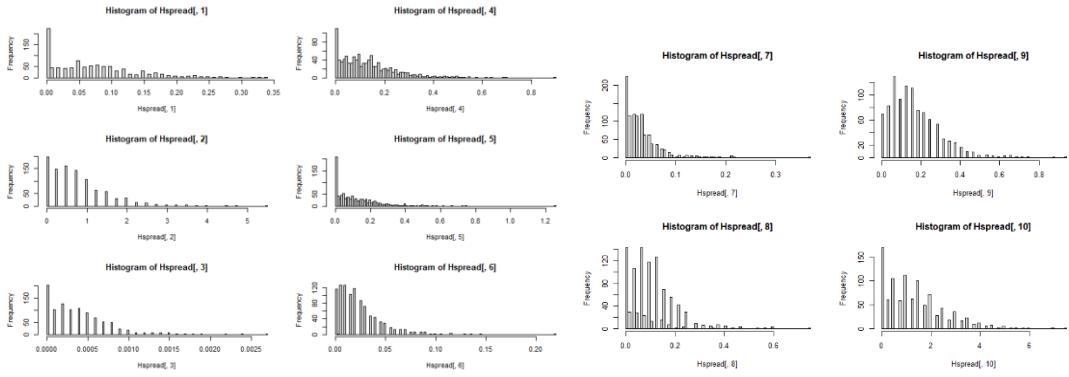
Table B.5: Dickey-Fuller Test of open-to-open difference



Graph B.7: Ljung-Box test of volume

Table B.5: Ljung-Box test of volume

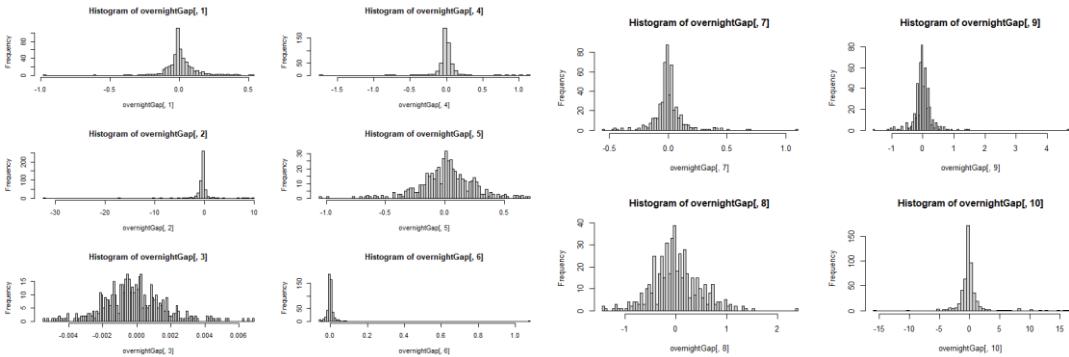
series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	white noise	= 0.05791
6	non-white noise	= 2.745e-07
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16



Graph B.8: Ljung-Box test of daily spread

Table B.6: Ljung-Box test of daily spread

series	OP auto-correlation(p-value)	p-value
1	non-white noise	= 1.532e-09
2	white noise	= 9.616e-05
3	non-white noise	= 4.774e-15
4	non-white noise	< 2.2e-16
5	white noise	= 6.473e-14
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	white noise	= 1.016e-07

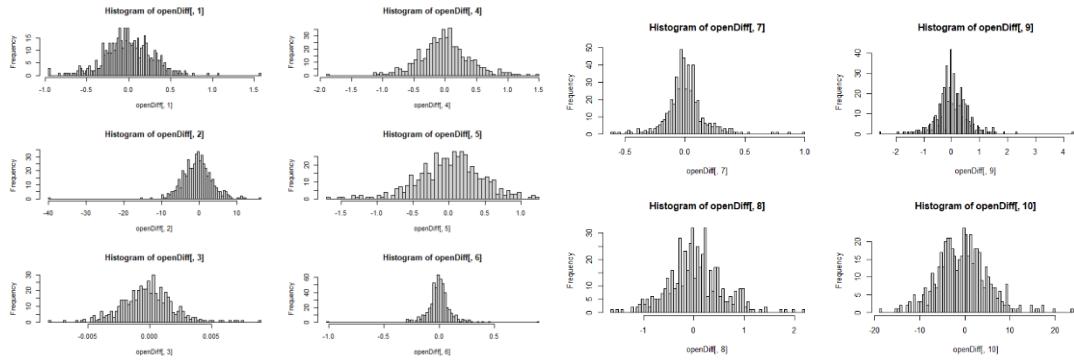


Graph B.9: Ljung-Box test of overnight gap

Table B.7: Ljung-Box test of overnight gap

series	OP auto-correlation(p-value)	p-value
1	white noise	= 0.7677
2	white noise	= 0.8944
3	white noise	= 0.5961
4	white noise	= 0.7158
5	white noise	= 0.4052

6	white noise	= 0.9969
7	non-white noise	= 1.891e-06
8	non-white noise	= 1.221e-15
9	white noise	= 0.3372
10	white noise	= 0.8472



Graph B.10: Ljung-Box test of open-to-open difference

Table B.8: Ljung-Box test of open-to-open difference

series	OP auto-correlation(p-value)	p-value
1	white noise	= 0.5016
2	white noise	= 0.1146
3	white noise	= 0.3992
4	non-white noise	= 0.02723
5	white noise	= 0.5481
6	non-white noise	= 0.000291
7	non-white noise	= 0.002019
8	non-white noise	< 2.2e-16
9	white noise	= 0.7261
10	non-white noise	= 0.04832

```

#####
# Johansen-Procedure #
#####

Test type: maximal eigenvalue statistic (lambda max) , with linear trend
Eigenvalues (Lambda):
[1] 0.372152998 0.0929146426 0.0855103747 0.0606051996 0.0412756301 0.0396997391 0.0315908840 0.0242244536 0.0069764818 0.0001996895

values of teststatistic and critical values of test:
test 10Pct 5Pct 1Pct
r <= 9 | 3.49 12.90 14.90 19.19
r <= 8 | 3.49 12.90 14.90 19.19
r <= 7 | 12.21 18.90 21.07 25.75
r <= 6 | 20.17 30.84 33.32 38.78
r <= 5 | 20.99 36.28 39.43 44.59
r <= 4 | 31.13 42.06 44.91 51.30
r <= 3 | 31.13 42.06 44.91 51.30
r <= 2 | 31.13 42.06 44.91 51.30
r <= 1 | 48.56 54.01 57.00 63.37
r = 0 | 231.80 59.01 62.42 68.61

Eigenvectors, normalised to first column:
(These are the cointegration relations)

a.12 b.12 c.12 d.12 e.12 f.12 g.12 h.12 i.12 j.12
a.12 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000
b.12 -0.04131573 0.2908269 1.0664889 2.388202 0.09104705 -0.01049434 -0.26150312 -0.043880459 -0.07478196 3.766011e-03
c.12 366.98533362 -321.8761550 241.4349995 10537.125404 -22.77297134 -71.34151472 83.85257792 53.389300540 188.68139252 -1.192521e+02
d.12 -2.116114261 14.6661061 0.23114123 -67.075829 -0.56383388 0.1981388 0.17203168 -0.15199492 8.392145e-01
e.12 1.23739887 4.2426148 2.42426148 -2.07094368 0.27130102 0.26646444 0.26646444 -0.16361763 0.16361763 -0.02
f.12 1.27324770 -2.7094368 -286.163670 2.26623206 -2.19502460 3.35987788 -0.567718632 11.80000609 2.036341e-02
g.12 37.42533449 -47.0657096 49.0315047 -202.001382 3.69949523 1.53131976 5.57979096 -0.02677097 -12.81803575 3.21367e+00
h.12 -30.00541039 -1.629518 2.2881511 35.648192 -1.3631577 0.05939971 0.41616022 0.001378267 -11.26515939 1.267465e+00
i.12 14.21716803 5.86451202 -7.0353524 35.762908 -0.99574923 -0.35590653 -1.64809007 0.144350010 5.27672217 -3.889193e-01
j.12 0.19979308 -0.871398 -5.492442 -0.165227992 0.02178988 0.06931598 0.039266933 0.12745798 -4.279355e-02

weights w:
(This is the loading matrix)

a.12 b.12 c.12 d.12 e.12 f.12 g.12 h.12 i.12 j.12
a.d 1.513102e-03 -1.023121e-03 1.186792e-03 -1.783842e-03 -6.464035e-03 -2.285758e-02 2.590821e-03 -1.45193e-03 7.00338e-03 -0.115689e-05
b.d 1.729894e-03 1.329274e-03 2.07981e-02 3.059636e-04 -6.618108e-02 -1.04387e-01 1.212160e-01 1.05089e-02 4.302486e-03 3.032961e-03
c.d 9.589957e-07 -1.063833e-05 -1.704281e-05 -2.02502917e-06 5.638832e-03 1.993381e-05 -1.420320e-06 8.728690e-06 -7.403663e-06 1.558598e-06
d.d -0.423802e-03 -4.485158e-03 -3.182509e-03 -2.055777e-03 5.638832e-03 1.993381e-05 -1.420320e-06 8.728690e-06 -7.403663e-06 1.303023e-04
e.d -7.772702e-04 1.753777e-04 -6.186160e-04 2.288711e-04 8.136905e-04 -1.3631577e-03 -1.45193e-03 -1.05089e-02 -3.308723e-04
f.d 0.404951e-04 9.358573e-05 9.798724e-04 -2.117133e-05 6.601124e-05 1.81241e-03 -2.121101e-03 1.45193e-03 -1.3631577e-03 -1.932959e-04
g.d 1.183924e-03 1.3233616e-03 -1.848979e-03 -1.651534e-04 -2.07094368e-04 3.35987788e-04 -0.567718632e-04 1.717479e-04 5.584059e-06 -0.582272e-05
h.d 1.325696e-03 5.738812e-05 -1.383268e-03 -2.117133e-05 3.254386e-03 5.154927e-03 9.086909e-04 -3.493965e-03 -3.217227e-05 -1.568900e-04
i.d -4.234682e-03 1.998524e-03 -3.237798e-03 -3.490723e-05 5.863858e-04 2.159282e-03 7.929334e-03 -1.630812e-02 -5.608793e-04 -1.190437e-03
j.d 6.255398e-03 1.005277e-02 4.148212e-02 2.2123363e-03 9.023998e-03 -6.234911e-03 -1.011754e-02 6.620518e-03

> slotnames(cotest)
[1] "Z0"      "Z1"      "ZK"      "type"   "model"  "scdet"  "lag"    "p"      "season" "dumvar" "cval"
[11] "teststat" "Lambda"  "vorg"   "v"      "pi"     "DELTa"  "GAMMA" "R0"     "Rk"     "bp"      "spec"
[25] "call"    "test.name"


```

Figures B.11: Cointegration Test of close price

```

#####
# Johansen-Procedure #
#####

Test type: maximal eigenvalue statistic (lambda max) , with linear trend
Eigenvalues (Lambda):
[1] 0.33031521 0.29298378 0.27510502 0.23436517 0.16492879 0.13682509 0.12638641 0.10864854 0.06573928 0.02191363

values of teststatistic and critical values of test:
test 10Pct 5Pct 1Pct
r <= 9 | 11.03 6.50 8.18 11.65
r <= 8 | 11.03 6.50 8.18 11.65
r <= 7 | 57.28 18.90 21.07 25.75
r <= 6 | 67.29 24.78 27.14 32.14
r <= 5 | 73.27 30.46 33.32 38.78
r <= 4 | 80.62 36.28 39.43 44.59
r <= 3 | 132.99 42.06 44.91 51.30
r <= 2 | 160.22 48.43 51.07 57.07
r <= 1 | 121.80 59.01 62.42 68.61
r = 0 | 199.67 59.00 62.42 68.61

Eigenvectors, normalised to first column:
(These are the cointegration relations)

a.12 b.12 c.12 d.12 e.12 f.12 g.12 h.12 i.12 j.12
a.12 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000
b.12 -0.3245884 -0.03364033 -0.04898897 0.3084233 0.00169918 -0.0546357192 0.2594746 0.014963194 0.202998184 -0.471282493
c.12 -3.05613651 0.32762904 1.09562351 -2.5820121 -0.68886273 0.2636156735 12.5500891 1.17361311 0.288508106 0.013092362
d.12 2.69713920 0.42920909 -1.02255024 0.3084233 0.00169918 -0.0546357192 0.2594746 0.014963194 0.202998184 -0.471282493
e.12 165.02 1.44217120 21.44217120 -21.44217120 3.0596364 -3.0596364 -3.0596364 -3.0596364 -3.0596364 -3.0596364
f.12 28.64346766 -2.68815476 3.55723640 -3.1668805 10.91640249 0.5081546323 5.001787 -3.86925048 0.098143739 0.199614013
g.12 1.46899616 0.10461474 -0.03480152 0.5092800 -0.024754359 0.000409957 0.1095783 -0.06584176 0.003377406 -0.06694807
h.12 -1.2723993 0.15118258 0.09870333 -1.5444501 0.235828471 0.1048223069 4.3513039 0.36385867 -0.611519941 -0.316431728
i.12 -2.2723993 0.15118258 0.09870333 -1.5444501 0.235828471 0.1048223069 4.3513039 0.36385867 -0.611519941 -0.316431728
j.12 0.0044410805 -0.022535800 -0.026387381 0.002179268 -0.037658362 -0.32219571 -1.5790856 -0.0308702382 0.109500877 0.0266548800

weights w:
(This is the loading matrix)

a.12 b.12 c.12 d.12 e.12 f.12 g.12 h.12 i.12 j.12
a.d 0.0000512307 -0.0202324980 -0.0049016040 -0.028160080 -0.017610449 -0.25278775 -1.741286e-03 -0.012121938 -0.037701542 -0.0004996450
b.d 0.0024832230 0.006632471 0.029266476 -0.0225052493 -0.018436955 0.19157333 -1.938659e-02 -0.0924268519 -0.289023246 0.0907957630
c.d 0.0050939399 0.120500204 0.311526870 0.0074547163 -0.068363233 -0.03496704 -1.120386e-03 0.0040851327 0.002343972 -0.003986331
d.d 0.0020536811 0.029492919 0.00119867621 0.0012359358 -0.01165651 0.001165651 -0.001746988 0.0012359358 -0.002343972 -0.003986331
e.d 0.0020510734 -0.047139096 0.004085639 0.026111268 -0.01380984 -0.02131231 3.878380e-03 0.0083435040 -0.028028449 0.0035112921
f.d 0.0111810734 -0.047139096 0.004085639 0.026111268 -0.01380984 -0.02131231 3.878380e-03 0.0083435040 -0.028028449 0.0035112921
g.d 0.0427082302 0.455889717 0.188254356 -0.0249360137 -0.371944830 0.79945289 3.820438e-02 -0.3346931394 0.041334097 -0.024780896
h.d 0.0427082302 0.455889717 0.188254356 -0.0249360137 -0.371944830 0.79945289 3.820438e-02 -0.3346931394 0.041334097 -0.024780896
i.d 0.2869562096 -3.008587178 1.010309404 -0.1635293407 -0.63293257 2.55242655 -1.781610e-02 0.3860981328 -0.065346738 -0.0145589213
j.d 0.0044410805 -0.022535800 -0.026387381 0.002179268 -0.037658362 -0.32219571 -1.5790856 -0.0308702382 0.109500877 0.0266548800

> slotnames(cotest)
[1] "Z0"      "Z1"      "ZK"      "type"   "model"  "scdet"  "lag"    "p"      "season" "dumvar" "cval"
[11] "teststat" "Lambda"  "vorg"   "v"      "pi"     "DELTa"  "GAMMA" "R0"     "Rk"     "bp"      "spec"
[25] "call"    "test.name"


```

Figures B.12: Cointegration Test of volume

```

*****# Johansen-Procedure*****
*****# Test type: maximal eigenvalue statistic (lambda max) , with linear trend
Eigenvalues (lambda):
[1] 0.349070 0.342832 0.3163549 0.3021869 0.2894548 0.2759976 0.2452845 0.2389289 0.1921782 0.1596325

Values of teststatistic and critical values of test:

$$\begin{array}{ccccccccc} \text{test} & 10pc & 5pc & 1pc \\ r <= 1 & 17.57 & 5.60 & 8.18 & 11.65 \\ r <= 2 & 27.72 & 18.90 & 20.19 & 23.19 \\ r <= 3 & 27.48 & 18.90 & 20.17 & 25.75 \\ r <= 4 & 28.05 & 24.78 & 27.14 & 32.14 \\ r <= 5 & 28.05 & 24.78 & 27.14 & 32.14 \\ r <= 6 & 34.01 & 36.25 & 39.43 & 44.59 \\ r <= 7 & 34.01 & 36.25 & 39.43 & 44.59 \\ r <= 8 & 359.08 & 42.06 & 44.91 & 51.30 \\ r <= 9 & 359.08 & 42.06 & 44.91 & 51.30 \\ r <= 10 & 359.08 & 42.06 & 44.91 & 51.30 \\ r = 1 & 418.98 & 54.01 & 57.00 & 63.37 \\ r = 2 & 428.51 & 59.00 & 62.42 & 68.61 \end{array}$$

Eigenvectors, normalised to first column:
(These are the cointegration relations)

$$\begin{array}{ccccccccc} x_1 & -1.0000000 & 1.0000000 & 1.0000000 & 1.0000000 & 1.0000000 & 1.0000000 & 1.0000000 & 1.0000000 \\ x_2 & -0.2116040 & 0.4210640 & 0.4210640 & 0.4210640 & 0.4210640 & 0.4210640 & 0.4210640 & 0.4210640 \\ x_3 & -494.2238252 & 27.0558158 & 389.9737006 & -26.2684706 & 6685.26513 & 21.7137468 & 160.91789702 & -146.32168837 \\ x_4 & 0.074453008 & 0.105668868 & -0.65570278 & -0.88286097 & 70.32168 & -0.23129843 & 0.57426222 & 0.9186706 \\ x_5 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 \\ x_6 & 0.19555010 & 0.7446961 & -0.28535508 & -1.0303400 & 316.02214 & 6.02513392 & 4.90538451 & -1.32720361 \\ x_7 & -2.31252532 & -5.5065534 & -2.28387263 & 0.7463804 & 8.01304 & 2.0494458 & 3.47934088 & 3.02653414 \\ x_8 & 0.912 & 0.3214635 & 0.2122629 & -0.10087733 & 0.46642347 & 46.5187 & 2.3143968 & -1.41742743 \\ x_9 & 0.102 & -0.02125033 & -0.1548611 & 0.07539882 & -0.01057633 & 7.66979 & 0.01098037 & -0.10772058 & 0.04814550 \\ x_{10} & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 \end{array}$$

weights wi
(This is the Loading matrix)

$$\begin{array}{ccccccccc} x_1 & -1.12 & x_2 & -1.12 & x_3 & -1.12 & x_4 & -1.12 & x_5 & -1.12 & x_6 & -1.12 & x_7 & -1.12 & x_8 & -1.12 & x_9 & -1.12 & x_{10} & -1.12 \\ x_1 & -0.034241981 & -0.069507429 & -0.2448383176 & -1.7073248 & -0.288152683 & -0.188674902 & -0.0866129494 & -0.0160462084 & -0.000105406 & -0.0000000 \\ x_2 & 0.089821008 & -0.516220193 & 0.099320193 & 0.149820193 & -0.240480193 & 0.182520193 & -0.182520193 & -0.309420193 & -0.444813748 & -0.583613748 \\ x_3 & 0.000629174 & -0.000597693 & 0.000763129 & 0.000428733 & -3.183179 & 0.0000778311 & -0.0001263888 & 0.0001272351 & 0.0002022027 & -3.836615e-06 \\ x_4 & -0.015839091 & 0.131042826 & 0.135251181 & 0.044971983 & -0.044971983 & 0.134831117 & -0.0731711714 & 0.0204505670 & 0.287133280 & 5.162920e-03 \\ x_5 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 \\ x_6 & -0.000844913 & 0.000612428 & 0.018165439 & 0.0040130239 & -4.4673438 & -0.0261720508 & 0.0216063983 & 0.033425858 & -0.0048318192 & 0.0048318192 \\ x_7 & 0.015712407 & 0.041932190 & 0.02381178 & -0.028440573 & 3.249746 & -0.016488663 & 0.0154926130 & -0.047079448 & 0.0115408000 & -8.107704e-03 \\ x_8 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 & 0.0000000 \\ x_9 & -0.0001174487 & 0.0001073688 & 0.073966378 & -0.151377176 & 4.6384645 & -0.036023398 & 0.0358568472 & -0.0283004891 & 0.103363347 & -3.139983e-03 \\ x_{10} & 0.53339597 & 1.333093045 & -0.962083802 & 0.954362674 & -3.9138812 & -2.2524834567 & 1.393505109 & -9.455381264 & -0.21907262 & 3.421974e-03 \end{array}$$

slotnames(cotest)
[1] "F" "Fteststat" "Lambda" "Vorg" "Zk" "type" "model" "ecdet" "GARMA" "IRDA" "P" "Season" "dumar" "cvat" "spec"
[15] "test" "call"

```

Figures B.13: Cointegration Test of daily spread

Figures B.14: Cointegration Test of overnight gap

```

##### Johansen-Procedure #####
#####
Test type: maximal eigenvalue statistic (Lambda max) , with linear trend
Eigenvalues (Lambda):
[1] 0.565037 0.4842614 0.4046332 0.3878169 0.3685255 0.3632730 0.3498701 0.3050718 0.2910761 0.2796544
value of teststatistic and critical values of test:
      test Statistic 90% 95% 99%
r <= 1 183.03 6.50 8.18 11.65
r <= 8 170.97 12.91 14.90 19.19
r <= 12 167.00 13.00 14.00 19.29
r <= 6 214.00 24.78 27.14 32.14
r <= 5 224.35 30.84 33.32 38.78
r <= 4 234.93 34.59 36.59 39.59
r <= 3 243.93 42.06 44.91 51.30
r <= 2 257.73 48.43 51.07 57.07
r <= 1 267.73 54.37 57.37 62.37
r = 0 413.75 59.00 62.42 68.61

Eigenvectors, normalized to first column:
These are the cointegration relations:
      (these are the co-integration relations)

      b.12   b.12   c.12   d.12   e.12   f.12   g.12   h.12   i.12   j.12
a.12  1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000 1.00000000
b.12 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734
d.12  0.01946188 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734 -0.02473734
d.12  0.50137370 0.06842248 0.24090908 0.46509374 -1.0281996e+00 1.5106537 -0.145386773 0.52676283 0.354891111 -1.3288380
e.12 -0.41996000 0.79386651 1.16867478 2.66907398 -3.9186660 0.466077990 0.61051566 -0.19771355 2.4383721
f.12  0.69938800 0.69938800 0.69938800 0.69938800 0.69938800 0.69938800 0.69938800 0.69938800 0.69938800 0.69938800
g.12 -14.78017800 20.74786400 2.705198 0.1 3.49874807 9.039107e-01 -0.9200810 1.61313862 -0.157773820 2.3093533
h.12  10.99398000 10.99398000 10.99398000 10.99398000 10.99398000 10.99398000 10.99398000 10.99398000 10.99398000 5.2623153
j.12  0.02341244 0.02341244 0.02341244 0.02341244 0.02341244 0.02341244 0.02341244 0.02341244 0.02341244 0.02341244
j.12 -0.15194229 0.02346488 1.017462e-01 -0.131921043 -1.891183e-02 -0.4962106 0.009719346 -0.04867372 -0.006718696 0.2913732

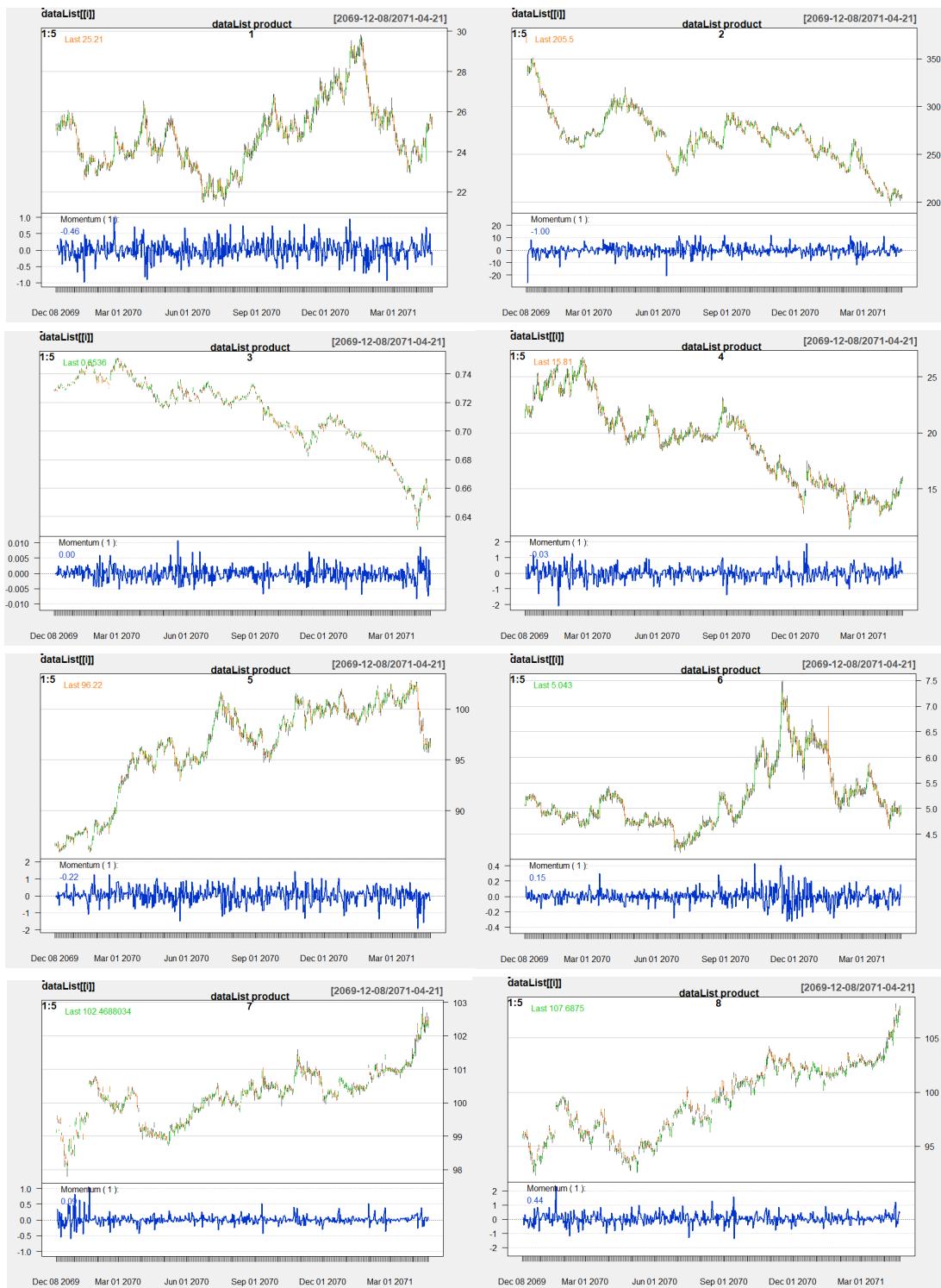
weights w:
(This is the loading matrix)
      b.12   b.12   c.12   d.12   e.12   f.12   g.12   h.12   i.12   j.12
a.-d -0.49521e-01 -0.12454628 -0.057307e-01 -0.01092777e-01 -0.076693193 -0.044923672 -0.744893671 0.017460283 -0.159797429 0.006677164
b.-d 0.77848600 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
c.-d -1.184002e-06 5.437989e-05 0.000038098 0.000038098 0.000038098 0.000038098 0.000038098 0.000038098 0.000038098 0.000038098
d.-d -0.1402732e-03 3.115434e-02 -0.1818986993 0.0111254295 0.7290864364 0.0355113867 -0.056861578 -0.119016703 0.0033839596
e.-d 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
f.-d 0.247415e-04 -0.152543e-04 0.0461276740 0.0294820891 0.0294820891 0.0294820891 0.0294820891 0.0294820891 0.0294820891 0.0294820891
g.-d 0.820830e-06 0.31377664e-02 -0.0210878573 -0.001247115 0.0058712045 0.0058712045 0.0058712045 0.0058712045 0.0058712045 0.0058712045
h.-d 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
j.-d 3.610446e-02 4.66461e-02 0.1745339189 0.0188017987 -2.2102742291 0.027039706 0.335405648 -0.0818480826 -0.0883440848 0.057109209
j.d 0.489376e-03 -2.402972e-01 -1.6848023447 0.5478235825 0.8730725644 0.9928239841 -5.964023923 2.8727989155 1.3653639949 -0.1234682719

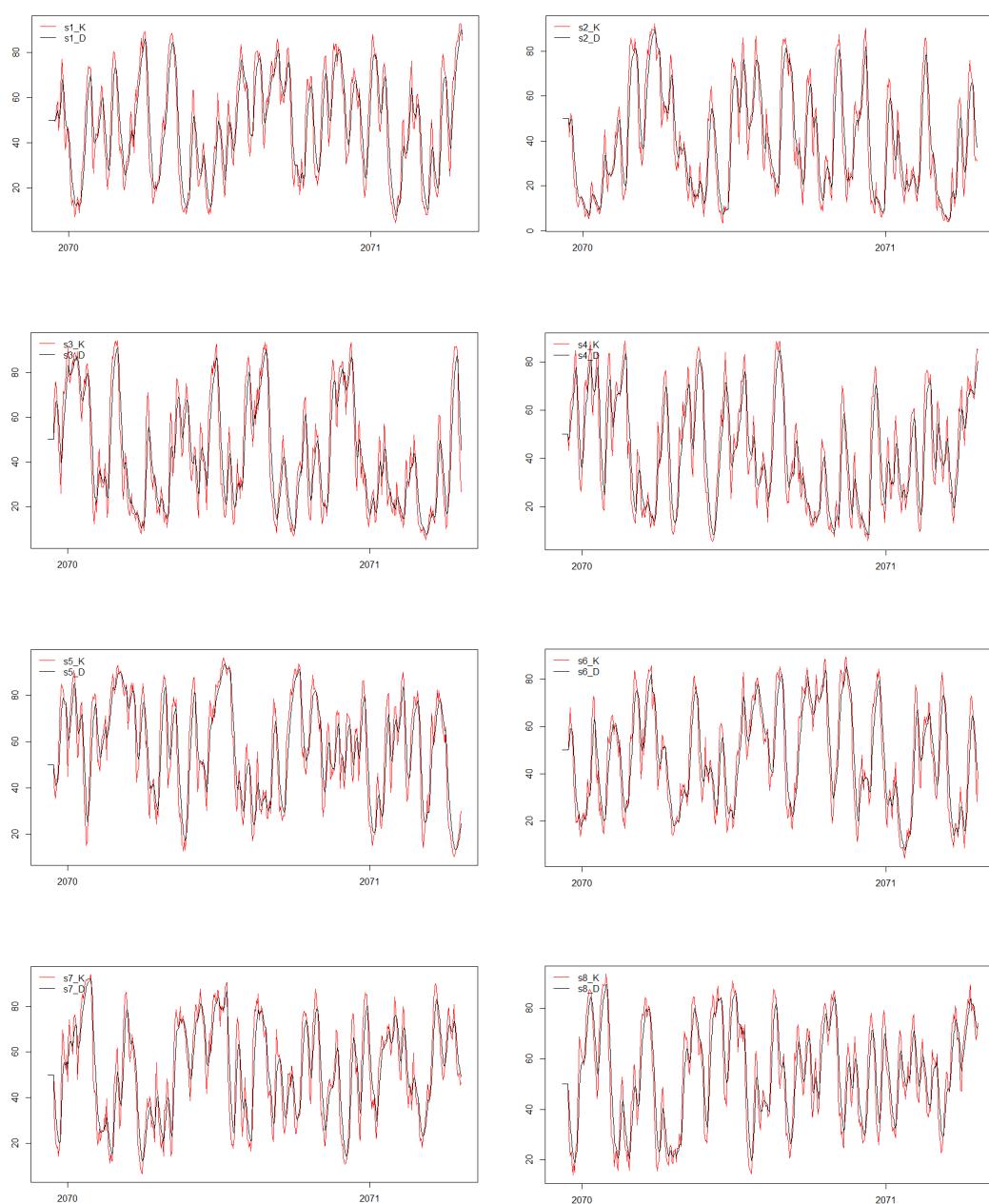
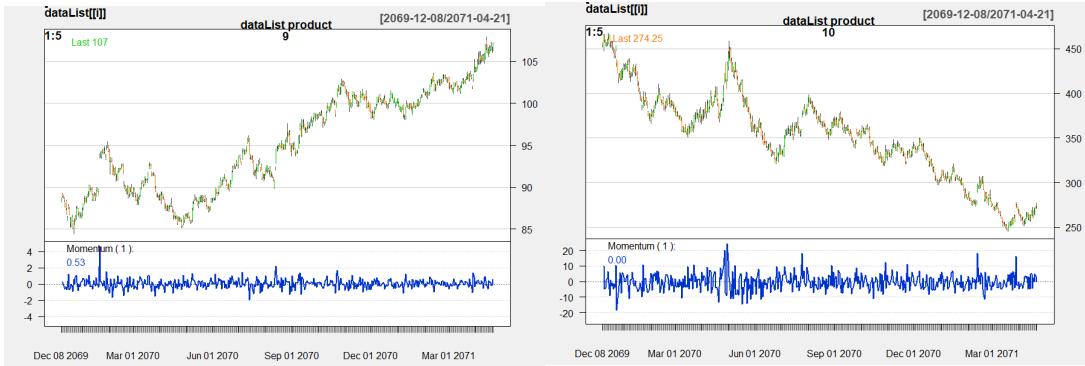
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[7] "```type```"
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[11] "```cdet```"
[12] "```DELTA```"
[13] "```lag```"
[14] "```gamma```"
[15] "```p```"
[16] "```R0```"
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[18] "```season```"
[19] "```dumvar```"
[20] "```cval```"
[21] "```spec```"

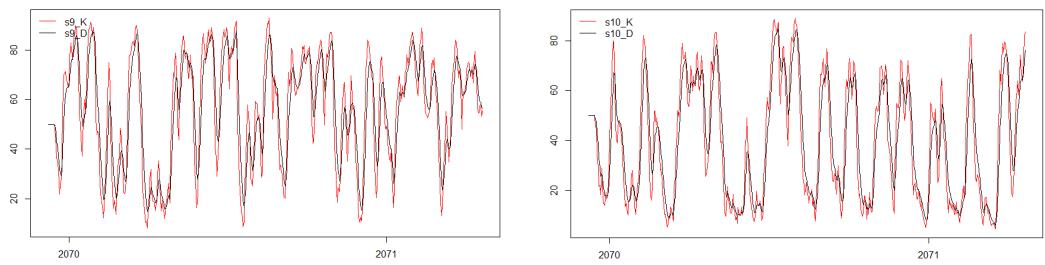
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Graph B.15: Cointegration Test of open-to-open difference

## Appendix C

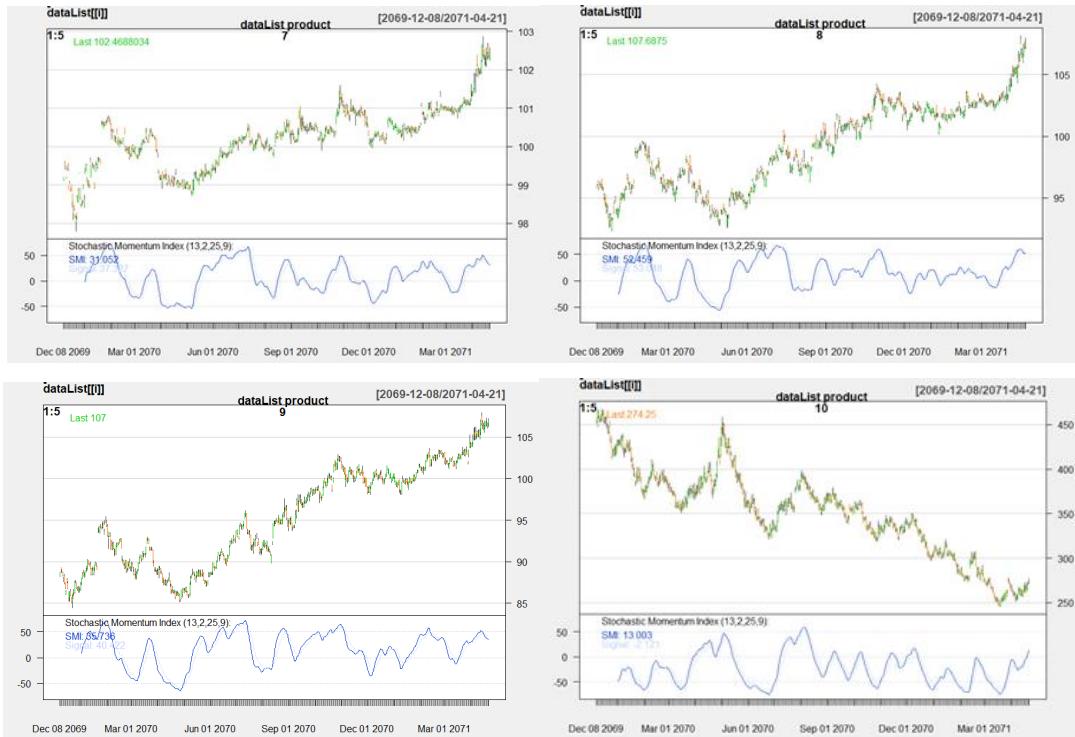






Graph C.2: Stochastic Oscillator graph

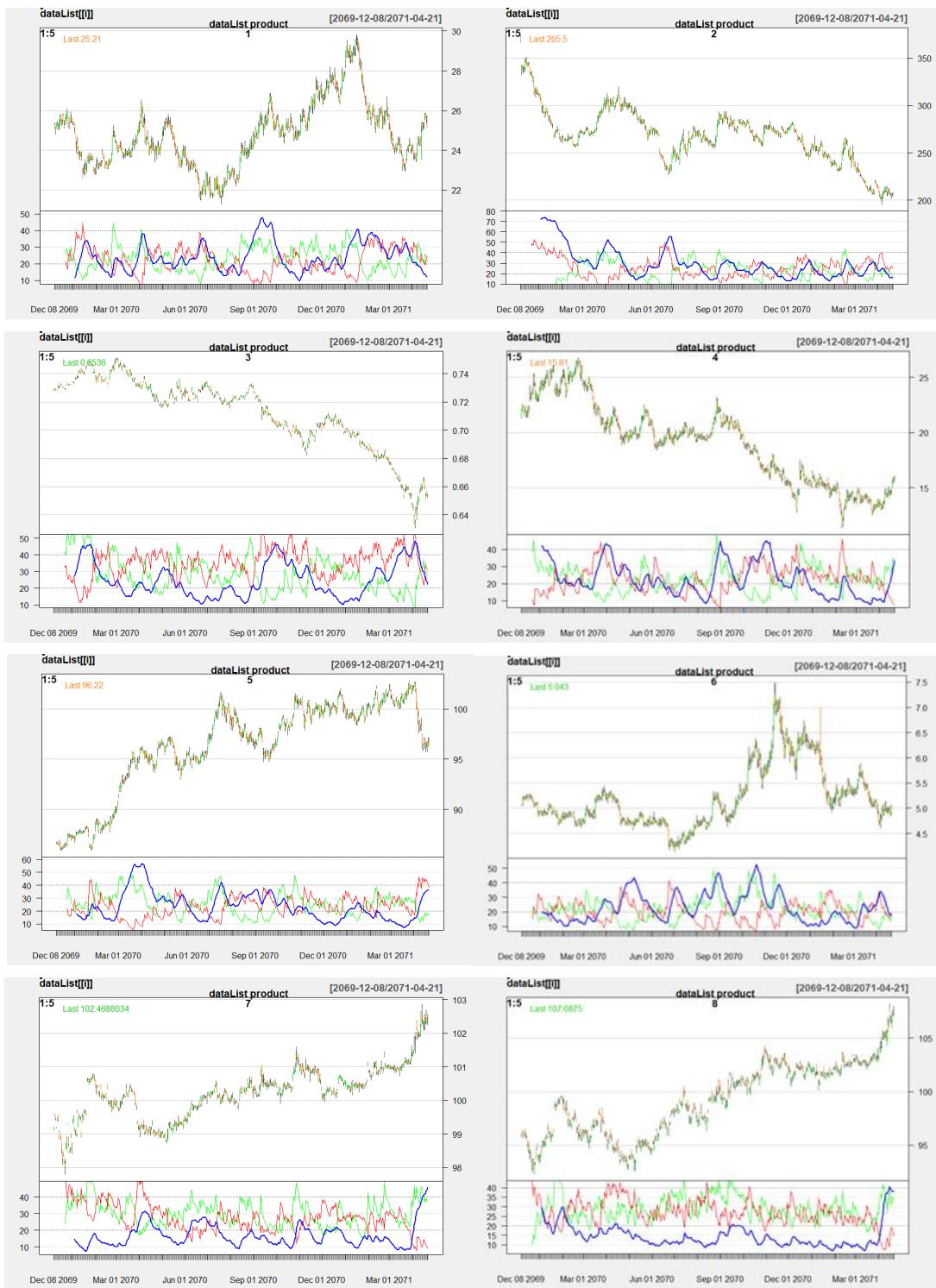


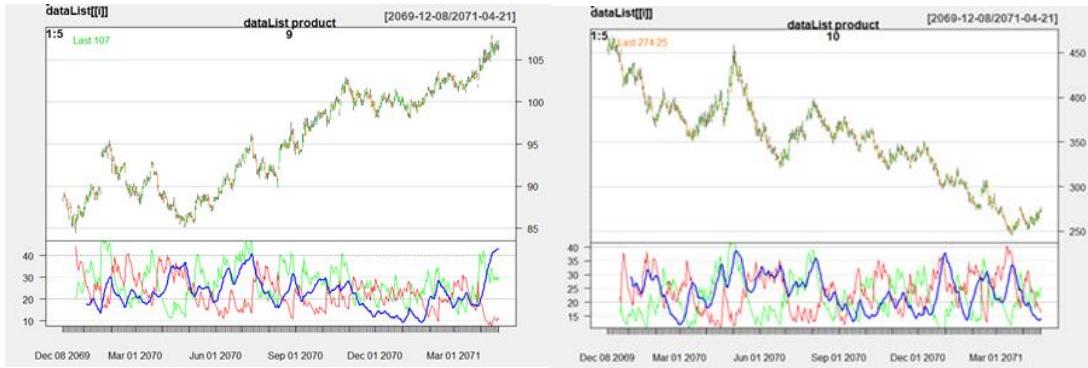


Graph C.3: SMI graph

HLC							
Stochastic Momentum Index							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	56.769223	-70.266305	-6.488703	-10.719545	34.499569	1190.220277
	0-250days	49.260895	-70.266305	-17.212666	-21.048261	28.454829	809.677307
	251-500days	51.345764	-62.49471	-1.901548	-2.30886	35.595466	1267.037169
time series 02	0-500days	65.235129	-81.604312	-20.815218	-22.891716	38.152281	1455.596577
	0-250days	65.235129	-81.604312	-20.713646	-27.74959	44.415805	1972.763719
	251-500days	65.59565	-72.754634	-23.672187	-27.233779	31.646113	1001.476467
time series 03	0-500days	69.284428	-76.271838	-15.11183	-27.555434	39.842806	1587.449226
	0-250days	69.284428	-66.153134	-5.771574	-13.116586	37.874729	1434.495086
	251-500days	58.856062	-76.271841	-30.046994	-41.819466	36.486724	1331.281048
time series 04	0-500days	47.482858	-76.755342	-16.923431	-17.682481	30.533033	932.266128
	0-250days	47.482858	-65.683137	-10.346624	-13.258508	30.004109	900.246563
	251-500days	46.639832	-76.97	-26.745645	-26.893949	28.048384	786.711842
time series 05	0-500days	78.512684	-62.543672	17.904573	19.757079	32.766714	1073.657544
	0-250days	78.512684	-32.571677	33.327846	36.104463	28.814371	830.26797
	251-500days	55.602555	-62.543672	8.157503	15.547545	28.965043	838.973724
time series 06	0-500days	60.7277	-77.816135	-7.357658	-10.213559	33.062096	1093.102194
	0-250days	55.039821	-54.809278	-12.216972	-16.050524	30.07176	904.31075
	251-500days	61.073111	-77.816253	-7.045622	-7.977853	34.536758	1192.787629
time series 07	0-500days	73.239113	-54.511705	8.492149	11.125374	31.32959	981.543181
	0-250days	73.239113	-54.511705	7.728216	11.125374	38.402417	1474.745656
	251-500days	49.948104	-44.238172	7.368745	7.589069	23.795251	566.213982
time series 08	0-500days	70.666151	-56.020302	13.707006	15.213821	28.989227	840.375301
	0-250days	70.666151	-56.020302	10.232831	15.831642	37.029155	1371.15835
	251-500days	25	-27.966466	15.660203	13.889235	19.300569	372.511969
time series 09	0-500days	71.968918	-63.909969	17.017605	21.641924	32.736687	1071.690676
	0-250days	71.968918	-63.909969	8.900345	13.028506	39.546526	1563.927703
	251-500days	64.324575	-34.775109	22.942159	25.913143	23.488895	551.728194
time series 10	0-500days	59.03804	-75.110661	-23.222335	-24.653004	32.498641	1056.161642
	0-250days	59.03804	-75.110661	-16.971914	-22.017204	38.691115	1497.002399
	251-500days	27.874564	-73.858659	-30.048816	-28.751134	25.394208	644.865798

Figures C.3: SMI figures





Graph C.4: ADX graph

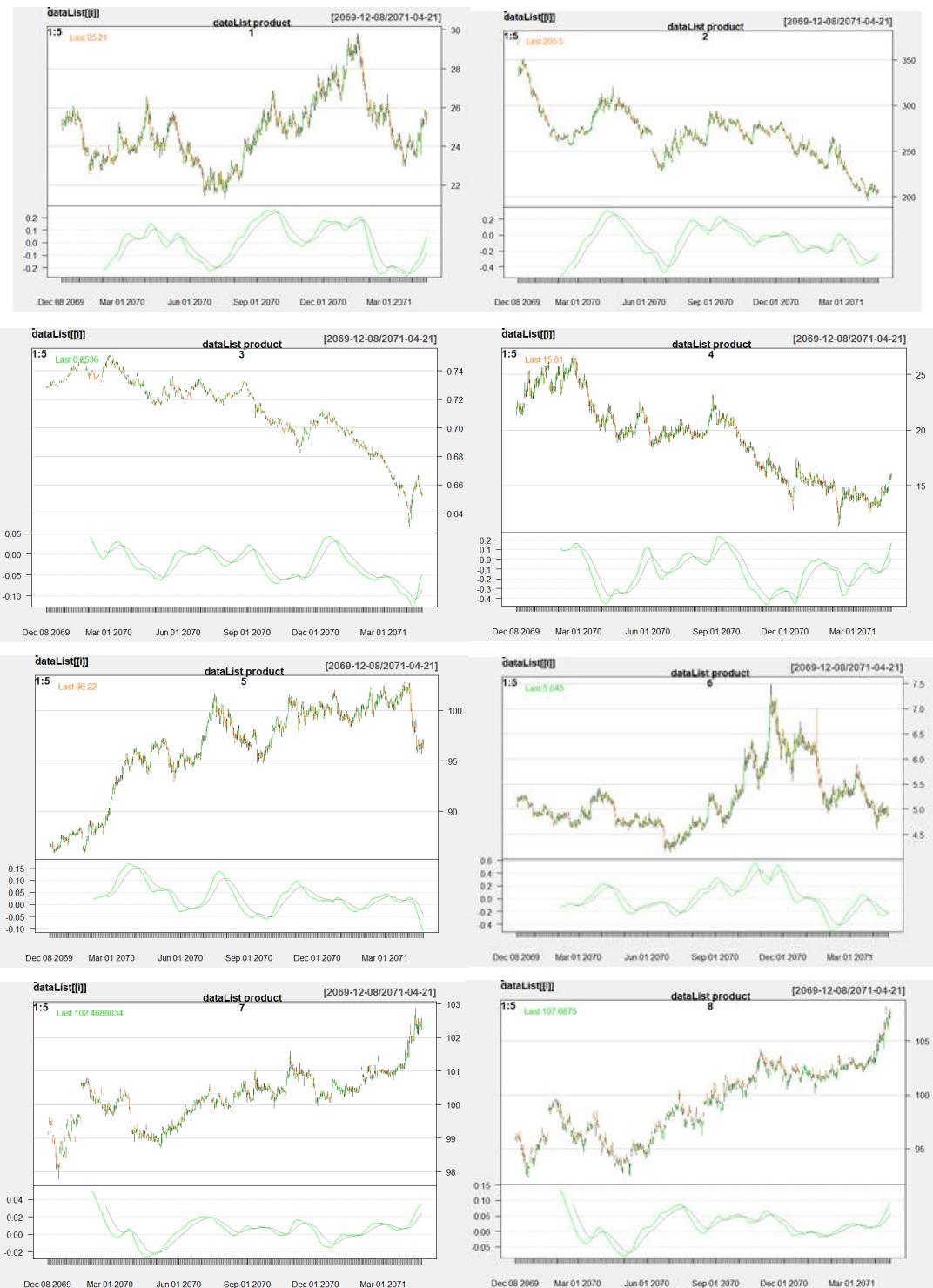
HLC							
Average Directional Movement Index							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	47.756967	9.578371	24.164865	22.599124	8.299317	68.878656
	0-250days	37.931331	11.571381	21.628866	20.839455	6.114643	37.388856
	251-500days	53.881044	9.713286	26.108409	23.857289	9.680404	93.710224
time series 02	0-500days	73.928305	12.603509	29.313846	25.716249	14.025609	196.717697
	0-250days	73.928305	13.943189	37.42976	31.809978	16.056358	257.806626
	251-500days	38.448343	12.615596	22.364028	22.548993	5.712354	32.630992
time series 03	0-500days	48.231995	10.113305	24.957956	22.806045	10.070696	101.418914
	0-250days	46.186076	10.616153	22.689276	20.951368	8.861826	78.531964
	251-500days	48.231986	10.109816	28.070832	28.376837	10.366048	107.454955
time series 04	0-500days	44.905427	7.673263	22.359747	20.17762	88.626831	9.414182
	0-250days	43.147671	8.340935	23.124375	20.73531	8.346998	69.672376
	251-500days	44.546191	7.673236	21.176464	19.435554	10.030395	100.608827
time series 05	0-500days	56.977861	7.323334	23.718561	22.576848	10.90169	118.846839
	0-250days	56.977861	11.650936	27.401753	25.4188	12.164919	147.985265
	251-500days	36.540608	7.32334	18.774234	18.217524	7.322729	53.622357
time series 06	0-500days	52.349481	8.733928	30.081919	23.354502	9.78913	95.827064
	0-250days	43.427194	10.216243	22.338438	19.720448	8.658894	74.976439
	251-500days	53.160018	8.733974	23.111681	20.97021	10.356266	107.252237
time series 07	0-500days	45.671275	7.159019	16.863306	15.215158	6.741443	45.447057
	0-250days	31.390343	7.159019	17.194462	15.466155	6.267426	39.280629
	251-500days	45.671275	7.998874	16.381084	14.33377	7.612348	57.947841
time series 08	0-500days	40.292275	6.845857	14.526978	12.482412	5.995004	35.94007
	0-250days	29.746055	8.474975	15.484462	14.528794	4.687421	21.971916
	251-500days	40.292282	6.845922	14.840616	11.281477	8.303221	68.943472
time series 09	0-500days	43.191316	9.142372	22.86607	22.476153	7.264081	52.766879
	0-250days	40.984433	13.51076	25.14133	23.453605	6.440974	41.486141
	251-500days	43.191318	9.14283	20.169055	19.294681	7.515421	56.48156
time series 10	0-500days	38.548807	11.99224	23.592909	23.380351	6.288581	39.546252
	0-250days	38.548807	11.99224	26.319369	26.78338	5.851978	34.245644
	251-500days	37.884065	9.987011	21.037853	20.100512	6.189553	38.310562

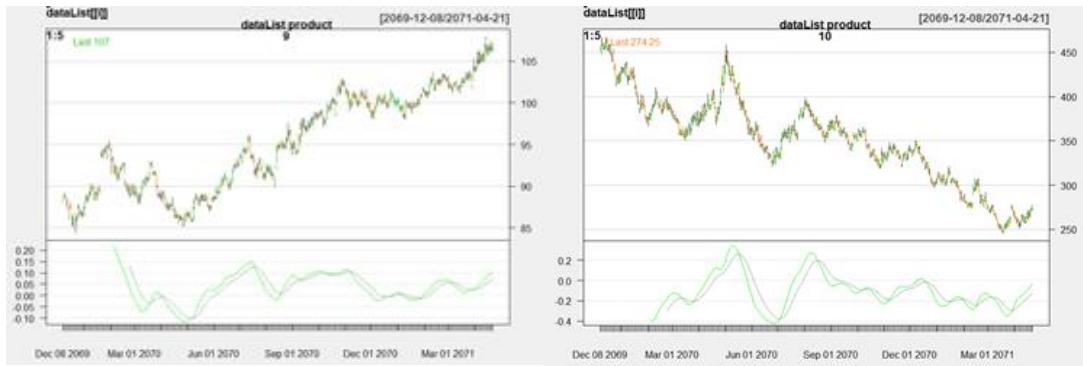
Figures C.4: ADX figures

Table C.1: Up/Down times of ADX in the beginning 1-500 days

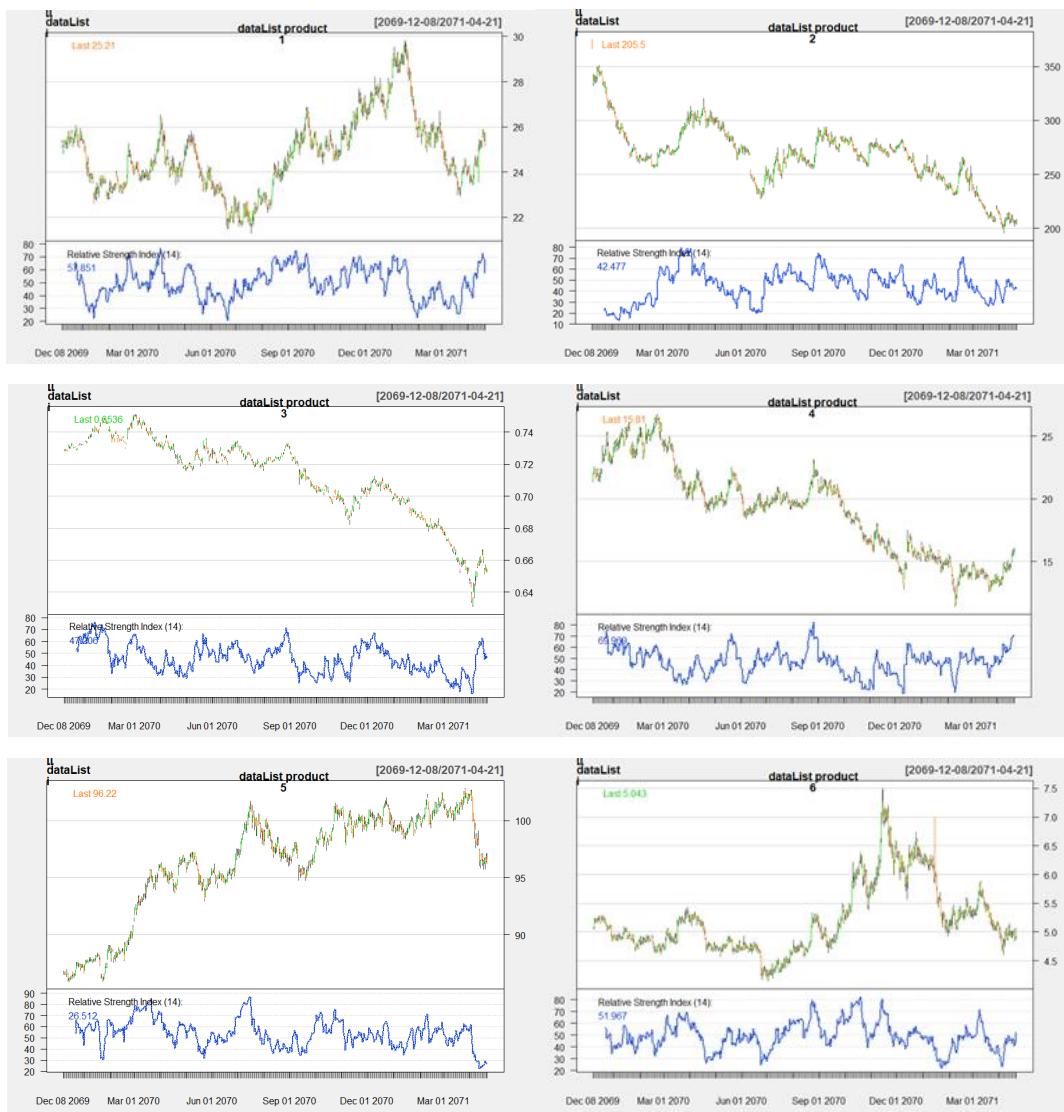
Times	ADX 0-25	ADX 25-50	ADX 50-75	ADX 75-100
Trend Strength	Absent or Weak Trend	Strong Trend	Very Strong Trend	Extremely Strong Trend
1	304	169	0	0
2	216	257	40	0
3	277	196	0	0
4	323	150	0	0
5	284	189	20	0
6	290	183	4	0
7	413	60	0	0

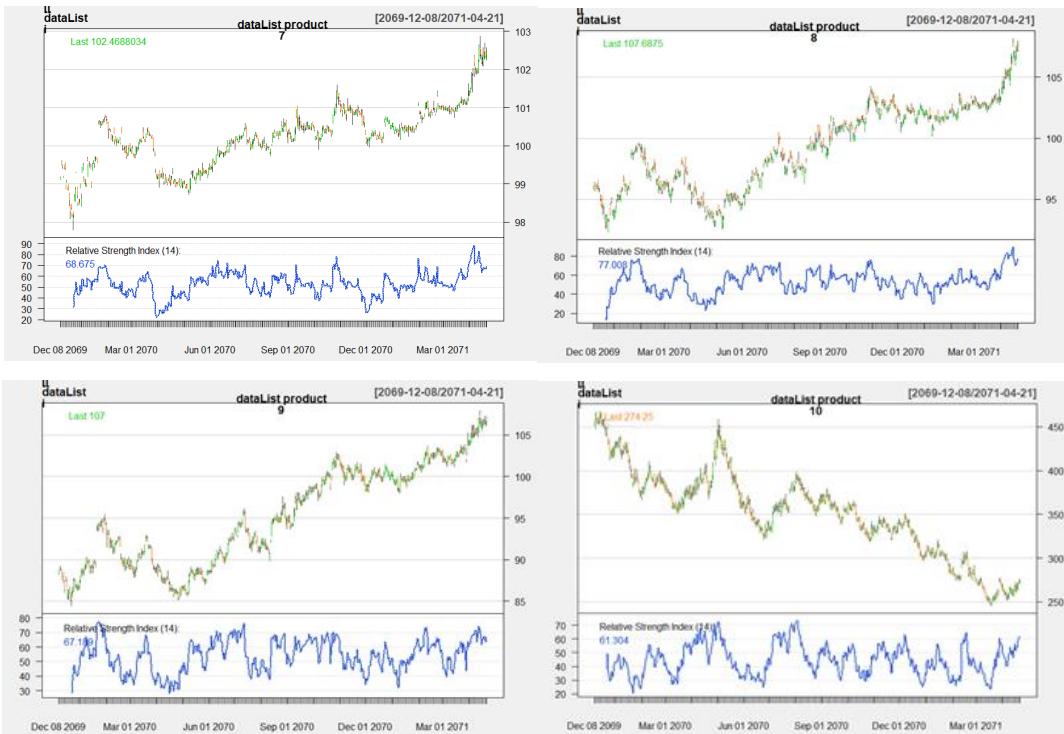
8	445	28	0	0
9	315	158	0	0
10	276	197	0	0





Graph C.5: Triple Exponential Moving Average graph





Graph C.6: RSI graph

OP							
Relative Strength Index							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	76.035136	23.025437	49.903846	48.95684	11.671867	136.232474
	0-250days	76.035136	23.328234	47.537181	47.226632	10.183882	103.711461
	251-500days	74.406393	23.025344	50.90712	51.707461	12.104279	146.513566
time series 02	0-500days	79.96574	17.621724	44.542455	44.937707	13.586088	184.581796
	0-250days	79.96574	17.621724	43.745057	44.062245	15.965392	254.893756
	251-500days	77.781448	21.948573	45.273398	44.936661	11.303477	127.768587
time series 03	0-500days	80.554097	11.774571	45.351242	43.916056	13.601058	184.988772
	0-250days	80.554097	28.519803	50.087513	48.784482	12.165727	148.004904
	251-500days	72.121212	11.774572	40.075288	38.204274	12.93397	167.287572
time series 04	0-500days	83.811288	18.717914	46.825795	46.979302	11.435661	130.774336
	0-250days	78.535539	24.503794	48.356141	48.057677	10.895833	118.719182
	251-500days	75.721227	18.725501	44.869741	46.240874	11.215596	125.789589
time series 05	0-500days	83.577095	20.984461	54.308183	54.25562	11.833074	140.021651
	0-250days	83.577095	29.053584	58.267104	58.026138	11.84466	140.295976
	251-500days	76.587963	20.984461	51.315754	51.90474	10.525782	110.792095
time series 06	0-500days	80.267313	23.478936	49.825919	48.605709	11.458633	131.300281
	0-250days	71.806663	24.602033	47.955969	47.444853	10.405504	108.274512
	251-500days	80.421997	23.478937	51.619566	49.196027	12.192079	148.646796
time series 07	0-500days	85.670924	24.546292	52.546505	52.527609	9.708241	94.249939
	0-250days	74.364766	24.546292	51.470946	52.387141	9.810285	96.241682
	251-500days	85.670924	26.121042	53.034616	52.079509	9.740921	94.885544
time series 08	0-500days	77.493293	26.599047	52.551353	53.143074	8.670759	75.182069
	0-250days	73.683724	26.599047	51.221035	51.38727	9.85214	97.064664
	251-500days	77.493293	34.971113	53.87829	53.533216	7.401132	54.77676
time series 09	0-500days	81.655324	25.029542	54.390034	55.276681	11.812712	139.540174
	0-250days	81.655324	25.029542	52.013656	52.725207	13.904053	193.322693
	251-500days	76.929525	34.287703	56.06763	56.454098	8.960243	80.285955
time series 10	0-500days	74.751731	23.627246	45.103241	44.583606	10.493757	110.118931
	0-250days	74.751731	23.627246	46.633962	45.461209	11.8322	140.000949
	251-500days	62.756199	25.028596	43.388591	43.726105	8.835673	78.069123

Figures C.6: RSI figures

Table C.2: Up/Down times of RSI in the beginning 1-500 days

TIMES/CP	RSI 80-100	RSI 50-80	RSI 20-50	RSI 0-20
1	0	231	255	0
2	0	176	290	20
3	0	172	311	3
4	1	184	298	3
5	12	303	171	0
6	3	205	278	0
7	5	310	171	0
8	9	304	171	2
9	0	312	174	0
10	0	154	332	0

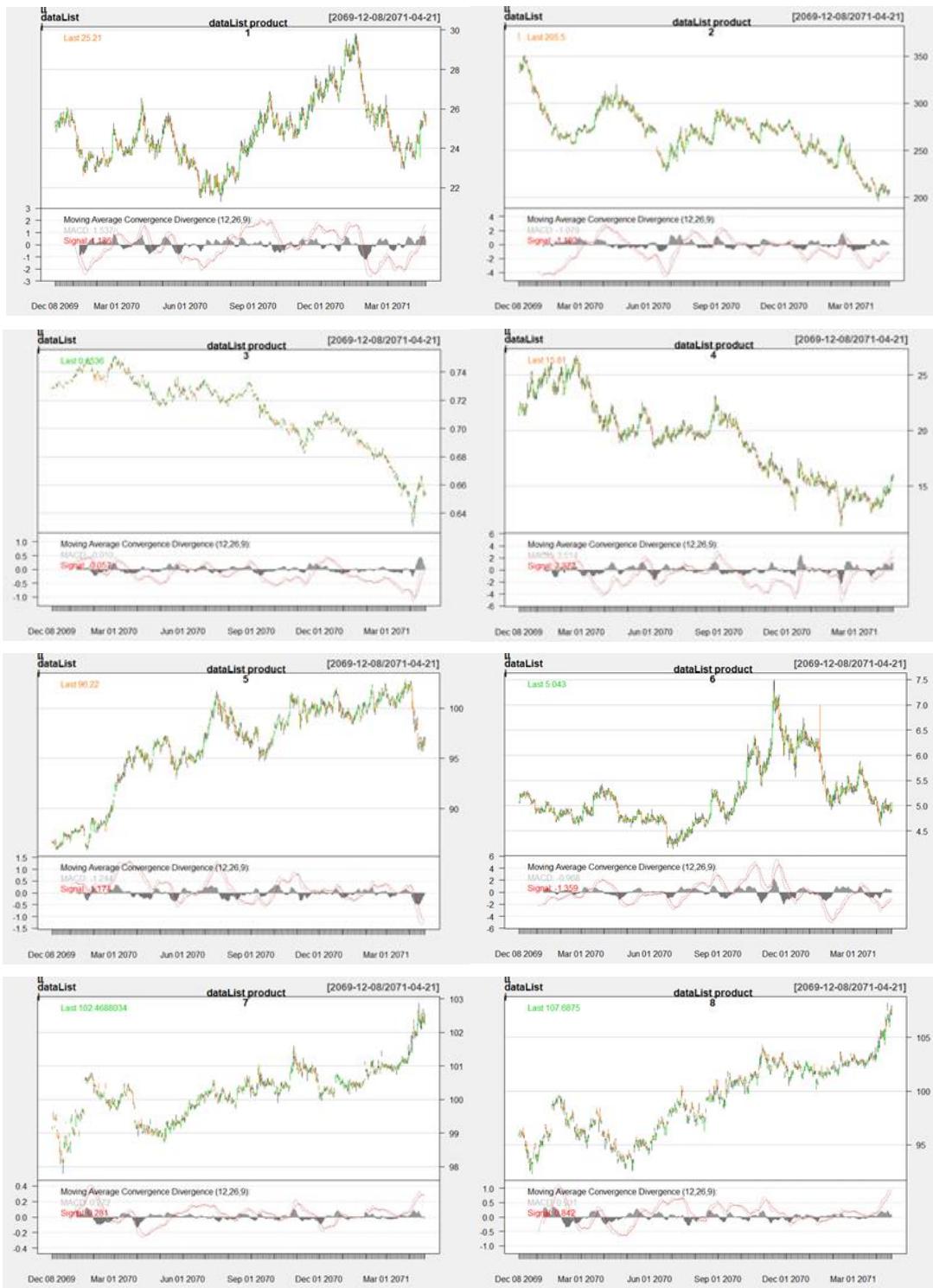


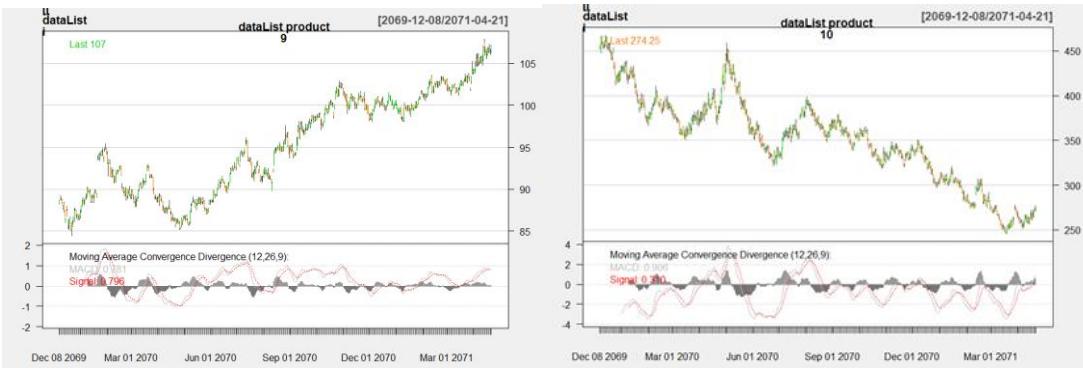


Graph C.7: OBV graph

OP							
On Balance Volume							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	145994	-162938	-56762.16	-64810	59697.74	3563820000
	0-250days	64311	-152000	-53552.71	-64075	56732.67	3218595000
	251-500days	189667	-140429	-18387.66	-23198	70881.68	5024212000
time series 02	0-500days	704775	-3420570	-1316725	-1286430	785782	6.17453E+11
	0-250days	704775	-3420570	-1237264	-1179312	1067458	1.13947E+12
	251-500days	421382	-1022382	-298448.9	-278368.5	356689.8	1.27228E+11
time series 03	0-500days	34150	-589955	-123278.8	-75787	130182.2	16947420000
	0-250days	34150	-81998	-45964.2	-75562	36808.43	1354860000
	251-500days	135068	-418667	-66153.61	-263.5	129318.3	16723220000
time series 04	0-500days	438524	-1476866	-563534.3	-592606	476285.3	2.26848E+11
	0-250days	438524	-921044	-252657.8	-285328.5	381568.9	1.45595E+11
	251-500days	476177	-788567	-240550.5	-305416.5	290551.8	84420370000
time series 05	0-500days	108992	1784	71293.04	77309.5	24105.58	581079000
	0-250days	101425	1784	57445.86	65598	26603.91	707768000
	251-500days	26192	-5347	11982.41	12679	7451.158	55519750
time series 06	0-500days	417573	-163958	134572.5	131858.5	164079	26921930000
	0-250days	130393	-163958	-17749.98	-23068	58736.28	3449950000
	251-500days	371714	-7461	178149.4	178416	84028.4	7060772000
time series 07	0-500days	28010	-66307	-13641.89	-11345.5	19869.63	394802200
	0-250days	9814	-66307	-24417.34	-25605	18718.73	350390700
	251-500days	31429	-59844	-12521.35	-17815.5	21468.5	460896400
time series 08	0-500days	767312	-1384128	-407382.7	-638888	598482.5	3.58181E+11
	0-250days	711982	-1314378	-763300.6	-905487.5	429897.6	1.84812E+11
	251-500days	1686450	-53829	730284.2	756501	428626.4	1.83721E+11
time series 09	0-500days	13765080	-7823699	1896458	-227042	5794974	3.35817E+13
	0-250days	636986	-7823699	-3079359	-2827839	2267560	5.14183E+12
	251-500days	10617530	-1139559	4937631	5117789	2323175	5.39714E+12
time series 10	0-500days	67370	-836466	-536040.9	-555914.5	160171	25654740000
	0-250days	67370	823715	-469773.5	-468740	188410.4	35498490000
	251-500days	28315	-398678	-146788.5	-124434	106393.5	11319580000

Figures C.7: OBV figures





Graph C.8: MACD graph

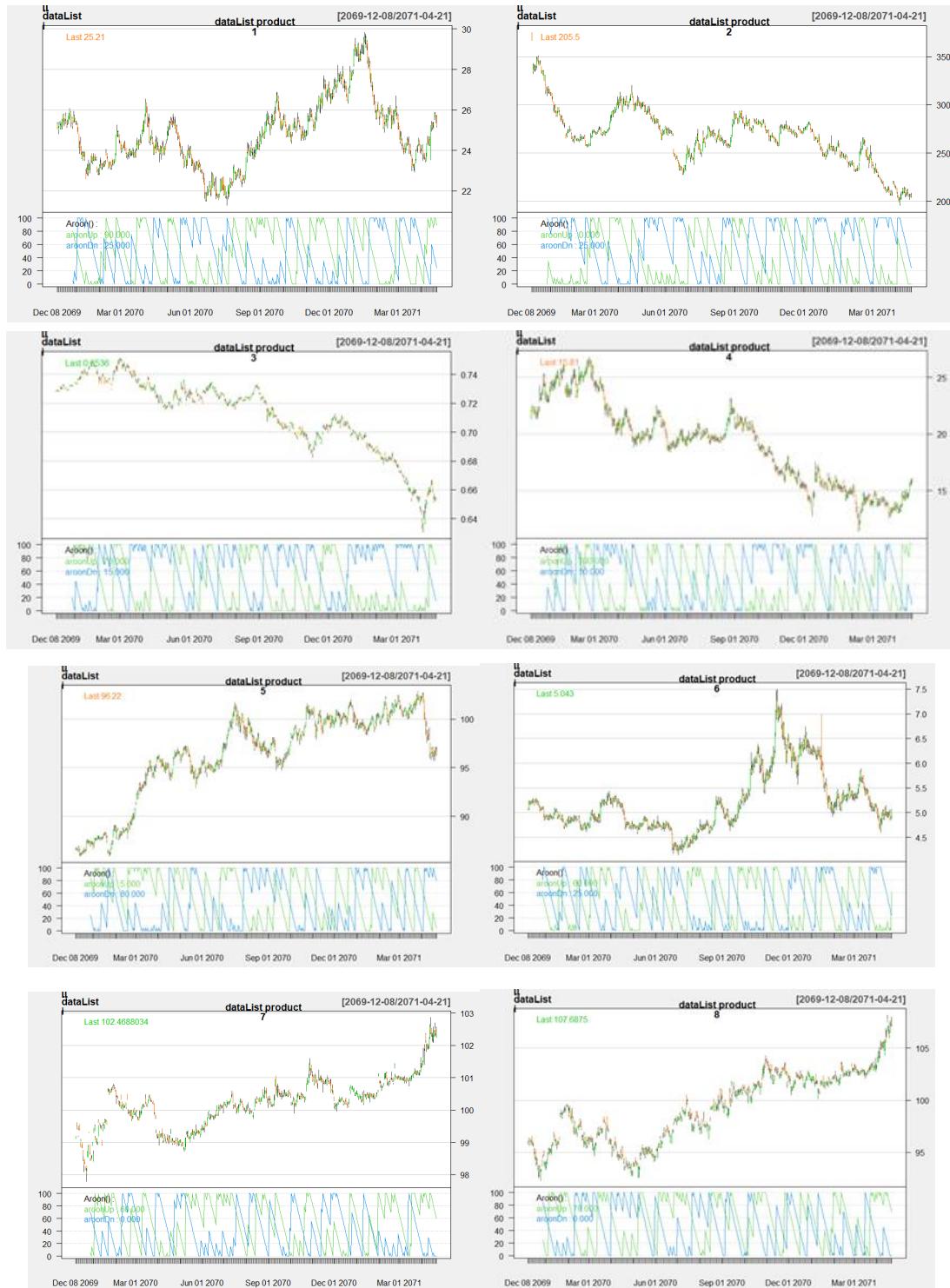
OP MACD Oscillator							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	2.172842	-2.628603	-0.069625	-0.040772	1.246156	1.552904
	0-250days	2.034943	-2.440741	-0.375335	-0.389251	1.006781	1.013607
	251-500days	2.148708	-2.628604	0.053481	0.172111	1.364022	1.860557
time series 02	0-500days	2.935757	-4.548208	-0.7504	-0.683055	1.790873	3.207225
	0-250days	2.935757	-4.548208	-0.870995	-0.837188	2.192394	4.80659
	251-500days	4.06295	-3.530566	-0.687492	-0.913112	1.428193	2.039736
time series 03	0-500days	0.478033	-1.208599	-0.159063	-0.195646	0.335904	0.112832
	0-250days	0.478033	-0.549318	-0.031696	-0.041056	0.264821	0.07013
	251-500days	0.465385	-1.208599	-0.326012	-0.373699	0.343553	0.118029
time series 04	0-500days	3.262832	-5.230133	-0.71883	-0.56189	1.794571	3.220483
	0-250days	2.773061	-4.365689	-0.426093	-0.348893	1.777409	3.159184
	251-500days	3.262832	-5.230134	-1.25173	-1.036149	1.622799	2.633476
time series 05	0-500days	1.392993	-1.346887	0.202255	0.198642	0.500419	0.250419
	0-250days	1.392993	-0.59913	0.416412	0.362223	0.489116	0.239234
	251-500days	0.891598	-1.346887	0.069758	0.101413	0.416581	0.173539
time series 06	0-500days	5.394207	-5.30666	-0.082963	-0.25946	1.939051	3.75992
	0-250days	2.258007	-2.95864	-0.419361	-0.50666	1.281529	1.642316
	251-500days	5.393075	-5.306663	0.005861	-0.143502	2.371363	5.623361
time series 07	0-500days	0.418373	-0.256199	0.04159	0.041231	0.121809	0.014837
	0-250days	0.418373	-0.256199	0.03487	0.041532	0.14417	0.020785
	251-500days	0.326345	-0.196862	0.042025	0.028855	0.102058	0.010416
time series 08	0-500days	1.124194	-0.698047	0.13885	0.139775	0.37118	0.137775
	0-250days	1.124194	-0.698047	0.085064	0.06855	0.460994	0.212516
	251-500days	0.911837	-0.35008	0.153227	0.130487	0.253067	0.064043
time series 09	0-500days	1.847281	-1.006794	0.266432	0.286405	0.574725	0.330309
	0-250days	1.847281	-1.006794	0.166349	0.161729	0.721533	0.52061
	251-500days	1.045864	-0.48327	0.29598	0.269753	0.357647	0.127911
time series 10	0-500days	3.953251	-3.531508	-0.840229	-0.78123	1.555448	2.419419
	0-250days	3.953251	-3.529098	-0.663554	-0.740689	1.997221	3.98889
	251-500days	0.903274	-3.531508	-1.009114	-0.794778	1.03422	1.069611

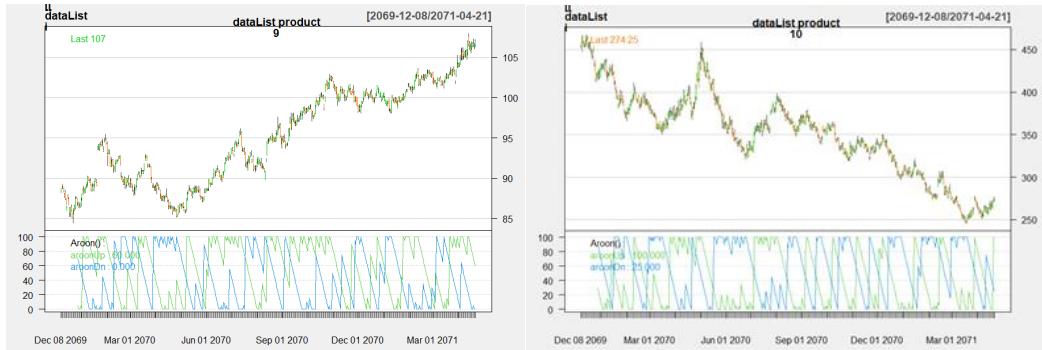
Figures C.8: MACD figures

Table C.3: Up/Down times of MACD in the beginning 1-500 days

Times	MACD>Signal,MACD,Signal>0	MACD<Signal,MACD,Signal<0
1	129	102
2	85	141
3	80	184
4	82	160
5	173	80
6	107	115
7	164	63
8	180	76

9	191	77
10	62	180





Graph C.9: Aroon graph

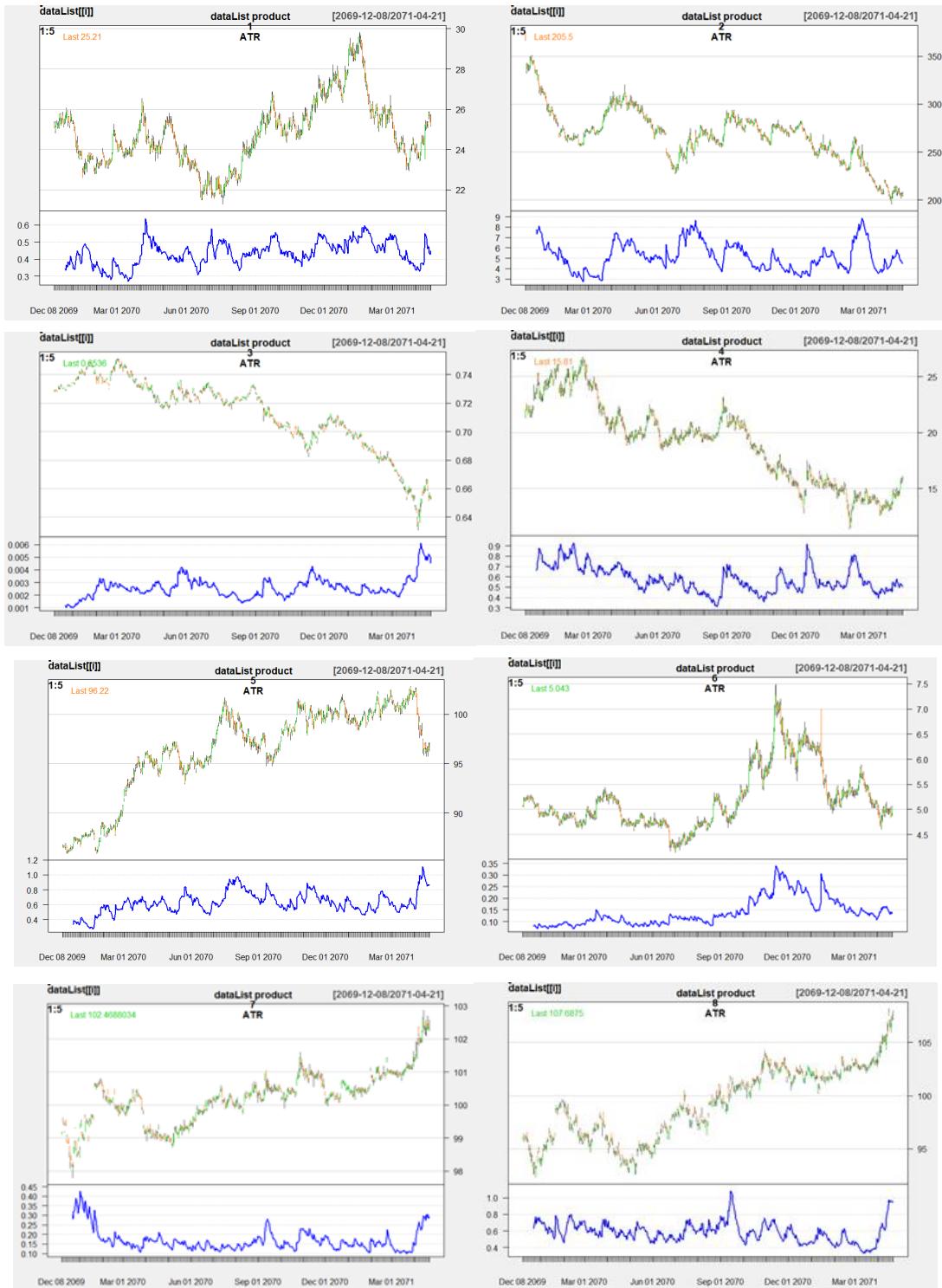
HL							
Aroon							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	100	-100	3.635417	35	63.590075	4043.697699
	0-250days	100	-100	-8.326087	-25	60.497593	3659.958705
	251-500days	100	-100	9.782609	40	64.680577	4183.576989
time series 02	0-500days	100	-100	-21.895833	-45	63.861064	4078.235473
	0-250days	100	-100	-14.413043	-30	69.428288	4820.287165
	251-500days	100	-100	-28.456522	-45	58.454516	3416.930416
time series 03	0-500days	100	-100	-22.541667	-47.5	67.148127	4508.870912
	0-250days	100	-100	-9.413043	-30	67.093292	4501.509873
	251-500days	95	-100	-44.695652	-65	57.535965	3310.387317
time series 04	0-500days	100	-100	-15.697917	-30	61.0322	3724.929432
	0-250days	100	-100	-2.26087	-15	61.11498	3735.04082
	251-500days	100	-100	-35.456522	-47.5	54.349149	2953.829979
time series 05	0-500days	100	-100	16.322917	35	62.173321	3865.521812
	0-250days	100	-85	33.978261	52.5	59.010579	3482.248434
	251-500days	100	-100	6.282609	25	59.096052	3492.343364
time series 06	0-500days	100	-100	-1.4375	-15	61.627342	3797.92928
	0-250days	100	-100	-4.23913	-25	59.252691	3510.881432
	251-500days	100	-100	-0.456522	17.5	65.000069	4225.009018
time series 07	0-500days	100	-100	14.333333	30	59.070509	3489.324983
	0-250days	100	-100	12.673913	35	61.629281	3798.168312
	251-500days	100	-100	13.717391	25	57.839434	3345.400133
time series 08	0-500days	100	-100	10.927083	20	57.953304	3358.585486
	0-250days	100	-100	2.369565	25	65.568844	4299.273305
	251-500days	100	-100	16.608696	20	49.005604	2401.549269
time series 09	0-500days	100	-100	14.46875	35	63.911956	4084.738061
	0-250days	100	-100	3.869565	25	69.053365	4768.367192
	251-500days	100	-100	21.978261	35	58.627865	3437.2266
time series 10	0-500days	100	-100	-18.489583	-45	65.516734	4292.44248
	0-250days	100	-100	-9.217391	-20	69.678273	4855.061705
	251-500days	100	85	-22.630435	-45	60.749812	3690.539681

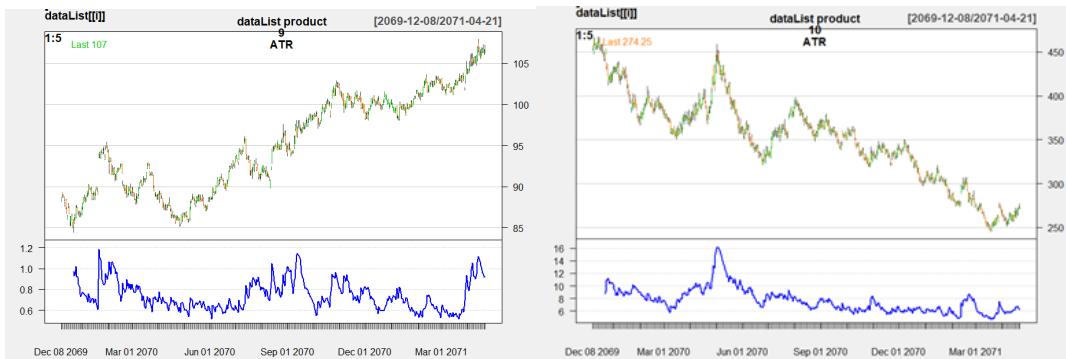
Figures C.9: Aroon figures

Table C.4: Up/Down times of Aroon in the beginning 1-500 days

Times	Aroon_UP	Aroon_DOWN	Aroon_UP	Aroon_DOWN
Trend Strength	Buy	Buy	Sell	Sell
1	163	238	203	0
2	117	154	270	7
3	138	146	280	5
4	111	158	268	4
5	204	268	162	1
6	132	218	226	0
7	197	268	156	9
8	206	235	156	15

9	226	251	164	7
10	135	168	266	3





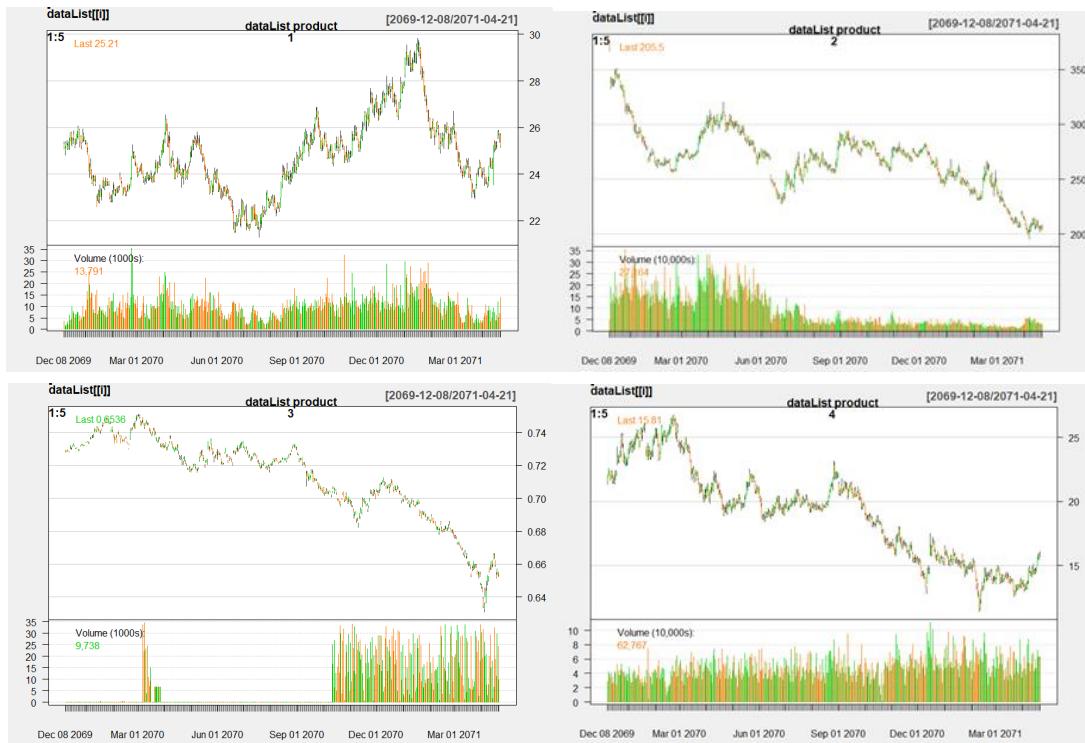
Graph C.10: ATR graph

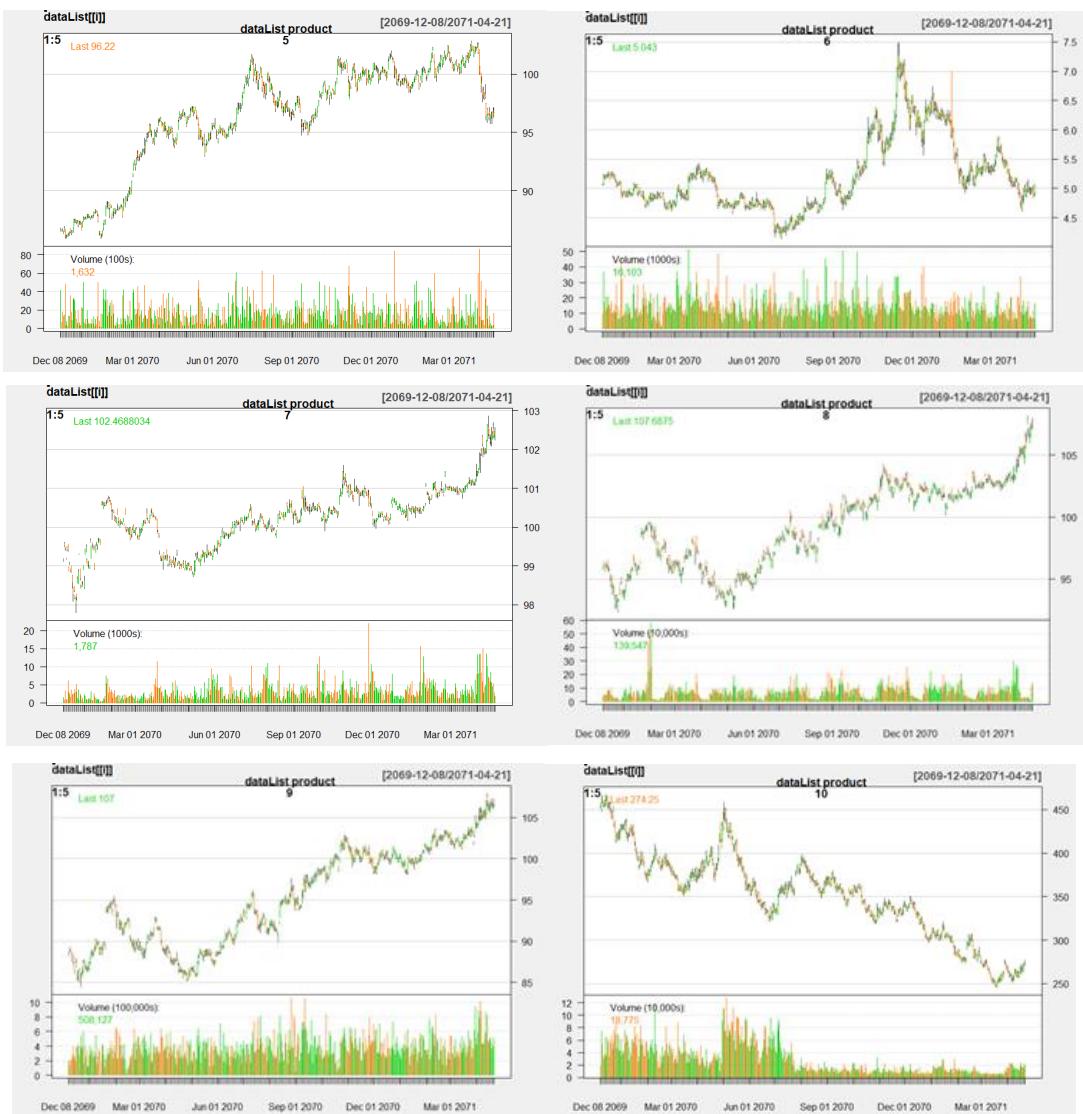
HLC							
Average True Range							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	29.33	21.3	24.557094	24.41	1.614494	2.606591
	0-250days	25.85	21.3	23.579157	23.6	1.101929	1.214246
	251-500days	29.33	22.93	25.537912	25.3	1.446299	2.091782
time series 02	0-500days	345.5	196	264.903808	267	27.812089	773.512315
	0-250days	345.5	227.5	277.75	271.25	24.84264	617.156754
	251-500days	287.5	196	252.064257	257.5	24.59443	604.885975
time series 03	0-500days	0.7495	0.631	0.710734	0.7196	0.025344	0.000642
	0-250days	0.7495	0.716	0.729961	0.7294	0.008521	0.000073
	251-500days	0.7309	0.631	0.691456	0.6966	0.021731	0.000472
time series 04	0-500days	26.25	11.4	18.773146	19.38	3.599087	12.953428
	0-250days	26.25	18.4	21.462731	20.74	2.183654	4.768345
	251-500days	21.88	11.4	16.080964	15.3	2.588664	6.701181
time series 05	0-500days	102.17	85.94	96.042565	96.82	4.427763	19.605089
	0-250days	100.99	85.94	93.071165	94.45	4.287769	18.384967
	251-500days	102.17	94.74	99.009759	99.4	1.809511	3.27433
time series 06	0-500days	7.03	4.145	5.138411	4.995	0.575131	0.330776
	0-250days	5.31	4.145	4.774606	4.735	0.261611	0.06844
	251-500days	7.03	4.605	5.504357	5.325	0.572091	0.327288
time series 07	0-500days	102.351601	97.796898	100.128508	100.195297	-0.057388	0.773909
	0-250days	100.656197	97.796898	99.576058	99.718803	0.583836	0.340865
	251-500days	102.351601	99.898399	100.680344	100.523399	0.499557	0.249558
time series 08	0-500days	107.093803	92.343803	98.883832	98.968803	3.33451	11.118959
	0-250days	99.781197	92.343803	95.983182	95.8125	1.701772	2.896027
	251-500days	98.031197	107.093803	101.790666	101.875	1.578146	2.490544
time series 09	0-500days	106.4375	84.4688	94.784071	94.2188	5.860023	34.339867
	0-250days	95.4688	84.4688	89.551585	89.1875	2.484092	6.170712
	251-500days	106.4375	93.7188	100.018325	100	2.790694	7.787975
time series 10	0-500days	461	246	346.792585	353.5	48.759682	2377.506591
	0-250days	461	321	382.03012	379.25	31.230052	975.316125
	251-500days	371.5	246	311.46988	319.25	36.022795	1297.64173

Figures C.10: ATR figures

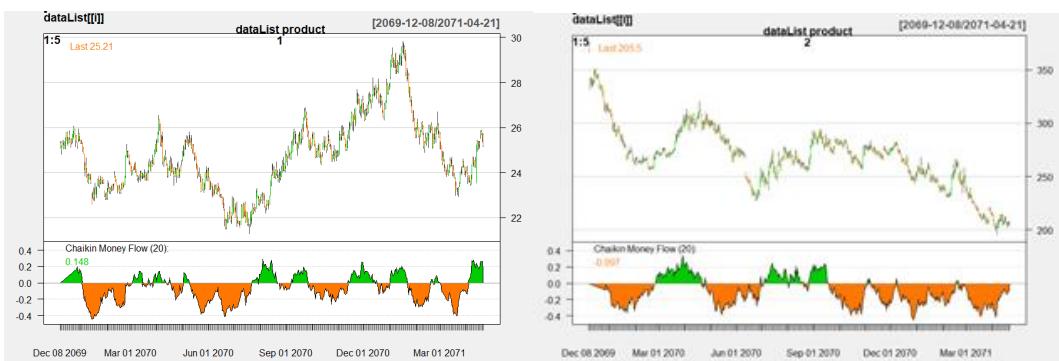
HLC							
True Range							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	1.69	0.15	0.434329	0.4	0.185866	0.034546
	0-250days	1.22	0.15	0.404859	0.37	0.18316	0.033548
	251-500days	1.69	0.17	0.463293	0.43	0.184514	0.034046
time series 02	0-500days	35.5	1.25	5.196393	4.5	3.056859	9.344385
	0-250days	35.5	1.25	5.521084	4.75	3.441959	11.847084
	251-500days	14.75	1.75	4.880522	4.25	2.586806	6.691565
time series 03	0-500days	0.0113	0.0003	0.002588	0.0022	0.001621	0.000003
	0-250days	0.0107	0.0003	0.002367	0.0021	0.001477	0.000002
	251-500days	0.0113	0.0004	0.002816	0.0024	0.001725	0.000003
time series 04	0-500days	2.89	0.09	0.577715	0.5	0.296205	0.087737
	0-250days	2.11	0.2	0.615904	0.56	0.292787	0.085724
	251-500days	2.89	0.09	0.540602	0.48	0.295503	0.087322
time series 05	0-500days	2.18	0.12	0.625671	0.56	0.318469	0.101423
	0-250days	1.94	0.12	0.591165	0.54	0.309264	0.095644
	251-500days	2.18	0.19	0.659076	0.57	0.324653	0.1054
time series 06	0-500days	1.145	0.02	0.139381	0.115	0.096826	0.009375
	0-250days	0.41	0.02	0.097474	0.085	0.04962	0.002462
	251-500days	1.145	0.05	0.181386	0.16	0.113256	0.012827
time series 07	0-500days	1.101501	0.031197	0.172001	0.132805	0.12622	0.015932
	0-250days	1.101501	0.031197	0.176767	0.132797	0.140092	0.019626
	251-500days	0.546906	0.031296	0.167391	0.132805	0.110976	0.012316
time series 08	0-500days	2.5	0.156197	0.590804	0.5	0.323958	0.104949
	0-250days	2.5	0.156197	0.603788	0.5	0.320217	0.102539
	251-500days	2	0.1875	0.576178	0.468803	0.327331	0.107146
time series 09	0-500days	28.75	2	7.676854	7	3.644522	13.28254
	0-250days	28.75	3.25	9.039157	8.25	3.865	14.938229
	251-500days	22	2	6.307229	5.75	2.823788	7.973778
time series 10	0-500days	4.9374	0.1875	0.748934	0.6563	0.403039	0.16244
	0-250days	4.9374	0.1875	0.752257	0.6563	0.446371	0.199247
	251-500days	2.2188	0.25	0.746109	0.6563	0.356178	0.126862

Figures C.11: TR figures





Graph C.11: Volume graph

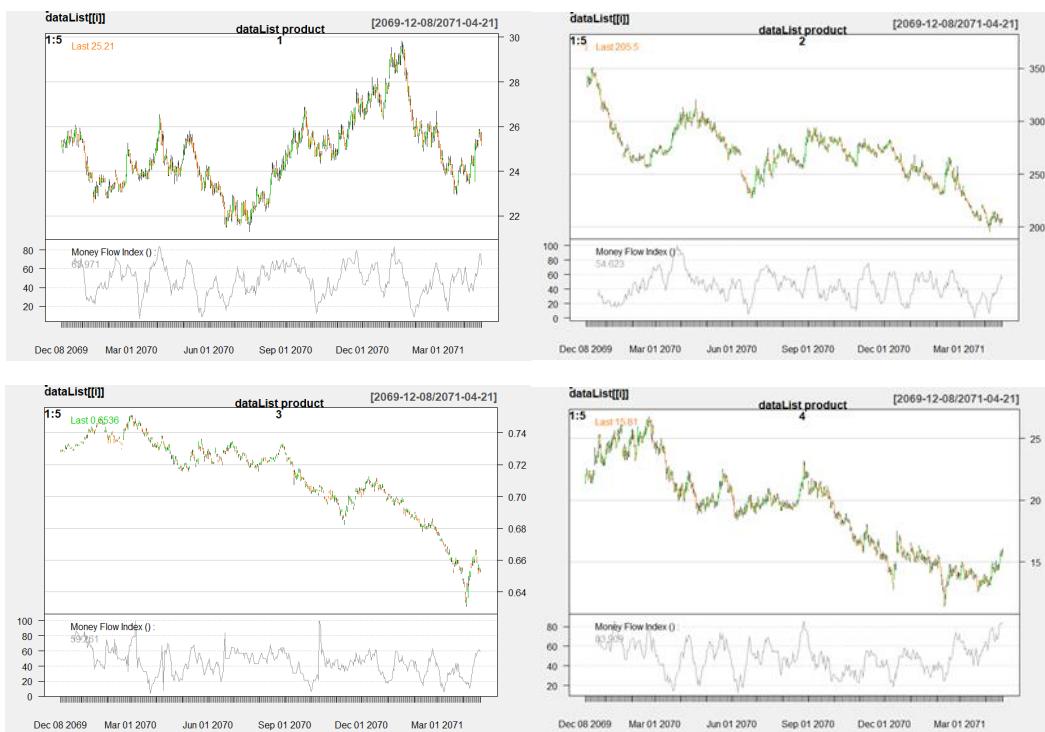


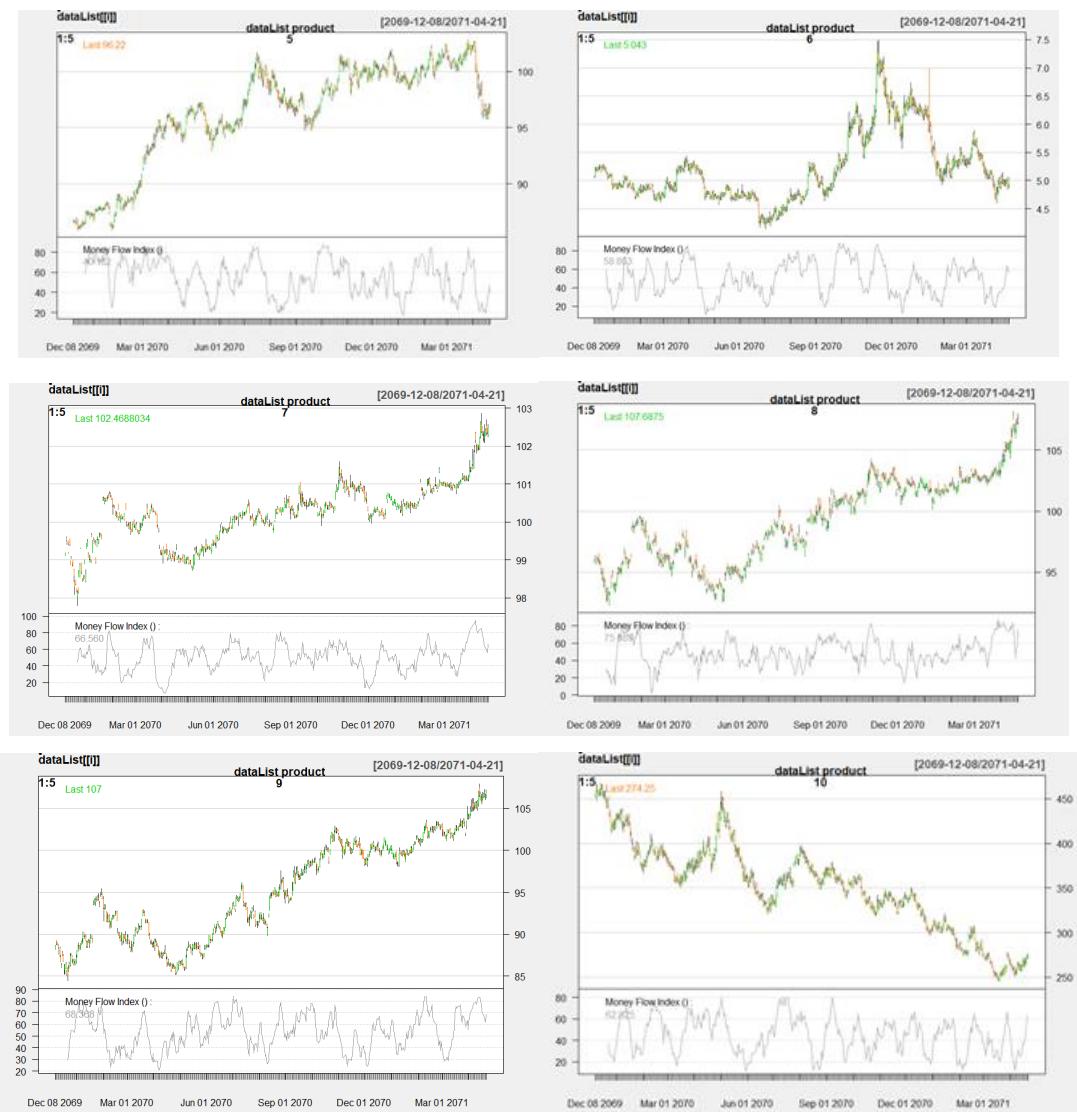


Graph C.12: CMF graph

HLC							
Chaikin Money Flow							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	0.290819	-0.449265	-0.065445	-0.068648	0.165979	0.027549
	0-250days	0.290819	-0.449265	-0.106867	-0.108892	0.171469	0.029402
	251-500days	0.274723	-0.405087	-0.029561	-0.043382	0.155376	0.024142
time series 02	0-500days	0.239329	-0.448762	-0.171545	-0.193686	0.142154	0.020208
	0-250days	0.352352	-0.379003	-0.051939	-0.07028	0.177079	0.031357
	251-500days	0.239329	-0.448762	-0.171545	-0.193686	0.142154	0.020208
time series 03	0-500days	0.797258	-0.896828	0.013936	-0.008863	0.197125	0.038858
	0-250days	0.464513	-0.896828	0.032167	0.018744	0.206815	0.042773
	251-500days	0.797258	-0.359374	-0.021343	-0.060746	0.180349	0.032526
time series 04	0-500days	0.319345	-0.505968	-0.120342	-0.150728	0.177499	0.031506
	0-250days	0.319345	-0.42497	-0.046457	-0.029061	0.18893	0.035694
	251-500days	0.162133	-0.505968	-0.194959	-0.209675	0.130948	0.017147
time series 05	0-500days	0.419459	-0.476551	-0.002024	0.007794	0.179517	0.032226
	0-250days	0.444669	-0.258342	0.070529	0.067721	0.148146	0.021947
	251-500days	0.419459	-0.476551	-0.002024	0.007794	0.179517	0.032226
time series 06	0-500days	0.34505	-0.487434	-0.006414	0.006388	0.171263	0.029331
	0-250days	0.34505	-0.348373	-0.040898	-0.060831	0.154869	0.023984
	251-500days	0.338245	-0.487434	0.021458	0.057932	0.18386	0.033804
time series 07	0-500days	0.52751	-0.521256	0.044472	0.055335	0.172933	0.029906
	0-250days	0.429917	-0.3162	0.002301	-0.006382	0.173732	0.030183
	251-500days	0.52751	-0.521256	0.081753	0.096926	0.168867	0.028516
time series 08	0-500days	0.644731	-0.447912	0.017766	0.003838	0.158276	0.025051
	0-250days	0.24492	-0.447912	-0.021709	-0.003401	0.13448	0.018085
	251-500days	0.644731	-0.232789	0.058303	0.017246	0.174004	0.030277
time series 09	0-500days	0.688019	-0.321276	0.073398	0.042556	0.181305	0.032871
	0-250days	0.299947	-0.271155	0.014339	0.01228	0.138339	0.019138
	251-500days	0.688019	-0.321276	0.073398	0.042556	0.181305	0.032871
time series 10	0-500days	0.275449	-0.540997	-0.153972	-0.153466	0.135155	0.018267
	0-250days	0.275449	-0.44034	-0.114881	-0.119194	0.147562	0.021775
	251-500days	0.022765	-0.540997	-0.198738	-0.180917	0.109347	0.011957

Figures C.12: CMF figures





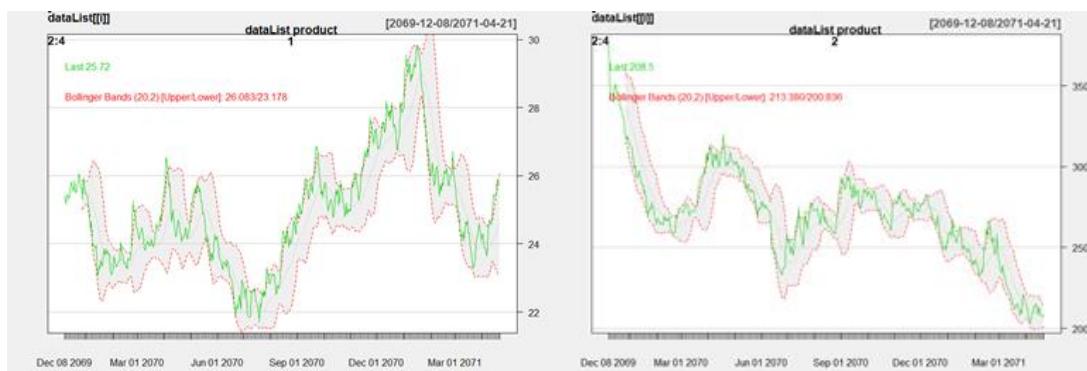
Graph C.13: MFI graph

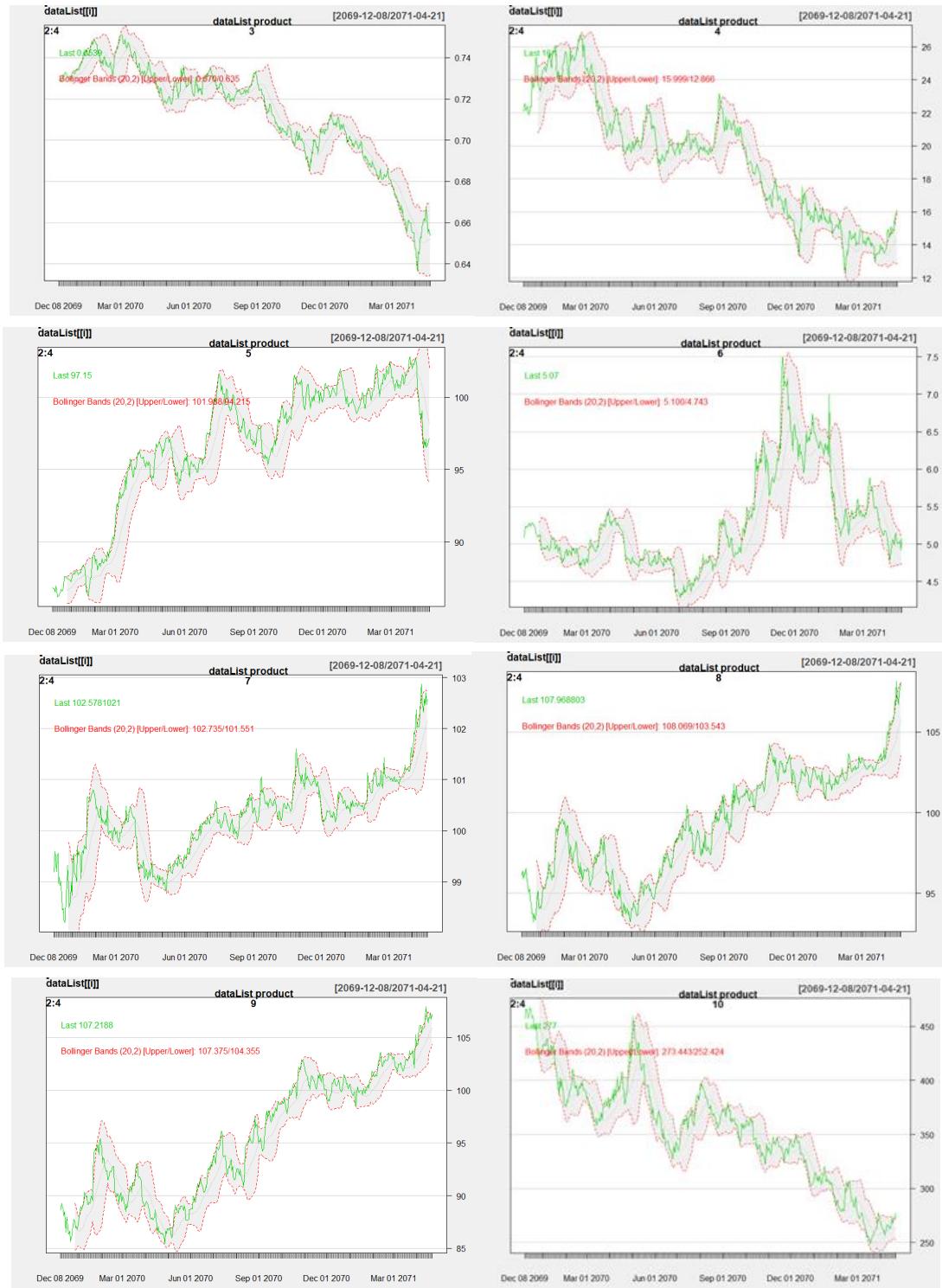
HLC Money Flow Index							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	84.012318	6.906951	48.096486	48.760695	15.842462	250.983617
	0-250days	84.012318	6.906951	46.142918	46.481293	15.683823	245.982296
	251-500days	83.416123	8.891077	49.114643	50.147905	15.853422	251.330982
time series 02	0-500days	100	0	43.568408	43.681473	18.010299	324.370872
	0-250days	100	5.747526	47.002104	47.671839	19.017999	361.684303
	251-500days	75.991973	0	40.415983	39.813531	16.787848	281.831832
time series 03	0-500days	99.913855	3.768834	44.501558	44.889903	17.109908	292.748952
	0-250days	99.797144	3.768834	49.716237	50.056611	17.297358	299.198587
	251-500days	99.913855	6.190189	38.601848	38.837139	15.271014	233.203854
time series 04	0-500days	85.480452	12.771079	49.145905	49.241689	15.314112	234.522016
	0-250days	85.244176	12.771079	51.083822	54.204155	15.427171	237.997611
	251-500days	83.908849	18.640948	46.321023	46.408156	14.445778	208.680511
time series 05	0-500days	87.721944	16.952799	54.808535	57.043569	17.591111	309.447194
	0-250days	86.585902	19.447475	58.254028	62.799832	17.189069	295.464088
	251-500days	87.721944	16.952799	52.33607	53.074241	17.297201	299.193163
time series 06	0-500days	87.969	10.697652	49.032859	48.720299	17.94809	322.133942
	0-250days	85.484546	10.697652	47.758394	47.54176	17.351458	301.073094
	251-500days	87.969	12.47459	49.375508	48.720299	18.543226	343.851218
time series 07	0-500days	95.087949	7.056043	50.179931	51.034198	16.41214	269.358351
	0-250days	82.136634	7.056043	47.338479	49.305125	16.096773	259.106097
	251-500days	95.087949	12.737895	51.80645	52.079199	16.104123	259.342768
time series 08	0-500days	87.576088	2.216344	49.491809	47.93488	15.424577	237.917573
	0-250days	85.867418	2.216344	46.038214	45.750412	15.322786	234.787765
	251-500days	87.576088	13.680597	52.960435	52.728912	15.072153	227.169791
time series 09	0-500days	83.982193	21.124838	53.759793	54.241336	15.102659	228.090299
	0-250days	83.982193	21.124838	51.425004	51.341409	15.149572	229.509543
	251-500days	83.826682	24.244186	55.753018	55.628392	14.90458	222.146504
time series 10	0-500days	81.122503	11.580189	44.400131	46.074167	16.482126	271.660478
	0-250days	81.122503	11.931957	48.522408	49.777523	17.090826	292.096325
	251-500days	80.971896	11.580189	41.776214	43.877712	14.292136	204.265147

Figures C.13: MFI figures

Table C.5: Up/Down times of MFI in the beginning 1-500 days

Times	MFI<50	MFI>80	MFI 50-80
1	253	4	229
2	311	14	161
3	293	12	181
4	251	8	227
5	186	32	268
6	250	19	217
7	227	17	242
8	266	10	210
9	202	12	272
10	291	4	191

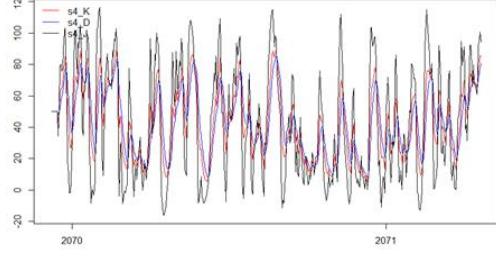
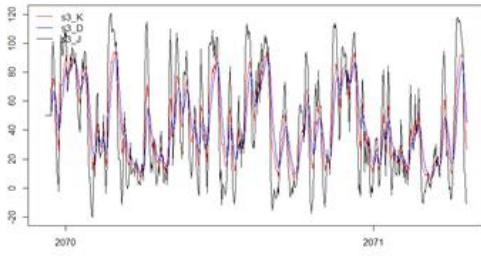
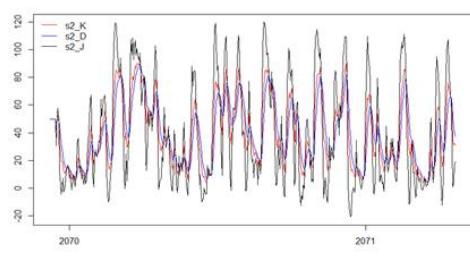
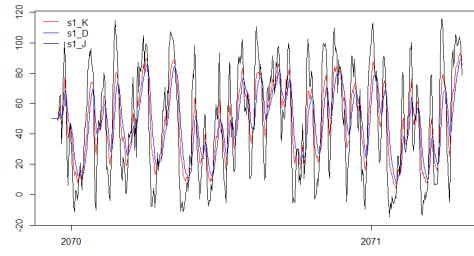


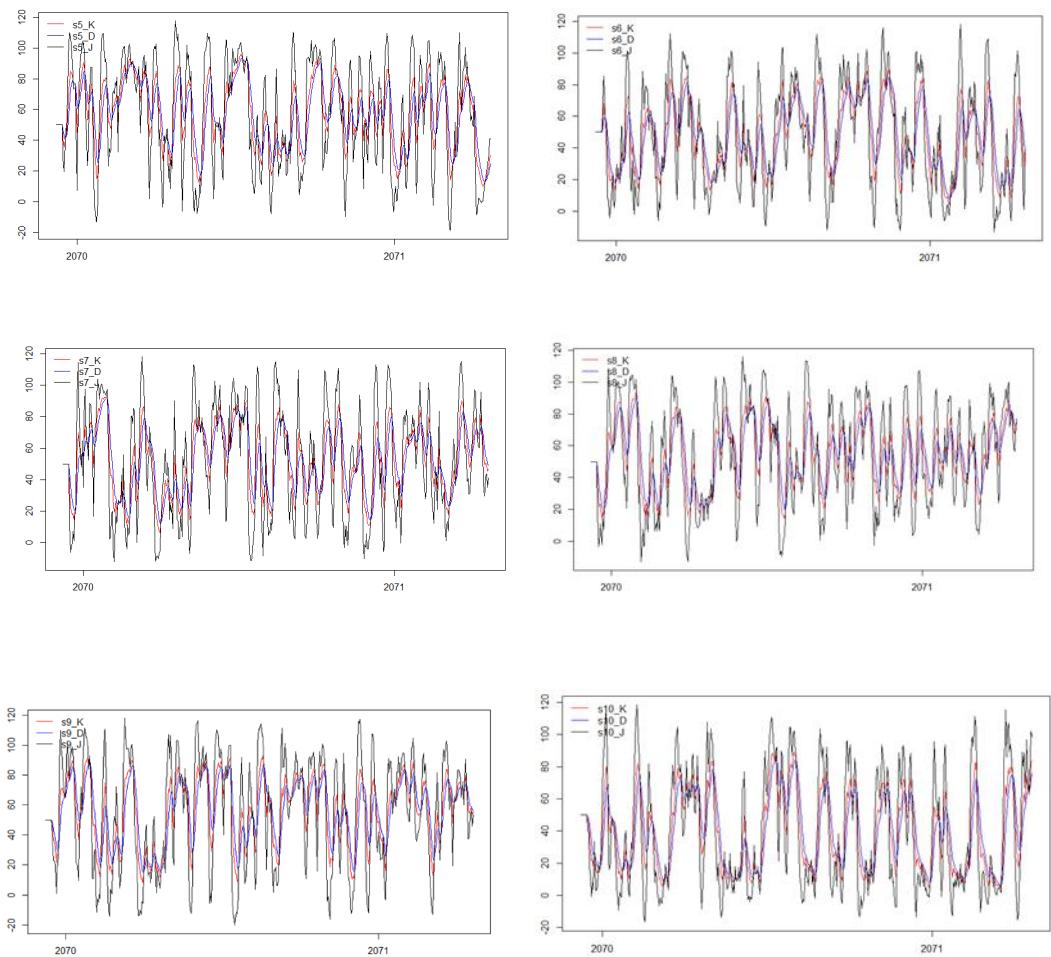


Graph C.14: BBands graph

B%							
Bollinger Bands							
time series	period	the highest data	the lowest data	mean	medium	standart deviation	variance
time series 01	0-500days	1.346801	-0.29494	0.520386	0.510336	0.340621	0.340621
	0-250days	1.346801	-0.29494	0.464973	0.398314	0.337484	0.113895
	251-500days	1.169977	-0.141812	0.549428	0.617942	0.337473	0.113888
time series 02	0-500days	1.286224	-0.457566	0.410442	0.355887	0.330437	0.109189
	0-250days	1.286224	-0.457566	0.429091	0.369366	0.340973	0.116262
	251-500days	1.159294	-0.114506	0.385675	0.352556	0.305296	0.093206
time series 03	0-500days	1.1629	-0.253462	0.403503	0.318494	0.341207	0.116422
	0-250days	1.1629	-0.124893	0.48368	0.447682	0.341297	0.116484
	251-500days	1.044128	-0.253462	0.28583	0.209801	0.291378	0.084901
time series 04	0-500days	1.327299	-0.260663	0.44297	0.408062	0.328141	0.107676
	0-250days	1.292332	-0.152366	0.482681	0.458897	0.317479	0.100793
	251-500days	1.201817	-0.260663	0.363178	0.335919	0.300911	0.090548
time series 05	0-500days	1.311123	-0.360912	0.578822	0.64175	0.330283	0.109087
	0-250days	1.273671	-0.360912	0.630668	0.711221	0.326754	0.106768
	251-500days	1.311123	-0.213368	0.555824	0.574802	0.326396	0.106534
time series 06	0-500days	1.374196	-0.45824	0.494535	0.470922	0.345057	0.119064
	0-250days	1.221182	-0.45824	0.470032	0.454485	0.343079	0.117703
	251-500days	1.265049	-0.284496	0.49255	0.465574	0.339193	0.115052
time series 07	0-500days	1.542856	-0.330913	0.575882	0.586803	0.328987	0.108233
	0-250days	1.320414	-0.330913	0.559095	0.638133	0.336915	0.113512
	251-500days	1.542856	-0.328323	0.578035	0.561075	0.325647	0.106046
time series 08	0-500days	1.301789	-0.191969	0.580042	0.615069	0.31924	0.101914
	0-250days	1.251329	-0.141545	0.537496	0.528816	0.339381	0.115179
	251-500days	1.301789	-0.191969	0.601194	0.627836	0.295526	0.087336
time series 09	0-500days	1.460383	-0.150643	0.597199	0.664627	0.325378	0.105871
	0-250days	1.460383	-0.043537	0.549479	0.554921	0.3493	0.122011
	251-500days	1.196487	-0.150643	0.631998	0.71793	0.2999	0.08994
time series 10	0-500days	1.285094	-0.172261	0.42409	0.386517	0.332732	0.110711
	0-250days	1.285094	-0.172261	0.460362	0.40219	0.354432	0.125622
	251-500days	1.19807	-0.117873	0.40043	0.351249	0.311226	0.096861

Figures C.14: BBands figures





Graph C.15: KDJ graph

## Appendix D

Table D.1: Dickey-Fuller Test of RSI

series	tau1 statistic	tau1 95% critical value	stationary
1	-0.8346541	-1.95	stationary
2	-0.9467928	-1.95	stationary
3	-1.210595	-1.95	stationary
4	-1.069005	-1.95	stationary
5	-1.098799	-1.95	stationary
6	-1.010973	-1.95	stationary
7	-0.6065455	-1.95	stationary
8	-0.3626032	-1.95	stationary
9	-0.7760943	-1.95	stationary
10	-0.7856672	-1.95	stationary

Table D.2: Dickey-Fuller Test of SMI

series	tau1 statistic	tau1 95% critical value	stationary
1	-5.616651	-1.95	non-stationary
2	-4.891298	-1.95	non-stationary
3	-4.665977	-1.95	non-stationary
4	-5.038486	-1.95	non-stationary
5	-5.059755	-1.95	non-stationary
6	-5.348861	-1.95	non-stationary
7	-4.860597	-1.95	non-stationary
8	-5.222044	-1.95	non-stationary
9	-5.235759	-1.95	non-stationary
10	-5.063762	-1.95	non-stationary

Table D.3: Dickey-Fuller Test of OBV

series	tau1 statistic	tau1 95% critical value	stationary
1	-1.063469	-1.95	stationary
2	-0.4817806	-1.95	stationary
3	1.449609	-1.95	stationary
4	-0.5133212	-1.95	stationary
5	0.5576344	-1.95	stationary
6	-0.6468439	-1.95	stationary
7	-1.968156	-1.95	non-stationary
8	-1.309318	-1.95	stationary
9	0.754348	-1.95	stationary
10	-0.3046065	-1.95	stationary

Table D.4: Dickey-Fuller Test of MACD

series	tau1 statistic	tau1 95% critical value	stationary
1	-3.413449	-1.95	non-stationary
2	-3.293864	-1.95	non-stationary
3	-3.58127	-1.95	non-stationary
4	-3.868722	-1.95	non-stationary
5	-3.291692	-1.95	non-stationary
6	-3.679439	-1.95	non-stationary
7	-2.768136	-1.95	non-stationary
8	-3.213734	-1.95	non-stationary
9	-3.645938	-1.95	non-stationary
10	-3.594306	-1.95	non-stationary

Table D.5: Dickey-Fuller Test of ATR

series	tau1 statistic	tau1 95% critical value	stationary
1	-0.2099946	-1.95	stationary
2	-1.718366	-1.95	stationary
3	0.08505053	-1.95	stationary
4	-1.056743	-1.95	stationary
5	-0.1209102	-1.95	stationary
6	-0.7025465	-1.95	stationary
7	-1.410355	-1.95	stationary
8	-0.4552171	-1.95	stationary
9	-0.9588831	-1.95	stationary
10	-1.021279	-1.95	stationary

Table D.6: Dickey-Fuller Test of TR

series	tau1 statistic	tau1 95% critical value	stationary
1	-6.904579	-1.95	non-stationary
2	-9.259689	-1.95	non-stationary
3	-7.729136	-1.95	non-stationary
4	-7.342634	-1.95	non-stationary
5	-6.366633	-1.95	non-stationary
6	-7.771892	-1.95	non-stationary
7	-8.763373	-1.95	non-stationary
8	-7.554388	-1.95	non-stationary
9	-8.408749	-1.95	non-stationary
10	-7.82363	-1.95	non-stationary

Table D.7: Dickey-Fuller Test of ADX

series	tau1 statistic	tau1 95% critical value	stationary
1	-1.573687	-1.95	stationary
2	-2.331366	-1.95	non-stationary
3	-1.403337	-1.95	stationary
4	-1.59778	-1.95	stationary
5	-1.09641	-1.95	stationary
6	-1.827408	-1.95	stationary
7	-0.06967325	-1.95	stationary
8	-0.4263232	-1.95	stationary
9	-0.547444	-1.95	stationary
10	-1.36128	-1.95	stationary

Table D.8: Dickey-Fuller Test of MFI

series	tau1 statistic	tau1 95% critical value	stationary
1	-1.558745	-1.95	stationary
2	-1.405721	-1.95	stationary
3	-1.938031	-1.95	stationary
4	-1.031745	-1.95	Stationary
5	-1.572803	-1.95	stationary
6	-1.44776	-1.95	stationary
7	-1.187686	-1.95	stationary
8	-1.01485	-1.95	stationary
9	-0.9324695	-1.95	stationary
10	-1.471979	-1.95	stationary

Table D.9: Dickey-Fuller Test of Aroon

series	tau1 statistic	tau1 95% critical value	stationary
1	-4.046609	-1.95	non-stationary
2	-3.682566	-1.95	non-stationary
3	-3.179995	-1.95	non-stationary
4	-4.20912	-1.95	non-stationary
5	-4.059053	-1.95	non-stationary
6	-4.424858	-1.95	non-stationary
7	-4.380719	-1.95	non-stationary
8	-4.523486	-1.95	non-stationary
9	-3.944631	-1.95	non-stationary
10	-4.120582	-1.95	non-stationary

Table D.10: Dickey-Fuller Test of BBands

series	tau1 statistic	tau1 95% critical value	stationary
1	-0.1231814	-1.95	stationary
2	-0.7768517	-1.95	stationary
3	-1.142671	-1.95	stationary
4	-1.102971	-1.95	stationary
5	-0.07341521	-1.95	stationary
6	-0.4314873	-1.95	stationary
7	1.450815	-1.95	stationary
8	1.424895	-1.95	stationary
9	1.345562	-1.95	stationary
10	-0.9321105	-1.95	stationary

Table D.11: Ljung-Box test of SMI

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.12: Ljung-Box test of ADX

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.13: Ljung-Box test of RSI

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-1
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.14: Ljung-Box test of OBV

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.15: Ljung-Box test of MACD

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.16: Ljung-Box test of Aroon

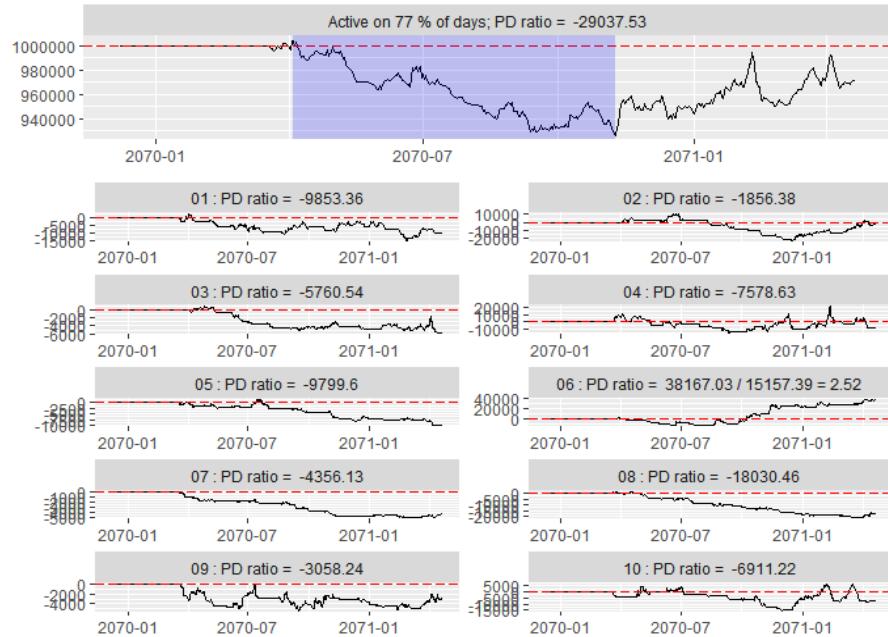
series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-1
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

Table D.17: Ljung-Box test of BBands

series	OP auto-correlation(p-value)	p-value
1	non-white noise	< 2.2e-16
2	non-white noise	< 2.2e-16
3	non-white noise	< 2.2e-16
4	non-white noise	< 2.2e-16
5	non-white noise	< 2.2e-16
6	non-white noise	< 2.2e-16
7	non-white noise	< 2.2e-16
8	non-white noise	< 2.2e-16
9	non-white noise	< 2.2e-16
10	non-white noise	< 2.2e-16

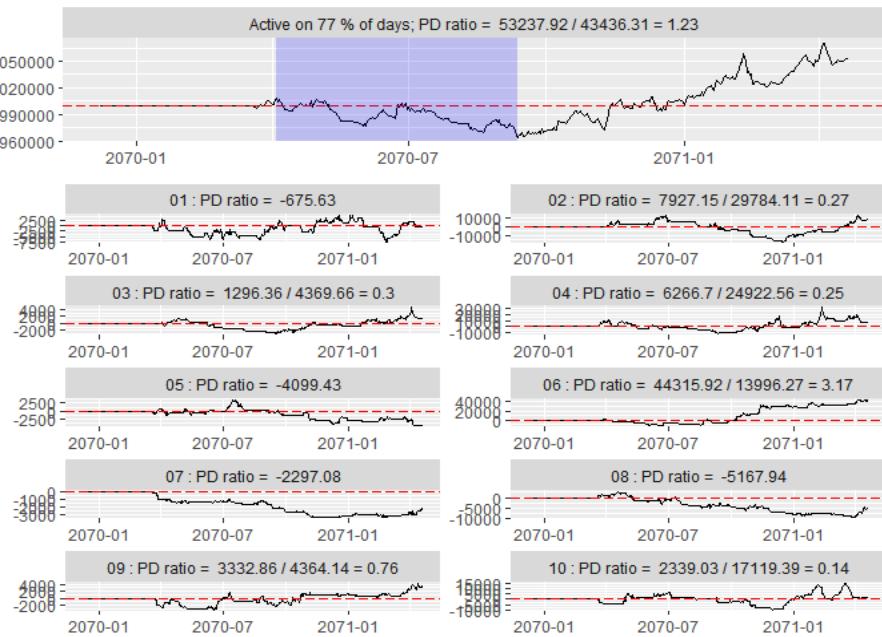
## Appendix E

### Triple moving average Strategy



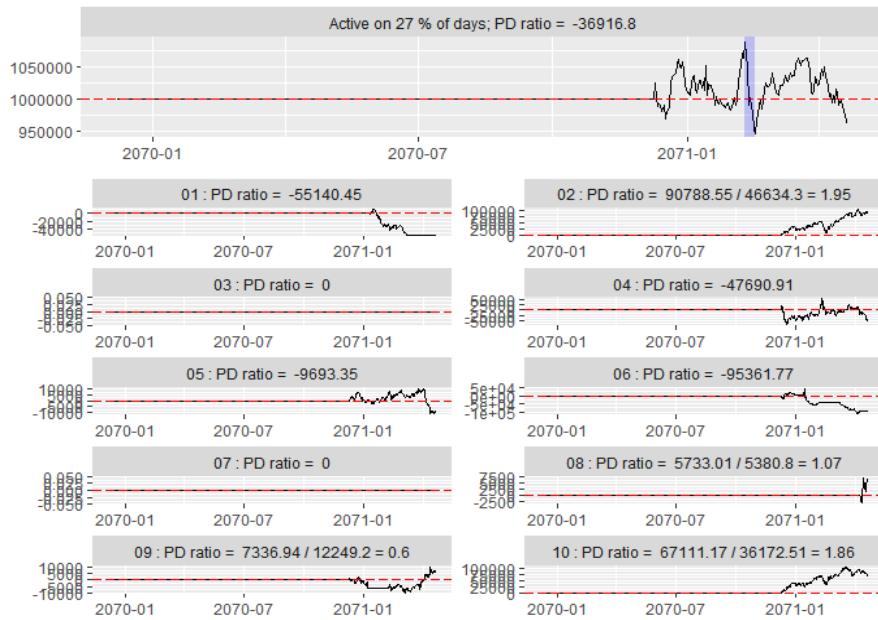
Graph E.1: Triple Moving Average Strategy (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

### Triple moving average Strategy



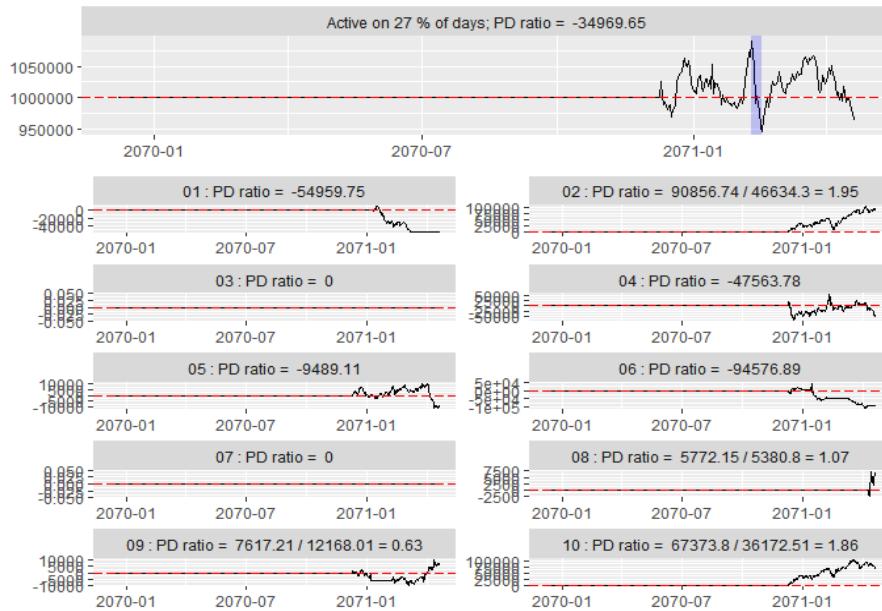
Graph E.2: Triple Moving Average Strategy (day 1-500 without slippage and \$100,000 wager per time per series)

## Relative strength Strategy



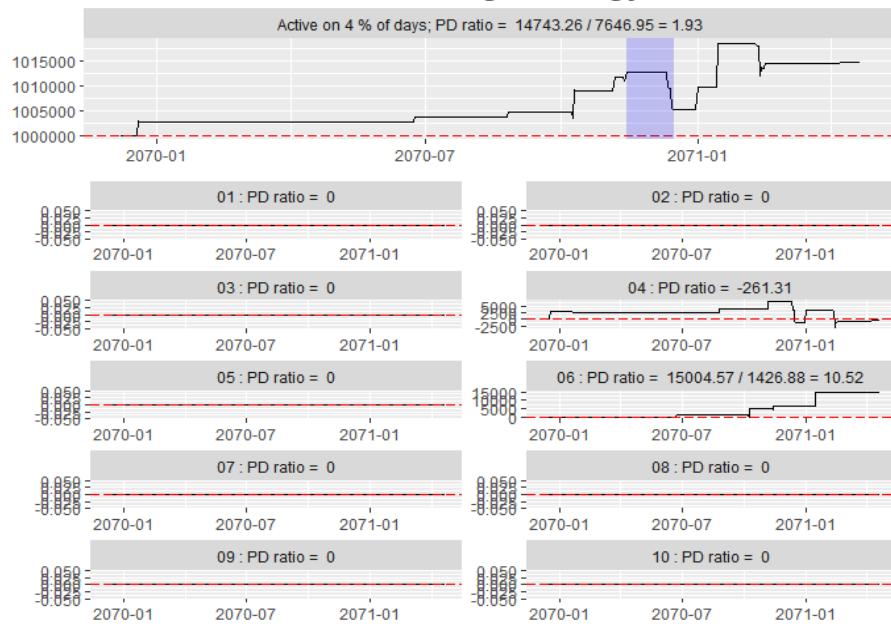
Graph E.3: Relative Strength Strategy (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

## Relative strength Strategy



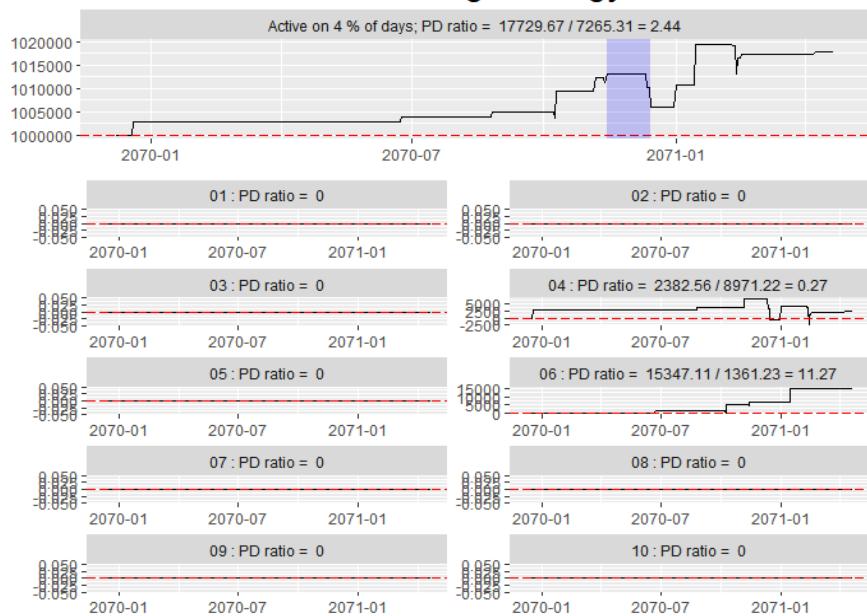
Graph E.4: Relative Strength Strategy (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

## Market Making Strategy



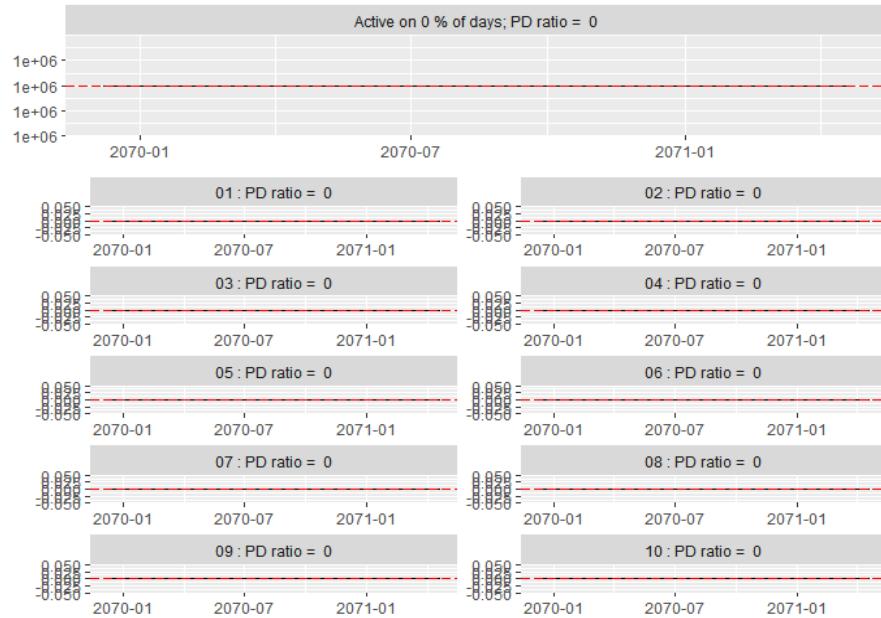
Graph E.5: Market Making Strategy (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

## Market Making Strategy



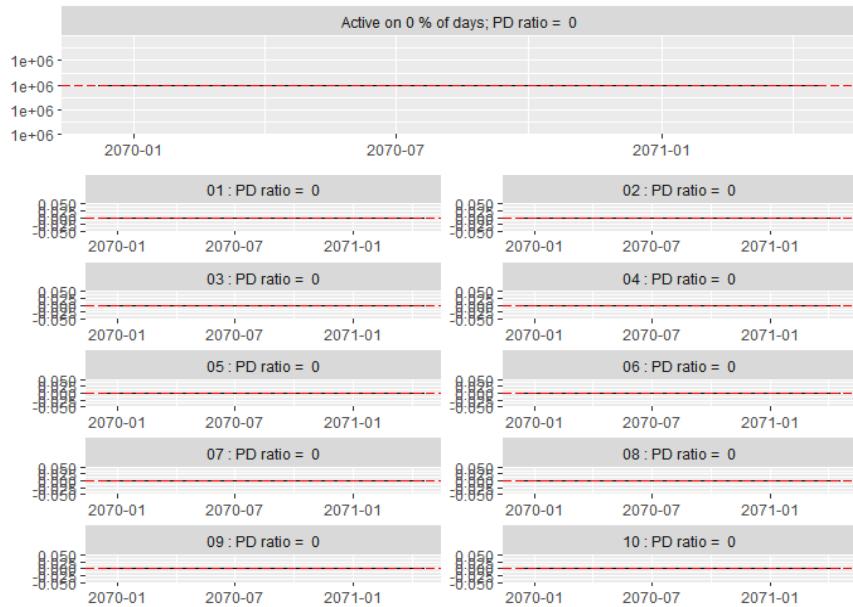
Graph E.6: Market Making Strategy (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

## The Jump Trading Strategy



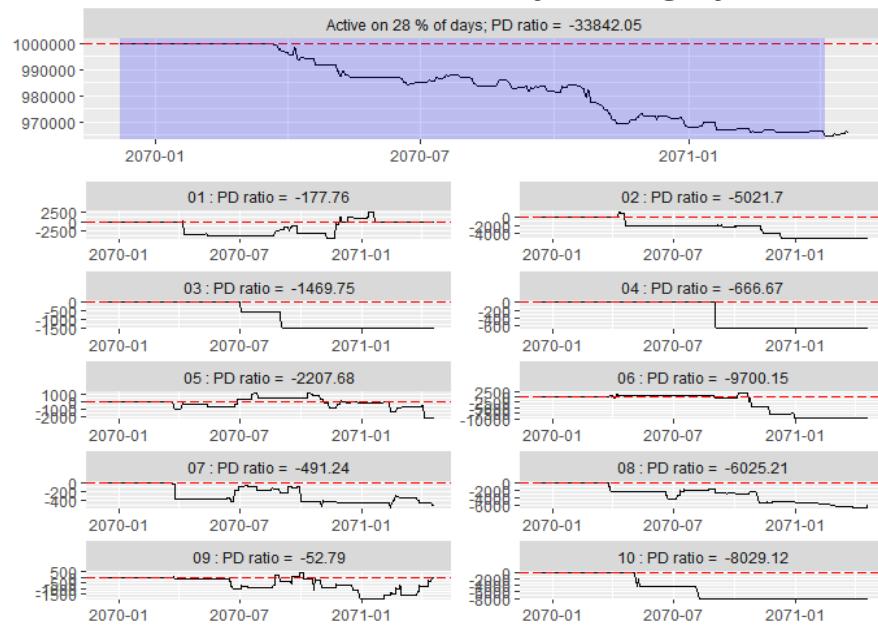
Graph E.7: The Jump Trading Strategy (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

## The Jump Trading Strategy



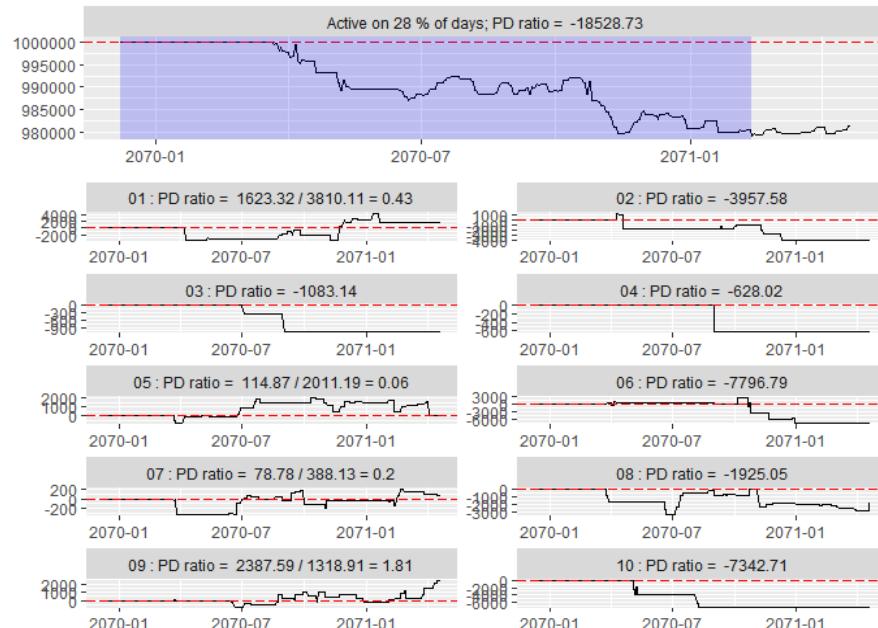
Graph E.8: The Jump Trading Strategy (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

## Lawrence Macmillan Volatility Trading System



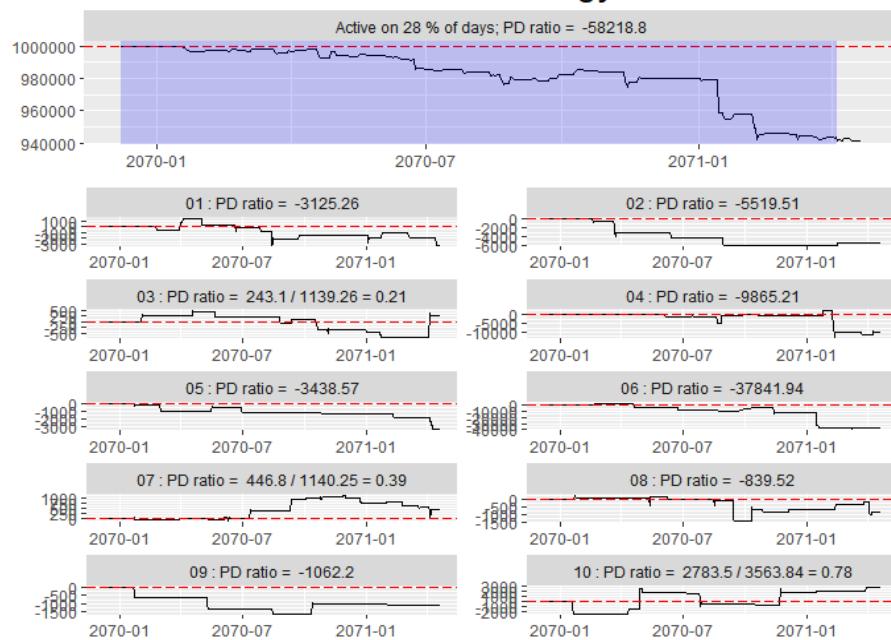
Graph E.9: Lawrence Macmillan Volatility Trading System (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

## Lawrence Macmillan Volatility Trading System



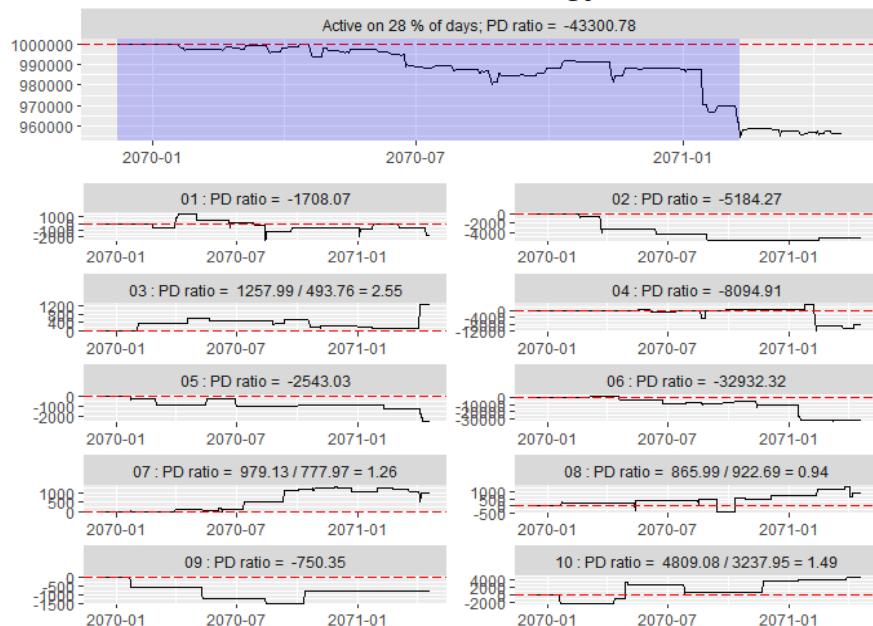
Graph E.10: Lawrence Macmillan Volatility Trading System (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

### Bbands based Strategy-mr

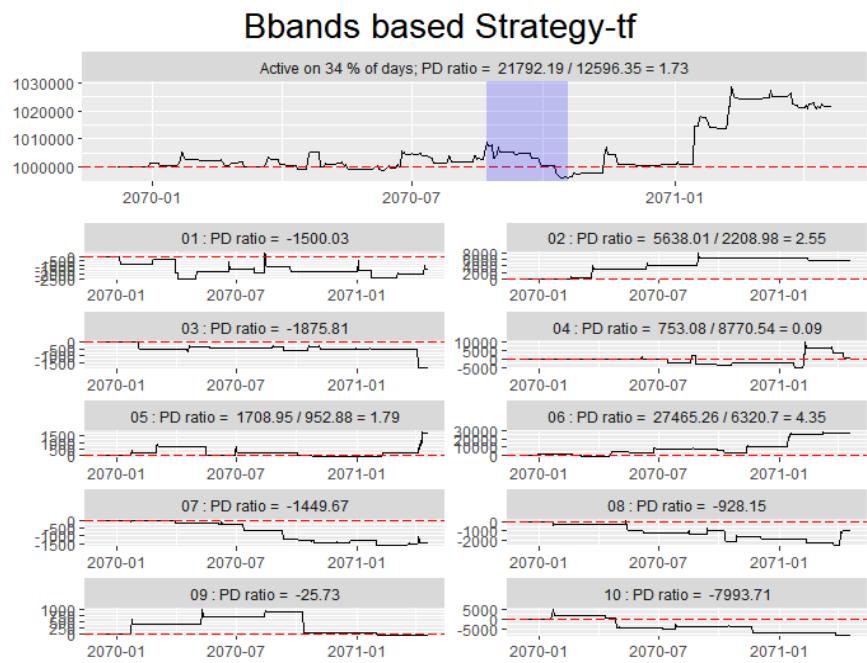


Graph E.11: BBands based Strategy (Mean-reversion) (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

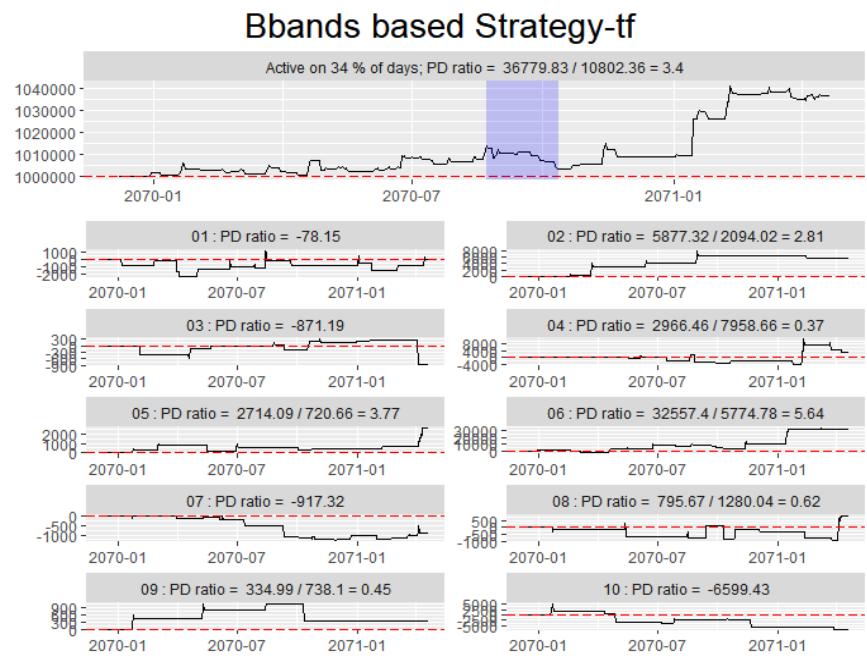
### Bbands based Strategy-mr



Graph E.12: BBands based Strategy (Mean-reversion) (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

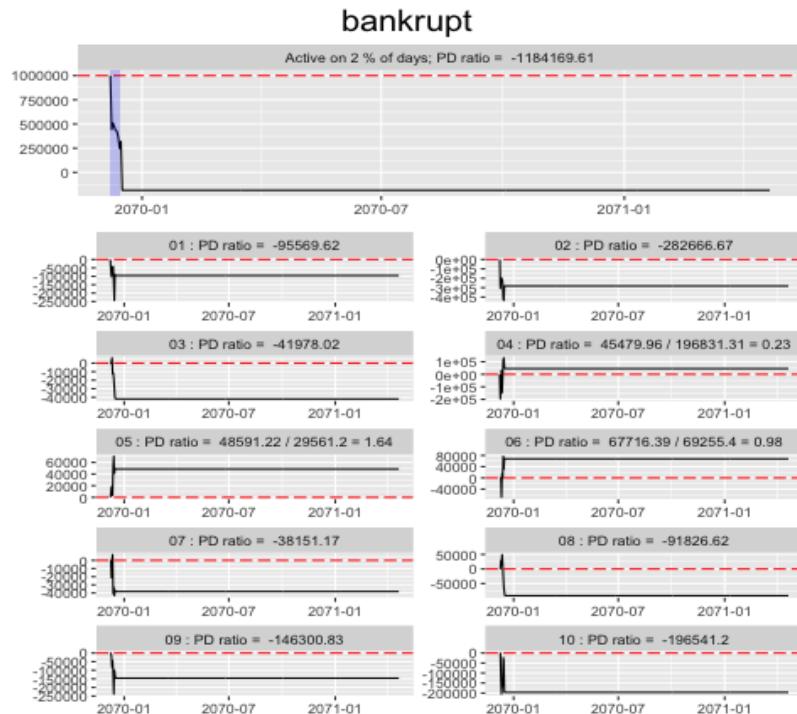


Graph E.13: BBands based Strategy (Trend-following) (day 1-500 with 0.2 slippage and \$100,000 wager per time per series)

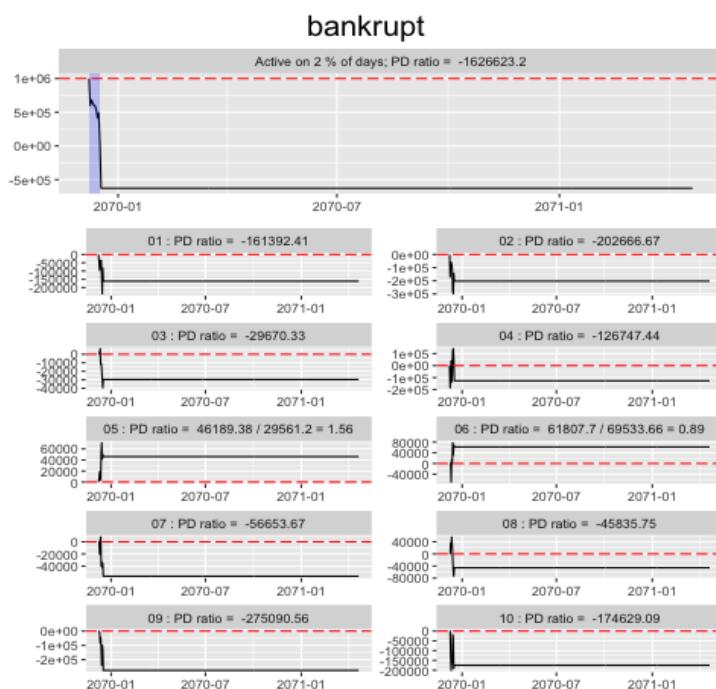


Graph E.14: BBands based Strategy (Trend-following) (day 1-500 without 0.2 slippage and \$100,000 wager per time per series)

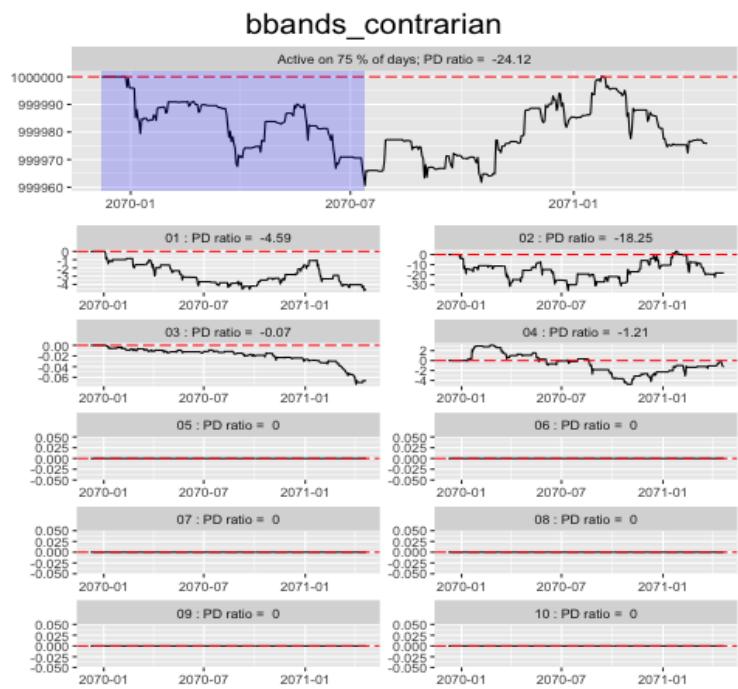
## Appendix F



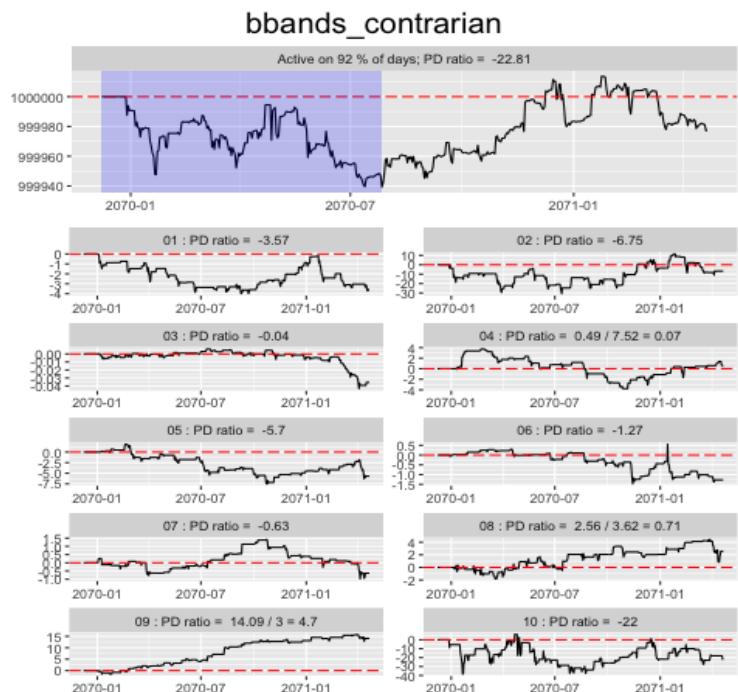
Graph F.1: Bankrupt (day 1-500 with 0.2 slippage and 1-unit fixed wager)



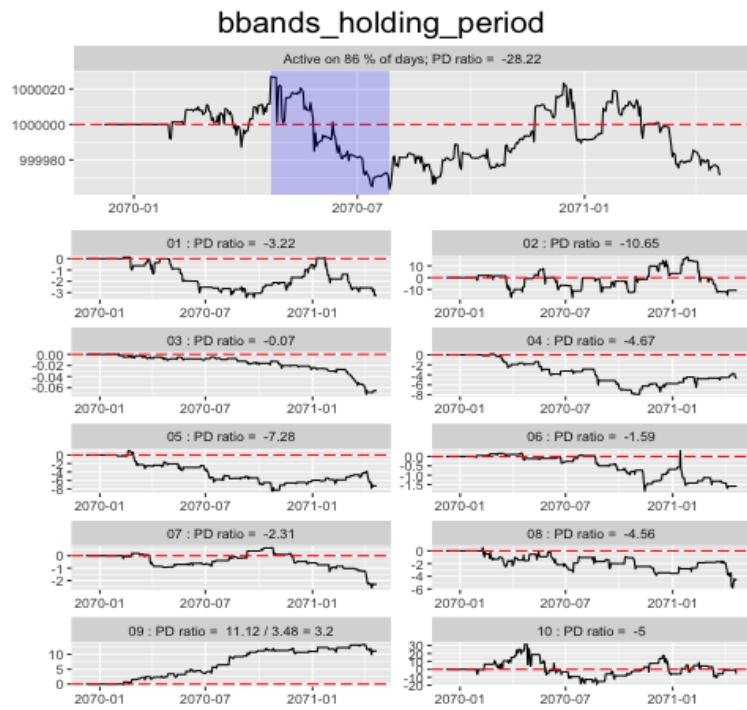
Graph F.2: Bankrupt(day 1-500 without 0.2 slippage and 1-unit fixed wager)



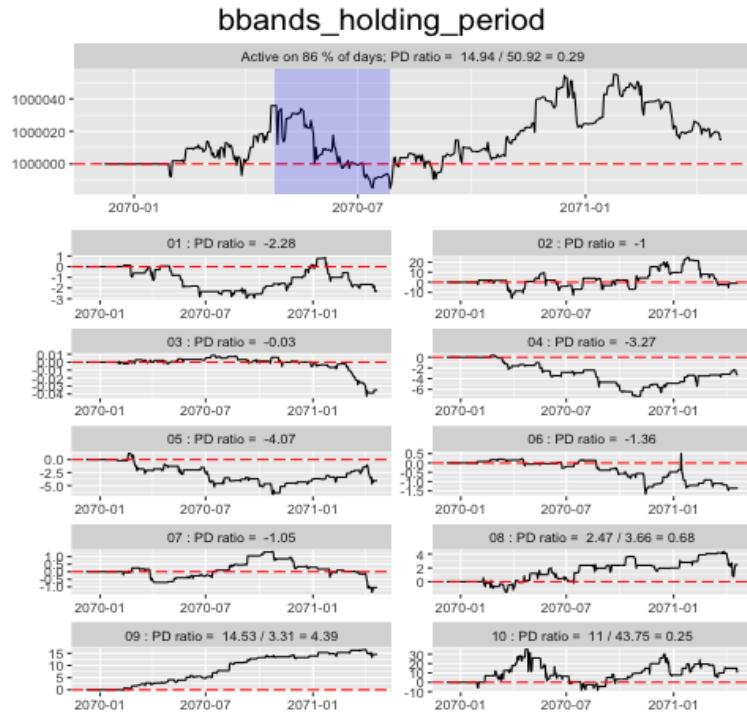
Graph F.3: BBands contrarian (day 1-500 with 0.2 slippage and 1-unit fixed wager)



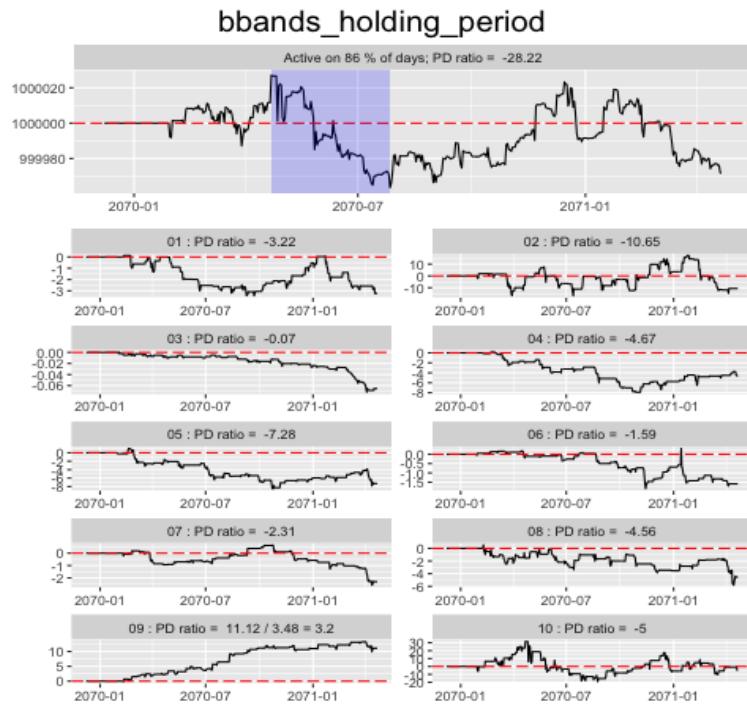
Graph F.4: BBands contrarian (day 1-500 without 0.2 slippage and 1-unit fixed wager)



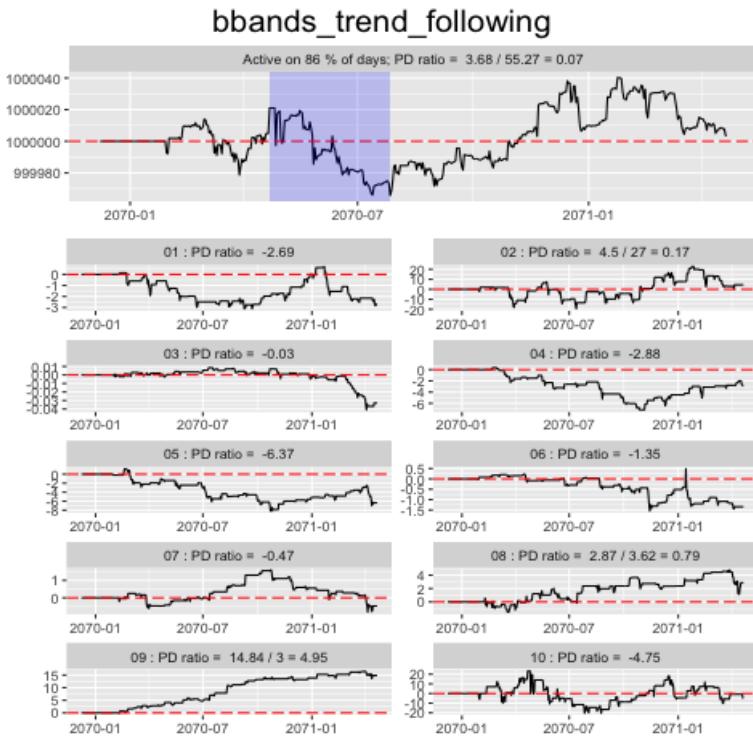
Graph F.5: BBands holding period (day 1-500 with 0.2 slippage and 1-unit fixed wager)



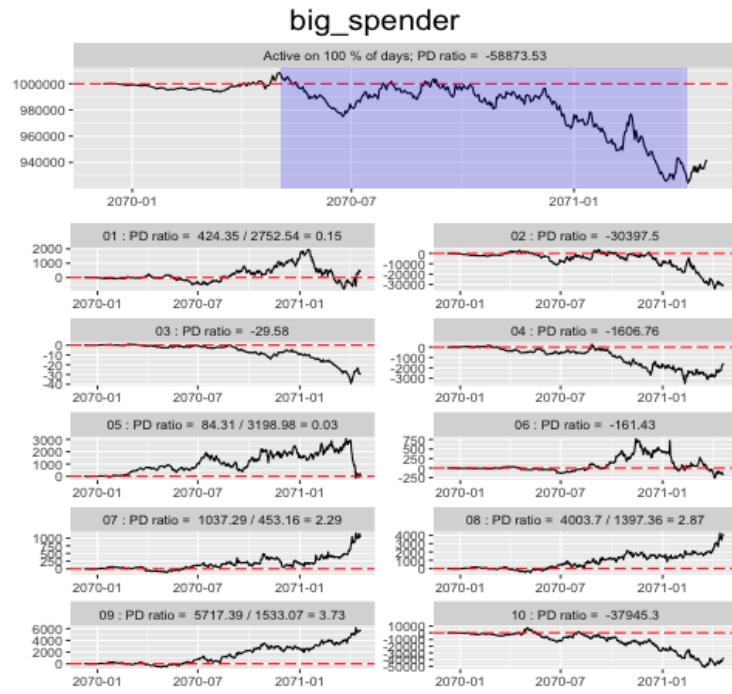
Graph F.6: BBands holding period (day 1-500 without 0.2 slippage and 1-unit fixed wager)



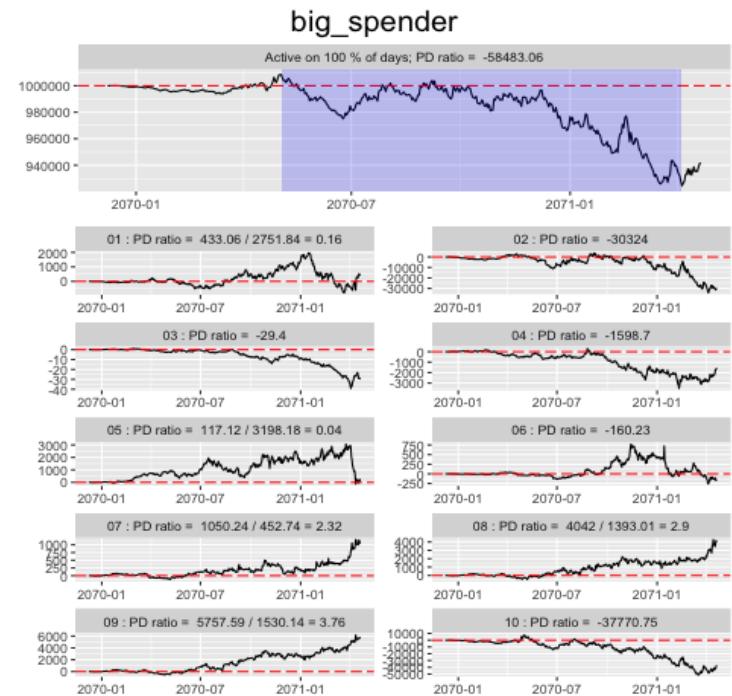
Graph F.7: BBands trend following (day 1-500 with 0.2 slippage and 1-unit fixed wager)



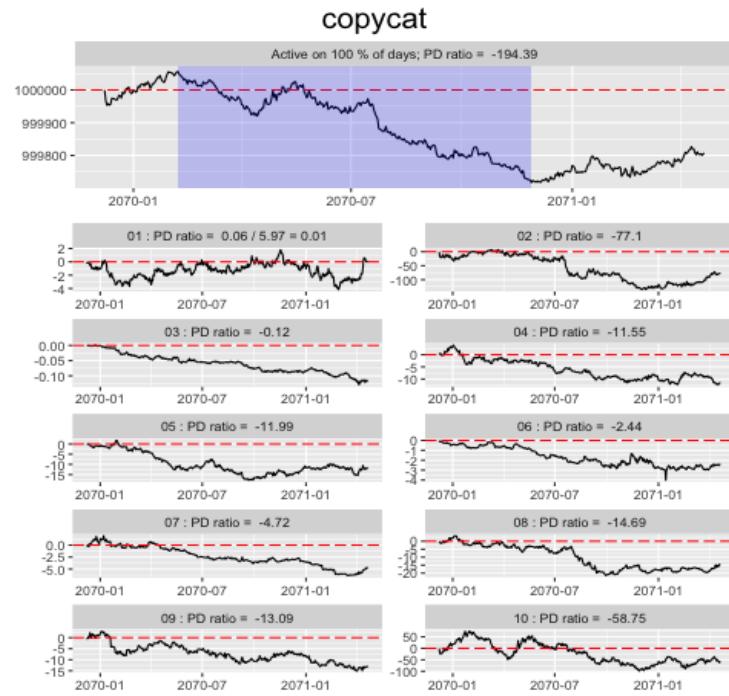
Graph F.8: BBands trend following (day 1-500 without 0.2 slippage and 1-unit fixed wager)



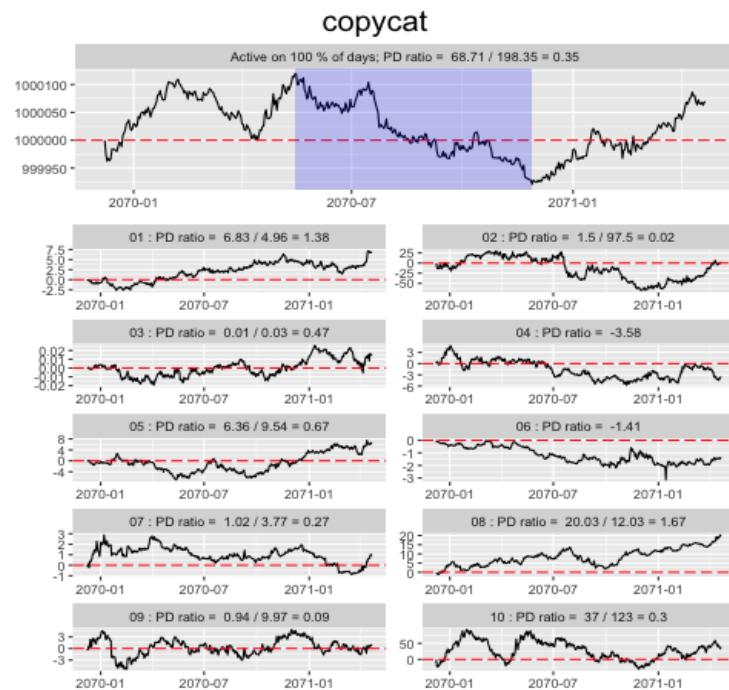
Graph F.9: Big spender (day 1-500 with 0.2 slippage and 1-unit fixed wager)



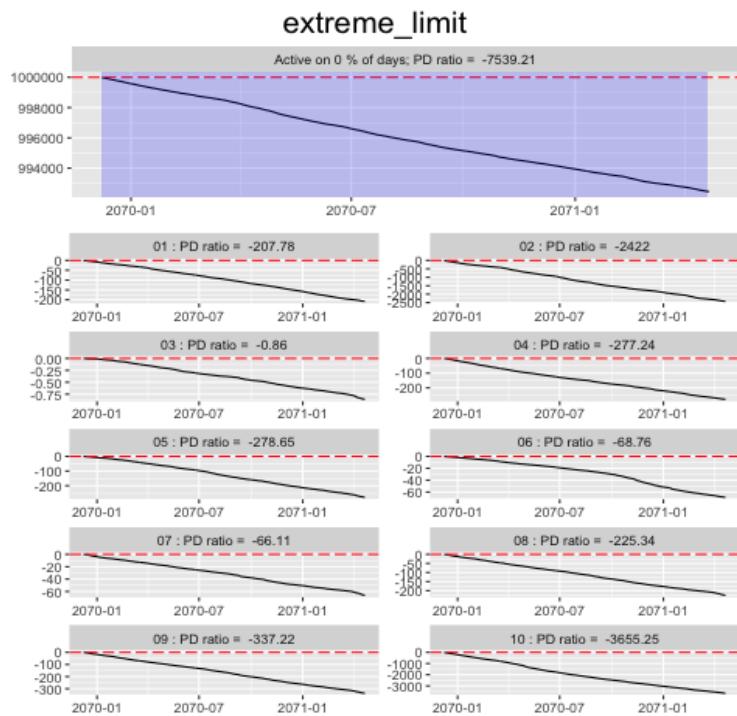
Graph F.10: Big spender (day 1-500 without 0.2 slippage and 1-unit fixed wager)



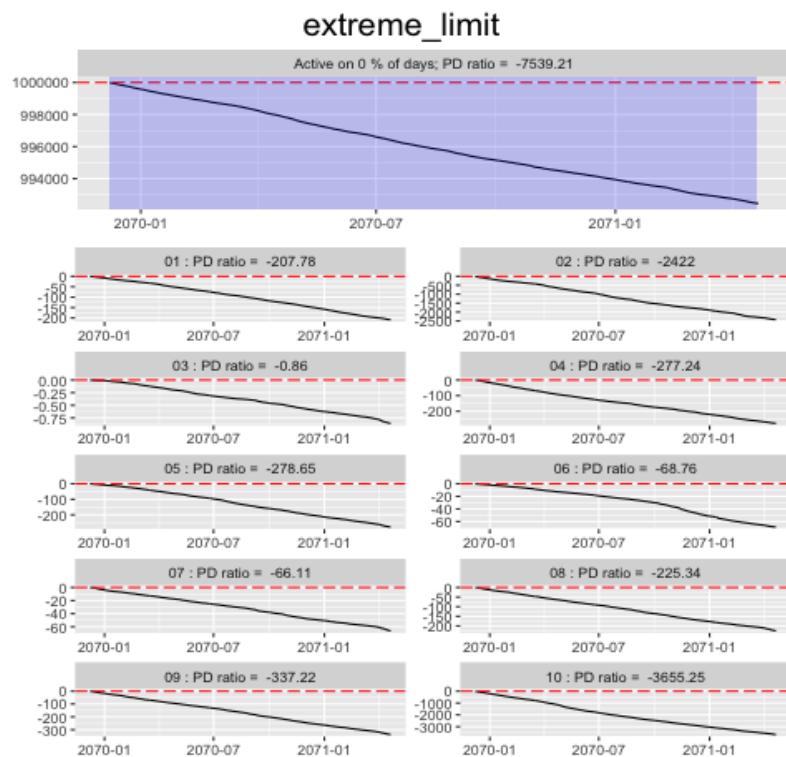
Graph F.11: Copycat (day 1-500 with 0.2 slippage and 1-unit fixed wager)



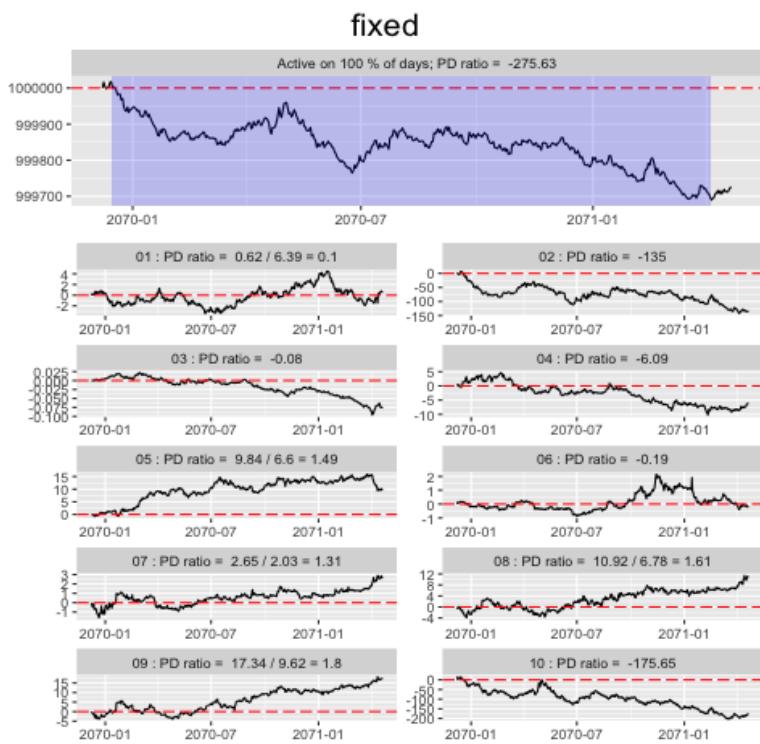
Graph F.12: Copycat (day 1-500 without 0.2 slippage and 1-unit fixed wager)



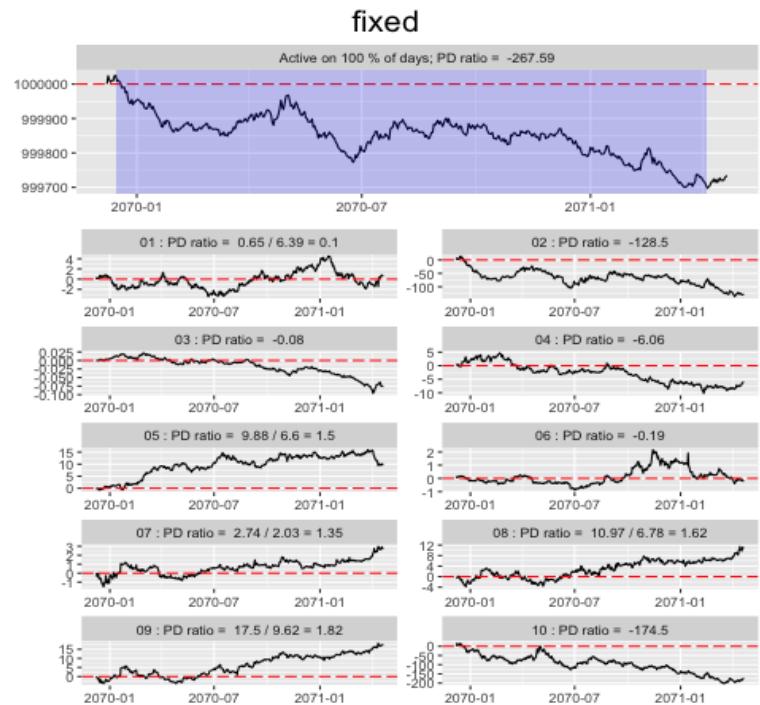
Graph F.13: Extreme limit (day 1-500 with 0.2 slippage and 1-unit fixed wager)



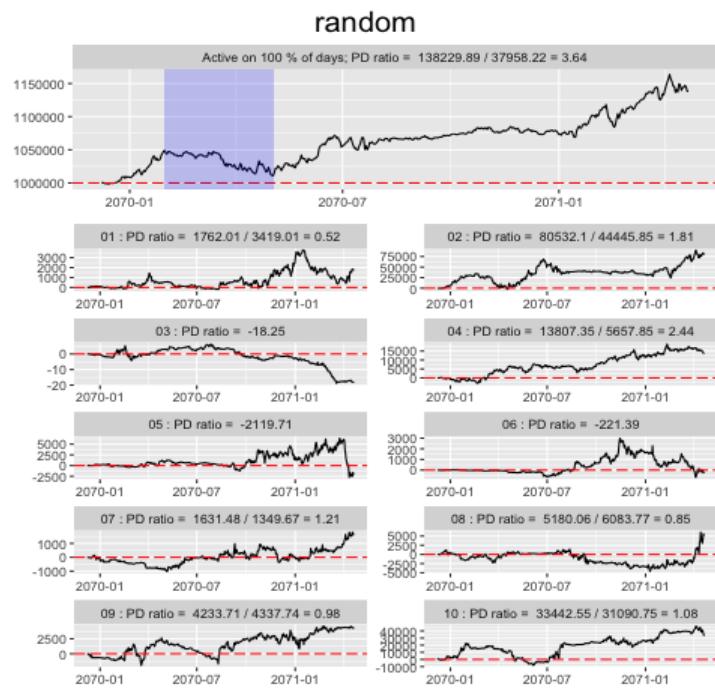
Graph F.14: Extreme limit (day 1-500 without 0.2 slippage and 1-unit fixed wager)



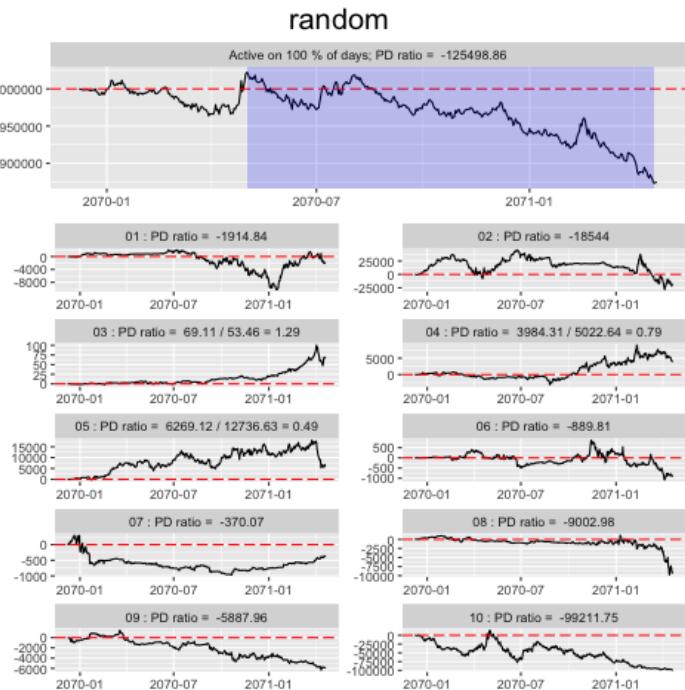
Graph F.15: Fixed (buy & hold) (day 1-500 with 0.2 slippage and 1-unit fixed wager)



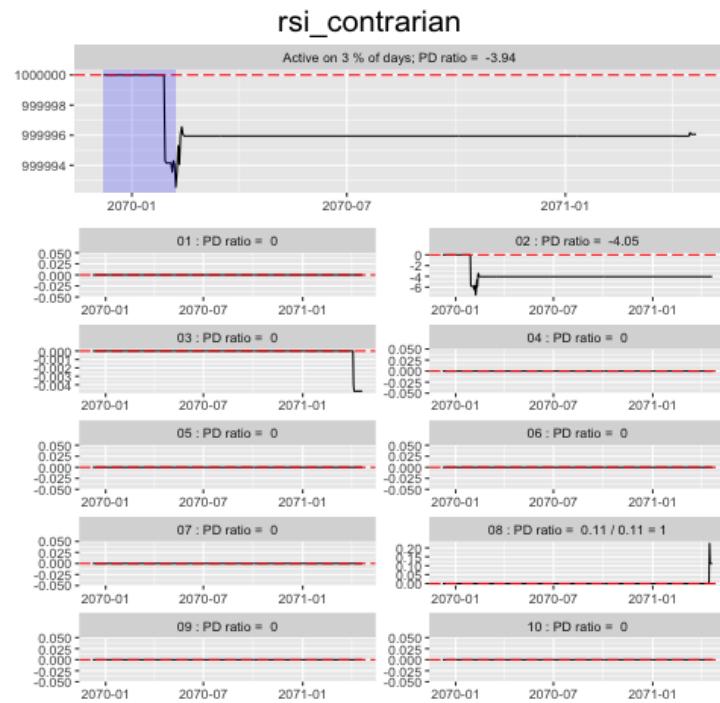
Graph F.16: Fixed (buy & hold) (day 1-500 without 0.2 slippage and 1-unit fixed wager)



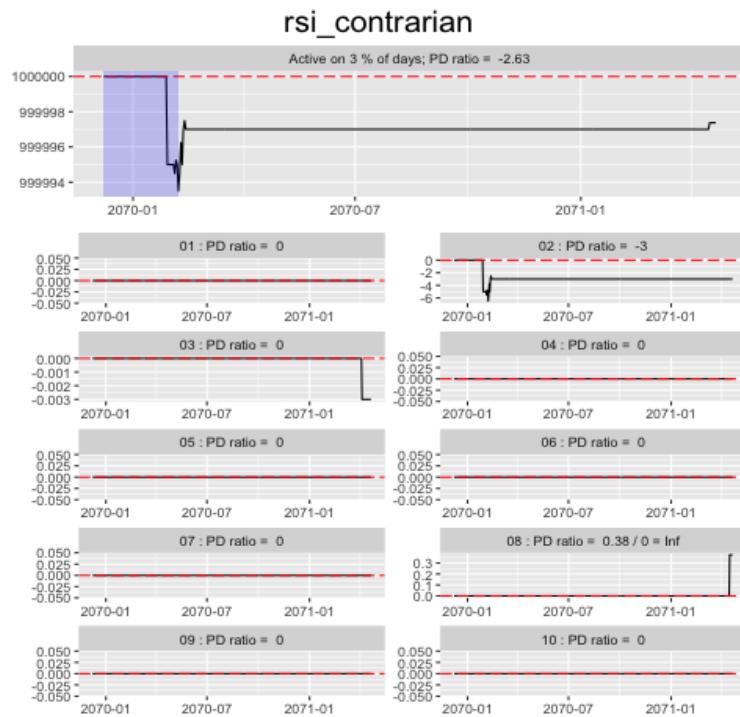
Graph F.17: Random (day 1-500 with 0.2 slippage and 1-unit fixed wager)



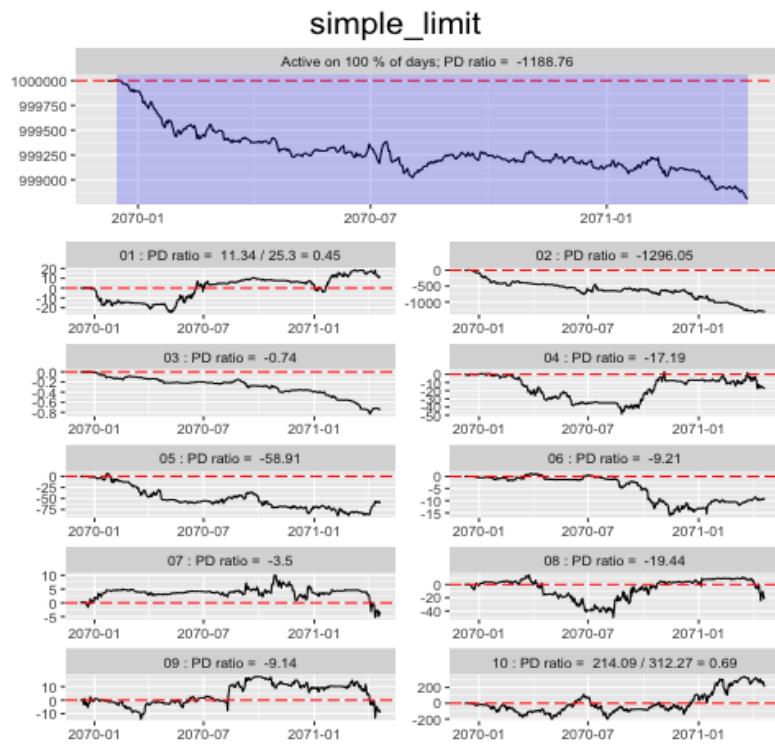
Graph F.18: Random (day 1-500 without 0.2 slippage and 1-unit fixed wager)



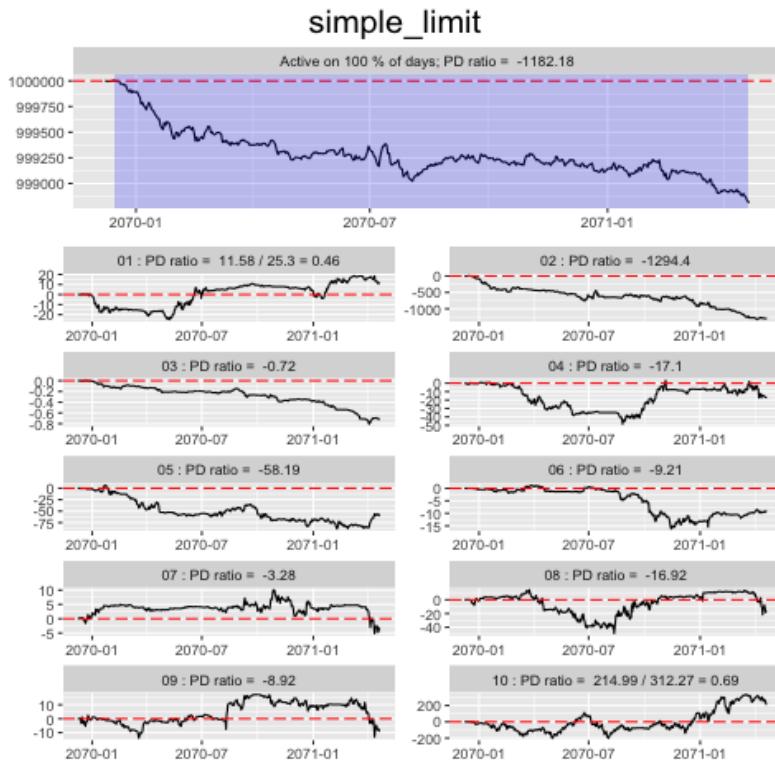
Graph F.19: Rsi contrarian (day 1-500 with 0.2 slippage and 1-unit fixed wager)



Graph F.20: Rsi contrarian (day 1-500 without 0.2 slippage and 1-unit fixed wager)

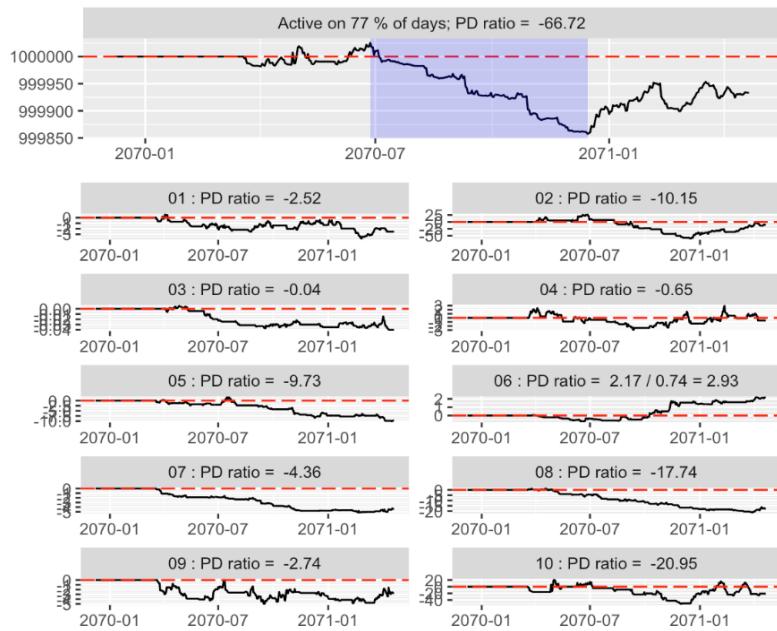


Graph F.21: Simple limit (day 1-500 with 0.2 slippage and 1-unit fixed wager)



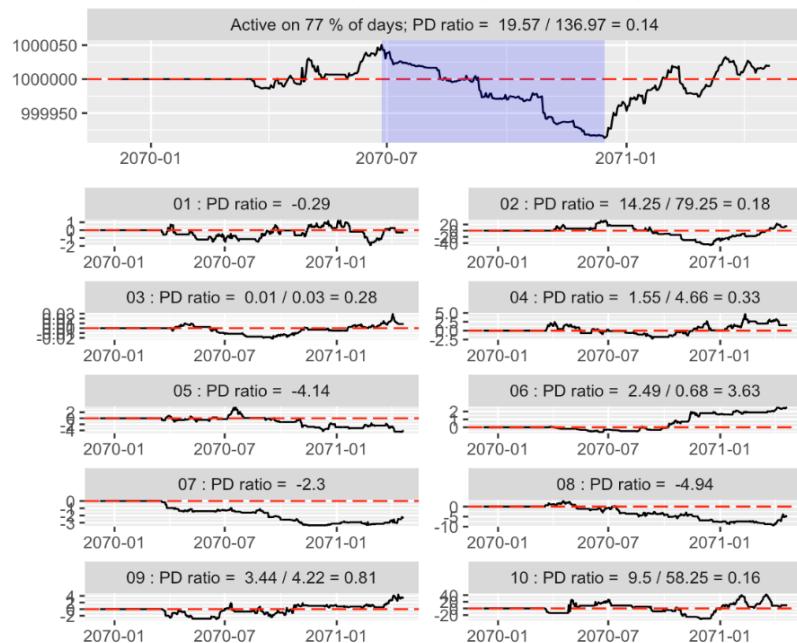
Graph F.22: Simple limit (day 1-500 without 0.2 slippage and 1-unit fixed wager)

### Triple moving average Strategy



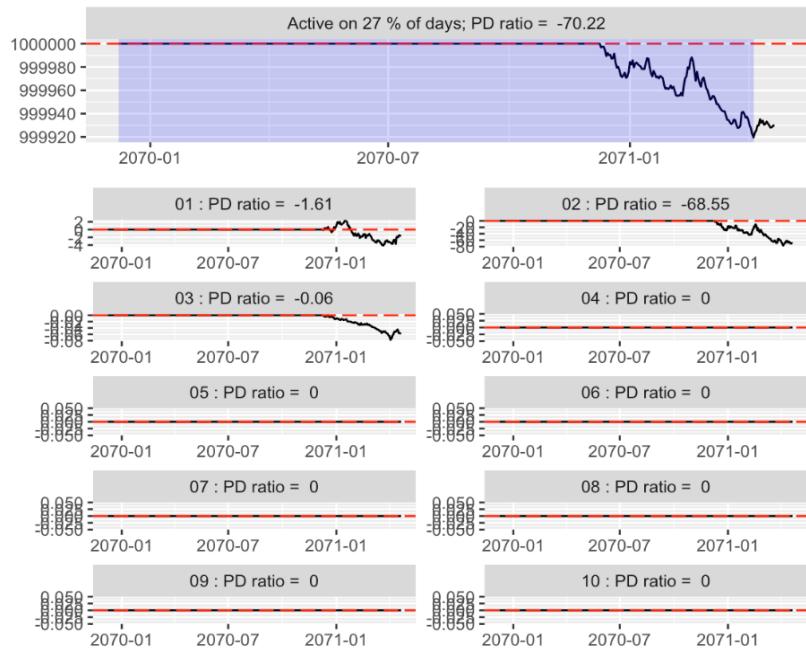
Graph F.23: Triple Moving Average Strategy (day 1-500 with 0.2 slippage and 1-unit fixed wager)

### Triple moving average Strategy



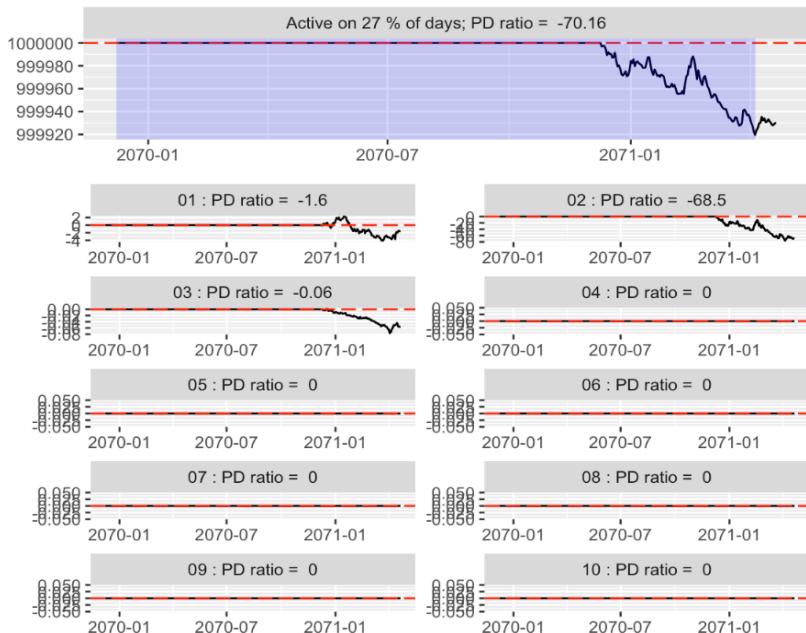
Graph F.24: Triple Moving Average Strategy (day 1-500 without 0.2 slippage and 1-unit fixed wager)

## Relative strength Strategy



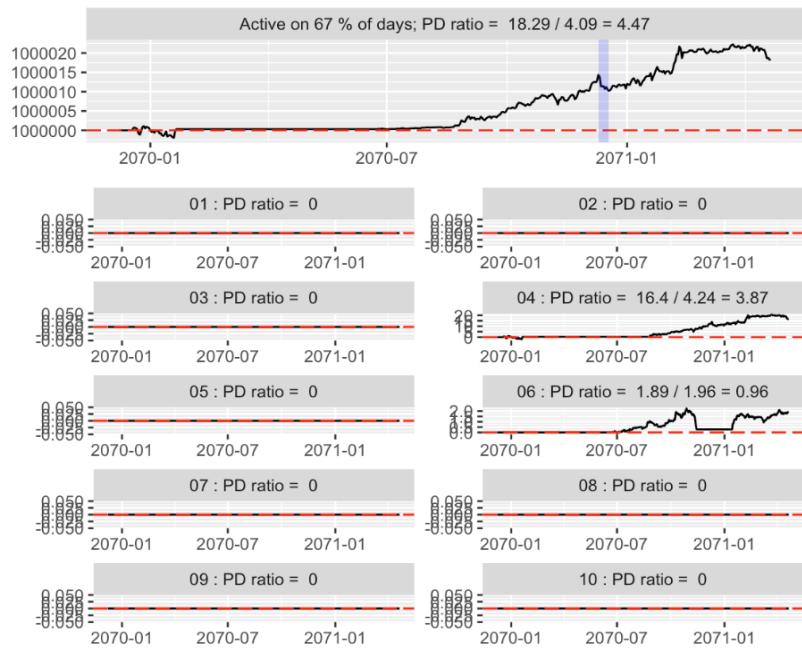
Graph F.25: Relative Strength Strategy (day 1-500 with 0.2 slippage and 1-unit fixed wager)

## Relative strength Strategy



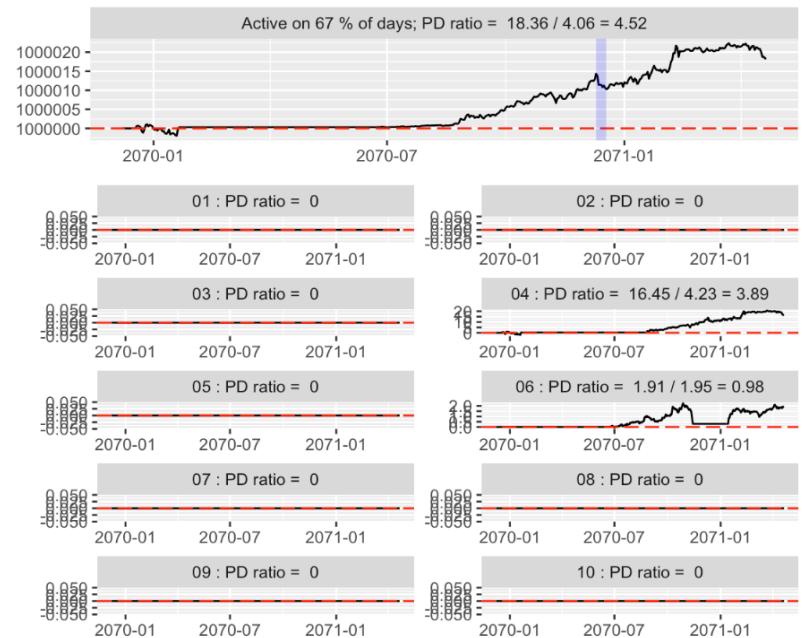
Graph F.26: Relative Strength Strategy (day 1-500 without 0.2 slippage and 1-unit fixed wager)

## Market Making Strategy



Graph F.27: Market Making Strategy (day 1-500 with 0.2 slippage and 1-unit fixed wager)

## Market Making Strategy



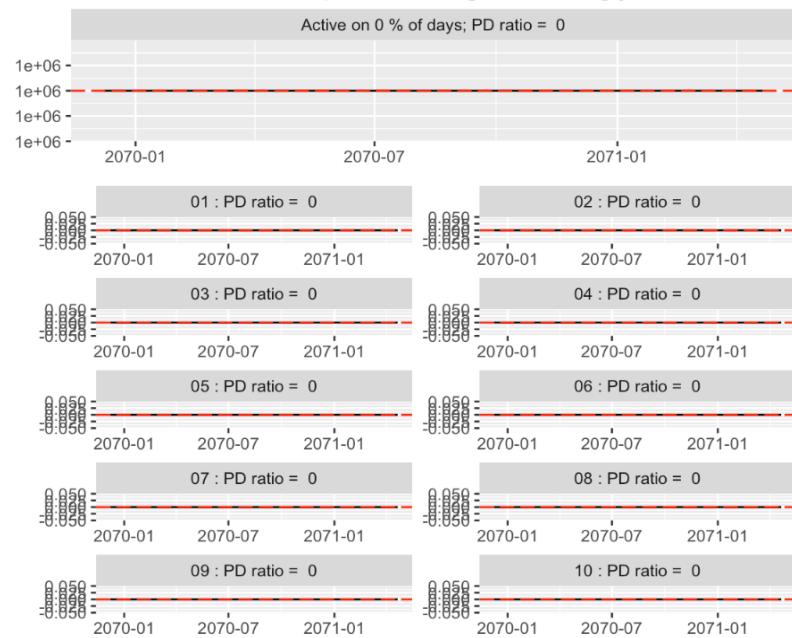
Graph F.28: Market Making Strategy (day 1-500 without 0.2 slippage and 1-unit fixed wager)

## The Jump Trading Strategy



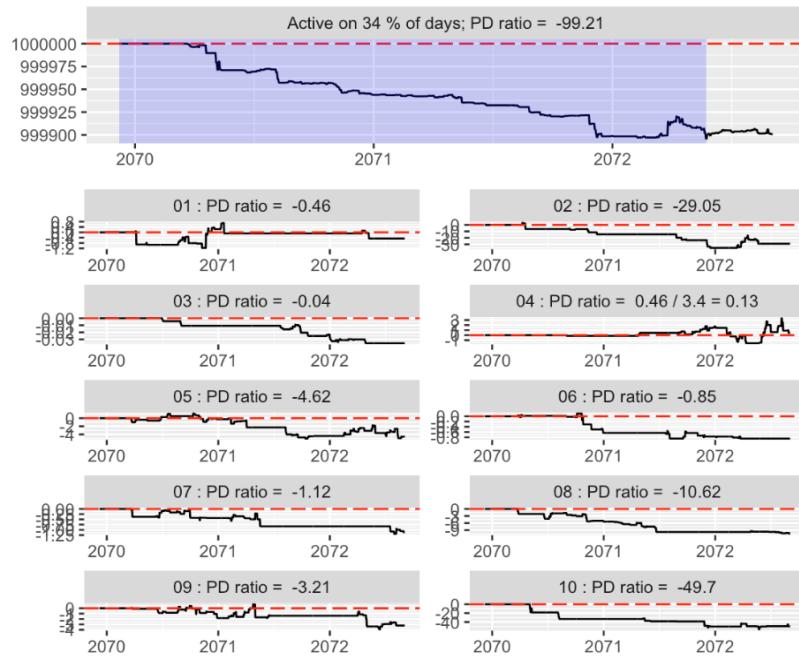
Graph F.29: The Jump Trading Strategy (day 1-500 with 0.2 slippage and 1-unit fixed wager)

## The Jump Trading Strategy



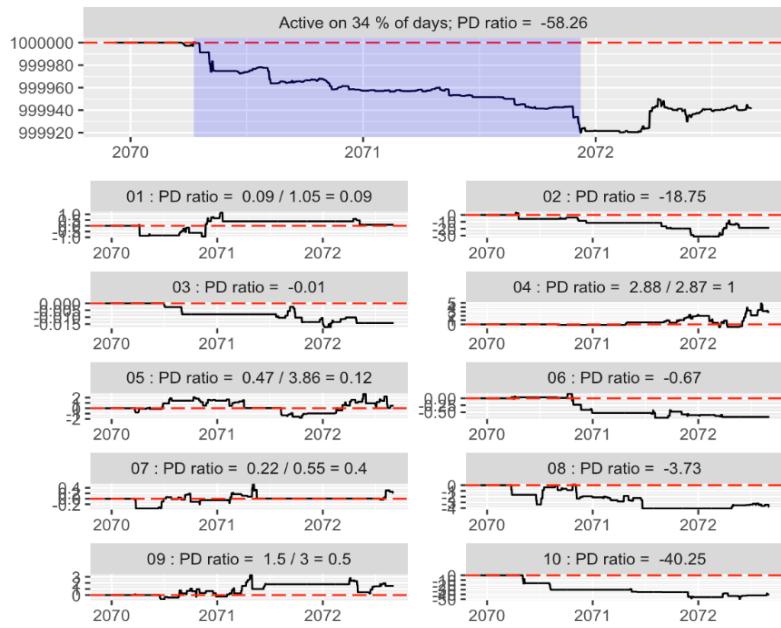
Graph F.30: The Jump Trading Strategy (day 1-500 without 0.2 slippage and 1-unit fixed wager)

## Lawrence Macmillan Volatility Trading System

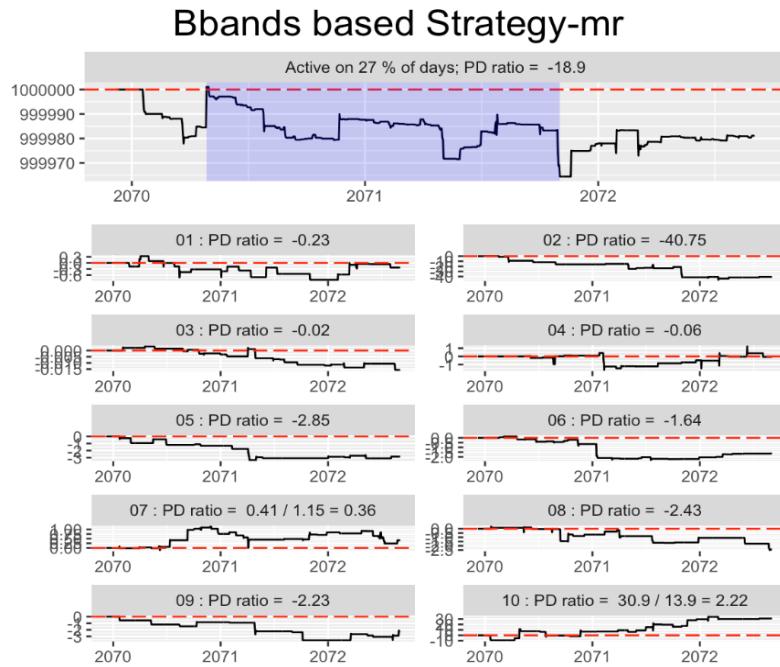


Graph F.31: Lawrence Macmillan Volatility Trading System (day 1-500 with 0.2 slippage and 1-unit fixed wager)

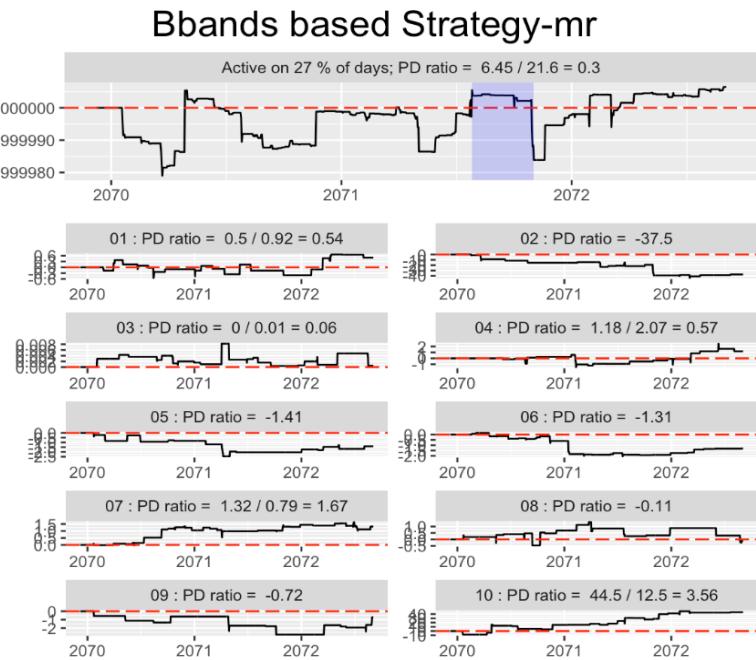
## Lawrence Macmillan Volatility Trading System



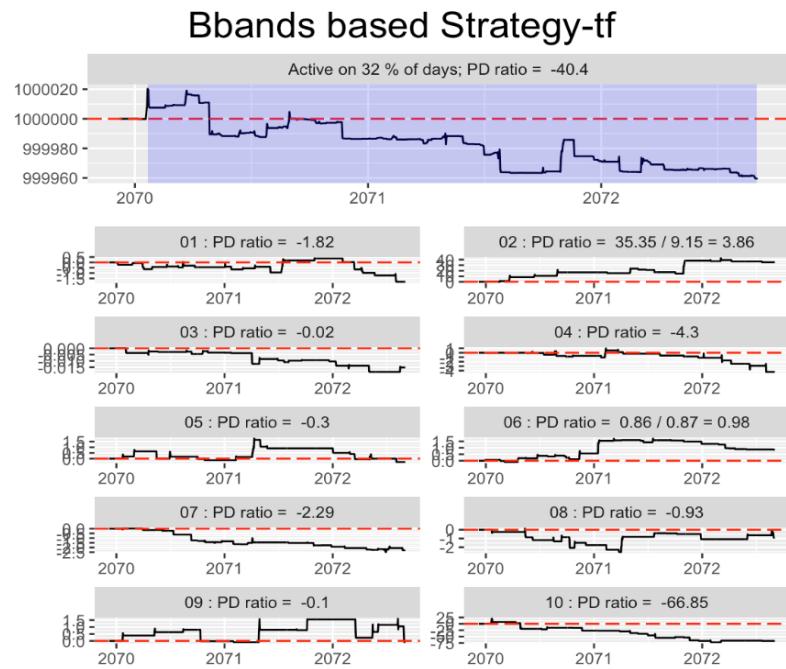
Graph F.32: Lawrence Macmillan Volatility Trading System (day 1-500 without 0.2 slippage and 1-unit fixed wager)



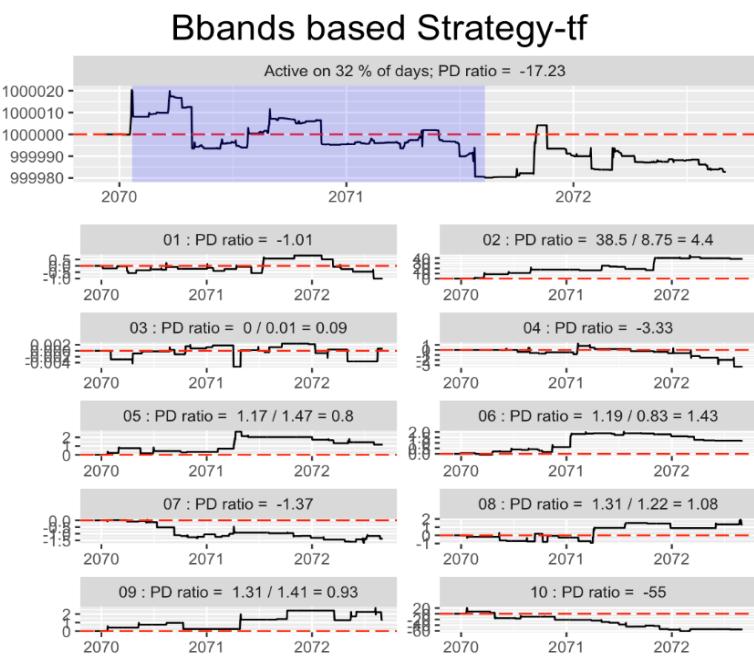
Graph F.33: BBands based Strategy (Mean-reversion) (day 1-500 with 0.2 slippage and 1-unit fixed wager)



Graph F.34: BBands based Strategy (Mean-reversion) (day 1-500 without 0.2 slippage and 1-unit fixed wager)



Graph F.35: BBands based Strategy (Trend-following) (day 1-500 with 0.2 slippage and 1-unit fixed wager)



Graph F.36: BBands based Strategy (Trend-following) (day 1-500 without 0.2 slippage and 1-unit fixed wager)