Design

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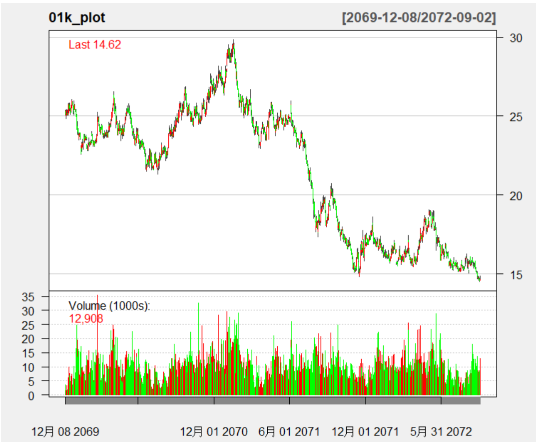
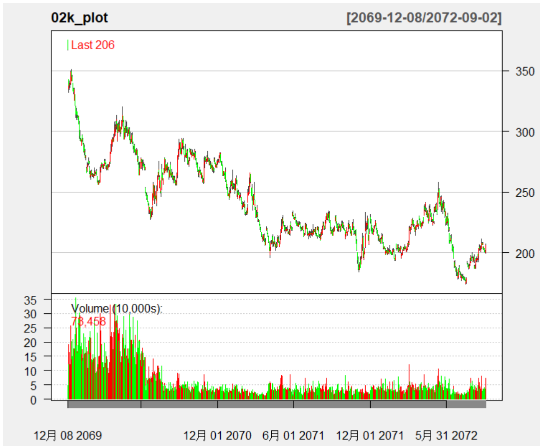
Section 1: Analysis of time series

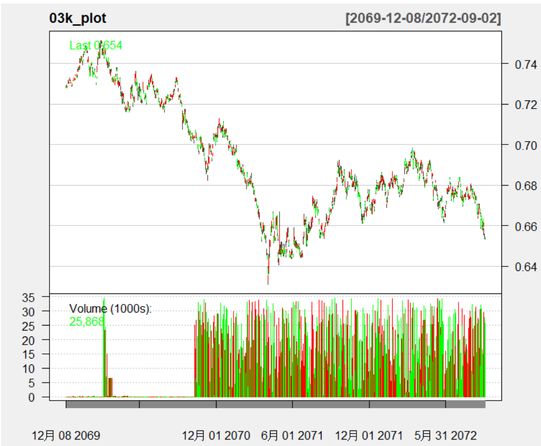
In this section, we are trying to analyze the data for all the series to provide some necessary support for the later strategy development.

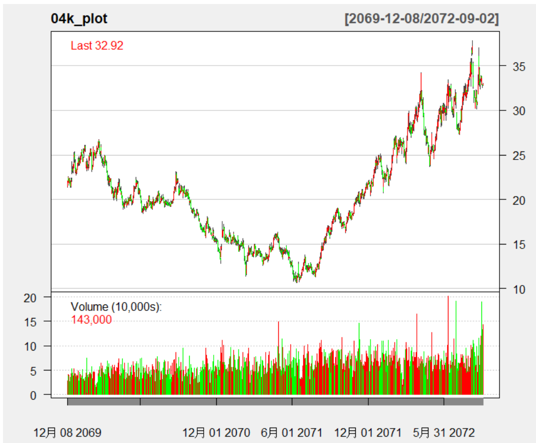
Section 1.1 Simple analyzing

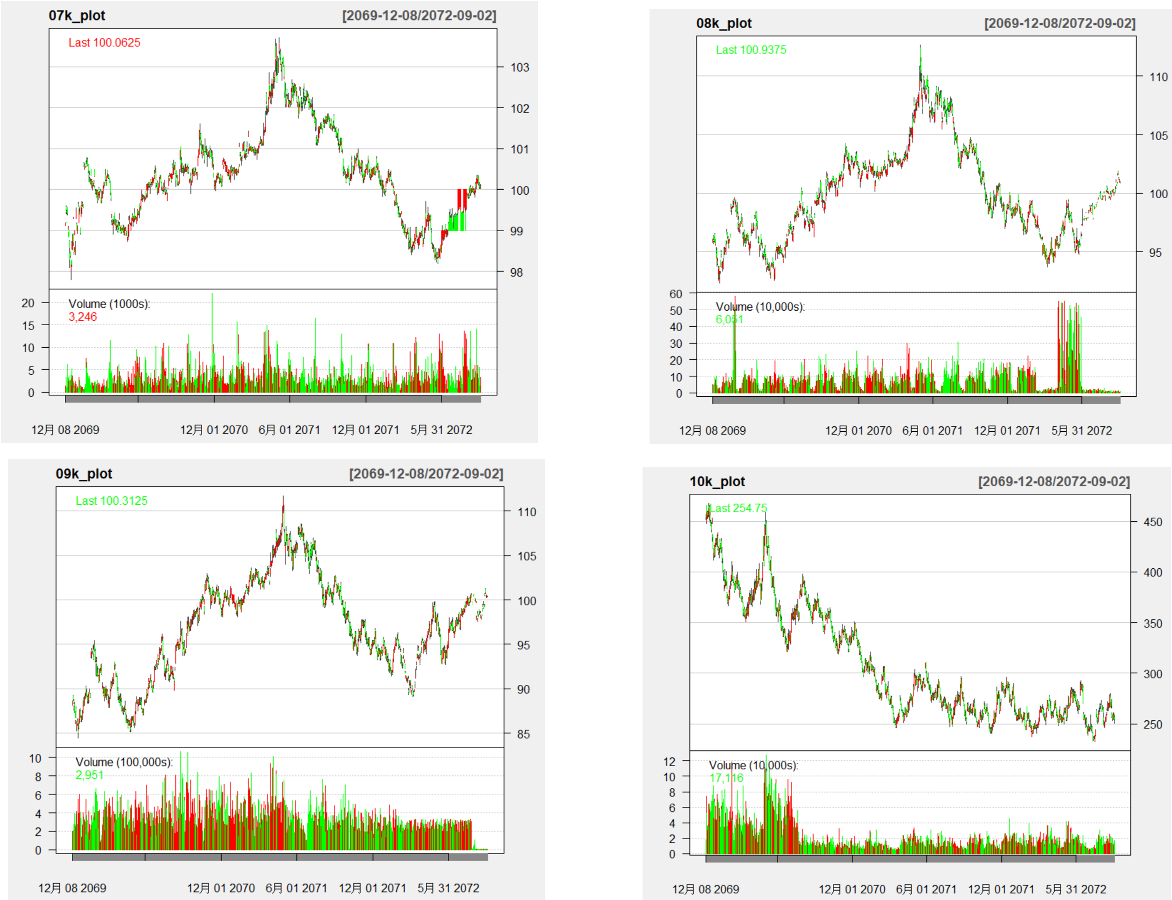
To make strategies better, we started by briefly analyzing the data by depicting Candlestick charts.











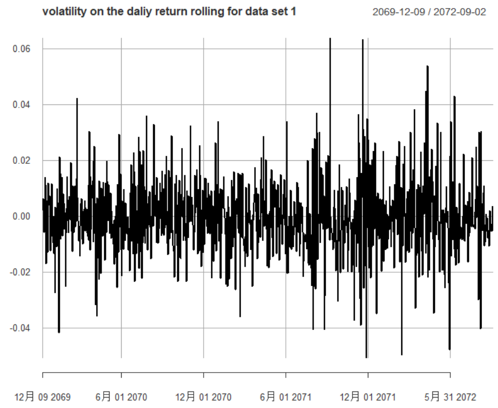
(red lines: increasing trends in days; green lines: decreasing trends)

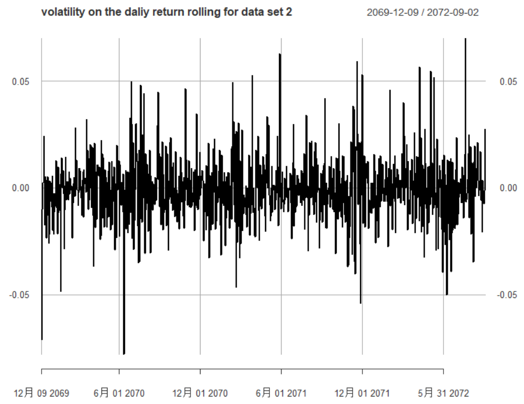
With Candlestick charts, we can roughly observe the price trends for each series, which can help we create strategies for these series.

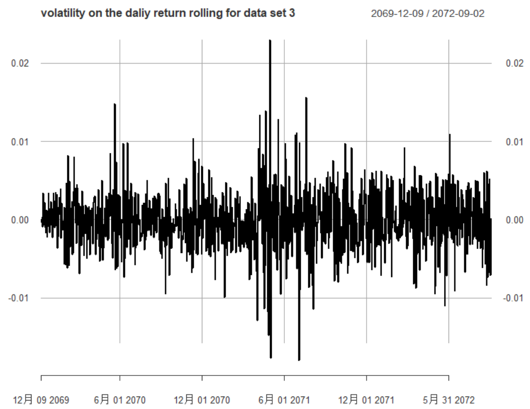
To test the volatility, we will conduct a deeper analysis of the data. Besides, In the subsequent strategy development, we initially decided to use limit orders for volatile series, where slippage is greater.

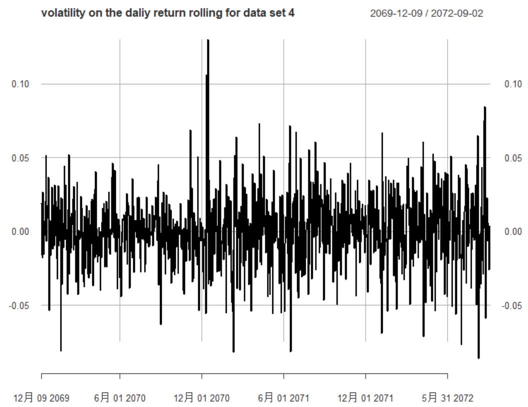
Section 1.2 Volatility analysis

To test the volatility, we first calculated the daily return of each series and plotted the return, then represent the volatility by calculating the standard deviation of daily return for each series. Below we will give some graphs to visualize the volatility.


volatility on the daliy return rolling for data set 1
2069-12-09 / 2072-09-02
0.06
0.04
0.02
0.00
-0.02
-0.04
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072


volatility on the daliy return rolling for data set 2
2069-12-09 / 2072-09-02
0.05
0.00
-0.05
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072


volatility on the daliy return rolling for data set 3
2069-12-09 / 2072-09-02
0.02
0.01
0.00
-0.01
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072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0.05
0.00
-0.05
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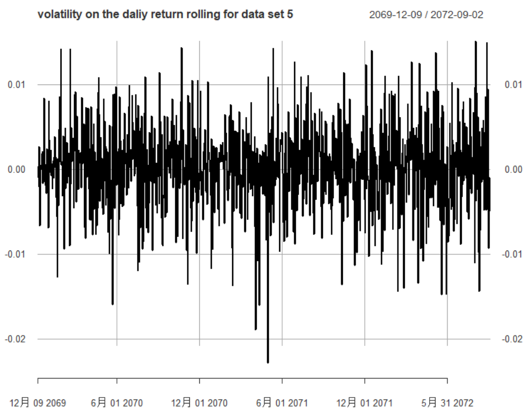
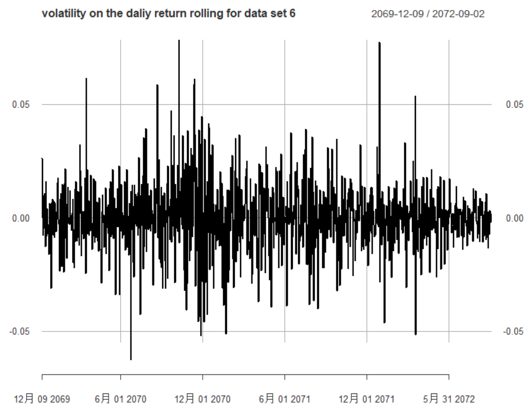
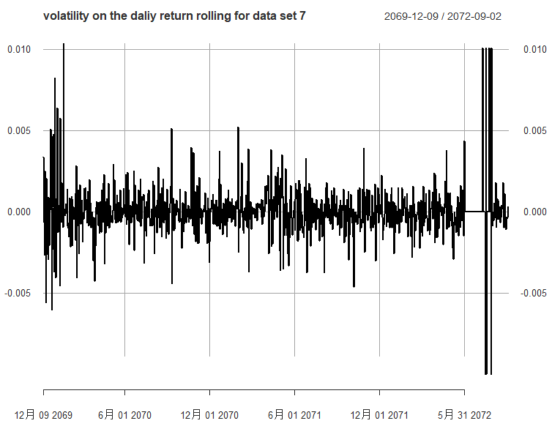
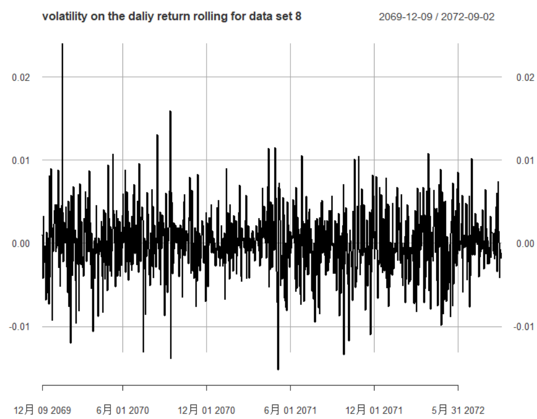
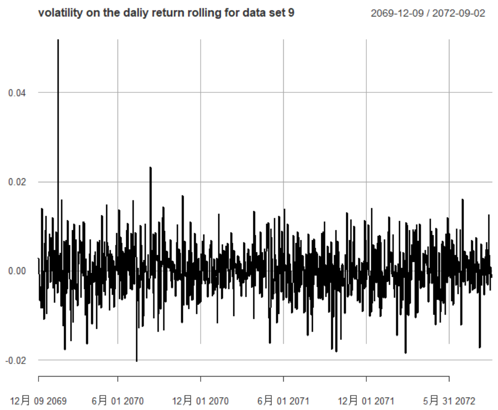
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072

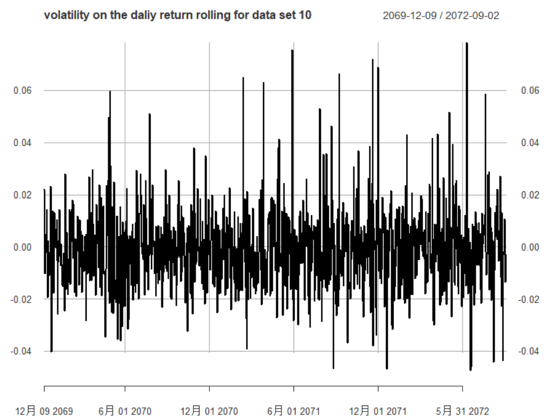

volatility on the daliy return rolling for data set 5
2069-12-09 / 2072-09-02
0.01
0.00
-0.01
-0.02
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072


volatility on the daliy return rolling for data set 6
2069-12-09 / 2072-09-02
0.05
0.00
-0.05
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072


volatility on the daliy return rolling for data set 7
2069-12-09 / 2072-09-02
0.010
0.005
0.000
-0.005
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072


volatility on the daliy return rolling for data set 8
2069-12-09 / 2072-09-02
0.02
0.01
0.00
-0.01
12月 09 2069
6月 01 2070
12月 01 2070
6月 01 2071
12月 01 2071
5月 31 2072





The properties of daily returns are the average return is approximately zero and return variability changes through time.

This is sample code that how to calculate the standard deviation.

```
> library(PerformanceAnalytics)
> price_list <- as.xts(read.zoo("02.csv",header=TRUE,sep=","))
> data_set_ret <- CalculateReturns(price_list)
> data_set_ret <- data_set_ret[-1,]
> data_set_ret <- data_set_ret[,-5]
> data_set_ret <- data_set_ret[,-1]
> data_set_ret <- data_set_ret[,-2]
> data_set_ret <- data_set_ret[,-3]
> data_set_ret <- data_set_ret[,-1]
> library(xts)
> sd(data_set_ret)
[1] 0.01509527
>
```

Series	1	2	3	4	5	6	7	8	9	10
standard deviation	0.0133	0.0151	0.0039	0.0239	0.0051	0.0154	0.00157	0.0039	0.00597	0.01595

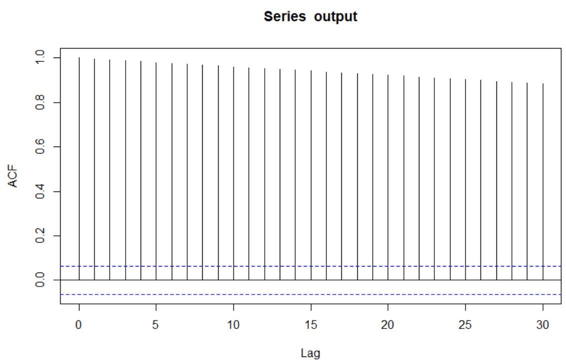
The standard deviation is bigger, the volatility is higher. So from the above chart, the volatility of series 4 is highest (sd=0.024). These series are different since some series are stable while others appear to be more volatile and vary more. When we develop our strategies, we think some series with high volatility will make most of the strategies play badly. Therefore, it is important to pay more attention to these high volatility series. The strategies ensure that stable series can be very profitable while ensuring that high volatility series can also have stable returns.

Section 1.3 ACF test

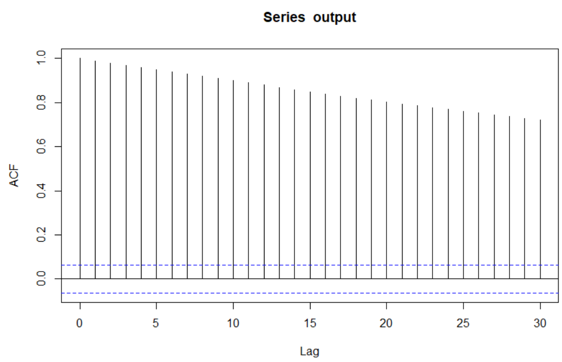
The main purpose for the stationary test is to make sure that the strategy that we implement is sustainable. This requires that the basic characteristics of the dataset must remain unchanged. To verify this, we have implemented ACF test. The autocorrelation graph shows that the autocorrelation coefficient of the series has always been relatively small, and is always controlled within the range of 2 times the standard deviation. It can be considered that the series fluctuates near the zero axis from beginning to end. This is usually a stable time series with strong randomness.

```
series <- read.csv("D:/RStudio/backtester_v5.6/DATA/PART1/10.csv")
output <- ts(series$Close)
acf(output)
```

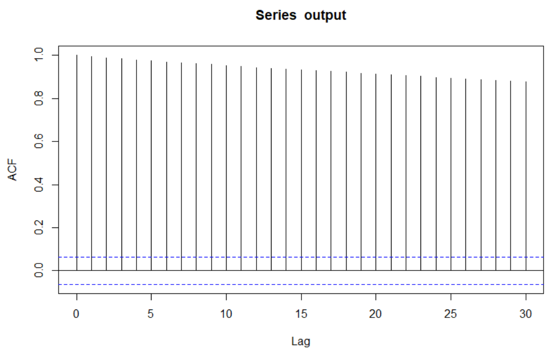
Result:



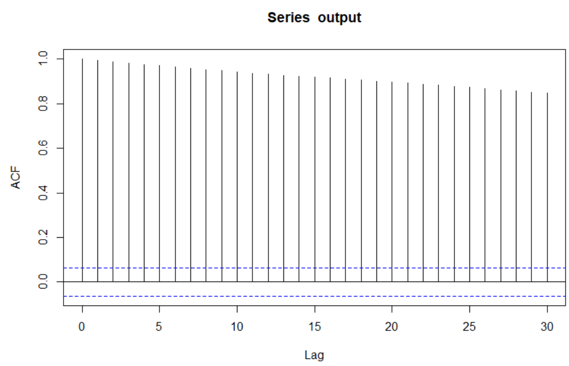
series 1



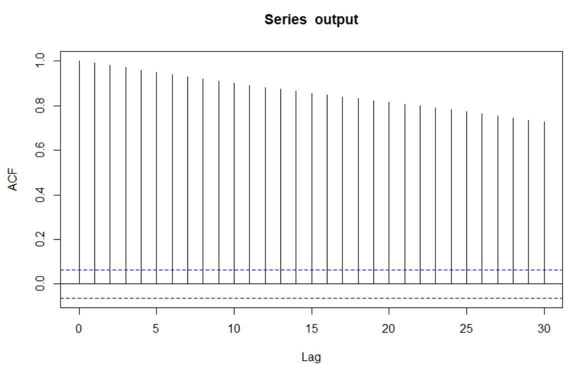
series 2



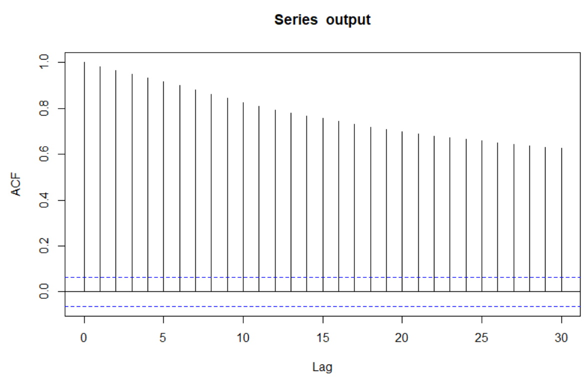
series 3



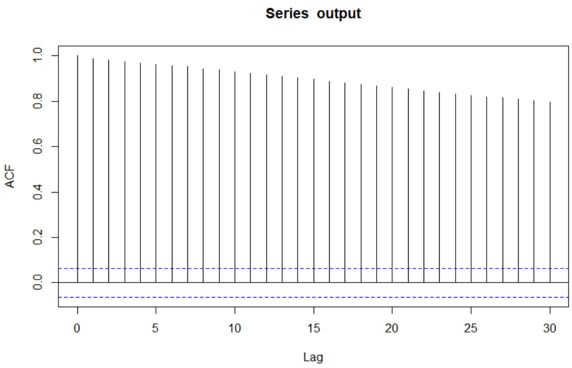
series 4



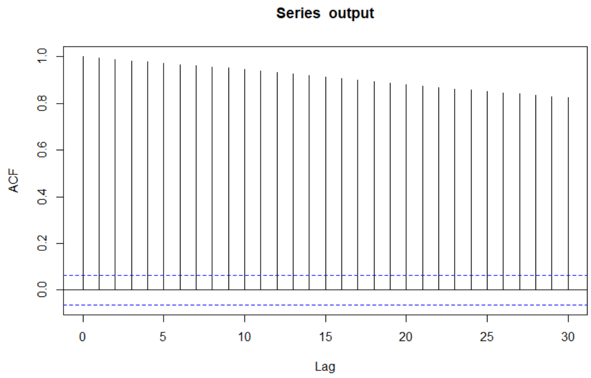
series 5



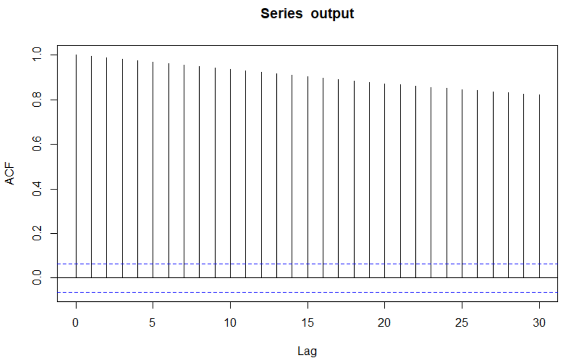
series6



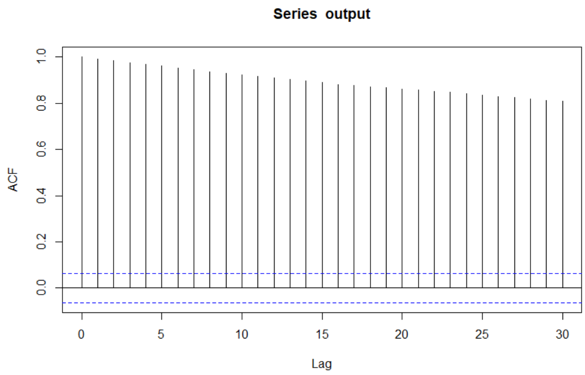
series 7



series 8



series 9



series 10

Section 2: Trading strategies

To trade all series, we develop three strategies (CCI trend following strategy, Turtle Trend Following Strategy, Momentum trading strategy). The first strategy uses four CCI lines as short term buy and stop loss signals, when the price reaches the middle of the two lines we long. Meanwhile, use the MACD indicator as a long-term sell signal to prevent blindly following the market. The second strategy is trying to detect the blooming or decline trend using the Donchain channel to determine the position and calculate position sizing with respect to the volatility to mitigate the risk. The last strategy makes trading decision when we find a linear relation between past return and future return through the calculation of correlation coefficient of lookback period and hold days. After finding a linear relation, we long if lookback period gives a positive return and short if lookback period gives a negative return.

Section 2.1 CCI trend following Strategy

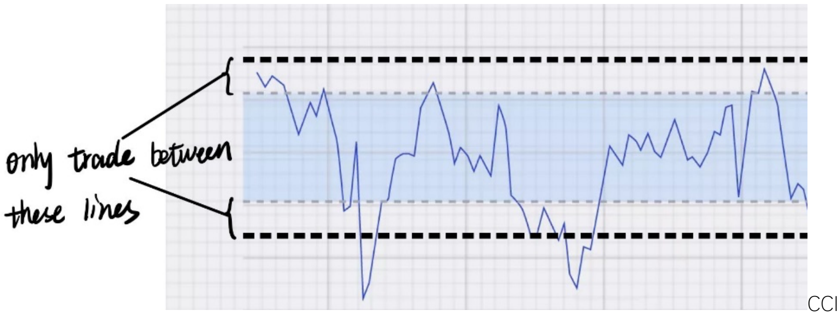
We believe when the external market conditions cannot be referenced, short-term trading is needed to capture small fluctuations. In this case, a strategy with CCI as the core and MACD as the auxiliary was formulated. CCI is a sensitive indicator, so this strategy use it as a guide for the short-term trading. At the same time, adding the MACD indicator is reasonable, because this can be a long-term control of strategy to let the strategy can remain calm even when the market is crazy. One advantage is that in this way, this strategy can perform well regardless of whether the volatility is large or small. In addition, since CCI is generally regarded as a better indicator of market entry rather than exit (AVATRADE, 2007-2021), MACD will be the main signal for selling, while CCI mainly used as a buy signal.

```
"cciMacd"=list(cciLookback=20, macdLookback=50, series=c(1,2,3,5,6,7,8,9,10),
               cciMeanDev=0.015,
               macdFast=12, macdSlow=26, macdSig=9, macdMa="SMA")
```

We now leave the relevant data required by TTR functions, and plan to make adjustments in the next stage. However, time Series 4 does not apply to the strategy, so we do not consider it.

```
ccioverSold <- -100
ccioverBought <- 100
cciStop <- 1.02 # clear the position when the price reaches this variable's
                # multiple times of cci lines
```

This strategy kept the overbought and oversold lines of the CCI indicator as the default values., however we adjusted the stop loss multiplier.



The core idea of using cciStop to stop loss is to add two more lines to the original two CCI lines to become two pairs. Since this part of the strategy is trend-following, buying between the two lines of each pair can stop the loss when the trend reverses.

The cciStop indicator was explored to control transaction interval (Test 1).

Test 1: Test the effect of the change of cciStop value on the overall PD ratio (both in in-sample and out-of-sample).

Result:

cciStop	In-sample PD	Out-if-sample PD
1.1	0.43	0.62
1.09	0.53	1.12
1.08	0.53	1.16
1.07	0.65	1.19
1.06	0.65	1.18
1.05	0.65	1.13
1.04	0.88	1.18
1.03	0.89	1.18
1.02	0.89	1.19
1.01	1.01	1.12

The highest values were marked in the two columns. In summary, we can find a trend in the in-sample data column that the closer the cciStop is to 1, the better the overall PD performance. But somehow, out-of-sample data does not appear such a trend.

If only the current in-sample data is selected as the sample, there is no doubt that cciStop equal to 1.01 is the optimal. But considering that in the next stage we may use all the current PART 1 data as the sample, and when cciStop=1.01, the out-of-sample PD performance is not good, we tend to choose 1.02 as the final cciStop, as it has the best overall performance.

```
for (i in 1:length(params$series)) {

  cl <- newRowList[[params$series[i]]]$Close
  cci <- last(CCI(store$cl[startIndex:store$iter,i],
                  n=params$lookback,c=params$cciMeanDev))

  # if the cci value is below the oversold line,
  # we add one short position or decrease our long position,
  # because the market may be overly depressed
  if (cci < ccioverSold && !is.na(cci)) {
    pos[params$series[i]] <- -1
  }

  # if the cci value is higher than the overbought line,
  # we add one long position, because the market may be too mad
  else if (cci > ccioverBought && !is.na(cci)) {
    pos[params$series[i]] <- 1
  }

  # stop loss when the price reaches cciStop times of lines
  if (cci < cciStop*ccioverSold && !is.na(cci) |
      cci > cciStop*ccioverBought && !is.na(cci)) {
    pos[params$series[i]] <- -currentPos[params$series[i]]
  }
}
```

The above is the code of the CCI indicator. The following is the code of the MACD indicator, which treats signal>MACD value as a sell signal to lighten up the position. Only TTR functions are used.

```
# this if statement is focused on MACD
if (store$iter > params$macdLookback) {

  startIndex <-  store$iter - params$macdLookback

  for (i in 1:length(params$series)) {

    macd <<- last(MACD(store$cl[startIndex:store$iter,i],
                  nFast=params$macdFast, nSlow=params$macdSlow,
                  maType=params$macdMa, percent=TRUE))

  # I think the market has issued a sell signal at this time,
  # so I lighten up a share
  if (macd[,"signal"] > macd[,"macd"]) {
    pos[params$series[i]] <- -1
  }
 }
}
```

Considerations:

1. Using EMA or SMA in MACD indicator?

SMA. In CCI+MACD strategy, MACD is used in long-term trading. In the circumstance of SMA put all data in the equal weight while EMA give more weighting to recent prices, we believe SMA is more suitable, because this calculation method may imply that EMA is more suitable for short-term investment, while SMA is more suitable for long-term investment.

2. RSI or CCI?

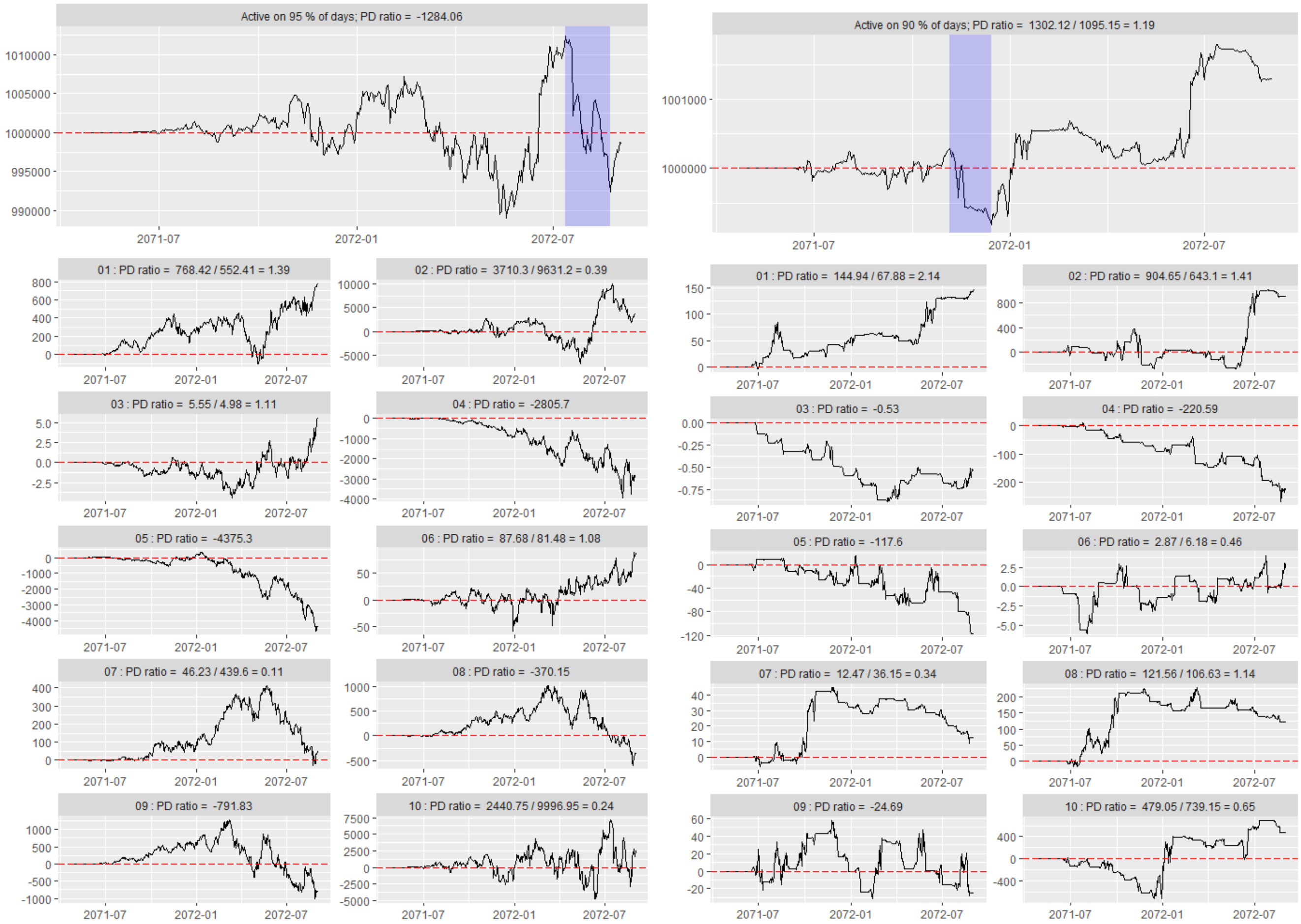
RSI tracks the speed of price changes to observe overbought and oversold conditions, while CCI focuses on the normal deviation from the asset's moving average price to find deviations from the normal trend cycle (Ross, 2020). Because the core idea of the CCI indicator is to observe the deviation between the price and the moving average, the coordination between CCI and MACD may be better, compared to RSI (Test 2).

Test 2: A 500-day out-sample test on the performance of RSI and CCI respectively, with the same parameter of 20 days lookback and the same MACD settings.

Core code for RSI (The code for CCI is shown at the end of this strategy):

```
rsiOverSold <- 30
rsiOverBought <- 70

 for (i in 1:length(params$series)) {

   cl <- newRowList[[params$series[i]]]$Close
   rsi <- last(RSI(store$cl[startIndex:store$iter,i],n=14,
                maType=list(maUp=list(EMA),maDown=list(WMA))))

   if (rsi < rsiOverSold && !is.na(rsi)) {
     pos[params$series[i]] <- 1
   }
   else if (rsi > rsiOverBought && !is.na(rsi)) {
     pos[params$series[i]] <- -1
   }
```

Result:



RSI CCI

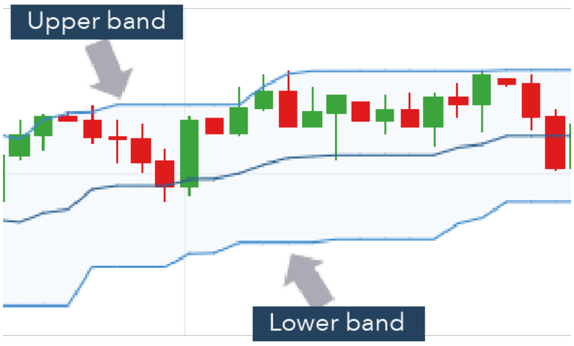
When using the CCI indicator, a small part of the time series will have good gains, and another small part will have some loss, but not much. The remaining time series mostly hover around 0. However, when using the RSI indicator, nearly half of the time series showed high losses, which was very unstable. In summary, CCI may be better in the strategy.

The CCI is an unbounded oscillator, which means that it can rise or fall indefinitely, and it can perform well even under extreme continuous rise and fall. In particular, in time series 5, It can be observed a continuous rise, and in time series 2 and 10, there was a shock drop. Therefore, this strategy may achieve better performance in these three time series.

But like any other strategy, when the price fluctuates repeatedly within a range, it may suffer losses due to the inevitable lag of the indicator. So it should not be applicable to time series 4 with the highest volatility. For the remaining time series, it cannot be expected too high or too low profit.

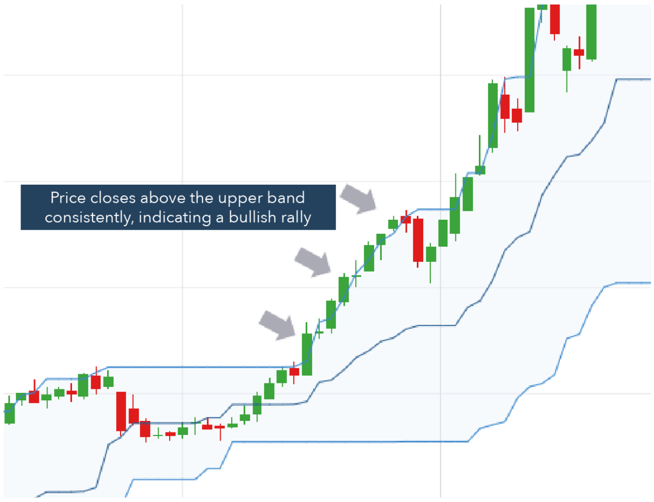
Section 2.2 Turtle Trend Following Strategy

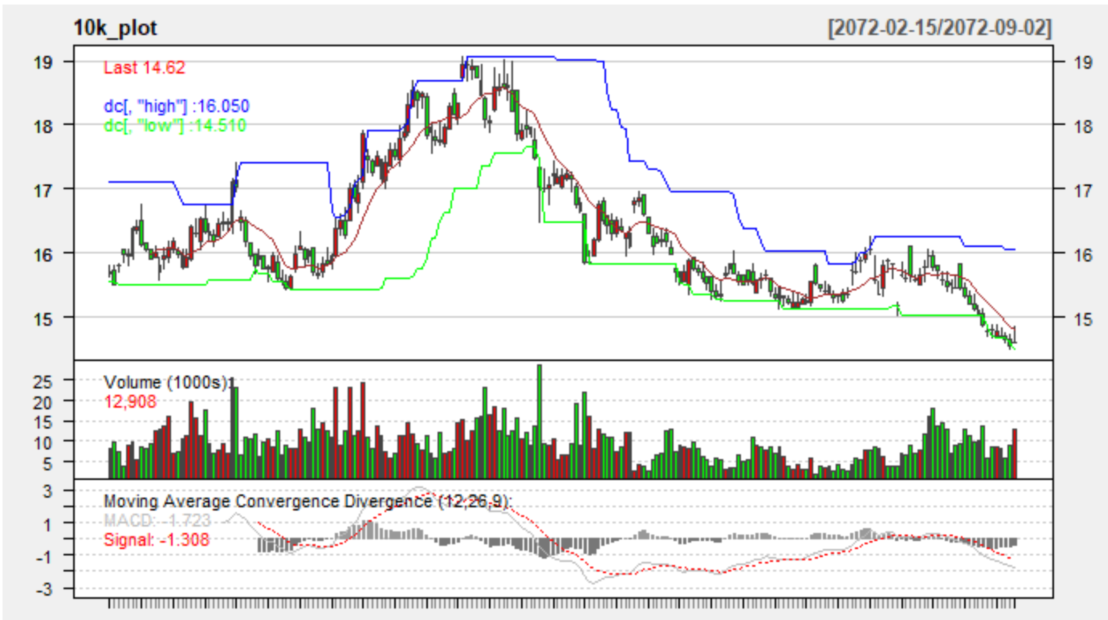
If a serial has a clear trend, we can implement the turtle strategy to follow the trend. It performs most effective in breakout trading. But its shortage is also obvious, it performs badly when the market is volatile.



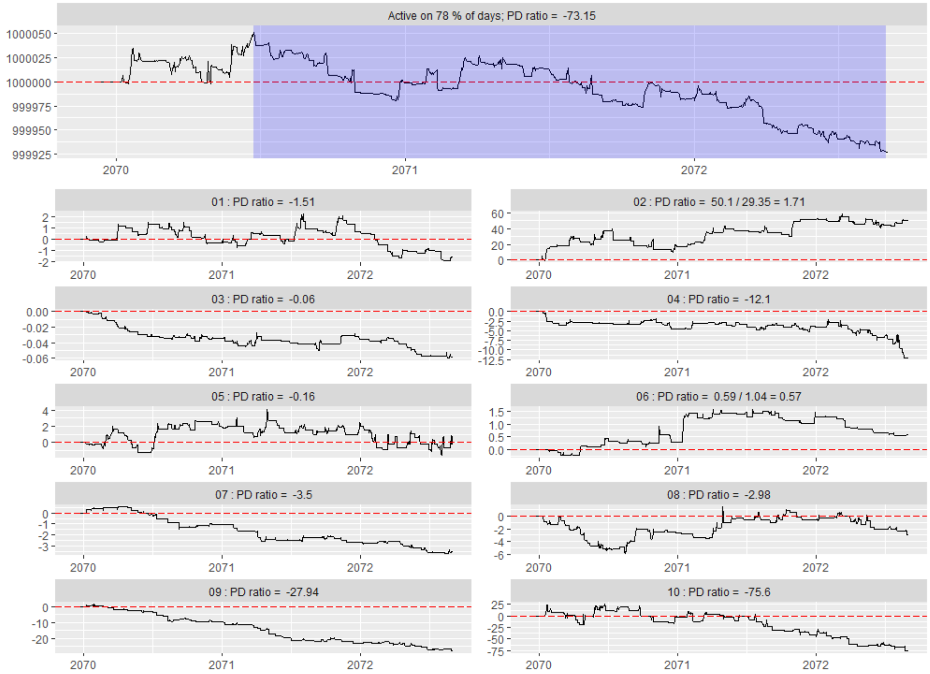
It uses moving average of price in past m days to get a price which is a standard and all of these prices can be considered as a line (candlestick). Once the candlestick crosses the upper line, strategy hold the long position until its return the channel. In terms of the time in the channel, strategy clear the position or deduct the position size.

When the price breaks though the upper band then this could signal a bullish rally. This strategy is mainly focus on this type of trend and looking for the serial contain this breakout feature.

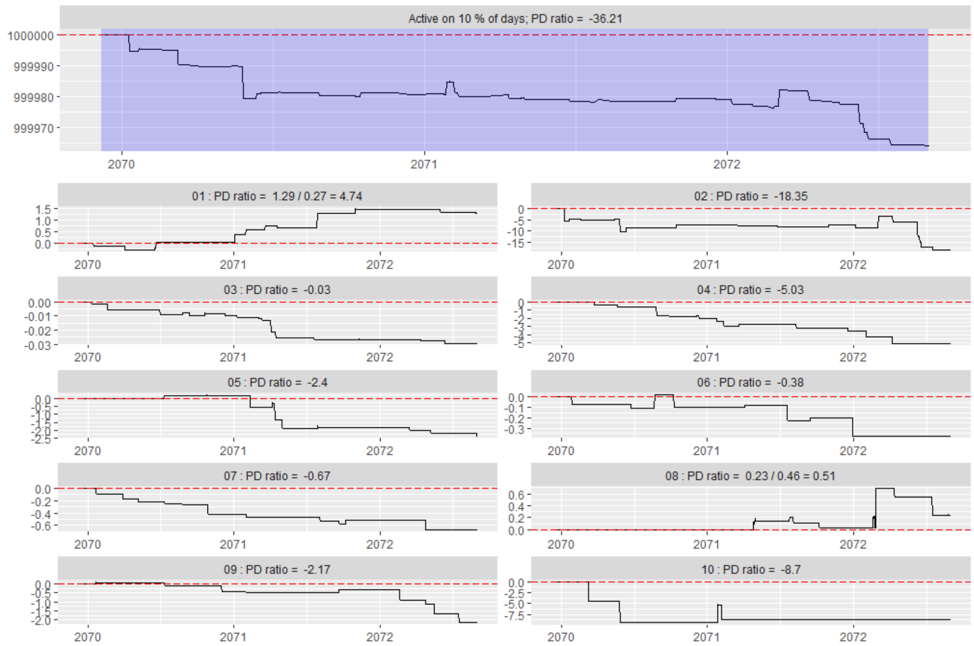




Turtle strategy uses 2 parameters lookback and moving average. The former chooses the highest and lowest price in previous n days. If we keep looking back over and over again, we can get two lines (Donchian Channel). One for the upper line and one for the lower line. Besides, MA could estimate the trend and detect the chance enter the market.



Using closing price as indicator to trade



Using moving average as indicator to trade

The figures display the activity of two methods and it can be seen that changing to moving average significantly decreases the trading frequency and gets a better PD ratio.

We begin by merging the high, low and close price of each series into one dataframe and calculate the Donchian Channel using the TTR function embedded in the quantmod package. Then we test the result accordingly with MA and daily close price by changing the if condition.

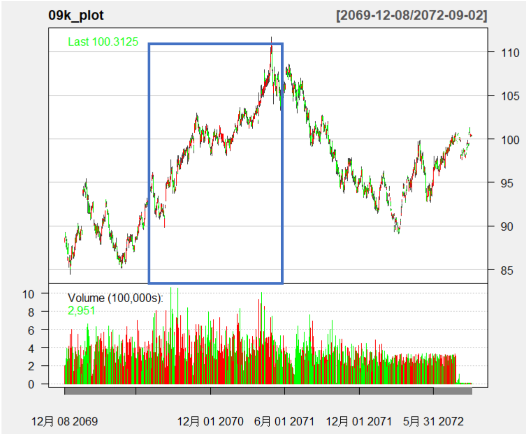
The core of this strategy is the way to manage the position sizing. The algorism establishes a negative correlation between the market volatility and the position size. Using this method to mitigate the shortage of the strategy. Moreover, using moving average to determine the enter and exit can be more reasonable than just looking today' s close price, which means that trading is not as frequent and sensitive, and it will reduce unnecessary trading operations.

The coding of the strategy implementation using the example strategy template is as follows:

```
if (store$iter > params$lookback) {
  startIndex <<-  store$iter - params$lookback
  for (i in 1:length(params$series)) {
    cl <- newRowList[[params$series[i]]]$Close
    Merge <<- cbind(store$high[startIndex:store$iter,i],store$low[startIndex:store$iter,i],store$cl[startIndex:store$iter,i])
    Merge <<- as.data.frame(Merge)
    colnames(Merge)[1] <<- "High"
    colnames(Merge)[2] <<- "Low"
    colnames(Merge)[3] <<- "Close"
    dc <<- last(DonchianChannel(Merge[,c("High","Low")],n=params$lookback,include.lag = TRUE))
    movingAverage <<- last(SMA(Merge[,c("Close")],n=params$ma))


   if (newRowList[[params$series[i]]]$Low< dc[,3]) {
     #if the moving average is lower than the Donchian Channel Low-bound, short the position
     #replace the first if condition for movingAverage
     ##### if the lowest price of the day is smaller than the Donchian Channel Low-bound, short the position

     pos[params$series[i]] <- -1
   }
   else if (newRowList[[params$series[i]]]$High > dc[,1]) {
     #if the moving average is bigger than the Donchian Channel High-bound, long the position
     #replace the first if condition for movingAverage
     ##### if the highest price of the day is bigger than the Donchian Channel High-bound, long the position
     pos[params$series[i]] <- 1
   }
   else{
     pos[params$series[i]] <- 0
   }
   }
 }
```

Section 2.3 Momentum trading strategy

Momentum trading strategy work well when the future return is positively correlated to past return, which indicated that an up move will probably be followed by another up move.



Take series 9 as an example, a continuous rise can be seen from December 2069 to June 2071 regardless of many fluctuations in the short term. This time period shows a strong linear relation between past return and future return.

Momentum strategy is good if we find a clear momentum like series 9 and react to it before the market reacts to the information.

Momentum trading strategy is very simple and the pons are very obvious. Firstly, the ease of risk management, which means momentum strategy survives risk well (Chan 2013). Momentum strategy can give two common types of exit strategies: time-based and stop loss. And stop losses are highly consistent with momentum strategy. When the direction of momentum changes, we would suffer from great losses with original positions but a stop loss can let us exit it early. Apart from that, with a limited downside, the upside of momentum strategy is unlimited (Chan 2013). With a strong trend like "black swan" event, momentum strategy benefits a lot from that.

When it comes to how the strategy works, firstly, choose the proper lookback period and holddays which means the maximum of the day you are holding the position and testlength. Testlength is the number of day that you use to test the correlation coefficient between past return(lookback) and future return(holddays).

For example, as the picture shows, the figures are 60, 30, 180 respectively. It means in the past 180 days, we calculate the correlation coefficient between the return of 60 days and that of the following 30 days. The codes for calculating are as follows:

```
lookback <- 60
holddays <- 30
testlength <- 180
```

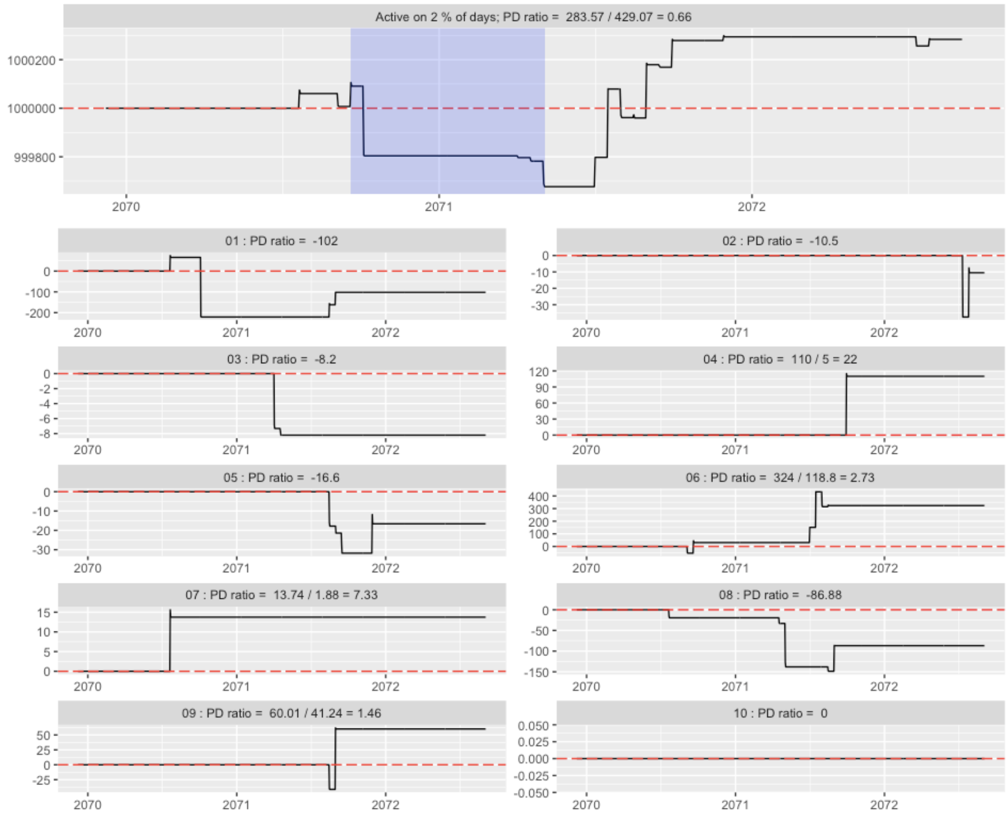
```
for (d in numOfDay-testlength:numOfDay-1) {
  lookback_return <- c()
  holddays_return <- c()
  for (k in 1:testlength-holddays-lookback) {
    lookback_return <- c(lookback_return, dfm[numOfDay-testlength+lookback+k-2,3*i-2]-
                          dfm[numOfDay-testlength+k-1,3*i-2])
    holddays_return <- c(holddays_return, dfm[numOfDay-lookback-holddays+k-1,3*i-2]-
                          dfm[numOfDay-lookback-2*holddays+k,3*i-2])
  }

}

cor <- cbind(0,0,0,0,0,0,0,0,0,0)
cor[i] <- cor(lookback_return,holddays_return)
```

In the past 180 days, from the first day to the 90th day, we get a pair of return including return of 60 days and return of next 30 days every day. Consequently, we get two vectors with the same length of 90. Then we use cor() function to get the correlation coefficient of lookback period and hold days of series i. And a positive result indicates a linear relation. How we react to the positive correlation coefficient results are as follows:

```
if(cor[i]>0.2){
  # the past 180 days showed a relatively strong linear relation
  # if the past lookback period saw a positive return, long
 if (dfm[numOfDay-1] - dfm[numOfDay-60] > 0) {
    limitPrice[params$series[i]] <- newRowList[[params$series[i]]]$Close
    limitPos[params$series[i]] <- params$posSizes[params$series[i]]
 }
  # if the past lookback period saw a negatie return, short
  else {
    limitPrice[params$series[i]] <- newRowList[[params$series[i]]]$Close
    limitPos[params$series[i]] <- -params$posSizes[params$series[i]]
  }
}
```

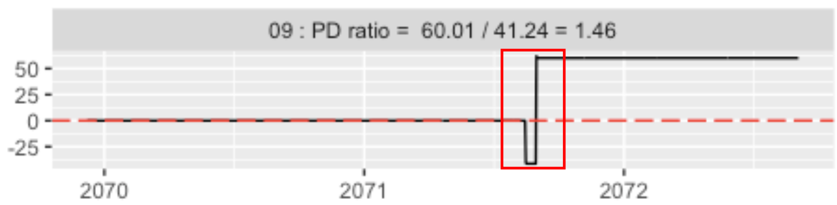
With a positive correlation bigger than for example 0.2, we long if the return of the past lookback period(60 days) are positive and hold the position for holddays(30 days) unless stop losses trigger off.

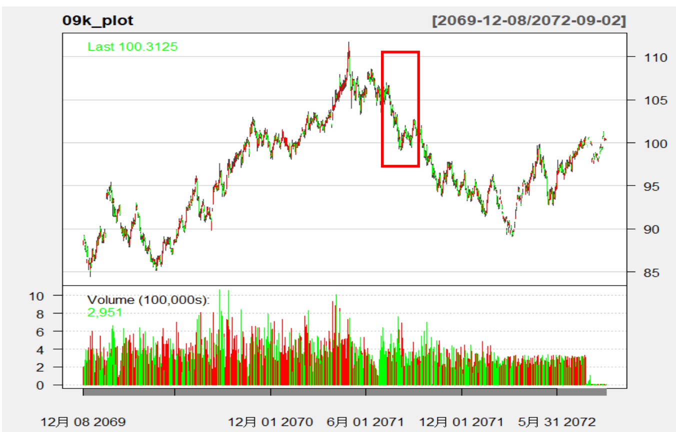
The preliminary test results are as follows:



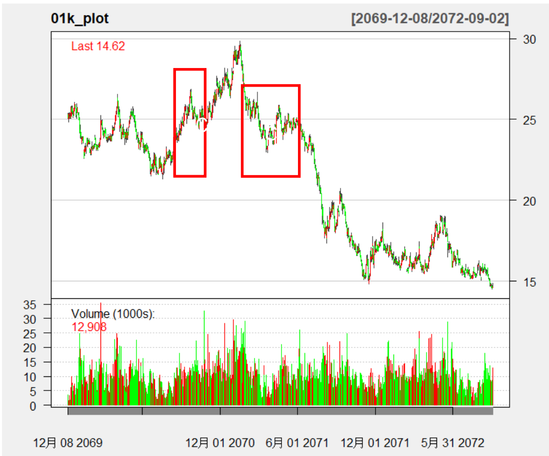
Analysis of the test results:

The results show that in most cases, our momentum strategy can catch a clear momentum and make a profit from that. For instance:





For series 9, it is obvious that we succeeded in catch the continuous decrease between June 2071 to December 2081 and made a profit. However, the strategy failed to catch an earlier up momentum. It seemed that the strategy did not react to that due to unknown reasons.



As to series 1, the strategy succeeded in catching the up momentum from June 2070 to December 2071. However, during the rapid downside after that, we had a great lose for we failed to catch the momentum and the stop loss are not perfect enough to help us avoid the risk.

Section 3: Risk management

This section will briefly demonstrate that how three strategies do risk management such as position sizing. Besides, we will discuss the possibility of bankrupt as well as how to avoid that.

Section 3.1 CCI trend following Strategy

Judging from the results of multiple tests, this strategy is unlikely to cause bankrupt, which may be due to the stricter stop loss conditions. This strategy will only conduct buying transactions in a small portion of the overbought and oversold areas of the CCI. However, regardless of whether the price is in the overbought or oversold area of CCI, the cciStop line is only 1.02 times the overbought and oversold lines, which means that we will only earn/loss 2% per transaction. Although this limits the possibility of more profits, it also reduces losses.

Position management is automatic. When the CCI trading rules are triggered, it will buy or sell/short 1 unit. When the stop loss rule is triggered, the position is cleared directly. When the MACD rule is triggered, it will sell/short 1 unit, because the current market may be too mad.

Section 3.2 Turtle Trend Following Strategy

The algorism will look at a 20-day exponential moving average true range to decide the size of the position. When the volatility is low in the market, the position sizing will be expanded.

TR（true range）:

TR1=Max (High1−Low1, High1−Close0, Close0−Low1)

ATR（Average true range）:

ATR20 = mean (TR1, TR2 ···TR19, TR20)

Index 1 refers to today price, 0 refers to yesterday price.

This method guarantees that the loss will not exceed the n% of the total assets.

Stoploss:

The channel has a great way to build the stoploss point. For instance, when the price hits the lower boundary and current position is long, it will trigger the stoploss.

Section 3.3 Momentum trading strategy

Position sizing: Our momentum strategy is a long-term, low-frequency strategy. The goal is to maximize the net worth in the long term. Due to this, short-term high volatility and drawdowns are paid little attention and our position tend to be high. Since we start with 1000K equity, and from Part 1 data we noticed that only 2% days are active, every time we make a trading decision, we long or short the assets worth 100K. And we will divide the trading decision into 30 days. That means if we make a long decision at the first day of the month, we will only buy one-thirtieth of total capital (100K). And buy one-thirtieth every day in the following 29 days.

Stop Loss: We will set a maximum drawdown to make sure the absolute value of drawdown will never exceed the certain maximum.

The probability of bankrupt exits but is very low in momentum trading strategy. Because the low-frequency strategy makes trading decision monthly and stays flat in many cases and the stop loss sets a limited downside for every long or short decision we make. So, unless almost every trading decision we make makes a loss, we probably will not go bankrupt.

Section 4: Plan

In the section of plan, we will illustrate what will we do when we get part 2 of the data while how to do parameter optimization. Moreover, we want to use in-sample and out-sample test to prevent over-fitting although it may still lead to overfit in some cases.

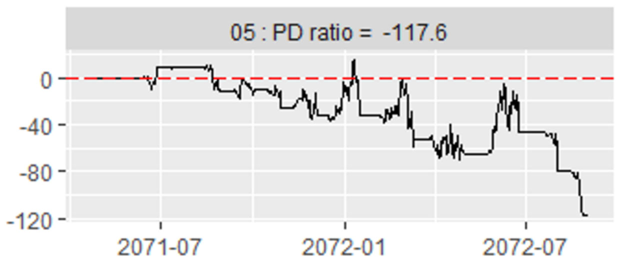
After getting the data of PART 2

We will immediately use the new data to test strategies and check the profitability. If the return is not good, the overall structure of the strategy will be reconsidered. If the benefits are acceptable, we will continue to consider the fine-tuning of strategies such as parameter optimization. Considering the group as a whole, we will discuss how to combine different strategies more effectively, such as funding allocation and strategic priority issues.

Section 4.1 CCI trend following Strategy

1. Parameter optimization

   As predicted earlier, this strategy performs the worst on the time series 4. But unlike the prediction, this strategy also failed to obtain overall positive returns on the time series 5, and the returns are almost keeping negative from the beginning.



   We think this is because the parameters of the MACD curve have not been adjusted, perhaps too strict and conflict with the existing CCI indicators. Thus, we will study where the best CCI overbought and oversold areas are. Meanwhile, because the CCI indicator changes too fast, we hope to reduce the time required for the fast and slow lines of MACD so that MACD can "catch up" with changes in CCI to a certain extent. It cannot be too fast, which will lose the effect of the MACD indicator as a "sedative", but it cannot be too slow, which may send a signal opposite to the CCI and cause trading losses. we might first halve macdFast and macdLow (parameters in the code) to see the effect. Also, we will consider slightly reducing (increasing) CCI's lookback and increasing (decreasing) its mean deviation to make the indicator more agile (sluggish) if this strategy is tested bad with PART 2 data.

2. This strategy currently does not use limit orders, and we plan to continue to consider this issue in the next phase.
3. The current strategy does not include the "divergence" consideration, we hope it can be completed before the integration strategy.

Section 4.2 Turtle Trend Following Strategy

1. Inject new indicators

   As we show above, this sub-strategy is a basic and easy strategy, so to maximize the profit, it's necessary to inject more indicators in the sub-strategy to predict different scenarios and avoid useless transactions. For instance, the entry signal of turtle strategy is determined as today's close price in the first place, however, after reviewing some source of it, we prefer to using moving average instead of current close price. This is a kind of example for future optimization, looking for better indicators to mitigate the sensitivity of the entry.

2. Parameter optimization

   Deal with parameters, the crucial thing that we concern is how to utilize data efficiently. When we get the second part of data, the first thing is to cut the data down into several parts. In design part, we try to find out the best combination of MA and channel lookback, the mathematic relationship between two parameters imply the MA is way smaller than lookback, following that intuition we initially try MA for 3 and lookback should be 20, then we have the figure shows above (Moving Average).

3. Categorize the data

   Categorize the serial will assist the strategy to match the perfect serial and maximize the profit. Like others, this section needs to analyze the part 2 data first and conclude some features to match the perfect strategy. During this part, we can compare the first part of design document and validate the result in first part. After concluding and analyzing the first part of data, one problem shows up. The volatility has so many situations. A serial continuously takes off for a week, the volatility is huge. Another serial fluctuates around a line but has a huge standard deviation, large volatility as well. But we can only benefit from first situation. That is the problem we need to solve in the second task.

Section 4.3 Momentum trading strategy

1. Parameter optimization

   we will further adjust the figures for lookback, holddays and testlength with Part 2 data. Probably, the best combination for different series differs. After getting Part 2 data, we can expand testlength to 1000 days to get a more appreciate correlation coefficient of returns of lookback and holddays using Part 1 data and then use Part 2 data to check the results.

2. Parameter range

   In order to ensure enough active trading days demanded, holddays cannot be too long, so we would set a range from 15 to 60 holddays. And lookback will range from 1*holddays to 3*holddays.

In-sample/out-of-sample test

With three years' data in total, we prefer to use one year's data as sample, and the remaining two years as out-of-sample. Because usually one year's data is considered to be a "complete" data, and many characteristics are usually better reflected in the time of the year.

Section 5: Breakdown of team work

Tianyi Wang

Background Research

1. I proposed that since time series have three characteristics: stationarity, trend and seasonality, we should start with this. I gave the method of detecting seasonality such as ts() and decompose() function, studied the approaches of detecting stationarity, and ways to eliminate or reduce trend and seasonality such as Difference Transform, Logarithmic Transform and Augmented Dickey-Fuller (ADF) Test. I also read ARIMA models chapter in one book. Some of the above content contributed to the documentation.
2. Researched MACD, RSI, CCI, KDJ indicators, summarized their respective usage, characteristics and situations that I think may be applicable, and attached all reference links to help team members understand. This file is placed in my personal folder in the GitHub repository, so that all team members can check it at any time, written in Chinese.

Coding

1. In the first offline group meeting, I took bbands_holding_period as an example to understand how the code works with the group members. For example, how the main file is linked to the example_strategies file and the strategy files and runs. I am one of the members who have solved the most problems.
2. Created a code template to help group members who are not familiar with the code quickly start to implement their own strategies.
3. I completed all the codes and a series of tests in my strategy (CCI Trend Following) with Shi’ s help in debugging at the end and helped some other team members solve problems together.

Strategy Ideas

1. I thought about two strategies on my own: CCI Trend Following and KDJ Trend Following. After consideration, I chose the first one to implement.
2. I was the first person to complete the framework of my own strategy. After completion, I helped another group member to determine his strategy in one group meeting.

Presentation and Report

1. Presentation: Explain and answer questions about individual strategies, as well as the overall ideas of our group.
2. Report: All content related to personal strategy is contained in sections 2, 3, and 4.

Kechen Shi

Background Research

1. In the first few weeks, I' m mainly responsible for searching the strategy and going through the suggestion materials. The first strategy is grid trading strategy, but its logic is simple, and we can easily implement this idea on other strategy so this one is remains in our alternative document. The turtle strategy is the trend following sub-strategy in our main strategy.

Coding

1. After searching and understanding the basic elements and logic, Xu and I start coding and match the getOrder format.
2. Wang and I coded the first part of the CCI Trend Following strategy, this sub strategy is consisted of several indicators which is intuitive, so this is a temple version of the sub strategy at the beginning.

Strategy Ideas

1. I discussed a strategy named the Turtle strategy with Xu.

Presentation and Report

1. Presentation: Explain and answer the overall ideas of our group.
2. Report: I' m responsible for helping complete the part about Turtle Trend Following Strategy in design document in section 2, 3, 4 and combining the image to explain the code part.

Shengying Li

Background Research

1. I read the materials provided by the teacher and watched the video to understand the meaning and role of the strategy. I discussed the development of the pre-strategy with my group members and provided some information and insights.
2. I also studied the method of detecting seasonality after Wang proposed the characteristics of time series. And I found that the decompose() function only works with time series that have a high periodicity, however our series does not have this property. So I don't think this is the right thing to use.

Coding

1. I discussed one example of strategy - bbands_holding_period with members. During the discussion, we each provided insights into the code. In the end, we managed to understand most of the code and drive our own strategy code to completion.
2. I worked with Huang to build the basic framework and base code for Momentum trading strategy.

Strategy Ideas

1. I worked with Huang on Momentum strategy and finalized the basic idea of the strategy.
2. I presented my thoughts on the stop loss in the strategy and discussed and analyzed it with Huang and Wang.

Presentation and Report

1. Presentation: Introduce and explain the content of the document. Explain and answer the overall ideas of our group.
2. Report: This is the part I am mainly responsible for. I collected group ideas and strategy content and participated in the editing of all content in the document. Finally, I completed the task of writing the document.

Zheyu Huang

Background Research

3. I finished reading four chapters of suggested reading *Algorithmic Trading: Winning Strategies and Their Rationale*, and got a brief idea of how mean reversion strategies and momentum strategies work. During the group meeting, I shared the strategies with teammates.
4. Searched on GitHub and Google about code examples of momentum strategies and learned about various indicators for momentum strategies. After comparison, chose to test two indicators: correlation coefficient and past performance.

Coding

4. Started reading example codes at an early stage and pointed out several critical questions on the meeting to help the team understand the codes.
5. Built the basic logic of the coding of momentum strategies with the help of Shengying and finished the coding by myself. After testing two indicators, chose the correlation coefficient of lookback period and hold days as the trigger of trading. I also tried parameter optimization and got a combination of lookback period and hold days with relatively good performance.

Strategy Ideas

3. I learned about mean reversion and momentum strategies through reading and searching online. I finally chose to focus on momentum strategies, considering that the other strategies of my teammates are high-frequency and short-term, I would like to give a long-term strategies with low frequency.

Presentation and Report

3. Presentation: Explain and answer questions about momentum strategies.
4. Report: Responsible for all content related to momentum strategies contained in sections 2, 3, and 4.

Zhangyuan Xu

Background Research

1. In the beginning, I was responsible for the analysis of the time series. I have researched graph representation using TTR package to show the K-plot, volatility and stationarity test to verify if the data is suitable for strategy.
2. I have also done research on the turtle trend following strategy, to be more specific, I studied the Donchian Channel and tested the possible implementation of the turtle strategy.

Coding

3. I have done all the part1 coding, including the K-plot, volatility, as well as stationarity test and graph representation.
4. I and Shi designed the turtle trend following strategy, where he focused more on the strategy idea, and I was responsible for the coding and debug testing.

Strategy Ideas

2. I and Shi designed and implemented the turtle trend following strategy together.

Presentation and Report

3. Presentation: Explain the part 1 of the data analysis.
4. Report: I was responsible for the part 1 data analysis and some modification of the turtle trend following strategy.

Section 6: References

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