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IDP Institute of Data Analysis
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Project work at Engineering and Management

Allocation tool for asset management from Mobiliar

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Abstract

1. Introduction

The main purpose of trading is buying and selling stocks, bonds, or other financial instruments with increasing the returns of the investments in mind while maintaining relatively low risk. With the help of a trading strategy, an investor can try to improve his performance. One can simply divide the strategies into passive and active. The praised and well established passive strategy buy-and-hold takes no short price movements into account. Positioning and trading based on these short price movements are considered active trading.

This paper applies time-series analysis to these short price movements to create active trading strategies. The objective of these developed strategies is to outperform the buy-and-hold strategy.

1.1. Data Analysis

The dataset which will be analyzed in this paper contains 4 tradeable indexes, a visualization of the data is shown below in figure 1.



Figure 1: Visualization of the 4 indexes

Each time-series has 4306 observations and starts from October 2003 to April 2020. In all indexes is an upward drift observable, during the time period of the great recession (2008) is a slight bump visible. Also later in 2013 and 2016 are small break-ins evident. More interesting is the up and down behavior at the end of the series during the Covid19 pandemic.

In addition, to the indexes, the dataset contains 8 different interest rates of treasury bonds which will be used for further analysis. A few key-values of the interest rates are shown in the following table 1.

Table 1: Summary of the 8 interest rates.

	Maturity	Mean	Volatility	Min.	Max.
Interest 1	3M	4.09	4.95	-0.28	16.27
Interest 2	6M	4.47	5.05	0.01	16.73
Interest 3	1Y	4.64	4.22	0.20	10.51
Interest 4	2Y	5.42	4.58	0.49	16.58
Interest 5	3Y	6.16	4.33	0.75	16.51
Interest 6	5Y	7.41	3.82	1.06	16.44
Interest 7	7Y	9.50	3.31	1.71	16.63
Interest 8	10Y	11.61	2.93	3.13	17.47

A typical characteristic of interest rates is shown in the given data. A bond with longer maturities is often associated with higher returns compared with those with shorter maturities. An investor which invests in short-term treasury bonds will have his gain earlier but will be confronted with a lower return.

A more in depth analysis of the given dataset will follow in section 3.1.

1.2. Objective of this paper

The objective of this paper is to trade these 4 indexes with an active trading strategy. The main objective is to outperform the passive buy-and-hold strategy. Methods such as the Moving-Average-Filter or the ARMA-GARCH-Model provide signals for either long or short the position to maximize the return of the investments in these indexes.

The performance of these strategies are build open various different parameters and conditions. The lengths of the filters applied to a Moving-Average may result in different solutions. Models could perform differently for any given length of the in-sample or out-of-sample scope. The necessity of including a historical crisis in the starting-sample can decide if a model performs better or worse than another. The correct validation of model parameters could have a significant impact on the forecasts.

In addition to all criteria and conditions, the strategies can be further adjusted by composing different weighted portfolios. Estimated predicted volatility can be used to modulate the position size to mitigate the risk.

Challenging will be finding the most optimal model in this wide field of conditions and parameters. The buy-and-hold strategy will be used as a benchmark to be compared with the developed active trading strategies. Computing and comparing the Sharpe ratios of each model can serve as an indicator to rely on for better or worse models.

2. Theory

It is assumed that the reader of this paper already has basic knowledge of the mathematical principles of time series analysis. Therefore, this section will only briefly describe the mathematical models and processes.

2.1. Time-Series

Almost anything with a data point to a given timestamp can be named a time-series. The monthly gross domestic product, the weekly US gasoline production, or daily stock price movements. In this paper lies the focus of the analysis of financial time series. Due to trades often only take place during the week, there are gaps in the time series on the weekends, an exception would be the trading of cryptocurrencies like Bitcoin which are also tradeable at the weekends.

A series of data points with more or less equidistant time points t with the sample length of T , is called a time-series $x_t, t = 1, \dots, T$ [1]. The analysis of a time-series x_t involves creating a reasonable model that can be utilized to perform forecast predictions.

2.1.1. Stationarity

In order to fit a suitable model with a given time series x_t , the assumptions of stationarity must be met. In this practical application, only the following weak-stationarity properties are required.

$$E[x_t] = \mu \tag{1}$$

$$Var(x_t) = \sigma_x^2 \tag{2}$$

$$Cov(x_t, x_{t-k}) = R(k) \tag{3}$$

Many financial time-series are subject to shift, trends or changing volatility. In figure 2 are the stock prices of Alphabet Inc Class A (Google) visualized. This time-series shows a clear upwards drift and towards the end the volatility increases.

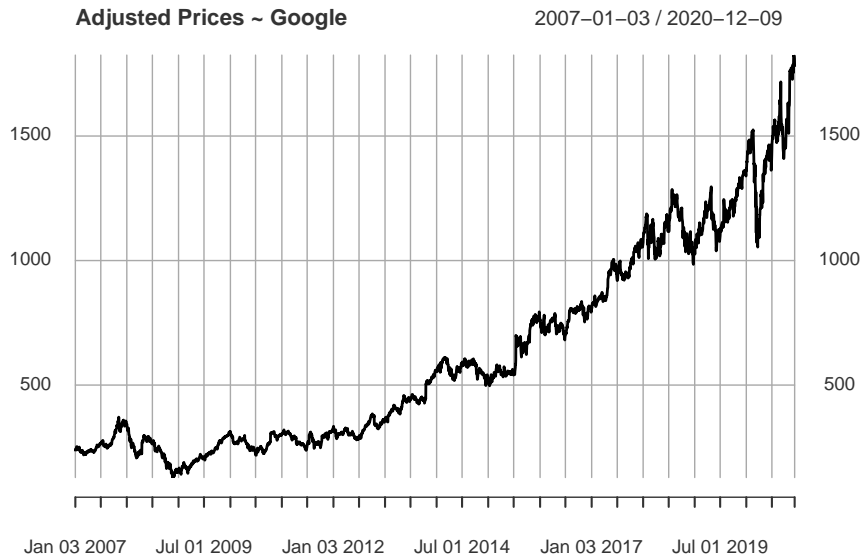


Figure 2: Visualization of the adjusted prices of the Alphabet Inc Class A Stock.

To improve the violated properties the first difference can be applied and additionally a logarithmic transformation can be performed [2]. The log-returns transformation can only be performed on strict positive data.

$$\text{LogReturn} = \log(x_t) - \log(x_{t-1})$$

The result is the so-called log-returns.

Applying the transformation to the data causes the drift to disappear, but the series still contains stronger and weaker volatile phases. This effect often occurs in non-stationary financial data and is called volatility cluster. This special property is used for the modeling of forecast models, which will be discussed in chapter 2.2.

In the following examples, we will only work with a section of the time series, as it often makes no sense to look long into the past. The further a value lies in the past, the smaller its influence on a future value will be.

2.1.2. Autocorrelation

The autocorrelation function (ACF) reveals how the correlation between any two data points of the time series changes as their separation changes [3]. More precisely, acf measures the dependence between x_t and $x_{t \pm k}$ at lag k . The partial autocorrelation (PACF) measures the dependency between x_t and x_{t-k} at lag k [1]. For stationary time series, ACF can be used to identify the model order of a MA-process, PACF for AR-processes.

In the following figure 4 are ACF and PACF of the non-stationary adjusted Google stock visualized. Both graphics show the typical pattern of a non-stationary time series. The plot above shows the dependence structure of the time series. This means that it takes a long time until the series changes. Often a large value is followed by another large value, which indicates a strong trend. This property of the series can be seen in figure 2 as the long upward drift. The plot below indicates a significant partial autocorrelation at lag $k = 1$.

In the following section 2.2. the characteristics of the autocorrelation function can be used for the verification of ARIMA and ARCH-processes.

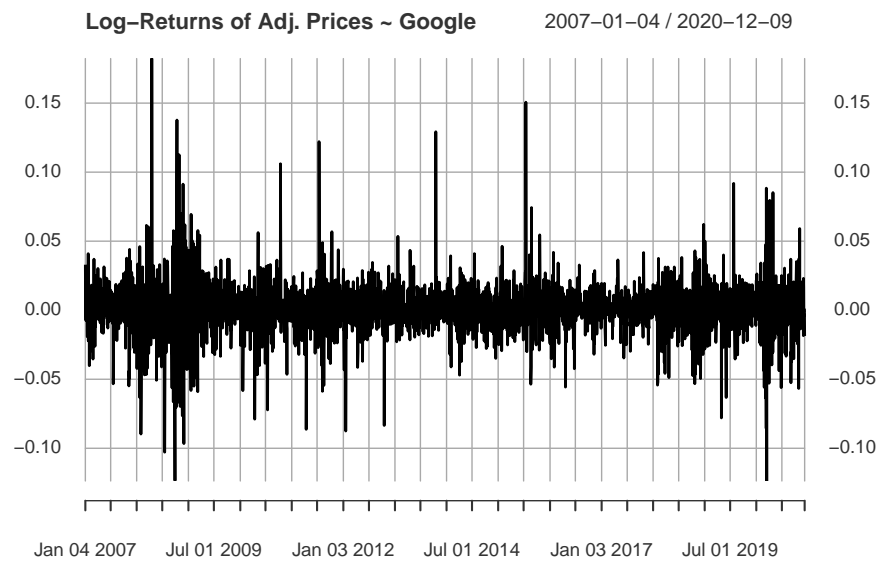


Figure 3: Visualization of the Log-Returns

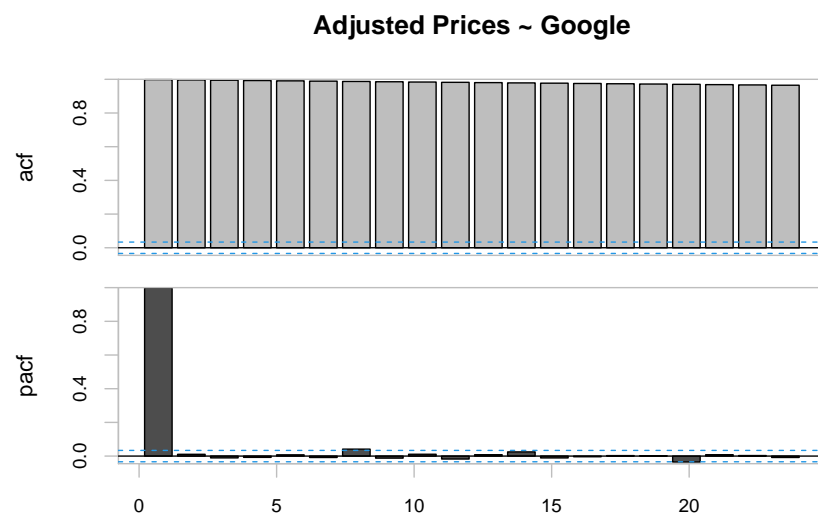


Figure 4: Acf and Pacf of the Adjusted Prizes of Google.

2.2. Models

The following processes are used to determine certain properties and characteristics of a time series so that they are transformed into a model. The goal is to fit the time series as well as possible in order to create reliable forecasts.

2.2.1. ARIMA

An ARIMA(p, d, q) process is defined as follows.

$$x_t = c + a_1x_{t-1} + \dots + a_px_{t-p} + \epsilon_t + b_1\epsilon_{t-1} + \dots + b_q\epsilon_{t-q} \quad (4)$$

- p and q are the AR- and MA-model orders
- a and b are the AR- and MA-model parameters
- d is the differential parameter
- ϵ_t is a white noise sequence
- x_t is the given data x_1, \dots, x_T

The mean of an ARIMA-process can be computed as:

$$\mu = \frac{c}{1 - a_1 - \dots - a_p}$$

ARIMA processes can be divided into 4 different models. Choosing a model that best represents the time series is a difficult task. The goal is to find the best possible model with as few parameters as possible.

The previously introduced ACF and PACF can help to determine the orders of simple models. Provided that the time series is stationary, the model orders can be determined directly. For an AR(p)-process (ARIMA($p, 0, 0$)), the ACF plot will gradually decrease and simultaneously the PACF should have a sharp drop after p significant lags. For an MA(q)-process (ARIMA($0, 0, q$)) the opposite is true, the ACF should show a sharp drop after a certain q number of lags while PACF should show a gradual decreasing trend. If both ACF and PACF show a gradual decreasing pattern, then the ARIMA($p, 0, q$)-process should be considered for modeling [4]. If the time series is not stationary, differentiation can be considered (ARIMA(p, d, q)).

The application of an analysis method to Google prices finds an $ARIMA(1,1,0)$ as the optimal model. This makes sense if you look back at figure 4. Long dependency structures in the ACF plot indicating an $AR(p)$ process and at the same time after $lag=1=p$ the PACF has a strong drop. The differential operator $d=1$ transforms the non-stationary series into a stationary one.

To convince yourself of the quality of the model, you can use the Ljung-Box statistics shown in figure 5. For the lags where the p-values are above the 5% line, the forecasts are reliable. Here the values from the 6 lag are below the significant line, but since one only wants to make short-term forecasts (for example 1 day into the future), the lag is sufficient up to 5. If you want to forecast further than 5 days into the future, you might have to adjust the ARIMA model.

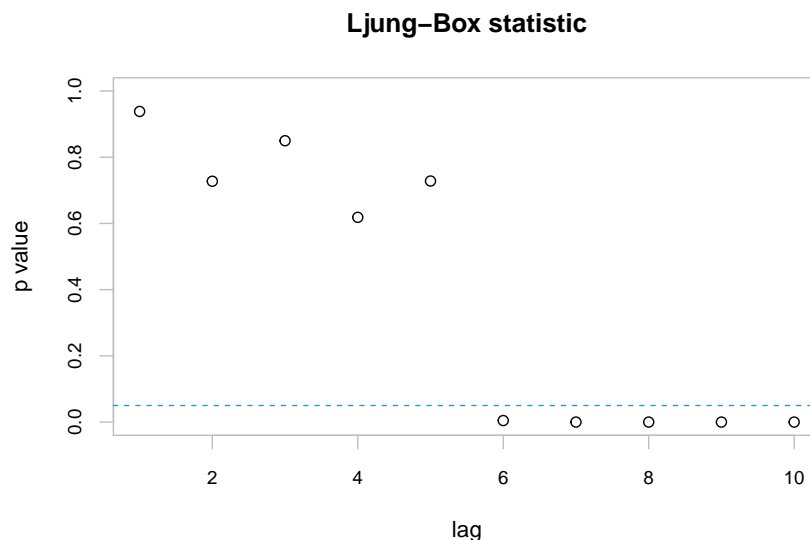


Figure 5: Ljung-Box statistic of Google log returns.

In figure 6 you can see the prediction of the model. The whole representation is shifted by one day so that one can compare the model with a true value. The **green dot** is the actual value of the time series. The **red dots** indicate the upper and lower 95% interval limits respectively. These indicate that a future value will be within this band. The **blue dot** is the point forecast predicted by the model.

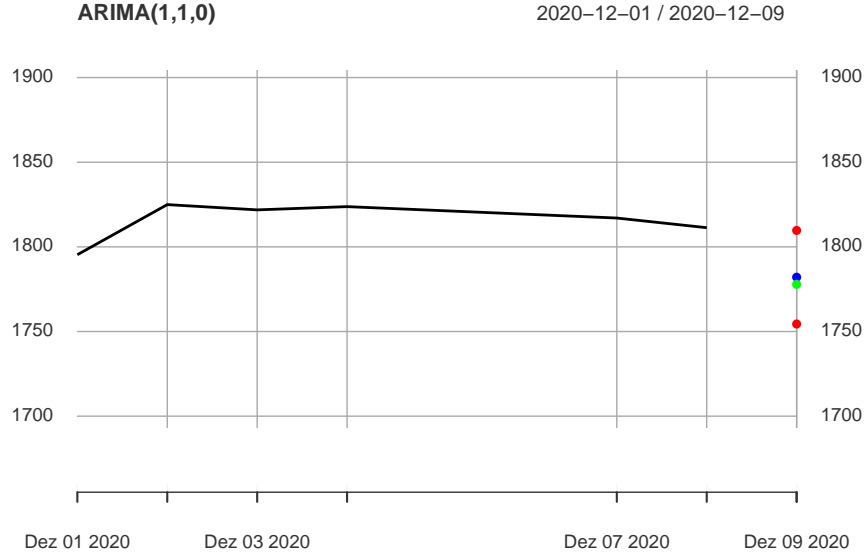


Figure 6: ARIMA-Forecast.

2.2.2. GARCH

The volatility clustering mentioned in section 2.1.1 can be handled with an generalized auto-regressive conditional heteroscedastic process.

$$\begin{aligned}
 \epsilon_t &= \log(x_t) - \log(x_{t-1}) \\
 \epsilon_t &= \sigma_t u_t \\
 \sigma_t^2 &= c\sigma^2 + \sum_{j=1}^n \alpha_j \sigma_{t-j}^2 + \sum_{k=1}^m \beta_k \epsilon_{t-k}^2
 \end{aligned} \tag{5}$$

with

- x_t is the original data (often non-stationary)
- ϵ_t is the stationary log-return
- u_t is independent and identically distributed (iid) and a standardized random variable
- σ^2 is the unconditional variance of the process ϵ_t .
- σ_t^2 is the conditional variance of the process ϵ_t .

With a GARCH(n, m)-process it is possible to model the volaclusters of a time series. The GARCH($1, 1$) model has become widely used in financial time series modeling and is implemented in most statistics and econometric software packages. Those models are favored over other stochastic volatility models by many economists due to their relatively simple implementation [5].

Table 2: Coefficients GARCH(1,1).

	Estimate	Std. Error	p-Value
ω	1.090851e-05	1.845483e-06	3.401915e-09
α_1	7.356039e-02	1.077494e-02	8.671508e-12
β_1	8.950358e-01	1.377254e-02	0.000000e+00

For an optimal model some conditions must be fulfilled. Suppose you want to model the Google time series with a GARCH(1,1).

In table 2 the estimated coefficients of the process can be seen. The p-values are all lower than 0.05 and thus indicate that they are essential for the model. (Note: $\omega = c\sigma^2$)

The following parameter restrictions are also examined:

$$c + \sum_{j=1}^n \alpha_j + \sum_{k=1}^m \beta_k = 1 \quad (6)$$

with

$$c > 0, \alpha_k \geq 0, j = 1, \dots, n, \beta_k \geq 0, 1, \dots, m$$

To satisfy formula 6, c needs to be determined from ω . First calculate the unconditional variance.

$$\sigma^2 = \frac{\omega}{1 - \alpha_1 - \beta_1}$$

Calculate c with:

$$c = \frac{\omega}{\sigma^2}$$

and then check for the restriction in 6.

For the coefficients of GARCH(1,1) the restrictions are fulfilled. You can see that $c = 1 - \alpha_1 - \beta_1$. So this restriction can be determined easily with:

$$\sum_{j=1}^n \alpha_j + \sum_{k=1}^m \beta_k < 1 \quad (7)$$

If the parameter restrictions are not fulfilled, complications may arise, the forecast of the conditional variance $\hat{\sigma}_t^2$ may diverge to the unconditional variance σ^2 of the process.

Furthermore, the Ljung-Box statistics are important for the standardized residuals. Looking back at formula 5 standardized residuals u_t are proportional to the conditional volatilities σ_t , which should lead to the log returns ϵ_t . The conditional volatilities map the volacluster in the time series. To achieve the best possible model, one does not want to find these volacluster effects in the standardized residuals, but only in the conditional volatilities. The Ljung-Box statistics check this property. In figure 7 Ljung-Box statistics of the \hat{u}_t and the \hat{u}_t^2 are shown.

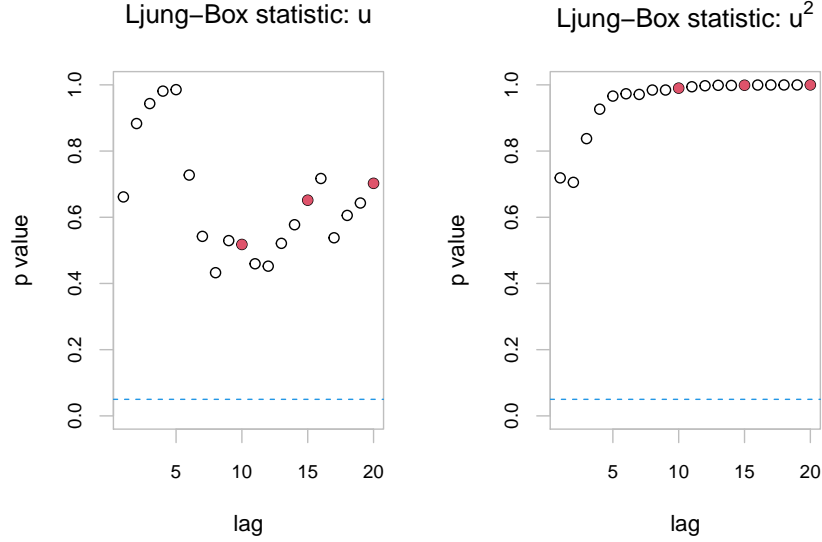


Figure 7: Ljung-Box statistic of the standardized residuals.

The plot shows reliable statistics for forecasts from the Google-GARCH(1,1) model. For all lags up to 20, the p-values are above the 5% line and thus hypothesis tests are discarded. However, if for a given lag=k the p-values would fall below the 5% line, then forecasts would only be reliable up to a forecast horizon k.

If one wants to improve the the standardized residuals \hat{u}_t (if autocorrelations exists in the \hat{u}_t), an ARMA part would have to be added to the existing model (see 2.2.3). This can again be optimized with different model orders. If you want to improve the squared standardized residuals \hat{u}_t^2 (if volaclustering exists within the \hat{u}_t^2), then you should modify the GARCH model order.

Now an optimal model has been found and a forecast can be made. Since a GARCH(n,m) process is white noise sequence the expected value $E[\epsilon_{T+h}|\epsilon_T, \dots, \epsilon_1] = \mu = 0$ can be assumed (if the mean value in the fit object was also estimated and is significant, then the expected value is the estimated μ).

Calculating the forecast variance is a recursive process. With increasing model order the calculation becomes more and more difficult. For this work the rather simple calculation for a GARCH(1,1) model is sufficient. One receives:

$$\hat{\sigma}_{T+h}^2 = \omega + (\alpha_1 + \beta_1)^2 \hat{\sigma}_{T+h-1}^2$$

If the parameter restriction from formula 7 is true, the forecast variance converges with the increasing forecast horizon to the unconditional variance of the process.

$$\hat{\sigma}_{T+h}^2 = \frac{\omega}{1 - \alpha_1 - \beta_1} = \sigma^2$$

The 95% forecast interval is calculated as follows:

$$E[\epsilon_{T+h} | \epsilon_T, \dots, \epsilon_1] \pm 1.96 \sqrt{\sigma_{T+h}^2}$$

Figure 8 shows the GARCH(1,1) forecast for 20 days. The blue line represents the expected value of the time series. Reds are the two 95%-interval limits and green shows the actual values of the series.

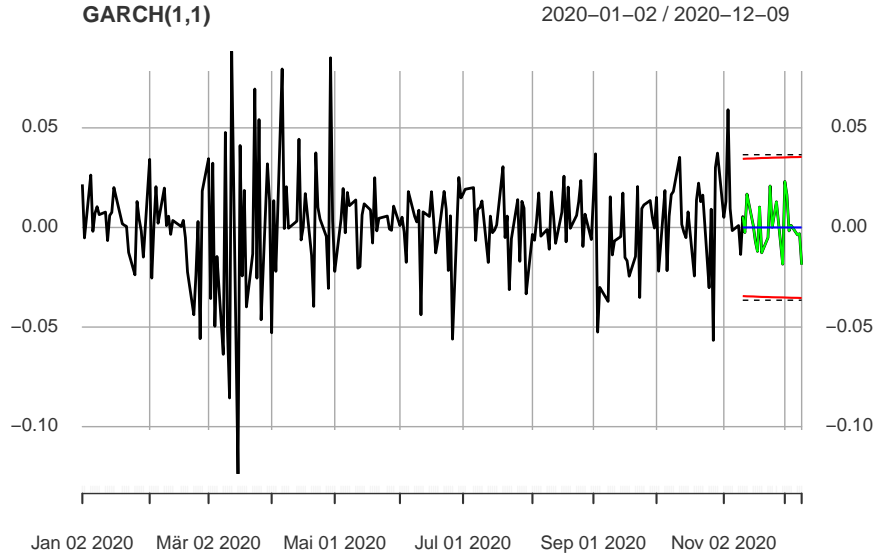


Figure 8: GARCH-Forecast.

You can see how the red lines are approaching the black dotted lines ($0 \pm 1.96 * \sqrt{\sigma^2}$) as the forecast horizon increases. This means that the forecast variance converges to the unconditional variance and thus there is another proof for the satisfaction of the parameter restrictions.

2.2.3. ARMA-GARCH

If you want to adopt a GARCH model and you discover non-vanishing autocorrelations in the standardized residuals \hat{u}_t , the model can be extended with an ARMA part to counteract the autocorrelations.

$$y_t = \mu + a_1 y_{t-1} + \dots + a_p y_{t-p} + \epsilon_t + b_1 \epsilon_{t-1} + \dots + b_q \epsilon_{t-q} \quad (8)$$

$$\epsilon_t = \sigma_t u_t$$

$$\sigma_t^2 = c\sigma^2 + \sum_{j=1}^n \alpha_j \sigma_{t-j}^2 + \sum_{k=1}^m \beta_k \epsilon_{t-k}^2 \quad (9)$$

This model contains now 4 different model orders: p, q, n and m . Experience shows that for financial time series, a model order of $n=m=1$ and $p, q \leq 1$ is often sufficient to fit the data to an ARMA-GARCH model.

The equation 8 is called the *mean-equation* and describes the conditional mean of the process, which is used to obtain optimal point forecast. The equation 9 defines the variance of the process and is called *variance-equation*, which is used for the forecast error variance [6].

2.2.4. M-GARCH

The last model that is considered as a forecast model in this thesis is the so-called MGARCH model. Highly volatile phases indicate downturns. Market participants tend to oversell during these downturns. Overselling leads to inflated volumes and this in turn leads to inflated volatilities. This model can be helpful since it emphasizes recession and crisis dynamics.

$$\begin{aligned}r_t &= \log(x_t) - \log(x_{t-1}) \\r_t &= \mu + e\sigma_t + \epsilon_t \\ \epsilon_t &= \sigma_t u_t\end{aligned}\tag{10}$$

where

- x_t is the original data (typically non-stationary)
- r_t are the log-returns (stationary)
- μ is the long-term drift
- ϵ_t is a volacluster process (GARCH)
- e is a constant (a parameter to be estimated), $e > 0$ implies a larger expected return. $e < 0$ would imply a smaller expected return. If $e = 0$ then the MGARCH-effect vanishes [7].

For this model, the in-sample conditional standard deviations (volatilities) from any GARCH process are determined and the out-of-sample conditional standard deviation for obtaining forecasts of the future returns is then calculated by regression.

$$\hat{r}_{t+1} = \hat{\mu} + \hat{e}\hat{\sigma}_{t+1}$$

2.3. Moving Average Filters

Moving average filters are basically used to identify trends and smooth out price fluctuations. As a commonly used tool, moving average filters are very simple in their usage, historical data from a timeframe L gets summarized and divided by the length of the filter (L). Depending on the length of the filter, the application to the timeseries the MA gets shifted, longer filters have a higher shift then shorter ones we visualize this behavior in 9. Many different indicators are built upon the Moving Average principle, mostly they are used in combinations of different lengths to create signals. In the following section, we introduce some of the most popular indicators based on the MA principle.

The actual challenge in using Moving average filters, is to figure out which length of the filter brings the most useful information.

2.3.1. Equally-weighted Moving Average or SMA

SMA stands for Simple Moving Average, depending on the length of the filter(L), L observations since the last noted observation will be considered. The observations are getting summarized and divided by the filterlength L . As stated in the name, all past observations are weighted equally. For every timestep, a new observation is considered and the last one eliminated [8]. SMA's are very easily customized by changing the length of the filter.

EqMA

$$y_t = \frac{1}{L} \sum_{k=0}^{L-1} x_{t-k} \quad (11)$$

- L = filterlength
- x = original series price e.g.

2.3.1.1 Momentum Momentum is an indicator wether a market is bullish or bearish, it measures the “speed” of the trend direction in the market. for a timespan k the last price p_k , k timesteps ago is subtracted from the last price. This is equivalent to applying and EqMA on the returns of a series.

Momentum

$$y_t = p_t - p_{t-K} \quad (12)$$

- p_t = prices of the series
- K = Lag

2.3.2. Exponentially-weighted Moving Average

Since not all observations are having the same influence on the future value, we can apply a weight to past observations. One method will be exponentially weighted Moving average. So we chose an optimal parameter to give past observations weights decreasing by α^k . In comparison to the SMA 2.3.1. [9], a EMA from the same length L, reacts faster than to price changes.

A skillful trader chooses an optimal α to increase the performance of the measurement. Weights could also be given individually by adding a weight vector to the filter.

EMA

$$y_t = \frac{1}{\sum_{k=0}^m \alpha^k} \sum_{k=0}^m \alpha^k x_{t-k} \quad (13)$$

- m = filterlength
- α = Parameter to weigh the observations

2.3.3. Moving Average Crossings

Moving average crossings are basically just different MA's with different lengths applied to a time-series. The points the filters then cross, will be used as a trading signal to go long, short or hold. The “death” and “golden” cross are very popular trading patterns [9]. If a shorter MA crosses the longer MA from above, its called a “golden cross” it is an indicator that the price will rise in the future and can be used to created the buy signal. In contrast stands the “death cross” vise versa, a shorter MA (popular $L = 50$) crosses a longer MA (popular $L = 200$) from below, signaling that further losses are in store.

Moving Average Crossing

$$y_t = \frac{1}{L_1} \sum_{k=0}^{L_1-1} x_{t-k} - \frac{1}{L_2} \sum_{k=0}^{L_2-1} x_{t-k} \quad (14)$$

- L_1 = filterlength 1
- L_2 = filterlength 2
- $0 < \alpha < 1$ = Parameter to weigh the observations

An example of MA average crossings with 2 SMAs of different length is visualized in figure 9. The prices are in green while the blue line represents an 50 day SMA and the red line a 250 (1 year) SMA. The crossing points of those two SMAs could now be used as trading signals. In this example these crossings wouldn't perform very well, therefore as mentioned earlier, finding the right length of the filter depends on each timeseries, their behavior and the preferences of the trader.

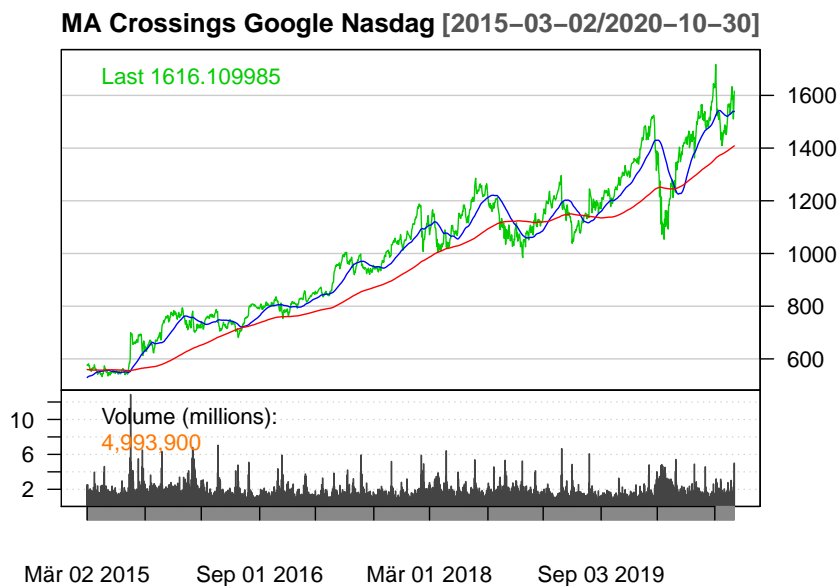


Figure 9: Moving Average Crossing

2.4. Relative Strength Index

The Relative strength index is a tool to measure momentum, the value indicates if positions are overvalued or undervalued. the scale goes from 0 to 100. [10].

$$U_t = \begin{cases} 1, & \text{if } x_t \geq x_{t-1} \\ 0, & \text{otherwise} \end{cases} \quad D_t = \begin{cases} 1, & \text{if } x_t < x_{t-1} \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

- X_t =Original timeseries

We then apply SMA or EMA of length N to U_t and D_t which converts them in $up_t(N)$ and $down_t(N)$ The RSI is now computed by:

$$RSI_t(N) = 100 \frac{up_t(N)}{up_t(N) + down_t(N)} \quad (16)$$

The original developer J. Welles Wilder Jr. proposed a length of N =14 in its work from 1978 [11]. Traditional tradings signals based on the RSI are the upper 70 or lower 30 limit to buy or sell. Usually when the RSI is going over 70 it suppose that the asset is overvalued and in contrast when its under 30 then its undervalued.



Figure 10: RSI

2.5. Moving Average Convergence Divergence

The MACD is also a commonly used filter. The basic principle is to Subtract a longer EMA with length L as in section 2.3.3 from a shorter EMA from length S then smooth the result with another EMA with length R . As a result with can use the crossing of the 2 generated curves for trading. As an alternative we could use SMA's instead of EMA's

$$macd_t = \frac{1}{\sum_{k=0}^{t-1} \alpha^k} \sum_{k=0}^{t-1} \alpha^k x_{t-k} - \frac{1}{\sum_{k=0}^{t-1} \beta^k} \sum_{k=0}^{t-1} \beta^k x_{t-k} \quad (17)$$

$$MACDsignal_t = \frac{1}{\sum_{k=0}^{t-1} \gamma^k} \sum_{k=0}^{t-1} \gamma^k macd_{t-k} \quad (18)$$

- x_t = prices or log prices
- S = length of the $short_1$ EMA usually 12
- L = length of the $long_1$ EMA usually 26
- R = length of the “double smoothing ema” usually 9
- $\alpha = 1 - \frac{1}{S}$, $\beta = 1 - \frac{1}{L}$, $\gamma = 1 - \frac{1}{R}$

₁ short and long in the meaning s<l, not buy sell



Figure 11: MACD

2.6. Bollinger bands

Bollinger bands are a analysis tool founded by John Bollinger. It contains a moving average and an upper and lower band . The bands are defined by adding a constant K times a standard deviation σ_t to the *Moving Average* for the upper , and subtracting it for the lower band.

$$U_t = MA_t + K\sigma, L_t = MA_t - K\sigma \quad (19)$$

the variance from bollingers theory is calculated by:

$$\sigma_t^2 = \frac{1}{N} \sum_{k=0}^{N-1} (x_{t-k} - MA_t)^2 \quad (20)$$

The calculated σ_t could be problematic because its derived from the original series and increases with the level, its non stationary. Therefore an other method to calculate the standard deviation could be used. As done in section 2.2.2. σ_t could be provided by a GARCH, which would handle the increasing volatility.

- N = usually the filterlength and the length considered for σ are the same
- K = Constant usually equals 2
- σ_p = standard deviation of the series
- U_t = upper band
- L_t = lower band

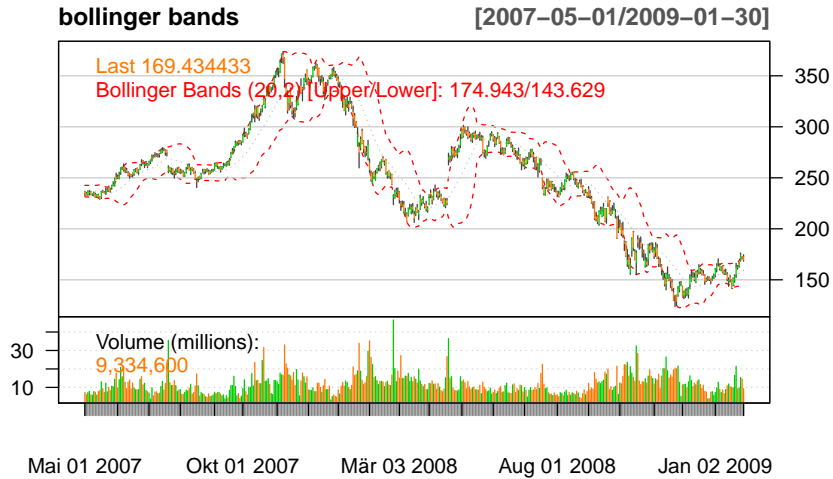


Figure 12: Bollinger Bands

2.7. Performance Indicators

2.7.1. Sharpe Ratio

Sharpe ratio is a very powerful and widely used ratio to measure performance. It describes return per risk.

$$\text{SharpeRatio} = \frac{R_p - R_f}{\sigma} \quad (21)$$

- R_p = Return of Portfolio
- R_f = Risk free Rate, mostly treasury bonds
- σ_p = standard deviation of portfolios excess return (risk)

For comparing different series often the sharpe ratio is annualized with $\sqrt{250}$ and the R_f is considered 0.

2.7.2. Drawdown Drawdown describes the maximum cumulated loss an investor is going to face if he isnt leaving a falling market at the turning point from rise to fall of an index.

$$\text{MDD} = \frac{\text{bottomvalue} - \text{peakvalue}}{\text{peakvalue}} \quad (22)$$

Maximum drawdown is used as an indicator for risk or can be used as an optimization criterion[12].

2.7.3. MSE – understandig what it does first

2.8. Carry

Carry trades are trading strategies were usually money is borrowed at a lower interest rate, than the investment is giving in return. the risk of this strategy is based in the currency risk.

3. Methodology

In this section, different models are created and compared with the buy and hold strategy. You start with pure data analysis and then work your way from simple models to more and more complex ones.

3.1. Data Analysis

As mentioned in section 1.1 we are now going to analyze the data further to gain as much information as possible just by using some simple tools and comparisons.

3.1.1. Correlation

One could nearly tell just by looking at the indexes how strong they're correlated. The correlation matrix in table 3 confirms the assumption, the correlation is nearly 1 for every index to each other.

Table 3: Correlations of the four indexes

	Index 1	Index 2	Index 3	Index 4
Index 1	1.0000000	0.9899111	0.9788826	0.9672956
Index 2	0.9899111	1.0000000	0.9975499	0.9921171
Index 3	0.9788826	0.9975499	1.0000000	0.9983460
Index 4	0.9672956	0.9921171	0.9983460	1.0000000

3.1.2. transformation, volatility and clusters

Applying the natural logarithm to the series is an approach to cancel out increasing volatility 13. The strong upward drift is still visible, the original series has more than doubled to its original price over the whole timespan (index 4) 1.



Figure 13: Visualization log indices

By taking the returns of the transformed series we can visualize volatility clusters as seen in figure 14. The first value of the series is eliminated because of the differences, Clearly visible are the high spikes in the times of the financial crisis 2007-2009. Also at the end of the series, the impact of COVID19 in march 2020 is remarkable.

Table 4: Sharpe Ratio and Volatility of the 4 indexes (log-returns).

	Index 1	Index 2	Index 3	Index 4
Volatility	0.0008	0.0020	0.0029	0.0039
Sharpe-Ratio	1.6710	1.0601	0.9143	0.7922

As we can see in the table the volatility of index 4 is as much as x x xx times higher than the volatility of index 1 and the sharperatio behaves inverse to the risk.

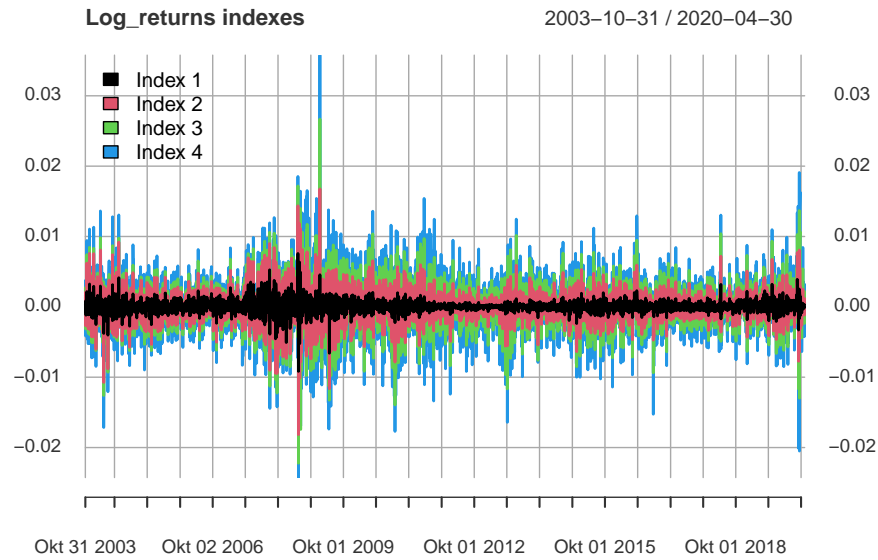


Figure 14: Log returns

3.1.2.1. Autocorrelation of log returns

By computing the ACF of the squared log-returns we see that the volatility cluster has very long dependency structures.



Figure 15: ACF log returns

For further analysis, we concentrate on different timespans, because in most models it makes little sense to consider the whole time-series from 2003 till today.

3.2. Trading

In section 2 we have learned different indicators and models for time-series-analysis. Some of these models and indicators are now used to trade the indexes we've introduced in the previous section.

To do so we need to create trading signals based on the models and indicators. For example, we are using the MA Crossings, as mentioned 2.3.3. the points where the two MAs cross, are now used to create a trading signal. when the longer MA comes from below to the crossing we are going long the asset and if it approaches the point from above we're shorting the position. Technically we apply a 1 to a vector at each crossing, where we intend to buy and apply a -1 at the points we want to sell.

3.2.1. Buy and Hold Performance

As mentioned earlier the goal of this work is trying to outperform the buy and hold strategy. Because the series all have a strong upward trend this task is very tricky. Buy and hold has very low trading costs because the underlying is just bought once. According to swissquote [13] costs for asset trades over 50k, are 190 USD per trade ¹, so these costs should also be taken into consideration for choosing the strategy. In this work, we've excluded these costs and only concentrate on the trades themselves.

¹ notice: This fee is only for private investors, conditions may differ for institutions.

For the following models a good comparability should be achieved. To ensure this, all models are created with the same out-of-sample range, with the start date 2019-01-01.

3.2.1.1. Portfolios

By focussing on trading we build a portfolio for the 4 indexes. One approach would be the equally weighted portfolio with weights for every index of $\frac{1}{4}$. As we've seen in figure 14 The volatility of the indexes strongly differs, meaning that index 4 would have the most impact, nearly 50 %, on the portfolio by weighing it equally. To cancel this effect, it may be useful to size the position with the inverse volatility, so the indexes have the weights seen in the table on the right side.

$$procentualshare\sigma_k = \frac{\sigma_k}{\sum_{k=1}^4 \sigma_k} \quad (23)$$

Table 5: shares

	percentage of vola when equally weighted	weights when weighed with inverse vola
Index 1	3.70980	70.246503
Index 2	16.15568	16.130577
Index 3	31.55567	8.258436
Index 4	48.57885	5.364485

3.3. AR trading

As with the theory data set, these 4 indexes are non-stationary series. For the AR models, the stationary log-returns of the time series are used. First we look at index 1, the series with the lowest volatility but with the highest sharpe ratio (highest return with lowest risk). To find the best possible AR model, different $AR(p)$ models are fitted with different model orders p for different in-sample ranges. The parameters p and start date are so called hyper parameters, parameters which are set before modelling. For each model the out-of-sample sharpe is calculated. The execution of this calculation leads to the solution shown in table 6.

Table 6: Solution of the AR-Model calculation.

StartDate	AR-Sharpe	p	StartDate	AR-Sharpe	p
2003-01-01	3.296	1	2011-01-01	2.004	3
2004-01-01	3.037	1	2012-01-01	1.852	3
2005-01-01	3.146	1	2013-01-01	2.033	4
2006-01-01	2.957	1	2014-01-01	1.954	3
2007-01-01	2.722	1	2015-01-01	1.932	5
2008-01-01	1.867	1	2016-01-01	3.449	2
2009-01-01	2.473	1	2017-01-01	2.163	4
2010-01-01	2.651	1	2018-01-01	3.765	2

With these calculations, the optimal model is an $AR(2)$ with the start date 2018-01-01. Note that the Index 1 series has a very flat rising trend and a rising upward trend towards the end of 2018, so only a short in-sample is needed for this optimal model. It is interesting that the long in-sample ranges (2003 to 2007) also lead to relatively good performances. This probably has something to do with the fact that trend at the beginning of the series has a greater influence on the model than the middle part.

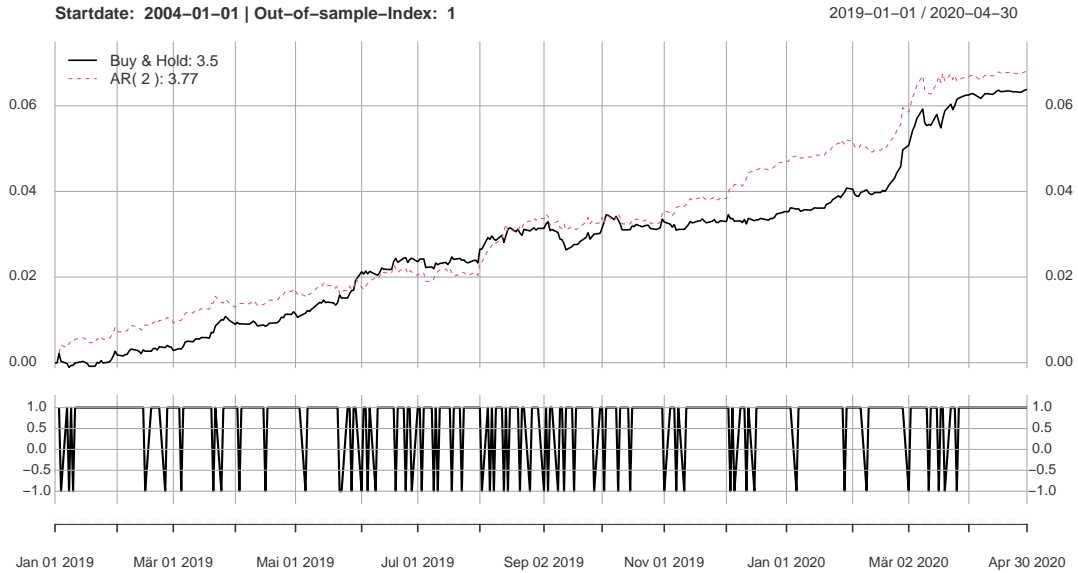


Figure 16: Visualization of the optimal $AR(2)$ -Model.

The upper part of figure 16 shows the optimal model compared to buy and hold. The $AR(2)$ has a higher sharpe than buy and hold. Regarding performance, it should be mentioned that the sharpe optimization of the algorithm is based on daily trades. The signals for a trade are newly generated with each daily forecast and could lead to high trading costs (positive signals = long, negative signals = short).

The lower part of figure 16 shows the trading signals visually. If one were to trade exactly according to the AR(2) forecasts, one would make a trade at each vertical line, a total of 111 trades would have to be made during out-of-sample periods. If you want to include trading costs in the performance, an AR model with daily trades would have to be much better than this one to outperform buy-and-hold.

But what influence do the trading costs really have? If you assume a fictitious investment amount of 1 million USD and you have to pay 190 USD for each trade, as mentioned in section 3.2.1. Invest this amount at the beginning of the out-of-sample period. With the buy-and-hold strategy, a return of USD 63832 is achieved by the end of the out-of-sample range. Without trading costs the AR(2) would yield USD 68130, with trading costs only USD 47040. To get at least the same return on the investment, the trading costs should not exceed USD 39. Note that in addition to the trading costs, the initial investment amount also matters.

Thus it can be said that for index 1, the buy-and-hold strategy cannot be outperformed by an AR(2) model. Nevertheless, one would like to apply this procedure also to the other indexes, possibly the generated models perform better for the other time-series.

Table 7: Optimal AR-Models.

	StartDate	AR-Sharpe	p	B&H-Sharpe	Trades
Index 1	2018-01-01	3.765	2	3.505	111
Index 2	2004-01-01	3.100	1	2.476	19
Index 3	2005-01-01	2.528	1	2.155	21
Index 4	2003-01-01	2.218	1	1.945	9

Table 7 shows the solutions of all 4 indexes. The algorithm finds an optimal AR model with model order 1 for all 3 remaining time-series. In contrast to index 1, it is noticeable that a much longer in-sample range is required for the optimal model. This also makes sense because the indexes show an increasing trend during the complete in-sample range. Index 1 is less volatile and has a less strong trend compared to the others, so a strong increase in the trend (spring 2018) has a greater effect on model performance. The other 3 series are more volatile, have larger peaks and therefore the model performance is less influenced by single events (like the increasing trend in spring 2018). The number of trades is much smaller for all models than for the first one. The out-of-sample performances are better than the corresponding buy-and-hold performances for all AR models.

Because of the trading costs, it has been seen with index 1 that the AR model, despite better performance, generates a lower return than buy-and-hold. But what about the other indexes. You choose the same investment amount and trading costs as before and you get the following table 8.

Table 8: Out-of-Sample Returns.

	Buy & Hold	AR without tradingcost	AR with tradingcost
Index 1	63832	68130	47040
Index 2	106055	131723	128113
Index 3	143291	167284	163294
Index 4	184657	209858	208148

Despite the trading costs, daily trading with the indexes 2-4 generates a higher return than the passive buy and hold strategy.

Figure 17 shows the out-of-sample performance of the second index. Right at the beginning of the series, the AR model signals a trade (one goes short and immediately long again). This trade immediately leads to an increase in performance which already outperforms the passive strategy. Further signaled trades will only occur again later. During the Corona crisis (spring 2020), one can see several close consecutive trades. The volatility increases sharply during this period, the AR model catches this event well and remains positive.

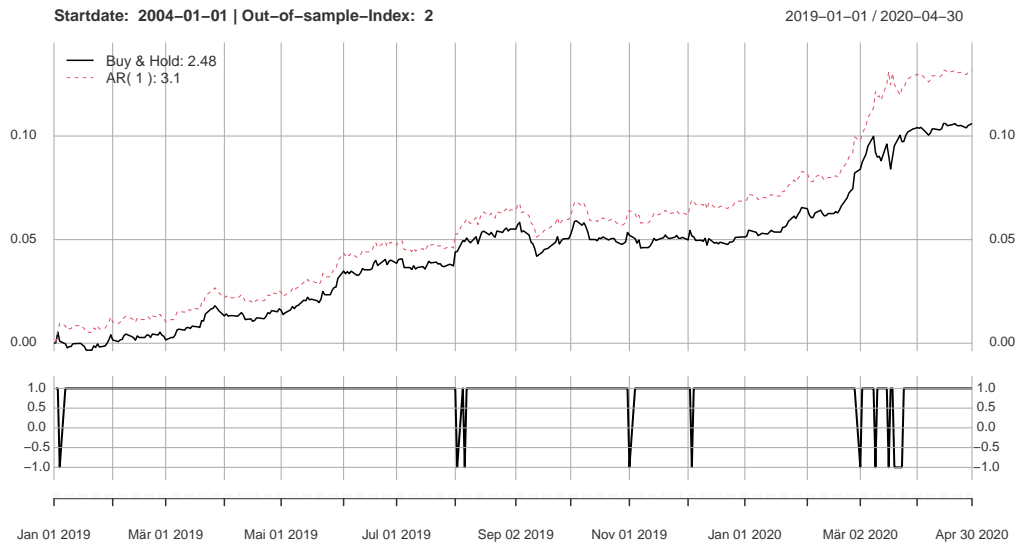


Figure 17: Visualization of the optimal Index 2 AR(1)-Model.

The optimal AR model for the third index shows almost the same behavior as index 2 (as seen in figure 18), the only difference being an additional trade in spring 2019.

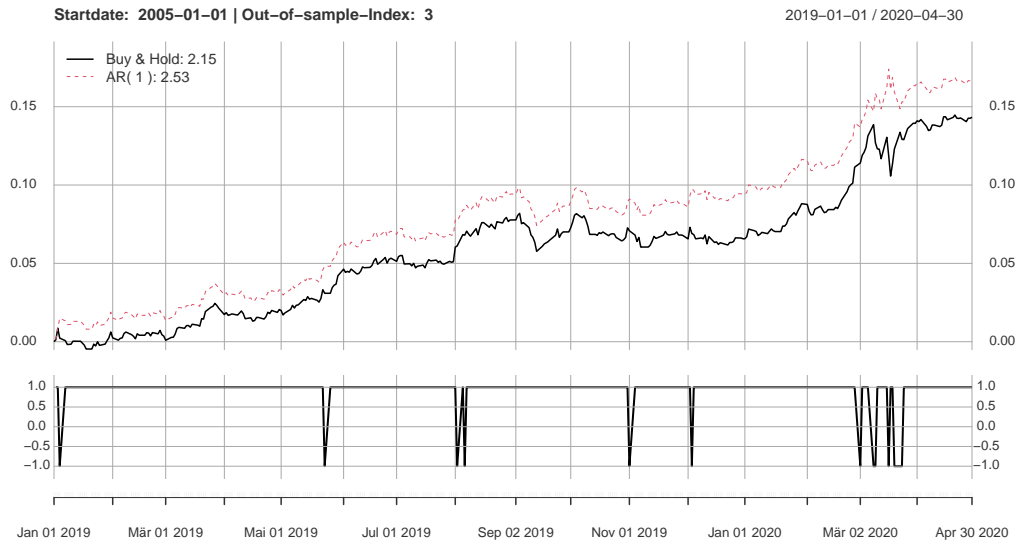


Figure 18: Visualization of the optimal Index 3 AR(1)-Model..

The fourth index, which is shown in the lower figure 18, is interesting again. The optimal AR model predicts almost the same behavior as buy-and-hold for almost the entire duration. Only during the highly volatile phase of the Corona crisis are the same trades listed as for index 2 and 3.

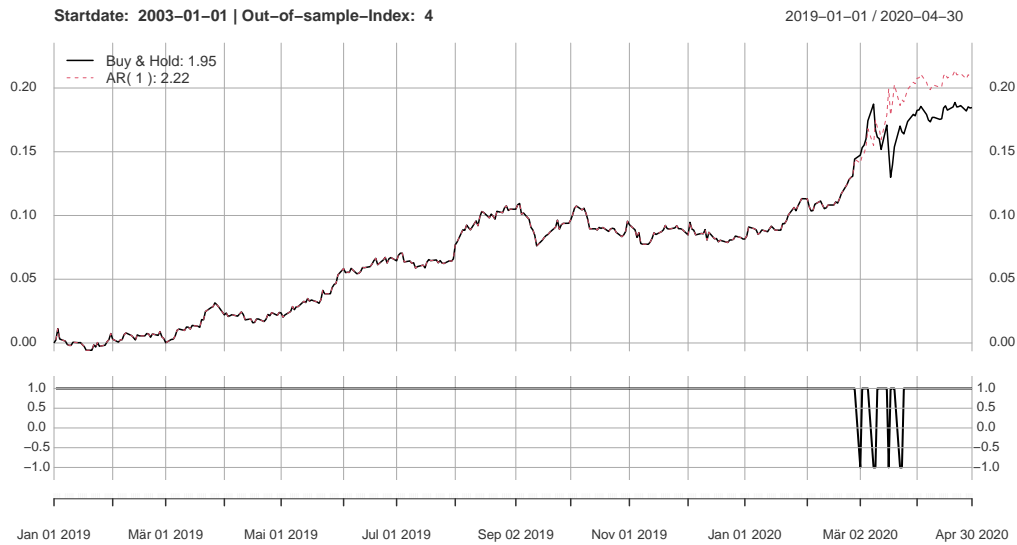


Figure 19: Visualization of the optimal Index 4 AR(1)-Model.

So it can be said that with very simple autoregressive models, a tool has been found with which it is possible to outperform the popular buy-and-hold strategy. Consider that this is only the case in this example with defined conditions. Depending on how high the trading costs and the amount of investment are, the returns can vary greatly. In addition to the buy-and-hold strategy, where you only buy and hold, you have to trade effectively with an active trading strategy.

3.4. Single Simple Moving average trading

Next thing to look at is the optimisation with a single simple moving average. For AR models, the start date is a hyperparameter, as is the model order p . For SMA models there is no model order but a filter length L . The filter length is limited to:

$$5 < L < 500$$

Additionally the in-sample range is varied again. For each start date the in-sample performances are calculated for each filter length in the interval $5 < L < 500$. The AR model was only limited to the performance indicator sharpe ratio. Here the optimisation is completed with the drawdown and MSE indicators. Thus, for each start date, for each filter length L , the three different indicators are calculated and an optimal model can be chosen.

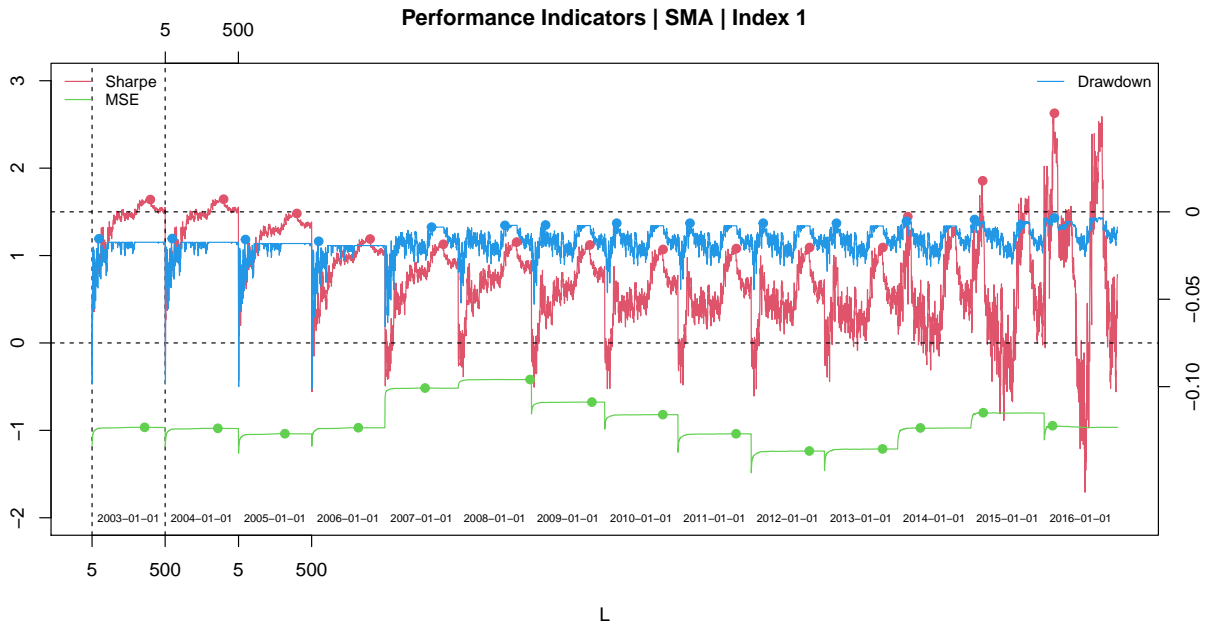


Figure 20: Optim

asdasd

asdasd

Table 9: SMA-Optima by performance indicators | Index 1

StartDate	Sharpe	L_Sharpe	Drawdown	L_Drawdown	MSE	L_MSE
2003-01-01	1.64	395	-0.016885	47	-0.965	356
2004-01-01	1.64	395	-0.016766	47	-0.977	356
2005-01-01	1.48	395	-0.017368	47	-1.038	314
2006-01-01	1.19	395	-0.018482	47	-0.970	315
2007-01-01	1.13	395	-0.009597	315	-0.516	271
2008-01-01	1.15	395	-0.008487	316	-0.418	486
2009-01-01	1.12	395	-0.008263	95	-0.676	409
2010-01-01	1.07	395	-0.007125	81	-0.820	393
2011-01-01	1.08	395	-0.007129	81	-1.039	393
2012-01-01	1.09	395	-0.007124	81	-1.236	393
2013-01-01	1.09	395	-0.007143	81	-1.212	393
2014-01-01	1.45	68	-0.005884	59	-0.972	153
2015-01-01	1.86	79	-0.004819	24	-0.798	83
2016-01-01	2.63	69	-0.003817	69	-0.947	56

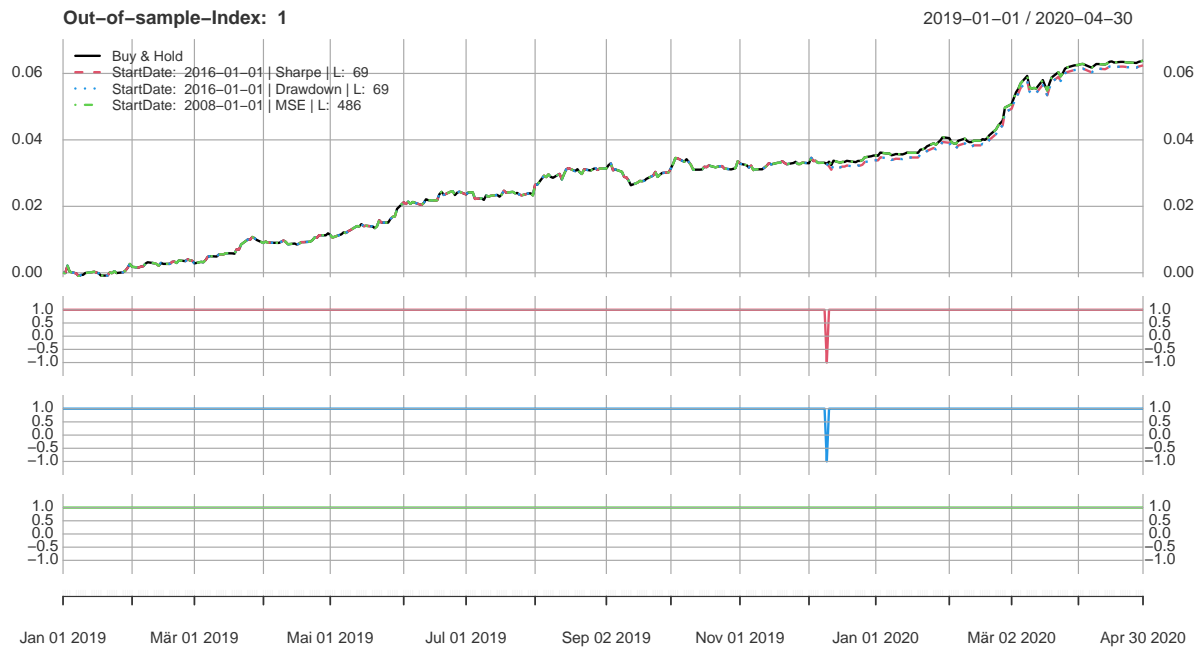


Figure 21: Best

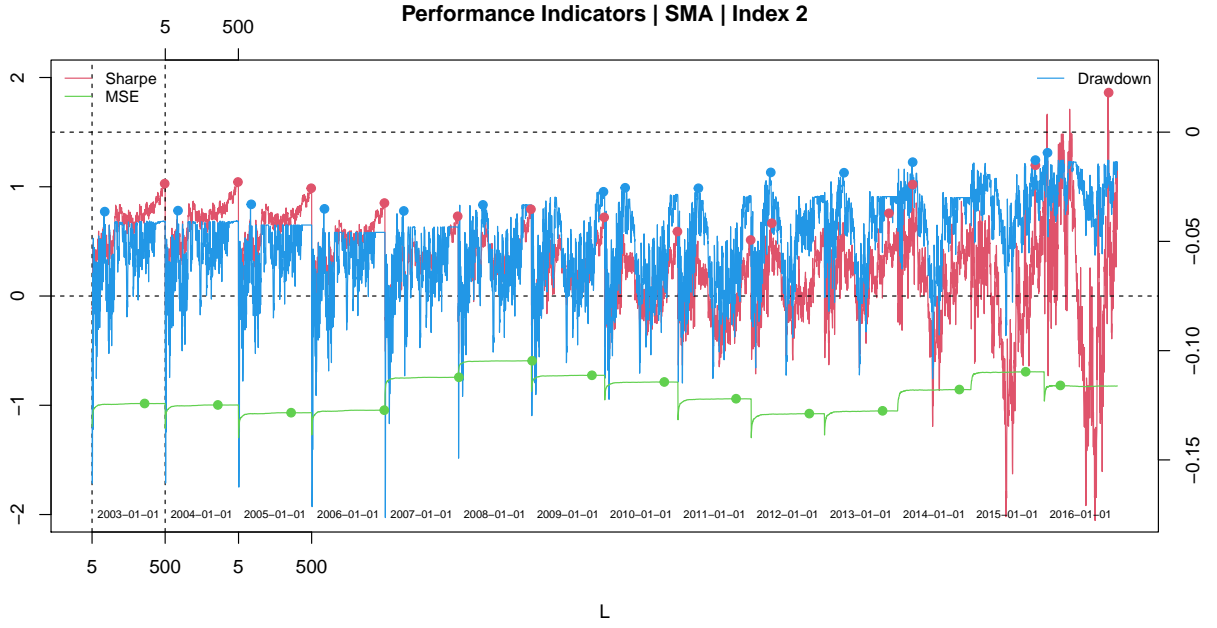


Figure 22: Optim

asdasd

Table 10: SMA-Optima by performance indicators | Index 2

StartDate	Sharpe	L_Sharpe	Drawdown	L_Drawdown	MSE	L_MSE
2003-01-01	1.03	492	-0.039010	86	-0.984	356
2004-01-01	1.04	492	-0.038522	86	-0.997	356
2005-01-01	0.99	492	-0.035429	86	-1.068	356
2006-01-01	0.85	492	-0.037649	86	-1.045	491
2007-01-01	0.73	492	-0.038677	127	-0.744	500
2008-01-01	0.79	492	-0.035709	167	-0.593	500
2009-01-01	0.72	492	-0.029269	487	-0.726	409
2010-01-01	0.59	492	-0.027305	138	-0.787	403
2011-01-01	0.51	492	-0.027542	138	-0.940	393
2012-01-01	0.67	139	-0.019760	132	-1.076	393
2013-01-01	0.76	436	-0.019920	132	-1.051	393
2014-01-01	1.02	101	-0.014730	101	-0.856	417
2015-01-01	1.20	436	-0.013729	436	-0.693	370
2016-01-01	1.86	436	-0.010118	22	-0.818	109

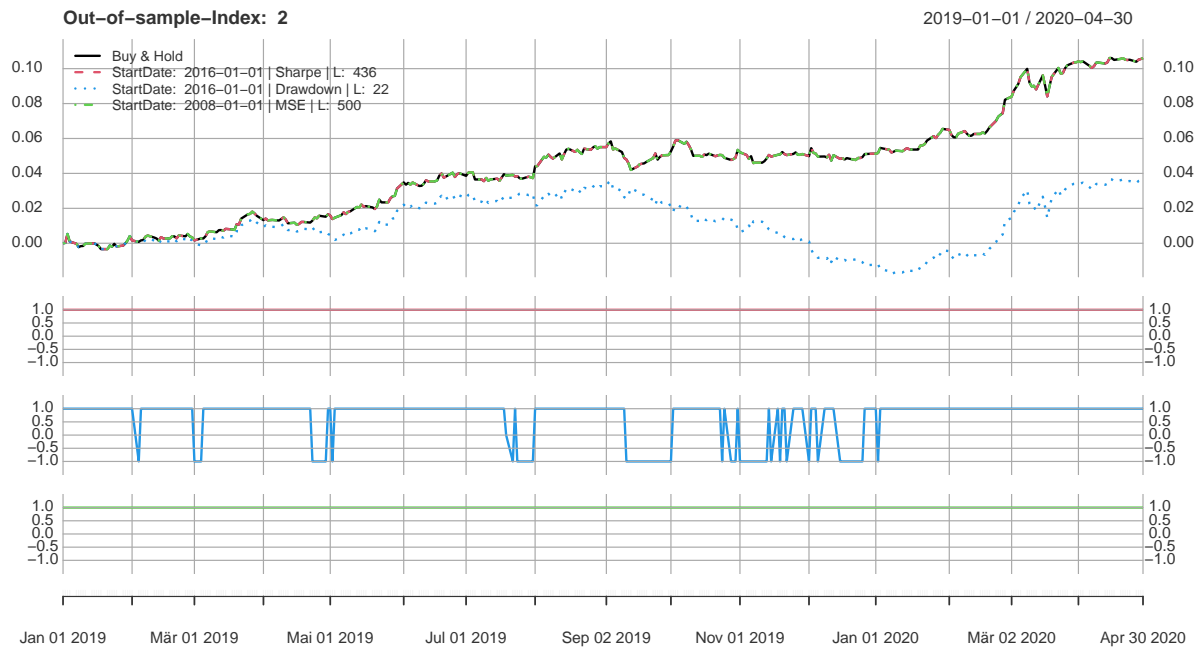


Figure 23: Best

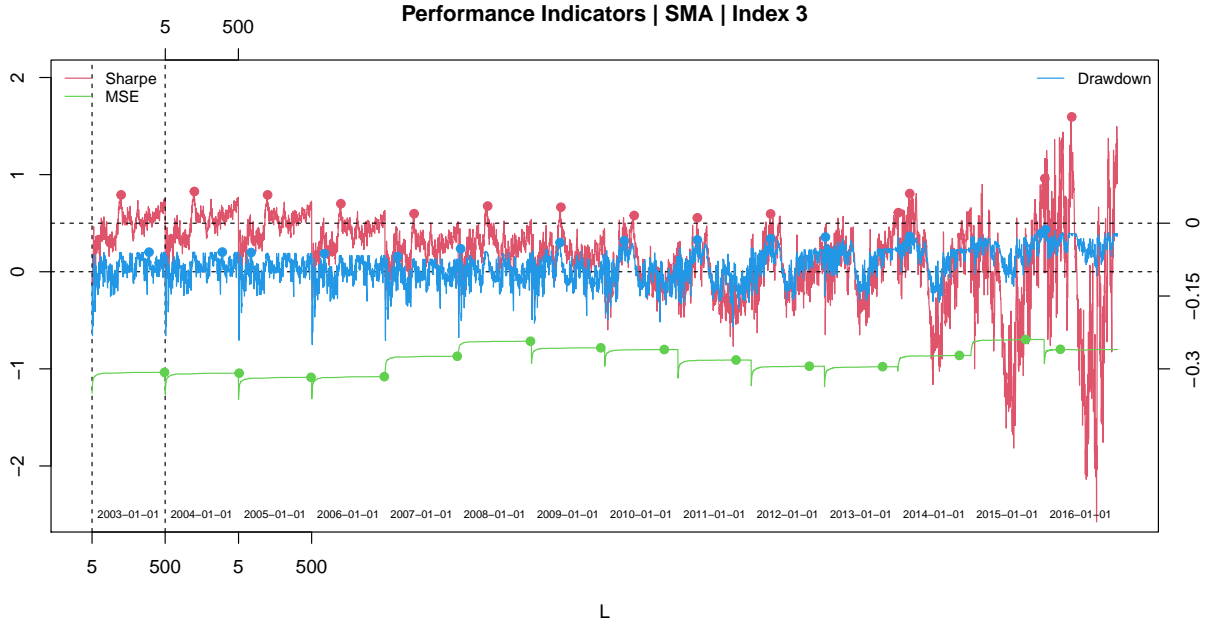


Figure 24: Optim

asdasd

Table 11: SMA-Optima by performance indicators | Index 3

StartDate	Sharpe	L_Sharpe	Drawdown	L_Drawdown	MSE	L_MSE
2003-01-01	0.79	197	-0.060662	386	-1.036	491
2004-01-01	0.83	197	-0.060434	386	-1.045	500
2005-01-01	0.79	197	-0.061444	85	-1.087	491
2006-01-01	0.70	197	-0.063696	85	-1.080	491
2007-01-01	0.60	197	-0.069731	85	-0.870	489
2008-01-01	0.68	199	-0.053510	16	-0.715	489
2009-01-01	0.66	199	-0.040467	193	-0.783	469
2010-01-01	0.58	199	-0.036689	132	-0.801	403
2011-01-01	0.56	131	-0.035098	131	-0.908	393
2012-01-01	0.60	131	-0.032591	131	-0.973	393
2013-01-01	0.61	500	-0.029062	6	-0.977	393
2014-01-01	0.80	81	-0.027517	81	-0.862	417
2015-01-01	0.96	500	-0.021496	474	-0.697	370
2016-01-01	1.59	186	-0.013063	10	-0.798	109

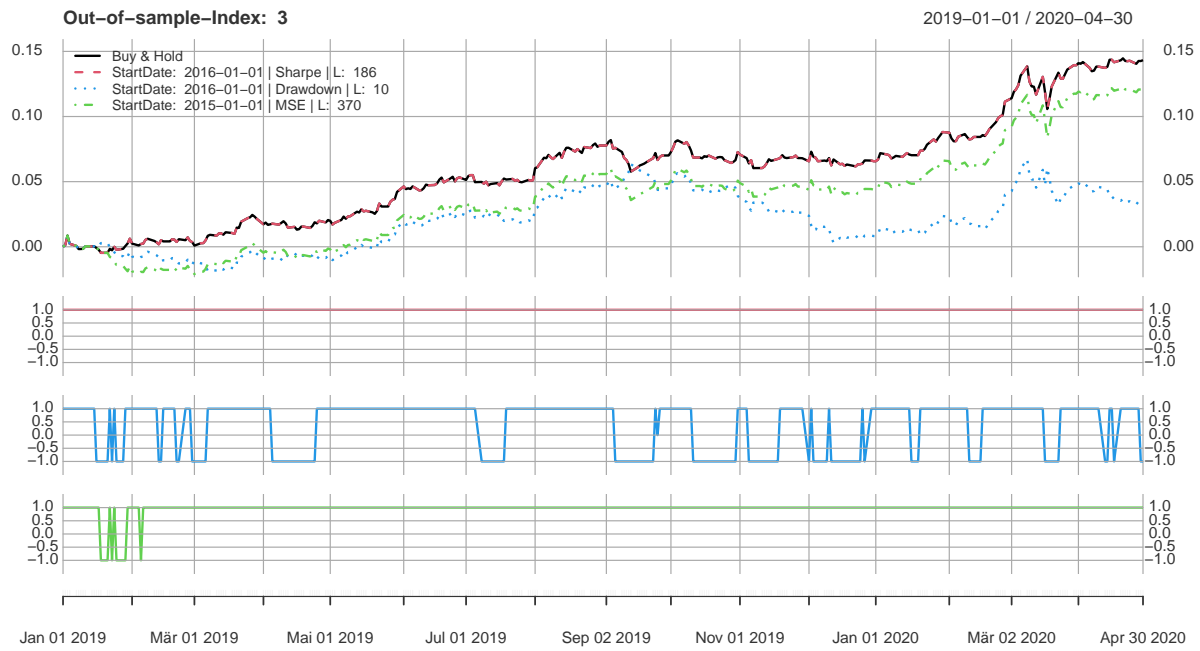


Figure 25: Best

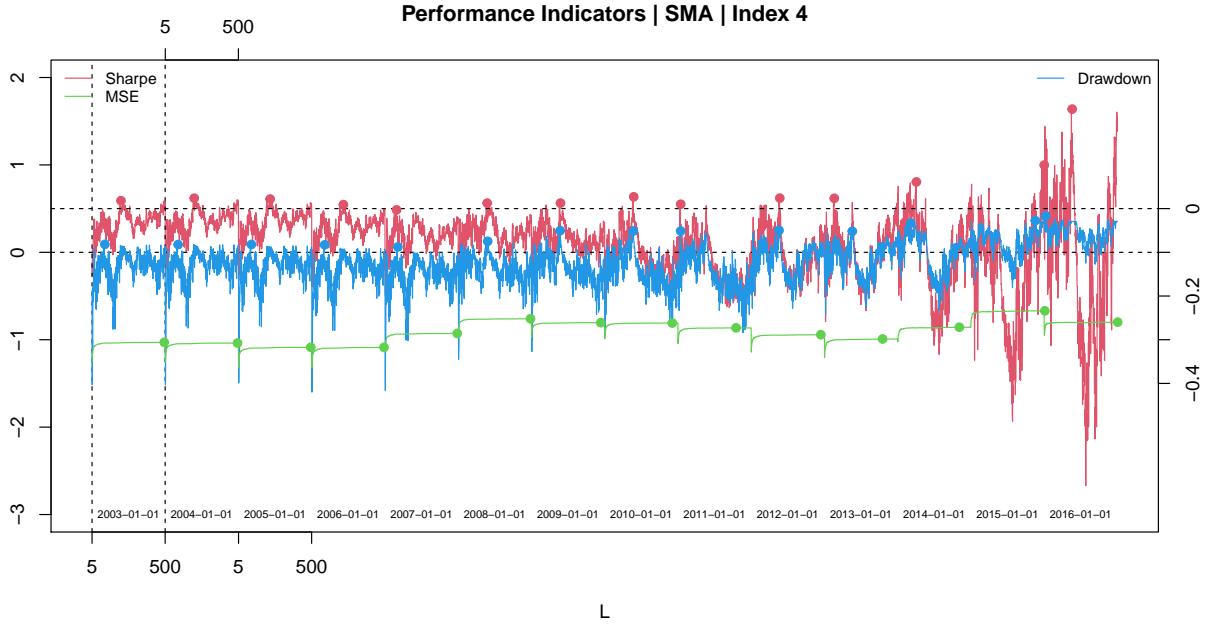


Figure 26: Optim

asdasd

Table 12: SMA-Optima by performance indicators | Index 4

StartDate	Sharpe	L_Sharpe	Drawdown	L_Drawdown	MSE	L_MSE
2003-01-01	0.59	196	-0.081763	87	-1.030	489
2004-01-01	0.62	196	-0.082296	87	-1.038	489
2005-01-01	0.61	214	-0.082023	87	-1.087	489
2006-01-01	0.55	214	-0.082992	87	-1.088	489
2007-01-01	0.49	78	-0.087710	87	-0.928	489
2008-01-01	0.56	196	-0.074848	199	-0.760	489
2009-01-01	0.56	196	-0.050453	194	-0.805	469
2010-01-01	0.63	196	-0.051127	194	-0.809	457
2011-01-01	0.55	18	-0.051190	18	-0.864	393
2012-01-01	0.62	193	-0.049622	188	-0.943	471
2013-01-01	0.62	66	-0.051850	188	-0.992	393
2014-01-01	0.81	126	-0.033376	88	-0.857	417
2015-01-01	1.00	496	-0.027309	435	-0.669	500
2016-01-01	1.64	189	-0.017155	9	-0.799	497

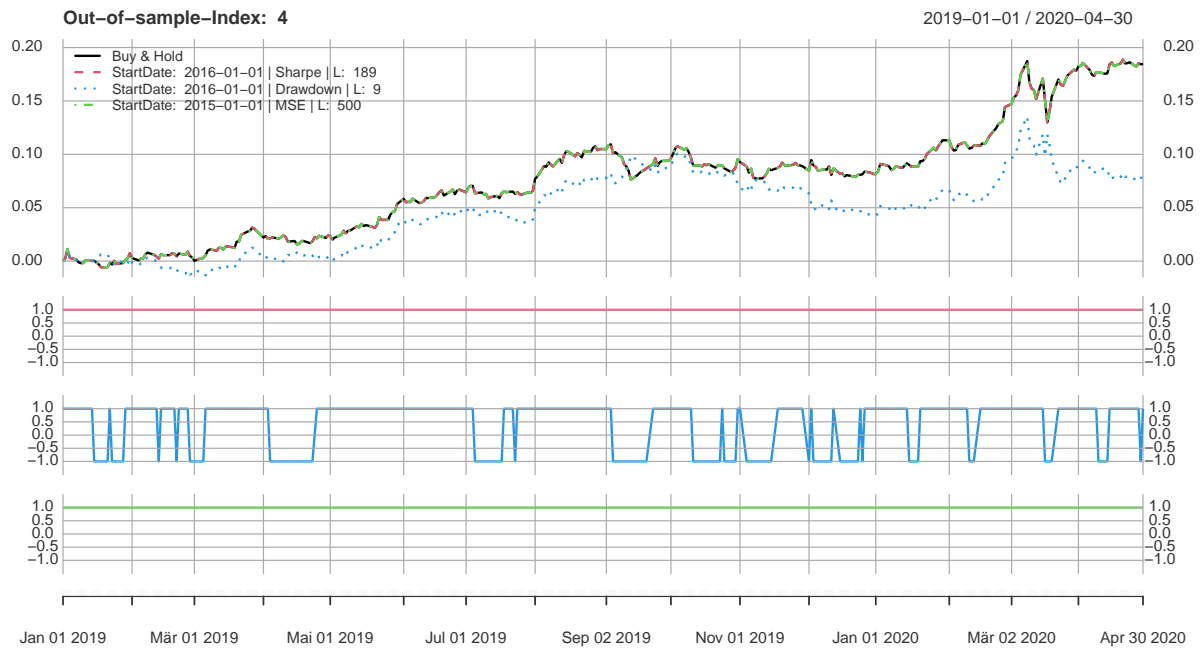


Figure 27: Best

3.5. Moving average crossings trading

As a third approach we apply 2 SMAs on every time series and trade them with the common Ma crossings rules introduced in 2.3.3.. With an optimization we're trying to find the best filterlengths for the 2 SMA's.

3.5.1. Optimization

For the Optimization the same procedure as in the previous sections gets executed.

The optimization has two levels, the “first level” or outer level is narrowing the insample timespan from (2003-01 / 01-2019) to (01-2018 / 01-2019). In the inner level “second level” the real optimization is calculated by finding the optimal combination of filters, regarding maximum sharpe and maximum drawdown trading them with the common crossing trading rules.

Hyperparameter:

- date = startdate for the insample timespan $2003-01-01 < \text{date} \leq 2018-01-01$, by 1 trading year

Parameters₂:

- $L1$ = length of shorter SMA with $1 < L1 \leq 50$
- $L2$ = length of longer SMA with $100 < L1 \leq 250$

Figure 28 visualizes one iteration of the optimization. For the fixed $L1 = 1$, $L2$ is variable and the optimal sharpe is calculated. This procedure is done for every filterlength as described in 2 and further visualized in 29. The drawdown is also calculated as seen in plot 30. Notice that the visualization is from the starting date 2015-10-30, which is randomly chosen for explaining the optimization process.

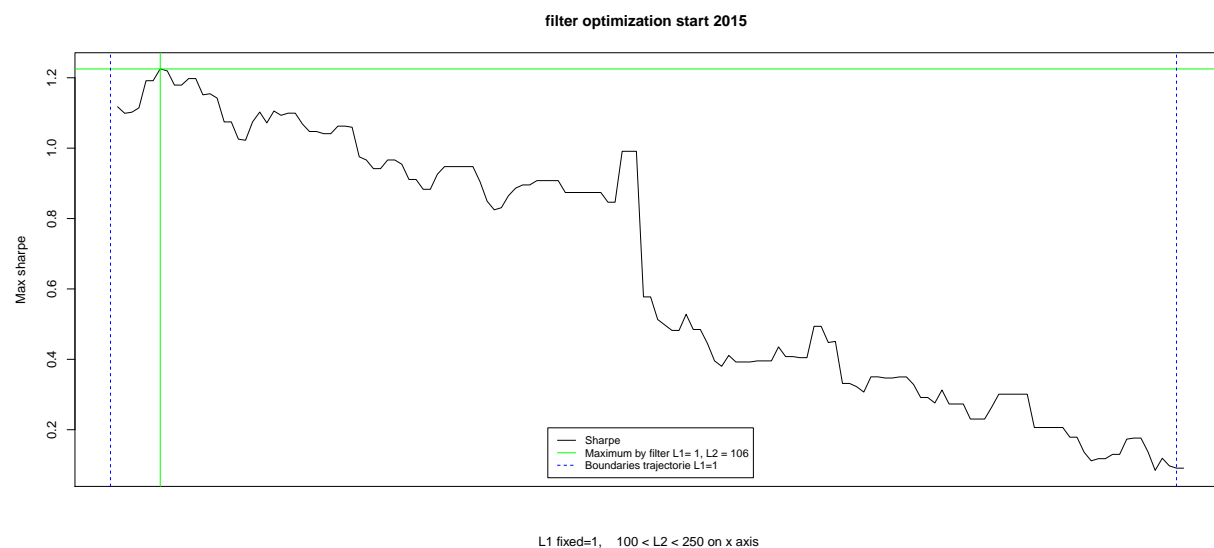


Figure 28: optimization sharpe $L1=1$, $L2$ = variable

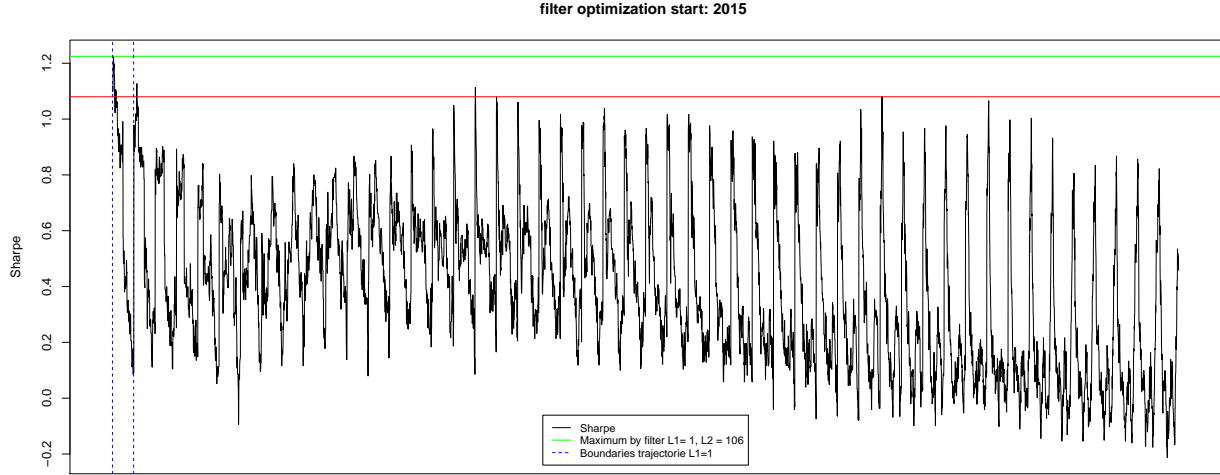


Figure 29: sharpe index 1

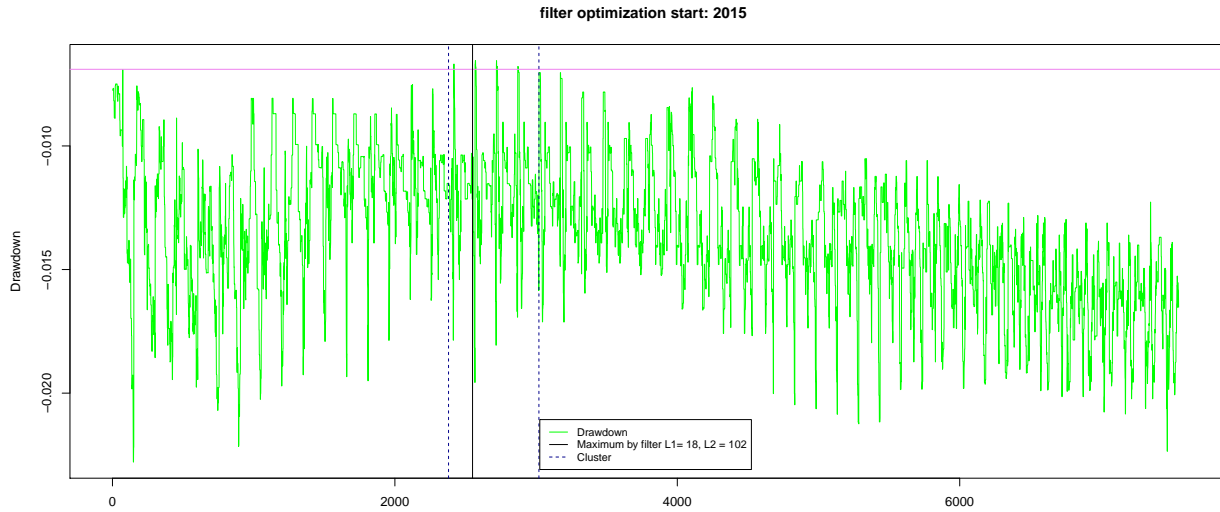


Figure 30: drawdown index 1

The pattern we observe in 29 is the repeating optimization by fixing $L1$ and vary $L2$. The maximum sharpe was found with $L1 = 1$, $L2 = 106$, sharpe = 1.225, which is also visualized in 29, where the “window” (blue dotted lines) is shown. When we look at the red line we can clearly see there are other similar high spikes in other filter lengths. The green pattern in 30 shows interesting news. at $L1 = 17, 18, 19$ and 20 we see a cluster (blue dotted lines) of high spikes, all very similar. The optimum in this plot is by $L1 = 18$ and $L2 = 102$ and a drawdown $6.55e-3$, laying in the described cluster. But when we look at the violet line drawn, we can clearly see there’s another high spike at the beginning of the plot. This spike is identical with the maximum sharpe in 29. So these results could just be random and the solution is not finite, this problem will be further discussed₃.

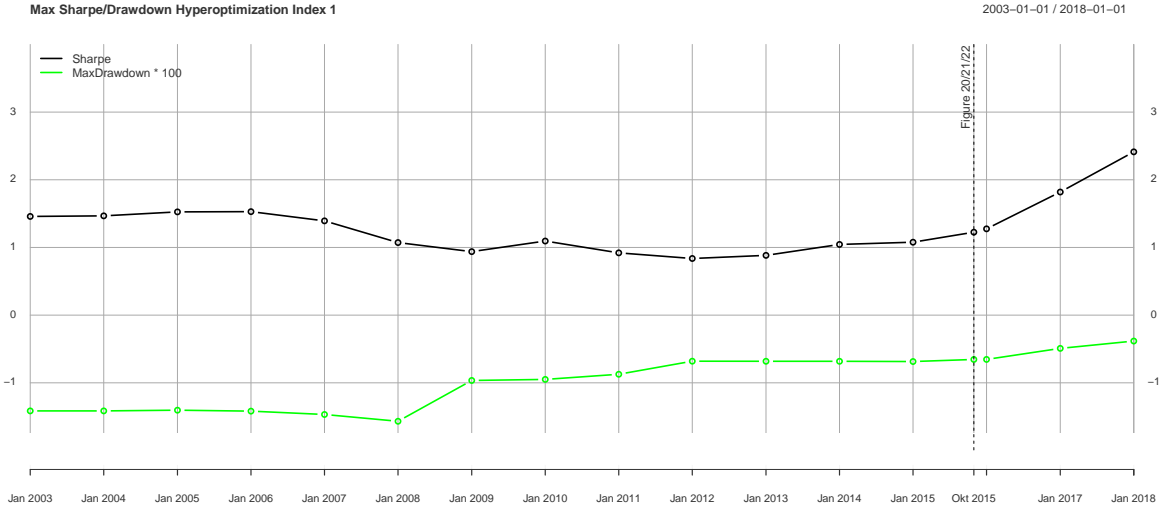


Figure 31: Hyperoptimization Index 1

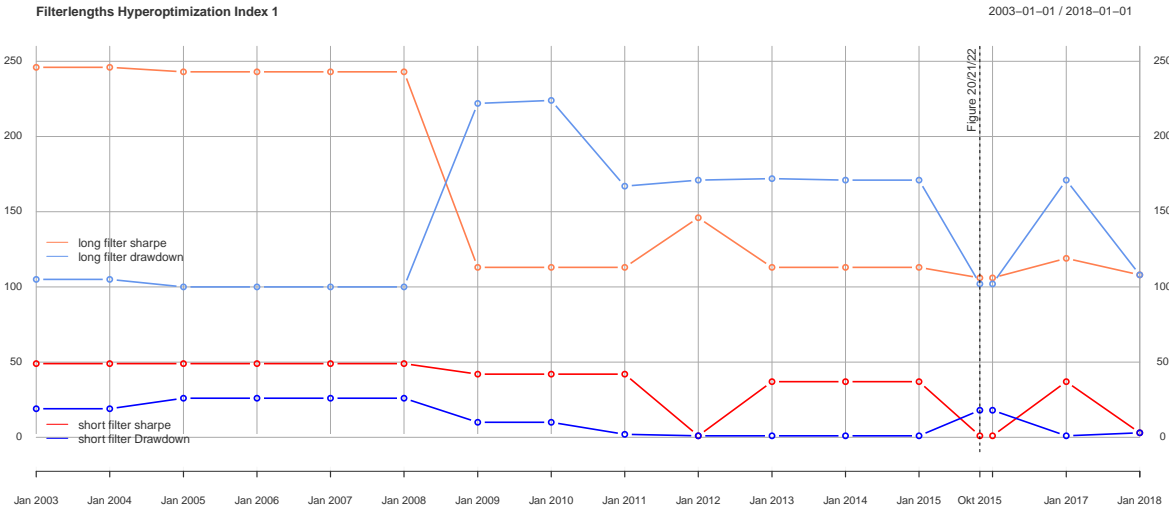


Figure 32: Hyperoptimization Index 1

By plotting the sharperatio / max drawdown₁ in 31 and the optimal filterlengths L1/L2 in 32, for every insample timestep as described at the beginning of 3.5.1., the Hyperoptimization is visualized. The results from the trajectories in 29 and 30 are showed at the black dotted line. Because of the problem we've mentioned in 3 the best result could also be just random. Therefore the ten best results for each insample timesteps are calculated and visualized in 33 and 34 to get an idea about the accuracy of these filters and analyze them a bit further.

₁ Note: maxdrawdown is scaled by the factor 100 to visualize it in the same plot

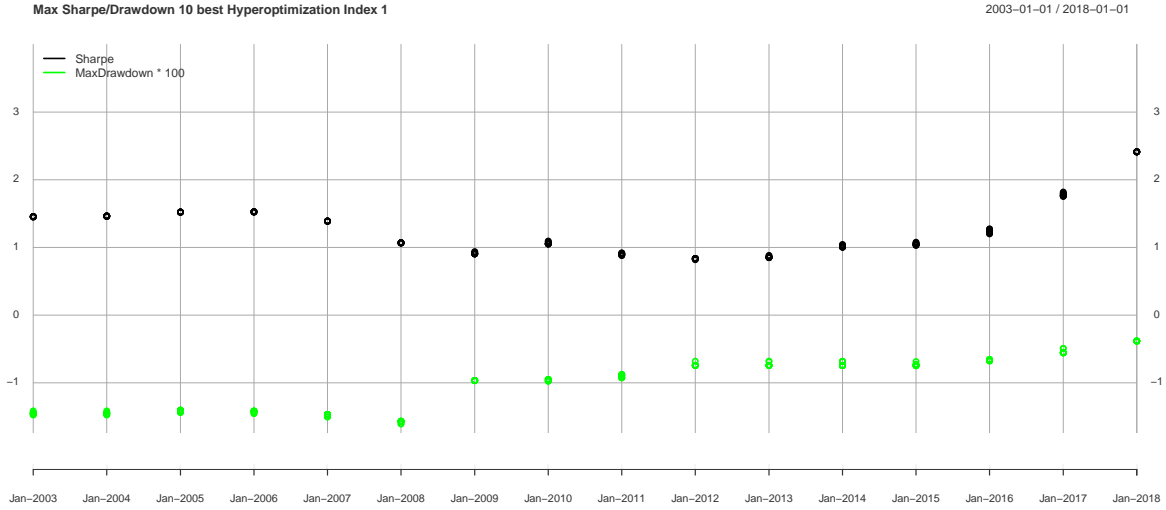


Figure 33: Hyperoptimization 10 best Index 1

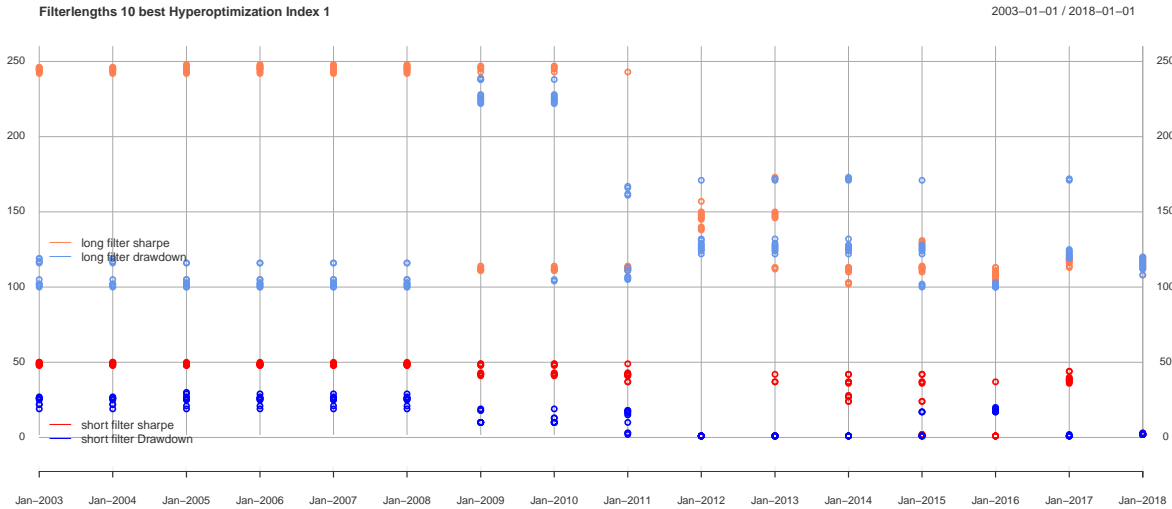


Figure 34: Hyperoptimization 10 best Index 1

Whilst the ten best sharperatios / drawdowns in 33 are always very close together, the filterplot 33 shows a completely different and interesting image. We can observe differences, specially in the long filters in 2009 2010 2011 the result nearly diverge 150 units. Also in the timespan 2011 to 2018 the filters fluctuate strongly. What further catches the eye, are the long- and the shortfilter sharpes from 2003 to 2011. They are all concentrated at their upper limits of 50 and 250, which indicates that they actually wanted to be longer than the restriction. The same behaviour is observed for the short drawdown from 2011 to 2018 where the observations are concentrated around length 1. The plot would shurely look different if the restrictions of the filterlengths would be greater. Also the steps of the insample timespan are always one year. Changing the restriction would have a massive impact on the optimization time and would most likely deliver different results. But we take the risk in good knowledge of maybe not finding the right filterlenght and use this optimization for trading the series in the next section.

As noticed the Visualizations are only done for index one, they are shown in the tables [13](#),[14](#),[15](#),[16](#). For

Table 13: index 1 best

	sharpe	sharpe_l1	sharpe_l2	drawdown	drawdown_l1	drawdown_l2
2003-01-01	1.458	49	246	-0.014	19	105
2004-01-01	1.467	49	246	-0.014	19	105
2005-01-01	1.526	49	243	-0.014	26	100
2006-01-01	1.529	49	243	-0.014	26	100
2007-01-01	1.393	49	243	-0.015	26	100
2008-01-01	1.072	49	243	-0.016	26	100
2009-01-01	0.938	42	113	-0.010	10	222
2010-01-01	1.095	42	113	-0.009	10	224
2011-01-01	0.920	42	113	-0.009	2	167
2012-01-01	0.837	1	146	-0.007	1	171
2013-01-01	0.883	37	113	-0.007	1	172
2014-01-01	1.044	37	113	-0.007	1	171
2015-01-01	1.078	37	113	-0.007	1	171
2016-01-01	1.275	1	106	-0.007	18	102
2017-01-01	1.819	37	119	-0.005	1	171
2018-01-01	2.413	3	108	-0.004	3	108

3.5.2 Trading

Based on the optimal filterlengths calculated in the last section the SMAs are now applied to the “out of sample” span from 2019-01-01 to 2020-04-01. Keeping in mind that the Moving Averages need the same initialization time as the length of filter itself, the initialization phase of the filter is taken out of sample.

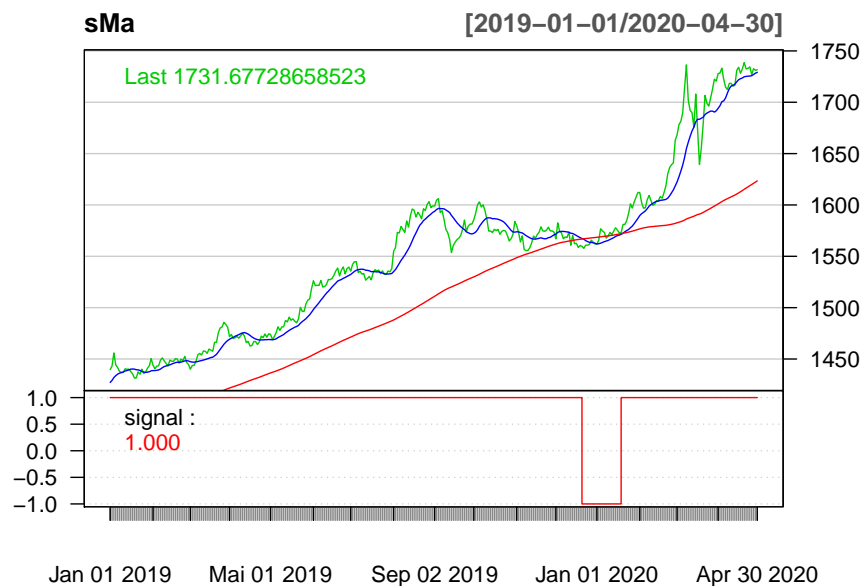


Figure 35: conversion data

The intuition says that this strategy may not be so bad, why leaving a trend market instead of buy and hold?

Keeping in mind that the filterlengths L need the same initialization time as the length of filter itself. For example when the optimization

Naive Buy Rule

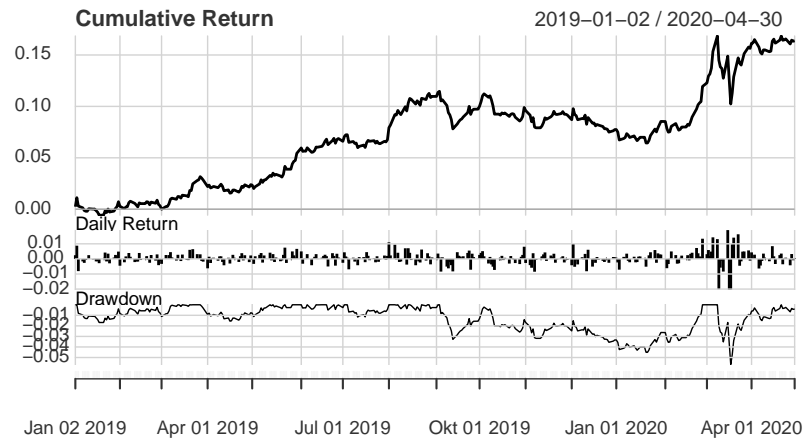


Figure 36: conversion data

4. Results

4.1

4.1 Key Take Away

Here's a short list of key takeaways from this project work

5. References

- [1] M. Wildi, *Econometrics 1: Time series analysis*. Winterthur: ZHAW, 2017, p. 221.
- [2] M. Wildi, *Econometrics 3: Conditional heteroscedasticity models, part 1*. ZHAW, 2020, p. 56.
- [3] A. H. A. L. Kholkin D. A. Kiselev, *Encyclopedia of materials: Science and technology (second edition)*. Elsevier, 2001, p. 10388.
- [4] M. Masum, “Time series analysis: Identifying ar and ma using acf and pacf plots.” <https://towardsdatascience.com/identifying-ar-and-ma-terms-using-acf-and-pacf-plots-in-time-series-forecasting-ccb9fd073db8> (accessed Nov. 16, 2020).
- [5] B. Williams, *GARCH(1,1) models*. Ruprecht-Karls-Universität Heidelberg, 2011, p. 42.
- [6] M. Wildi, *An introduction to conditional volatility models*. Winterthur: ZHAW, 2020, p. 32.
- [7] M. Wildi, *Econometrics 3: Conditional heteroscedasticity models, part 3*. ZHAW, 2020, p. 53.
- [8] A. Hayes, “Simple moving average.” <https://www.investopedia.com/terms/s/sma.asp> (accessed Sep. 22, 2020).
- [9] A. Hayes, “Exponential moving average.” <https://www.investopedia.com/terms/e/ema.asp> (accessed Sep. 10, 2020).
- [10] M. Wildi, *Econometrics 2: Trading indicators*. ZHAW, 2020, p. 78.
- [11] J. Fernando, “Relative strength index (rsi).” <https://www.investopedia.com/terms/r/rsi.asp> (accessed Nov. 30, 2020).
- [12] J. Gordon, “Relative strength index (rsi).” <https://www.investopedia.com/terms/m/maximum-drawdown-mdd.asp#:~:text=What%20Is%20a%20Maximum%20Drawdown,over%20a%20specified%20time%20period>. (accessed Mar. 24, 2020).
- [13] swissquote, “Trading fees.” https://library.swissquote.com/shared-images/brochure-trading-pricing-bank-de?_ga=2.183413157.222455671.1606673517-1327743316.1606673517 (accessed Nov. 29, 2020).

6. Attachment

6.3.3 AR

6.3.4 Single Ma

6.3.5 Best ma crossings

```
loop_func_v3 <- function(data, minyear = 3, maxyear = 18, returnmax = 10) {  
  # This function uses the cross_optim_easy_v2 function an  
  # loops the function through the insample timespan and  
  # returns a data frame  
  
  year_list <- NULL  
  for (year in minyear:maxyear) {  
    year_list <- c(year_list, paste(2000 + year, "-01-01",  
                                   sep = ""))  
  }  
  
  pb <- txtProgressBar(min = 1, max = length(year_list), style = 3)  
  startdate = as.Date(paste(2000 + minyear, "-01-01", sep = ""))  
  
  datevec <- as.data.frame(c(rep(startdate, returnmax)))  
  colnames(datevec) = "startdate"  
  iteration <- cross_optim_easy_v3(x = data, start = startdate,  
                                  returnmax = returnmax)  
  iteration_withdate = cbind(datevec, iteration)  
  
  # Loop through years  
  for (i in 2:length(year_list)) {  
    startdate <- year_list[i]  
    iteration <- cross_optim_easy_v3(x = data, start = startdate,  
                                    returnmax = returnmax)  
  
    datevec <- as.data.frame(c(rep(as.Date(startdate), returnmax)))  
    colnames(datevec) = "startdate"  
  
    iteration_withdate_loop = cbind(datevec, iteration)  
    iteration_withdate = rbind(iteration_withdate, iteration_withdate_loop)  
  
    setTxtProgressBar(pb, i)  
  }  
  close(pb)  
  iteration_withdate <- xts(iteration_withdate[, -1], iteration_withdate[,  
                           1])  
  return(iteration_withdate)  
}  
  
cross_optim_easy_v3 <- function(x, start, end = "2018-12-31",  
                               L1min = 1, L1max = 50, L2min = 100, L2max = 250, returnmax = 10) {  
  ### This function optimizes the ma crossings with the given  
  ### filterlength in the given timespan and returns a dataframe  
  ### with the 'returnmax' sharpe and drawdownfilter which where
```

```

### found by common trading rules of ma crossings.
horizon <- paste(start, ":", end, sep = "")

sharpmat <- matrix(NA, L1max, L2max) ## creating empty matrizes for sharpe and maxdrawdown
drawmat <- matrix(NA, L1max, L2max)

pb = txtProgressBar(min = L1min, max = L1max, style = 3)
for (k in L1min:L1max) {

  for (j in L2min:L2max) {

    # Simple Moving Averages
    sma1 <- SMA(x, k)
    sma2 <- SMA(x, j)

    # Signals
    signal <- rep(0, length(sma1))
    signal[which(sma1 > sma2 & lag(sma1) < lag(sma2))] <- 1
    signal[which(sma1 < sma2 & lag(sma1) > lag(sma2))] <-
      -1
    signal[which(sma1 > sma2)] <- 1
    signal[which(sma1 < sma2)] <- -1
    signal <- reclass(signal, sma1)

    # Trading
    trade <- Lag(signal[horizon], 1)
    return <- diff(log(x))
    ret <- return * trade
    ret <- na.exclude(ret)

    # Sharpe
    sharpmat[k, j] <- sqrt(250) * mean(ret)/sqrt(var(ret))

    # Drawdown
    drawmat[k, j] <- -max(abs(Drawdowns(ret, geometric = F)))
  }
  setTxtProgressBar(pb, k)
}
close(pb)

# finding the [returnmax] best sharpevalues an thei indexes
# =l1 / l2
sharpmax <- which(sharpmat >= sort(sharpmat, decreasing = T)[returnmax],
  arr.ind = T)
sharpmax = head(sharpmax, returnmax)
# finding the [returnmax] best drawevalues an thei indexes =l1
# / l2
drawmax <- which(drawmat >= sort(drawmat, decreasing = T)[returnmax],
  arr.ind = T)
drawmax = head(drawmax, returnmax)

maximus = cbind(sharpmat[sharpmax], sharpmax, drawmat[drawmax],
  drawmax) #combining the vector to return each value

```

```

colnames(maximus) = c("sharpe", "sharpe_l1", "sharpe_l2",
  "drawdown", "drawdown_l1", "drawdown_l2")
return(as.data.frame(maximus))
}

```

Table 14: index 2 best

	sharpe	sharpe_l1	sharpe_l2	drawdown	drawdown_l1	drawdown_l2
2003-01-01	0.714	35	242	-0.044	50	249
2004-01-01	0.718	35	242	-0.044	50	249
2005-01-01	0.747	39	250	-0.040	30	118
2006-01-01	0.881	32	250	-0.034	37	100
2007-01-01	0.880	32	250	-0.034	14	119
2008-01-01	0.713	32	250	-0.036	14	119
2009-01-01	0.592	38	106	-0.034	14	127
2010-01-01	0.749	35	182	-0.032	39	197
2011-01-01	0.606	35	182	-0.024	15	131
2012-01-01	0.545	35	182	-0.025	15	131
2013-01-01	0.502	35	182	-0.023	15	133
2014-01-01	0.733	38	106	-0.019	27	119
2015-01-01	0.764	16	135	-0.019	27	119
2016-01-01	1.052	17	111	-0.014	17	106
2017-01-01	1.096	17	111	-0.014	19	100
2018-01-01	1.869	24	178	-0.014	16	100

Table 15: index 3 best

	sharpe	sharpe_l1	sharpe_l2	drawdown	drawdown_l1	drawdown_l2
2003-01-01	0.567	18	188	-0.055	22	120
2004-01-01	0.571	18	188	-0.055	22	120
2005-01-01	0.554	18	188	-0.055	6	105
2006-01-01	0.660	28	102	-0.050	37	106
2007-01-01	0.651	31	102	-0.051	37	106
2008-01-01	0.640	31	102	-0.053	37	106
2009-01-01	0.501	28	102	-0.055	5	139
2010-01-01	0.603	18	188	-0.054	5	139
2011-01-01	0.572	24	104	-0.041	14	178
2012-01-01	0.417	16	185	-0.038	18	172
2013-01-01	0.416	18	115	-0.038	18	172
2014-01-01	0.691	17	118	-0.028	20	121
2015-01-01	0.768	17	118	-0.029	20	121
2016-01-01	0.990	16	111	-0.021	14	102
2017-01-01	0.929	18	102	-0.020	19	101
2018-01-01	1.414	16	111	-0.020	14	100

6.3.5 Optimization code

Table 16: index 4 best

	sharpe	sharpe_l1	sharpe_l2	drawdown	drawdown_l1	drawdown_l2
2003-01-01	0.511	7	116	-0.078	15	129
2004-01-01	0.514	7	116	-0.078	15	129
2005-01-01	0.563	7	116	-0.078	9	154
2006-01-01	0.635	12	103	-0.076	9	154
2007-01-01	0.621	11	101	-0.078	9	154
2008-01-01	0.610	11	101	-0.081	11	100
2009-01-01	0.490	12	103	-0.083	15	130
2010-01-01	0.624	13	148	-0.062	6	115
2011-01-01	0.696	13	146	-0.049	4	198
2012-01-01	0.569	13	146	-0.051	14	166
2013-01-01	0.711	13	146	-0.042	13	146
2014-01-01	0.782	15	136	-0.038	15	136
2015-01-01	0.731	15	136	-0.040	21	106
2016-01-01	0.998	12	134	-0.025	19	101
2017-01-01	0.861	11	103	-0.026	12	100
2018-01-01	1.379	11	103	-0.026	10	100