

### 3. Methodology

In this section models are created, trying to outperform the buy and hold strategy. starting by analyzing the data and using simple models, more complex models and combined tools are added step by step in different approaches.

#### 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 confirms the assumption, the correlation is nearly 1 for every index to each other.

Table 1: Correlations oft 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 ???. The strong upward is still visible the original series more than doubled its original price over the whole timespan(index 4)??.

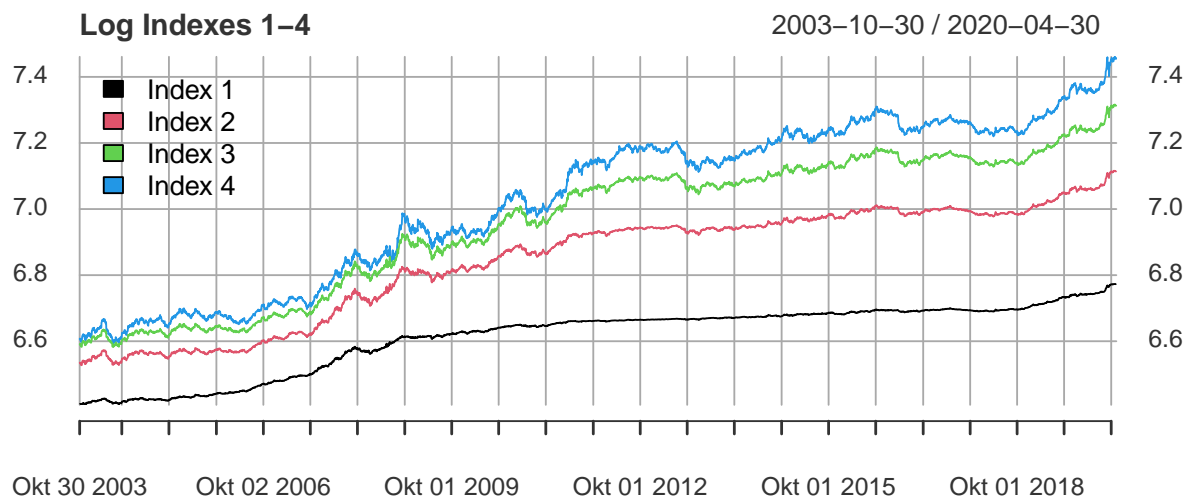


Figure 1: Visualization log\_indizes

By taking the returns of the transformed series we can visualize volatility clusters as seen in figure. 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 covid 19 in march 2020 is remarkable.

the unconditional volatility of the indexes are  $0.64e-06$ ,  $4.1e-06$ ,  $8.5e-06$ ,  $15.6e-06$ . Which means the the index 1 is as much as 24 times volatiler than the fourth index.

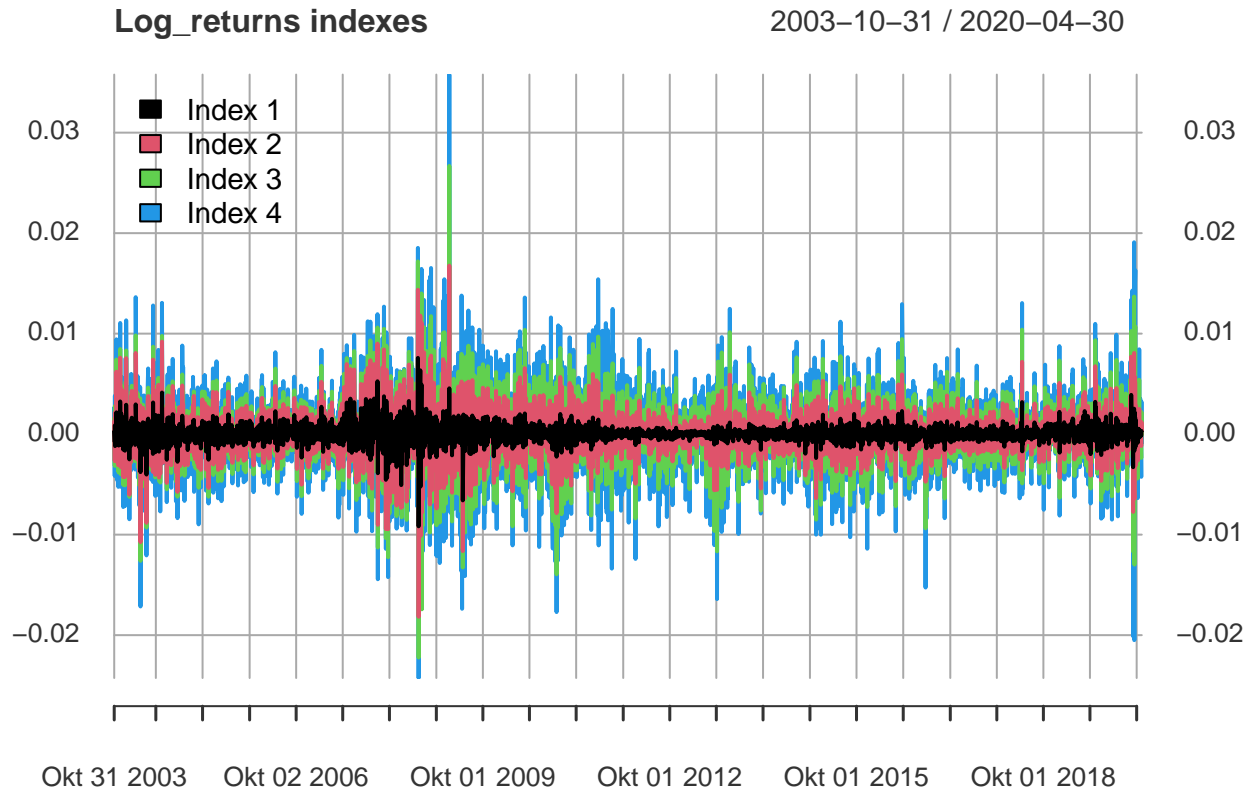


Figure 2: Log returns

### 3.1.2.1 Autocorrelation of log returns

By computing the acf of the squared log\_returns we see that the volatility cluster have very long dependency structures.

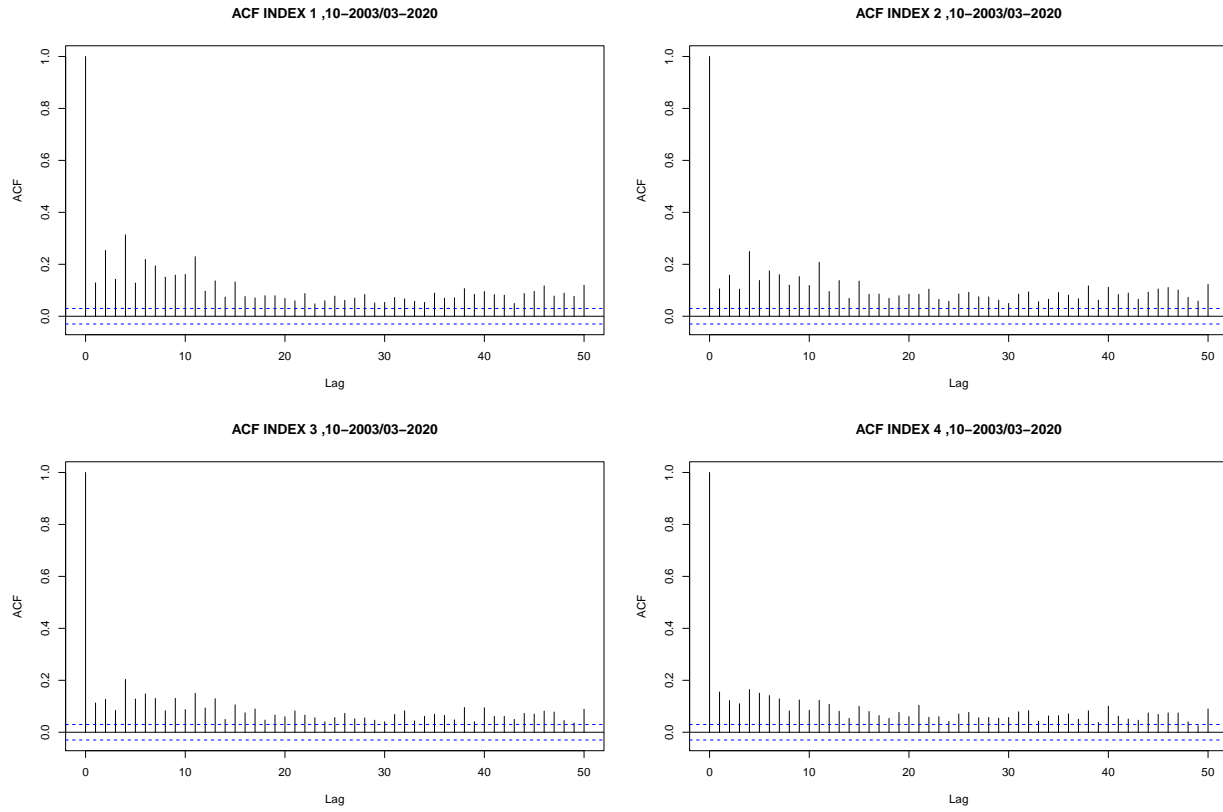


Figure 3: ACF log returns

For further analysis we concentrate on different timespans, because in most models it makes few sense to consider the whole timeseries from 2003 till today

### 3.1.2.2. periodicity

## 3.2. Trading signals

in Section 2 we have learned different indicators and models for timeseries-analysis. These models and indicators are now used to trade the indexes we've introduced in the previous section.

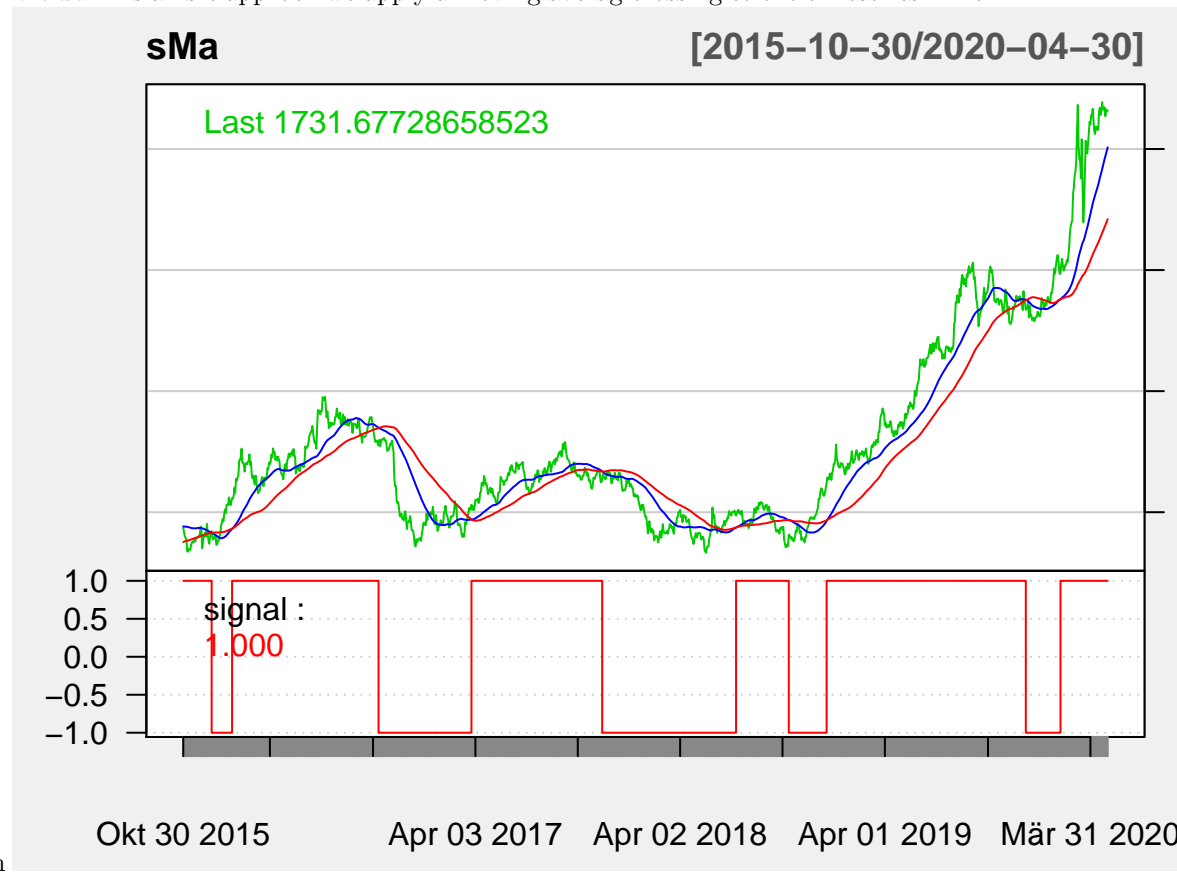
To do so we need to create trading signals based on the models and indicators. For example we're using the MA Crossings, as mentioned 2.3.3. the points where the two MAs cross, are now used to create a trading signal. when the longer MA comes from below to the crossing we are going long the asset and 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 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 underlyings are just bought once. According to swissquote [swissquote] costs for asset trades over 50k are 190 USD per trade <sup>1</sup>, so these costs must also be taken in consideration for the strategy.

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

**3.2.2. sma signals to trade** As a first approach we apply a moving average crossing to the timeseries. The



trading horizon is from

## Naive Buy Rule

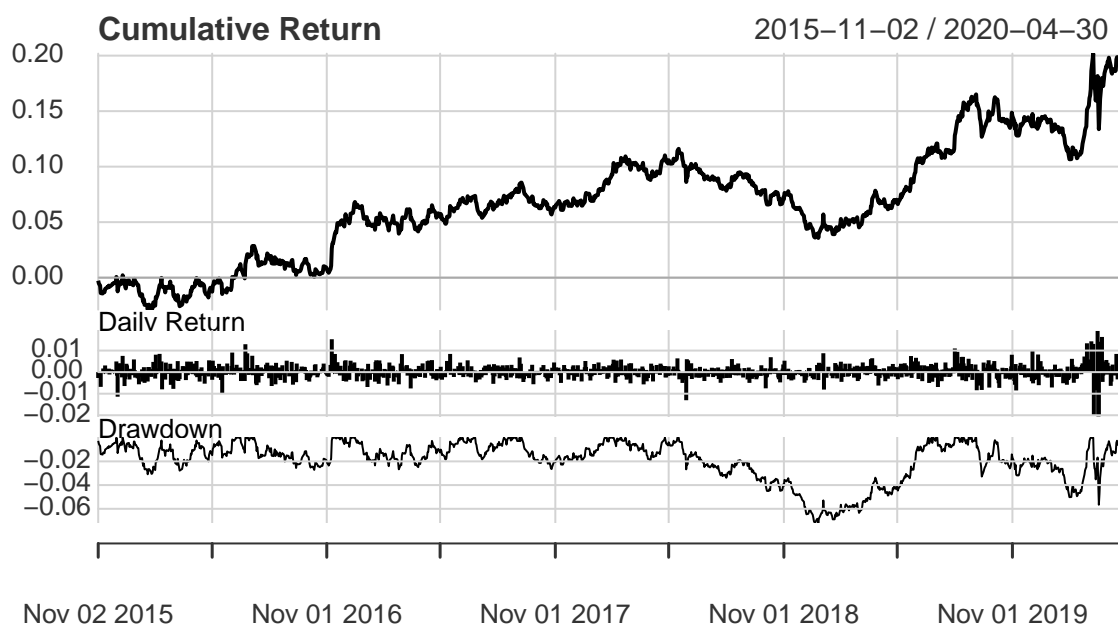


Figure 4: conversion data