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Contents

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. The data used in this paper

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

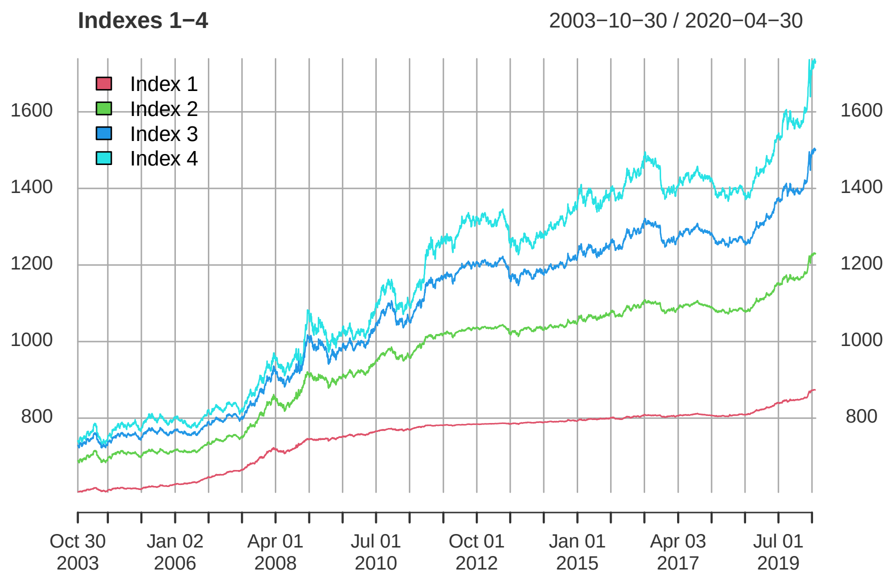

Figure 1: Visualization of the 4 indexes

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. Ojective 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 $x_t, t = 1, ..., T$ [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.

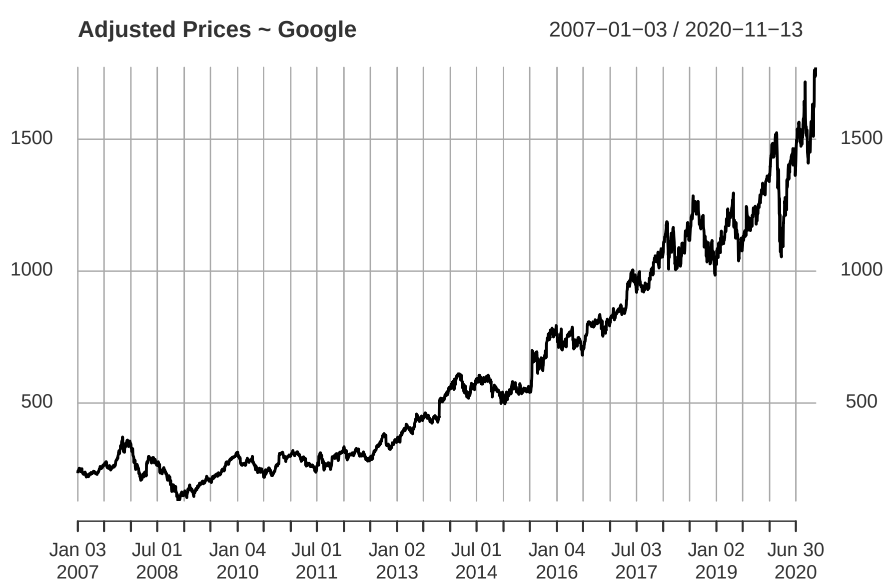

Figure 2: Visualization of the adjusted prices of the Alphabet Inc Class A Stock.

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 performed to strict positive data.

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

The result is the so-called log-returns.

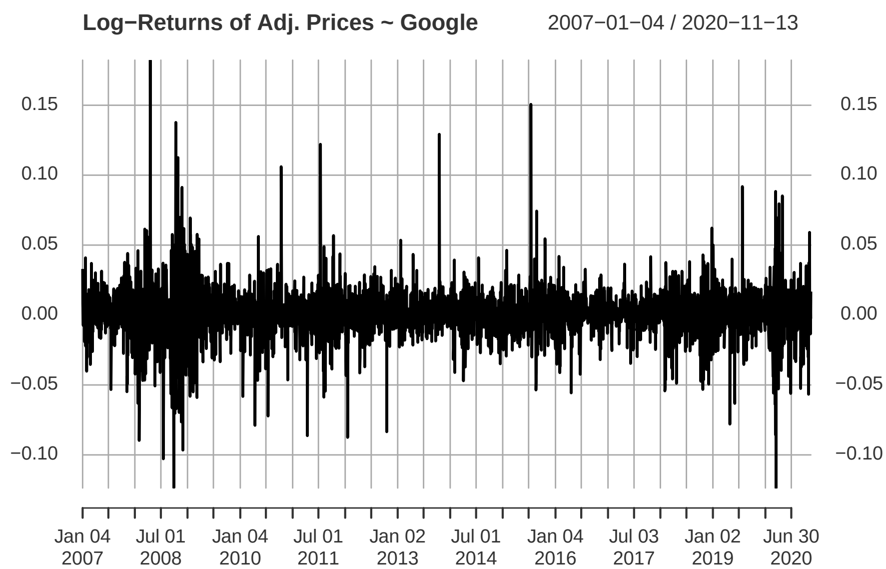

Figure 3: Visualization of the Log-Returns

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 modelling of forecast models, which will be discussed in chapter 2.2.

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's of the non-stationary adjusted Google stock and their log-returns visualized. Both graphics show the typical pattern of a non-stationary time series. The left plot 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. In the right plot the acf of the log-returns are visualized. Remember figure 3, there is no trend visible and therefore no long dependency structures are visible, only slight dependencies can be seen.

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

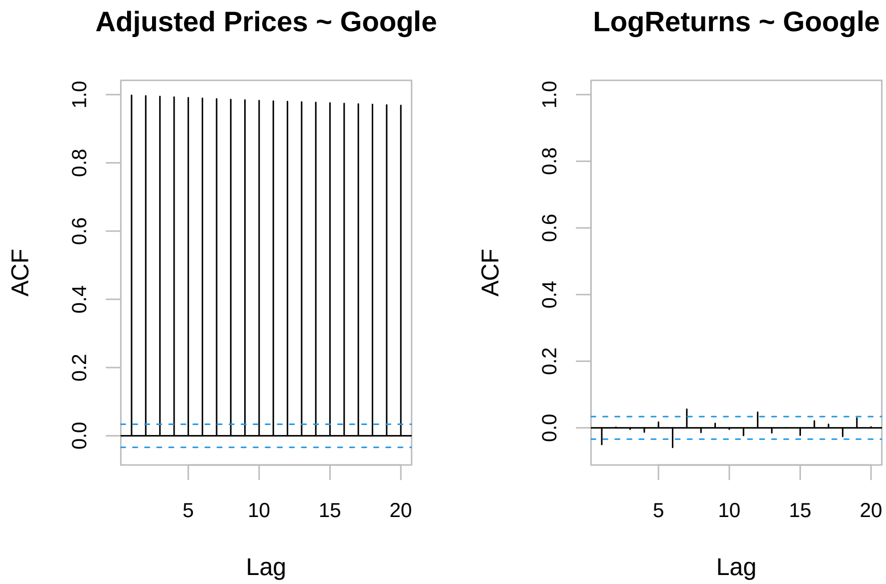

Figure 4: Acf and Pacf of the LogReturns of Google

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.

$$x_t = c + a_1 x_{t-1} + ... + a_p x_{t-p} + \epsilon_t + b_1 \epsilon_{t-1} + ... + b_q \epsilon_{t-q} \tag{4}$$

- 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 $x_1, ..., x_T$

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

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

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 choose 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 ARMA-process should be considered for modeling [4].

2.2.2. ARCH & GARCH

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

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

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 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.

The ARCH-process can be generalized by adding the lagged conditional variances to the equation 5.

$$\begin{aligned} \epsilon_t &= \log(x_t) - \log(x_{t-1}) \\ \epsilon_t &= \sigma_t u_t \\ \sigma_t^2 &= c\sigma^2 + \sum_{j=1}^{n} \alpha_j \sigma_{t-j}^2 + \sum_{k=1}^{m} \beta_k \epsilon_{t-k}^2 \end{aligned} \tag{6}$$

2.2.3. ARIMA-GARCH

Another process is the combination of ARIMA and GARCH processes.

$$y_t = \mu + a_1 y_{t-1} + ... + a_p y_{t-p} + \epsilon_t + b_1 \epsilon_{t-1} + ... + b_q \epsilon_{t-q} \tag{7}$$

$$\epsilon_t = \sigma_t u_t$$

$$\sigma_t^2 = c\sigma^2 + \sum_{j=1}^{n} \alpha_j \sigma_{t-j}^2 + \sum_{k=1}^{m} \beta_k \epsilon_{t-k}^2 \tag{8}$$

Is called the mean-equation 7

Is called the variance-equation 8

[5]

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 its usage, historical data was summarized and divided bi the length of the filter. 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

EqMA

$$y_t = \frac{1}{L} \sum_{k=0}^{L-1} x_{t-k} \tag{9}$$

2.3.2. Exponentially-weighted Moving Average

EMA

$$y_t = \frac{1}{\sum_{k=0}^{m} \alpha^k} \sum_{k=0}^{L-1} \alpha^k x_{t-k} \tag{10}$$

2.3.3. Moving Average Crossings

2.4. Real Strength Index

2.5. Sharpe Ratio

2.6. Carry

2.7. Value

Try other github branch

3. Methodology

3.1. Time-Series Analysis

Plots of the timeseries, decomposition. Stationarity (refer to the theory section)

4. Conclusion

5. References

[1] M. Wildi, *Econometrics 1: Time series analysis*. Winterthur: ZHAW, 2017, p. 221.

[2] M. Wildi, *Econometrics 3: Conditional heteroscedasticity models*. 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] M. Wildi, *An introduction to conditional volatility models*. Winterthur: ZHAW, 2020, p. 32.

Attachment