**Practical 1**

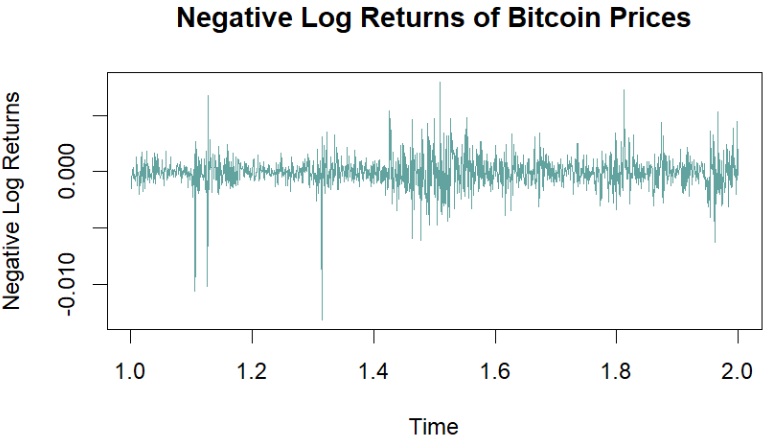
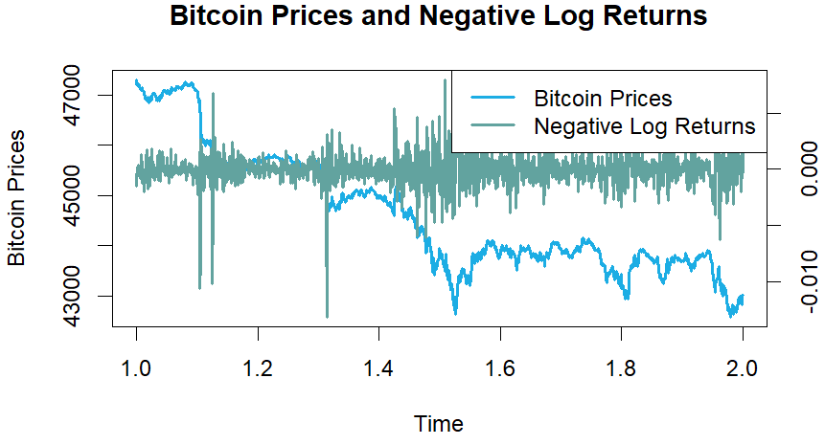
**Part 1: Financial returns and normality**

1. **Read Crypto data.csv. Then, assess the stationarity of the (raw) Bitcoin prices.**

The cumulative periodogram (Appendix 1.1) shows clearly that the data base **is not stationary** as the observations are outside the confidence interval of white noise stationarity. This statement is confirmed by the Dickey Fuller Test (Appendix 1.2) with a p value higher than 0.5.

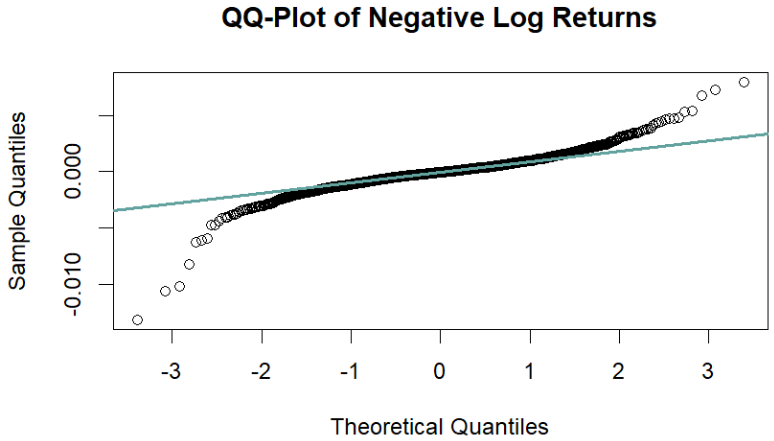
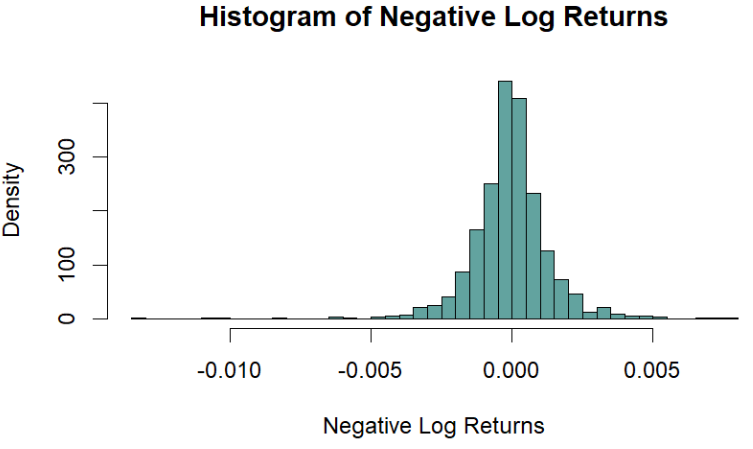
1. **Create a function to transform the Bitcoin prices into their negative log returns. Plot the latter series and assess their stationarity. To compare the series, also plot the negative log returns on a common scale.**

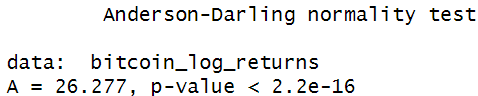
This graph suggests us that the negative log returns are more similar to a stationary data base than the original one.



1. **Are the negative log returns normally distributed? Draw histograms, check QQ-plots and use an Anderson-Darling testing procedure to answer this question.**

The histogram suggests a normal distribution while the QQplot shows some desviations at the tails that make us believe that there could be some problems with the normality.



Finally, as the p value is lower than 5% we can reject the normality and confirm that the negative log returns are not normally distributed

1. **Fit a t-distribution to the negative log returns using fitdistr(). Using a QQ-plot, decide whether the t is better than with a Normal distribution, based on your answer in (3).**

Comparing the appendix 1.3 QQ Plot graphs with the normal distribution plot, we can say that the normal distribution was better than the t distribution as it is closer to the blue line.

1. **Compare the tails of the densities of the t-distribution and the normal distribution. Can we expect more extreme, unexpected events in t-distribution or in normal distribution? What can you conclude about the extreme events of our bitcoin data?**

Both tails deviate significantly from the blue line, indicating that Bitcoin is prone to extreme events. However, the t-distribution exhibits greater tail density compared to the normal distribution, suggesting that the t-distribution allows for a higher likelihood of unexpected, extreme events.

**Practical 3**

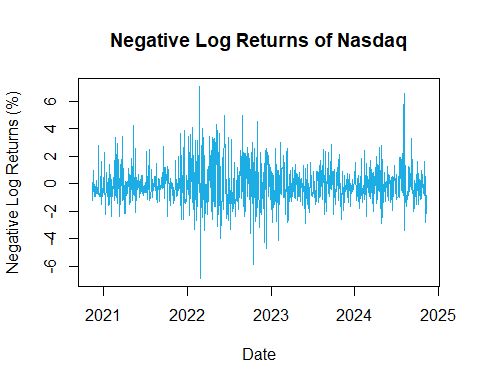
In the following report we will be analyzing the NASDAQ Composite Index during the periods of Nov 2020 – Nov 2024 to answer the following research questions:

* If an investor had implemented a stop-loss strategy based on historical VaR levels, how many times would it have triggered between 2021 and 2024, and would it have reduced overall losses?
* How well do common risk models (like historical VaR) predict actual losses during the most volatile periods in the Nasdaq Composite Index, and could an alternative model improve accuracy?

The objective is to understand the movements of the index to manage the risk for a potential financial portfolio. To do it, we will review the Value at Risk, Expected Shortfall, and Extreme Values Theory methods to **select the best Stop Loss Strategy**.

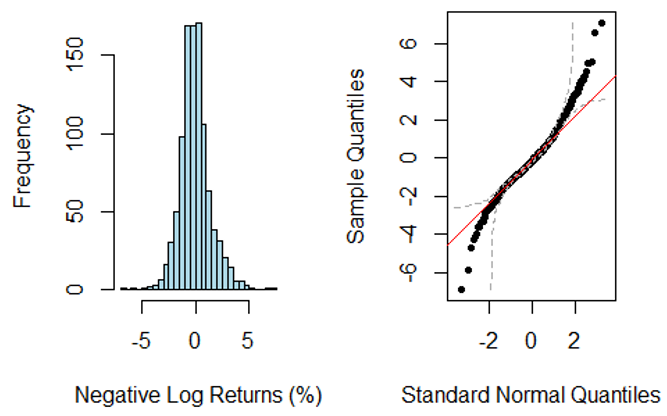
1. **Data Pre-Processing**
   1. **Checking Stationarity**

It is simple to see that the index historical open price is not stationary (Appendix 3.1). Then, we proceed to calculate the negative log returns.



Together the plot and the Dickey-Fuller test (Appendix 3.2), we can conclude that the negative log return is stationary as the p value of the test is less than 5%.

* 1. **Checking Normality**

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Confirmed by the Shapiro test (Appendix 3.3), the daily returns are not normally distributed. Therefore, using parametric Value at Risk and Expected Shortfall could result in under/overestimating the risk.

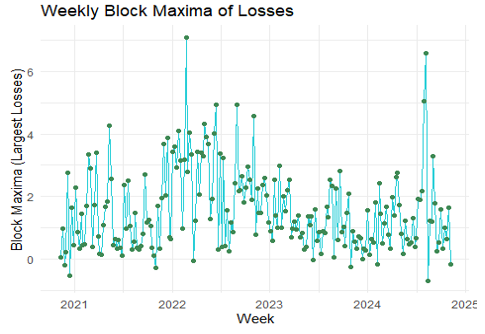
1. **Extreme Values Theory**
   1. **Block Maxima**
      1. **Calculation**

Weekly blocks were created by grouping the data into weeks based on the Date column. For each week, the **maximum return** (largest loss) was calculated, representing the **worst weekly loss** due to the negative log transformation used in the return calculation.

The table shows the **weekly block maxima** (largest losses) for the first six weeks in the dataset:

|  |  |
| --- | --- |
| **Year - Week** | **Block Max** |
| 2020-45 | 0.0641 |
| 2020-46 | 0.989 |
| 2020-47 | -0.189 |
| 2020-48 | 0.224 |
| 2020-49 | 2.77 |
| 2020-50 | -0.539 |

Each row highlights the **largest weekly loss** for the index. For example, in the 49th week of 2020, the worst weekly loss was **2.7711**, which reflects a significant drop in returns during that week.



The graph visualizes the weekly **largest losses** over time, highlighting periods of heightened market stress, such as in 2022, where weekly losses reached their most extreme values. Outside of 2022, the general trend indicates that most weekly losses are less severe, reflecting a relatively stable risk profile during those periods. This visualization provides a clear timeline of extreme losses, offering insights into when and where the market experienced the most significant volatility.

1. **VaR and ES**

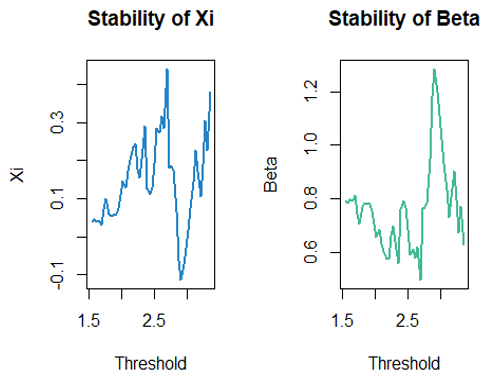
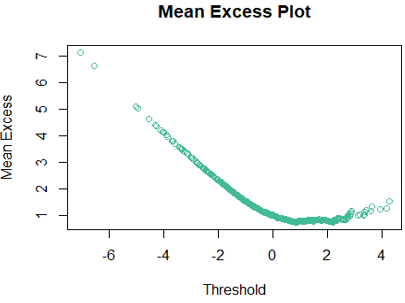
The table compares Value at Risk (VaR) and Expected Shortfall (ES) for 95% and 99% confidence levels using historical and parametric approaches.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Confidence Level** | **Historical VaR** | **Historical ES** | **Parametric VaR** | **Parametric ES** |
| 95% | 0.612% | -0.206% | 0.049% | -0.871% |
| 99% | 0.272% | -0.504% | 0.402% | -0.483% |

The parametric approach shows a wider range, especially in ES at 95%, where the estimated loss magnitude is significantly higher. This discrepancy reflects the sensitivity of the parametric method, which assumes a heavier-tailed GEV model. However, since the underlying distribution is known to be non-normal, the parametric estimates might overstate risks, particularly at lower confidence levels, emphasizing the need for careful model validation.

* 1. **Peaks Over Threshold**
     1. **Calculation**

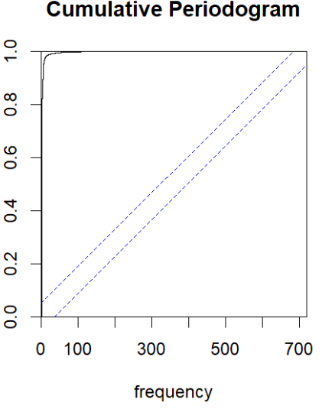
The choice of threshold is crucial in the POT method. An appropriate threshold balances bias and variance in parameter estimates.The mean excess plot helps identify a suitable threshold where the mean excess over the threshold is linear. Based on the plot, a suitable threshold would be around -2 to 0, where the mean excess stabilizes and becomes linear.



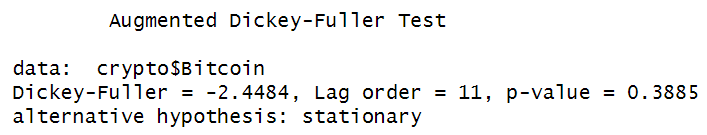
The parameter stability plots provided a guidance to select a threshold. The region 2.2 and 2.8 shows stability, making it reliable range for analyzing extreme events.

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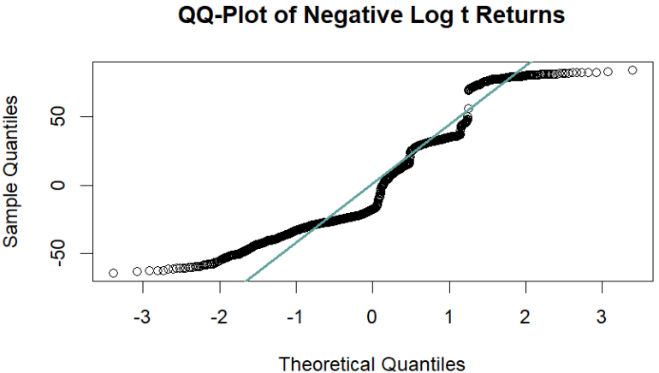
1. **VaR and ES**
2. **Stop-Loss Strategy**
3. **Conclusions**
4. **Recommendations**
5. **Appendix:**
   1. **Dickey Fuller Test**

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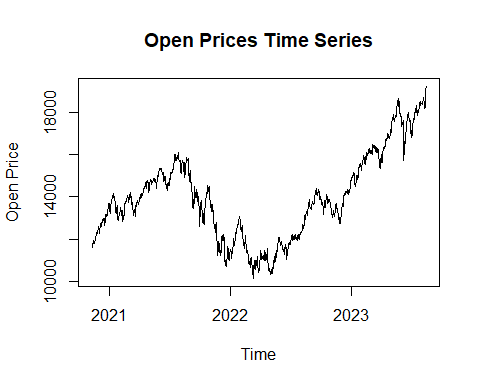
* 1. **Dickey Fuller Test**



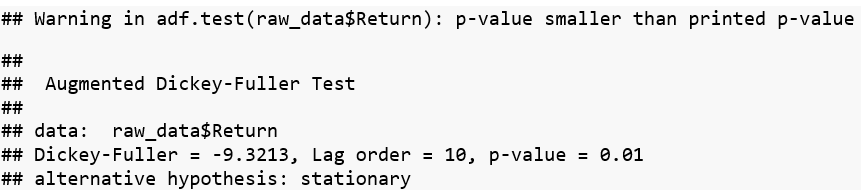
**1.3 QQ plot t fitted**



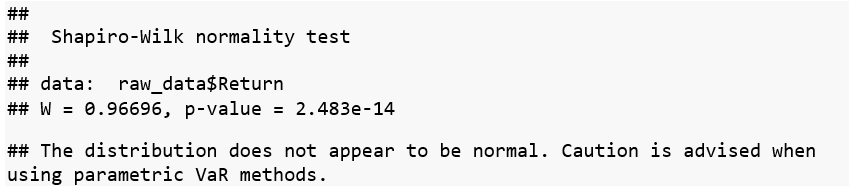
1. **Practical 2**
2. **Practical 3**
   1. **Open Prices Time Series**



* 1. **Dickey Fuller Test**

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* 1. **Shapiro Wilk Normality Test**

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