Risk Analytics - Practical 1
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Part 1: Financial Returns and Normality

a) Assessing Stationarity of Bitcoin Prices

In this section, we analyze the raw Bitcoin prices to assess stationarity, as this determines whether transformations or differencing are required before applying time series models.

We first plotted the Bitcoin prices (see Figure 1) to visually inspect for any apparent trends or patterns. From the plot, we can already observe a clear trend and some repeating patterns, which suggest that the series may be non-stationary. However, to formally confirm this, we applied the Augmented Dickey-Fuller (ADF) test (see Table 1), which is a statistical test used to determine whether the series has a unit root—a key indicator of non-stationarity.

The result of the ADF test gave a p-value of 0.3885, which is greater than the common significance level of 0.05. As a result, we fail to reject the null hypothesis (H0) that the series is non-stationary. This confirms that the raw Bitcoin prices are indeed non-stationary, reinforcing our initial visual observation of trends and structural patterns over time.

b) Computing Negative Log Returns and Assessing Stationarity

Since the raw Bitcoin prices were found to be non-stationary, as identified in part a, we proceed by computing the negative log returns. Negative log returns are commonly used in financial time series analysis because they often result in a stationary series, making them more suitable for modeling and forecasting.

Upon visual inspection, the plot of the negative log returns also appears to be stationary (see Figure 2). To formally assess this, we applied the Augmented Dickey-Fuller (ADF) test (see Table 2), which resulted in a p-value of 0.01. Since this is less than 0.05, we reject the null hypothesis (H0) that the series is non-stationary, confirming that the negative log returns are indeed stationary.

c) Assessing the Normality of Negative Log Returns

To evaluate whether the negative log returns of Bitcoin follow a normal distribution, we first examined the data visually using a histogram (see Figure 3) and a QQ-plot (see Figure 4).

The histogram of the negative log returns suggests that the data may be approximately normally distributed, though some deviations from normality could exist. Additionally, the QQ-plot shows that the returns are normally distributed for non-extreme values, but there are noticeable deviations in the tails, indicating that the negative log returns may not follow a perfect normal distribution.

To formally test for normality, we applied the Anderson-Darling test (see Table 3), which gave a p-value less than 0.05. As a result, we reject the null hypothesis (H0) that the data is normally distributed. This

confirms that, despite appearing somewhat normal in the central part of the distribution, the negative log returns are not normally distributed, especially due to the extreme values.

Appendices

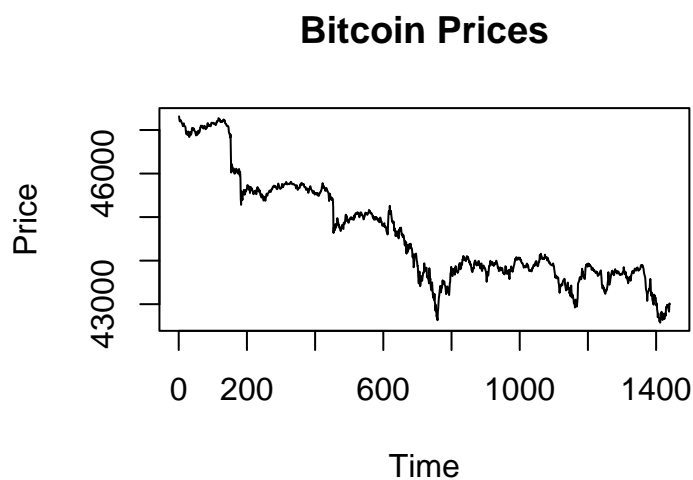## Figures

Figure 1: Bitcoin Prices Over Time

Bitcoin Prices

Figure 2: Negative Log Returns of Bitcoin Over Time

Negative Log Returns of Bitcoin

Figure 3: Histogram of Negative Log Returns
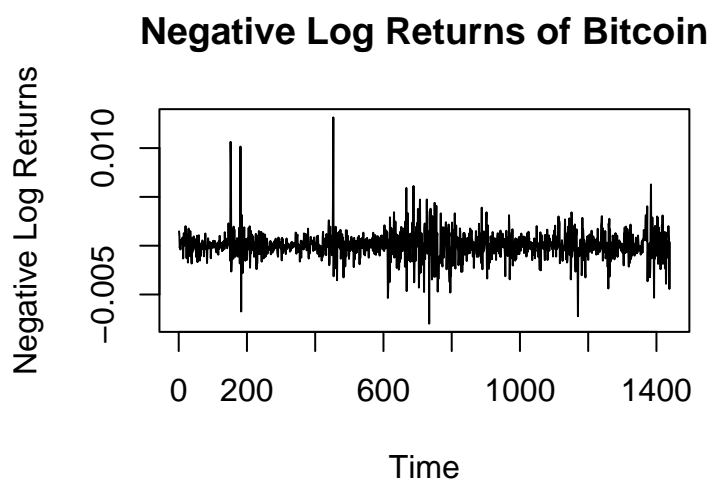
Histogram of Negative Log Returns
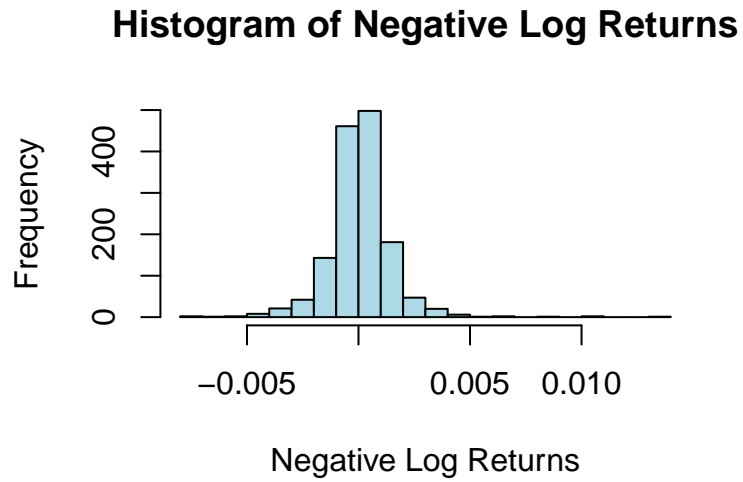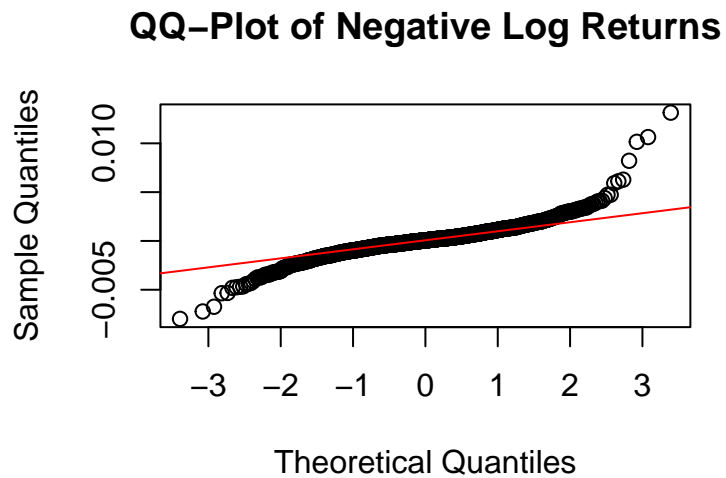
Figure 4: QQ-Plot of Negative Log Returns

QQ−Plot of Negative Log Returns

Results tables

Table 1: Augmented Dickey-Fuller Test for Bitcoin Prices

```
##
##   Augmented Dickey-Fuller Test
##
## data:  bitcoin_prices
## Dickey-Fuller = -2.4484, Lag order = 11, p-value = 0.3885
## alternative hypothesis: stationary
```

Table 2: Augmented Dickey-Fuller Test for Negative Log Returns

```
##
##  Augmented Dickey-Fuller Test
##
## data:  bitcoin_negative_log_returns
## Dickey-Fuller = -11.035, Lag order = 11, p-value = 0.01
## alternative hypothesis: stationary
```

Table 3: Anderson-Darling Test for Normality of Negative Log Returns

```
##
##  Anderson-Darling normality test
##
## data:  bitcoin_negative_log_returns
## A = 26.277, p-value < 2.2e-16
```

Code Appendix