# Cryptocurrencies and the Risk-Free Rate

**Final Project**

Digital Tools for Finance (L) (03SMDFOEC008)
Department of Banking and Finance, University of Zurich
Igor Pozdeev

**Authors**

Jakob Pirs (22-714-166, jakob.pirs@uzh.ch)
Nina Erminia Cantoni (17-709-221, ninaerminia.cantoni@uzh.ch)
Rohit Koonireddy (22-714-166, rohit.koonireddy@bf.uzh.ch)
Yunxiang Guo (20-751-566, yunxiang.guo@uzh.ch)

**Abstract**

This paper investigates the tie between the risk free rate (approximated by the 10 year treasury yield) and the returns of the cryptocurrencies Bitcoin, Etherium, XRP and Litecoin, as well as the cryptocurrency market (approximated by CMC Crypto 200 Index by Solactive). For this purpose a data set is created using the yahoo API. The paper finds weak covariance and neglegible correlation. It is to conclude, that the cryptocurrency returns are not related to spikes in the risk free rate.

December, 2022

# Contents

## List of Figures



## List of Tables

# 1 Context and motivation

The goal of this paper is to analyze the connection between the 10 year treasury yield and cryptocurrencies. The 10 year treasury rate is the yield one receives for investing in US government securities with a maturity of 10 years. It is a common proxy for the risk-free rate. The risk-free rate is a basic component of most pricing theories and thus a very relevant factor in the finance world. This paper will shed light on the influence of the risk-free rate on the return of cryptocurrencies by analyzing price data over a period of 5 years. It will also be examined, whether the cryptocurrency market as a whole is influenced.

To answer the research question, this paper looks at four different cryptocurrencies, namely Bitcoin, Etherium, XRP (by Ripple) and Litecoin. Find an overview of the four currencies in Table 1 below.

**Table 1: Cryptocurrencies overview**

| Logo | Name | Symbol | Market Cap as of Nov 25, 2022 | Ranking as of Nov 25, 2022 |
|---|---|---|---|---|
| | Bitcoin | BTC | \$ 318 bn | 1 |
| | Ethereum | ETH | \$ 149 bn | 2 |
| | XRP | XRP | \$ 20 bn | 7 |
| | Litecoin | LTC | \$ 6 bn | 13 |

*Note.* Data as of November 25, 2022, retrieved from CoinGecko (www.coingecko.com).

Besides these single cryptocurrencies, we also consider a cryptocurrency index. By looking at an index, we can replicate the cryptocurrency market as a whole and abstract from indiosyncratic risks of single currencies. The index that was considered is the CMC Crypto 200 Index by Solactive. The CMC Crypto 200 Index tracks the price movementes of the top 200 cryptocurrencies by market capitalization. It was launched at year end 2018 and is calculated and distributed by Solactive AG. The index is published in USD. The calculation of the index price is conducted on a daily basis (Solactive AG, 2019). As of November 2022, the four cryptocurrencies analyzed in this paper (Bitcoin, Etherium, XRP and Litecoinwere) were within the 13 cryptocurrencies with the highest market capitalization and therefore also part of the CMC Crypto 200 (see Table 1).

## 2 Data set

### 2.1 Raw data

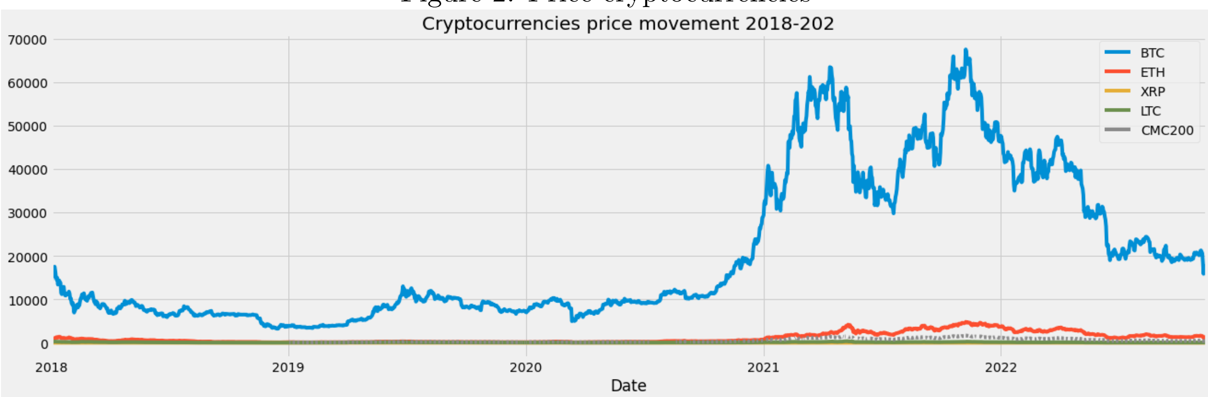
This paper is based on a data set consisting of prices of the four cryptocurrencies of interest Bitcoin, Etherium, XRP and Litecoin, of the CMC Crypto 200 Index and of the 10 year US treasury bond. The data was sourced form Yahoo! through its Application Programming Interface (API). For each of the above mentioned assets, the daily (adjusted) closing price was retrieved. The data set spans from January 1, 2018 to November 12, 2022.

To get a feel for the data set, in Figure 1 we plotted the movement of the 10 year treasury yield over the whole time span form 2018 to 2022. Analogously, in Figure 2 we depicted the price movements of all the cryptocurrencies and the cryptocurrency index.

Figure 1: 10 year treasury yield


*Note.* Own representation based on raw data set 2018-2022.

Figure 2: Price cryptocurrencies

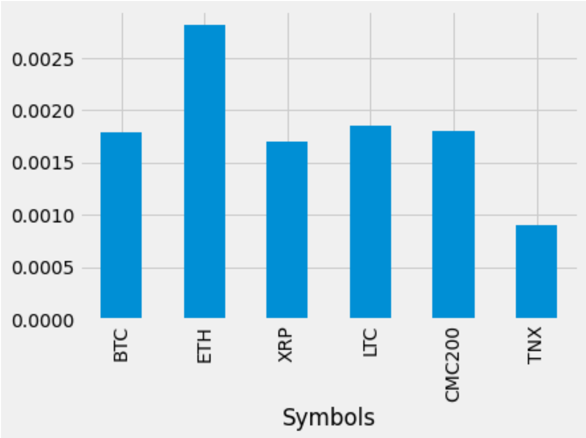



*Note.* Own representation based on raw data set 2018-2022.

### 2.2 Final data set

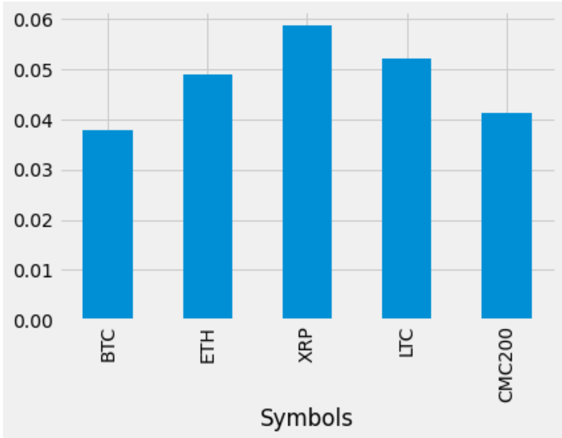
As the CMC Crypto 200 Index was launched only at year end 2018, there is a lack of data with respect to the index for the first year within our sample. Therefore we decided to excluded year 2018 from our data set to avoid bias in our figures. All follwing figures and analyses will be based on this reduced time span of 4 years, from 2019-2022. We also did some cleaning the data set and replaced any NaN values with zeros. Finally, we calculated the returns of the cryptocurrencies. These compose our final data set. The means of all variables (Figure 3) and

Figure 3: Means




*Note.* Own representation based on final data set 2019-2022.

Figure 4: Standard deviations




*Note.* Own representation based on final data set 2019-2022.

the standard deviations (Figure 4) of the cryptocurrencies. These two statistics are based on the final data set, excluding year 2018. ETH has clearly the highest closing price on average, the 10 year treasury bond (referred to as TNX) the lowest. Regarding standard deviation, XRP has the highest value.
The final data set is openly accessible on our GitHub page, allowing for reproduction of our exact results:

**Object name** data_adjusted_small.parquet

**Format names and versions** Parquet

**Creation date** 2022-11-15

**Dataset creator** Jakob Pirs (co-author)

**Language** English

**Repository name** GitHub

**Repository path** `https://github.com/ncanto/group-work.git`

# 3 Method

The goal of this paper is to assess whether there is any connection between the 10 year treasury yield and the return of cryptocurrencies. To detect a potential connection we relied on two classical statistical measures: covariance and correlation.

## 3.1 Covariance

The covariance is a measure to relate the movement of two random variables. A positive covariance indicates that the two variables move in the same direction. A negative covariance means that the variables move inversely, meaning that if one increases, the other one will decrease and vice versa. Therefore, covariance measures the direction of a relation. The covariance is given by the following formula (Bonamente, 2013):

$$cov_{x,y} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{N-1}$$

By calculating the Covariance we can examine the direction of a potential relationship between the 10 year treasury yield and the cryptocurrencies.

### 3.2 Pearson's Correlation

Similarly to the covariance, also the correlation is a measure for relationship. The correlation measures the strength of a relationship. The correlation coefficient lives on the interval between negative one and one. The higher the absolute value, the stronger is the observed relationship. A correlation of zero indicates no relationship between the observed variables. Therefore, this measure is very interesting for our research question. Depending on the correlation we can assess how strong the relationship between the 10 year treasury yield and the cryptocurrencies is (if any).

First, we assess the Pearson's correlation. The Pearson coefficient will will measure any linear relationships between the variables. There is a linear relationship when a change in the first variable causes a proportional change in the second variable. (Schober, Boer, & Schwarte, 2018)

### 3.3 Spearman's Correlation

As we have seen above, the Pearson's correlation has its limits. Namely it is limited at measuring linear relationships. We therefore also introduce a second correlation measure, called the Spearman's correlation. The Spearman's correlation coefficient extends the concept to non-linear, monotonic functions. Simply put, monotonic functions are functions that do not change direction but can have different steepness throughout. (Schober et al., 2018)

### 3.4 Implementation

The analysis was conducted using the programming language Python, making use of its functionalities. For the computations we relied on the *pandas* package. We calculated the covariances within our data set using the *data.cov()* function. Similarly, correlation was computed using the *data.corr()* function, with specifications *method='pearson'* and *method='spearman'* accordingly. These are basic functions available in many programming languages.

### 3.5 Reproducibility

When creating this project we put an emphasis on reproducibility and robustness of results. For anyone to reproduce our analysis we have set up the following two possibilities:

**Binder** One can use a simple online service called Binder Interactive (`mybinder.org`). To interactively run our code on jupyter lab one can use the following link directly without downloading: `https://mybinder.org/v2/gh/ncanto/group-work.git/main?labpath=final-project%2Ffinal-code%2FResearch_Final.ipynb`

**Docker** Using the docker image file we created one can get our docker image from the following link on docker hub: *docker pull rkooniredd y/d2ff-final*

Finally, we have also provided a Python **app** built using the Flask web framework. To use the app, please follow the instructions provided in the README file on GitHub. This app allows users to interactively explore and visualize the results of our analysis (`https://github.com/ncanto/group-work/blob/main/final-project/README.md`).

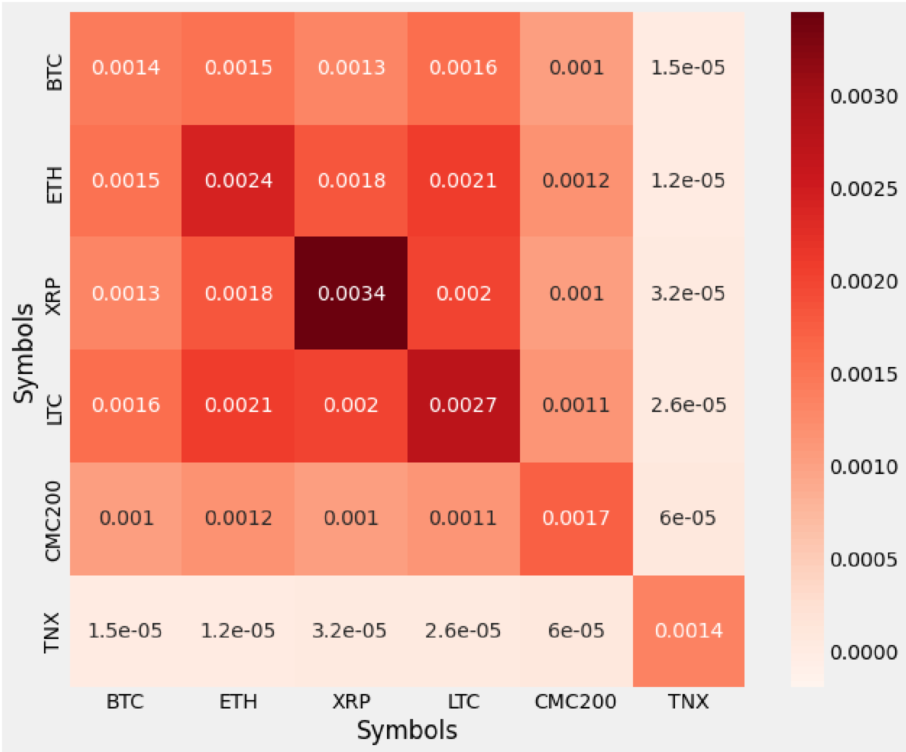
## 4 Results and discussion

In a first step, we evaluated the covariance of the cryptocurrencies (BTC, ETH, XRP, LTC and the CMC200 index) and the 10 year treasury bond (TNX). The results are depicted in Figure 5 below. We found small ($\leq$0.0021, ignoring covariance with oneself), positive values throughout. The magnitude is not significant to interpret. Instead, we focus on the sign. All values are positive, indicating a positive relation of prices. Of most interest are the covariances of the 10 year tresury bond with the cryptocurrencies. These values are allocated along the bottom and right edge. The light pink color indicates very small values, close to zero. The covariance of two variables is close to zero if either both values are very small or if there is no relationship. Referring back to Figure 3 we see that indeed the mean values of are variables are small ($<$0.003). We can therefore conclude that the risk-free rate and cryptocurrency returns are probably moving in the same direction.

But what about the magnitude of the relation? This question can be answered with the Perason's correlation measure. The results are summarized below in Figure 6. We find a strong correlation between the various cryptocurrencies. This is not surprising. The different cryptocurrencies are substitutes of one another and most likely face the same demand trends. More interesting for our research question is the correlation between the 10yr treasury yield and the cryptocurrencies. The correlations are very weak. All of them are below 0.1 which according to Schober et al. (2018) should be interpreted as a negligible connection. The highest correlation with the risk-free rate is achieved by the CMC 200 index, however also with very low magnitude (0.039).

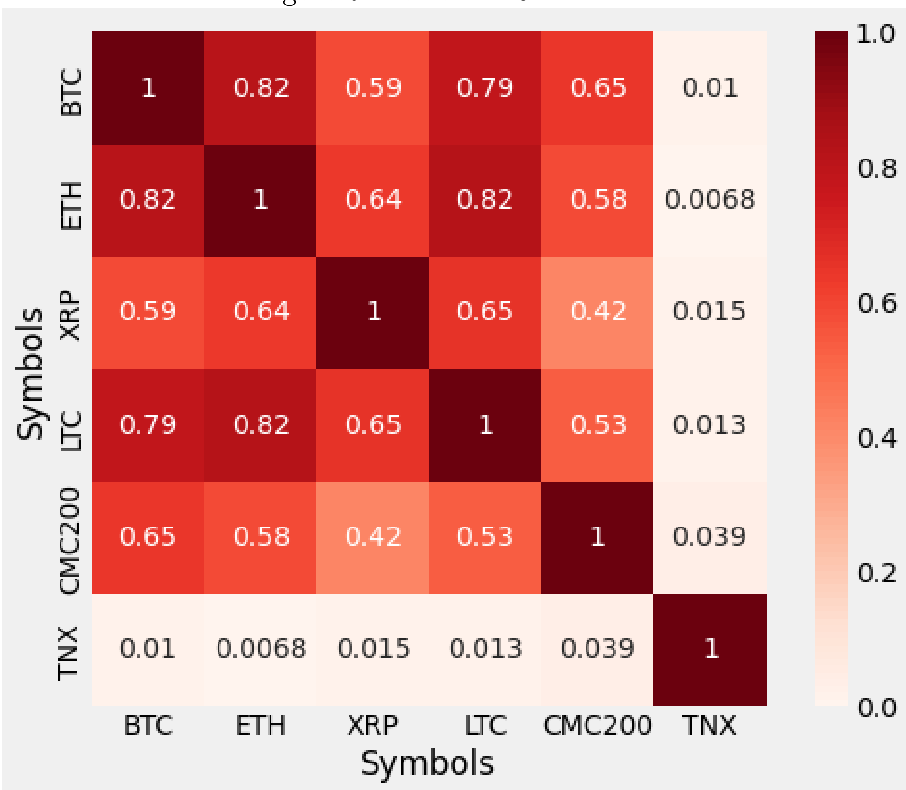
The last part of the analysis consists of calcualting the Spearman's correlation coefficient. With this approach we try to control for potential non-linear relationships. However, the results are fairly similar to before. Especially, the correlation between the risk-free rate and the cryptocurrencies is still negligible.

Figure 5: Covariance




*Note.* Own representation.

Figure 6: Pearson's Correlation




*Note.* Own representation.

# 5 Conclusion

In the previous sections we analyzed our data set to find a potential tie between the 10 year treasury yield and the return of various cryptocurrencies. We find a close-to-zero covariance and a neglibile correlation of the risk-free rate and the returns of Bitcoin, Etherium, XRP and Litecoin. The same holds for the relation of the bond to the cryptocurrency market, approximated by the CMC Crypto 200 Index. We conclude that there is no significant correlation between hikes in the risk-free rate and cryptocurrency returns.

# References

Bonamente, M. (2013). *Statistics and Analysis of Scientific Data.* New York: Springer Science+Business Media. DOI: 10.1007/978-1-4614-7984-0

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia Analgesia*, *126*(5), 1763–1768. DOI: 10.1213/ANE.0000000000002864

Solactive AG. (2019). *Index Guideline: Solactive Index.* Retrieved 2022-12-10, from https://www.solactive.com/wp-content/uploads/2019/04/Solactive-Index-Guideline-CMC200.pdf