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Preface

This thesis was written to take a closer look at the future of blockchain and cryptocurrency. It explores the use of an extreme value analysis (EVA) to further understand the tail risk of investing in cryptocurrency. The research was documented to fulfill the requirements of a master's thesis at the University of Stavanger (UIS). The research and writing took place from January to June 2021.

The research question was formed together with my supervisor, Håkon Abrahamsen after discussing my own interests. Researching and understanding this subject possessed a challenge at times, given the little knowledge that is available on this new technology. However, with time and interest, I was able to understand the subject at hand to develop a sufficient solution.

First off, I would like to thank Jörg Osterrieder and Julian Lorenz, who both are the authors of the research paper: "A statistical risk assessment of Bitcoin and its extreme tail behaviour" which was my main inspiration for writing this thesis. Secondly, I want to thank my supervisor Håkon Abrahamsen, for the help he provided throughout the semester.

I also want to give a special thanks to Mohsin Raza for helping me with the overall structure of the thesis and Oskar Føyn Føyen and Kamshan Karunaharan for proof reading. In addition I want to thank friends and family for supporting me by engaging in discussions and pushing me to achieve better. Even though this topic was very interesting, at times it was easy to lose focus and your support reeled me back in to finish this thesis.

I hope you appreciate the thoughts, contribution and results from this thesis.
Jeremi Ainos Joseph, *Stavanger, June 4, 2021.*

Abstract

With the digitization in the world becoming almost a necessity, the wake of Bitcoin (BTC) made headlines around the world. A new and emerging technological advancement like cryptocurrency and blockchain results in volatile investments. This thesis was written in order to see if the volatile tails of crypto assets justified an extreme value analysis and to evaluate the assets from a tail risk perspective. The thesis will check if an EVA is justified by looking at the volatility and normal distribution fits. Once the EVA is justified, the paper will take a further look into the Generalized Pareto distribution (GPD) fit and the Generalized Extreme Value (GEVD) fit to evaluate how accurate they are compared to the real life samples. Lastly, an estimation of value-at-risk (VaR) and expected shortfall (ES) will be calculated. Throughout the dissertation, the calculations will be performed on the NOK/USD exchange to compare the crypto market to FIAT currencies. The paper also aims to state a few future plans and price drivers for the assets to see how external factors affect the price.

The results from the research and calculations show major risk in the crypto assets compared to the FIAT currency chosen. The EVA exhibits that the GP and GEV fits are both much more accurate, and therefore it was concluded that the analysis was successful. The VaR and ES results show how much risk these assets carry, with the ES being the more optimal risk measure for crypto assets.

Navigating the Thesis

The aim of this chapter is to give a clear idea of where reader's can find the information they are looking for.

Chapter 1: Introduction. In this chapter, the reader can get acquainted with the motivation behind the thesis and the research questions. A short summary of the results is also presented.

Chapter 2: Background. A brief introduction to the core aspects of the thesis is presented here to give the reader some background knowledge.

Chapter 3: Data. This chapter briefly explains the sources my data sets were gathered from and discusses their authenticity and credibility.

Chapter 4: Literature Review. The inspiration and literature for this thesis is discussed and evaluated in this chapter. Checking for credibility.

Chapter 5: Theory / Method. In this chapter, the reader will find the material used to research and solve the research questions. The approach/method of this thesis can also be found here.

Chapter 6: Results. The research questions are solved and the results are presented. In this chapter, the reader will find all the results and notes regarding the results.

Chapter 7: Future. A few external price drivers are discussed together with future development in the market and the consequences of that development.

Chapter 8: Conclusion. Last chapter of the thesis, takes a closer look at the both chapter 6 and 7, concluding on the research and touching back on the research questions.

List of Abbreviations

BTC Bitcoin

ETH Ethereum

DOGE Dogecoin

NFT Non-Fungible Token

SoK Strength of Knowledge

GPD Generalized Pareto Distribution

GEV (GEVD) Generalized Extreme Value (Distribution)

I.I.D / i.i.d Independent and Identically-Distributed Random Variables

VaR Value at Risk

CVaR Conditional Value at Risk

KDE Kernel Density Estimator

DPC Daily % Change / Daily Percentage Change

YPC Yearly % Change / Yearly Percentage Change

ES Expected Shortfall

V-C Variance-Covariance

Contents

Chapter 1

Introduction

In the last decade, the phenomena of cryptocurrencies has exploded to the point where big, dedicated investors are now scrambling to tap into this new market. It started off when Satoshi Nakamoto, an anonymous person/group, introduced Bitcoin. A decentralized digital currency that would allow users to gain control over their funds, without a centralized bank holding it for them. The whole concept built on a technology known as 'the blockchain', and allowed for secure transactions through cryptography, eventually resulting in the name 'cryptocurrencies'. As the global financial crisis exposed the weak structural integrity of centralized currencies, Bitcoin was in perfect position to pick up some popularity. However, as time progressed, the blockchain technology behind Bitcoin was implemented in several digital ventures, creating a whole new market of crypto coins and tokens. This sparked what is known as the crypto space (cryptocurrency market). Big investors started funding these new ideas, resulting in a huge upwards movement in the market (Betz 2021). Traders and small investors started to note the potential in this new emerging market, using the assets as investment instruments.

This thesis takes a look at crypto assets as investment instruments, and when taking that approach, there are a few hurdles one has to cross to understand the underlying risk.

1.1 Questions and problems

With the increasing popularity of cryptocurrency, often referred to as 'cryptos' (referred to as crypto/cryptos throughout this thesis), many questions are raised and problems are exposed:

- The volatility of the crypto market is too high and hard to predict as the assets react to speculation rather than actual use case.
- At this time, there's very little to no real value in the actual assets. Most of them are only used as investment instruments and the ones with real use cases are usually limited to certain areas or test regions.
- It is still relatively new. Paired with its high volatility, there's high risks with investing.

1.2 Research questions

The common denominator in the problems around cryptocurrency and the crypto space can be boiled down to uncertainity, which leads to high risk.
With these questions and problems in mind, this thesis aims to investigate and solve some of the uncertainties and take a closer look at the risk of investment in this market through an EVA, answering the research questions:

What is the tail risk of investing in cryptocurrency assets compared to NOK and how much can investors expect to lose with respect to their risk tolerance? Is an EVA justified and which EVA distribution provides the best fit?

The thesis will be looking at three selected cryptocurrencies (Bitcoin, Ethereum (ETH) and Dogecoin (DOGE)) to analyse their tail risk with respect to an investor's risk tolerance and the expected shortfall (ES) the investor will experience. The thesis will also take a brief look into the future plans for the crypto market to explore and research potential development that will significantly change the price prediction for the future.

1.3 Relevancy

Crypto is a relatively new topic. It has garnered a big audience the last few years (CoinMarketCap 2021), but is still a speculative investment instrument. As an investor, it is always important to stay on the forefront of emerging markets, not only to capitalize on their potential, but also help build the future. With enterprises, corporations, networks and companies like SpaceX, Google, Microsoft, Tesla, Warner Music Group, etc. already invested in different crypto projects, it is safe to say that the crypto market has the potential to change the way the world operates.

In the last 5 years, the crypto market has exploded from a market capitalization of almost \$6.8 billion (December 10th, 2016) to about \$2.2 trillion (May 2nd, 2021) (CoinMarketCap 2021). This is more than a 320 times increase. The surge in crypto investments has made millionaires out of ordinary traders. The idea behind this has motivated many, especially young investors, into diving into the crypto market, to find the next big opportunity.

There are also a few factors that attract more people to convert into the crypto market. One of the factors is the fact that the fees are lower compared to the stock market. Another important factor is the fact that anyone can invest and buy a fraction of a coin or token, unlike the stock market where investors generally have to buy at least one share. This allows for people with less monetary resources to actively partake in the biggest projects.

Zooming out, and looking at crypto from the global financial perspective, it brings some extremely promising opportunities. Excluding the centralized entity in a transaction (i.e banks), it allows for both the sender and receiver to be more in control of their assets. In an era where digitization has become a leading technological trend, the blockchain technology stands as the anti-fraud mechanism that gives people the trust and control they need.

1.4 Contribution

As the crypto market, and the technology behind blockchain, is relatively new, the price changes are often very speculative. Not only is the technology new, but it is evolving every single day, with the goal to revolutionize the digital world. Therefore, this thesis aims to stand in the forefront of understanding the high risk of investing in crypto assets. Investors can use the research and methods described in this paper to cautiously invest, getting a much better perspective on what risks these assets carry and how much they can expect to lose. In addition to taking a deep dive into Bitcoin, Ethereum and Dogecoin's tail risk, the paper contributes to future analyses of crypto by laying a solid foundation to assess any crypto asset with respect to the investor's risk tolerance.

1.5 Approach

The approach chosen for this thesis is a tail risk assessment, which is done by performing an EVA. The first step is to justify an EVA on the selected assets. This is done through a volatility assessment and comparing the data sets to a normal distribution fit. Second step involves the EVA itself, the assets will be evaluated using both the GPD and GEVD fits to assess the possible losses at a specific risk tolerance level. Lastly, both the VaR and ES will be estimated for all assets to obtain a better measurement of calculating loss. Throughout the analysis, the calculations will be performed on the NOK/USD exchange as well, to compare the results to that of a stable FIAT currency.

1.6 Results

As predicted, the crypto assets were much more volatile and risky compared to NOK. The EVA was justified and returned some interesting observations. Both the GPD and GEVD fits performed well at different aspects and the ES ranked the assets in the following order (from least risk to highest risk): Bitcoin, Dogecoin, Ethereum.

Chapter 2

Background

2.1 Pre-Crypto

The global financial crisis that hit in 2007 left a global mark on humanity (Marian Nastase & Stanef 2010). As a result, the distrust in banks and FIAT currency started rising. The global fear of a possible recession lasting for years, started to spread. As a result of this, people started looking for a potential solution.

2.2 Cryptocurrency

The concept of cryptocurrency stems back to 1998. Wei Dai, a chinese computer engineer with a bachelor's degree from the University of Washington, introduced a concept called "b-money" (Dai 1998). A decade later, this would prove to become the foundation of one of the largest cryptocurrencies. Introduced late 2008, Bitcoin was the first cryptocurrency to spark the global interest of a digital currency without any connection to a centralized bank or entity. Operating on a digital ledger, it quickly became a financial advancement with promise. Cryptocurrency, often referred to as a 'crypto', is in its generalized form, a digital asset stored on a public, digital ledger/database known as 'the blockchain'. Transactions are registered on this database, and secured by complex cryptography. What started out as a digital currency with aim to replace paper money, has now grown into a far more complex digital asset that aims to revolutionize the internet and digital world. The secret behind cryptocurrency is 'the blockchain'.

2.3 Blockchain Technology

The blockchain technology was first introduced back in 1991 by Stuart Haber and W. Scott Stornetta. In the article, they described the technology as network of *clients* with unique identification numbers that could digitally sign and store information (Haber & Stornetta 1991). The information would be time-stamped digitally, which is the equivalent of the transaction registration used in today's blockchain technology. Blockchains were however not used in real-life applications before Bitcoin was introduced in 2008. The blockchain BTC was built on was released as an open-source technology, which has laid the foundation for many different crypto projects in recent years (Nakamoto 2007). Simply put, the blockchain is a type of database where information is stored into blocks, the blocks are then placed into a chain. The chain cannot be edited, which makes it impossible to change any transaction made (given that the blockchain is decentralized). In a case where an external entity is able to edit a block in the chain, the following blocks in that chain will be rendered invalid, making the chain useless. This prevents hackers from accessing and infecting a chain (more on this later).

The way blockchain works is through a six step process. First off, a transaction is made using the digital asset/crypto. The transaction is passed through a selection of computers linked to the blockchain. This is done to verify the transaction and confirm it as a legit process. Multiple, verified transactions are then grouped into blocks and the blocks are placed in a chain, with timestamps. The timestamps verify the time at which the blocks were added to the chain. Another feature of a decentralized blockchain is the fact that it is open for the public, allowing anyone to see specific transactions and individual wallets. A detailed explanation with appropriate figures can be seen in Figure 2.1, provided by Investopedia (Conway 2020).

2.3.1 Forks

Rewinding back to the scenario of a hacker interfering with the blockchain. In an event where a hacker is able to penetrate the blockchain, the developers can perform a so called hard fork. Forking a blockchain is essentially splitting it off from

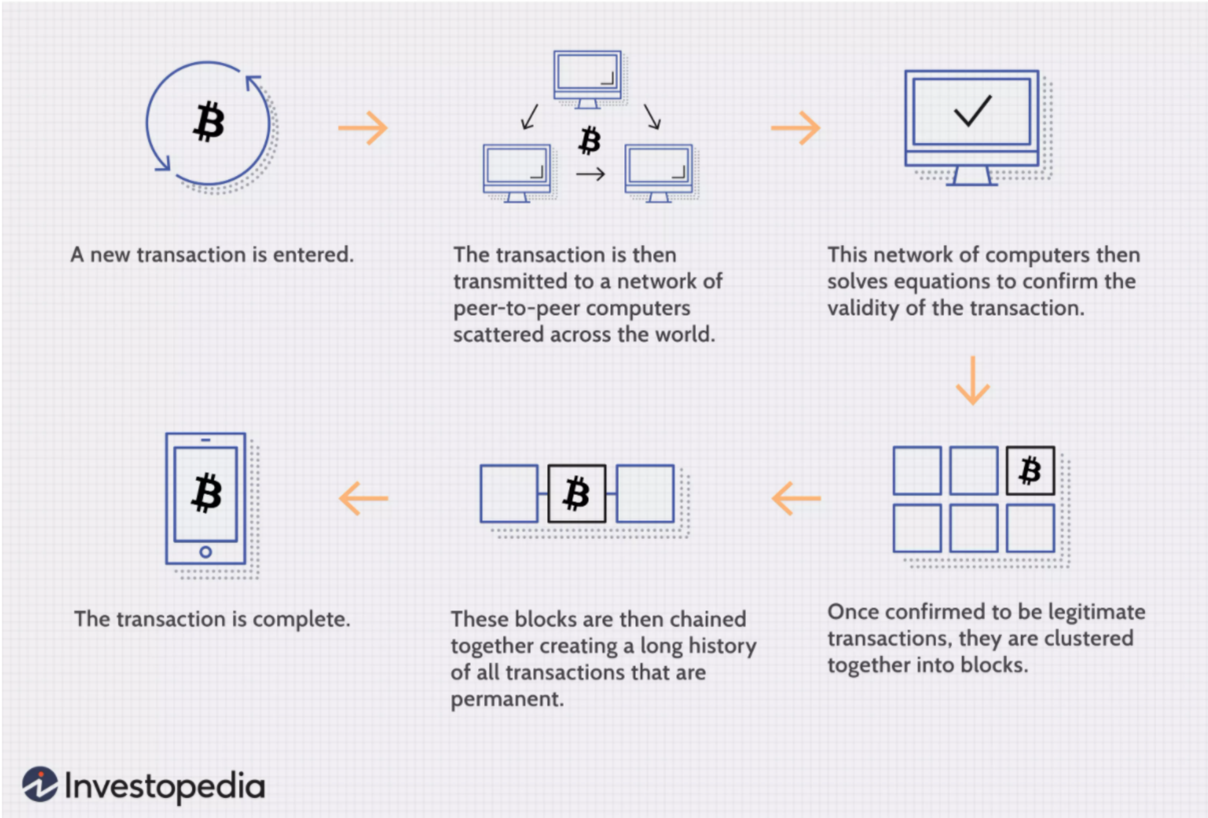

Figure 2.1: Explanation of Blockchain by Investopedia (Conway 2020).

its original state in order for changes to be implemented to the chain. Usually, developers will fork their blockchains if a change in the protocol needs to be made. This might be a technological advancement, a government regulation or a hack. In 2016, this was showcased by Ethereum's Vitalik Buterin. Around $64 million in Ether (at the time) was siphoned from a investment project by a hacker. To fix this, an Ethereum hard-fork was implemented, essenitally turning the ETH the hacker had gained into null (Ore 2016).

2.4 The Cryptocurrency Market

Following Bitcoin, many developers published their own crypto projects. Notably, Ethereum took the blockchain technology and turned it into a platform where people could develop their own decentralized finance apps (DeFi Apps). As a result, today's crypto market consists of a variety of different coins and tokens, all with different use cases. Crypto is now not only found in the finance sector, but has progressed into the digital and technological sectors.

The use cases often determine the price changes, but not exclusively. Just like the stock market, the crypto market is heavily influenced by community, strategies and reactive trading. As mentioned earlier, most cryptos have little or no real use case at this point in time, and are merely used as investment instruments.

2.4.1 Market Capitalization

Generally, the market cap (short for market capitalization) is the total amount of money available to trade in a market for an asset. The equation to calculate the market cap is as following:

$$Market\ Cap = \sum Shares\ For\ Sale\ *\ Current\ Market\ Price\ of\ One\ Share \tag{2.1}$$

In crypto, as it is based on digital assets, the total number of shares is not naturally limited. This means that a crypto could have an unlimited pool of coins. However, to prevent inflation, most crypto coins/tokens are hard-coded with a maximum amount that can ever be in circulation. An example is Bitcoin, which has a total amount of 21 000 000 coins (stated in the BTC source code). This procedure is used to create deflationary economy, making it more like gold and oil, rather than currencies. Essentially, this helps to store the value of the asset and keep the buying power unlike that of paper money.

Inflationary vs. Deflationary

Inflation is a result of increasing the money supply. This results in the value of a currency to drop, thus increasing the amount of that currency needed to purchase goods (Barro & Grilli 1994).

Deflation is the opposite. In a deflationary asset, the total amount of asset is locked. This results in the buying power of the currency going up, essentially making it able to buy more goods than before (O'Sullivan & Sheffrin 2003).

2.4.2 Trading Strategies

In the crypto market, just like the stock market, investors use trading strategies to predict movement. With the high volatility, which is a prominent characteristic of the crypto market, traders have been forced to find new and innovative ways to analyze and predict price movement. The strategies are based on technical analyses of the market. By looking at historical data, patterns are found in the movement. A popular method to predict how the crypto market will move is using previous bull runs. Bull runs are periods of time where the price rallies up to new highs. Notably, there has been three major bull runs in the history of BTC; 2013, 2017 and 2021.

A very unique way to derive trading strategies in the crypto market is using on-chain analytics. These are statistics available to anyone through the public ledger of the blockchain, where traders can find information on the holders, transaction times, price movers, etc (on-chain analytics are not utilized in this dissertation. Therefore, it will not be explained in detail, however a closer look at it will be taken in chapter **7**).

2.5 The Three Selected Cryptocurrencies

As mentioned earlier, this thesis will be based on three predetermined cryptocurrencies. Before diving into solving the research questions at hand, the thesis will take a closer look at why exactly these 3 were chosen.

2.5.1 Bitcoin (BTC)

History & Use

Bitcoin, which is described as **A Peer-to-Peer Electronic Cash System** (Nakamoto 2007), was introduced between 2008 and 2009. The unknown developer(s) behind it introduced themselves as Satoshi Nakamoto. To this day, the creator(s) of Bitcoin are still unknown. The idea behind Bitcoin started as a decentralized method for monetary transactions. In simpler terms, this meant that money could be transferred directly from A to B, without any financial institute meddling in the process. As stated in the introduction of the BTC white paper, the writer states: "What is needed is an electronic payment system based on cryptographic proof instead of trust..." when mentioning what is needed to combat the digital transaction systems of today (Nakamoto 2007). Through cryptographic proof, the transaction would then be secured against a reversing event, further securing the transaction.

Reasoning

Any discussion containing cryptocurrency will always include Bitcoin. As the leading crypto in both popularity and market cap, Bitcoin is often seen as the father of all cryptocurrencies. Looking at the market dominance chart, provided by TradingView, it is apparent that BTC is clearly dominating the market, which in itself is sufficient enough for picking BTC (TradingView 2021*b*). The market cap of BTC holds around 40% of the total market cap of crypto.

2.5.2 Ethereum

History & Use

Developed through 2013 and 2014, Ethereum is the second largest cryptocurrency in market cap. It was developed by Vitalik Buterin, who at the time was only 19 years old. Following Bitcoin's development, Ethereum was set to tackle the same features. However, unlike Bitcoin, Ethereum was developed to give the people ability to use the Ethereum blockchain as well. This laid a foundation for decentralized applications and smart contracts. Essentially, with Ethereum, Buterin made access to the blockchain technology widespread. With the ability to program directly on Ethereum's blockchain, developers have created popular crypto projects that have garnered investments, partners and reputation. Examples of these are; Chainlink, Maker, The Graph, etc. Late 2020 and early 2021, non-fungible tokens based on the ETH platform gained popularity. A non-fungible token (shortened to NFT) is a singular digital asset minted on a crypto network (such as Ethereum). These NFT's give creators/developers the ability to essentially mint any piece of digital asset onto the network. The most popular use for this came in the form of digital artworks and collectibles, and early 2021, digital assets were sold as NFTs for millions of dollars (Kastrenakes 2021).

Reasoning

Ethereum was picked as the second crypto, firstly because of it's popularity. As many cryptos are built on the Ethereum platform, it is important to research Ethereum's future. Secondly, unlike Bitcoin, the use case of Ethereum is varied. The diversity in projects built on ETH has given the token the potential to be the most important crypto in the space. As many promising projects stem from the ETH blockchain it is important to analyze and understand it, to know how it affects the market.

2.5.3 Dogecoin

History & Use

In the wake of Bitcoin's first big success, developers Billy Markus and Jackson Palmer, set out to create their own cryptocurrency. In 2013 they released Dogecoin, which raked up over 1 million visitors to their website shortly after. Based off the popular meme, 'Doge', Dogecoin was merely a community based crypto, without the intent to be used as a substitution of paper money. The technology and idea behind Dogecoin is very similar to BTC, essentially being another Proof-of-Work cryptocurrency. Even the originators of Dogecoin describes it as: "Dogecoin sets itself apart from other digital currencies with an amazing, vibrant community made up of friendly folks just like you" (Dogecoin.com 2021).

Reasoning

Dogecoin was, as mentioned, developed as a fun community-token. It does not have a real use case, and is fueled by a strong community instead. Looking at crypto from the other end of the spectrum, Doge can help understand the overall seriousness of the market. Being one of the older cryptos, and with a large market cap, Doge was picked to see future potential.

Chapter 3

Data

The data used in this thesis is gathered from a few different sources. To verify their authenticity, this chapter will explain the sources and provide needed information. The chapter's use is to strengthen our strength-of-knowledge (SoK) and present reasoning behind the data set choices.

3.1 Quandl

Quandl is a platform delivering data. Fronting a team with experience in finance, technology, data science and astrophysics, their main goal is to gather data and present it to the general population (Quandl 2020).

3.1.1 Bitcoin

The thesis will use historical data from Quandl's BTC/USD coin pairing. The benefit of using this exact data set is that it uses average market price from a selection of the most important exchanges. The data set used for the BTC/USD pairing can be found on Quandl using the code: BCHAIN/MKPRU.

3.2 Yahoo Finance

As part of the Yahoo! Network, Yahoo! Finance, much like Quandl, delivers financial data among other financial media. The reasoning behind a second data platform is that certain coin pairings needed for this thesis could not be found on Quandl.

3.2.1 Ethereum

The ETH/USD pairing will be extracted from Yahoo Finance. This one however will be based off of Coinbase, which is one of the major crypto exchanges.

3.2.2 Dogecoin

The DOGE/USD coin pairing from Yahoo! Finance is gathered from CoinMarketCap, which is one of the leading platforms for historical crypto data. However, to extract information straight from CoinMarketCap, an API key is needed. That's why this thesis will use Yahoo! Finance as a substitute.

3.2.3 Norwegian Kroner

Lastly, the NOK/USD coin pairing is also extracted from Yahoo! Finance. The NOK/USD pairing will be used to compare certain measures between cryptos and normal fiat currencies.

3.3 Null Values

At certain dates in the gathered data, the sites extracted null values as the platform did not have sufficient information. In the thesis, these days will be deleted and the measures will be calculated omitting the "null-days".

Chapter 4

Literature Review

4.1 A Statistical Risk Assessment of Bitcoin

The main inspiration behind this study was a paper written by Jörg Osterrieder and Julian Lorenz, named "A Statistical Risk Assessment of Bitcoin (Osterrieder & Lorenz 2017). The paper takes a deep dive into the tail ends of Bitcoin from the early years and discusses its volatile price movement. The data used by Osterrieder and Lorenz was also gathered from Quandl, however this is data from the early stages of Bitcoin's life cycle.

The paper is quite outdated as the crypto market has evolved hugely since 2016. Therefore, this thesis aims to re-check and analyze the crypto market in its current form. Throughout this thesis, a few new decisions were made. First off, instead of using the dollar returns to calculate volatility and derived data sets, the observations from the original data sets were turned into DPCs to give a better idea of the relative profit/loss every day. Secondly, this dissertation puts more focus on the investor's risk tolerance, as this is very important to how the assets are evaluated in a personal real-life context. Lastly, this dissertation will take a closer look at the EVA distributions to understand and assess the best fit.

Chapter 5

Theory / Method

5.1 Tail Risk Assessment

The concept of risk is based on uncertainty and the consequences this uncertainty brings after a triggering action/event. It can be described using the following risk description:

$$\textit{Risk description} : (A', C', Q, K) \tag{5.1}$$

where **A'** is the specified event, **C'** is the consequences given the specified event, **Q** is the probability of said event happening (this also includes the *Strength of Knowledge* (SoK)) and K is the knowledge based off data (Aven 2019)

Strength of Knowledge

Strength of Knowledge, abbreviated to SoK, tells how trustworthy and valid a piece of information is. Essentially, the source is evaluated to determine if it is reliable. The credibility of a source is very important in analyses like the ones performed in this dissertation (Aven 2019). (More on this under **Data**).

5.1.1 Extreme Value Analysis

The study of extreme values is based on the premise that extremely negative and extremely positive consequences can happen. It can be argued that in some cases,

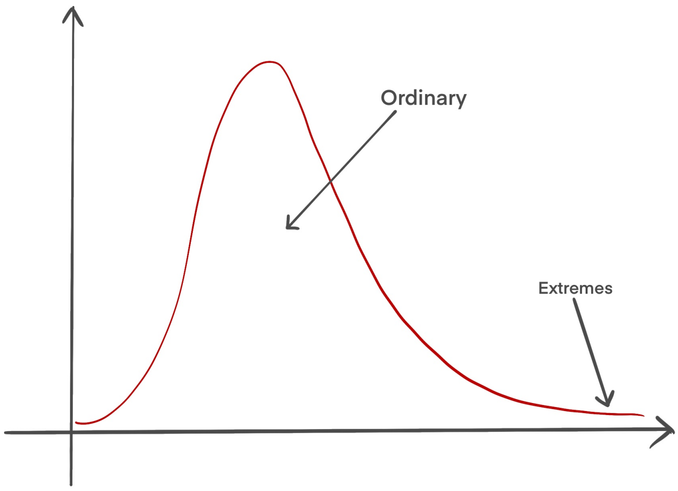

Figure 5.1: Extreme values on a distribution (made in ProCreate)

these extremes are too rare to be assessed, but the impact of the consequence is the motivation for extreme value analysis (Huang 2014).

As shown in figure 5.1, the extremes are located on the tail end of a distribution. This is why the thesis is focusing on tail behaviour of the selected cryptocurrencies. The left-tail signals the negative returns on a portfolio while the right-tail signals the positive returns. For the sake of this dissertation, the focus will be on the left tail, which signifies the losses.

Volatility

Simply put, the volatility is how an asset/market deviates from its mean price over time (Kennon 2020). Investors use different indexes to describe volatility. Calculating volatility is done by predetermining a time frame. The price from each day is collected and the mean price is calculated. Using the mean price, the deviation can be calculated by finding the difference between mean price and price for given day. The deviation is then squared, this results in the variance. The sum of the variances for each day in the selected time frame divided by the number of observed days results in the volatility (Kuepper & Westfall 2021).

$$Volatility = \sum Variance \div Number\ of\ Observations \tag{5.2}$$

The above formula presents the volatility as a deviation in currency. However, when dealing with stocks and crypto, it is much more interesting to look at volatility as a percentage. Firstly, the daily % change (DPC) is calculated by this formula:

$$Daily\ \%\ Change = \frac{Today's\ Price - Yesterday's\ Price}{Yesterday's\ Price} * 100 \tag{5.3}$$

Now, the variance is found using the DPC values and substituted into the volatility formula. This results in a percentage volatility for the given time frame.

Clustering & Risk Tolerance

Clustering, or cluster analysis is the process of discovering naturally clustered data. This is often done through machine learning, where a program will go through a data set and analyze the values. With predetermined clusters, the analysis can help to see how often specific values are observed. The information is useful to see patterns in the data set. For the sake of this thesis, the clustering will be used to see number of observations that exceed a predetermined limit (Brownlee 2020).

This is slightly different to the way cluster analyses are generally done. However, to take risk tolerance into account, a new approach to clustering was made. In this thesis, a predetermined risk tolerance level is chosen and all observations exceeding the chosen levels are categorized in separate bands/clusters (the chosen risk tolerances and visual representation of this is shown in chapter 6.3.2). This way the risk tolerance of different investors can be taken into account when performing an EVA. For the sake of this dissertation, a risk tolerance level of 5% was chosen (more on this in chapter 6.3.2).

5.1.2 Distributions

In the subject of extreme value theory, the two main distributions are: (1) the generalized Pareto distribution and (2) the generalized extreme value distribution. Both of which are used to characterize the tail end of a distribution.

Generalized Pareto Distribution

The generalized Pareto distribution (GPD) is a distribution used to model the tail ends of another, separate distribution. As an example, the GPD is used for a more complex look at the tail end of a distribution, which the original distribution cannot provide (MathWorks 2021*b*). In this case, the normal distribution fit on the daily % averages will close to accurately represent the central part of observations, however, with extreme cases (tail events), a GPD is optimal. A selection of the biggest negative returns is collected to create a histogram. The GPD is then fitted using MatLAB.

Generalized Extreme Value Distribution

The Generalized Extreme Value distribution (GEVD) focuses on the maximum or minimum value in a large set of observations. In this case, the largest negative observations are collected from each month. These observations are called block maxima and are modelled using the GEVD (MathWorks 2021*a*). In this case, the block maxima is found by collecting the largest negative daily % changes, which will allow for a GEVD to be fitted, again using MatLAB.

5.1.3 Theorems

In this section, a couple of important theorems will be explained, which are relevant background for the distributions used to solve the research questions at hand.

Pickands-Balkema-de Haan

Known as the second theorem in extreme value theory, the Pickands-Balkema-de Haan theorem puts its focus on observations over a threshold. This theorem is usually combined with the GPD. The theorem states that the GPD can be used to understand a set of independent and identically-distributed random variables (i.i.d) $(X_1, X_2, ...X_n)$ with conditional excess distribution function F_u, F_u (Balkema & Haan 1974) (Pickands 1975). This GPD is given by:

$$F_u(y) \to G_{k,\sigma}(y), \text{ as } u \to \infty \tag{5.4}$$

where $G_{k,\sigma}(y)$ depends on the value of k.

- if $k \neq 0$ then $G_{k,\sigma}(y) = 1 - (1 + ky/\sigma)^{-1/k}$
- if $k = 0$ then $G_{k,\sigma}(y) = 1 - e^{-y/\sigma}$

Fisher-Tippet-Gnedenko

Again, like the previous theorem, given a set of i.i.d $(X_1, X_2, ...X_n)$ with the cumulative distribution function F, one sequence of real numbers $a_n > 0$ and another sequence of real numbers $b_n \in R$ so that:

$$\lim_{n\to\infty} P\left(\frac{\max\{X_1,\ldots,X_n\} - b_n}{a_n} \leq x\right) = G(x) \tag{5.5}$$

also equal to:

$$\lim_{n\to\infty} F^n\left(a_n x + b_n\right) = G(x) \tag{5.6}$$

$G(x)$ is part of the Gumbel, Fréchet or Weibull family (which make up the GEVD) (Charpentier 2012).

5.1.4 Value-at-Risk

Value-at-Risk, abbreviated to VaR, is a risk measure meant to calculate the financial risk an entity is undertaking by investing in an asset (Kenton & Estevez 2021). The VaR can be calculated using different methods, this thesis will use (1) the historical method and (2) the Variance-Covariance method.

Historical simulation

The historical simulation method of calculating VaR depends on having a normally distributed set of observations. It takes the historical data of an asset, using it to predetermine possible VaR in the future. The advantage to this method is the simplicity of calculation, however, if the market experiences a significant change it reacts slower (NorthStarRisk 2021). Calculating the daily % changes, they can be normally distributed. With this distribution, the VaR at a given percentile can be calculated by this equation (FinanceTrain 2021):

$$VaR_{1-\alpha} = \mu(R) - R_\alpha \tag{5.7}$$

For the sake of this thesis, a significance level(α) of 0.05 has been chosen.

Variance-Covariance Method

Given a normal distribution, the variance-covariance method can be used to determine the VaR at a chosen significance level using this equation:

$$VaR_{1-\alpha} = \mu + \sigma * q(1 - \alpha) \tag{5.8}$$

where: α is the significance level, μ is the average return, σ is the standard deviation and q is the standard distribution quantile.

5.1.5 Expected Shortfall

The expected shortfall (ES), also referred to as the conditional value at risk (CVaR), is another risk measure. Different to the VaR, the CVaR is used for a conservative look at the possible negative returns. It goes beyond the VaR and is generally more suited towards volatile investments (Chen 2020). The expected shortfall is calculated by:

$$ES_{1-\alpha} = \mu(Observations \geq VaR_{1-\alpha}) \tag{5.9}$$

(This is the historical ES (Barrailler & Dufour 2014), and will be the only ES calculated in this thesis).

Chapter 6

Results

6.1 Pre Calculation

6.1.1 Time frame

The 4 assets are observed over different time frames, but all of them end at the same date. Daily data is collected for Bitcoin, Doge and NOK in the time period 01.01.2015 to 01.04.2021 (DD.MM.YYYY) and Ethereum in the time frame 01.01.2016 to 01.04.2021.

6.1.2 Price choice

With every data set, a selection of different prices are given for any observed day:

Open Market opening price

High Highest sell price

Close Market close price

Low Lowest sell price

There are different use cases for each price, but for the calculations from this thesis, the closing price is the optimal choice. This gives the price at the end of each day, thus presenting the price the market closed at that day.

Asset	Min	Max
BTC / USD	-39.14044339	27.96857603
ETH / USD	-42.34722148	35.54435493
DOGE / USD	-40.25698656	275.6431701
NOK / USD	-34.22263821	39.34915707
Limit	-42.34722148	275.6431701
Exchange	ETH / USD	DOGE / USD

Figure 6.1: Min. & Max. DPC for each asset (calculated using Excel)

6.2 Volatility

The aim of calculating volatility is to get an insight on the assets price movement. Before calculating the tail-risk, it is important to know whether or not a tail-risk assessment is necessary. High volatility normally signals higher tail activity and can justify a tail-risk assessment (extreme value analysis).

6.2.1 Daily % Change

The daily % change was calculated using Excel and presented in columns, showing the change for each day of return. To assess every asset up against each other, the percentage change was chosen to give a better understanding of the change, rather than calculating the volatility using the return prices. As explained in chapter 5, the daily percentage change is a more accurate value, compared to the daily price difference. In fig. 6.1, the minimum and maximum DPC for each asset is shown, together with the absolute maximum and minimum.

From figure 6.1, there are a couple notes that have to be explained. Firstly, the NOK/USD exchange seems to have quite large min. and max. values. Due to the stock market crash of 2020, the chart has some difficulty in representing the correct information. The stock market crash was quickly corrected after the initial surge (as shown in fig. 6.2) (Amadeo & Mansa 2021). As shown later in this thesis, these values do not represent the NOK/USD exchange very well. Secondly, all three crypto assets have similar minimum DPC, however the maximum does vary

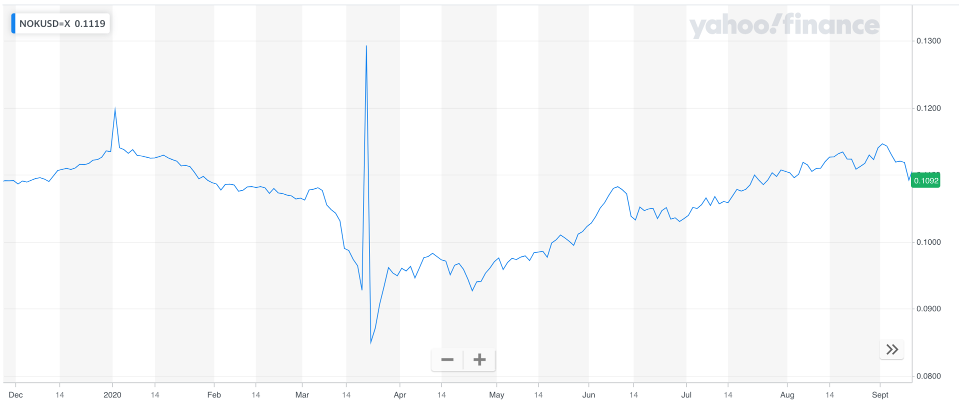

Figure 6.2: Correction in the NOK/USD exchange after the 2020 stock market crash. (Yahoo! Finance Price Chart)

Year	BTC / USD	ETH / USD	DOGE / USD	NOK / USD
2021	102.657219	170.7235342	990.343008	-10.474056
2020	302.557786	464.0612488	130.300049	-2.0332779
2019	92.4061113	-7.959525495	-15.217391	-5.1676713
2018	**-72.549272**	**-82.73865126**	**-73.667078**	-5.7752107
2017	**1319.79463**	**9159.424771**	**3835.08772**	**4.65276879**
2016	122.022529	740.6010818	44.8051948	3.14122212
2015	35.8026253	*No Data*	-17.486339	**-15.139365**

Figure 6.3: Min. & Max. YPC for each asset (calculated using Excel).

a significant amount.

6.2.2 Yearly % Change

To get a broader view of the returns, the yearly % change was calculated as well. In fig. 6.3 the results are shown. It is clear that the YPC is significantly larger for the crypto assets, further justifying that the crypto assets contain more investment risk, therefore also more tail-risk.

6.2.3 Volatility

Using the DPCs, the volatility is then calculated. The results of these calculations are shown in fig. 6.4.

As predicted, the three crypto exchanges have significantly higher volatility com-

Asset	Volatility
BTC / USD	15.2586507
ETH / USD	35.3247111
DOGE / USD	80.2120736
NOK / USD	2.40755066

Figure 6.4: Volatility of each asset over the time-frame (calculated using Excel).

pared to the FIAT currency. BTC is over **6** times as volatile as NOK, ETH is over **14** times as volatile as NOK and DOGE is over **33** times as volatile as NOK. By definition, higher volatility entails higher risk, and higher risk generally suggests more tail-movement. Showcasing the high volatility of the crypto assets, one of the justification criteria for an EVA is met.

6.3 Charts & Clusters

Plotting the DPCs onto a chart, the difference between the assets become apparent. Using the values, a band chart can be generated for further justification of a tail-risk assessment.

6.3.1 Charts

The charts are created using Excel with a top limit of 100% and a bottom limit of -50%. Following, the chart is shown in fig. 6.5 with all 4 assets over the given time-frame.
Visually, it becomes clear that NOK is much more matured with lower daily change across the time-frame. The crypto market (with respect to these 3 assets) has clearly not matured, with high extreme DPC-movement.

6.3.2 Bands (Clusters)

Using the NOK/USD exchange as a baseline (based on its much more mature and reliable price changes), the bands/cluster areas can be pre-determined. As men-

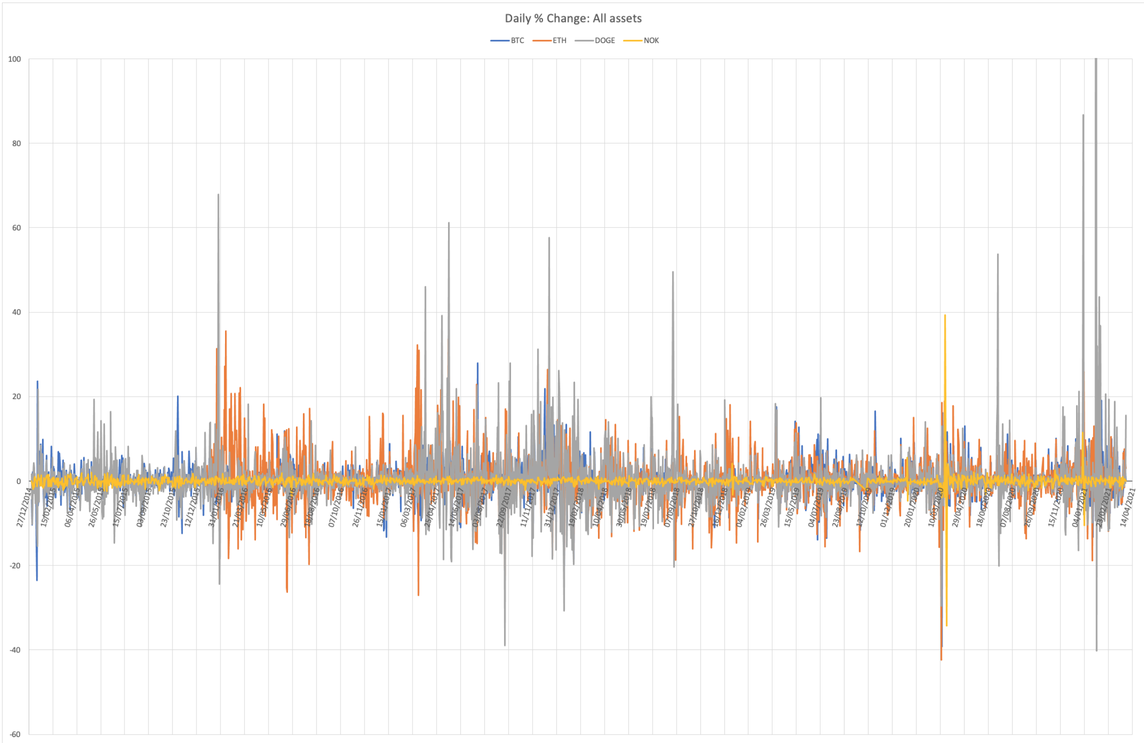

Figure 6.5: DPC Chart for all 4 assets (Excel).

tioned earlier, the risk tolerance was predetermined to be 5%. This creates the first band, stretching from -5% to +5% and signifies *LOW RISK*. Calculating the rest of the bands is simple, using 5% as standard deviation, the second band stretches up and down to ±10% and is marked as *MEDIUM RISK*. Continuing, the next band stretches up and down to ±15% and is marked as *HIGH RISK*. Lastly, everything over and under ±15% becomes *EXTREME EVENTS*. This is visually represented in fig. 6.6.

Notes

The assumptions in the previous subchapter are subject to personalized risk. Risk is a big topic, and the amount of risk an individual is willing to take is dependent on risk tolerance. Therefore, the risk bands were generated with the author's risk tolerance in mind. The idea and concept behind it is still the same and applicable to everyone. As mentioned, crypto is a much more volatile market than that of normal FIAT currencies (such as NOK, USD, YEN etc.) which results in higher acceptable DPC.

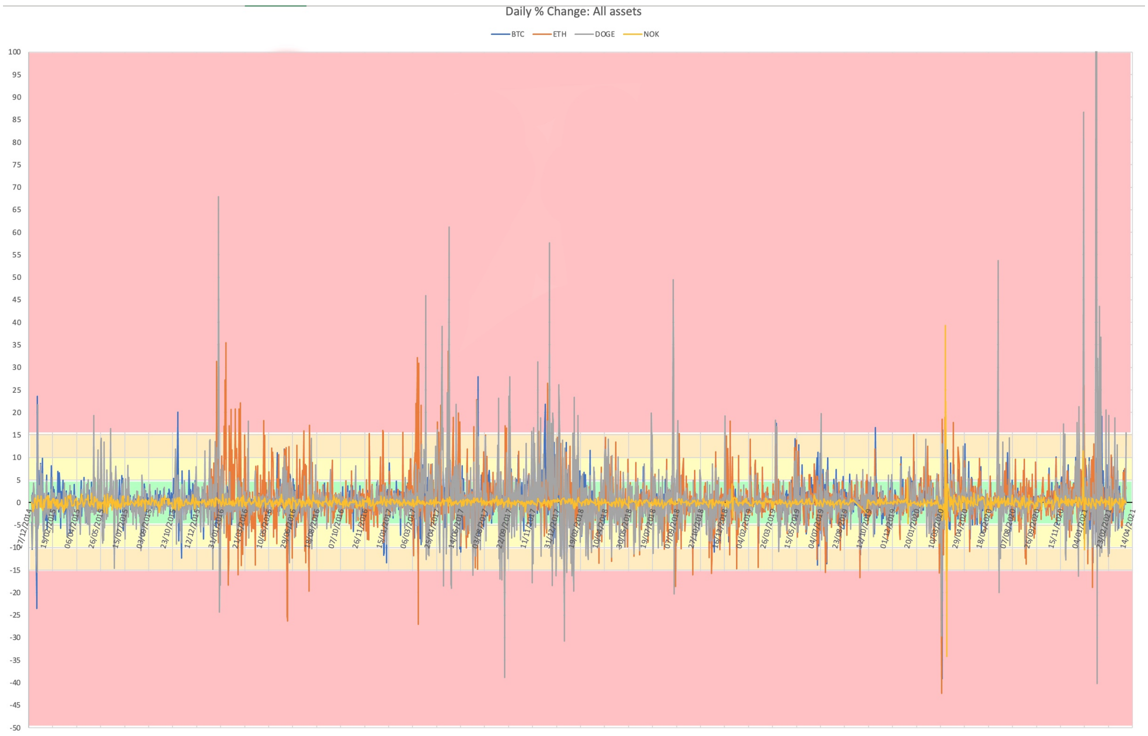

Figure 6.6: Full band chart for all 4 assets (Excel).

This method of calculating overruns was made for the sake of this thesis and gives a better result when taking into account an individual investor's own risk tolerance. Arguably, this would be the optimal way to move as every investor looks at losses with a different perspective and are ultimately the ones who are directly affected.

6.3.3 Plotting the band chart

Observing the band chart (fig. 6.6), the NOK/USD exchange performs extremely well in the *LOW RISK* band, only breaking out of it in very few occasions (will touch more on this under **Chapter 6.3.4: Overruns**). The three crypto assets however can be seen breaking out of *LOW RISK* quite frequently, and in many occasions it hits the *HIGH RISK* and *EXTREME EVENT* bands.

6.3.4 Overruns

With this thesis' focus being the tail-risk of investing in crypto, a negative threshold of -10% is chosen as it signals the start of the negative *HIGH RISK* band. Essentially, every DPC classified as a negative *HIGH RISK* change or a negative *EXTREME EVENT* change is counted (using Excel's COUNT-IF command) and marked as an overrun of the chosen threshold:

BTC 30 overruns

ETH 55 overruns

DOGE 73 overruns

NOK 2 overruns

Clearly, NOK shows its maturity and low risk capabilities from this calculation. Further evaluation shows that, through the calculations done up till this point, BTC is the most mature and stable crypto out of the chosen three, with ETH following after and DOGE being the least stable and highest risk asset. The calculations give a solid foundation to the oncoming extreme value analysis, while it also shows the current risk of investing in crypto.

6.3.5 Comparing to normal distribution fit

The best justification for an extreme value analysis is showing the data sets with a normal distribution fit. Using the distribution fitter in MATLAB, the resulting charts are shown in figures 6.7, 6.8, 6.9 and 6.10 (these can also be seen in higher detail appendix A).

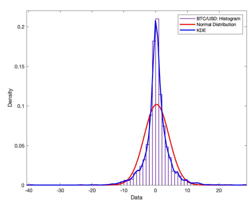

Figure 6.7: BTC with Normal Distribution and KDE

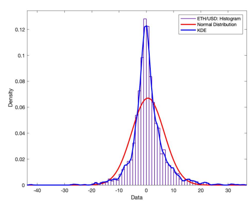

Figure 6.8: ETH with Normal Distribution and KDE

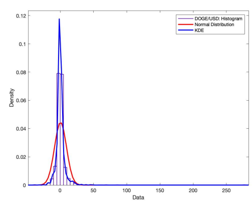

Figure 6.9: DOGE with Normal Distribution and KDE

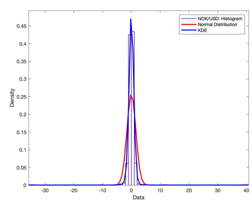

Figure 6.10: NOK with Normal Distribution and KDE

The normal distributions are shown in red, and don't have an accurate fit on any of the assets. Especially around the tails of the histograms, the normal distributions show a significant lack of fitment. For this thesis, the focus is on the left-tail, the one depicting the lowest returns. By sorting the data sets from lowest to highest DPCs, a new data set can be derived with the 200 lowest returns, with their correct dates.

6.4 Extreme Value Analysis

The tails were tested using both a generalized Pareto distribution and a generalized extreme value distribution (which are both described in chapter 5: Theory). The distributions are fitted onto the new data sets of the lowest 200 returns from each asset. Again, this is done by using the distribution fitter from MATLAB. The results from the EVA are used to show the predictability and risk of investing in crypto. Both the GPD and the GEVD are fitted to evaluate and assess which of the two fits that has the most accurate prediction.

6.4.1 Generalized Pareto Distribution

For the sake of the distribution fitter from MATLAB, the data set of the lowest 200 returns is inversed, so that the returns are positive. However, this is still counted as DPC loss. For all the assets, both the density plots and probability plots are recorded.

Density plots for GPD

The density plots show a much better tail-fit, compared to that of the normal distribution (more on this in summary). These can be seen in fig. 6.11, 6.12, 6.13 and 6.14, and also in better detail in appendix B.

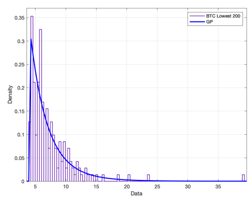

Figure 6.11: BTC with GP fit

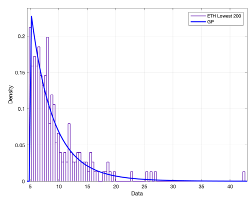

Figure 6.12: ETH with GP fit

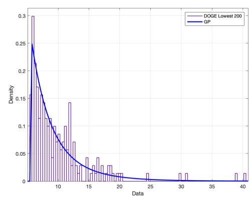

Figure 6.13: DOGE with GP fit

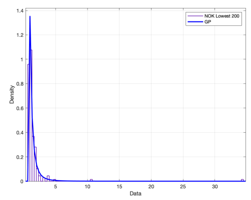

Figure 6.14: NOK with GP fit

It is very clear that the density of lower risk returns is much higher for NOK (closer to x = 0), compared to all the crypto assets. This is significant and shows that the crypto assets are indeed risky with very large deviations. The crypto assets have a higher density of returns spanning across the x-axis, which shows the higher risk. The x-axis shows the DPC, the higher it is, the bigger loss the asset has experienced. The y-axis shows the density at given DPC.

Probability plots for GPD

Probability plots can be used to predict the future. The better fit a probability plot has to a data set, the more accurate it is when it predicts future outcome. The probability plots for the GPD can be seen in fig. 6.15, 6.16, 6.17 and 6.18 (fitted using MatLAB).

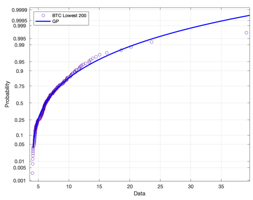

Figure 6.15: BTC Probability plot with GP fit

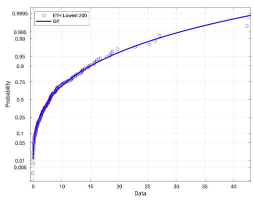

Figure 6.16: ETH Probability plot with GP fit

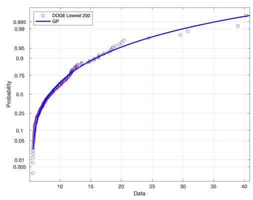

Figure 6.17: DOGE Probability plot with GP fit

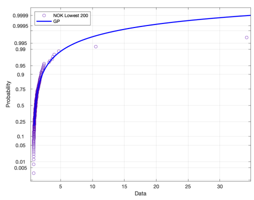

Figure 6.18: NOK Probability plot with GP fit

An extensive look into the fit of the GPD in regards to probability plots will be discussed later.

6.4.2 Generalized Extreme Value Distribution

Again, using the distribution fitter from MATLAB, the GEVD can be fitted to the same derived data sets. Since both the GPD and the GEVD are distributions used in EVA to model the tail of a data set, the GEVD is fitted to look for similarities or a potentially more accurate fit (compared to the GPD fit).

Density plot for GEVD

Visually, the difference between the GPD fit and the GEVD fit can be noticed by looking at the curved top. It seems to have a less accurate fit around the higher density area, close to $x = 0$, but has a slightly better fit as x moves up. The density plots for each asset can be seen in fig. 6.19, 6.20, 6.21 and 6.22 (fitted using MatLAB & the charts can be seen in higher detail in appendix D).

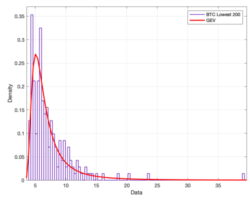

Figure 6.19: BTC with GEV fit

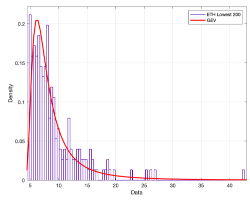

Figure 6.20: ETH with GEV fit

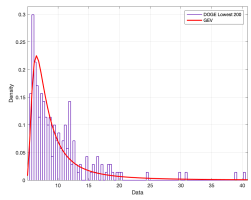

Figure 6.21: DOGE with GEV fit

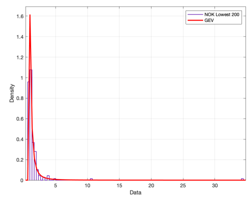

Figure 6.22: NOK with GEV fit

Again, like the GPD fit, the density plots show much higher accuracy in predicting the returns compared to the normal distribution. It also shows the same tendencies on how much riskier the crypto assets are compared to the FIAT currency of NOK.

Probability plots for GEVD

The same applies for GEVD, the probability plots are used to understand the future outcome of investing in the assets (fitted using MatLAB).

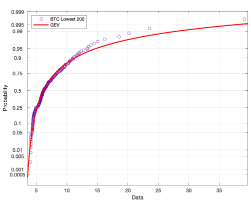

Figure 6.23: BTC Probability plot with GEV fit

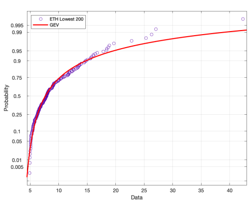

Figure 6.24: ETH Probability plot with GEV fit

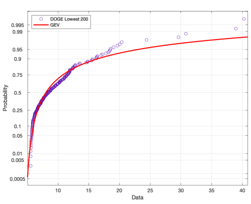

Figure 6.25: DOGE Probability plot with GEV fit

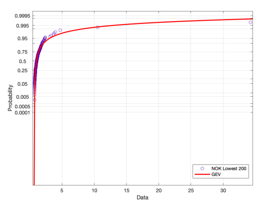

Figure 6.26: NOK Probability plot with GEV fit

This will also be discussed in more detail in the following sub chapter.

6.4.3 GPD vs. GEVD: Comparison & Summary

For the sake of simplicity, only the combined charts from the BTC/USD exchange are shown. The full charts can be viewed in appendices F and G, but the main takes apply for every crypto asset.

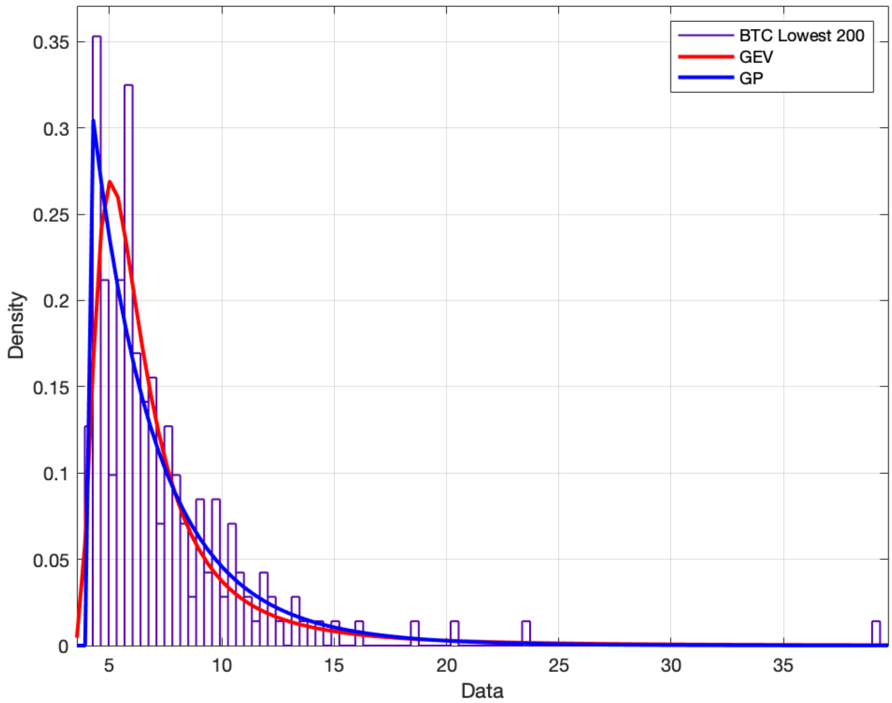

Figure 6.27: BTC combined density plot (fitted using MatLAB's distribution fitter).

Combined density plot

Fitting both the GPD and GEVD to the data set can be used to understand which EVA distribution might have the better fit and use case for these assets. The combined density plot can be seen in fig. 6.27.

Looking at the chart, starting from $x = 0$ and moving towards $x = \infty$, the GP fit (in blue) seems to have a closer approximation of the actual data set at the top. Moving into the area between ca. 5% and 10%, the GEV fit seems to be more accurate. From that point onwards, it seems as GP is the better fit. These results were consistent with each asset. The importance of both these fits is clear. Having a good understanding of the area between 5% and 10% could be considered the most important area to understand as most of the density lies in this area. It is also worth noting that the risk is correlated to the area created by the distribution fits and the x-axis. The larger the area, the higher the risk of the asset.

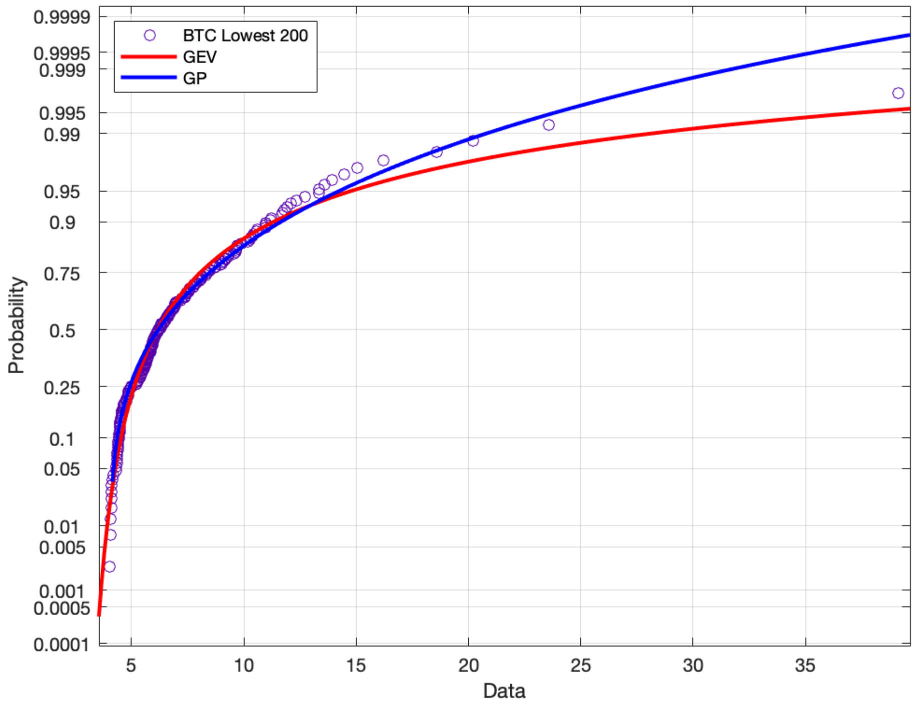

Figure 6.28: BTC combined probability plot (fitted using MatLAB's distribution fitter).

Combined probability plot

The probability plot is used to see how well a data set fits the distribution. It is often used to get an understanding of future outcomes by showing how often returns have been over or under the given distribution fit. This means that, the more accurate a fit is, the better it will theoretically perform in the future.

Close to $x = 0$, both fits seems to perform almost equally, but once it reaches 10% there is a split between the fits. The returns between 10% and 15% seem to be slightly higher than what both the fits predict, however the GP fit is the closest one. The GP fit continues to be more accurate in 15% through 25%. The GEVD finally takes over, being closer to the extreme value furthest out. Determining the best fit however should be done considering the highest density area, which from the probability plot, clearly is 0% to 15% where the GP fit seems to be a closer match.

Summary

Closing this sub chapter; both the fits seem to have their strong suits. The GPD fit seem to cover a bigger portion of the returns with more accuracy compared to the GEVD fit, while the GEVD fit seems to be closer to predict the more extreme returns. This will also be discussed more in the conclusion of this thesis.

6.5 Value-at-Risk & Expected Shortfall

To prevent investing with high risk potential, it is important to know what the value at risk is. This is a well-known risk measure, used to calculate how much an investor can risk to lose when investing in a specific asset. The expected shortfall, which is more optimal for tail-end analysis, could be argued as an even better risk measure for this thesis. Especially as it is sensitive to the more extreme returns. Both the VaR and ES can be calculated in various methods. For the sake of this thesis, a historical VaR, a variance-covariance VaR and a historical ES is calculated.

6.5.1 Value-at-Risk

For the calculations of VaR and ES, the derived data set with the 200 largest losses is utilized once again. The percentile is determined as the 95-percentile (using the predetermined significance level of 5%).

Historical VaR

At the 95-percentile, the historical VaR is shown in fig. 6.29
The historical VaRs of each asset shows very clearly that NOK has a much lower value at risk. The safest crypto is Bitcoin, which has a VaR, nearly 6 times higher than NOK.

Variance-Covariance method (V-C method)

To utilize the V-C method, the mean and std. error from each asset has to be gathered from the distribution fitter used earlier in chapter 6.4: Extreme Value

Asset	Historical VaR
Bitcoin	6.5746
Ethereum	10.3252
Dogecoin	10.1161
Norwegian kroner	1.1282

Figure 6.29: Historical VaR for all assets (calculated using MatLAB and Excel).

Asset	V-C VaR
Bitcoin	7.9644
Ethereum	12.2272
Dogecoin	18.0894
Norwegian kroner	3.0458

Figure 6.30: Variance-Covariance VaR for all assets (calculated using MatLAB and Excel)

Analysis. The full results from the distribution fitter can be found in appendix H. Using the V-C method, the V-C VaRs are calculated and presented in fig. 6.30. The VaR calculated using the V-C method shows higher values. These could be more accurate, however the V-C method relies on the data to be normally distributed. Since this is the case, the historical VaR is more appropriate.

6.5.2 Expected Shortfall

Since this thesis puts its focus on tail-risk and extreme value analysis. The expected shortfall measure is more optimal. Using the historical VaR from the previous section, the historical ES can be found. Taking the loss-returns that are bigger than the historical VaR, the 95-percentile of these new derived data sets result in the ES. This can be seen in fig. 6.31.
The V-C method is not used to calculate the ES, mainly because the V-C method relies on the data to be normally distributed. However, working with the tail end, it is known that these values are not normally distributed, making the V-C method

Asset	Historical ES
Bitcoin	9.971998
Ethereum	15.23357388
Dogecoin	14.694019
Norwegian kroner	2.1433656

Figure 6.31: Historical ES for all assets (calculated using MatLAB and Excel).

appear inaccurate. Comparing the historical VaR and historical ES, the ES is significantly higher.

6.5.3 Summary

From the values found as the historical VaRs, it is concluded that when an investor invests into these assets, they can predict to lose about 6.60% on BTC, 10.3% on ETH, 10.1% on DOGE and 1.13% on NOK every single day. However, when taking into account the expected shortfall, an investor should know that they can expect to lose as much as 9.97% on BTC, 15.2% on ETH, 14.7% on DOGE and 2.14% on NOK every single day.

It is worth noting that ETH appears to hold more invesment risk than Doge, even though the previous part of this thesis could suggest otherwise.

Chapter 7

Future

From the previous chapter, it is apparent that the crypto assets hold significant risk and uncertainty. Investing can lead to large profits, but also end in non-manageable loss. The whole market of cryptocurrencies is very new, which in return means that it has nowhere near matured enough for an investor to be confidently investing large amounts of money. In this chapter, a few topics will be discussed regarding the future of this market.

7.1 On-Chain Analysis

For this thesis it was chosen to focus on historical price charts as main data sets. However, a very unique way of interpreting data for the crypto market, is on-chain analysis. Since cryptocurrencies are built on blockchains, the data is stored on a public ledger that everyone has access to. With this comes a lot of opportunities to research, analyze and understand the market. A few examples are: wallet analysis, relative unrealized profit/loss, etc. which take information stored on this public ledger to understand who and how much is invested in the market. For a future thesis, this could be the foundation for interpreting data.

7.2 Future Plans

The crypto assets that were proposed in this thesis are all very new in the grand scheme of technology. As the whole market is now built on evolving projects, the external price drivers may very well vary as the teams behind these projects decide to work extensively on them. In this section of the chapter, a few of the big upcoming plans will be discussed to see if it will have a significant impact on the future price.

7.2.1 Bitcoin

Early 2020 it became apparent that Bitcoin's main goal of replacing the normal FIAT currencies was not possible. At this point in time, most investors and even the team behind the crypto have settled on the idea that Bitcoin is more of a store of value instead of an actual currency with real life use case (Binance 2021). Many organisations and businesses have tried to implement Bitcoin as a way of payment for their products, with Tesla's Elon Musk being the most notable of them. As of writing this thesis, major changes have been introduced in the relationship between Tesla and Bitcoin, with Elon Musk stating that Tesla is looking for another cryptocurrency to pursue as a viable payment method. This was a result of Bitcoin's high energy usage for mining and keeping the blockchain fully secure. Bitcoin is still the largest cryptocurrency with respect to market cap, but the price is most likely not going to be driven by technological advancement, but instead by sheer store of value capability and market dominance.

7.2.2 Ethereum

For Ethereum, the recent years have been very exciting. Unlike Bitcoin, Ethereum's goal was never to create a cryptocurrency that would replace FIAT currencies. Instead, the idea was to be part of the movement that shape the *new internet*. In the upcoming future, Ethereum's development team has stated that a big update to the network is coming, Ethereum 2. More scalability, faster transaction speeds, less network fees are few of the big updates coming (Ethereum 2021*b*). Considering the updates just mentioned are some of the most difficult aspects of Ethereum and crypto in general, a significant update to these sectors will drive the price of Ethereum to new highs.

Another exciting direction Ethereum has taken is through NFTs (non-fungible tokens). This is quite a broad topic to explain in detail, however very shortly it is a way for individuals to mint their own work on the Ethereum network. As this thesis is written, NFTs are mostly used for digital artwork and digital collectibles, essentially creating a way of certifying that the item is authentic (in digital terms). NFTs are not exclusively an Ethereum-network related idea, however the ETH network has been the most apparent in the NFT space. With the constant buzz and evolution of NFTs, Ethereum has set pace to go very far in the future.

An underlying problem however, with the Ethereum network, is its high network fees (Ethereum 2021*a*). This could be the biggest negative price driver for Ethereum, but as mentioned, if Ethereum 2 gets implemented with the features that the developers are promoting, the whole network is in for a significant positive gain.

There are too many external price drivers to mention, especially considering this is not the main part of this thesis, but the mentioned upgrades are the most significant.

7.2.3 Dogecoin

Up until now, Dogecoin has been one of those cryptocurrencies that don't have a real life use case nor any intention of introducing one. Mid 2021 however, Elon Musk, after announcing Tesla's end of Bitcoin relationship, mentioned, in a tweet, that he was in works with the Dogecoin developers to research the possibility of taking DOGE to the next level. As Tesla and Elon Musk are on the forefront of technology, it pumped the price and could be a determining price driver in the future if the correct implementation is possible. It is worth noting here that Elon Musk has had a significant impact on the crypto market, and being one of the technological leaders in the world, this is significant news. However, the whole story cannot be based solely on a statement made on Twitter and has to be evaluated.

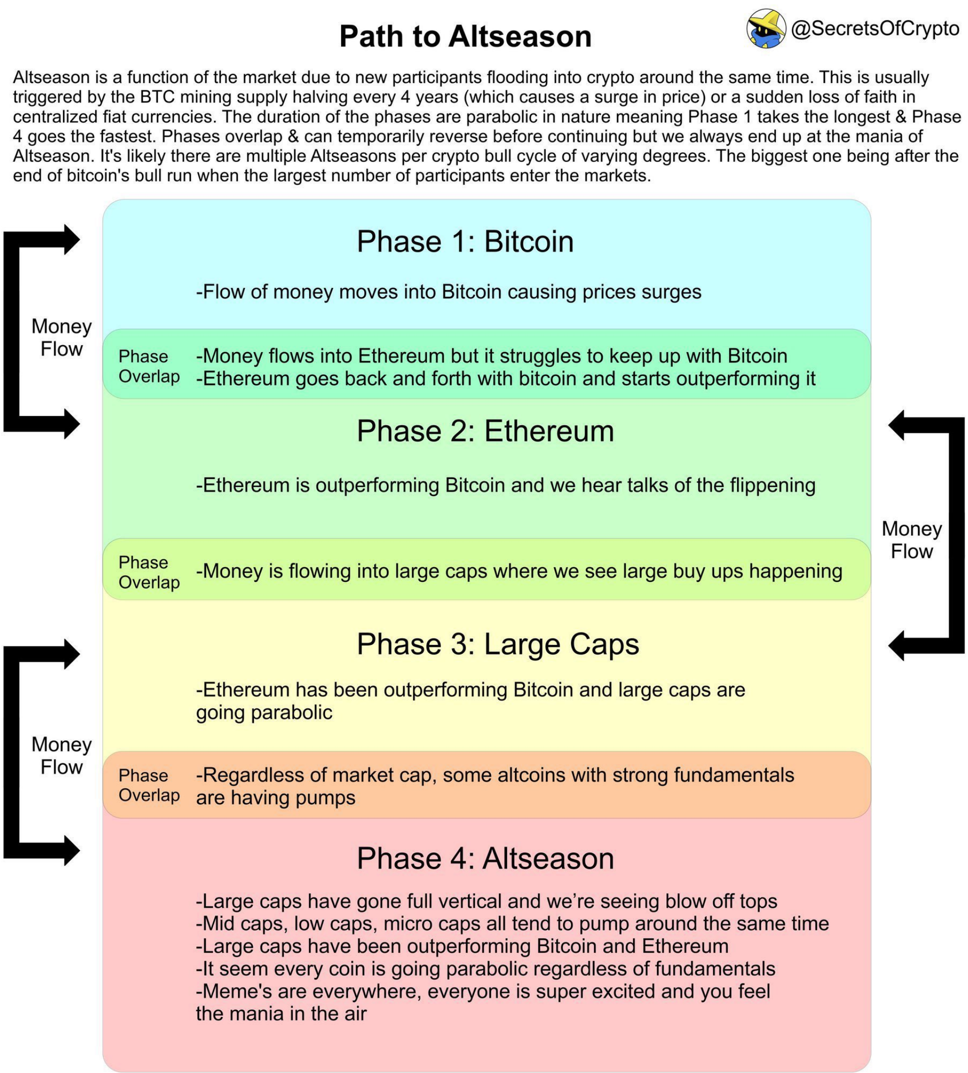

Figure 7.1: Crypto market cycle. (Graphics by Twitter user @SecretsOfCrypto)

7.3 Bear market

Historically, the crypto market has had a reoccurring cycle of events. This is shown in fig. 7.1.

At the end of this cycle (note that the cycle can be repeated a few times before it moves into bear market) the bear market often starts. In the bear market, losses are quite regular and good exit strategy needs to be applied to not lose funds. During the bear market, the VaR and ES will be much higher, as the calculated risk measures in this thesis is based on a big part of the life cycle of these assets. Taking into account that this bull market has been extremely profitable, the market is showing strong bubble tendencies. This could be detrimental for the future price of any of the mentioned assets. To determine the risk in that case is a different approach and not discussed in this thesis.

7.4 Competitors

As the crypto market picks up interest, with more eyes on it, many competitors are entering the market with good projects that have extremely well-made substitutions to the cryptos in this thesis. Bitcoin is challenged by Litecoin (LTC), Hedera Hashgraph (HBAR), etc. Ethereum is challenged by Binance Smart Chain(BNB / BSC), Cardano (ADA), Polygon (MATIC), etc. All of these projects hold good values and could be *the next big thing*. This is why many investors will add them to their portfolios. As for Dogecoin, there is no direct competitor, as DOGE is mainly driven by community interest. However, late Q1 of 2021, a surge of so called "shitcoins" (coins without any real use case, made for community interest) have challenged Dogecoin. Since all of these are community driven and don't offer a real use case, it is hard to predict how much DOGE price will be affected by competition.

7.5 Government, Rules and Regulations

Government intervening with crypto is nothing new. Late 2020, the United States Department of Justice filed a civil action with the goal of forfeiting over one billions USD (United States Dollar). This was based on the suspicion that the forfeited amount was stemming from a illegal, criminal online black market called "Silk Road" (U.SDepartmentOfJustice 2020). Bitcoin and other cryptos have often been under negative press and controversy, stating that the encrypted transactions lead to the possibility to launder money and partake in illegal activity without the money tracing back to the offenders. Countries have gone as far as banning crypto or imposing new regulations to decrease the use of cryptocurrency. Some examples of countries that have regulated the crypto legality are: Canada, China and Russia. As governing bodies start regulating and controlling cryptocurrency, the idea of a decentralized asset slowly fades away. In the long run this could be a deciding factor to the future of cryptocurrency.

7.6 Bitcoin Dominance & Market Change

Even though Bitcoin is losing its grips on the crypto market, it still is deemed the dominant force in the crypto world. In the beginning of 2021 Bitcoin was holding over 70% of the money invested into crypto. Comparing this to the numbers from mid May 2021, we can see how much the Bitcoin dominance has fallen. Holding a little over 40% of the total money invested in crypto, Bitcoin has lost a lot of its market dominance (TradingView 2021*a*). It's apparent that Bitcoin isn't as dominant and that the market is changing. Investors and traders are looking for new projects and funds are directed towards newer, fresher projects.

7.7 Summary

Summed up, there are many exciting factors to consider with cryptocurrency. In 10 years time, it is hard to know if the proposed cryptos will still be as prominent or if competitors will take over, but at this point in time, it is safe to assume that the crypto market is revolutionizing the digital world and the real world.

Chapter 8

Conclusion

Bringing back the research questions **What is the tail risk of investing in cryptocurrency assets compared to NOK and how much can investors expect to lose with respect to their risk tolerance? Is an EVA justified and which EVA distribution provides the best fit?**, this chapter aims to wrap up and conclude based on the calculations and analyses presented earlier in this dissertation.

The first section of this thesis aimed to justify the use of an extreme value analysis. The results clearly show that an EVA is justified. The high volatility was a clear sign that the crypto assets were significantly risky. To justify an EVA, there has to be significant difficulty in estimating the tail of a distribution, using the normal distribution. Comparing the normal distribution fit to the data set, it was apparent that there was very little accuracy. By categorizing the DPCs, the thesis exhibits how often the crypto assets move into the higher risk areas, compared to NOK.

The EVA was successful as both the GP distribution and the GEV distribution indicated much more accurate fits to the tails of the different data sets. From these analyses it was apparent that the area created by the distribution fit, on the density plots, and the x-axis was correlated to the risk. The bigger the area, the higher the risk of investing. This was a new find, which hasn't been discussed in earlier crypto related EVAs, which could be used in the future.

The VaRs and ES calculations confirmed that the crypto assets were much more risky to undertake compared to NOK. From all the analyses the crypto assets can be ranged (from safe to risky): Bitcoin, Dogecoin, Ethereum. This is a result of Ethereum having volatile movement for a longer period than DOGE. DOGE spent a lot of time consolidating, while Ethereum was moving up in price. The expected shortfall is the best risk measure for these assets as they are not yet matured and highly volatile.

8.1 GP or GEV?

An important part of this thesis is settling on one of the fits. If an investor had to pick one of the two fits described in this thesis, the thesis shows that the GP fit would give the best representation of the bigger density area.

8.2 Reflecting

The results of the EVA and the risk measures were expected. However, during research and analyses, it was becoming more apparent how much the crypto market has changed since its beginning. It's hard to know exactly how it will develop in the future, but gathering from all the social buzz and the promising projects and roadmaps, crypto might be the next step in technology. All in all, it feels like it's still early and has a lot of room to grow into. Coming into this thesis, expectations were that the ES of the different assets would be lower, but in reality they are much higher than first anticipated. There is a significant change in results in this thesis, compared to the literature used, which only exhibits the volatilty and immaturity of the crypto market. As an investor it is important to specify risk tolerance before trading cryptos, and it is important to know that, even though there is a lot of profit to be made, there is also a huge external price driver which could crash the market at any day. Managing risk and having a consistent portfolio strategy is therefore very important.

8.3 Recommendations for future research

Based on the results from this thesis, future researchers or writers should focus on external price drivers and competitors. As these two factors might be the major price changers in the future. Calculating for different time frames will also be optimal as the market grows and gets more mature, so long time investors can get better knowledge for price movement over longer periods. This thesis focused on the daily price change, while an analysis with monthly price change could possibly give good results as well.

This thesis has contributed to further understand the crypto market. Which is important as the crypto market has the potential to shape our future. The results from this thesis give a clear understanding of not only how volatile these crypto assets are compared to FIAT currency, but also how immature the market is at this point and the risk in investing in crypto in general. Using this thesis, EVAs can be performed on different crypto assets (even competitors) to determine future price change.

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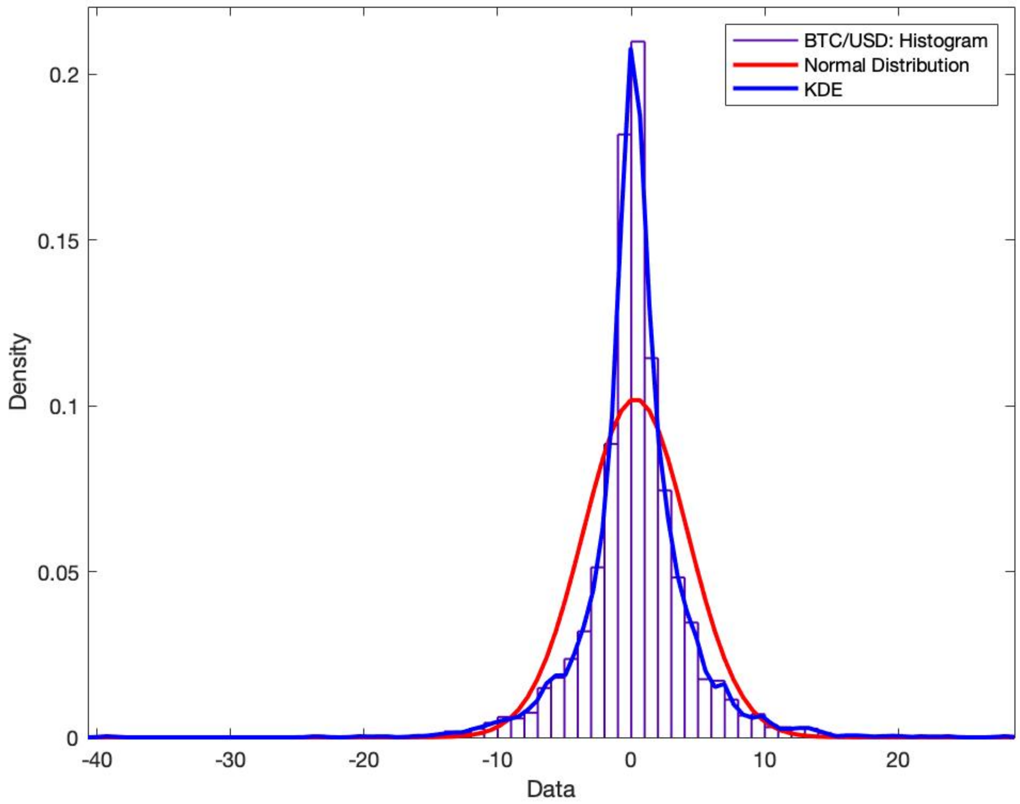
Appendix A

Normal Distribution Fits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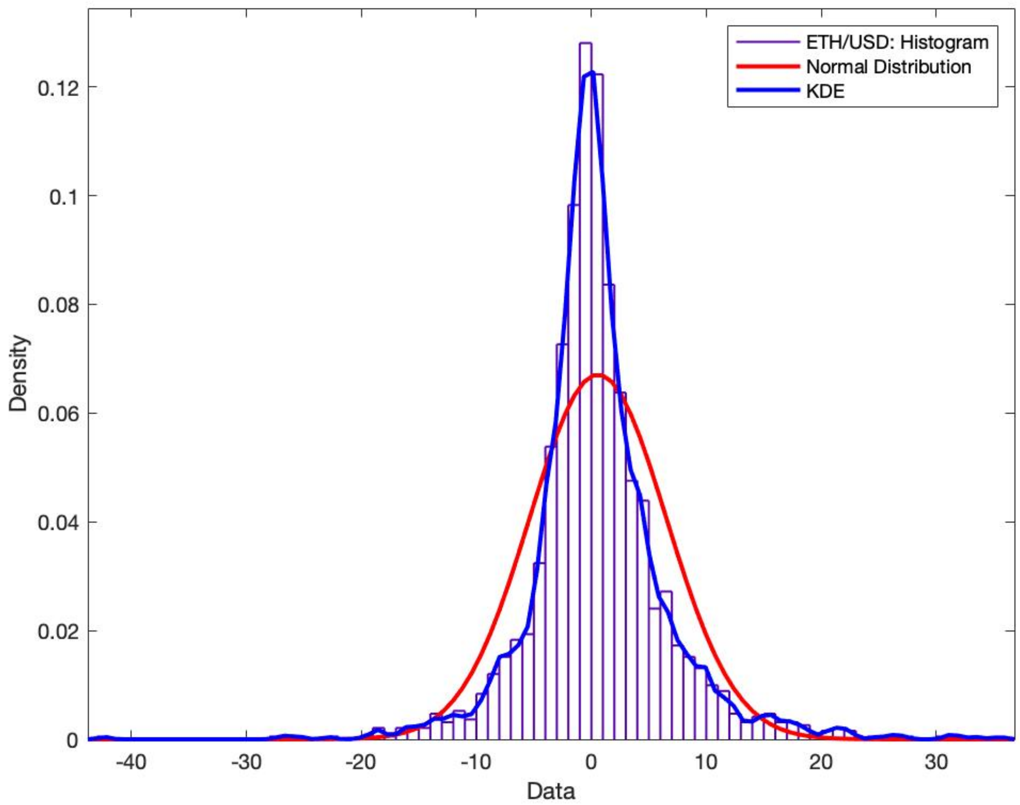
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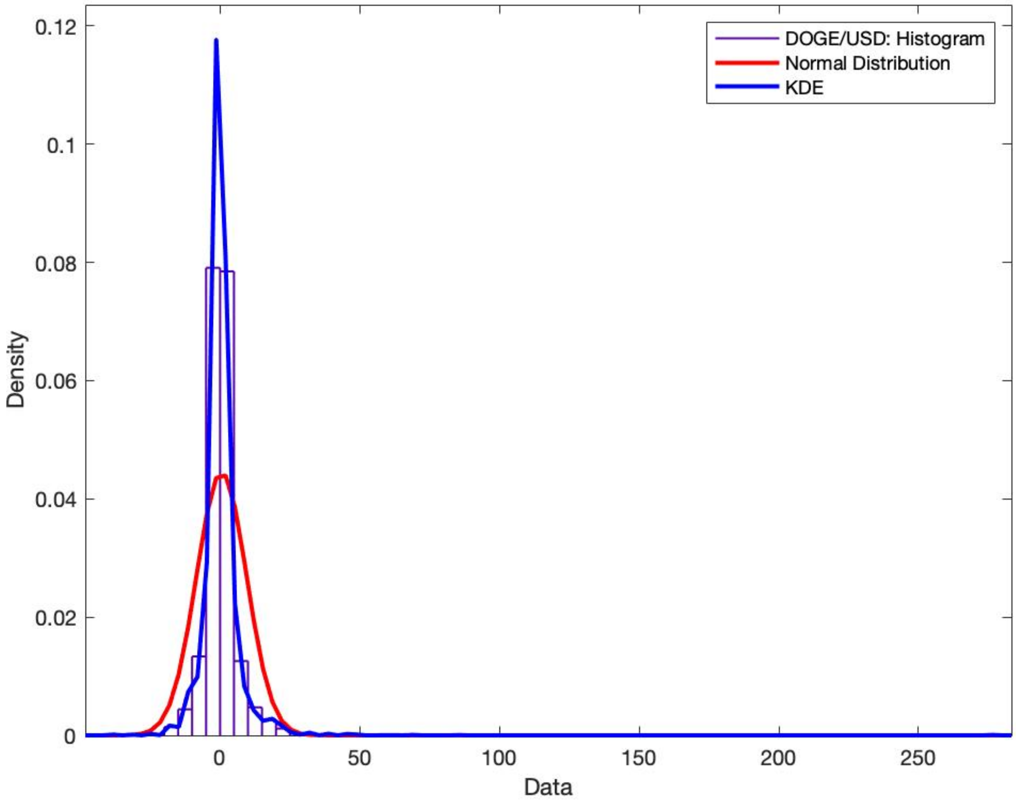
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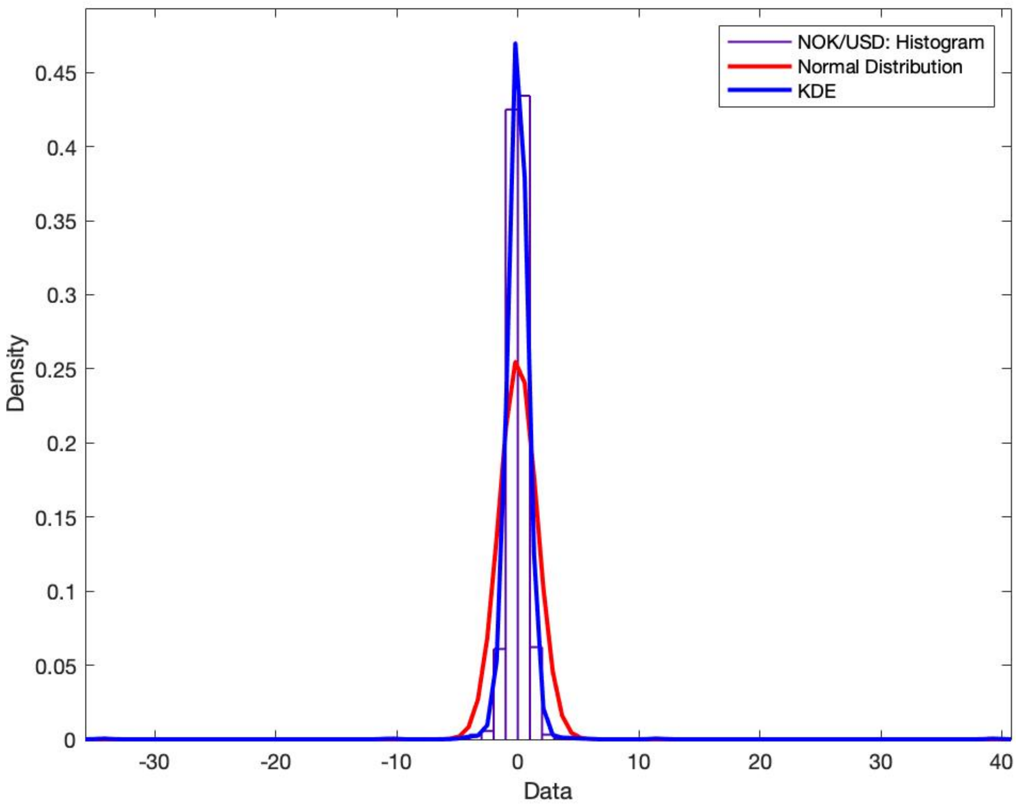
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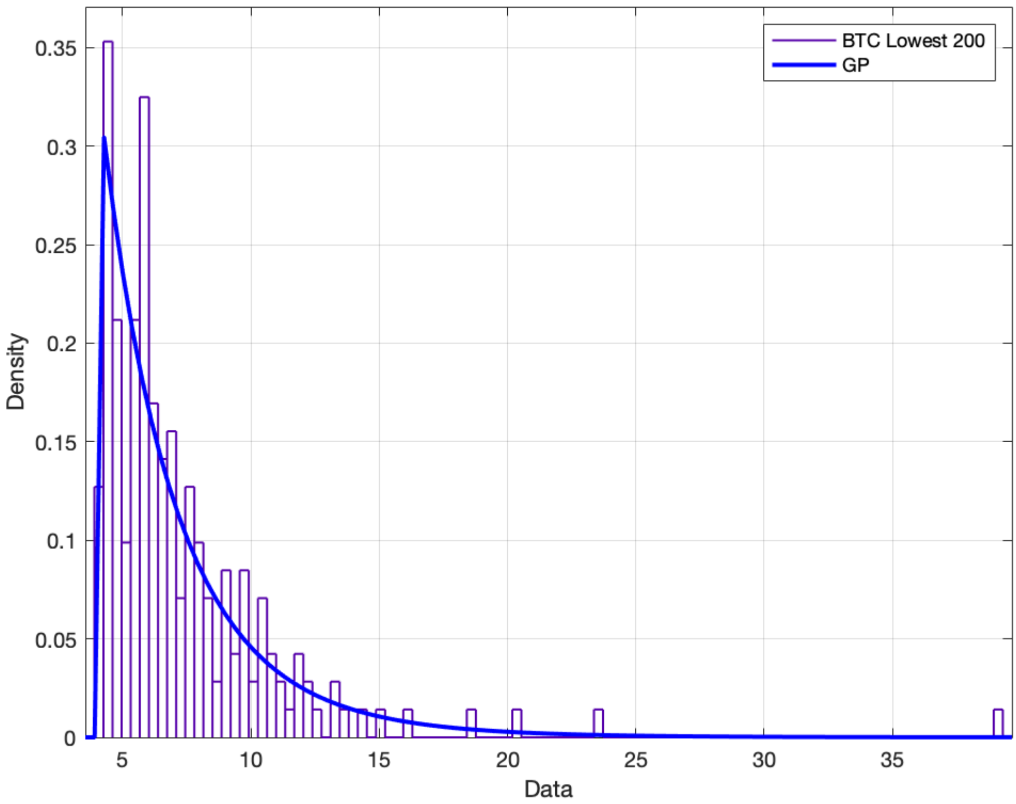
Appendix B

Generalized Pareto fit - Density plot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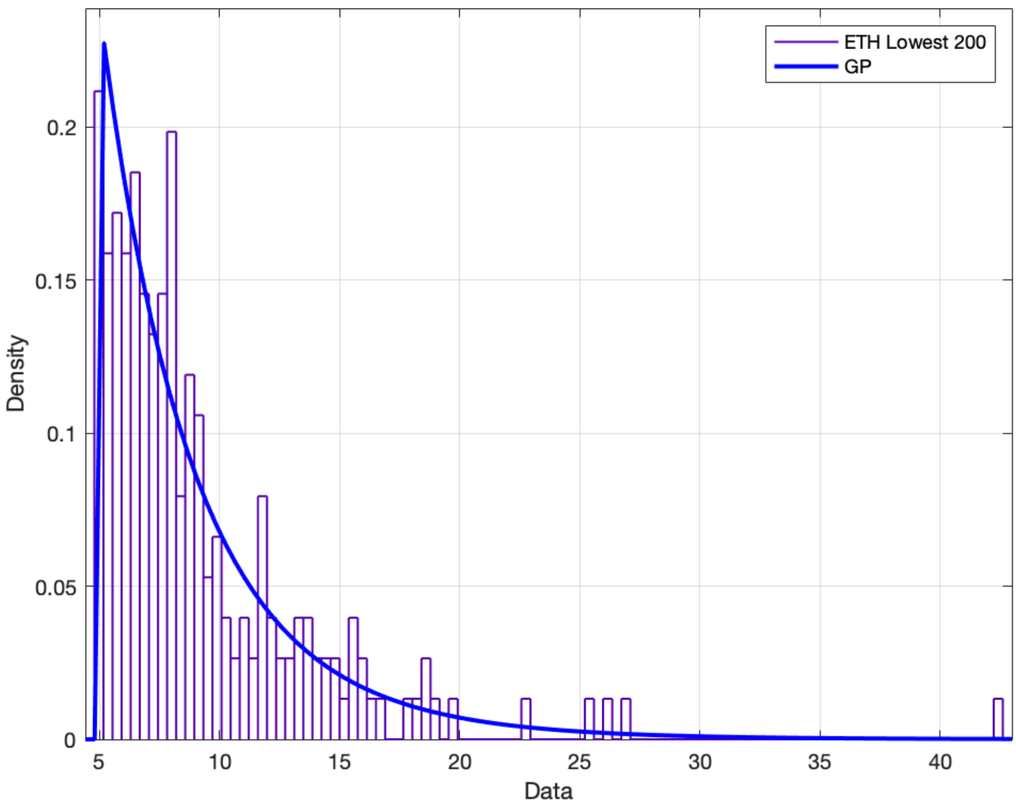
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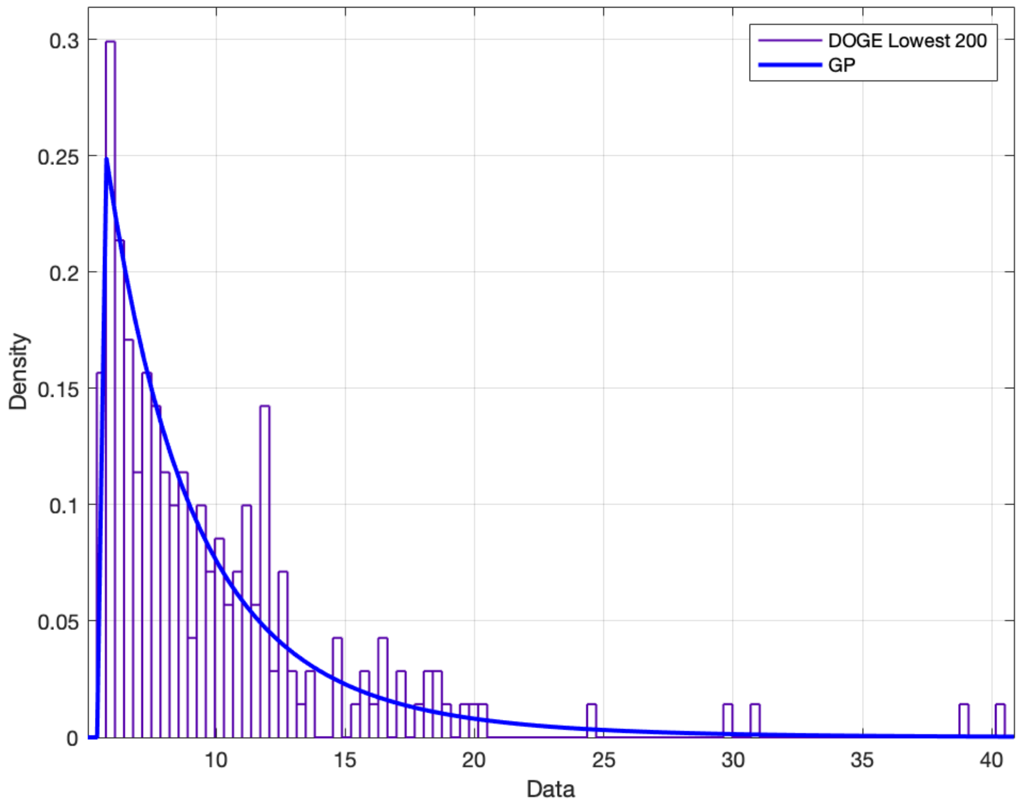
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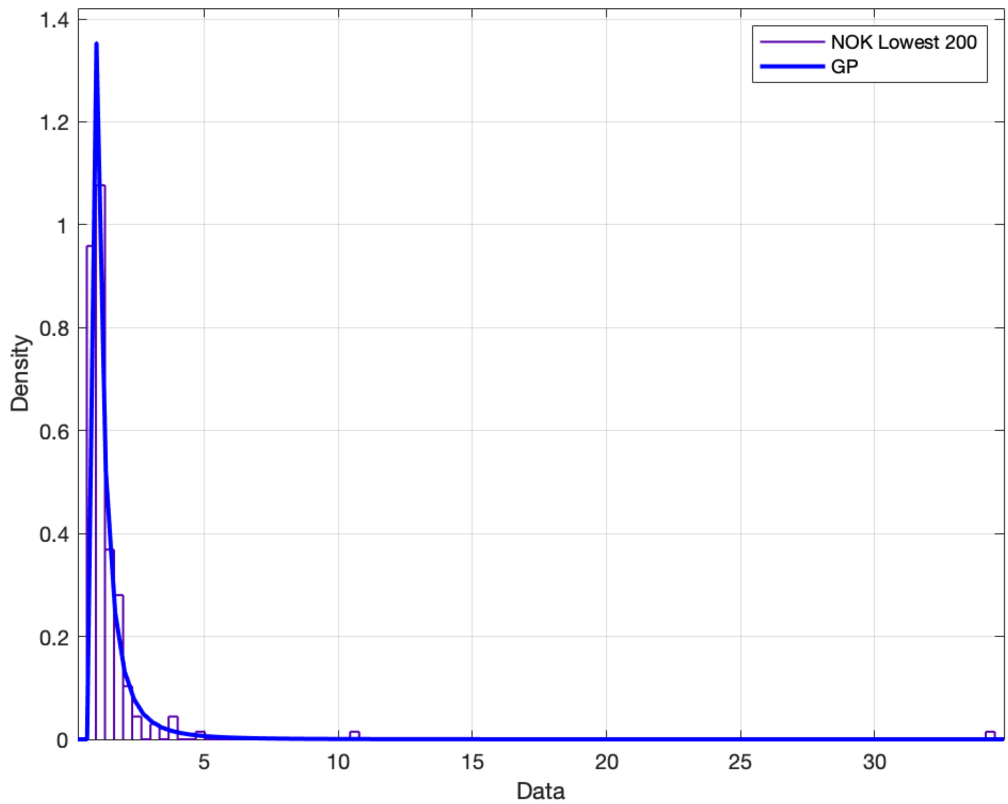
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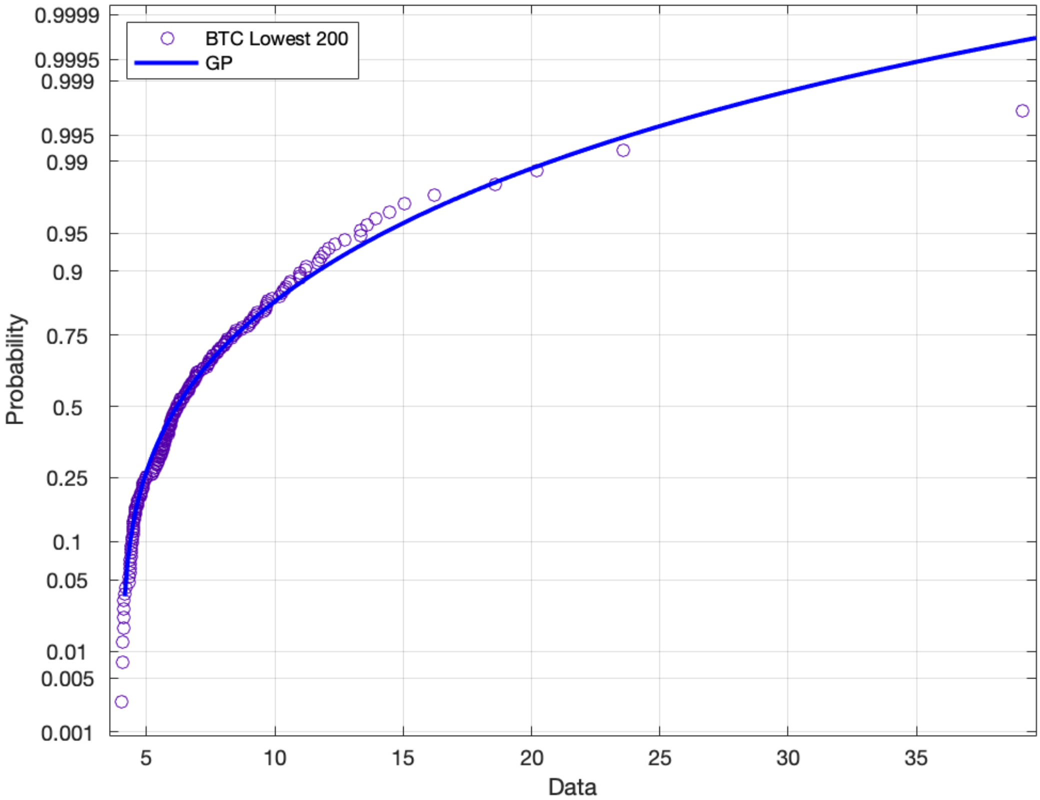
Appendix C

Generalized Pareto fit - Probability plot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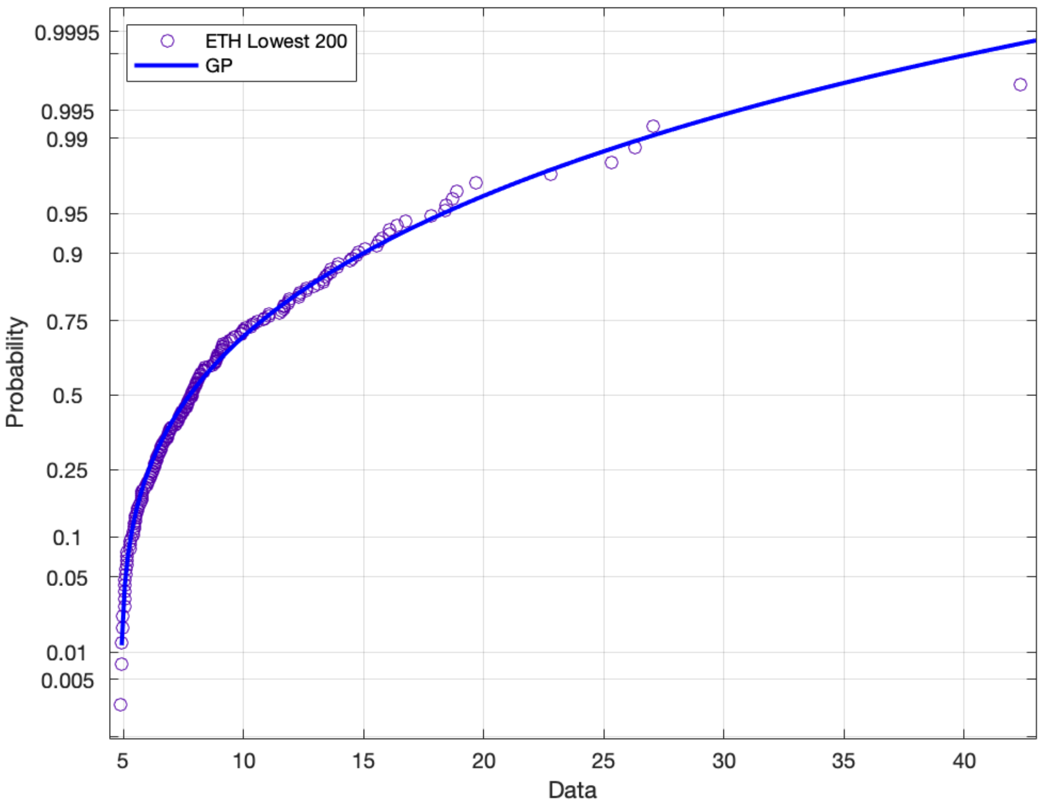
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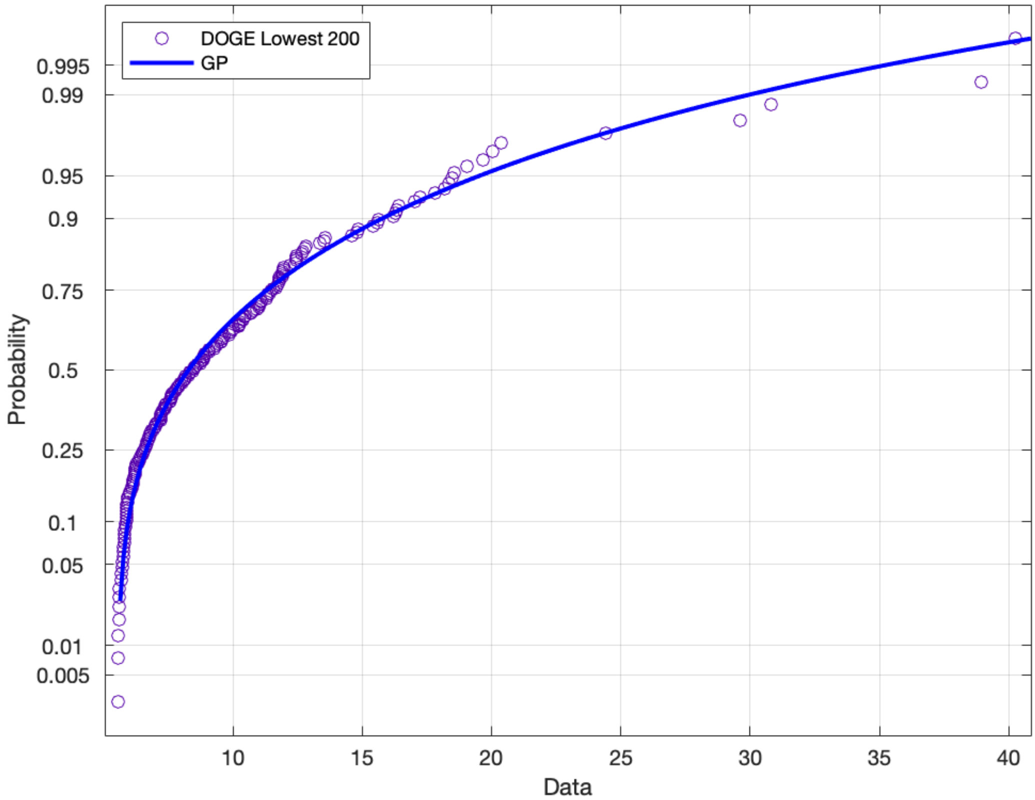
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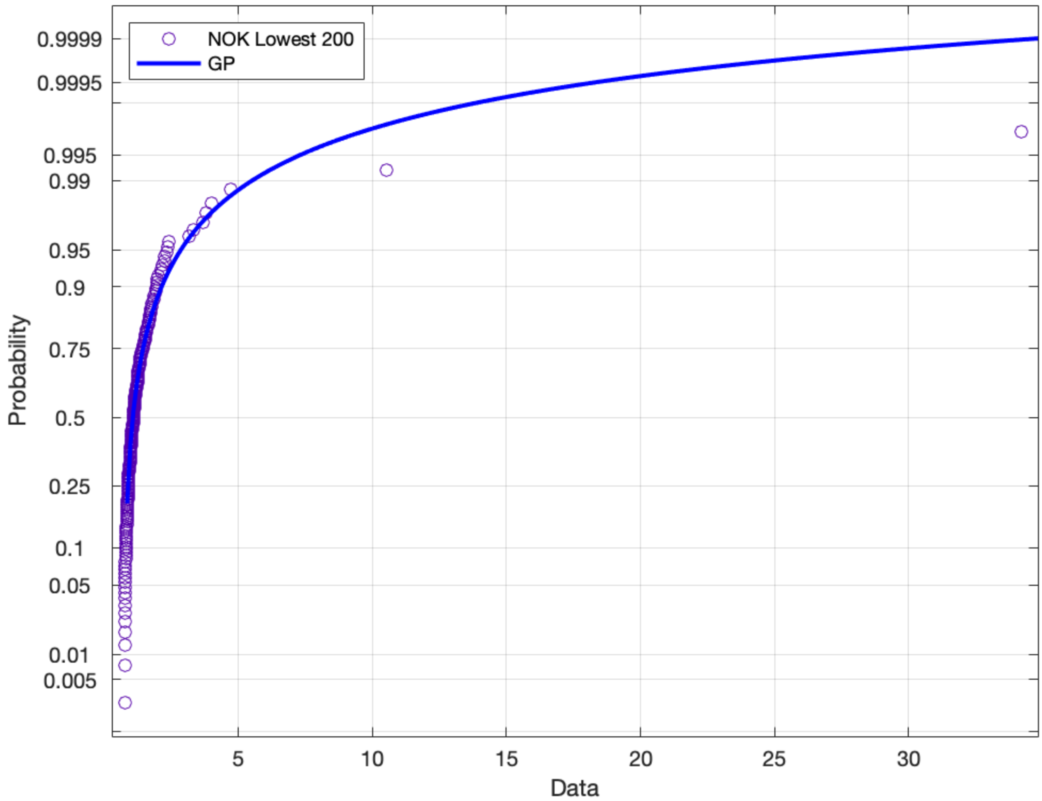
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Probability
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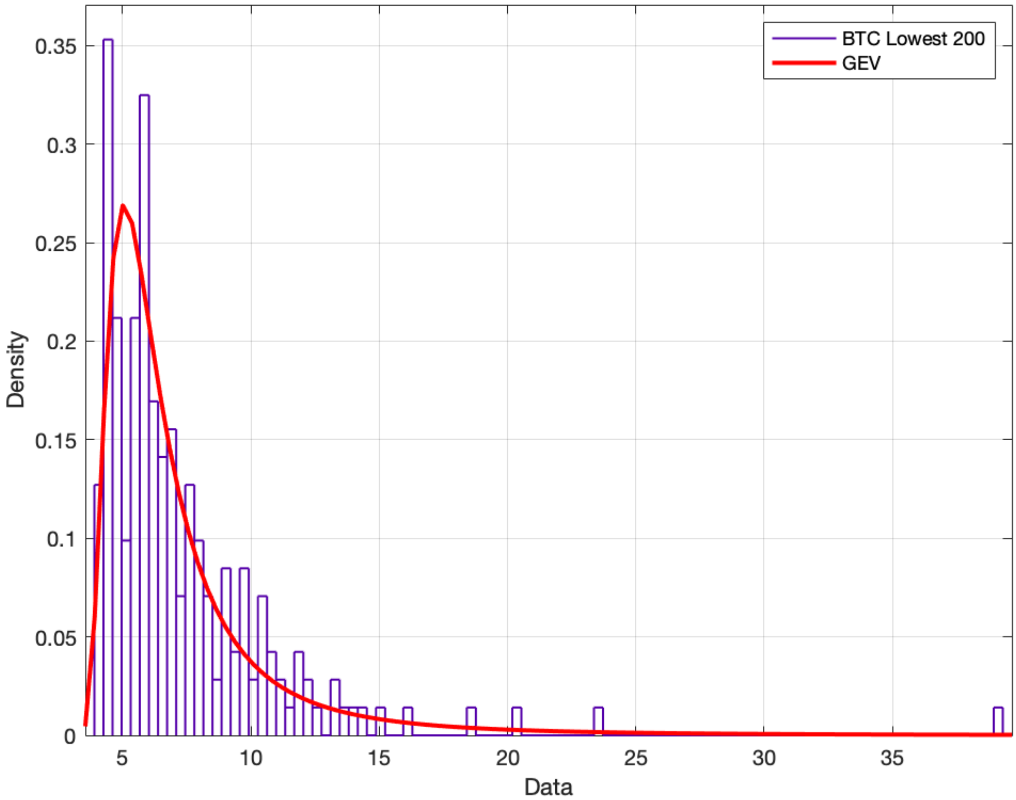
Appendix D

Generalized Extreme Value fit - Density plot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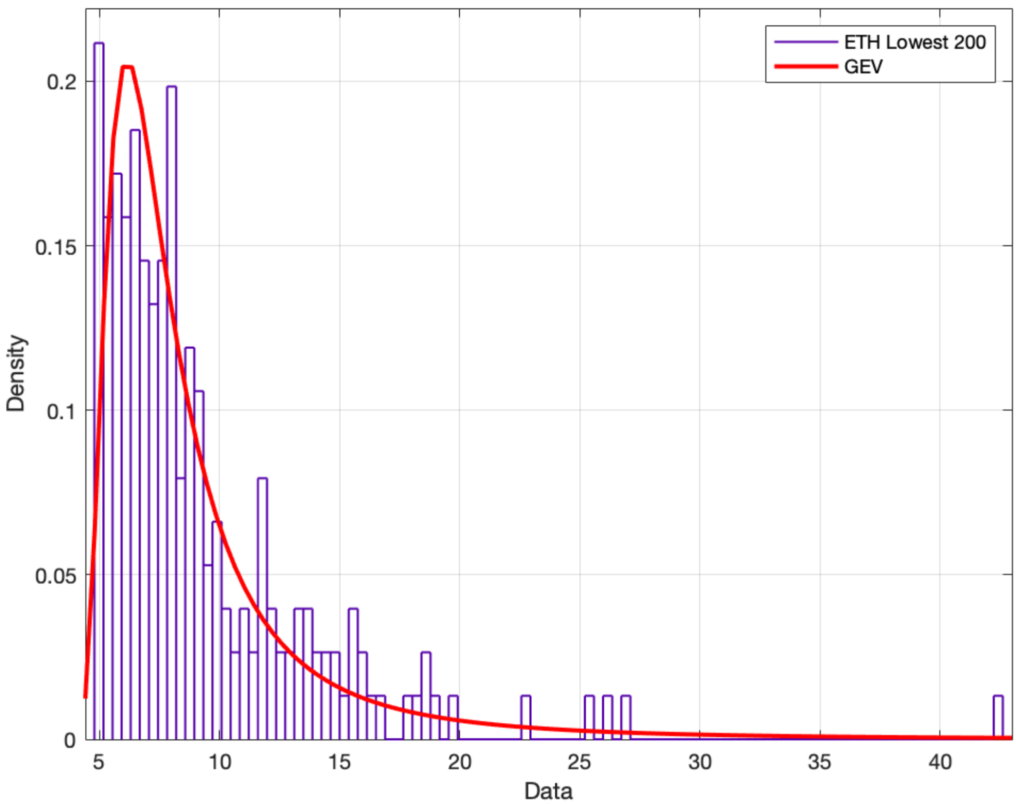
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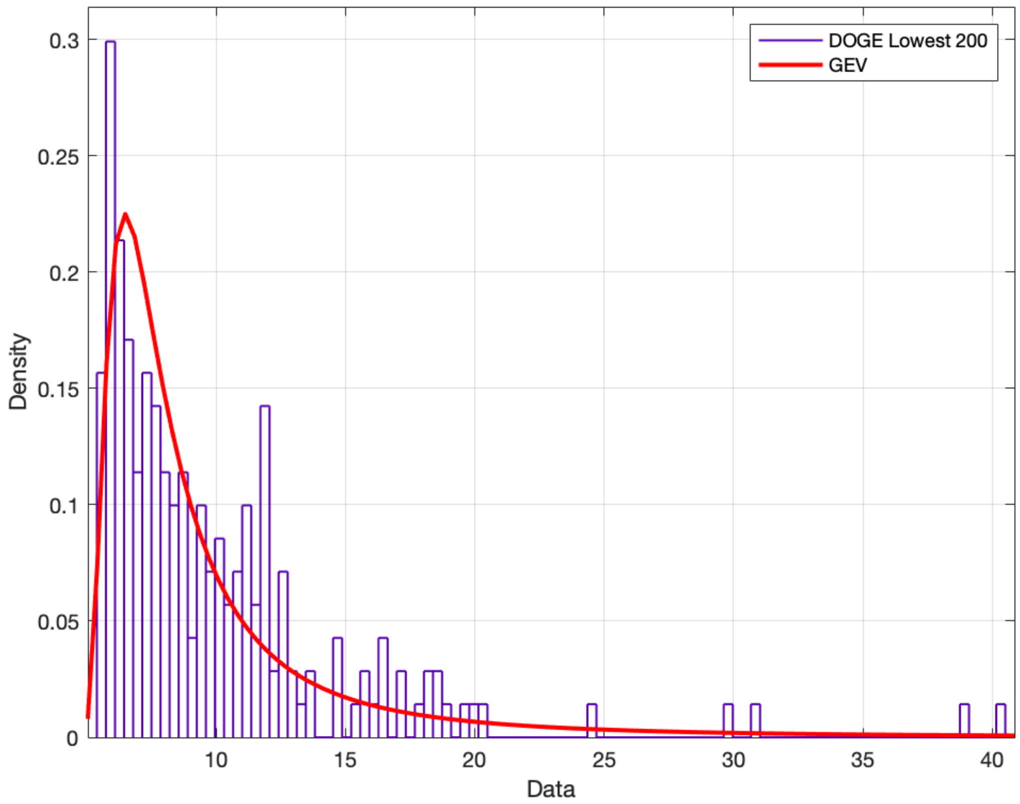
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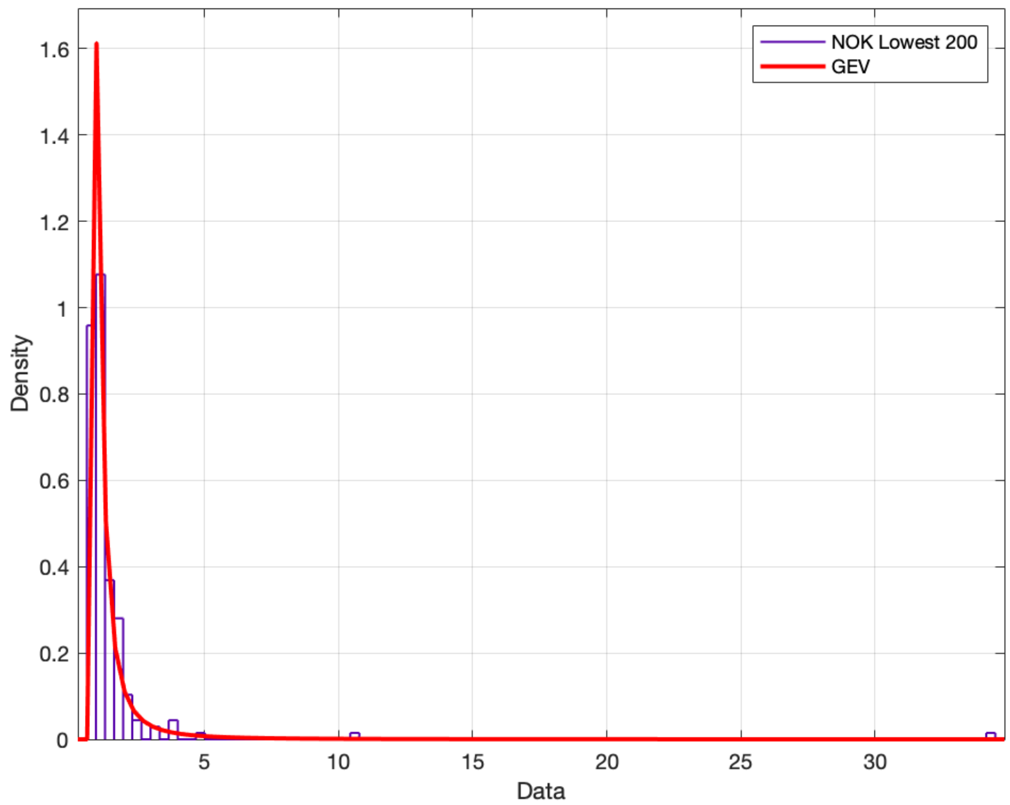
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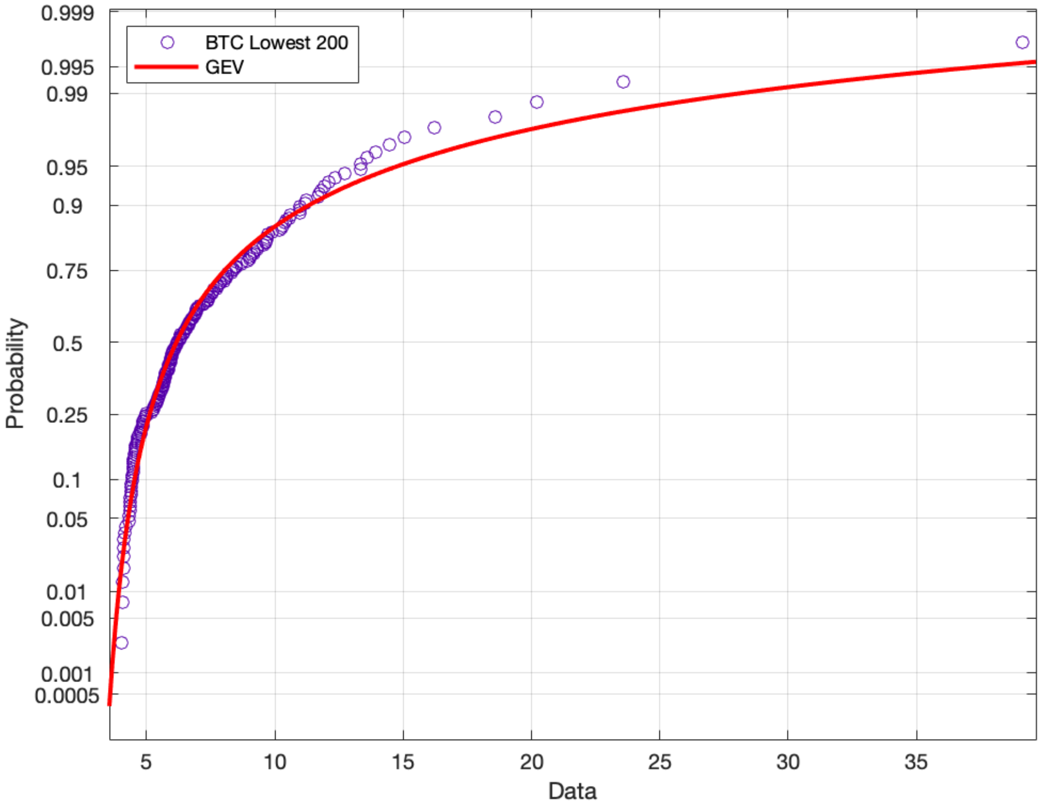
Appendix E

Generalized Pareto fit - Probability plot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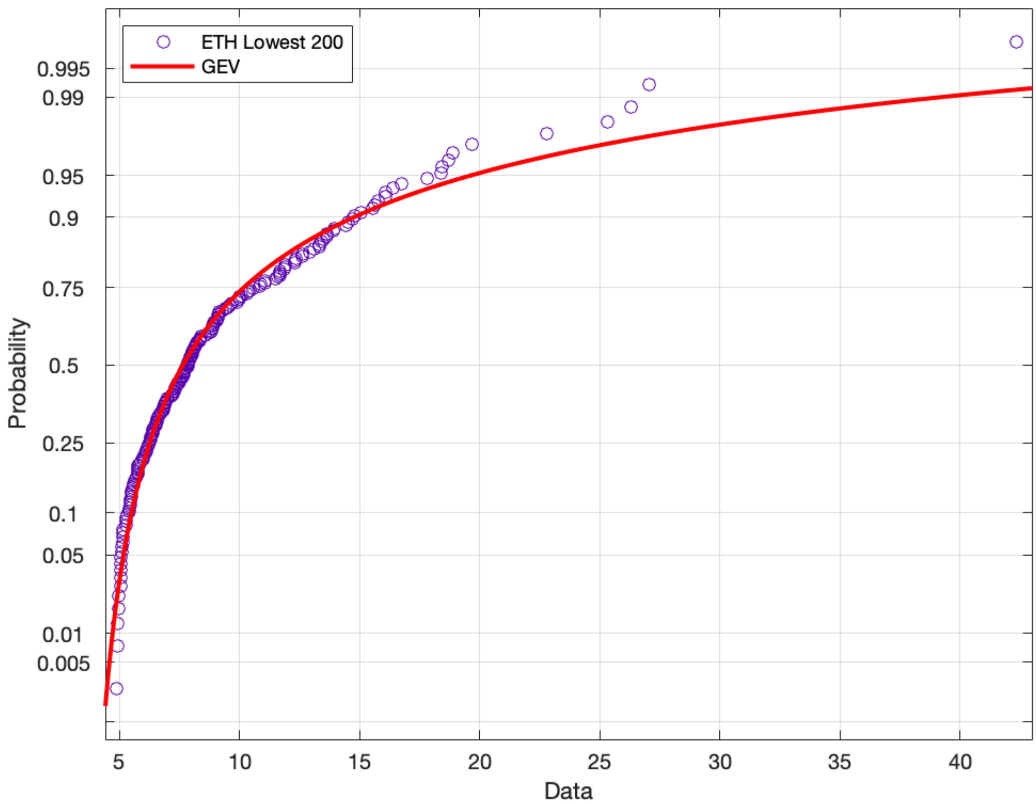
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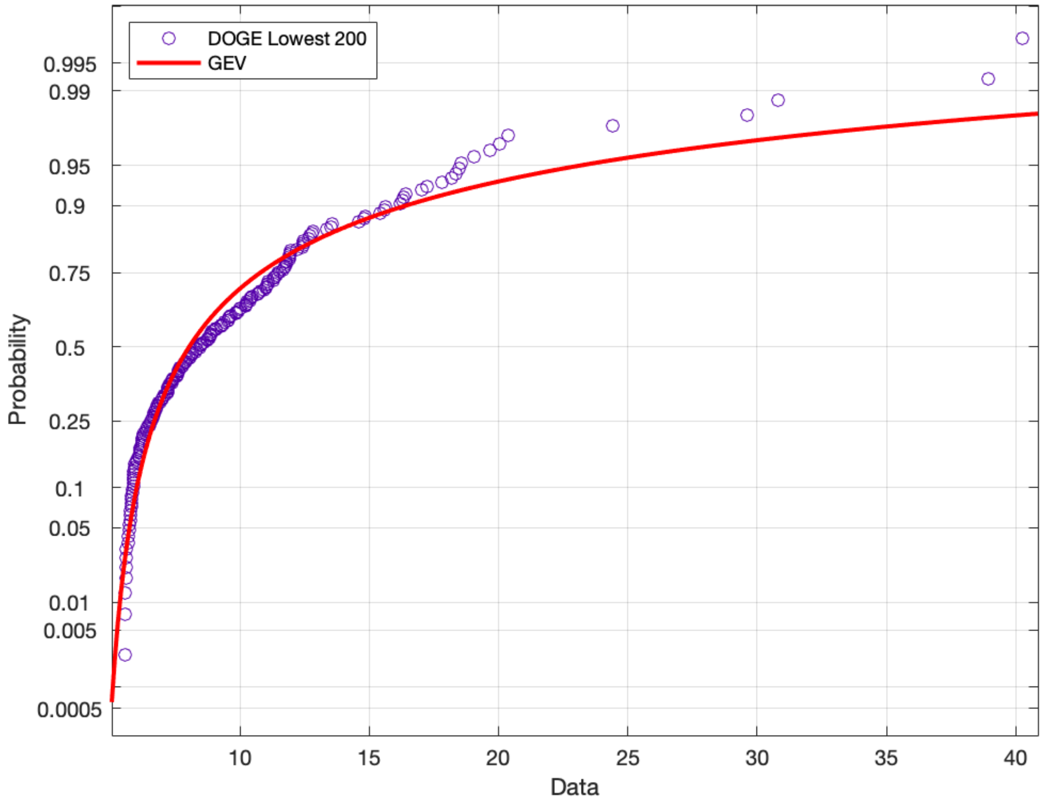
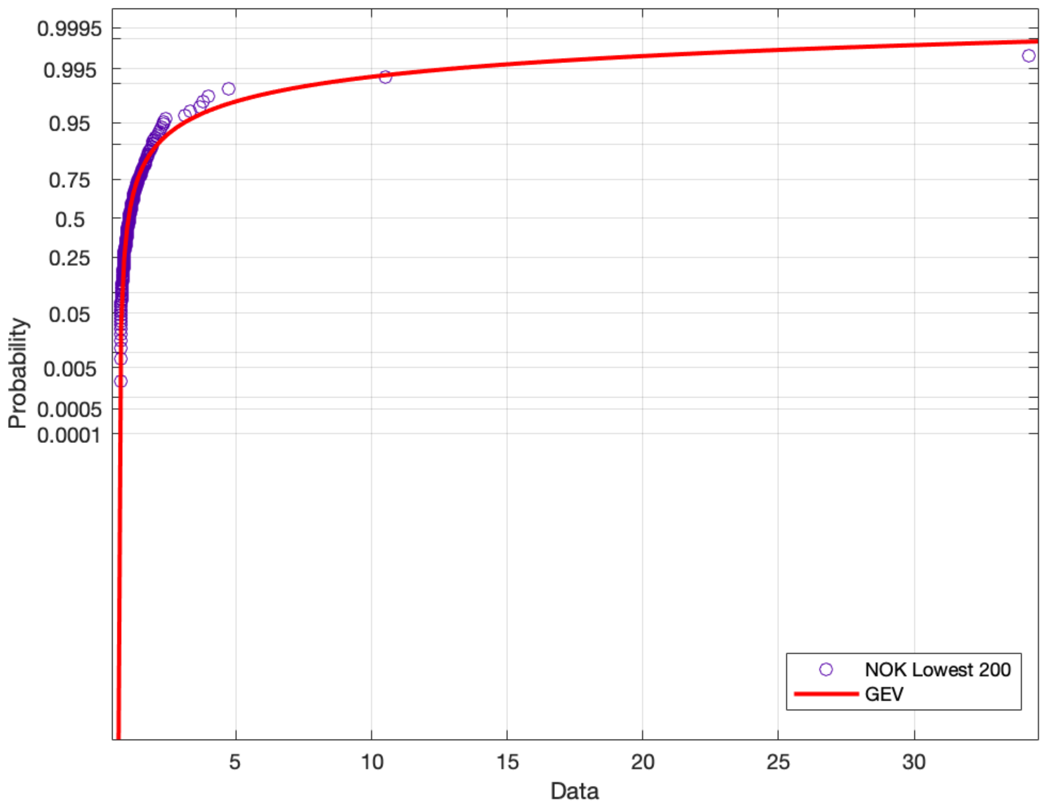
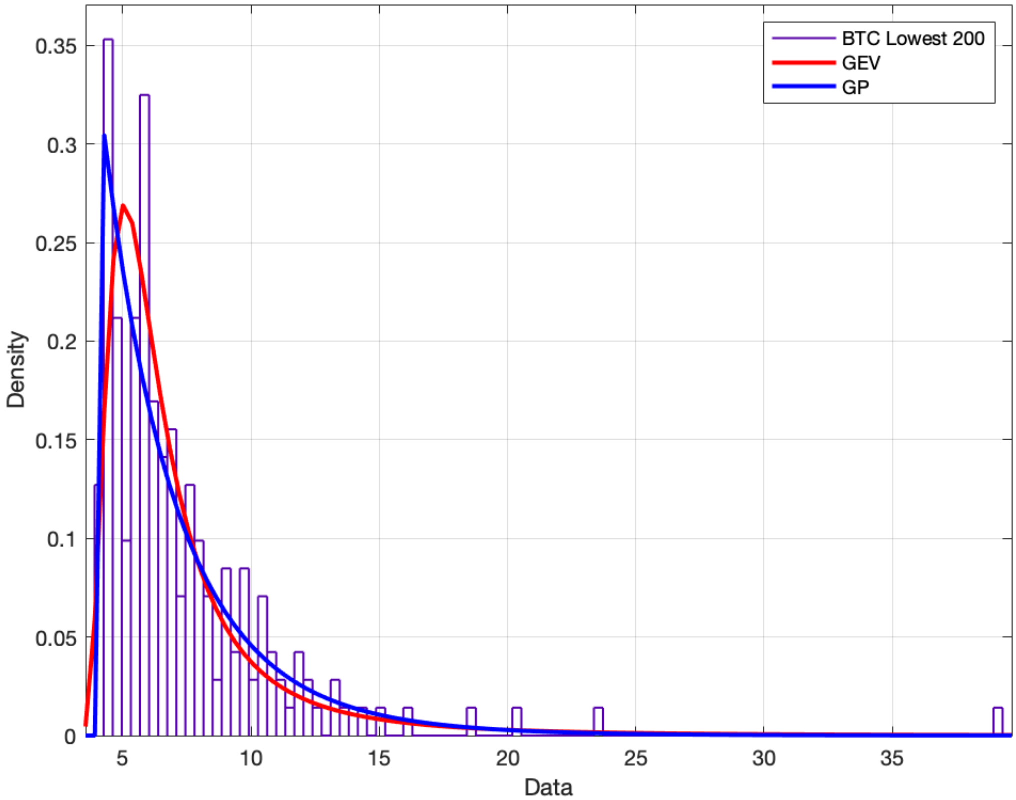
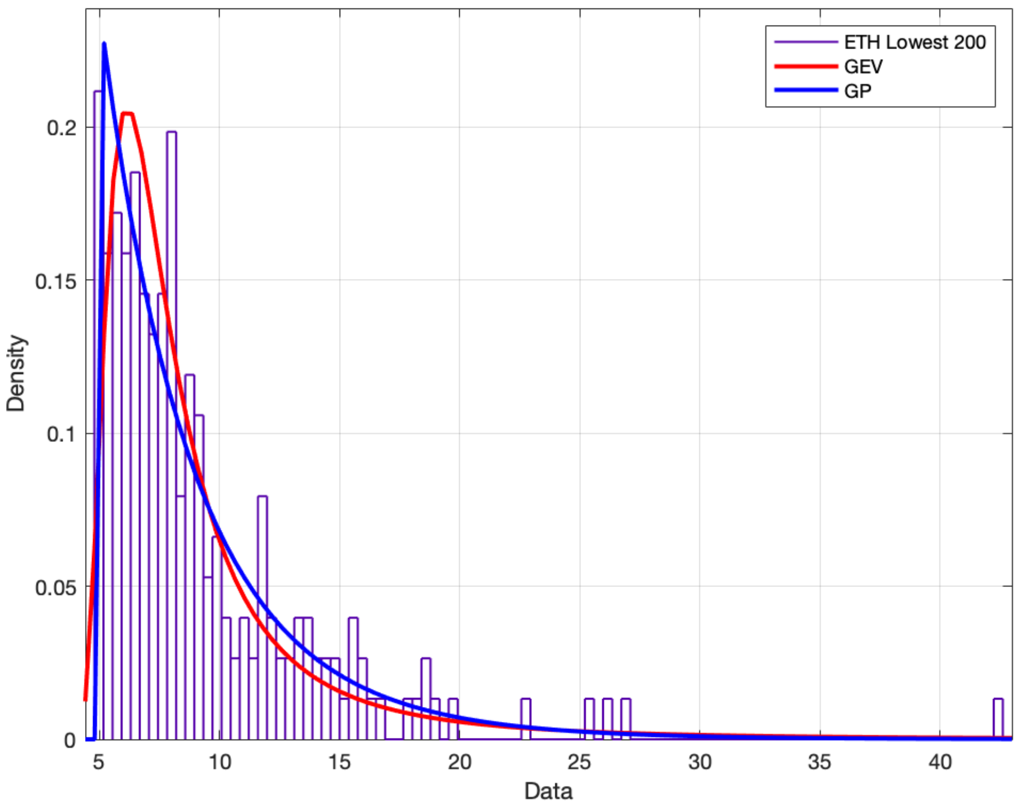

DOGE Lowest 200
GEV
Probability
0.995
0.99
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.01
0.005
0.0005
10
15
20
25
30
35
40
Data

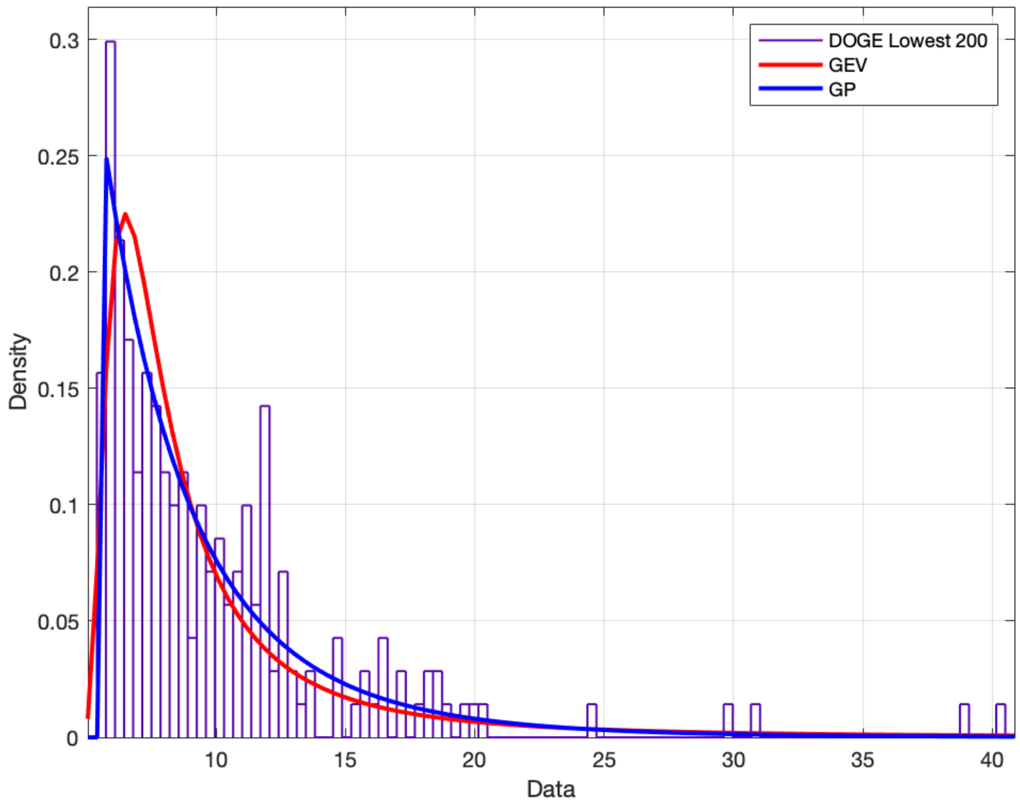

NOK Lowest 200
GEV
Probability
0.9995
0.995
0.95
0.75
0.5
0.25
0.05
0.005
0.0005
0.0001
5
10
15
20
25
30
Data

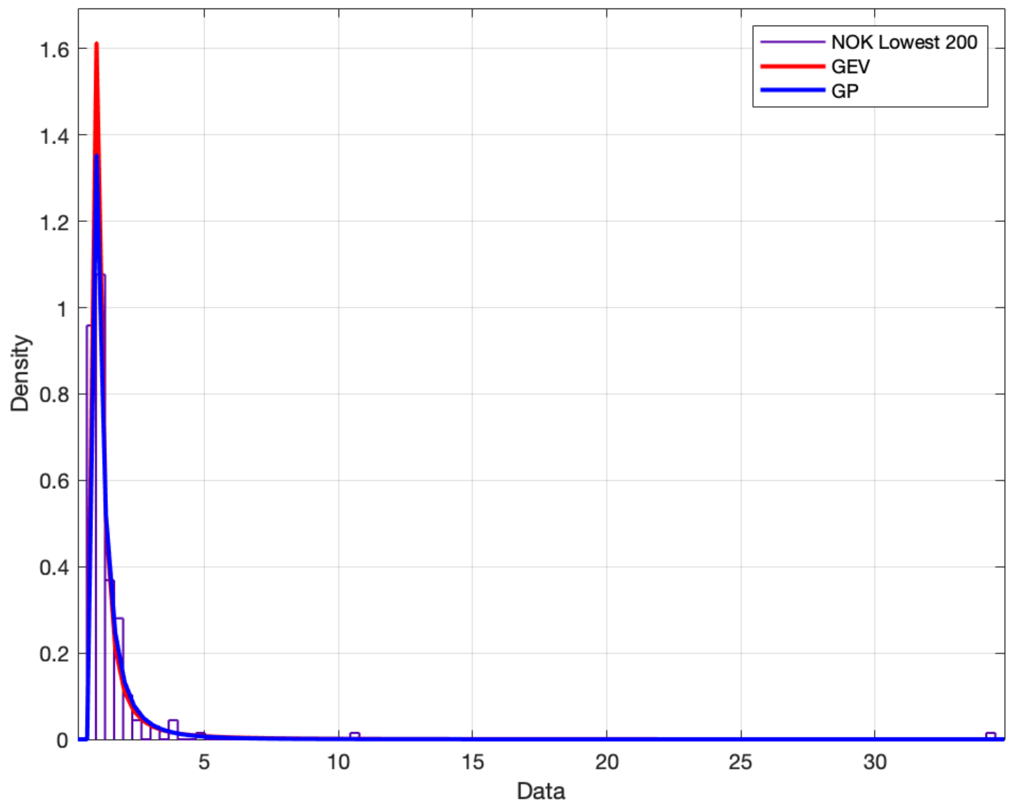
Appendix F

Combined - Density plot


BTC Lowest 200
GEV
GP
Density
Data
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
5
10
15
20
25
30
35

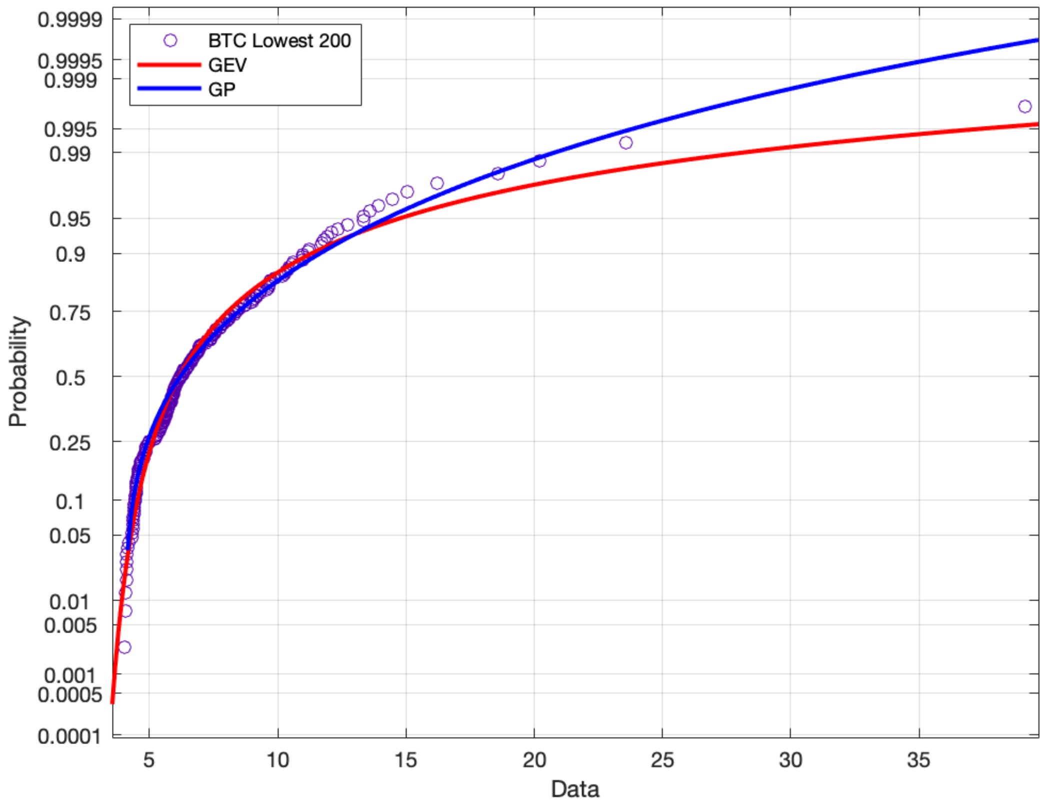

ETH Lowest 200
GEV
GP
Density
Data
0.2
0.15
0.1
0.05
0
5
10
15
20
25
30
35
40

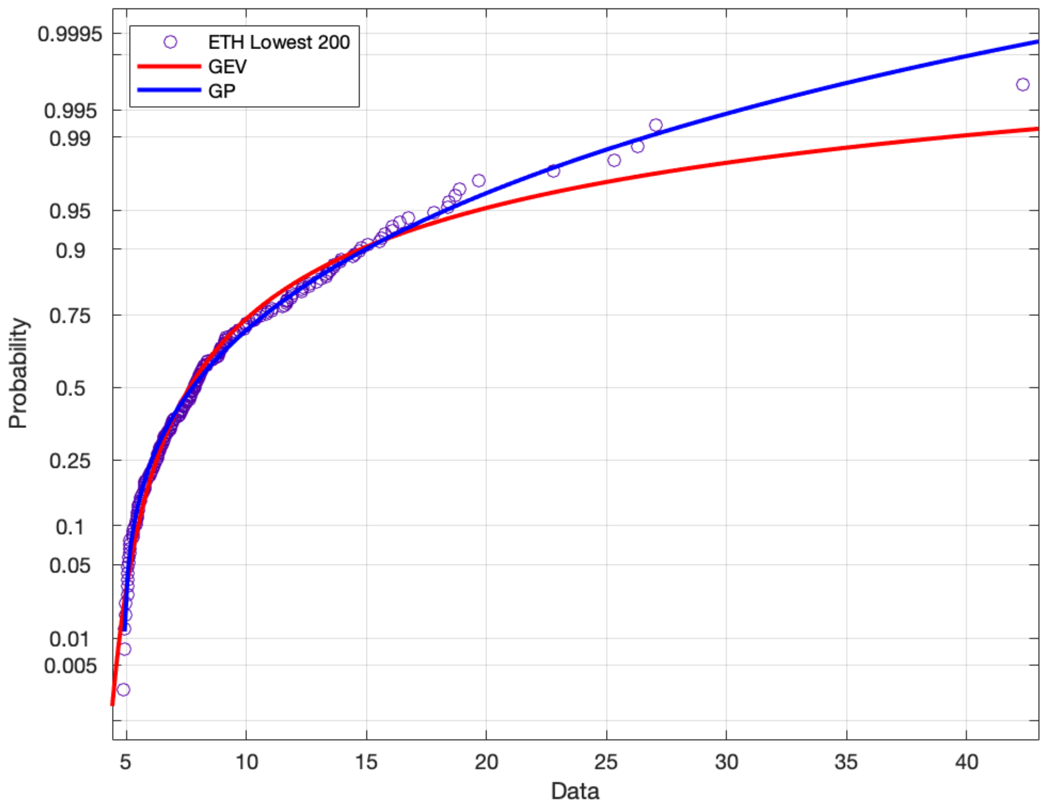

DOGE Lowest 200
GEV
GP
Density
Data
0
0.05
0.1
0.15
0.2
0.25
0.3
10
15
20
25
30
35
40

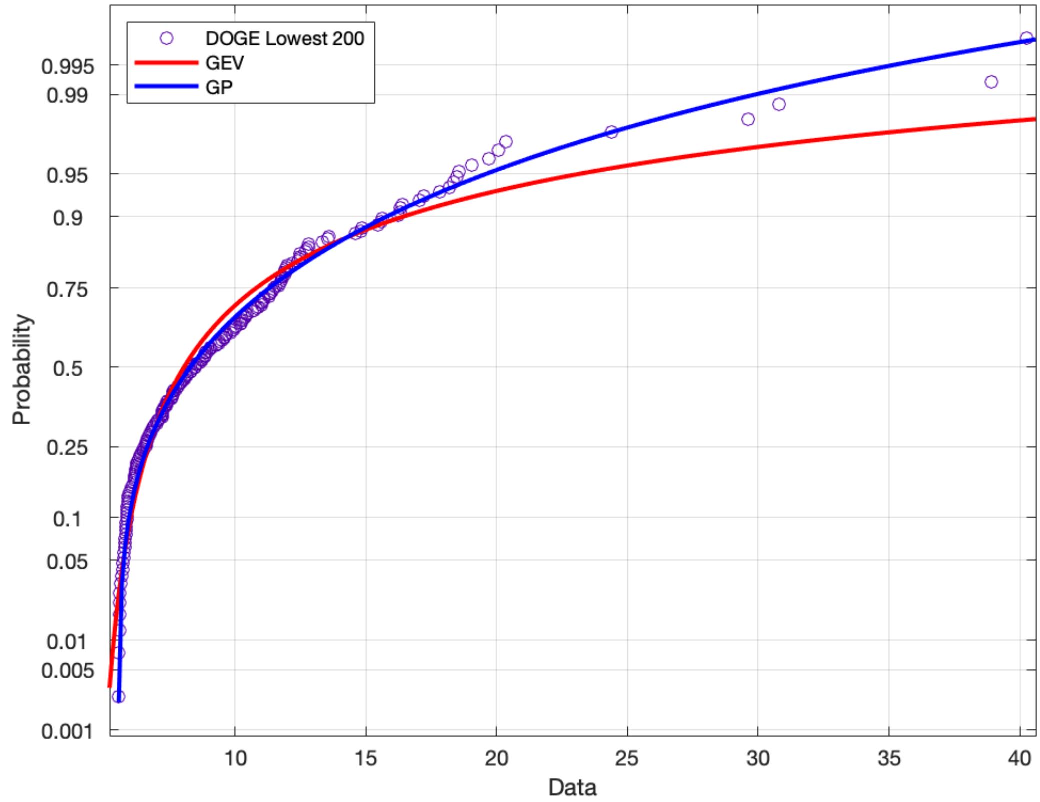

NOK Lowest 200
GEV
GP
Density
Data
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
5
10
15
20
25
30

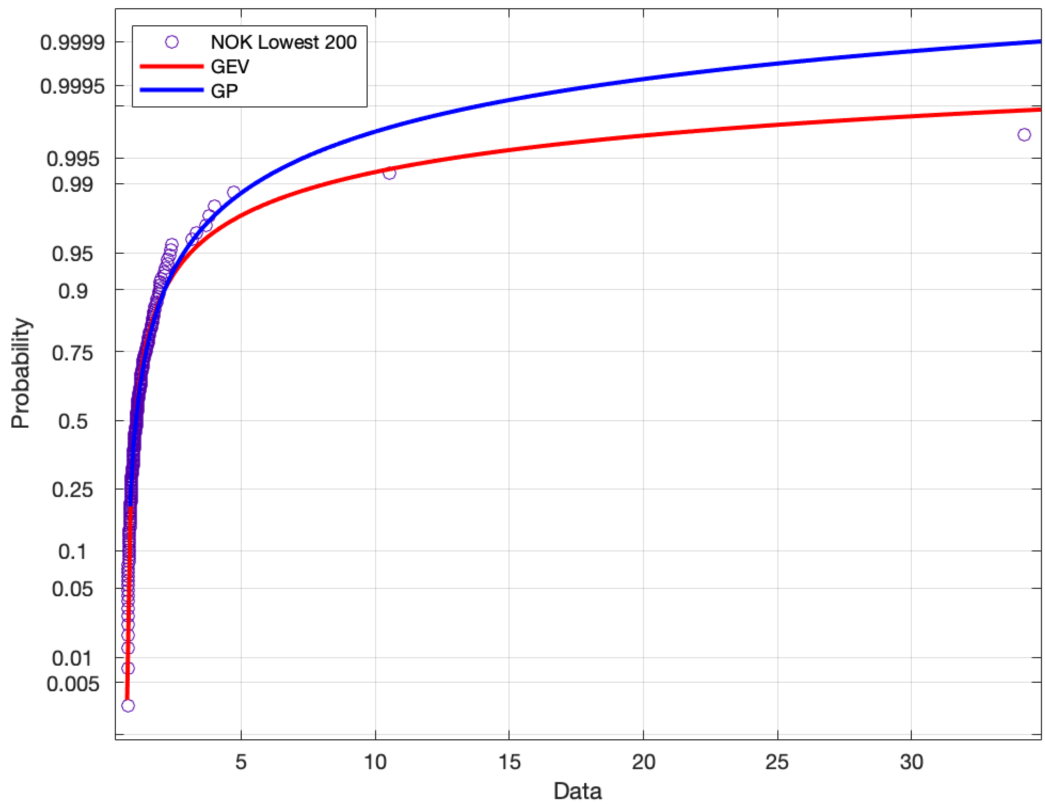
Appendix G

Combined - Probability plot


BTC Lowest 200
GEV
GP
Probability
0.9999
0.9995
0.999
0.995
0.99
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.01
0.005
0.001
0.0005
0.0001
5
10
15
20
25
30
35
Data


ETH Lowest 200
GEV
GP
Probability
0.9995
0.995
0.99
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.01
0.005
5
10
15
20
25
30
35
40
Data


DOGE Lowest 200
GEV
GP
Probability
Data
0.995
0.99
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.01
0.005
0.001
10
15
20
25
30
35
40


NOK Lowest 200
GEV
GP
Probability
Data
0.9999
0.9995
0.995
0.99
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.01
0.005
5
10
15
20
25
30

Appendix H

MATLAB Distribution Fitter results

[a]

```
BTC:
Distribution:    Normal
Log likelihood:  -6347.41
Domain:          -Inf < y < Inf
Mean:            0.306466
Variance:        15.2653

Parameter  Estimate  Std. Err.
mu         0.306466  0.0817891
sigma      3.90709   0.0578526

Estimated covariance of parameter estimates:
       mu           sigma
mu     0.00668946   1.6153e-19
sigma  1.6153e-19   0.00334693

Mean: 0.306466
Std. Dev: 3.90709
Quantile (95%, a=5%): 1.96
```

[b]

```
ETH:
Distribution:    Normal
Log likelihood:  -6123.95
Domain:          -Inf < y < Inf
Mean:            0.574996
Variance:        35.3432

Parameter  Estimate  Std. Err.
mu         0.574996  0.135924
sigma      5.94501   0.0961503

Estimated covariance of parameter estimates:
       mu           sigma
mu     0.0184753    3.43381e-19
sigma  3.43381e-19  0.00924488

Mean: 0.574996
Std. Dev: 5.94501
Quantile (95%, a=5%): 1.96
```

[c]

```
DOGE:
Distribution:    Normal
Log likelihood:  -8226.49
Domain:          -Inf < y < Inf
Mean:            0.531545
Variance:        80.2473

Parameter  Estimate  Std. Err.
mu         0.531545  0.187689
sigma      8.95809   0.13276

Estimated covariance of parameter estimates:
       mu           sigma
mu     0.0352271    2.74878e-19
sigma  2.74878e-19  0.0176251

Mean: 0.531545
Std. Dev: 8.95809
Quantile (95%, a=5%): 1.96
```

[d]

```
NOK:
Distribution:    Normal
Log likelihood:  -2986.2
Domain:          -Inf < y < Inf
Mean:            0.0036745
Variance:        2.40905

Parameter  Estimate   Std. Err.
mu         0.0036745  0.0387182
sigma      1.55211    0.0273907

Estimated covariance of parameter estimates:
       mu           sigma
mu     0.0014991    4.97589e-21
sigma  4.97589e-21  0.000750249

Mean: 0.0036745
Std. Dev: 1.55211
Quantile (95%, a=5%): 1.96
```

Figure H.1: (a) Bitcoin (b) Ethereum (c) Dogecoin (d) Norwegian Kroner