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VaR vs ES: The Battle of Major Cryptocurrencies

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ABSTRACT

Cryptocurrencies have been the subject of constant debates since the inception of the first cryptocurrency (Bitcoin) in 2009. The volatility of cryptocurrencies has recently attracted the attention of the public and researchers. The selection of these digital assets is based on an inclusion criterion of USD ($) 4 billion regarding market capitalisation during the period of the study. This thesis investigates investors' exposures to cryptocurrency market risks by examining the risk properties of six of the major cryptocurrencies in current circulation; Bitcoin, Ethereum, Litecoin, Ripple, Monero, and Stellar. Filtered Historical Simulation with the help of GARCH modelling is used as the approach examining the risk properties. The results show that Litecoin and Bitcoin are least volatile cryptocurrencies relative to the other investigated assets. Stellar represents the riskiest cryptocurrency during the period reviewed.

Keywords: "*Cryptocurrencies*", "*Value at Risk*", "*Expected Shortfall*", "*Filtered Historical Simulation*", "*GARCH Modelling*", "*Market Risk*", "*Bitcoin*", "*Ethereum*", "*Litecoin*", "*Monero*", "*Stellar"*

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I would like to give praises to God almighty for giving me the strength and the grace to write this thesis. I would also like to thank my parents for their emotional and financial support throughout my academic life. Pernille Sine Carslsen also deserves mention for her emotional support during this period of writing my thesis. Lastly, I would like to thank my supervisor, Slobodan Kacanski, for his academic guidance and support throughout during the development and exploration of this thesis.

1.0 INTRODUCTION

Almost every investor who invests or considers an investment in any asset considered risky ponders over the question "*OK, if things do not go as expected, what is the maximum amount I can lose in this investment?*" Over the past couple of years, the continuous digitisation of various spheres of life has presented this same question to investors taking positions within these forms of digital currencies known as cryptocurrencies. This introductory chapter gives an overview of the evolution of the cryptocurrencies through a digital revolution as well as presents the problem area that this thesis aims to investigate.

1.1 The Digital Revolution

Revolutions, by definition, are reflected in major changes to events. The development of the world has been attributed to several developments or revolutions by various researchers. From the domestication of farm animals to the development of steam engines and electricity, the world has witnessed the unprecedented transformation from the days of Neandertals living in caves (Brynjolfsson & McAfee, 2014). In his first paper which traced these monumental shifts of development in the world, Makridakis (1995) made some predictions about the impact of information technologies by the year 2015. In his view, by the end of this period, the development harnessed by the exponential progress of information technologies would be like the societal progress during the industrial revolution. He succinctly referred to this period as the "*information revolution*" (Makridakis, 1995).

Just as predicted, the "*information revolution*" helped to deliver extensive changes which dramatically altered the way and medium through which the world conducted business transactions, competed, obtained services, managed resources, and connected globally (Makridakis, 1995). The predicted driving force of that era was the digitisation of operations with the help of connected computing devices around the world. Just as the invention of the steam engine helped human beings overcome the limitations imposed by their human bodies and ushered in the industrial revolution, continuous digitisation in the form of "*information revolution*" helped the world to amplify the mental capabilities of human beings with the help of connected mobile computers. Recently, this wave of digitisation has hit the world of finance hard in the form of cryptocurrencies.

Public debates about the policy changes, regulation, dangers and the promise of these digital currencies are not in short. From questions about the classification of virtual currencies to the ethical questions about its ability to support untraceable exchanges. Even without a proper regulatory mechanism or framework, the adoption and popularity of cryptocurrencies have soared and show no sign of slowing down. But what constitutes a cryptocurrency? Are they the same as digital or virtual currencies?

1.2 Differentiating Between Digital Currencies and Cryptocurrency

The two terminologies (*digital/virtual currencies* and *cryptocurrency*) tend to be used interchangeably during reportage which often leads to misinformation and confusion. It is therefore imperative that this thesis clarifies for its readers the distinction between the two terminologies.

A report on "*Virtual Currency Schemes*" by the European Central Bank defined virtual or digital currencies as types of unregulated, digital money which are usually issued, controlled by its developers and widely used and accepted by members of a specific virtual community (European Central Bank, 2012). By this definition, digital currencies are exclusively limited to virtual formats with no physical forms like coins, banknotes and the likes that the world has been accustomed to handling.

Depending on the interactions between these virtual/digital currencies and official and convertible currencies, the same report classified digital currencies into three groups: "*closed virtual schemes (Type 1)*", "*virtual currency schemes with unidirectional flow (Type 2)*" and "*virtual currency schemes with bidirectional flow (Type 3)*" (European Central Bank, 2012, p. 13).[1] These groups are briefly presented below along with an explanation of the category that cryptocurrencies fall in:

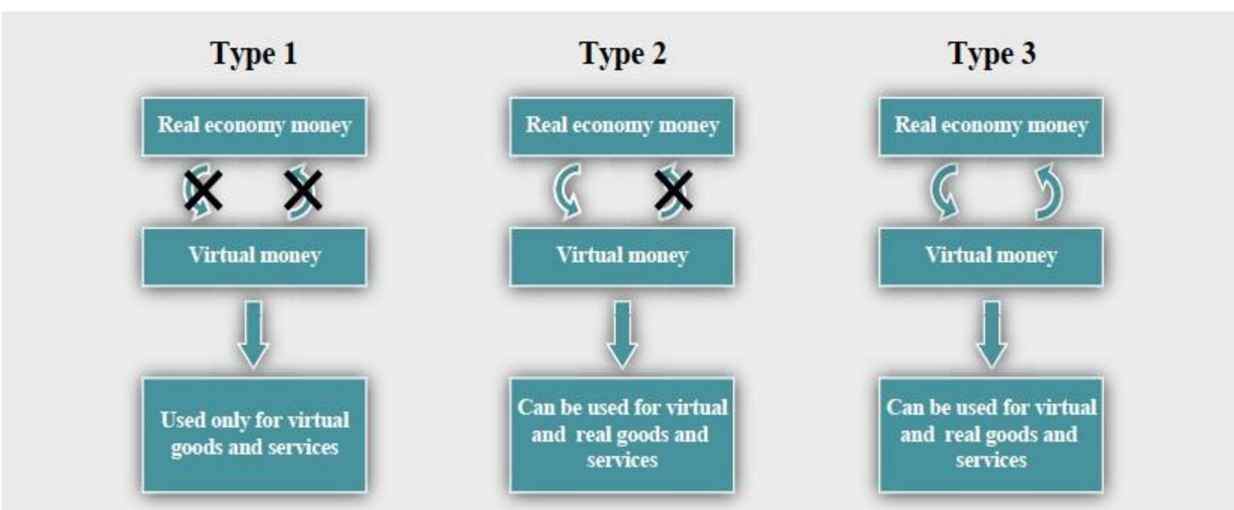
1. ***Closed Virtual Schemes (Type 1)***: With these type of schemes, users typically pay subscription fees with officially backed currencies (like EUR, USD) in exchange for virtual money. The use of digital currency acquired under these schemes are limited to virtual community obtained from such that one cannot purchase virtual goods and services offered by other virtual communities. The video/pc game industry are heavy users of closed virtual schemes. Video games like World of Warcraft (WoW), EA FIFA series and the likes rely

[1] The report "*Virtual Currency Schemes*" used the term "real money and real economy" as the focus of interactions where the interactions occurred through two channels; monetary flow through currency exchanges and the possibility to purchase goods and services.

on players buying digital tokens/coins for various enhancements or upgrades during gameplay.

2. ***Virtual Currency Schemes with Unidirectional Flow (Type 2)***: With this category of virtual currencies, users can exchange officially backed currencies at specific exchange rates for virtual currencies but prohibited from trading the acquired virtual currencies back to original currencies. This unidirectional flow is standard practice with gaming console manufacturers like Microsoft, Sony and Nintendo. All game console manufacturers have online web shops where its customers can buy points by converting real currencies into digital currencies. However, conversion from those acquired digital points to real currencies is not possible.[2]
3. ***Virtual Currency Schemes with Bidirectional Flow (Type 3)***: Virtual currency schemes under bidirectional flow facilitate the buying and selling of these types of currencies in exchange for official currencies. In an operational sense, virtual currencies in this category are like convertible currencies because of their ability to foster transactions either virtually or real goods and services. In this regard, Type 3 virtual currencies have the potential to replace real-world currencies entirely. Almost all the cryptocurrencies in current circulation can be regarded as belonging to this category. **Figure 1** translates visually the explanation given for the three categories above (European Central Bank, 2012, p. 15).

Figure 1. Classification of Digital Currencies.



[2] Explain PSN, Xbox and Nintendo points are simply digital currencies used by gamers to purchase content exclusively on web shops of each mentioned gaming platform.

1.3 Defining Cryptocurrencies

One can safely deduce from the three (3) categories (explained above) that all cryptocurrencies are indeed digital/virtual currencies but not all digital/virtual currencies are cryptocurrencies. One might ask then, what are cryptocurrencies? Even though there is still no one universally accepted definition for the term "cryptocurrency", a closer look at both the technical and practical perspectives can deliver a precise definition of what constitutes a cryptocurrency.

From a technical perspective, cryptocurrencies can be viewed as those types of digital currencies which rely on cryptography, usually alongside a proof-of-work scheme in the creation and management of those assets (Baur et al. , 2015). From a practical perspective, cryptocurrencies are merely digital currencies that employ the power of blockchain technology to eliminate the need for an external third party to overlook the checks and balances of various transactions. While cryptocurrencies have been in operation for some few years, their prominence and popularity rose considerably in 2017.

1.4 The Year of Cryptocurrencies (2017)

Digital currencies like cryptocurrencies have started to attract attention from the investors and researchers during the last years (Stavroyiannis, 2017). While digital currencies have been in existence for some few years, they experienced mainstream attention from the media and public in 2017. In 2017, cryptocurrencies represented major buzzwords across various formal, informal settings from family dinners, lunch breaks at workplaces around the world to college students gossiping about the latest value proposition offered by digital currency. According to internet search trends report by search engine giant Google, the search query "*how to buy bitcoin*" was one of the tops searched questions globally in 2017 (Google, 2018).

Bitcoin is the most popular and biggest cryptocurrency (regarding market capitalisation) currently in circulation. While it is understandable that Bitcoin has the attention of the world given that it is the most popular cryptocurrency, it is not the only digital currency in circulation. As of the end April 2018, there are over 1500 different types of cryptocurrencies operating across over 8700 digital markets without breaks with various innovative offerings (Coinmarketcap, 2018). The value propositions from these digital currencies range from simple cases of storing value to complex applications like smart contracts which are beyond the scope of this study. The volatility of the prices of the major cryptocurrencies especially Bitcoin (BTC) has grabbed mainstream media, public and the attention of researchers.

1.5 Problem Area

On December 17, 2017, the price of the world's most popular cryptocurrency, Bitcoin, hit $19,758 – a record figure – which sparked a worldwide frenzy with people scrambling to get into the cryptocurrency space. A few weeks later, the price of the same cryptocurrency plummeted to $6,701 (a 66% drop from its highest record price) on February 06, 2018. These sudden price changes are not limited to the world's most popular cryptocurrency. Like every tradeable financial instrument, cryptocurrencies are also susceptible to these sudden and price spikes and drops. Understandably, the volatility of the prices of various cryptocurrencies has attracted the attention of researchers. The lack of a regulatory risk management framework for digital currencies has also strengthened calls for more focus on investors' exposure to risk in cryptocurrency markets. So, what are some of the risk metrics that an existing or potential investor can quantify their risk exposure when dealing with cryptocurrency markets?

Littered in the history of the world are various episodes of global financial crises in which fortunes were lost to multiple financial schemes. Each episode typically ends with private and public calls for the strengthening of measures and assessment of market risks. The most recent installment in 2007 which threatened the financial sector globally led to requests for a review of the then de-facto standard measure of investors' exposure to risks; Value-At-Risk (VaR) (Hull, 2015).[3] The incoherence of VaR as a measure of risk was laid bare by the global financial crisis in 2007 which led to a review of financial risk management practices (idem). To this end, Expected Shortfall (ES) has emerged as a more coherent and recommended alternative to VaR for risk assessments of investors (Acerbi & Tasche, 2001).[4] The new Basel III accords which are aimed at strengthening global financial risk management practices post the 2007 crisis argues for change from VaR to ES for internal risk assessments (BIS, 2017, p. 67). With these developments as motivation, this thesis dives into the endless conversations of the riskiness of cryptocurrencies by

[3] Value at Risk, hereinafter, referred to as VaR

[4] Expected Shortfall, hereinafter, referred to as ES

using these two metrics as tools to understand and quantify for investors the market risks of the major cryptocurrencies.

1.5.1 Problem Statement

As far as this study is concerned, the central research question that drives the methodological and theoretical framework is:

- *To what extent does conventional risk metrics (VaR and ES) describe investors' exposure to cryptocurrency market risks?*

1.5.2 Research Questions

To answer this central research question, the following sub-research questions are addressed:

- *How does Blockchain technology facilitate the operations of cryptocurrencies?*
- *How volatile are the major cryptocurrencies regarding their VaR and ES estimates?*

1.5.3 Research Objectives

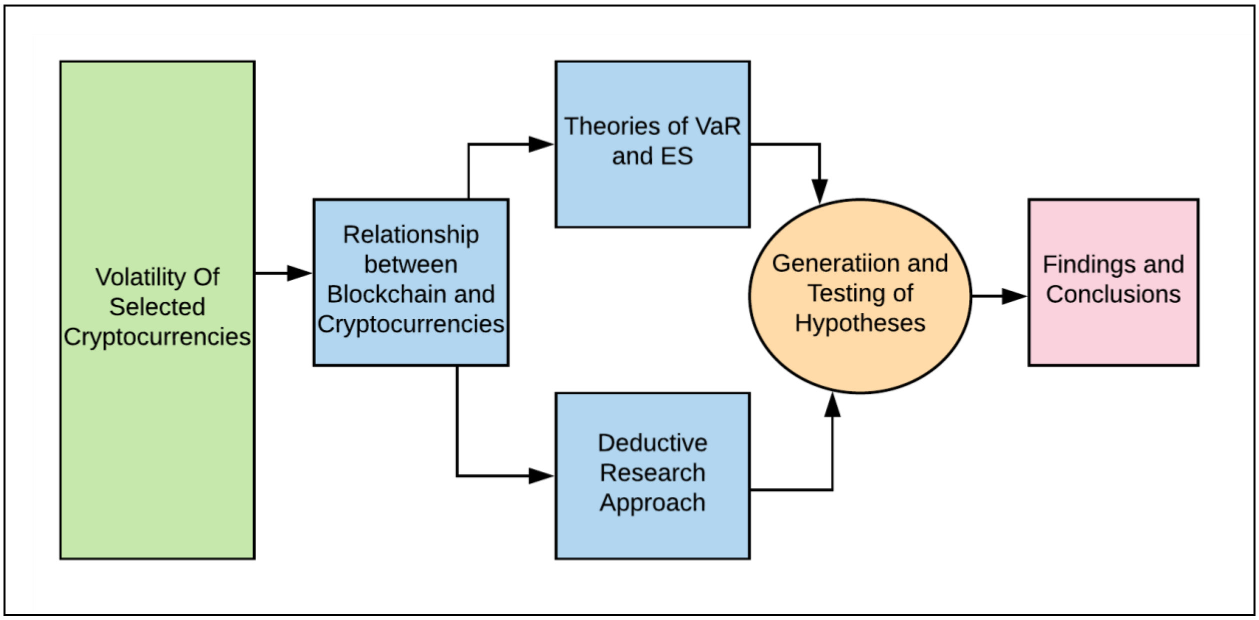
With the problem statement and working objectives in mind, the goals of this study and paper are:

- *Facilitate an understanding of the blockchain technology that has spawned the development of cryptocurrencies.*
- *Estimate the volatility of each of the identified major cryptocurrency by comparing their VaR and ES estimates.*
- *Recommend possible future directions for research and practitioners based on findings of the study.*

1.6 Structure of Paper

This study's flow of logic regarding structure is laid out in this subsection with the help of a diagram. This facilitates for readers a smooth and efficient navigation system for the various sections of this paper. This paper is structured as follows; First, the technology that powers cryptocurrencies is explained to readers. Secondly, a theoretical framework based on the two market risk metrics (VaR and ES) as well as a review of empirical literature of the problem at hand is presented. The methodological framework is presented next. The empirical results along with a discussion of these results are then presented. A conclusion if finally deduced from the findings. **Figure 2** visualises for readers the flow of these chapters.

Figure 2. Structure of Study



2.0 A CLOSE LOOK AT THE WORLD OF CRYPTOCURRENCIES

Given how coverage and reportage on cryptocurrencies are muddied with so many confusing terminologies which may be confusing for readers, this section attempts to decrypt such confusions surrounding cryptocurrencies. This decision not only delivers to readers a breakdown of the processes backing the development of cryptocurrencies but also facilitates an intimate connection with the subject of this study. As a result, this chapter is divided into the following sub-sections: "*Blockchain 101: deconstructing the technology powering cryptocurrencies*", "*an overview of cryptocurrencies*", "*factors accounting for the adoption of cryptocurrencies*", and "*pros and cons of cryptocurrencies*".

2.1 Blockchain 101: Deconstructing the Technology Powering Cryptocurrencies

Before giving a holistic overview of the cryptocurrency market, attention will now be switched to the framework which facilitates the operations of cryptocurrencies. Since the rise of cryptocurrencies is synonymous to the development of the blockchain framework upon all the cryptocurrencies take inspiration, this sub-section of the paper is devoted to giving readers an overview of how blockchain facilitate the operations of cryptocurrencies. The following sub-sections are dedicated to the coverage of the overview blockchain technology; "*What is Blockchain?*", "*What Problem Does Blockchain solve?*", "*Elements of Blockchain*", "*Types of Blockchain*", "*Advantages of Blockchain*", and "*Limitations of Blockchain*".

2.1.1 What is Blockchain?

Blockchain technology is one of the trending technologies with the widely acknowledged disruptive power to alter various essential facets of life as we know it (Gartner, 2016). The origins of Blockchain technology can be traced the white paper of Satoshi Nakamoto in 2008 (Nakamoto, 2008).[5] According to the resulting source code from that white paper, Nakamoto & Bitcoin Core Developers (2018, Line 165-167) described blockchain as;

> "*a tree-shaped structure starting with the genesis block at the root, with each block potentially having multiple candidates to be the next block.*"

[5] Satoshi Nakamoto, the person/people responsible for the creating the first application of Blockchain technology (Bitcoin), is an unknown person/people.

From a technical perspective, there exists an original block upon which every new block created is appended to which then leads to the creation of the tall structure of blocks. The name "Blockchain" originates from the fact that, by deliberate design, every new block created is "chained" together forever with all previously created blocks (Garzik & Donnelly, 2018). In this regard, blockchain can be considered as a digital public ledger which records all previous transactions in chronological order as a data structure, and the recorded transactions are distributed across a network (Niranjanamurthy et al., 2018). Simply put, blockchain offers a digital and open system of transactions where databases of records are decentralised and distributed across a global network of users (Beck & Müller-Bloch, 2017).

2.1.2 How Blockchain Technology Works

Still confused by the concept of "blocks" and the "chaining process"? While the workings of Blockchain may be complicated but at its core, this idea behind the technology is a simple one. A more practical perspective of blockchain clarifies any potential confusion. For this practical illustration, a similar analogical approach used by Skella (2017) to explain how blockchain works are adopted.

To make things as simple as possible, let's substitute the terms "blockchain" and "block" with something more relatable like "shared notebook" and "sheet" where every new entry in this shared notebook adds a new sheet to the shared notebook. Simply put, a shared notebook with sheets. These sheets can record practically every type of information. There exists not only one copy of this notebook in one central location, but many copies of this notebook are distributed across various locations (on computers) all over the world hence why this notebook is called a "shared notebook". Because the sheets can store various forms of information, there is a potential use of this shared notebook in practical situations which call for storage and retrieval of information. Keeping it simple once again, let's look one of these practical situations with an appropriate need for the storage and retrieval of information – a simulated act of receiving and sending of money between different parties. After all, the subject of this study can function as a medium of exchange between two or more parties.

Suppose Pernille (Party A) decides to send some money to her sister Josefine (Party B), a new sheet with all the details of this transaction is created and sent to all the locations with copies of the latest notebook full of all previous transactions. All the computers at these locations going through an authorisation process and either approve or reject this transfer to Josefine from Pernille. Once approval of the transfer after the authorisation process, the newly created sheet with the exact details of the transfer form Pernille to Josefine is added to shared notebook and copies of the freshly updated shared notebook is sent back all the computers as the latest copy of the initially shared notebook. What if Pernille realises that she mistakenly sent more money than she intended. The sheet of the transfer has already added to the shared notebook. An essential property of the shared notebook is any sheet once attached to it cannot be reversed and taken out of the notebook! If Josefine agrees to send back some of the money, a new sheet documenting all the details of the new transfer would have to be created and added to the notebook. The newly updated notebook with Josefine's transfer of excess funds to Pernille is once again distributed digitally to all the locations globally. It is worthwhile mentioning that the shared notebook would continue to exist forever so long as the internet exists in the world. A good question to all these could be "well, what is so special and revolutionary about this system? Isn't that what the banks do currently?"

The much-publicised selling point of this shared notebook is its ability to render useless the need for any intermediary agent completely. In the case of Pernille's transfer to Josefine, Pernille would have instructed merely her bank (for a fee) for the transfer from her account to Josefine's bank account. The reliance on any central institution like a bank as a central body is entirely negated using this shared notebook. On top of that, this notebook is not owned by any single corporation or organization as all parties using this notebook to keep track of whatever information is being shared own a copy. Even if one Pernille has more than one copy, it is fruitless trying to falsely alter the notebook as any every proposed new sheet must be approved by the many global computers on which each copy is kept. The verification process works as if these computers were present during an exchange and vouching that whatever information is contained on in the proposed sheet is correct. If either Pernille or Josefine brings a fraudulent sheet, the various computers reject this sheet. This practical example of a simulated exchange of money between Pernille and Josefine shows how blockchain allows the two parties to make an exchange without an intermediary like a financial institution but how does this technology translate into the creation of cryptocurrencies?

2.1.3 Translation of Blockchain into Cryptocurrencies

Digital currencies like cryptocurrencies have no physical form. Everything resides in the digital realm on computers all over the world. All one needs to create a cryptocurrency now is to create their notebook with the first sheet in this shared notebook specifying the amount of the new cryptocurrency in circulation. Using our two main illustrative subjects once again, let's say Josefine decides her cryptocurrency having fallen in love with the media hype creates a notebook (JoseCash) with its first sheet stating "*1,000 coins of JoseCash (JC) exist*".

Josefine decides to give some of her new 1000 JC to her friends or family either as a gift or in exchange for traditional currencies (like Danish Krone - DKK). Every time a transfer involving the pre-existing 1000 JC is made, a new sheet documenting all the details of the transfer is created, verified and added to JoseCash (notebook) with copies of the updated version of JoseCash sent all parties using JoseCash. In effect, every new sheet in JoseCash is the actual money being traded and comparable with all traditional fiat currencies the world has adopted. How can one receive a JoseCash then?

As with traditional currency exchanges, one needs some form of an account with a financial institution into which transfers can be either made from or made into said account. The same applies to cryptocurrencies as anyone wants to either receive or send a cryptocurrency needs a digital wallet address. Suppose Josefine distributes 400 of the 1000 JC digital coins into a digital wallet of her dad (Tom). Tom receives 400 JC along with a secretive code which gives Tom the sole ownership of the 400 JC coins. Once the sheet documenting this transfer has been verified and added to the original JoseCash notebook, Josefine only has 600 JC left, and Tom alone can decide what to his new 400 JC coins. This design feature makes it possible for everyone to have a copy of the JoseCash notebook but only those parties with access to the secret code received during an exchange to add new sheets to JoseCash notebook.

2.1.4 What Problems Does Blockchain Solve?

Any application without a valid use case is just a hobbyist's play toy. In a practical sense, blockchain is merely a non-erasable record book of all pertaining transactions that the record book is created to track. Blockchain forms a system based on the trust that records stored on each of the blocks have not been fraudulently tampered with (Risius & Spohrer, 2017). However, what prevents one from making the same transaction twice simultaneously with two different parties? That is the so-called "double spend" problem which ruined all previous attempts of digital currencies until the development of blockchain (Garzik & Donnelly, 2018). Until the development of blockchain, the world relied on intermediaries who keep ledgers of the account holder's balances to prevent double spending (Hofmann, Strewe, & Bosia, 2018).

Blockchain technology overcomes this double-spend problem by its verification system as well the inability to alter previously added blocks. When a new transaction is made, the blockchain records all the details of this transaction and the addition of this verified record to an already existing set of previously validated records further strengthens the integrity of the whole blockchain (Garzik & Donnelly, 2018). Even though the world finance appears to the most visible application of blockchain technology's ability to overcome this double-spending problem, this development has broader applications beyond finance.

In 2012, the supreme court of Ghana had to rule on a petition by a political party who had just lost the national presidential elections over allegations that the sitting government had tampered with the results of the polls (Bamfo, 2014). Allegations during presidential elections in most developing countries (Ghana included) is a recurring theme. Imagine a potential of a nationwide public ledger built with blockchain technology. Not only would the results of all kinds of elections not be susceptible to fraudulent alterations, but this public ledger would be available for public scrutiny and audits. Another potential application for developing countries as well as the area of land registries (Kshetri, 2017). While land titles can easily be switched by owners for generations without constant disputes over the ownership of these titles in developed countries, this exchange is still problematic in developing countries (Garzik & Donnelly, 2018). Blockchain technology offers a plausible alternative to overcome these challenges in developing countries. This technology has the potential to revolutionise and change the world economy (Tapscott & Tapscott, 2016; Underwood & Sarah, 2016).

2.1.5 Elements of Blockchain Technologies

Based on all the explanations and analogies used so far, blockchain technologies are composed of six elements (Niranjanamurthy et al., 2018). These elements are briefly explained:

- **Decentralized**: A fundamental element of blockchain is the non-reliance of blockchain systems on one central body or organisation. This feature requires the storage and updating of data in multiple locations. This element makes it possible for users of a blockchain system to have copies of the data stored.

- **Transparent**: Another element of all blockchain technologies is the transparency of data stored. This feature implies that all participants have access to the data stored and as a result can help increase the trustworthiness of the data stored. It is only users with valid private codes who can alter the data transferred to them.
- **Immutable**: By design, all data stored on a blockchain exists forever, and such data cannot be altered or tampered with once recorded unless a single user controls more than 51% of the entire network. This feature is why it is essential for users of a blockchain to have more users on the system so that power is distributed across the network instead of few agents.
- **Autonomy**: By design, every user in a blockchain system should be able to edit or update records stored so long as they have the valid code to make the desired edits. This aim of this feature is to create an autonomous self-governing system based on a trust of the whole system instead of a single central body.
- **Anonymity**: Blockchain technology negate the reliance on a single centralised body by placing trust between two parties. This ability allows parties using blockchain systems to make transfers or transactions anonymously. All one needs to make a transaction in such systems is a digital blockchain address.
- **Open Source**: Blockchain systems are usually open to public inspection and scrutiny. Unless designed to be used private, all records of a blockchain system are available publicly. However, some systems can also be created for exclusive private use. Even in such private use cases, members of that private network can still inspect the records stored. The openness of blockchain systems is a fundamental feature.

2.1.6 Types of Blockchain

Niranjanamurthy et al. (2018) find three different types of Blockchain according to according to the control of verification processes of transactions. These types are;

1. **Public Blockchain**: With this type of blockchain system, everyone can participate in the checking and verification of transactions or records. Additionally, the process of gaining an agreement or disagreement about the addition of every additional record is available to the public. Bitcoin is a prime example of a public blockchain system.
2. **Private Blockchain**: With this type of blockchain system, access to the verification and alteration of records are limited to some users as specified by the body responsible for the

design and implementation of the system. This feature allows adopters of this type of blockchain to enjoy its feature as an immutable database with a centralised form of control. As a result, this blockchain system is mostly used by private institutions.

3. **Consortium Blockchain**: Finally, this blockchain system is a crossbreed between private blockchains and public blockchain. By this assertion, the parties on the agreed network agree in advance on the consensus of the power to alter the records stored. As a result of this design feature, this system is well suited for partnership agreements between two or businesses which call for the need to share a common record system. An example of consortium blockchain is Hyperledger (Lai & LEE Kuo Chuen, 2018).

Having delivered the overview of the technology that facilitates the operations of cryptocurrencies, the attention of readers will now be switched back to the subject of the study by looking at current cryptocurrency markets.

2.2 An overview of Cryptocurrency Markets

As stated earlier, there are over 1500 different cryptocurrencies trading without pause every single day of the week over 8700 digital markets across the world (Coinmarketcap, 2018). As at April 29, 2018, the total market capitalisation of all cryptocurrencies in circulation stood at over $434 billion ($434,786,977,113.00 to be exact). Regarding the same metric, Bitcoin (BTC) represents 36.78% of the total cryptocurrency market. Ethereum (ETH) holds the second position with a market share of 15.69%. At the third slot is Ripple (XRP) with a market share of 7.91%. A new variant of Bitcoin, Bitcoin Cash (BCH) holds the fourth position with a market share of 5.64%. At fifth spot is EOS (EOS) with a market capitalisation above $17 billion (representing a market share of 3.93%).

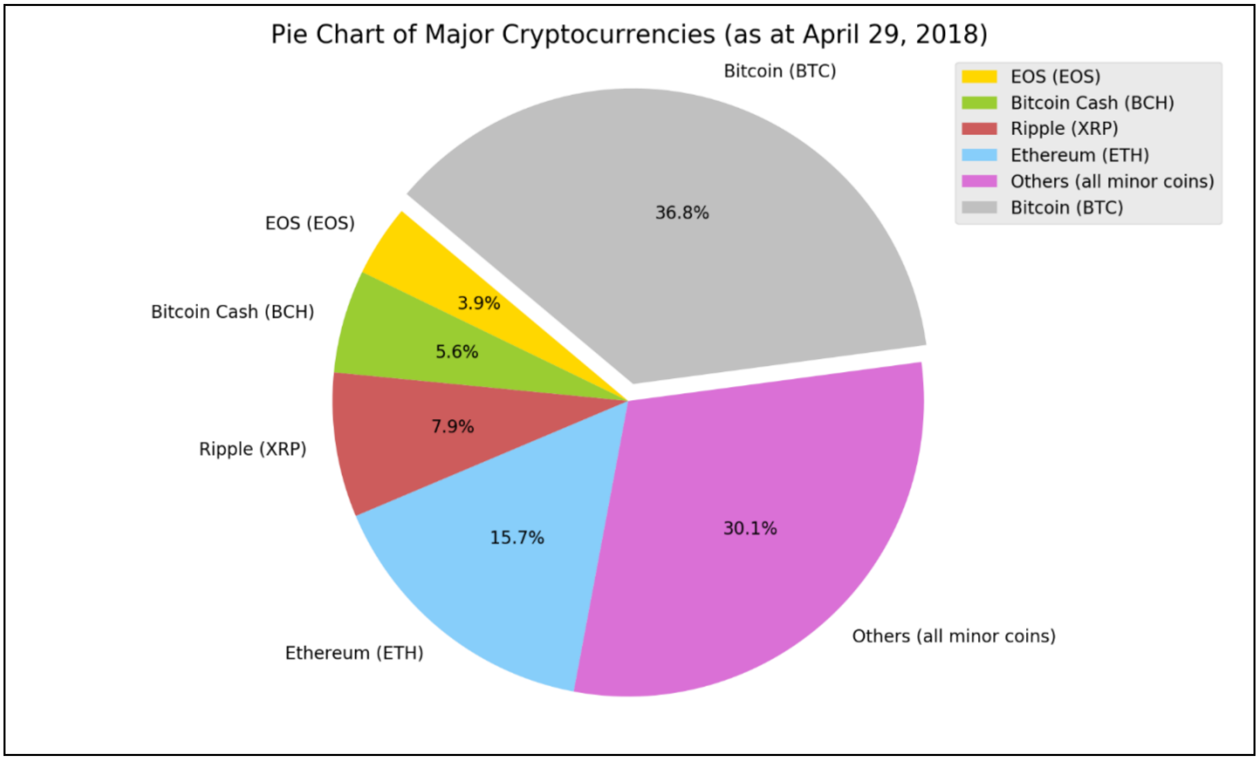
Given the vast number of cryptocurrencies currently in circulation, this thesis had to make a criterion of inclusion for the selection of coins for the investigation. Consequently, this study uses a market capitalisation figure of either equal to or above $4 billion as the selection criterion. It is of the opinion of the author any asset which meets this criterion deserved to be considered as a novelty asset but taken seriously for investment decisions. **Table 1**. provides for readers a summary of market capitalisation data (from (Coinmarketcap, 2018)) for all cryptocurrencies with a market capitalisation figure either equal to or above $4 billion.

Table 1. Market Capitalization of Major Cryptocurrencies as at April 29, 2018.

Name (Ticker Symbol)	**Market Capitalization (USD ($))**	**Percentage (%) of Total Market Capitalization**
Bitcoin (BTC)	159,921,919,639.00	36.78%
Ethereum (ETH)	68,206,942,394.00	15.69%
Ripple (XRP)	34,375,068,218.00	7.91%
Bitcoin Cash (BCH)	24,528,335,843.00	5.64%
EOS (EOS)	17,068,589,407.00	3.93%
Cardano (ADA)	9,642,169,644.00	2.22%
Litecoin (LTC)	8,626,270,532.00	1.98%
Stellar (XLM)	8,281,942,313.00	1.90%
IOTA (MIOTA)	5,707,047,041.00	1.31%
TRON (TRX)	5,584,726,197.00	1.28%
NEO (NEO)	5,151,515,295.00	1.18%
Monero (XMR)	4,096,032,863.00	0.94%
Others	83,596,417,727.00	19.23%
Total	**434,786,977,113.00**	**100.00%**

Figure 3 visually translates the information presented in **Table 1**. For the sake of brevity, the market share of the top 5 cryptocurrencies (regarding market capitalisation) in circulation as at April 29, 2018, is visually presented below:

Figure 3. Top 5 Cryptocurrencies in term of market capitalisation as at April 29,2018.



2.3 Factors Influencing the choice of Cryptocurrencies

According to a survey by Shehhi et al. (2014), the majority of early adopters of cryptocurrencies are male professionals between the ages of 26 and 35. The same survey report reveals that factors driving the choice and adoption of these digital currencies are: having a strong affiliation with a large community of adopters, the medium of exchange value, ease of use, popularity and potential of the cryptocurrency. Additionally, respondents in that survey stated a willingness to adopt specific cryptocurrencies based on the perceived originality of such a digital currency. This preference stems from the existence of "copycat" cryptocurrencies which offer nothing different but the same value propositions of the original cryptocurrency that these new cryptocurrencies aim to copy. Finally, half of the participants suggested that their decision on the choice of a cryptocurrency also much depended on the name and logo of the cryptocurrency. This revelation is significant for developers of cryptocurrencies as this study suggests that the marketing actions of cryptocurrencies matter as much as the value proposition of cryptocurrencies.

2.4 Pros and Cons of Cryptocurrencies

Like all systems every created, cryptocurrencies have some merits and demerits. Some of the profound good and bad sides of cryptocurrencies are highlighted and explained below:

2.4.1 Pros of Cryptocurrencies

According to Ivashchenko (2016), some of the pros of cryptocurrencies are:

- **No boundaries**: The design choices of cryptocurrencies based on immutability and ability to overcome the double-spending problem makes it ideal making payments. Unlike traditional currencies which can be duplicated or forged, cryptocurrencies offer a payment solution with the integrity. It is no surprise the accept of cryptocurrencies as a medium of exchange by currently supported by some major retail outlets (Elise, 2018).
- **Ease of use**: Compared to traditional (fiat) currencies, the procedure to acquire an account for cryptocurrencies is simple and straightforward. All one needs to own and use a cryptocurrency is access to the internet. Compare that the numerous (and sometimes unnecessary) processes one must go through to get a bank account opened with a bank.
- **Transparency**: The openness of the record keeping system adopted by cryptocurrencies makes auditing of records accessible and transparent. This feature of cryptocurrencies appeals to users who crave for transparent systems of payment and receipt. Also, the ledger of records contains all the information of all the transactions ever done with a cryptocurrency.
- **Anonymity**: Cryptocurrency allows one to anonymise their transactions as one only needs a digital wallet (which does not include any personal information) to facilitate a transaction. This feature makes cryptocurrencies an ideal medium for those who want to make transactions anonymously.
- **Unlimited possibilities of Transactions**: Every cryptocurrency owner is at liberty to do with their assets as they deem fit. Once an owner transfers ownership of a cryptocurrency to another party, the former owner or any other person cannot control how the recipient of the digital asset chooses to use the asset. The new owner can use the newly acquired cryptocurrency across the world for every transaction where cryptocurrencies are accepted

2.4.2 Cons of Cryptocurrencies

On the other hand, Bunjaku et al. (2017) document some of the disadvantages of cryptocurrencies.

- **Money laundering**: Given the anonymous feature of cryptocurrencies, it is of no surprise that money launderers have taken advantage of this feature for an illicit act like money laundering (Bryans, 2014; Richter & Kraus, 2015; Stokes, 2012).
- **High Volatility**: It is a well-documented in the literature that cryptocurrencies are more volatile than other asset classes. The prices of cryptocurrencies react daily to news and announcements from governments of various countries around the world seeking to provide some form of regulations for this unregulated market. Such levels of volatility present a problem for uninformed investors.
- **Illegal Transactions**: The security features backing the operations of cryptocurrencies also a prime tool for the payment of illicit transactions. After an extensive audit of Bitcoin's blockchain, researchers found links with Bitcoin and the horrendous act of child pornography (Matzutt et al., 2018). From child pornography to money laundering (C. Evans-Pughe, Novikov, & Vitaliev, 2014; Dostov & Shust, 2014) and even acts of terrorism, cryptocurrencies can support all forms of illicit transactions.
- **Lack of A Central Issuer:** If something goes wrong with the bank account of a customer, said a customer could file a complaint with the bank, and an inquiry into the issue could be commissioned. What happens when someone even mistakenly sends a cryptocurrency to someone? Not only can the transaction not be reversed, but details of the lucky recipient are also unknown to the sender making it impossible to retrieve the amount sent.
- **Risk of Hacks:** There are always risks of hacks and thefts with something which solely resides in the digital realm. Major cryptocurrencies have been the subject of numerous hacking attacks, thefts and disappearance of exchange markets (Chohan, 2018). Moore & Christin (2013) estimate that around 45% of all cryptocurrency exchange markets shut down. Some of these sudden exchange shutdowns are often well-designed Ponzi schemes which further fuels the view of cryptocurrencies as risky ventures.

3.0 THEORETICAL FRAMEWORK

As stated in the introductory chapter, the principal focus of this thesis is the assessment of the riskiness of the major cryptocurrencies. This section of the thesis introduces the theoretical foundations adopted to make such evaluations.

This chapter begins with by explaining the concept of risk and the metrics used in the measurement of risk. Next, the two popular metrics (VaR and ES) for the analysis of investors' exposure to market risk is presented and explained. Additionally, approaches available for the two metrics are presented along with a justification for the selected approach used in this study. Finally, the chapter concludes with a review of all empirical attempts to estimate the market risk of cryptocurrencies using the two reviewed theories as well as presented hypothesis generated from the review.

3.1 Concept of Risk Metrics in Finance

The trade-off between risk and returns is as ancient as the history of human beings. The advent of financial instruments and markets has facilitated the separation of physical risks from economic risks (Damodaran, 2007). For example, a person who invests in a cryptocurrency can be exposed to significant economic risk without the potential for physical risk, whereas a person who spends considerable time paragliding exposes himself/herself to significant physical risk with no potential economic returns (idem). This thesis is concerned with the potential economic risks investors face with cryptocurrencies. What then is a financial risk?"

3.1.1 Defining Risk

Discussions on the definition of risk have always centred on the notion of uncertainty. Knight, 1921 (pp. 19–20) supplied perhaps the most famous description of risk when he made a distinction between risks that could be objectively quantified and those that relied on subjective assessments. In his own words:

> "*The essential fact is that "risk" means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of character; and there are far-reaching and crucial differences in the bearings of the phenomenon depending on which of the two is present and operating..... It will appear that a "measurable" uncertainty or "risk" proper, as we shall use the term, is so far different from an "unmeasurable" one that is in effect an uncertainty at all.*"

In summary, Frank Knight's definition of risk only considers uncertainties that can be quantified as "risk". This definition of risk holistically ignores unquantifiable uncertainties as a form of risk. He justified this exclusion with an example of the drawing of red and black balls by two men from an urn (pp. 218-219).[6] The first man knows about the existence of red and black balls in the urn but is ignorant as to the number of each of the coloured balls. The second man, however, knows about the number of each coloured ball (3 red balls and one black ball). Knight argues that to the "first man" the probability of drawing a red ball seems like a fifty to fifty chance while to the "second man" the probability is a seventy-five to twenty-five chance. Knight then contests the assumption of the first man by arguing that first man's assumption not be a real probability because he is merely ignorant about the number of each red and black ball in the urn. To him, only the second man could objectively assess his exposure to the uncertainty of the balls he would draw. He considered subjective and unmeasurable uncertainties are just mere uncertainties. Thus, he postulated that only objective uncertainties could be classified as a risk.

Holton (2004) contests this objectivistic and parochial view of risk by Knight (1921) which wholly ignores unmeasurable uncertainties as a form of risk but rather mere uncertainties. Instead, he defines risk in generic terms as "*exposure to a proposition of which one is uncertain (p. 22).*" This generic risk definition by Holton (2004) suggests two essential components of risk; exposure and uncertainty which must both be present for something to be considered as a risk. The first component "exposure" means that for any proposition to be considered as a risk it must carry with it material consequence. One is not considered as exposed if this material consequence has no material consequence. As Holton succinctly puts it "*the litmus test for materiality is: Would we care? (p. 22)*". The other component "uncertainty" means a state where one does not know if a proposition is either true or false. To Holton, risk requires the presence of these two components such that a proposition is disregarded as a risk even if the proposition houses one of the elements.

Take this practical scenario of a potential bad weather announcement. An event coordinator planning a garden is exposed to a potential risk proposition of the event being ruined by bad weather but an individual who has no plans of even taking a walk on this day faces no such risky propositions because the proposition is of no functional consequence to him/her. Furthermore, if the weather announcement were something so sure to warrant an evacuation, then the event coordinator would not consider the organisation of the wedding as a risky proposition but operate

[6] An urn is a round vase used for storing items

with certainty that the ceremony would be impossible to organise. The weather announcement is only viewed as a risky proposition by the wedding coordinator if the announcement offers no certainty about the weather condition of the day of the wedding. It is then up to event planner to decide if it is worth taking the risk of going ahead with wedding given the uncertainty of bad weather on that day. Risk requires the presence of to two components (exposure and uncertainty). This notion of different kinds of exposure makes it impossible to operationally define risk hence why practitioners define a perception of risk unique to that field of practice (Holton, 2004). If so, how then are various forms of these perceived risks defined across different disciples?

3.1.2 Distinctions between Risk Definitions

The ubiquitous nature of our exposure to different kinds of risks propositions across different disciplines means that risk can be defined in different ways for different discipline (Damodaran, 2007). Damodaran (2007) categorises all these different ways of defining risks in three categories which are explained below:

- **Risk versus Probability**: This category deals with risk definitions which solely focus on the probability of events occurring and both the probability of an event happening along with the resulting consequence of the occurrence of that event. For example, the likelihood of a meteor hitting earth may be small, but the consequences of such an impact would be so destructive that such an event would be categorised as a high-risk event
- **Risk versus Threat**: This category handles risk definitions in some disciplines where contrasts are drawn between risks and threats. Threats are low-probability events which are difficult to assess with substantial negative consequences. On the other side, risks are high-probability events with the necessary information to evaluate both the consequences and probabilities of these events.
- **All outcomes versus Negative Outcomes**: The final category of risk definitions focuses on the downsides of scenarios as opposed to the more expansive option of considering all other situations as a risk. This category of risk definition is standard practice with engineering disciplines where risk is usually defined as the probabilities of undesirable events occurring and assessments of the expected negative consequences of the occurrence of that event.

In assessing the riskiness of cryptocurrencies compared to other asset classes, this thesis adopts some of the conventional risk metrics which fall into the third category of risk definitions distinctions.

3.1.3 Conventional Market Risk Metrics in Finance

In the world of finance, the typical indicators of risk are statistical concepts of variance, and standard deviation as these concepts measure the uncertainties (positive as well as negative) of expected results (Adamko et a., 2015).[7] These concepts allow investors to assess their exposures to risk for owning (or taking positions) either a single asset or a group of assets. What about if an investor wants to know his/her exposure to the risk of the whole market in which he/she holds that asset or group of assets? A metric for market risk assessment comes in handy for such queries from investors.

A market risk metric is a measure of the uncertainty in the future value of an asset that is a measure of the uncertainty of the asset's return of profits and losses due to changes in market factors (Alexander, 2008b). These forms of risk metrics solely focus on risks that arise from the movements in prices of financial instruments and assets on financial markets (Choudhry, 2013). Market risks apply to investors' exposure to unexpected changes in prices or rates of financially tradeable instruments (Duffie & Pan, 1997) as opposed to those financial assets held to maturity and never formally repriced (Choudhry, 2013). Examples of such risks include changes in currency exchange rates, changes in the prices of stock equities, changes economic states and the likes. Since the principal aim of this thesis is to understand and quantify the market risks of the major cryptocurrencies, the two popular metrics for the assessment of market risks – "Value at Risk" and "Expected Shortfall" – are reviewed and applied towards this goal.

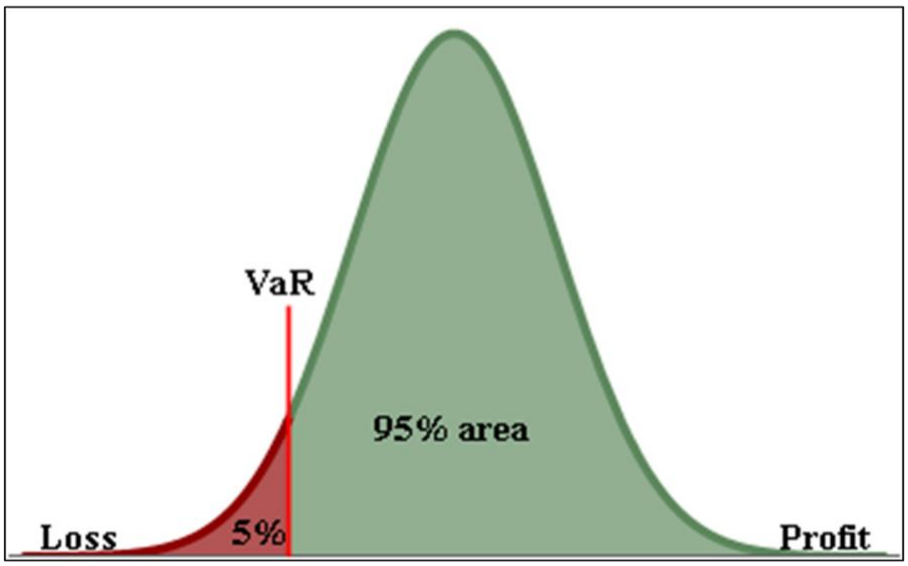
3.2 Value at Risk (VaR)

Value at Risk (VaR), in general terms, measures the potential loss in value of a risky asset or a portfolio of assets over a predetermined period for a given confidence interval (Damodaran, 2007). As Adamko et al. (2015) put it, VaR delivers a single number which represents the maximum amount that an investor can lose with a given level of confidence. The single number representing

[7] Standard deviation is a statistical measure of how much an observed value differ from the mean value of all observations. The square of standard deviation is the variance of such an observed value

a VaR assessment of an investment or group of investments measures with some degree of certainty the maximum amount an investor could lose over a specific period. For example, if the VaR of the asset or assets states "DKK 5 million at 5-days with a confidence level of 95%", then this estimation simply translates as "there is only a 5% chance the value of the asset could drop beyond 5 million Danish Kroner over any period of 5 days or there is a 95% confidence that the value of the asset will not drop beyond DKK 5 million over a period of 5 days". See **Figure 4** for a graphical representation of this practical example (adapted from Adamko et al., 2015).

Figure 4. Graphical representation of 95% VaR.



Choudhry (2013, p. 30) summarises all these with this technical definition of VaR:

> "*VaR is a measure of market risk. It is the maximum loss which can occur with X % confidence over a holding period of t days.*"

From the definition and description of VaR presented above, one can easily deduce the three vital elements of this measure as; a specified fixed period over which the assessment is made, a confidence level or interval and finally the resultant output in the form of the loss value. The last element is outside the direct control of the assessor, but the other two elements are at the individual supervision of the assessor. VaR estimations imply that necessity of choosing the first two elements namely the period over which risk is estimated and the confidence interval. This period over which risk is determined could be one day, ten business days, a month or even longer and the confidence intervals mainly depend on the purpose of the use of the VaR estimates (Adamko et al., 2015). For regulatory purposes, it is common practice for the confidence interval to be with the range of 95% and 99.9% where the range specified range could be aimed to ensure a low probability of insolvency or high rate high probability of insolvency (idem). Mathematically, VaR is determined by Elendner et al. (2016) as:

Given $\alpha \in (0,1)$*, the* VaR_α *for a random variable X with a distribution function* $F(\cdot)$ *is computed as*:

$$VaR_\alpha(X) = \inf\{x \mid F(x) \le \alpha\} \quad (1)$$

where α is the VaR level

3.2.1 Historical Development of VaR

Francis Edgeworth is credited with the first attempt to measure risk when he investigated potential losses in a portfolio made up of assets in 1988 (Adamko et al., 2015). According to the same authors, this first attempt by Edgeworth led to significant contributions in financial literature as it advocated the use of past experiences as a basis for estimating future probabilities and thus the risk of financial instruments. The notion of the term "Value at Risk" is attributed to the work of Dickson H. Leavens (Holton, 2002). Holton (2002) suggests that the example used by Leavens is the first VaR assessment ever published. Leavens' practical example involved considering a portfolio made up of ten government bonds over a period. Each bond either matures at the end of the period for $1,000 or the bond becomes worthless. Holton (2002) acknowledges that while Leavens did not use the term "Value at Risk" explicitly, he repeatedly mentioned "the spread between likely profit and loss" and that expression most likely meant standard deviation which is used to measure risk and an integral part of VaR assessments.

Even though term "Value at Risk" gained prominence only in the mid-1990s, the mathematical foundations of VaR can be traced to the breakthrough works of Harry Markowitz's Modern Portfolio Theory (MPT) and subsequent works that took inspiration from that theoretical breakthrough (Holton, 2002; Szegö, 2002). Even though the directions of these works were different, the goal of the various authors was geared towards engineering optimal portfolios for equity investors. Damodaran (2007) attributes the impetus for the use of VaR as a risk measure to the various financial crises that engulfed financial markets around the world and the regulatory responses to these crises. After the end of the great depression which nearly crippled the banking sector ended, the Securities Exchange Act established the Securities Exchange Commission (SEC) which required banks to keep the borrowings below 2000% of their total equity capital. As a result, banks designed various schemes and risk measures to ensure compliance with this capital requirement by SEC.

The development of new financial instruments and products (like financial derivatives and floating exchange rates) presented a different challenge for risk modelling in the financial industry between 1970 and 1980 (Adamko et al., 2015; Damodaran, 2007). If all the techniques for risk assessments relied on past experiences as a metric for risk assessments, what would be the metric for these new financial products with no historical data? A viable option that emerged to overcome this challenge was to find similar financial products which would then be used as a proxy for risk assessments of the new products (Adamko et al., 2015). As Adamko et al. (2015) acknowledge, all these bottlenecks of the then techniques for risk assessments served as an impetus for the development of a more understandable and reliable risk indicator. A series of events played an integral part in the development of this indicator as documented by (Damodaran, 2007).

First, SEC expanded and refined the capital requirements in a move named as "Uniform Net Capital Rule (UNCR) which was promoted and adopted in 1975 (Damodaran, 2007). UNCR categorised financial assets owned by banks based on risk into in twelve different categories with different specified capital requirements for each category. The capital requirements ranged from 0% for short-term assets like treasuries to 30% for stocks and equities, and banks were required to report these capital requirements in quarterly statutory reports named as Financial and Operating Combined Uniform Single (FOCUS) (idem). According to the same source, the next event occurred when the SEC tied the capital requirements of financial institutions to losses that would be incurred with a 95% confidence over a thirty (30) day period for each of the categories identified. This requirement was commonly referred to as a "haircuts" and not explicitly called "Value at Risk". In effect, this new measure was an attempt by the SEC to ensure that financial institutions had enough capital cover potential losses over a period of thirty (30) days. Finally, in 1986 Kevin Garbage of Banker's Trust presented risk measures known as "Value at Risk" for the internal risk assessment of the company's fixed income portfolios. This adoption of the approach of market risk assessment gained popularity and adoption so much so that many financial institutions used the various rudimentary variants of VaR in the early 1990s. However, significant losses incurred between 1993 and 1995 due to the use of financial derivatives as well as the collapse of financial institutions led to calls for even more comprehensive variants of the then novelty VaR measure.

The investment bank, JP Morgan, is widely accredited as the institution that helped popularised the adoption of the current comprehensive variants of VaR when it published a technical report – "RiskMetrics" – in 1994 on a simplified VaR variant already used by the company (Hull, 2015). Dennis Weatherstone, former JP Morgan Chairman, requested for complicated daily risk exposure reports to be simplified which eventually led to the development of a VaR report delivered to his desk every 4:15 pm. As a result of the delivery of the daily VaR report every 4:15 pm, it was infamously named as the "4:15 report". As Holton (2002) notes, the timing of this publication was perfect given the global turbulence in financial markets and the vast losses financial companies were incurring due to the advent of derivative markets. Software vendors implemented and promoted this less complicated this VaR measure to a broader audience. This risk measure was formally adopted and recommended by the Basel Committee on Banking Supervision (BCBS) as a methodology for financial institutions to calculate capital requirements regarding their market risk exposure in April 1995 (Adamko et al., 2015; Holton, 2002).[8] BCBS also approved the use of proprietary VaR variants.[9]

3.2.3Advantages of VaR

VaR has been the de-facto standard for the assessment of market risk by financial institutions in the last the two (2) decades. (Alexander, 2008b) highlights the main advantages of VaR as follows:

- It can be used to compare the market risks of all types of activities of an organisation.
- VaR is an intuitive approach for the assessment of market risks as its ability to provide a single number representing market risk exposures allows senior managers to understand this metric easily.
- As a concept, VaR can be extended by an organisation to other types of risk such organisations anticipate. This metric is not limited to financial market risks as it can be extended to accommodate credit and operational risks.

[8] Basel Committee on Banking Supervision, hereinafter, referred to as BCBS.
[9] See Holton (2004) for a more comprehensive history of VaR.

- VaR considers the correlations between various assets a variety of different methods can do categories and market risk assessments.
- VaR measures can also accommodate the inclusion of specific risks by including these individual risk categories among the overall risk factors under consideration.

3.2.4 Limitations of VaR

Over the last couple of years, the validity and coherency of VaR assessments have been challenged by various researchers and practitioners. Ever since VaR measures gained widespread adoption, it has not been short of critiques. Holton (2002) enlists the emergence three common themes of these VaR critiques as; different VaR methods produce different results, as a measure of risk VaR is conceptually flawed, and the widespread of use of VaR entails systemic risks. Alexander (2008b) and (Damodaran, 2007) expand these common VaR critiques by highlighting the main limitations of VaR are as follows:

- **Huge Cost of Implementation**: As Alexander (2008b) acknowledges, the cost of implementing a fully integrated VaR system across an organisation (or groups of organisations) is an expensive decision. Owing to such costly implementation and the various limitations, the justification of such colossal investment outlays is challenged.
- **Narrow Focus of Risk**: The simplistic and intuitive nature of VaR models relative to other similar metrics comes at the expense of a narrow definition view of risk (Damodaran, 2007). Market risks are everything but simplistic in real life. As a result, organisations that narrowly measure such risks with narrow definitions can be fooled into a false sense of complacency about the potential risks.
- **VaR Can Be Wrong**: As the overview with various VaR methods has shown, there is no precise measure of this metric as each method comes with it its advantages and limitations. He concedes that VaR assessments can be wrong and that sometimes errors can be large enough sometimes to make such assessments a misleading measure of risk exposure.
- **Short-Term Focus**: While VaR measures can be computed over any specified number of periods, it is common practice that such measures are limited to a single day, week or some few weeks Alexander (2008b). This short-term focus can be problematic for long-term risk considerations. According to Damodaran (2007), there are three reasons why such short term is the focus of VaR assessments. First, financial institutions that use VaR usually are

more focused on the day to day risk. Secondly, regulatory compliance requires most financial institutions to disclose short-term risk. Finally, inputs necessary for VaR measures are easiest to estimate for shorter periods than more prolonged periods.

3.2.6 Coherent Risk Measures

Over the past couple of years, VaR has been criticised as a "non-coherent" risk measure (Acerbi, 2002). Artzner et al. (1999) proposed four (4) properties or axioms that a risk measure should have for it to be considered as a coherent measure.[10] These properties or axioms as explained by Hull (2015) in the are:

- **Monotonicity**: A portfolio which produces a worse result than other portfolios for every state of the world should have a risk measure greater than the other portfolios. A portfolio that performs worse than the other should be seen by the risk measure as the risky one which needs lots of buffer capital to offset potential losses.
- **Translation Variance**: The addition of an amount of cash K to a portfolio should reduce the risk measure of the portfolio by the amount of cash added. The addition of an amount equal to cash K serves a buffer against losses and as a result, should reduce the capital requirement by the K amount.
- **Homogeneity**: The change in the size of a portfolio by a factor λ while retaining the relative amounts of different assets in the portfolio same should result in the risk measure being multiplicated by the λ. Consequently, the size of a portfolio should have a direct relationship with the capital requirements for potential losses such that doubling the portfolio's size requires doubling the capital buffer for potential bad times provided the portfolio size is not too large.
- **Subadditivity**: This condition implies that the risk measure from the combination of two portfolios should not be greater than the sum of the risk measure of each portfolio before they were combined. Thus, a measure of risk should be either be stay the same or is reduced after the combination.

[10] See Artzner et al. (1999) for mathematical proof of the axioms

VaR as a risk measure is considered as not a coherent measure because it fails to fulfil the last property explained – subadditivity (Roccioletti, 2016). As a risk measure, VaR is not sub-additive as it fails to account for the benefit of diversification rendering it as a non-coherent measure of risk. In light of the lack of coherency of VaR as a risk measure, another risk measure Expected Shortfall has emerged as a more coherent alternative metric as it fulfils all the four axioms or properties postulated by Artzner et al. (1999) for coherency.

3.3 Expected Shortfall (ES)

Expected Shortfall (ES), proposed by Acerbi & Tasche (2001), has emerged as a more coherent risk measure that fulfils all the four conditions necessary for a risk measure to be classified as a coherent measure. The intuition behind ES concept about VaR translates merely as while VaR attempts to answer the question "how bad can things go?", ES attempts to answer the question "what's the expected loss if things do go bad? (Hull, 2015)". Thus, ES is the conditional expectation of a loss given that this loss is greater than the VaR level (Yamai & Yoshiba, 2002). For example, suppose the VaR (with a confidence interval of 95%) of an asset is DKK 1 million over a 5-day period, the ES is simply the average amount lost on the condition that loss is greater than DKK 1 million over a 5-day period. As this practical example has shown, ES, just like VaR, needs two parameters for the risk estimate - period and a confidence level (Hull, 2015). Unsurprisingly, ES is also sometimes referred as "Conditional Value at Risk", "Expected Tail Loss", "Beyond VaR", "Tail VaR", "Mean Excess Loss" or "Conditional Tail Expectation" by different authors in literature. Mathematically, ES is defined by Elendner et al. (2016) as:

Given $\alpha \in (0,1)$, *the* VaR_α *for a random variable X with a distribution function* $F(\cdot)$ *is computed as*:

$$VaR_\alpha(X) = \inf\left\{x \mid F(x) \leq \alpha\right\}$$

ES is then computed as:

$$E\left[X \mid X > VaR_\alpha\right] \tag{2}$$

where E is the expected losses of X at VaR level of α

ES has emerged as an excellent substitute for VaR in risk management applications as it overcomes some of the criticisms usually levelled against VaR (Roccioletti, 2016). Also, as Yamai & Yoshiba (2005) revealed, the use of a single risk measure should not dominate the domains of financial risk management as each risk measure has its advantages and limitations. Instead, they recommend the pluralistic view of risk assessments where VaR estimates are complemented with ES estimates for a more comprehensive measure of investors' risk exposure in various markets. Thus, the decision of the paper to view the exposure of cryptocurrency investors using both risk measures (VaR and ES) is justified.

The main advantage of ES a risk measure over VaR is its ability to fulfil all the four conditions for coherency as detailed by (Artzner et al., 1999). This advantage implies that ES, unlike VaR can account for the diversification effect when considering for the riskiness of a portfolio made up of different assets with their risks. However, ES is not a flawless risk measure. The principal weakness for ES is that, unlike VaR, it cannot be easily backtested in the sense that ES estimates cannot be verified through comparison with historical observations (Chen, 2014).

3.4 Approaches to VaR and ES estimations

Generally, there are three basic approaches for VaR and ES measurements even though there exist many variants of each approach (Damodaran, 2007). The three approaches involve making assumptions about the distribution of an asset's returns for making market risks, or by using the variances and covariances of these risks. Finally, the last approach involves estimating hypothetical portfolios with historical data or through Monte Carlo simulations (idem). It is worthwhile mentioning that these three approaches can be grouped differently by different authors. Adamko et al. (2015) and Linsmeier & Pearson (1996) summarise these variants under the three (3) general approaches for VaR measurements as follows:

1. Variance-Covariance Method (or Analytic Method)
2. Historical Simulation
3. Monte Carlo Simulations (Stochastic Simulation)

3.4.1 Variance-Covariance Method (or Analytic Method)

The variance-covariance method is primarily based on the assumption that the underlying market factors follow a multivariate normal distribution(Linsmeier & Pearson, 1996). As VaR measures the probability of the value of an asset (or group of assets) not dropping below a specified value at a particular time interval, this method makes it relatively simple to for the risk assessment as it supplies the probability distribution of potential values (Damodaran, 2007). Take this practical example of the VaR assessment single asset like equity (ABC stock) over the period of one year with a 95% confidence interval. Suppose the average (mean) value of this ABC stock for the year is DKK 200 million with an annual standard deviation of DKK 10 million and the values follow a standardised normal distribution. A statistical property of normal distributions is that five (5) per cent of the time, outcomes only occur less than or equal to 1.65 standard deviations below the mean (Linsmeier & Pearson, 1996). Thus, a 5% per cent probability used in a VaR assessment based on an assumption of a standard normal distribution equates merely to the standard deviation times 1.65 times of such occurrences.[11] With regards to the simple, practical example presented above, the VaR figure is mathematically assessed as:

$$\begin{aligned} \text{VaR}_{(95\%,\ 1\ \text{Year})} &= 1.65 \times (\text{Standard Deviation of the change in the value of ABC stock}) \\ &= 1.65 \times \text{DKK 10 million} \\ \text{VaR}_{(95\%,\ 1\ \text{Year})} &= \text{DKK 16.50 million} \end{aligned}$$

The VaR output (DKK 16.50 million) translates as that over the period of one year, one can be 95% confident that the value of ABC stock will not fall below DKK 183.50 million (200 million minus 16.50 million) over a period of a year. As this practical example has highlighted, the selling point of this VaR method is its focus on simplicity. The computation of the standard deviation of changes in the value of an asset or a portfolio of assets is the principal focus of the variance-covariance method (Linsmeier & Pearson, 1996). For a portfolio made up of different assets, the covariance pairs needed to estimate the variance and thus the risk of the portfolio would complicate this simplified VaR method. A procedure is known as “risk mapping” helps overcome this bottleneck where the risk of individual investments is “mapped” to more general market risks when VaR is computed, and then an estimate is made based on these market risk exposure (Damodaran, 2007; Linsmeier & Pearson, 1996).

As Damodaran (2007) elaborates, the strength of variance-covariance method which is its simplicity based on an assumption of the distribution of the returns of the asset(s) under consideration is also is biggest Achilles heel. He identified three fundamental weaknesses of this approach because of the design choice explained above:

- **Wrong distributional assumption**: Since this method assumes that returns are normally distributed, this VaR approach suffers when the actual returns distribution are not normally

[11] A confidence interval of 90%, 95% and 99% respectively translates as 1.65, 1.96, 2.33 standard deviations either below or above a mean of a normal curve. A 95% confidence interval is approximately the 97.5 percentile point (approximately 1.65 standard deviations) of the standard normal distribution.

distributed. Thus, the computed VaR underestimates market exposures given that it fails to capture outliers in the actual returns distribution.

- **Input error**: Even if the assumption of normality of the actual returns distribution holds up, VaR estimates can still be wrong if the variances and covariances upon which the estimates were made are wrong. Estimations of variances and covariances with historical data are associated with standard errors, and large error items may lead to inaccurate VaR estimates.
- **Non-stationary variables**: It is very common for financial data to be non-stationary as the fundamentals driving such data changes over time. Data is considered as non-stationary when its variances and covariances change over time. Non-stationarity in financial data thus can lead to incorrect VaR estimates.

However, researchers have looked at various ways of overcoming these weaknesses explained above. Researchers have looked into VaR estimation techniques not based on the assumption of normal distribution of returns (Adamko et al., 2015). Damodaran (2007) asserts that the estimation of inputs based on non-normal distribution models is generally complicated to accomplish with historical data, and the probabilities of losses are more straightforward to compute based on the normal distributions. Also, a wave of research has been poured into VaR estimates that allow flexible estimates of variances and covariances. The most notable work is that of Robert F. Engle which improves conventional VaR estimates (Engle, 2001). Conventional VaR, as explained earlier, assumes that standard deviation (volatility) in returns does not change over time. A condition, technically known as Homoscedasticity. The empirical work of Engle, which earned him a Noble Prize in Economic Sciences in 2003, allows the standard deviation of models to change with time. A condition also technically referred to as Heteroscedasticity. Engle (2001) provides two variants for such these statistical innovations based on heteroscedasticity; AutoRegressive Conditional Heteroscedasticity (ARCH) and Generalised AutoRegressive Conditional Heteroscedasticity (GARCH).[12] Such statistical innovations, Engle and others contest provide better forecasts of variance and by extension, better VaR assessments.

[12] Generalized Auto Regressive Conditional Heteroscedasticity, hereinafter, referred to as GARCH.
Auto Regressive Conditional Heteroscedasticity, hereinafter, referred to as ARCH.

3.4.2 Historical Simulation

A historical simulation approach to VaR assessment involves using historical changes in market rates and prices to construct a hypothetical distribution of future profits and losses and then read of VaR estimate as the loss that is exceeded only by the chosen confidence interval (Linsmeier & Pearson, 1996). The heavy reliance on historical data means that rare events and crashes could potentially be included in the assessment of potential losses (Choudhry, 2013). This approach is considered the simplest and most intuitive approach especially when dealing portfolios made up many different assets. Estimation of the VaR of a portfolio is done by creating hypothetical time series of daily returns of each asset in the portfolio, obtained by running portfolio through the actual historical data of the assets and computing changes that would have occurred in each period (Damodaran, 2007). The VaR estimate for the portfolio is merely the quantile (as determined by the chosen confidence interval) of the hypothetical time series of the periodic returns. For single assets, it is as simple as calculating daily changes in prices, sorting these daily returns in ascending order and selecting the worst percentile depending on the chosen confidence interval (worst fifth percentile for 95% confidence interval and so forth) (Adamko et al., 2015).

Damodaran (2007) points out the implicit assumptions of this approach. First, with this approach, VaR depends on by actual price movements instead of distributional assumptions of normality. Next, the weight of each day in the time series under consideration is equal during the process of computing VaR estimates. This implicit equal weighting assumption of the historical simulation method is problematic if there is a trend in the variability of the data such that past trends carry the same weight as current ones. Lastly, as this approach banks on the assumption of history repeating itself, it opens itself up for critiques, and potential failure since catastrophic events are rarely repetitive. History suggests that market risks are typically unique.

Just as it was with Variance-covariance approach, there are modifications which attempt to correct or at least improve the highlighted implicit assumptions of the historical simulation approach to VaR. The main modified variants of the historical simulation approach to VaR are:

- **Focus on recent weights**: As pointed out assigning equal weights to daily returns with no interest in the recency of these returns is problematic. A reasonable argument against such decision is that more recent historical data are better predictors of the immediate future than those historical returns from distant past (Damodaran, 2007). To this end, Boudoukh et al., (1998) offer a solution with a historical simulation variant where more weights are assigned to more recent returns than those in the distant past using a decay factor for the weighting of returns. This variant of historical simulations with a focus on current returns is also known as Weighted Historical Simulation or the BRW method (P. F. Christoffersen, 2012; Pritsker, 2006).

- **Hybrid models**: Another popular variant is the modification of the conventional historical simulation method with the inclusion of other time series models. Barone-Adesi et al. (1998) and Barone-Adesi et al. (1999) combine the power conventional historical simulation with the flexibility of GARCH models to deliver a hybrid model which makes the conventional method more flexible and responsive to current data (Sharma, 2012). This hybrid model adjusts sampled historical returns with volatility estimated using a conditional volatility model like GARCH. This hybrid is popularly known as the Filtered Historical Simulation (FHS).[13]

In light of all the implicit assumptions and attempts to improve these assumptions, the main weaknesses of historical simulation approach are summarised by Damodaran (2007) as the following:

- **The past is not always a good predictor of the future**: Although every method for market risk assessment relies partly on historical data, historical simulation is the method which relies entirely on historical data. This restrictive design feature of this method leaves this method susceptible to critiques as it is not flexible enough to accommodate subjective assumptions which may help improve its coherency.
- **Data trends**: As pointed out earlier, the conventional historical simulation fails to consider the recency of data points as all data points in practice carry the same weight. This is problematic as the prices changes in the distant past affect market risk assessments with the same effect as the most recent price changes.
- **New forms of risk or assets**: Heavy reliance on historical data leaves historical simulation method entirely unprepared for new forms of risk never captured in historical data. Also, if a method relies exclusively on historical data, how would such a method assess the market risk exposure of an asset with no historical data?

[13] Filtered Historical Simulation (FHS), hereinafter, referred to as FHS

3.4.3 Monte Carlo Simulations (Stochastic Simulation)

The Monte Carlo simulation methodology is similar to the historical simulation methodology with the point of departure being that Monte Carlo simulations involve the generation of a hypothetical asset or portfolio profits and losses based on an assumed statistical distribution instead of historical data (Linsmeier & Pearson, 1996). Monte Carlo simulations involve the different generation scenarios for considered risk factors based on assumptions of the distribution of the historical data so that any market risk measure can be computed on the generated scenarios (Trenca et al., 2011). This approach allows the flexibility of countering potential scenarios based on an assumption of distribution that best describes the behaviour of historical events concerning the asset in question. Once a decision on the assumed distribution is made, some simulations (mostly thousands or even millions) are run with each run reflecting a new value of the asset or portfolio based on market risk variables of that particular simulated run (Damodaran, 2007). After the repeated series of simulated runs with the resulting value of the asset or portfolio matching each series, a market risk measure can easily be computed.

3.4.5 Selecting A VaR & ES Approach

Having gone through the various approaches to VaR assessments as well as the advantages and limitations of each approach, one might wonder about the criteria one adopts for the task of VaR and ES computations. Which one of these three general approaches yields the best and most reliable estimate if all approaches yield different results?

Damodaran (2007) argues that the decision on selecting the best approach to market risk assessments greatly depends on the task at hand. In his view, the variance-covariance approach works best for short-term risk assessments that exclude derivatives like options. Also, the historical simulations provide good risk estimates when there is substantial historical data where the volatility is stable. Finally, the Monte Carlo simulation approach is more suitable for risk assessments where the historical data is more volatile and non-stationary which makes assumptions about normality questionable.

In response to this argument, the paper selects a more contemporary and comprehensive approach – the FHS method – as the suitable approach for the assessment of an investor’s risk exposure within the domains of cryptocurrencies. This decision is justifiable for three reasons. First, FHS combines the strengths of both the historical simulation and Monte Carlo simulation methods into a single approach which helps overcomes the weaknesses of each separated approach. The components of FHS makes it possible to model non-stationary and more volatile data such that consideration is given more recent volatility while taking advantage of the power of Monte Carlo simulations (Pritsker, 2006; Trenca et al., 2011). Such flexibility offers a more comprehensive view of an estimate of an investors' exposure to risk. Secondly, the empirical works of Giannopoulos & Tunaru (2005) proves that ES estimates using FHS method is a coherent risk measure as combines one of best applied econometric modelling techniques (GARCH) in risk management with the most coherent risk measure. To this end, this choice of approach delivers the most comprehensive attempt to measure riskiness of cryptocurrencies to investors. Finally, the novelty of cryptocurrencies compared to other established asset classes like equities means that total reliance on its "limited" historical data with a single technique can be potentially disastrous. The oldest circulating cryptocurrency, Bitcoin, is only nine (9) years old.

3.5 Review of Empirical Literature: VaR & ES Assessment of Cryptocurrencies

This sub-section brings readers up to date with recent contributions on the estimation of market risks using the two metrics reviewed above with the help of the FHS method. First, the process for the review of the empirical contributions is presented to readers with the help of a concept map which lays out the thought process for the review. This sub-section continues by presenting previous notable findings on the subject under review. Finally, this chapter is closed by the presentation of hypotheses deduced from the review of previous contributions.

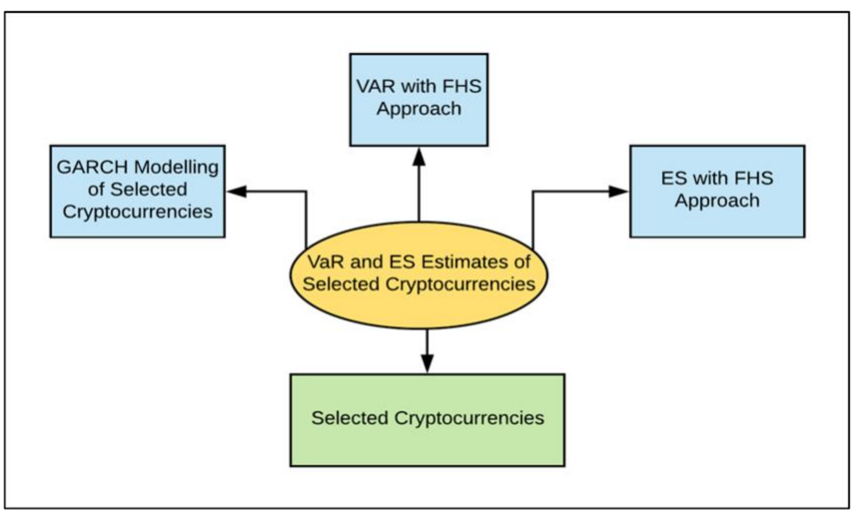
3.5.1 The Review Process

All forms of research in practice need to be informed by existing and current knowledge in a subject area (Baker, 2016). This not only prevents redundant inquirers but allow the whole scientific community to develop more comprehensive and intimate understanding of a subject area. To understand all previous works conducted, the conceptual framework recommended for empirical review by Rowley & Slack (2004) is adopted for this thesis. The conceptual framework involves the following processes:

- **Evaluation of information sources**: Due to the novelty of cryptocurrencies compared to other established financial asset classes, the range of sources of information on these asset classes are mostly limited to scholarly and research journals and some few books. The narrow focus review subjects (VaR and ES of cryptocurrencies using FHS) limited the decision on information sources exclusively to scholarly and research journals.

- **Searching and location of information sources**: The next stage involved the actual process of searching and locating relevant literature on the review subject. A vast number of tools is available for such tasks including library catalogues, online journal databases, and search engines (Baker, 2016). All the three tools were used for this process as relevant sources of information concerning
- **Development of the conceptual framework/mind map**: The next crucial stage of the review process involves the development of a concept map which comprises all the major and minor fundamental concepts of the review subject. Such a plan, Rowley & Slack (2004) stresses helps a reviewer to identify additional search terms, clarify thoughts about the structure of the review and help understand the theory, concepts and relationships between them. **Figure 5** below presents the conceptual map developed for this review.

Figure 5. Concept Map relating to VaR and ES estimates of Cryptocurrencies using FHS.



- **Presentation of review findings**: For the task of presentation of findings, a separate section for bitcoin and findings regarding the themes presented in the concept map regarding the alternative cryptocurrencies. This style of presentation offers a more coherent view of the limited and sparse literature on cryptocurrencies other than Bitcoin.

3.5.2 Presentation of previous findings

It is unsurprising that bitcoin, unlike other alternative cryptocurrencies, has enjoyed the majority share of researcher's attention with regards to the volatility of the most famous cryptocurrency in circulation. Research on the volatility of the alternative cryptocurrencies is very limited.

One of the earlier studies on the volatility of Bitcoin was the study by (Grinberg, 2011). In that empirical work, the author warned potential users and investors of Bitcoin of the risks involved in such young markets in 2011. The author, however, acknowledged that Bitcoin had the potential to succeed even without backing with commodities or government entities. Since then bitcoin matured as a viable alternative to traditional assets which can serve as a medium of exchange and a store of value. According to Glaser et al. (2014), even though Bitcoin can function as an acceptable medium of exchange, new bitcoin users prefer using it as a financial asset to store value for speculative reasons to using bitcoin as a currency. This view of Bitcoin is not limited to Bitcoin alone as most new investors of alternative cryptocurrencies invest in such markets for speculative reasons (idem). Bouoiyour & Selmi (2015) used a variant of the GARCH model (E-GARCH), which revealed the extreme volatility of Bitcoin is influenced by more negative (bad news) than positive shocks (good news). The study concluded that Bitcoin market was still at an immature stage and the market is highly driven by nonprofessional noisy traders and speculators. With the help of the standard GARCH model, Dyhrberg (2015a) found out that Bitcoin has many similarities the commodity gold and the fiat currency dollar Bitcoin reacted significantly to federal fund rates. Thus, bitcoin could be used by investors a tool (for storing value) for risk-averse investors who anticipate bad news. Furthermore, Bitcoin possesses significant hedging capabilities and could be used alongside gold to eliminate specific market risks (Dyhrberg, 2015b). Katsiampa (2017) expanded the ability of GARCH models the attempts to explain the volatility of Bitcoin. After testing six GARCH-type models to try to explain the volatility of Bitcoin, it was found that optimal model was the AR-GARCH model regarding goodness-of-fit to the Bitcoin data. Glaser et al. (2014) also corroborate all previous findings which postulated that Bitcoin is mainly used for investment purposes even though it could serve as a medium of exchange. With regards to the relationship between Bitcoin and other established assets like gold, fiat currencies or equities, Baur et al. (2017) show Bitcoin is different from gold and fiat currencies and uncorrelated with other established assets. Bitcoin has its unique risk-return characteristics as it follows a different volatility process as shown by the GARCH methodology employed for that findings. Stavroyiannis (2018) adopted the GJR-GARCH (1,1) model for VaR and ES estimations of Bitcoin using the FHS approach. It was revealed that revealed that Bitcoin is subjected to higher risk than S&P 500 and gold.

Owing to the limited attention on other cryptocurrencies, some researchers have shifted attention (at least partially) to the volatility of other alternative cryptocurrencies in circulation. Elendner et al. (2016) explored the volatility of eleven cryptocurrencies (including Bitcoin) with the help of the standard GARCH model. The study revealed a weak correlation between alternative cryptocurrencies and established financial assets as well as with each other. These findings indicate potential diversification use of these investigated cryptocurrencies in portfolios. Also, VaR and ES estimates (using the analytic method) revealed that Ripple had the lowest risk regarding the two risk measures with Ethereum being the riskiest cryptocurrency between September 2014 to July 2016. Osterrieder et al. (2017) showed that cryptocurrencies (including Bitcoin) show extreme volatility, and their prices exhibit heavy tail behaviour. A VaR and ES estimates using the historical method revealed that Monero represented the asset with the highest estimates. They concluded that cryptocurrencies are riskier than traditional fiat currencies. The heavy tail feature of cryptocurrencies in general was corroborated by Chan et al. (2017) when seven cryptocurrencies (including Bitcoin) were analysed . They also revealed that the generalised hyperbolic distribution gives the best distribution fit for Bitcoin and Litecoin. The normal inverse Gaussian distribution was the best fit for Dash, Monero, and Ripple. Finally, Laplace distribution gives the best fit to MaidSafeCoin. Chu et al. (2017) supply the most comprehensive attempt to find best distribution fits and GARCH models for most of the popular cryptocurrencies in 2017. After fitting all the popular GARCH-type models and popular distributions, they found that the standard GARCH and the integrated GARCH (IGARCH) models with an assumption as the best fits regarding the volatility modelling of the investigated cryptocurrencies. However, they cautioned the use of the Integrated GARCH (IGARCH) model as its success largely depends on structural changes in the data being fitted. However, Altun et al. (2018) contest that the empirical investigation of FHS models with skewed and fat-tailed innovation distributions showed that such innovation distributions are preferable to reduce VaR forecast errors of FHS models. The only attempt to use the FHS approach, an approach considered to be the most comprehensive, in VaR and ES estimates in literature is the working paper by (Stavroyiannis, 2017). In this working paper, a GRJ-GARCH model which was not back tested was adopted for VaR and ES estimation using FHS method for four cryptocurrencies. The findings from the two risk measures reveal that selected cryptocurrencies were subjected to much higher risk than proxy index markets. Additionally, it was found that Bitcoin was relatively more stable than Ethereum, Litecoin, and Ripple in terms of a comparison of their 10-day VaR and ES estimates.

This thesis aims to test the empirical findings of cryptocurrencies regarding their riskiness with the help of VaR and ES theories through the FHS method. The next stage involves the formulation of hypothesis from insights gained from previous contributions. As identified, the FHS relies on volatility estimates from a GARCH volatility modelling for adjusting historical returns. From previous empirical findings presented above, the GJR-GARCH (1,1) model seems to be a good fit for the volatility modelling of cryptocurrency. Consequently, the first hypothesis is;

> **Hypothesis 1**: *The GJR-GARCH (1,1) model with student-t distribution tends to be a good fit for the selected cryptocurrencies.*

Secondly, the standard GARCH model has also proven to be a good fit for cryptocurrencies as revealed in lendner et al. (2016) The next hypothesis builds on this previous finding as;

> **Hypothesis 2**: *The GJR-GARCH (1,1) model with student-t distribution tends to be a good fit for the selected cryptocurrencies.*

As revealed by the working paper by Stavroyiannis (2017), bitcoin proved to be least volatile regarding the 10-day VaR and ES estimates compared to Litecoin, Ethereum, and Ripple. The final hypothesis tests this previous finding by comparing the 10-day VaR estimates of Bitcoin with Ethereum, Ripple, Litecoin, Monero and Stellar.

Hypothesis 3: *The 10-day VaR and ES estimate (through FHS method) of bitcoin tends to be lower than the other selected cryptocurrencies.*

4.0 METHODOLOGICAL FRAMEWORK

This section covers the methodical adopted by this thesis in its bid to assess the market risk measures of the selected major cryptocurrencies via VaR and ES. First, the philosophical and scientific stance of this thesis in the inquiry process is laid out. Next, the process used in designing the whole research process is presented to readers. Thirdly, the econometric model used for the assessment is presented before the various statistical tests used to test the appropriateness of the data for the econometric model are laid out. Last but not the least, the reliability and validity concerns of the research process and results are addressed. Finally, the chapter closes when the limitations of the thesis are highlighted.

4.1 Philosophy of Science

All forms of research are heavily influenced by the philosophical beliefs about the process of knowledge creation (Creswell, 2013). These philosophical beliefs (sometimes referred to as paradigms) serve as a guide for researchers during the research journey. Since the foundations of any research process are the methodological, scientific or philosophical approaches, an overview of the concept of paradigms will be briefly explained as well present the implications of the selected paradigm by this study.

4.1.1 Selected Paradigm

Based on a critical evaluation of the different scientific approaches, this thesis adopts a contemporary philosophical approach known as critical rationalism. The reasons and justification of this adoption will now be presented. Critical rationalism is a paradigm accredited to its founder Karl Popper – an Anglo-Austrian philosopher. Ontologically, critical rationalist adopts realism (Gadenne, 2015).[14] This adoption means that for a critical rationalist, the phenomenon exists independently of the observer and social actor (Guba & Lincoln, 1994). Thus, as an observer of the market risk exposure between investors and cryptocurrencies, this thesis is free from a judgement which is not impacted by subjective interpretations. Epistemologically, critical rationalists assume that every theory can be fallible as one cannot tell if it is true or not (Gadenne, 2015). This epistemological assumption is why every theory should be subjected to rigorous

[14] Ontology refers to how the world is seen by an observer while epistemology refers to how an observer explains realities of this world (Guba & Lincoln, 1994).

testing. This assumption accounts for revisions of theories and the constant changes the world experiences.

The fundamental tenet of critical rationalism is the rejection of the positivistic ideology that knowledge acquisition could be acquired from empirical observation or methods using an inductive process (Holtz & Odağ, 2018). Positivists argue that researchers create true knowledge by developing a preliminary theory from observations about a phenomenon and continuously and vigorously testing theories against new observations (idem). Thus, scientific knowledge accumulates through a repetitive process of induction which generates better versions of existing theories according to the positivists. Such reliance on induction by positivists remain its weakness as identified by David Hunne when he referred to this flaw as the “problem of induction” (Ormerod, 2009). Hunne argued that no amount of confirmative observations can the rule out the possibility that the very next observation could reveal a different result to the most recent one (Holtz & Odağ, 2018).

Popper’s critical rationalism contests this flaw of the positivistic assertion of induction by positing that universal theories are never verified or confirmed as theories can only be falsified (Ormerod, 2009). To critical rationalists, the so-called “problem of induction” is solvable by taking this perspective of falsification that existing theories can never be considered true as they are subject to constant attempts to falsify claims of the theory by testing new observations. As a result, critical rationalism argues that the knowledge creation process is aided by the process of deduction and not induction as positivists contest (Holtz & Odağ, 2018)- Specifically, Popper advocates “hypothetico-deductive method” for scientific research where existing theories are invoked with no prior justification and critically tested (Gadenne, 2015). One does not even need a comprehensive study to realise the high volatilities in cryptocurrency markets. The theories of VaR and ES help quantify for investors their exposures to market risk. Furthermore, the adopted method for the VaR and ES quantifications – FHS – relies heavily on good forecasts of daily volatility through econometric modelling (GARCH models). GARCH modelling theories suggest that the accuracy of a generated model can be verified or falsified using a backtesting process. Consequently, this thesis attempts to verify (to the extent of the period under consideration) previous theoretical suggestions that the econometric (GARCH) model that FHS relies on can be checked for its accuracy.

4.2 Research Strategy

Blaikie (2010) posits that there are four different research strategies available to researchers in their attempted answer their research questions – inductive strategy, deductive strategy, strategy and abductive strategy. Each of these research strategies has its unique process for the conduct of research as well as a combination of ontological and epistemological assumptions (idem). With critical rationalism as its basis for scientific and philosophical reasoning, this study adopts the deductive strategy in the quest to compute the VaR and ES estimates using the FHS method of the selected major cryptocurrencies. In fact, Popper is also accredited as a major contributor to the development of this research strategy. The principal aim deductive research strategies are the testing of theories to reject the false ones and corroborate findings with those the survive the test Blaikie (2010). This type of research strategy also shares the same ontological and epistemological assumptions of critical rationalism (idem). As a result, for studies adopting this research strategy, the research process begins with the formulation of deductive arguments (hypothesis) from existing theories, then collecting data on the concepts relating to the theory and arguments so that the hypothesis can be tested to see if the results match the previous conclusion of the theory being tested (Creswell, 2013).

4.3 Research Method

According to Creswell (2013), there are three primary research methods available to researchers in their research journey – qualitative methods, quantitative methods and mixed methods (a combination of qualitative and quantitative methods). The hypothesis generated from previous empirical findings for this thesis is tested using quantitative methods

The quantitative research method is ideal for the testing of hypotheses as it enables an investigator to take an objective stand during the inquiry (Bryman, 2012). The generated theoretical assumptions are tested with the help of statistical analysis and results are objectively reported without any subjective attempt to influence the results. Quantitively research facilitate objective testing of previous findings and existing theories as it helps minimise subjective connotations during the research process. **Table 2** presents the steps followed by the quantitative research strategy adopted by this thesis (Bryman, 2012, p. 161).

Table 2. Steps in Quantitative Research.

Recommended Step	Relation to the Study
Theory	This study takes inspiration from a working paper by Stavroyiannis (2017) which attempts to make VaR and ES estimates of major cryptocurrencies with the FHS method without backtesting the volatility model.
Hypothesis	**Hypothesis 1**: *The GJR-GARCH (1,1) model with student-t distribution tends to be a good fit for the selected cryptocurrencies*. **Hypothesis 2**: *The GJR-GARCH (1,1) model with student-t distribution tends to be a good fit for the selected cryptocurrencies* **Hypothesis 3**: *The 10-day VaR and ES estimate (through the FHS method) of bitcoin tends to be lower than the other selected cryptocurrencies*
Research Design	This study adopts a deductive research strategy based on the scientific philosophy of critical rationalism.
Devise Measures of Concepts	VaR and ES estimates with the help of an econometric methodology (GARCH modelling)
Select Research Site(s)	Cryptocurrencies
Select Research Subjects	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Monero
Collect Data	The data was collected from CoinMarketCap
Process Data	The data were acquired and pre-processed accordingly with the help of two open source programming languages – (Python programming language and R Statistical Language).
Analyse Data	The econometric modelling (with the methodology described in this chapter) of the acquired data was accomplished entirely in R statistical language.
Findings/Conclusions	The main arguments from the review of previous empirical findings and the theories presented in this study are used to interpret the findings of this study.

Findings/Revision of Existing Theory	The new findings either corroborates with previous empirical findings and theory or rejects the previous knowledge of the subject under review.

4.4 Empirical Data

The selection of the major cryptocurrencies for further analysis is based on the inclusion criteria of a market capitalisation of either equal to or above $4 billion as the end of April 29, 2018. This criterion resulted in narrowing down the selected "major" cryptocurrencies to eleven cryptocurrencies. Furthermore, a decision was made to drop proceed with only six of cryptocurrencies that met the inclusion criteria as the remaining five (5) cryptocurrencies were relatively newly launched assets with very few data points. Consequently, the selected cryptocurrencies as "major" ones for further analysis are Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Monero. These selected cryptocurrencies represent 65.2% of the total market capitalisation of cryptocurrencies as of April 29,2018. A brief overview of each cryptocurrency that successfully the cut is presented below:

- **Bitcoin (BTC)**: Bitcoin is the most popular cryptocurrency and the first of its kind. Bitcoin uses "*peer-to-peer technology to operate with no central authority or banks; managing transactions the issuing of bitcoins is carried out collectively by the network* (Bitcoin, 2018)" Bitcoin relies on blockchain to keep track of all transactions. Although the idea had been described in 1998, the idea was published and operationalised in 2009 by an anonymous source – Satoshi Nakamoto (idem).
- **Ethereum (ETH)**: Ethereum was created in 2015 with its distinguishing feature being what is known as "smart contracts" with the help of blockchain technology. Smart Contracts are "*applications that run exactly as programmed without any possibility of downtime, censorship, fraud or third-party interference* (Ethereum, 2018)".
- **Ripple (XRP)**: The ripple network built with blockchain was established in 2012 with the aim of enabling the fastest and most scalable way to make real-time payments globally (Ripple, 2018). Ripple aims to solve the slow nature of the global transfer of funds which typically take 3-5 working days. It is currently adopted by notable companies including Seagate, Accenture and many others.

- **Litecoin (LTC)**: Litecoin was created with the intention to improve on some of the functionalities of Bitcoin. Charles Lee is accredited with the development of this cryptocurrency with the help of the Bitcoin community in 2011. Litecoin aims to facilitate "enable instant, near-zero cost payments to anyone in the world (Litecoin, 2018)".
- **Stellar (XLM)**: Stellar was created in 2014 by Jed McCaleb and Joyce Kim with the strategic aim of reimagining the traditional system of banking with the help of blockchain (Stellar, 2018). Stellar offers a cryptocurrency and a platform that people to banks and global payment systems by leveraging the advantages of the blockchain technology. Such a platform allows customers to send the digital currency instantaneously with little or no transaction fees across the world.
- **Monero (XMR)**: As most cryptocurrencies aim to offer transparent systems of records keeping, Monero opts for complete privacy by ensuring that all transactions are untraceable and confidential (Monero, 2018). Monero has been in operation since 2014 with the privacy of its users at the core of its value proposition.

4.4.1 Approach to Data Collection

This thesis mainly relies on secondary data. Secondary data refers to data used for research that was not directly and purposefully gathered for the research project under consideration (Hair et al., 2016). Secondary sources of data represent an authoritative source of data for research if they can overcome questions over the validity, potential bias and reliability concerns of such reliance. Such concerns with this decision are addressed when these external are presented. The external database from which the data on these selected cryptocurrencies were extracted from is;

CoinMarketCap: A popular source of data on the prices of cryptocurrencies is CoinMarketCap. Due to the transparent and open nature of cryptocurrencies, availability of data on such markets is relatively easy. CoinMarketCap acts a data curator by gathering all the available data on every single cryptocurrency for users. Any potential source of bias, reliability and validity concerns are laid to rest by the fact that it is easy to crosscheck data from with other data suppliers. Also, most of the previous studies reviewed in this thesis relied on CoinMarketCap for the data (Coinmarketcap, 2018).

4.4.2 Approach to Data Analysis

The next stage after the successful acquisition of the necessary data from the two external sources is the analysis of this data with the goal of this thesis in mind. For this stage, two open source programming languages (Python and R) were used.[15] Python and specifically "Pandas" a python package helped in acquiring all the cryptocurrency data from CoinMarketCap (McKinney, 2017). Additionally, the same Python Package (Pandas) handled all the data pre-processing. All the econometric modelling of the acquired data was handled with "*rugarch*" a package designed for the R statistical programming language (Ghalanos, 2018). Additionally, most of the figures in this thesis were generated with the help "ggplot2", a package also designed for R statistical programming language (Wickham, 2016). Finally, the use of these programming languages enabled the automation of the complex calculations which reduces the potential occurrence of computational errors due to manual calculations.

4.5 Econometric Model

The dynamics of the two (2) GARCH models are specified and explained in this section. As explained earlier, two conditional volatility models (GJR-GARCH and S-GARCH) are built to account for the conditional volatility of the daily returns of each asset. The daily returns of each of the asset are defined as the successive logarithmic differences of the closing (or adjusted) price of each of the cryptocurrencies. These daily returns are multiplied by 100 to convert the computed daily figures as percentages. Mathematically, the daily log returns (r_t) of an asset (A) are at the time (t) is defined as:

$$r_t = \ln\left(\frac{A_t}{A_{t-1}}\right) \tag{3}$$

where:

A_t denotes closing price at the end of day t, A_{t-1} is the closing price of the previous day t, and ln denotes the logarithmic term

All GARCH model variants are composed of two essential elements – A conditional mean model and a conditional volatility model – which specifies the behaviour of the returns of an asset or a portfolio of assets (Alexander, 2008a). The conditional mean model and conditional volatility model used in this thesis are given below:

[15] Python and R are both open source programming languages available for freely offered to the public.

4.5.1 Conditional Mean Model

The conditional mean model used in this study as specified by Alexander (2008a) as:

$$\begin{aligned} &r_t = \mu + \varphi r_{t-1} + \varepsilon_t \\ &\textit{where } r_t \text{ is the return at time t, } \mu \text{ is the constant mean,} \\ &\varphi r_{t-1} \text{ is the conditional variance of previous time period,} \\ &\text{and } \varepsilon_t \text{ is the GARCH error term} \end{aligned} \tag{4}$$

The lags (ARMA terms) for each of the log returns of the cryptocurrency time series are determined using the Bayesian Information Criteria (BIC). This same conditional mean model is used for both the S-GARCH and GJR-GARCH models constructed for this study.

4.5.2 S-GARCH Volatility model

The standard GARCH (1,1) model which is the most popular model in the GARCH family of volatility forecasting models. As proposed by Bollerslev (1986), the S-GARCH (1,1) can be expressed as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

where:

α is the ARCH coefficient , β is the GARCH coefficient,
ω is the weighted long run variance, ${\sigma^2}_{t-1}$ is the previous variance,
and ${\varepsilon^2}_{t-1}$ is the previous squared return

It was decided that the residuals follow the "*Student-t*" distribution as all previous findings regarding the selected cryptocurrencies show that the distribution of daily log returns of such assets exhibits fatter tails than a normal distribution. Additionally, FHS approach with fat-tailed innovations is known to reduce forecast errors (Altun et al., 2018). The standardised Student-t distribution is specified by Ghalanos (2018) as:

$$f\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{\sigma} f(z) = \frac{1}{\sigma} \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{(v-2)\pi\Gamma\left(\frac{v}{2}\right)}} \left(1 + \frac{z^2}{(v-2)}\right)^{-\left(\frac{v+1}{2}\right)} \tag{6}$$

4.5.3 GJR-GARCH Volatility model

The GJR-GARCH model offers the same dynamics as the standard GARCH model with the addition of a leverage effect to enhance the forecasting abilities of this model over the standard GARCH model. The dynamics of the GJR-GARCH (1,1) model as expressed by Glosten et al. (1993) are:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2 \tag{7}$$

where:

α is the ARCH coefficient, β is the GARCH coefficient

γ refers to the leverage effect

I refers to the indicator function which takes the value 1 when $(\varepsilon_{t-1} < 0)$ and 0 otherwise

The residuals of this constructed GJR-GARCH model also follows the standardised Student-t distribution specified in equation (6).

4.5.4 Backtesting Criteria

The verification of volatility model is accomplished with the help of backtesting of the model with the data. A model is considered a good and applicable one if it successfully survives a VaR backtesting. As explained in the chapter on the theoretical foundations of this thesis, one of the advantages of VaR is that it can easily be backtested (Chen, 2014). For VaR, the new Basel III accords recommend the use of a 99% VaR as a measure of exposure to market risks (BIS, 2017). Consequently, this paper only considers either of the models specified as useful only if the model accurately models the data at 99% confidence level according to two statistical tests. The two tests that are used to determine the statistical significance of the accuracy of the model – the unconditional coverage test and the conditional coverage level. The VaR for a confidence level is the quantile that solves the equation $VaR_\theta = -\inf\{q \in R \mid F(x) \geq q\}$ where *F* is cumulative of the distribution of the probability density function specified for each GARCH model created (Stavroyiannis, 2018). Thus, the VaR estimate for each fitted GARCH model is computed as:

$$VaR = \mu_t + F^{-1}(1-\theta)\sigma_t \tag{8}$$

where:

F^{-1} is the inverse of the cumulative distribution function at the specified confidence level.

The *Kupiec test* is inspired by the work of Kupiec (1995) and used to test the proportion of failures of the model. The model is considered as violated and penalised when each time an observation exceeds the VaR border. The Kupiec test only measures the number of possible VaR violations permissible under the specified confidence interval. With a null hypothesis that the number of breaks or violations is consistent with a specified confidence interval, the accuracy of the volatility model is tested for the number of VaR violations or breaks with the help of the Kupiec test. The Kupiec test is conducted as a likelihood-ratio test which is asymptotically chi-squared distributed with one degree of freedom (Stavroyiannis, 2018). A model passes this test if it fails to reject this null hypothesis of correct exceedance (a p-value higher than the specified confidence interval).

The final test adopted in verifying the generated model using the VaR backtesting criterion is the conditional coverage test developed by (P. Christoffersen & Pelletier, 2004). This test combines the Kupiec test and (P. F. Christoffersen, 1998) unconditional coverage test. The unconditional coverage test examines whether VaR violations/breaks are independent (spread over time) or form clusters (Stavroyiannis, 2018). As a result, the Christoffersen test checks two conditions – whether the number of VaR violations are consistent with the chosen confidence interval and that these violations are independent. This conditional coverage test is also a likelihood-ratio test which asymptotically chi-squared distributed with two degrees of freedom.

4.5.5 FHS via Bootstrapping

The final step is the implementation of the FHS in ascertaining the VaR and ES estimates using one of the models which pass the VaR backtest. The FHS approach was implemented by following the six steps recommended by Brandolini & Colucci (2012). Thus, the VaR and ES estimates were computed as follows:

1) **Fitting of the best autoregressive moving average generalised autoregressive conditional heteroscedasticity (ARMA-GARCH) model**: A good ARMA-GARCH model is needed to filter out the stylised facts of the autocorrelation and volatility clustering of the observed data.
2) **Standardization of residuals**: The residuals from fitting the ARMA-GARCH model are standardised by dividing them by the estimated sigmas of the fitted model ($Z_t = \varepsilon_t / \sigma_t$).
3) **Bootstrapping of standardised residuals**: Instead of drawing from an assumed distribution, the samples are picked with replacement from the collection of standardized residuals.

4) **Passing of bootstrapped standardised residuals in a forward simulation using the estimated ARMA-GARCH model**: The standardised residuals are plugged back into the selected ARMA-GARCH model for each selected asset to reintroduce heteroskedasticity and autocorrelation in a forward simulation of 10 trading days.
5) **Estimation of returns**: The hypothetical daily returns are then collected from the forward simulation and summed for the 10-day horizon using Equation (4) and the best conditional volatility model (Equation (5) or Equation (7)). 100,000 simulations are used for this study.
6) **VaR and ES estimations**: The VaR at each specified level is computed as the quantile level of the hypothetical returns. ES is also calculated as the empirical average of all the data points which exceeds the empirical quantile (specified by the VaR level) of the data (Acerbi & Tasche, 2002).

4.6 Statistical Tests

The various statistical tests that were employed to assess the viability of the acquired data for the econometric modelling process described in this chapter are presented below.

4.6.1 Test for Heteroskedasticity

Homoscedasticity refers to a condition where the variance of error terms some observations do not change over some period. Homoscedasticity assumes constant variance of error terms, an assumption that rarely holds up with financial time series data. Financial data tend to suffer from heteroskedasticity hence why GARCH models are employed to model the variance of the error terms (Engle, 2001). The Lagrange Multiplier (LM) test based on Engle's work for AutoRegressive Conditional Heteroskedasticity (ARCH) effects was employed to detect the presence of heteroskedasticity (Tsay, 2010). The null hypothesis assumes homoscedasticity. Lagrange Multiplier (LM) test assumes homoskedasticity and as such the p-value must be significant at the chosen level to reject this null hypothesis.

4.6.2 Test for stationarity

A foundation of time series analysis is stationarity (at least weak stationarity) as the ability of observations to achieve stationarity enables one to make an inference (predictions) concerning future observations (Tsay, 2010). It is common, in financial literature, assume are asset returns are at least weakly stationary hence the need to test that assumption. A popular test for stationarity or the lack of is the ADF test. *Augmented Dickey-Fuller Test* usually referred to as the *ADF test* tests for unit roots with the null hypothesis that the observations are non-stationary with an alternative hypothesis that the observations are stationary (Said & Dickey, 1984).

4.6.3 Test for Serial Correlation/Autocorrelation

The two terms – Serial Correlation and Autocorrelation – tend to be used interchangeably in financial literature as they mean the same thing. Autocorrelation refers to situations where the errors of a set of observations are correlated with each other. Unlike other forms of data, time series data are ordered by time and as such financial time series are notoriously noted for suffering from autocorrelation (Tsay, 2010). The Ljung-Box (LB) test was employed to on both the observations and the squared residuals of the observations with a lag of up to 12 days (Ljung & Box, 1978). The LB test is based on the null hypothesis of the independence of the time series.

4.6.4 Test for Normality

A set of observation is normally distributed if most of the values observed are clustered around the middle of the range of the observations. A famous test for the normality of set of observations is the Jacque Berra (JB) test. The JB test checks for the skewness and kurtosis by assuming a null hypothesis of normality – normal distribution of the observed data) (Cromwell et al., 1994).

4.7 Reliability and Validity

Reliability and validity are two of the most important considerations for any research study (Kothari, 2004). Reliability as a concept is related to the question of whether the findings and results of a study can be repeated (Bryman, 2012). As with all quantitative studies, researchers must ensure comprehensive and proper documentation of the methods employed towards the generation of the findings such studies espouse. To this end, this thesis has explained in detail all the empirical methods and statistical tests adopted to generate the VaR and ES estimates of the selected cryptocurrencies and the comparison of such market risk estimates with the proxy market. Additionally, all the Python and R codes that were used for acquiring and analysing the data are including in this thesis report (See Appendix). Finally, a GitHub project has been created specifically for this thesis with all the professional documentation processes adopted.[16] The thesis project hosted on GitHub also include all the data files acquired, a decision which makes it possible for everyone to replicate the findings of this study even in the unfortunate scenario of the two sources of data blocking access of data acquisition.

Validity as a concept relates the integrity of the conclusions of a study and is divided into three components by Bryman (2012) as; measurement validity, internal and external validity. According to the same source, measurement validity questions whether a researcher measures what is purported to be measured. As explained earlier the two (2) credible sources of data renders such measurement validity concerns moot as the study duly used the data on prices of the assets under consideration. Internal validity relates to the relationship between the measured variables. As the review of an empirical review of the literature on FHS approach revealed, volatility modelling is central to this approach. Internal validity of this study is maintained by the selection of inputs based on the theories of VaR and ES and previous empirical findings. Finally, this study overcomes external validity concerns as it aims not for generalisations based on findings as the study only involves a specific sample of time for all the assets under review.

4.8 Limitations of Study

Every research study is not without some limitations. This thesis is not any different in that regard. There are two limitations regarding the conduct of this research. First, this thesis relies exclusively on secondary data. Such reliance on secondary sources of data raises questions about the reliability and validity of the findings of the study (Creswell, 2013). However, the open nature, as well as the availability of the data from two credible sources frequently cited in academic journals, allay such potential fears and concerns. Secondly, cryptocurrencies as a market are continuously changing, and one can say such markets are still maturing. This thesis takes a snapshot of the “life” of the selected cryptocurrencies and as such the VaR and ES estimates only account for the period under consideration by this study. Notwithstanding this limitation, the findings of this study add to the limited literature on a growing sense of understanding the riskiness of cryptocurrency markets.

[16] Project Link: https://bitbucket.org/pimpfada/var-es-assessment-of-cryptos/src/master/

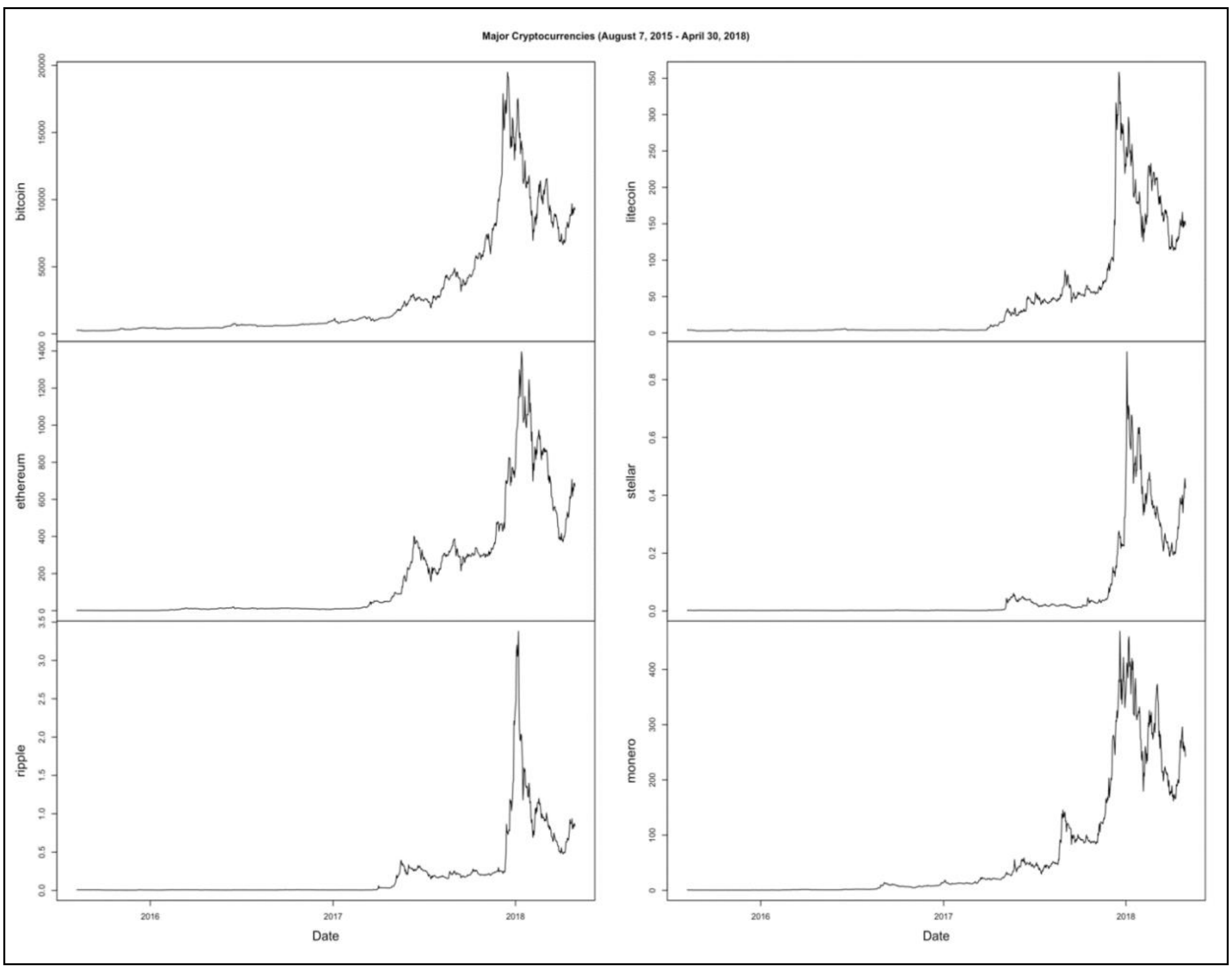
5.0 EMPIRICAL FINDINGS AND DISCUSSION

This section presents the findings described in earlier chapters and as well a discussion and conclusion based on findings using the methodological and theoretical framework.

5.1 Descriptive Statistics and Stylized Facts

The daily closing prices of the six selected cryptocurrencies as major cryptocurrencies were sourced from (Coinmarketcap, 2018). The starting period was August 07, 2015 and the data ends on April 30, 2018. As a result, each cryptocurrency had 998 data points as their daily closing prices. **Figure 6** shows the closing prices of each of the selected cryptocurrencies between the stated starting and ending periods.

Figure 6. Daily Closing Prices of the Selected Cryptocurrencies between August 07, 2015 and April 30, 2018.



The daily logarithmic returns calculated using Equation (3) accordingly account for these developments. From **Figure 7**, it appears that there is some evidence of volatility clustering with all the cryptocurrencies under consideration. Periods of extreme volatility of the daily returns are followed by the sharp rise and falls in returns while periods with no such sharp movements tended to be followed by the same calm movements.

Figure 7. Daily logarithmic returns of the selected cryptocurrencies between August 07, 2016 and April 30, 2018.

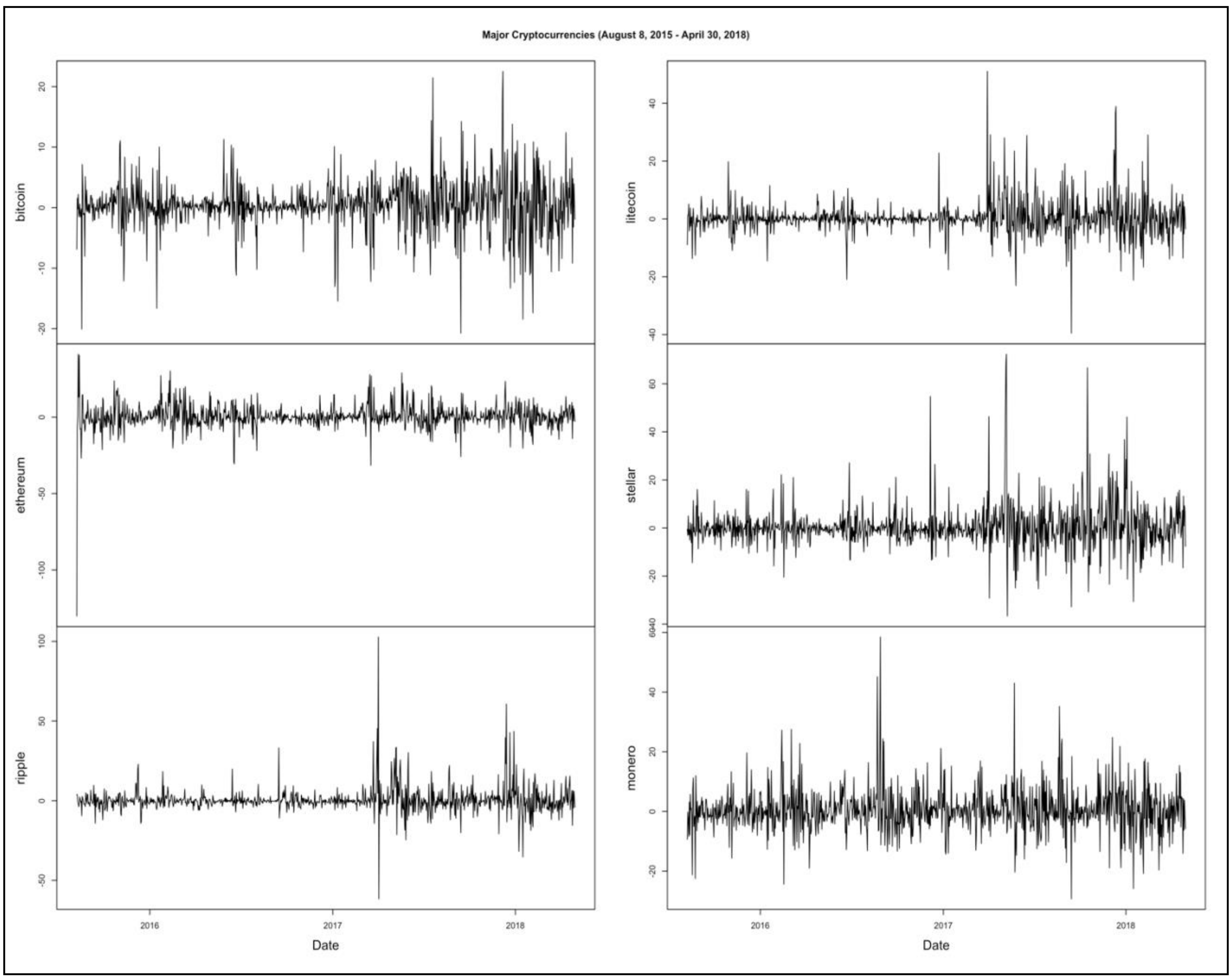


Table 3 below provides the standard summary statistics of the calculated logarithmic returns with a confidence interval of 95%. As the descriptive statistics of the daily returns in **Table 3** reveals, all the financial series exhibit statistically significant skewness and kurtosis. Bitcoin and Ethereum are the only series with negatively skewed. Monero has the highest average daily returns with a

value of 0.58% (followed by Ethereum and Stellar) while Bitcoin has the lowest average daily returns with a value of 0.35%. The daily volatility or risk, as measured by standard deviation (SD), shows that Bitcoin is the least volatile cryptocurrency for the period under consideration. Stellar with a volatility value of 8.95 is the most volatile asset in the series followed by Ethereum (SD = 8.31%) and Monero (SD = 7.46%). This insight confirms the trade-off between risks and returns often realised with financial literature and observations. The riskier an asset, the higher potential rewards for investors.

Table 3. Descriptive Statistics of the daily logarithmic returns of the selected assets.

	Bitcoin	**Ethereum**	**Ripple**	**Litecoin**	**Stellar**	**Monero**
Observations	997	997	997	997	997	997
Minimum	-20.752981	-130.210586	-61.627274	-39.515075	-36.635772	-29.317634
Maximum	22.511900	41.233727	102.735576	51.034818	72.305526	58.463706
1st Quantile	-0.914539	-2.690097	-2.038140	-1.500028	-3.236161	-2.808534
3rd Quantile	1.955353	3.548575	1.857551	1.703619	3.282294	4.082199
Mean	0.350859	0.550483	0.464662	0.357371	0.517811	0.580627
Median	0.326592	-0.040251	-0.356103	0.000000	-0.319489	0.000000
Variance	17.175546	69.110172	63.847870	35.800410	80.126669	55.783321
Standard Deviation	4.144339	8.313253	7.990486	5.983344	8.951350	7.468823
Skewness	-0.265470	-3.532563	3.045664	1.366851	2.020730	1.063290
Kurtosis	4.770842	62.561086	37.955838	12.950342	14.153999	7.046561

Attention will now be turned to the statistical tests conducted. The results of all various statistical tests employed on financial observations acquired are presented below in **Table 4**. Given how the descriptive statistics showed statistically significant skewness, it is unsurprising that all the series showed deviation from normality from the Jacque-Bera (JB) test by rejecting the null hypothesis of normality. Additionally, the ARCH Test for 12 lags shows that all the observed series exhibit heteroskedasticity at the 5% critical value as all the series rejected the null hypothesis of no heteroskedasticity. Therefore, GARCH modelling is applicable for the observed series. Additionally, all the cryptocurrencies showed an ability to achieve stationarity at the same critical value after the Augmented Dickey-Fuller (ADF) Test was performed. The ability of observed data to achieve stationarity is important as it facilitates the ability to make accurate predictions of future observations(Alexander, 2008a). Finally, as suspected earlier in **Figure 7**, where there appeared to be the formation of clusters of volatility was confirmed by the Ljung-Box (LB) test for serial correlation. The LB test (for 12 lags) for the daily returns shows that all series exhibit serial correlation at the at the 5% critical value except bitcoin. This result suggests that Bitcoin, unlike the other selected cryptocurrencies, is an efficient market as the prices are random. A repeated LB test (12 lags) for the squared returns show that squared returns of all the series exhibited serial autocorrelation at the 5% critical value.

Table 4. Test of Normality, Heteroskedasticity, Serial Correlation, and Stationarity.[17]

	Bitcoin	**Ethereum**	**Ripple**	**Litecoin**	**Stellar**	**Monero**
JB Test	963.47 ***< 2.2e-16***	165350 ***< 2.2e-16***	61653 ***< 2.2e-16***	7312.9 ***< 2.2e-16***	9043.4 ***< 2.2e-16***	2263 ***< 2.2e-16***
ARCH (1) Test	49.833 ***1.674e-12***	1.9868 ***0.1587***	82.784 ***< 2.2e-16***	22.398 ***2.216e-06***	161.2 **< 2.2e-16**	21.19 ***4.159e-06***
ARCH (5) Test	69.879 ***1.086e-13***	235.79 ***< 2.2e-16***	93.494 ***< 2.2e-16***	36.259 ***8.429e-07***	176.77 ***< 2.2e-16***	44.848 ***1.558e-08***
ARCH (12) Test	87.202 ***1.714e-13***	105.29 ***< 2.2e-16***	104.75 ***< 2.2e-16***	61.058 ***1.447e-08***	178.86 ***< 2.2e-16***	109.56 **< 2.2e-16**
ADF Unit Root Test	-9.2289 ***0.01***	-9.2393 ***0.01***	-7.7773 ***0.01***	-9.7283 ***0.01***	-8.8414 ***0.01***	-9.5276 ***0.01***
LB (12) Test	9.8469 ***0.6294***	25.155 ***0.0141***	41.94 ***3.408e-05***	25.388 ***0.01309***	28.253 **0.005079**	33.566 **0.0007893**
LB-2 (12) Test	142.78 ***< 2.2e-16***	20.713 ***0.05475***	142.83 ***< 2.2e-16***	81.904 ***1.786e-12***	257.2 ***< 2.2e-16***	125.9 **< 2.2e-16**

[17] The p-values, thus statistical significance, are represent below each statistical value as bold and ***italicised*** text.

Table 5 below looks at the correlation between the daily logarithmic returns of the selected assets. Interestingly, the daily returns of all assets under consideration are positively correlated. The least correlated pair is Ethereum and Ripple with a correlation of 0.15. The pair with the strongest form of correlation is Bitcoin and Litecoin with a moderate Pearson correlation coefficient of 0.56. For investors, such stylized facts about the daily returns imply that it would be a poor choice to construct a portfolio made up of the selected cryptocurrencies in this study.

Table 5. Pearson Correlation of the daily returns of the selected cryptocurrencies.

	Bitcoin	**Ethereum**	**Ripple**	**Litecoin**	**Stellar**	**Monero**
Bitcoin	1.0000000	0.3144383	0.2516020	0.5686193	0.3162466	0.4441754
Ethereum	0.3144383	1.0000000	0.1586632	0.2958378	0.1977332	0.3008284
Ripple	0.2516020	0.1586632	1.0000000	0.3049489	0.5296588	0.2391921
Litecoin	0.5686193	0.2958378	0.3049489	1.0000000	0.3402801	0.3735172
Stellar	0.3162466	0.1977332	0.5296588	0.3402801	1.0000000	0.3442802
Monero	0.4441754	0.3008284	0.2391921	0.3735172	0.3442802	1.0000000

As described in the theoretical framework, the conditional mean model (ARMA) contains two lag elements known as the AR and MA terms. The lags for the each of time series assets being modelled are determined using the Bayesian Information Criterion (BIC). **Table 6** presents the selected lag order for all the selected assets for the conditional mean model.

Table 6. Selected ARMA lag terms used for the conditional mean model.

	Selected ARMA Order
Bitcoin	AR (3), MA (1)
Ethereum	AR (2), MA (0)
Ripple	AR (1), MA (0)
Litecoin	AR (3), MA (1)
Stellar	AR (2), MA (0)
Monero	AR (2), MA (0)

5.2 VaR Backtesting Results

The verification of the two constructed conditional volatility models – S-GARCH and GJR-GARCH – is done according to the current requirements of the new BIS III accords which recommend a calibration of VaR models at 99% level. This verification is carried out with the help of two (2) tests as described in the methodological framework; the unconditional coverage (UC) test by Kupiec (1995) and the conditional coverage (CC) test by Christoffersen & Pelletier (2004). The null hypothesis of both tests is that the model tested passes thus a successful model is the one that fails to reject these null hypotheses. **Table 7** and **Table 8** present the p-value of the two tests at the 95% confidence interval (CI).

The results of the two backtesting tests of the two constructed GARCH models presented in **Table 7** (S-GARCH) and **Table 8** (GJR-GARCH) below. From **Table 7** below, all the assets under review passed both the UC test for correct exceedance and CC test for both correct exceedance and independence of failures at the 95% confidence interval. At this specified confidence interval, the backtesting model expected only 8.5 VaR exceedance for each of series tested. The S-GARCH model failed to reject the null hypothesis for both the UC and CC tests. These results indicate the suitability of the S-GARCH for all the GARCH modelling for all the selected cryptocurrencies.

Table 7. Conditional and Unconditional coverage results (S-GARCH).

	UC Test p-value (95 % CI)	**CC Test p-value (95% CI)**	**Expected Exceedance**	**Actual Exceedance**
Bitcoin $VaR_{1\%}$	0.251	0.436	8.5	12
Ethereum $VaR_{1\%}$	0.368	0.639	8.5	6
Ripple $VaR_{1\%}$	0.601	0.823	8.5	12
Litecoin $VaR_{1\%}$	0.251	0.19	8.5	12
Stellar $VaR_{1\%}$	0.87	0.914	8.5	8
Monero $VaR_{1\%}$	0.194	0.418	8.5	5

The results GJR-GARCH (1,1) (as indicated in **Table 8)** shows that the GJR-GARCH model constructed failed the backtesting test for Monero by failing to reject the null hypothesis of the UC test (p-value = 0.29). The GJR-GARCH (1,1) model, however, passed the CC and UC tests for the other remaining series. The failure of the GRJ-GARCH (1,1) model with the backtesting criteria implies that it is unsuitable for the FHS approach as this approach requires the use of GARCH model with good forecasting abilities.

Table 8. Conditional and Unconditional coverage results (GJR-GARCH).

	UC Test p-value (95 % CI)	CC Test p-value (95% CI)	Expected Exceedance	Actual Exceedance
Bitcoin $VaR_{1\%}$	0.081	0.104	8.5	14
Ethereum $VaR_{1\%}$	0.601	0.823	8.5	7
Ripple $VaR_{1\%}$	0.601	0.823	8.5	7
Litecoin $VaR_{1\%}$	0.251	0.19	8.5	12
Stellar $VaR_{1\%}$	0.87	0.914	8.5	8
Monero $VaR_{1\%}$	**0.029**	0.092	8.5	3

Thus, this thesis adopts the S-GARCH (1,1) model as the conditional volatility model for the FHS approach in assessing the market risk of the selected cryptocurrencies via VaR and ES estimates.

5.3 Stylized facts according to the adopted ARMA and S-GARCH model

The results of the successfully backtested univariate S-GARCH (1,1) model also explains the dynamics of the returns of all the series. **Table 9** presents the statistical results of these dynamics below. The constant in the conditional mean equation (μ) is only statistically significant for Bitcoin, Ripple and Stellar with Bitcoin having the most substantial value. The constant for conditional variance equation (ω) is significant all the series except for Litecoin and Stellar with Monero having the largest value. The GARCH error parameter (α) which measures the reaction of conditional volatility to market shocks was significant with values above 0.1 for all the selected cryptocurrencies (Alexander, 2008a). This GARCH error parameter result implies that the volatility of all the assets under review are very sensitive to market events (idem). The GARCH lag parameter (β) which measures the persistence in conditional volatility irrespective of other market events is also significant for all the cryptocurrencies under review. However, as Alexander (2008a) contests, only (β) values above 0.9 (β > 0.9) indicate that volatility takes a long time to die out following the crisis in a market. Even though all the time series were statistically significant, none of them had a β value above 0.9. This result implies that the volatility of the investigated cryptocurrencies takes relatively short time to die out after some crisis in that market space. Finally, the shape parameter (insert shape symbol here) is significant for all the assets. An indication of good fit and fat tail distribution of the returns of all the investigated assets.

Table 9. Univariate results of ARMA, S-GARCH (1,1) model for the selected assets.[18]

	Bitcoin	**Ethereum**	**Ripple**	**Litecoin**	**Stellar**	**Monero**
Mu (μ)	0.370971 ***0.003956***	0.084253 ***0.54014***	-0.296943 ***0.000055***	-0.00351 **0.940263**	-0.385256 **0.000186**	0.002247 ***0.986886***
AR1	0.907267 ***0.000000***	-0.008639 ***0.79724***	-0.043364 ***0.155493***	-0.67336 ***0.361610***	-0.134771 ***0.000027***	-0.084576 ***0.007714***
AR2	-0.002530 ***0.947759***	0.001691 ***0.94953***	-	-0.13985 ***0.148108***	-0.050158 ***0.089888***	-0.042062 ***0.167116***
AR3	0.059748 ***0.044346***	-	-	-0.06547 ***0.117537***	-	-
MA1	-0.940144 **0.000000**	-	-	0.54580 ***0.461714***	-	-
Omega (ω)	0.146415 ***0.039503***	3.266777 **0.00859**	0.671635 ***0.012316***	0.11844 ***0.087687***	1.568116 ***0.084122***	3.798016 ***0.005580***
Alpha1 (α)	0.162713 ***0.000000***	0.303853 **0.00000**	0.205830 ***0.000000***	0.11470 ***0.000001***	0.206370 ***0.000082***	0.246836 ***0.000037***
Beta1 (β)	0.836287 ***0.000000***	0.695147 ***0.00000***	0.793170 **0.000000**	0.88430 ***0.000000***	0.792630 ***0.000000***	0.752163 ***0.000000***
Shape (ν)	3.336419 ***0.000000***	3.536040 ***0.00000***	2.944373 ***0.000000***	2.78569 ***0.000000***	3.169110 ***0.000000***	3.248521 ***0.000000***

An essential consideration for FHS method is the need for independence of the standardised residuals (Barone-Adesi et al., 2004). **Table 10** presents a test of serial autocorrelation (Ljung-Box (LB) test) of the standardised residuals of the fitted model.

[18] The p-values are reported under each statistical value as **bold** and ***italicized***

Table 10. LB-Test for Serial correlation of residuals of the adopted S-GARCH model.[19]

	LB-2 (12) test of Standardized Squared Residuals
Bitcoin	4.1579 ***0.9804***
Ethereum	14.948 ***0.2443***
Ripple	0.97036 **1**
Litecoin	0.41931 **1**
Stellar	1.0502 **1**
Monero	12.204 ***0.4295***

As can be seen from **Table 10**, all standard squared residuals of all the time series data fail to reject the null hypothesis of no serial correlation of the LB-Test with a lag order of 12. Thus, it can be concluded that the adopted model has proven to be a good fit for the daily returns of all the selected cryptocurrencies as the standardised residuals of each asset are all independently and identically distributed (technically known as IDD). The final step in the process involves bootstrapping these standardised residuals and passing the bootstrapped residuals in the ARMA-S-GARCH estimated model in a forward simulation. From this simulation hypothetical daily returns

5.4 VaR and ES estimates using the S-GARCH model

The final steps of the FHS approach involve the bootstrapping of the standardised residuals in the forward simulation of the adopted ARMA and S-GARCH (1,1) model so that hypothetical daily returns can be computed. The VaR and ES estimates are based on these hypothetical daily returns.

By the new BIS III accords, the VaR and ES estimates using FHS methods for investors taking long positions with the selected cryptocurrencies are reported below in **Table 11**. The levels

[19] P-values are reported under the statistical value as **bold** and ***italicised***.

for $VaR = 1-\theta \in [0.10, 0.05, 0.25, 0.01]$ are thus reported in percentages (%). From **Table 11**, it appears that Stellar represents the most volatile cryptocurrency over a horizon of 10 trading days after April 30, 2018. Thus, investors interested in taking long positions in Stellar should be aware of the magnitude of potential losses. A Stellar investor would have expected to have lost cumulatively approximately 65.50% over the 10-day horizon regarding the ES estimate at 99% VaR level. Ethereum, Ripple and Monero follow Stellar regarding cryptocurrencies with the highest VaR and ES estimates over the same 10-day horizon.

Interestingly, Litecoin (closely followed by Bitcoin) represented the least volatile cryptocurrency at all levels of the VaR and ES estimates. The expected loss at the critical level of 99% VaR recommended by the new Basel accords for Litecoin is 38.46% and 42.7% for Bitcoin respectively. The same accords call for the replacement for the 99% VaR with the 97.5% ES. In this regard, the expected average losses at that level for Litecoin is 59.75% and 64.64% for Bitcoin.

Table 11. VaR and ES estimates (in %) for the selected cryptocurrencies over a horizon of 10 trading days (from April 30, 2018).

	Bitcoin	**Ethereum**	**Ripple**	**Litecoin**	**Stellar**	**Monero**
VaR (0.10)	-12.17864	-16.91532	-18.71914	-13.00659	-20.67716	-16.17477
ES (0.10)	-25.30122	-29.50305	-29.80962	-23.9834	-32.88902	-27.89781
VaR (0.05)	-19.83258	-24.83124	-25.78204	-19.06959	-28.61295	-23.55697
ES (0.05)	-35.09755	-38.65375	-37.81491	-32.3564	-41.57597	-36.36385
VaR (0.025)	-28.58803	-33.30821	-32.81451	-26.28359	-36.72934	-31.46354
ES (0.025)	-46.53613	-48.81864	-46.755	-42.60049	-51.09527	-45.80125
VaR (0.01)	-42.73473	-45.97665	-43.69378	-38.45515	-48.43299	-43.10521
ES (0.01)	-64.64366	-64.22107	-60.87325	-59.75449	-65.49946	-60.05854

5.4 Discussion

Public debates about cryptocurrencies show no sign of going away. Opinions continue to be split on this peculiar asset assets. From notable naysayers including Warren Buffet who label cryptocurrencies as nothing but modern-day scams to advocates like an economist, David Friedman, who believe cryptocurrencies are the assets of the future. While the world is engulfed in these discussions, investors are pouring into this unregulated market. No one can accurately predict with absolute certainty the future of cryptocurrencies. With regards the fate of these peculiar classes of assets, only time will tell. The lack of a proper regulatory framework coupled with the high volatility rates of cryptocurrencies calls for particular attention to the volatility dynamics in this market. Investors can only be offered protection by relying on well-informed studies like this grounded in traditional financial literature so that they can make more informed investment choices. The high volatility of cryptocurrencies is not necessarily a bad thing for well-informed investors and adopters.

Goldman Sachs, one of the most prestigious financial institution, appears to the first major bank to have taken the plunge into this virtual space with credible reports of the launch of a trading operation. In response to the high volatility of cryptocurrencies and confirmation of these plans, Rana Yared, an executive of Goldman Sachs, opined that:

> "*It is not a new risk that we don't we don't understand. It is just a heightened risk that we need to be extra aware of here (Popper, 2018).*"

Will Goldman Sachs be on the major bank to succumb to the pressure of customers who advocate for the adoption of these virtual assets? Or will Goldman Sachs even sanction the expansion of cryptocurrency trading to include other cryptocurrencies other than Bitcoin? It is a hard guess right now as critics of cryptocurrency trading would have to play the waiting game until such successful realisations and implementations. Early adopters like Goldman Sachs would have the competitive advantage based on merit as a first mover in this cryptocurrency space. Regardless of how the future of cryptocurrencies might or might not turn out, there's an undeniable need not only to quantify the exposure to their market risks but understand the dynamics of their volatilities.

In this regard, the thesis offers such investors a thorough look at an investor's exposure to cryptocurrency market risk using the two standard market risk metrics – VaR and ES. Additionally, the use of FHS method with the two risk metric computations incorporates GARCH modelling which allows the behavioural dynamics of the daily returns of the selected major cryptocurrencies to be studied. While cryptocurrencies, in general, are more volatile than other traditional asset classes like equities and fiat currencies (Stavroyiannis, 2018), the results of this study show that their volatility take a short time to die out and this presents investors opportunities of buying low and selling high when the market stabilises. Investors can, for example, purchase some of the studied cryptocurrencies when the market participants panic and try to get rid of their cryptocurrencies as this study has corroborated with other previous findings which show that the selected cryptocurrencies react significantly to market events. The positive correlation of the daily logarithmic returns of all these selected cryptocurrencies also offers some options for investors. Construction of a portfolio with only these selected cryptocurrencies would be a poor choice by an investor given the positive correlation of the daily returns of all the cryptocurrencies reviewed in this thesis. Such positive correlations would render the diversification of risks in such portfolios unfeasible. On the other hand, other studies have found that the returns of cryptocurrencies, in general, are weakly correlated with other traditional assets (Elendner et al., 2016). Investors could, therefore, take advantage of such relationships by including some of the selected cryptocurrencies to diversify their risk exposures.

With regards to the VaR theory, a limitation of VaR estimates is that it can be misleading was confirmed in this study (Damodaran, 2007). This disadvantage is highlighted in the results presented above for Bitcoin and Litecoin. With the 90% VaR (VaR 0.10), Bitcoin was less risky than Litecoin with an estimated loss of 12.18% to the 13.00% estimate for Litecoin. However, the ES estimate at that same level showed that investors would have lost more than at that level. At that 90% level, investors would have lost on the average 25.30% for bitcoin and 23.98% for Litecoin. A further indication that the sole reliance on VaR can be misleading for investors. The new BIS accords hypothesise that the 99% VaR is approximately the same as the 97.5% VaR. This hypothesis appears consistent with the results of this study as the VaR and ES estimates at those levels are almost the same with standard errors between 2% to 3% (BIS, 2017).

As the empirical review has shown, research on cryptocurrencies other than bitcoin is very limited. A problem highlighted by Chu et al. (2017) that needs empirical attention given the soaring popularity and adoption of cryptocurrencies. In fact, the only comprehensive attempt for VaR and ES estimates using the FHS method is a working paper by Stavroyiannis (2017). Consequently, that working paper serves as motivation for this thesis with the point of departure of this thesis being the identified two weaknesses of the methodological approach adopted for that particular working paper by Stavroyiannis (2017). First, the GARCH model (an integral component of the FHS method) used for the forecasting of the daily volatility was unverified as the GARCH was not backtested with the historical data to check how the model performs against the data. Such a methodological approach leads to reliability concerns of the results produced by Stavroyiannis (2017). Lastly and on a minor note, there was lack of a definition of what constitutes a "major cryptocurrency”. In the absence of such definition, leaves readers with a vague notion of a what a “major cryptocurrency” represents.

Thus, the main contribution of this thesis to current limited (but increasing) literature of the assessment of the market risk of cryptocurrency investors is that this thesis communicates for the first time VaR and ES estimates of the major cryptocurrencies using FHS method used with a backtested GARCH model.

5.5 Possible Extensions of Study

The findings presented in thesis also point to opportunities of the authors to contribute to existing literature on the subject at hand. First, it was realised that the daily logarithmic returns of the selected cryptocurrencies were all positively correlated. This implies some sort of a dependence with regards to the movement of the closing prices of the selected cryptocurrencies. A study based on multivariate GARCH modelling would be suited for such assessment to understand the relationship between movement of prices among cryptocurrencies. Secondly, the empirical reveal of literature revealed a negative correlation of the daily returns of cryptocurrencies with other asset classes like gold (Baur et al., 2017) and equities (Stavroyiannis, 2018). This realization offers investors some diversification possibilities with the inclusion of cryptocurrencies in their portfolios. Finally, this study used an inclusion criteria of market capitalization of either equal to USD ($) 4 billion for selecting cryptocurrencies as “major” assets. Eleven assets met this criterion. However, five of this eleven major assets were dropped because there were relatively new assets with very few financial observations to warrant meaningful analysis. A potential contribution would be the replication of the findings of this study with the inclusion of these dropped cryptocurrencies Follow up study which includes more cryptocurrencies at a later date when there are enough financial data points.

6.0 CONCLUSION

The new Basel III accords aim at strengthening financial institutions against systemic risks after the recent financial crisis in 2007. Cryptocurrencies have attracted the attention of some financial institutions despite its high volatility relative to other traditional asset classes. This thesis assessed investors’ exposure to the market risk of six of the popular cryptocurrencies in circulation. Two conditional volatility models were constructed to find the best fit in terms of volatility modelling of the selected cryptocurrencies. After backtesting of the two models, it was revealed that the standard GARCH (1,1) model was the best volatility model for the selected cryptocurrencies after it passed a 99% VaR backtest. As a result, an ARMA-GARCH (1,1) model is employed to model the stylised facts of volatility clustering, serial correlation and VaR and ES estimates are computed using FHS over a horizon of 10 trading days. The results showed that Litecoin (closely followed) Bitcoin are the least volatile cryptocurrencies between August 07, 2015 and April 30, 2018. Stellar, Ethereum, Ripple and Monero represents the riskiest options out of the investigated digital assets. As a result, investors should be aware that these four cryptocurrencies are subject to a much higher risk than Litecoin and Bitcoin and may require higher capital to cover for potential losses.

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8.0 APPENDIX

8.1 Python Script for Data Acquisition

```
'''
Stage 1 involves selected the major cryptos
based on a criteria of exceedance of market capitalization above $4bn

Don't forget to set the folder in which this script is held in
as the current working folder before running the script
'''

# import needed libraries
import pandas as pd
pd.options.mode.chained_assignment = None

# read historical market cap table
df = pd.read_html('https://coinmarketcap.com/historical/20180429/')

# first item is the market cap table
df = df[0]
df.head()

# unneeded columns
df.drop(['#', 'Circulating Supply', 'Volume (24h)',
        '% 1h', '% 24h', '% 7d'
       ], axis=1, inplace=True)

# drop minor cryptos
df = df.iloc[:30]

'''
Split the DF into two separate dfs in or to apply a function to the columns with numbers
'''

# make a right side of the final table by converting all string figures into floats
right_df = df[df.columns[2:4]].replace('[\$,]', '', regex=True).astype(float)

# make a left side of final table
left_df = df.loc[0:30, ['Name', 'Symbol']]

# make a main df by combining the left and right dataframes
main_df = pd.concat([left_df, right_df], axis=1)

# select all with a market cryptos above $4 billion
```

```
selected_cryptos = main_df.loc[main_df['Market Cap'] >= 4000000000]

# drop the ticker tags on the names
no_ticker = selected_cryptos.Name.str.replace('^\w\w\w+\s', '')
selected_cryptos.loc[:, 'Name'] = no_ticker

# rename properly bitcoin-cash
selected_cryptos.loc[3, 'Name'] = 'Bitcoin-cash'

# a list of crypto names
crypto_names = list(selected_cryptos['Name'].str.lower())

# a dictionary to store all the crypto data
all_dfs = dict()

# loop through the crypto_names list and get the data from coinmarketcap.com
for name in crypto_names:
  link = f'https://coinmarketcap.com/currencies/{name}/historical-
data/?start=20090101&end=20180501'

  all_dfs[name] = pd.read_html(link)[0]

# get only the date and close prices from the dict
for keys, values in all_dfs.items():
  values = values[['Date', 'Close**']]

# separate the data for each crypto
bitcoin = all_dfs.get('bitcoin')[['Date', 'Close**']]
ethereum = all_dfs.get('ethereum')[['Date', 'Close**']]
ripple = all_dfs.get('ripple')[['Date', 'Close**']]
bitcoin_cash = all_dfs.get('bitcoin-cash')[['Date', 'Close**']]
eos = all_dfs.get('eos')[['Date', 'Close**']]
cardano = all_dfs.get('cardano')[['Date', 'Close**']]
litecoin = all_dfs.get('litecoin')[['Date', 'Close**']]
stellar = all_dfs.get('stellar')[['Date', 'Close**']]
iota = all_dfs.get('iota')[['Date', 'Close**']]
tron = all_dfs.get('tron')[['Date', 'Close**']]
neo = all_dfs.get('neo')[['Date', 'Close**']]
monero = all_dfs.get('monero')[['Date', 'Close**']]

# combine closing price data for each crypto into a master dataframe
master_df_close = pd.concat([bitcoin, ethereum, ripple,
               bitcoin_cash, eos, cardano,
               litecoin, stellar, iota, tron,
```

```python
                    neo, monero], axis=1, join='outer')

# rename columns
cols = ['Date','bitcoin', 'Date_eth','ethereum', 'Date_ripple','ripple',
        'Date_bcash','bitcoin_cash', 'Date_eos','eos',
        'Date_cardano','cardano', 'Date_litecoin','litecoin','Date_stellar','stellar',
        'Date_iota','iota', 'Date_tron','tron', 'Date_neo','neo', 'Date_monero', 'monero']

master_df_close.columns = cols

# drop cryptos with few data points
final_df = master_df_close.drop(columns=['Date_bcash', 'bitcoin_cash',
                     'Date_cardano', 'cardano',
                     'Date_eos', 'eos',
                     'Date_iota', 'iota',
                     'Date_tron', 'tron',
                     'Date_eth', 'Date_ripple',
                     'Date_litecoin', 'Date_stellar',
                     'Date_neo', 'neo', 'Date_monero'
                    ], axis=1)

crypto_df = final_df.dropna(axis=0)

# set date column from crypto data as datetime,
#set it as index and sort the index in an ascending order
crypto_df['Date'] = pd.to_datetime(crypto_df['Date'])
crypto_df.set_index('Date', drop=True, inplace=True)
crypto_df.sort_index(inplace=True)

# subset the period under consideration
final_df = crypto_df['2015-08-07':'2018-04-30']

# rename index as 'date'
final_df.index.rename("date", inplace=True)

# save output file as master dataset
final_df.to_csv("master_dataset.csv", index=True)
```

8.2 R Code for Econometric Modelling (S-GARCH)

8.2.1 Bitcoin

```
################## IMPORT NEEDED LIBRARIES
############################################
library(quantmod)
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET
########################################################
df <- read.csv.zoo("master_dataset.csv")

bitcoin_df <- df$bitcoin

########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE
##########################
bitcoin_returns <- log(bitcoin_df / lag(bitcoin_df,-1)) * 100

#bitcoin_returns_num <- coredata(bitcoin_returns)


# GGPLOT Daily Returns
ggplot(data = bitcoin_returns, mapping = aes(index(bitcoin_returns),
                              coredata(bitcoin_returns))) +
  geom_line() +
  labs(title = "Daily Returns of Bitcoin",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of Bitcoin.png")

# GGPLOT Daily Returns Squared
ggplot(data = bitcoin_returns, mapping = aes(index(bitcoin_returns),
                              coredata(bitcoin_returns)^2)) +
  geom_line() +
  labs(title = "Daily Logarithmic Returns of Bitcoin",
       x = "Year",
       y = "Daily Returns (%)") +
```

```
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of Bitcoin.png")

# GGPLOT Distribution of Daily Returns
ggplot(data = bitcoin_returns, mapping = aes(x = coredata(bitcoin_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of Bitcoin Daily Returns",
       x = "Daily Return Values (%)",
       y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of Bitcoin Daily Returns.png")

############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
###########

## 1 Statistical Summary

bitcoin_ret_summary <- fBasics::basicStats(bitcoin_returns, ci = 0.95)
bitcoin_ret_summary <- as.data.frame(bitcoin_ret_summary)

# Save Summary
write.csv(bitcoin_ret_summary, "bitcoin_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(bitcoin_returns),
               file = "bitcoin_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(bitcoin_returns, lags = 1),
               file = "bitcoin_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(bitcoin_returns, lags = 5),
               file = "bitcoin_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(bitcoin_returns, lags = 12),
               file = "bitcoin_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(bitcoin_returns),
```

```
           file = "bitcoin_ADF_Test.txt")


## 7. LB-2(12)  Ljung–Box test statistic for serial correlation on the squared residuals with 12 lags respectively
capture.output(Box.test (bitcoin_returns, lag = 12, type = "Ljung-Box"),
           file = "bitcoin_LB12_Test.txt")

capture.output(Box.test (bitcoin_returns^2, lag = 12, type = "Ljung-Box"),
           file = "bitcoin_LB12_Squared_Test.txt")




############################## MEAN MODEL ############################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(bitcoin_returns, trace = TRUE,
                        test = "kpss", ic = c("bic")),
           file = "bitcoin_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL ###########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                     garchOrder = c(1,1)),
                        mean.model = list(armaOrder = c(3,1)),
                        distribution.model = "std")


############################## FIT GJR-GARCH MODEL ###############################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = bitcoin_returns)

capture.output(model_fit, file = "bitcoin_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?
```

```
################################ BACKTESTING OF
MODEL####################################
model_roll <- rugarch::ugarchroll(spec = model_spec, data = bitcoin_returns,
                        n.ahead = 1,
                        n.start = 150, refit.every = 30,
                        refit.window = "recursive"
                        )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
          file = "bitcoin_BackestConf99_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
          file = "bitcoin_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
          file = "bitcoin_BackestConf95_results.txt")

# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################## BOOTSTRAPPING ################################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Squared_Test.txt")


set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
           custom.dist = list(name = "sample", distfit = myz, type = "myz"),
           rseed = 10)

sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)
```

```
VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])

VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])

############################ VAR AND ES ESTIMATES
###################################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")

write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```

8.2.2 Ethereum

```
################## IMPORT NEEDED LIBRARIES
#############################################
library(quantmod)
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET
#########################################################
df <- read.csv.zoo("master_dataset.csv")
```

```
ethereum_df <- df$ethereum

########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE
##########################
ethereum_returns <- log(ethereum_df / lag(ethereum_df,-1)) * 100

#ethereum_returns_num <- coredata(ethereum_returns)


# GGPLOT Daily Returns
ggplot(data = ethereum_returns, mapping = aes(index(ethereum_returns),
                                              coredata(ethereum_returns))) +
  geom_line() +
  labs(title = "Daily Returns of ethereum",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of ethereum.png")

# GGPLOT Daily Returns Squared
ggplot(data = ethereum_returns, mapping = aes(index(ethereum_returns),
                                              coredata(ethereum_returns)^2)) +
  geom_line() +
  labs(title = "Daily Logarithmic Returns of ethereum",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of ethereum.png")

# GGPLOT Distribution of Daily Returns
ggplot(data = ethereum_returns, mapping = aes(x = coredata(ethereum_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of ethereum Daily Returns",
       x = "Daily Return Values (%)",
       y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of ethereum Daily Returns.png")
```

```
############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
###########

## 1 Statistical Summary

ethereum_ret_summary <- fBasics::basicStats(ethereum_returns, ci = 0.95)
ethereum_ret_summary <- as.data.frame(ethereum_ret_summary)

# Save Summary
write.csv(ethereum_ret_summary, "ethereum_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(ethereum_returns),
        file = "ethereum_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(ethereum_returns, lags = 1),
        file = "ethereum_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(ethereum_returns, lags = 5),
        file = "ethereum_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(ethereum_returns, lags = 12),
        file = "ethereum_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(ethereum_returns),
        file = "ethereum_ADF_Test.txt")


## 7. LB-2(12)  Ljung–Box test statistic for serial correlation on the squared residuals with 12
lags respectively
capture.output(Box.test (ethereum_returns, lag = 12, type = "Ljung-Box"),
        file = "ethereum_LB12_Test.txt")

capture.output(Box.test (ethereum_returns^2, lag = 12, type = "Ljung-Box"),
        file = "ethereum_LB12_Squared_Test.txt")
```

```
############################## MEAN MODEL
###########################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(ethereum_returns, trace = TRUE,
                        test = "kpss", ic = c("bic")),
        file = "ethereum_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL
###########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                        garchOrder = c(1,1)),
                        mean.model = list(armaOrder = c(2,0)),
                        distribution.model = "std")


############################## FIT GJR-GARCH MODEL
##############################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = ethereum_returns)

capture.output(model_fit, file = "ethereum_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?

############################### BACKTESTING OF
MODEL###################################
model_roll <- rugarch::ugarchroll(spec = model_spec, data = ethereum_returns,
                        n.ahead = 1,
                        n.start = 150, refit.every = 30,
                        refit.window = "recursive"
                        )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
        file = "ethereum_BackestConf99_results.txt")
```

```
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
        file = "ethereum_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
        file = "ethereum_BackestConf95_results.txt")

# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################## BOOTSTRAPPING ##############################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
        file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
        file = "standardized_LB12_Squared_Test.txt")

standadized_residuals <- standadized_residuals[2:997]

set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
         custom.dist = list(name = "sample", distfit = myz, type = "myz"),
         rseed = 10)

sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)

VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])

VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])
```

```
############################ VAR AND ES ESTIMATES
####################################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")

write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```

8.2.3 Litecoin

```
################## IMPORT NEEDED LIBRARIES
############################################
library(quantmod)
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET
########################################################
df <- read.csv.zoo("master_dataset.csv")

litecoin_df <- df$litecoin

########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE
##########################
litecoin_returns <- log(litecoin_df / lag(litecoin_df,-1)) * 100

#litecoin_returns_num <- coredata(litecoin_returns)


# GGPLOT Daily Returns
ggplot(data = litecoin_returns, mapping = aes(index(litecoin_returns),
                                   coredata(litecoin_returns))) +
  geom_line() +
```

```
  labs(title = "Daily Returns of litecoin",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of litecoin.png")

# GGPLOT Daily Returns Squared
ggplot(data = litecoin_returns, mapping = aes(index(litecoin_returns),
                                        coredata(litecoin_returns)^2)) +
  geom_line() +
  labs(title = "Daily Logarithmic Returns of litecoin",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of litecoin.png")

# GGPLOT Distribution of Daily Returns
ggplot(data = litecoin_returns, mapping = aes(x = coredata(litecoin_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of litecoin Daily Returns",
       x = "Daily Return Values (%)",
       y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of litecoin Daily Returns.png")

############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
###########

## 1 Statistical Summary

litecoin_ret_summary <- fBasics::basicStats(litecoin_returns, ci = 0.95)
litecoin_ret_summary <- as.data.frame(litecoin_ret_summary)

# Save Summary
write.csv(litecoin_ret_summary, "litecoin_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(litecoin_returns),
```

```
            file = "litecoin_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(litecoin_returns, lags = 1),
            file = "litecoin_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(litecoin_returns, lags = 5),
            file = "litecoin_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(litecoin_returns, lags = 12),
            file = "litecoin_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(litecoin_returns),
            file = "litecoin_ADF_Test.txt")


## 7. LB-2(12)  Ljung–Box test statistic for serial correlation on the squared residuals with 12
lags respectively
capture.output(Box.test (litecoin_returns, lag = 12, type = "Ljung-Box"),
            file = "litecoin_LB12_Test.txt")

capture.output(Box.test (litecoin_returns^2, lag = 12, type = "Ljung-Box"),
            file = "litecoin_LB12_Squared_Test.txt")




############################## MEAN MODEL
############################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(litecoin_returns, trace = TRUE,
                        test = "kpss", ic = c("bic")),
            file = "litecoin_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL
###########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                    garchOrder = c(1,1)),
                       mean.model = list(armaOrder = c(3,1)),
                       distribution.model = "std")
```

```
###########FIT GJR-GARCH MODEL ###############################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = litecoin_returns)

capture.output(model_fit, file = "litecoin_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?

#################### BACKTESTING OF MODEL##################################
model_roll <- rugarch::ugarchroll(spec = model_spec, data = litecoin_returns,
                        n.ahead = 1,
                        n.start = 150, refit.every = 30,
                        refit.window = "recursive"
                        )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
          file = "litecoin_BackestConf99_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
          file = "litecoin_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
          file = "litecoin_BackestConf95_results.txt")

# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################ BOOTSTRAPPING ##############################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
```

```
            file = "standardized_LB12_Squared_Test.txt")


set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
             custom.dist = list(name = "sample", distfit = myz, type = "myz"),
             rseed = 10)

sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)

VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])

VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])

####################VAR AND ES ESTIMATES ##################################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")

write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```

8.2.4 Monero

```
################# IMPORT NEEDED LIBRARIES
##########################################
library(quantmod)
```

```
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET
########################################################
df <- read.csv.zoo("master_dataset.csv")

monero_df <- df$monero

########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE
##########################
monero_returns <- log(monero_df / lag(monero_df,-1)) * 100

#monero_returns_num <- coredata(monero_returns)


# GGPLOT Daily Returns
ggplot(data = monero_returns, mapping = aes(index(monero_returns),
                                coredata(monero_returns))) +
  geom_line() +
  labs(title = "Daily Returns of monero",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of monero.png")

# GGPLOT Daily Returns Squared
ggplot(data = monero_returns, mapping = aes(index(monero_returns),
                                coredata(monero_returns)^2)) +
  geom_line() +
  labs(title = "Daily Logarithmic Returns of monero",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of monero.png")
```

```
# GGPLOT Distribution of Daily Returns
ggplot(data = monero_returns, mapping = aes(x = coredata(monero_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of monero Daily Returns",
       x = "Daily Return Values (%)",
       y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of monero Daily Returns.png")

############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
############

## 1 Statistical Summary

monero_ret_summary <- fBasics::basicStats(monero_returns, ci = 0.95)
monero_ret_summary <- as.data.frame(monero_ret_summary)

# Save Summary
write.csv(monero_ret_summary, "monero_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(monero_returns),
           file = "monero_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(monero_returns, lags = 1),
           file = "monero_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(monero_returns, lags = 5),
           file = "monero_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(monero_returns, lags = 12),
           file = "monero_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(monero_returns),
           file = "monero_ADF_Test.txt")
```

7. LB-2(12) Ljung–Box test statistic for serial correlation on the squared residuals with 12 lags respectively

```
capture.output(Box.test (monero_returns, lag = 12, type = "Ljung-Box"),
          file = "monero_LB12_Test.txt")

capture.output(Box.test (monero_returns^2, lag = 12, type = "Ljung-Box"),
          file = "monero_LB12_Squared_Test.txt")




############################## MEAN MODEL
###########################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(monero_returns, trace = TRUE,
                        test = "kpss", ic = c("bic")),
          file = "monero_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL
##########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                       garchOrder = c(1,1)),
                       mean.model = list(armaOrder = c(2,0)),
                       distribution.model = "std")


############################## FIT GJR-GARCH MODEL
#############################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = monero_returns)

capture.output(model_fit, file = "monero_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?

############################### BACKTESTING OF
MODEL###################################
```

```
model_roll <- rugarch::ugarchroll(spec = model_spec, data = monero_returns,
                        n.ahead = 1,
                        n.start = 150, refit.every = 30,
                        refit.window = "recursive"
                        )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
          file = "monero_BackestConf99_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
          file = "monero_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
          file = "monero_BackestConf95_results.txt")

# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################## BOOTSTRAPPING ###############################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Squared_Test.txt")


set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
           custom.dist = list(name = "sample", distfit = myz, type = "myz"),
           rseed = 10)

sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)

VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])
```

```
VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])

############################ VAR AND ES ESTIMATES
###################################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")

write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```

8.2.5 Ripple

```
################## IMPORT NEEDED LIBRARIES
#############################################
library(quantmod)
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET
########################################################
df <- read.csv.zoo("master_dataset.csv")

ripple_df <- df$ripple
```

```
########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE
##########################
ripple_returns <- log(ripple_df / lag(ripple_df,-1)) * 100

#ripple_returns_num <- coredata(ripple_returns)


# GGPLOT Daily Returns
ggplot(data = ripple_returns, mapping = aes(index(ripple_returns),
                          coredata(ripple_returns))) +
  geom_line() +
  labs(title = "Daily Returns of ripple",
     x = "Year",
     y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of ripple.png")

# GGPLOT Daily Returns Squared
ggplot(data = ripple_returns, mapping = aes(index(ripple_returns),
                          coredata(ripple_returns)^2)) +
  geom_line() +
  labs(title = "Daily Logarithmic Returns of ripple",
     x = "Year",
     y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of ripple.png")

# GGPLOT Distribution of Daily Returns
ggplot(data = ripple_returns, mapping = aes(x = coredata(ripple_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of ripple Daily Returns",
     x = "Daily Return Values (%)",
     y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of ripple Daily Returns.png")

############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
###########
```

```
## 1 Statistical Summary

ripple_ret_summary <- fBasics::basicStats(ripple_returns, ci = 0.95)
ripple_ret_summary <- as.data.frame(ripple_ret_summary)

# Save Summary
write.csv(ripple_ret_summary, "ripple_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(ripple_returns),
          file = "ripple_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(ripple_returns, lags = 1),
          file = "ripple_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(ripple_returns, lags = 5),
          file = "ripple_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(ripple_returns, lags = 12),
          file = "ripple_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(ripple_returns),
          file = "ripple_ADF_Test.txt")


## 7. LB-2(12)  Ljung–Box test statistic for serial correlation on the squared residuals with 12 lags respectively
capture.output(Box.test (ripple_returns, lag = 12, type = "Ljung-Box"),
          file = "ripple_LB12_Test.txt")

capture.output(Box.test (ripple_returns^2, lag = 12, type = "Ljung-Box"),
          file = "ripple_LB12_Squared_Test.txt")



############### MEAN MODEL ############################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(ripple_returns, trace = TRUE,
                         test = "kpss", ic = c("bic")),
```

```
            file = "ripple_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL
###########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                               garchOrder = c(1,1)),
                          mean.model = list(armaOrder = c(1,0)),
                          distribution.model = "std")


############### FIT GJR-GARCH MODEL ###################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = ripple_returns)

capture.output(model_fit, file = "ripple_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?

############################### BACKTESTING OF
MODEL####################################
model_roll <- rugarch::ugarchroll(spec = model_spec, data = ripple_returns,
                          n.ahead = 1,
                          n.start = 150, refit.every = 30,
                          refit.window = "recursive"
                          )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
            file = "ripple_BackestConf99_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
            file = "ripple_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
            file = "ripple_BackestConf95_results.txt")
```

```
# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################## BOOTSTRAPPING ###############################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
          file = "standardized_LB12_Squared_Test.txt")


set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
            custom.dist = list(name = "sample", distfit = myz, type = "myz"),
            rseed = 10)

sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)

VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])

VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])

############################ VAR AND ES ESTIMATES ########################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")
```

```
write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```

8.2.6 Stellar

```
################# IMPORT NEEDED LIBRARIES ################################
library(quantmod)
library(zoo)
library(ggplot2)
library(FinTS)
library(e1071)
library(tseries)
library(forecast)
library(rugarch)

########## LOADING OF DATASET ########################################
df <- read.csv.zoo("master_dataset.csv")

stellar_df <- df$stellar

########### CALCULATION OF LOGARITHMIC RETURNS AS PERCENTAGE ###############
stellar_returns <- log(stellar_df / lag(stellar_df,-1)) * 100

#stellar_returns_num <- coredata(stellar_returns)


# GGPLOT Daily Returns
ggplot(data = stellar_returns, mapping = aes(index(stellar_returns),
                                coredata(stellar_returns))) +
  geom_line() +
  labs(title = "Daily Returns of stellar",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Daily Returns plot
ggsave("Daily Returns of stellar.png")

# GGPLOT Daily Returns Squared
ggplot(data = stellar_returns, mapping = aes(index(stellar_returns),
                                coredata(stellar_returns)^2)) +
```

```
  geom_line() +
  labs(title = "Daily Logarithmic Returns of stellar",
       x = "Year",
       y = "Daily Returns (%)") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Squared Daily Returns plot
ggsave("Daily Returns Squared of stellar.png")

# GGPLOT Distribution of Daily Returns
ggplot(data = stellar_returns, mapping = aes(x = coredata(stellar_returns))) +
  geom_histogram(fill = "black") +
  labs(title = "Distribution of stellar Daily Returns",
       x = "Daily Return Values (%)",
       y = "Frequency") +
  theme(plot.title = element_text(hjust = 0.5))

# Save Histogram of Daily Returns
ggsave("Distribution of stellar Daily Returns.png")

############ STATISTICAL PRETESTING OF DATASET FOR GARCH MODELLING SUITABILITY
###########

## 1 Statistical Summary

stellar_ret_summary <- fBasics::basicStats(stellar_returns, ci = 0.95)
stellar_ret_summary <- as.data.frame(stellar_ret_summary)

# Save Summary
write.csv(stellar_ret_summary, "stellar_Ret_Summary.csv")

## 2. Jarque-Bera test
capture.output(tseries::jarque.bera.test(stellar_returns),
               file = "stellar_JB_Test.txt")


## 5. The ARCH test
capture.output(FinTS::ArchTest(stellar_returns, lags = 1),
               file = "stellar_ARCH1_Test.txt")

capture.output(FinTS::ArchTest(stellar_returns, lags = 5),
               file = "stellar_ARCH5_Test.txt")

capture.output(FinTS::ArchTest(stellar_returns, lags = 12),
```

```r
          file = "stellar_ARCH12_Test.txt")

## 6. ADF test
capture.output(tseries::adf.test(stellar_returns),
          file = "stellar_ADF_Test.txt")


## 7. LB-2(12)  Ljung–Box test statistic for serial correlation on the squared residuals with 12
lags respectively
capture.output(Box.test (stellar_returns, lag = 12, type = "Ljung-Box"),
          file = "stellar_LB12_Test.txt")

capture.output(Box.test (stellar_returns^2, lag = 12, type = "Ljung-Box"),
          file = "stellar_LB12_Squared_Test.txt")




############################## MEAN MODEL
############################################
# Get the best ARIMA model for the mean modelling of the GARCH model
capture.output(forecast::auto.arima(stellar_returns, trace = TRUE,
                         test = "kpss", ic = c("bic")),
          file = "stellar_Best_ARMAorder.txt")

############################## SPECIFY GARCH MODEL
###########################################
model_spec <- rugarch::ugarchspec(variance.model = list(model = "sGARCH",
                                    garchOrder = c(1,1)),
                       mean.model = list(armaOrder = c(2,0)),
                       distribution.model = "std")


############################## FIT GJR-GARCH MODEL
###############################################
model_fit <- rugarch::ugarchfit(spec =  model_spec, data = stellar_returns)

capture.output(model_fit, file = "stellar_sGARCH_Model_Summary.txt")

#plot(model_fit, which="all")


#mean: mu
#constant: omega
```

```
#ARCH term: alpha1
#GARCH term: beta1
#Gamma: gamma1
# Indicator function?

################################ BACKTESTING OF
MODEL##################################
model_roll <- rugarch::ugarchroll(spec = model_spec, data = stellar_returns,
                    n.ahead = 1,
                    n.start = 150, refit.every = 30,
                    refit.window = "recursive"
                    )


# save backtesting results
capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.99),
        file = "stellar_BackestConf99_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.975),
        file = "stellar_BackestConf975_results.txt")

capture.output(report(model_roll, type = "VaR", VaR.alpha = 0.01, conf.level = 0.95),
        file = "stellar_BackestConf95_results.txt")

# Success/Fail Ratio - Expected Exceed / Actual Exceed
# Unconditional Coverage - Proportion Of Failure (POF) Kupiece Test p-value
# Conditional Coverage - Christoffersen Test p-value

############################## BOOTSTRAPPING ###############################
standadized_residuals <- model_fit@fit$residuals / model_fit@fit$sigma

capture.output(Box.test (standadized_residuals, lag = 12, type = "Ljung-Box"),
        file = "standardized_LB12_Test.txt")

capture.output(Box.test (standadized_residuals^2, lag = 12, type = "Ljung-Box"),
        file = "standardized_LB12_Squared_Test.txt")


set.seed(123)
myz <- matrix(sample(standadized_residuals, size = 1000000, replace = TRUE), nrow = 10)

sim1<- ugarchsim(model_fit, n.sim = 10, m.sim = 100000, startMethod = "sample",
          custom.dist = list(name = "sample", distfit = myz, type = "myz"),
          rseed = 10)
```

```
sims <- sim1@simulation$seriesSim

hypo_rets <- colSums(sims)

VaR_010 <- quantile(hypo_rets, p = 0.10)
ES_010 <- mean(hypo_rets[hypo_rets < VaR_010])

VaR_005 <- quantile(hypo_rets, p = 0.05)
ES_005 <- mean(hypo_rets[hypo_rets < VaR_005])

VaR_025 <- quantile(hypo_rets, p = 0.025)
ES_025 <- mean(hypo_rets[hypo_rets < VaR_025])

VaR_001 <- quantile(hypo_rets, p = 0.01)
ES_001 <- mean(hypo_rets[hypo_rets < VaR_001])

############################# VAR AND ES ESTIMATES
####################################

write(VaR_010, file = "VaR_01.txt")
write(ES_010, file = "ES_010.txt")

write(VaR_005, file = "VaR_005.txt")
write(ES_005, file = "ES_005.txt")

write(VaR_025, file = "VaR_025.txt")
write(ES_025, file = "ES_025.txt")

write(VaR_001, file = "VaR_001.txt")
write(ES_001, file = "ES_001.txt")
```